APPLICATION OF NEURAL NETWORKS IN PAVEMENT MANAGEMENT

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by

SJ BREDENHANN Pr.Eng, B.Eng (Stell.)

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Prof. MFC van de Ven, Ir, Ing
Study Leader

Prof F Hugo, Pr. Eng, PhD, Ding
Internal Examiner

Mr MG Henderson, Pr. Eng, Msc (Eng), GDE
External Examiner

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Stellenbosch

DECLARATION

I, the undersigned, do hereby declare that the work contained in this Thesis is my own original work and has not been submitted previously in its entirety or in part at any university for a degree.

SJ BREDENHANN

SYNOPSIS

The intent of this thesis is to examine the solving of problems with neural networks. Three cases are investigated: the calculation of a Visual Condition Index (VCI), the determination of the reseal need, and the back-calculation of E-moduli from measured deflection basins.

The calculation of a Visual Condition Index (VCI) is a very good example of how a neural network can be applied to reach a conclusion through the association of a number of facts with one single outcome. Visual assessments of the road condition are done on a yearly basis and the Assessor gives his impression of the condition of a road. A neural network simulates the association between the inputs of elements of distress on the road and the eventual assessment of the overall condition expressed as the VCI, very well.

Reseal need is determined by the Provincial Administration: Western Cape (PAWC) with a Reseal Expert System. Data produced by the expert system was used to train a neural network to determine the reseal need. The strength of using these two methods in combination is shown. Meaningful results could not be obtained due to insufficient data in certain categories.

Deflection measurements with a Falling Weight Deflectometer are meaningful indicators of pavement strength. Back-calculation is used to calculate E-moduli of pavement layers which can be used in a mechanistic approach to estimate remaining pavement life from pavement response. Conventional back-calculation programs, when implemented in a pavement management system, result in very long computing times due to the large volumes of data available. Neural networks offer the alternative of very fast processing, making the implementation of back-calculation in real-time possible. It is shown that neural networks can back-calculate E-moduli, but with varying degrees of success. The main problem identified is the basis on which the dataset used to train neural networks, is generated using linear elastic theory. The biggest limitation in the linear elastic theory is that non-linear and stress dependent behaviour of materials cannot be simulated, two aspects that have a major influence on the back-calculated E-moduli. Improvements in the data generation process using a theory that accommodates non-linear and stress dependent behaviour of materials may result in improved performance of the neural networks. It is also shown that it is very difficult to design a single neural network that can be successfully used on all the possible pavement types. It is better to identify representative pavement types and train neural networks for each of these.

Neural networks can be applied with success in the pavement management field and the combination of Expert Systems, Neural Networks and Fuzzy Logic can be a very powerful method to solve complicated problems. Care should be taken in the design of the neural networks and a good understanding of the data is a prerequisite for success.

SAMEVATTING

Die bedoeling met die tesis is om die vermoë van neurale netwerke om probleme op te los, te ondersoek. Drie gevalle word beskou: die berekening van 'n Visuele Toestand Indeks (VTI), die bepaling van die herseël behoefte en die terugberekening van die E-moduli vanaf defleksie metings.

Die berekening van die VTI demonstreer die vermoë van neurale netwerke om,deur middel van die assosiasie tussen 'n hele aantal veranderlikes tot 'n enkele uitkoms, tot 'n gevolgtrekking te kom. Visuele opnames van paaie word op 'n jaarlikse basis gedoen waar die opnemer sy indrukke gee van die toestand van die pad. 'n Neurale netwerk simuleer die assosiasie tussen die insette (waargenome gebreke) en die uiteindelike toestands beskrywing van die pad, uitgedruk as die VTI, baie goed.

Die Provinsiale Administrase: Wes-Kaap bepaal die jaarlikse herseëlbehoefte met behulp van 'n Herseël Ekspertstelsel. Die uitsette van hierdie stelsel is gebruik om 'n neurale netwerk op te lei om die herseëlbehoefte te bepaal. Die voordele om die twee stelsels saam aan te wend, word getoon. Betekenisvolle resultate kom nie bekom word nie vanweë onvoldoende inligting in sekere kategorieë.

Defleksiemetings deur 'n vallende-gewig meetapparaat is betekenisvolle indikators van die plaveiselsterkte. Die E–moduli van die plaveisellae word bepaal deur terugberekenings vanaf defleksiemetings. Hierdie E-moduli kan gebruik word om met behulp van meganistiese metodes die oorblywende leeftyd van 'n plaveisel te bepaal. Konvensionele terugberekenings programme, geïmplementeer in 'n plaveiselbestuurstelsel, neem lank om die groot hoeveelheid defleksiemetings te verwerk. Neurale netwerke bied die alternatief van die intydse berekening van E-moduli vanweë die besonder hoë berekeningspoed wat behaal word. In hierdie tesis word aangetoon dat neurale netwerke aangewend kan word om die terugberekenigs te doen, maar met 'n wisselende mate van sukses. Die gebruik van die lineêre elastiese teorie om die data vir die neurale netwerke te genereer, word as 'n probleem geïdentifiseer. Die grootste tekortkoming wat met die lineêre elastiese teorie ondervind word is dat dit nie die nie-lineêre en spanningsafhanklike gedrag van materiale voldoende simuleer nie. Beide hierdie twee aspekte het 'n groot invloed op die akkuraatheid van terugberekende E-moduli. Verbeteringe in die generering van data deur 'n teorie te gebruik wat nie-lineêre en spanningsafhanklike gedrag van materiale behoorlik simuleer, mag lei tot 'n beter prestasie van die neurale netwerke. Dit word ook getoon dat dit moeilik is om 'n enkele neurale netwerk te ontwerp wat suksesvol gebruik kan word op alle plaveiseltipes. Dit is beter om verteenwoordigende plaveiseltipes te identifiseer en dan neurale netwerke vir elkeen te ontwerp.

Neurale netwerke kan met sukses in die plaveiselbestuur veld toegepas word en die kombinasie van ekspertstelsels, neurale netwerke en vaagheidstelsels (fuzzy) kan tot kragtige metodes lei om komplekse probleme op te los. Sorg moet aan die dag gelê word met die ontwerp van neurale netwerke en 'n goeie begrip van die data is 'n voorvereiste vir sukses.

DEDICATION

This thesis is dedicated to my wife, Douwleen, and two daughters, Stephanie and Rosanne. Without their understanding, love, support and encouragement this thesis would not have been possible.

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DISCLAIMER

The views, opinions and conclusions expressed in this thesis are those of the Author and do not represent PAWC, ENTECH or any other body.
The author cannot accept any liability for the consequences of the application of the findings expressed in this thesis.

LIST OF SUBJECTS COMPLETED

CODE	SUBJECT	CREDITS
	UNIVERSITY OF PRETORIA	
SHC789	Statistical Methods	4
SVC781	Transportation Planning	4
SVC782	Transportation Studies	4
SVC784	Traffic Flow Theory	4
	UNIVERSITY OF STELLENBOSCH	
DS02	Decision and Risk in Design	4
GP01	Pavement Materials I	4
GP02	Flexible Pavement Design School	4
GP03	Pavement Engineering	4
GP04	Pavement Construction (Pavement Management School)	2
GP05	Pavement Materials II (Advanced Course in Bitumen Technology)	2
	Additional Courses (Stellenbosch)	
TW01	Applied Mathematics	
GG04	Engineering Geology	
TOTAL		**36**

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EXECUTIVE SUMMARY

The work presented in this thesis is organised in five chapters:

The work done in Chapter 1 was prepared in 1998 and presented at the 4th International Conference on Managing Pavements in Durban in March 1998, as part of a tutorial on artificial intelligence. The presentation at the tutorial was part of the thesis that is required from the author. Additional work was done subsequently and added to this chapter to make the introduction to neural networks more complete.

The design of neural networks is very much a trial and error process so that Chapter 2 was included to give advice on the selection of neural networks, based on experienced gained with this thesis.

Chapters 3 – 5 describe some application of neural networks in the field of pavement management, demonstrating the strength of neural networks and showing some of the pitfalls in the application of this technology.

Chapter 6 summarizes the most important conclusions and recommendations for future research.

Artificial Intelligence is introduced using three subsets as examples: Expert Systems, Neural Networks and Fuzzy Logic. Emphasis is placed on neural networks and the application thereof in pavement management.

An expert system is a set of rules by which the input data can be analysed and is based on the knowledge and experience of a human expert. Expert systems are a special form of artificial intelligence that use deductive methods to simulate the decision making process of humans. A neural network is a network of interconnected elements with the function to produce an output pattern when presented with an input pattern. Similar to the brain an artificial neural network is also a network of interconnected elements (neurons) that receive and send information back and forth through connections. The strength of the connections is set by training the neural network and represents the association between the inputs (facts) and the outputs. A fuzzy system is a way of handling data, in some ways similar to neural networks and in some ways similar to expert systems. It is a problem solving method that can be applied to neural networks, expert systems and other computing methods. Neural networks and fuzzy systems are similar in that they both process inexact information inexactly. Expert Systems, Neural Networks and Fuzzy Logic can be used individually in problem solving or in combinations to improve results and better simulate the problem.

Neural networks operate much like a black box in the sense that no relationship is explained other than the set of weights. No equation is produced that can be understood and analysed by the user. It is therefore very important that a good understanding is obtained of the data domain being investigated and that a systematic approach is followed in the design of the neural network. It is very easy to present a lot of data to a neural network and obtain an answer within milliseconds, especially with the user-friendly software that can be downloaded from the Internet. The results obtained in such a way cannot be guaranteed.

The intent of this thesis is to show that a problem can be solved with a neural network by trying to think like a neural network. A neural network learns by association, quite similar to the human. Facts must be presented to the neural network and no association can be made outside the facts available, extrapolation is therefore not possible. Neural networks are, however, very good at interpolation (known as generalization by neural network users), explained by the associative nature of the neural network. If the user is willing to say: what would I do with these facts; how can I interprete these facts; and what more facts do I need to come to a conclusion, then he will be able to design a successful neural network delivering consistent good results.

The calculation of a Visual Condition Index (VCI) is a very good example of how a neural network can be applied to come to a conclusion through association of a lot of facts with one single outcome. Visual assessments of the road condition are done on a yearly basis and the Assessor gives his impression of the condition of a road. A neural network simulates the association between the inputs of elements of distress on the road and the eventual assessment of the overall condition expressed as the VCI, very well.

Reseal need is determined by the Provincial Administration: Western Cape (PAWC) with a Reseal Expert System. Data produced by the expert system was used to train a neural network to determine the reseal need. The strength of using these two methods in combination is shown. Meaningful results could not be obtained due to insufficient data in certain categories.

Deflection measurements with a Falling Weight Deflectometer are meaningful indicators of pavement strength. Back-calculation is used to back-calculate E-moduli of pavement layers that can be used in a mechanistic approach to estimate remaining pavement life from pavement response. Conventional back-calculation programs, when implemented in a pavement management system, result in very long computing times due to the large volumes of data available. Neural networks offer the alternative of very fast processing, making the implementation of back-calculation in real-time possible. It is shown that neural networks can back-calculate E-moduli, but with different degrees of success. The main problem identified is the basis on which the dataset used to train neural networks, is generated using linear elastic theory. The biggest limitation in the linear elastic theory is that non-linear and stress dependent behaviour of materials cannot be simulated, two aspects that have a major influence on the back-calculated E-moduli. Neural networks can back-calculate E-moduli very successfully from ideal deflection basins at lightning fast speeds. Improvements in the data generation process using a theory that accommodates non-linear and stress dependent behaviour of materials may result in improved performance of the neural networks. It is also shown that it is very difficult to design a single neural network that can be successfully used on all the possible pavement types. It is better to identify representative pavement types and train neural networks for each of these.

Neural networks can be applied with success in the pavement management field and the combination of Expert Systems, Neural Networks and Fuzzi Logic can be a very powerful method to solve complicated problems. Care should be taken in the design of the neural networks and a good understanding of the data is a prerequisite for success.

It is recommended that a panel of experts be appointed to investigate the modification of the VCI formula. Results obtained with the neural network can be used as a guideline to revise the TRH22 weight set and to adjust the constants in the VCI formula. As far as the reseal program is concerned, it is recommended that the dataset be augmented from historic reseal data and workshop sessions with experts to fill in data where inadequate data exists. Recommendations regarding the back-calculation of E-moduli are that programs be developed that either make use of finite element analysis or dynamic solutions to effectively simulate the non-linear behaviour of pavement materials, alternative neural network architectures be investigated, more variables be introduced and to add noise to the synthetic (simulated) deflection basins.

GLOSSARY OF TERMINOLOGY

(Lawrence, 1993)

Adaptability: The ability to modify a response to changing conditions and is produced by four processes.

Artificial Neural Network: A model made to simulate a biological neural system. It consists of highly interconnected neurons organised in layers.

Back-propagation: A supervised learning method in which an error signal is fed back through the network, altering weights as it goes.

Back-propagation Network: A feedforward network that uses the Back-Propagation Rule.

Back-propagation Rule: A variation of the Generalized Delta Rule for a network with hidden neurons.

Bias: Model has too little flexibility; number of degrees of freedom is large compared to the size of the dataset.

Computational energy: A mathematical function defining the stable states of a network and the paths leading to it.

Connection: A unique line of communication between two neurons along which signals are sent.

Convergence: The changing state of the network as it moves toward a stable state.

Curse of Dimensionality: Adding features to a neural network beyond a certain point.

Degradation: Reduced speed and/or accuracy.

Delta Rule: The learning rule that states that, if there is a difference between the actual output pattern and the desired output pattern during training, the weights are changed to reduce the difference.

Deterministic weight decay: An additional term introduced to the learning process to avoid small barriers in the weight space during convergence.

Dimensionality: The number of features evaluated with a neural network.

Dynamic stability: The ability of a network to remain within its functional boundaries and reach a stable state.

Energy function: A mathematical function that describes the energy state of a network.

Energy minima: Stable states; the valleys appearing when the computation energy is plotted as a curved surface.

Excitatory: The tendency of a connection to cause firing of the receiving neuron.

Expert systems: A program that uses rules and facts to solve a particular problem.

Fault tolerance: The ability to keep processing when a small number of neurons are disabled or destroyed.

Feedback network: A network in which neurons can take their inputs from any other neuron, including their own output.

Feedforward network: A network in which neurons take their inputs from the previous layer only.

Fuzzy: unclear, indistinct, noisy.

Fuzzy Logic: Processing information that is ambiguous.

Generalization: The ability of a network to formulate an answer to a problem it has never seen before by using related or similar information.

Generalized Delta Rule: A variation of the Delta Rule.

Gradient: The maximum rate of change in a variable or function.

Hidden layer: A layer of neurons in an artificial neural network that does not connect to the outside world, but connects to other layers of neurons.

Inhibitory: The tendency of a connection to prevent firing of a receiving neuron.

Knowledge base: The definable portion of an expert system that contains rules and facts.

Learning: The process of repeatedly presenting information to a neural network so that it can learn and leaning occurs as changes to the weights.

Learning rate: A factor to scale all connections while learning; intended to improve the speed of convergence of the network.

Learning rule: An equation that tells the network how to modify its weights.

Local minima: A "trap" sometimes found with gradient descent. It looks like the lowest place but it isn't.

Localization: A phenomenon that occurs when a set of neurons that are close together, receives a set of signals in parallel and responds as a unit.

Mapping: The transformation of the inputs into an internal representation in the network such that the topological relations of the inputs are similar to those of the internal representation.

Memorization: A network's ability to produce the desired output when given input data that it saw during training.

Neuron: A processing element that has a number of inputs and a single output. The inputs are summed and compared against a threshold value, and if the threshold value is reached, an output signal is generated.

Noise: Irrelevant or imprecise data present in input patterns; or random values added to all weights to prevent the network from getting stuck in local minima; or imprecise data purposely put in the initial state to improve a network's accuracy.

Normalization: An adjustment that keeps weights within a prescribed range of acceptable limits.

Pattern recognition: The ability to recognise a set of input data instantaneously and without conscious thought.

Period of Latent Summation: The time taken to aggregate the inputs at a neuron.

Plasticity: The ability of a group of neurons to adapt their functions to different needs over time.

Processing element: A neuron.

Refractory Period: The neuron is in a state of non-excitability for a certain time after firing.

Reinforcement learning: No information is supplied as to whether the network outputs are good or bad and again no actual designed values are given.

Rule: A statement in an expert system.

Self-organization: When a network modifies all its neurons at once according to a learning rule.

Stable state: A stable state is reached when a network settles into a fixed pattern after a process of reaction-stimulation-reaction between neurons.

State of a neuron: At a certain time can be discrete or continuous, but not both.

Supervised learning: At each instant of time when the input is applied, the teacher provides the desired response of the system.

Temporal association: The mechanism by which timed sequences are memorized and reconstructed.

Temporal patterns: Sequences of spatial patterns.

Training: See learning.

Transfer function: A mathematical function applied to the neuron's activation value to generate the neuron's output.

Threshold: A response is only realised (the neuron fires) if the sum of the incoming impulses exceeds the inhibition by a certain *threshold.*

Unsupervised learning: The desired response is not known and learning must be accomplished based on observation of responses to inputs for which marginal or no knowledge exists.

Variance: Model has too much flexibility; number of degrees of freedom small compared to the size of the dataset.

Weight: Value assigned to each connection at the input of a neuron.

LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BCI	Base Curvature Index
BDI	Base Damage Index
BLI	Base Layer Index (refer SCI)
COLTO	Committee of Land Transport Officials
CSRA	Committee of State Road Authorities (superseded by COLTO)
DOT	Department of Transport
DR	District road
FWD	Falling Weight Deflectometer
LLI	Lower Layer Index (refer BCI)
MLI	Middle Layer Index (refer BDI)
MR	Main road
MSE	Mean Square Error
NN	Neural Network
OPC	Overall Pavement Condition
PMES	Pavement Management Expert System
RMSE	Root Mean Square Error
SANRA	South African National Roads Agency
SCI	Surface Curvature Index
SHRP	Strategic Highway Research Program
SI	Structural Index
TR	Trunk road
PAWC	Provincial Administration Western Cape
PMS	Pavement Management System
TMH	Technical Methods for Highways
TRH	Technical Recommendations for Highways
VCI	Visual Condition Index

LIST OF SYMBOLS

a_j	Transfer function
B	Depth to stiff layer
D	Deflection measured with FWD
D_n	Degree rating
E	Young's modulus
E_n	Extent rating
F_n	Product of degree and extent rating and weight of defect
H	Layer thickness
M_r	Resilient modulus
N_j	Excitation level of a processing element modelled mathematically as a weighted sum of its inputs
R	Offset of geophone on FWD
S_n	Small degree factor
W_n	Weight per item in visual assessment
Y_n	Extent weight factor
α	Learning rate
β	Momentum factor
δ_j	Gradient of the error surface
θ	Bulk stress
θ_j	Threshold value
σ	Stress
τ_{oct}	Octahedral shear stress
d_{ci}	Calculated deflection at offset *i*
d_{mi}	Measured deflection at *i*
n_d	Number of deflections in basins
p_a	Atmospheric pressure
x_i	Signal strength coming from the i^{th} processing elements in the proceeding layer
w_{ij}	Weight assigned to a connection

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QUALIFICATION

The South African decimal system requires a comma as the decimal. In this thesis a point will be used to be consistent with computer printouts where the point is used as the decimal.

Where no reference is made in captions to Tables or Figures, those tables or figures were produced by the author.

CHAPTER 1

1 INTRODUCTION TO NEURAL NETWORKS AND EXPERT SYSTEMS AND THEIR USE IN PAVEMENT MANAGEMENT SYSTEMS

1.1 INTRODUCTION

The work in this chapter was done by the author in 1998 and presented at the 4th International Conference on Managing Pavements in Durban in March 1998, as part of a tutorial on artificial intelligence. The presentation at the tutorial was part of the thesis that is required from the author. Additional work was done subsequently and added to this chapter to make the introduction to neural networks more complete.

Expert systems are well known to civil engineers and are widely applied in pavement management and pavement rehabilitation design. They are easy to understand due to the logical processes that are followed which greatly simulate the human thought process. More recently neural networks, as a subset of artificial intelligence, were introduced in problem solving as, in some cases, an alternative to expert systems and in other cases to compliment the expert systems.

Expert systems are a special form of artificial intelligence and it would therefore be wrong to see only neural networks as an artificial intelligence application. The definition of artificial intelligence may cloud the importance of neural networks or expert systems. This chapter will concentrate on the applicability of the two methods and how they compliment each other, with special emphasis on neural networks. Fuzzy Logic will only be touched on and will not be discussed in any extent.

A neural network is called such because it is a network of neurons, all interconnected, just as the brain is composed of neurons. A typical neuron receives input from many neurons and when a threshold level is reached the neuron reacts (or fires) giving input to many other neurons eventually producing an output pattern (Picton, 1994).

Artificial neural networks exhibit many characteristics attributed to human intelligence: they can reason deductively; they perform complex mathematical calculations; they can learn new solutions to old problems; they display good judgement and massive knowledge (Lawrence, 1993). Artificial neural networks learn by association and deduce results from examples.

A neural network is normally associated with the brain and the nervous system, while the term *artificial* neural network is used when reference is made to a computer simulation of a neural network. Further on in this thesis discussions and references to neural networks should be interpreted as being artificial neural networks. A reference to *neural network* should be read as an abbreviation of *artificial neural network*.

1.2 INTRODUCTION TO ARTIFICIAL INTELLIGENCE

Artificial intelligence as discussed here, is seen as comprising mainly of artificial neural networks, expert systems and fuzzy logic systems. A short description of each process is given.

1.2.1 The Human Brain as a Role Model

The human brain, a portion of the central nervous system, is a mass of pinkish-gray tissue composed of billions of nerve cells (neurons) all connected through dendrites, axons and synapses. These neurons send information back and forth to each other through the dendrites/axons; the result is an intelligent being capable of learning, analysis, prediction and recognition (Lawrence, 1993).

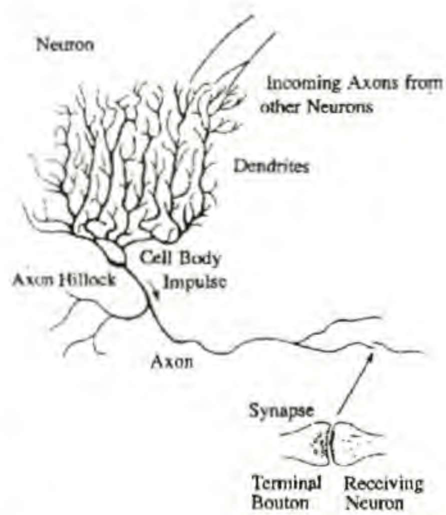


Figure 1-1: Schematic diagram of a neuron (Zurada, 1992)

Zurada (1992) describes the central nervous system in Figure 1-2 and states that the human brain consists of approximately 10^{11} neurons and that each neuron is connected to approximately 10^4 synapses per neuron. The central nervous system and especially the brain can therefore be best described as a neural network.

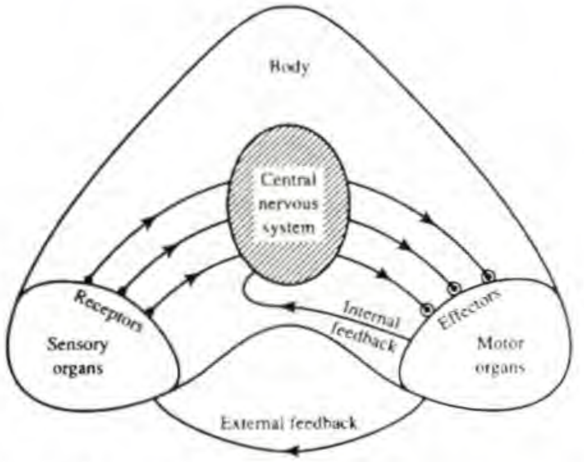


Figure 1-2: Information flow in central nervous

A schematic diagram of a neuron is given in Figure 1-1 (Zurada, 1992). The three major regions of the nerve cell, e.g. the cell body (soma), the axon and dendrites are shown. Dendrites receive information from neurons through axons. The axon-dendrite contact organ is called a synapse and this is where the neuron introduces its signal to the neighbouring neuron.

The operation of a neuron is complex, however, and an elementary description is necessary for gaining insight into neural networks. A receiving neuron either generates a pulse to its axon or produces no response. A response is only realised (the neuron fires) if the sum of the incoming impulses exceeds the inhibition by a certain *threshold*. Incoming pulses are either *excitatory* or *inhibitory* and a number of these pulses are required to fire a neuron. The time taken to aggregate the inputs is called the *period of latent summation* and after firing the neuron is in a state of non-excitability for a certain time called the *refractory period*. (Lawrence, 1993).

1.2.2 What are Neural Networks?

It was already stated that a neural network is a network of interconnected elements with the function to produce an output pattern when presented with an input pattern. Similar to the brain an artificial neural network is also a network of interconnected elements (neurons) that receive and send information back and forth through connections.

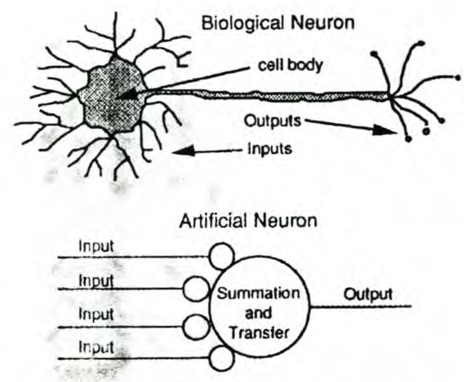


Figure 1-3: Comparison of artificial and biological neurons (Lawrence, 1993)

An artificial neuron is compared with a biological neuron in Figure 1-3 (Lawrence, 1993). A network of artificial interconnected neurons is called an artificial neural network. The artificial neurons in the neural network are highly connected and process information in parallel. The neurons in the neural network are usually organized in layers: an input layer, one or more hidden layer(s) and an output layer. Information flows from the input layer to the hidden layer, where the association between input and output is made, and then to the output layer. Hidden layers are hidden because they have no connections with the outside world.

A neural network learns by association: an output is guessed from the available inputs and with the feedback from the guess adjustments are made to improve the guess until a satisfactory level of confidence is reached.

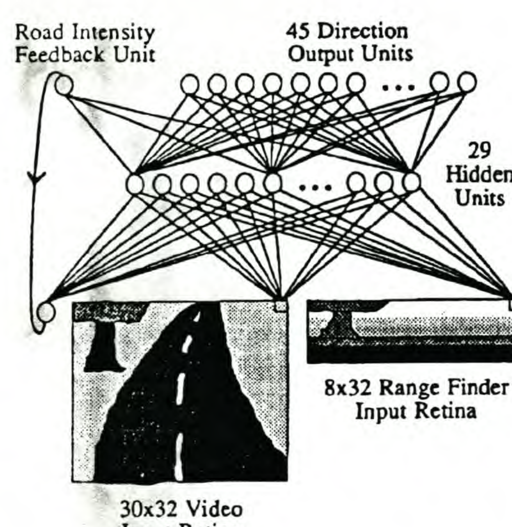


Figure 1-4: Autonomous vehicle driver (Zurada, 1992)

The architecture of the neural network ALVINN (Autonomous Land Vehicle in a Neural Network) is shown in Figure 1-4

(Zurada, 1992 after Pomerleau, 1989) demonstrating the most import elements of a neural network: an input layer, a hidden layer, an output layer, a feedback unit and the inter-connectivity of the network. The ALVINN network takes as input, road images from a camera and a laser range finder and produces, as output, and the direction in which a vehicle should travel.

Neural networks can either be constructed as a hardware model or simulators can be developed with specialized software. Quite a few of these software simulators are available. Hardware models are rather fixed in design and cannot be changed easily, while software simulators can be adjusted with relative ease. Hardware models usually have a marked advantage as far as speed of operation is concerned. With new developments in computer processor technology the software option will gain in popularity.

Lawrence (1993) gives a brief list of neural network abilities along with an example of each in Table 1-1

Table 1-1: Typical Neural Network Applications (Lawrence, 1993)

ABILITY OR TALENT	EXAMPLE APPLICATION
pattern recognition	identify submarines from sonar
generalization	assess real estate
trend prediction	decide when to buy and sell stock
behaviour prediction	predict outcome of surgery
evaluation	accept/deny loan applications
tolerant of messy data	optical character recognition
tolerant of incorrect data	predict non-court settlements
filtering	clean up video signals
fast operation	robot arm control
grasp subtle relationships	medical expert advice
graceful degradation	mechanical control in space
good at optimising	flight scheduling
analyse large amounts of data	correlate insurance claims
extrapolation	diagnose production failures

Neural networks are good at pattern recognition, modelling, control, signal filtering, noise reduction, image analyses, classification and evaluation, but are poor at deduction or logic thinking (Lawrence, 1993). For example, suppose a neural network is told that flowers are red, roses are flowers and Crimson Glories are roses, then the network will most probably not be able to deduce that Crimson Glories are red.

1.2.3 What are Expert Systems?

An expert system is a set of rules by which the input data can be analysed and is based on the knowledge and experience of a human expert. A prerequisite for an expert system is that the problem must be defined and that a clear understanding of the domain of the problem must exist. Expert systems are a special form of artificial intelligence that use deductive methods to simulate the decision making process of humans. Lawrence (1993) describes an expert system as:

- a computer program that contains a modifiable knowledge base (rules and facts),
- an interface to users, and
- an inference engine which makes logic-based decisions.

A knowledge base is similar to a database, but stores only facts and rules. The user interface gathers facts from the user by asking questions, reading instruments or data files to evaluate the current state of affairs. The user interface also provides information to the user on procedures to be followed while the inference engine is the part where rules and facts are processed by deductive reasoning to produce a result.

Rules in expert systems usually follow the form of **IF** (something is true) **THEN** (do something about it). Case statements are also often found in expert systems where a choice is allowed after the rule is established. It is therefore clear that to implement an expert system knowledge of a high level programming language is required in addition to knowledge required to understand the problem that is about to be solved.

Simple expert systems follow an all or nothing approach, it is assumed that a fact is either true or false. However, uncertainty is present in almost all problems so that probability must be accommodated in an expert system. The probability of a rule or fact can be determined by intuitive calculation based on experience and technical knowledge or can be measured. There are three commonly used techniques for dealing with uncertainties in expert systems: Bayesian analysis, Dempster-Shafer theory and fuzzy logic (Lawrence, 1993). Bayesian analysis is a method for calculating conditional probability, the probability of one event given the condition or occurrence of another event, therefore reflecting the likelihood that an event will happen. Dempster-Shafer theory includes Bayesian analysis and represents the degree to which the evidence supports the occurrence of a given event. Fuzzy logic allows for vagueness in contrast to uncertainty or probability.

1.2.4 What are Fuzzy Systems

Lawrence (1993) describes fuzzy systems as a way of handling data, in some ways similar to neural networks and in some ways similar to expert systems. It is a problem solving method that can be applied to neural networks, expert systems and other computing methods. Neural networks and fuzzy systems are similar in that they both process inexact information inexactly. It was shown that neural networks use examples rather than rules to recognise patterns. Fuzzy systems are similar to expert systems in that they both use rule-based logic during problem solving.

Fuzzy systems permit information to belong to more than one set or class. The principle of fuzzy sets may be summed up as the transformation of ambiguous and fuzzy information into numerical data in a systematic way so that subjective information such as expert opinions, rules of thumb and other non-quantifiable but significant information can be directly used in the solution process (Juang et al, 1993).

A number of analytical approaches to problem solving in civil engineering is listed in Table 1-2 (Juang et al, 1993).

Table 1-2: Analytic Approaches to Problem Solving in Civil Engineering (Juang et al, 1993)

Type of Approach	Type of Input Data	Model	Type of Output
I	non-fuzzy number	deterministic	non-fuzzy number
II	fuzzy number	deterministic	fuzzy number
III	non-fuzzy number	probabilistic	probability distribution
IV	fuzzy number	probabilistic	fuzzy probability
V	non-fuzzy number	fuzzy	fuzzy number
VI	fuzzy number	fuzzy	fuzzy number

The Type I approach is the most commonly used by the Engineer and requires considerable judgement and data of a quantitive nature in crisp, clear, numerical terms. Juang et al (1993) states that if a non-random uncertainty exists in the information from which the data is derived, the engineer will be faced with the burden of eliciting the numerical input from ambiguous or fuzzy information. In this case a Type I approach will be very difficult if not impossible and a Type II approach may be more appropriate, i.e. retaining the deterministic model, but with a fuzzy input and therefore output.

Fuzziness describes the ambiguous case, rather than the uncertainty of an occurrence and is almost always expressed in linguistic terms, which must then be transformed into numerical data. Rather than translating a linguistic term into a certain number (and ignoring the associated uncertainty), a fuzzy number may be used. (Juang et al, 1993). The statement "It's kind of hot to day" is an ambiguous fuzzy statement and we understand it is more hot than usual, but not very hot, i.e. perhaps it's a 35°C summer day. (Lawrence, 1993).

Fuzzy numbers can be grouped into four classes as shown in Figure 1-5 (Juang et al, 1993).

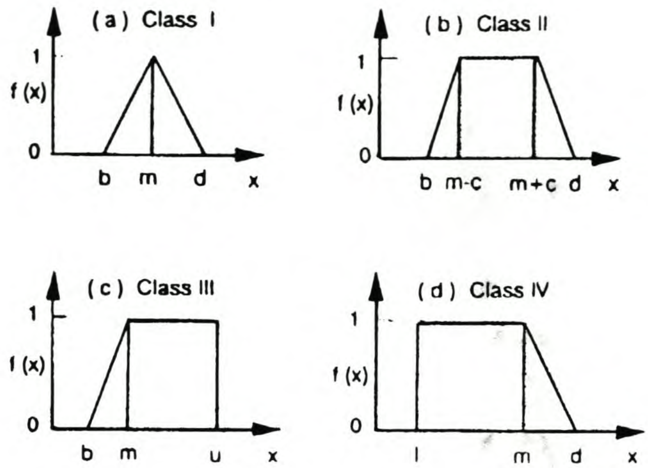


Figure 1-5: Four classes of fuzzy numbers (Juang et al, 1993)

The Class I fuzzy number is used to represent a fuzzy point estimate (FPE) or a linguistic term of "about m". The Class II fuzzy number is used to represent a fuzzy interval estimate (FIE) or a linguistic term such as "about from m - c to m + c". The Class III fuzzy number is used to represent the notion of "greater than about m" while the Class IV fuzzy number is used to represent the notion of "less than about m". (Juang et al, 1993)

1.3 EXPERT SYSTEMS VS ARTIFICIAL NEURAL NETWORKS

From the preceding discussion it is clear that the main difference between an artificial neural network and an expert system is that the neural network requires no understanding of the problem, but that full understanding of the problem is required with an expert system. Lawrence (1993) compares neural networks and expert systems as follows:

1.3.1 Neural Networks

Neural networks provide inductive power using examples. Their strength is the ability of instant pattern recognition; the learning by examples and the network can easily be expanded when new information becomes available. Neural networks are not easy to understand as their behaviour is based on the biological processes of the brain. With a neural network, however, one needs not to understand the problem and explain how the answer is derived. Relevant information is gathered and the network is trained.

1.3.2 Expert Systems

Expert systems are capable of deductive reasoning using rules. Their strength is the step-by-step logical, sequential operations depending on the rules. When new information becomes available, an expert system can easily be expanded to accept the new facts and rules. However, new information can in many cases mean the complete rewriting of the program. Expert systems may be easier to understand but more difficult to implement as they follow the IF-THEN-ELSE logic of the human thought process. Expert systems design often takes long times of collecting information and understanding information and translating these into rules and facts.

Expert systems are good at procedural type of problems and are better than manuals. They ask users only for relevant information and incorporate past experience into solving the problem. A major weakness is, however, that they rely entirely on precise, up-to-date rules. An expert system cannot generalize or extrapolate. Noisy incoming data or data outside the set of rules can result in unreliable answers. Development time is normally long.

1.3.3 Common Applications for Neural Networks and Expert Systems

Some common applications for neural networks and expert systems are depicted in Table 1-3.

Table 1-3: Neural Network and Expert System Application (Lawrence, 1993)

APPLICATION	NEURAL NETWORK	EXPERT SYSTEM
Management and Administration		
cost estimation	✓	✓
scheduling	✓	✓
intelligent document retrieval		✓
Science and Engineering		
engine analyses........	✓	✓
prediction of chemical reactions	✓	
bacteria identification	✓	✓
carbohydrate identification	✓	✓
equipment configuration design		✓
Industrial		
instructions for repair		✓
process control modelling	✓	✓
process control procedures		✓
manufacturing quality control	✓	✓
Financial and Legal		
investment strategies		✓

APPLICATION	NEURAL NETWORK	EXPERT SYSTEM
prediction of financial trends	✓	
loan application analysis	✓	✓
real estate price evaluation	✓	
estate planning		✓
Medical		
recognition of cancer cells	✓	
medical diagnoses	✓	✓
medical reports		✓
Military and Space		
classification of fingerprints	✓	
computer security		✓
signal or target recognition	✓	
Other		
education/evaluation		✓
contextual recognition of words	✓	
language processing		✓
text to speech translation	✓	
prediction of sporting events	✓	✓
handwriting recognition	✓	
optical character recognition	✓	

It is important to note that neural networks and expert systems can be used together as hybrid systems. Neural networks can be used to recognise patterns that are then acted upon by the rules of an expert system. Expert systems, on the contrary, can be used to train a neural network. A neural network can be used to generate rules for an expert system. Neural networks can be combined with expert systems to provide some intuition to the logic of an expert system.

1.4 NEURAL NETWORK THEORY

1.4.1 Introduction

Artificial neural networks can be described in terms of the direction of flow of signals in the network, the behaviour of neurons, interconnection scheme and the type of learning in the network. More than 40 models are available (Lawrence, 1993) making it impossible to discuss all models in detail. A brief discussion will be given of the main neural network types.

As an introduction to the description of network types a few characteristics of artificial neural networks will be given (Lawrence, 1993):

Adaptability is the ability to modify a response to changing conditions and is produced by four processes: learning, self-organization, generalization and training.

Plasticity is the ability of a group of neurons to adapt their functions to different needs over time (i.e., when a portion of the network is damaged other neurons will take over the functions of the neurons in the damaged part). With *self-organization* a network modifies all its neurons at once according to a learning rule. *Generalization* is the ability of a network to formulate an answer to a problem it has never seen before by using related or similar information. *Learning* occurs as changes to the weights.

Training (or learning) is the process of repeatedly presenting information to a neural network so that it can learn (back-propagation).

Generalization stems from the naturally high dimensionality of the data collected. A classifier system must be designed to classify correctly a previously unseen image vector and is referred to as generalization. (Bishop, 1995). One technique to alleviate the problems of dimensionality and generalization is called feature extraction where several variables are combined to make a smaller number of variables called features. Adding features beyond a certain point may actually lead to a reduction in the performance of the neural network and is known as the curse of dimensionality. Pre-processing plays an important role in reducing dimensionality. Generalization can also be described through the central goal in any neural network, i.e. to produce a system that makes good predictions for new data and therefore exhibits good generalization. The best generalization is determined by the trade-off between the competing properties of *bias* (model has too little flexibility) and *variance* (model has too much flexibility) and occurs when the number of degrees of freedom in the model is relatively small compared to the size the data set (Bishop, 1995).

Dynamic stability is the ability of a network to remain within its functional boundaries and reach a stable state. *Convergence* is the changing state of the network as it moves toward a stable state. A *stable state* is reached when a network settles into a fixed pattern after a process of reaction-stimulation-reaction between neurons. *Fault tolerance* is the ability to keep processing when a small number of neurons are disabled or destroyed. *Normalization* is an adjustment that keeps weights within a prescribed range of acceptable limits.

The *state of a neuron* at a certain time can be discrete or continuous, but not both.

Discrete time and *continuous time* describe the nature of the variable used for time (t). *Temporal association* is the mechanism by which timed sequences are memorized and reconstructed while *temporal patterns* are sequences of spatial patterns.

The relationship of input patterns to a network can be described as *orthogonal patterns* that are mathematically at right angles to each other, *conceptually orthogonal patterns* as in the case of associating a bell with the sight of food and *spatial patterns* that are parallel values of signals over space at a given time (e.g. the arrangement of numbers on a telephone).

1.4.2 Feedback Network

A feedback artificial neural network is depicted in Figure 1-6. The output of neurons directly feeds back into neurons in the same or preceding layers. The output of some neurons therefore becomes the input of other neurons. Because of the inherent random element in networks it sometimes happens that feedback networks do not render repeatability, i.e., the same result is not always obtained with the same input set (Lawrence, 1993).

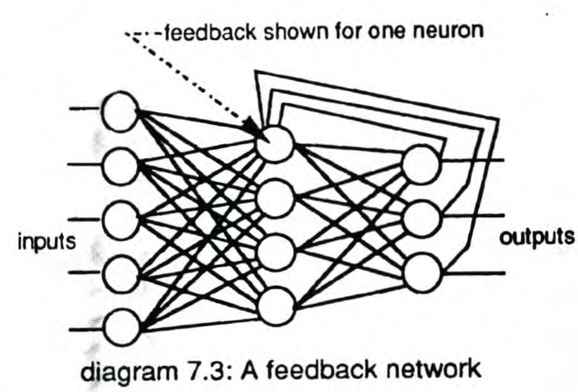


Figure 1-6: Feedback network (Lawrence, 1993)

Feedback is meaningful in situations where the present output, for example, controls the following instant of the output, as is the case in discrete-time networks. In discrete-time networks the time delay is introduced by delay elements in the feedback loop. With feedback it is therefore possible to create artificial neural networks with continuous-time output vectors.

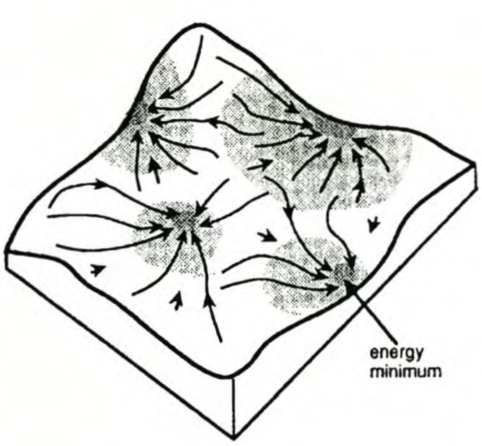


Figure 1-7: A neural network energy surface (Lawrence, 1993)

The convergence of feedback networks to a final answer is defined by a mathematical function called the *computational energy* (Lawrence, 1993), a mathematical function defining the stable states of a network and the paths leading to it. The energy of a neural network can be visualized in three dimensions as is depicted in Figure 1-7. More than one *energy minimum* exists so that networks can settle into local minima instead of a global minimum. The initial state of a network is an important factor in determining the eventual energy state in which the network will settle.

Picton (1994) reported that the implementation of probabilistic neural networks might be used to overcome this problem as probabilistic neural networks allow occasional jumps to higher states enabling a new search direction.

Feedback should not be confused with back-propagation that is a learning method and will be discussed later in the thesis.

1.4.3 Feedforward Networks

An artificial neural network is of the feedforward type as depicted in Figure 1-8 if a neuron's output is never dependent on the output of subsequent neurons. Signals only go forward through the network with no loops.

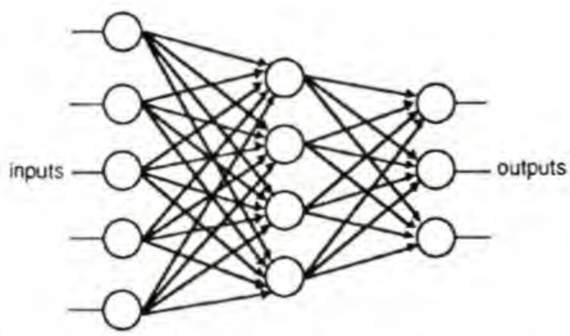


Figure 1-8: Feedforward network (Lawrence, 1993)

Feedforward networks use less memory (more variables can be analysed with the same memory) and normally executes faster than feedback networks. Although the detail mathematical derivation of neural networks is not presented in this paper, it can be shown mathematically that any feedback network has an equivalent feedforward network that performs the same task (Lawrence, 1993). Feed forward networks are also less susceptible to the curse of dimensionality (Bishop, 1995).

1.4.4 Probabilistic Neural Networks

A probabilistic neural network is a multi-layer feedforward model that uses nonlinear neurons and is called a neural network because of its architecture and not the learning method (Lawrence, 1993). It contains four layers: input and output layers similar to feedforward networks and two inner layers, a pattern layer to store training patterns and a summing layer which can serve as characterization neurons. Training takes a limited amount of time as it is based on patterns rather than individual neurons.

A probability calculation is made for each output neuron based on the chance of any given pattern falling within each category and the entire set of available patterns is used in the identification process.

1.4.5 Learning (Training)

Learning in a neural network is the process in which the network is forced to yield a particular response to a specific input and is required where the inputs/outputs are not known or incomplete (Zurada, 1992). Goh (1996) describes learning as the process of the adaptation of the network's connection weights as the hidden neurons organize themselves so that different neurons learn to recognize different features of the total input space.

If the inputs/outputs were known beforehand learning would not be required as the network could be designed in advance. Two learning modes exist: learning *with* supervision and learning *without* supervision. These two learning modes are shown diagrammatically in Figure 1-9 (Zurada, 1992).

In *supervised learning* it is assumed that at each instant of time when the input is applied, the desired response of the system is provided by the teacher. A *training set* of input/output values is required for this learning mode. The output values can be considered target values of the system.

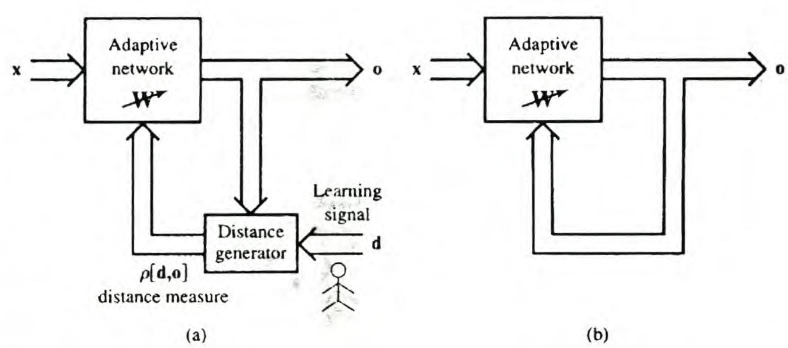


Figure 1-9: Block diagram to explain basic learning modes: (a) Supervised and (b) Unsupervised (Zurada, 1992)

In *unsupervised learning* the desired response is not known and learning must now be accomplished based on observation of responses to inputs for which marginal or no knowledge exists. In this mode of learning the network must discover for itself any possibility of existing patterns.

There is a third form of learning, called *reinforcement* learning, in which information is supplied as to whether the network outputs are good or bad, but again no actual designed values are given (Bishop, 1995).

Several learning rules are used in training networks. Each learning rule will not be discussed in detail, but rather a summary of the learning rules is given in Table 1-4 (Zurada, 1992).

Table 1-4: Summary of Learning Rules for Neural Networks (Zurada, 1992)

LEARNING RULE	INITIAL WEIGHTS	LEARNING MODE	NEURON CHARACTERISTICS	NEURON/ LAYER
Hebbian	0	Unsupervised	Any	Neuron
Perceptron	Any	Supervised	Binary bipolar or Binary unipolar	Neuron
Delta	Any	Supervised	Continuous	Neuron
Widrow-Hoff	Any	Supervised	Any	Neuron
Correlation	0	Supervised	Any	Neuron
Winner-take-all	Random Normalized	Unsupervised	Continuous	Layer of neurons
Outstar	0	Supervised	Continuous	Layer of neurons

1.4.6 Back-propagation

Back-propagation is in actual fact a subset of feed-forward networks, but is such a valuable tool and is used so often that a separate discussion is necessitated.

Back-propagation provides a way of using examples of a target function to find the weights that make the mapping function approximate the target function as closely as possible. The method usually used to calculate the weight changes is the gradient descent. Training begins with an arbitrary set of weights. A series of computations (iterations) is done in which the calculated output is compared with the known values, adjusting the weights in such a way that the difference between the calculated values and the target function is minimized (Smith, 1993).

With each iteration the hidden layer passes information through based on values of the weights in memory and the output values are calculated. The output nodes are then informed of the difference between the actual and target values. Each output neuron determines in which direction its weights must be adjusted to reduce the error and propagates the information to the hidden layer, which in turn determines in which direction its weights must be changed. At the hidden layer level the weights are adjusted in such a way as to reduce the error across the full set of output neurons thus minimizing the error in the network. For each iteration there is thus a forward pass followed by a backward pass during which error information is propagated backward from the output neurons to the hidden neurons.

It is normal practice to divide the target function's known input data and use 2/3 as test data against which the network is trained (learning phase) and use the remainder 1/3 of the input data to verify the trained network.

It is reported by Lawrence (1993) that the consensus of opinion is that back-propagation is the best general-purpose model and probably the best at generalization. A good understanding of feedforward networks and back-propagation is therefore essential when applying artificial neural networks and is best illustrated in Figure 1-10 (Hajek and Hurdal, 1993).

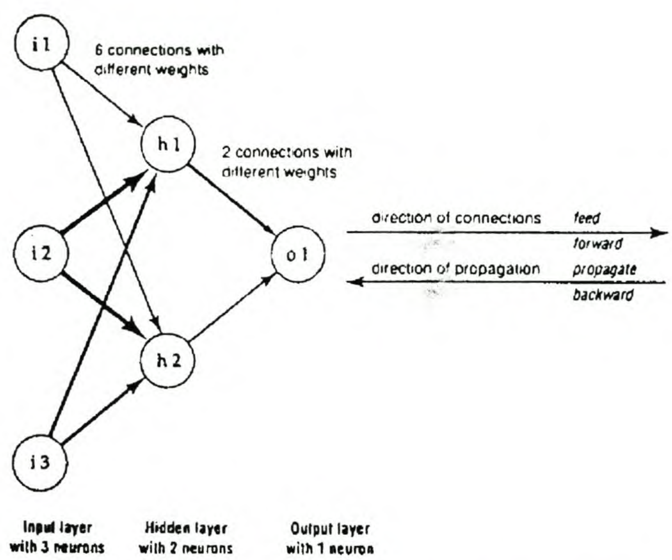


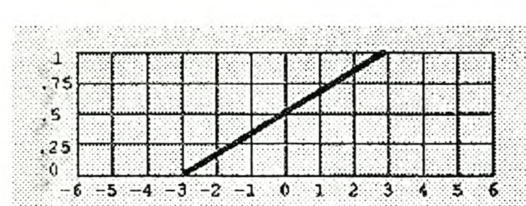
Figure 1-10: Illustration of back-propagation on a feedforward network. (Hajek and Hurdal, 1993)

1.4.7 Transfer functions

A transfer function is applied to the neuron's activation value to generate the neuron's output. A few examples of transfer functions are given below (Lawrence, 1993, including figures).

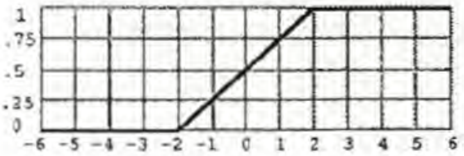
1.4.7.1 Linear Transfer Functions

A linear transfer function is a function in which the output has a constant slope. Linear transfer functions are not very useful and sometimes only allow the partial solving of problems. The gain is the slope of the line and centre is the value where the output is half the maximum value.



1.4.7.2 Linear Threshold Function

A linear threshold function is a linear transfer function with boundary values Low and High. The transfer function has a constant slope and centre is the value of the input at which the output is equal to (High+Low)/2. Due to the boundary values the transfer function as a unit is not linear and realizes more interesting results.

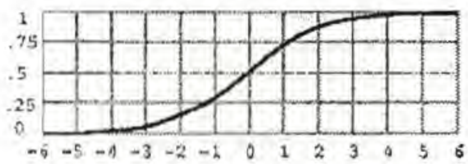


1.4.7.3 Step Transfer Function

A step transfer function is a function in which the output is limited to two possible values. It therefore acts just like a digital logic chip. Centre is the value of the input at which the output jumps from Low to High.

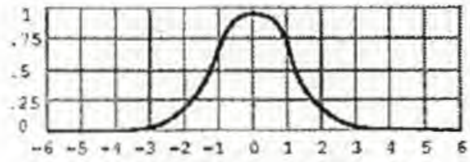
1.4.7.4 Sigmoid Transfer Function

A sigmoid function is a function in which the output is a continuous, monotonic function of the input. It asymptotically approaches the values High and Low and centre is the input value at which the output is (High+Low)/2. This function is semi-linear and yields particular good results with back-propagation.



1.4.7.5 Gaussian Transfer Function

A Gaussian transfer function is not monotonic and almost acts as two sigmoid functions. Each half of the Gaussian transfer is therefore monotonic. The function is continuous and centre is the input value at which the output is High. The gain is proportional to the standard deviation of the Gaussian.



1.4.8 Combination of Layers and Transfer Functions

The combined effect of the layers in a network and the transfer function determine the shape of the output function that the network will approximate. Linear transfer functions will produce a linear output, no matter how many layers are utilized in the network. Nonlinear network output is caused by nonlinear transfer functions.

Figure 1-11 demonstrates that a network with three layers and sigmoidal transfer functions can approximate a smooth multivariate mapping to arbitrary accuracy. (Bishop, 1995)

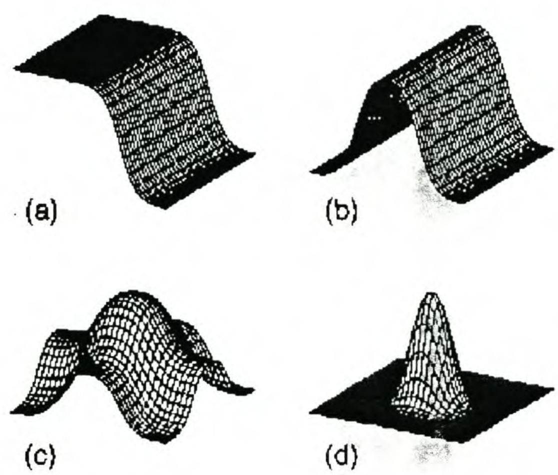


Figure 1-11: Demonstration of output function as a combination of three layers with sigmoidal transfer function (Bishop, 1995)

In (a) we see the output of a single sigmoidal unit as a function of two input variables. Adding the outputs from two such units can produce the ridge-like function in (b), while adding two ridges can give a function with a maximum (c). Transforming this function with another sigmoid gives the localised response as is illustrated in (d). Linear combinations of the localised functions will produce an approximation of any smooth functional mapping (Bishop, 1995).

1.4.9 Classifying of Artificial Neural Networks

An artificial neural network is classified in terms of the definition discussed so far:

- With/without feedback.
- Type of transfer function, i.e., linear or nonlinear.
- Learning algorithm, i.e., supervised or unsupervised.

A specific network can therefore, for example, be classified as a nonlinear, supervised feedforward network.

1.5 MATHEMATICAL REPRESENTATION OF NEURAL NETWORKS

Many of the important issues concerning the application of neural networks can be introduced in the simpler context of polynomial curve fitting. Consider the problem to fit a polynomial to a set of N data points by the technique of minimizing an error function (Bishop, 1995).

Consider an Mth-order polynomial given by:

$$y(x) = w_0 + w_1.x + w_2x^2 + \ldots + w_m.x^m = \sum_{j=0}^{m} w_j.x^j$$

Eq. 1-1

This Mth-order polynomial can be regarded as a nonlinear mapping, which takes x as input and produces y as output. The precise form of the function y is determined by the values of the parameters $w_o \ldots w_m$, which are analogous to the weights in a neural network.

The polynomial can be written as a functional mapping in the form $y = y(x; w)$, with w denoting the set of parameters $(w_o \ldots w_m)$.

Consider a set of data with N data points each consists of a value x, denoted by x^n, and a corresponding desired value for the output y, denoted by t^n. The desired outputs are called target values in the neural network context. In order to find suitable values for the parameters w the error between the desired output t^n, for a particular input x^n, and the corresponding value predicted by $y(x; w)$, is considered. Standard curve fitting procedures are used to minimize the square of this error, summed over all data points, given by:

$$E = \frac{1}{2}\sum_{n=1}^{N}\left\{y(x^n;w) - t^n\right\}^2$$

Eq. 1-2

E is being regarded as a function of w so that the polynomial can be fitted to the data by choosing a value for w, denoted by w^*, which minimizes E.

Meier and Rix (1994) describes the mathematical representation of an artificial neural network and used the popular multi-layer feedforward network with back-propagation as an example. A typical multi-layer feedforward network is schematically shown in Figure 1-8. A basic processing element of multi-layer feedforward network is depicted in Figure 1-12.

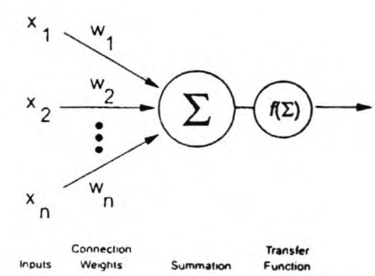


Figure 1-12: Basic processing element of a multi-layer, feedforward network (Meier and Rix, 1994)

The processing elements pass information in the form of signal patterns from the input layer of the network through a series of hidden layers to the output layer. Signals travel between processing elements along connections whose strengths can be adjusted to amplify or alternate the signal it propagates. Each processing element sums the impinging signals to determine a net level of excitation.

The excitation level of a processing element is modelled mathematically as a weighted sum of its inputs:

$$N_j = \sum_{i=1}^{n} w_{ji}.x_i$$

Eq. 1-3

Where x_i is the signal strength coming from the i^{th} processing elements in the proceeding layer, and w_{ij} is the weight assigned to that connection. The weights determine the degree of signal amplification or attenuation on the incoming connection.

The processing elements response to the net excitation N_j is then modelled through an activation function, usually a sigmoid function:

$$a_j = f(N_j) = \frac{1}{1+e^{-N_j}}$$

Eq. 1-4

Sometimes a threshold level θ_j is introduced to each processing element with the transfer function (or activation function) then

$$a_j = f(N_j) = \frac{1}{1+e^{-(N_j-\theta_j)}}$$

Eq. 1-5

A sigmoidal transfer function accepts input over the range $[-\infty,\infty]$ and uniquely maps it into the range [0,1]. The signals are therefore bounded and nonlinearity is introduced into the network. More examples of transfer functions are given in 0.

The Generalized Delta Rule is used to train the network and is essentially a gradient descent scheme that seeks a global minimum of the error surface that relates the output errors to the connection weights. Weight changes at each step are calculated as follows:

$$\Delta w_{ij} = \alpha \nabla E(w_{ij})$$

Eq. 1-6

Where $\nabla E(w_{ij})$ is the gradient of the error surface with respect to the weight in question and α is the "learning" rate.

A more advanced form of the generalization rule uses an additional momentum term to help the gradient descent avoid shallow minima:

$$\Delta w_{ij}(t) = \alpha \nabla E(w_{ij}) + \beta \Delta W_{ij}(t-1)$$

Eq. 1-7

Where $\Delta w_{ij}(t-1)$ and $\Delta w_{ij}(t)$ are the weight changes applied on successive steps and β regulates the amount of momentum.

The gradient of the error surface with respect to an individual connection weight, w_{ij}, can be expressed as:

$$\nabla E(w_{ij}) = \frac{\partial E(w_{ij})}{\partial N_j} \frac{\partial N_j}{\partial w_{ij}} = \delta_j \frac{\partial N_j}{\partial w_{ij}} = \delta_j a_i$$

Eq. 1-8

Where the δ_j (from which the generalized delta rule takes its name) are the gradients of the error surface with respect to the next excitation level of each processing element, and the a_i are the individual inputs to each processing element.

At the output units the δ_j are computed as the product of the output error and the derivative of the transfer function:

$$\delta_j = (t_j - a_j) \frac{df(N_j)}{dN_j}$$

Eq. 1-9

Where t_j is the target output, with

$$\frac{df(N_j)}{dN_j} = a_j(1 - a_j)$$

Eq. 1-10

Therefore:

$$\delta_j = a_j(t_j - a_j)(1 - a_j)$$

Eq. 1-11

At the processing elements in the other network layers, the target outputs are not known a-priori and the errors attributed to those processing elements are estimated by assessing each elements relative contribution to the outputs and, thus, the errors of the element's in the succeeding layers:

$$\delta_j = \frac{df(N_j)}{dN_j} \sum_{k=1}^{n} \delta_k w_{jk}$$

Eq. 1-12

By working backwards from the output layer, errors can be apportioned successively to the processing elements in the remaining layers of the network.

1.6 CLOSURE

In this chapter an introduction was given into neural networks, expert systems and fuzzy systems. Further on in this thesis three applications of neural networks in Pavement Management Systems will be discussed. It is necessary to investigate the design of neural networks in more depth prior to the application thereof. The selection and design of a neural network is discussed in the following chapter and the principles and guidelines will be applied in the applications discussed in chapters three to five.

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CHAPTER 2

2 HOW TO SELECT THE RIGHT ARTIFICIAL NEURAL NETWORK FOR AN APPLICATION

2.1 INTRODUCTION

It is necessary to establish the network architecture at the onset of any neural network solution. The neural network architecture is the combination of the input layer, hidden layers and output layer with the accompanying definition of the connectivity between these layers. Figure 1-10 illustrates the neural network architecture of a feedforward network.

As can be deduced from the discussion in Chapter 1, at least an input and an output layer is required. The number of neurons in the input layer will be determined by the problem input parameters (the known values) and the number of neurons in the output layer by the problem output parameters (number of unknown values) to be determined. However, there are neither well-established methods to determine the number of hidden layers required nor a method to determine the number of neurons in the hidden layers. Trial and error must therefore be used to strike a balance between insufficient knowledge capacity (not enough neurons or connections) and excessive capacity (too many neurons). Understanding of the problem and the data to be analysed is essential.

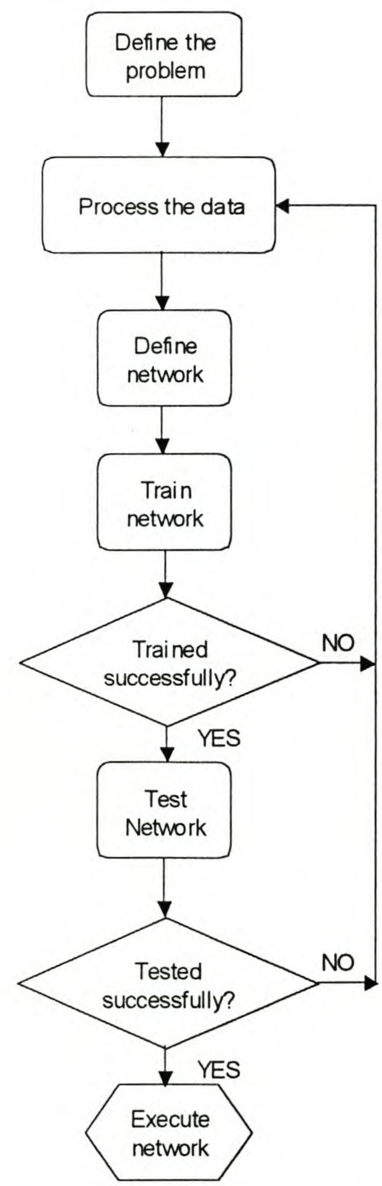

Figure 2-1: Neural network design (Adapted from Lawrence, 1993)

Information provided in this Chapter was gleaned from several references by the author, mainly program manuals. It is not possible to acknowledge every source and reference so that references are only given where specific information is highlighted. The author also added to the information from his own experience gained in the application of neural networks and presented in this thesis.

2.2 NEURAL NETWORK DESIGN

Figure 2-1 shows a diagram of the steps to follow in the selection of a neural network for a specific application (adapted from Lawrence, 1993).

The following steps will help in determining neural network architecture:

- Define the problem. Decide what information to use and what the neural network is required to do, i.e. what result is envisaged.
- Process the data. Decide how to represent the data and gather it.
- Define the neural network. Select network inputs, outputs and hidden layers.
- Train the network.
- Repeat the training with different hidden layer and number of nodes per layer configurations.
- Perform sensitivity analysis to test the influence of each input on the outcome of the system.
- Test the network on new data and compare the network's results to reality.

2.2.1 Define the Problem

Neural networks are not black boxes, even under the best of circumstances. A thorough understanding of the data is required and a good idea of what is to be achieved is required for the simplest of problems.

2.2.1.1 Understand and Analyse the Data

Neural networks learn by making associations between inputs and outputs. Try not to think about procedures, rules or formulas, only try to think of what kind of input the neural network can use to make an association with the desired output.

Explore the data in as many ways as possible:

- Try to understand the physical process that produced the data.
- Investigate relations between data, i.e. plot each input against another, search for patterns.

- Examine the statistics within each input stream (average and standard deviation) and correlations between different inputs.
- Try to determine what inputs will have little or no influence on the outcome and eliminate these inputs. At a later stage once the network is trained, a sensitivity analysis on each input will help to identify superfluous inputs.

Certain techniques can be employed to help determine the proper number of inputs to use in a network. Principle Component Analysis is perhaps the most known method, but be careful, as this is a linear method so that nonlinear relationships may be missed.

An estimate of the number of training examples needed for a given network is bounded by the following two relationships (LDC, 1996):

- Upper bound = W/e.log(N/e)
- Lower bound = W/e

where:

W = Number of weights
N = Number of processing elements
e = acceptable classification error

Lawrence (1993) gives as a rule of thumb that the number of patterns (or facts) should not exceed 10 times the number of connections in the network.

2.2.1.2 Conceptualise and Formulate the Problem

Decide on the goal to be achieved by the neural network, i.e. precisely what the neural network must predict, generalize or recognise, and define the aim of what to do with the prediction. Determine the data required to achieve the goal and decide on the form the data should be represented in. The same systematic approach normally followed in problem solving, applies in the formulation of the problem in neural networks.

2.2.2 Process the Data

The insight gained in the investigation of the data to understand it is now encoded into the data. The majority of neural networks require some form of pre-processing to give a new set of data. This new dataset is then treated as the input to the neural network as is shown in Figure 2-2.

2.2.2.1 Transform the data

Data can be transformed to better represent features of the known physical process. Neural networks require data in either of two classes: continuous valued and binary. Typically the following data types need transformation:

- Unbound data, i.e. a stock's future value has no upper bound and problems will be created once the stock's value moves outside the historic values, which can be avoided by using a percentage change format that is bounded, i.e ±5%.
- Data with implied ranking, i.e. values of 1 to 12 to represent the months in the year implies a predetermined ranking for each month, that may not be true and can be avoided by using 12 separate nodes in binary format to represent the 12 months.
- Inputs that need to be presented in binary format, i.e. values will either be 0 or 1 for married/unmarried.
- Inputs that need to be presented in continuous format, i.e. the months in the year will be represented as values from 1 to 12.

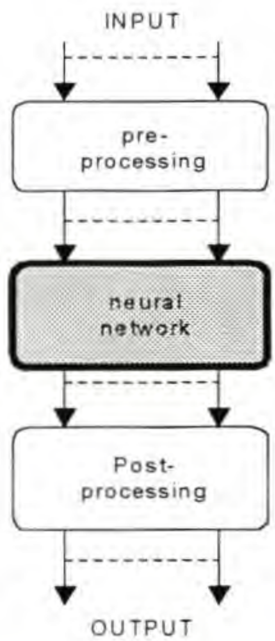

Figure 2-2: Data processing (Adapted from Bishop, 1995)

2.2.2.2 Feature Extraction

Feature selection is the process where the dimensionality is reduced by selecting a subset of the original data. This can either be achieved by eliminating superfluous input streams and try to transform data to a more compact representation, or identifying data input sets with very strong correlations and eliminate these as the same information is repeated in several variables. This process should be seen as the replacement of a number of the inputs with one or more inputs that represent the replaced inputs adequately. Feature extraction is normally required in datasets with multiple correlation within the input dataset. This should not be confused with the correlation between the inputs and outputs as the neural network is used to determine such a relationship.

2.2.2.3 Data Normalization

Back-propagation neural networks require that all training targets be normalized between 0 and 1 for training. This is because an output node's signal is restricted to a 0 to 1 range. Even if the training data is already between the limits 0 and 1, normalization may still be desirable. For example, if all target data were between .01 and .02, it would be better to normalize the data over a wider range so that the network can resolve and predict the targets over an optimal range.

2.2.2.4 Linearize the input data

Even though a neural network is exceptionally suitable to handle nonlinear functions, any operation to linearize input variables would help training and network accuracy. It is sometimes better to use the logarithm of a variable rather than the unmodified variable itself. Linearization is also helpful when a continuous data stream with a large number of small values represents an input variable.

2.2.2.5 Post-processing

The output from the neural network needs to undergo some post-processing depending on the type of pre-processing done on the input. In almost all the cases the input would at least have been normalized and the raw output from the neural network would therefore be in normalized format and need to be transformed to show natural dimensions again.

2.2.3 Create the Neural Network

The network architecture determines how the nodes (or neurons or processing elements) are interconnected in the network, which learning rules may be used and the transfer function to be applied in each layer. Typically a decision should be made between feedforward and feedbackward networks, the number of layers in the hidden structure, and then the choice of learning rules and transfer functions will follow.

2.2.3.1 Input and Output Layers

The number of neurons in the input layer will be determined by the problem input parameters (the known values) and the number of neurons in the output layer by the problem output parameters (number of unknown values) to be determined.

2.2.3.2 Hidden Layers

Choosing the number of hidden layers or even the number of nodes per hidden layer is not a trivial process. A process of trial and error must be used to strike a balance between insufficient knowledge capacity (not enough neurons or connections) and excessive capacity (too many neurons). Factors that influence the choice of the number of hidden layers are the number of training patterns, the number of input and output variables and the relationship between the input and output variables. Avoid the trap of "the bigger the brain the better" unless complete memorization is the target. Start with a small hidden processing structure and increase this structure and try different combinations if the network does not train or perform poorly.

2.2.3.3 Learning Rules

The learning rule is the heart of the neural network as it decides how the weights are adjusted as the network gains experience. First of all it should be determined whether supervised or unsupervised learning is required. Once the learning method is selected, the learning rule should be selected. Examples of learning rules are Back-propagation (supervised), Quick Propagation (supervised), Kohonen Winner Take All (unsupervised) and Simulated Annealing (supervised). Learning rules are best suited to certain applications and again trial and error should be used to determine the best learning rule for a particular problem.

2.2.3.4 Transfer Functions

Transfer functions serve the purpose of controlling the output signal strength for a node with the sigmoid being the most widely used transfer function for back-propagation neural networks.

2.2.3.5 Parameter Selection

Parameter selection involves the choice of parameters used to train the network and normally at least requires a learning rate and a momentum factor. The behaviour and choice of these parameters is discussed in section 2.2.4.1.

2.2.4 Train the Network

Lawrence (1993) describes training a neural network as a process where a set of facts is repeatedly presented to the network. The network takes in each input, makes a guess as to the output and compares this guess against the supplied output and then makes corrections to the internal connections if the guess was incorrect. This process is repeated for each fact until the neural network has learnt the facts sufficiently to be useful. Training is usually stopped when a certain accuracy is reached, either in terms of some error measurement or an accuracy range.

If possible, a subset of the training set (input patterns) should be set aside as an independent test set (normally 10-20% of the total available data set) to cross-validate the training set and to test for over-training. Training should be repeated as neural networks are highly nonlinear and can have many local minima in the weight space. Repeated training with different initial conditions will increase the changes of finding the global minimum. Some of the general key parameters used in training will be discussed, with some useful hints gleaned from manuals of some commercial software. The discussion will be based on the most popular neural network, the feedforward neural network with back-propagation and supervised learning. The points raised are, however, equally applicable to other networks and learning methods as for the feedforward network.

2.2.4.1 Learning Rates, Momentum and Weights Decay

Back-propagation is a gradient descent method where network weights are adjusted so that the overall network continually progresses downhill. LDC (1996) implements weight adjustment as shown in Eq. 2-1 and Eq. 2-2.

$$\Delta w = g(w) + \beta \cdot \Delta w_{old} + (1-\beta)(w \cdot w_d)$$

Eq. 2-1

And

$$w_{new} = w_{old} - \alpha \cdot \Delta w$$

Eq. 2-2

Where Δw denotes the weight adjustment for a particular weight w and $g(w)$ the gradient of the error with respect to the weight. α is the learning rate parameter, β the momentum parameter and w_d the weights decay parameter.

The learning rate is the most important parameter and it scales the magnitude of weight adjustments and therefore influences the rate at which a neural network learns. The momentum parameter improves performance by adding inertia to the trajectory of the weights during learning, while weights decay has the effect of controlling the growth of weights and results in the learning rule preferring smaller weights (LDC, 1996).

Successful training of a neural network depends on the choice of these three parameters. Experience showed that it is better to start with a small α to point the network in the right direction and then to increase α up to a point where sustained and stable training is achieved. α Varies from 0 to 1 and will depend on the number of facts presented to the network before weights are updated. Typically α can be higher when weights are updated after each fact is presented and smaller when weights are updated in batch mode, i.e. updating takes place after all the facts were presented.

High values of β can cause training to overshoot a goal and it is therefore advisable to use small β values when in doubt. From Eq. 2-1 it is clear that β adds in memory of the previous weight change, therefore smoothing the search.

The secret in choosing the right values for these parameters lies in practice. It is best to train the network for a few iterations (sometimes called epochs) with a certain choice of these parameters and to study the error curve. Usually the parameters need adjustment when training slows down or strange behaviour is observed. An example taken from one of the neural networks created in chapter 5 is given in Figure 2-3 below.

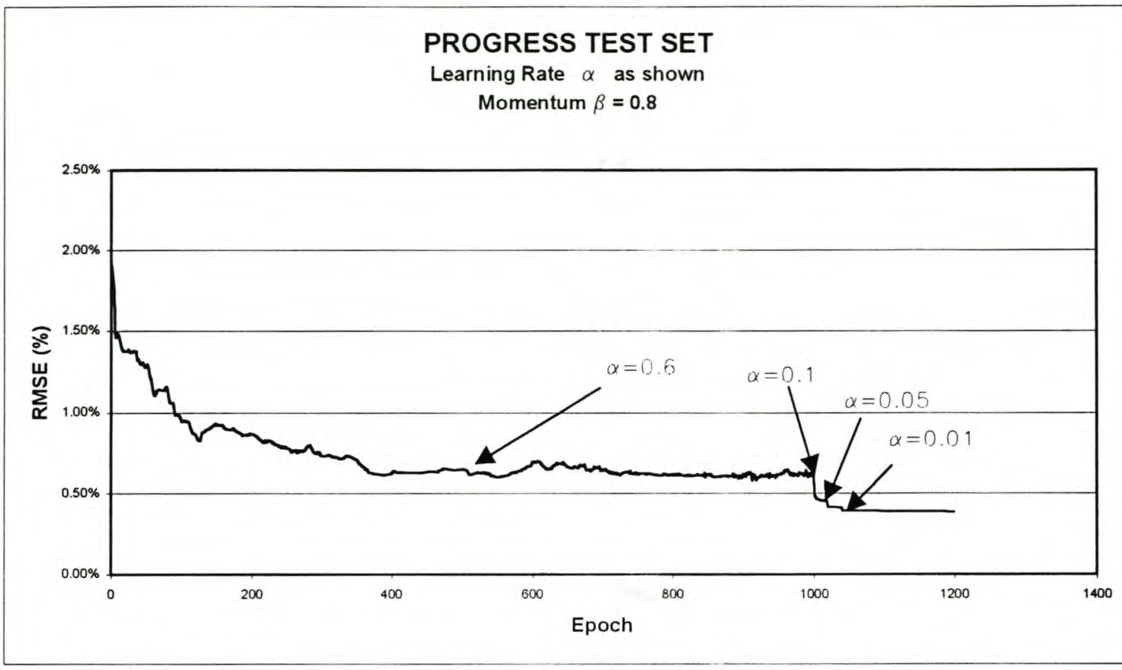

Figure 2-3: Example of influence of Learning Rate on training (taken from a neural network trained in Chapter 5)

In the example in Figure 2-3 a constant momentum factor was used and the Root Mean Square error (RMSE) quickly reduced as the learning rate was adjusted. A plateau was soon reached and no further improvement in the RMSE was achieved. From the 1000th iteration the learning rate was reduced from 0.6 to 0.1, 0.05 and 0.01 after every further 20 iterations. A drastic improvement in the RMSE was immediately evident, illustrating the importance of close observation during the training process.

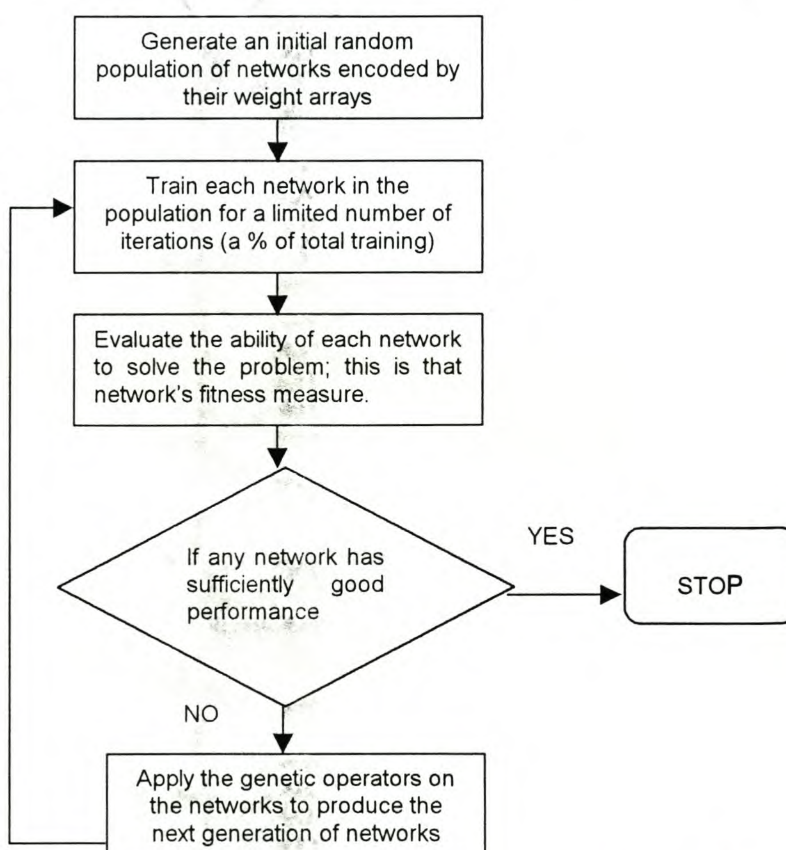

Figure 2-4: Genetic algorithm (After Taha and Hana, 1995)

Taha and Hanna (1995) investigated a method, Genetic Algorithms, to assist in the selection of back-propagation parameters. Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics. Taha and Hanna (1995) present a genetic algorithm method that evolves a neural network model to select an optimum maintenance strategy. The process in evolving the neural network is shown in Figure 2-4. Automatic selection of parameters, as described here, is not readily available in commercial software yet.

2.2.4.2 Over Training

Over training occurs when the test set error increases while the training set error continues to decrease, an indication that memorization is the predominant learning mode. A misconception exists that training should be stopped at a minimum test set error. This minimum only implies that a certain action should be taken to correct over training (LDC, 1996). Training continues as long as the weights are adjusted and over training should rather be addressed by one of the following actions:

- Add more data to the training set
- Decrease the size of the hidden processing structure
- Add or increase the noise to the inputs to the network (see paragraph 5.5.3)
- Decrease the number of inputs to the network
- Introduce a weights decay factor

2.2.5 Validate the Network

Validation of the network entails the performance of sensitivity analysis, statistical analysis, presenting new data and adding noise. The networks generalization ability should be tested thoroughly. Bishop (1995) states that the best generalization is determined by the trade-off between the competing properties of:

- Bias: The model has too little flexibility; and
- Variance: The model has too much flexibility and occurs when the number of degrees of freedom is relatively small compared to the size of the data.

Certain validation issues will be discussed in more detail hereinafter.

2.2.5.1 Sensitivity Analysis

Sensitivity analysis measures the effect of small (incremental) changes of input variables on the output and should be computed over the whole training set, determining the importance of each input to the outputs.

Information obtained from the sensitivity analysis is important to the understanding of how the neural network uses the available information and can be used to either improve the performance of the network, i.e. sensitivity analysis can help to identify superfluous variables in the input data, or provide information on how to improve generalization in the neural network.

One approach to performing a sensitivity analysis is to record the influence of a small incremental change to a single input on the outputs (in effect calculating the derivative of the output with respect to the input). In a nonlinear problem the calculated derivative can be influenced by small changes in other inputs. A second approach is to eliminate individual inputs from the network and retrain the network.

2.2.5.2 Statistical Analysis

A statistical analysis is performed on output data, i.e. test the correlation between actual and calculated values per output variable. Draw graphs of the actual versus calculated output variables and inspect the spread of the data - a perfect fit should be a straight line between the actual and calculated output variables.

2.2.5.3 Test the Network with New Data

Put the network to use and test it with new data not presented to the network during the training process. Evaluate whether the neural network generalize well to the new data by comparing the neural network predictions with known outcomes.

2.2.5.4 Adding Noise

Adding noise to the inputs of a network is one way of improving the generalization of the neural network. In the real world all methods of measurements to obtain data are subject to error. Adding noise to the input values is a way of addressing this behaviour, with the added benefit that in effect additional data is added to the training set as each training sample is presented in a different way with each iteration.

2.2.6 Update the Network

Occasionally the network should be updated with new data accumulated over time and the entire training process should be repeated.

2.3 COMMERCIAL NEURAL NETWORK SOFTWARE

A search on the Internet revealed the following computer programs (only Windows programs were considered):

- **ThinksPro** from Logical Designs Consulting Inc.
- **NeuroSolutions** from NeuroDimension Inc.
- **Qnet2000** from Vesta Services Inc.
- **AiNet32** from Ainet.
- **Qwiknet32** from Craig Jensen.
- **EasyNN** from Neural Planner Software.
- **NeuroCX** from Alpha Systems.
- **MPIL** from Universal Problem Solvers, Inc.

The Internet search was not exhaustive, only programs available from the University of Stellenbosch FTP (ftp.sun.ac.za) site were included.

Other commercial software, i.e. Brainmaker and Statistica, were not available and could not be assessed.

The Provincial Administration: Western Cape (PAWC) bought **ThinksPro** in 1997 for their investigation into the calculation of a Visual Condition Index (see Chapter 3), (Van der Gryp et al, 1998). The available ThinksPro at PAWC is a 16-bit version and can analyse several neural network types. The 16-bit ThinksPro's main limitation is that the latest software (i.e. Excel and Qpro) are 32-bit applications and that neural network solutions are dependent on these third party applications.

ThinksPro, like almost all other commercial software packages, makes available a Dynamic Link Library (DLL) to recall results from a trained neural network. The implication of the 16-bit/32-bit incompatibility between ThinksPro and Excel is that neural networks trained with ThinksPro can not be implemented in Excel. New data will therefore have to be presented to a neural network in ThinksPro and results studied in ThinksPro. No manipulation of data by the user is possible in ThinksPro. An obvious solution is to upgrade to a later 32-bit version of ThinksPro, something that was not possible due to limited funds as ThinksPro is a rather expensive package.

After evaluation of the mentioned software it was decided to buy the **Qnet2000** program. It is cost-effective and easy to operate, although only Multi Layer Feedback networks with back-propagation (with a Quickprop modification) is available. All the work in this thesis was therefore done with **Qnet2000**.

2.4 EXAMPLE

Let us consider a simple example and let:

$$Y = (X + 2)(X + 5)$$

Eq. 2-3

and

$$Z = 0.5Y^{0.3}$$

Eq. 2-4

Eq. 2-4 is a three-dimensional equation. 150 random numbers were generated between 0 and 5 as X values in a spreadsheet application. First Y was calculated from Eq. 2-3 and then Z from Eq. 2-4. A neural network with X and Y as input and Z as output was created. The program QNET was used for this problem with results as shown in Figure 2-5 and Figure 2-6. The network comprised of:

- Input Layer:
  - Nodes: 2 (X,Y)
  - Transfer Function: Linear
- Hidden Layer 1:
  - Nodes: 5
  - Transfer Function: Sigmoid
- Hidden Layer 2:
  - Nodes: 3
  - Transfer Function: Sigmoid
- Output Layer:
  - Nodes: 1 (Z)
  - Transfer Function: Sigmoid

125 of the input/output pairs were used for training and 25 for testing and after 15,000 training iterations the network converged to almost a perfect match as is illustrated in Figure 2-5 with Root Mean Square error as follows:

- RMS Training Error: 0.001897
- RMS Test Set Error: 0.002594

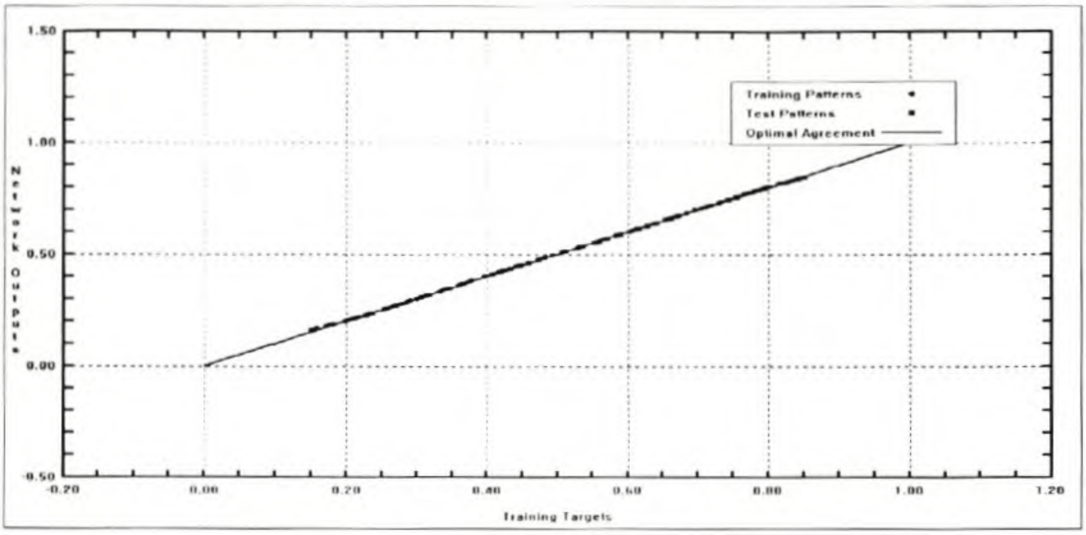

Figure 2-5: Predicted vs Calculated Z-values

To illustrate that the same effect can be achieved with a much simpler network design, the same problem was run with only one hidden layer with three nodes:

- Input Layer:
  - Nodes: 2
  - Transfer Function: Linear
- Hidden Layer 1:
  - Nodes: 3
  - Transfer Function: Sigmoid
- Output Layer:
  - Nodes: 1
  - Transfer Function: Sigmoid

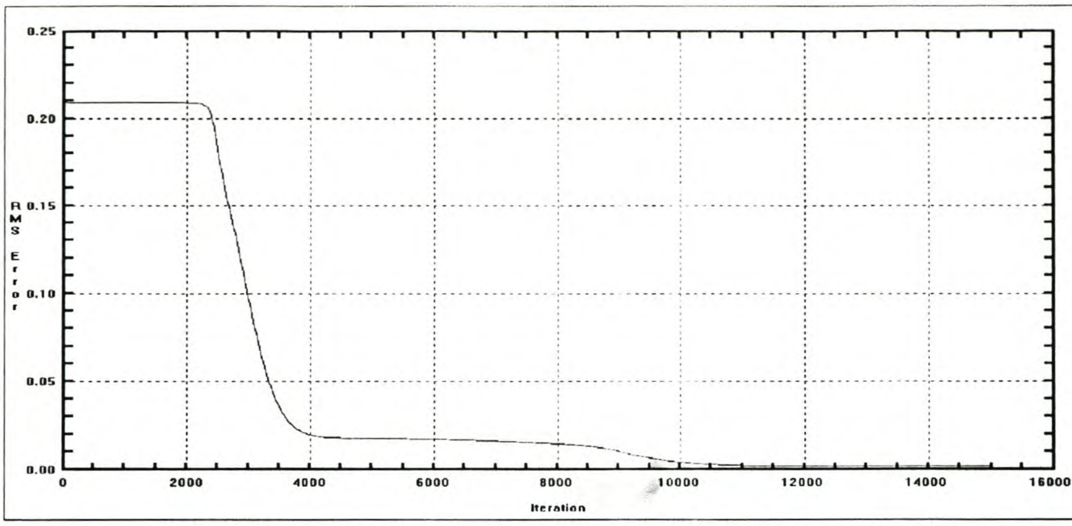

Figure 2-6: Training Iterations

After 15,000 training iterations this network converged to an almost better match with Root Mean Square error as follows:

- Training Error: 0.001452
- Test Set Error: 0.002059

This example illustrates the ability of neural networks to approximate mathematical functions to great accuracy. The same ability can be applied in other problems with unknown mathematical relationships. Simplicity should be kept in mind so that network architecture can be as simple as possible. Networks with fewer connections (due to fewer hidden layers and nodes) train faster and eventually execute faster.

2.5 CLOSURE

So far neural networks were introduced and the theory behind them studied. In this chapter the design and selection of neural networks was discussed. It is now possible to proceed to the application of neural networks in real world situations. Determining a Visual Condition index for a road network will be investigated in Chapter 3, determining reseal types in Chapter 4 and back-calculation of E-moduli from FWD deflection measurements in Chapter 5.

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CHAPTER 3

3 DETERMINING THE VISUAL CONDITION INDEX OF FLEXIBLE PAVEMENTS USING ARTIFICIAL NEURAL NETWORKS

3.1 INTRODUCTION

The calculation of a Visual Condition Index (VCI) from visual distress data in a Pavement Management System is common practice. The VCI is described in TRH22 (CSRA, 1994) and the collection of distress data in TMH9 (CSRA, 1992). In the PMS managed by the Provincial Administration: Western Cape (PAWC) visual assessments are done on an annual basis and the VCI is calculated from the distress data collected. An example of the Visual Evaluation form completed by the Assessor is included in Appendix A.1. As part of the assessment, the Assessor must give his/her overall impression of the road as the last entry on the form, the so-called Overall Pavement Condition (OPC). Visual assessments are in their very nature subjective while the VCI formula was determined by a group of experts, who agreed on the weights to be used in the formula, adding to the subjectivity of the process. The OPC will also be the subjective opinion of an individual, but it is felt the opinion is at least formed with the information fresh in the mind of the Assessor and more importantly, on the road being assessed. An investigation into the relationship between the inputs the Assessor receive through the visual assessment and his eventual assessment of the road in terms of the OPC might reveal some important information that can be used to either improve the VCI formula, or replace it with a totally new method.

Some of the work described in this chapter was originally done in 1997/98 and the results published at the 4th International Conference on Managing Pavements in Durban in March 1998 (Van der Gryp et al, 1998). The author contributed to this work as a co-author of the paper. Subsequently the author did more work on this subject in an endeavour to improve the accuracy of the prediction of the neural network. This work is presented here together with a summary of the work presented at the 4th International Conference on Managing Pavements, for the sake of completeness.

3.2 GOALS AND OBJECTIVES

The goals of the project in this chapter are:

- To investigate the relationship between the VCI and OPC;
- to evaluate the capabilities of neural networks in determining the VCI of flexible pavements in a PMS, using distress data collected through visual assessments of the pavement surface; and
- compare it with the current method of calculating the VCI.

The objective is to implement the neural network in the PMS should the calculation of VCI proves successful.

3.3 VISUAL CONDITION INDEX CALCULATION

Various methods of calculating Visual Condition Index (VCI) are available and used by the major road authorities in South Africa. A committee was established with the objective of determining an acceptable method that will produce results with a good correlation with the judgement of a panel of experts. (CSRA, 1994). The method proposed by the committee in the TRH22 (CSRA, 1994), is described here.

3.3.1 Standard Visual Condition Index Calculation Method

The VCI a road network is calculated as follows:

- Calculate F_n from Eq. 3-2, the factor describing the product of weight rating, extent rating and weight of distress.
- Apply Eq. 3-1 and calculate a preliminary VCI, the VCI_p.
- Transform the preliminary VCI_p with Eq. 3-3 to obtain the VCI.

Equations used in the calculation of the VCI are defined below (CSRA, 1994).

$$VCI_p = 100\left(1 - C \times \sum_{n=1}^{N} F_n\right)$$

Eq. 3-1

$$F_n = D_n \times E_n \times W_n$$

Eq. 3-2

where:

VCI_p = Preliminary VCI

n = *Visual assessment item number as currently in use by PAWC*

D_n = Degree rating of defect n

Range: 0 to 4 for functional defects

0 to 5 for other defects

E_n = Extent rating of defect n

Range: Default 3 for functional defects

0 to 5 for other defects

W_n = Weight per item number for defect n (Table 3-2)

F_n = Degree and Extent factor.

C = $1/\left[\sum_{n=1}^{N} F_n(\max)\right]$

$F_n(\max)$ = F_n with degree and extent ratings set at maximum.

Eq. 3-3 is applied to transform the VCI_p to a standard percentage scale.

$$VCI = \left(a \times VCI_p + b \times VCI_p^2\right)^2$$

Eq. 3-3

where:

a = 0,02509

b = 0,0007

VCI_{max} = 100

VCI_{min} = 0

Factors "a" and "b" have been derived from processing condition data collected through an expert panel throughout South Africa (CSRA, 1994) and van der Gryp et al (1998) is of the opinion that this is to "fit" the preliminary index (VCI_p) to an acceptable 0 to 100 scale that is compatible with the condition categories shown in Table 3-1.

Table 3-1: Condition Categories (CSRA, 1994)

DESCRIPTION OF CATEGORY	CONDITION INDEX RANGE
Very good	$85 \leq VCI \leq 100$
Good	$70 \leq VCI < 85$
Fair	$50 \leq VCI < 70$
Poor	$30 \leq VCI < 50$
Very poor	$0 \leq VCI < 30$

Intervals between different condition categories are not uniform. The interval for the very poor category is 30 percentage points where after the intervals are gradually reduced to 15 percentage points for the very good category.

Table 3-2: Weight set for VCI formula (CSRA, 1994)

ITEM NO.	ASSESSMENT ITEMS	WEIGHT (W_n)	SMALL DEGREE (S_n)	EXTENT WEIGHT (Y_n)
1	Surfacing failure/patching	6,5	1,0	1,2
2	Surfacing cracks	5,0	1,0	1,1
3	Aggregate loss	4,0	1,0	1,1
4	Binder condition	3,0	0,5	0,9
5	Bleeding/flushing	3,0	0,5	1,0
6N	Block/stabilisation cracks (narrow spacing)	8,0	1,0	1,2
6M	Block/stabilisation cracks (medium spacing)	6,0	1,0	1,0
6L	Block/stabilisation cracks (large spacing)	5,0	1,0	1,0
7	Longitudinal/slip cracks	4,5	1,0	1,0
8	Transverse cracks	4,5	1,0	1,0
9	Crocodile cracks	10,0	1,0	1,3
10	Pumping	10,0	1,0	1,3
11	Rutting	8,0	0,5	1,0
12	Undulation/settlement	4,0	0,5	1,0
13	Patching	8,0	0,8	1,1
14	Failures/Potholes	15,0	1,0	1,3
15	Riding quality	5,5	0,8	1,0
16	Skid resistance	3,0	0,5	1,0
17	Surface drainage	3,0	0,5	1,0
18	Unpaved shoulders	3,5	1,0	1,0
19	Edge breaking	3,5	0,8	1,0

The highest weight is allocated to failure/potholes, with pumping and rutting sharing the second place. Skid resistance scores a low value, indicating that the structural condition of the road is rated higher than the safety of the road. This is a reflection of the opinion of the panel of experts that determined the weight set.

3.3.2 Modified Visual Condition Index Calculation Method

TRH22 (CSRA, 1994) introduces a modification (refer TRH22 Appendix A for a complete discussion) to Eq. 3-2 in an endeavour to improve the correlation of the VCI with the OPC based on the engineering judgement of an expert panel. The modification to the formula is applied with an extent weight factor (Y_n) and a small degree factor (S_n). The purpose of the extent weight factor (Y_n) is to provide weighting to the extent rating for distress types. The purpose of the small degree factor (S_n) is to reduce the contribution of certain defects to the total index value when their degree rating is small. These factors are shown in Table 3-2.

To accommodate these factors Eq. 3-2 is adjusted as follows:

$$F_n = D_n\left(E_n^{\,Y_n}\right) W_n S_n$$

Eq. 3-4

The product of $D_n\left(E_n^{\,Y_n}\right)$ is limited to a maximum of 12 for functional defects, i.e., item no.'s 15, 16, 17 & 18 and to maximum of 25 for the other defects. The small degree factor (S_n) is set to 1 for functional defects degree rating > 1, or for other defects degree rating > 2, or else the S_n is according to Table 3-2. The values for the constants "a" and "b" in Eq. 3-3 are adjusted to 0,04 and 0,0006 respectively in the modified approach.

The factors in Table 3-2, i.e., W_n, S_n and Y_n, are subjective factors based on a panel appreciation of the importance of one distress type compared with the other. This is one of the reasons why the factors S_n and Y_n were introduced to try and further improve the correlation (Van der Gryp et al, 1998).

It was the purpose of the original study to show that the subjectivity can to a large extent be avoided by the use of a neural network as the neural network solution is trained from survey data and is not affected by any subjectivity beyond that inherent in the data. The application of the VCI formula is difficult due to the complicated calculation method followed.

3.4 CURRENT PRACTICE AT THE PAWC

The VCI calculation method at the PAWC, at the time of the original study, is based on the aggregated formula as described in paragraph 3.3. Provision is made to implement the modified calculation method as described in paragraph 3.3.2, but the S_n and Y_n factors in Table 3-2 are set to 1 (not implemented). The standard calculation method for VCI as described in paragraph 3.3.1 is followed with constants a = 0.02509 and b = 0.0007, (Van der Gryp, 2000). PAWC therefore provides for the future implementation of the modified VCI formula, but has not implemented it at present as the increased subjective nature of the modification is questioned (Van der Gryp, 1999).

3.5 ORIGINAL NEURAL NETWORK SOLUTION (1997)

3.5.1 Selection of input and output parameters

An example of the pavement assessment form is given in Appendix A.1.

In an effort to determine the VCI with Neural Networks, the input parameters (independent variables) as described in TMH 9 (CSRA, 1992) were selected as described in Appendix A.2. The OPC was selected as the output parameter (dependent variable) in the training set. These selections were made to be consistent with the standard used in South Africa. Parameters are summarised in Table 3-3.

Table 3-3: Summary of Input/Output Parameters for Neural Network (CSRA,1994)

PARAMETER I = Input O = Output	DEFECT	LEVELS	RANGE
I1 & I2	Failure/Patching Degree & Extent	6	0 – 5
I3 & I4	Surface cracks Degree & Extent	6	0 – 5
I5 & I6	Aggregate loss Degree & Extent	6	0 – 5
I7 & I8	Binder condition Degree & Extent	6	0 – 5
I9 & I10	Bleeding/Flushing Degree & Extent	6	0 – 5
I11 & I12	Block/Stabilisation cracks Degree & Extent	3	1 – 3
I13	Block/Stabilisation cracks Spacing	6	0 – 5
I14 & I15	Longitudinal/Slip cracks Degree & Extent	6	0 – 5
I16 & I17	Transverse cracks Degree & Extent	6	0 – 5
I18 & I19	Crocodile/Failure cracks Degree & Extent	6	0 – 5
I20 & I21	Pumping Degree & Extent	6	0 – 5
I22 & I23	Rutting Degree & Extent	6	0 – 5
I24 & I24	Undulation/Settlement Degree & Extent	6	0 – 5
I26 & I27	Patching Degree & Extent	6	0 – 5
I28 & I29	Failures/Potholing Degree & Extent	6	0 – 5
I30	Riding quality	9	0 – 4
I31	Skid resistance	9	0 – 4
I32	Surface drainage	3	0 – 4*
I33	Unpaved shoulders	3	0 – 4*
I34 &I35	Edge breaking Degree & Extent	6	0 – 5
O1	Overall Pavement Condition	9	1 – 5

* only values 0, 2 and 4.

The data was normalised and the normalisation factors are taken as the maximum of the range, i.e., 5 for a range of 0 - 5.

3.5.2 Data preparation

Van der Gryp et al (1998) determined that a total of approximately 13 500 visual assessments (data points) are available in the PAWC PMS database (the total population). An effort was made to evaluate all these data points in the neural network. However, the magnitude of the data led to long computing times. A screening process had to be implemented to reduce the data used in the neural network model. An inspection of the data revealed that approximately 50 data points were available in the low (very poor) OPC category (OPC = 1), see Figure 3-1. It was decided to select data uniformly from all OPC categories on a random basis. Data was selected on a random basis to avoid bias in the selection process. The 1996 data was excluded and used as the test set.

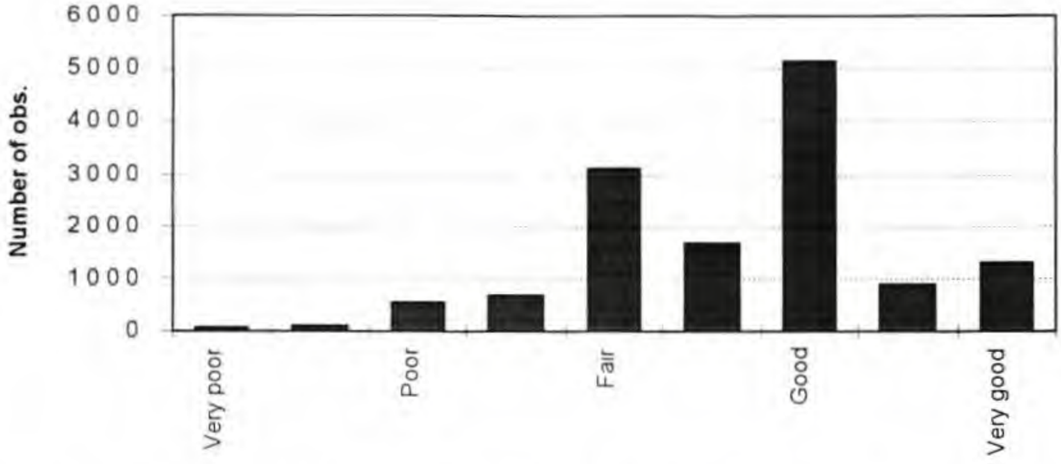

Figure 3-1: Data points per OPC category in PAWC PMS database (Van der Gryp et al, 1998)

The first runs of the neural network revealed certain anomalies in the data. Close investigation showed that data errors were present in the assessment of the OPC. These errors were corrected before being included in the final model. The distribution of the data points after verification is shown in Table 3-4.

Table 3-4: Data points per OPC category before and after data verification (Van der Gryp et al, 1998)

OPC	BEFORE VERIFICATION	AFTER VERIFICATION
Very poor	32	24
Very poor/Poor	50	50
Poor	50	47
Poor/Fair	50	51
Fair	50	44
Fair/Good	50	54
Good	50	54
Good/Very good	50	53
Very Good	50	55

The data verification process gave an indication of another useful application of neural networks, i.e. to identify individual data anomalies during the verification process.

3.5.3 Neural Network Architecture

Van der Gryp et al (1998) tested several neural network architectures with the ThinksPro (LDC, 1996) program and decided to use a Multilayer Normal Feed Forward neural network with the Jacob's Enhanced Back Propagation (JEBP) learning rule (a learning rule available in the Thinks software), Mean Square Error (MSE) network error type, one hidden layer with 12 neurons. The Sigmoid Transfer Function was used for the hidden layer and the Threshold Linear Transfer Function for the output layer.

The Jacob's Enhanced Back Propagation (JEBP) learning rule is an extension of the standard back-propagation learning algorithm with added functionality. The same learning rate and momentum factors are implemented and an adjustment factor for the learning rate is introduced that enables the program to adjust the learning rate during run time for optimum training speed and accuracy in the search for the global minimum. Limits on the magnitude of the weights are also introduced.

3.5.4 Findings

After training the ANN and using the training set (432 data points) described in the previous paragraphs, the 1996 visual data (1912 data points) was used for the testing set and evaluated. Figure 3-2 shows the MSE

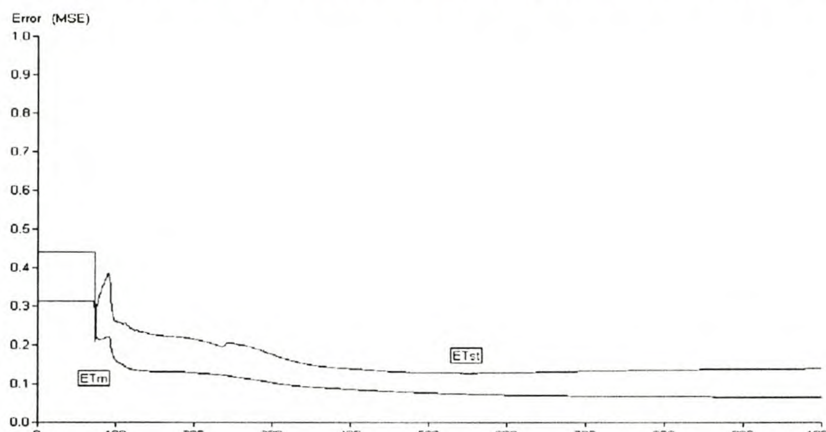

Figure 3-2: Error graph (Van der Gryp et al, 1998)

for both the training and test set over the number of iterations. The MSE after 1 000 iterations for the training set is 0.067 and for the test set 0.141. It should be noted that the MSE for the test set reached a minimum after approximately 550 iterations, whereafter the network memorises the facts instead of generalizing (indicated by the increase in the fast set MSE as discussed in Chapter 1 and 2). At this point the MSE for the training and test sets are 0.073 and 0.112 respectively. These values should have been reported in the 1998 paper as the MSE results.

3.5.5 Comparison of Neural Network with VCI

The neural network output values (OPC), which are still normalised with values in the range [0,1], were converted to VCI by multiplying by 100, and then compared with to the VCI in the PMS database calculated with Eq. 3-3. This comparison is shown in Figure 3-3.

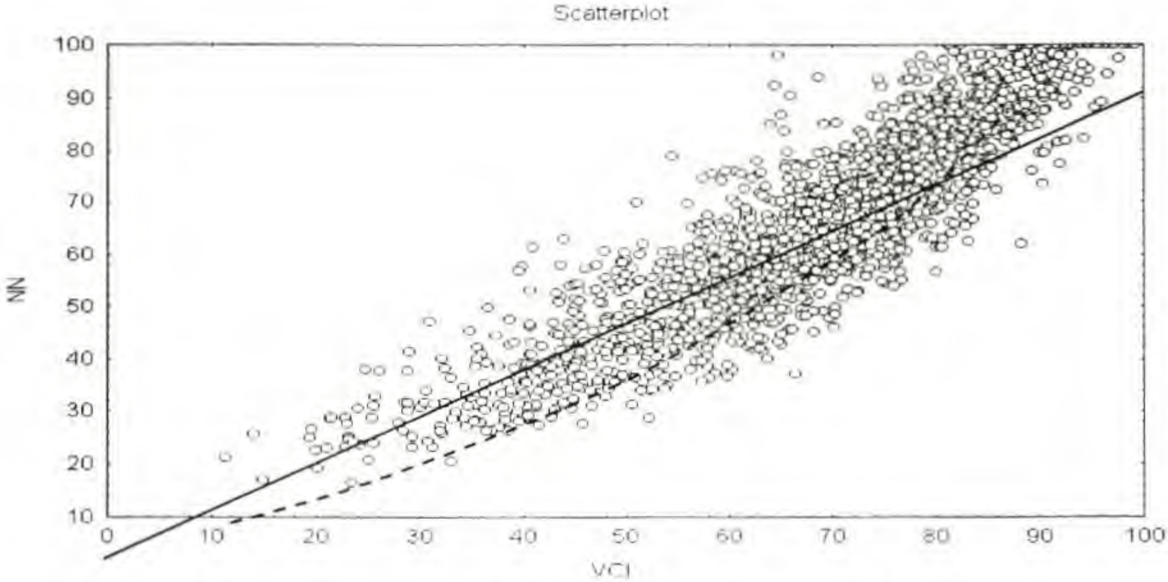

Figure 3-3: Scatterplot of VCI vs. Neural Network index (Van der Gryp et al, 1998)

Van der Gryp et al (1998) did not report a correlation between the neural network predicted VCI and VCI values from the PMS database, as determined with the TRH22 method. Visually it is recognized that a relationship exists between the neural network predicted VCI's and the calculated VCI's, although a rather wide scatter is indicated. Van der Gryp et al (1998) reported on a statistical analysis comparing the two datasets (NN versus TRH22) and determined that the datasets of the two distributions are not statistically the same. Further work is reported further on in this thesis regarding the correlation between the NN and TRH22 VCI's.

3.5.6 Categorising indexes

In practice, the VCI is used to categorise the road condition as per the definition given in Table 3-1. The total road length is categorised in the condition categories by aggregating road sections in the individual categories. This is shown in Figure 3-4.

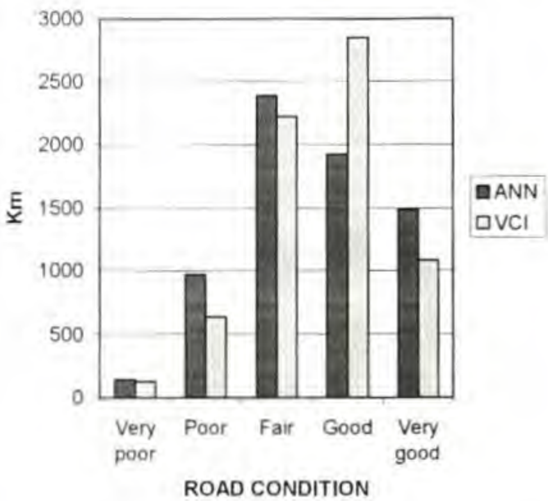

Figure 3-4: Distance (km) per OPC (Van der Gryp, 1998)

It is clear from Figure 3-4 that the number of road sections in the Very Poor and Poor categories have increased in terms of the neural network calculated index at the expense of the Good condition. A similar trend is observed for the other conditions and the increase in the Very Good category should especially be noted.

Table 3-5 shows the distribution of road sections in the different condition categories in terms of kilometres, as displayed in Figure 3-4, and in terms of the condition as a percentage.

Table 3-5: Distribution of Condition Categories (Van der Gryp et al, 1998)

CONDITION CATEGORY	KILOMETRES		PERCENTAGE	
	NN	VCI	NN	VCI
Very poor	147,52	131,99	2,13	1,91
Poor	968,28	633,76	14,01	9,17
Fair	2384,57	2218,89	34,51	32,11
Good	1924,48	2846,39	27,85	41,19
Very good	1485,37	1079,19	21,50	15,62

From Table 3-5 it is deduced that, using the VCI calculated with the TRH22 method, 1.9% of the road network is in the Very Poor condition, while the Neural Network prediction resulted in 2.1% of the road network being in the Very Poor condition. A similar trend is observed for the other condition categories except for roads in the Good condition where the length of road in good condition has decreased from 41.2% to 27.9%.

3.5.7 Conclusion from 1997 Investigation

Van der Gryp et al (1998) concluded that the application of a neural network for determining the VCI of surfaced roads has been proven as a feasible method and they are of the opinion that the subjectivity in determining the VCI is minimised by the use of a neural network solution rather than the TRH22 formula, with the only remaining subjectivity lying with the original evaluation of the Assessor. No subjective functions and factors are built into the final answer that is in contrast to the method currently used to calculate the VCI. Van der Gryp et al (1998) recommended that one of the following be done to calibrate the Neural Network solution:

- Obtain results from an expert panel by visiting and evaluating at least the 5 major categories of the OPC. The problem with this method is that it is very costly and to obtain enough samples with the various combinations within each category is an almost impossible task.
- Use the existing neural network configuration and the existing complete database to determine the VCI using a neural network solution. This is then updated annually with the addition of new data, as they become available. In such a way more examples per category can be identified. The

disadvantage of this method is that the neural network solution would become biased towards the Fair condition, as this is currently the condition with the highest occurrence.

Van der Gryp et al (1998) recommended the latter method.

3.6 FOLLOW-UP INVESTIGATION

The dataset used in the 1997 investigation was extended to include all the data available up to that point, plus the data from the 1997 and 1998 visual assessments. The 1999 visual assessment data was taken as the test set. This time the Qnet2000 program was used (see Chapter 2 for a discussion on neural network software).

Work presented in this section is based on work done by the author.

3.6.1 Data Preparation

Van der Gryp et al (1998) expressed their concern that, if the majority of the data is in one or two condition categories, the neural network solution will become biased towards those categories. The frequency distribution of the condition indices for the different categories is shown in Figure 3-5 (refer Table 3-1 for a description and definition of the condition categories).

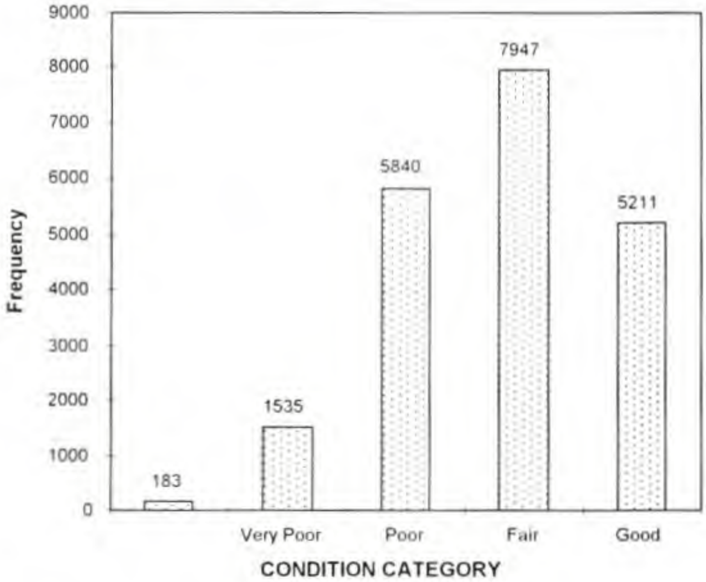

Figure 3-5: Frequency Distribution of VCI per Condition Category

Figure 3-5 shows clearly that almost all the road sections fall in the Fair, Good and Very Good categories, with only 183, or less than 1%, in the Very Poor category. Even the Very Poor and Poor categories combined represent only 8% of the dataset, so that a concern for a biased result from the neural network seems justified.

To investigate the neural network's ability to generalize, even with distributions as per Figure 3-5, two sets of data were prepared. The first set of data includes all the data in PAWC PMS database (18360 records all together) and the second set a random selection of 250 records per condition category (1162 records in total), except for the Very Poor category where only 183 records are available of which 162 were selected.

The two datasets are compared in Table 3-6.

Table 3-6: Comparison of two datasets to test bias due to different data distributions

DATASET	DATASET 1	DATASET 2
Training (visual data up to 1998)	18360	1162
Testing (visual data for 1999)	2356	2356
TOTAL	20716	3518

The distribution of data in the two datasets therefore differs quite considerably. With the first data set the neural network will be presented with 43 times more facts in the Good category than in the Very Poor category, while with the second data set the neural network will be presented with facts evenly distributed in all the condition categories.

3.6.2 Neural Network Architecture

Three neural networks were created to test various network architectures (i.e. combinations of neurons and hidden layers) and different input/output combinations for each dataset. Multilayer Normal Feedforward neural networks with a back-propagation learning rule and sigmoid transfer functions were used for all the neural networks. Several hidden layer configurations were tested and a summary of these neural networks is shown in Table 3-7. For each network created the Root Mean Square Error (RMSE), correlation and tolerance values (% of test set input patterns correct) for the test set were recorded and is reported in the table.

Table 3-7: Summary of Neural Networks created for the two Datasets

No	INPUTS	OUTPUTS	LAYERS (CONNECTIONS)	RMSE (%)	CORR* (%)	TOLERANCE 5%	TOLERANCE 10%
DATASET 1							
1	I1 to I35	VCI	35-15-7-1 (637)	0.0691	0.8485	60.0	85.9
2			35-7-1 (252)	0.0707	0.8400	57.5	85.3
3			35-43-13-1 (2077)	0.0708	0.8396	57.8	85.4
DATASET 2							
4	I1 to I35	VCI	35-15-7-1 (637)	0.0719	0.8258	58.8	84.3
5			35-9-3-1 (345)	0.0733	0.8174	58.1	84.2
6			35-9-1 (324)	0.0734	0.8168	57.5	84.0

* Corr = Correlation

Lawrence (1993) recommended as a rule of thumb that the number of facts presented to a network should not exceed 10 times the connections in the network. Applying this rule, Dataset 1 would require a network with a minimum of 1836 connections and Dataset 2 a network with a minimum of 116 connections. For Dataset 1 Network 3 has more than the required connections, with no significant improvement in accuracy, but rather a decrease as far as RMSE is concerned. For Dataset 2 all the networks have more connections than required. Networks 1 and 4 were selected for the two datasets respectively.

The distributions of the VCI calculated by the two neural networks (NN1 and NN4) are shown in Figure 3-6 from which it is clear that the two distributions are almost identical.

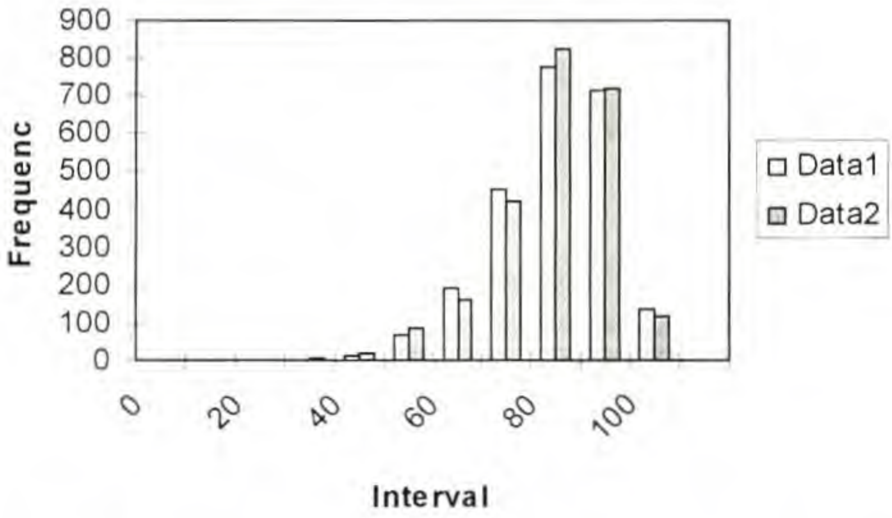

Figure 3-6: Comparison of VCI frequency distributions of two datasets to test bias due to different data distributions

Statistical tests were done on the two frequency distributions to determine equality, the result of which is shown in Table 3-8.

Table 3-8: Statistical comparison of two datasets

DESCRIPTION	DATASET 1	DATASET 2
Mean Variance	74.302 132.705	74.344 132.932
Correlation	0.9796	
t-Statistic t-Critical for two-tail (α = 5%) Test	-0.885 1.961 -1.961 < -0.885 < 1.961 Therefore Means are equal	

Table 3-8 shows a very good correlation between the two datasets and that there is no significant statistical difference between the datasets. It is therefore not necessary to do extensive data manipulation to ensure an equal distribution.

It was decided to use the results from the full dataset (Dataset 1) because a better correlation and tolerance with a smaller RMSE is obtained. There is, however, such a small difference between the results of the two datasets that the smaller, evenly distributed dataset could just as well have been used.

3.6.3 Comparison of VCI with different factors as per TRH22

Eq. 3-3 is recommended in TRH22 to calculate VCI from VCI_p, but two different constants are reported (see discussion in paragraph 3.3). The VCI calculated with Eq. 3-3 for the two different sets of constants is compared in Figure 3-7. It was already reported that the purpose of Eq. 3-3 is to transform the VCI_p,

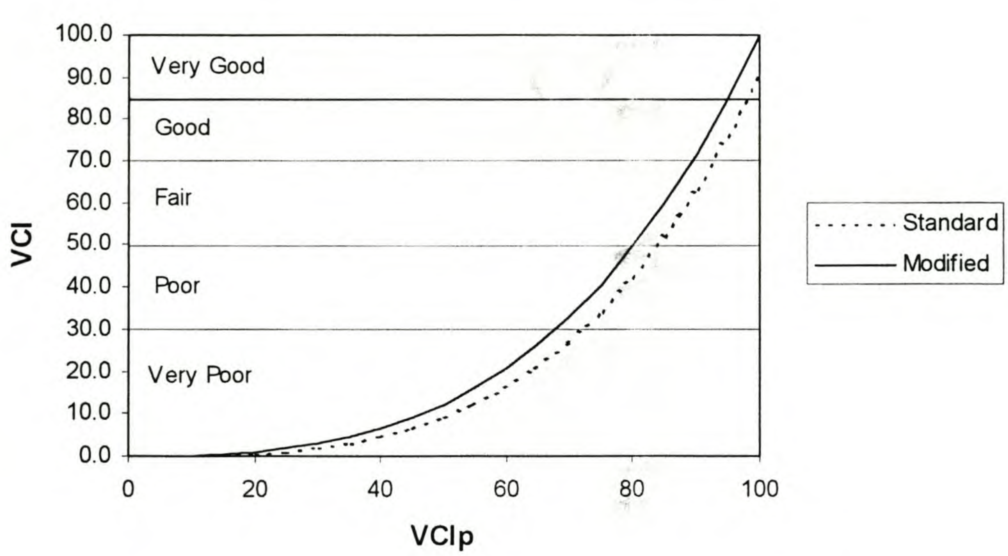

Figure 3-7: Influence of factors "a" and "b" on Eq. 3-3

calculated with Eq. 3-1 to a standard (national) percentage scale.

The VCI, as calculated with the two different sets of constants, is compared in Table 3-9 at the upper boundaries of the condition categories described in Table 3-1.

Table 3-9: Comparison of VCI with different factors in Condition Categories

VCI	VCI_p	
	STANDARD	MOD. (APP. A)
a=	0.02509	0.04000
b=	0.0007	0.0006
30	72.3	67.9
50	84.2	80.2
70	92.9	89.4
85	98.2	95.0
100	102.9	100.0

Form Table 3-9 it is deduced that all VCI_p values up to 72.3% and 67.9%, respectively, are converted to VCI = 30, i.e. falls in the Very Poor condition category.

Van der Gryp et al (1998) compared the neural network results with the VCI from Eq. 3-3 (Figure 3-3). As an alternative approach one can compare the neural network result with the VCI_p (Eq. 3-1). Figure 3-7 shows that the "standard percentage scale" can be understood as a "National Scale" and that it does not contribute to the behaviour of any formula with a purpose of interpreting visual assessments. As is the case with Eq. 3-1, it merely translates visual results to a standard national scale. Such a viewpoint implies that results from the neural network should rather be compared with VCI_p (Eq. 3-1) and not VCI (Eq. 3-3). This aspect will be investigated further in paragraph 3.6.6.

3.6.4 Contribution of Inputs (Defects) Towards Overall Pavement Condition

The Qnet2000 program has the facility to interrogate the inputs to determine the contribution of each input to the result, in this case the OPC (or the VCI, as it is the intention of replacing the VCI-formula with the neural network assessment). The average contribution of each input towards the OPC is shown in Table 3-10 and these contributions are compared with the weight set for the VCI-formula from Table 3-2.

Table 3-10: Average contribution of inputs towards OPC compared with Weights in PAWC formula

INPUT	DEFECT	CONTRIBUTION TOWARDS OPC (%)			WEIGHTS Table 3-2
		DEGREE	EXTENT	TOTAL	
1 + 2	Failure/Patching	1.24	1.40	2.64	**6.5**
3 + 4	Surface cracks	3.40	1.13	4.53	**5.0**
5 + 6	Aggregate loss	1.21	2.20	3.41	**4.0**
7 + 8	Binder condition	3.58	1.34	4.92	**3.0**
9 + 10	Bleeding/Flushing	1.03	0.83	1.86	**3.0**
11+12+13	Block/Stabilisation cracks	3.23	2.73 + 1.43	7.39	**8, 6, 5**
14 + 15	Longitudinal/Slip cracks	1.44	3.04	4.48	**4.5**
16 + 17	Transverse cracks	1.06	2.46	3.52	**4.5**
18 + 19	Crocodile/Failure cracks	2.53	8.85	11.38	**10.0**
20 + 21	Pumping	1.60	4.91	6.51	**10.0**
22 + 23	Rutting	2.22	2.42	4.64	**8.0**
24 + 25	Undulation/Settlement	1.33	1.68	3.01	**4.0**
26 + 27	Patching	1.43	2.07	3.50	**8.0**
28 + 29	Failures/Potholing	1.01	6.89	7.90	**15.0**
30	Riding quality	18.09	-	18.09	**5.5**
31	Skid resistance	6.94	-	6.94	**3.0**
32	Surface drainage	2.88	-	2.88	**3.0**
33	Unpaved shoulders	0.85	-	0.85	**3.5**
34 + 35	Edge breaking	0.79	0.74	1.53	**3.5**

The following observations are made from Table 3-10:

- Riding Quality has the highest contribution (18.09%) towards the VCI, followed by Crocodile Cracks (11.38%).
- Unpaved Shoulders has the lowest contribution (0.85%) towards the VCI, followed by Edge Break (1.53%).
- Sometimes the degree of a defect influences the Assessor more than the extent (i.e. Surface Cracks and Binder Condition) and other times the opposite is true (i.e. Failures/Potholing and Crocodile Cracks).
- The four functional defects (Riding Quality, Skid Resistance, Surface Drainage and Unpaved Shoulders) contribute approximately 29% towards the VCI.
- The weights from Table 3-2 were include to compare the relative importance the two methods allocate (neural network vs TRH22) to certain defects. Failures/potholing is ranked as the highest priority in TRH22 while it is only ranked 3rd by the neural network. Similarly, Riding Quality is ranked as the highest priority by the neural network (the Assessor) while it is ranked only 8th in TRH22. The two methods are in agreement on the 2nd priority: the Crocodile/failure Cracks defect.

It was concluded that the neural network indicates that the OPC is a function of riding quality and that the neural network ranks riding quality higher than the TRH22. The question immediately raised is what influences the type of vehicle driven by the Assessor and its speed will have on the Assessor's OPC rating. All assessments are done at the same speed so that speed will not so much influence the relative OPC rating. The type of vehicle, and especially the comfort zone created by the vehicle, will influence the OPC rating if the neural network weight is accepted. A case is therefore to be made for human interference in the allocation of weights indicating that the application of a formula will be preferred ahead of a total neural network approach.

NOTE: The weights allocated by the neural network cannot be used directly in Eq. 3-2 as two totally different calculation methods are used.

By studying Table 3-10 one starts to understand what influences the Assessor to make a decision regarding the OPC. One must keep in mind that the Assessor is at the point where the decision is to be made of what the OPC is and at the time of his decision the memory of what he has just observed will determine the outcome of his decision.

3.6.5 Evaluation of Calculated OPC

The OPC values calculated with the neural network are compared with the target OPC values of the Assessors from the test dataset (1999 visual data) in Figure 3-8.

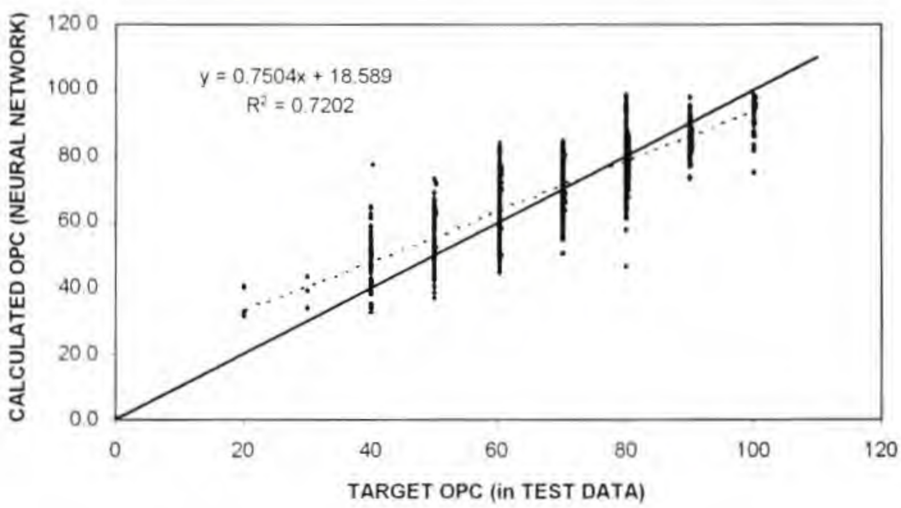

Figure 3-8: Calculated versus Target OPC values

The straight lines of the data are caused by the discreet values of the OPC by the Assessors, i.e. only specific discreet values are entered on the assessment form.

A linear regression fit of the calculated and target OPC values is shown as a dotted line in Figure 3-8. The linear regression fit shows a conditional bias, with the lower OPC values being over-predicted and higher

OPC values being under-predicted on average. Owusu-Ababio (1995) mentioned that parametric estimators such as linear regression are high-bias estimators in that they assume an a-priori model (e.g. a linear relationship) while neural networks are analogous to nonparametric regression methods in that they make no a-priori assumptions about the problem: the data is allowed to speak for itselve. Too much must not be read into the linear regression comparison.

NOTE: Dataset 2 gives the same conditional bias so that the conditional bias is not caused by the method, but is inherent in the neural network's interpretation of the data.

3.6.6 Comparison of OPC and VCI_p

It was argued in paragraph 3.6.3 that the OPC should be compared with the VCI_p. This comparison will be done in this section, following the methodology shown in Figure 3-9.

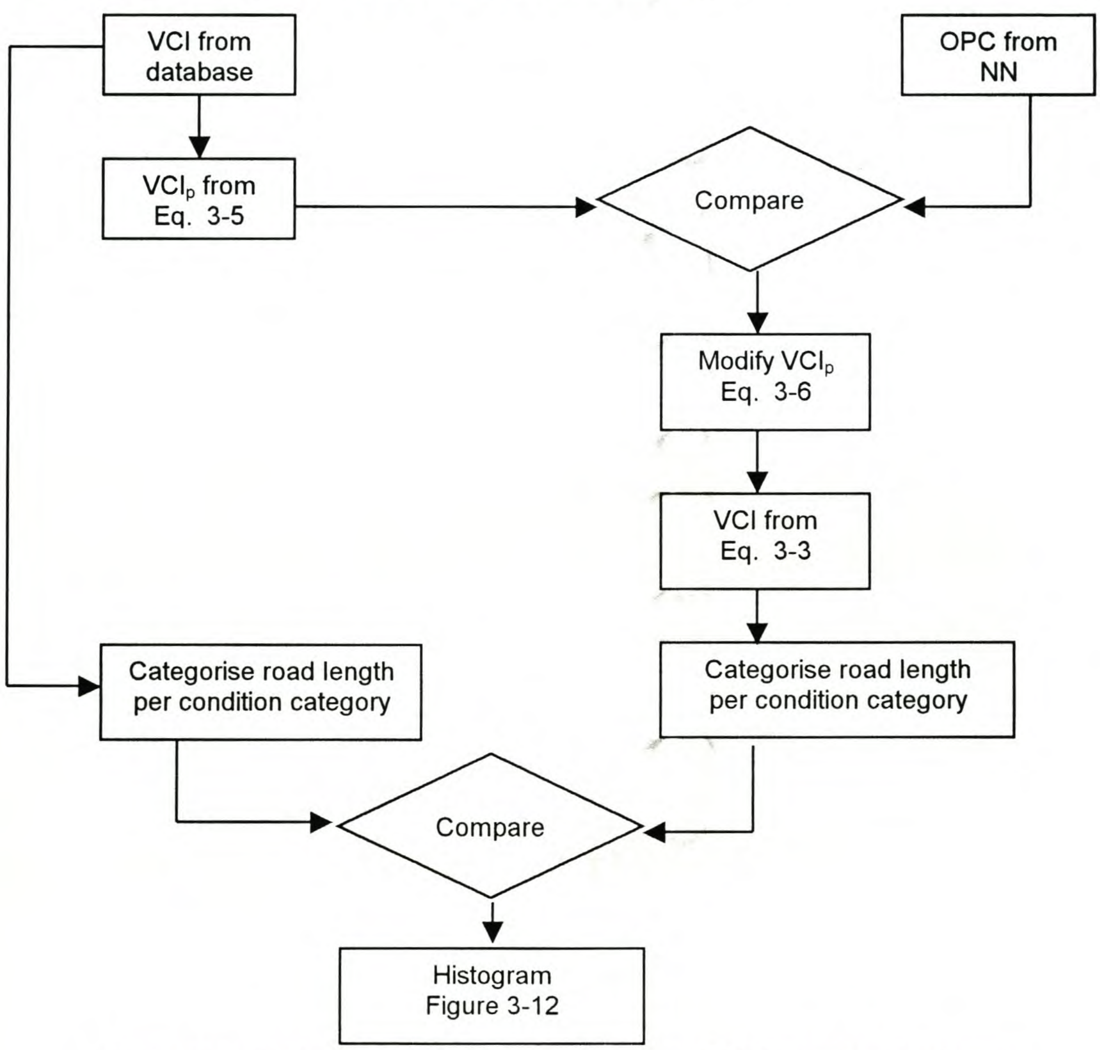

Figure 3-9: Methodology to compare VCI_p with OPC from neural network

Only the VCI value is available in the PMS database so that VCI_p had to be back-calculated with Eq. 3-5.

$$VCI_p = \frac{1}{2b}\left(-a+\sqrt{a^2+4b\sqrt{VCI}}\right)$$

Eq. 3-5

The OPC calculated with the neural network is compared in Figure 3-10 with the VCI_p back-calculated from the VCI in the PMS database (1999 visual data) with Eq. 3-5.

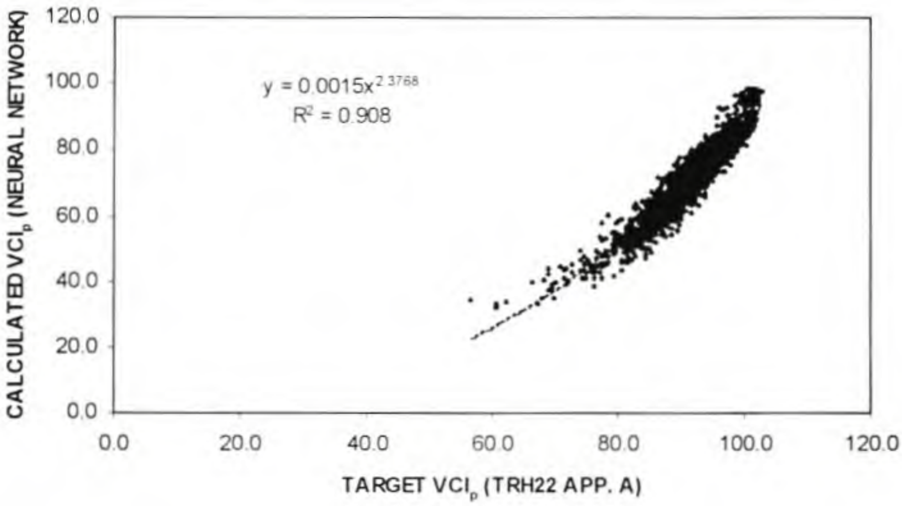

Figure 3-10: Relationship of VCI_p from Neural Network (OPC) with VCI_p from PMS

A regression analysis with a power function showed a strong correlation ($R^2 = 0.908$) so that Eq. 3-1 can be modified as shown in Eq. 3-6.

$$VCI_p = 0.0015\left[100\left(1-C\times\sum_{n=1}^{N}F_n\right)\right]^{2.3768}$$

Eq. 3-6

With definition for variables as per Eq. 3-3.

The relationship between the neural network VCI_p and the VCI_p calculated with Eq. 3-6 is shown in Figure 3-11.

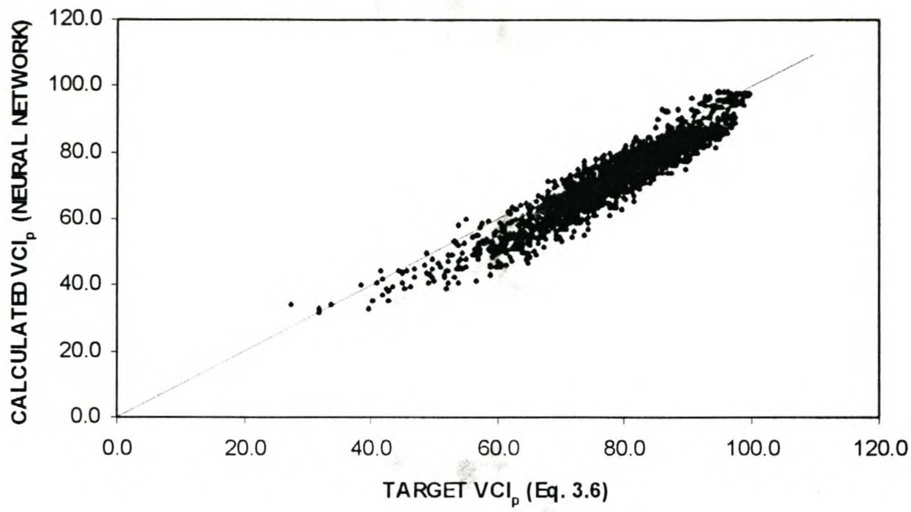

Figure 3-11: Relationship of VCI_p from Neural Network (OPC) with modified VCI_p from Eq. 3-6

A histogram of VCI values calculated with the modified VCI_p from Eq. 3-6 is compared with the original VCI values in the PMS database, as calculated from VCI_p (Eq. 3-1), is shown in Figure 3-12.

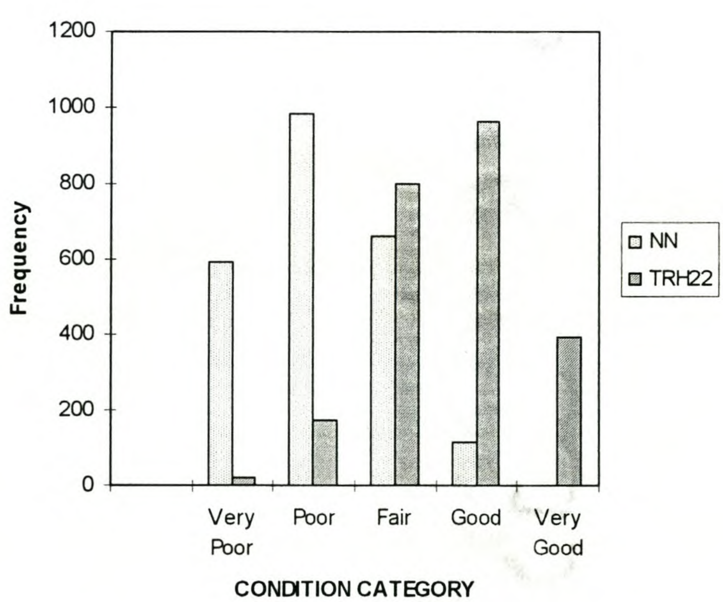

Figure 3-12: Histogram of VCI from modified VCI_p formula compared with original VCI in condition categories

The histogram in Figure 3-12 shows that modifying VCI_p from a comparison between the OPC and VCI_p, and then applying the VCI formula, is a very drastic approach. It is not believed that the current approach is so wrong that a total shift in network condition is justified. It is believed that there is merit in the approach of comparing OPC and VCI_p so that a rethink on the "a" and "b" factors is justified. The result in Figure 3-12 can easily be modified to acceptable limits by adjusting the factors "a" and "b". The shape of the VCI formula depicted in Figure 3.8 is the main reason why such a shift has occurred. A less dramatic function as the double quadratic function of Eq. 3-3 would not have had such a drastic effect.

3.6.7 Comparison of OPC and VCI

The OPC from the neural network can be compared with the VCI following the methodology in Figure 3-9.

The "a" and "b" factors in Eq. 3-3 can be re-calculated so that the VCI calculated with Eq. 3-3 reflects the OPC calculated with the neural network. The relation between the OPC from the neural network and VCI_p with the regression result is shown in Figure 3-13.

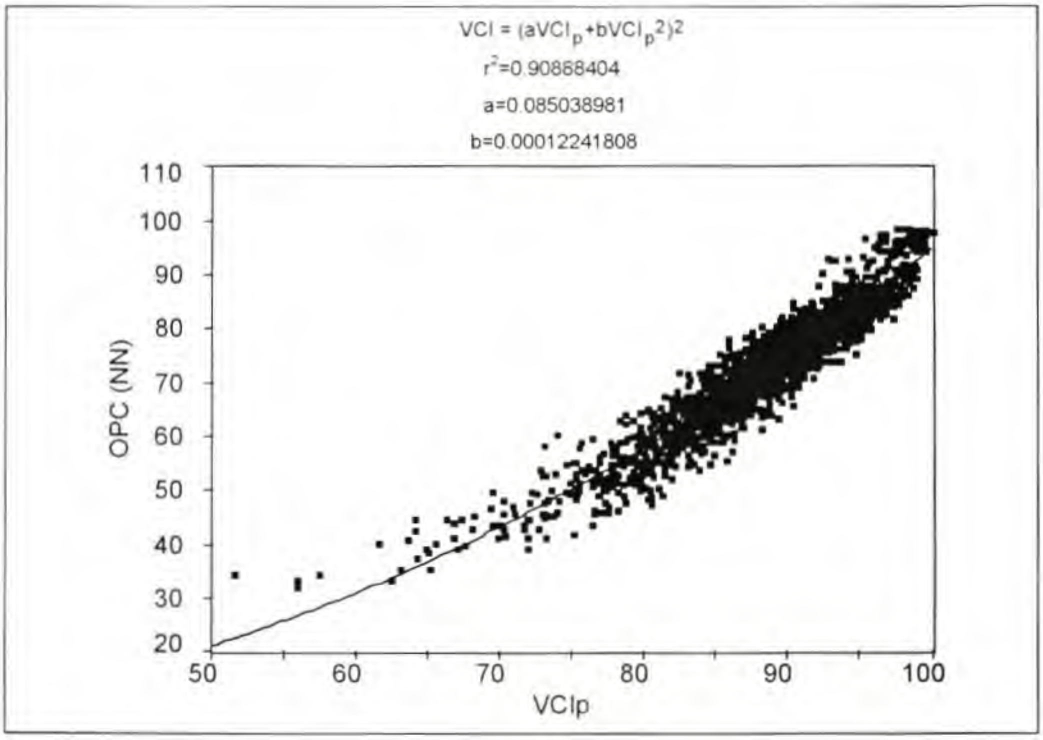

Figure 3-13: Relationship between VCI from Neural Network (OPC) with VCI_p

From Figure 3-13 it is clear that Eq. 3-3 can be applied with constants "a" and "b" as follows:

a = 0.08504

b = 0.0001224

(R^2 = 0.9089)

The above "a" and "b" differs quite substantially from the "a" and "b" values recommended by TRH22 (i.e. a = 0.2509 and b = 0.007).

Using the above constants "a" and "b" in Eq. 3-3 allows the user to continue using the TRH22 formula, but have a good match with the neural network result.

The alternative to the application of the formula set out in TRH22 is to apply the neural network solution directly. This will mean that the weight set, normalisation factors and the network solution are available. Normally a Dynamic Link Library (DLL) is made available from which the neural network result is extracted. Implementation of the neural network approach requires slightly more complicated and higher level programming. Fortunately an alternative is available due to the fact that the constants in Eq. 3-3 could be adjusted to give a good correlation with the neural network solution.

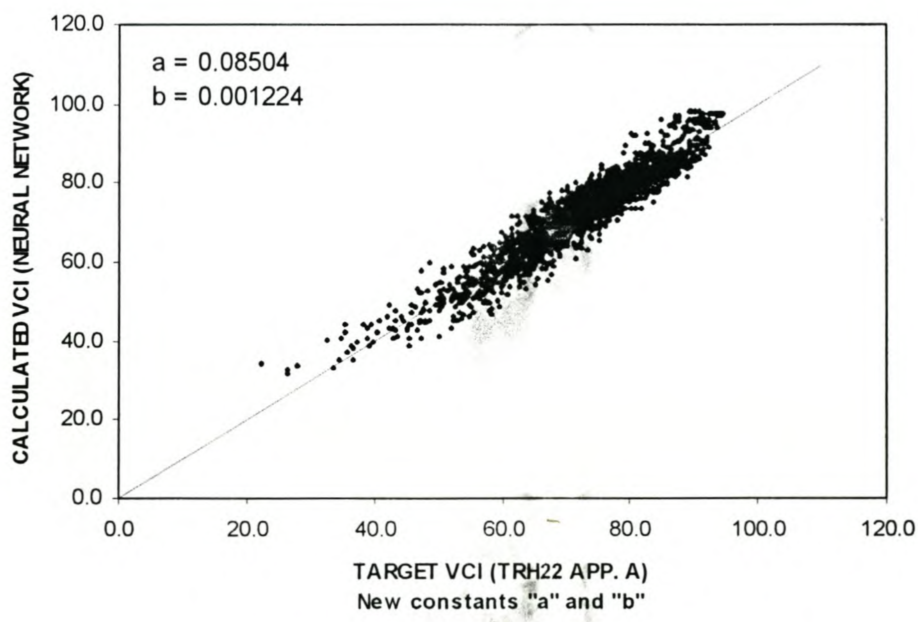

Figure 3-14: Relation between VCI (Neural Network) and VCI (TRH22) with new constants "a" and "b"

The modified VCI now shows good correlation (r^2 = 0,9083) with the neural network's OPC.

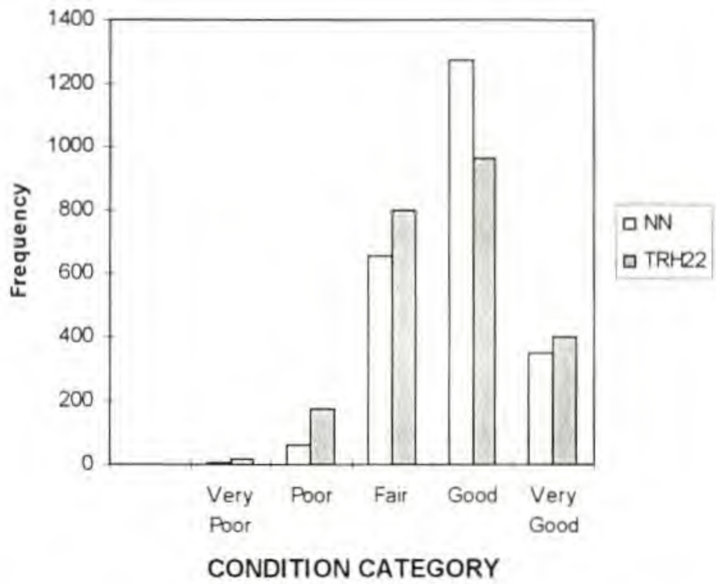

Figure 3-15: Histogram of VCI (new constants a = 0,08504 and b = 0,001224) compared with original VCI in condition categories

The histogram comparing the "old" and "new" VCI values now shows that a shift has occurred and that more road sections are now in a Good condition and less in a Poor and Fair condition.

3.7 DISCUSSION

The question of subjectivity has been mentioned several times. In his motivation to use automated methods, Chou et al (1995) states that visual assessments are inconsistent, costly, tedious, labour intensive and subjective. TRH22 (CSRA, 1994) recommends that a system of quality assurance should be introduced for all condition surveys (visual and instrument surveys) consisting of calibration procedures before the survey commences and quality checks during and after the surveys. Calibration of visual surveys entails annual calibration workshops. Although these workshops will reduce the subjectivity, a certain degree of subjectivity will remain. In addition to the subjectivity issue, TRH22 (CSRA, 1994) also reports that both systematic and random errors occur in visual assessments:

- Leniency error: Constant tendency of assessor to rate too high or too low.
- Halo effect: Tendency of assessors to force ratings of a particular mode of distress in the direction of the overall impression of the item rated.
- Central tendency error: Hesitancy of assessors to give extreme judgements of the visual condition

observed, therefore ratings tend towards the mean.

The compilation of the set of equations (Eq. 3-1, Eq. 3-2 and Eq. 3-3) has been done to produce a good correlation with the judgement of an expert panel of assessors. It is not reported in the TRH22 that these equations were developed to address either the subjectivity issue or provide a means to correct errors. It is safe to assume that at least the subjectivity issue has inherently been addressed, the expert panel of assessors being taken as not subjective. But, the question remains: do the VCI formule give the best result? Van der Gryp et al's (1998) concerns show that at least one road authority is investigating the issue. PAWC has implemented the neural network solution to determining the VCI (Van der Gryp, 1999). The objective of having a national formula as defined in TRH22 has therefore been compromised.

It has been shown that neural networks can be trained to successfully calculate the OPC and that these results can be used in at least two ways to interrogate the VCI formula:

- Compare VCI_p from Eq. 3-1 with neural network OPC and adjust constants "a" and "b" in Eq. 3-3 to yield an acceptable VCI (discussed in 3.5.6).
- Compare VCI from Eq. 3-3 with neural network OPC and adjust constants "a" and "b" for a best fit. Either the modified VCI formula or neural network can then be used to calculate the VCI (discussed in 3.5.7).

From the results reported it seems that the second approach will yield the best results.

Although the neural network can be applied directly to calculate the VCI (thus assuming VCI = OPC) it is not recommended for the following reasons:

- Accepting VCI = OPC means accepting all the subjectivity in the assessment without any question.
- The opinion of the panel of experts is totally ignored.
- Direct comparison of VCI values on a national basis is lost as datasets from different road authorities may result in different VCI results.

The recommended approach to follow is to use the neural network as a guiding tool to adjust "a" and "b" in Eq. 3-3.

- Extend the study described here to include data from other road authorities and investigate differences in datasets from these authorities and combinations thereof.
- Obtain database of previous rating by panel of experts and apply a neural network.
- Investigate various combinations of "a" and "b" combinations in Eq. 3-3.
- Consider an alternative Eq. 3-3.
- Report result to panel of experts.

- Select most appropriate VCI formula.

3.8 CONCLUSION

Van der Gryp et al's (1998) conclusion that the application of a neural network to determine the VCI is a feasible method has been re-affirmed, but a different approach in the implementation thereof is proposed. With the new work done in this project the first update suggested in the previous study has been done. In addition it has been shown that the neural network can be used to modify the constants in the TRH22 equation (Eq. 3-3). The question whether the neural network results are less subjective is still not proven and will probably never be. However, the fact remains that the neural network result only contains subjectivity inherent in the method of data collection, with no subjective actions built into formulae to calculate the VCI. However, a formula to calculate VCI may just be the right tool to solve the problem with the subjectivity inherent in the data. The solution to this problem lies in the careful and intelligent application of both approaches.

The application of a neural network to determine the VCI is probably one of the best applications of a neural network as the artificial intelligence attribute of a neural network is utilized completely, bringing the solution to a complex problem somewhat more in line with human behaviour.

Specific conclusions are summarised as follows:

- The Overall Pavement Condition (OPC) of a road is determined by an Assessor and is therefore subject to the subjective opinion of an individual.

- Certain measures were introduced to standardize the assessment, inter alia though training, and to curb the subjectivity of the assessed OPC to an extent.

- The individually assessed distress items are transformed into a Visual Condition Index (VCI) by applying a formula defined by a panel of experts. Again an element of subjectivity is introduced into the process.

- The VCI formula is applied using a weight set determined by the same panel of experts.

- The OPC is not used in the calculation of the VCI although the OPC is a good indicator of the condition of the road because it was determined by an experienced practitioner at the time of the assessment, with the vision of the road condition imprinted in his mind.

- A relationship must exist between the OPC and the VCI and this relationship can be used to strengthen the calculative power of the VCI formula, or alternatively, replace the VCI formula.

- Shortcomings in the method of calculating the VCI is recognised in the TRH22 with the proposed modification to the initial VCI, the VCI_p. These shortcomings had to be addressed with the introduction of two factors, namely a small degree and an extent weight factor. These factors complicate the calculation method.

- The calculation of the VCI is a cumbersome process that puts high demands on computer capacity, especially memory requirements.

- It is possible to create a neural network to calculate the VCI that is closely related to the OPC as the neural network was trained with the assessment items as input, as is the case with the VCI formula, and the OPC as output.

- The neural network's result was very similar to the results obtained with the TRH22 formula, with only slight shifts of the road length in certain condition categories.

- A comparison of the weights of distress types between the neural network results and those used in the TRH22, shows fundamental differences. The NN showed that riding quality has the highest weight, while the TRH22 ranks failures/potholing the highest. It cannot be concluded which method is correct, but further investigation is required. The author cannot agree that riding quality should have the highest weight, therefore putting the neural network result in doubt. Similarly, the author can also not agree that the skid resistance should have such a low value in the TRH22, now putting the TRH22 method in doubt. A rethink on the weight set in the TRH22 method is suggested, using the neural network weights as one of the inputs.

- The superiority of one method, neural network versus TRH22, could not be proved. Preference towards the neural network method lies in the belief that it is a less subjective method.

- The neural network was not sensitive to the number of data points in a certain condition category and showed no bias if one category has substantially more data points in a certain category. Although not investigated, it is reasonable to expect that data should at least be distributed in such a manner that all categories contain data. The neural network cannot learn if it is not presented by facts.

- The neural network architecture plays an important role in the successful implementation of neural networks. Unfortunately the process to create a neural network involves a trial and error system which is time consuming. Fortunately this is a once-off process.

- A direct comparison of OPC from the neural network resulted in a dramatic shift in network condition from on average good to on average poor. This can be ascribed to the double quadratic function used to calculate the VCI. A direct comparison of the OPC and VCI_p is only possible if the VCI formula is also modified.

- Comparing the OPC from the neural network with the VCI gives better results than a direct comparison between OPC and VCI_p. The result is, however, measured with the TRH22 method that is being investigated in this thesis. The neural network result is accepted and implemented by PAWC, a major road authority; giving credibility to the method.

- The neural network can be used to great advantage to modify current VCI_p and VCI formulae. It is believed that the modified formulae will be less subjective, but will still maintain the advantage that experts designed them. A certain manipulation of the formulae seems to be necessary as was illustrated by the importance of the role that the vehicle of the assessor can play. The careful and intelligent application of both approaches will improve the VCI calculation.

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CHAPTER 4

4 DETERMINING RESEAL TYPES FOR FLEXIBLE PAVEMENTS USING EXPERT SYSTEM PREDICTIONS TO TRAIN ARTIFICIAL NEURAL NETWORKS

4.1 INTRODUCTION

Expert systems were described in Chapter 1 as systems that are good at solving procedural type of problems. They are capable of deductive reasoning using rules and their strength is the step-by-step logical, sequential operations depending on the rules. When new information becomes available, an expert system can easily be expanded to accept the new facts and rules. However, new information can in many cases mean the complete rewriting of the program. Expert systems may be easier to understand but more difficult to implement as they follow the IF-THEN-ELSE logic of the human thought process. Expert systems design often takes long times of collecting information and understanding information and translating these into rules and facts.

An expert system cannot generalize or extrapolate. Noisy incoming data or data outside the set of rules can result in unreliable answers. Development time is normally long. It is especially the limitation of handling noisy data that can create problems, a problem that can be solved with the implementation of a neural network that is able to handle noisy data.

Lee and Galdiero (1989) describe a Pavement Management Expert System (PMES) in Figure 4-1, showing the added functionality supplied by the knowledge base to the database, the knowledge base being a database with a related expert system.

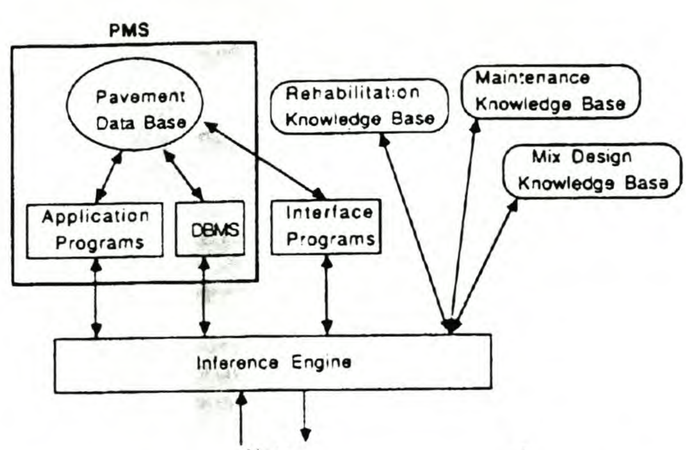

Figure 4-1: Conceptual architecture of PMES (Lee and Galdiero, 1989)

It has long been recognised that a

neural network can either be created from its own database allowing it to make its own associations, or to use a dataset created by an expert system. In the second case the neural network will provide the extra features and it may be easier in feature to add additional features.

The Provincial Administration: Western Cape (PAWC) makes use of several expert systems, one of them being the Reseal Expert System. The Reseal Expert System is used in the PMS to determine the reseal need from visual assessments. An effort will be made to take the input/output from the Reseal Expert System and to create a neural network to solve the same problem. An alternative will be to collect information from historic data where the reseal action taken, is known. This data is not readily available at present and could not be obtained within a reasonable. In the future these historic data can be used to either replace or augment the data created with the expert system.

4.2 GOALS AND OBJECTIVES

The goal with the thesis in this chapter will be to show that neural networks can be used to predict reseal actions to an acceptable level of accuracy in comparison with an equivalent expert system.

The objective would be to demonstrate that a neural network can be implemented as a replacement of an expert system, or be used together with an expert system to compliment the expert system.

4.3 EXAMPLE FROM LITERATURE

Hajek and Hurdal (1993) compared advantages and disadvantages of using rule-based paradigm versus neural-network-based paradigm for developing expert systems involving structured selection problems. The two alternative paradigms were compared by testing their individual abilities to solve the selection of pavement sections that would benefit most from the routing and sealing maintenance treatment (R&S-crack sealing). Training data for the neural network was generated by an existing expert system ROSE. (It should be noted that training data can be generated in other ways, i.e. data gathered from previous successful maintenance actions or from examples generated by a panel of experts).

The structured selection process is described by Hajek and Hurdal (1993) as a selection made from a known set of possible pavement preservation treatments using a reasoning process based on judgement and expertise. Such a process is usually implemented (or has been in the past) using rule-based expert systems, requiring many input parameters, a large number of possible solutions, often leading to complex search strategies and consequently considerable development and programming effort. It was hypothesized by Hajek and Hurdal (1993) that this effort could be substantially reduced by employing an alternative neural network solution.

A comparison of the basic functions by the system developer and system software for the expert and the neural network systems is shown in Figure 4-2 (Hajek and Hurdal, 1993).

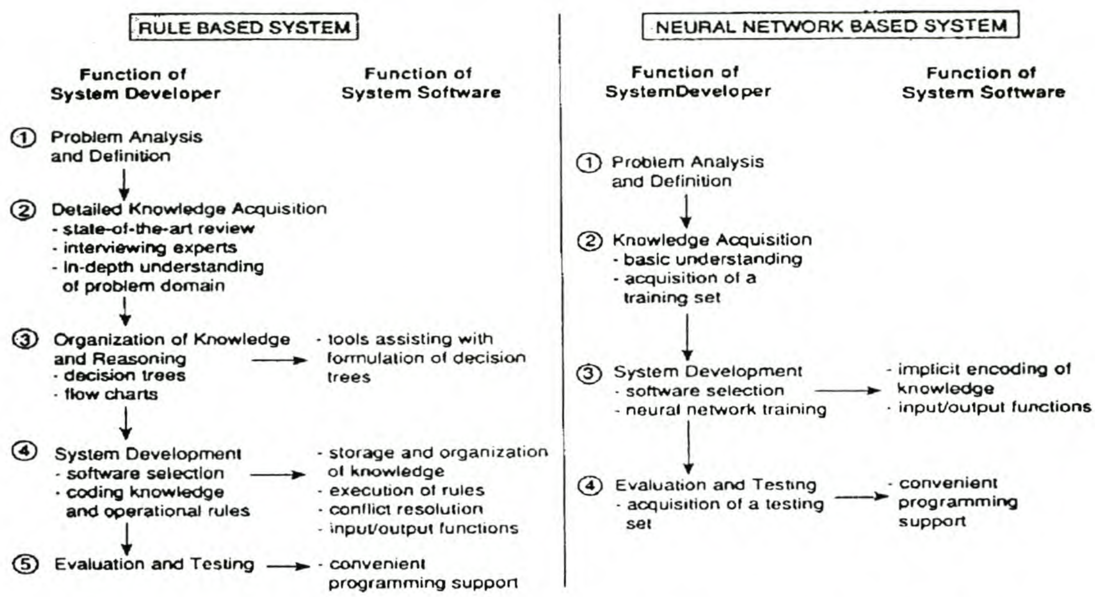

Figure 4-2: Comparison of basic functions by system developer and system software for expert and neural network systems. (Hajek and Hurdal, 1993)

Figure 4-2 shows the basic steps to follow in the procedure to develop either expert or neural network systems. It should especially be noted that expert systems require detailed knowledge of the problem and that it is often necessary to select, evaluate, or combine different points of view and to provide conflict resolution when necessary. Neural networks do not require detail knowledge of the problem as neural networks make predictions based on experience acquired through the learning process, therefore only a set of inputs is required that can be tested against known results.

Hajek and Hurdal (1993) selected 148 representative pavement sections with known predicted R&S values. 40 input (undefined) variables were used with the R&S output consisting of a 10-point scale, 0 denoting no action and 10 the highest desirability. The neural network was created with the Brainmaker programme and the expert system with the EXSYS program. The number of hidden layers and neurons in the neural network is not reported.

Hajek and Hurdal (1993) found that for the lower desirability (0-5) there are substantial differences between the expert system and the neural network, but that for the higher desirability (6-10) the results provided by the two systems were quite similar. (This outcome was quite acceptable as only road sections with the higher desirability will receive treatment).

A comparison of the advantages and disadvantages of the two systems are summarised in Table 4-1 (as deduced from Hajek and Hurdal (1993)).

Table 4-1: Comparison of advantages and disadvantages of using Expert Systems and Neural Networks (Hajek and Hurdal (1993).

EXPERT SYSTEM	NEURAL NETWORK
1. Expert systems can explain how the system reached its conclusion.	1. Neural networks can not explain how a conclusion is reached.
2. Expert systems demand detailed encoding of the domain knowledge. The benefit of this is that discrepancies can be identified and guidelines can be developed (based on the rules).	2. Neural networks do not require detailed domain knowledge. The benefit of this is that a neural network can still be created although no effective way to explain reasoning exists or no models or algorithms are available.
3. Updating of expert systems can be very complicated, especially if the context of the rules should be changed.	3. Updating of the neural network is easy, especially if only new facts are to be added.
4. Expert systems can not deal with situations that are not covered by the rule.	4. Neural networks have greater generalization ability and can include uncertainty implicitly as part of the training process (adding noise).
5. An exact linguistic match is required between the names of variables in the rules and those used by the user.	5. Exact linguistic matching is not required.
6. Expert system can be designed to handle exceptional cases.	6. Neural networks require special training to accommodate unusual cases and an adequate solution is not guaranteed.

Hajek and Hurdal (1993) concluded that, since expert systems and neural networks exhibit strengths and weaknesses in different areas and supplement each other, their combination in one software system or their use for one application would be advantageous.

Flintsch et al (1996) developed a neural network for selecting (screening and recommending) pavement rehabilitation projects. Data were collected from a database with several years of pavement condition and characteristics with associated selections selected for rehabilitation. The Neural Network was allowed to learn from the historic project selection (1960 – 1996).

An interesting finding from Flintsch et al (1996) was that very poor results were obtained from his first data selection on a random basis from each programming year. To improve network performance an equal number of non-programmed and programmed sections were used (after Lawrence, 1993). Flintsch et al's (1996) approach did not include any output from an expert system, although a quasi-expert system in terms of a rating formula was originally used as an initial project selector from which manual selections were done.

4.4 RESEAL EXPERT SYSTEM AT PAWC

The Reseal Expert System is used in the PMS to determine the reseal need from visual assessments. A four-stage process is used to determine the seal type required (PAWC, 1995):

- The first stage is to determine a preliminary seal type per road section from the visual assessment data in the PMS, according to the Flow Diagram shown in Appendix B.5. Six flow diagrams are used for six texture types of the existing seal, i.e.:
  - Medium/Fine or Fine texture
  - Varying: Fine to Coarse texture (varying over the width of the road)
  - Varying: Medium to Coarse texture
  - Varying: Medium to Fine texture
  - Coarse texture
  - Medium texture
- An initial seal type, after applying an expert system based on the flow diagrams in Appendix B.5, is reported in the PMS database.
- The initial seal type needs to be adjusted for existing Cape Seal types, cemented bases and heavy traffic. A Structured Query Language (SQL) query is required to extract the information from the PMS database. The definition of the query was design by the author in cooperation with van der Gryp (1999) and the programming was done by PAWC. The source code of the SQL query is included in Appendices B.1 and B.2.
- The initial seal type is now reported together with the existing seal type, base type and heavy traffic count. The author developed a spreadsheet to make the adjustments for existing seal type, base type and heavy traffic.
- In the second stage an adjustment is made if the existing seal type is a Cape Seal, as is described in paragraph 4.4.1.
- In the third stage an adjustment is made for heavy traffic, as described in paragraph 4.4.2.
- In the fourth stage and adjustment is made for a cemented base course, as is described in paragraph 4.4.3.

A detailed description of seal types in use in the Western Cape is given in Appendix B.3. Only the seal types shown in Table 4-3, Table 4-4 and Table 4-5 are used in the Reseal Expert System. A description of these seal types is given in Table 4-2.

Table 4-2: Seal types used in Reseal Expert System

SEAL TYPE	DESCRIPTION
R13	13 mm Rubber Bitumen Modified Single Seal
L13	13 mm Latex Modified Single Seal
T13	13 mm Single Seal
R9	9 mm Rubber Bitumen Modified Single Seal
L9	9 mm Latex Modified Single Seal
T9	9 mm Single Seal
T7	7 mm Single Seal
SL2M	Coarse Slurry (Modified)
SL2	Coarse Slurry
SS	Sand Seal or Grit Seal
SE	Diluted Emulsion

4.4.1 Adjustment for Cape Seal

The identified seal type is adjusted when the existing seal type is a cape seal (denoted as S19 or S13), but only if the age of the cape seal is 12 years or less. The adjustment is noted in Table 4-3.

Table 4-3: Adjustment to Identified Seal Type if existing seal is Cape Seal

IDENTIFIED SEAL	ADJUSTED SEAL TYPE	
Seal Type	19mm CAPE SEAL (S19)	13mm CAPE SEAL (S13)
R13	R13	R9
L13	L13	L9
T13	T13	T9
R9	R13	R9
L9	L13	L9
T9	T13	T9
T7	T13	T9
SL2M	L13	L9
SL2	T13	T9
SS	T13	T9
SE	(Not Applicable)	
None	(Not Applicable)	

As an example: A R13 (13mm Rubber Bitumen Modified Single Seal) will be adjusted to a R9 (9mm Rubber Bitumen Modified Single Seal) if the existing seal type is 13mm Cape Seal.

4.4.2 Adjustment for Heavy Traffic

The currently identified seal type (either altered or unaltered due to a cape seal) is adjusted for the average heavy traffic according to Table 4-4.

Table 4-4: Adjustment to Currently Identified Seal Type for Heavy Traffic Count

CURRENTLY IDENTIFIED SEAL Seal Type	ADJUSTED SEAL TYPE FOR HEAVY TRAFFIC COUNT		
	> 300	> 100 & < 300	< 50
R13	R13	R13	T13
L13	R13	L13	T13
T13	R13	L13	T13
R9	R9	R13	T9
L9	R9	L9	T9
T9	R9	L9	T9
T7	R9	L9	T7
SL2M	R9	SL2M	SL2
SL2	R9	SL2M	SL2
SS	R9	SL2M	SS
SE	(Not Applicable)		
None	(Not Applicable)		

As an example: A R13 (13mm Rubber Bitumen Modified Single Seal) will be adjusted to a T13 (13mm Single Seal with standard bitumen) if the heavy traffic count is less than 50 vehicles per day.

4.4.3 Adjustment for Cemented Base course

If a cemented base course is present in a road section and represents more than half of the road section, the currently identified seal type (either altered or unaltered due to a cape seal or heavy traffic) is adjusted according to Table 4-5.

Table 4-5: Adjustment to Currently Identified Seal Type for Cemented Base course

CURRENTLY IDENTIFIED SEAL Seal Type	ADJUSTED SEAL TYPE
R13	R13
L13	L13
T13	L13
R9	R9
L9	L9
T9	L9
T7	L9
SL2M	SL2M
SL2	SL2M
SS	SL2M
SE	(Not Applicable)
None	(Not Applicable)

As an example: A T13 (13mm Single Seal with standard bitumen) will be adjusted to a L13 (13mm Latex Modified Single Seal) if the base course on the road section is cemented.

4.5 DETERMINING RESEAL NEED WITH NEURAL NETWORKS

A SQL query was developed by the PAWC to extract data from the PMS database showing the visual assessment per road section and the first stage reseal need as determined by the Reseal Expert System. The query included the existing seal type, heavy traffic count and base type. The definition of the data types for the query is shown in Appendix B.1 with the details of the query shown in Appendix B.2.

4.5.1 Data Preparation

The query extracted 3145 candidate road sections qualifying for reseal as determined by the Reseal Expert System for the period 1991 to 1999. The data obtained with the query was entered into a spreadsheet and the adjustments for Cape Seal, heavy traffic and cemented base course done in the spreadsheet by the author. The distribution of candidate road sections per year is shown in Table 4-6.

Table 4-6: Distribution of candidate road section for reseal per year

YEAR	NUMBER OF CANDIDATE ROAD SECTIONS
1991	15
1992	2
1993	12
1994	389
1995	1
1996	15
1997	4
1998	451
1999	2256
TOTAL	3145

The very large variation in the candidate road sections from year to year can not be explained fully and it is not certain whether an error was made during the data extraction process. One can expect that the number of candidate road sections will vary from year to year: a large number of reseal actions in one year will be followed by a small reseal need, while a period of little reseal activity will be followed by a high reseal need in subsequent years. The large number of candidate road sections in 1999 might be an indication of a backlog in reseals. The data will have to be verified by the PAWC and could unfortunately not be done in time.

It was the intention to follow the same procedure as with the determination of the Visual Condition Index (VCI) in Chapter 3: use data up to 1998 to train a neural network and then apply the 1999 data as a test set (and get the prediction for 1999 as well). From Table 4-6 it can be deduced that 889 training patterns will be obtained following this strategy, with 2256 test patterns. The VCI was determined successfully with this strategy of having less training patterns than test patterns. It is normal practice to have more training patterns than test patterns, i.e. in the order of nine training patterns for every test pattern. However, the VCI was determined as a number and then categorised before any interpretations were made from the results, while with seals a specific value is required, i.e. a seal must be determined and not a range of possibilities. In this case it is felt that a substantial number of training patterns are required to present the neural network with enough facts to learn from. If enough facts are not presented during training the resulting neural network can be biased (Bishop, 1995). The envisaged training and test sets were therefore analysed to determine the number of patterns available for each seal type, with results as shown in Table 4-7.

Table 4-7: Distribution of Data Patterns per Seal Type

SEAL TYPE	TRAINING SET 1991 - 1998	TEST SET 1999	COMBINED DATASET 1991 - 1999
R13	143	302	445
L13	36	81	117
T13	61	95	156
R9	106	218	324
L9	40	45	85
T9	76	69	145
T7	0	1	1
SL2M	15	6	21
SL2	3	3	6
SS	11	6	17
SE	398	1430	1828
TOTAL	889	2256	3145

The data is not evenly distributed and should the strategy set out be followed, only three training patterns will be available for an SL2 seal with no training patterns available for a T7 seal. Without doing any further investigations and even trying to train a neural network, one can see that the success rate will be doubtful.

An alternative is to combine the datasets as is shown in Table 4-7, but there would still be only one training pattern for a T7 seal and six training patterns for the SL2 seal, which is considered inadequate.

It is important to keep in mind that different combinations of the elements in a visual assessment can result in the same seal required for a specific road section. It is exactly this variation that requires a certain minimum number of training patterns to put the neural network in position to learn.

Thirty-seven input parameters from the PMS database were identified to play a role in the determination of a seal type. These parameters are shown Appendix B.4 and are summarised in Table 4-8. In Table 4-8 the data is also given of the six SL2 seal types identified in the combined database.

Table 4-8: Input parameters identified for the determination of the reseal need showing data for six SL2 seal types identified

Parameter	Defect	DEGREE						EXTENT					
		1	2	3	4	5	6	1	2	3	4	5	6
I1	Texture Varying	-	-	-	-	-	-						
I2	First Texture	2	2	2	1	1	1						
I3	Second texture	5	5	4	4	4	4						
I4	Voids Varying	-	-	-	-	-	-						
I5	First Voids	2	2	2	1	1	1						
I6	Second Voids	5	5	4	4	4	4						
I7/I8	Failure/Patching	3	3	3	4	4	4	3	3	2	2	2	2
I9/I10	Surface cracks	3	3	0	0	0	0	1	1	0	0	0	0
I11/I12	Aggregate loss	1	1	0	0	0	0	2	2	0	0	0	0
I13/I14	Binder condition	2	2	2	2	2	2	5	5	5	5	5	5
I15/I16	Bleeding/Flushing	2	2	3	0	0	0	2	2	1	0	0	0
I17/I18	Block/Stabilisation cracks	0	0	0	3	3	3	0	0	0	3	3	3
I19	Block/Stabilisation cracks Spacing	-	-	-	M	M	M						
I20/I21	Longitudinal/Slip cracks	0	0	3	0	0	0	0	0	3	0	0	0
I22/I23	Transverse cracks	3	3	3	0	0	0	1	1	1	0	0	0
I24/I25	Crocodile/Failure cracks	3	3	0	3	3	3	2	2	0	1	1	1
I26/I27	Pumping	0	0	0	0	0	0	0	0	0	0	0	0
I28/I29	Rutting	0	0	2	0	0	0	0	0	2	0	0	0
I30/I31	Patching	3	3	0	5	5	5	2	2	0	1	1	1
I32/I33	Failures/Potholing	4	4	0	3	3	3	1	1	0	1	1	1
I34	Skid resistance	4	4	4	4	4	4	3	3	3	3	3	3
I35	Existing Seal Type (Cape seal)	No Cape Seal											
I36	Heavy Traffic	< 50 vpd											
I37	Base course Type (Cemented)	No Cemented Base											

Patterns 1 & 2 and 4, 5 & 6 are identical respectively, therefore showing three sets of patterns in six training patterns, clearly demonstrating the need for a minimum number of training patterns per seal type.

The data can either be augmented by adding data from experienced personnel in the PAWC or go back to historic data and obtain reseal actions undertaken during the years preceding 1991. This data is not readily available and would require a substantial amount of work and time.

4.5.2 Neural Network Architecture

Three neural networks were created to test for each dataset. Multilayer Normal Feedforward neural networks with a back-propagation learning rule and sigmoid transfer functions were used for all the neural networks. Several hidden layer configurations were tested and a summary of these neural networks is shown in Table 4-9. For each network created the Root Mean Square Error (RMSE), correlation and tolerance values (% of test set input patterns correct) for the test set were recorded and is reported in the table.

The datasets for the three neural networks were compiled as follows:

- Dataset 1: Training set of 889 patterns and test set of 2256 patterns as per Table 4-7.
- Dataset 2: Combine dataset as per Table 4-7.
- Dataset 3: 889 Patterns of which 90 % is used in the training set, and 10 %, selected on a random basis, in the test set.

Table 4-9: Summary of neural networks created for the determination of the reseal need

No	INPUTS	OUTPUTS	LAYERS	DATASET	RMSE (%)	CORR. (%)	TOLERANCE 5%	TOLERANCE 10%
1	I_1 to I_{37}	O_1	37-15-7-1	Train	0.1935	0.8790	36.1	57.1
				Test	0.2432	0.8081	49.2	62.6
2	I_1 to I_{37}	O_1	37-15-7-1	Train	0.0674	0.9864	84.3	94.6
				Test	0.1424	0.9385	84.3	94.6
3	I_1 to I_{37}	O_1	37-15-7-1	Train	0.0785	0.9813	71.1	88.5
				Test	0.2059	0.8657	56.0	76.0

RMSE, correlation and tolerance are shown for both the training and the test sets. The consistently higher RMSE and correlations for the test set indicate that the neural networks train successfully, but do not perform well when presented with new, unknown facts.

The neural network trained with Dataset 2 (the combined data set) performed the best with the lowest RMSE values in both the training and the test set. However, even with this, a tolerance of 84 % correct predictions within 5 % of the measured data is not acceptable.

4.6 CONCLUSION

It was shown that a neural network can be trained to do the same work as an expert system and the advantages and disadvantages of both systems were discussed. It was also shown that a thorough knowledge and understanding of the data presented to the neural network is required. The available dataset for this thesis is not adequate to expect a successful outcome and the dataset needs to be augmented from other sources.

Specific conclusions are:

- Data collection for the reseal neural network can be obtained from the following sources:
  - Expert System prediction
  - Historic reseal data
  - Panel of experts

- Only the initial seal predicted by the expert system is reported in the PMS database. The initial seal needs to be adjusted through a complicated process involving SQL database queries and spreadsheet manipulation.

- A thorough understanding of the data is required and the formulation of the problem must be clear.

- Data was inadequate in certain seal type categories and lacking in a specific type.

- Meaningful results could not be obtained due to inadequate or a lack of data in certain seal categories.

- Neural networks can be trained with data obtained from expert systems and the two techniques can be used together as hybrid systems.

- Neural network results must be validated as they do not always deliver planned results.

The main conclusion is that it is possible to train a neural network to determine seal types for a reseal action, but the predicted seal types are not accurate within acceptable limits due inadequate or a lack of data in certain seal categories. The result obtained here show that neural networks cannot be implemented for every problem.

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CHAPTER 5

5 APPLICATION OF ARTIFICIAL NEURAL NETWORKS IN THE BACK-CALCULATION OF FLEXIBLE PAVEMENT LAYER MODULI FROM DEFLECTION MEASUREMENTS

5.1 INTRODUCTION

The Falling-Weight Deflectometer (FWD) is used widely to non-destructively assess the structural properties of flexible pavements. Evaluation of FWD test results entails back-calculation of in situ pavement layer moduli from measured deflections. Back-calculation is usually accomplished by comparing measured deflection basins with calculated theoretical deflection basins for a specific road structure or an assumed road structure if the pavement structure is not known. Theoretical deflection basins are calculated using static, linear-elastic analysis of multi-layer systems. With all the conventional back-calculation programs available user intervention is required to obtain results that can be considered representative of the pavement structure. Application of back-calculated moduli has therefore not yet been applied on a grand scale in Pavement Management Systems (PMS) in South Africa due to the complexity of the process to be followed. Solutions that are obtained in real-time are required for PMS applications due to the large volume of data that is to be processed on a regular (yearly) basis. The successful application of neural networks in the back-calculation process can make the incorporation thereof possible in a PMS due to the execution speed associated with neural network solutions.

The application of neural networks to back-calculate E-moduli will be investigated using data from the Provincial Administration: Western Cape PMS database. At present, certain parameters are deduced from deflection measurements, i.e. the Base Layer Index (BLI), Middle Layer Index (MLI) and Lower Layer Index (LLI). The BLI is equivalent to the Surface Curvature Index (SCI), the MLI to the Base Damage Index (BDI) and the LLI to the Base Curvature Index (BCI). Certain relationships are then applied with these parameters as a basis, to determine remaining life, etc. If back-calculated E-moduli were available, it would be possible to use a mechanistic approach based on pavement response values such as the strain at the bottom of the asphalt layer, to determine remaining life.

Deflection measurements in the PAWC database are normalized for weight (Van der Gryp, 1999). No adjustments were made for surface temperature. Correction factors for temperature must therefore be applied to back-calculated E-Moduli.

5.2 GOALS AND OBJECTIVES

The goal of the project in this chapter is to determine whether neural networks can be applied on a real-time basis to back-calculate E-moduli from measured deflections in a pavement management system (PMS). The PMS dataset from the Provincial Administration: Western Cape, with 35834 deflection measurements, will be used.

Where neural networks can be successfully applied, the objective will be to demonstrate the application of the neural networks to back-calculate E-moduli in the PMS and not to fully implement a total solution as the implementation of the total solution would require extensive programming and perhaps further research. The amount of work is outside the scope of this thesis.

5.3 BACKGROUND TO BACK-CALCULATION

Ullidtz and Coetzee (1995) define back-calculation as the procedure that involves the calculation of theoretical deflection under applied load using assumed pavement layer moduli. The procedure followed is that these calculated deflections are compared with measured deflections, the assumed moduli are then adjusted in an iterative procedure until the theoretical, and measured deflection basins reach an acceptable match. This implies that knowledge of the existing layer thicknesses and the behaviour of the pavement materials is required.

The purpose of back-calculation is to consider the derived moduli as representative of the pavement response to load and can be used to calculate stresses and strains in the pavement structure for analyses purposes.

Usually linear-elastic layer theory is used to calculate deflections and the moduli derived should therefore be judged with the limits and assumptions of the theory used, in mind. Experience in the application of the back-calculation method is required to judge whether goodness-of-fit is the measure to apply or whether the condition of the pavement violates the assumptions of the linear-elastic layer theory to such an extend that other acceptance criteria should be used to decide whether a solution is realistic and representative of the pavement under consideration.

5.3.1 Conventional Back-calculation Methods

Conventional back-calculation methods fall into two broad groups (Meier and Rix, 1994)

- The first approach is to employ gradient search techniques to adjust the pavement layer moduli iteratively until the theoretical and experimental deflection basins agree within a specified tolerance. An initial estimate (seed moduli) is required to start the iterative search process.

- The second approach is to interpolate within a database of deflection basins, generated for a prescribed pavement. Pattern searching algorithms are used to choose deflection basins in the database that most closely matches the experimental basin. The moduli of the experimental basin are then calculated through interpolation.

5.3.2 Problems Encountered in Back-calculation

Ullidtz and Coetzee (1995) described some of the problems encountered with back-calculation and it is necessary to take note of these problems with the application of neural networks in the back-calculation of pavement layer moduli. A short description of the most common problems experienced is discussed below. (Ullidtz and Coetzee, 1995).

5.3.2.1 Input Data Effects

In conventional back-calculation methods, the input data may have an effect on the derived moduli. Some of these input data effects are the choice of seed moduli, modulus limits in the program used, and layer thickness. Seed moduli that are consistent with test conditions (i.e. temperature, moisture, pavement age, cracking) should be used.

5.3.2.2 Subgrade Stiff Layer

Stiff layers in the subgrade and bedrock are probably the most common problems encountered in the back-calculation of E-moduli. The stiff layers can be real or apparent (see discussion on nonlinearity) and can even be observed where a shallow water table is encountered. A rule of thumb is that a deflection of less than 25 microns at the outer sensors (1500mm) is an indication of a rigid layer or nonlinear behaviour of subgrade material. Conventional back-calculation programs sometimes include a rigid layer at some depth (i.e. 6m, Ullidtz and Coetzee, 1995) to compensate for stiff layers in the subgrade. The subgrade can also be divided into a number of layers to allow the back-calculation program to determine different stiffness values with increased depth.

5.3.2.3 Nonlinearity Effect

Pavement materials do not reflect linear elastic behaviour and especially the stress dependent behaviour of granular materials creates problems in the application of the linear-elastic theory. The nonlinear elastic behaviour of pavement materials is illustrated with the mathematical model in Eq. 5-1 (Rohde et al, 1992).

$$M_R = (k_1 p_a)\left(\frac{\theta}{p_a}\right)^{k_2}\left(\frac{\tau_{oct}}{p_a}\right)^{k_3}$$

Eq. 5-1

Where:

$M_r =$ Resilient Modulus of the granular material

$\theta =$ Bulk stress $(\sigma_1 + \sigma_2 + \sigma_3)$

$k_i =$ Constants

$p_a =$ Atmospheric pressure

$\tau_{oct} =$ Octahedral shear = $\sqrt{\frac{2}{3}(\sigma_1\sigma_2 + \sigma_2\sigma_3 + \sigma_3\sigma_1)}$

In the above model $k_2 = k_3 = 0$ implies a linear-elastic material.

The behaviour of granular and fine-grained soils will differ (Rohde et al, 1992):

- Fine-grained soil behaviour is a function of deviator stress that decreases with depth, resulting in an <u>increase in effective stiffness with depth</u>.
- Sandy or granular material behaviour is a function of both confining pressure and deviator stress. Confining pressure is caused by the weight of overlying material (and thus bulk stress) causing static stress to increase with depth and, together with decreasing load related stress with depth, result in a rapid <u>increase in effective stiffness</u> with depth.

Dynamic stresses caused by the applied load, and influenced by factors such as speed, usually have only an influence for shallow depths, say 1.5m. Dynamic stresses therefore are the dominant stresses in the pavement layers and static stresses in the subgrade.

5.3.2.4 Compensating Layer Effect

Usually the deflection values at the outer sensors are used to estimate subgrade moduli. Very small deflections are measured when a rigid or stiff layer is encountered at shallow depth. These small deflection values lead to high estimates of the subgrade E-modulus. Due to the iterative nature of the back-calculation process, the modulus of the next layer is adjusted to compensate for the high subgrade modulus resulting in a low modulus value. This process is continued and high/low moduli are estimated for alternating layers.

5.3.2.5 Pavement Layer Thickness Effects

Normally program limitations dictate that layer thicknesses are assumed at fixed values over a pavement section. However, pavement thickness values vary due to a number of reasons of which construction tolerance and maintenance activities are the most important. The geometry of the measuring system also causes those layers of thickness less than 75mm not to be reliably characterised.

5.3.2.6 Relative Layer Stiffness Effects

The combination of a specific layer thickness and modulus needs to be significant in relation to other pavement layers to influence surface deflections. A stiff base on a soft subgrade will be successfully identified by surface deflection measurements, but a granular base/subbase combination that sometimes differs only in terms of gradation and indicator specification, will have very similar E-moduli and will therefore not be successfully identified with surface deflection measurements. Layers that would therefore not significantly contribute to the stiffness of the overall pavement should be combined and as few layers as possible should be used.

5.3.2.7 Seasonal and Temperature Effects

Seasonal and temperature effects are unpredictable. Normally subgrade becomes stiffer during periods of low rainfall and less stiff with periods of high rainfall. Granular bases have been observed to increase in stiffness during very hot days, possibly due to higher confinement pressures caused by material expansion. Asphalt behaviour is well known: low moduli are experienced under high temperature and high moduli under low temperatures.

5.3.3 Conventional Back-calculation process

The fundamental elements in most known back-calculation programs are shown in Figure 5-1 (DOT, 1997)

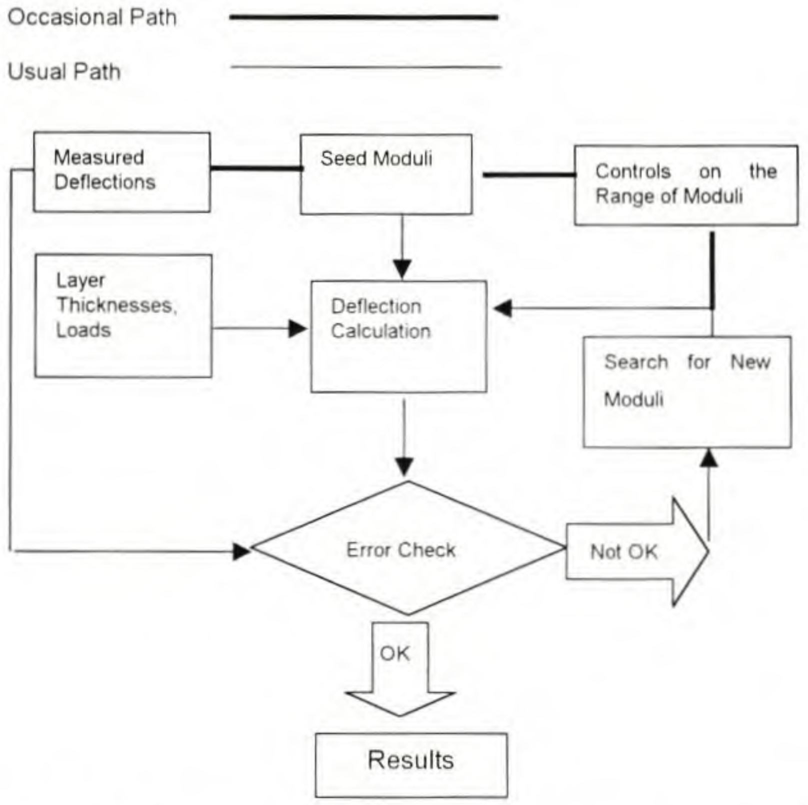

Figure 5-1: Common elements of back-calculation programs (After DOT (1997)

Seed moduli (initial moduli) are selected and used in the computer program to calculate deflections and compare these with the measured deflections. The error check is performed and reported as a Root Mean Square Error (RMSE) using Eq. 5-2 (DOT, 1997).

$$RMSE\ (\%) = \left(\sqrt{\frac{1}{n_d} \sum_{i=1}^{N} \left(\frac{d_{ci} - d_{mi}}{d_{mi}} \right)^2} \right) (100)$$

Eq. 5-2

Where RMSE = Root mean square error.

and

d_{ci} = Calculated deflection at offset i

d_{mi} = Measured deflection at i

n_d = Number of deflections in basins

Back-calculation results should be interpreted with care as is depicted in the following quote (Ullidtz after DOT, 1997):

> *"It is important to realize, however, that layer elastic theory is only a rather poor approximation to the extremely complex conditions of real pavement structures. Most pavement materials will show viscous, visco-elastic and/or plastic deformations under stress, in addition to the elastic deformations. Pavement materials are often inhomogeneous, anisotropic and have nonlinear stress-strain (or stress-strain rate) relations. Many materials are even particulate, i.e. consisting of discrete particles. Discontinuities, like, edges, joints or cracks, are often present and the conditions at the interfaces (rough or smooth) are not well known".*

5.4 ESTIMATING THE DEPTH TO RIGID LAYERS

The influence of stiff layers in the subgrade, albeit real due to bedrock or apparent due to seasonal effects or nonlinearity, is so important that it warrants a separate discussion. The approach by Rohde et al (1992) is well documented and implemented in back-calculation programs such as Modulus.

A fundamental assumption with the method is that the measured pavement surface deflection is a result of deformation of the various materials in the applied stress zone as is illustrated in Figure 5-2. Therefore, the measured surface deflection at any distance from the load is the direct result of the deflection below a specific depth in the pavement structure. The surface deflection D_c in Figure 5-2 indicates the zero deflection point on the surface, in relation to the depth at which zero deflection in the subgrade occurs (Rohde et al, 1992).

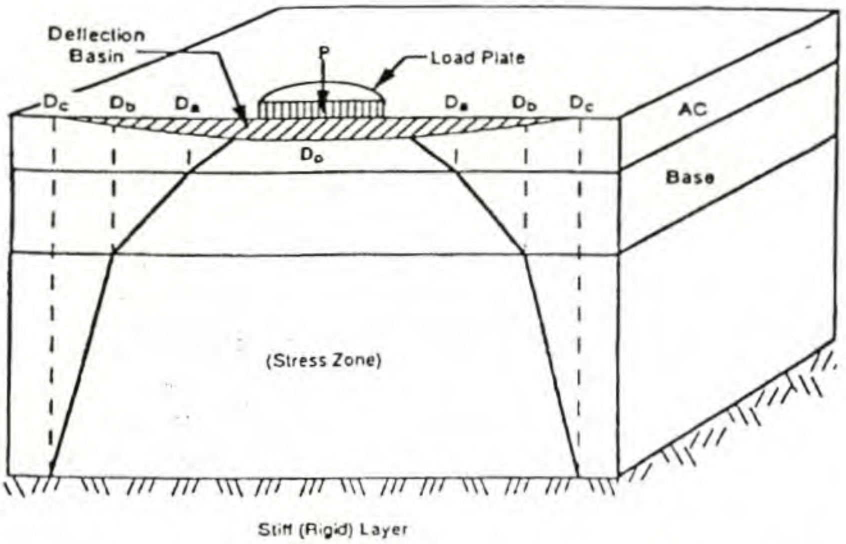

Figure 5-2: Illustration of zero deflection (D_c) due to a stiff layer (DOT, 1997)

An estimate of the depth at which zero deflection occurs can be obtained from a plot of the measured surface deflections and the inverse of the corresponding offsets (1/r) and is illustrated in Figure 5-3. The middle portion of the plot is linear with either end curved due to the nonlinear behaviour of the upper layers and the subgrade respectively.

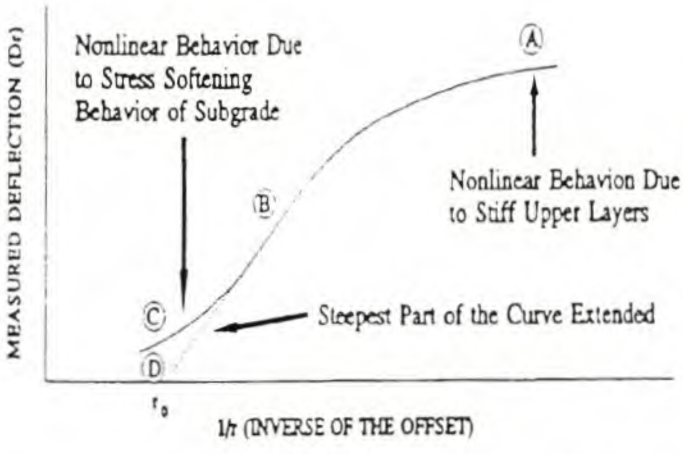

Figure 5-3: Plot of inverse of deflection offset vs. measured deflection (DOT, 1997)

The zero surface deflection is estimated by extending the linear portion (or steepest section) of the D_r vs. 1/r plot to $D_r = 0$, with the 1/r intercept being designated as r_0. Regression equations for the D_r vs. 1/r relationship were developed for a 40 kN load and

- E_1/E_{sg} ratios of 10 - 100,
- E_2/E_{sg} ratios of 0.3 – 10,
- $E_{rigid}/E_{sg} = 100$,
- T_1 = 25mm – 250mm,
- T_2 = 150mm – 300mm,
- B (depth to stiff layer) of 1.5m to 15m.

In an attempt to improve the fit (the estimate of r_0 may not be reliable due to pavement specific factors), deflection basin shape factors Surface Curvature Index (SCI), Base Curvature Index (BCI) and Base Damage Index (BDI) were included in the regression equations.

Regression equations for four AC thicknesses were developed with the dependent variable 1/B and the independent variables r_0, SCI, BCI and BDI. These relationships are shown in the following equations.

Note:

$SCI = D_0 - D_{300}$
$BDI = D_{300} - D_{600}$
$BCI = D_{600} - D_{900}$
B = Depth to stiff layer (m)
R = Offset of geophones (m)
H_1 = Thickness of asphalt layer

$H_1 < 50$mm

$$\frac{1}{B} = 0.1188 - 0.3242r_0 + 3.1308r_o^2 - 2.1982r_0^3 - 0.0005(BCI)$$

Eq. 5-3

50mm < H_1 < 100mm

$$\frac{1}{B} = 0.0212 + 0.1652r_0 + 1.6548r_0^2 - 1.0222r_0^3$$

Eq. 5-4

<u>100mm < H_1 < 150mm</u>

$$\frac{1}{B} = 0.1356 + 0.9929 r_0 - 0.0001(SCI) + 0.0008(BDI) - 0.2552 \log\left(\frac{BCI}{25.4}\right)$$

Eq. 5-5

<u>H_1 > 150mm</u>

$$\frac{1}{B} = 0.1342 + 0.5669 r_0 + 0.9186 r_0^2 + 0.0004(BDI) - 0.2182 \log\left(\frac{BCI}{25.4}\right)$$

Eq. 5-6

To test the Rohde formula (Eq. 5-3), the author generated synthetic pavement structures with H_1 (20–50mm), H_2 (100–200mm), H_3 (100–200mm), H_4 (1500–15000mm), E_1 (300-9000MPa), E_2 (300-7000MPa), E_3 (300-6000MPa), E_4 (50-600MPa) and E_5 = 10000MPa. E_4 represents the modulus of the subgrade E_{sg}. E_5 represents the E-modulus of the stiff layer with the sum of H_1, H_2, H_3 and H_4 equivalent to the depth to the stiff layer. The method to generate the synthetic pavement structures is discussed in detail later in paragraph 5.6.1. Synthetic pavement structures were generated with the WES5 linear elastic program. Note that no neural networks are involved at this stage. The predicted depth to the stiff layer, B, was calculated with Eq. 5-3, and compared with the sum of H_1, H_2, H_3 and H_4 values of the synthetic pavement structures, the result of which is shown in Figure 5-4.

<u>Qualification</u>: Synthetic pavement structures are equivalent to simulated pavement structures. The term synthetic pavement structures is used in this thesis, after Meier and Rix (1993), who introduced the term in their paper.

To be able to apply Eq. 5-3 in a spreadsheet, B-values were calculated for the intervals D_{300}-D_{600}, D_{600}-D_{900}, D_{900}-D_{1200} and D_{1200}-D_{1500} separately and then the minimum B-value was selected. This is equivalent to selecting the steepest section of the curve.

As can be seen from Figure 5-4 almost no correlation exists between the calculated and target values. It should be kept in mind that the deflection basins were generated on a random basis, therefore ignoring the E_1/E_{sg}, etc., ratios in Rohde's method totally. The Rohde method must therefore be applied with great care and due cognisance to the limitations of the parameters for which the method was developed.

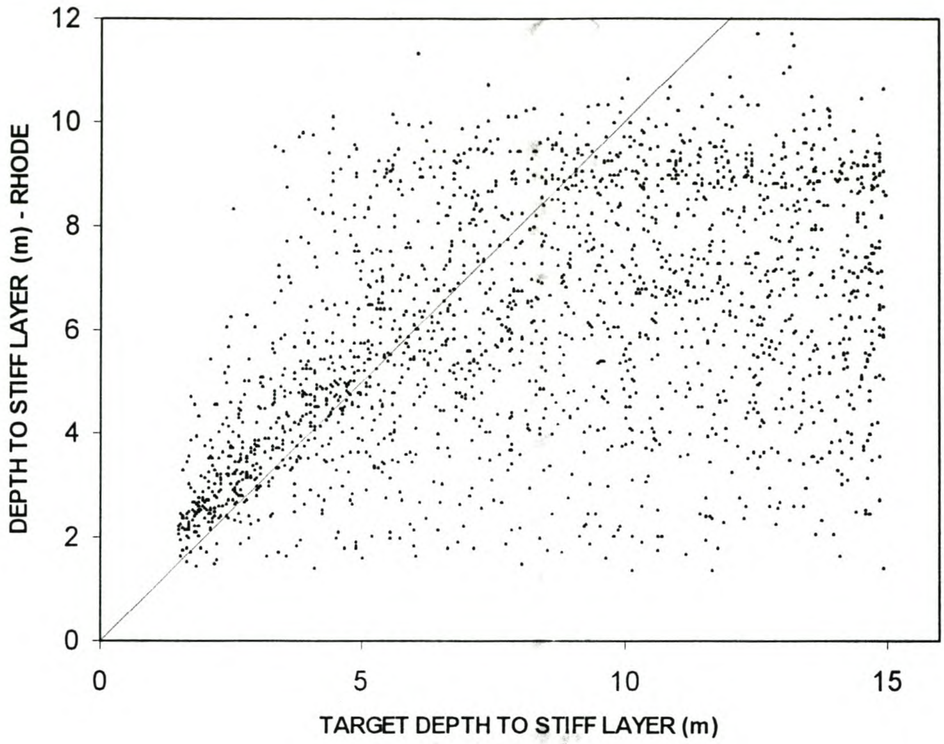

Figure 5-4: Comparison of depth to stiff layer with Rohde known values from synthetic generated deflection basins for H_1 < 50 mm

Subgrade E-moduli can be estimated from deflection measurements with Eq. 5-7 (DOT, 1997)

$$E_r = \frac{P\,(1-\mu^2)}{\pi r\, D_r}$$

Eq. 5-7

Where:

D_r = Surface deflection at offset r

P = Point load (40 kN for FWD)

μ = Poisson's ration

r = Horizontal offset from the loads

E_r = Representative Young's modulus of the halfspace for the sensor r

Eq. 5-7 is normally applied to the D600 sensor up to the outer sensor, D1500, and E_{sg} is equivalent the minimum of the equivalent E_r values.

Applying this method to the PAWC deflection measurements reveal a frequency distribution of estimated subgrade moduli for the PAWC road network as shown in Figure 5-5.

From Figure 5-5 it is clear that the estimated subgrade E-moduli, E_{sg}, are rather high, i.e. more than 100 MPa.

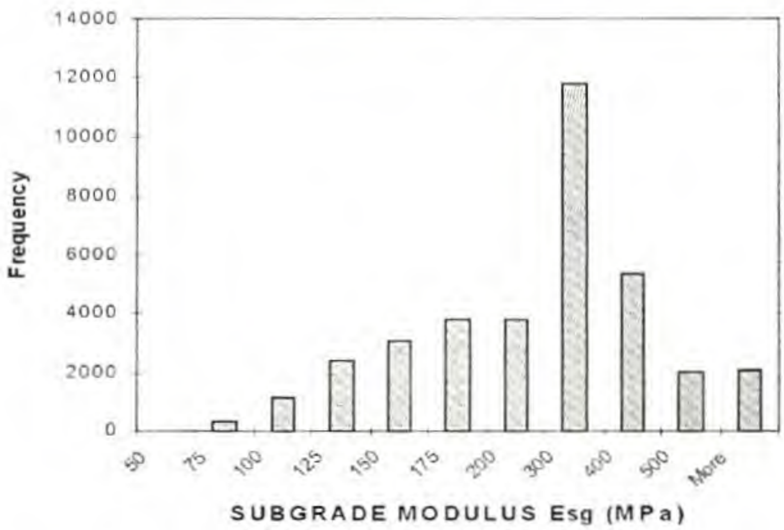

Figure 5-5: Frequency distribution of estimated subgrade moduli of the PAWC road network

Rohde's method used a ratio of $E_{rigid}/E_{sg} = 100$, therefore E rigid = 10 000 MPa is a reasonable estimate of the modulus of the stiff layer.

A typical South African pavement with a granular base and subbase will have E-moduli as follows (Theyse, 1996):

E_1 = 2 200 MPa (Continuously graded asphalt @ 40 °C)
E_2 = 300 MPa (G1 material)
E_3 = 200 MPa (G2 material)

Now, the E_2/E_{sg} ratio in Rohde's method was varied from a minimum of 0,3 to a maximum of 10, therefore the corresponding E_2 values are 30 MPa to 1 000 MPa for E_{sg} = 100 MPa and 120 MPa to 4 000 MPa for E_{sg} = 400 MPa.

The typical E_2 = 300 MPa for granular bases therefore is within the limits of the Rohde formula (Eq. 5-3).

With the majority of pavements in the PAWC road network consisting of thin surfacings and granular bases, it is therefore concluded that Rohde's method can be applied to pavements in the Western Cape. The contribution from the thin surfacing should be small enough not to influence the results significantly.

5.5 BACK-CALCULATION WITH ARTIFICIAL NEURAL NETWORKS

Meier and Rix (1994) present a fundamentally different approach to FWD back-calculation by using artificial neural networks. A neural network is "trained" to map deflection basins onto their corresponding pavement layer moduli. Synthetic deflection basins are generated from many different combinations of pavement layer properties. No seed moduli are required when using a neural network and the mathematically simplicity of the neural network makes them computationally efficient. It was found by Meier and Rix (1994) that the neural networks trained in their study executed three orders of magnitude faster than conventional gradient search algorithms. With the latest computer technology, it can be expected that this speed enhancement may have improved and will further improve in the future. The increase in computation speed was not determined by the author, mainly because the neural networks execute so fast that it could not be measured.

5.5.1 Neural Network Architecture

Meier and Rix (1994) chose to model a three-layer pavement consisting of an asphalt surfacing (AC), an unstabilized base course and a subgrade with assumed ranges of properties shown in Table 5-1. The neural model developed is therefore only suitable for one pavement type, i.e. a three-layer system with infinite subgrade. The model developed is therefore rather limited in it's application in the South African situation, but serves it's purpose well in demonstrating the applicability of neural networks in the back-calculation of pavement layer moduli. Any substantial difference from the selected pavement structure will require re-modelling. The pavement structure is apparently representative of the majority of pavements in the USA (Meier, 1999).

Table 5-1: Pavement Layer Properties used to train Neural Network

LAYER	MODULUS (MPa)	THICKNESS (mm)	POISSON's RATIO
Asphalt layers	1725 - 20,685	50 - 300	0.325
Base course (granular)	35 - 1035	150 - 750	0.350
Subgrade	35 – 345	30,500	0.350

The neural network architecture used is shown in Figure 5-6 with the number of neurons in the input layer chosen to represent the deflection at each sensor, surfacing thickness and base thickness (nine neurons in total) with three neurons in the output layer, representing the moduli of the surfacing, base and subgrade.

The hidden layers in the network architecture and the number of neurons in each hidden layer were determined through a process of trial and error, endeavouring to obtain a balance between insufficient knowledge (too few connections) and excessive capacity. During each pass through the network, 9,750 of the 10,000 examples were used to train the network with the remaining 250 examples used to test the network.

A training set of 10,000 synthetic deflection basins were generated with the static, multi-layer, linear-elastic program WESLEA with a dynamic load of 40 kN acting over an area with a radius of 150 mm. Fixed sensor spacings of 0, 200,300,450, 600, 900, 1500 mm (SHRP standard spacing) were used.

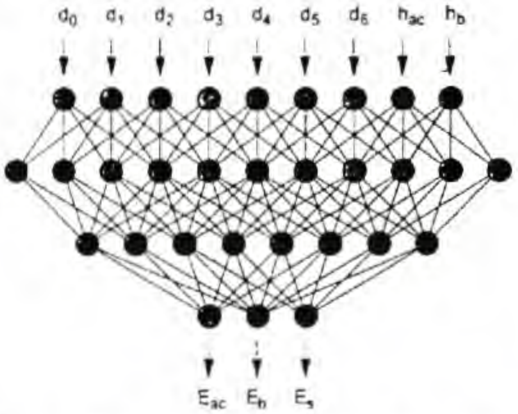

Figure 5-6: Neural network architecture used for Back-calculating pavement layer moduli from synthetic deflection basins (Meier and Rix, 1994)

5.5.2 Results of Simulation

The result of the simulation is shown in Figure 5-7. Initially the mean square error dropped rapidly and then approaches some minimum level as is clear from Figure 5-7(a). Training of the network should continue

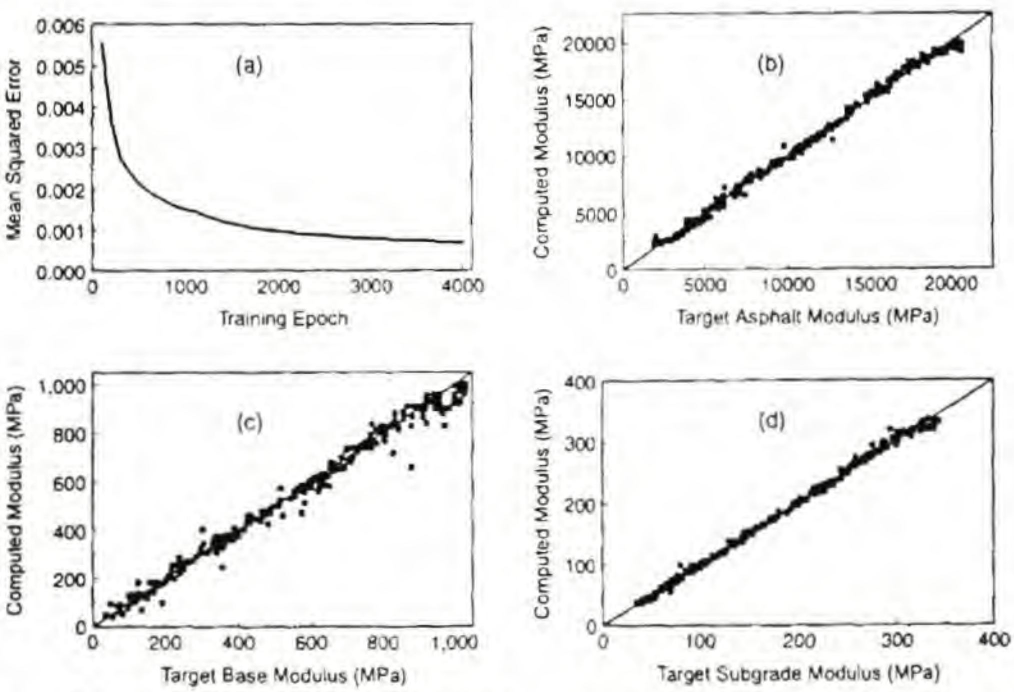

Figure 5-7: (a) Training progress; moduli for (b) surfacing, (b) base and (d) subgrade (Meier and Rix, 1994)

until it is clear that a minimum level is substantially reached. Figure 5-7(b), (c) and (d) compare the actual and computed moduli for the 250 test basins.

A good relationship is reported, clearly showing that the neural network was successfully trained to back-calculate the moduli of the selected pavement. Meier and Rix (1994) concluded that, in a broader context, the results obtained showed that neural networks could be taught to solve complex, nonlinear inverse problems using training data generated by solving the forward problem.

5.5.3 Increasing Network Robustness

It is unrealistic to expect field measurements of deflections to be perfectly accurate. Two sources of deflection measurement error exist (Meier and Rix, 1994):

- Systematic errors (i.e. not greater than 2% of the measured deflection); and
- Repeatability errors (i.e. not greater than 2 μm).

Random noise was introduced into the deflection basins (known as the process of noise injection) used to train the neural network to simulate the error experienced in practice. The result of the new simulation is shown in Figure 5-8.

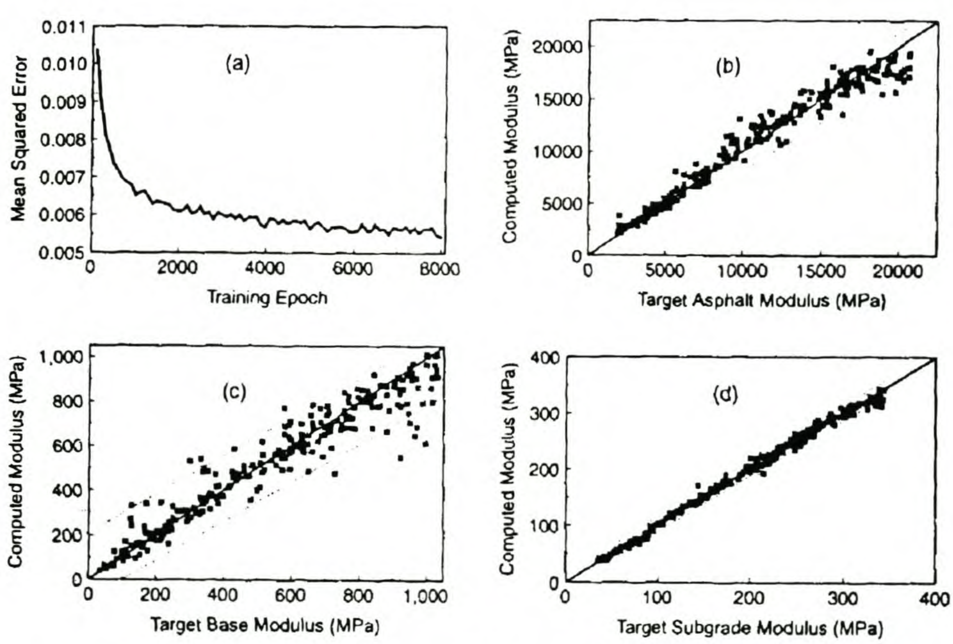

Figure 5-8: (a) Training progress; moduli for (a) surfacing, (b) base and (d) subgrade, for the network with noise injection (Meier and Rix, 1994)

From Figure 5-8 Meier and Rix (1994) deduced that the increased robustness in the neural network was obtained with a decrease in accuracy as the mean squared error increased from 0.0007 to 0.0055 and that twice as many iterations were required to train the network. A significant scatter of the target versus calculated moduli was now reported, indicating results that are more representative of the real world situation (Meier and Rix, 1994).

5.5.4 Back-calculation with experimental data

Meier and Rix (1994) used SHRP experimental pavement sections to test the neural network's performance. The pavement properties are shown in Table 5-2 and compared with the back-calculations not only from the neural network, but also with data from two commercially available programs, i.e. MODULUS and WESDEF.

Table 5-2: Comparison of Back-calculated data for SHRP test sections (Meier and Rix, 1994)

SECTION	LAYER	THICKNESS (mm)	BACKCALCULATED MODULI		
			NEURAL NETWORK	MODULUS V4.0	WESDEF
A	Asphalt	126	8922	8619	11570
	Base (granular)	645	290	283	221
	Subgrade	Semi-infinite	221	207	228
B	Asphalt	107	5895	6350	10343
	Base (granular)	127	365	386	138
	Subgrade	Semi-infinite	186	186	200

From Table 5-2 Meier and Rix (1994) deduced that neural network back-calculations compare well with MODULUS, but that little or no comparison exists with WESDEF. There is also little comparison between MODULUS and WESDEF so that it is impossible to make any conclusive deduction as far as the Neural Network's accuracy is concerned. The results are, however, promising and warrant further investigation.

5.6 APPLICATION OF NEURAL NETWORKS FOR BACK-CALCULATION IN SOUTH AFRICAN TYPE PAVEMENTS

In South Africa, the majority of rural roads are constructed with thin surfacings and a granular base/subbase or a granular base/cemented subbase on top of selected layers and the subgrade. Typical South African pavements were investigated by the author and each pavement investigated will be discussed individually. These pavements analysed should not be seen as a totally representative sample of South African pavements, but rather as examples to illustrate the application of neural networks in the back-calculation of moduli.

The four pavement types selected are:

- Type 1: Bituminous surfacing seal on a granular base with a granular subbase. DR1005 is analysed as an example. See paragraph 5.6.2.
- Type 2: Asphalt surfacing on a granular base with a granular subbase. TR1102 was analysed as an example. See paragraph 5.6.3.
- Type 3: Bituminous surfacing on a granular base with a cemented subbase. MR188 was analysed as an example. See paragraph 5.6.4.
- Type 4: Asphalt surfacing on a bituminous base with a cemented subbase. TR901 was analysed as an example. See paragraph 5.6.5.

The extent of each pavement type in the total road network could not be determined due to a lack of resources to complete an SQL database query in time. It was established that granular bases represent 84 % of the road network. Type 1, 2 and 3 pavements therefore represent the majority of surfaced roads in the PAWC area.

It must be emphasized that the roads selected were analysed as examples, but the neural networks, as will be described later, were trained to represent the pavement type.

5.6.1 Methodology followed in analysing South African pavements

Two linear elastic programs were tried to generate synthetic deflection basins:

- ELSYM5, a commercial software package, and
- WES5, a subroutine in the Basins program, of which the source code was available.

<u>Qualification</u>: The qualification in paragraph 5.4 that synthetic pavement structures are equivalent to simulated pavement structures is still valid.

Synthetic deflection basins for varying layer thicknesses and moduli were generated with ELSYM5, and the result files were converted to text-delimited files that can be imported into any spreadsheet application. The FORTRAN source code of the convert program is included in Appendix C.1. The text-delimited files could be manipulated in the spreadsheet application, a very important aspect as data can be copied into neural network applications from spreadsheets via the Windows clipboard.

Deflection basins were created in sequential order and neural networks created with this data as a basis could not be trained. It is assumed that the sequential nature of the data led the neural network to memorise the pattern instead of generalizing. Deflection basins generated in a sequential order also shows evenly distributed E-moduli and there will be patterns within the dataset. When a neural network is presented with a deflection basin that does not exactly fit one of the basins in the database no match was found. This method to generate synthetic deflection basins was abandoned as laborious and ineffective. It was not conclusively proven that this method would not work; the method was abandoned simply due the amount of work involved in generating the data. It must be emphasized that the data generated with ELSYM5 created a problem and not the neural network created from the data.

Dr Roger Meier of the University of Memphis, USA, kindly made available the following FORTRAN source code:

- Basins, a program based on WES5 used to generate synthetic deflection basins, and
- BackProp, a feedforward, back propagation neural network program.

The basins program was used to generate synthetic deflection basins and commercial software was used to create the neural networks (BackProp was therefore not used). The FORTRAN source code for Basins is included as Appendix C.2. Basins generates synthetic deflection basins using random layer thicknesses and moduli that can be selected to closely reflect the measured basins for a road section. The process is stochastic giving representative data ranges from which neural networks can be created. This was a much-improved method in relation to the previous method to create deflection basins.

The methodology used to create synthetic deflection basins is illustrated in Figure 5-9.

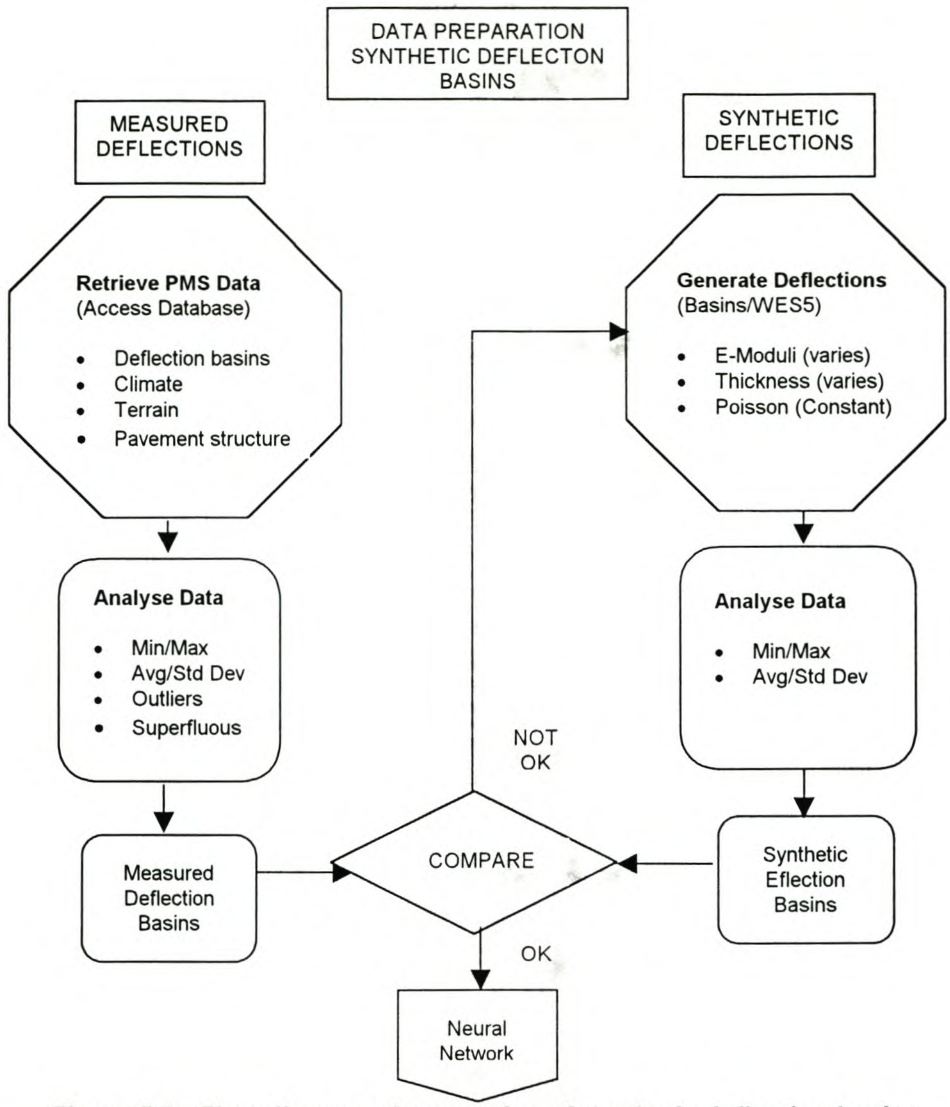

Figure 5-9: Flow diagram of generation of synthetic deflection basins

5.6.2 Pavement Type 1: Bituminous Surfacing Seal on granular base/subbase (DR1005)

The District Road off the N2 freeway to Sir Lowry's Pass Village (DR01005) was investigated, a road in a medium climate and rolling terrain. No information is available on the pavement structure for this road. This road was selected because it is well known to the author, as the author has been involved in several projects in the area.

The methodology followed to create a neural network for a Type 1 pavement is as follows:

- The available data for DR1005 is analysed to establish the bounds of the deflection measurements.

- Synthetic deflection basins were generated with WES5 (Basins program) using the methodology set out in 5.6.1.
- Several neural networks were created covering options to back-calculate E-moduli only (excluding stiff layer), E-moduli and depth to stiff layer, depth to stiff layer only and an effort to calculate all the E-moduli (including the stiff) as well as the depth to stiff layer with one neural network.
- E-moduli were also calculated with MODCOMP to allow a comparison of the neural network back-calculated E-moduli with results from the conventional method.
- DR1005 was used to test the neural network and for MODCOMP calculations.

5.6.2.1 Data Analysis

Deflection measurements for DR1005 were done in November 1997 and are shown in Table 5-3. It should be noted that values for BLI, MLI, LLI, SI, etc. are quoted from the PMS database and are not calculated in this thesis. Appendix C.3 gives a description of the data presentation in Appendix C.4.

Table 5-3: Deflection measurements DR01005 (40kN Load, 18°C Surface Temperature, Nov 1997)

POSITION (km)	D0	D200	D300	D600	D900	D1200	D1500
0.00	334	201	124	52	33	24	20
0.20	912	543	335	65	20	9	8
0.40	705	414	247	56	29	25	14
0.60	621	361	214	65	40	24	18
0.80	566	313	203	74	39	21	14
1.00	1252	853	618	323	191	120	86
1.20	1109	779	532	244	139	97	69
1.40	616	368	232	107	74	59	46
1.54	818	639	486	222	119	80	60
Minimum	334	201	124	52	20	9	8
Maximum	1252	853	618	323	191	120	86
Average	770	497	332	134	76	51	37
Std. Dev.	285	221	172	101	60	40	29

The variation in minimum and maximum deflections at each sensor is rather large and the large variation is reflected in the standard deviation.

The correlation between the deflections measured was investigated and is shown in Figure 5-10.

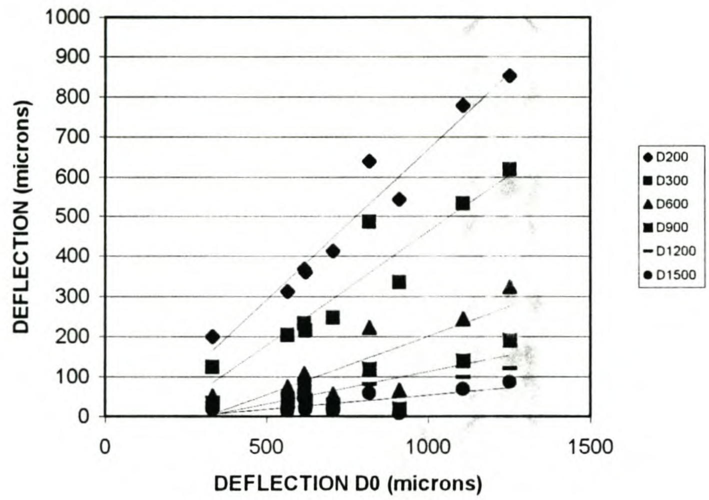

Figure 5-10: Relationship of deflection at centre line of load D0 with deflection at various geophone spacings

A good correlation exists between the maximum deflection at the centre of the load and the deflections at the other sensors. Although a good relationship between different inputs indicates that a reduction in inputs is possible, it was not done in this case as the definition of the shape of the deflection basin will be lost.

The measured deflections at the outer two sensors (D_{1200} and D_{1500}) are very small and are an indication that a stiff layer is present at shallow depth. The method developed by Rohde (1992) and described in paragraph 5.4 was applied to the data. A graphical representation of D_r vs. 1/r is given in Figure 5-11.

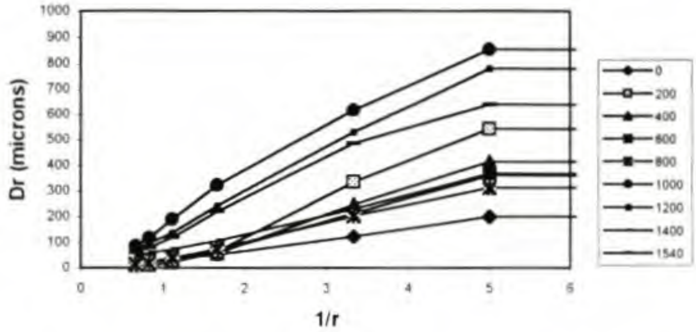

Figure 5-11: Dr vs 1/r relationships for the determination of r_0

It should be noted that the D_r vs. 1/r curves does not reflect the typical shape at the bottom that indicates nonlinear material behaviour. Strictly speaking, the Rohde equations cannot be applied as they were developed for asphalt base layers. The equation for an asphalt layer with a thickness less than 50mm was, however, applied as it was considered representative of a thin surfacing (See paragraph 5.4 for a discussion in this regard). Restrictions as far as stiffness ratios still apply.

To be able to apply the Rohde method in a spreadsheet, the steepest gradient of the different sections D_{300}-D_{600}, D_{600}-D_{900}, D_{900}-D_{1200} and D_{1200}-D_{1500} was selected and Eq. 5-3 applied.

The estimated depth to the stiff layer, calculated with the Rohde method, is shown in Table 5-4.

Table 5-4: Estimated depth to stiff layer with Rohde method

POSITION (km)	DEPTH TO STIFF LAYER (m)
0.00	2.4
0.20	1.4
0.40	2.1
0.60	1.3
0.80	1.5
1.00	4.1
1.20	3.7
1.40	5.7
1.54	2.6

The estimated depth to the stiff layer varies from 1.3m to 5.7m as is shown in Table 5-4. These values will be used as a guideline when synthetic deflection basins are generated.

5.6.2.2 Synthetic Deflection Basins

It is intended to generate a set of data to represent measured deflection basins using existing computer programs based on linear elastic theory. It is only possible to create deflection basins with linear elastic programs by varying input parameters such as layer thickness and E-moduli. Synthetic deflection basins are therefore generated using linear elastic theory with inputs of layer thickness, E-moduli, poisson ratios, etc. and the deflection basin.

Repeated runs of the program Basins were done on a trial and error basis following the algorithm of Figure 5-9 to determine the appropriate range of layer thicknesses and E-moduli to best cover the range of measured deflections in the basins.

The pavement structure of DR1005 for which synthetic deflection basins were created, is shown in Table 5-5. A total of 10 000 synthetic deflection basins were created of which 9 500 were used as the training set and 500 as the test set.

Table 5-5: Pavement Structure used in Neural Network for DR1005

LAYER	MODULUS (MPa)	THICKNESS (mm)	POISSON's RATIO
1. Granular Base	400 – 1000	100 – 200	0.35
2. Granular Subbase	50 – 600	100 – 200	0.35
3. Upper Granular Selected	100 – 600	100 – 200	0.35
4. Subgrade to Stiff Layer	30 – 350	2000 - 7000	0.35
5. Stiff Layer	10000	infinite	0.35

The stiff layer modulus was selected at 10000 MPa. Rohde used a ratio of E_{rigid}/E_{sg} = 100, thus an E_{sg} = 100 suggests an E_{rigid} = 10000 MPa. A value of 3500 MPa (or higher) is suggested in the MODCOMP program.

Meier and Rix (1994, 1997) restricted their models to a three-layer system, mainly to reduce network complexity, which in effect meant that layers four and five were pre-selected at fixed thicknesses and moduli. In this investigation, it was endeavoured to design a number of neural networks representing different pavement types. With the very small deflections measured at the outer sensors, it was necessary to bring a stiff layer at shallow depth into consideration, as previously discussed in paragraph 5.6.2.1.

The statistics for the measured and synthetic deflection basins are compared in Table 5-6. It was possible to select an adequate range of layer thicknesses and E-moduli to enclose the range of measured deflections. It is considered important that the bounds of the training data at each sensor offset is adequate to enclose the future inputs to a neural network. Well-trained neural networks are very good at interpolation (often called generalization), but notoriously poor at extrapolation (Tutumluer and Meier, 1996). If the synthetic basins are not generated in such a way that the bounds of deflections generated cover the bounds of deflections measured, accurate results will not be possible as interpolation will not be the mode of calculation.

Table 5-6: Comparison of statistics for measured and synthetic deflection basins

DESCRIPTION		D0	D200	D300	D600	D900	D1200	D1500
Measured Deflection Basins	Minimum	334	201	124	52	20	9	8
	Maximum	1252	853	618	323	191	120	86
	Average	770	497	332	134	76	51	37
	Std. Dev.	285	221	172	101	60	40	29
Synthetic Deflection Basins	Minimum	202.0	106.6	72.0	28.2	13.9	7.6	4.9
	Maximum	1455.3	979.1	741.4	383.7	231.6	148.6	98.1
	Average	416.3	244.0	178.2	89.1	51.5	30.7	18.2
	Std. Dev.	139.1	105.0	88.6	60.5	40.8	26.6	16.8

From Table 5-6 it is clear that the bounds of the training data are adequate to enclose the measured deflections on DR1005.

5.6.2.3 Network Architecture

Twenty-five neural networks were created to test various network architectures (i.e. combinations of neurons and hidden layers) and different input/output combinations. Multilayer Normal Feedforward neural networks with a back-propagation learning rule and sigmoid transfer functions were used for all the neural networks. Several hidden layer configurations were tested and a summary of these neural networks is shown in Table 5-7. For each network created the Root Mean Square Error (RMSE), correlation and tolerance values (% of test set input patterns correct) for the test set were recorded and is reported in the table.

Table 5-7: Summary of Neural Networks created for DR1005

No	INPUTS	OUTPUTS	LAYERS*	RMSE (%)	CORR** (%)	TOLERANCE	
						5%	**10%**
CALCULATE E-MODULI (EXCL. STIFF LAYER E_5 = 10 000 MPa) ONLY							
1	H_1, H_2, H_3, H_4 D_0 thru D_{1500}	E_1, E_2, E_3, E_4	11-25-4	7.75	96.51	59.3	85.6
2			11-7-4	7.95	96.30	62.7	86.9
3			11-13-4	6.93	97.23	66.3	89.2
4			11-19-11-4	5.43	98.34	74.8	95.0
5			11-25-11-4	4.38	98.90	81.8	96.6
6			11-15-11-7-4	3.21	99.42	92.3	98.6
7			11-15-17-11-4	2.60	99.61	94.2	99.2
8	H_1, H_2, H_3, H_4 D_0 thru D_{1500}	E_1, E_2, E_3, E_4	11-15-17-11-4	3.62	92.25	92.3	98.0
CALCULATE E-MODULI (EXCL. STIFF LAYER E_5 = 10 000 MPa) AND DEPTH TO STIFF LAYER							
9	H_1, H_2, H_3 D_0 thru D_{1500}	E_1, E_2, E_3, E_4 H_4	10-15-5	6.45	97.60	65.1	89.2
10			10-25-11-5	4.80	98.69	77.4	95.6
11			10-15-21-5	5.14	98.52	75.8	94.3
12			10-15-21-11-5	2.88	99.52	93.4	98.5
CALCULATE E-MODULI (INCL. STIFF LAYER) AND DEPTH TO STIFF LAYER							
13	H_1, H_2, H_3 D_0 thru D_{1500}	E_1, E_2, E_3, E_4, E_5 H_4	10-15-21-11-6	11.97	91.13	67.7	80.5
14			10-15-21-11-8-6	11.90	91.24	67.3	80.8
15	D_0 thru D_{1500}	E_1, E_2, E_3, E_4, E_5 H_4	7-15-21-11-6	11.71	91.35	75.4	83.4
16			7-15-21-11-6	10.51	93.13	76.1	85.2
CALCULATE LAYER THICKNESS							
17	D_0 thru D_{1500}	H_1, H_2, H_3, H_4	7-21-11-1	-	-	-	-
CALCULATE DEPTH TO STIFF LAYER							
18	D_0 thru D_{1500}	H_4	7-15-1	10.02	94.06	39.6	70.8
19			7-21-11-1	6.62	97.45	61.4	87.4
20			7-21-11-7-1	29.44	-	8.4	18.0
21	D_0 thru D_{1500}	$1/H_4$	7-15-1	6.59	97.07	58.0	87.6
22			7-21-11-1	3.94	98.94	81.8	97.8
23			7-14-8-1	4.86	98.40	73.4	95.0
24	D_0 thru D_{1500} SCI, BDI, BCI	$1/H_4$	10-21-11-1	4.80	98.45	72.0	95.8
25	D_0 thru D_{1500} Ln(SCI), Ln(BDI), Ln(BCI)	$1/H_4$	10-21-11-1	4.86	98.41	73.4	95.6

* Layers are given in the order input-hidden 1-hidden 2-...-output.

** Corr = Correlation

Remarks (Table 5-7):

- Neural Networks 1-8 were created to test the influence of different network architectures on the accuracy of the network. Neural Network No. 8 was created to test the influence of a greater range in E-moduli. Neural Network No. 7 was selected as the preferred network with a RMSE = 2.60%, correlation = 99.40% and 94.2% of the test set input patterns within 5% of the correct answer. Inputs were the layer thicknesses and the measured deflections. The outputs were the E-moduli.
- Neural Networks 9-12 were created to investigate the possibility to calculate the E-moduli as well as H_4, the depth to the stiff layer. It is shown that it can be done successfully, thus eliminating the

need for an additional calculation with an external method such as that of Rohde. In terms of the goal set at the beginning of the Chapter, this is a very important finding as calculation speed is increased dramatically. Neural Network No.12 was selected as the preferred network with a RMSE = 2.88%, correlation = 99.52% and 93.4% of the test set input patterns within 5% of the correct answer. Inputs were the layer thicknesses (excl. H_4) and the measured deflections. The outputs were the E-moduli and H_4, the depth to the stiff layer.

- Neural Networks 13-16 were created to investigate the possibility of also back-calculating the E-modulus of the stiff layer. Although it was possible to train a network successfully to do this, the accuracy of the result was considered inadequate. If layer thickness is ignored as an input (networks 15 and 16), the accuracy is only improved slightly.
- Neural Network 17 was created to investigate the possibility to back-calculate layer thicknesses, with the aim of doing back-calculation as a two-stage process: first the layer thicknesses are calculated and then the E-moduli. No meaningful result could be obtained, the number of outputs outweigh the number of inputs, the most probable reason for the failure.
- Neural Networks 18-25 were created as standalone networks to calculate H_4, the depth to the stiff layer. Different combinations were tested, i.e. not only the linear variables were tested, but also the inverse ($1/H_4$). The influence of indicators such as SCI, BDI and BCI were also investigated. The best results were achieved with network no. 22, with $1/H_4$ a function of D_0 thru D_{1500}, SCI, BDI and BCI.

Networks can be selected using the criteria of RMSE, correlation or tolerance. If a tolerance for a dataset is known, i.e. from quality control in a manufacturing process, it is usually the best to specify this tolerance and to select a network producing an acceptable number of correct predictions in the test set within the tolerance. The correlation reported in Table 5-7 is for four or five variables (E-moduli plus thickness H_4 where applicable) and the correlation can vary from variable to variable. Correlation for networks 13-16 are more than 90 %, but the correlation for E_5 is very poor, with only 68-76 % of the test cases within a 5 % tolerance. Network 7 has a correlation of 99.6 % and 94 % of the test cases within a 5 % tolerance. Experience with this type of network showed that acceptable results could only be obtained with RMSE in the order of 3 % or less, and more than 90 % of the test cases within a tolerance of 5 %. Correlation was found not to be a good indicator for this application.

The contribution of the different inputs to the outputs, calculated with Neural Network No. 7, is shown in Table 5-8. The Qnet2000 program is not exactly clear on the method followed to calculate the contribution of each input on the outputs. It is gleaned from program documentation that the contribution can be interpreted as the influence of a unit change in an input value on the output. A query lodged with Vesta Services Inc. resulted in the following explanation:

For each available case in the training and test sets, Qnet2000 cycles through each input node computing the delta in the output response for the following:

Two Delta changes are computed for each test case and input node:

- *Absolute Value (Output(input node at test value) - Output(input node at node minimum))*
- *Absolute Value (Output(input node at test value) - Output(input node at node maximum))*

These deltas are summed over all cases for each input node.

The Percent contribution is then:

(Delta Sum at input node i)/(Sum of all input node Delta Sums)

The results are shown in Table 5-8.

Table 5-8: Average contribution of inputs (thicknesses and deflections) to the outputs (E-moduli) with Neural Network No. 7

INPUT NODES: THICKNESSES (H) DEFLECTIONS (D)	OUTPUT NODES: LAYER MODULI							
	BASE E_1		SUBBASE E_2		SELECTED E_3		SUBGRADE E_4	
H_1: Base (150mm)	3.85	8.03	4.29	11.37	5.13	19.98	0.67	6.86
H_2: Subbase (150mm)	0.86		1.59		3.65		0.37	
H_3: Selected (150mm)	0.67		1.14		3.66		0.40	
H_4: Subgrade (varies)	2.65		4.35		7.54		5.42	
D_0	16.67	91.97	13.00	88.63	9.07	80.02	14.35	93.14
D_{200}	12.81		13.95		11.92		13.71	
D_{300}	14.46		12.88		12.26		9.30	
D_{600}	12.94		13.81		12.18		17.11	
D_{900}	13.85		12.25		12.10		16.12	
D_{1200}	12.00		12.00		11.81		14.58	
D_{1500}	9.24		10.74		10.68		7.97	
TOTALS	100.00		100.00		100.00		100.00	

From Table 5-8 it is deduced that the major contribution to the back-calculated E-moduli are the measured deflections. It should especially be noted that the influence of H_4 (depth to stiff layer) varies from 2.65% to 7.54%, indicating that the method used to calculate the depth to stiff layer would not influence the result very much.

The contribution of the different inputs towards the outputs where E_5 and H_4 are included as per Neural Network No. 14, was also investigated, with results shown in Table 5-9.

Table 5-9: Average contribution of inputs (thicknesses and deflections) to outputs (E-moduli) with Neural Network No. 14

	OUTPUT NODES: LAYER MODULI AND H_4											
	BASE E_1		SUBBASE E_2		SELECTED E_3		SUBGRADE E_4		STIFF LAYER E_5		DEPTH H_4	
H_1: Base	2.75		4.68		5.31		1.83		3.70		3.80	
H_2: Subbase	0.88	4.09	2.19	7.88	4.54	12.78	1.65	4.37	3.13	8.44	3.54	9.19
H_3: Selected	0.46		1.01		2.93		0.89		1.61		1.85	
D_0	17.51		13.41		11.58		11.78		8.37		7.68	
D_{200}	16.58		12.97		10.77		16.13		11.08		11.67	
D_{300}	12.60		11.83		12.85		12.83		14.49		12.60	
D_{600}	15.15	95.91	14.81	92.12	14.89	87.22	8.54	95.63	14.66	91.56	13.09	90.81
D_{900}	12.24		12.61		12.88		15.61		14.10		12.53	
D_{1200}	10.15		14.92		12.04		17.63		12.07		13.06	
D_{1500}	11.68		11.57		12.21		13.11		16.79		20.18	
TOTALS	100.0		100.0		100.0		100.0		100.0		100.0	

The influence of measured deflections on the calculated E-moduli (E_1 to E_4) has increased, while the influence of the layer thickness (H_1 to H_3) has decreased. Omitting layer thickness (H_1 to H_3) from the model may even benefit the accuracy of the model as was indicated with NN15 and NN16 (Table 5-7), although it is not recommended as it is not proven sufficiently.

5.6.2.4 Evaluation of Back-calculated E-moduli for DR1005

The results of the back-calculated E-moduli are given in Appendix C.4 where measured and calculated deflections basins are compared both in tabular form and graphically. Four cases were investigated as is described in Table 5-10.

The measured and calculated deflections for Case (a) are shown in Figure 5-12. A good correlation is exhibited. Scatter and correlation for the other cases are similar, but are not reported here due to space considerations. (See Appendix C.4)

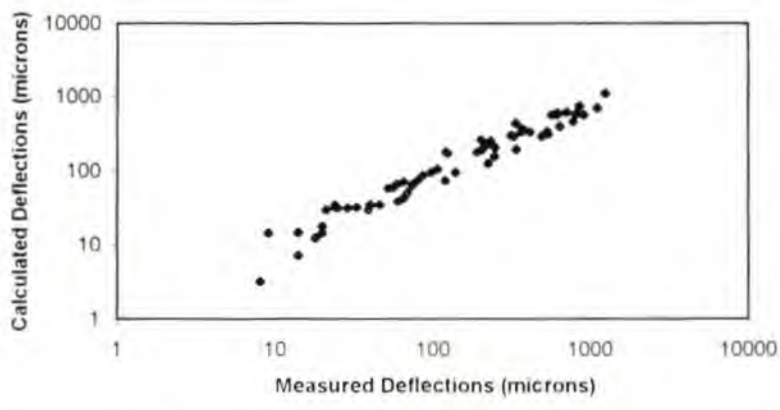

Figure 5-12: Calculated vs. Measured Deflections Case (a)

The overall Root Mean Square Error (RMSE) for the five cases was calculated and is compared in Table 5-10. The overall RMSE is the RMSE for the combined basins, i.e. all the sensors and the measurements at each measurement position combined (9 measurement positions). No significance should be attached to the RMSE values as they are only used as a indication of the relative performance of each calculation method used.

Table 5-10: Comparison of RMSE for the different cases investigated

CASE	DESCRIPTION	OVERALL RMSE (%)
a	Depth to stiff layer (H_4) calculated with NN22 and E-moduli (excl. E_5) back-calculated with NN7	27.9
b	Both depth to stiff layer (H_4) and E-moduli (excl. E_5) back-calculated with NN12	43.19
c	Depth to stiff layer (H_4) calculated with NN22 and E-moduli (excl. E_5) back-calculated with NN8	41.53
d	Both depth to stiff layer (H_4) and E-moduli (incl. E_5) back-calculated with NN14	34.33
e	Both depth to stiff layer (H_4) and E-moduli (incl. E_5) back-calculated with NN16, $H_1 = H_2 = H_3 = 150$mm	39.16

The best relative performance is obtained with Case (a) using a two-step process: first the depth to stiff layer is calculated with NN22 and secondly the E-moduli with NN7, using the output from NN22 as one of the inputs to NN7. The worst relative performance is that of Case (b) where the depth to stiff layer and E-moduli is calculated in one process.

The results obtained with Case (d) are better than expected, considering the lower correlation and tolerance values reported in Table 5-7. The correlation for E_5 is, however, very poor for Case (d) – see the graph in Appendix C.4 (d), showing the correlation of each layer individually.

E-moduli back-calculated with each of the selected neural networks for the different cases investigated are compared in Appendix C.4 with a comparison of one deflection basin at chainage 0.00 km, in Table 5-11.

Table 5-11: Comparison of E-moduli for Pd = 0.000 km for the different cases investigated

POSITION (Km	CASE	BACK-CALCULATED E-MODULI (MPa)					
		E_1	E_2	E_3	E_4	E_5	RMSE (%)
0.00	A	999.9	75.6	599.9	305.3	10000.0	23.21
	B	1000.1	61.3	599.9	319.3	10000.0	30.22
	C	1652.3	76.1	1199.3	246.1	10000.0	26.65
	D	885.4	186.5	586.8	335.1	265.6	12.98
	E	1130.6	70.5	600.0	383.0	485.2	19.88

Note: The RMSE reported in Table 5-11 is calculated with Eq. 5-2 and should not be confused with the neural network RMSE.

The compensating layer effect is evident in the results shown in Table 5-11. Again, the more complex neural network in Case (d) performs rather well in comparison with the simpler network in Case (a). The results from Case (a) and Case (d) are compared in Table 5-12.

Table 5-12: Comparison of Back-calculated E-moduli between Case (a): H_4 with Rohde's method and Case (d): H_4 from NN

POSITION (Km)	CASE	BACK-CALCULATED E-MODULI (MPa)					
		E_1	E_2	E_3	E_4	E_5	RMSE (%)
0.00	a	999.9	75.6	599.9	305.3	10000.0	23.21
	d	885.4	186.5	568.8	335.1	265.6	12.98
0.20	a	688.2	53.5	599.1	263.2	10000.0	39.32
	d	348.7	65.4	104.2	246.0	2643.2	29.95
0.40	a	605.5	58.2	599.9	248.0	10000.0	13.05
	d	765.6	114.6	572.8	223.5	2610.6	29.93
0.60	a	698.1	64.4	599.9	185.2	10000.0	14.68
	d	644.5	97.4	567.2	233.6	2614.5	18.21
0.80	a	534.2	96.6	368.0	169.0	10000.0	23.86
	d	400.4	142.5	163.3	177.3	2560.5	4.27
1.00	a	458.9	60.9	120.0	53.6	10000.0	8.24
	d	260.8	125.3	107.9	52.9	2315.3	14.46
1.20	a	757.0	56.2	599.9	107.3	10000.0	34.20
	d	476.2	74.3	502.2	51.6	2333.9	21.71
1.40	a	712.1	69.7	599.9	157.6	10000.0	12.87
	d	803.8	328.9	593.0	160.4	150.3	22.08
1.54	a	999.9	56.6	599.9	137.1	10000.0	36.80
	d	727.3	66.7	72.1	77.0	2469.4	9.37

The calculated E-moduli should be viewed with the bounds to thickness and modulus specified in Table 5-5 in mind. With reference to Case (a): except for those moduli at Pd 0.80 and Pd 1.00, all the moduli calculated for layer 3 reflected the maximum allowed. The maximum E-moduli are not reached with Case (d).

The E-modulus for the stiff layer is calculated at ≈ 2 500 MPa. A very poor correlation was obtained with NN14 and this poor correlation was mainly caused by the E_5 modulus. Investigation of the correlation of the different outputs (see Appendix C.4(d)) reveals that almost no correlation was obtained for E_5 and that E_5

was calculated at values ranging from 2 000 – 3 000 MPa regardless of the target values. This explains the rather constant E_5 moduli calculated, showing that E_5 moduli calculated with NN14 can not be trusted.

5.6.2.5 Comparison of Back-calculated Moduli with MODCOMP

The same measured deflection basins of DR1005 were analysed with the MODCOMP program. Estimates by MODCOMP to bedrock level and E_{sg} were used in the analysis. The purpose of the analysis is to compare the results from the methods (i.e. MODCOMP vs. neural networks), and not to back-calculate exact moduli. Considerable user intervention was required to obtain meaningful results with MODCOMP. Realistic back-calculated E-moduli could only be obtained with fixed values for the stiff layer (3500 MPa recommended by MODCOMP) and by assigning sensors to specific layers by hand, thus overriding the computer assigned sensors. With this much user intervention a program like MODCOMP can definitely not be used in a PMS database.

The estimated subgrade moduli and depth to stiff layer by MODCOMP is given in Table 5-13. These estimated subgrade moduli were used as seed moduli with 400 MPa, 300 MPa, 200 MPa and 120 MPa for the upper four layers respectively.

Table 5-13: MODCOMP Estimated Subgrade Moduli and Depth to Stiff Layer DR1005

POSITION (km)	ESTIMATED SUBGRADE MODULUS (MPa)	ESTIMATED DEPTH TO STIFF LAYER (m)
0.00	358	> 15, 15 assumed
0.20	287	not statistical significant, 15 m assumed
0.40	333	not statistical significant, 15 m assumed
0.60	287	3.7
0.80	252	2.7
1.00	58	3.8
1.20	76	5.4
1.40	158	> 15, 15 assumed
1.54	84	5.4

The estimated depth to the stiff layer by the three methods used (Rohde, Neural Network and MODCOMP), is compared in Table 5-14.

Table 5-14: Comparison of Estimated Depth to Stiff Layer by Rohde, Neural Network and MODCOMP

POSITION (km)	ESTIMATED DEPTH TO STIFF LAYER (m)		
	ROHDE	NEURAL NETWORK	MODCOMP
0.00	2.4	7.0	> 15
0.20	1.4	1.4	not statistical significant
0.40	2.1	3.4	not statistical significant
0.60	1.3	2.2	3.7
0.80	1.5	1.5	2.7
1.00	4.1	5.0	3.8
1.20	3.7	7.0	5.4
1.40	5.7	7.0	> 15
1.54	2.6	6.9	5.4

From Table 5-14 it is deduced that significant differences occur in the estimation of the depth to the stiff layer between the different methods used for this purpose.

Results of the back-calculated E-moduli, calculated deflections and associated Root Mean Square errors calculated with the MODCOMP program are compared with those calculated with the Neural Network No. 7, in Table 5-15.

Table 5-15: Back-calculated E-Moduli with MODCOMP compared with Neural Network No. 7

POSITION (Km)	METHOD	BACK-CALCULATED E-MODULI (MPa)					
		E_1	E_2	E_3	E_4	E_5	RMSE (%)
0.00	Neural Network	999.9	75.6	599.9	305.3	10000.0	23.21
	MODCOMP	1190.0	132.0	628.0	339.0	3500.0	4.15
0.20	Neural Network	688.2	53.5	599.1	263.2	10000.0	39.32
	MODCOMP	499.0	31.6	74.0	382.0	3500.0	54.94
0.40	Neural Network	605.5	58.2	599.9	248.0	10000.0	13.05
	MODCOMP	319.0	248.0	30.2	408.0	3500.0	21.83
0.60	Neural Network	698.1	64.4	599.9	185.2	10000.0	14.68
	MODCOMP	564.0	77.2	185.0	225.0	3500.0	4.91
0.80	Neural Network	534.2	96.6	368.0	169.0	10000.0	23.86
	MODCOMP	599.0	86.9	354.0	195.0	3500.0	8.30
1.00	Neural Network	458.9	60.9	120.0	53.6	10000.0	8.24
	MODCOMP	294.0	112.0	51.0	48.2	3500.0	2.54
1.20	Neural Network	757.0	56.2	599.9	107.3	10000.0	34.20
	MODCOMP	403.0	77.5	50.3	71.1	3500.0	3.60
1.40	Neural Network	712.1	69.7	599.9	157.6	10000.0	12.87
	MODCOMP	526.0	93.9	540.0	158.0	3500.0	7.88
1.54	Neural Network	999.9	56.6	599.9	137.1	10000.0	36.80
	MODCOMP	1210.0	25.0	591.0	82.4	3500.0	3.39

In general, the RMSE for the back-calculated E-moduli with MODCOMP is smaller than those calculated with the Neural Network. Since the E-moduli back-calculated with the Neural Network are bounded (refer

Table 5-5), the maximum E-moduli calculated will not exceed the maximum values on which the network was trained. It is important to note that the back-calculated E-moduli with both methods show the same magnitudes and trends, i.e. weak subbase (E_2 in Table 5.15), which can be attributed to the compensating layer effect.

With MODCOMP the number of layers can be increased. This was done by increasing the number of layers to seven and then back-calculating E-moduli for a known E_7 = 10 000 MPa and as a separate case for all seven layers unknown. The results for one deflection basin are shown in Table 5-16.

Table 5-16: Comparison of E-moduli calculated between NN and MODCOMP with seven layers

LAYER NO.	NEURAL NETWORK	MODCOMP		
		FOUR LAYERS	SEVEN LAYERS	
			E_7 = UNKNOWN	E_7 = 10 000 MPa
1	999.9	1 190.0	867.0	1 180.0
2	75.6	132.0	255.0	148.0
3	599.9	628.0	165.0	350.0
4	305.3	339.0	285.0	282.0
5	10 000.0	3 500.0	232.0	1 120.0
6	-	-	6 520.0	318.0
7	-	-	6.9	10 000.0

Table 5-16 new shows that, with seven layers in the pavement structure, the subbase is now no longer the weak layer (E_2 = 255 MPa in comparison with E_2 = 75,6 MPa with NN). This trend was observed with all the back-calculations with seven layers. The influence of the subgrade stiffness is also shown with E_2 = 148 MPa if E_7 = 10 000 MPa is pre-selected. Increasing the number of layers is a well-known solution to the compensating layer effect. Unfortunately, not many computer programs are readily available to handle the more layers.

The demonstration in Table 5-16, where more layers are used in the pavement structure, showed that the compensating layer effect was present in both the neural network and MODCOMP results for a five layer system. Neural networks therefore exhibit the same problems in back-calculation experienced with conventional programs.

E_1-values in Table 5-15, calculated with the Neural Network, at Pd 0.00 and Pd 1.54 reflect the maximum value of 1000 MPa, while moduli calculated with MODCOMP indicates that the Neural Network moduli should be higher. Neural Network No. 8 was created to investigate the effect of a wider range in the E_1 and E_3 moduli. The new E-moduli are compared with the old ones in Table 5-17.

Table 5-17: Comparison of Back-calculated E-Moduli with Neural Network No. 7 and No. 8 to investigate the effect of a wider range of E-moduli

POSITION (Km)	NEURAL NETWORK	BACK-CALCULATED E-MODULI (MPa)					
		E_1	E_2	E_3	E_4	E_5	RMSE (%)
0.00	NN7	999.9	75.6	599.9	305.3	10000.0	23.21
	NN8	1652.3	76.1	1199.3	246.1	10000.0	26.65
0.20	NN7	688.2	53.5	599.1	263.2	10000.0	39.32
	NN8	674.7	62.5	1193.9	208.0	10000.0	33.99
0.40	NN7	605.5	58.2	599.9	248.0	10000.0	13.05
	NN8	874.8	72.6	1199.4	246.9	10000.0	30.42
0.60	NN7	698.1	64.4	599.9	185.2	10000.0	14.68
	NN8	980.3	72.2	1199.5	158.3	10000.0	33.17
0.80	NN7	534.2	96.6	368.0	169.0	10000.0	23.86
	NN8	535.6	98.4	367.5	157.0	10000.0	19.39
1.00	NN7	458.9	60.9	120.0	53.6	10000.0	8.24
	NN8	518.4	60.1	145.0	43.5	10000.0	11.20
1.20	NN7	757.0	56.2	599.9	107.3	10000.0	34.20
	NN8	982.5	59.3	1178.9	37.7	10000.0	44.30
1.40	NN7	712.1	69.7	599.9	157.6	10000.0	12.87
	NN8	899.7	71.9	1199.5	156.2	10000.0	16.88
1.54	NN7	999.9	56.6	599.9	137.1	10000.0	36.80
	NN8	1800.0	60.4	985.5	38.4	10000.0	39.44

From Table 5-17 it is deduced that the RMSE has increased, except for Pd 0.20 and Pd 0.80 where small improvements are recorded. This may be an indication that the choice of the range of E-moduli is important, i.e. a wider range will not necessarily give a better answer.

In practice, high (or low) unrealistic moduli would be ignored and realistic moduli would be assigned to a layer. Any value above 800 MPa for E_1 is considered too high and in practice, these moduli would be adjusted to ≈ 800 MPa.

The calculated versus measured deflections with the MODCOMP program is shown in Figure 5-13.

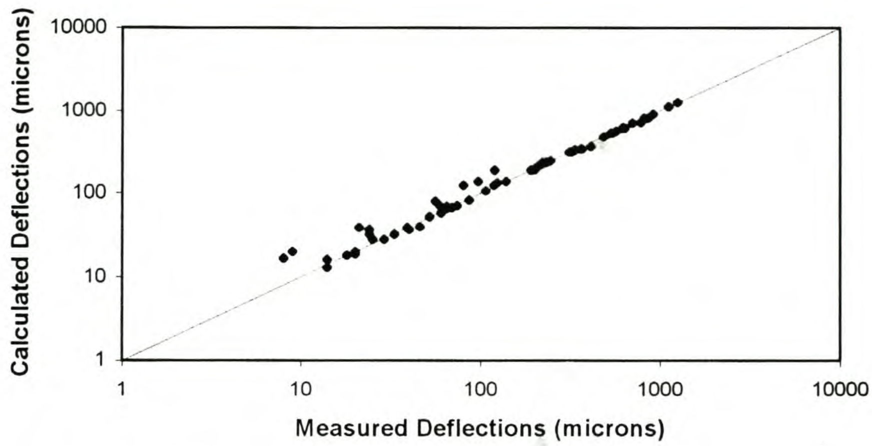

Figure 5-13: Calculated vs. Measured Deflections with MODCOMP

A very good correlation is achieved with the MODCOMP program with the higher deflections at the closer sensor spacings, with some scatter at the low deflections measured at the outer sensors.

The deflections measured on DR1005 proved to be very difficult for the back-calculation programs, mainly due to the very low deflections measured at the outer sensors.

5.6.2.6 Conclusion from Work on DR1005

It was shown that at least six approaches could be followed to back-calculate E-moduli with neural networks, these approaches being summarised as follows:

a. The depth to stiff layer can be calculated with the Rohde method and then the E-moduli with a neural network (modulus of stiff layer assumed constant at 10000 MPa).
b. The depth to the stiff layer can be calculated with a neural network and the E-moduli with a second neural network in a two-stage process (modulus of stiff layer assumed constant at 10000 MPa).
c. The depth to a stiff layer can be back-calculated together with the E-moduli with one neural network in a one-stage process (modulus of stiff layer assumed constant at 10000 MPa).
d. The depth to stiff layer can be back-calculated together with the E-moduli with one neural network in a one-stage process and the modulus of stiff layer is also being back-calculated.

The objective set at the beginning was to design neural networks to be used in a PMS to back-calculate E-moduli in real-time. The choices that will be investigated further will therefore be as set out in paragraphs 5.6.2.6(a) and 5.6.2.6(c), with the main motivation the ease of implementation in an neural network.

5.6.3 Pavement Type 2: Asphalt Surfacing on granular base/subbase (TR1102)

The trunk road from Malmesbury to Moorreesburg in the Western Cape (TR1102) was investigated. TR1102 is situated in an area with a moderate climate and a rolling terrain. Information gleaned from the PMS database revealed the pavement structure as shown in Table 5-18 for TR1104.

The methodology followed to create a neural network for a Type 2 pavement is similar to the one used for a Type 1 pavement. The knowledge gained from the work done to create a neural network for a Type 1 pavement was used to reduce the work required to create a neural network for a Type 2 pavement. It was learned that the modulus of the stiff layer couldn't be calculated successfully with a neural network but that the depth to the stiff layer and the E-moduli of the base, subbase and selected layers can be calculated with one neural network. Only two neural networks were therefore created:

- the first neural network calculates only E-moduli of base, subbase and subgrade while the depth to the stiff layer is estimated with Rohde's method.
- the second neural network also calculates E-moduli of the base, subbase and subgrade and estimates the depth to the stiff layer.

Comparisons are made between the results obtained from the two neural networks and MODCOMP.

The alternative to estimate the depth to the stiff layer with the Rohde method was included because it was shown that, with neural networks, the layer thickness plays a less important role in the back-calculation process. Although Rohde's method cannot always be applied, the option is left for the use thereof.

Table 5-18: Pavement Structure TR1102 obtained from PMS database

SECTION (km)	SURFACING	BASE	SUBBASE	SELECTED	SUBGRADE
0.000 – 6.810	35 AC	150 G3	150 G5	250 G8	G9M
6.810 – 7.410	35 AC	200 G3	150 G5	250 G8	G9M
7.410 – 8.780	85 AC	150 G3	150 G5	250 G8	G9M
8.780 – 12.490	35 AC	200 G3	150 G6D	250 G8	G9M
12.490 – 17.410	85 AC	150 G3	150 G5	250 G8	G9M
17.410 – 18.970	35 AC	150 G3	150 G5	250 G8	G9M

Explanations and specifications for the material codes are as defined in TRH14 (Appendix C2). It should be noted that the material codes were slightly modified in two instances, i.e. G6D subbase means a subbase with drainage properties and G9M means an in-situ material modified to G9 standard.

Deflection measurements for TR1102 were done in July 1996 and are shown in Appendix C.5.

Several runs with WES5 were again done to ensure that the layer moduli and thicknesses selected, reflected the range of measured deflections. It was found that the range of material properties indicated in Table 5-19 covers the bounds of measured deflections adequately. A neural network was designed to accommodate both 35mm and 85AC sections.

Table 5-19: Pavement Structure used in Neural Network for TR1102

LAYER	MODULUS (MPa)	THICKNESS (mm)	POISSON's RATIO
1. 35mm or 85 mm AC Surfacing	5000 – 11000	30 – 90	0.44
2. G3 Granular Base	300 – 700	100 – 250	0.35
3. G5 Granular Subbase	200 – 600	100 – 200	0.35
4. Granular Selected	50 – 600	1500 – 10000	0.35
5. In-situ Subgrade	10000	infinite	0.35

The following should be noted from Table 5-19:

- The modulus of the AC surfacing is rather high (deflection measurements were done in July 1996 with surface temperatures at 17°C).
- The deflection measurements were done in the rainy season (June 1996).
- High subgrade moduli can be expected, probably due to a rigid layer or high water table.

Multilayer Normal Feedforward neural networks with a back-propagation learning rule and sigmoid transfer functions were used for both neural networks. Hidden layer configurations are as per NN7 and NN12 respectively from Table 5-7.

The approach established with DR1005 in paragraph 5.6.2 was followed to create a neural network to back-calculate E-Moduli. Two neural networks were used: the first one to back-calculate E-moduli only and H_4 are estimated with the Rohde's method (NN7 from Table 5-7) and secondly both the E-moduli and H_4 is back-calculated (NN12 from Table 5-7). Results obtained with the neural networks for TR1102 are shown in Table 5-20.

Table 5-20: Summary of Neural Networks created for TR1102

No	INPUTS	OUTPUTS	LAYERS	RMSE (%)	CORR (%)	TOLERANCE	
						5%	10%
Case (a) : CALCULATE E-MODULI (EXCL. STIFF LAYER E_5 = 10000 MPa) ONLY							
1	H_1, H_2, H_3, H_4 D_0 thru D_{1500}	E_1, E_2, E_3, E_4	11-15-17-11-7	2.39	99.64	94.6	99.7
Case (b) : CALCULATE E-MODULI (EXCL. STIFF LAYER LAYER E_5 = 10000 MPa) AND DEPTH TO STIFF LAYER							
2	H_1, H_2, H_3 D_0 thru D_{1500}	E_1, E_2, E_3, E_4 H_4	10-15-21-11-5	3.27	99.32	89.3	98.8

The RMSE, correlation and tolerance parameters are better for Case (a) (depth to stiff layer calculated with Rohde's method), but can be attributed to the fact that one less variable is calculated.

5.6.3.1 Evaluation of Back-calculated E-moduli for TR1102

Detail results from the back-calculation of E-moduli are reported in Appendix C.5 and a comparison of a few back-calculations is given in Table 5-21.

Table 5-21: Comparison of back-calculated E-moduli between Case (a), Case (b) and MODCOMP for 35 AC surfacing layer

POSITION (Km)	METHOD	BACK-CALCULATED E-MODULI (MPa)					RMSE (%)
		E_1	E_2	E_3	E_4	E_5	
0.00	Case (a)	5056.8	699.7	468.4	116.9	10000.0	146.58
	Case (b)	10999.1	700.0	248.3	153.3	10000.0	40.82
	MODCOMP	8000.0	3850.0	287.0	200.0	3500.0	50.96
3.60	Case (a)	10998.9	316.9	200.1	477.9	10000.0	33.38
	Case (b)	10999.1	300.0	600.0	131.6	10000.0	25.67
	MODCOMP	8000.0	641.0	68.1	268.0	25100.0	25.32
6.20	Case (a)	9627.0	699.4	200.6	185.4	10000.0	51.73
	Case (b)	10998.5	700.0	200.2	372.9	10000.0	33.74
	MODCOMP	8000.0	762.0	85.2	183.0	107000.0	51.33
10.20	Case (a)	10998.8	306.0	204.2	161.0	10000.0	10.74
	Case (b)	10997.7	302.6	291.3	126.3	10000.0	9.82
	MODCOMP	8000.0	506.0	90.7	242.0	66.1	12.27
18.20	Case (a)	10998.9	699.8	208.6	85.8	10000.0	53.14
	Case (b)	10999.1	700.0	200.2	150.4	10000.0	10.43
	MODCOMP	8000.0	1870.0	21.5	360.0	83.9	19.76

As far as the two neural networks are concerned, the best results are obtained in Case (b) where the depth to stiff layer is calculated with the neural network. The Case (b) neural network results compare well the MODCOMP results with a RMSE that is even better in three instances.

MODCOMP calculated extremely high E-moduli for layer 1, the 35AC surfacing layer. It is very difficult to identify layer thicknesses of less than 50 mm with deflection measurements, and therefore it is difficult to back-calculate moduli for such thin layers. E_1 was therefore fixed at 8000 MPa, a modulus considered realistic for the asphalt surface temperature of 17°C reported. The E_1 = 8000 MPa was determined from 16 laboratory results taken from a typical wearing course constructed in the Western Cape. The Francken formula (University of Stellenbosch, 1997) was used to determine E_1, based on the volumetric calculations obtained from the laboratory samples. It should be noted that fixing E_1 at a predetermined level is not possible with a neural network, or for that matter fixing the modulus of any layer.

The results for the 85 AC surfacing section are shown in Table 5-22.

Table 5-22: Comparison of back-calculated E-moduli between Case (a), Case (b) and MODCOMP for 85 AC surfacing layer

POSITION (Km)	METHOD	BACK-CALCULATED E-MODULI (MPa)					RMSE (%)
		E_1	E_2	E_3	E_4	E_5	
7.60	Case (a)	10998.0	306.0	201.0	294.0	10000	20.70
	Case (b)	126.6	516.7	598.3	215.1	10000	42.49
	MODCOMP	8000.0	421.0	85.2	183.0	48800	44.83
8.60	Case (a)	10900.0	302.0	600.0	251.0	10000	53.59
	Case (b)	9004.0	300.0	600.0	84.2	10000	101.43
	MODCOMP	3560.0	147.0	262.0	394.0	3500	7.36
12.80	Case (a)	5027.0	587.0	201.0	146.0	10000	24.51
	Case (b)	10244.3	300.0	600.0	54.9	10000	14.40
	MODCOMP	3300.0	502.0	68.1	108.0	3500	11.47
15.00	Case (a)	9993.0	700.0	201.0	83.0	10000	38.93
	Case (b)	107.1	538.0	599.6	167.4	10000	53.37
	MODCOMP	8000.0	591.0	124.0	218.0	18.1	19.93
17.00	Case (a)	5055.0	433.0	200.0	327.0	10000	37.90
	Case (b)	9947.6	300.0	600.0	52.6	10000	58.68
	MODCOMP	4260.0	331.0	84.0	162.0	3500	29.78

As MODCOMP was more successful in determining E_1 the value E_1 was only predetermined at E_1 = 8000 MPa when high E_1 were calculated. RMSE values in Table 5-23 are high for all three the methods used, with no conclusive evidence that one method yields better results than the other.

High RMSE values are reported with all three methods used, including the MODCOMP results. Meier (1999) is of the opinion that it will be difficult to back-calculate E-moduli for deflection basins where high deflections are measured close to the load and very small deflections at the outer sensors. This is typically the type of deflection measurements experienced in the Western Cape.

5.6.4 Pavement Type 3: Bituminous surfacing on granular base and a cemented subbase (MR188)

A section of the main road from Durbanville to Klipheuwel in the Western Cape (MR00188) was investigated. MR188 is situated in an area with a moderate climate and a rolling terrain. Information obtained from the PMS database revealed the pavement structure as shown in Table 5-23 for MR188.

The methodology established with the creation of a neural network for a Type 2 pavement is applied to a Type 3 pavement.

Table 5-23: Pavement Structure MR188 from PMS database

SECTION (km)	SURFACING	BASE	SUBBASE	SELECTED	SUBGRADE
16.100 – 21.140	S19	150 G2	250 C4	150 G7	G9M
22.960 – 24.820	S19	200 G2	250 C4	150 G7	G9M
24.820 – 26.980	40AC	150 G2	300 C3	150 G7	G9M

Explanations and specifications for the material codes are as defined in TRH14 (See Appendix C2). The S19 surfacing seal referred to is a 19mm Cape Seal.

Deflection measurements for MR188 were done in July 1996 and are shown in Appendix C.6. It should be noted that values for BLI, MLI, LLI, SI, etc. are quoted from the PMS database and are not calculated in this thesis.

Several runs with WES5 were again done to ensure that the layer moduli and thicknesses selected, reflected the range of measured deflections. It was found that the range of material properties indicated in Table 5-24 covers the bounds of measured deflections adequately.

Table 5-24: Pavement Structure used in Neural Network for MR188

LAYER	MODULUS (MPa)	THICKNESS (mm)	POISSON's RATIO
1. Surfacing/G Granular Base	100 – 1200	100– 250	0.35
3. G5 Granular Subbase	100 – 7000	100 – 350	0.35
4. Granular Selected	100 – 900	100 – 200	0.35
5. In-situ Subgrade	50 – 900	1500 – 10000	0.35
	10000	infinite	0.35

Note: The surfacing and base were combined and analysed as a base of either 169 mm or 190 mm thickness.

The same approach established with DR1005 in paragraph 5.6.2 was again followed to create a neural network to back-calculate E-Moduli. Two neural networks were used: the first one to back-calculate E-moduli only and H_4 is estimated with Rohde (NN7 from Table 5-7) and secondly both the E-moduli and H_4 are back-calculated (NN12 from Table 5-7). Results obtained with the neural networks for MR188 are shown in Table 5-25.

Table 5-25: Summary of Neural Networks created for MR188

No	INPUTS	OUTPUTS	LAYERS	RMSE (%)	CORR . (%)	TOLERANCE 5%	TOLERANCE 10%
Case (a) : CALCULATE E-MODULI (EXCL. STIFF LAYER E_5 = 10000 MPa) ONLY							
1	H_1, H_2, H_3, H_4 D_0 thru D_{1500}	E_1, E_2, E_3, E_4	11-15-17-11-7	7.46	96.70	69.8	88.4
Case (b) : CALCULATE E-MODULI (EXCL. STIFF LAYER LAYER E_5 = 10000 MPa) AND DEPTH TO STIFF LAYER							
2	H_1, H_2, H_3 D_0 thru D_{1500}	E_1, E_2, E_3, E_4 H_4	10-15-21-11-5	4.38	98.89	84.8	96.3

The RMSE, correlation and tolerance parameters are better for Case (b) (depth to stiff layer calculated with Neural Network), even with one more variable being calculated. This is in contradiction with the result obtained with TR1102, but is of no significance. What is of significance is that the RMSE and tolerance are lower than is acceptable for this application (see discussion in paragraph 5.6.2.3).

5.6.4.1 Evaluation of Back-calculated E-moduli for MR188

Detail results from the back-calculation of E-moduli are reported in Appendix C.5 and comparison of a few back-calculations is given in Table 5-26.

Table 5-26: Comparison of back-calculated E-moduli between Case (a), Case (b) and MODCOMP for MR188

POSITION (Km)	METHOD	BACK-CALCULATED E-MODULI (MPa)					RMSE (%)
		E_1	E_2	E_3	E_4	E_5	
18.40	Case (a)	1199.7	164.6	899.8	92.9	10000	73.87
	Case (b)	1199.7	185.6	899.9	288.4	10000	38.43
	MODCOMP	397.0	3000.0	78.7	217.0	671.0	21.60
19.60	Case (a)	780.1	439.9	381.4	183.1	10000	12.90
	Case (b)	928.9	539.3	844.5	189.0	10000	12.96
	MODCOMP	396.0	3000.0	93.5	227.0	689000	14.27
20.40	Case (a)	1187.3	6973.8	121.5	875.8	10000	59.43
	Case (b)	1015.5	6999.4	100.1	896.8	10000	57.53
	MODCOMP	1830.0	3000.0	28.6	279.0	689000	20.71
24.00	Case (a)	1199.3	224.0	899.1	291.9	10000	8.34
	Case (b)	1199.2	338.3	899.7	233.7	10000	18.20
	MODCOMP	479.0	3000.0	85.0	316.0	5760.0	15.02
25.20	Case (a)	1199.7	198.1	899.8	147.8	10000	26.57
	Case (b)	1199.7	204.0	899.9	210.5	10000	15.51
	MODCOMP	452.0	3000.0	37.7	934.0	8.5	23.25

The surfacing and the base were combined into one layer for all three methods. Results with MODCOMP could be obtained by predetermining E_2 = 3000.0.

High RMSE values are again calculated for all three methods. The neural network results compare well with the MODCOMP results.

5.6.5 Pavement Type 4: Asphalt Surfacing on Bituminous Base and a cemented subbase (TR901)

The trunk road from Cape Town to Bellville in the Western Cape (TR901) was investigated. TR901 is situated in an area with a moderate climate and a rolling terrain. Information from the PMS database revealed the pavement structure as shown in Table 5-28 for TR901.

The methodology established with the Type 2 pavement was again employed to create a neural network for a Type 4 pavement.

Table 5-27: Pavement Structure TR901 from PMS database

SECTION (km)	SURFACING	BASE	SUBBASE	SELECTED	SUBGRADE
0.000 – 7.900	20RAO + 40AC	150 TS	150 C2	250 G8	G8
7.900 – 10.790	R13 + 40AC	150 TS	150 C2	250 G8	G8
10.790 – 11.800	20RAO + 40AC	150 TS	150 C2	250G8	G8
11.800 – 12.610	20RAO + 40AC	150 BCI	150 C2	250G8	G8
12.610 – 18.700	25AO + 50AG	150 TS	150 C2	250 G8	G8

Explanations and specifications for the material codes are as defined in TRH14 (see Appendix C2). RAO refers to an open graded mix modified with rubber, AO to a standard open graded mix and R13 to a 13mm rubber modified seal. TS refers to semi-gap graded tar hot mix base and BC to a continuously graded bituminous treated base.

It should be noted that the base is wrongly described in Appendix C.7 as G1.

Deflection measurements for TR901 were done in July 1996 and are shown in Appendix C.7. It should be noted that values for BLI, MLI, LLI, SI, etc. are quoted from the PMS database and are not calculated in this thesis.

Several runs with WES5 were done to ensure that the layer moduli and thicknesses selected, reflected the range of measured deflections. It was found that the range of material properties indicated in Table 5-28 covers the bounds of measured deflections adequately.

Table 5-28: Pavement Structure used in Neural Network for TR901

LAYER	MODULUS (MPa)	THICKNESS (mm)	POISSON's RATIO
1. Surfacing	300 – 9000	20– 80	0.44
2. TS Base	300 – 7000	100 – 200	0.44
3. Cemented Subbase	300 – 6000	100 – 200	0.35
4. Granular Selected	50 – 600	1500 – 10000	0.35
5. In-situ Subgrade	10000	infinite	0.35

Again the approach established with DR1005 in paragraph 5.6.2 was followed to create a neural network to back-calculate E-Moduli. Two neural networks were used: the first one to back-calculate E-moduli only and H_4 is estimated with Rohde (NN7 from Table 5-7) and secondly both the E-moduli and H_4 are back-calculated (NN12 from Table 5-7). Results obtained with the neural networks for TR901 are shown in Table 5-29.

Table 5-29: Summary of Neural Networks created for TR901

No	INPUTS	OUTPUTS	LAYERS	RMSE (%)	CORR* (%)	TOLERANCE 5%	TOLERANCE 10%
Case (a) : CALCULATE E-MODULI (EXCL. STIFF LAYER E_5 = 10000 MPa) ONLY							
1	H_1, H_2, H_3, H_4 D_0 thru D_{1500}	E_1, E_2, E_3, E_4	11-15-17-11-7	3.95	99.08	87.5	97.0
Case (b) : CALCULATE E-MODULI (EXCL. STIFF LAYER LAYER E_5 = 10000 MPa) AND DEPTH TO STIFF LAYER							
2	H_1, H_2, H_3 D_0 thru D_{1500}	E_1, E_2, E_3, E_4 H_4	10-15-21-11-5	6.78	97.16	75.8	90.6

* CORR = Correlation

The RMSE, correlation and tolerance parameters are better for Case (a) (depth to stiff layer calculated with Rohde's method), a similar result to that obtained from TR1102.

5.6.5.1 Evaluation of Back-calculated E-moduli for TR901

Detail results from the back-calculation of E-moduli are reported in Appendix C.5 and comparison of a few back-calculations is given in Table 5-30.

Table 5-30: Comparison of back-calculated E-moduli between Case (a), Case (b) and MODCOMP for TR901

POSITION (Km)	METHOD	BACK-CALCULATED E-MODULI (MPa) E_1	E_2	E_3	E_4	E_5	RMSE (%)
0.20	Case (a)	8999.0	715.5	5974.2	85.2	10000	34.55
	Case (b)	8999.4	895.7	5998.1	55.2	10000	14.25
	MODCOMP	8000.0	1490.0	806.0	115.0	192.0	25.04
3.20	Case (a)	8999.0	590.0	5442.5	230.9	10000	35.89
	Case (b)	8999.4	1279.7	5999.6	291.6	10000	42.59
	MODCOMP	8000.0	1980.0	23.5	212.0	689000	74.11
4.40	Case (a)	5099.2	1463.9	5939.4	144.0	10000	7.65
	Case (b)	3523.1	1451.1	5964.7	150.9	10000	4.57
	MODCOMP	8000.0	1770.0	2170.0	214.0	51.0	12.49
4.80	Case (a)	8999.0	1158.6	5999.6	125.9	10000	32.31
	Case (b)	8999.4	2063.5	5999.7	76.5	10000	3.10
	MODCOMP	8000.0	2020.0	3220.0	178.0	689000	13.24
6.60	Case (a)	8432.2	1326.5	3259.2	89.1	10000	297.48
	Case (b)	8999.2	3847.5	5999.7	59.1	10000	149.55
	MODCOMP	8000.0	16000.0	2360.0	95.3	689000	310.5

High RMSE values are again calculated with all three methods. The neural network results compare well with the MODCOMP results and even out perform MODCOMP in some instances.

5.7 EVALUATION OF BACK-CALCULATION RESULTS

Back-calculation results are evaluated by comparing neural networks with MODCOMP and secondly comparing the influence of the method used to calculate the depth to stiff layer. A comparison per pavement type has already been discussed before. A summary of the evaluation so far is given below.

5.7.1 Comparison of neural network with MODCOMP

It was shown that neural networks could be trained to back-calculate E-moduli from deflection basins. The E-moduli back-calculated with the neural network (depth to stiff calculated with NN) was compared with those back-calculated with MODCOMP in Appendices C.4, C.5, C.6 and C.7. The RMSE values for all four pavement types investigated are compared in the histogram in Figure 5-14.

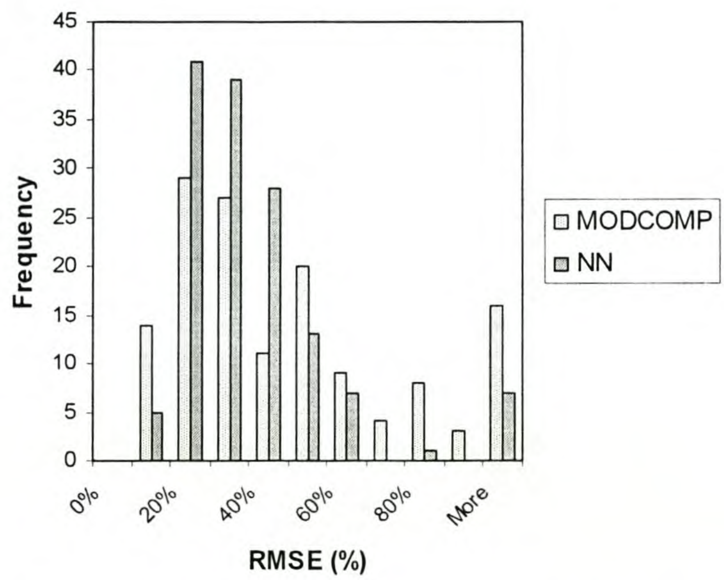

Figure 5-14: Comparison of RMSE calculated with NN vs MODCOMP

The RMSE values for both the neural network and MODCOMP are high, higher than would be accepted. Meier (1999) indicated that RMSE values in the order of 15 % would not be uncommon for the measured deflection basins. Almost all the RMSE values are more than 15 %. The reason for this can be find in the linear elastic theory being applied. The linear elastic theory is not suitable for materials that show nonlinear behaviour. The deflection measurements in the PAWC database indicate nonlinear material behaviour at least in the subgrade.

An important observation from Figure 5-14 is that both results have the same shape. It is concluded that two totally different methods interpreted the data presented to it, similarly.

From Figure 5-14 it is deduced that MODCOMP showed more results in the RMSE = 10% to 20% interval, with the neural network showing more results in the 20% - 30%, 30% - 40% and 40% - 50% intervals respectively.

With MODCOMP it was determined that 101 deflection basins have RMSE values < 50 %, while the neural network showed 126 RMSE values < 50 %. In this sense, the neural network has performed better than MODCOMP.

5.7.2 Influence of method used to calculate depth to stiff layer

Six random deflection basins were selected, two each from TR1102, MR188 and TR901, to compare the results obtained with the two methods used to calculate depth to stiff layer, i.e. neural network and Rohde's method. Results are presented graphically in Appendix C.8. Except for one deflection at chainage 2.200km, the neural network deflection basins showed a closer match with the measured basin.

Deflections calculated from back-calculated E-moduli for the two methods are compared in Figure 5-15.

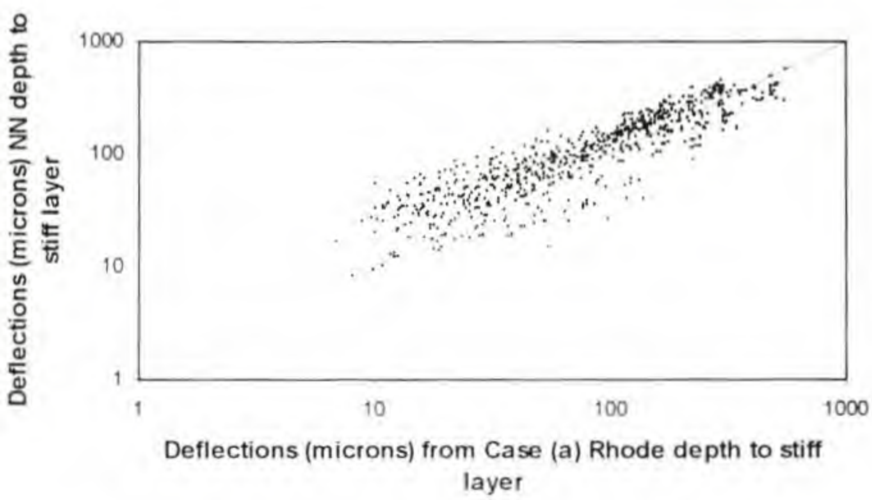

Figure 5-15: Calculated deflections from neural network back-calculated E-moduli: Depth to stiff layer estimated with Rohde vs NN

Deflections calculated with the two methods show a strong correlation (r^2 = 0.89). It was reported in paragraph 5.6.2.3 that the influence of layer thickness is small compared to the deflection measurements on back-calculated E-moduli. The strong correlation shown in Figure 5-15 is result of this.

It is concluded that both methods may be used to estimate the depth to the stiff layer. The author prefers the neural network method because it is fast and back-calculation results are obtained with one calculation. It will therefore be implemented more easily in a PMS.

5.7.3 Frequency Distribution of Deflections at Geophone, from PAWC PMS database

Frequency distributions of deflection measurements at each geophone, based on the deflection measurements in the PAWC PMS database, is included in Appendix C.9.

5.8 ADDING NOISE TO THE SYNTHETIC DEFLECTION BASINS

Adding noise to input patterns usually improve network robustness and increases the generalization ability of a network. Meier and Rix (1994) reported two reasons to introduce noise in the synthetic deflection basins (paragraph 5.5.3). These reasons can also serve as an estimator of the magnitude of noise required.

It was not possible to introduce noise in the networks used in this thesis due to program limitations, as Qnet 2000 does not provide this feature. Future work on the back-calculation of E-moduli should definitely include the option to add noise to the input patterns.

5.9 INCREASING NETWORK ACCURACY

Meier and Rix (1995) showed that increased network accuracy could be obtained using dynamic solutions to pavement response instead of the normal practice of static analysis of pavement response. Dynamic solutions are not easily implemented in conventional back-calculation routines due to the complex nature of the method. However, neural network solutions are independent of the complexity of the problem analysed allowing the implementation of a complex dynamic solution as a complementary standalone program providing input to the neural network via the synthetically generated dynamic deflection basins.

Static and dynamic deflection basins as a function of depth to bedrock are compared in Figure 5-16. They show that static deflection basins are strongly influenced by the depth to bedrock, whereas the dynamic deflections are nearly independent of the depth to bedrock. Using dynamic back-calculating techniques poses not only the benefit of increased accuracy, but can solve the depth to stiff layer problem.

Meier and Rix(1995) used an elasto-dynamic Green function solution based on a stiffness matrix formulation of the pavement system. This was unavailable to the author in this thesis and could therefore not be implemented in this thesis.

Finite element analysis techniques may also be implemented in generating synthetic deflection basins for the same reason, i.e. the neural network's ability to solve problems independent of the complexity of the problem.

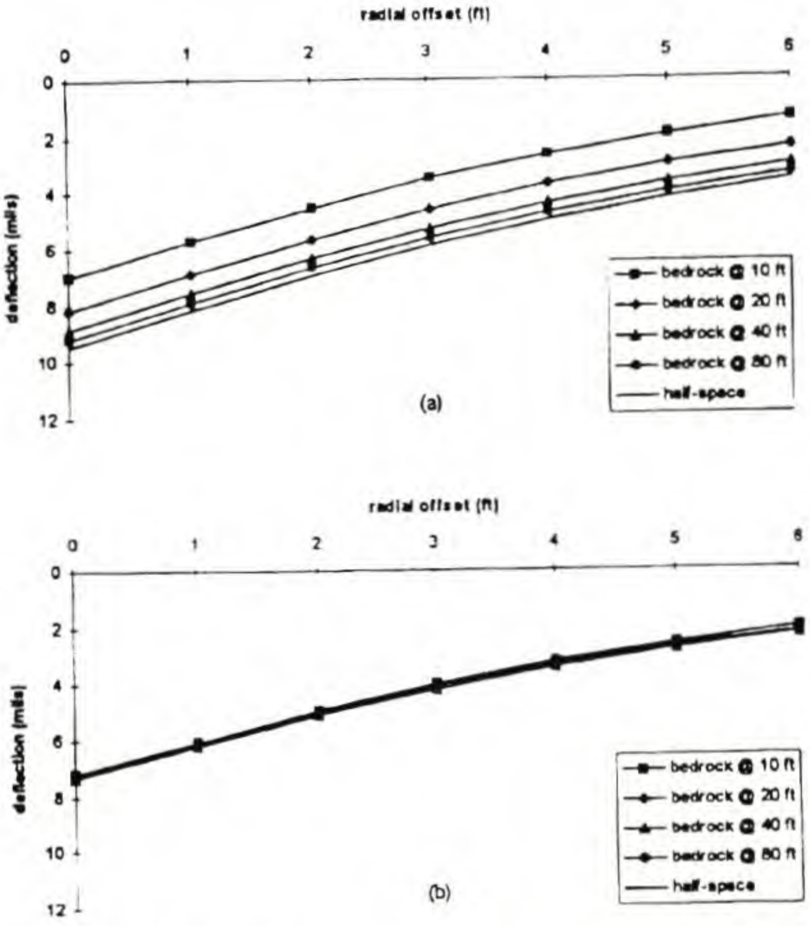

Figure 5-16: Static (a) and dynamic (b) deflection basins as a function of depth to bedrock (Meier and Rix, 1995)

Future research into the back-calculation of layer moduli with neural networks should include the dynamic solution and finite element analysis techniques.

5.10 DISCUSSION

It has been shown that neural networks can be trained to back-calculate E-moduli orders of magnitude faster than conventional programs. The same problems are encountered as with conventional back-calculation programs (see discussion in paragraph 5.3.2). These problems are inherent in the calculation method, i.e. the application of linear elastic theory and not a limitation of the neural network as proved by the similar results obtained with MODCOMP, a conventional back-calculation program.

The successful creation of a neural network to back-calculate E-moduli from deflection measurements is very much dependent on prior knowledge of the problem. It was found that E-moduli back-calculated with neural networks showed similar problems as those encountered when using conventional back-calculation programs, especially the compensating layer effect is particularly evident. Increasing the number of layers is a well-known method to solve or soften the effects of the compensating layer effect. This was done by increasing the number of layers for one of the cases investigated from five to seven layers, using a conventional back-calculation program. The result of this was a drastically different solution, and showed that more layers should be used in the back-calculation process. Unfortunately, this could not be tested in this thesis due to program limitations, but should be included in future studies.

It was not possible to train a single network to use to back-calculate E-moduli for all the pavement types in use in the Western Cape. Typical pavement types identified were:

- Granular base with a granular subbase and a thin surfacing seal (DR1005 was used as an example).

- Granular base with granular subbase and an asphalt surfacing (TR1102 was used as an example).

- Granular base with a cemented subbase and a thin surfacing seal (MR188 was used as an example).

- Bituminous treated base (hot-mix) with a cemented subbase and an asphalt wearing course (TR901 was used as an example).

More pavement types are used in South Africa and even in the Western Cape a few more will be added in the future. A complete description of base groups used in the Western Cape is included in Appendix C.3(b). Unfortunately these descriptions do not include any reference to subbase type.

Neural networks were created for each of the four pavement types used as examples. All possible pavement types in use should be identified and neural networks created for each of these should the method of back-calculation with neural networks be implemented on a regional or national scale in a PMS. In the Western Cape the base groups have already been identified (see Appendix C.3(b)) so that neural networks can be trained for these base groups or combinations thereof. The base groups should be extended to include the subbase type.

Results from the limited back-calculation of E-moduli, done in this thesis, yielded E-moduli with varying degrees of accuracies. In general, it can be stated that the neural networks trained successfully and that tests with test data extracted from the synthetically generated deflection basins showed a very good correlation. However, tests with real deflection basins met with varying degrees of success.

Some of the problems experienced are due to the method used to generate synthetic deflection basins on which the neural networks were trained (linear elastic analysis). It is assumed that the accuracy will be increased if another method is used to generate synthetic deflection basins, especially if such a method can incorporate the nonlinearity and stress-dependant behaviour of granular materials. Neural networks are not dependent on the method used to generate data and merely make deductions from the facts presented to it. Complicated methods used to generate data for the neural network will therefore not influence the operation of the neural network, only the accuracy of the calculated results.

The value of neural networks lies in the extremely high execution speeds that can be obtained. Although time is required to create and train neural networks, a vast amount of time is later saved in the back-calculation process, especially if a large number of deflection basins are to be analysed.

On a current project 96 deflection basins had to be analysed. Approximately 12 hours were required to back-calculate E-moduli with MODCOMP, while the same result was achieved in less than 2 minutes with a neural network (time to enter data included in both cases). More investigative work to increase the accuracy of neural networks and to identify pavement types is therefore well justified.

The objective state at the beginning was reached: it was shown that neural networks can be applied on a real-time basis to back-calculate E-moduli in a PMS, provided further work is done to improve accuracy and robustness and to cover all the pavement types. Back-calculation of E-moduli on this scale will enable road authorities to use a more fundamental approach to estimate remaining life.

5.11 CONCLUSIONS

Neural networks can be successfully trained to back-calculate E-moduli from measured deflection basins and these neural networks can be implemented in a PMS to back-calculate E-moduli in real-time. Further investigative work is required to identify pavement types and train neural networks suitable for these pavement types. Methods to improve the accuracy of neural networks as far as the back-calculation of E-moduli is concerned should also receive attention, especially the use of a more sophisticated method to generate synthetic deflection basins. Improvements in the data generation process using a theory that does accommodate nonlinear and stress dependent behaviour of materials may result in improved performance of the neural networks.

Specific conclusions are:

- Problems are experienced with the back-calculation of E-moduli, even with conventional methods. A typical problem experienced is the compensating layer effect.

- The depth to a stiff layer influences back-calculation results. The stiff layer can be real, as with bedrock, or apparent, due to the nonlinear behaviour of subgrade material or the presence of a shallow water table. The small deflections at the outer sensors reported in the PAWC PMS database indicate that a stiff layer is present in most of the pavement sections in the PAWC road network.

- Rohde's method to estimate the depth to the stiff layer should be implemented with great care and due cognisance of the ratio's specified.

- Meier and Rix (1994) showed that neural networks could be taught to solve complex, nonlinear inverse problems such as the back-calculation of E-moduli from deflection basin measurements. They also showed that the introduction of random noise gives a better representation of the real world situation where errors occur in measurement and that dynamic back-calculation gives better results than static back-calculation.

- Synthetic (simulated) deflection basins can be generated with linear elastic programs to use as training and testing data to train neural networks to back-calculate E-moduli.

- The author trained several neural networks and selected four neural networks to apply on South African pavements.

- A neural network can also be trained to estimate the depth to the stiff layer. Two methods were successful:

    - A one-step process: Both E-moduli and depth to stiff layer are calculated with one neural network.
    - A two-step process: Two neural networks are used, one for the depth to stiff layer and a second one to back-calculate E-moduli.

- The two-step process is more accurate than the one-step process, but the one-step process is preferred because time is saved.

- The E-modulus of the stiff layer could not be modelled successfully.

- Neural networks could not be trained to back-calculate layer thicknessess and E-moduli in a one-step process (a two-step process was not investigated).

- The influence of layer thicknessess on the resultant E-moduli in the back-calculation process is much less than the deflections measured, less than $^{1}/_{5}$. The method used to estimate the depth to stiff layer is therefore not important; the influence of any variations will be small.

- Neural networks exhibit some of the same problems experienced with conventional back-calculation methods, e.g. the compensating layer effect. Linear elastic theory was used to generate the data on which neural networks were trained and the same theory is used by MODCOMP, the conventional back-calculation program used in this thesis. Therefore, the problem is not caused by the method used to do back-calculations, but by the theory used.

- With conventional back-calculation programs, the user interacts with the program during the back-calculation process. The user can therefore identify problems and take action. This is not possible with neural networks.

- The RMSE values of the back-calculated deflection basins, calculated from back-calculated E-moduli, are high due to the shape of measured deflection basins. More than 50 % of deflections measured at the D1500 sensor are less than 25 microns, making it difficult to fit the measured basins.

- Neural network results compare well with those obtained with MODCOMP.

- The amount of variance inherent in the neural networks trained to back-calculate E-moduli, must be investigated. Variance is the phenomena when a model has too much flexibility and occurs when the number of degrees of freedom is relatively small compared to the size of the data.

- A neural network's ability to solve problems is independent of the complexity of the problem or method used to generate data. Complex theories (dynamic back-calculation, finite element analysis) can therefore be used to generate data. These theories will improve the modelling of the pavement structure.

- Back-calculating with neural networks is extremely fast therefore justifying further research to increase the accuracy of the method.

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CHAPTER 6

6 CONCLUSIONS AND RECOMMENDATIONS

The following conclusions and recommendations can be drawn from this thesis:

6.1 CONCLUSIONS

It is concluded that:

Specific conclusions pertaining to neural networks

- A thorough understanding of the data from which a neural network is going to be trained, is required, together with a formulation of the problem to be solved.
- The neural network architecture plays an important role in the successful implementation of neural networks.
- Training neural networks is a time consuming process that takes place once, thereafter solving problems is a quick and relatively easy process.
- The neural network was not sensitive to the number of data points in a certain condition category and showed no bias if one category has substantially more data points in a certain category. Although not investigated, it is reasonable to expect that data should at least be distributed in such a manner that all categories contain data. The neural network cannot learn if it is not presented with facts.
- Neural networks can be used in solving problems as standalone solutions or in conjunction with expert systems and fuzzy logic systems as a hybrid system, where the strength of the different techniques are combined to offer a superior solution.
- Neural networks can be taught to solve complex problems. The introduction of random noise to data gives a better representation of the real world situation where errors occur in measurement.
- A neural network's ability to solve problems is independent of the complexity of the problem or method used to generate data. Complex theories can therefore be used to generate data.
- Neural network results must be validated, as they do not always deliver the planned result.

Specific conclusions pertaining to the determining of the Visual Condition Index (VCI)

- A certain measure of subjectivity is build into the process to determine the Visual Condition Index (VCI). Firstly, the visual assessments are subject to the subjectivity of the individual performing the assessment, and secondly, the TRH22 method used to determine the VCI contains an element of subjectivity introduced by the designers of the method.
- The subjectivity issue causes continuous questioning of the VCI and a search to improve the TRH22 method used in the calculation of the VCI.
- A neural network was designed that successfully calculates the VCI and it was found that three options exist whereby neural networks could be utilized to improve the TRH22 VCI calculation method:

- Directly calculating the VCI;
- Using neural network results to modify the TRH22 VCI formulae; and
- Adjusting the existing TRH22 VCI weight set by comparing the influence of each distress type on the VCI, as determined by the neural network, with the current TRH22 weight set.

<u>Specific conclusions pertaining to determining seal types for a reseal program</u>

- Data used to train the neural network was inadequate in certain seal type categories and lacking in specific seal type categories.

- Meaningful results could not be obtained with the neural network due to inadequacy or lack of data in certain seal type categories.

- Indications are that, if data is augmented from other sources, a neural network can be designed to determine seal types for a reseal program.

- The lack of a meaningful result with this investigation showed that neural networks couldn't be implemented for every problem.

<u>Specific conclusions pertaining to the back-calculation of E-moduli</u>

- Problems are experienced with the back-calculation of E-moduli from deflection measurements in the PAWC PMS database, due to small deflections measured at the outer sensors. Even conventional back-calculation programs experience problems to fit deflection basins where large deflections are measured under the load and small deflections are measured at the outer sensors.

- The small deflections at the outer sensors of the deflection basins reported in the PAWC PMS database, indicate that a stiff layer is present in the pavement structure. This stiff layer can be real, as with bedrock, or apparent, due to the nonlinear behaviour of subgrade material or the presence of a shallow water table.

- The depth to the stiff layer can either be estimated with Rohde's method or a neural network can be trained to estimate the depth from deflection measurements.

- Synthetic (simulated) deflection basins can be generated using computer programs based on linear elastic theory. The synthetic deflection basins serve as a training and test set to train networks to back-calculate E-moduli from deflection measurements.

- Neural networks can be designed and trained to back-calculate E-moduli from deflection measurements. Results obtained with neural networks compare well with those obtained with a conventional back-calculation program.

- Neural networks exhibit some of the same problems as those experienced with conventional back-calculation methods, e.g. the compensating layer effect. Linear elastic theory is used to generate the data from which neural networks are trained and the same theory is used in the conventional back-calculation programs. The problems experienced can therefore be attributed to the theory used not being able to model the behaviour of pavement materials adequately. A more comprehensive theory is required to adequately model the behaviour of pavement materials.

- Layer thickness plays a less important role in the back-calculation of E-moduli with neural networks. Small errors in the estimation of layer thickness can therefore be tolerated.

- Back-calculation with neural networks is extremely fast, making them excellent candidates for implementation in a PMS where large numbers of deflection basins need to be analysed. Further research to increase the accuracy of the method is justified.

6.2 RECOMMENDATIONS

From the preceding chapters and the above conclusions the following recommendations are made:

Recommendations regarding the determining of the Visual Condition Index (VCI)

> Note: The formulae to calculate the VCI_p, F_n and VCI are defined in Chapter 3 and repeated here for easy reference. Symbols are defined in Chapter 3, paragraph 3.3.

- A panel of experts should be appointed to investigate the modification of the VCI_p formula, Eq. 6-1, The modification can be done by revising the weights W_n in the extent and weight factor F_n , Eq. 6-2. The contribution of each distress type towards the Overall Pavement Condition (OPC) indicator was determined with a neural network. The weights in Eq. 6-2 can be revised using the contribution of each distress type towards the distress type as a guideline.

$$VCI_p = 100\left(1 - C \times \sum_{n=1}^{N} F_n\right)$$

Eq. 6-1

$$F_n = D_n \times E_n \times W_n$$

Eq. 6-2

- The same panel of experts should also address the VCI formula, Eq. 6-3. It was shown that the neural network results can be used to determine new values for the constants a and b in Eq. 6-3.

$$VCI = \left(a \times VCI_p + b \times VCI_p^2\right)^2$$

Eq. 6-3

- The panel of experts should reconsider the need for Eq. 6-3 in favour of a slight modification to Eq. 6-1 to directly reflect the VCI.

Recommendations regarding the determining of seal types for a reseal program

- The data generated with the Reseal Expert System should be augmented with additional data from the following sources:
  - Historic reseal data; and
  - Workshop sessions with experts to fill in data in seal categories where inadequate data exists.
- Design a neural network, using the network designed in this thesis as the basis, to predict seal types.

Recommendations regarding the cack-balculation of E-moduli

- Computer programs should be developed to adequately model the behaviour of pavement layer and subgrade material. Computer programs are available that are able to model nonlinear pavement materials and dynamic effects. The source code for these programs needs to be obtained for modification to generate synthetic (simulated) deflection basins. The following two possibilities should especially be considered:

- Finite element analysis; and
- Dynamic solutions of pavement response.

- As an alternative to the above recommendation, the use of a linear elastic program that can accommodate more layers can be investigated.

- Alternative network architectures should be investigated. Due to financial constraints only one neural network software program, Qnet2000, was used in this thesis. Qnet2000 was limited to only one neural network architecture, a multi-layer feedforward model with back-propagation. The development of a dedicated program can also be considered.

- The introduction of more input variables should be investigated for more versatile neural networks. Provision should be made to accommodate the following:

  - Defining the number of sensors so that the network is not limited to one FWD configuration; and
  - Defining the load so that different FWD loads can be used.

- Provision should be made to add noise to generated deflections to increase network robustness and achieve a better representation of the real world situation where errors occur in measurement. this aspect was not investigated in this thesis because Qnet2000 cannot inject noise into data.

- A total approach should be investigated where more than one neural network is utilized in the back-calculation process. A two-step process where the depth to stiff layer is estimated and then used as an input to the back-calculation neural network, has already been introduced in this thesis.

****

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APPENDIX A

VISUAL CONDITION INDEX OF FLEXIBLE PAVEMENTS INFORMATION SHEETS

Appendix A.1

PAWC: Transport and Public Works : Visual Evaluation (Source : PAWC)

Appendix A.2

Description of Input Parameters to Neural Network for the Calculation of the Overall Pavement Condition and the Visual Condition Index (Source : Van der Gryp et al, 1998 after TRH22, 1994)

Appendix A.1

P.A.W.C. Transport and Public Works
VISUAL EVALUATION

ROUTE/SECTION: ASSESSOR: ____________

SEGMENT: Km: from: to DATE: ____________

DISTRICT:

CLIMATE: | Very Wet | Wet | Moderate | Dry | TERRAIN: | Mountains | Rolling | Flat |

ROAD WIDTH m:_____ m:_____ m:_____ m:_____
km:____ km:____ km:____ km:____ DC:

SURFACING

CURRENT SURFACE					
	TEXTURE	VARYING	FINE	MEDIUM	COARSE
	VOIDS	VARYING	NONE	FEW	MANY

		DEGREE					EXTENT				
		Slight				Severe	Isolated				Common
	0	1	2	3	4	5	1	2	3	4	5
FAILURE/PATCHING											
CRACKS											
AGGREGATE LOSS											
BINDER CONDITION											
BLEEDING/FLUSHING											

STRUCTURE

		DEGREE					EXTENT				
		Small/Slight				Large/Severe	Isolated				Common
	0	1	2	3	4	5	1	2	3	4	5
BLOCK/STAB. CRACKS (N M L)											
LONGITUDINAL/SLIP CRACKS											
TRANSVERSE CRACKS											
CROCODILE/FAILURE CRACKS											
PUMPING											
RUTTING											
UNDULATION/SETTLEMENT											
PATCHING											
FAILURES/POTHOLING											

OCCURRENCE	STRUCTURES	EDGES	DEPRESSIONS	GRADES	CUTTINGS	GENERAL

FUNCTIONAL

RIDING QUALITY		VERY GOOD	GOOD	FAIR	POOR	VERY POOR
	Problem			UNDULATION	SETTLEMENT	CORRUGATION
SKID RESISTANCE		VERY GOOD	GOOD	FAIR	POOR	VERY POOR
	Problem				BLEEDING	POLISHED

SURFACE DRAINAGE		ADEQUATE	WARNING	INADEQUATE		
	Problem	RUTTING	SHOULDERS	UNDULATION	FAILURE	SIDE DRAINS

UNPAVED SHOULDERS		SAFE	WARNING	UNSAFE			
	Problem	ERODED	RUTTED	TOO HIGH	NARROW	INCLUDED	OVERGROWN

	0	1	2	3	4	5	1	2	3	4	5
EDGE BREAKING											

SUMMARY

TYPE ACTION NEEDED	NONE	STRUCTURE			SURFACE			ROUTINE		
		C	B	A	C	B	A	C	B	A
OVERALL PAVEMENT CONDITION	VERY GOOD	GOOD	FAIR	POOR	VERY POOR					

Appendix A.2

Description of Input Parameters to Neural Network for the Calculation of the Overall Pavement Condition (OPC) and the Visual Condition Index (VCI)

Parameter	Defect	Levels	Range
I1	Failure/Patching Degree	6	0 – 5
I2	Failure/Patching Extent	6	0 – 5
I3	Surface cracks Degree	6	0 – 5
I4	Surface cracks Extent	6	0 – 5
I5	Aggregate loss Degree	6	0 – 5
I6	Aggregate loss Extent	6	0 – 5
I7	Binder condition Degree	6	0 – 5
I8	Binder condition Extent	6	0 – 5
I9	Bleeding/Flushing Degree	6	0 – 5
I10	Bleeding/Flushing Extent	6	0 – 5
I11	Block/Stabilisation cracks Degree	3	1 – 3
I12	Block/Stabilisation cracks Extent	6	0 – 5
I13	Block/Stabilisation cracks Spacing	6	0 – 5
I14	Longitudinal/Slip cracks Degree	6	0 – 5
I15	Longitudinal/Slip cracks Extent	6	0 – 5
I16	Transverse cracks Degree	6	0 – 5
I17	Transverse cracks Extent	6	0 – 5
I18	Crocodile/Failure cracks Degree	6	0 – 5
I19	Crocodile/Failure cracks Extent	6	0 – 5
I20	Pumping Degree	6	0 – 5
I21	Pumping Extent	6	0 – 5
I22	Rutting Degree	6	0 – 5
I23	Rutting Extent	6	0 – 5
I24	Undulation/Settlement Degree	6	0 – 5
I25	Undulation/Settlement Extent	6	0 – 5
I26	Patching Degree	6	0 – 5
I27	Patching Extent	6	0 – 5
I28	Failures/Potholing Degree	6	0 – 5
I29	Failures/Potholing Extent	6	0 – 5
I30	Riding quality	9	0 – 4
I31	Skid resistance	9	0 – 4
I32	Surface drainage	3	0 - 4*
I33	Unpaved shoulders	3	0 - 4*
I34	Edge breaking Degree	6	0 – 5
I35	Edge breaking Extent	6	0 – 5
D1	Overall Pavement Condition	9	1 – 5

* only values 0, 2 and 4.

APPENDIX B

RESEAL TYPES FOR FLEXIBLE PAVEMENTS INFORMATION SHEETS AND DIAGRAMS

Appendix B.1

Build Neural Table Source Code Header File
(Source : PAWC)

Appendix B.2

SQL Query to Extract Reseal Need from PMS Database
(Source : PAWC)

Appendix B.3

Description of Seals
(Source : PAWC)

Appendix B.4

Description of Input Parameters to Neural Network for the Determination of the Reseal Types
(Source : PAWC)

Appendix B.5

Conditions for Seal Types
(Source : PAWC)

Appendix B.1

Build Neural Table Source Code Header File

Appendix B.1

Build Neural Table Source Code Header File SQL Query

```
create table temp_PMSneuraldata
            (  RoadNo           char(7)             ,
               CarWay           char(1)             ,
               Startkm          number(5,2)         ,
               Endkm            number(5,2)         ,
               VisYear          number(4)           ,
               VisMonth         number(2)           ,
               TextDir          char(1)             ,
               TextOne          number(1)           ,
               TextTwo          number(1)           ,
               VoidDir          char(1)             ,
               VoidOne          number(1)           ,
               VoidTwo          number(1)           ,
               DGenSurf         number(1)           ,
               EGenSurf         number(1)           ,
               DFailPatc        number(1)           ,
               EFailPatc        number(1)           ,
               DCrac            number(1)           ,
               ECrac            number(1)           ,
               DAggrLoss        number(1)           ,
               EAggrLoss        number(1)           ,
               DBindCond        number(1)           ,
               EBindCond        number(1)           ,
               DBleeFlus        number(1)           ,
               EBleeFlus        number(1)           ,
               DGenCrac         number(1)           ,
               EGenCrac         number(1)           ,
               DBlocStab        number(1)           ,
               EBlocStab        number(1)           ,
               SBlocStab        char(1)             ,
               DLongSlip        number(1)           ,
               ELongSlip        number(1)           ,
               DTran            number(1)           ,
               ETran            number(1)           ,
               DCrocFail        number(1)           ,
               ECrocFail        number(1)           ,
               DPump            number(1)           ,
               EPump            number(1)           ,
               DGenDefe         number(1)           ,
               EGenDefe         number(1)           ,
               DRutt            number(1)           ,
               ERutt            number(1)           ,
               DUnduSett        number(1)           ,
               EUnduSett        number(1)           ,
               DPatc            number(1)           ,
               Epatc            number(1)           ,
               DFailPoth        number(1)           ,
               EFailPoth        number(1)           ,
               RideQual         number(3,1)         ,
```

```
    RQProblem           char(3)          ,
    SkidResi            number(3,1)      ,
    SRProblem           char(2)          ,
    SurfDrai            number(1)        ,
    SDProblem           char(5)          ,
    UnpaShou            number(1)        ,
    USProblem           char(6)          ,
    DEdgeBrea           number(1)        ,
    EEdgeBrea           number(1)        ,
    TANStru             number(1)        ,
    TANSurf             number(1)        ,
    TANRout             number(1)        ,
    OPC                 number(2,1)      ,
    PavementIndex       number(4,1)      ,
    ReSealIndex         number(4,1)      ,
    SurfIndx            number(4,1)      ,
    StruIndx            number(4,1)      ,
    FuncIndx            number(4,1)      ,
    YearofSeal      number(4)        ,
    TypeofSeal      varchar2(4)      ,
  SealCode    number(1)        ,
    Basecourse      varchar2(4)      ,
  BasecourseCode  number(1)        ,
    HeavyCount      number(6)        ,
  HeavyCode   number(1)
);
```

Appendix B.2

SQL Query to Extract Reseal Need Data From PMS Database

Appendix B.2

SQL Query to Extract Reseal Need From PMS Database

```
DECLARE
  CURSOR NodePoints IS
                select roadno, carway, visstartkm   kmnode from visual
        union (  select roadno, carway, visendkm     kmnode from visual)
     union (   select roadno, carway, sealstartkm  kmnode from reseal)
     union (   select roadno, carway, sealendkm    kmnode from reseal)
     union (   select roadno, carway, trafstartkm  kmnode from trafficvolume)
     union (   select roadno, carway, trafendkm    kmnode from trafficvolume)
     union (   select roadno, carway, strucstartkm kmnode from structure
              where layercode = 20)
     union (   select roadno, carway, strucendkm   kmnode from structure
              where layercode = 20)                              ;

  NodeRecord        NodePoints%ROWTYPE                                   ;
  RoadNumber        visual.RoadNo%TYPE                                   ;
  CarriageWay       visual.CarWay%TYPE                                   ;
  Startkm           visual.visstartkm%TYPE                               ;
  Endkm             visual.visendkm%TYPE                                 ;
  SectionVisYear    visual.visyear%TYPE                                  ;

  YearofSeal         reseal.SealYear%TYPE                                ;
  TypeofSeal         reseal.SealType%TYPE                                ;
  SealCode           number(1)                                           ;

  Basecourse         structure.materialcode%TYPE                               ;
  BasecourseCode    number(1)                                      ;

  HeavyCount         trafficvolume.heavy%TYPE                                  ;
  HeavyCode     number(1)                                          ;

  vRoadNo           char(7)                                              ;
  vCarWay           char(1)                                              ;
  vStartkm          number(5,2)                                          ;
  vEndkm            number(5,2)                                          ;
  vVisYear          number(4)                                            ;
  vVisMonth         number(2)                                            ;
  vTextDir          char(1)                                              ;
  vTextOne          number(1)                                            ;
  vTextTwo          number(1)                                            ;
  vVoidDir          char(1)                                              ;
  vVoidOne          number(1)                                            ;
  vVoidTwo          number(1)                                            ;
  vDGenSurf         number(1)                                            ;
  vEGenSurf         number(1)                                            ;
  vDFailPatc        number(1)                                            ;
  vEFailPatc        number(1)                                            ;

  vDCrac            number(1)                                            ;
  vECrac            number(1)                                            ;
```

```
  vDAggrLoss        number(1)                                      ;
  vEAggrLoss        number(1)                                      ;
  vDBindCond        number(1)                                      ;
  vEBindCond        number(1)                                      ;
  vDBleeFlus        number(1)                                      ;
  vEBleeFlus        number(1)                                      ;
  vDGenCrac         number(1)                                      ;
  vEGenCrac         number(1)                                      ;
  vDBlocStab        number(1)                                      ;
  vEBlocStab        number(1)                                      ;
  vSBlocStab        char(1)                                        ;
  vDLongSlip        number(1)                                      ;
  vELongSlip        number(1)                                      ;
  vDTran            number(1)                                      ;
  vETran            number(1)                                      ;
  vDCrocFail        number(1)                                      ;
  vECrocFail        number(1)                                      ;
  vDPump            number(1)                                      ;
  vEPump            number(1)                                      ;
  vDGenDefe         number(1)                                      ;
  vEGenDefe         number(1)                                      ;
  vDRutt            number(1)                                      ;
  vERutt            number(1)                                      ;
  vDUnduSett        number(1)                                      ;
  vEUnduSett        number(1)                                      ;
  vDPatc            number(1)                                      ;
  vEpatc            number(1)                                      ;
  vDFailPoth        number(1)                                      ;
  vEFailPoth        number(1)                                      ;
  vRideQual         number(3,1)                                    ;
  vRQProblem        char(3)                                        ;
  vSkidResi         number(3,1)                                    ;
  vSRProblem        char(2)                                        ;
  vSurfDrai         number(1)                                      ;
  vSDProblem        char(5)                                        ;
  vUnpaShou         number(1)                                      ;
  vUSProblem        char(6)                                        ;
  vDEdgeBrea        number(1)                                      ;
  vEEdgeBrea        number(1)                                      ;
  vTANStru          number(1)                                      ;
  vTANSurf          number(1)                                      ;
  vTANRout          number(1)                                      ;
  vOPC              number(2,1)                                    ;
  vPavementIndex    number(4,1)                                    ;
  vReSealIndex      number(4,1)                                    ;
  vSurfIndx         number(4,1)                                    ;
  vStruIndx         number(4,1)                                    ;
  vFuncIndx         number(4,1)                                    ;

BEGIN

  Startkm       := -1                                              ;
  Endkm         := -1                                              ;
  RoadNumber    := '9999999'                                       ;
  CarriageWay   := '*'                                             ;
```

```
OPEN NodePoints                                                    ;
LOOP
      FETCH NodePoints INTO NodeRecord                       ;
      IF NodePoints%NOTFOUND THEN
       CLOSE NodePoints                                      ;
       exit                                                  ;
      END IF                                                 ;
      IF RoadNumber<>NodeRecord.RoadNo or CarriageWay<>NodeRecord.CarWay THEN
       RoadNumber  := NodeRecord.RoadNo                            ;
       CarriageWay := NodeRecord.CarWay                            ;
       Startkm     := NodeRecord.kmnode                            ;
       Endkm       := -1                                           ;
      ELSE
       IF Endkm <> -1 THEN
             Startkm  := Endkm                                     ;
       END IF;
       Endkm       := NodeRecord.kmnode                            ;
      END IF;
      IF Endkm <> -1 THEN
/*           We have a section definition so start extracting data for it
      */
/*    Begin with visual as we want the latest year                  */
        BEGIN
         select max(visyear)
           into SectionVisYear
           from visual
          where visual.roadno = RoadNumber
            and visual.carway = CarriageWay
            and (least(endkm,visendkm)-greatest(startkm,visstartkm))>0       ;
        EXCEPTION
        WHEN NO_DATA_FOUND THEN
/*          this scenario is possible and no point writing a record with no
      */
/*          visual data, so we can skip the rest of the loop             */
               SectionVisYear := 0                                ;
        END;

      IF SectionVisYear <> 0 THEN

/*         start looking through the reseal data                      */
/*                 Look for the last reseal done before the inspection year
      */
         BEGIN
               select max(SealYear)
                 into YearofSeal
                 from Reseal
                where reseal.roadno = RoadNumber
                  and reseal.carway = CarriageWay
                  and reseal.sealyear <= SectionVisYear
                  and (least(endkm,sealendkm)-greatest(startkm,sealstartkm))>0
      ;
           EXCEPTION
           WHEN NO_DATA_FOUND THEN
           YearofSeal := 0                                        ;
         END                                                      ;

           BEGIN
```

```
            select SealType
              into TypeofSeal
              from Reseal
             where reseal.roadno = RoadNumber
               and reseal.carway = CarriageWay
               and reseal.sealyear = YearofSeal
               and (least(endkm,sealendkm)-greatest(startkm,sealstartkm))>0
       group by SealType                                        ;
         EXCEPTION
         WHEN NO_DATA_FOUND THEN
             YearofSeal   := 0                                        ;
             TypeofSeal   := '----'                                   ;
         SealCode    := 0                                   ;
        WHEN TOO_MANY_ROWS THEN
             YearofSeal   := 0                                        ;
             TypeofSeal   := '----'                                   ;
         SealCode    := 0                                   ;
         END                                                    ;

        IF TypeofSeal = 'S13' THEN
            SealCode := 2                                   ;
        ELSIF TypeofSeal = 'S19' THEN
            SealCode := 1                                   ;
        ELSE
          SealCode    := 0                                  ;
        END IF                                              ;

/*      and move on to the structure data                             */

          BEGIN
             select MaterialCode
               into Basecourse
               from Structure
              where structure.roadno = RoadNumber
                and structure.carway = CarriageWay
             and structure.layercode = 20
                and                         (least(endkm,strucendkm)-
greatest(startkm,strucstartkm))>0;
          EXCEPTION
          WHEN NO_DATA_FOUND THEN
              Basecourse   := '----'                                  ;
            BasecourseCode    := 0                              ;
          END                                                   ;

        IF substr(BaseCourse,1,1) = 'C' THEN
          BasecourseCode    := 1                                ;
        ELSE
          BasecourseCode    := 0                                ;
        END IF                                              ;

/*      and move on to traffic                                   */
          BEGIN
             select Heavy
               into HeavyCount
               from TrafficVolume
              where trafficvolume.roadno = RoadNumber
                and trafficvolume.carway = CarriageWay
```

```
          and (least(endkm,trafendkm)-greatest(startkm,trafstartkm))>0
;
       EXCEPTION
       WHEN NO_DATA_FOUND THEN
            HeavyCount   := 0                                         ;
      HeavyCode   := 0                                 ;
       END                                                     ;

    IF HeavyCount > 300 THEN
      HeavyCode   := 3                                 ;
    ELSIF HeavyCount >= 100 AND HeavyCount <= 300 THEN
      HeavyCode   := 2                                 ;
    ELSIF HeavyCount >= 50 AND HeavyCount < 100 THEN
      HeavyCode   := 1                                 ;
    ELSE
      HeavyCode   := 0                                 ;
    END IF                                             ;

/*  and finally get the visual data                          */
    BEGIN
        select     RoadNo              ,
              CarWay         ,
              Startkm        ,
              Endkm          ,
              VisYear        ,
              VisMonth       ,
              TextDir        ,
              TextOne        ,
              TextTwo        ,
              VoidDir        ,
              VoidOne        ,
              VoidTwo        ,
              DGenSurf       ,
              EGenSurf       ,
              DFailPatc      ,
              EFailPatc      ,
              DCrac          ,
              ECrac          ,
              DAggrLoss      ,
              EAggrLoss      ,
              DBindCond      ,
              EBindCond      ,
              DBleeFlus      ,
              EBleeFlus      ,
              DGenCrac       ,
              EGenCrac       ,
              DBlocStab      ,
              EBlocStab      ,
              SBlocStab      ,
              DLongSlip      ,
              ELongSlip      ,
              DTran          ,
              ETran          ,
              DCrocFail      ,
              ECrocFail      ,
              DPump          ,
              EPump          ,
```

```
    DGenDefe        ,
    EGenDefe        ,
    DRutt           ,
    ERutt           ,
    DUnduSett       ,
    EUnduSett       ,
    DPatc           ,
    Epatc           ,
    DFailPoth       ,
    EFailPoth       ,
    RideQual        ,
    RQProblem       ,
    SkidResi        ,
    SRProblem       ,
    SurfDrai        ,
    SDProblem       ,
    UnpaShou        ,
    USProblem       ,
    DEdgeBrea       ,
    EEdgeBrea       ,
    TANStru         ,
    TANSurf         ,
    TANRout         ,
    OPC             ,
    PavementIndex   ,
    ReSealIndex     ,
    SurfIndx        ,
    StruIndx        ,
    FuncIndx
 into vRoadNo          ,
    vCarWay          ,
    vStartkm         ,
    vEndkm           ,
    vVisYear         ,
    vVisMonth        ,
    vTextDir         ,
    vTextOne         ,
    vTextTwo         ,
    vVoidDir         ,
    vVoidOne         ,
    vVoidTwo         ,
    vDGenSurf        ,
    vEGenSurf        ,
    vDFailPatc       ,
    vEFailPatc       ,
    vDCrac           ,
    vECrac           ,
    vDAggrLoss       ,
    vEAggrLoss       ,
    vDBindCond       ,
    vEBindCond       ,
    vDBleeFlus       ,
    vEBleeFlus       ,
    vDGenCrac        ,
    vEGenCrac        ,
    vDBlocStab       ,
    vEBlocStab       ,
```

```
Carriageway         ,
Startkm             ,
Endkm               ,
vVisYear            ,
vVisMonth           ,
vTextDir            ,
vTextOne            ,
vTextTwo            ,
vVoidDir            ,
vVoidOne            ,
vVoidTwo            ,
vDGenSurf           ,
vEGenSurf           ,
vDFailPatc          ,
vEFailPatc          ,
vDCrac              ,
vECrac              ,
vDAggrLoss          ,
vEAggrLoss          ,
vDBindCond          ,
vEBindCond          ,
vDBleeFlus          ,
vEBleeFlus          ,
vDGenCrac           ,
vEGenCrac           ,
vDBlocStab          ,
vEBlocStab          ,
vSBlocStab          ,
vDLongSlip          ,
vELongSlip          ,
vDTran              ,
vETran              ,
vDCrocFail          ,
vECrocFail          ,
vDPump              ,
vEPump              ,
vDGenDefe           ,
vEGenDefe           ,
vDRutt              ,
vERutt              ,
vDUnduSett          ,
vEUnduSett          ,
vDPatc              ,
vEpatc              ,
vDFailPoth          ,
vEFailPoth          ,
vRideQual           ,
vRQProblem          ,
vSkidResi           ,
vSRProblem          ,
vSurfDrai           ,
vSDProblem          ,
vUnpaShou           ,
vUSProblem          ,
vDEdgeBrea          ,
vEEdgeBrea          ,
vTANStru            ,
```

```
                vTANSurf            ,
                vTANRout            ,
                vOPC                ,
                vPavementIndex      ,
                vReSealIndex        ,
                vSurfIndx           ,
                vStruIndx           ,
                vFuncIndx           ,
                YearofSeal      ,
                TypeofSeal      ,
                SealCode        ,
                       Basecourse       ,
                  BasecourseCode        ,
                HeavyCount      ,
                HeavyCode
              );
              commit;
           END IF;

        END IF;
      END IF;
  END LOOP;
END;
/
```

Appendix B.3

Description of Seals

Appendix B.3

Description of Seal Types

MATCODE	MATDESCRIP
D13	13mm + 7mm Double Seal
D13L	13mm + 7mm Latex Modified Double Seal
D19	19mm + 7mm Double Seal
D19L	19mm + 7mm Latex Modified Double Seal
H13	13mm Single Seal with Hot Bitumen
H9	9mm Single Seal with Hot Bitumen
L13	13mm Latex Modified Single Seal
L13G	13mm Latex Modified Seal + Grit (in wet emulsion)
L7	7mm Latex Modified Single Seal
L9	9mm Latex Modified Single Seal
L9G	9mm Latex Modified Seal + Grit (in wet emulsion)
M13	13mm RMB Single Seal (Synthetic)
M9	9mm RMB Single Seal (Synthetic)
R13	13mm Rubber Bitumen Modified Single Seal
R16	16mm Rubber Bitumen Modified Single Seal
R9	9mm Rubber Bitumen Modified Single Seal
S13	13mm Cape Seal
S19	19mm Cape Seal
SE	Diluted Emulsion
SEM	Diluted Emulsion (Modified)
SL1	Fine Slurry
SL2	Coarse Slurry
SL2M	Coarse Slurry (Modified)
SR	Rejuvenator
SS	Sand Seal or Grit Seal
T13	13mm Single Seal
T13G	13mm Single Seal + Grit (in wet emulsion)
T7	7mm Single Seal
T9	9mm Single Seal
T9G	9mm Single Seal + Grit (in wet emulsion)

Appendix B.4

Description of Input Parameters to Neural Network for the Determination of the Reseal Types

Appendix B.4

Description of Input Parameters to Neural Network for the Determination of the Reseal Types

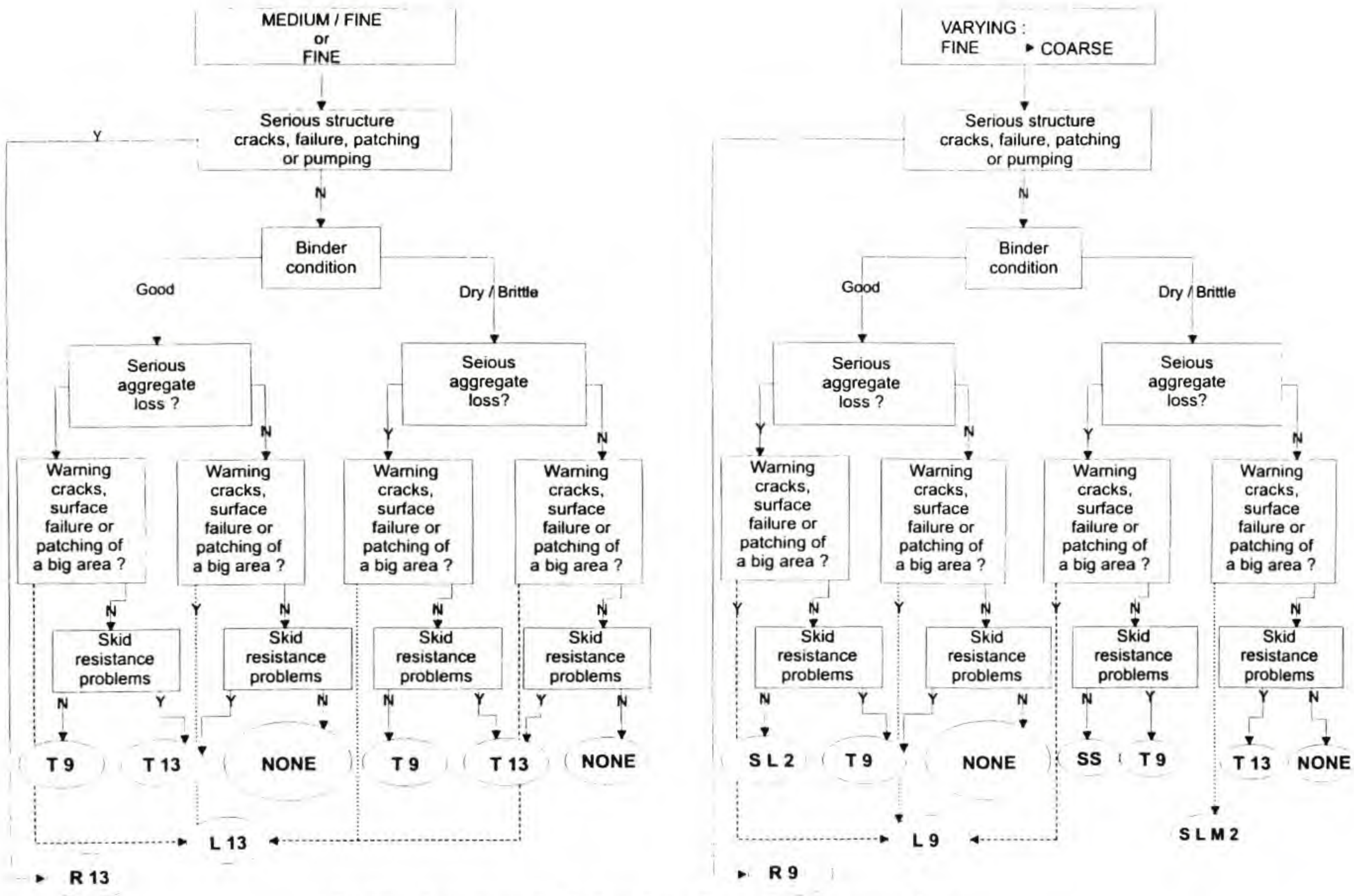
Parameter	Defect	Levels	Range
I1	Texture Varying	2	0 – 1
I2	First Texture	6	0 – 5
I3	Second texture	6	0 – 5
I4	Voids Varying	2	0 – 1
I5	First Voids	6	0 – 5
I6	Second Voids	6	0 – 5
I7	Failure/Patching Degree	6	0 – 5
I8	Failure/Patching Extent	6	0 – 5
I9	Surface cracks Degree	6	0 – 5
I10	Surface cracks Extent	6	0 – 5
I11	Aggregate loss Degree	6	0 – 5
I12	Aggregate loss Extent	6	0 – 5
I13	Binder condition Degree	6	0 – 5
I14	Binder condition Extent	6	0 – 5
I15	Bleeding/Flushing Degree	6	0 – 5
I16	Bleeding/Flushing Extent	6	0 – 5
I17	Block/Stabilisation cracks Degree	3	1 – 3
I18	Block/Stabilisation cracks Extent	6	0 – 5
I19	Block/Stabilisation cracks Spacing	6	0 – 5
I20	Longitudinal/Slip cracks Degree	6	0 – 5
I21	Longitudinal/Slip cracks Extent	6	0 – 5
I22	Transverse cracks Degree	6	0 – 5
I23	Transverse cracks Extent	6	0 – 5
I24	Crocodile/Failure cracks Degree	6	0 – 5
I25	Crocodile/Failure cracks Extent	6	0 – 5
I26	Pumping Degree	6	0 – 5
I27	Pumping Extent	6	0 – 5
I28	Rutting Degree	6	0 – 5
I29	Rutting Extent	6	0 – 5
I30	Patching Degree	6	0 – 5
I31	Patching Extent	6	0 – 5
I32	Failures/Potholing Degree	6	0 – 5
I33	Failures/Potholing Extent	6	0 – 5
I34	Skid resistance	9	0 – 4
I35	Existing Seal Type (Cape seal)	3	0 – 2
I36	Heavy Traffic	4	0 – 3
I37	Existing Basecourse Type (Cemented)	2	0 – 1
O1	Seal Type	11	0 – 10

Appendix B.5

Conditions for Seal Types for:

- Medium/Fine or Fine and Fine to Coarse Surfaces
- Medium to Coarse and Medium to Fine Surfaces
- Coarse and Medium Surfaces

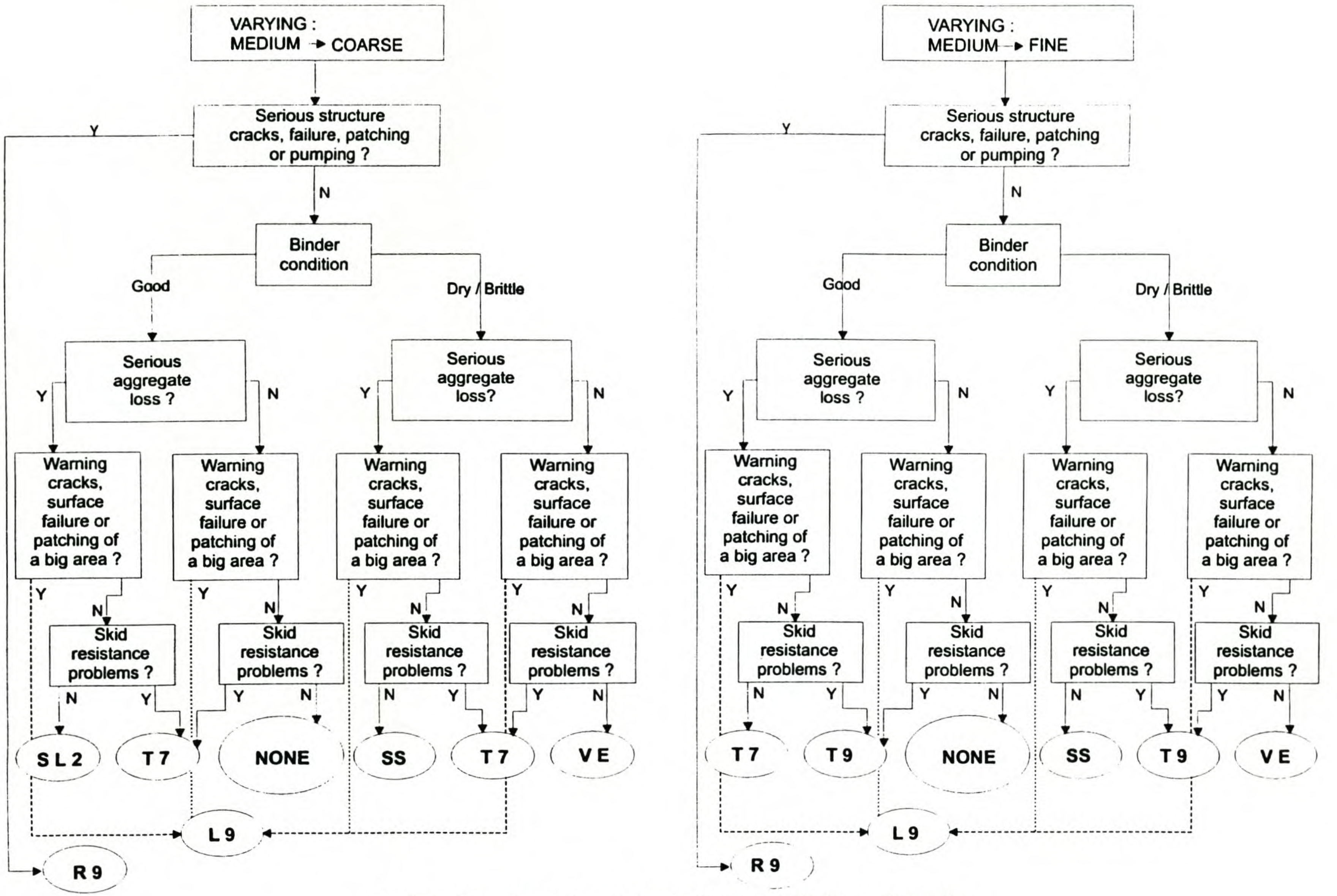
Diagrams in Appendix B.5 are extracts from the PAWC PMS Technical Manual (1995)



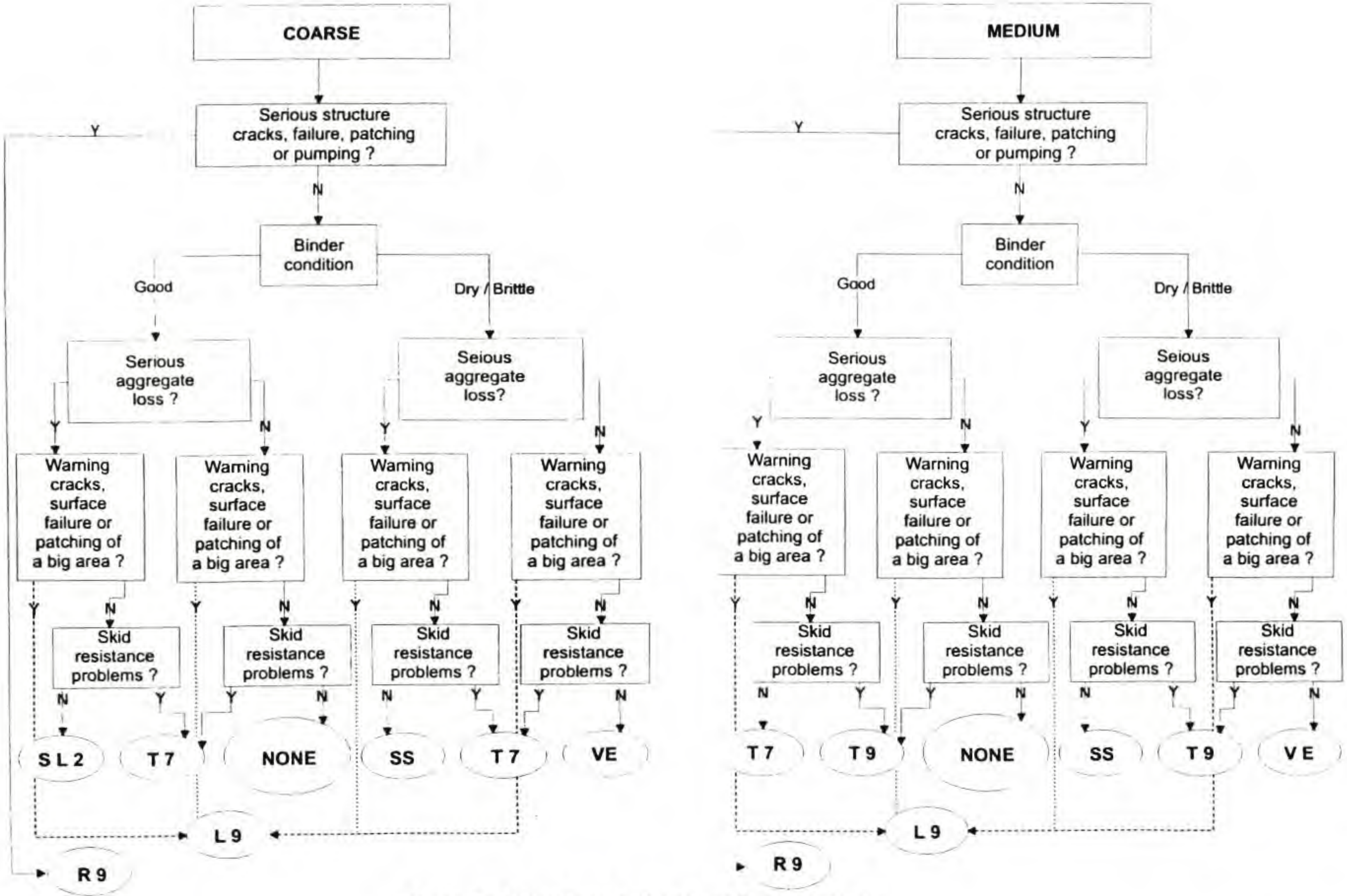
Conditions for seal types for Medium / Fine or Fine and Fine to Coarse surfaces

B5 - 1

Appendix B.5



Conditions for seal types for a Medium to Coarse and a Medium to Fine surface



Conditions for seal types for Coarse and Medium surfaces

APPENDIX C

SOURCE CODE AND DATA SHEETS FOR THE BACK-CALCULATION OF E-MODULI FROM FWD DEFLECTION MEASUREMENTS

Appendix C.1
Fortran Source Code

Appendix C.2
South African Road Building Materials with their Material Codes

Appendix C.3 (a)
Description of Data in Deflection Measurements Database
(Source : PAWC)

Appendix C.3 (b)
Base Group Descriptions used in Deflection Measurement Database
(Source : PAWC)

The following Appendices contain data and results from work done by the Author.

Appendix C.4
Data and Result sheets (DR1005)

Appendix C.5
Data and Result sheets (TR1102)

Appendix C.6
Data and Result sheets (MR188)

Appendix C.7
Data and Result sheets (TR901)

Appendix C.8
Comparison of Back-calculation results for six Deflection Basins: Depth to stiff layer calculated with Rohde's method vs Neural Network

Appendix C.9
Frequency Distribution of Deflections at each Geophone, from PAWC PMS Database

Appendix C.1

Fortran Source Code

Appendix C.1(a): Source Code Fortran Program ConvFile for the Conversion of ELSYM5 Output Files

```
      PROGRAM ConvFile
C
C     N = Layer Number
C     T = Layer Thickness
C     P = Poisson ratio
C     E = Young's Modulus
C
      INTEGER L,M,L1,L2,L3,L4
      CHARACTER FIN*14,FOUT*14,
     +LAY1*6,LAY2*6,LAY3*6,LAY4*6,UZ*84

      WRITE(*,100)
100   FORMAT(//////////15X' ****************************************'/
     +                 15X' *                                      *'/
     +                 15X' *     Convert Elsym 5 Full Output      *'/
     +                 15X' *       to a delimited file for        *'/
     +                 15X' *        input to a spreadsheat        *'/
     +                 15X' *                                      *'/
     +                 15X' *       INPUT FILE  filename.EL5       *'/
     +                 15X' *       OUTPUT FILE filename.TXT       *'/
     +                 15X' *                                      *'/
     +                 15X' *  Note that vertical displacements in *'/
     +                 15X' *  ELSYM5 must be calculated at fixed  *'/
     +                 15X' *         (7 in total), i.e.           *'/
     +                 15X' *  0, 200, 300, 600, 900, 1200, 1500   *'/
     +                 15X' *  and that this program can handle    *'/
     +                 15X' *  four (4) layers in the pavement     *'/
     +                 15X' *                                      *'/
     +                 15X' *       Created by SJ Bredenhann       *'/
     +                 15X' *               (1999)                 *'/
     +                 15X' *                                      *'/
     +                 15x' ****************************************'/)
C
      WRITE(*,200)
200   FORMAT(/20X,' NAME OF INPUT FILE '/
     +          20X,' (e.g. B:XYZ.EL5) -->'\)
      READ(*,210) FIN
210   FORMAT(A14)

      WRITE(*,300)
300   FORMAT(/20X,' NAME OF OUTPUT FILE '/
     +          20X,' (e.g. B:XYZ.TXT) -->'\)
      READ(*,310) FOUT
310   FORMAT(A14)

      OPEN(1,FILE=FIN,STATUS='OLD',ACCESS='SEQUENTIAL',
     +     ACTION='READ')
      REWIND 1
      OPEN(2,FILE=FOUT,STATUS='REPLACE',ACCESS='SEQUENTIAL',
     +     ACTION='WRITE')
C
```

```
C      The first line in the Full Elsym5 output file that contains
C      UZ (Vertical DISPLACEMENTS) is line 69 and thereafter 89 must
C      be added each time to read the next line with UZ values.
C      The layer data is on lines Line-38 thru Line-35
C
       L = 1
       M = 69
       L1 = M-38
       L2 = M-37
       L3 = M-36
       L4 = M-35
       DO WHILE (.NOT.EOF(1))
             IF (L.EQ.L1) THEN
                   READ(1,400) LAY1
             ELSE IF (L.EQ.L2) THEN
                   READ(1,400) LAY2
             ELSE IF (L.EQ.L3) THEN
                   READ(1,400) LAY3
             ELSE IF (L.EQ.L4) THEN
                   READ(1,400) LAY4
             ELSE
                   READ(1,410) UZ
             END IF
             IF (L.EQ.M) THEN
                   WRITE(2,450) LAY1//'  '//LAY2//'  '//LAY3//'  '//LAY4//UZ
                   M = M + 89
                   L1 = M-38
                   L2 = M-37
                   L3 = M-36
                   L4 = M-35
             END IF
             L = L + 1
       END DO

400    FORMAT(45X,A6)
410    FORMAT(7X,A77)
450    FORMAT(A110)

       CLOSE(1)
       CLOSE(2)

       STOP
       END
```

Appendix C.1(b): Source Code Fortran Program Basins

```
C ***********************************************************************
C      THIS PROGRAM GENERATES RANDOM PAVEMENT PROFILES AND COMPUTES
C      CORRESPONDING FWD DEFLECTION BASINS USING ELASTIC ANALYSIS
C
C             Program created by Dr Roger E. Meier,
C             University of Michigan, USA, and adapted by
C             SJ Bredenhann, University of Stellenbosch, RSA
C
C ***********************************************************************
C VARIABLE NAME                   DESCRIPTION
C *************   *******************************************************
C E1-E5           LAYER MODULI, PSI
C H1-H4           LAYER THICKNESSES, IN
C U1-U5           LAYER POISSON RATIO
C LA1-LA3         LAYER INTERFACE; 1=NO SLIP, >1=PARTIAL SLIP
C L               NUMBER OF LOADED AREAS
C P()             PRESSURE, PSI
C A()             RADIUS OF LOADED AREA, IN
C XC(),YC()       X,Y CO-ORDINATES OF LOADED AREAS, IN
C L1              NUMBER OF EVALUATION POSITIONS
C LS()            LAYER NUMBER FOR EVALUATION POSITIONS
C XS(),YS(),ZS()  X,Y,Z CO-ORDINATES OF EVALUATION POSITIONS, IN
C RESULT(,1,)     ARRAY CONTAINING COMPUTED RESULTS
C IRQST           REQUEST FOR OUTPUT TYPE (1 OR 2)
C ***********************************************************************
C THREE-LAYER PAVEMENT SYSTEM:
C ***************************
C E1,H1,U1        Layer 1 Properties, i.e. unbound base or AC
C E2,H2,U2        Layer 2 Properties, i.e. Unbound Base/Subbase
C E3,H3,U3        Layer 3 Properties, i.e. Unbound Subbase/Selected
C E4,H4,U4        Subgrade Properties
C E5,  ,U5        Bedrock Properties
C ***********************************************************************

      PROGRAM GENERATE

      IMPLICIT NONE

      INTEGER NBASINS
      PARAMETER (NBasins=10000)

C      REAL RANDOM
      INTEGER I,J,L,L1,LS(50),IRQST
      REAL*8 xL,xA,xP,PI,MPaPSI,kPaPSI,INmm
      REAL*8 E1,E2,E3,E4,E5,H1,H2,H3,H4,U1,U2,U3,U4,U5
      REAL*8 E1max,E1min,E2max,E2min,E3max,E3min,E4max,E4min,E5max,E5min
      REAL*8 H1max,H1min,H2max,H2min,H3max,H3min,H4max,H4min
      REAL*8 LA1,LA2,LA3
      REAL*8 P(20),A(20),XC(20),YC(20)
      REAL*8 XS(50),YS(50),ZS(50)
      REAL*8 RESPONSE(50,1,19),R(50)
      REAL*8 H(4),E(5)
```

```
      Character(30) InputFilename

C ... The arrays E() and H() are only used in the WRITE statement!!

      PI = DATAN2(0.0D0,-1.0D0)
      MPaPSI = 145.038D0
      kPaPSI = 0.145038D0
      INmm = 25.4D0

      CALL RANDOM_SEED()

C ... Get the Input FileName and open both Input and Output Data File

      Write(*,*) 'Enter the input definition filename:'
      Read (*,'(A30)') InputFilename
      Open (1,File=InputFilename)
      Open (2,File='training.txt',Form='FORMATTED')

C ... Calculate the Metric load paramaters
C ... xL = Single Wheel Load in kN
C ... xP = Contact Pressure in kPa
C ... xA = Contact Radius in mm

      Read (1,*) xL
      Read (1,*) xA
      xP = xL/PI/xA/xA*1.0D6

C ... Establish Single Loaded Area for FWD Simulation
C ... Convert contact radius from mm to inches
C ... Convert contact pressure from kPa to psi

      L = 1
      A(1) = xA/INmm
      P(1) = xP*kPaPSI
      XC(1) = 0.0D0
      YC(1) = 0.0D0

C ... Establish Sensor Locations for FWD Simulation

      Read (1,*) L1

      DO I = 1,L1
            LS(I) = 1
            YS(I) = 0.0D0
            ZS(I) = 0.0D0
      END DO

C ... Sensor Spacings are converted from mm to inches

      Read (1,*) (XS(I),I=1,L1)

      DO I = 1,L1
            XS(I) = XS(I)/INmm
      END DO

C ... Establish Displacement Output for FWD Simulation
```

```
      Read (1,*) IRQST

C ... Establish Invariant Layer Slips (No Slip Allowed)

      Read (1,*) LA1,LA2,LA3

C ... Establish Invariant Layer Poisson's Ratios

      Read (1,*) U1,U2,U3,U4,U5

C ... Set minimum and maximum thicknesses in mm

      Read (1,*) H1min,H1max
      Read (1,*) H2min,H2max
      Read (1,*) H3min,H3max
      Read (1,*) H4min,H4max

C ... Set minimum and maximum moduli in MPa

      Read (1,*) E1min,E1max
      Read (1,*) E2min,E2max
      Read (1,*) E3min,E3max
      Read (1,*) E4min,E4max
      Read (1,*) E5min,E5max

C ... Create Training Set Through Stochastic Repetition

      Do 400 J = 1,NBasins

C ... Establish Layer Thicknesses in mm and convert to inches
C ... Invariant Thicknesses will have equal min and max values

C ... first the thicknesses in mm with a stochastic process

      CALL RANDOM_NUMBER(H1)
      H1 = H1*(H1max-H1min) + H1min
      CALL RANDOM_NUMBER(H2)
      H2 = H2*(H2max-H2min) + H2min
      CALL RANDOM_NUMBER(H3)
      H3 = H3*(H3max-H3min) + H3min
      CALL RANDOM_NUMBER(H4)
      H4 = H4*(H4max-H4min) + H4min

C ... then the conversion to inches

      H1 = H1/INmm
      H2 = H2/INmm
      H3 = H3/INmm
      H4 = H4/INmm

C ... Establish Layer Moduli in MPa and convert to psi
C ... Invariant Moduli will have equal min and max values

C ... first the moduli in MPa with a stochastic process

  210 CALL RANDOM_NUMBER(E1)
      E1 = E1*(E1max-E1min) + E1min
```

```
  220 CALL RANDOM_NUMBER(E2)
      E2 = E2*(E2max-E2min) + E2min
      CALL RANDOM_NUMBER(E3)
      E3 = E3*(E3max-E3min) + E3min
      CALL RANDOM_NUMBER(E4)
      E4 = E4*(E4max-E4min) + E4min
      CALL RANDOM_NUMBER(E5)
      E5 = E5*(E5max-E5min) + E5min

C ... then the conversion to psi

      E1 =E1*MPaPSI
      E2 =E2*MPaPSI
      E3 =E3*MPaPSI
      E4 =E4*MPaPSI
      E5 =E5*MPaPSI

C ... Eliminate Ambiguous Profiles

C       If ((E2/E3.GT.0.90).AND.(E2/E3.LT.1.10)) Go To 220

C ... Normalize Layer Parameters E and H for Output

C       IF ((E1max-E1min).EQ.0) THEN
C            E(1) = 1.0D0
C      ELSE
C            E(1) = (E1-E1min)/(E1max-E1min)
C      END IF
C      IF ((E2max-E2min).EQ.0) THEN
C            E(2) = 1.0D0
C      ELSE
C            E(2) = (E2-E2min)/(E2max-E2min)
C      END IF
C       IF ((E3max-E3min).EQ.0) THEN
C            E(3) = 1.0D0
C      ELSE
C            E(3) = (E3-E3min)/(E3max-E3min)
C      END IF
C       IF ((E4max-E4min).EQ.0) THEN
C            E(4) = 1.0D0
C      ELSE
C            E(4) = (E4-E4min)/(E4max-E4min)
C      END IF
C       IF ((E5max-E5min).EQ.0) THEN
C            E(5) = 1.0D0
C      ELSE
C            E(5) = (E5-E5min)/(E5max-E5min)
C      END IF
C
C       IF ((H1max-H1min).EQ.0) THEN
C            H(1) = 1.0D0
C      ELSE
C            H(1) = (H1-H1min)/(H1max-H1min)
C      END IF
C       IF ((H2max-H2min).EQ.0) THEN
C            H(2) = 1.0D0
```

```
C     ELSE
C           H(2) = (H2-H2min)/(H2max-H2min)
C     END IF
C      IF ((H3max-H3min).EQ.0) THEN
C           H(3) = 1.0D0
C     ELSE
C           H(3) = (H3-H3min)/(H3max-H3min)
C     END IF
C      IF ((H4max-H4min).EQ.0) THEN
C           H(4) = 1.0D0
C     ELSE
C           H(4) = (H4-H4min)/(H4max-H4min)
C     END IF

      E(1) = E1
      E(2) = E2
      E(3) = E3
      E(4) = E4
      E(5) = E5

      H(1) = H1
      H(2) = H2
      H(3) = H3
      H(4) = H4

C ... Compute Deflection Basin

      CALL WES5(E1,E2,E3,E4,E5,H1,H2,H3,H4,U1,U2,U3,U4,U5,LA1,
     &          LA2,LA3,L,P,A,XC,YC,L1,LS,XS,YS,ZS,RESPONSE,IRQST)

C ... Normalize Deflection Parameters for Output

C      DO I = 1,L1
C           R(I) = -100*RESPONSE(I,1,15)
C      END DO

C ... the conversion to microns

      DO I = 1,L1
           R(I) = -1000*RESPONSE(I,1,15)*INmm
      END DO

C ... then the conversion to mm

      DO I = 1,4
           H(I) = H(I)*INmm
      END DO

C ... then the conversion to MPa

      DO I = 1,5
           E(I) =E(I)/MPaPSI
      END DO

C ... Output Inputs and Outputs to ANN Training File - Note: Not normalized

      WRITE(2,810) (H(I),I=1,4),(E(I),I=1,5),(R(I),I=1,7)
```

```
      WRITE(*,830) J

  400 CONTINUE

      Close(1)
      Close(2)
      CALL BEEPQQ(5000, 1000)


      STOP
  810 FORMAT(4F10.4,5F15.2,7E14.6)
  820 FORMAT(5F8.4,7E14.6)
  830 FORMAT(I8)
      END
```

Appendix C.2

South African Road Building Material with their Material Codes

(Source : DOT Report RR93/296)

TABLE 6.2: SOUTH AFRICAN ROAD BUILDING MATERIALS WITH THEIR MATERIAL CODES (CONTINUED)

SYMBOL	CODE	MATERIAL	ABBREVIATED SPECIFICATIONS
	C1	Cemented crushed stone or gravel	UCS 6 to 12 MPa at 100 % mod AASHTO ; spec. at least G2 before treatment ; dense - graded
	C2	Cemented crushed stone or gravel	UCS 3 to 6 MPa at 100 % mod. AASHTO ; spec. generally G2 or G4 before treatment ; dense - graded
	C3	Cemented natural gravel	UCS 1,5 to 3,0 MPa and ITS $\geq$ 250 kPa at 100 % mod. AASHTO ; max. size 63 mm ; fines PI $\leq$ 6 after stabilization.
	C4	Cemented natural gravel	UCS 0,75 to 1,5 MPa and ITS $\geq$ 200 kPa at 100 % mod. AASHTO ; max. size 63 mm ; fines PI $\leq$ 6 after stabilization.
	EBM	Bitumen Emulsion Modified gravel	0,6% - 1,5% residual bitumen
	EBS	Bitumen Emulsion Stabilised gravel	1,5% - 5,0% residual bitumen
	BC1	Hot - mix asphalt	Continuously - graded ; max. size 53 mm
	BC2	Hot - mix asphalt	Continuously - graded ; max. size 37,5 mm
	BC3	Hot - mix asphalt	Continuously - graded ; max. size 26,5 mm
	BS	Hot - mix asphalt	Semi - gap - graded ; max. size 37,5 mm
	PCC	Portland cement Concrete	Modulus of rupture $\nless$ 4,5 MPa ; max size $\ngtr$ 75 mm
	AG	Asphalt surfacing	Gap graded
	AC	Asphalt surfacing	Continuously graded
	AS	Asphalt surfacing	Semi-gap graded
	AO	Asphalt surfacing	Open graded
	AP	Asphalt surfacing	Porous (Drainage) Asphalt
	S1	Surface seal	Single seal
	S2	Surface seal	Multiple seal
	S3	Surface seal	Sand seal
	S4	Surface seal	Cape seal
	S5	Slurry	Fine grading
	S6	Slurry	Medium grading
	S7	Slurry	Coarse grading
	S8	Surface renewal	Rejuvenator
	S9	Surface renewal	Diluted emulsion
	WM1	Waterbound macadam	Max. size 75 mm, PI of fines $\ngtr$ 6, 88-90% of apparent density
	WM2	Waterbound macadam	Max. size 75 mm, PI of fines $\ngtr$ 6, 86-88% of apparent density
	PM	Penetration macadam	Coarse stone + keystone + bitumen
	DR	Dumprock	Upgraded waste rock, max size $\frac{2}{3}$ layer thickness

UCS : Unconfined Compressive Strength.

ITS : Indirect Tensile Strength.

TABLE 6.2: SOUTH AFRICAN ROAD BUILDING MATERIALS WITH THEIR MATERIAL CODES.

SYMBOL	CODE	MATERIAL	ABBREVIATED SPECIFICATIONS
	G1	Graded crushed stone	Dense - graded unweathered crushed stone ; Max size 37,5mm; 88% apparent relative density; fines PI < 4.0 (min 6 tests)
	G2	Graded crushed stone	Dense - graded crushed stone ; Max size 37,5 mm ; 100 - 102% mod. AASHTO or 85% bulk relative density; fines PI < 6 (min 6 tests)
	G3	Graded crushed stone	Dense - graded stone and soil binder ; max size 37,5 mm, 98 - 100% mod. AASHTO ; fines PI < 6
	G4	Natural gravel	CBR* $\nless$ 80 ; max size 53mm ; 98 - 100% mod. AASHTO ; PI < 6 Swell 0,2 @ 100% mod. AASHTO.
	G5	Natural gravel	CBR* $\nless$ 45 ; max size 63mm ; or $\frac{2}{3}$ layer thickness , density as per prescribed layer of usage , PI < 10 ; Swell 0,5 @ 100% mod. AASHTO.
	G6	Natural gravel	CBR* $\nless$ 25 ; max size 63mm ; or $\frac{2}{3}$ layer thickness , density as per prescribed layer of usage , PI < 12 ; Swell 1,0 @ 100% mod. AASHTO.
	G7	Gravel-soil	CBR* $\nless$ 15 ; max size $\frac{2}{3}$ layer thickness , density as per prescribed layer of usage , PI < 12 or 2 GM + 10 ; Swell 1,5 @ 100% mod. AASHTO.
	G8	Gravel-soil	CBR $\nless$ 10 ; at insitu density ; max size $\frac{2}{3}$ layer thickness , density as per layer of usage , PI < 12 or 2 GM + 10 ; Swell 1,5 @ 100% mod. AASHTO.
	G9	Gravel-soil	CBR $\nless$ 7 ; at insitu density ; max size $\frac{2}{3}$ layer thickness , density as per layer of usage , PI < 12 or 2 GM + 10 ; Swell 1,5 @ 100% mod. AASHTO.
	G10	Gravel-soil	CBR $\nless$ 3 ; at insitu density ; max size $\frac{2}{3}$ layer thickness , density as per layer of usage , or 90% mod. AASHTO.

* CBR at field compaction density

GM: Grading Modulus

$$GM = \frac{P_{2,00mm} + P_{0,425mm} + P_{0,075mm}}{100}$$

where $p_{2.00\,mm}$ etc., denote the percentage retained on indicated sieve size.

Appendix C.3 (a)

Description of Data in Deflection Measurements Database

Appendix C.3 (a)

Description of Data in Deflection Measurements Database

Date: Nov-97
Temp: 18 °C
Load: 40 kN

Pos (Km)	Year	Month	Temp	LOAD	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
0.00	1996	9	14	40	664	488	360	198	139	112	95	304	162	59	42.70	G1	1.92	4.30	6	24345	9.60
0.20	1996	9	14	40	1028	800	583	287	178	99	52	445	296	109	14.30	G1	1.33	3.00	6	3283	1.50
0.40	1996	9	14	40	646	439	304	155	88	53	31	342	149	67	33.50	G1	1.60	3.00	6	8777	3.80
0.60	1996	9	14	40	757	501	325	156	116	73	48	432	169	40	16.20	G1	2.11	6.80	6	40835	15.00
0.80	1996	9	14	40	952	681	500	301	202	144	106	452	199	99	13.40	G1	1.41	3.00	6	4474	2.00

HEADING	DESCRIPTION
Pos (km)	Peg distance (position) of deflection measurement
D0 to D1500	Deflection at sensor, i.e. D0 = under load, D200 = deflection at 200mm from load, etc.
BLI	Base Layer Index = D300 - D0
MLI	Middle Layer Index = D600 – D300
LLI	Lower Layer Index = D900 – D600
SI	Structural Index
Base	Base group – se Appendix 5.3(b) for a description of the different base groups used
SN	Structural number
CBR	California Bearing Ratio of the subgrade
E80	Estimate past E80's from traffic data
Res. E80	Estimated residual E80's
Res. Life	Estimated residual pavement life in years

Appendix C.3 (b)

Base Group Descriptions used in Deflection Measurement Database

Appendix C.3 (b)

Base Group Descriptions Used in Deflection Measurement Database

GROUPCODE	SEALCODE	BASECODE	GROUPDESCRIPTION
A1	S13	G1	13mm Cape Seal and Graded crushed stones Base (no fines added)
A2	S19	G1	19mm Cape Seal and Graded crushed stones Base (no fines added)
A3	S13	G2	13mm Cape Seal and Graded crushed stones Base (fines added)
A4	S19	G2	19mm Cape Seal and Graded crushed stones Base (fines added)
A5	S13	G2M	13mm Cape Seal and Graded crushed stones Base (lime added)
A6	S19	G2M	19mm Cape Seal and Graded crushed stones Base (lime added)
B1	S13	G3	13mm Cape Seal and Graded crushed stones Base (foreign fines added)
B2	S19	G3	19mm Cape Seal and Graded crushed stones Base (foreign fines added)
B3	S13	G3M	13mm Cape Seal and Graded crushed stones Base (lime added)
B4	S19	G3M	19mm Cape Seal and Graded crushed stones Base (lime added)
C1	S13	G4	13mm Cape Seal and Natural gravel Base
C2	S19	G4	19mm Cape Seal and Natural gravel Base
C3	S13	G5	13mm Cape Seal and Crushed stone or Natural Gravel Base
C4	S19	G5	19mm Cape Seal and Crushed stone or Natural Gravel Base
C5	S13	G4M	13mm Cape Seal and Natural gravel (lime added)
C6	S19	G4M	19mm Cape Seal and Natural gravel (lime added)
D1	D19L	G3	19mm + 7mm Latex Modified Double Seal and Graded crushed stones Base (foreign fines added)
D10	D19L	G3M	19mm + 7mm Latex Modified Double Seal and Graded crushed stones Base (lime added)
D11	D13L	G3M	13mm + 7mm Latex Modified Double Seal and Graded crushed stones Base (lime added)
D12	D19	G3M	19mm + 7mm Double Seal and Graded crushed stones Base (lime added)
D13	D13	G3M	13mm + 7mm Double Seal and Graded crushed stones Base (lime added)
D14	T13G	G3M	13mm Single Seal + Grit (in wet emulsion) and Graded crushed stones Base (lime added)
D15	T9G	G3M	9mm Single Seal + Grit (in wet emulsion) and Graded crushed stones Base (lime added)

GROUPCODE	SEALCODE	BASECODE	GROUPDESCRIPTION
D17	T9	G3M	9mm Single Seal and Graded crushed stones Base (lime added)
D18	T7	G3M	7mm Single Seal and Graded crushed stones Base (lime added)
D2	D13L	G3	13mm + 7mm Latex Modified Double Seal and Graded crushed stones Base (foreign fines added)
D3	D19	G3	19mm + 7mm Double Seal and Graded crushed stones Base (foreign fines added)
D4	D13	G3	13mm + 7mm Double Seal and Graded crushed stones Base (foreign fines added)
D5	T13G	G3	13mm Single Seal + Grit (in wet emulsion) and Graded crushed stones Base (foreign fines added)
D6	T9G	G3	9mm Single Seal + Grit (in wet emulsion) and Graded crushed stones Base (foreign fines added)
D7	T13	G3	13mm Single Seal and Graded crushed stones Base (foreign fines added)
D8	T9	G3	9mm Single Seal and Graded crushed stones Base (foreign fines added)
D9	T7	G3	7mm Single Seal and Graded crushed stones Base (foreign fines added)
E1	D19L	G4	19mm + 7mm Latex Modified Double Seal and Natural gravel Base
E10	D19L	G4M	19mm + 7mm Latex Modified Double Seal and Natural gravel Base (lime added)
E11	D13L	G4M	13mm + 7mm Latex Modified Double Seal and Natural gravel Base (lime added)
E12	D19	G4M	19mm + 7mm Double Seal and Natural gravel Base (lime added)
E13	D13	G4M	13mm + 7mm Double Seal and Natural gravel Base (lime added)
E14	T13G	G4M	13mm Single Seal + Grit (in wet emulsion) and Natural gravel Base (lime added)
E15	T9G	G4M	9mm Single Seal + Grit (in wet emulsion) and Natural gravel Base (lime added)
E16	T13	G4M	13mm Single Seal and Natural gravel Base (lime added)
E17	T9	G4M	9mm Single Seal and Natural gravel Base (lime added)
E18	T7	G4M	7mm Single Seal and Natural gravel Base (lime added)
E2	D13L	G4	13mm + 7mm Latex Modified Double Seal and Natural gravel Base
E3	D19	G4	19mm + 7mm Double Seal and Natural gravel Base
E4	D13	G4	13mm + 7mm Double Seal and Natural gravel Base
E5	T13G	G4	13mm Single Seal + Grit (in wet emulsion) and Natural gravel Base
E6	T9G	G4	9mm Single Seal + Grit (in wet emulsion) and Natural gravel Base
E7	T13	G4	13mm Single Seal and Natural gravel Base
E8	T9	G4	9mm Single Seal and Natural gravel Base
E9	T7	G4	7mm Single Seal and Natural gravel Base

GROUPCODE	SEALCODE	BASECODE	GROUPDESCRIPTION
F1	AG	G1	Asphalt Concrete - Gap Graded and Graded crushed stones Base (no fines added)
F10	AG	C5	Asphalt Concrete - Gap Graded and Crushed stone or Natural gravel CTS
F11	AG	BC	Asphalt Concrete - Gap Graded and BTB: Continuously graded Base
F12	AG	BS	Asphalt Concrete - Gap Graded and BTB : Semi gap graded Base
F13	AG	G2M	Asphalt Concrete - Gap Graded and Graded crushed stone (lime added)
F14	AG	G3M	Asphalt Concrete - Gap Graded and Graded crushed stone (lime added)
F15	AG	G4M	Asphalt Concrete - Gap Graded and Natural gravel (lime added)
F16	AC	G1	Asphalt Concrete - Continuously Graded and Graded crushed stones Base (no fines added)
F17	AC	G2	Asphalt Concrete - Continuously Graded and Graded crushed stones Base (fines added)
F18	AC	G3	Asphalt Concrete - Continuously Graded and Graded crushed stones Base (foreign fines added)
F19	AC	G4	Asphalt Concrete - Continuously Graded and Natural gravel Base
F2	AG	G2	Asphalt Concrete - Gap Graded and Graded crushed stones Base (fines added)
F20	AC	G5	Asphalt Concrete - Continuously Graded and Crushed stone or Natural gravel Base
F21	AC	C1	Asphalt Concrete - Continuously Graded and Graded crushed stone CTB (no fines added)
F22	AC	C2	Asphalt Concrete - Continuously Graded and Graded crushed stone CTB (fines added)
F23	AC	C3	Asphalt Concrete - Continuously Graded and Graded crushed stone CTB (foreign fines added)
F24	AC	C4	Asphalt Concrete - Continuously Graded and Natural gravel CTB
F25	AC	C5	Asphalt Concrete - Continuously Graded and Crushed stone or Natural gravel CTS
F26	AC	BC	Asphalt Concrete - Continuously Graded and BTB: Continuously graded Base
F27	AC	BS	Asphalt Concrete - Continuously Graded and BTB: Semi gap graded Base
F28	AC	G2M	Asphalt Concrete - Continuously Graded and Graded crushed stone (lime added)
F29	AC	G3M	Asphalt Concrete - Continuously Graded and Graded crushed stone (lime added)
F3	AG	G3	Asphalt Concrete - Gap Graded and Graded crushed stones Base (foreign fines added)
F30	AC	G4M	Asphalt Concrete - Continuously Graded and Natural gravel (lime added)
F31	AS	G1	Asphalt Concrete - Semi Gap Graded and Graded crushed stones Base (no fines added)
F32	AS	G2	Asphalt Concrete - Semi Gap Graded and Graded crushed stones Base (fines added)
F33	AS	G3	Asphalt Concrete - Semi Gap Graded and Graded crushed stones Base (foreign fines added)
F34	AS	G4	Asphalt Concrete - Semi Gap Graded and Natural gravel Base

GROUPCODE	SEALCODE	BASECODE	GROUPDESCRIPTION
F35	AS	G5	Asphalt Concrete - Semi Gap Graded and Crushed stone or Natural gravel Base
F36	AS	C1	Asphalt Concrete - Semi Gap Graded and Graded crushed stone CTB (no fines added)
F37	AS	C2	Asphalt Concrete - Semi Gap Graded and Graded crushed stone CTB (fines added)
F38	AS	C3	Asphalt Concrete - Semi Gap Graded and Graded crushed stone CTB (foreign fines added)
F39	AS	C4	Asphalt Concrete - Semi Gap Graded and Natural gravel CTB
F4	AG	G4	Asphalt Concrete - Gap Graded and Natural gravel Base
F40	AS	C5	Asphalt Concrete - Semi Gap Graded and Crushed stone or Natural gravel CTS
F41	AS	BC	Asphalt Concrete - Semi Gap Graded and BTB: Continuously graded Base
F42	AS	BS	Asphalt Concrete - Semi Gap Graded and BTB: Semi gap graded Base
F43	AS	G2M	Asphalt Concrete - Semi Gap Graded and Graded crushed stone (lime added)
F44	AS	G3M	Asphalt Concrete - Semi Gap Graded and Graded crushed stone (lime added)
F45	AS	G4M	Asphalt Concrete - Semi Gap Graded and Natural gravel (lime added)
F46	AO	G1	Asphalt Concrete - Open Graded and Graded crushed stones Base (no fines added)
F47	AO	G2	Asphalt Concrete - Open Graded and Graded crushed stones Base (fines added)
F48	AO	G3	Asphalt Concrete - Open Graded and Graded crushed stones Base (foreign fines added)
F49	AO	G4	Asphalt Concrete - Open Graded and Natural gravel Base
F5	AG	G5	Asphalt Concrete - Gap Graded and Crushed stone or Natural gravel Base
F50	AO	G5	Asphalt Concrete - Open Graded and Crushed stone or Natural gravel Base
F51	AO	C1	Asphalt Concrete - Open Graded and Graded crushed stone CTB (no fines added)
F52	AO	C2	Asphalt Concrete - Open Graded and Graded crushed stone CTB (fines added)
F53	AO	C3	Asphalt Concrete - Open Graded and Graded crushed stone CTB (foreign fines added)
F54	AO	C4	Asphalt Concrete - Open Graded and Natural gravel CTB
F55	AO	C5	Asphalt Concrete - Open Graded and Crushed stone or Natural gravel CTS
F56	AO	BC	Asphalt Concrete - Open Graded and BTB: Continuously graded Base
F57	AO	BS	Asphalt Concrete - Open Graded and BTB: Semi gap graded Base
F58	AO	G2M	Asphalt Concrete - Open Graded and Graded crushed stone (lime added)
F59	AO	G3M	Asphalt Concrete - Open Graded and Graded crushed stone (lime added)
F6	AG	C1	Asphalt Concrete - Gap Graded and Graded crushed stone CTB (no fines added)

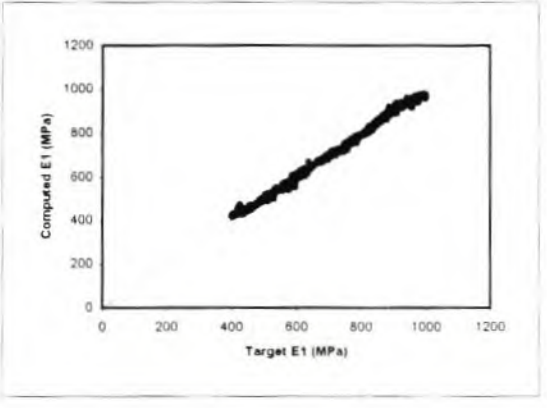
GROUPCODE	SEALCODE	BASECODE	GROUPDESCRIPTION
F60	AO	G4M	Asphalt Concrete - Open Graded and Natural gravel (lime added)
F61	ASP	G1	Asphalt Concrete - Type unknown and Graded crushed stones Base (no fines added)
F62	ASP	G2	Asphalt Concrete - Type unknown and Graded crushed stones Base (fines added)
F63	ASP	G3	Asphalt Concrete - Type unknown and Graded crushed stones Base (foreign fines added)
F64	ASP	G4	Asphalt Concrete - Type unknown and Natural gravel Base
F65	ASP	G5	Asphalt Concrete - Type unknown and Crushed stone or Natural gravel Base
F66	ASP	C1	Asphalt Concrete - Type unknown and Graded crushed stone CTB (no fines added)
F67	ASP	C2	Asphalt Concrete - Type unknown and Graded crushed stone CTB (fines added)
F68	ASP	C3	Asphalt Concrete - Type unknown and Graded crushed stone CTB (foreign fines added)
F69	ASP	C4	Asphalt Concrete - Type unknown and Natural gravel CTB
F7	AG	C2	Asphalt Concrete - Gap Graded and Graded crushed stone CTB (fines added)
F70	ASP	C5	Asphalt Concrete - Type unknown and Crushed stone or Natural gravel CTS
F71	ASP	BC	Asphalt Concrete - Type unknown and BTB: Continuously graded Base
F72	ASP	BS	Asphalt Concrete - Type unknown and BTB: Semi gap graded Base
F73	ASP	G2M	Asphalt Concrete - Type unknown and Graded crushed stone (lime added)
F74	ASP	G3M	Asphalt Concrete - Type unknown and Graded crushed stone (lime added)
F75	ASP	G4M	Asphalt Concrete - Type unknown and Natural gravel (lime added)
F8	AG	C3	Asphalt Concrete - Gap Graded and Graded crushed stone CTB (foreign fines added)
F9	AG	C4	Asphalt Concrete - Gap Graded and Natural gravel CTB

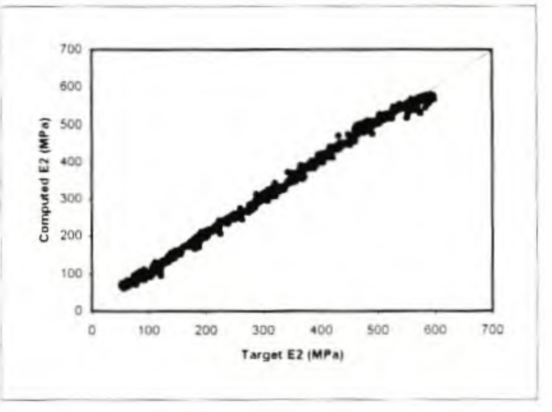
Appendix C.4

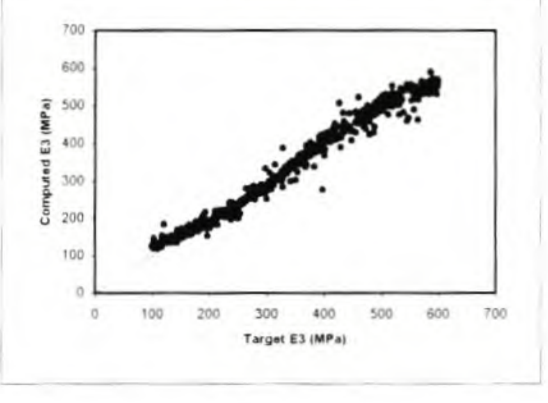
Results of Back-calculations for Type 1 pavements (DR1005)

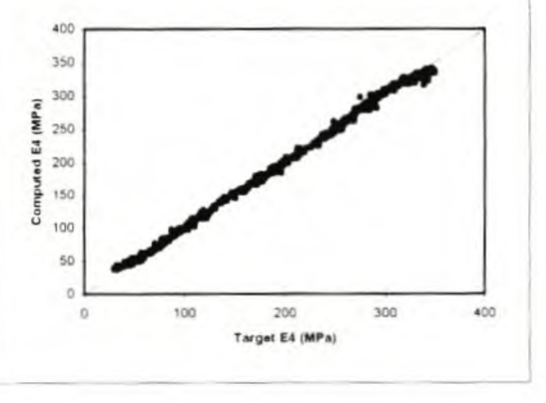
APPENDIX C.4 :DR1005 CASE(a)

RESULTS OF BACK-CALCULATIONS (E-MODULI LAYERS 1-4 FROM DEFLECTIONS) FROM TEST SET OF A TYPICAL SOUTH AFRICAN PAVEMENT: GRANULAR BASE/SUBBASE WITH A THIN SURFACING (DR1005): CASE (a) :DEPTH TO STIFF LAYER (H4) CALCULATED WITH NN22 AND E5 = 10000MPa









DR1005: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (a)

Date: Nov-97
Temp: 18 deg C
Load: 40 kN

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
0.00	334	201	124	52	33	24	20	210	72	19	66.90	G1	3.70	25.00	47	1493	0.10
0.20	912	543	335	65	20	9	8	577	270	45	2.10	G1	2.41	13.10	47	67996	3.70
0.40	705	414	247	56	29	25	14	458	191	27	12.60	G1	3.08	25.00	47	150039	7.80
0.60	621	361	214	65	40	24	18	407	149	25	20.30	G1	3.19	25.00	47	322919	15.10
0.80	566	313	203	74	39	21	14	363	129	35	28.80	G1	3.09	19.90	47	150972	7.80
1.00	1252	853	618	323	191	120	86	634	295	132	0.00	G1	1.20	3.00	47	1490	0.10
1.20	1109	779	532	244	139	97	69	577	288	105	2.10	G1	1.24	3.00	47	1723	0.10
1.40	616	368	232	107	74	59	46	384	125	33	24.60	G1	3.25	25.00	47	3575	0.20
1.54	818	639	486	222	119	80	60	332	264	103	35.80	G1	1.47	3.00	47	3513	0.20

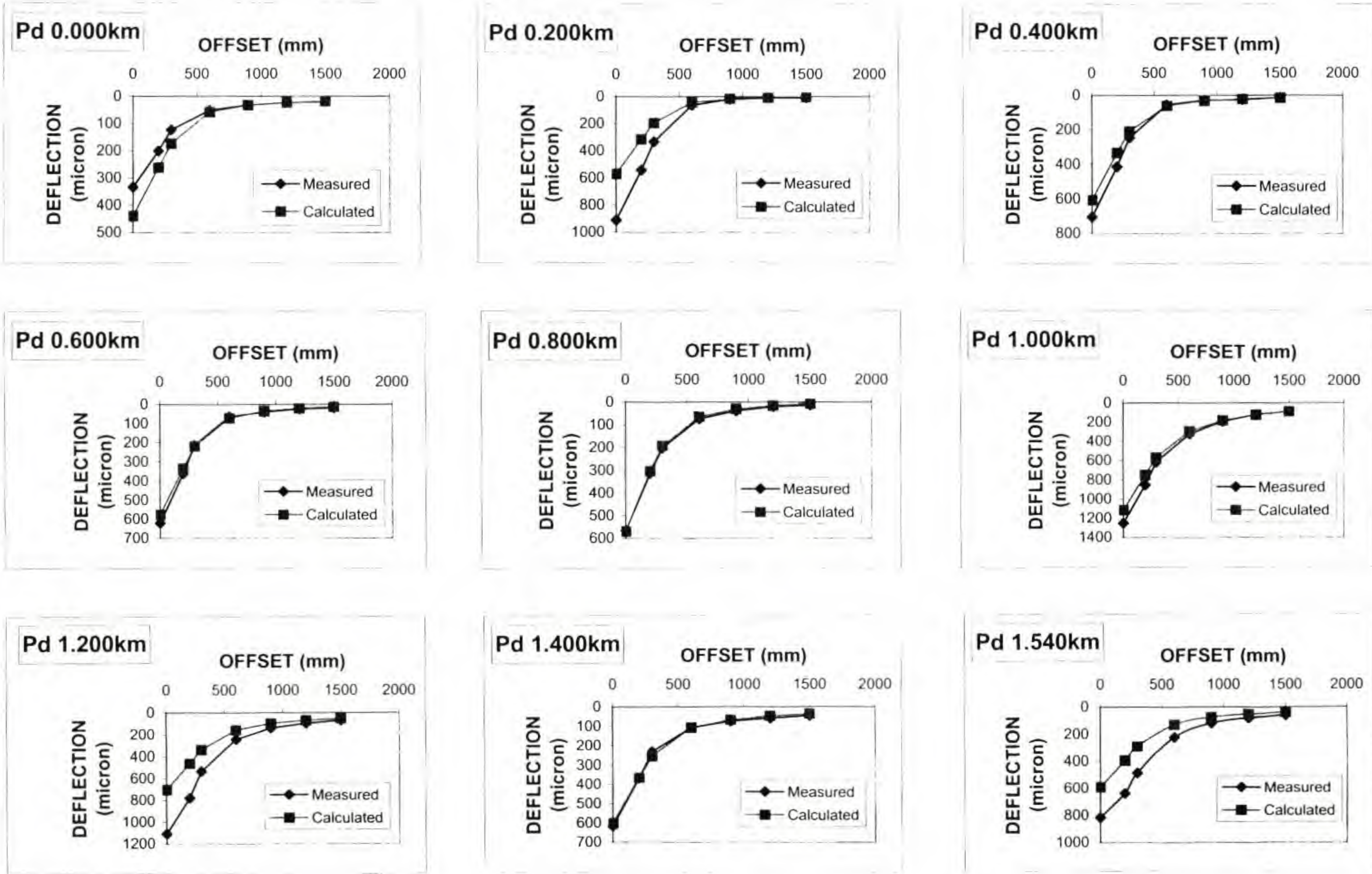
NEURAL NETWORK: BACK-CALCULATED E-MODULI

					0	200	300	600	900	1200	1500					
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	150	150	150	6997	334	201	124	52	33	24	20	999.9	75.6	599.9	305.3	10000
0.20	150	150	150	1355	912	543	335	65	20	9	8	688.2	53.5	599.1	263.2	10000
0.40	150	150	150	3441	705	414	247	56	29	25	14	605.5	58.2	599.9	248.0	10000
0.60	150	150	150	2205	621	361	214	65	40	24	18	698.1	64.4	599.9	185.2	10000
0.80	150	150	150	1493	566	313	203	74	39	21	14	534.2	96.6	368.0	169.0	10000
1.00	150	150	150	4951	1252	853	618	323	191	120	86	458.9	60.9	120.0	53.6	10000
1.20	150	150	150	6986	1109	779	532	244	139	97	69	757.0	56.2	599.9	107.3	10000
1.40	150	150	150	7000	616	368	232	107	74	59	46	712.1	69.7	599.9	157.6	10000
1.54	150	150	150	6923	818	639	486	222	119	80	60	999.9	56.6	599.9	137.1	10000

WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	150	150	150	6997	440	261	174	58	32	24	18	999.9	75.6	599.9	305.3	10000.0
0.20	150	150	150	1355	570	316	195	43	15	7	3	688.2	53.5	599.1	263.2	10000.0
0.40	150	150	150	3441	606	333	209	60	32	21	15	605.5	58.2	599.9	248.0	10000.0
0.60	150	150	150	2205	576	333	219	71	35	21	12	698.1	64.4	599.9	185.2	10000.0
0.80	150	150	150	1493	569	302	192	64	30	15	7	534.2	96.6	368.0	169.0	10000.0
1.00	150	150	150	4951	1114	748	569	291	180	122	87	458.9	60.9	120.0	53.6	10000.0
1.20	150	150	150	6986	703	460	338	156	96	68	51	757.0	56.2	599.9	107.3	10000.0
1.40	150	150	150	7000	601	365	254	107	66	47	35	712.1	69.7	599.9	157.6	10000.0
1.54	150	150	150	6923	591	394	290	127	75	52	39	999.9	56.6	599.9	137.1	10000.0

DR 1005: MEASURED vs CALCULATED DEFLECTION BASINS: CASE(a)

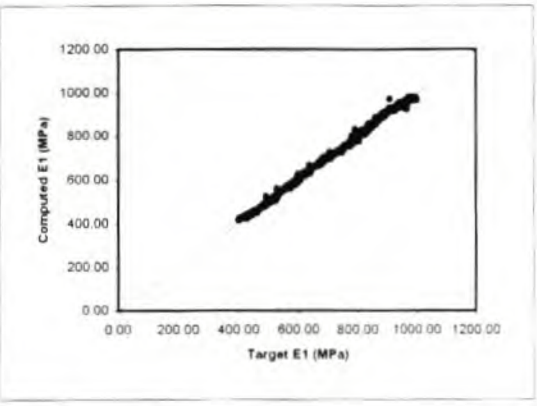


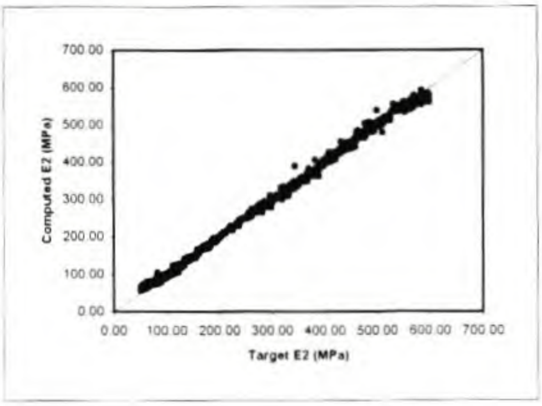
DR1005: COMPARISON OF MEASURED DEFLECTIONS WITH CALCULATED DEFLECTIONS WITH ROOT MEAN SQUARE ERROR: CASE (a)

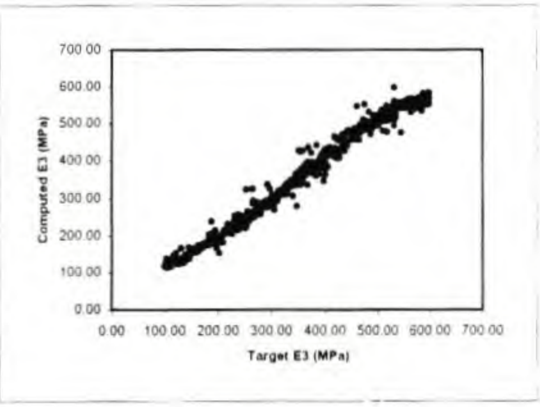
Pos (Km)	H1	D0	D200	D300	D600	D900	D1200	D1500	RMSE (%)
0.000	Measured	334	201	124	52	33	24	20	23.21%
	Calculated	440	261	174	58	32	24	18	
0.200	Measured	912	543	335	65	20	9	8	39.32%
	Calculated	570	316	195	43	15	7	3	
0.400	Measured	705	414	247	56	29	25	14	13.05%
	Calculated	606	333	209	60	32	21	15	
0.600	Measured	621	361	214	65	40	24	18	14.68%
	Calculated	576	333	219	71	35	21	12	
0.800	Measured	566	313	203	74	39	21	14	23.86%
	Calculated	569	302	192	64	30	15	7	
1.000	Measured	1252	853	618	323	191	120	86	8.24%
	Calculated	1114	748	569	291	180	122	87	
1.200	Measured	1109	779	532	244	139	97	69	34.20%
	Calculated	703	460	338	156	96	68	51	
1.400	Measured	616	368	232	107	74	59	46	12.87%
	Calculated	601	365	254	107	66	47	35	
1.540	Measured	818	639	486	222	119	80	60	36.80%
	Calculated	591	394	290	127	75	52	39	

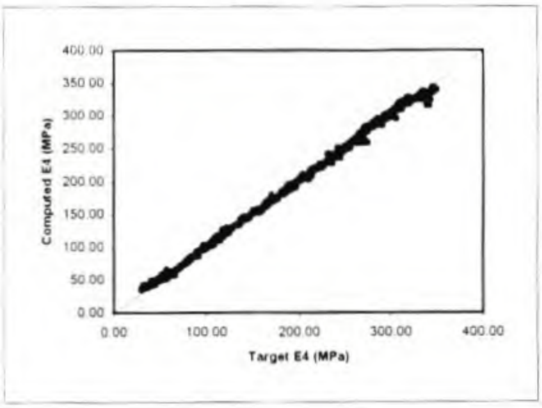
APPENDIX C.4 :DR1005 CASE (b)

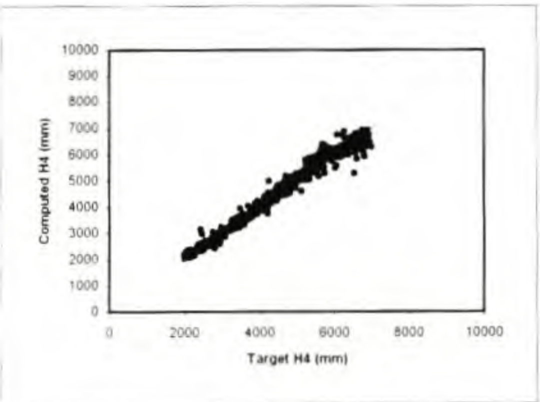
RESULTS OF BACK-CALCULATIONS (E-MODULI LAYERS 1-4 FROM DEFLECTIONS) FROM TEST SET OF A TYPICAL SOUTH AFRICAN PAVEMENT: GRANULAR BASE/SUBBASE WITH A THIN SURFACING (DR1005): CASE (b) :DEPTH TO STIFF LAYER CALCULATED WITH THIS NN AND E5 = 10000MPa











DR1005: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE(b)

Date: Nov-97
Temp: 18 deg C
Load: 40 kN

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
0.00	334	201	124	52	33	24	20	210	72	19	66.90	G1	3.70	25.00	47	1493	0.10
0.20	912	543	335	65	20	9	8	577	270	45	2.10	G1	2.41	13.10	47	67996	3.70
0.40	705	414	247	56	29	25	14	458	191	27	12.60	G1	3.08	25.00	47	150039	7.80
0.60	621	361	214	65	40	24	18	407	149	25	20.30	G1	3.19	25.00	47	322919	15.10
0.80	566	313	203	74	39	21	14	363	129	35	28.80	G1	3.09	19.90	47	150972	7.80
1.00	1252	853	618	323	191	120	86	634	295	132	0.00	G1	1.20	3.00	47	1490	0.10
1.20	1109	779	532	244	139	97	69	577	288	105	2.10	G1	1.24	3.00	47	1723	0.10
1.40	616	368	232	107	74	59	46	384	125	33	24.60	G1	3.25	25.00	47	3575	0.20
1.54	818	639	486	222	119	80	60	332	264	103	35.80	G1	1.47	3.00	47	3513	0.20

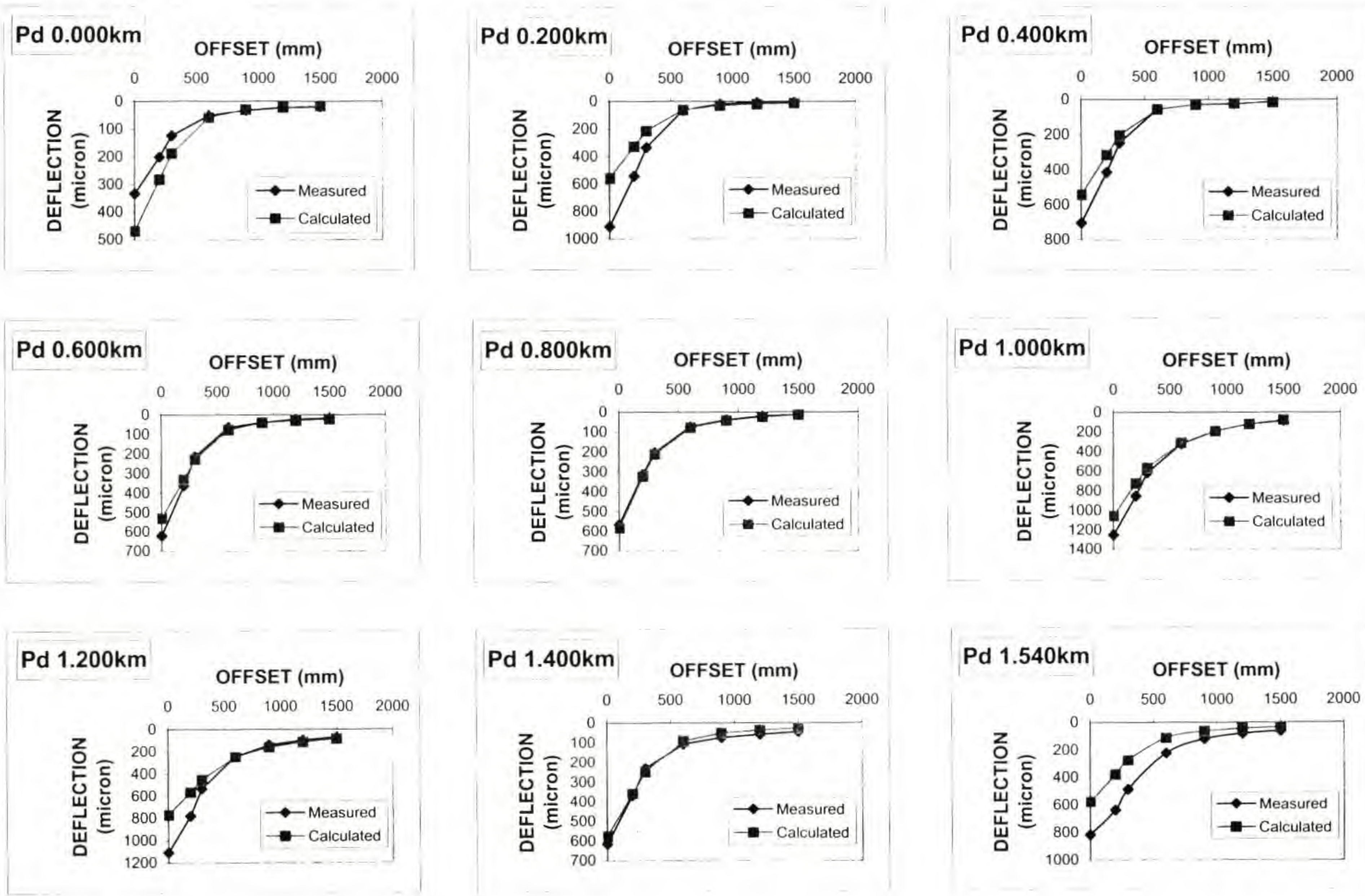
NEURAL NETWORK: BACK-CALCULATED E-MODULI

					0	200	300	600	900	1200	1500					
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	150	150	150	6990.4	334	201	124	52	33	24	20	1000.0	61.3	599.9	319.3	10000
0.20	150	150	150	3376.4	912	543	335	65	20	9	8	790.8	53.7	599.9	256.2	10000
0.40	150	150	150	6988.2	705	414	247	56	29	25	14	807.1	52.3	599.9	327.7	10000
0.60	150	150	150	6693.3	621	361	214	65	40	24	18	968.9	53.0	599.9	242.0	10000
0.80	150	150	150	2116.9	566	313	203	74	39	21	14	566.0	85.3	592.4	158.2	10000
1.00	150	150	150	2124.6	1252	853	618	323	191	120	86	516.4	56.8	599.9	35.0	10000
1.20	150	150	150	6301.0	1109	779	532	244	139	97	69	1000.0	54.0	599.9	63.9	10000
1.40	150	150	150	7000.0	616	368	232	107	74	59	46	864.8	53.9	599.9	198.0	10000
1.54	150	150	150	6989.1	818	639	486	222	119	80	60	1000.0	52.7	599.9	162.9	10000

WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	150	150	150	6990	469	282	188	58	30	22	17	1000.0	61.3	599.9	319.3	10000.0
0.20	150	150	150	3376	557	327	213	62	30	20	14	790.8	53.7	599.9	256.2	10000.0
0.40	150	150	150	6988	541	314	203	56	29	22	17	807.1	52.3	599.9	327.7	10000.0
0.60	150	150	150	6693	529	329	226	77	40	29	22	968.9	53.0	599.9	242.0	10000.0
0.80	150	150	150	2117	584	322	211	78	42	24	14	566.0	85.3	592.4	158.2	10000.0
1.00	150	150	150	2125	1053	724	563	310	193	122	76	516.4	56.8	599.9	35.0	10000.0
1.20	150	150	150	6301	770	563	449	246	159	112	83	1000.0	54.0	599.9	63.9	10000.0
1.40	150	150	150	7000	576	358	248	91	51	36	28	864.8	53.9	599.9	198.0	10000.0
1.54	150	150	150	6989	577	378	273	111	62	44	33	1000.0	52.7	599.9	162.9	10000.0

DR 1005: MEASURED vs CALCULATED DEFLECTION BASINS: CASE (b)

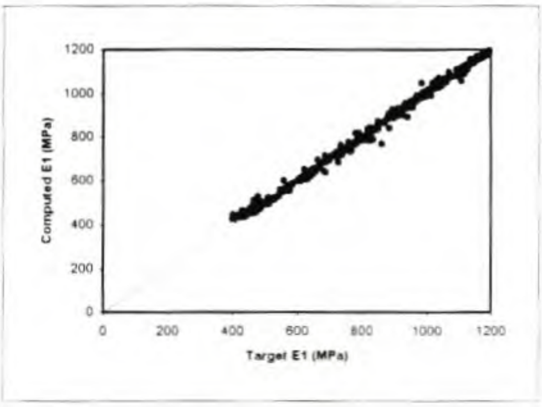


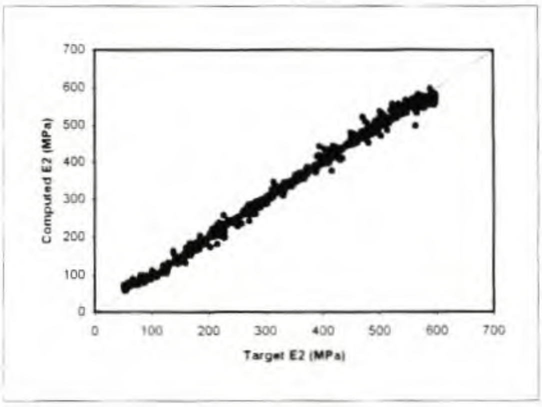
DR1005: COMPARISON OF MEASURED DEFLECTIONS WITH CALCULATED DEFLECTIONS WITH ROOT MEAN SQUARE ERROR: CASE (b)

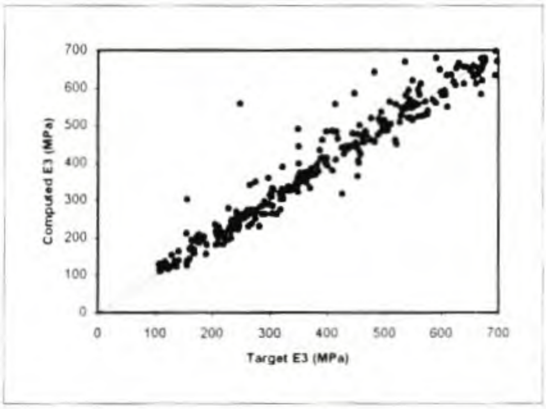
Pos (Km)	H1	D0	D200	D300	D600	D900	D1200	D1500	RMSE (%)
0.000	Measured	334	201	124	52	33	24	20	30.22%
	Calculated	469	282	188	58	30	22	17	
0.200	Measured	912	543	335	65	20	9	8	62.43%
	Calculated	557	327	213	62	30	20	14	
0.400	Measured	705	414	247	56	29	25	14	16.98%
	Calculated	541	314	203	56	29	22	17	
0.600	Measured	621	361	214	65	40	24	18	14.64%
	Calculated	529	329	226	77	40	29	22	
0.800	Measured	566	313	203	74	39	21	14	7.33%
	Calculated	584	322	211	78	42	24	14	
1.000	Measured	1252	853	618	323	191	120	86	10.06%
	Calculated	1053	724	563	310	193	122	76	
1.200	Measured	1109	779	532	244	139	97	69	19.96%
	Calculated	770	563	449	246	159	112	83	
1.400	Measured	616	368	232	107	74	59	46	25.12%
	Calculated	576	358	248	91	51	36	28	
1.540	Measured	818	639	486	222	119	80	60	43.63%
	Calculated	577	378	273	111	62	44	33	

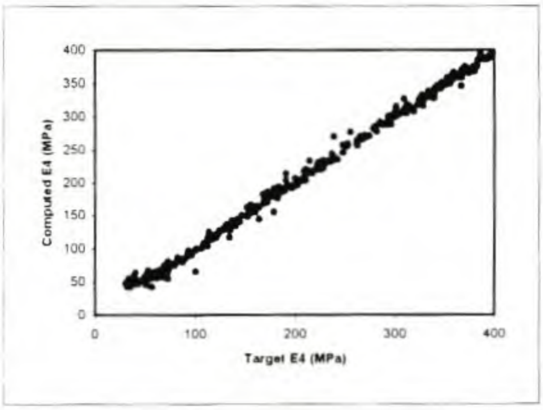
APPENDIX C.4 : DR1005 CASE(c)

RESULTS OF BACK-CALCULATIONS (E-MODULI LAYERS 1-4 FROM DEFLECTIONS) FROM TEST SET OF A TYPICAL SOUTH AFRICAN PAVEMENT: GRANULAR BASE/SUBBASE WITH A THIN SURFACING (DR1005): CASE (c) :DEPTH OF STIFF LAYER CALCULATED WITH NN22 AND E5 = 10000MPa. REACH OF E1 - E2 INCREASED.









DR1005: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (c)

Date: Nov-97
Temp: 18 deg C
Load: 40 kN

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
0.00	334	201	124	52	33	24	20	210	72	19	66.90	G1	3.70	25.00	47	1493	0.10
0.20	912	543	335	65	20	9	8	577	270	45	2.10	G1	2.41	13.10	47	67996	3.70
0.40	705	414	247	56	29	25	14	458	191	27	12.60	G1	3.08	25.00	47	150039	7.80
0.60	621	361	214	65	40	24	18	407	149	25	20.30	G1	3.19	25.00	47	322919	15.10
0.80	566	313	203	74	39	21	14	363	129	35	28.80	G1	3.09	19.90	47	150972	7.80
1.00	1252	853	618	323	191	120	86	634	295	132	0.00	G1	1.20	3.00	47	1490	0.10
1.20	1109	779	532	244	139	97	69	577	288	105	2.10	G1	1.24	3.00	47	1723	0.10
1.40	616	368	232	107	74	59	46	384	125	33	24.60	G1	3.25	25.00	47	3575	0.20
1.54	818	639	486	222	119	80	60	332	264	103	35.80	G1	1.47	3.00	47	3513	0.20

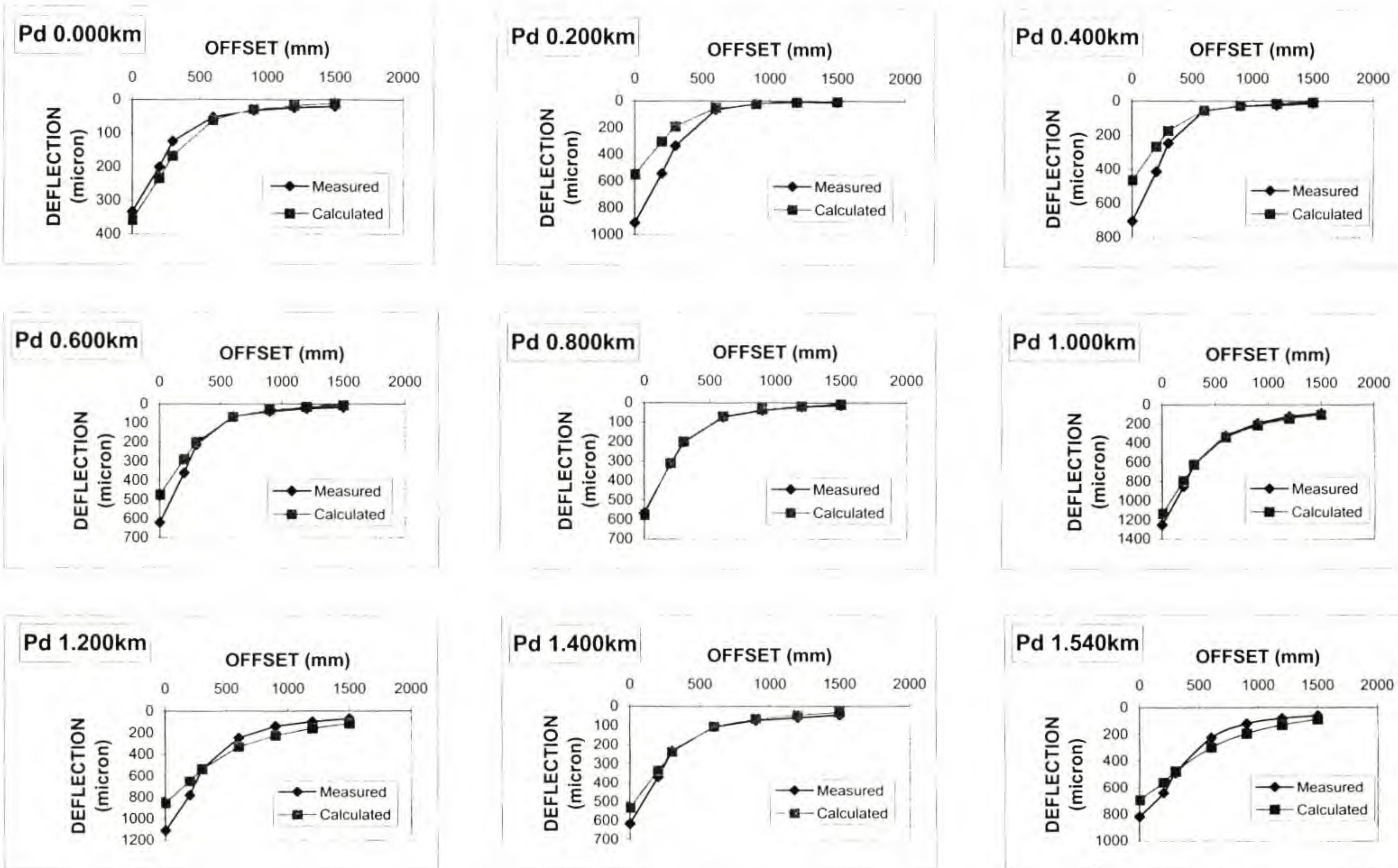
NEURAL NETWORK: BACKCALCULATED E-MODULI

					0	200	300	600	900	1200	1500					
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	150	150	150	2426	334	201	124	52	33	24	20	1652.3	76.1	1199.3	246.1	10000
0.20	150	150	150	1359	912	543	335	65	20	9	8	674.7	62.5	1193.9	208.0	10000
0.40	150	150	150	2107	705	414	247	56	29	25	14	874.8	72.6	1199.4	246.9	10000
0.60	150	150	150	1347	621	361	214	65	40	24	18	980.3	72.2	1199.5	158.3	10000
0.80	150	150	150	1508	566	313	203	74	39	21	14	535.6	98.4	367.5	157.0	10000
1.00	150	150	150	4108	1252	853	618	323	191	120	86	518.4	60.1	145.0	43.5	10000
1.20	150	150	150	3706	1109	779	532	244	139	97	69	982.5	59.3	1178.9	37.7	10000
1.40	150	150	150	5733	616	368	232	107	74	59	46	899.7	71.9	1199.5	156.2	10000
1.54	150	150	150	2649	818	639	486	222	119	80	60	1800.0	60.4	985.5	38.4	10000

WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	150	150	150	2426	358	234	167	61	29	17	11	1652.3	76.1	1199.3	246.1	10000.0
0.20	150	150	150	1359	549	302	189	50	21	10	4	674.7	62.5	1193.9	208.0	10000.0
0.40	150	150	150	2107	463	266	173	53	26	15	9	874.8	72.6	1199.4	246.9	10000.0
0.60	150	150	150	1347	474	289	197	67	29	14	6	980.3	72.2	1199.5	158.3	10000.0
0.80	150	150	150	1508	574	309	199	69	33	17	8	535.6	98.4	367.5	157.0	10000.0
1.00	150	150	150	4108	1133	793	622	337	211	142	100	518.4	60.1	145.0	43.5	10000.0
1.20	150	150	150	3706	853	648	534	328	224	158	113	982.5	59.3	1178.9	37.7	10000.0
1.40	150	150	150	5733	531	334	238	104	63	44	32	899.7	71.9	1199.5	156.2	10000.0
1.54	150	150	150	2649	691	557	473	294	192	128	87	1800.0	60.4	985.5	38.4	10000.0

DR 1005: MEASURED vs CALCULATED DEFLECTION BASINS: CASE (c)

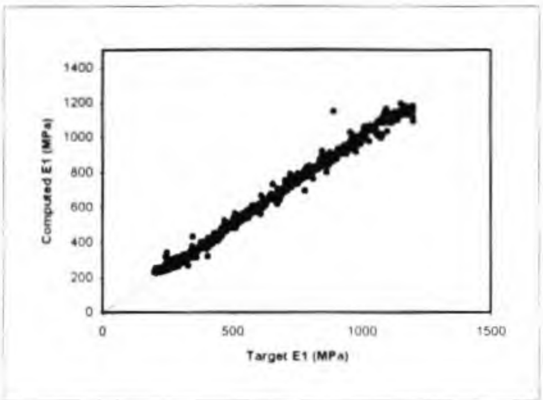


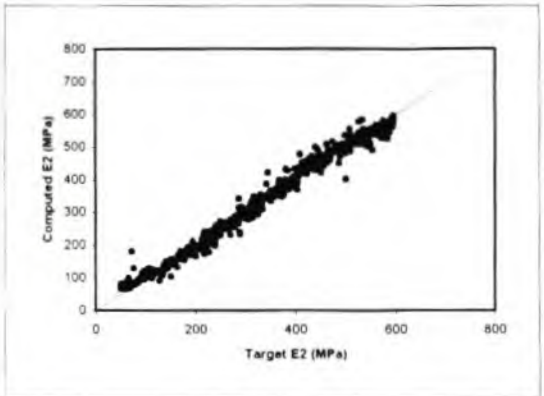
DR1005: COMPARISON OF MEASURED DEFLECTIONS WITH CALCULATED DEFLECTIONS WITH ROOT MEAN SQUARE ERROR: CASE (c)

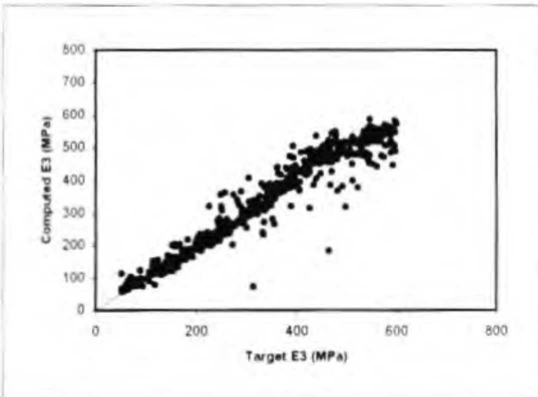
Pos (Km)	H1	D0	D200	D300	D600	D900	D1200	D1500	RMSE (%)
0.000	Measured	334	201	124	52	33	24	20	26.65%
	Calculated	358	234	167	61	29	17	11	
0.200	Measured	912	543	335	65	20	9	8	33.99%
	Calculated	549	302	189	50	21	10	4	
0.400	Measured	705	414	247	56	29	25	14	30.42%
	Calculated	463	266	173	53	26	15	9	
0.600	Measured	621	361	214	65	40	24	18	33.17%
	Calculated	474	289	197	67	29	14	6	
0.800	Measured	566	313	203	74	39	21	14	19.39%
	Calculated	574	309	199	69	33	17	8	
1.000	Measured	1252	853	618	323	191	120	86	11.20%
	Calculated	1133	793	622	337	211	142	100	
1.200	Measured	1109	779	532	244	139	97	69	44.30%
	Calculated	853	648	534	328	224	158	113	
1.400	Measured	616	368	232	107	74	59	46	16.88%
	Calculated	531	334	238	104	63	44	32	
1.540	Measured	818	639	486	222	119	80	60	39.44%
	Calculated	691	557	473	294	192	128	87	

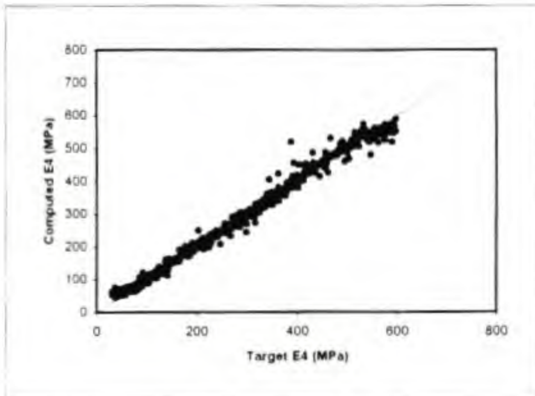
APPENDIX C.4: DR1005 CASE (d)

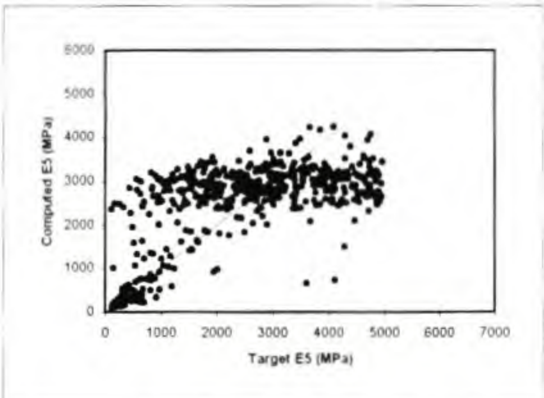
RESULTS OF BACK-CALCULATIONS (E-MODULI LAYERS 1-5 AND DEPTH TO STIFF LAYERSFROM DEFLECTIONS) FROM TEST SET OF A TYPICAL SOUTH AFRICAN PAVEMENT: GRANULAR BASE/SUBBASE WITH A THIN SURFACING (DR1005): CASE (d)

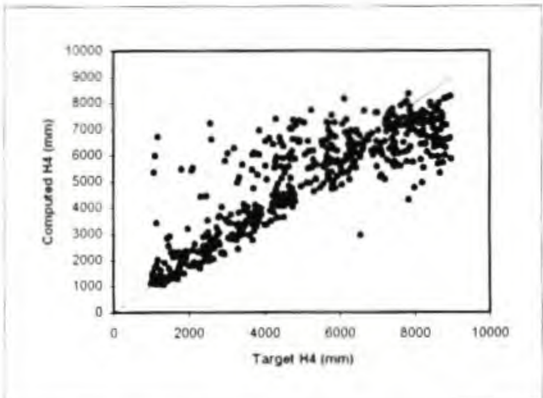












DR1005: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (d)

Date: Nov-97
Temp: 18 deg C
Load: 40 kN

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
0.00	334	201	124	52	33	24	20	210	72	19	66.90	G1	3.70	25.00	47	1493	0.10
0.20	912	543	335	65	20	9	8	577	270	45	2.10	G1	2.41	13.10	47	67996	3.70
0.40	705	414	247	56	29	25	14	458	191	27	12.60	G1	3.08	25.00	47	150039	7.80
0.60	621	361	214	65	40	24	18	407	149	25	20.30	G1	3.19	25.00	47	322919	15.10
0.80	566	313	203	74	39	21	14	363	129	35	28.80	G1	3.09	19.90	47	150972	7.80
1.00	1252	853	618	323	191	120	86	634	295	132	0.00	G1	1.20	3.00	47	1490	0.10
1.20	1109	779	532	244	139	97	69	577	288	105	2.10	G1	1.24	3.00	47	1723	0.10
1.40	616	368	232	107	74	59	46	384	125	33	24.60	G1	3.25	25.00	47	3575	0.20
1.54	818	639	486	222	119	80	60	332	264	103	35.80	G1	1.47	3.00	47	3513	0.20

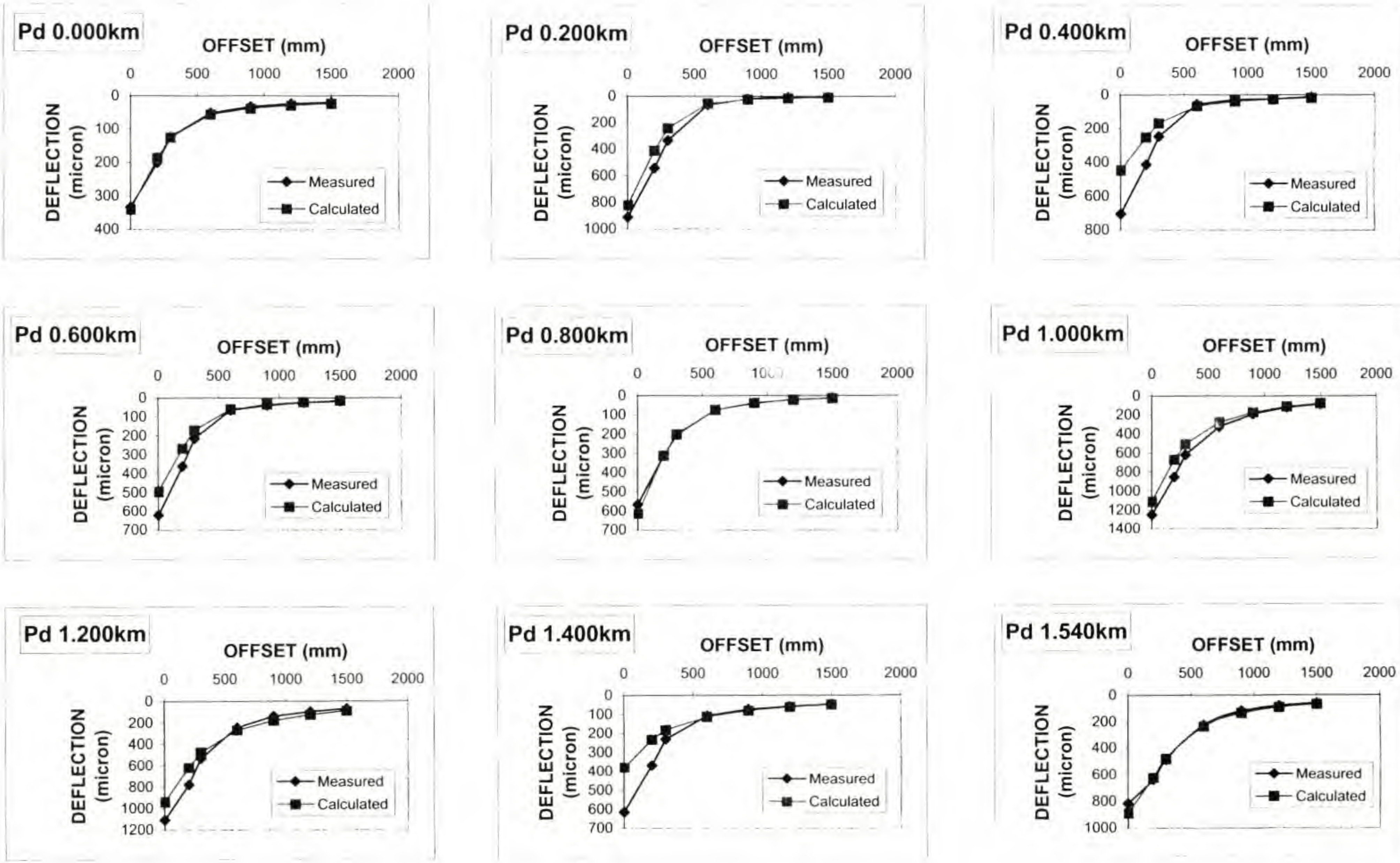
NEURAL NETWORK: BACK-CALCULATED E-MODULI

					0	200	300	600	900	1200	1500					
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	150	150	150	5909	334	201	124	52	33	24	20	885.4	186.5	586.8	335.1	265.6
0.20	150	150	150	2033	912	543	335	65	20	9	8	348.7	65.4	104.2	246.0	2643.2
0.40	150	150	150	3459	705	414	247	56	29	25	14	765.6	114.6	572.8	223.5	2610.6
0.60	150	150	150	2734	621	361	214	65	40	24	18	644.5	97.4	567.2	233.6	2614.5
0.80	150	150	150	2020	566	313	203	74	39	21	14	400.4	142.5	163.3	177.3	2560.5
1.00	150	150	150	3572	1252	853	618	323	191	120	86	260.8	125.3	107.9	52.9	2315.3
1.20	150	150	150	4150	1109	779	532	244	139	97	69	476.2	74.3	502.2	51.6	2333.9
1.40	150	150	150	5840	616	368	232	107	74	59	46	803.8	328.9	593.0	160.4	150.3
1.54	150	150	150	6596	818	639	486	222	119	80	60	727.3	66.7	72.1	77.0	2469.4

WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	150	150	150	5909	340	186	125	56	38	29	24	885.4	186.5	586.8	335.1	265.6
0.20	150	150	150	2033	821	411	242	55	23	15	9	348.7	65.4	104.2	246.0	2643.2
0.40	150	150	150	3459	447	252	168	66	39	26	18	765.6	114.6	572.8	223.5	2610.6
0.60	150	150	150	2734	496	266	170	60	34	22	14	644.5	97.4	567.2	233.6	2614.5
0.80	150	150	150	2020	613	311	200	74	38	22	13	400.4	142.5	163.3	177.3	2560.5
1.00	150	150	150	3572	1111	668	505	275	170	111	76	260.8	125.3	107.9	52.9	2315.3
1.20	150	150	150	4150	940	619	476	269	179	124	89	476.2	74.3	502.2	51.6	2333.9
1.40	150	150	150	5840	379	234	181	112	80	61	48	803.8	328.9	593.0	160.4	150.3
1.54	150	150	150	6596	890	624	480	232	134	91	67	727.3	66.7	72.1	77.0	2469.4

DR 1005: MEASURED vs CALCULATED DEFLECTION BASINS: CASE (d)

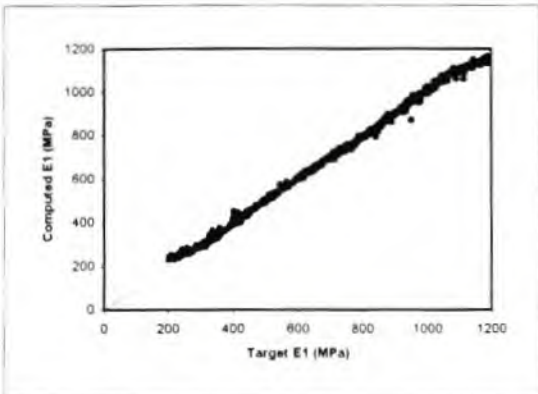


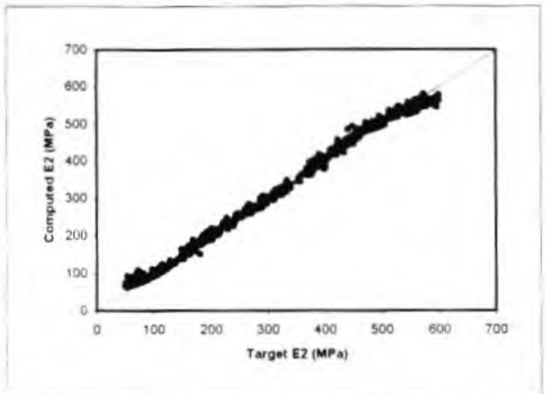
DR1005: COMPARISON OF MEASURED DEFLECTIONS WITH CALCULATED DEFLECTIONS WITH ROOT MEAN SQUARE ERROR: CASE (d)

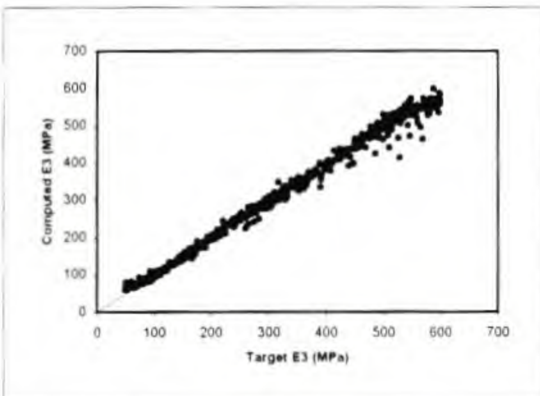
Pos (Km)	H1	D0	D200	D300	D600	D900	D1200	D1500	RMSE (%)
0.000	Measured	334	201	124	52	33	24	20	12.98%
	Calculated	340	186	125	56	38	29	24	
0.200	Measured	912	543	335	65	20	9	8	29.95%
	Calculated	821	411	242	55	23	15	9	
0.400	Measured	705	414	247	56	29	25	14	29.93%
	Calculated	447	252	168	66	39	26	18	
0.600	Measured	621	361	214	65	40	24	18	18.21%
	Calculated	496	266	170	60	34	22	14	
0.800	Measured	566	313	203	74	39	21	14	4.27%
	Calculated	613	311	200	74	38	22	13	
1.000	Measured	1252	853	618	323	191	120	86	14.46%
	Calculated	1111	668	505	275	170	111	76	
1.200	Measured	1109	779	532	244	139	97	69	21.71%
	Calculated	940	619	476	269	179	124	89	
1.400	Measured	616	368	232	107	74	59	46	22.08%
	Calculated	379	234	181	112	80	61	48	
1.540	Measured	818	639	486	222	119	80	60	9.37%
	Calculated	890	624	480	232	134	91	67	

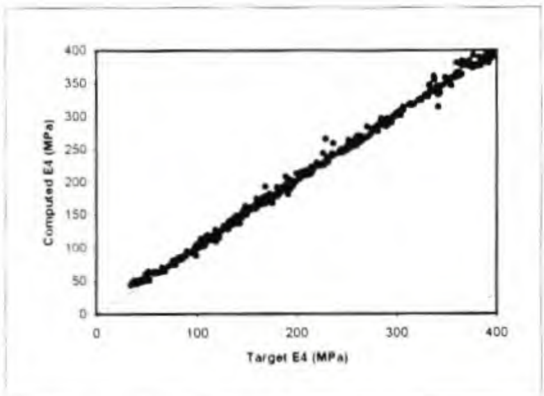
APPENDIX C.4 DR1005 CASE (e)

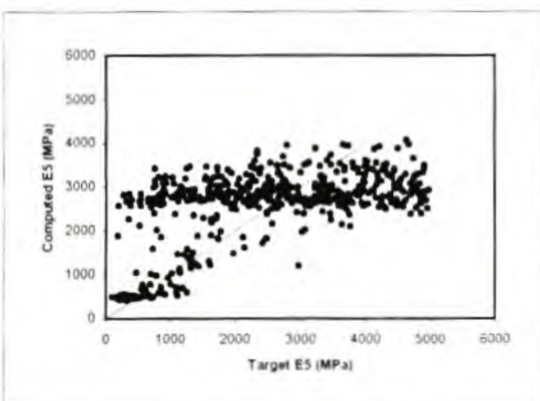
RESULTS OF BACK-CALCULATIONS (E-MODULI LAYERS 1-5 AND DEPTH TO STIFF LAYER FROM DEFLECTIONS) FROM TEST SET OF A TYPICAL SOUTH AFRICAN PAVEMENT: GRANULAR BASE/SUBBASE WITH A THIN SURFACING (DR1005): CASE (e): H1=H2=H3=150 mm

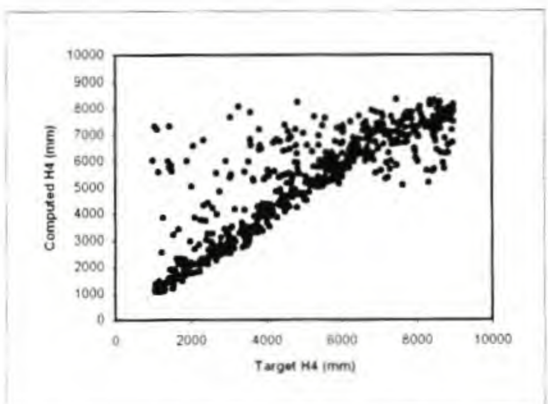












DR1005: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (e)

Date: Nov-97
Temp: 18 deg C
Load: 40 kN

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
0.00	334	201	124	52	33	24	20	210	72	19	66.90	G1	3.70	25.00	47	1493	0.10
0.20	912	543	335	65	20	9	8	577	270	45	2.10	G1	2.41	13.10	47	67996	3.70
0.40	705	414	247	56	29	25	14	458	191	27	12.60	G1	3.08	25.00	47	150039	7.80
0.60	621	361	214	65	40	24	18	407	149	25	20.30	G1	3.19	25.00	47	322919	15.10
0.80	566	313	203	74	39	21	14	363	129	35	28.80	G1	3.09	19.90	47	150972	7.80
1.00	1252	853	618	323	191	120	86	634	295	132	0.00	G1	1.20	3.00	47	1490	0.10
1.20	1109	779	532	244	139	97	69	577	288	105	2.10	G1	1.24	3.00	47	1723	0.10
1.40	616	368	232	107	74	59	46	384	125	33	24.60	G1	3.25	25.00	47	3575	0.20
1.54	818	639	486	222	119	80	60	332	264	103	35.80	G1	1.47	3.00	47	3513	0.20

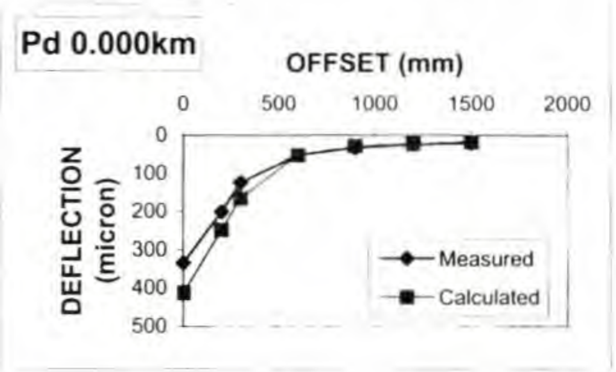
NEURAL NETWORK: BACK-CALCULATED E-MODULI

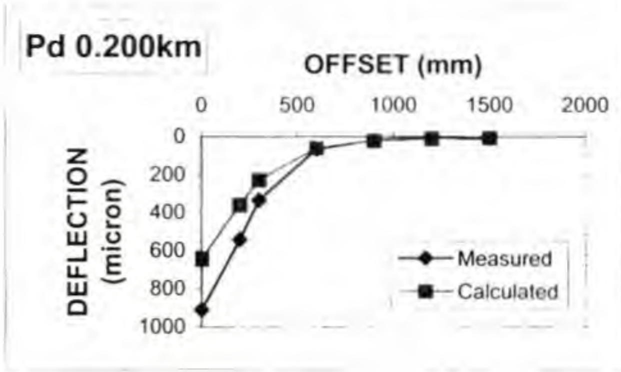
					0	200	300	600	900	1200	1500					
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	150	150	150	3276	334	201	124	52	33	24	20	1130.6	70.5	600.0	383.0	485.2
0.20	150	150	150	1111	912	543	335	65	20	9	8	597.6	53.7	600.0	168.8	3302.6
0.40	150	150	150	1469	705	414	247	56	29	25	14	775.2	55.0	600.0	283.2	3010.9
0.60	150	150	150	1065	621	361	214	65	40	24	18	1021.3	53.3	600.0	146.0	2637.5
0.80	150	150	150	2252	566	313	203	74	39	21	14	526.8	83.9	599.9	180.0	3773.0
1.00	150	150	150	2979	1252	853	618	323	191	120	86	403.7	57.4	599.9	68.9	3667.9
1.20	150	150	150	1463	1109	779	532	244	139	97	69	805.5	53.7	600.0	89.6	2522.4
1.40	150	150	150	3415	616	368	232	107	74	59	46	890.6	56.2	600.0	218.5	286.3
1.54	150	150	150	2242	818	639	486	222	119	80	60	1199.8	233.5	600.0	98.5	2565.5

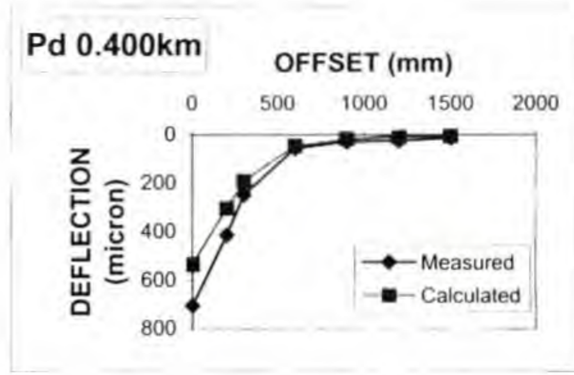
WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

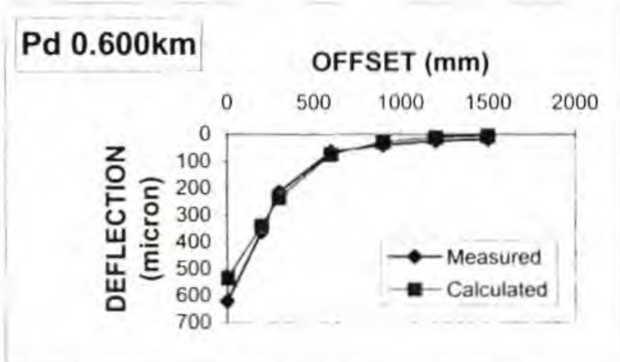
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	150	150	150	3276	413	248	165	52	28	21	17	1130.6	70.5	600.0	383.0	485.2
0.20	150	150	150	1111	644	360	227	59	22	10	4	597.6	53.7	600.0	168.8	3302.6
0.40	150	150	150	1469	534	303	191	45	17	9	5	775.2	55.0	600.0	283.2	3010.9
0.60	150	150	150	1065	535	339	235	74	27	11	5	1021.3	53.3	600.0	146.0	2637.5
0.80	150	150	150	2252	589	314	200	71	39	23	14	526.8	83.9	599.9	180.0	3773.0
1.00	150	150	150	2979	950	573	408	194	119	77	51	403.7	57.4	599.9	68.9	3667.9
1.20	150	150	150	1463	675	439	316	126	60	31	16	805.5	53.7	600.0	89.6	2522.4
1.40	150	150	150	3415	554	343	237	87	51	38	30	890.6	56.2	600.0	218.5	286.3
1.54	150	150	150	2242	393	268	210	120	75	48	31	1199.8	233.5	600.0	98.5	2565.5

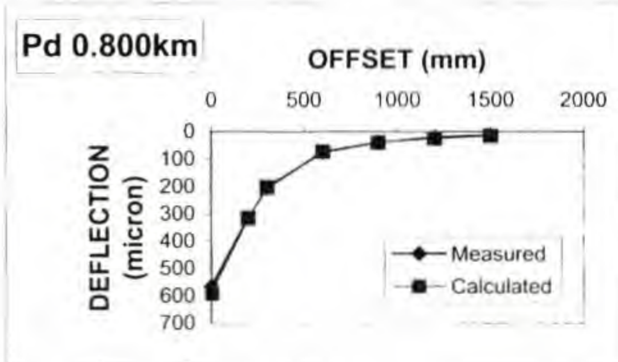
DR 1005: MEASURED vs CALCULATED DEFLECTION BASINS: CASE (e)

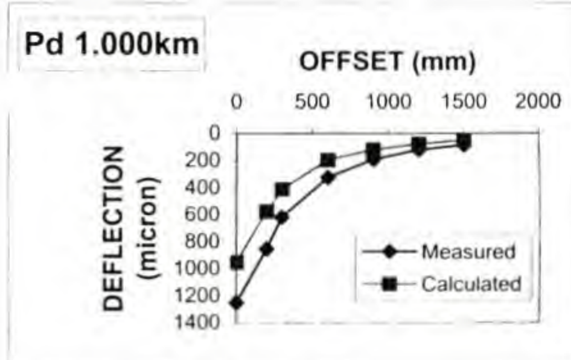


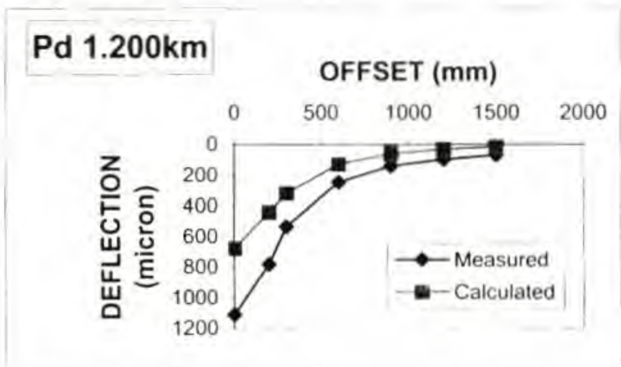


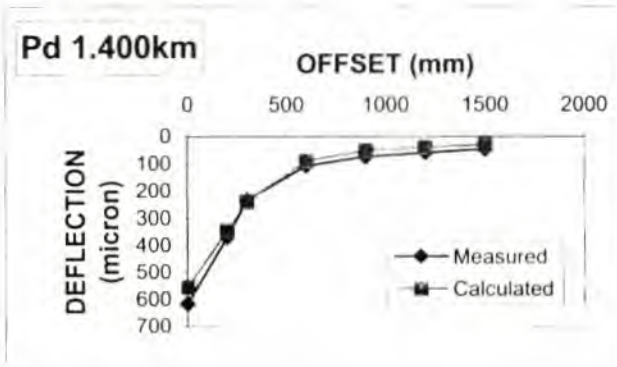


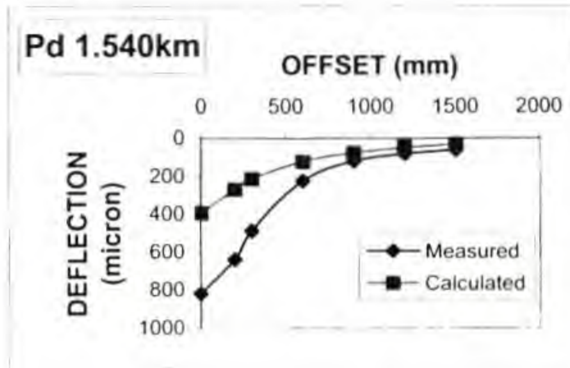












DR1005: COMPARISON OF MEASURED DEFLECTIONS WITH CALCULATED DEFLECTIONS WITH ROOT MEAN SQUARE ERROR: CASE (e)

Pos (Km)	H1	D0	D200	D300	D600	D900	D1200	D1500	RMSE (%)
0.000	Measured	334	201	124	52	33	24	20	19.88%
	Calculated	413	248	165	52	28	21	17	
0.200	Measured	912	543	335	65	20	9	8	28.37%
	Calculated	644	360	227	59	22	10	4	
0.400	Measured	705	414	247	56	29	25	14	40.81%
	Calculated	534	303	191	45	17	9	5	
0.600	Measured	621	361	214	65	40	24	18	37.31%
	Calculated	535	339	235	74	27	11	5	
0.800	Measured	566	313	203	74	39	21	14	5.03%
	Calculated	589	314	200	71	39	23	14	
1.000	Measured	1252	853	618	323	191	120	86	35.50%
	Calculated	950	573	408	194	119	77	51	
1.200	Measured	1109	779	532	244	139	97	69	55.03%
	Calculated	675	439	316	126	60	31	16	
1.400	Measured	616	368	232	107	74	59	46	23.98%
	Calculated	554	343	237	87	51	38	30	
1.540	Measured	818	639	486	222	119	80	60	48.93%
	Calculated	393	268	210	120	75	48	31	

DR1005: E-MODULI BACK-CALCULATED WITH MODCOMP

Date: Nov-97
Temp: 18 deg C
Load: 40 kN

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
0.00	334	201	124	52	33	24	20	210	72	19	66.90	G1	3.70	25.00	47	1493	0.10
0.20	912	543	335	65	20	9	8	577	270	45	2.10	G1	2.41	13.10	47	67996	3.70
0.40	705	414	247	56	29	25	14	458	191	27	12.60	G1	3.08	25.00	47	150039	7.80
0.60	621	361	214	65	40	24	18	407	149	25	20.30	G1	3.19	25.00	47	322919	15.10
0.80	566	313	203	74	39	21	14	363	129	35	28.80	G1	3.09	19.90	47	150972	7.80
1.00	1252	853	618	323	191	120	86	634	295	132	0.00	G1	1.20	3.00	47	1490	0.10
1.20	1109	779	532	244	139	97	69	577	288	105	2.10	G1	1.24	3.00	47	1723	0.10
1.40	616	368	232	107	74	59	46	384	125	33	24.60	G1	3.25	25.00	47	3575	0.20
1.54	818	639	486	222	119	80	60	332	264	103	35.80	G1	1.47	3.00	47	3513	0.20

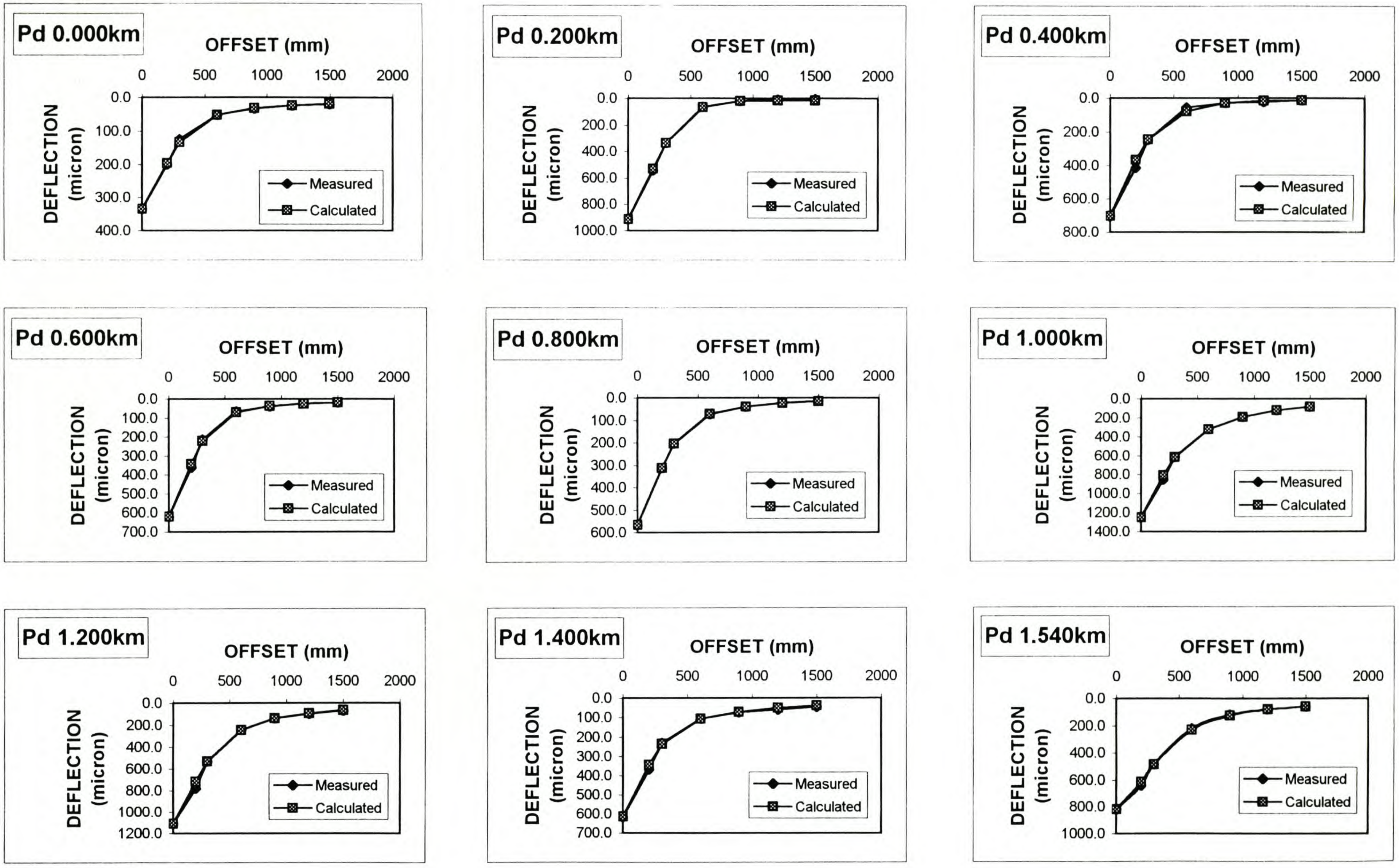
MODCOMP: BACK-CALCULATED E-MODULI

					0	200	300	600	900	1200	1500					
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	150	150	150	15000	334.0	201.0	124.0	52.0	33.0	24.0	20.0	1190.0	132.0	628.0	339.0	3500.0
0.20	150	150	150	15000	912.0	543.0	335.0	65.0	20.0	9.0	8.0	499.0	31.6	74.0	382.0	3500.0
0.40	150	150	150	15000	705.0	414.0	247.0	56.0	29.0	25.0	14.0	319.0	248.0	30.2	408.0	3500.0
0.60	150	150	150	3700	621.0	361.0	214.0	65.0	40.0	24.0	18.0	564.0	77.2	185.0	225.0	3500.0
0.80	150	150	150	2700	566.0	313.0	203.0	74.0	39.0	21.0	14.0	599.0	86.9	354.0	195.0	3500.0
1.00	150	150	150	3800	1252.0	853.0	618.0	323.0	191.0	120.0	86.0	294.0	112.0	51.0	48.2	3500.0
1.20	150	150	150	5400	1109.0	779.0	532.0	244.0	139.0	97.0	69.0	403.0	77.5	50.3	71.1	3500.0
1.40	150	150	150	15000	616.0	368.0	232.0	107.0	74.0	59.0	46.0	526.0	93.9	540.0	158.0	3500.0
1.54	150	150	150	5400	818.0	639.0	486.0	222.0	119.0	80.0	60.0	1210.0	25.0	591.0	82.4	3500.0

MODCOMP: DEFLECTIONS FROM BACK-CALCULATED E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	150	150	150	15000	334.1	196.5	133.5	52.6	32.4	23.9	18.6	1190.0	132.0	628.0	339.0	3500.0
0.20	150	150	150	15000	911.5	529.6	334.9	65.6	20.1	17.9	16.6	499.0	31.6	74.0	382.0	3500.0
0.40	150	150	150	15000	703.1	366.6	245.8	79.5	28.3	15.8	12.8	319.0	248.0	30.2	408.0	3500.0
0.60	150	150	150	3700	621.1	343.8	220.8	69.9	36.9	25.1	17.9	564.0	77.2	185.0	225.0	3500.0
0.80	150	150	150	2700	565.9	312.7	203.3	71.5	38.9	24.6	15.9	599.0	86.9	354.0	195.0	3500.0
1.00	150	150	150	3800	1251.0	805.8	617.6	322.6	190.4	122.1	83.1	294.0	112.0	51.0	48.2	3500.0
1.20	150	150	150	5400	1109.4	717.3	531.7	244.5	138.8	92.6	67.2	403.0	77.5	50.3	71.1	3500.0
1.40	150	150	150	15000	614.3	345.0	235.0	107.2	70.6	51.4	39.4	526.0	93.9	540.0	158.0	3500.0
1.54	150	150	150	5400	818.5	612.6	485.0	232.5	125.2	80.4	57.8	1210.0	25.0	591.0	82.4	3500.0

DR 1005: MEASURED vs CALCULATED DEFLECTION BASINS BY MODCOMP



DR1005: COMPARISON OF MEASURED AND CALCULATED DEFLECTIONS BY MODCOMP

Pos (Km)	H1	D0	D200	D300	D600	D900	D1200	D1500	RMSE (%)
0.000	Measured	334	201	124	52	33	24	20	4.15%
	Calculated	334	197	133	53	32	24	19	
0.200	Measured	912	543	335	65	20	9	8	54.94%
	Calculated	912	530	335	66	20	18	17	
0.400	Measured	705	414	247	56	29	25	14	21.83%
	Calculated	703	367	246	80	28	16	13	
0.600	Measured	621	361	214	65	40	24	18	4.91%
	Calculated	621	344	221	70	37	25	18	
0.800	Measured	566	313	203	74	39	21	14	8.30%
	Calculated	566	313	203	72	39	25	16	
1.000	Measured	1252	853	618	323	191	120	86	2.54%
	Calculated	1251	806	618	323	190	122	83	
1.200	Measured	1109	779	532	244	139	97	69	3.60%
	Calculated	1109	717	532	244	139	93	67	
1.400	Measured	616	368	232	107	74	59	46	7.88%
	Calculated	614	345	235	107	71	51	39	
1.540	Measured	818	639	486	222	119	80	60	3.39%
	Calculated	818	613	485	232	125	80	58	

Appendix C.4

Comparison of E-moduli for the different cases investigated for DR1005

POSITION (Km	CASE	BACK-CALCULATED E-MODULI (MPa)					
		E1	E2	E3	E4	E5	RMSE (%)
0.00	Case (a)	999.9	75.6	599.9	305.3	10000.0	23.21
	Case (b)	1000.1	61.3	599.9	319.3	10000.0	30.22
	Case (c)	1652.3	76.1	1199.3	246.1	10000.0	26.65
	Case (d)	885.4	186.5	586.8	335.1	265.6	12.98
	Case (e)	1130.6	70.5	600.0	383.0	485.2	19.88
	ModComp	1190.0	132.0	628.0	339.0	3500.0	4.15
0.20	Case (a)	688.2	53.5	599.1	263.2	10000.0	39.32
	Case (b)	790.8	53.7	599.9	256.2	10000.0	62.43
	Case (c)	674.7	62.5	1193.9	208.0	10000.0	33.99
	Case (d)	348.7	65.4	104.2	246.0	2643.2	29.95
	Case (e)	597.6	53.7	600.0	168.8	3302.6	28.37
	ModComp	499.0	31.6	74.0	382.0	3500.0	54.94
0.40	Case (a)	605.5	58.2	599.9	248.0	10000.0	13.05
	Case (b)	807.1	52.3	599.9	327.7	10000.0	16.98
	Case (c)	874.8	72.6	1199.4	246.9	10000.0	30.42
	Case (d)	765.6	114.6	572.8	223.5	2610.6	29.93
	Case (e)	775.2	55.0	600.0	283.2	3010.9	40.81
	ModComp	319.0	248.0	30.2	408.0	3500.0	21.83
0.60	Case (a)	698.1	64.4	599.9	185.2	10000.0	14.68
	Case (b)	968.9	53.0	599.9	242.0	10000.0	14.64
	Case (c)	980.3	72.2	1199.5	158.3	10000.0	33.17
	Case (d)	644.5	97.4	567.2	233.6	2614.5	18.21
	Case (e)	1021.3	53.3	600.0	146.0	2637.5	37.31
	ModComp	564.0	77.2	185.0	225.0	3500.0	4.91
0.80	Case (a)	534.2	96.6	368.0	169.0	10000.0	23.86
	Case (b)	566.0	85.3	592.4	158.2	10000.0	7.33
	Case (c)	535.6	98.4	367.5	157.0	10000.0	19.39
	Case (d)	400.4	142.5	163.3	177.3	2560.5	4.27
	Case (e)	526.8	83.9	599.9	180.0	3773.0	5.03
	ModComp	599.0	86.9	354.0	195.0	3500.0	8.30
1.00	Case (a)	458.9	60.9	120.0	53.6	10000.0	8.24
	Case (b)	516.4	56.8	599.9	35.0	10000.0	10.06
	Case (c)	518.4	60.1	145.0	43.5	10000.0	11.20
	Case (d)	260.8	125.3	107.9	52.9	2315.3	14.46
	Case (e)	403.7	57.4	599.9	68.9	3667.9	35.50
	ModComp	294.0	112.0	51.0	48.2	3500.0	2.54

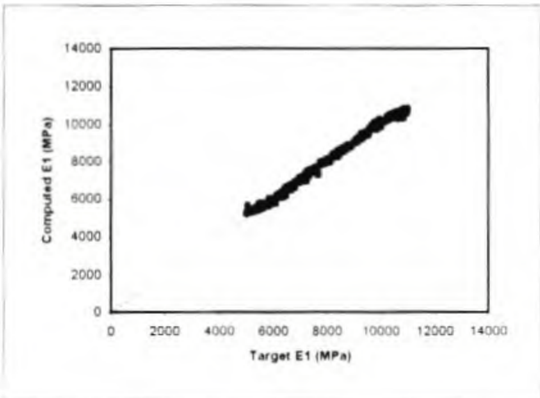
1.20	Case (a)	757.0	56.2	599.9	107.3	10000.0	34.20
	Case (b)	1000.0	54.0	599.9	63.9	10000.0	19.96
	Case (c)	982.5	59.3	1178.9	37.7	10000.0	44.30
	Case (d)	476.2	74.3	502.2	51.6	2333.9	21.71
	Case (e)	805.5	53.7	600.0	89.6	2522.4	55.03
	ModComp	403.0	77.5	50.3	71.1	3500.0	3.60
1.40	Case (a)	712.1	69.7	599.9	157.6	10000.0	12.87
	Case (b)	864.8	53.9	599.9	198.0	10000.0	25.12
	Case (c)	899.7	71.9	1199.5	156.2	10000.0	16.88
	Case (d)	803.8	328.9	593.0	160.4	150.3	22.08
	Case (e)	890.6	56.2	600.0	218.5	286.3	23.98
	ModComp	526.0	93.9	540.0	158.0	3500.0	7.88
1.54	Case (a)	999.9	56.6	599.9	137.1	10000.0	36.80
	Case (b)	1000.0	52.7	599.9	162.9	10000.0	53.63
	Case (c)	1800.0	60.4	985.5	38.4	10000.0	39.44
	Case (d)	727.3	66.7	72.1	77.0	2469.4	9.37
	Case (e)	1199.8	233.5	600.0	98.5	2565.5	48.93
	ModComp	1210.0	25.0	591.0	82.4	3500.0	3.39

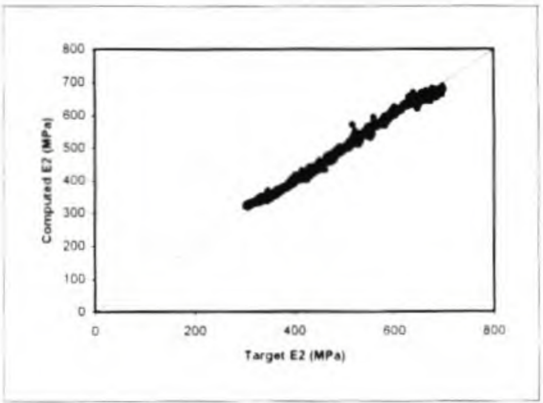
Appendix C.5

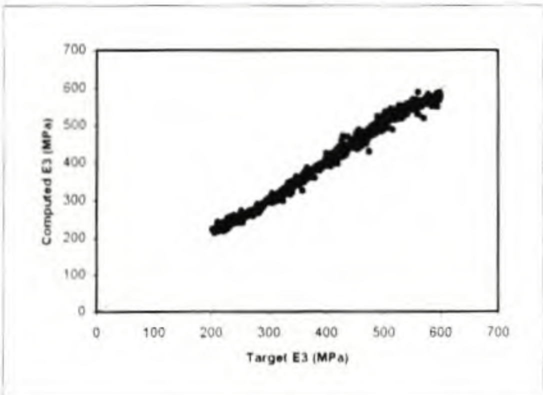
Results of Back-calculations for Type 2 pavements (TR1102)

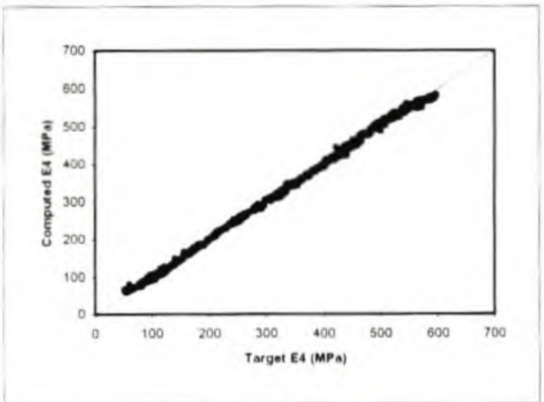
APPENDIX C.5: TR1102: CASE (a)

RESULTS OF BACK-CALCULATIONS (E-MODULI LAYERS 1-4 FROM DEFLECTIONS) FROM TEST SET OF A TYPICAL SOUTH AFRICAN PAVEMENT: GRANULAR BASE/SUBBASE WITH AN ASPHALT SURFACING (35mm and 85mm THICKNESS): CASE (a): DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000MPa









TR01102: 35AC: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (a)
DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
0.00	185	148	125	75	41	24	16	60	50	34	89.00	F18	6.54	24.40	418	16028350	43.50
0.40	427	313	230	92	39	20	15	197	138	53	40.00	F18	4.23	18.30	418	1298192	7.30
0.80	572	472	375	194	111	61	49	197	181	83	40.00	F18	2.55	3.00	418	81511	0.50
1.20	191	136	104	35	12	9	8	87	69	23	82.20	F18	6.00	25.00	418	3487245	16.50
1.60	206	144	104	48	28	25	19	102	56	20	77.60	F18	6.01	25.00	418	8790559	31.10
2.00	234	180	141	61	30	23	26	93	80	31	80.40	F18	5.70	25.00	418	6159858	24.80
2.20	461	344	263	106	45	26	15	198	157	61	39.60	F18	3.92	14.10	418	1142196	6.50
2.40	165	133	103	46	22	19	14	62	57	24	88.60	F18	6.56	25.00	418	16432238	44.00
2.60	369	276	216	95	48	31	22	153	121	47	58.50	F18	4.69	21.80	418	1877238	10.10
2.80	332	238	169	61	28	19	14	163	108	33	54.30	F18	4.90	25.00	418	2384155	12.30
3.20	330	244	180	81	43	29	23	150	99	38	59.70	F18	5.01	25.00	734	2713229	8.50
3.60	420	298	205	62	30	21	16	215	143	32	32.80	F18	4.47	25.00	734	1435359	4.80
3.80	440	299	198	60	32	22	17	242	138	28	23.00	F18	4.39	25.00	734	1317141	4.50
4.20	316	228	169	65	31	20	19	147	104	34	61.00	F18	5.02	25.00	734	4897212	13.90
4.60	548	404	289	109	54	36	26	259	180	55	17.70	F18	3.82	17.30	734	375960	1.30
5.00	321	220	154	62	35	24	18	167	92	27	52.60	F18	5.01	25.00	734	2150671	7.00
5.40	399	295	213	78	39	26	24	186	135	39	44.60	F18	4.60	25.00	734	797253	2.80
5.80	260	183	122	53	33	25	16	138	69	20	64.60	F18	5.47	25.00	734	1330334	4.50
6.20	413	295	222	85	37	24	18	191	137	48	42.50	F18	4.53	25.00	592	1249882	5.20
6.60	336	239	176	66	31	20	16	160	110	35	55.60	F18	4.89	25.00	592	4165379	14.50
6.80	354	241	169	56	30	20	15	185	113	26	45.00	F18	4.78	25.00	592	2543336	9.70
7.20	445	326	241	101	52	39	19	204	140	49	37.10	F18	4.17	13.50	592	1199445	5.00
8.80	263	178	116	42	26	19	15	147	74	16	61.00	F18	5.63	25.00	592	10553632	28.10
9.00	502	346	217	68	39	30	20	285	149	29	10.90	F18	4.39	25.00	592	1307211	5.40
9.40	569	421	313	134	78	52	37	256	179	56	18.60	F18	3.06	5.30	592	265309	1.20
9.80	398	312	241	109	53	29	15	157	132	56	56.80	F18	3.84	6.80	592	1023897	4.30
10.20	431	291	211	102	65	43	31	220	109	37	30.90	F18	4.01	9.60	592	1297140	5.40
10.60	629	458	348	158	92	61	40	281	190	66	11.90	F18	2.48	3.00	592	87735	0.40
10.80	558	413	320	157	89	51	36	238	163	68	24.40	F18	2.68	3.00	592	136649	0.60
11.20	486	371	275	116	64	39	28	211	159	52	34.30	F18	3.58	7.60	592	1019187	4.30
11.60	387	300	235	117	69	44	31	152	118	48	58.90	F18	3.96	6.60	592	1376963	5.70
12.00	464	342	232	96	47	27	14	232	136	49	26.50	F18	3.90	11.00	592	732079	3.10
12.40	530	395	305	139	74	48	32	225	166	65	29.00	F18	3.12	4.90	592	127694	0.60
17.80	409	294	219	86	36	21	16	190	133	50	42.90	F18	4.54	25.00	592	1269657	5.30
18.20	375	299	246	137	83	57	39	129	109	54	68.10	F18	3.75	5.20	592	519040	2.30
18.60	518	390	292	113	60	40	31	226	179	53	28.60	F18	3.75	13.70	592	274618	1.20
19.00	415	301	221	95	49	34	26	194	126	46	85.20	A4	4.44	25.00	592	1386248	5.70

TR01102: 35AC: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (a)
DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

NEURAL NETWORK: BACKCALCULATED E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	35	150	150	9823	185	148	125	75	41	24	16	5056.8	699.7	468.4	116.9	10000.0
0.40	35	150	150	10834	427	313	230	92	39	20	15	10998.9	699.3	200.3	308.3	10000.0
0.80	35	150	150	12937	572	472	375	194	111	61	49	10998.9	300.5	200.4	124.5	10000.0
1.20	35	150	150	9320	191	136	104	35	12	9	8	5012.5	699.5	379.8	596.3	10000.0
1.60	35	150	150	9191	206	144	104	48	28	25	19	10998.8	699.9	287.5	232.1	10000.0
2.00	35	150	150	9681	234	180	141	61	30	23	26	6429.0	699.7	240.5	187.8	10000.0
2.20	35	150	150	11325	461	344	263	106	45	26	15	10994.5	699.5	200.5	196.6	10000.0
2.40	35	150	150	9363	165	133	103	46	22	19	14	10998.9	699.8	215.6	226.2	10000.0
2.60	35	150	150	10493	369	276	216	95	48	31	22	10371.3	699.6	203.0	138.0	10000.0
2.80	35	150	150	9775	332	238	169	61	28	19	14	10998.9	699.3	200.5	327.8	10000.0
3.20	35	150	150	10020	330	244	180	81	43	29	23	10998.9	698.4	200.8	206.6	10000.0
3.60	35	150	150	9728	420	298	205	62	30	21	16	10998.9	316.9	200.1	477.9	10000.0
3.80	35	150	150	9542	440	299	198	60	32	22	17	10998.9	300.3	200.1	466.5	10000.0
4.20	35	150	150	9823	316	228	169	65	31	20	19	10998.7	699.7	201.7	193.5	10000.0
4.60	35	150	150	10953	548	404	289	109	54	36	26	10998.9	300.5	200.1	423.8	10000.0
5.00	35	150	150	9497	321	220	154	62	35	24	18	10998.9	385.2	200.7	283.1	10000.0
5.40	35	150	150	10070	399	295	213	78	39	26	24	10998.9	698.3	200.3	338.0	10000.0
5.80	35	150	150	9191	260	183	122	53	33	25	16	10996.6	301.3	600.0	264.2	10000.0
6.20	35	150	150	10549	413	295	222	85	37	24	18	9627.0	699.4	200.6	185.4	10000.0
6.60	35	150	150	9872	336	239	176	66	31	20	16	10998.6	699.6	201.0	211.8	10000.0
6.80	35	150	150	9452	354	241	169	56	30	20	15	10998.9	698.1	200.3	420.8	10000.0
7.20	35	200	150	10604	445	326	241	101	52	39	19	10998.9	302.2	200.1	348.4	10000.0
8.80	35	200	150	9025	263	178	116	42	26	19	15	10998.8	300.8	598.2	437.4	10000.0
9.00	35	200	150	9588	502	346	217	68	39	30	20	10998.3	300.8	599.9	414.3	10000.0
9.40	35	200	150	11013	569	421	313	134	78	52	37	10998.9	300.4	200.1	329.1	10000.0
9.80	35	200	150	11013	398	312	241	109	53	29	15	10998.9	699.4	200.5	191.7	10000.0
10.20	35	200	150	9970	431	291	211	102	65	43	31	10998.8	306.0	204.2	161.0	10000.0
10.60	35	200	150	11655	629	458	348	158	92	61	40	10998.2	304.8	200.1	319.7	10000.0
10.80	35	200	150	11792	558	413	320	157	89	51	36	10998.9	316.7	200.1	288.6	10000.0
11.20	35	200	150	10776	486	371	275	116	64	39	28	10998.9	300.2	200.2	311.5	10000.0
11.60	35	200	150	10549	387	300	235	117	69	44	31	10998.9	698.7	200.6	153.6	10000.0
12.00	35	200	150	10604	464	342	232	96	47	27	14	10998.8	300.5	598.3	286.1	10000.0
12.40	35	200	150	11587	530	395	305	139	74	48	32	10998.9	633.8	200.1	371.9	10000.0
17.80	35	150	150	10661	409	294	219	86	36	21	16	10992.2	699.5	200.4	213.7	10000.0
18.20	35	150	150	10893	375	299	246	137	83	57	39	10998.9	699.8	208.6	85.8	10000.0
18.60	35	150	150	10834	518	390	292	113	60	40	31	10998.9	697.4	200.2	353.8	10000.0
19.00	35	150	150	10438	415	301	221	95	49	34	26	10998.9	656.2	200.2	315.6	10000.0

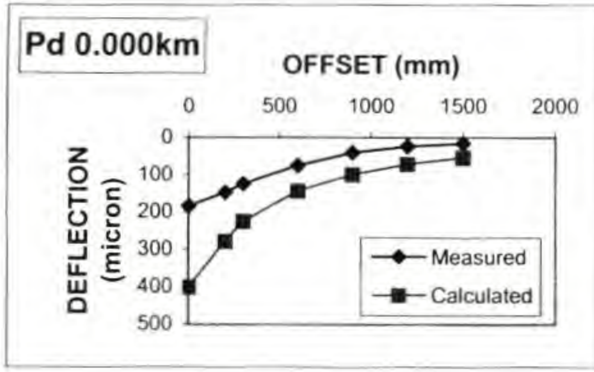
TR01102: 35AC: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (a)
DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000 Mpa

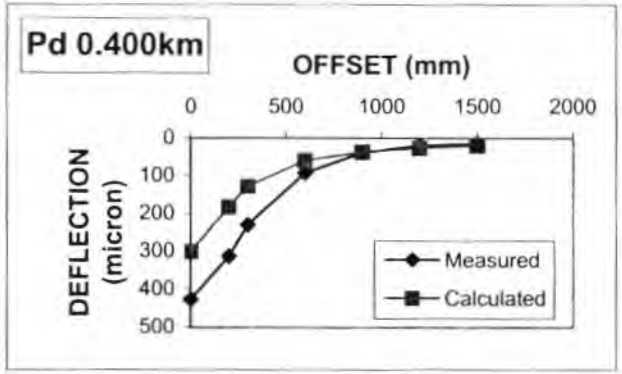
Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

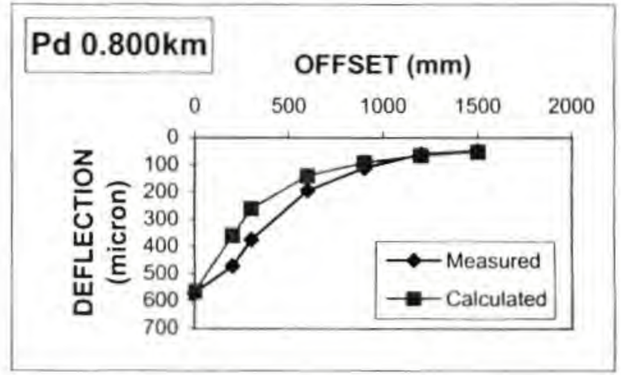
WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

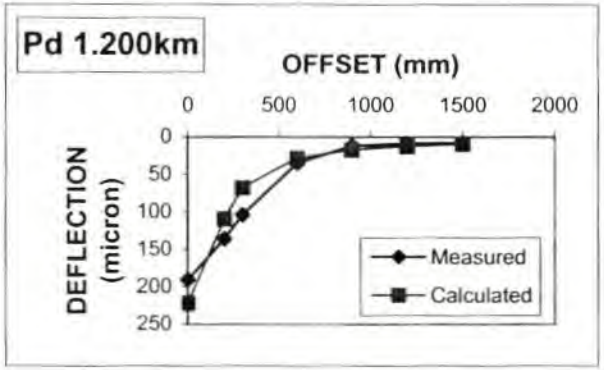
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	35	150	150	9823	401	278	225	144	99	71	54	5056.8	699.7	468.4	116.9	10000.0
0.40	35	150	150	10834	301	183	127	59	36	26	20	10998.9	699.3	200.3	308.3	10000.0
0.80	35	150	150	12937	565	360	261	139	91	66	51	10998.9	300.5	200.4	124.5	10000.0
1.20	35	150	150	9320	222	109	67	28	17	12	9	5012.5	699.5	379.8	596.3	10000.0
1.60	35	150	150	9191	309	195	142	75	48	34	25	10998.8	699.9	287.5	232.1	10000.0
2.00	35	150	150	9681	360	232	174	94	60	43	33	6429.0	699.7	240.5	187.8	10000.0
2.20	35	150	150	11325	355	233	173	91	58	41	32	10994.5	699.5	200.5	196.6	10000.0
2.40	35	150	150	9363	330	211	154	78	49	34	27	10998.9	699.8	215.6	226.2	10000.0
2.60	35	150	150	10493	411	285	222	126	82	59	44	10371.3	699.6	203.0	138.0	10000.0
2.80	35	150	150	9775	294	177	122	55	33	24	18	10998.9	699.3	200.5	327.8	10000.0
3.20	35	150	150	10020	347	225	167	86	54	38	29	10998.9	698.4	200.8	206.6	10000.0
3.60	35	150	150	9728	366	183	102	35	22	16	12	10998.9	316.9	200.1	477.9	10000.0
3.80	35	150	150	9542	376	188	104	36	23	17	13	10998.9	300.3	200.1	466.5	10000.0
4.20	35	150	150	9823	355	233	174	91	58	41	31	10998.7	699.7	201.7	193.5	10000.0
4.60	35	150	150	10953	385	195	111	40	25	19	15	10998.9	300.5	200.1	423.8	10000.0
5.00	35	150	150	9497	387	218	141	61	38	27	21	10998.9	385.2	200.7	283.1	10000.0
5.40	35	150	150	10070	292	174	119	54	32	23	18	10998.9	698.3	200.3	338.0	10000.0
5.80	35	150	150	9191	361	192	123	63	42	30	23	10996.6	301.3	600.0	264.2	10000.0
6.20	35	150	150	10549	366	241	181	96	61	44	33	9627.0	699.4	200.6	185.4	10000.0
6.60	35	150	150	9872	343	222	164	84	53	37	29	10998.6	699.6	201.0	211.8	10000.0
6.80	35	150	150	9452	273	157	104	43	26	19	14	10998.9	698.1	200.3	420.8	10000.0
7.20	35	200	150	10604	397	210	126	50	31	22	18	10998.9	302.2	200.1	348.4	10000.0
8.80	35	200	150	9025	325	155	87	38	25	18	14	10998.8	300.8	598.2	437.4	10000.0
9.00	35	200	150	9588	329	159	90	40	26	19	15	10998.3	300.8	599.9	414.3	10000.0
9.40	35	200	150	11013	403	215	131	53	33	24	19	10998.9	300.4	200.1	329.1	10000.0
9.80	35	200	150	11013	326	215	164	92	60	43	32	10998.9	699.4	200.5	191.7	10000.0
10.20	35	200	150	9970	486	295	205	105	68	49	37	10998.8	306.0	204.2	161.0	10000.0
10.60	35	200	150	11655	403	217	133	55	34	25	19	10998.2	304.8	200.1	319.7	10000.0
10.80	35	200	150	11792	406	223	141	61	38	28	21	10998.9	316.7	200.1	288.6	10000.0
11.20	35	200	150	10776	408	220	136	56	35	25	20	10998.9	300.2	200.2	311.5	10000.0
11.60	35	200	150	10549	354	242	189	112	74	53	41	10998.9	698.7	200.6	153.6	10000.0
12.00	35	200	150	10604	362	189	117	58	39	28	22	10998.8	300.5	598.3	286.1	10000.0
12.40	35	200	150	11587	274	159	108	50	30	21	16	10998.9	633.8	200.1	371.9	10000.0
17.80	35	150	150	10661	343	222	163	84	53	37	29	10992.2	699.5	200.4	213.7	10000.0
18.20	35	150	150	10893	508	378	310	195	132	96	72	10998.9	699.8	208.6	85.8	10000.0
18.60	35	150	150	10834	288	170	116	51	31	22	17	10998.9	697.4	200.2	353.8	10000.0
19.00	35	150	150	10438	305	183	126	57	35	25	19	10998.9	656.2	200.2	315.6	10000.0

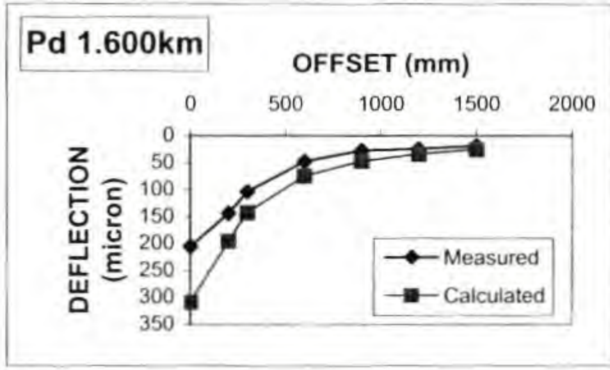
TR1102: AC35: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)

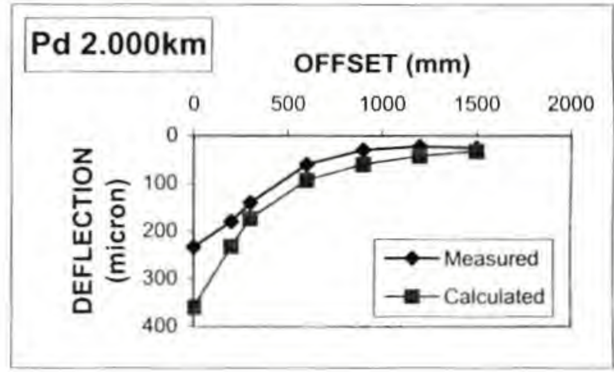


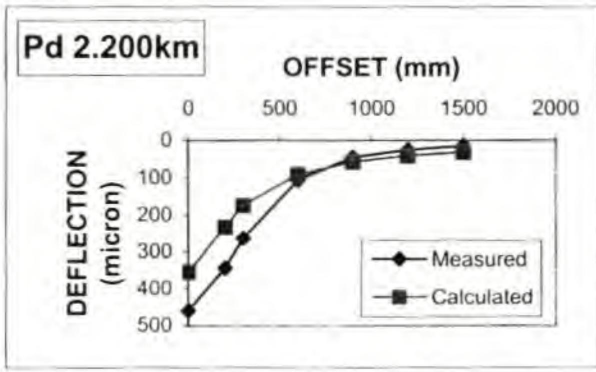


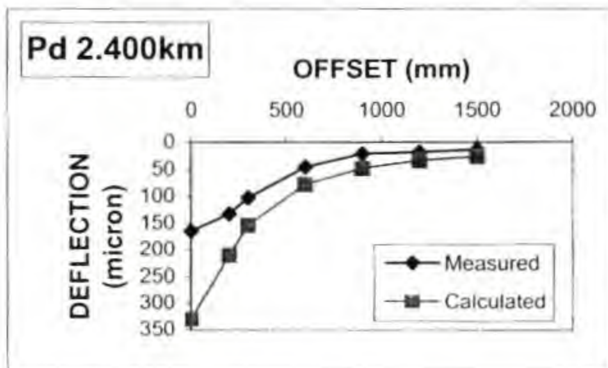


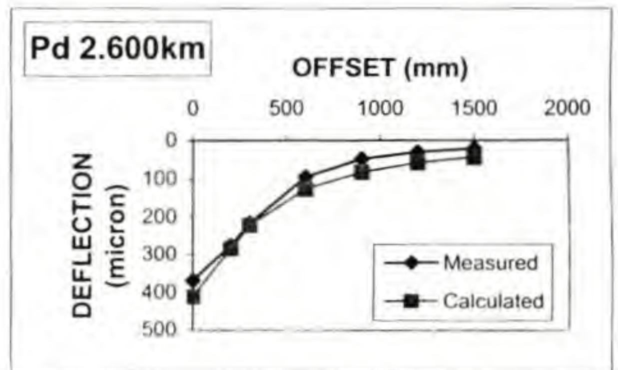




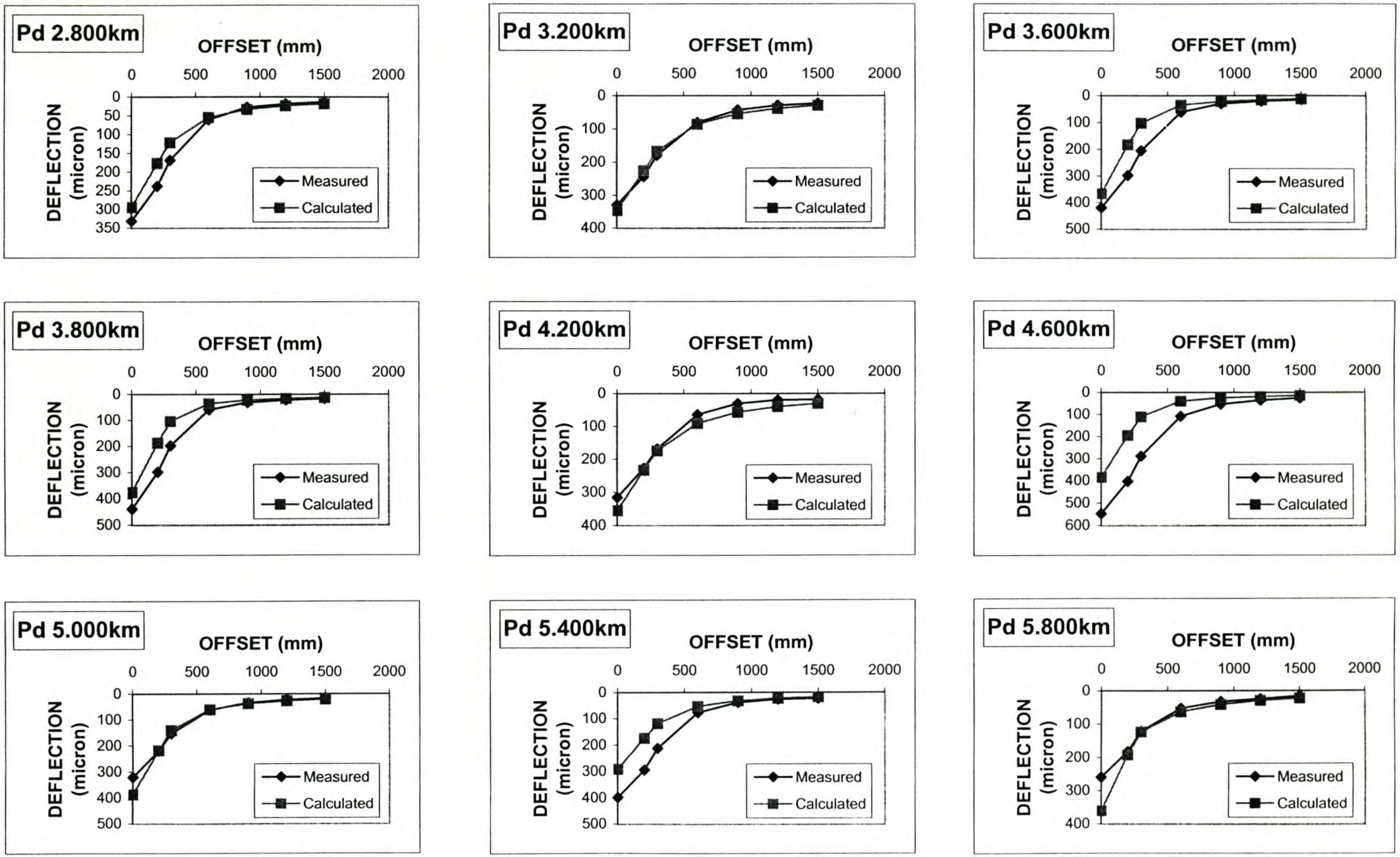




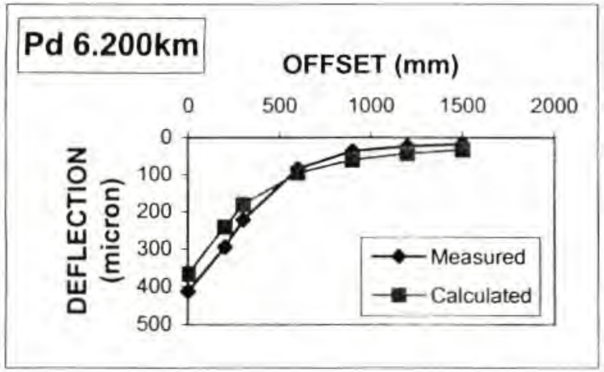


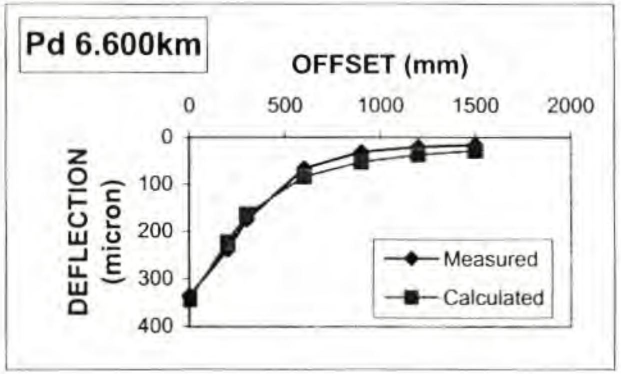


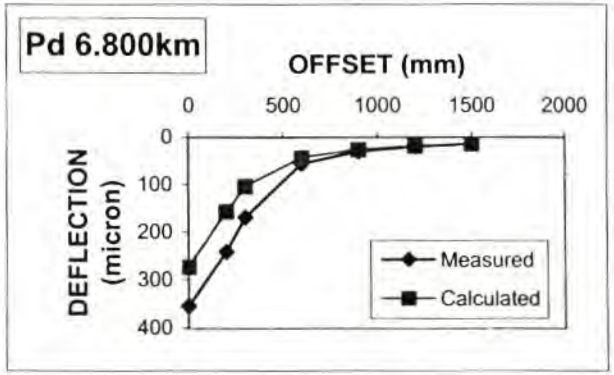
TR1102: AC35: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)

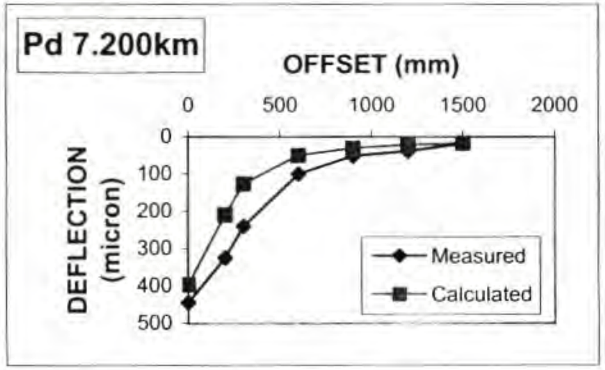


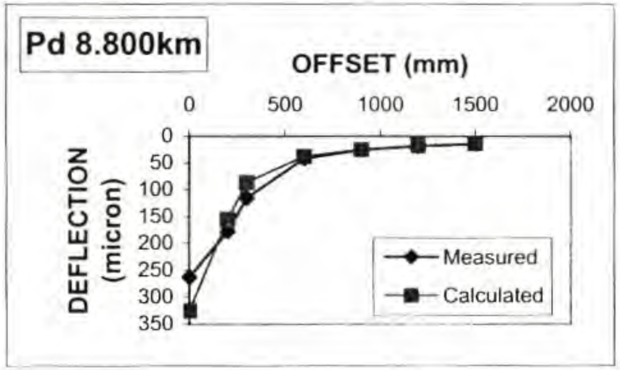
TR1102: AC35: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)

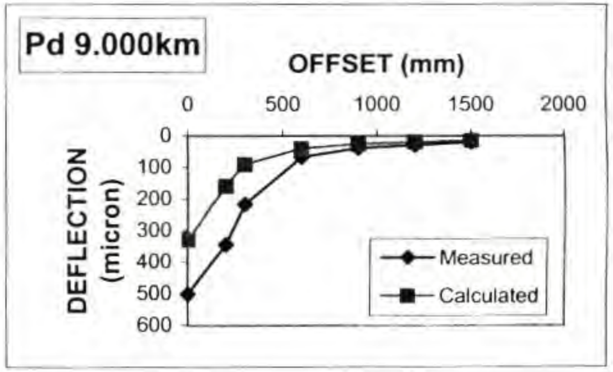


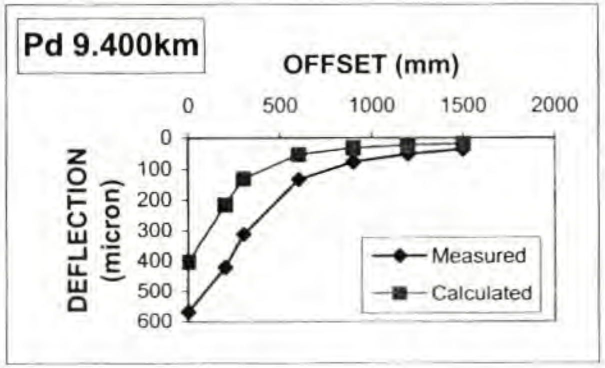


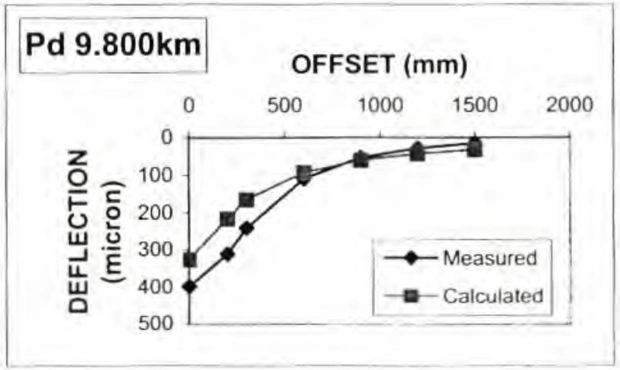


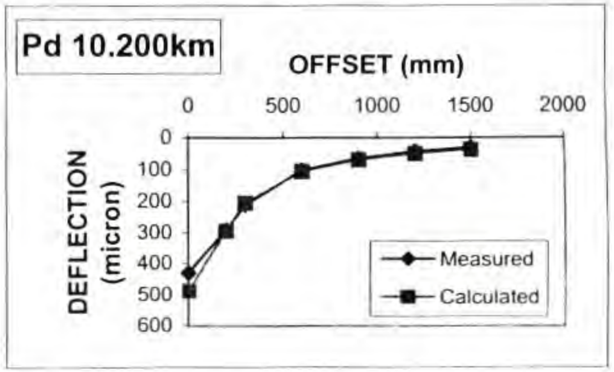




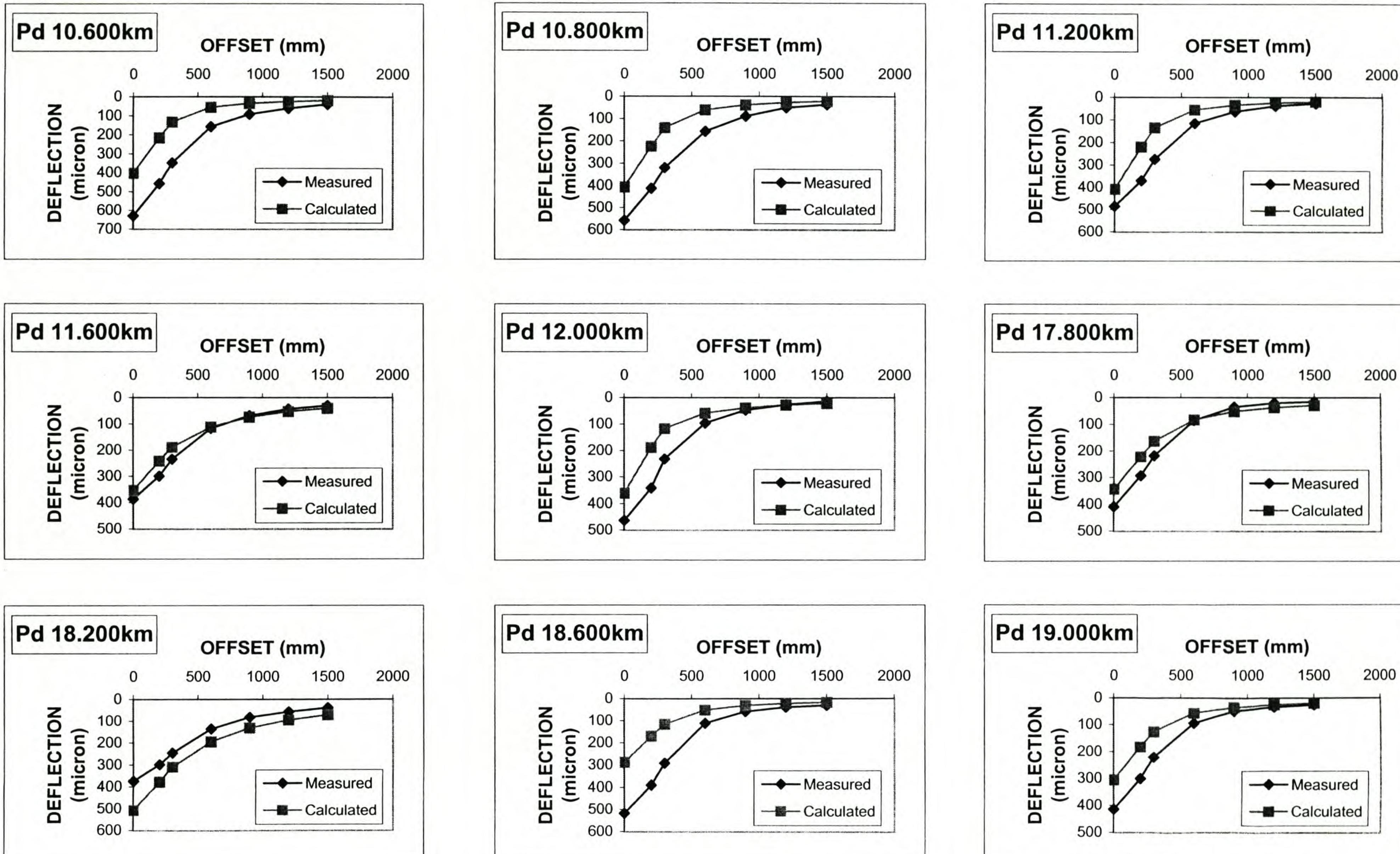








TR1102: AC35: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)



TR1102: AC35: COMPARISON OF MEASURED AND CALCULATED DEFLECTIONS: CASE (a)

Pos (Km)\Offset (mm)		0	200	300	600	900	1200	1500	RMSE (%)
0.000	Measured	185	148	125	75	41	24	16	146.58%
	Calculated	401	278	225	144	99	71	54	
0.400	Measured	427	313	230	92	39	20	15	33.34%
	Calculated	301	183	127	59	36	26	20	
0.800	Measured	572	472	375	194	111	61	49	19.69%
	Calculated	565	360	261	139	91	66	51	
1.200	Measured	191	136	104	35	12	9	8	28.22%
	Calculated	222	109	67	28	17	12	9	
1.600	Measured	206	144	104	48	28	25	19	47.10%
	Calculated	309	195	142	75	48	34	25	
2.000	Measured	234	180	141	61	30	23	26	59.95%
	Calculated	360	232	174	94	60	43	33	
2.200	Measured	461	344	263	106	45	26	15	52.80%
	Calculated	355	233	173	91	58	41	32	
2.400	Measured	165	133	103	46	22	19	14	84.39%
	Calculated	330	211	154	78	49	34	27	
2.600	Measured	369	276	216	95	48	31	22	59.33%
	Calculated	411	285	222	126	82	59	44	
2.800	Measured	332	238	169	61	28	19	14	22.94%
	Calculated	294	177	122	55	33	24	18	
3.200	Measured	330	244	180	81	43	29	23	19.30%
	Calculated	347	225	167	86	54	38	29	
3.600	Measured	420	298	205	62	30	21	16	33.38%
	Calculated	366	183	102	35	22	16	12	
3.800	Measured	440	299	198	60	32	22	17	32.83%
	Calculated	376	188	104	36	23	17	13	
4.200	Measured	316	228	169	65	31	20	19	58.53%
	Calculated	355	233	174	91	58	41	31	
4.600	Measured	548	404	289	109	54	36	26	51.37%
	Calculated	385	195	111	40	25	19	15	
5.000	Measured	321	220	154	62	35	24	18	12.39%
	Calculated	387	218	141	61	38	27	21	
5.400	Measured	399	295	213	78	39	26	24	30.17%
	Calculated	292	174	119	54	32	23	18	
5.800	Measured	260	183	122	53	33	25	16	26.24%
	Calculated	361	192	123	63	42	30	23	
6.200	Measured	413	295	222	85	37	24	18	51.73%
	Calculated	366	241	181	96	61	44	33	
6.600	Measured	336	239	176	66	31	20	16	52.25%
	Calculated	343	222	164	84	53	37	29	
6.800	Measured	354	241	169	56	30	20	15	24.21%
	Calculated	273	157	104	43	26	19	14	
7.200	Measured	445	326	241	101	52	39	19	37.19%
	Calculated	397	210	126	50	31	22	18	
8.800	Measured	263	178	116	42	26	19	15	15.06%
	Calculated	325	155	87	38	25	18	14	
9.000	Measured	502	346	217	68	39	30	20	42.05%
	Calculated	329	159	90	40	26	19	15	
9.400	Measured	569	421	313	134	78	52	37	52.06%
	Calculated	403	215	131	53	33	24	19	
9.800	Measured	398	312	241	109	53	29	15	51.50%
	Calculated	326	215	164	92	60	43	32	
10.200	Measured	431	291	211	102	65	43	31	10.74%
	Calculated	486	295	205	105	68	49	37	
10.600	Measured	629	458	348	158	92	61	40	56.42%
	Calculated	403	217	133	55	34	25	19	
10.800	Measured	558	413	320	157	89	51	36	48.92%
	Calculated	406	223	141	61	38	28	21	
11.200	Measured	486	371	275	116	64	39	28	40.32%
	Calculated	408	220	136	56	35	25	20	
11.600	Measured	387	300	235	117	69	44	31	18.24%
	Calculated	354	242	189	112	74	53	41	
12.000	Measured	464	342	232	96	47	27	14	37.57%
	Calculated	362	189	117	58	39	28	22	
12.400	Measured	530	395	305	139	74	48	32	57.48%
	Calculated	274	159	108	50	30	21	16	
17.800	Measured	409	294	219	86	36	21	16	47.88%
	Calculated	343	222	163	84	53	37	29	
18.200	Measured	375	299	246	137	83	57	39	53.14%
	Calculated	508	378	310	195	132	96	72	
18.600	Measured	518	390	292	113	60	40	31	50.79%
	Calculated	288	170	116	51	31	22	17	
19.000	Measured	415	301	221	95	49	34	26	33.53%
	Calculated	305	183	126	57	35	25	19	

TR01102: 85AC: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (a)
DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
7.60	317	252	200	87	39	26	18	117	113	48	72.50	F18	5.29	25.00	592	6897001	21.10
8.00	360	250	180	63	24	14	10	180	117	39	47.10	F18	4.93	25.00	592	6784360	20.90
8.20	219	169	132	60	26	15	9	87	72	34	82.20	F18	6.09	25.00	592	12157536	30.60
8.40	244	190	150	70	33	17	11	94	80	37	80.10	F18	5.86	25.00	592	7431145	22.20
8.60	346	226	136	43	25	19	13	210	93	18	34.70	F18	5.02	25.00	592	4907550	16.50
12.80	475	362	294	161	99	67	47	181	133	62	46.70	F18	3.04	3.00	592	213676	1.00
13.20	388	311	260	140	69	38	23	128	120	71	68.40	F18	3.45	3.50	592	473292	2.10
13.60	383	285	221	101	46	26	20	162	120	55	54.70	F18	4.75	20.50	592	2463080	9.40
13.80	600	447	337	134	58	35	23	263	203	76	16.60	F18	3.30	8.60	592	3213	0.00
14.20	556	414	323	164	94	61	47	233	159	70	26.10	F18	2.75	3.20	592	71737	0.30
14.40	626	442	335	155	81	49	33	291	180	74	9.60	F18	2.47	3.10	592	42270	0.20
14.60	246	179	146	80	42	26	15	100	66	38	78.20	F18	5.82	21.30	592	1921198	7.60
14.80	451	360	298	175	95	53	30	153	123	80	58.50	F18	3.12	3.00	592	36302	0.20
15.00	321	277	245	152	93	65	47	76	93	59	85.20	F18	4.17	3.70	592	391672	1.70
15.20	318	250	192	85	39	22	13	126	107	46	69.20	F18	5.20	22.80	592	1014249	4.30
15.60	299	221	167	71	39	26	20	132	96	32	66.90	F18	5.42	25.00	592	3447833	12.50
16.00	214	169	122	53	30	20	16	92	69	23	80.70	F18	6.20	25.00	592	2865363	10.70
16.20	153	126	105	58	34	24	18	48	47	24	91.50	F18	7.37	25.00	592	29881385	49.70
16.60	280	215	174	78	35	22	16	106	96	43	76.30	F18	5.55	25.00	592	6428892	20.10
17.00	416	303	232	108	52	34	24	184	124	56	45.40	F18	4.52	18.10	592	1534114	6.20
17.40	337	276	230	125	61	35	21	107	105	64	75.90	F18	4.11	5.60	592	942222	4.00

TR01102: 85AC: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (a)
DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

NEURAL NETWORK: BACKCALCULATED E-MODULI

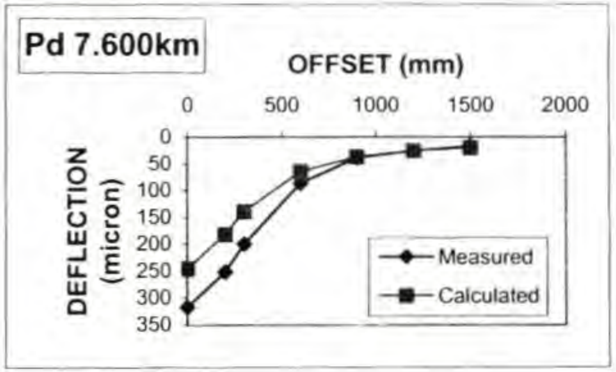
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
7.60	85	150	150	10549	317	252	200	87	39	26	18	10998	306	201	294	10000
8.00	85	150	150	10070	360	250	180	63	24	14	10	5225	322	200	477	10000
8.20	85	150	150	9823	219	169	132	60	26	15	9	10995	673	201	359	10000
8.40	85	150	150	9970	244	190	150	70	33	17	11	10996	561	201	305	10000
8.60	85	150	150	9107	346	226	136	43	25	19	13	10900	302	600	251	10000
12.80	85	150	150	11390	475	362	294	161	99	67	47	5027	587	201	146	10000
13.20	85	150	150	12005	388	311	260	140	69	38	23	6117	699	201	144	10000
13.60	85	150	150	10953	383	285	221	101	46	26	20	5200	603	200	375	10000
13.80	85	150	150	12376	600	447	337	134	58	35	23	7063	301	200	382	10000
14.20	85	150	150	11933	556	414	323	164	94	61	47	5025	306	200	161	10000
14.40	85	150	150	12225	626	442	335	155	81	49	33	5009	504	200	278	10000
14.60	85	150	150	10020	246	179	146	80	42	26	15	5050	700	291	147	10000
14.80	85	150	150	12690	451	360	298	175	95	53	30	5192	642	200	172	10000
15.00	85	150	150	11198	321	277	245	152	93	65	47	9993	700	201	83	10000
15.20	85	150	150	10438	318	250	192	85	39	22	13	10987	301	600	367	10000
15.60	85	150	150	9728	299	221	167	71	39	26	20	10598	302	245	301	10000
16.00	85	150	150	9320	214	169	122	53	30	20	16	10873	302	600	189	10000
16.20	85	150	150	9363	153	126	105	58	34	24	18	10999	700	219	225	10000
16.60	85	150	150	10277	280	215	174	78	35	22	16	6866	699	201	216	10000
17.00	85	150	150	11013	416	303	232	108	52	34	24	5055	433	200	327	10000
17.40	85	150	150	11521	337	276	230	125	61	35	21	9271	699	200	194	10000

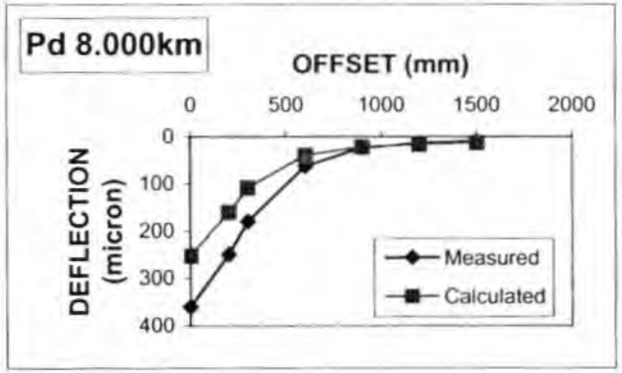
TR01102: 85AC: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (a)
DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000 Mpa

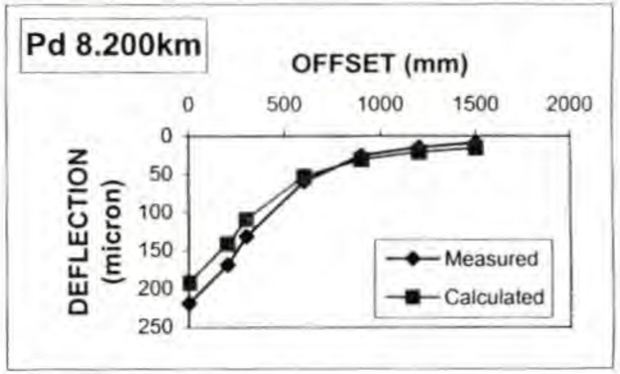
Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

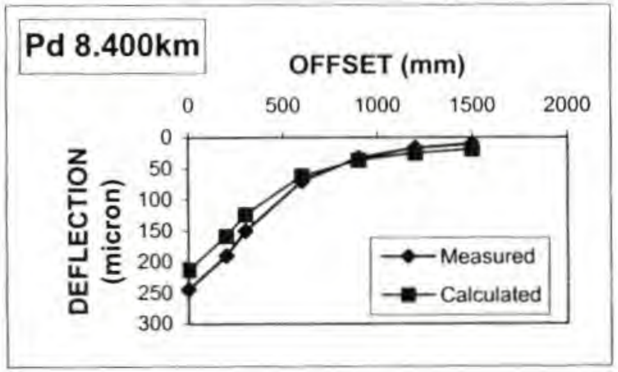
WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

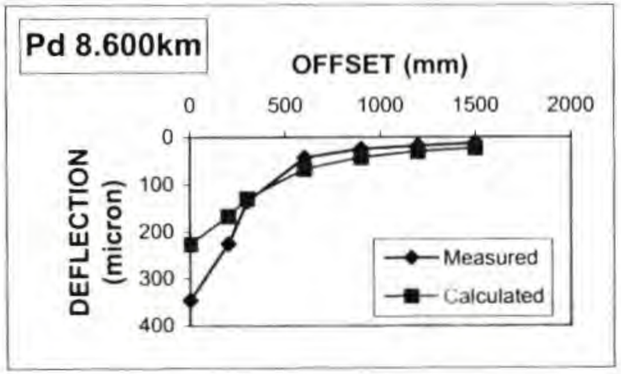
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
7.60	85.00	150.00	150.00	10549	246	182	139	64	37	26	20	10998	306	201	294	10000
8.00	85.00	150.00	150.00	10070	252	160	109	39	22	16	13	5225	322	200	477	10000
8.20	85.00	150.00	150.00	9823	192	141	109	53	31	21	16	10995	673	201	359	10000
8.40	85.00	150.00	150.00	9970	213	158	124	62	36	25	19	10996	561	201	305	10000
8.60	85.00	150.00	150.00	9107	227	167	130	67	43	31	23	10900	302	600	251	10000
12.80	85.00	150.00	150.00	11390	333	252	204	120	78	56	42	5027	587	201	146	10000
13.20	85.00	150.00	150.00	12005	312	242	200	121	80	57	43	6117	699	201	144	10000
13.60	85.00	150.00	150.00	10953	226	152	112	51	30	21	16	5200	603	200	375	10000
13.80	85.00	150.00	150.00	12376	254	173	124	50	28	21	16	7063	301	200	382	10000
14.20	85.00	150.00	150.00	11933	373	271	210	110	70	50	38	5025	306	200	161	10000
14.40	85.00	150.00	150.00	12225	266	184	138	67	41	29	22	5009	504	200	278	10000
14.60	85.00	150.00	150.00	10020	300	228	187	114	77	55	41	5050	700	291	147	10000
14.80	85.00	150.00	150.00	12690	302	226	182	104	68	48	37	5192	642	200	172	10000
15.00	85.00	150.00	150.00	11198	383	323	283	193	137	100	76	9993	700	201	83	10000
15.20	85.00	150.00	150.00	10438	196	138	103	48	30	21	16	10987	301	600	367	10000
15.60	85.00	150.00	150.00	9728	238	174	133	61	36	25	19	10598	302	245	301	10000
16.00	85.00	150.00	150.00	9320	256	195	156	87	57	41	31	10873	302	600	189	10000
16.20	85.00	150.00	150.00	9363	226	175	142	79	50	34	26	10999	700	219	225	10000
16.60	85.00	150.00	150.00	10277	255	190	151	83	52	37	28	6866	699	201	216	10000
17.00	85.00	150.00	150.00	11013	261	176	127	57	34	24	19	5055	433	200	327	10000
17.40	85.00	150.00	150.00	11521	254	197	161	92	59	42	31	9271	699	200	194	10000

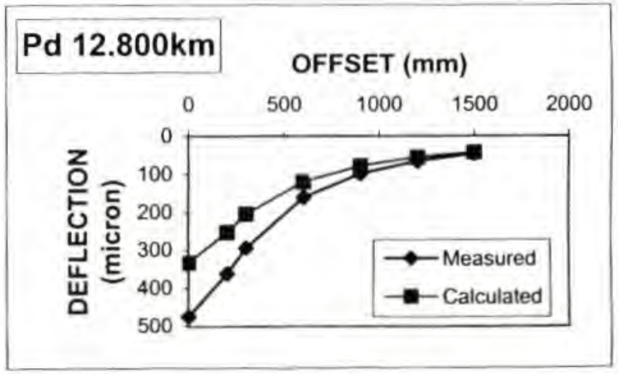


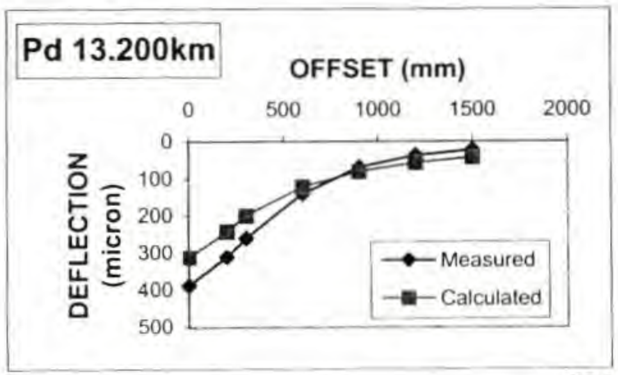


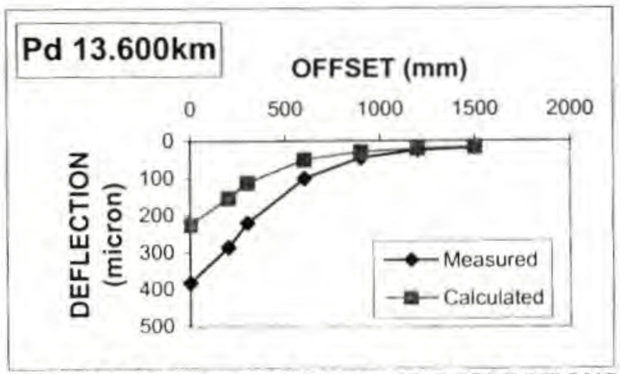


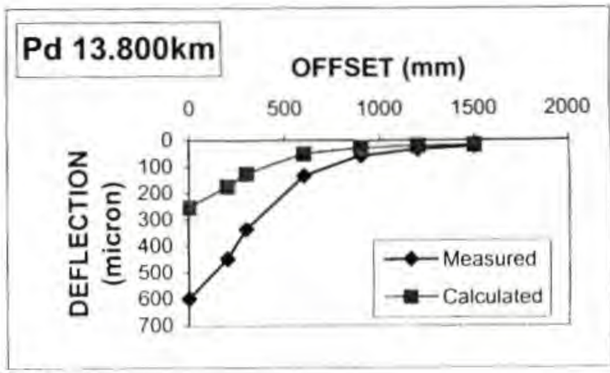




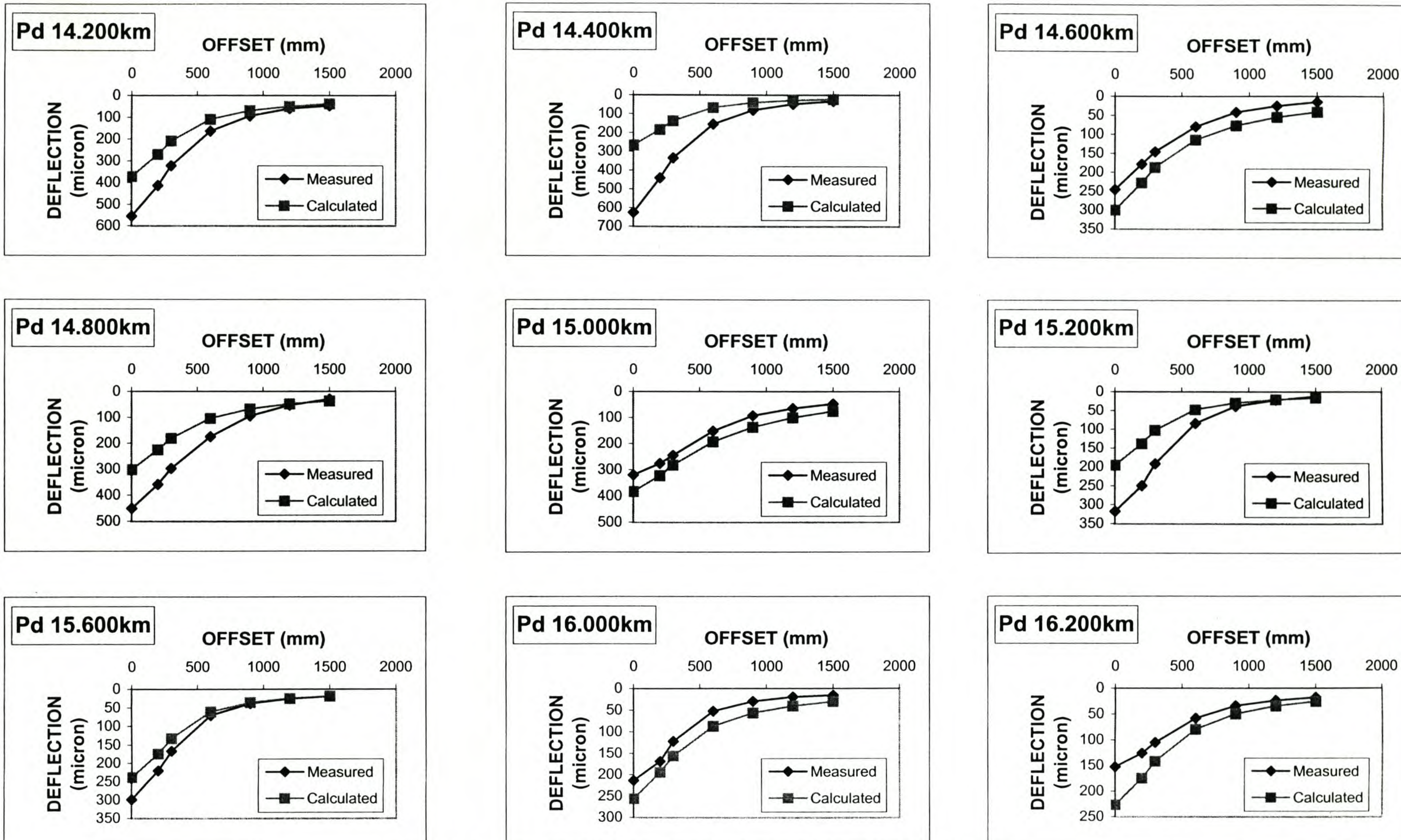








TR1102: AC85: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)



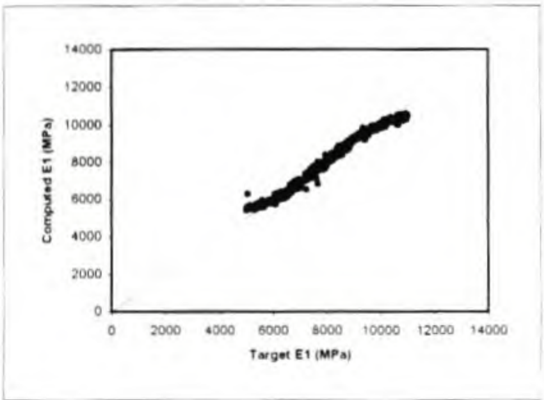
TR1102: AC85: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)

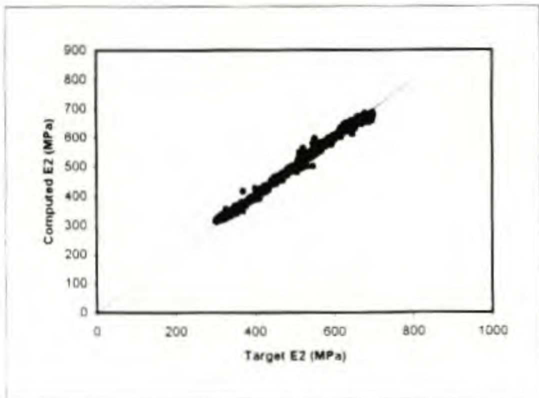
TR1102: AC85: COMPARISON OF MEASURED AND CALCULATED DEFLECTIONS: CASE (a)

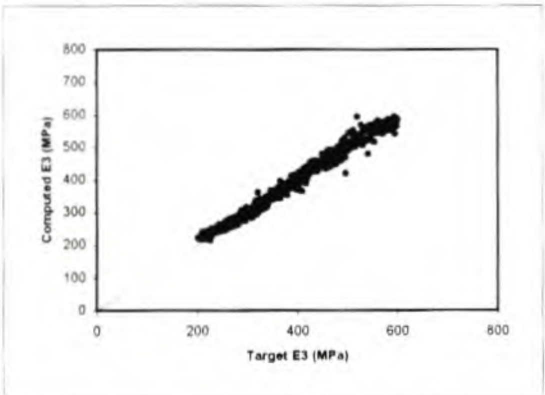
Pos (Km)\Offset (mm)		0	200	300	600	900	1200	1500	RMSE (%)
7.600	Measured	317	252	200	87	39	26	18	20.70%
	Calculated	246	182	139	64	37	26	20	
8.000	Measured	360	250	180	63	24	14	10	29.68%
	Calculated	252	160	109	39	22	16	13	
8.200	Measured	219	169	132	60	26	15	9	35.85%
	Calculated	192	141	109	53	31	21	16	
8.400	Measured	244	190	150	70	33	17	11	34.97%
	Calculated	213	158	124	62	36	25	19	
8.600	Measured	346	226	136	43	25	19	13	53.59%
	Calculated	227	167	130	67	43	31	23	
12.800	Measured	475	362	294	161	99	67	47	24.51%
	Calculated	333	252	204	120	78	56	42	
13.200	Measured	388	311	260	140	69	38	23	41.54%
	Calculated	312	242	200	121	80	57	43	
13.600	Measured	383	285	221	101	46	26	20	39.13%
	Calculated	226	152	112	51	30	21	16	
13.800	Measured	600	447	337	134	58	35	23	53.68%
	Calculated	254	173	124	50	28	21	16	
14.200	Measured	556	414	323	164	94	61	47	29.17%
	Calculated	373	271	210	110	70	50	38	
14.400	Measured	626	442	335	155	81	49	33	51.53%
	Calculated	266	184	138	67	41	29	22	
14.600	Measured	246	179	146	80	42	26	15	87.85%
	Calculated	300	228	187	114	77	55	41	
14.800	Measured	451	360	298	175	95	53	30	31.83%
	Calculated	302	226	182	104	68	48	37	
15.000	Measured	321	277	245	152	93	65	47	38.93%
	Calculated	383	323	283	193	137	100	76	
15.200	Measured	318	250	192	85	39	22	13	35.49%
	Calculated	196	138	103	48	30	21	16	
15.600	Measured	299	221	167	71	39	26	20	15.06%
	Calculated	238	174	133	61	36	25	19	
16.000	Measured	214	169	122	53	30	20	16	69.11%
	Calculated	256	195	156	87	57	41	31	
16.200	Measured	153	126	105	58	34	24	18	41.72%
	Calculated	226	175	142	79	50	34	26	
16.600	Measured	280	215	174	78	35	22	16	42.20%
	Calculated	255	190	151	83	52	37	28	
17.000	Measured	416	303	232	108	52	34	24	37.90%
	Calculated	261	176	127	57	34	24	19	
17.400	Measured	337	276	230	125	61	35	21	28.66%
	Calculated	254	197	161	92	59	42	31	

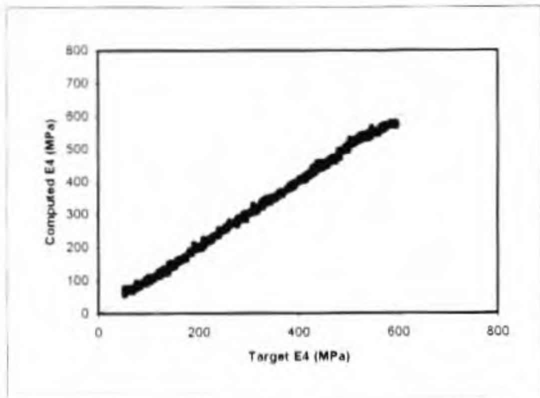
APPENDIX C.5: TR1102 CASE (b)

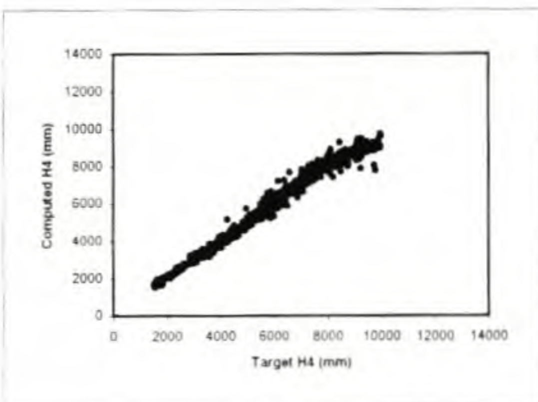
RESULTS OF BACK-CALCULATIONS (E-MODULI LAYERS 1-4 FROM DEFLECTIONS) OF A TYPICAL SOUTH AFRICAN PAVEMENT: GRANULAR BASE/SUBBASE WITH AN ASPHALT SURFACING (35mm and 85mm THICKNESS): CASE (b): DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000MPa











TR01102: 35AC: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (b)
DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
0.00	185	148	125	75	41	24	16	60	50	34	89.00	F18	6.54	24.40	418	16028350	43.50
0.40	427	313	230	92	39	20	15	197	138	53	40.00	F18	4.23	18.30	418	1298192	7.30
0.80	572	472	375	194	111	61	49	197	181	83	40.00	F18	2.55	3.00	418	81511	0.50
1.20	191	136	104	35	12	9	8	87	69	23	82.20	F18	6.00	25.00	418	3487245	16.50
1.60	206	144	104	48	28	25	19	102	56	20	77.60	F18	6.01	25.00	418	8790559	31.10
2.00	234	180	141	61	30	23	26	93	80	31	80.40	F18	5.70	25.00	418	6159858	24.80
2.20	461	344	263	106	45	26	15	198	157	61	39.60	F18	3.92	14.10	418	1142196	6.50
2.40	165	133	103	46	22	19	14	62	57	24	88.60	F18	6.56	25.00	418	16432238	44.00
2.60	369	276	216	95	48	31	22	153	121	47	58.50	F18	4.69	21.80	418	1877238	10.10
2.80	332	238	169	61	28	19	14	163	108	33	54.30	F18	4.90	25.00	418	2384155	12.30
3.20	330	244	180	81	43	29	23	150	99	38	59.70	F18	5.01	25.00	734	2713229	8.50
3.60	420	298	205	62	30	21	16	215	143	32	32.80	F18	4.47	25.00	734	1435359	4.80
3.80	440	299	198	60	32	22	17	242	138	28	23.00	F18	4.39	25.00	734	1317141	4.50
4.20	316	228	169	65	31	20	19	147	104	34	61.00	F18	5.02	25.00	734	4897212	13.90
4.60	548	404	289	109	54	36	26	259	180	55	17.70	F18	3.82	17.30	734	375960	1.30
5.00	321	220	154	62	35	24	18	167	92	27	52.60	F18	5.01	25.00	734	2150671	7.00
5.40	399	295	213	78	39	26	24	186	135	39	44.60	F18	4.60	25.00	734	797253	2.80
5.80	260	183	122	53	33	25	16	138	69	20	64.60	F18	5.47	25.00	734	1330334	4.50
6.20	413	295	222	85	37	24	18	191	137	48	42.50	F18	4.53	25.00	592	1249882	5.20
6.60	336	239	176	66	31	20	16	160	110	35	55.60	F18	4.89	25.00	592	4165379	14.50
6.80	354	241	169	56	30	20	15	185	113	26	45.00	F18	4.78	25.00	592	2543336	9.70
7.20	445	326	241	101	52	39	19	204	140	49	37.10	F18	4.17	13.50	592	1199445	5.00
8.80	263	178	116	42	26	19	15	147	74	16	61.00	F18	5.63	25.00	592	10553632	28.10
9.00	502	346	217	68	39	30	20	285	149	29	10.90	F18	4.39	25.00	592	1307211	5.40
9.40	569	421	313	134	78	52	37	256	179	56	18.60	F18	3.06	5.30	592	265309	1.20
9.80	398	312	241	109	53	29	15	157	132	56	56.80	F18	3.84	6.80	592	1023897	4.30
10.20	431	291	211	102	65	43	31	220	109	37	30.90	F18	4.01	9.60	592	1297140	5.40
10.60	629	458	348	158	92	61	40	281	190	66	11.90	F18	2.48	3.00	592	87735	0.40
10.80	558	413	320	157	89	51	36	238	163	68	24.40	F18	2.68	3.00	592	136649	0.60
11.20	486	371	275	116	64	39	28	211	159	52	34.30	F18	3.58	7.60	592	1019187	4.30
11.60	387	300	235	117	69	44	31	152	118	48	58.90	F18	3.96	6.60	592	1376963	5.70
12.00	464	342	232	96	47	27	14	232	136	49	26.50	F18	3.90	11.00	592	732079	3.10
12.40	530	395	305	139	74	48	32	225	166	65	29.00	F18	3.12	4.90	592	127694	0.60
17.80	409	294	219	86	36	21	16	190	133	50	42.90	F18	4.54	25.00	592	1269657	5.30
18.20	375	299	246	137	83	57	39	129	109	54	68.10	F18	3.75	5.20	592	519040	2.30
18.60	518	390	292	113	60	40	31	226	179	53	28.60	F18	3.75	13.70	592	274618	1.20
19.00	415	301	221	95	49	34	26	194	126	46	85.20	A4	4.44	25.00	592	1386248	5.70

TR01102: 35AC: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (b)
DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000 Mpa

Date	Jul-96
Load:	40 kN
Temp.:	17 deg C

NEURAL NETWORK: BACKCALCULATED E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	35	150	150	1673	185	148	125	75	41	24	16	10999.1	700.0	248.3	153.3	10000.0
0.40	35	150	150	1527	427	313	230	92	39	20	15	10999.1	314.1	200.8	120.7	10000.0
0.80	35	150	150	1510	572	472	375	194	111	61	49	10999.1	300.0	600.0	53.7	10000.0
1.20	35	150	150	10000	191	136	104	35	12	9	8	10999.1	700.0	200.2	599.8	10000.0
1.60	35	150	150	10000	206	144	104	48	28	25	19	10999.1	618.6	201.1	551.4	10000.0
2.00	35	150	150	10000	234	180	141	61	30	23	26	10999.1	700.0	200.1	552.3	10000.0
2.20	35	150	150	2052	461	344	263	106	45	26	15	10999.1	677.7	200.2	167.1	10000.0
2.40	35	150	150	10000	165	133	103	46	22	19	14	10999.1	700.0	200.1	574.6	10000.0
2.60	35	150	150	9932	369	276	216	95	48	31	22	10999.1	700.0	200.2	347.5	10000.0
2.80	35	150	150	1724	332	238	169	61	28	19	14	10999.1	303.8	200.7	200.0	10000.0
3.20	35	150	150	2321	330	244	180	81	43	29	23	10999.1	304.4	249.0	170.6	10000.0
3.60	35	150	150	1604	420	298	205	62	30	21	16	10999.1	300.0	600.0	131.6	10000.0
3.80	35	150	150	1695	440	299	198	60	32	22	17	10999.1	300.0	600.0	140.9	10000.0
4.20	35	150	150	9965	316	228	169	65	31	20	19	10999.1	681.0	200.1	390.6	10000.0
4.60	35	150	150	1528	548	404	289	109	54	36	26	10999.1	300.0	600.0	83.6	10000.0
5.00	35	150	150	3550	321	220	154	62	35	24	18	10999.1	307.1	292.3	213.9	10000.0
5.40	35	150	150	2038	399	295	213	78	39	26	24	10999.1	300.0	543.0	135.5	10000.0
5.80	35	150	150	5265	260	183	122	53	33	25	16	10999.1	300.0	600.0	233.1	10000.0
6.20	35	150	150	9924	413	295	222	85	37	24	18	10998.5	700.0	200.2	372.9	10000.0
6.60	35	150	150	9202	336	239	176	66	31	20	16	10999.1	675.9	200.1	346.1	10000.0
6.80	35	150	150	9005	354	241	169	56	30	20	15	10999.1	397.4	200.1	324.8	10000.0
7.20	35	200	150	1698	445	326	241	101	52	39	19	10999.1	300.3	203.2	117.1	10000.0
8.80	35	200	150	6620	263	178	116	42	26	19	15	10999.1	300.0	600.0	286.5	10000.0
9.00	35	200	150	8799	502	346	217	68	39	30	20	10999.1	300.0	600.0	109.0	10000.0
9.40	35	200	150	1821	569	421	313	134	78	52	37	10999.1	300.0	600.0	80.5	10000.0
9.80	35	200	150	1508	398	312	241	109	53	29	15	10999.1	300.0	600.0	72.0	10000.0
10.20	35	200	150	4059	431	291	211	102	65	43	31	10997.7	302.6	291.3	126.3	10000.0
10.60	35	200	150	5028	629	458	348	158	92	61	40	10976.0	325.1	200.1	123.1	10000.0
10.80	35	200	150	1571	558	413	320	157	89	51	36	10999.0	334.4	200.4	86.2	10000.0
11.20	35	200	150	1516	486	371	275	116	64	39	28	10999.1	300.0	600.0	62.9	10000.0
11.60	35	200	150	1674	387	300	235	117	69	44	31	10999.1	300.1	597.1	79.0	10000.0
12.00	35	200	150	1509	464	342	232	96	47	27	14	10999.1	300.0	600.0	67.6	10000.0
12.40	35	200	150	4064	530	395	305	139	74	48	32	10999.1	490.8	200.1	148.4	10000.0
17.80	35	150	150	3605	409	294	219	86	36	21	16	10999.1	697.3	200.2	236.5	10000.0
18.20	35	150	150	9869	375	299	246	137	83	57	39	10999.1	700.0	200.2	150.4	10000.0
18.60	35	150	150	2198	518	390	292	113	60	40	31	10999.1	300.0	204.7	108.2	10000.0
19.00	35	150	150	3524	415	301	221	95	49	34	26	10999.1	348.0	200.3	185.4	10000.0

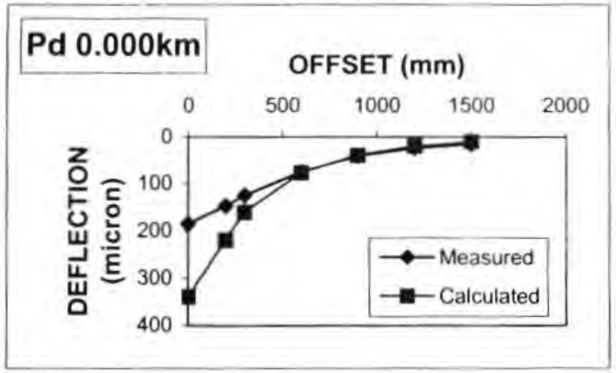
TR01102: 35AC: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (b)
DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000 Mpa

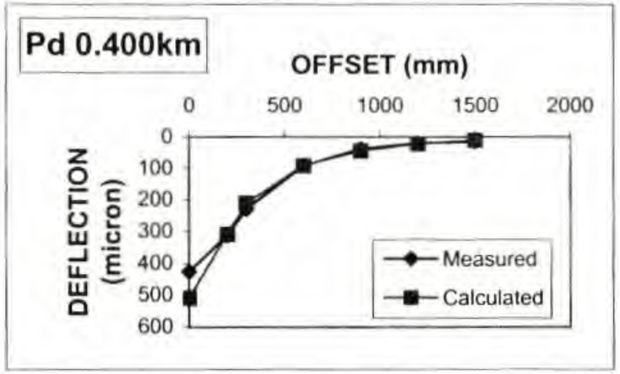
Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

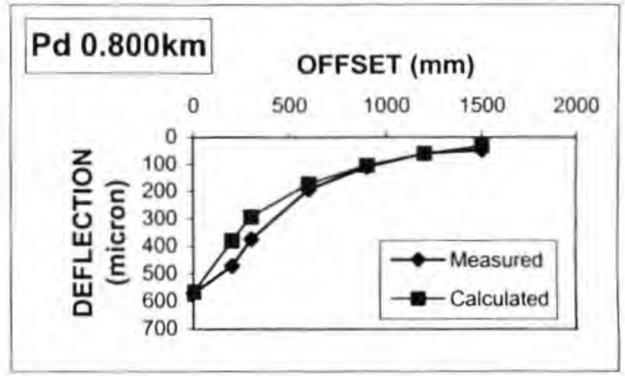
WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

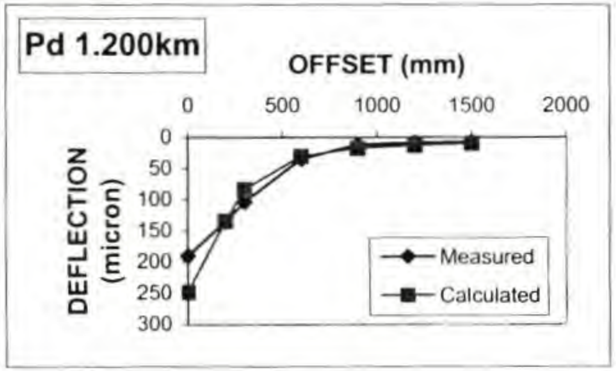
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	35	150	150	1673	339	219	161	77	39	20	10	10999.1	700.0	248.3	153.3	10000.0
0.40	35	150	150	1527	509	309	211	91	44	22	10	10999.1	314.1	200.8	120.7	10000.0
0.80	35	150	150	1510	566	380	293	172	103	61	33	10999.1	300.0	600.0	53.7	10000.0
1.20	35	150	150	10000	248	134	84	30	18	13	10	10999.1	700.0	200.2	599.8	10000.0
1.60	35	150	150	10000	266	143	89	32	19	14	11	10999.1	618.6	201.1	551.4	10000.0
2.00	35	150	150	10000	253	139	88	33	19	14	11	10999.1	700.0	200.1	552.3	10000.0
2.20	35	150	150	2052	353	228	166	78	41	23	13	10999.1	677.7	200.2	167.1	10000.0
2.40	35	150	150	10000	251	137	86	32	18	13	10	10999.1	700.0	200.1	574.6	10000.0
2.60	35	150	150	9932	289	172	117	52	31	22	17	10999.1	700.0	200.2	347.5	10000.0
2.80	35	150	150	1724	443	247	155	58	28	14	8	10999.1	303.8	200.7	200.0	10000.0
3.20	35	150	150	2321	454	262	173	76	41	24	15	10999.1	304.4	249.0	170.6	10000.0
3.60	35	150	150	1604	418	242	165	81	44	23	12	10999.1	300.0	600.0	131.6	10000.0
3.80	35	150	150	1695	411	236	160	78	42	23	12	10999.1	300.0	600.0	140.9	10000.0
4.20	35	150	150	9965	282	163	109	46	28	20	15	10999.1	681.0	200.1	390.6	10000.0
4.60	35	150	150	1528	484	304	221	119	67	37	19	10999.1	300.0	600.0	83.6	10000.0
5.00	35	150	150	3550	417	233	150	68	40	26	17	10999.1	307.1	292.3	213.9	10000.0
5.40	35	150	150	2038	430	252	174	88	50	29	17	10999.1	300.0	543.0	135.5	10000.0
5.80	35	150	150	5265	371	201	130	66	42	29	21	10999.1	300.0	600.0	233.1	10000.0
6.20	35	150	150	9924	282	166	112	49	29	21	16	10998.5	700.0	200.2	372.9	10000.0
6.60	35	150	150	9202	293	173	118	52	31	22	17	10999.1	675.9	200.1	346.1	10000.0
6.80	35	150	150	9005	367	202	128	53	33	24	18	10999.1	397.4	200.1	324.8	10000.0
7.20	35	200	150	1698	501	303	209	97	51	28	14	10999.1	300.3	203.2	117.1	10000.0
8.80	35	200	150	6620	359	186	114	55	36	25	19	10999.1	300.0	600.0	286.5	10000.0
9.00	35	200	150	8799	488	307	227	140	98	72	55	10999.1	300.0	600.0	109.0	10000.0
9.40	35	200	150	1821	488	305	223	127	78	48	28	10999.1	300.0	600.0	80.5	10000.0
9.80	35	200	150	1508	494	310	227	128	77	45	25	10999.1	300.0	600.0	72.0	10000.0
10.20	35	200	150	4059	490	301	213	114	72	48	34	10997.7	302.6	291.3	126.3	10000.0
10.60	35	200	150	5028	511	323	233	124	78	53	38	10976.0	325.1	200.1	123.1	10000.0
10.80	35	200	150	1571	525	337	245	124	67	37	18	10999.0	334.4	200.4	86.2	10000.0
11.20	35	200	150	1516	516	331	246	143	87	52	29	10999.1	300.0	600.0	62.9	10000.0
11.60	35	200	150	1674	487	303	221	124	75	45	26	10999.1	300.1	597.1	79.0	10000.0
12.00	35	200	150	1509	504	320	236	135	81	48	27	10999.1	300.0	600.0	67.6	10000.0
12.40	35	200	150	4064	399	256	190	101	62	41	28	10999.1	490.8	200.1	148.4	10000.0
17.80	35	150	150	3605	319	199	141	65	37	23	16	10999.1	697.3	200.2	236.5	10000.0
18.20	35	150	150	9869	394	270	208	116	75	53	40	10999.1	700.0	200.2	150.4	10000.0
18.60	35	150	150	2198	553	347	245	117	64	37	22	10999.1	300.0	204.7	108.2	10000.0
19.00	35	150	150	3524	448	264	178	79	46	29	20	10999.1	348.0	200.3	185.4	10000.0

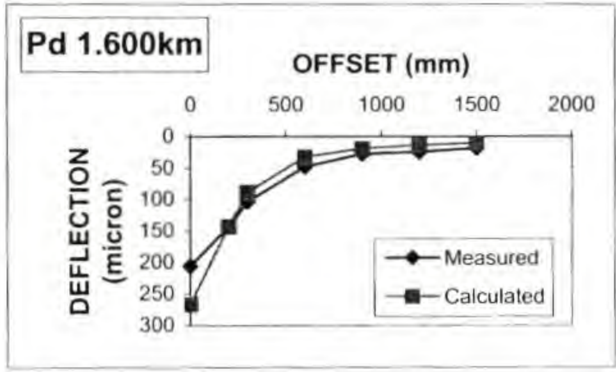
TR1102: AC53: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

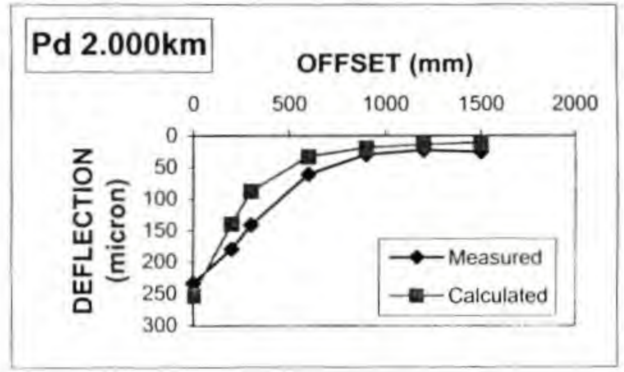


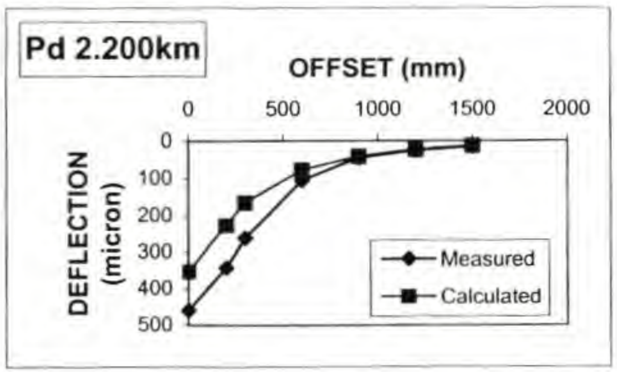


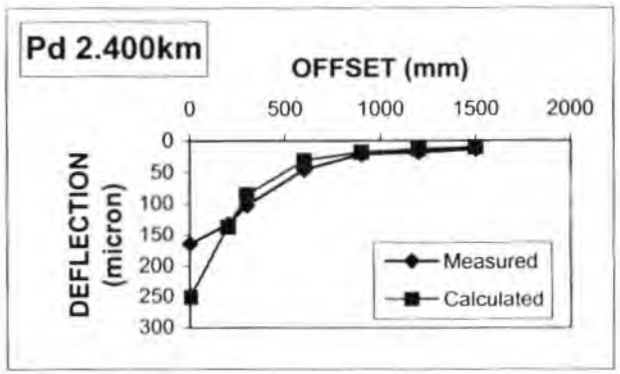


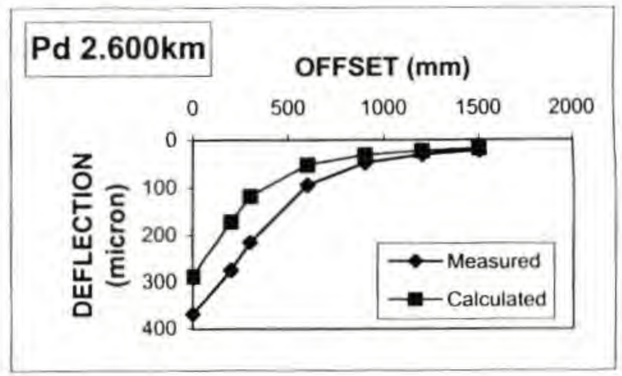




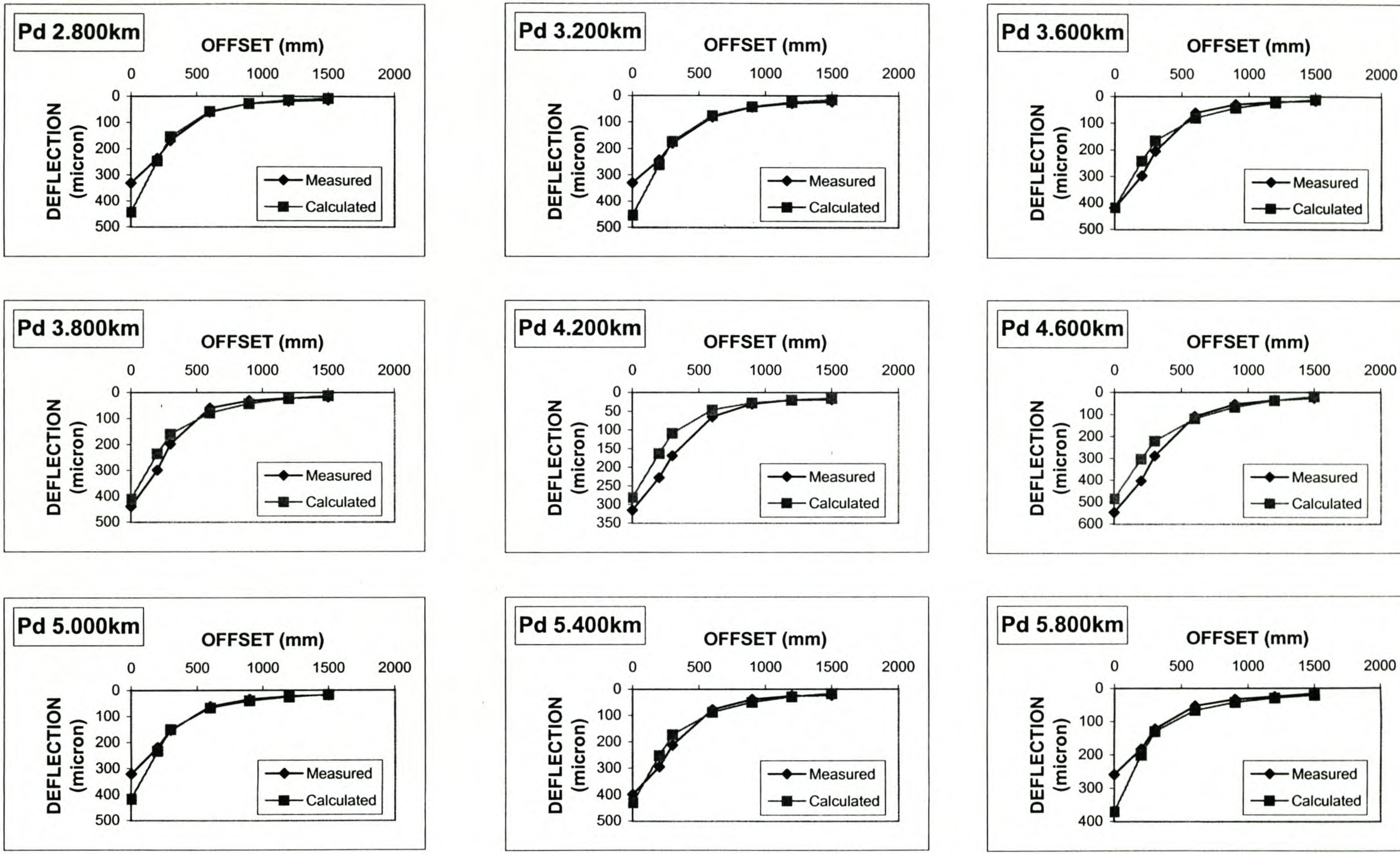




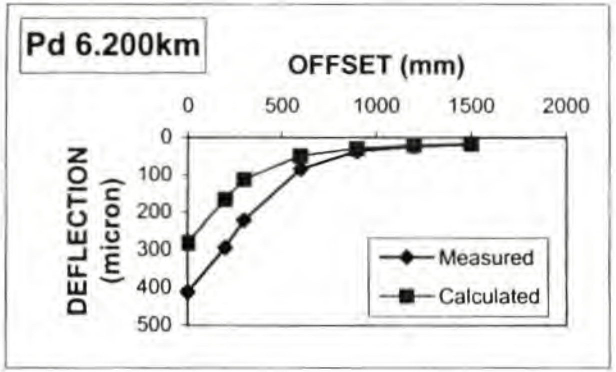


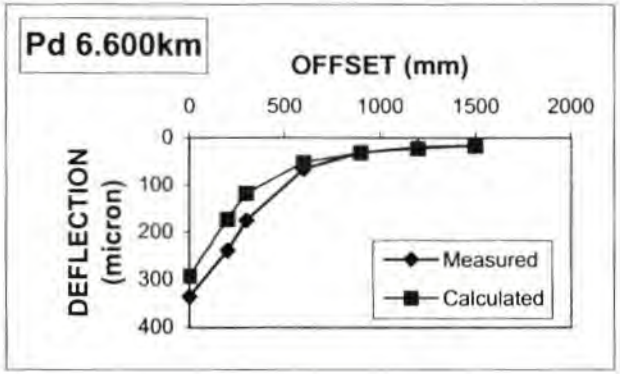


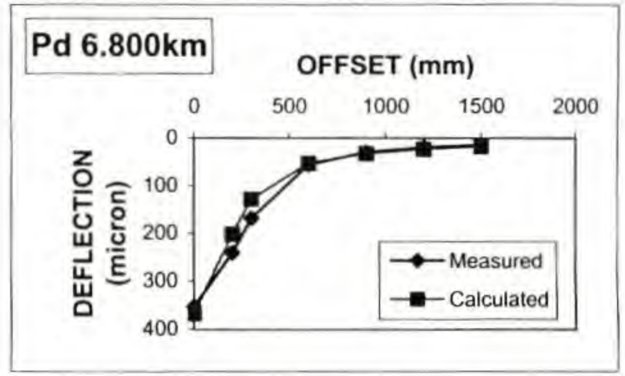
TR1102: AC35 MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

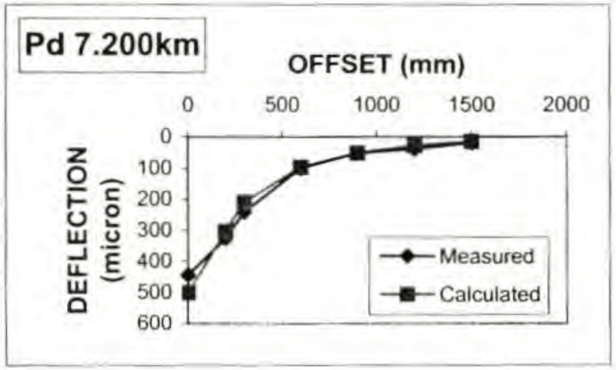


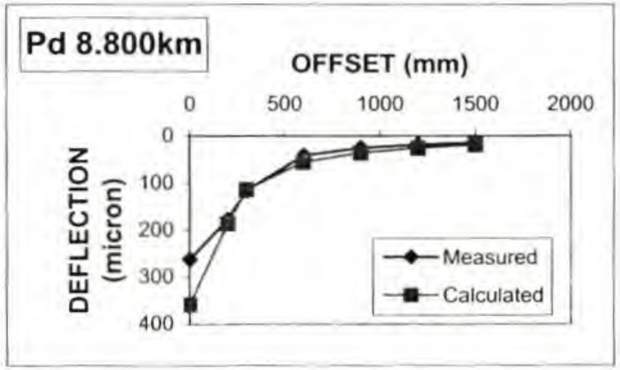
TR1102: A035: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

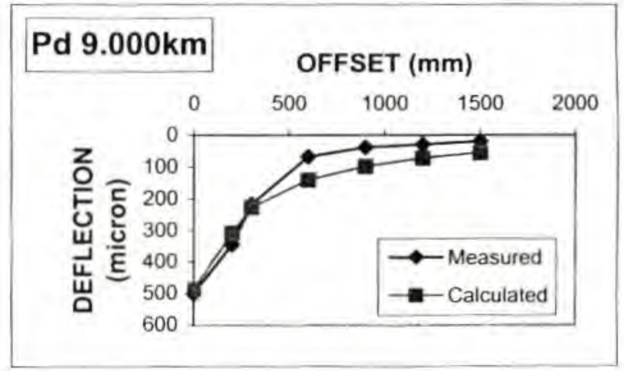


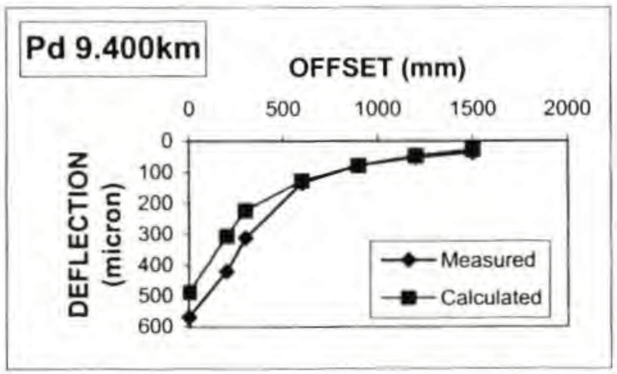


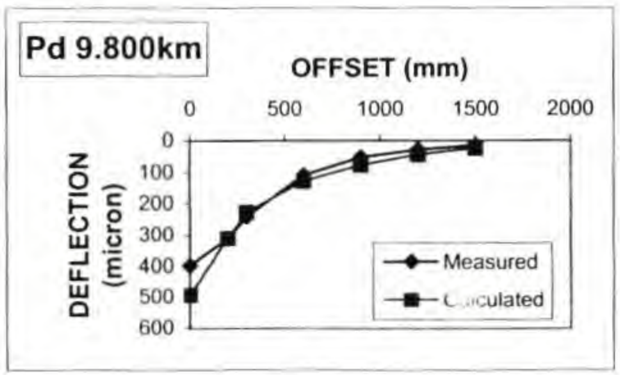


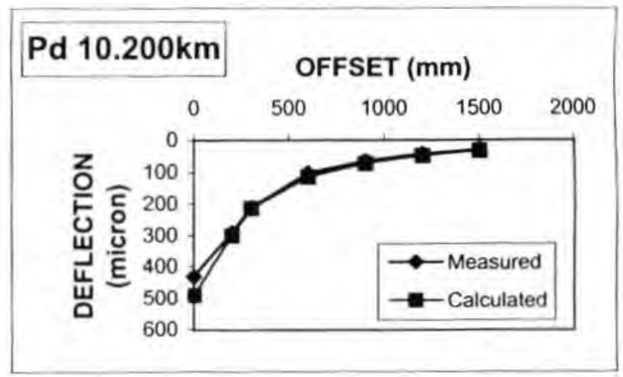




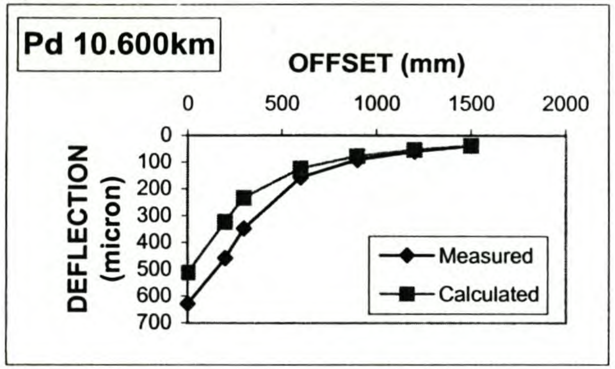


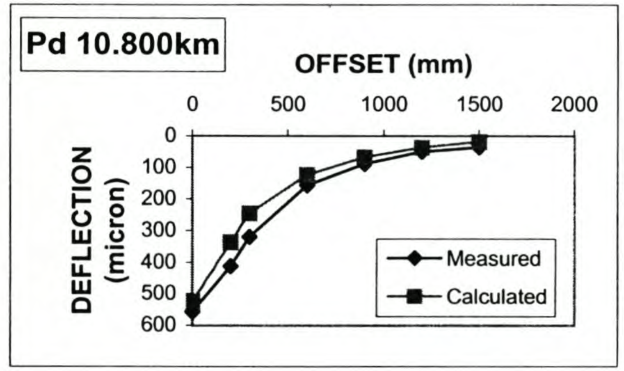


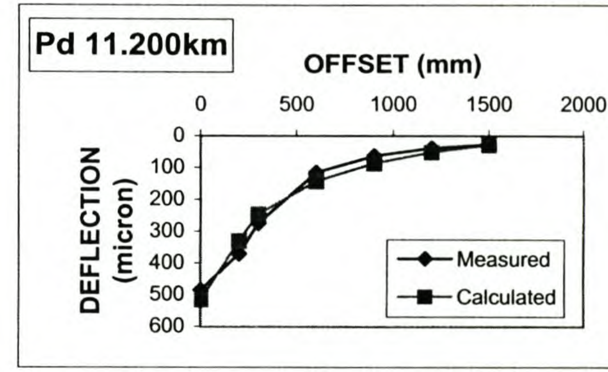


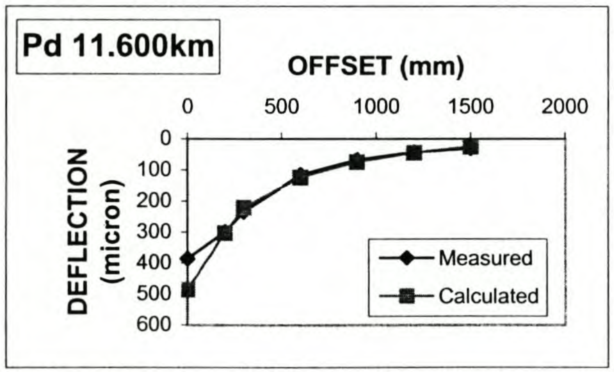


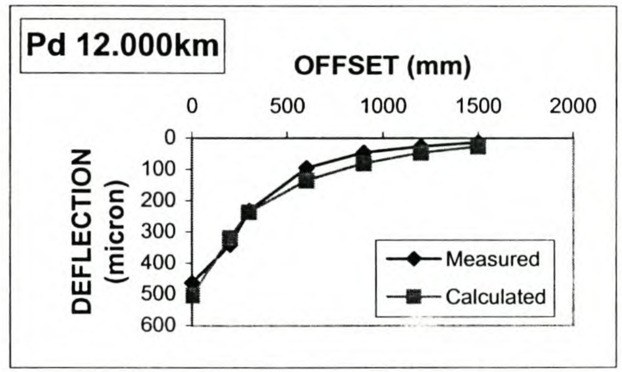
TR1102: AC35: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

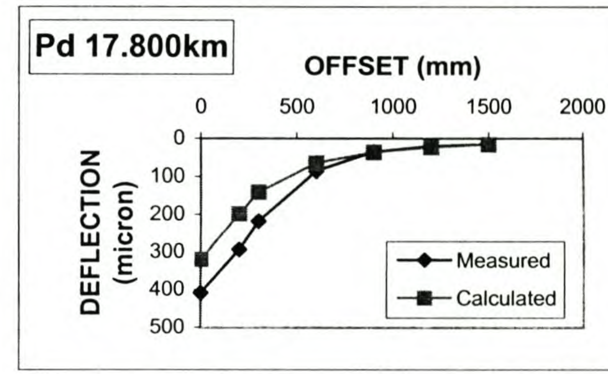


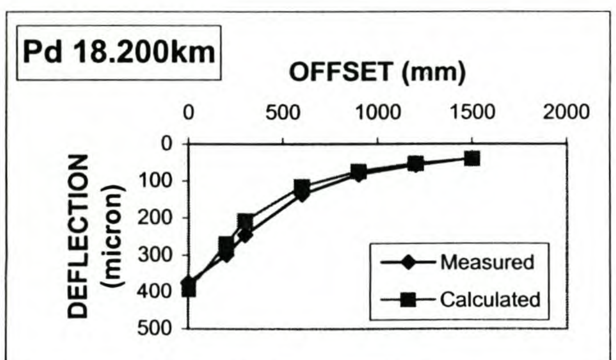


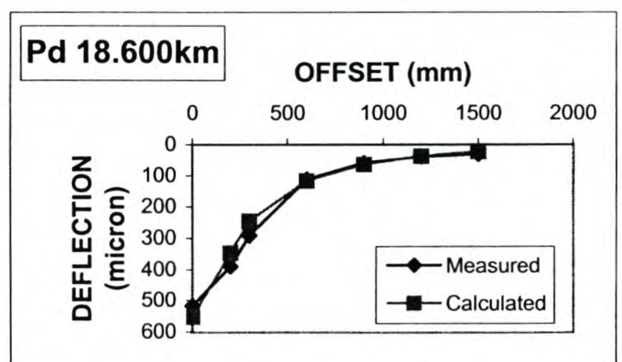


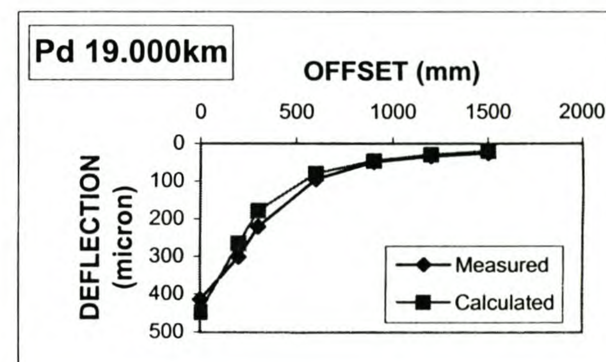












TR1102: AC35: COMPARISON OF MEASURED AND CALCULATED DEFLECTIONS: CASE (b)

Pos (Km)\Offset (mm)		0	200	300	600	900	1200	1500	RMSE (%)
0.000	Measured	185	148	125	75	41	24	16	40.82%
	Calculated	339	219	161	77	39	20	10	
0.400	Measured	427	313	230	92	39	20	15	16.16%
	Calculated	509	309	211	91	44	22	10	
0.800	Measured	572	472	375	194	111	61	49	17.40%
	Calculated	566	380	293	172	103	61	33	
1.200	Measured	191	136	104	35	12	9	8	28.90%
	Calculated	248	134	84	30	18	13	10	
1.600	Measured	206	144	104	48	28	25	19	31.47%
	Calculated	266	143	89	32	19	14	11	
2.000	Measured	234	180	141	61	30	23	26	38.65%
	Calculated	253	139	88	33	19	14	11	
2.200	Measured	461	344	263	106	45	26	15	24.73%
	Calculated	353	228	166	78	41	23	13	
2.400	Measured	165	133	103	46	22	19	14	28.87%
	Calculated	251	137	86	32	18	13	10	
2.600	Measured	369	276	216	95	48	31	22	34.77%
	Calculated	289	172	117	52	31	22	17	
2.800	Measured	332	238	169	61	28	19	14	23.66%
	Calculated	443	247	155	58	28	14	8	
3.200	Measured	330	244	180	81	43	29	23	21.09%
	Calculated	454	262	173	76	41	24	15	
3.600	Measured	420	298	205	62	30	21	16	25.67%
	Calculated	418	242	165	81	44	23	12	
3.800	Measured	440	299	198	60	32	22	17	22.87%
	Calculated	411	236	160	78	42	23	12	
4.200	Measured	316	228	169	65	31	20	19	22.38%
	Calculated	282	163	109	46	28	20	15	
4.600	Measured	548	404	289	109	54	36	26	19.39%
	Calculated	484	304	221	119	67	37	19	
5.000	Measured	321	220	154	62	35	24	18	13.56%
	Calculated	417	233	150	68	40	26	17	
5.400	Measured	399	295	213	78	39	26	24	19.43%
	Calculated	430	252	174	88	50	29	17	
5.800	Measured	260	183	122	53	33	25	16	25.19%
	Calculated	371	201	130	66	42	29	21	
6.200	Measured	413	295	222	85	37	24	18	33.74%
	Calculated	282	166	112	49	29	21	16	
6.600	Measured	336	239	176	66	31	20	16	19.50%
	Calculated	293	173	118	52	31	22	17	
6.800	Measured	354	241	169	56	30	20	15	15.66%
	Calculated	367	202	128	53	33	24	18	
7.200	Measured	445	326	241	101	52	39	19	16.36%
	Calculated	501	303	209	97	51	28	14	
8.800	Measured	263	178	116	42	26	19	15	28.34%
	Calculated	359	186	114	55	36	25	19	
9.000	Measured	502	346	217	68	39	30	20	109.87%
	Calculated	488	307	227	140	98	72	55	
9.400	Measured	569	421	313	134	78	52	37	18.86%
	Calculated	488	305	223	127	78	48	28	
9.800	Measured	398	312	241	109	53	29	15	37.70%
	Calculated	494	310	227	128	77	45	25	
10.200	Measured	431	291	211	102	65	43	31	9.82%
	Calculated	490	301	213	114	72	48	34	
10.600	Measured	629	458	348	158	92	61	40	21.31%
	Calculated	511	323	233	124	78	53	38	
10.800	Measured	558	413	320	157	89	51	36	27.10%
	Calculated	525	337	245	124	67	37	18	
11.200	Measured	486	371	275	116	64	39	28	21.58%
	Calculated	516	331	246	143	87	52	29	
11.600	Measured	387	300	235	117	69	44	31	12.73%
	Calculated	487	303	221	124	75	45	26	
12.000	Measured	464	342	232	96	47	27	14	55.35%
	Calculated	504	320	236	135	81	48	27	
12.400	Measured	530	395	305	139	74	48	32	25.65%
	Calculated	399	256	190	101	62	41	28	
17.800	Measured	409	294	219	86	36	21	16	22.40%
	Calculated	319	199	141	65	37	23	16	
18.200	Measured	375	299	246	137	83	57	39	10.43%
	Calculated	394	270	208	116	75	53	40	
18.600	Measured	518	390	292	113	60	40	31	13.92%
	Calculated	553	347	245	117	64	37	22	
19.000	Measured	415	301	221	95	49	34	26	15.22%
	Calculated	448	264	178	79	46	29	20	

TR01102: 35AC: E-MODULI BACK-CALCULATED WITH MODCOMP
H4 AND E5 FROM MODCOMP

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
0.00	185	148	125	75	41	24	16	60	50	34	89.00	F18	6.54	24.40	418	16028350	43.50
0.40	427	313	230	92	39	20	15	197	138	53	40.00	F18	4.23	18.30	418	1298192	7.30
0.80	572	472	375	194	111	61	49	197	181	83	40.00	F18	2.55	3.00	418	81511	0.50
1.20	191	136	104	35	12	9	8	87	69	23	82.20	F18	6.00	25.00	418	3487245	16.50
1.60	206	144	104	48	28	25	19	102	56	20	77.60	F18	6.01	25.00	418	8790559	31.10
2.00	234	180	141	61	30	23	26	93	80	31	80.40	F18	5.70	25.00	418	6159858	24.80
2.20	461	344	263	106	45	26	15	198	157	61	39.60	F18	3.92	14.10	418	1142196	6.50
2.40	165	133	103	46	22	19	14	62	57	24	88.60	F18	6.56	25.00	418	16432238	44.00
2.60	369	276	216	95	48	31	22	153	121	47	58.50	F18	4.69	21.80	418	1877238	10.10
2.80	332	238	169	61	28	19	14	163	108	33	54.30	F18	4.90	25.00	418	2384155	12.30
3.20	330	244	180	81	43	29	23	150	99	38	59.70	F18	5.01	25.00	734	2713229	8.50
3.60	420	298	205	62	30	21	16	215	143	32	32.80	F18	4.47	25.00	734	1435359	4.80
3.80	440	299	198	60	32	22	17	242	138	28	23.00	F18	4.39	25.00	734	1317141	4.50
4.20	316	228	169	65	31	20	19	147	104	34	61.00	F18	5.02	25.00	734	4897212	13.90
4.60	548	404	289	109	54	36	26	259	180	55	17.70	F18	3.82	17.30	734	375960	1.30
5.00	321	220	154	62	35	24	18	167	92	27	52.60	F18	5.01	25.00	734	2150671	7.00
5.40	399	295	213	78	39	26	24	186	135	39	44.60	F18	4.60	25.00	734	797253	2.80
5.80	260	183	122	53	33	25	16	138	69	20	64.60	F18	5.47	25.00	734	1330334	4.50
6.20	413	295	222	85	37	24	18	191	137	48	42.50	F18	4.53	25.00	592	1249882	5.20
6.60	336	239	176	66	31	20	16	160	110	35	55.60	F18	4.89	25.00	592	4165379	14.50
6.80	354	241	169	56	30	20	15	185	113	26	45.00	F18	4.78	25.00	592	2543336	9.70
7.20	445	326	241	101	52	39	19	204	140	49	37.10	F18	4.17	13.50	592	1199445	5.00
8.80	263	178	116	42	26	19	15	147	74	16	61.00	F18	5.63	25.00	592	10553632	28.10
9.00	502	346	217	68	39	30	20	285	149	29	10.90	F18	4.39	25.00	592	1307211	5.40
9.40	569	421	313	134	78	52	37	256	179	56	18.60	F18	3.06	5.30	592	265309	1.20
9.80	398	312	241	109	53	29	15	157	132	56	56.80	F18	3.84	6.80	592	1023897	4.30
10.20	431	291	211	102	65	43	31	220	109	37	30.90	F18	4.01	9.60	592	1297140	5.40
10.60	629	458	348	158	92	61	40	281	190	66	11.90	F18	2.48	3.00	592	87735	0.40
10.80	558	413	320	157	89	51	36	238	163	68	24.40	F18	2.68	3.00	592	136649	0.60
11.20	486	371	275	116	64	39	28	211	159	52	34.30	F18	3.58	7.60	592	1019187	4.30
11.60	387	300	235	117	69	44	31	152	118	48	58.90	F18	3.96	6.60	592	1376963	5.70
12.00	464	342	232	96	47	27	14	232	136	49	26.50	F18	3.90	11.00	592	732079	3.10
12.40	530	395	305	139	74	48	32	225	166	65	29.00	F18	3.12	4.90	592	127694	0.60
17.80	409	294	219	86	36	21	16	190	133	50	42.90	F18	4.54	25.00	592	1269657	5.30
18.20	375	299	246	137	83	57	39	129	109	54	68.10	F18	3.75	5.20	592	519040	2.30
18.60	518	390	292	113	60	40	31	226	179	53	28.60	F18	3.75	13.70	592	274618	1.20
19.00	415	301	221	95	49	34	26	194	126	46	85.20	A4	4.44	25.00	592	1386248	5.70

TR01102: 35AC: E-MODULI BACK-CALCULATED WITH MODCOMP
H4 AND E5 FROM MODCOMP

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

NEURAL NETWORK: BACKCALCULATED E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	35	150	150	9823	185	148	125	75	41	24	16	8000.0	3850.0	287.0	200.0	3500.0
0.40	35	150	150	10834	427	313	230	92	39	20	15	8000.0	741.0	80.5	191.0	689000.0
0.80	35	150	150	12937	572	472	375	194	111	61	49	8000.0	757.0	86.4	88.3	689000.0
1.20	35	150	150	9320	191	136	104	35	12	9	8	8000.0	1690.0	166.0	495.0	689000.0
1.60	35	150	150	9191	206	144	104	48	28	25	19	8000.0	1340.0	229.0	549.0	34.4
2.00	35	150	150	9681	234	180	141	61	30	23	26	8000.0	1530.0	194.0	280.0	689000.0
2.20	35	150	150	11325	461	344	263	106	45	26	15	8000.0	931.0	34.4	178.0	689000.0
2.40	35	150	150	9363	165	133	103	46	22	19	14	8000.0	2260.0	301.0	381.0	689000.0
2.60	35	150	150	10493	369	276	216	95	48	31	22	8000.0	935.0	126.0	162.0	2070.0
2.80	35	150	150	9775	332	238	169	61	28	19	14	8000.0	870.0	108.0	261.0	62400.0
3.20	35	150	150	10020	330	244	180	81	43	29	23	8000.0	908.0	162.0	205.0	5570.0
3.60	35	150	150	9728	420	298	205	62	30	21	16	8000.0	641.0	68.1	268.0	251000.0
3.80	35	150	150	9542	440	299	198	60	32	22	17	8000.0	560.0	70.9	277.0	6590.0
4.20	35	150	150	9823	316	228	169	65	31	20	19	8000.0	979.0	114.0	271.0	689000.0
4.60	35	150	150	10953	548	404	289	109	54	36	26	8000.0	572.0	56.5	142.0	5810.0
5.00	35	150	150	9497	321	220	154	62	35	24	18	8000.0	793.0	146.0	272.0	1120.0
5.40	35	150	150	10070	399	295	213	78	39	26	24	8000.0	787.0	76.6	226.0	689000.0
5.80	35	150	150	9191	260	183	122	53	33	25	16	8000.0	912.0	228.0	332.0	689000.0
6.20	35	150	150	10549	413	295	222	85	37	24	18	8000.0	762.0	85.2	183.0	107000.0
6.60	35	150	150	9872	336	239	176	66	31	20	16	8000.0	892.0	110.0	243.0	30200.0
6.80	35	150	150	9452	354	241	169	56	30	20	15	8000.0	1000.0	32.4	860.0	3500.0
7.20	35	200	150	10604	445	326	241	101	52	39	19	8000.0	584.0	63.9	173.0	689000.0
8.80	35	200	150	9025	263	178	116	42	26	19	15	8000.0	735.0	145.0	448.0	643.0
9.00	35	200	150	9588	502	346	217	68	39	30	20	8000.0	383.0	54.0	262.0	689000.0
9.40	35	200	150	11013	569	421	313	134	78	52	37	8000.0	493.0	40.4	138.0	126.0
9.80	35	200	150	11013	398	312	241	109	53	29	15	8000.0	506.0	51.4	156.0	11000.0
10.20	35	200	150	9970	431	291	211	102	65	43	31	8000.0	506.0	90.7	242.0	66.1
10.60	35	200	150	11655	629	458	348	158	92	61	40	8000.0	454.0	40.0	108.0	147.0
10.80	35	200	150	11792	558	413	320	157	89	51	36	8000.0	508.0	63.6	104.0	180.0
11.20	35	200	150	10776	486	371	275	116	64	39	28	8000.0	578.0	54.5	137.0	413.0
11.60	35	200	150	10549	387	300	235	117	69	44	31	8000.0	750.0	104.0	157.0	156.0
12.00	35	200	150	10604	464	342	232	96	47	27	14	8000.0	548.0	42.4	183.0	689000.0
12.40	35	200	150	11587	530	395	305	139	74	48	32	8000.0	540.0	60.1	105.0	1100.0
17.80	35	150	150	10661	409	294	219	86	36	21	16	8000.0	927.0	45.4	228.0	689000.0
18.20	35	150	150	10893	375	299	246	137	83	57	39	8000.0	1870.0	21.5	360.0	83.9
18.60	35	150	150	10834	518	390	292	113	60	40	31	8000.0	674.0	56.4	144.0	1930.0
19.00	35	150	150	10438	415	301	221	95	49	34	26	8000.0	720.0	107.0	174.0	36000.0

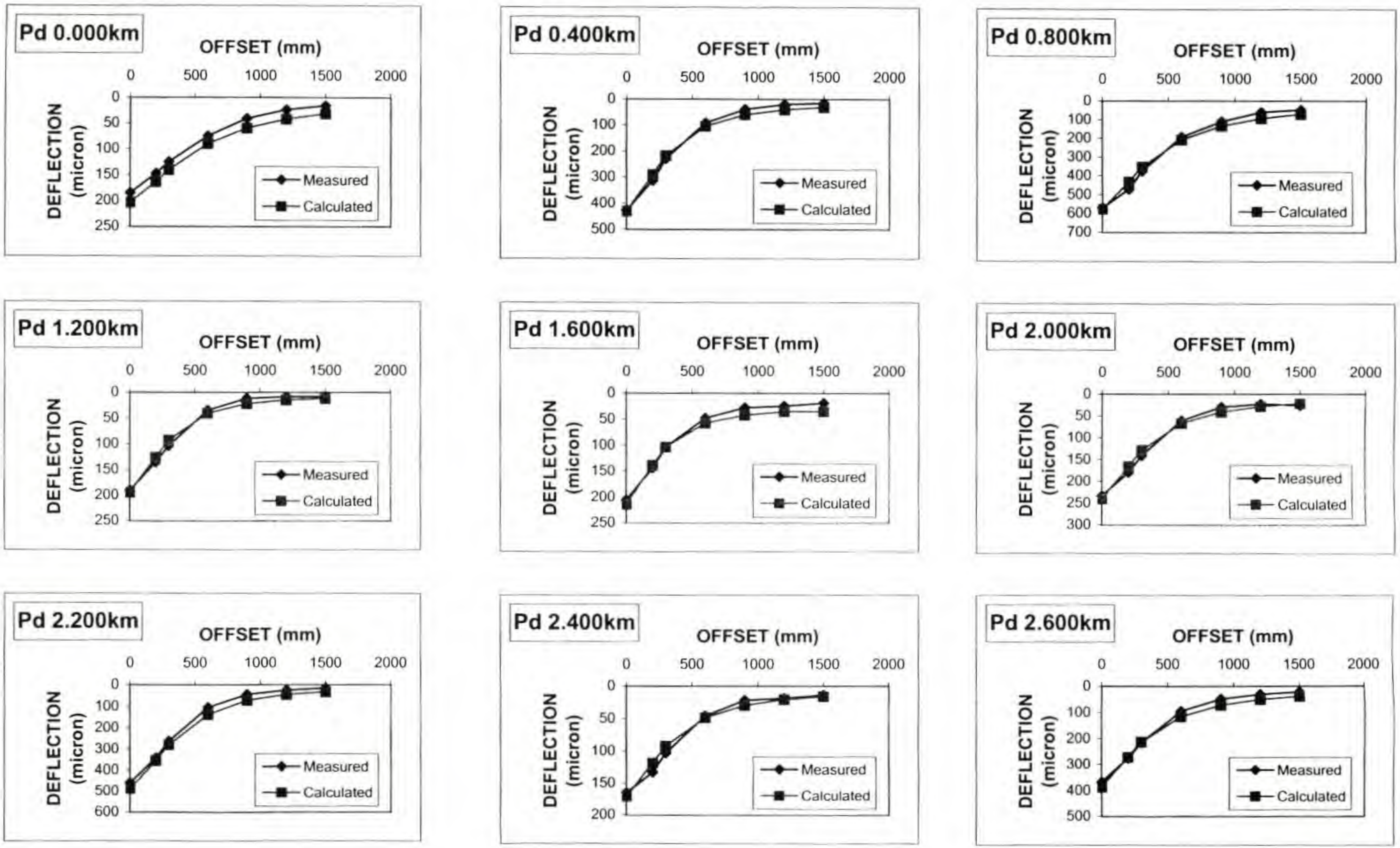
TR01102: 35AC: E-MODULI BACK-CALCULATED WITH MODCOMP
H4 AND E5 FROM MODCOMP

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

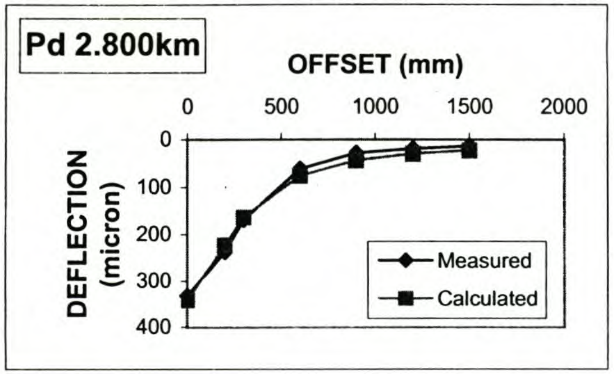
WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

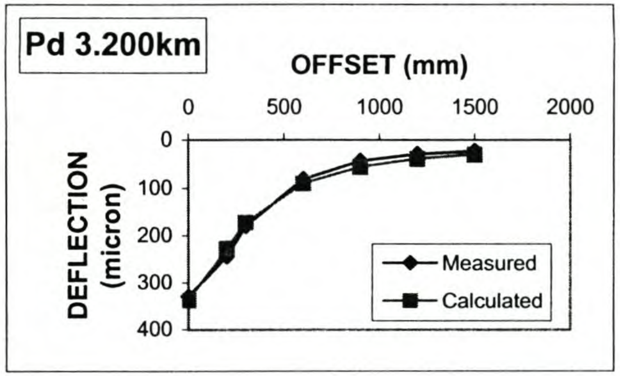
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	35	150	150	9823	203	164	141	90	60	42	32	8000.0	3850.0	287.0	200.0	3500.0
0.40	35	150	150	10834	431	291	218	104	60	41	31	8000.0	741.0	80.5	191.0	689000.0
0.80	35	150	150	12937	577	432	353	209	134	95	72	8000.0	757.0	86.4	88.3	689000.0
1.20	35	150	150	9320	195	127	93	41	22	15	12	8000.0	1690.0	166.0	495.0	689000.0
1.60	35	150	150	9191	214	138	104	58	42	36	35	8000.0	1340.0	229.0	549.0	34.4
2.00	35	150	150	9681	241	166	129	67	41	28	21	8000.0	1530.0	194.0	280.0	689000.0
2.20	35	150	150	11325	489	356	280	138	73	45	33	8000.0	931.0	34.4	178.0	689000.0
2.40	35	150	150	9363	171	118	92	49	30	20	16	8000.0	2260.0	301.0	381.0	689000.0
2.60	35	150	150	10493	387	272	213	116	72	50	38	8000.0	935.0	126.0	162.0	2070.0
2.80	35	150	150	9775	342	223	163	75	43	29	22	8000.0	870.0	108.0	261.0	62400.0
3.20	35	150	150	10020	338	227	173	90	55	39	30	8000.0	908.0	162.0	205.0	5570.0
3.60	35	150	150	9728	427	272	192	78	41	28	22	8000.0	641.0	68.1	268.0	251000.0
3.80	35	150	150	9542	443	274	189	74	39	27	21	8000.0	560.0	70.9	277.0	6590.0
4.20	35	150	150	9823	319	210	156	73	41	29	22	8000.0	979.0	114.0	271.0	689000.0
4.60	35	150	150	10953	567	389	294	142	82	55	42	8000.0	572.0	56.5	142.0	5810.0
5.00	35	150	150	9497	328	207	149	70	42	30	23	8000.0	793.0	146.0	272.0	1120.0
5.40	35	150	150	10070	402	268	198	91	50	34	26	8000.0	787.0	76.6	226.0	689000.0
5.80	35	150	150	9191	262	161	115	54	33	23	18	8000.0	912.0	228.0	332.0	689000.0
6.20	35	150	150	10549	427	290	219	107	63	43	33	8000.0	762.0	85.2	183.0	107000.0
6.60	35	150	150	9872	345	228	169	80	46	32	24	8000.0	892.0	110.0	243.0	30200.0
6.80	35	150	150	9452	360	239	171	58	17	6	5	8000.0	1000.0	32.4	860.0	3500.0
7.20	35	200	150	10604	448	301	229	118	69	47	35	8000.0	584.0	63.9	173.0	689000.0
8.80	35	200	150	9025	265	155	106	47	27	19	15	8000.0	735.0	145.0	448.0	643.0
9.00	35	200	150	9588	505	307	211	85	43	28	22	8000.0	383.0	54.0	262.0	689000.0
9.40	35	200	150	11013	573	399	309	165	99	68	53	8000.0	493.0	40.4	138.0	126.0
9.80	35	200	150	11013	513	347	263	134	78	52	39	8000.0	506.0	51.4	156.0	11000.0
10.20	35	200	150	9970	422	266	193	98	62	48	39	8000.0	506.0	90.7	242.0	66.1
10.60	35	200	150	11655	641	454	357	198	123	85	65	8000.0	454.0	40.0	108.0	147.0
10.80	35	200	150	11792	574	407	323	188	122	86	67	8000.0	508.0	63.6	104.0	180.0
11.20	35	200	150	10776	502	351	274	151	92	63	48	8000.0	578.0	54.5	137.0	413.0
11.60	35	200	150	10549	392	274	217	127	83	60	48	8000.0	750.0	104.0	157.0	156.0
12.00	35	200	150	10604	491	332	252	124	69	44	32	8000.0	548.0	42.4	183.0	689000.0
12.40	35	200	150	11587	557	397	316	182	116	80	61	8000.0	540.0	60.1	105.0	1100.0
17.80	35	150	150	10661	426	298	228	105	54	34	26	8000.0	927.0	45.4	228.0	689000.0
18.20	35	150	150	10893	368	286	236	125	65	38	27	8000.0	1870.0	21.5	360.0	83.9
18.60	35	150	150	10834	531	372	286	142	82	55	42	8000.0	674.0	56.4	144.0	1930.0
19.00	35	150	150	10438	424	286	215	108	65	45	35	8000.0	720.0	107.0	174.0	36000.0

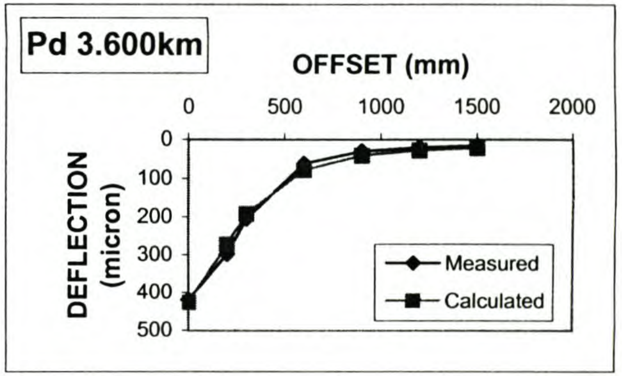
TR1102: AC35: MEASURED vs CALCULATED DEFLECTIONS: MODCOMP

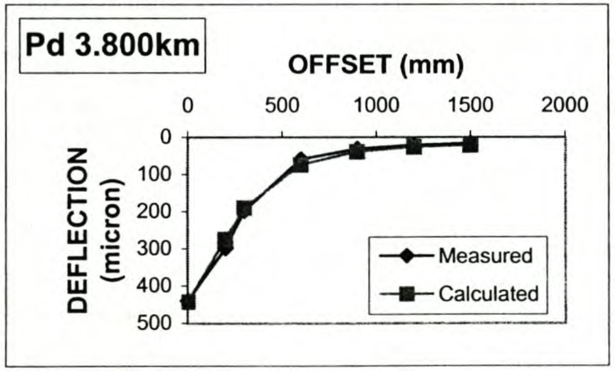


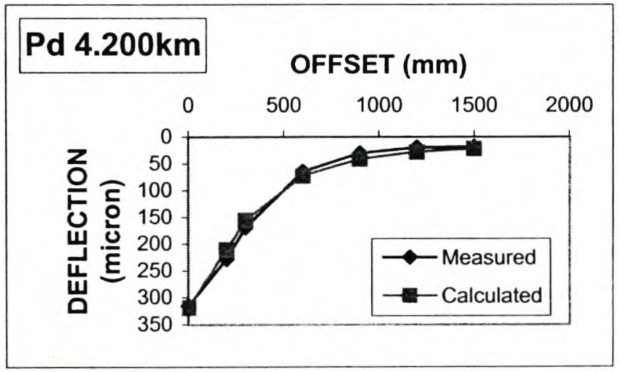
TR1102: AC35: MEASURED vs CALCULATED DEFLECTIONS: MODCOMP

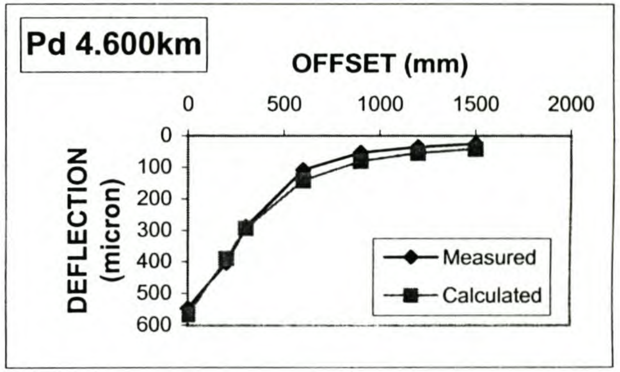


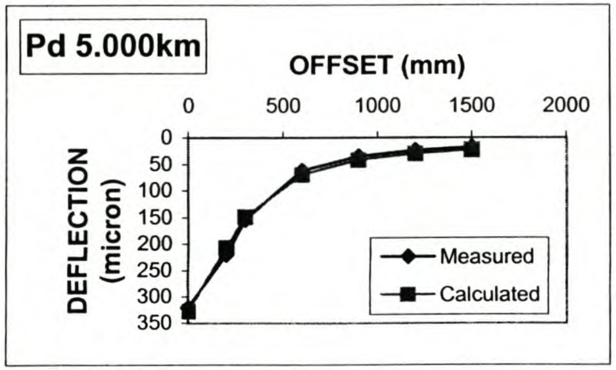


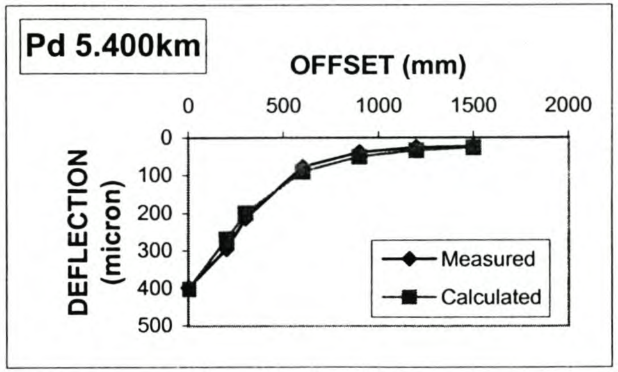


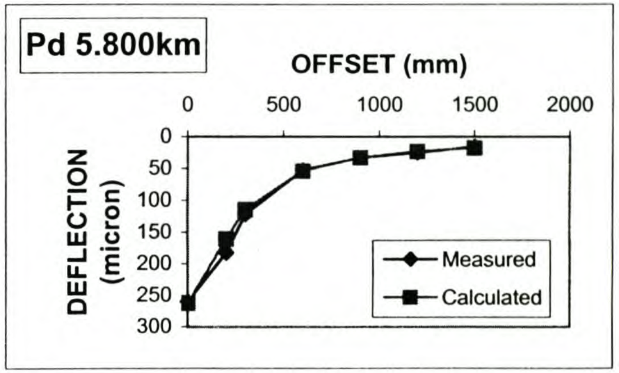




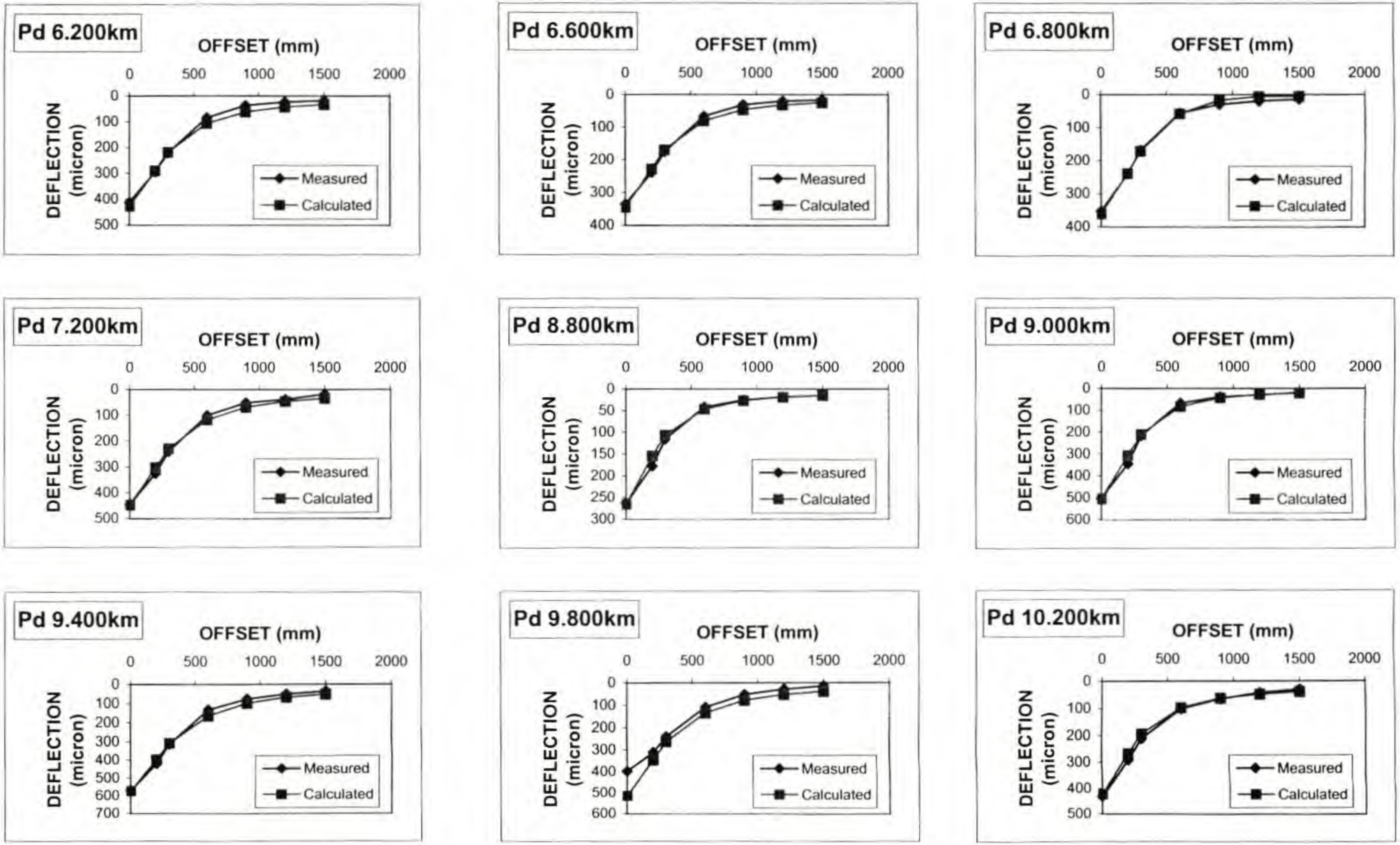




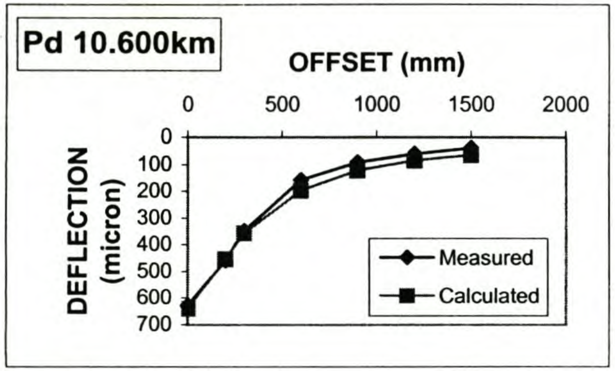


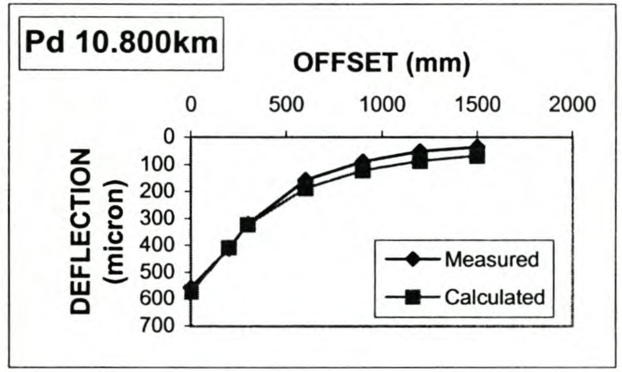


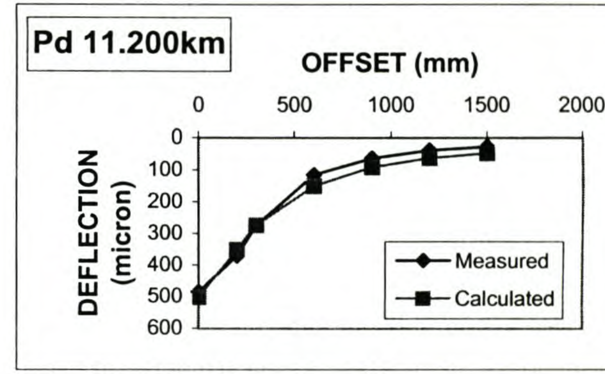
TR1102: AC35: MEASURED vs CALCULATED DEFLECTIONS: MODCOMP

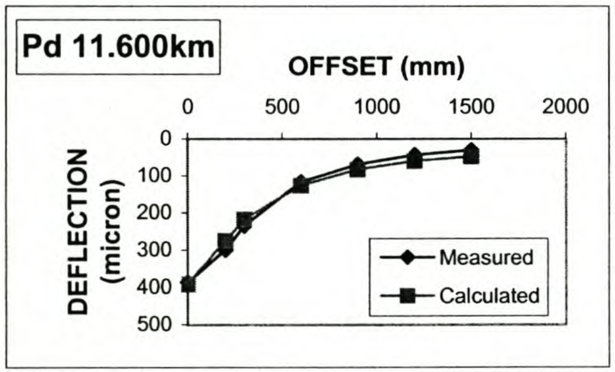


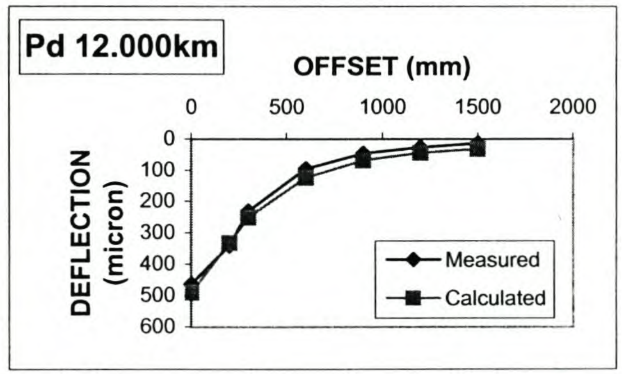
TR1102: AC35: MEASURED vs CALCULATED DEFLECTIONS: MODCOMP

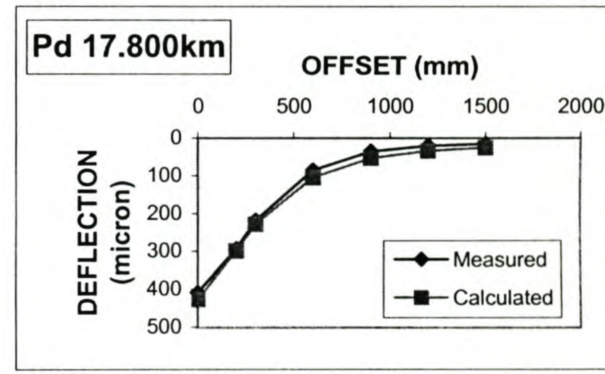


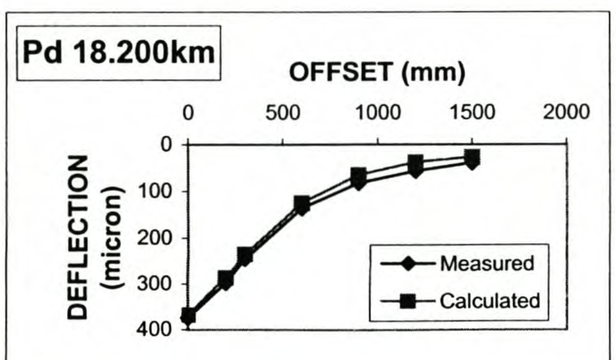


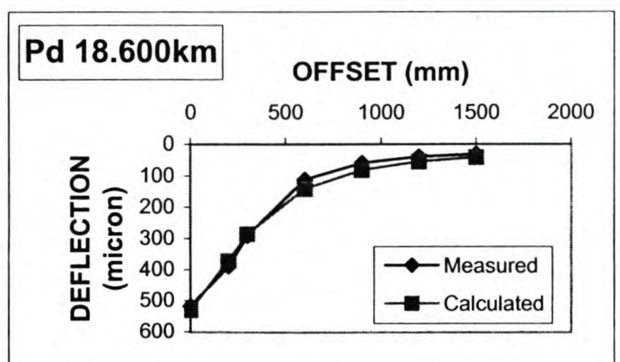


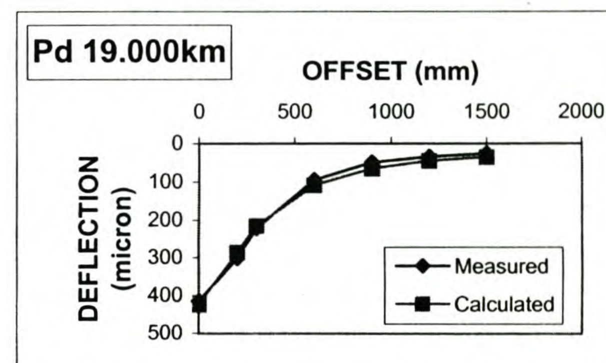












TR1102: AC35: COMPARISON OF MEASURED AND CALCULATED DEFLECTIONS: MODCOMP

Pos (Km)\Offset (mm)		0	200	300	600	900	1200	1500	RMSE (%)
0.000	Measured	185	148	125	75	41	24	16	50.96%
	Calculated	203	164	141	90	60	42	32	
0.400	Measured	427	313	230	92	39	20	15	60.41%
	Calculated	431	291	218	104	60	41	31	
0.800	Measured	572	472	375	194	111	61	49	28.90%
	Calculated	577	432	353	209	134	95	72	
1.200	Measured	191	136	104	35	12	9	8	44.93%
	Calculated	195	127	93	41	22	15	12	
1.600	Measured	206	144	104	48	28	25	19	41.36%
	Calculated	214	138	104	58	42	36	35	
2.000	Measured	234	180	141	61	30	23	26	18.91%
	Calculated	241	166	129	67	41	28	21	
2.200	Measured	461	344	263	106	45	26	15	59.04%
	Calculated	489	356	280	138	73	45	33	
2.400	Measured	165	133	103	46	22	19	14	15.56%
	Calculated	171	118	92	49	30	20	16	
2.600	Measured	369	276	216	95	48	31	22	41.48%
	Calculated	387	272	213	116	72	50	38	
2.800	Measured	332	238	169	61	28	19	14	37.81%
	Calculated	342	223	163	75	43	29	22	
3.200	Measured	330	244	180	81	43	29	23	20.56%
	Calculated	338	227	173	90	55	39	30	
3.600	Measured	420	298	205	62	30	21	16	25.32%
	Calculated	427	272	192	78	41	28	22	
3.800	Measured	440	299	198	60	32	22	17	17.69%
	Calculated	443	274	189	74	39	27	21	
4.200	Measured	316	228	169	65	31	20	19	22.11%
	Calculated	319	210	156	73	41	29	22	
4.600	Measured	548	404	289	109	54	36	26	38.39%
	Calculated	567	389	294	142	82	55	42	
5.000	Measured	321	220	154	62	35	24	18	16.51%
	Calculated	328	207	149	70	42	30	23	
5.400	Measured	399	295	213	78	39	26	24	17.72%
	Calculated	402	268	198	91	50	34	26	
5.800	Measured	260	183	122	53	33	25	16	6.95%
	Calculated	262	161	115	54	33	23	18	
6.200	Measured	413	295	222	85	37	24	18	51.33%
	Calculated	427	290	219	107	63	43	33	
6.600	Measured	336	239	176	66	31	20	16	36.07%
	Calculated	345	228	169	80	46	32	24	
6.800	Measured	354	241	169	56	30	20	15	39.35%
	Calculated	360	239	171	58	17	6	5	
7.200	Measured	445	326	241	101	52	39	19	35.15%
	Calculated	448	301	229	118	69	47	35	
8.800	Measured	263	178	116	42	26	19	15	7.23%
	Calculated	265	155	106	47	27	19	15	
9.000	Measured	502	346	217	68	39	30	20	11.86%
	Calculated	505	307	211	85	43	28	22	
9.400	Measured	569	421	313	134	78	52	37	24.63%
	Calculated	573	399	309	165	99	68	53	
9.800	Measured	398	312	241	109	53	29	15	70.67%
	Calculated	513	347	263	134	78	52	39	
10.200	Measured	431	291	211	102	65	43	31	12.27%
	Calculated	422	266	193	98	62	48	39	
10.600	Measured	629	458	348	158	92	61	40	32.00%
	Calculated	641	454	357	198	123	85	65	
10.800	Measured	558	413	320	157	89	51	36	44.73%
	Calculated	574	407	323	188	122	86	67	
11.200	Measured	486	371	275	116	64	39	28	40.67%
	Calculated	502	351	274	151	92	63	48	
11.600	Measured	387	300	235	117	69	44	31	26.22%
	Calculated	392	274	217	127	83	60	48	
12.000	Measured	464	342	232	96	47	27	14	58.78%
	Calculated	491	332	252	124	69	44	32	
12.400	Measured	530	395	305	139	74	48	32	49.22%
	Calculated	557	397	316	182	116	80	61	
17.800	Measured	409	294	219	86	36	21	16	38.76%
	Calculated	426	298	228	105	54	34	26	
18.200	Measured	375	299	246	137	83	57	39	19.76%
	Calculated	368	286	236	125	65	38	27	
18.600	Measured	518	390	292	113	60	40	31	26.16%
	Calculated	531	372	286	142	82	55	42	
19.000	Measured	415	301	221	95	49	34	26	22.51%
	Calculated	424	286	215	108	65	45	35	

APPENDIX C.5: TR1102

Comparison of back-calculated E-moduli between Case (b) and ModComp for 35AC surfacing layer

POSITION (Km)	METHOD	BACK-CALCULATED E-MODULI (Mpa)					RMSE (%)
		E1	E2	E3	E4	E5	
0.00	Case (b)	10999.1	700.0	248.3	153.3	10000.0	40.82
	ModComp	8000.0	3850.0	287.0	200.0	3500.0	50.96
0.40	Case (b)	10999.1	314.1	200.8	120.7	10000.0	16.16
	ModComp	8000.0	741.0	80.5	191.0	689000.0	60.41
0.80	Case (b)	10999.1	300.0	600.0	53.7	10000.0	17.4
	ModComp	8000.0	757.0	86.4	88.3	689000.0	28.9
1.20	Case (b)	10999.1	700.0	200.2	599.8	10000.0	28.9
	ModComp	8000.0	1690.0	166.0	495.0	689000.0	44.93
1.60	Case (b)	10999.1	618.6	201.1	551.4	10000.0	31.47
	ModComp	8000.0	1340.0	229.0	549.0	34.4	41.36
2.00	Case (b)	10999.1	700.0	200.1	552.3	10000.0	38.65
	ModComp	8000.0	1530.0	194.0	280.0	689000.0	18.91
2.20	Case (b)	10999.1	677.7	200.2	167.1	10000.0	24.73
	ModComp	8000.0	931.0	34.4	178.0	689000.0	59.04
2.40	Case (b)	10999.1	700.0	200.1	574.6	10000.0	28.87
	ModComp	8000.0	2260.0	301.0	381.0	689000.0	15.56
2.60	Case (b)	10999.1	700.0	200.2	347.5	10000.0	34.77
	ModComp	8000.0	935.0	126.0	162.0	2070.0	41.48
2.80	Case (b)	10999.1	303.8	200.7	200.0	10000.0	23.66
	ModComp	8000.0	870.0	108.0	261.0	62400.0	37.81
3.20	Case (b)	10999.1	304.4	249.0	170.6	10000.0	21.09
	ModComp	8000.0	908.0	162.0	205.0	5570.0	20.56
3.60	Case (b)	10999.1	300.0	600.0	131.6	10000.0	25.67
	ModComp	8000.0	641.0	68.1	268.0	251000.0	25.32
3.80	Case (b)	10999.1	300.0	600.0	140.9	10000.0	22.87
	ModComp	8000.0	560.0	70.9	277.0	6590.0	17.69
4.20	Case (b)	10999.1	681.0	200.1	390.6	10000.0	22.38
	ModComp	8000.0	979.0	114.0	271.0	689000.0	22.11
4.60	Case (b)	10999.1	300.0	600.0	83.6	10000.0	19.39
	ModComp	8000.0	572.0	56.5	142.0	5810.0	38.39
5.00	Case (b)	10999.1	307.1	292.3	213.9	10000.0	13.56
	ModComp	8000.0	793.0	146.0	272.0	1120.0	16.51
5.40	Case (b)	10999.1	300.0	543.0	135.5	10000.0	19.43
	ModComp	8000.0	787.0	76.6	226.0	689000.0	17.72
5.80	Case (b)	10999.1	300.0	600.0	233.1	10000.0	25.19
	ModComp	8000.0	912.0	228.0	332.0	689000.0	6.95
6.20	Case (b)	10998.5	700.0	200.2	372.9	10000.0	33.74
	ModComp	8000.0	762.0	85.2	183.0	107000.0	51.33
6.60	Case (b)	10999.1	675.9	200.1	346.1	10000.0	19.5
	ModComp	8000.0	892.0	110.0	243.0	30200.0	36.07
6.80	Case (b)	10999.1	397.4	200.1	324.8	10000.0	15.66
	ModComp	8000.0	1000.0	32.4	860.0	3500.0	39.35
7.20	Case (b)	10999.1	300.3	203.2	117.1	10000.0	16.36
	ModComp	8000.0	584.0	63.9	173.0	689000.0	35.15
8.80	Case (b)	10999.1	300.0	600.0	286.5	10000.0	28.34
	ModComp	8000.0	735.0	145.0	448.0	643.0	7.23
9.00	Case (b)	10999.1	300.0	600.0	109.0	10000.0	109.87
	ModComp	8000.0	383.0	54.0	262.0	689000.0	11.86

9.40	Case (b)	10999.1	300.0	600.0	80.5	10000.0	18.86
	ModComp	8000.0	493.0	40.4	138.0	126.0	24.63
9.80	Case (b)	10999.1	300.0	600.0	72.0	10000.0	37.7
	ModComp	8000.0	506.0	51.4	156.0	11000.0	70.67
10.20	Case (b)	10997.7	302.6	291.3	126.3	10000.0	9.82
	ModComp	8000.0	506.0	90.7	242.0	66.1	12.27
10.60	Case (b)	10976.0	325.1	200.1	123.1	10000.0	21.31
	ModComp	8000.0	454.0	40.0	108.0	147.0	32
10.80	Case (b)	10999.0	334.4	200.4	86.2	10000.0	27.1
	ModComp	8000.0	508.0	63.6	104.0	180.0	44.73
11.20	Case (b)	10999.1	300.0	600.0	62.9	10000.0	21.58
	ModComp	8000.0	578.0	54.5	137.0	413.0	40.67
11.60	Case (b)	10999.1	300.1	597.1	79.0	10000.0	12.73
	ModComp	8000.0	750.0	104.0	157.0	156.0	26.22
12.00	Case (b)	10999.1	300.0	600.0	67.6	10000.0	55.35
	ModComp	8000.0	548.0	42.4	183.0	689000.0	58.78
12.40	Case (b)	10999.1	490.8	200.1	148.4	10000.0	25.65
	ModComp	8000.0	540.0	60.1	105.0	1100.0	49.22
17.80	Case (b)	10999.1	697.3	200.2	236.5	10000.0	22.4
	ModComp	8000.0	927.0	45.4	228.0	689000.0	38.76
18.20	Case (b)	10999.1	700.0	200.2	150.4	10000.0	10.43
	ModComp	8000.0	1870.0	21.5	360.0	83.9	19.76
18.60	Case (b)	10999.1	300.0	204.7	108.2	10000.0	13.92
	ModComp	8000.0	674.0	56.4	144.0	1930.0	26.16
19.00	Case (b)	10999.1	348.0	200.3	185.4	10000.0	15.22
	ModComp	8000.0	720.0	107.0	174.0	36000.0	22.51

TR01102: 85AC: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (b)
DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
7.60	317	252	200	87	39	26	18	117	113	48	72.50	F18	5.29	25.00	592	6897001	21.10
8.00	360	250	180	63	24	14	10	180	117	39	47.10	F18	4.93	25.00	592	6784360	20.90
8.20	219	169	132	60	26	15	9	87	72	34	82.20	F18	6.09	25.00	592	12157536	30.60
8.40	244	190	150	70	33	17	11	94	80	37	80.10	F18	5.86	25.00	592	7431145	22.20
8.60	346	226	136	43	25	19	13	210	93	18	34.70	F18	5.02	25.00	592	4907550	16.50
12.80	475	362	294	161	99	67	47	181	133	62	46.70	F18	3.04	3.00	592	213676	1.00
13.20	388	311	260	140	69	38	23	128	120	71	68.40	F18	3.45	3.50	592	473292	2.10
13.60	383	285	221	101	46	26	20	162	120	55	54.70	F18	4.75	20.50	592	2463080	9.40
13.80	600	447	337	134	58	35	23	263	203	76	16.60	F18	3.30	8.60	592	3213	0.00
14.20	556	414	323	164	94	61	47	233	159	70	26.10	F18	2.75	3.20	592	71737	0.30
14.40	626	442	335	155	81	49	33	291	180	74	9.60	F18	2.47	3.10	592	42270	0.20
14.60	246	179	146	80	42	26	15	100	66	38	78.20	F18	5.82	21.30	592	1921198	7.60
14.80	451	360	298	175	95	53	30	153	123	80	58.50	F18	3.12	3.00	592	36302	0.20
15.00	321	277	245	152	93	65	47	76	93	59	85.20	F18	4.17	3.70	592	391672	1.70
15.20	318	250	192	85	39	22	13	126	107	46	69.20	F18	5.20	22.80	592	1014249	4.30
15.60	299	221	167	71	39	26	20	132	96	32	66.90	F18	5.42	25.00	592	3447833	12.50
16.00	214	169	122	53	30	20	16	92	69	23	80.70	F18	6.20	25.00	592	2865363	10.70
16.20	153	126	105	58	34	24	18	48	47	24	91.50	F18	7.37	25.00	592	29881385	49.70
16.60	280	215	174	78	35	22	16	106	96	43	76.30	F18	5.55	25.00	592	6428892	20.10
17.00	416	303	232	108	52	34	24	184	124	56	45.40	F18	4.52	18.10	592	1534114	6.20
17.40	337	276	230	125	61	35	21	107	105	64	75.90	F18	4.11	5.60	592	942222	4.00

TR01102: 85AC: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (b)
DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

NEURAL NETWORK: BACKCALCULATED E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
7.60	85	150	150	2038	317	252	200	87	39	26	18	126.6	516.7	598.3	215.1	10000
8.00	85	150	150	1509	360	250	180	63	24	14	10	8807.9	300.0	600.0	55.0	10000
8.20	85	150	150	3476	219	169	132	60	26	15	9	242.6	555.1	205.1	275.5	10000
8.40	85	150	150	3224	244	190	150	70	33	17	11	240.1	551.3	207.7	268.0	10000
8.60	85	150	150	1509	346	226	136	43	25	19	13	9004.0	300.0	600.0	84.2	10000
12.80	85	150	150	1510	475	362	294	161	99	67	47	10244.3	300.0	600.0	54.9	10000
13.20	85	150	150	1524	388	311	260	140	69	38	23	42.9	372.0	600.0	92.2	10000
13.60	85	150	150	1507	383	285	221	101	46	26	20	86.2	300.1	600.0	58.1	10000
13.80	85	150	150	1511	600	447	337	134	58	35	23	10458.3	300.0	600.0	51.8	10000
14.20	85	150	150	1510	556	414	323	164	94	61	47	10423.0	300.0	600.0	53.2	10000
14.40	85	150	150	1510	626	442	335	155	81	49	33	10781.3	300.0	600.0	54.7	10000
14.60	85	150	150	3429	246	179	146	80	42	26	15	209.2	533.2	276.4	227.3	10000
14.80	85	150	150	1509	451	360	298	175	95	53	30	41.5	300.2	600.0	58.7	10000
15.00	85	150	150	3405	321	277	245	152	93	65	47	107.1	538.0	599.6	167.4	10000
15.20	85	150	150	2113	318	250	192	85	39	22	13	202.7	519.1	393.6	235.6	10000
15.60	85	150	150	2232	299	221	167	71	39	26	20	78.2	459.7	600.0	189.8	10000
16.00	85	150	150	4269	214	169	122	53	30	20	16	253.2	558.9	201.7	310.4	10000
16.20	85	150	150	3787	153	126	105	58	34	24	18	195.1	549.5	312.6	284.5	10000
16.60	85	150	150	2369	280	215	174	78	35	22	16	176.5	521.6	521.2	215.2	10000
17.00	85	150	150	1510	416	303	232	108	52	34	24	9947.6	300.0	600.0	52.6	10000
17.40	85	150	150	2280	337	276	230	125	61	35	21	140.8	538.9	594.4	204.7	10000

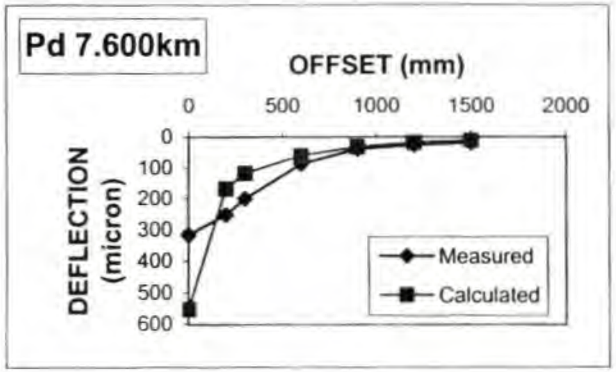
TR01102: 85AC: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (b)
DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000 Mpa

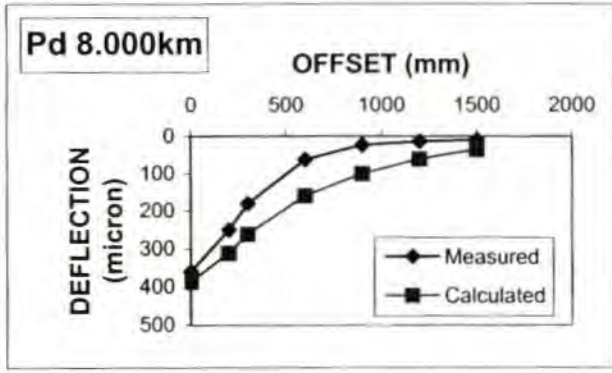
Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

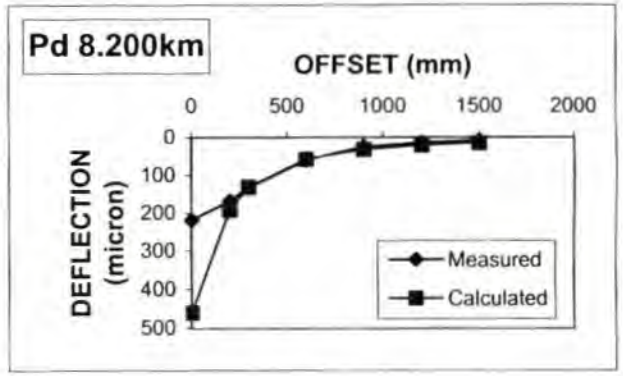
WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

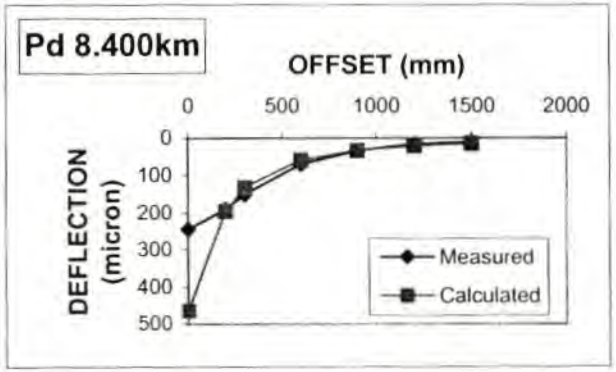
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
7.60	85.00	150.00	150.00	2038	552	167	117	60	32	17	10	126.6	516.7	598.3	215.1	10000
8.00	85.00	150.00	150.00	1509	386	311	261	159	100	61	36	8807.9	300.0	600.0	55.0	10000
8.20	85.00	150.00	150.00	3476	460	192	131	58	33	21	15	242.6	555.1	205.1	275.5	10000
8.40	85.00	150.00	150.00	3224	463	194	132	58	32	21	15	240.1	551.3	207.7	268.0	10000
8.60	85.00	150.00	150.00	1509	323	251	204	114	67	38	21	9004.0	300.0	600.0	84.2	10000
12.80	85.00	150.00	150.00	1510	375	306	259	159	100	61	36	10244.3	300.0	600.0	54.9	10000
13.20	85.00	150.00	150.00	1524	1236	287	215	120	57	38	45	42.9	372.0	600.0	92.2	10000
13.60	85.00	150.00	150.00	1507	992	401	314	185	102	56	12	86.2	300.1	600.0	58.1	10000
13.80	85.00	150.00	150.00	1511	383	314	267	166	105	65	39	10458.3	300.0	600.0	51.8	10000
14.20	85.00	150.00	150.00	1510	379	310	263	163	103	63	37	10423.0	300.0	600.0	53.2	10000
14.40	85.00	150.00	150.00	1510	372	305	258	159	100	61	36	10781.3	300.0	600.0	54.7	10000
14.60	85.00	150.00	150.00	3429	490	201	141	68	40	26	18	209.2	533.2	276.4	227.3	10000
14.80	85.00	150.00	150.00	1509	1413	400	312	185	103	62	-6	41.5	300.2	600.0	58.7	10000
15.00	85.00	150.00	150.00	3405	642	210	158	91	55	34	24	107.1	538.0	599.6	167.4	10000
15.20	85.00	150.00	150.00	2113	462	173	118	56	30	16	10	202.7	519.1	393.6	235.6	10000
15.60	85.00	150.00	150.00	2232	749	187	132	70	39	21	15	78.2	459.7	600.0	189.8	10000
16.00	85.00	150.00	150.00	4269	443	184	123	53	31	21	14	253.2	558.9	201.7	310.4	10000
16.20	85.00	150.00	150.00	3787	466	172	117	56	33	22	15	195.1	549.5	312.6	284.5	10000
16.60	85.00	150.00	150.00	2369	485	175	124	63	35	20	13	176.5	521.6	521.2	215.2	10000
17.00	85.00	150.00	150.00	1510	384	314	266	165	104	64	38	9947.6	300.0	600.0	52.6	10000
17.40	85.00	150.00	150.00	2280	529	174	125	66	37	20	14	140.8	538.9	594.4	204.7	10000

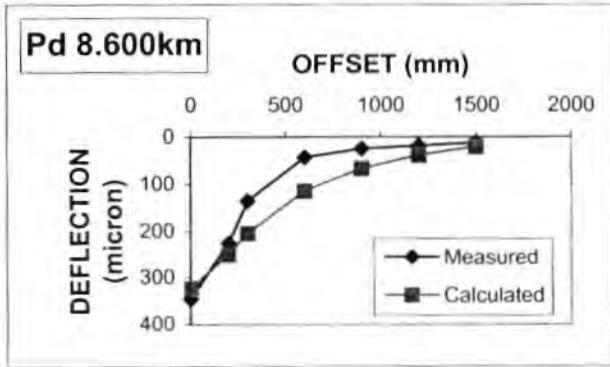
TR1102: AC85: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

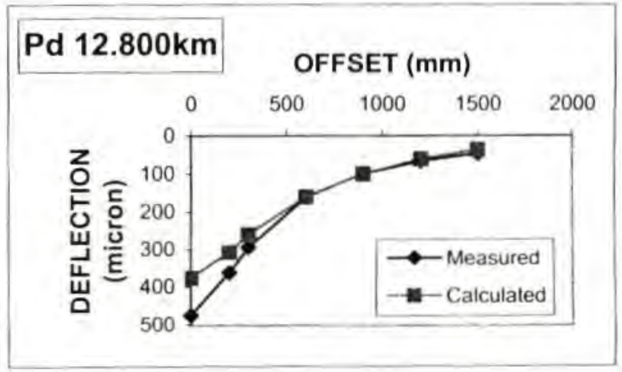


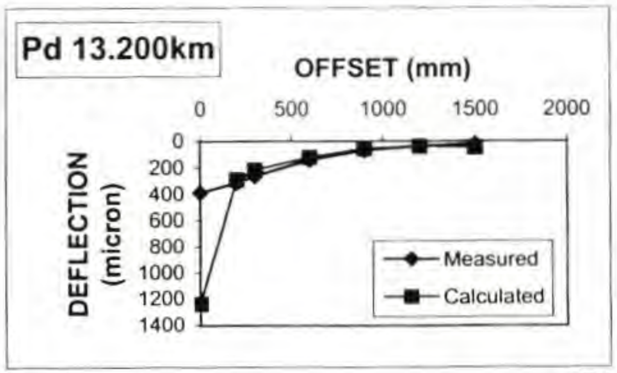


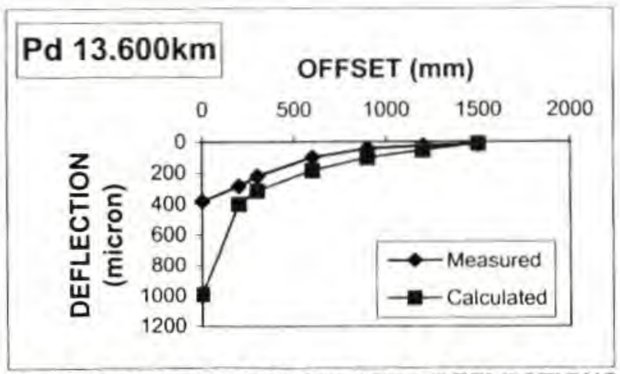


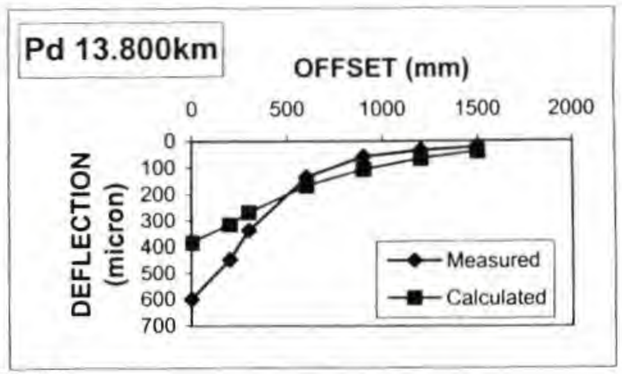




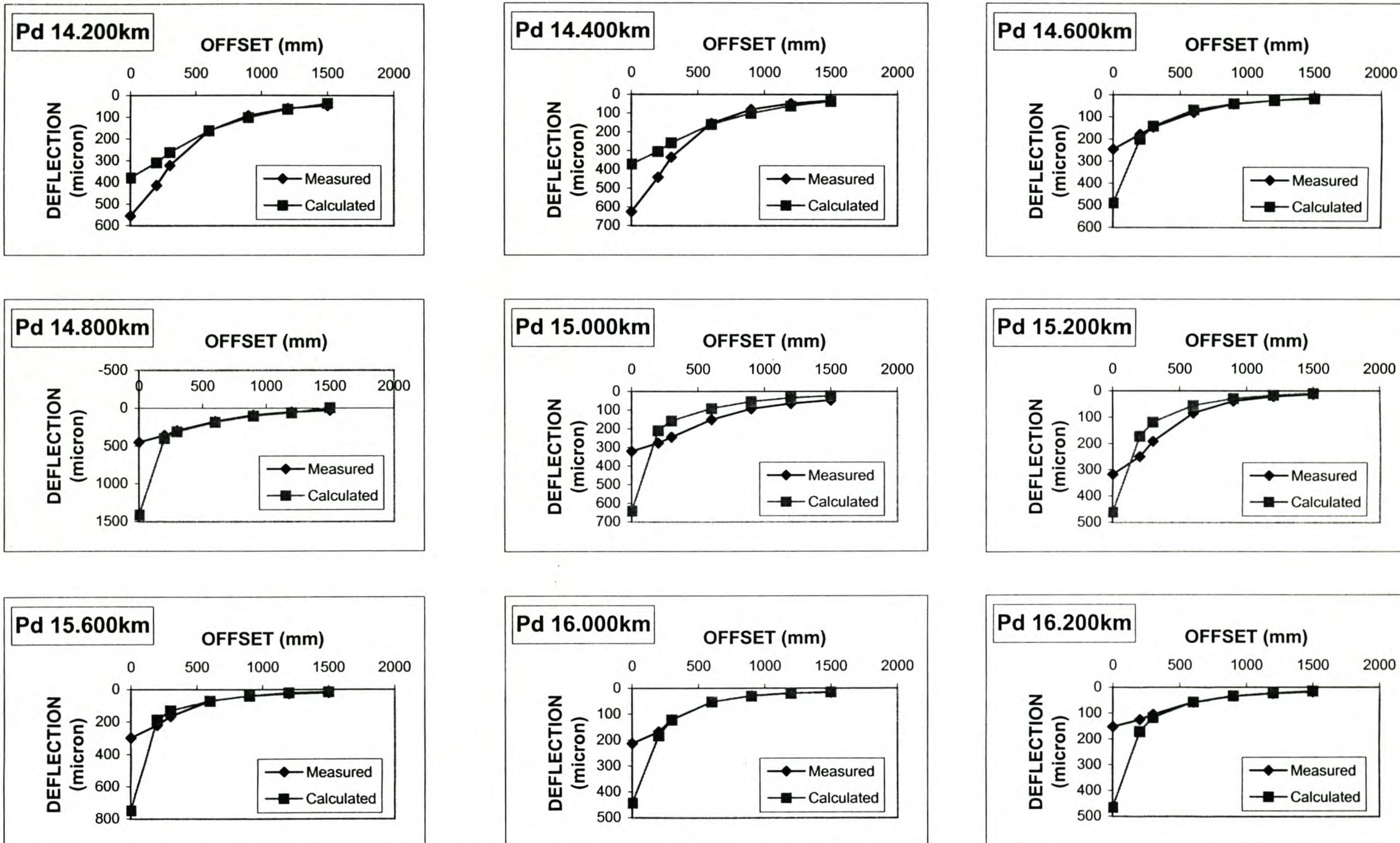








TR1102: AC85: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)



TR1102: AC85: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

TR1102: AC85: COMPARISON OF MEASURED AND CALCULATED DEFLECTIONS: CASE (b)

Pos (Km)\Offset (mm)		0	200	300	600	900	1200	1500	RMSE (%)
7.600	Measured	317	252	200	87	39	26	18	42.49%
	Calculated	552	167	117	60	32	17	10	
8.000	Measured	360	250	180	63	24	14	10	208.51%
	Calculated	386	311	261	159	100	61	36	
8.200	Measured	219	169	132	60	26	15	9	52.47%
	Calculated	460	192	131	58	33	21	15	
8.400	Measured	244	190	150	70	33	17	11	38.01%
	Calculated	463	194	132	58	32	21	15	
8.600	Measured	346	226	136	43	25	19	13	101.43%
	Calculated	323	251	204	114	67	38	21	
12.800	Measured	475	362	294	161	99	67	47	14.40%
	Calculated	375	306	259	159	100	61	36	
13.200	Measured	388	311	260	140	69	38	23	90.97%
	Calculated	1236	287	215	120	57	38	45	
13.600	Measured	383	285	221	101	46	26	20	96.66%
	Calculated	992	401	314	185	102	56	12	
13.800	Measured	600	447	337	134	58	35	23	55.81%
	Calculated	383	314	267	166	105	65	39	
14.200	Measured	556	414	323	164	94	61	47	18.94%
	Calculated	379	310	263	163	103	63	37	
14.400	Measured	626	442	335	155	81	49	33	25.18%
	Calculated	372	305	258	159	100	61	36	
14.600	Measured	246	179	146	80	42	26	15	39.25%
	Calculated	490	201	141	68	40	26	18	
14.800	Measured	451	360	298	175	95	53	30	92.99%
	Calculated	1413	400	312	185	103	62	-6	
15.000	Measured	321	277	245	152	93	65	47	53.37%
	Calculated	642	210	158	91	55	34	24	
15.200	Measured	318	250	192	85	39	22	13	32.91%
	Calculated	462	173	118	56	30	16	10	
15.600	Measured	299	221	167	71	39	26	20	59.08%
	Calculated	749	187	132	70	39	21	15	
16.000	Measured	214	169	122	53	30	20	16	40.82%
	Calculated	443	184	123	53	31	21	14	
16.200	Measured	153	126	105	58	34	24	18	79.00%
	Calculated	466	172	117	56	33	22	15	
16.600	Measured	280	215	174	78	35	22	16	32.04%
	Calculated	485	175	124	63	35	20	13	
17.000	Measured	416	303	232	108	52	34	24	58.68%
	Calculated	384	314	266	165	104	64	38	
17.400	Measured	337	276	230	125	61	35	21	43.53%
	Calculated	529	174	125	66	37	20	14	

TR01102: 85AC: E-MODULI BACK-CALCULATED WITH MODCOMP
H4 AND E5 FROM MODCOMP

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
7.60	317	252	200	87	39	26	18	117	113	48	72.50	F18	5.29	25.00	592	6897001	21.10
8.00	360	250	180	63	24	14	10	180	117	39	47.10	F18	4.93	25.00	592	6784360	20.90
8.20	219	169	132	60	26	15	9	87	72	34	82.20	F18	6.09	25.00	592	12157536	30.60
8.40	244	190	150	70	33	17	11	94	80	37	80.10	F18	5.86	25.00	592	7431145	22.20
8.60	346	226	136	43	25	19	13	210	93	18	34.70	F18	5.02	25.00	592	4907550	16.50
12.80	475	362	294	161	99	67	47	181	133	62	46.70	F18	3.04	3.00	592	213676	1.00
13.20	388	311	260	140	69	38	23	128	120	71	68.40	F18	3.45	3.50	592	473292	2.10
13.60	383	285	221	101	46	26	20	162	120	55	54.70	F18	4.75	20.50	592	2463080	9.40
13.80	600	447	337	134	58	35	23	263	203	76	16.60	F18	3.30	8.60	592	3213	0.00
14.20	556	414	323	164	94	61	47	233	159	70	26.10	F18	2.75	3.20	592	71737	0.30
14.40	626	442	335	155	81	49	33	291	180	74	9.60	F18	2.47	3.10	592	42270	0.20
14.60	246	179	146	80	42	26	15	100	66	38	78.20	F18	5.82	21.30	592	1921198	7.60
14.80	451	360	298	175	95	53	30	153	123	80	58.50	F18	3.12	3.00	592	36302	0.20
15.00	321	277	245	152	93	65	47	76	93	59	85.20	F18	4.17	3.70	592	391672	1.70
15.20	318	250	192	85	39	22	13	126	107	46	69.20	F18	5.20	22.80	592	1014249	4.30
15.60	299	221	167	71	39	26	20	132	96	32	66.90	F18	5.42	25.00	592	3447833	12.50
16.00	214	169	122	53	30	20	16	92	69	23	80.70	F18	6.20	25.00	592	2865363	10.70
16.20	153	126	105	58	34	24	18	48	47	24	91.50	F18	7.37	25.00	592	29881385	49.70
16.60	280	215	174	78	35	22	16	106	96	43	76.30	F18	5.55	25.00	592	6428892	20.10
17.00	416	303	232	108	52	34	24	184	124	56	45.40	F18	4.52	18.10	592	1534114	6.20
17.40	337	276	230	125	61	35	21	107	105	64	75.90	F18	4.11	5.60	592	942222	4.00

TR01102: 85AC: E-MODULI BACK-CALCULATED WITH MODCOMP
H4 AND E5 FROM MODCOMP

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

NEURAL NETWORK: BACKCALCULATED E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
7.60	85	150	150	10549	317	252	200	87	39	26	18	8000.0	421.0	85.2	183.0	48800.0
8.00	85	150	150	10070	360	250	180	63	24	14	10	4470.0	324.0	64.6	308.0	689000.0
8.20	85	150	150	9823	219	169	132	60	26	15	9	8000.0	566.0	176.0	253.0	689000.0
8.40	85	150	150	9970	244	190	150	70	33	17	11	8000.0	527.0	159.0	210.0	689000.0
8.60	85	150	150	9107	346	226	136	43	25	19	13	3560.0	147.0	262.0	394.0	3500.0
12.80	85	150	150	11390	475	362	294	161	99	67	47	3300.0	502.0	68.1	108.0	3500.0
13.20	85	150	150	12005	388	311	260	140	69	38	23	5590.0	877.0	20.0	188.0	3500.0
13.60	85	150	150	10953	383	285	221	101	46	26	20	5450.0	390.0	53.7	232.0	3500.0
13.80	85	150	150	12376	600	447	337	134	58	35	23	5140.0	80.1	59.9	138.0	3500.0
14.20	85	150	150	11933	556	414	323	164	94	61	47	3820.0	200.0	105.0	101.0	3500.0
14.40	85	150	150	12225	626	442	335	155	81	49	33	2040.0	261.0	57.9	106.0	3500.0
14.60	85	150	150	10020	246	179	146	80	42	26	15	2330.0	1450.0	140.0	199.0	3500.0
14.80	85	150	150	12690	451	360	298	175	95	53	30	6700.0	286.0	223.0	73.8	3500.0
15.00	85	150	150	11198	321	277	245	152	93	65	47	8000.0	591.0	124.0	218.0	18.4
15.20	85	150	150	10438	318	250	192	85	39	22	13	8000.0	303.0	88.8	196.0	689000.0
15.60	85	150	150	9728	299	221	167	71	39	26	20	8000.0	363.0	105.0	251.0	1070.0
16.00	85	150	150	9320	214	169	122	53	30	20	16	8000.0	347.0	189.0	356.0	1010.0
16.20	85	150	150	9363	153	126	105	58	34	24	18	8000.0	690.0	520.0	329.0	731.0
16.60	85	150	150	10277	280	215	174	78	35	22	16	6910.0	542.0	141.0	201.0	15300.0
17.00	85	150	150	11013	416	303	232	108	52	34	24	4260.0	331.0	84.0	162.0	3500.0
17.40	85	150	150	11521	337	276	230	125	61	35	21	8000.0	505.0	119.0	115.0	689000.0

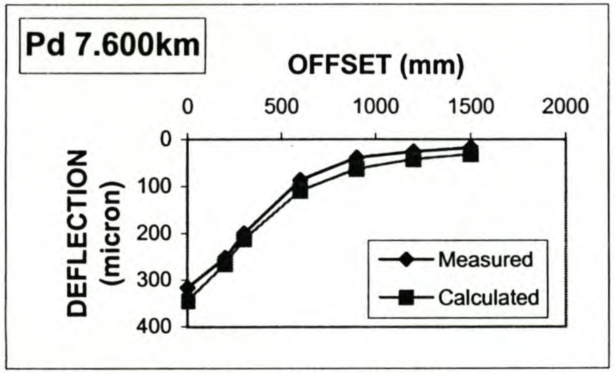
TR01102: 85AC: E-MODULI BACK-CALCULATED WITH MODCOMP
H4 AND E5 FROM MODCOMP

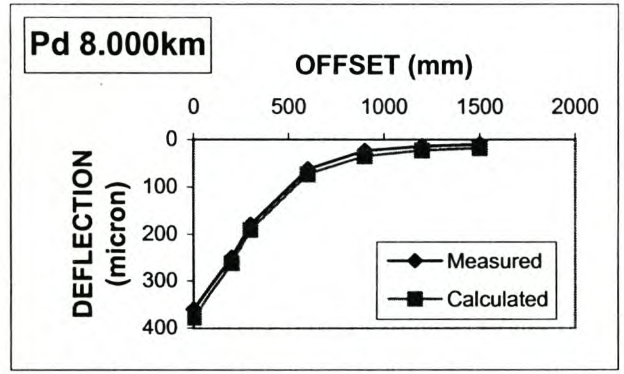
Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

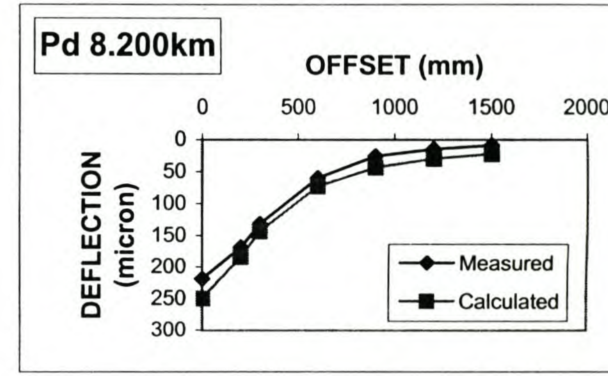
WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

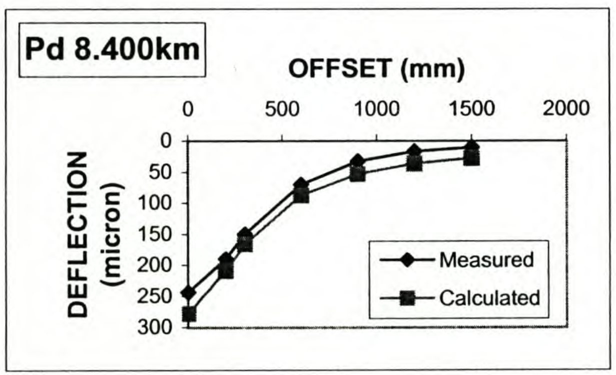
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
7.60	85.00	150.00	150.00	10549	345	266	212	109	63	42	32	8000	421	85	183	48800
8.00	85.00	150.00	150.00	10070	378	262	191	73	35	23	18	4470	324	65	308	689000
8.20	85.00	150.00	150.00	9823	249	184	144	73	44	30	23	8000	566	176	253	689000
8.40	85.00	150.00	150.00	9970	278	209	166	87	53	37	28	8000	527	159	210	689000
8.60	85.00	150.00	150.00	9107	357	215	137	44	26	20	15	3560	147	262	394	3500
12.80	85.00	150.00	150.00	11390	500	382	312	177	110	76	57	3300	502	68	108	3500
13.20	85.00	150.00	150.00	12005	416	336	282	162	90	52	33	5590	877	20	188	3500
13.60	85.00	150.00	150.00	10953	390	287	221	100	51	33	25	5450	390	54	232	3500
13.80	85.00	150.00	150.00	12376	639	477	364	154	80	55	43	5140	80	60	138	3500
14.20	85.00	150.00	150.00	11933	582	434	340	179	112	79	61	3820	200	105	101	3500
14.40	85.00	150.00	150.00	12225	669	477	367	184	110	76	58	2040	261	58	106	3500
14.60	85.00	150.00	150.00	10020	271	200	164	96	60	42	31	2330	1450	140	199	3500
14.80	85.00	150.00	150.00	12690	507	412	349	222	154	113	86	6700	286	223	74	3500
15.00	85.00	150.00	150.00	11198	320	253	210	130	94	77	68	8000	591	124	218	18
15.20	85.00	150.00	150.00	10438	358	271	213	102	57	38	29	8000	303	89	196	689000
15.60	85.00	150.00	150.00	9728	307	227	175	81	45	31	24	8000	363	105	251	1070
16.00	85.00	150.00	150.00	9320	246	172	127	54	31	22	18	8000	347	189	356	1010
16.20	85.00	150.00	150.00	9363	181	129	99	54	36	26	20	8000	690	520	329	731
16.60	85.00	150.00	150.00	10277	295	222	176	93	56	39	29	6910	542	141	201	15300
17.00	85.00	150.00	150.00	11013	437	319	246	120	70	48	37	4260	331	84	162	3500
17.40	85.00	150.00	150.00	11521	384	309	259	155	101	71	53	8000	505	119	115	689000

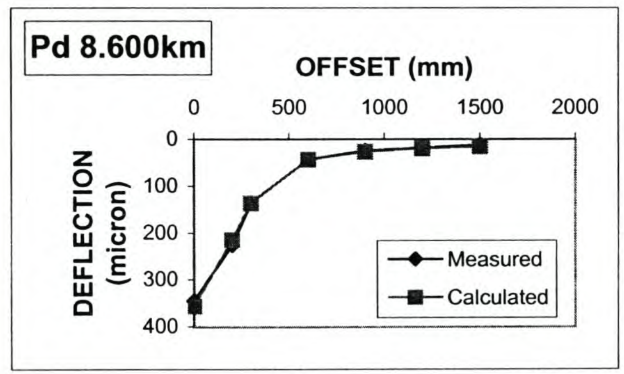
TR1102: AC85: MEASURED vs CALCULATED DEFLECTIONS: MODCOMP

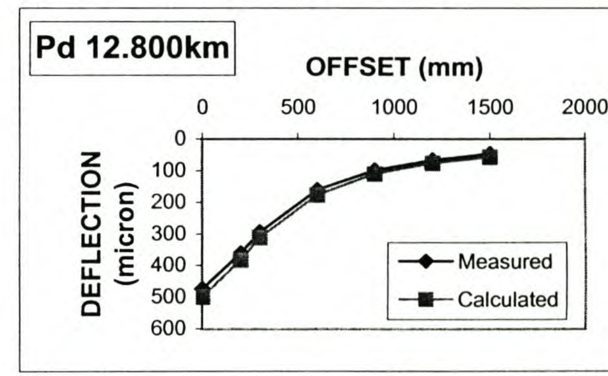


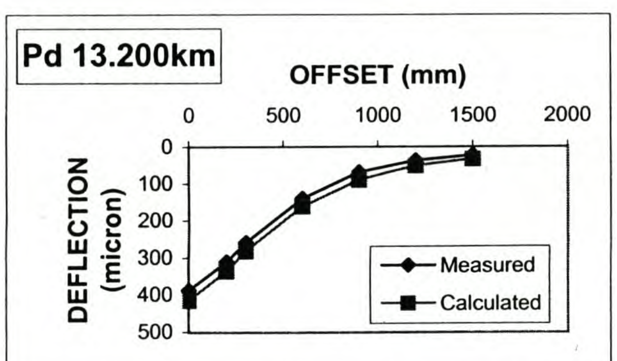


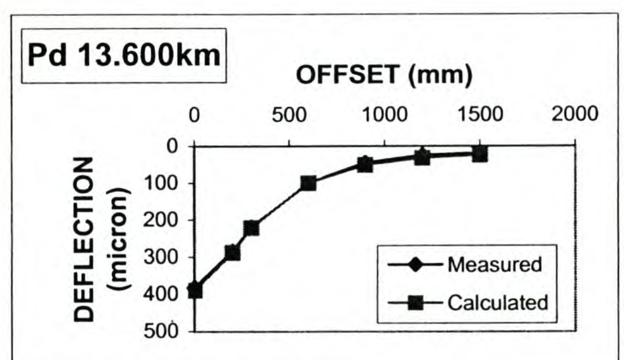


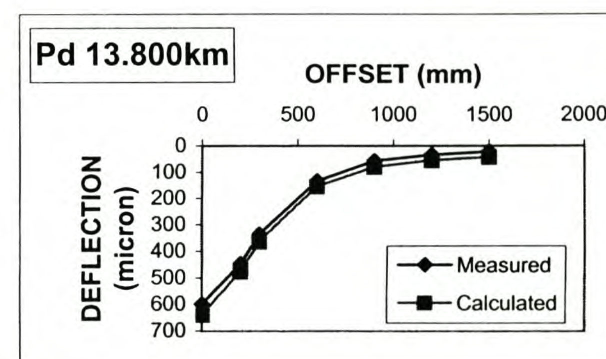




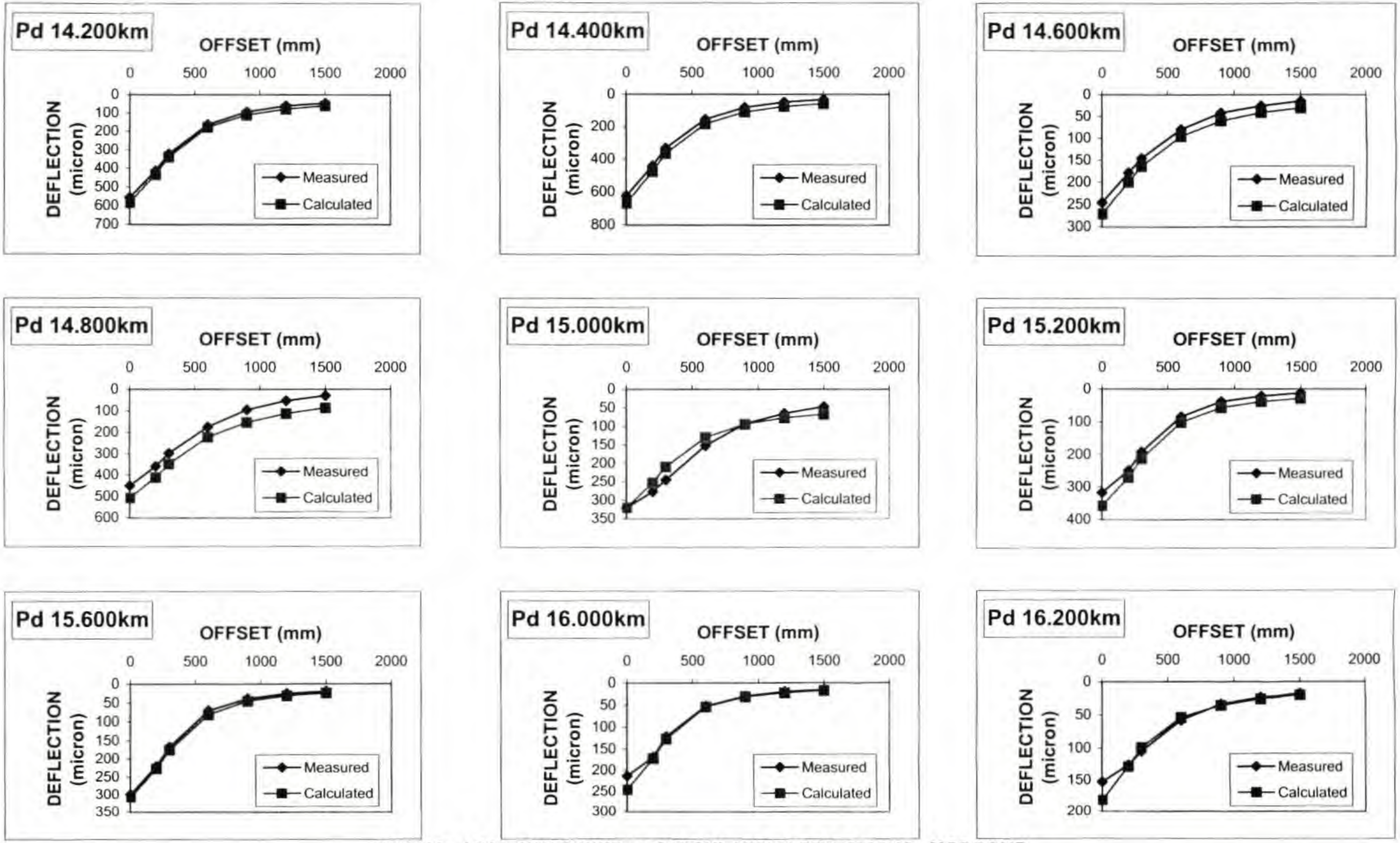








TR1102: AC85: MEASURED vs CALCULATED DEFLECTIONS: MODCOMP



TR1102: AC85: MEASURED vs CALCULATED DEFLECTIONS: MODCOMP

TR1102: AC85: COMPARISON OF MEASURED AND CALCULATED DEFLECTIONS: MODCOMP

Pos (Km)\Offset (mm)		0	200	300	600	900	1200	1500	RMSE (%)
7.600	Measured	317	252	200	87	39	26	18	44.83%
	Calculated	345	266	212	109	63	42	32	
8.000	Measured	360	250	180	63	24	14	10	43.87%
	Calculated	378	262	191	73	35	23	18	
8.200	Measured	219	169	132	60	26	15	9	74.59%
	Calculated	249	184	144	73	44	30	23	
8.400	Measured	244	190	150	70	33	17	11	76.33%
	Calculated	278	209	166	87	53	37	28	
8.600	Measured	346	226	136	43	25	19	13	7.36%
	Calculated	357	215	137	44	26	20	15	
12.800	Measured	475	362	294	161	99	67	47	11.47%
	Calculated	500	382	312	177	110	76	57	
13.200	Measured	388	311	260	140	69	38	23	25.34%
	Calculated	416	336	282	162	90	52	33	
13.600	Measured	383	285	221	101	46	26	20	14.10%
	Calculated	390	287	221	100	51	33	25	
13.800	Measured	600	447	337	134	58	35	23	42.32%
	Calculated	639	477	364	154	80	55	43	
14.200	Measured	556	414	323	164	94	61	47	17.92%
	Calculated	582	434	340	179	112	79	61	
14.400	Measured	626	442	335	155	81	49	33	39.11%
	Calculated	669	477	367	184	110	76	58	
14.600	Measured	246	179	146	80	42	26	15	50.75%
	Calculated	271	200	164	96	60	42	31	
14.800	Measured	451	360	298	175	95	53	30	87.34%
	Calculated	507	412	349	222	154	113	86	
15.000	Measured	321	277	245	152	93	65	47	19.93%
	Calculated	320	253	210	130	94	77	68	
15.200	Measured	318	250	192	85	39	22	13	58.46%
	Calculated	358	271	213	102	57	38	29	
15.600	Measured	299	221	167	71	39	26	20	13.57%
	Calculated	307	227	175	81	45	31	24	
16.000	Measured	214	169	122	53	30	20	16	8.50%
	Calculated	246	172	127	54	31	22	18	
16.200	Measured	153	126	105	58	34	24	18	9.54%
	Calculated	181	129	99	54	36	26	20	
16.600	Measured	280	215	174	78	35	22	16	48.59%
	Calculated	295	222	176	93	56	39	29	
17.000	Measured	416	303	232	108	52	34	24	29.78%
	Calculated	437	319	246	120	70	48	37	
17.400	Measured	337	276	230	125	61	35	21	74.68%
	Calculated	384	309	259	155	101	71	53	

APPENDIX C.5: TR1102

Comparison of back-calculated E-moduli between Case (b) and ModComp for 85AC surfacing layer

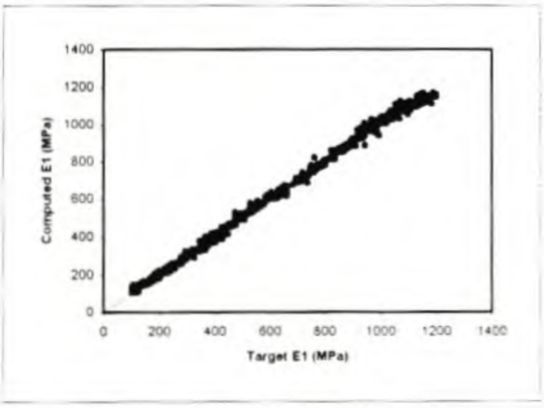
POSITION (Km)	METHOD	BACK-CALCULATED E-MODULI (Mpa)					RMSE (%)
		E1	E2	E3	E4	E5	
7.60	Case (b)	126.6	516.7	598.3	215.1	10000	42.49
	ModComp	8000.0	421.0	85.2	183.0	48800.0	44.83
8.00	Case (b)	8807.9	300.0	600.0	55.0	10000	208.51
	ModComp	4470.0	324.0	64.6	308.0	689000.0	43.87
8.20	Case (b)	242.6	555.1	205.1	275.5	10000	52.47
	ModComp	8000.0	566.0	176.0	253.0	689000.0	74.59
8.40	Case (b)	240.1	551.3	207.7	268.0	10000	38.01
	ModComp	8000.0	527.0	159.0	210.0	689000.0	76.33
8.60	Case (b)	9004.0	300.0	600.0	84.2	10000	101.43
	ModComp	3560.0	147.0	262.0	394.0	3500.0	7.36
12.80	Case (b)	10244.3	300.0	600.0	54.9	10000	14.4
	ModComp	3300.0	502.0	68.1	108.0	3500.0	11.47
13.20	Case (b)	42.9	372.0	600.0	92.2	10000	90.97
	ModComp	5590.0	877.0	20.0	188.0	3500.0	25.34
13.60	Case (b)	86.2	300.1	600.0	58.1	10000	96.66
	ModComp	5450.0	390.0	53.7	232.0	3500.0	14.1
13.80	Case (b)	10458.3	300.0	600.0	51.8	10000	55.81
	ModComp	5140.0	80.1	59.9	138.0	3500.0	42.32
14.20	Case (b)	10423.0	300.0	600.0	53.2	10000	18.94
	ModComp	3820.0	200.0	105.0	101.0	3500.0	17.92
14.40	Case (b)	10781.3	300.0	600.0	54.7	10000	25.18
	ModComp	2040.0	261.0	57.9	106.0	3500.0	39.11
14.60	Case (b)	209.2	533.2	276.4	227.3	10000	38.25
	ModComp	2330.0	1450.0	140.0	199.0	3500.0	50.75
14.80	Case (b)	41.5	300.2	600.0	58.7	10000	92.99
	ModComp	6700.0	286.0	223.0	73.8	3500.0	87.34
15.00	Case (b)	107.1	538.0	599.6	167.4	10000	53.37
	ModComp	8000.0	591.0	124.0	218.0	18.4	19.93
15.20	Case (b)	202.7	519.1	393.6	235.6	10000	32.91
	ModComp	8000.0	303.0	88.8	196.0	689000.0	58.46
15.60	Case (b)	78.2	459.7	600.0	189.8	10000	59.08
	ModComp	8000.0	363.0	105.0	251.0	1070.0	13.57
16.00	Case (b)	253.2	558.9	201.7	310.4	10000	40.82
	ModComp	8000.0	347.0	189.0	356.0	1010.0	8.5
16.20	Case (b)	195.1	549.5	312.6	284.5	10000	79
	ModComp	8000.0	690.0	520.0	329.0	731.0	9.54
16.60	Case (b)	176.5	521.6	521.2	215.2	10000	32.04
	ModComp	6910.0	542.0	141.0	201.0	15300.0	48.59
17.00	Case (b)	9947.6	300.0	600.0	52.6	10000	58.68
	ModComp	4260.0	331.0	84.0	162.0	3500.0	29.78
17.40	Case (b)	140.8	538.9	594.4	204.7	10000	43.53
	ModComp	8000.0	505.0	119.0	115.0	689000.0	74.68

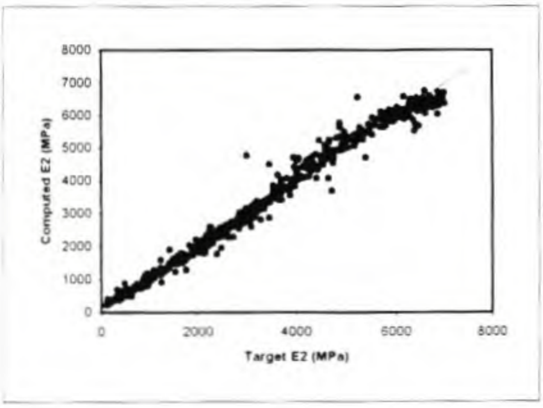
Appendix C.6

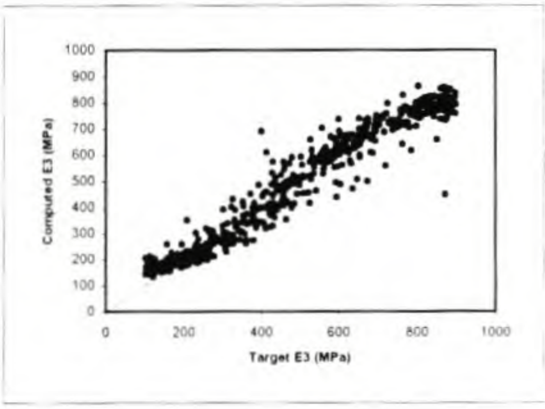
Results of Back-calculations for Type 3 pavements (MR188)

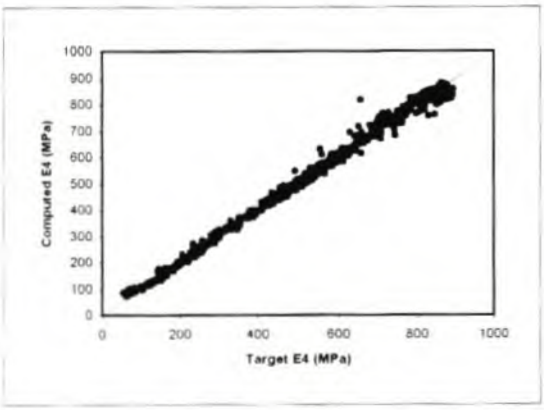
APPENDIX C.6: MR188 CASE (a)

RESULTS OF BACK-CALCULATIONS (E-MODULI FROM DEFLECTIONS) OF A TYPICAL SOUTH AFRICAN PAVEMENT: GRANULAR BASE/CEMENTED SUBBASE WITH A THIN SURFACING : CASE (a): DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000MPa









MR188: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (a)
DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
18.00	251	192	133	65	44	31	24	118	68	21	96.60	A4	5.61	25.00	312	46712	0.40
18.20	323	222	154	80	54	38	28	169	74	26	89.80	A4	5.11	21.10	312	1841073	13.80
18.40	330	269	182	86	58	42	33	148	96	28	93.00	A4	5.23	25.00	312	314	0.00
18.60	253	172	125	79	47	30	20	128	46	32	95.50	A4	5.41	19.70	312	310	0.00
18.80	271	193	140	84	58	43	38	131	56	26	95.20	A4	5.56	25.00	312	5191626	31.80
19.00	397	244	164	73	45	30	25	233	91	28	76.00	A4	4.91	25.00	312	347	0.00
19.20	198	141	95	50	30	21	16	103	45	20	98.10	A4	5.93	25.00	235	1309941	13.10
19.40	211	155	108	75	54	38	32	103	33	21	98.10	A4	5.99	25.00	235	13546521	69.60
19.60	322	192	145	80	54	41	27	177	65	26	88.40	A4	4.67	11.80	235	1826218	17.50
19.80	242	167	113	60	42	30	25	129	53	18	95.40	A4	5.66	25.00	235	10953948	62.00
20.00	283	191	138	81	55	35	23	145	57	26	93.40	A4	4.81	11.10	235	364	0.00
20.20	288	184	131	81	53	39	33	157	50	28	91.70	A4	5.43	25.00	235	793574	8.40
20.40	172	123	107	84	44	34	24	65	23	40	100.00	A4	6.36	25.00	235	20841771	86.20
20.60	288	204	150	75	44	29	21	138	75	31	94.30	A4	5.37	25.00	235	4185978	33.40
20.80	273	204	156	94	62	43	31	117	62	32	96.70	A4	4.97	11.80	235	4611373	35.80
21.00	256	178	139	90	60	41	28	117	49	30	96.70	A4	4.94	9.90	235	342	0.00
23.00	351	254	190	79	39	27	20	161	111	40	91.10	A4	5.06	25.00	235	19307752	83.20
23.20	513	357	257	100	48	31	22	256	157	52	69.50	A4	4.56	24.40	235	8921143	55.00
23.40	398	273	193	64	27	14	11	205	129	37	82.80	A4	4.85	25.00	235	17655973	79.60
23.60	449	330	245	102	50	31	22	204	143	52	83.00	A4	4.62	21.10	235	4987886	37.90
23.80	196	137	108	68	44	29	17	88	40	24	99.30	A4	5.66	15.10	235	17872105	80.10
24.00	264	165	116	60	36	26	18	148	56	24	93.00	A4	5.48	25.00	235	16350604	76.70
24.20	296	207	148	78	43	26	20	148	70	35	93.00	A4	5.32	25.00	235	11443704	63.50
24.40	281	191	122	57	32	24	20	159	65	25	91.40	A4	5.37	25.00	235	9034675	55.50
24.60	269	136	95	43	20	12	9	174	52	23	89.00	A4	5.37	25.00	235	17946389	80.30
24.80	215	137	98	62	41	27	22	117	36	21	96.70	A4	5.85	25.00	235	26259197	95.60
25.00	274	195	143	81	53	37	23	131	62	28	67.30	F17	5.30	5.70	235	12815552	67.60
25.20	292	205	149	79	50	40	35	143	70	29	62.60	F17	6.31	25.00	235	28699328	99.30
25.40	292	239	175	98	62	45	35	117	77	36	72.50	F17	6.36	25.00	235	64641532	134.90
25.60	254	170	126	68	48	32	29	128	58	20	68.40	F17	6.64	25.00	235	159442102	176.60
25.80	376	272	206	105	62	40	25	170	101	43	51.30	F17	4.47	5.70	298	7673824	43.20
26.00	305	216	154	66	36	24	16	151	88	30	59.30	F17	6.04	25.00	298	49167059	112.30
26.20	299	221	164	70	38	26	21	135	94	32	65.70	F17	6.11	25.00	298	91046471	139.70
26.40	368	292	235	152	112	77	53	133	83	40	66.50	F17	4.30	3.00	298	6229499	37.50
26.60	147	101	67	34	26	19	15	80	33	8	84.10	F17	8.32	25.00	298	806806672	242.30
26.80	315	226	166	79	48	32	22	149	87	31	60.10	F17	5.97	23.40	298	56420518	242.30
26.98	173	118	88	47	32	23	17	85	41	15	82.70	F17	7.79	25.00	298	0	242.30

MR188: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (a)
DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

NEURAL NETWORK: BACKCALCULATED E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
18.00	169	250	150	9234	251	192	133	65	44	31	24	1199.7	169.6	899.8	114.4	10000.0
18.20	169	250	150	9452	323	222	154	80	54	38	28	1199.7	168.5	899.8	119.2	10000.0
18.40	169	250	150	9542	330	269	182	86	58	42	33	1199.7	164.6	899.8	92.9	10000.0
18.60	169	250	150	9728	253	172	125	79	47	30	20	1199.7	181.9	884.7	149.5	10000.0
18.80	169	250	150	9452	271	193	140	84	58	43	38	1199.7	176.4	899.8	127.6	10000.0
19.00	169	250	150	9542	397	244	164	73	45	30	25	1191.1	304.3	899.8	266.9	10000.0
19.20	169	250	150	9191	198	141	95	50	30	21	16	1199.7	173.8	899.8	181.1	10000.0
19.40	169	250	150	9234	211	155	108	75	54	38	32	1199.7	172.6	899.8	139.4	10000.0
19.60	169	250	150	9452	322	192	145	80	54	41	27	780.1	439.9	381.4	183.1	10000.0
19.80	169	250	150	9107	242	167	113	60	42	30	25	1199.7	166.4	899.8	139.4	10000.0
20.00	169	250	150	9452	283	191	138	81	55	35	23	1199.7	195.1	899.8	159.9	10000.0
20.20	169	250	150	9542	288	184	131	81	53	39	33	1199.6	220.7	899.8	210.2	10000.0
20.40	169	250	150	10121	172	123	107	84	44	34	24	1187.3	6973.8	121.5	875.8	10000.0
20.60	169	250	150	9681	288	204	150	75	44	29	21	1199.7	186.2	899.7	174.0	10000.0
20.80	169	250	150	9728	273	204	156	94	62	43	31	1199.7	184.5	899.8	115.8	10000.0
21.00	169	250	150	9634	256	178	139	90	60	41	28	1199.6	262.4	566.5	138.8	10000.0
23.00	169	250	150	10121	351	254	190	79	39	27	20	1199.5	190.1	856.2	227.6	10000.0
23.20	169	250	150	10776	513	357	257	100	48	31	22	1134.3	323.5	899.2	258.9	10000.0
23.40	169	250	150	9970	398	273	193	64	27	14	11	1196.8	232.4	897.1	370.4	10000.0
23.60	169	250	150	10776	449	330	245	102	50	31	22	1199.0	216.9	889.5	196.8	10000.0
23.80	169	250	150	9363	196	137	108	68	44	29	17	1199.7	446.4	276.4	190.6	10000.0
24.00	169	250	150	9363	264	165	116	60	36	26	18	1199.3	224.0	899.1	291.9	10000.0
24.20	169	250	150	9872	296	207	148	78	43	26	20	1199.7	176.7	899.6	169.1	10000.0
24.40	169	250	150	9407	281	191	122	57	32	24	20	1199.7	157.4	899.8	131.8	10000.0
24.60	169	250	150	9320	269	136	95	43	20	12	9	690.6	712.8	140.1	768.6	10000.0
24.80	169	250	150	9234	215	137	98	62	41	27	22	1199.7	207.1	899.3	222.7	10000.0
25.00	190	300	150	9542	274	195	143	81	53	37	23	1199.7	202.5	899.8	146.9	10000.0
25.20	190	300	150	9588	292	205	149	79	50	40	35	1199.7	198.1	899.8	147.8	10000.0
25.40	190	300	150	9921	292	239	175	98	62	45	35	1199.7	189.7	899.8	101.1	10000.0
25.60	190	300	150	9191	254	170	126	68	48	32	29	1199.6	234.3	899.8	222.5	10000.0
25.80	190	300	150	10277	376	272	206	105	62	40	25	1199.5	243.1	899.8	171.8	10000.0
26.00	190	300	150	9634	305	216	154	66	36	24	16	1199.7	206.6	899.8	187.0	10000.0
26.20	190	300	150	9728	299	221	164	70	38	26	21	1199.7	210.0	899.8	195.5	10000.0
26.40	190	300	150	10121	368	292	235	152	112	77	53	1199.7	216.6	899.8	88.0	10000.0
26.60	190	300	150	8711	147	101	67	34	26	19	15	1199.7	186.5	899.9	223.8	10000.0
26.80	190	300	150	9681	315	226	166	79	48	32	22	1199.7	213.3	899.8	161.1	10000.0
26.98	190	300	150	8985	173	118	88	47	32	23	17	1199.7	193.7	899.8	264.2	10000.0

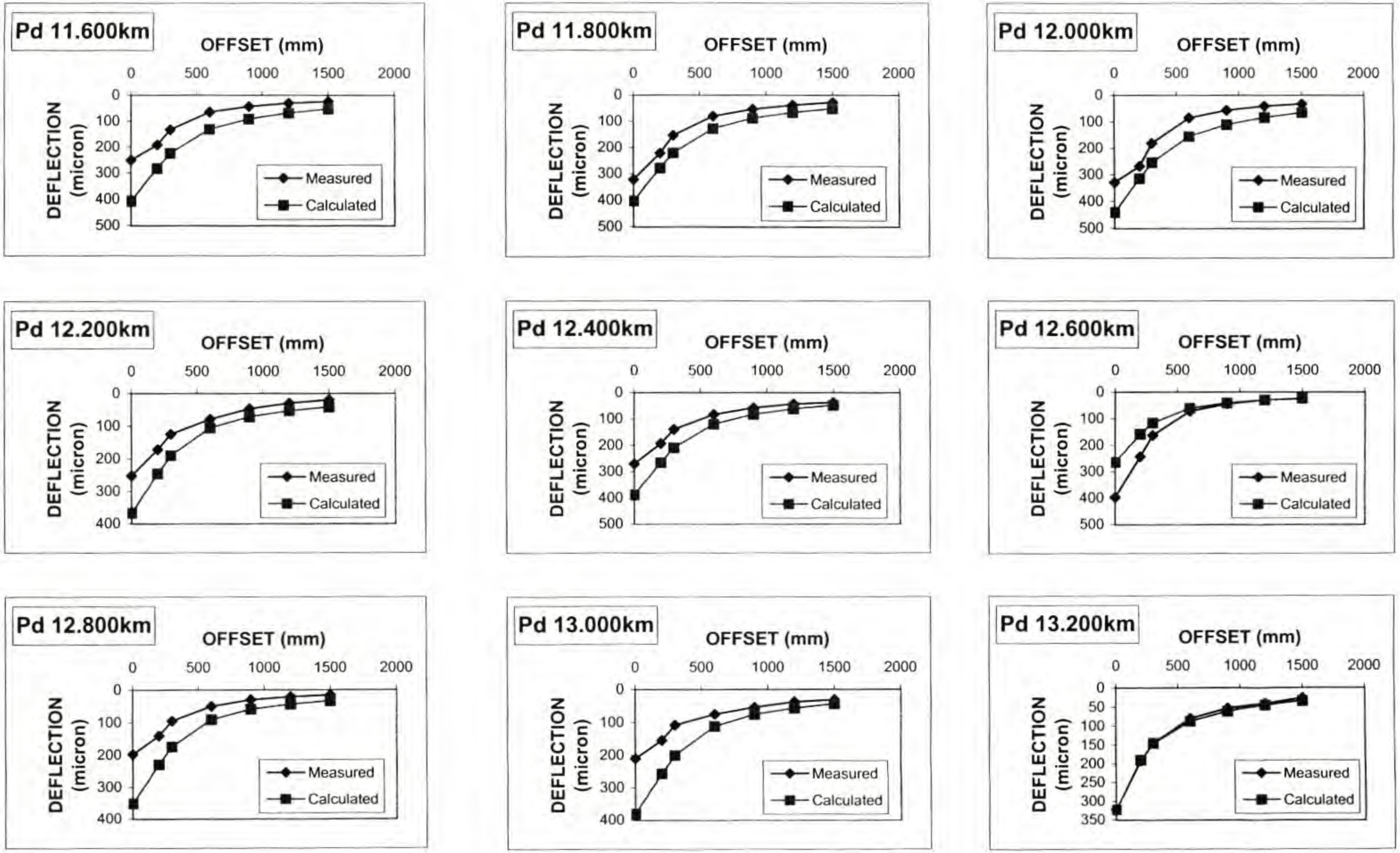
MR188: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (a)
DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

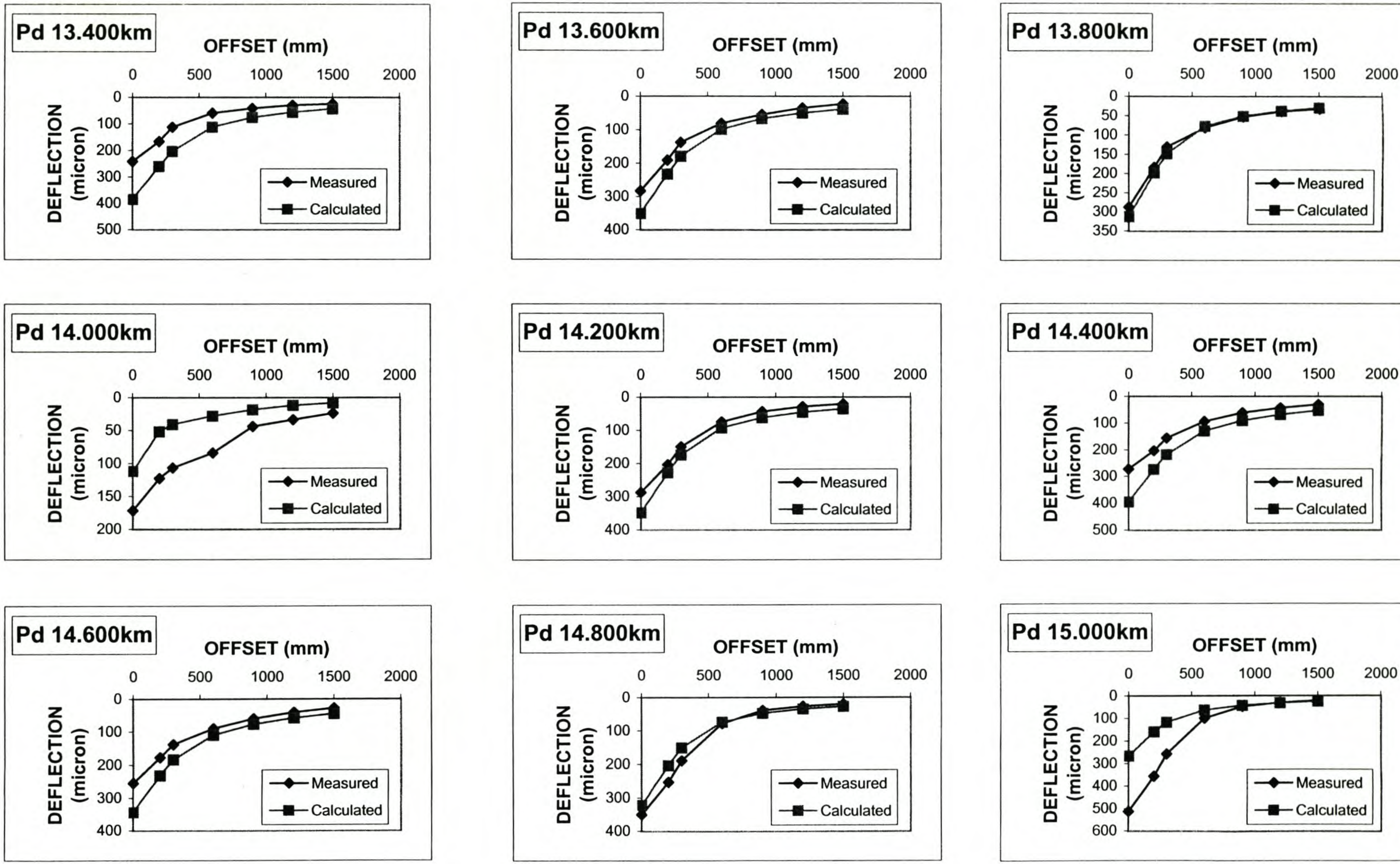
WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
18.00	169	250	150	9234	407	283	225	131	91	69	53	1199.7	169.6	899.8	114.4	10000.0
18.20	169	250	150	9452	403	279	221	127	88	66	52	1199.7	168.5	899.8	119.2	10000.0
18.40	169	250	150	9542	440	315	255	156	111	84	66	1199.7	164.6	899.8	92.9	10000.0
18.60	169	250	150	9728	367	246	191	105	72	53	42	1199.7	181.9	884.7	149.5	10000.0
18.80	169	250	150	9452	389	266	209	120	83	62	48	1199.7	176.4	899.8	127.6	10000.0
19.00	169	250	150	9542	264	159	117	61	41	30	24	1191.1	304.3	899.8	266.9	10000.0
19.20	169	250	150	9191	352	230	174	90	59	44	34	1199.7	173.8	899.8	181.1	10000.0
19.40	169	250	150	9234	381	258	201	111	76	56	44	1199.7	172.6	899.8	139.4	10000.0
19.60	169	250	150	9452	323	190	145	88	61	45	35	780.1	439.9	381.4	183.1	10000.0
19.80	169	250	150	9107	385	261	203	112	76	56	44	1199.7	166.4	899.8	139.4	10000.0
20.00	169	250	150	9452	351	233	179	98	67	50	39	1199.7	195.1	899.8	159.9	10000.0
20.20	169	250	150	9542	312	198	149	77	52	38	30	1199.6	220.7	899.8	210.2	10000.0
20.40	169	250	150	10121	112	52	41	28	18	12	8	1187.3	6973.8	121.5	875.8	10000.0
20.60	169	250	150	9681	348	229	174	93	62	46	36	1199.7	186.2	899.7	174.0	10000.0
20.80	169	250	150	9728	396	274	218	129	91	69	53	1199.7	184.5	899.8	115.8	10000.0
21.00	169	250	150	9634	344	232	184	110	77	58	45	1199.6	262.4	566.5	138.8	10000.0
23.00	169	250	150	10121	323	204	151	74	48	35	28	1199.5	190.1	856.2	227.6	10000.0
23.20	169	250	150	10776	266	159	117	63	43	32	25	1134.3	323.5	899.2	258.9	10000.0
23.40	169	250	150	9970	267	156	109	47	29	21	17	1196.8	232.4	897.1	370.4	10000.0
23.60	169	250	150	10776	321	206	156	83	56	42	33	1199.0	216.9	889.5	196.8	10000.0
23.80	169	250	150	9363	281	182	144	86	59	43	33	1199.7	446.4	276.4	190.6	10000.0
24.00	169	250	150	9363	286	173	124	58	37	27	21	1199.3	224.0	899.1	291.9	10000.0
24.20	169	250	150	9872	358	236	181	96	64	47	37	1199.7	176.7	899.6	169.1	10000.0
24.40	169	250	150	9407	399	273	214	118	80	60	46	1199.7	157.4	899.8	131.8	10000.0
24.60	169	250	150	9320	239	109	72	32	16	10	7	690.6	712.8	140.1	768.6	10000.0
24.80	169	250	150	9234	314	198	147	74	48	36	28	1199.7	207.1	899.3	222.7	10000.0
25.00	190	300	150	9542	337	228	180	104	71	53	42	1199.7	202.5	899.8	146.9	10000.0
25.20	190	300	150	9588	339	229	181	104	71	53	41	1199.7	198.1	899.8	147.8	10000.0
25.40	190	300	150	9921	385	274	224	139	100	77	61	1199.7	189.7	899.8	101.1	10000.0
25.60	190	300	150	9191	287	183	139	73	48	35	28	1199.6	234.3	899.8	222.5	10000.0
25.80	190	300	150	10277	305	201	157	90	62	47	37	1199.5	243.1	899.8	171.8	10000.0
26.00	190	300	150	9634	313	205	159	86	57	42	33	1199.7	206.6	899.8	187.0	10000.0
26.20	190	300	150	9728	308	201	154	83	55	41	32	1199.7	210.0	899.8	195.5	10000.0
26.40	190	300	150	10121	388	280	232	152	113	88	70	1199.7	216.6	899.8	88.0	10000.0
26.60	190	300	150	8711	309	199	151	76	47	34	27	1199.7	186.5	899.9	223.8	10000.0
26.80	190	300	150	9681	323	215	169	96	65	49	38	1199.7	213.3	899.8	161.1	10000.0
26.98	190	300	150	8985	294	185	138	66	41	29	23	1199.7	193.7	899.8	264.2	10000.0

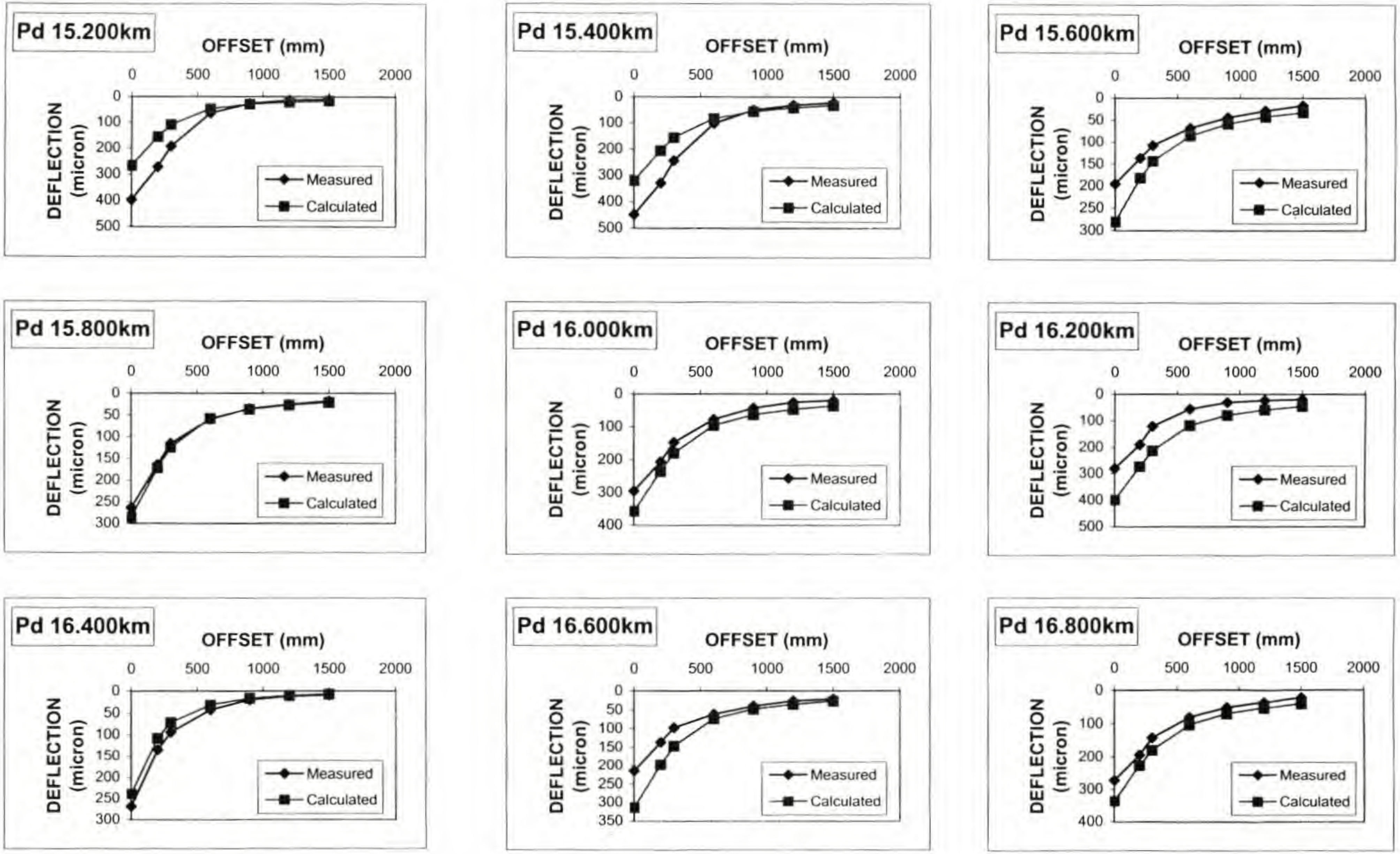
MR188: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)



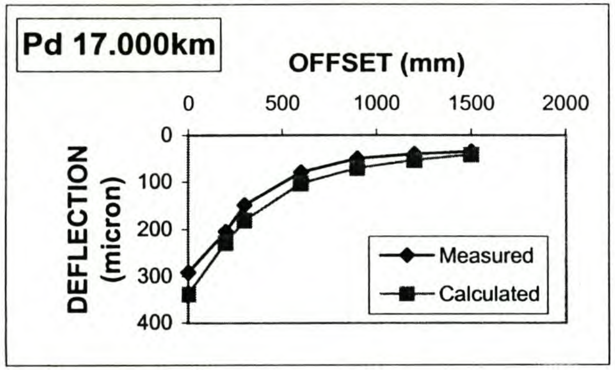
MR188: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)

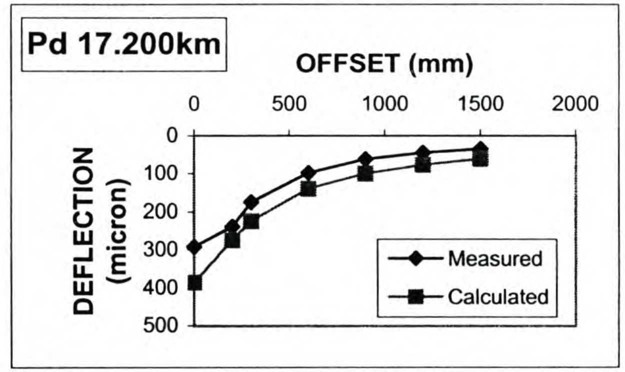


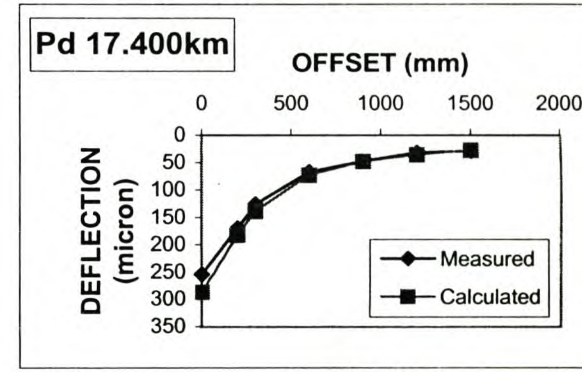
MR188: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)

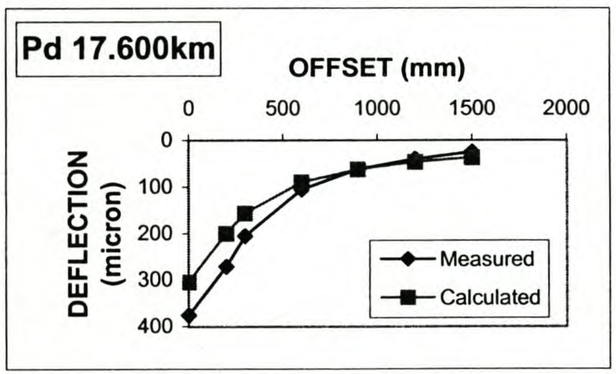


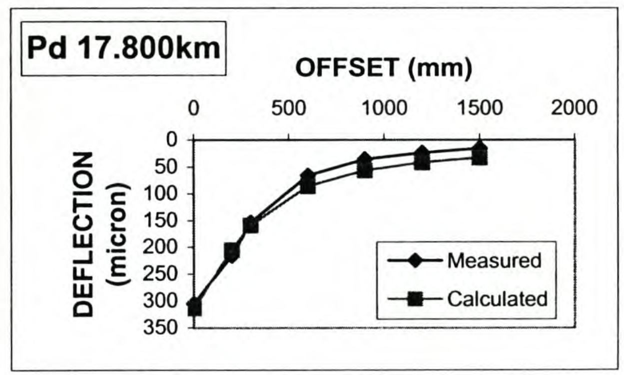
MR188: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)

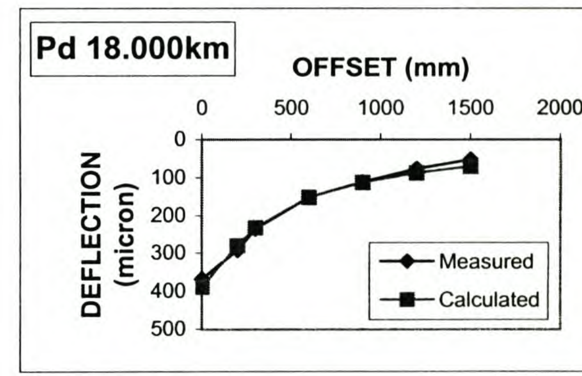


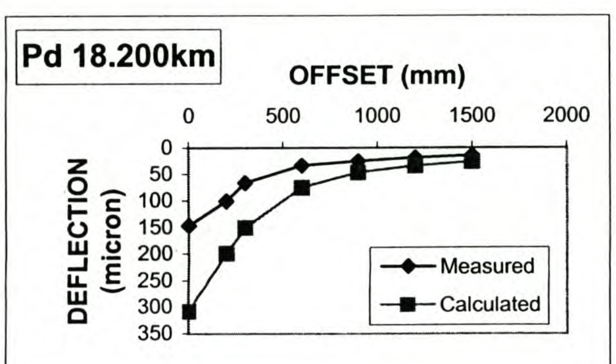


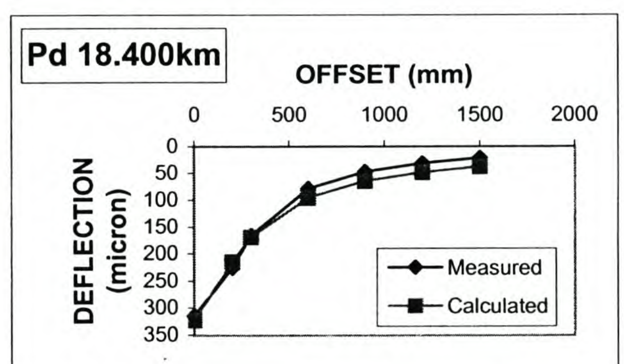


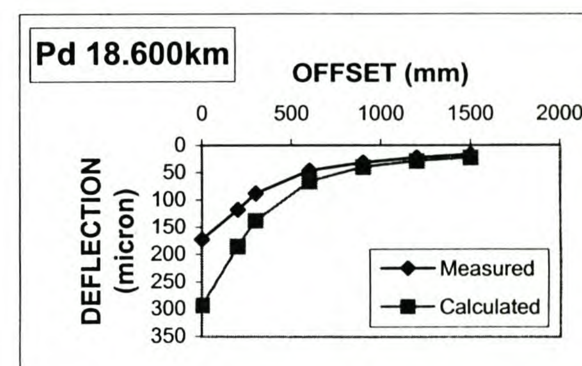










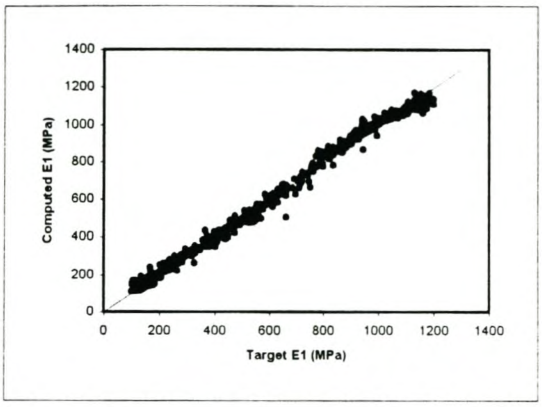


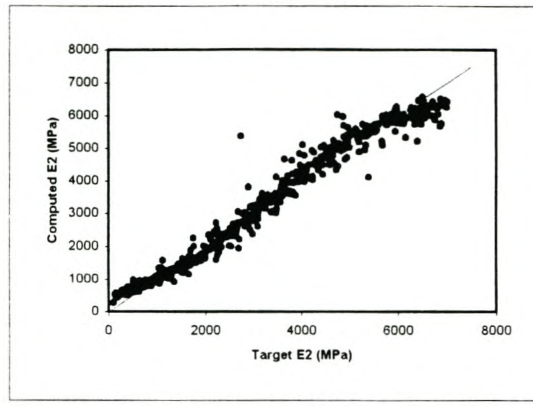
MR188: COMPARISON OF MEASURED AND CALCULATED DEFLECTIONS: CASE (a)

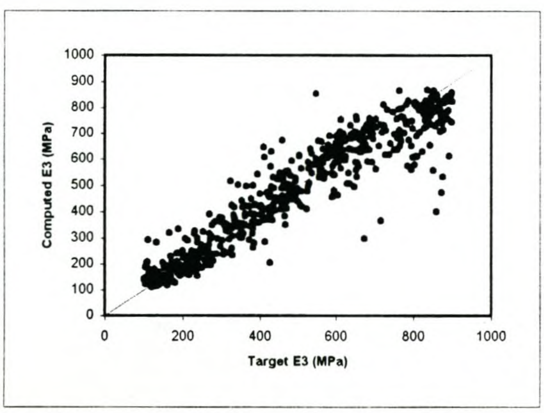
Pos (Km)\Offset (mm)		0	200	300	600	900	1200	1500	RMSE (%)
18.000	Measured	251	192	133	65	44	31	24	94.23%
	Calculated	407	283	225	131	91	69	53	
18.200	Measured	323	222	154	80	54	38	28	57.52%
	Calculated	403	279	221	127	88	66	52	
18.400	Measured	330	269	182	86	58	42	33	73.87%
	Calculated	440	315	255	156	111	84	66	
18.600	Measured	253	172	125	79	47	30	20	63.48%
	Calculated	367	246	191	105	72	53	42	
18.800	Measured	271	193	140	84	58	43	38	41.53%
	Calculated	389	266	209	120	83	62	48	
19.000	Measured	397	244	164	73	45	30	25	22.50%
	Calculated	264	159	117	61	41	30	24	
19.200	Measured	198	141	95	50	30	21	16	89.98%
	Calculated	352	230	174	90	59	44	34	
19.400	Measured	211	155	108	75	54	38	32	60.89%
	Calculated	381	258	201	111	76	56	44	
19.600	Measured	322	192	145	80	54	41	27	12.90%
	Calculated	323	190	145	88	61	45	35	
19.800	Measured	242	167	113	60	42	30	25	75.72%
	Calculated	385	261	203	112	76	56	44	
20.000	Measured	283	191	138	81	55	35	23	36.42%
	Calculated	351	233	179	98	67	50	39	
20.200	Measured	288	184	131	81	53	39	33	8.00%
	Calculated	312	198	149	77	52	38	30	
20.400	Measured	172	123	107	84	44	34	24	59.43%
	Calculated	112	52	41	28	18	12	8	
20.600	Measured	288	204	150	75	44	29	21	40.32%
	Calculated	348	229	174	93	62	46	36	
20.800	Measured	273	204	156	94	62	43	31	49.48%
	Calculated	396	274	218	129	91	69	53	
21.000	Measured	256	178	139	90	60	41	28	37.44%
	Calculated	344	232	184	110	77	58	45	
23.000	Measured	351	254	190	79	39	27	20	23.39%
	Calculated	323	204	151	74	48	35	28	
23.200	Measured	513	357	257	100	48	31	22	37.85%
	Calculated	266	159	117	63	43	32	25	
23.400	Measured	398	273	193	64	27	14	11	39.65%
	Calculated	267	156	109	47	29	21	17	
23.600	Measured	449	330	245	102	50	31	22	32.76%
	Calculated	321	206	156	83	56	42	33	
23.800	Measured	196	137	108	68	44	29	17	48.58%
	Calculated	281	182	144	86	59	43	33	
24.000	Measured	264	165	116	60	36	26	18	8.34%
	Calculated	286	173	124	58	37	27	21	
24.200	Measured	296	207	148	78	43	26	20	50.48%
	Calculated	358	236	181	96	64	47	37	
24.400	Measured	281	191	122	57	32	24	20	108.99%
	Calculated	399	273	214	118	80	60	46	
24.600	Measured	269	136	95	43	20	12	9	19.90%
	Calculated	239	109	72	32	16	10	7	
24.800	Measured	215	137	98	62	41	27	22	35.94%
	Calculated	314	198	147	74	48	36	28	
25.000	Measured	274	195	143	81	53	37	23	41.35%
	Calculated	337	228	180	104	71	53	42	
25.200	Measured	292	205	149	79	50	40	35	26.57%
	Calculated	339	229	181	104	71	53	41	
25.400	Measured	292	239	175	98	62	45	35	50.77%
	Calculated	385	274	224	139	100	77	61	
25.600	Measured	254	170	126	68	48	32	29	8.62%
	Calculated	287	183	139	73	48	35	28	
25.800	Measured	376	272	206	105	62	40	25	24.75%
	Calculated	305	201	157	90	62	47	37	
26.000	Measured	305	216	154	66	36	24	16	55.16%
	Calculated	313	205	159	86	57	42	33	
26.200	Measured	299	221	164	70	38	26	21	33.94%
	Calculated	308	201	154	83	55	41	32	
26.400	Measured	368	292	235	152	112	77	53	13.71%
	Calculated	388	280	232	152	113	88	70	
26.600	Measured	147	101	67	34	26	19	15	101.13%
	Calculated	309	199	151	76	47	34	27	
26.800	Measured	315	226	166	79	48	32	22	37.91%
	Calculated	323	215	169	96	65	49	38	
26.980	Measured	173	118	88	47	32	23	17	47.31%
	Calculated	294	185	138	66	41	29	23	

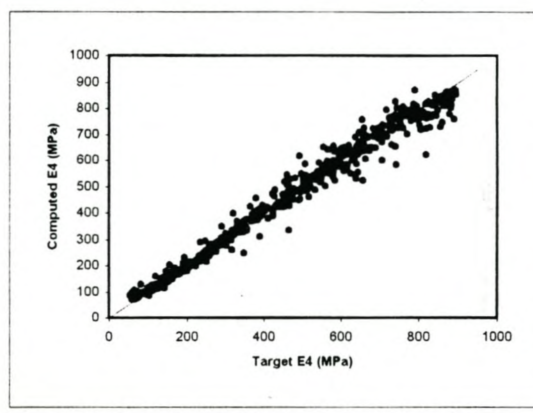
APPENDIX C.6: MR188 CASE (b)

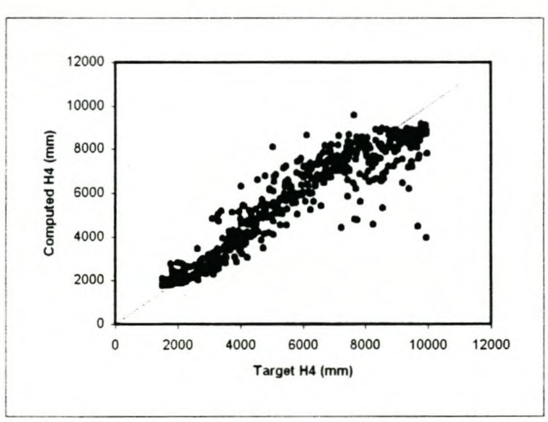
RESULTS OF BACK-CALCULATIONS (E-MODULI LAYERS 1-4 FROM DEFLECTIONS) OF A TYPICAL SOUTH AFRICAN PAVEMENT: GRANULAR BASE/CEMENTED SUBBASE WITH A THIN SURFACING : CASE (b): DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000MPa











MR188: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (b)
DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
18.00	251	192	133	65	44	31	24	118	68	21	96.60	A4	5.61	25.00	312	46712	0.40
18.20	323	222	154	80	54	38	28	169	74	26	89.80	A4	5.11	21.10	312	1841073	13.80
18.40	330	269	182	86	58	42	33	148	96	28	93.00	A4	5.23	25.00	312	314	0.00
18.60	253	172	125	79	47	30	20	128	46	32	95.50	A4	5.41	19.70	312	310	0.00
18.80	271	193	140	84	58	43	38	131	56	26	95.20	A4	5.56	25.00	312	5191626	31.80
19.00	397	244	164	73	45	30	25	233	91	28	76.00	A4	4.91	25.00	312	347	0.00
19.20	198	141	95	50	30	21	16	103	45	20	98.10	A4	5.93	25.00	235	1309941	13.10
19.40	211	155	108	75	54	38	32	103	33	21	98.10	A4	5.99	25.00	235	13546521	69.60
19.60	322	192	145	80	54	41	27	177	65	26	88.40	A4	4.67	11.80	235	1826218	17.50
19.80	242	167	113	60	42	30	25	129	53	18	95.40	A4	5.66	25.00	235	10953948	62.00
20.00	283	191	138	81	55	35	23	145	57	26	93.40	A4	4.81	11.10	235	364	0.00
20.20	288	184	131	81	53	39	33	157	50	28	91.70	A4	5.43	25.00	235	793574	8.40
20.40	172	123	107	84	44	34	24	65	23	40	100.00	A4	6.36	25.00	235	20841771	86.20
20.60	288	204	150	75	44	29	21	138	75	31	94.30	A4	5.37	25.00	235	4185978	33.40
20.80	273	204	156	94	62	43	31	117	62	32	96.70	A4	4.97	11.80	235	4611373	35.80
21.00	256	178	139	90	60	41	28	117	49	30	96.70	A4	4.94	9.90	235	342	0.00
23.00	351	254	190	79	39	27	20	161	111	40	91.10	A4	5.06	25.00	235	19307752	83.20
23.20	513	357	257	100	48	31	22	256	157	52	69.50	A4	4.56	24.40	235	8921143	55.00
23.40	398	273	193	64	27	14	11	205	129	37	82.80	A4	4.85	25.00	235	17655973	79.60
23.60	449	330	245	102	50	31	22	204	143	52	83.00	A4	4.62	21.10	235	4987886	37.90
23.80	196	137	108	68	44	29	17	88	40	24	99.30	A4	5.66	15.10	235	17872105	80.10
24.00	264	165	116	60	36	26	18	148	56	24	93.00	A4	5.48	25.00	235	16350604	76.70
24.20	296	207	148	78	43	26	20	148	70	35	93.00	A4	5.32	25.00	235	11443704	63.50
24.40	281	191	122	57	32	24	20	159	65	25	91.40	A4	5.37	25.00	235	9034675	55.50
24.60	269	136	95	43	20	12	9	174	52	23	89.00	A4	5.37	25.00	235	17946389	80.30
24.80	215	137	98	62	41	27	22	117	36	21	96.70	A4	5.85	25.00	235	26259197	95.60
25.00	274	195	143	81	53	37	23	131	62	28	67.30	F17	5.30	5.70	235	12815552	67.60
25.20	292	205	149	79	50	40	35	143	70	29	62.60	F17	6.31	25.00	235	28699328	99.30
25.40	292	239	175	98	62	45	35	117	77	36	72.50	F17	6.36	25.00	235	64641532	134.90
25.60	254	170	126	68	48	32	29	128	58	20	68.40	F17	6.64	25.00	235	159442102	176.60
25.80	376	272	206	105	62	40	25	170	101	43	51.30	F17	4.47	5.70	298	7673824	43.20
26.00	305	216	154	66	36	24	16	151	88	30	59.30	F17	6.04	25.00	298	49167059	112.30
26.20	299	221	164	70	38	26	21	135	94	32	65.70	F17	6.11	25.00	298	91046471	139.70
26.40	368	292	235	152	112	77	53	133	83	40	66.50	F17	4.30	3.00	298	6229499	37.50
26.60	147	101	67	34	26	19	15	80	33	8	84.10	F17	8.32	25.00	298	806806672	242.30
26.80	315	226	166	79	48	32	22	149	87	31	60.10	F17	5.97	23.40	298	56420518	242.30
26.98	173	118	88	47	32	23	17	85	41	15	82.70	F17	7.79	25.00	298	0	242.30

MR188: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (b)
DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

NEURAL NETWORK: BACKCALCULATED E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
18.00	169	250	150	4542.8	251	192	133	65	44	31	24	1199.7	187.8	899.9	329.6	10000.0
18.20	169	250	150	4277.2	323	222	154	80	54	38	28	1199.7	200.6	899.9	281.7	10000.0
18.40	169	250	150	4529.5	330	269	182	86	58	42	33	1199.7	185.6	899.9	288.4	10000.0
18.60	169	250	150	1578.4	253	172	125	79	47	30	20	1199.7	237.0	899.4	152.8	10000.0
18.80	169	250	150	3620.4	271	193	140	84	58	43	38	1199.7	223.8	899.9	198.9	10000.0
19.00	169	250	150	3919.4	397	244	164	73	45	30	25	1192.8	456.8	899.9	245.9	10000.0
19.20	169	250	150	3320.8	198	141	95	50	30	21	16	1199.7	204.2	899.9	342.4	10000.0
19.40	169	250	150	2790.2	211	155	108	75	54	38	32	1199.7	261.4	899.9	216.0	10000.0
19.60	169	250	150	7083.4	322	192	145	80	54	41	27	928.9	539.3	844.5	189.0	10000.0
19.80	169	250	150	4623.8	242	167	113	60	42	30	25	1199.7	204.9	899.9	335.0	10000.0
20.00	169	250	150	3391.3	283	191	138	81	55	35	23	1199.7	322.8	899.9	233.5	10000.0
20.20	169	250	150	1982.0	288	184	131	81	53	39	33	1199.5	326.8	863.6	155.9	10000.0
20.40	169	250	150	9998.1	172	123	107	84	44	34	24	1015.5	6999.4	100.1	896.8	10000.0
20.60	169	250	150	1809.0	288	204	150	75	44	29	21	1199.7	219.5	899.9	195.0	10000.0
20.80	169	250	150	2192.7	273	204	156	94	62	43	31	1199.7	222.6	899.9	175.7	10000.0
21.00	169	250	150	1675.7	256	178	139	90	60	41	28	1199.4	395.2	899.2	132.5	10000.0
23.00	169	250	150	1999.3	351	254	190	79	39	27	20	1199.7	188.9	877.9	242.8	10000.0
23.20	169	250	150	1597.1	513	357	257	100	48	31	22	1199.7	187.7	899.9	202.5	10000.0
23.40	169	250	150	1562.2	398	273	193	64	27	14	11	1199.7	182.5	899.9	242.7	10000.0
23.60	169	250	150	1549.6	449	330	245	102	50	31	22	1199.7	178.8	899.9	174.2	10000.0
23.80	169	250	150	1695.9	196	137	108	68	44	29	17	1199.6	383.3	899.8	171.2	10000.0
24.00	169	250	150	2267.1	264	165	116	60	36	26	18	1199.2	338.3	899.7	233.7	10000.0
24.20	169	250	150	1546.4	296	207	148	78	43	26	20	1199.7	181.0	899.5	153.9	10000.0
24.40	169	250	150	3950.1	281	191	122	57	32	24	20	1199.7	190.2	899.9	360.1	10000.0
24.60	169	250	150	8948.0	269	136	95	43	20	12	9	685.5	1018.3	102.8	768.7	10000.0
24.80	169	250	150	1931.0	215	137	98	62	41	27	22	1199.2	521.3	899.9	204.9	10000.0
25.00	190	300	150	3108.2	274	195	143	81	53	37	23	1199.7	205.4	899.9	258.9	10000.0
25.20	190	300	150	5285.5	292	205	149	79	50	40	35	1199.7	204.0	899.9	210.5	10000.0
25.40	190	300	150	2708.2	292	239	175	98	62	45	35	1199.7	192.8	899.9	221.3	10000.0
25.60	190	300	150	3250.1	254	170	126	68	48	32	29	1198.7	457.4	899.9	224.4	10000.0
25.80	190	300	150	2124.8	376	272	206	105	62	40	25	1199.7	205.8	899.9	229.7	10000.0
26.00	190	300	150	3154.8	305	216	154	66	36	24	16	1199.7	197.0	899.9	323.6	10000.0
26.20	190	300	150	1736.3	299	221	164	70	38	26	21	1199.7	203.1	899.9	213.0	10000.0
26.40	190	300	150	2855.6	368	292	235	152	112	77	53	1199.7	205.9	899.9	166.0	10000.0
26.60	190	300	150	4867.2	147	101	67	34	26	19	15	1199.7	215.5	899.9	389.3	10000.0
26.80	190	300	150	3219.5	315	226	166	79	48	32	22	1199.7	201.3	899.9	286.7	10000.0
26.98	190	300	150	3245.8	173	118	88	47	32	23	17	1199.7	313.6	899.9	282.0	10000.0

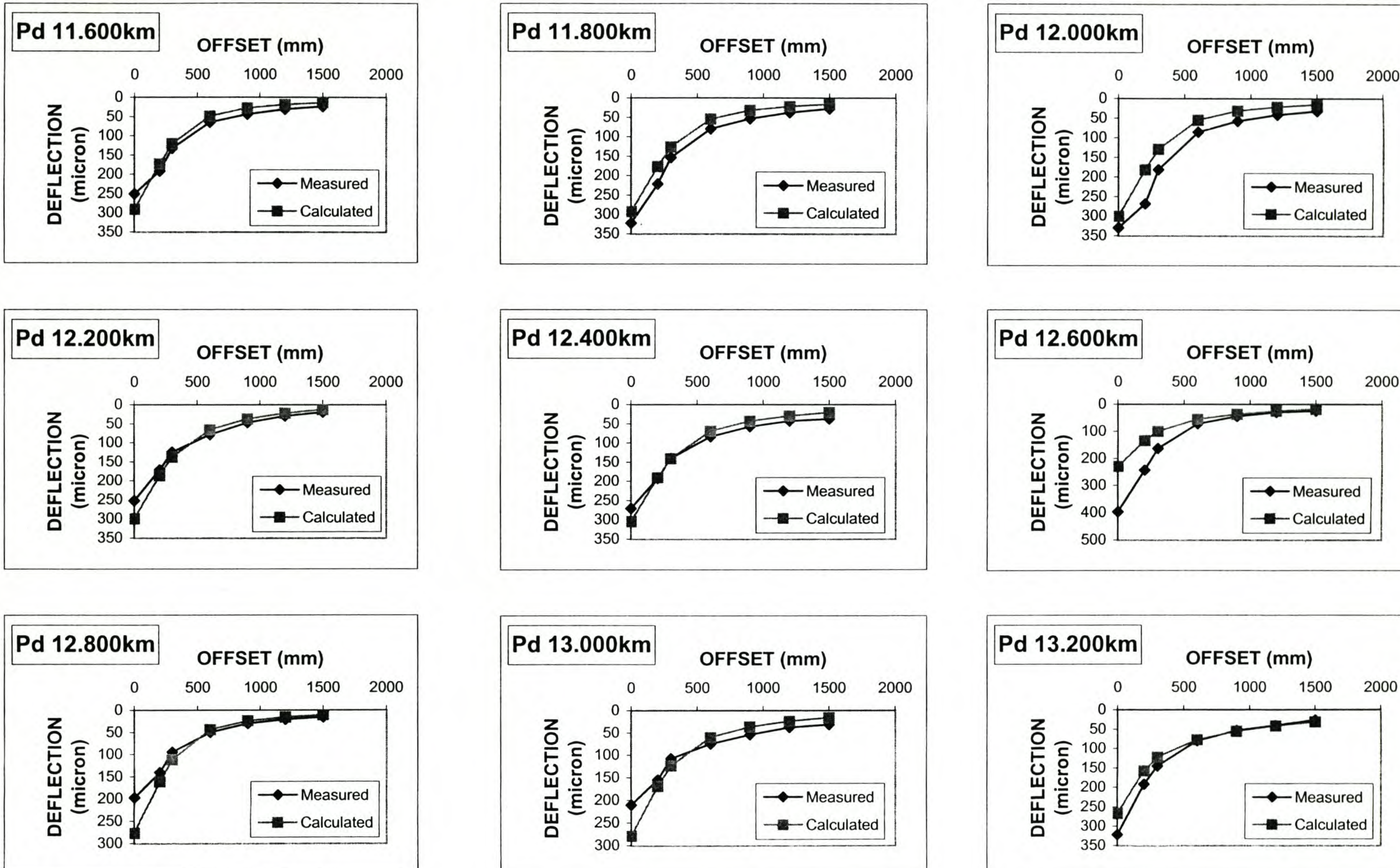
MR188: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (b)
DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

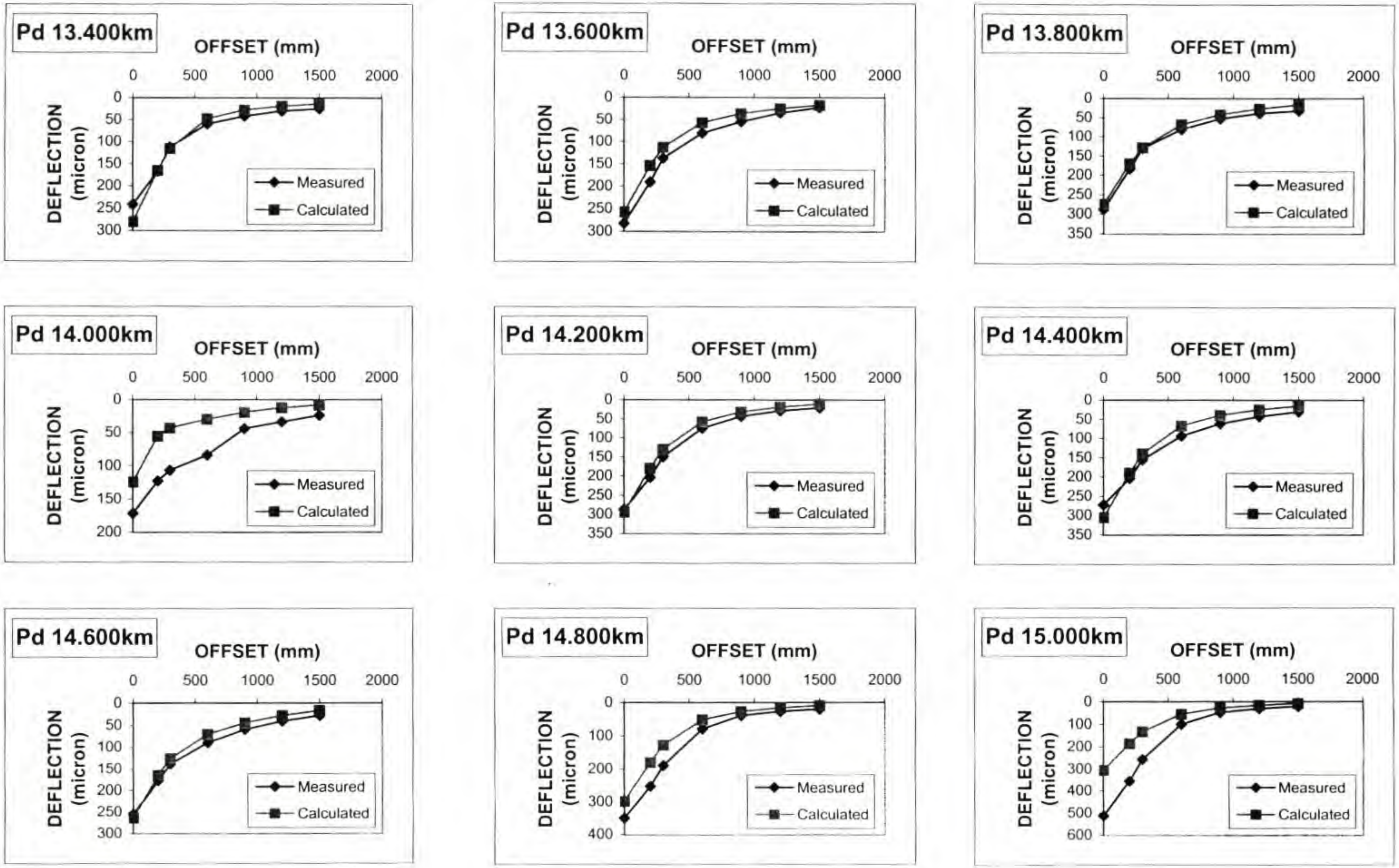
WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
18.00	169	250	150	4543	291	173	121	49	28	19	14	1199.7	187.8	899.9	329.6	10000.0
18.20	169	250	150	4277	293	177	126	54	32	22	16	1199.7	200.6	899.9	281.7	10000.0
18.40	169	250	150	4530	300	182	129	55	32	22	16	1199.7	185.6	899.9	288.4	10000.0
18.60	169	250	150	1578	299	186	138	66	37	22	13	1199.7	237.0	899.4	152.8	10000.0
18.80	169	250	150	3620	304	190	141	69	43	29	21	1199.7	223.8	899.9	198.9	10000.0
19.00	169	250	150	3919	230	134	100	55	36	25	18	1192.8	456.8	899.9	245.9	10000.0
19.20	169	250	150	3321	277	162	112	44	24	16	11	1199.7	204.2	899.9	342.4	10000.0
19.40	169	250	150	2790	279	169	124	60	36	24	16	1199.7	261.4	899.9	216.0	10000.0
19.60	169	250	150	7083	267	157	122	77	55	41	31	928.9	539.3	844.5	189.0	10000.0
19.80	169	250	150	4624	281	166	116	48	28	19	14	1199.7	204.9	899.9	335.0	10000.0
20.00	169	250	150	3391	257	154	113	57	36	25	17	1199.7	322.8	899.9	233.5	10000.0
20.20	169	250	150	1982	275	170	128	68	42	27	17	1199.5	326.8	863.6	155.9	10000.0
20.40	169	250	150	9998	124	55	43	30	19	12	8	1015.5	6999.4	100.1	896.8	10000.0
20.60	169	250	150	1809	294	180	130	58	32	19	11	1199.7	219.5	899.9	195.0	10000.0
20.80	169	250	150	2193	305	190	140	67	40	25	16	1199.7	222.6	899.9	175.7	10000.0
21.00	169	250	150	1676	264	165	126	71	45	28	17	1199.4	395.2	899.2	132.5	10000.0
23.00	169	250	150	1999	298	180	127	52	27	16	10	1199.7	188.9	877.9	242.8	10000.0
23.20	169	250	150	1597	306	187	133	55	28	16	9	1199.7	187.7	899.9	202.5	10000.0
23.40	169	250	150	1562	297	178	124	47	23	13	7	1199.7	182.5	899.9	242.7	10000.0
23.60	169	250	150	1550	320	200	144	62	32	18	10	1199.7	178.8	899.9	174.2	10000.0
23.80	169	250	150	1696	250	150	112	58	35	22	13	1199.6	383.3	899.8	171.2	10000.0
24.00	169	250	150	2267	247	145	105	51	31	19	12	1199.2	338.3	899.7	233.7	10000.0
24.20	169	250	150	1546	328	207	152	68	36	21	12	1199.7	181.0	899.5	153.9	10000.0
24.40	169	250	150	3950	283	166	115	44	24	16	12	1199.7	190.2	899.9	360.1	10000.0
24.60	169	250	150	8948	228	104	73	35	19	11	8	685.5	1018.3	102.8	768.7	10000.0
24.80	169	250	150	1931	220	128	95	52	32	20	13	1199.2	521.3	899.9	204.9	10000.0
25.00	190	300	150	3108	279	172	126	56	31	21	14	1199.7	205.4	899.9	258.9	10000.0
25.20	190	300	150	5285	299	191	145	73	45	32	24	1199.7	204.0	899.9	210.5	10000.0
25.40	190	300	150	2708	293	184	136	62	35	22	15	1199.7	192.8	899.9	221.3	10000.0
25.60	190	300	150	3250	222	131	99	55	37	25	18	1198.7	457.4	899.9	224.4	10000.0
25.80	190	300	150	2125	280	172	126	56	30	18	12	1199.7	205.8	899.9	229.7	10000.0
26.00	190	300	150	3155	271	163	117	48	25	16	11	1199.7	197.0	899.9	323.6	10000.0
26.20	190	300	150	1736	281	173	127	55	29	17	10	1199.7	203.1	899.9	213.0	10000.0
26.40	190	300	150	2856	306	198	151	77	47	31	21	1199.7	205.9	899.9	166.0	10000.0
26.60	190	300	150	4867	257	152	108	44	24	17	12	1199.7	215.5	899.9	389.3	10000.0
26.80	190	300	150	3220	276	168	122	53	29	19	13	1199.7	201.3	899.9	286.7	10000.0
26.98	190	300	150	3246	237	139	101	49	29	20	14	1199.7	313.6	899.9	282.0	10000.0

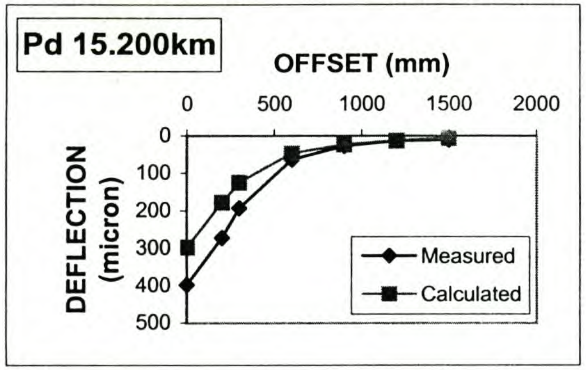
MR188: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

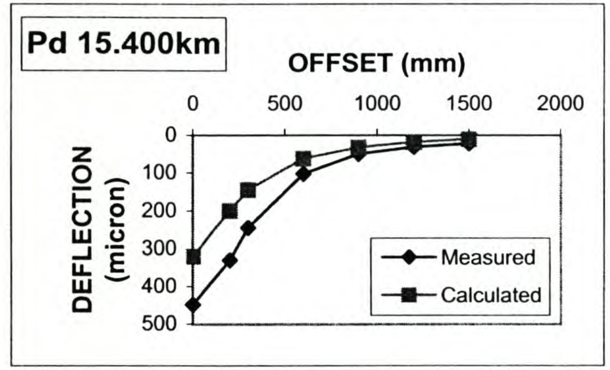


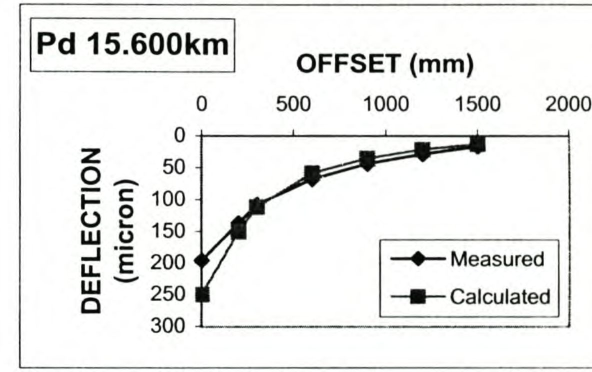
MR188: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

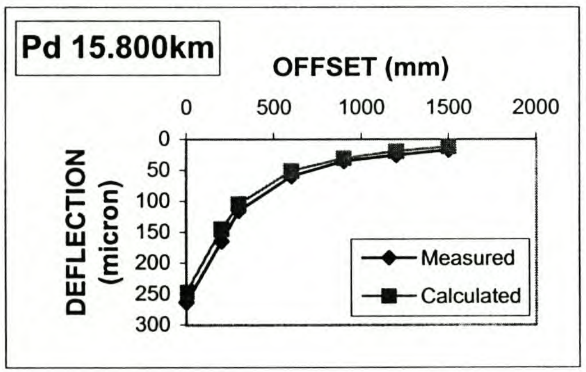


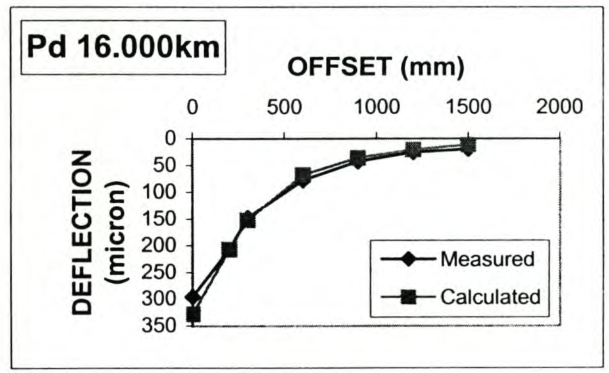
MR188: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

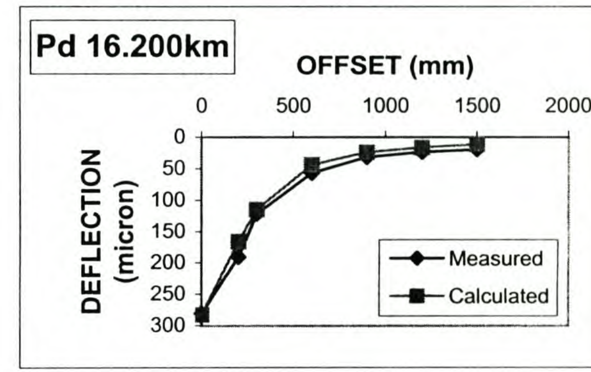


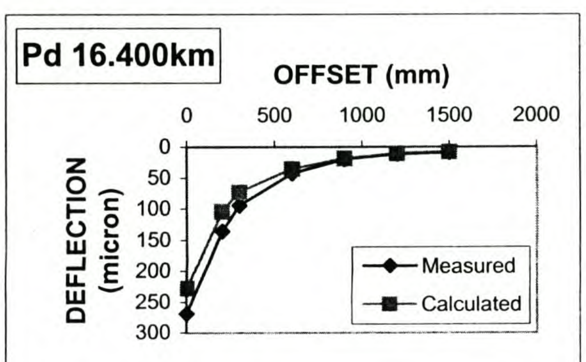


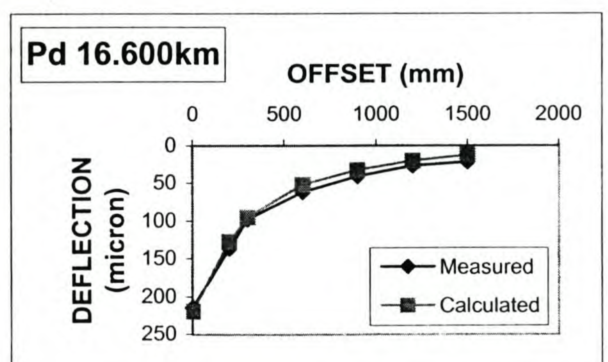


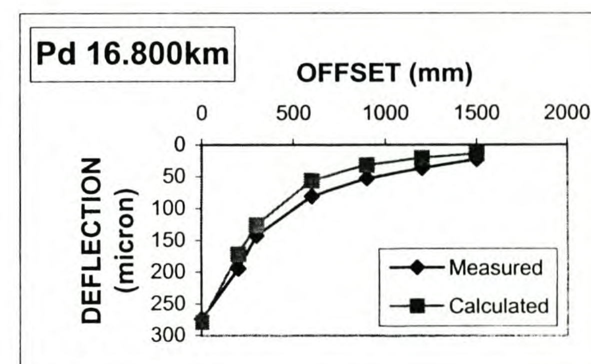




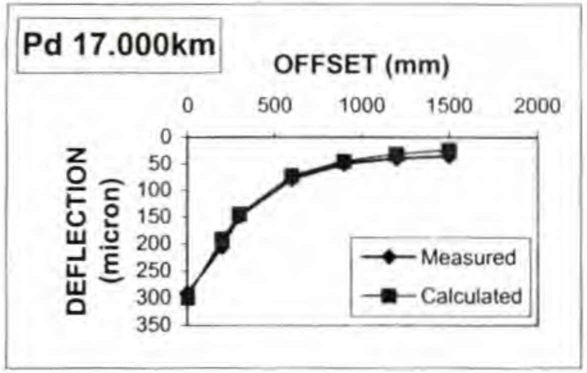


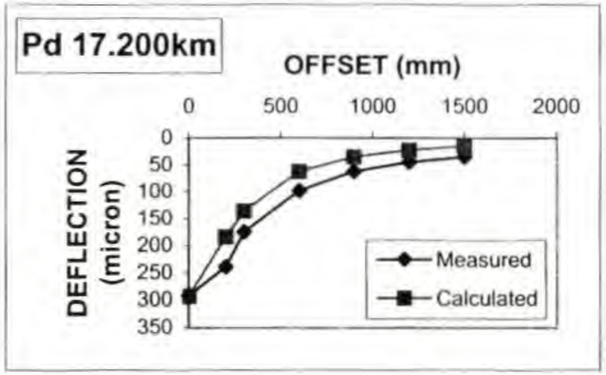


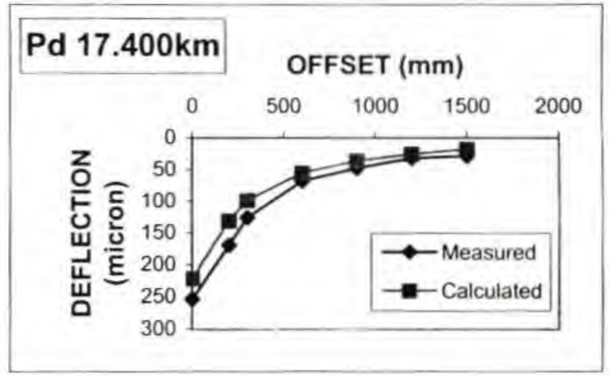


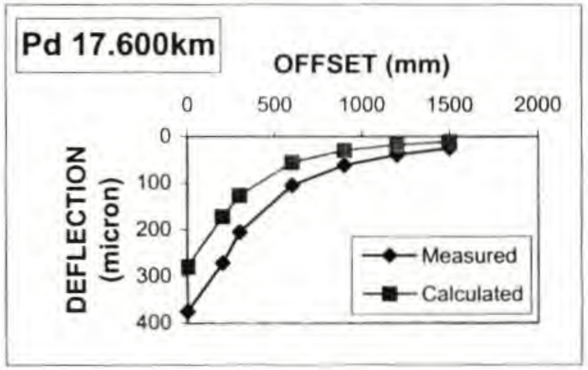


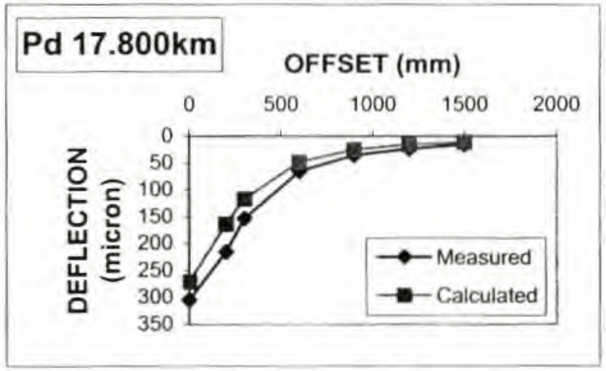
MR188: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

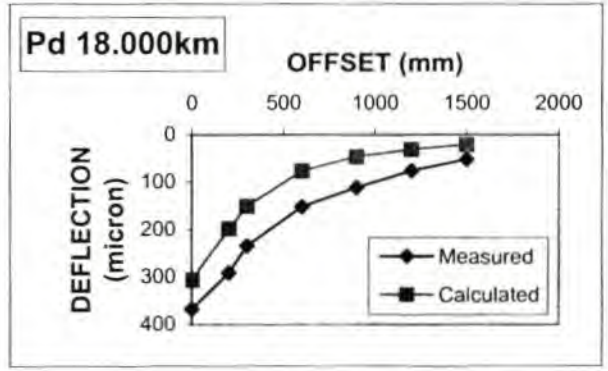


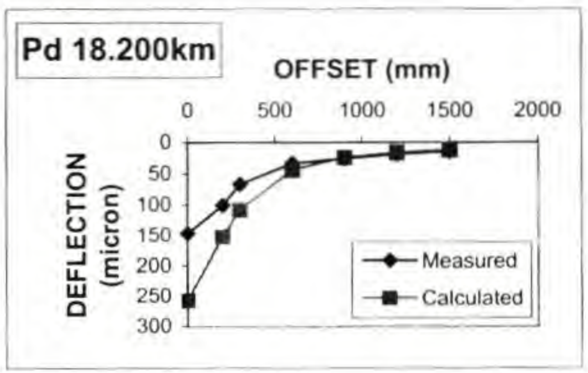


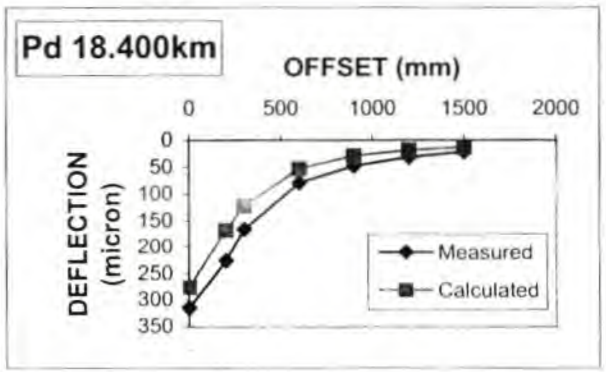


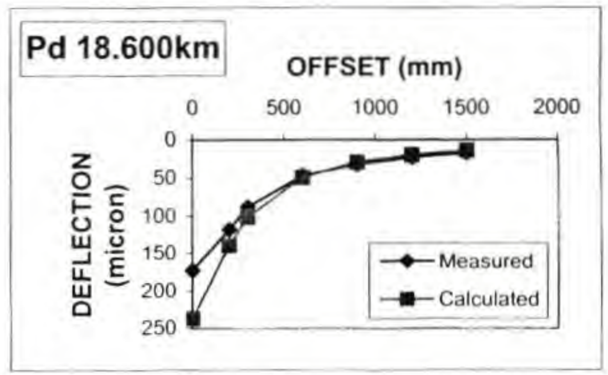












MR188: COMPARISON OF MEASURED AND CALCULATED DEFLECTIONS: CASE (b)

Pos (Km)\Offset (mm)		0	200	300	600	900	1200	1500	RMSE (%)
18.000	Measured	251	192	133	65	44	31	24	28.32%
	Calculated	291	173	121	49	28	19	14	
18.200	Measured	323	222	154	80	54	38	28	32.05%
	Calculated	293	177	126	54	32	22	16	
18.400	Measured	330	269	182	86	58	42	33	38.43%
	Calculated	300	182	129	55	32	22	16	
18.600	Measured	253	172	125	79	47	30	20	21.76%
	Calculated	299	186	138	66	37	22	13	
18.800	Measured	271	193	140	84	58	43	38	24.43%
	Calculated	304	190	141	69	43	29	21	
19.000	Measured	397	244	164	73	45	30	25	32.31%
	Calculated	230	134	100	55	36	25	18	
19.200	Measured	198	141	95	50	30	21	16	24.61%
	Calculated	277	162	112	44	24	16	11	
19.400	Measured	211	155	108	75	54	38	32	30.99%
	Calculated	279	169	124	60	36	24	16	
19.600	Measured	322	192	145	80	54	41	27	12.96%
	Calculated	267	157	122	77	55	41	31	
19.800	Measured	242	167	113	60	42	30	25	27.06%
	Calculated	281	166	116	48	28	19	14	
20.000	Measured	283	191	138	81	55	35	23	24.88%
	Calculated	257	154	113	57	36	25	17	
20.200	Measured	288	184	131	81	53	39	33	24.23%
	Calculated	275	170	128	68	42	27	17	
20.400	Measured	172	123	107	84	44	34	24	57.53%
	Calculated	124	55	43	30	19	12	8	
20.600	Measured	288	204	150	75	44	29	21	26.58%
	Calculated	294	180	130	58	32	19	11	
20.800	Measured	273	204	156	94	62	43	31	30.66%
	Calculated	305	190	140	67	40	25	16	
21.000	Measured	256	178	139	90	60	41	28	23.26%
	Calculated	264	165	126	71	45	28	17	
23.000	Measured	351	254	190	79	39	27	20	35.00%
	Calculated	298	180	127	52	27	16	10	
23.200	Measured	513	357	257	100	48	31	22	47.70%
	Calculated	306	187	133	55	28	16	9	
23.400	Measured	398	273	193	64	27	14	11	28.08%
	Calculated	297	178	124	47	23	13	7	
23.600	Measured	449	330	245	102	50	31	22	40.74%
	Calculated	320	200	144	62	32	18	10	
23.800	Measured	196	137	108	68	44	29	17	19.58%
	Calculated	250	150	112	58	35	22	13	
24.000	Measured	264	165	116	60	36	26	18	18.20%
	Calculated	247	145	105	51	31	19	12	
24.200	Measured	296	207	148	78	43	26	20	19.70%
	Calculated	328	207	152	68	36	21	12	
24.400	Measured	281	191	122	57	32	24	20	24.00%
	Calculated	283	166	115	44	24	16	12	
24.600	Measured	269	136	95	43	20	12	9	16.98%
	Calculated	228	104	73	35	19	11	8	
24.800	Measured	215	137	98	62	41	27	22	21.34%
	Calculated	220	128	95	52	32	20	13	
25.000	Measured	274	195	143	81	53	37	23	30.17%
	Calculated	279	172	126	56	31	21	14	
25.200	Measured	292	205	149	79	50	40	35	15.51%
	Calculated	299	191	145	73	45	32	24	
25.400	Measured	292	239	175	98	62	45	35	37.98%
	Calculated	293	184	136	62	35	22	15	
25.600	Measured	254	170	126	68	48	32	29	23.84%
	Calculated	222	131	99	55	37	25	18	
25.800	Measured	376	272	206	105	62	40	25	45.09%
	Calculated	280	172	126	56	30	18	12	
26.000	Measured	305	216	154	66	36	24	16	26.38%
	Calculated	271	163	117	48	25	16	11	
26.200	Measured	299	221	164	70	38	26	21	29.52%
	Calculated	281	173	127	55	29	17	10	
26.400	Measured	368	292	235	152	112	77	53	47.08%
	Calculated	306	198	151	77	47	31	21	
26.600	Measured	147	101	67	34	26	19	15	43.79%
	Calculated	257	152	108	44	24	17	12	
26.800	Measured	315	226	166	79	48	32	22	33.07%
	Calculated	276	168	122	53	29	19	13	
26.980	Measured	173	118	88	47	32	23	17	19.28%
	Calculated	237	139	101	49	29	20	14	

MR188: E-MODULI BACK-CALCULATED WITH MODCOMP

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
18.00	251	192	133	65	44	31	24	118	68	21	96.60	A4	5.61	25.00	312	46712	0.40
18.20	323	222	154	80	54	38	28	169	74	26	89.80	A4	5.11	21.10	312	1841073	13.80
18.40	330	269	182	86	58	42	33	148	96	28	93.00	A4	5.23	25.00	312	314	0.00
18.60	253	172	125	79	47	30	20	128	46	32	95.50	A4	5.41	19.70	312	310	0.00
18.80	271	193	140	84	58	43	38	131	56	26	95.20	A4	5.56	25.00	312	5191626	31.80
19.00	397	244	164	73	45	30	25	233	91	28	76.00	A4	4.91	25.00	312	347	0.00
19.20	198	141	95	50	30	21	16	103	45	20	98.10	A4	5.93	25.00	235	1309941	13.10
19.40	211	155	108	75	54	38	32	103	33	21	98.10	A4	5.99	25.00	235	13546521	69.60
19.60	322	192	145	80	54	41	27	177	65	26	88.40	A4	4.67	11.80	235	1826218	17.50
19.80	242	167	113	60	42	30	25	129	53	18	95.40	A4	5.66	25.00	235	10953948	62.00
20.00	283	191	138	81	55	35	23	145	57	26	93.40	A4	4.81	11.10	235	364	0.00
20.20	288	184	131	81	53	39	33	157	50	28	91.70	A4	5.43	25.00	235	793574	8.40
20.40	172	123	107	84	44	34	24	65	23	40	100.00	A4	6.36	25.00	235	20841771	86.20
20.60	288	204	150	75	44	29	21	138	75	31	94.30	A4	5.37	25.00	235	4185978	33.40
20.80	273	204	156	94	62	43	31	117	62	32	96.70	A4	4.97	11.80	235	4611373	35.80
21.00	256	178	139	90	60	41	28	117	49	30	96.70	A4	4.94	9.90	235	342	0.00
23.00	351	254	190	79	39	27	20	161	111	40	91.10	A4	5.06	25.00	235	19307752	83.20
23.20	513	357	257	100	48	31	22	256	157	52	69.50	A4	4.56	24.40	235	8921143	55.00
23.40	398	273	193	64	27	14	11	205	129	37	82.80	A4	4.85	25.00	235	17655973	79.60
23.60	449	330	245	102	50	31	22	204	143	52	83.00	A4	4.62	21.10	235	4987886	37.90
23.80	196	137	108	68	44	29	17	88	40	24	99.30	A4	5.66	15.10	235	17872105	80.10
24.00	264	165	116	60	36	26	18	148	56	24	93.00	A4	5.48	25.00	235	16350604	76.70
24.20	296	207	148	78	43	26	20	148	70	35	93.00	A4	5.32	25.00	235	11443704	63.50
24.40	281	191	122	57	32	24	20	159	65	25	91.40	A4	5.37	25.00	235	9034675	55.50
24.60	269	136	95	43	20	12	9	174	52	23	89.00	A4	5.37	25.00	235	17946389	80.30
24.80	215	137	98	62	41	27	22	117	36	21	96.70	A4	5.85	25.00	235	26259197	95.60
25.00	274	195	143	81	53	37	23	131	62	28	67.30	F17	5.30	5.70	235	12815552	67.60
25.20	292	205	149	79	50	40	35	143	70	29	62.60	F17	6.31	25.00	235	28699328	99.30
25.40	292	239	175	98	62	45	35	117	77	36	72.50	F17	6.36	25.00	235	64641532	134.90
25.60	254	170	126	68	48	32	29	128	58	20	68.40	F17	6.64	25.00	235	159442102	176.60
25.80	376	272	206	105	62	40	25	170	101	43	51.30	F17	4.47	5.70	298	7673824	43.20
26.00	305	216	154	66	36	24	16	151	88	30	59.30	F17	6.04	25.00	298	49167059	112.30
26.20	299	221	164	70	38	26	21	135	94	32	65.70	F17	6.11	25.00	298	91046471	139.70
26.40	368	292	235	152	112	77	53	133	83	40	66.50	F17	4.30	3.00	298	6229499	37.50
26.60	147	101	67	34	26	19	15	80	33	8	84.10	F17	8.32	25.00	298	806806672	242.30
26.80	315	226	166	79	48	32	22	149	87	31	60.10	F17	5.97	23.40	298	56420518	242.30
26.98	173	118	88	47	32	23	17	85	41	15	82.70	F17	7.79	25.00	298	0	242.30

MR188: E-MODULI BACK-CALCULATED WITH MODCOMP

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

NEURAL NETWORK: BACKCALCULATED E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
18.00	169	250	150	8600	251	192	133	65	44	31	24	528.0	3000.0	118.0	317.0	261.0
18.20	169	250	150	6500	323	222	154	80	54	38	28	395.0	3000.0	82.7	254.0	216.0
18.40	169	250	150	14300	330	269	182	86	58	42	33	397.0	3000.0	78.7	217.0	671.0
18.60	169	250	150	3500	253	172	125	79	47	30	20	632.0	3000.0	27.9	310.0	110000.0
18.80	169	250	150	16000	271	193	140	84	58	43	38	542.0	3000.0	45.6	604.0	9.3
19.00	169	250	150	8300	397	244	164	73	45	30	25	314.0	3000.0	65.2	267.0	1820.0
19.20	169	250	150	7300	198	141	95	50	30	21	16	715.0	3000.0	108.0	403.0	5020.0
19.40	169	250	150	15000	211	155	108	75	54	38	32	840.0	3000.0	97.4	370.0	30.6
19.60	169	250	150	15000	322	192	145	80	54	41	27	396.0	3000.0	93.5	227.0	689000.0
19.80	169	250	150	15000	242	167	113	60	42	30	25	537.0	3000.0	113.0	481.0	40.9
20.00	169	250	150	3600	283	191	138	81	55	35	23	495.0	3000.0	85.2	186.0	689000.0
20.20	169	250	150	15000	288	184	131	81	53	39	33	486.0	3000.0	38.6	712.0	10.2
20.40	169	250	150	12100	172	123	107	84	44	34	24	1830.0	3000.0	28.6	279.0	689000.0
20.60	169	250	150	4500	288	204	150	75	44	29	21	479.0	3000.0	53.0	241.0	2970.0
20.80	169	250	150	5500	273	204	156	94	62	43	31	617.0	3000.0	53.2	209.0	233.0
21.00	169	250	150	4400	256	178	139	90	60	41	28	670.0	3000.0	65.2	210.0	272.0
23.00	169	250	150	6000	351	254	190	79	39	27	20	368.0	3000.0	30.7	286.0	689000.0
23.20	169	250	150	4000	513	357	257	100	48	31	22	263.0	3000.0	18.3	205.0	689000.0
23.40	169	250	150	15000	398	273	193	64	27	14	11	289.0	3000.0	47.2	484.0	689000.0
23.60	169	250	150	3600	449	330	245	102	50	31	22	312.0	3000.0	16.8	189.0	145000.0
23.80	169	250	150	3200	196	137	108	68	44	29	17	963.0	3000.0	67.4	236.0	513000.0
24.00	169	250	150	5900	264	165	116	60	36	26	18	479.0	3000.0	85.0	316.0	5760.0
24.20	169	250	150	3900	296	207	148	78	43	26	20	480.0	3000.0	39.0	236.0	4420.0
24.40	169	250	150	15000	281	191	122	57	32	24	20	429.0	3000.0	67.6	402.0	131000.0
24.60	169	250	150	3700	269	136	95	43	20	12	9	397.0	3000.0	32.3	68900.0	26.2
24.80	169	250	150	6600	215	137	98	62	41	27	22	690.0	3000.0	104.0	362.0	227.0
25.00	190	300	150	3900	274	195	143	81	53	37	23	532.0	3000.0	82.9	204.0	773.0
25.20	190	300	150	15000	292	205	149	79	50	40	35	452.0	3000.0	37.7	934.0	8.5
25.40	190	300	150	13100	292	239	175	98	62	45	35	575.0	3000.0	39.4	193.0	98100.0
25.60	190	300	150	15000	254	170	126	68	48	32	29	535.0	3000.0	75.4	599.0	16.9
25.80	190	300	150	3300	376	272	206	105	62	40	25	392.0	3000.0	26.0	147.0	3880.0
26.00	190	300	150	3900	305	216	154	66	36	24	16	411.0	3000.0	53.1	283.0	10900.0
26.20	190	300	150	8600	299	221	164	70	38	26	21	437.0	3000.0	44.5	314.0	689000.0
26.40	190	300	150	4600	368	292	235	152	112	77	53	528.0	3000.0	28.6	172.0	40.8
26.60	190	300	150	13500	147	101	67	34	26	19	15	938.0	3000.0	435.0	571.0	350.0
26.80	190	300	150	4200	315	226	166	79	48	32	22	422.0	3000.0	56.6	219.0	1780.0
26.98	190	300	150	7700	173	118	88	47	32	23	17	860.0	3000.0	192.0	421.0	571.0

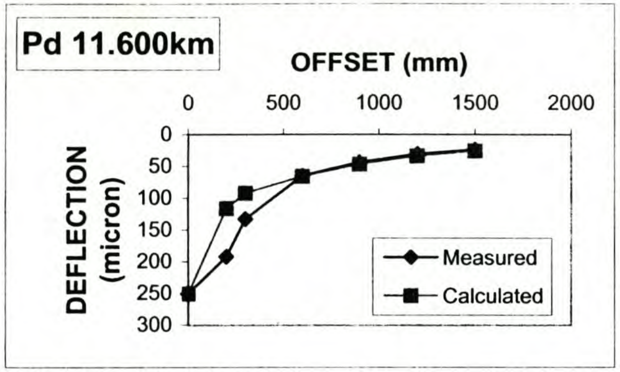
MR188: E-MODULI BACK-CALCULATED WITH MODCOMP

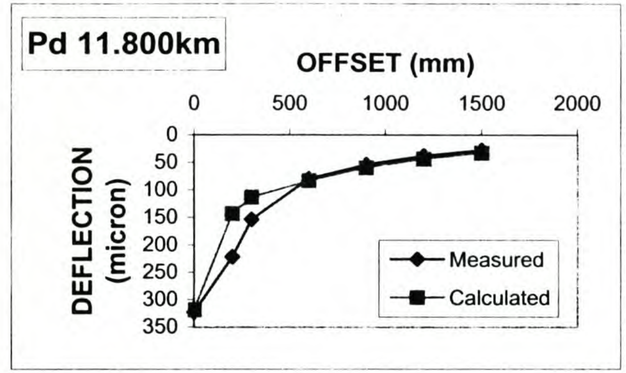
Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

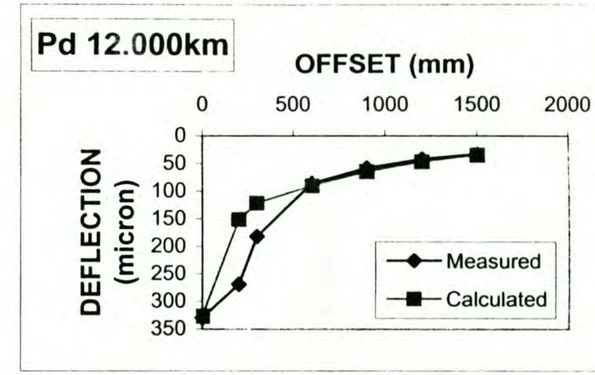
WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

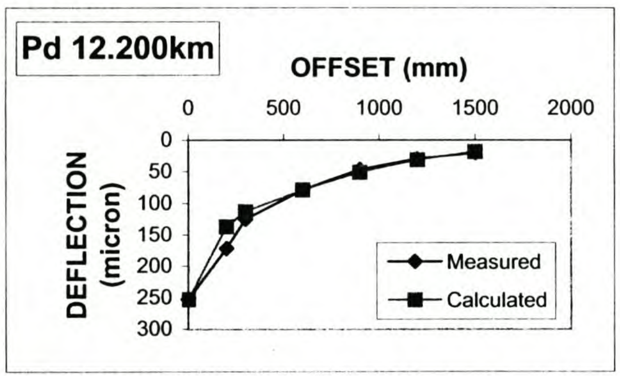
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
18.00	169	250	150	8600	251	116	92	66	46	34	26	528.0	3000.0	118.0	317.0	261.0
18.20	169	250	150	6500	319	143	113	83	59	43	33	395.0	3000.0	82.7	254.0	216.0
18.40	169	250	150	14300	326	151	121	90	64	46	34	397.0	3000.0	78.7	217.0	671.0
18.60	169	250	150	3500	253	137	113	79	51	31	18	632.0	3000.0	27.9	310.0	110000.0
18.80	169	250	150	16000	275	142	118	89	68	55	48	542.0	3000.0	45.6	604.0	9.3
19.00	169	250	150	8300	361	143	109	78	52	35	25	314.0	3000.0	65.2	267.0	1820.0
19.20	169	250	150	7300	198	95	75	50	33	22	15	715.0	3000.0	108.0	403.0	5020.0
19.40	169	250	150	15000	207	118	99	74	56	44	37	840.0	3000.0	97.4	370.0	30.6
19.60	169	250	150	15000	318	143	114	83	59	42	31	396.0	3000.0	93.5	227.0	689000.0
19.80	169	250	150	15000	241	109	86	62	46	36	30	537.0	3000.0	113.0	481.0	40.9
20.00	169	250	150	3600	284	140	114	82	56	37	24	495.0	3000.0	85.2	186.0	689000.0
20.20	169	250	150	15000	291	145	119	89	67	53	46	486.0	3000.0	38.6	712.0	10.2
20.40	169	250	150	12100	175	126	111	83	61	43	31	1830.0	3000.0	28.6	279.0	689000.0
20.60	169	250	150	4500	288	139	112	80	54	35	23	479.0	3000.0	53.0	241.0	2970.0
20.80	169	250	150	5500	273	155	131	98	72	52	39	617.0	3000.0	53.2	209.0	233.0
21.00	169	250	150	4400	256	146	123	92	67	49	37	670.0	3000.0	65.2	210.0	272.0
23.00	169	250	150	6000	344	155	123	87	57	36	23	368.0	3000.0	30.7	286.0	689000.0
23.20	169	250	150	4000	461	203	162	118	79	50	31	263.0	3000.0	18.3	205.0	689000.0
23.40	169	250	150	15000	362	128	91	61	38	23	15	289.0	3000.0	47.2	484.0	689000.0
23.60	169	250	150	3600	425	204	167	123	84	53	33	312.0	3000.0	16.8	189.0	145000.0
23.80	169	250	150	3200	196	115	96	68	46	30	19	963.0	3000.0	67.4	236.0	513000.0
24.00	169	250	150	5900	263	116	90	62	41	27	18	479.0	3000.0	85.0	316.0	5760.0
24.20	169	250	150	3900	295	147	120	85	57	36	23	480.0	3000.0	39.0	236.0	4420.0
24.40	169	250	150	15000	279	116	88	60	39	26	18	429.0	3000.0	67.6	402.0	131000.0
24.60	169	250	150	3700	292	117	87	59	38	27	22	397.0	3000.0	32.3	68900.0	26.2
24.80	169	250	150	6600	215	109	88	62	44	32	25	690.0	3000.0	104.0	362.0	227.0
25.00	190	300	150	3900	264	125	99	75	56	41	30	532.0	3000.0	82.9	204.0	773.0
25.20	190	300	150	15000	293	132	103	81	64	53	46	452.0	3000.0	37.7	934.0	8.5
25.40	190	300	150	13100	276	146	121	95	72	54	41	575.0	3000.0	39.4	193.0	98100.0
25.60	190	300	150	15000	248	111	86	66	52	43	37	535.0	3000.0	75.4	599.0	16.9
25.80	190	300	150	3300	354	169	136	106	78	55	38	392.0	3000.0	26.0	147.0	3880.0
26.00	190	300	150	3900	295	118	88	64	44	29	19	411.0	3000.0	53.1	283.0	10900.0
26.20	190	300	150	8600	289	122	93	68	48	34	23	437.0	3000.0	44.5	314.0	689000.0
26.40	190	300	150	4600	349	208	181	153	127	106	91	528.0	3000.0	28.6	172.0	40.8
26.60	190	300	150	13500	145	63	47	33	24	19	15	938.0	3000.0	435.0	571.0	350.0
26.80	190	300	150	4200	304	131	101	76	55	39	27	422.0	3000.0	56.6	219.0	1780.0
26.98	190	300	150	7700	168	79	61	44	32	24	18	860.0	3000.0	192.0	421.0	571.0

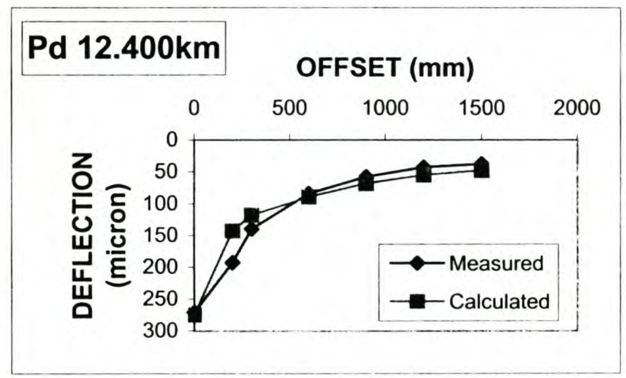
MR188: MEASURED vs CALCULATED DEFLECTIONS BY MODCOMP

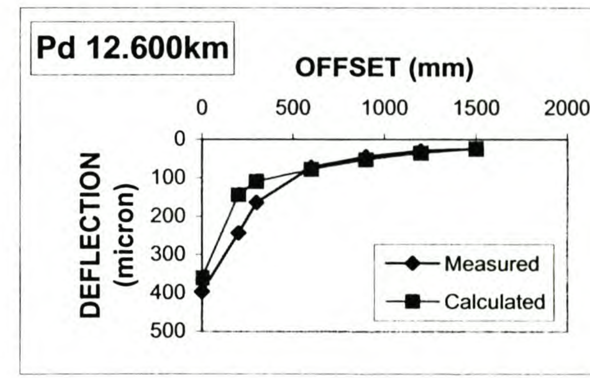


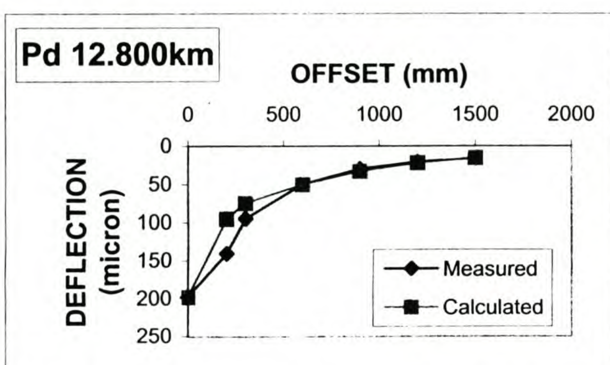


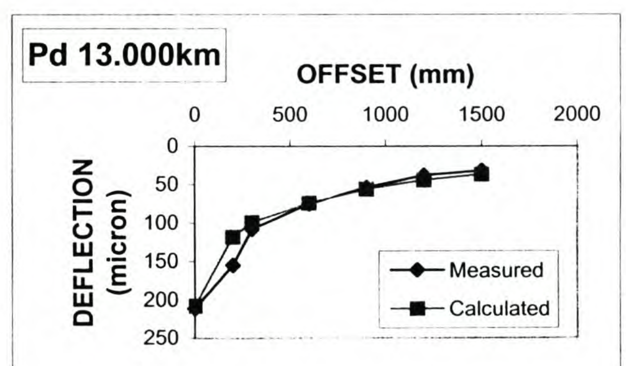


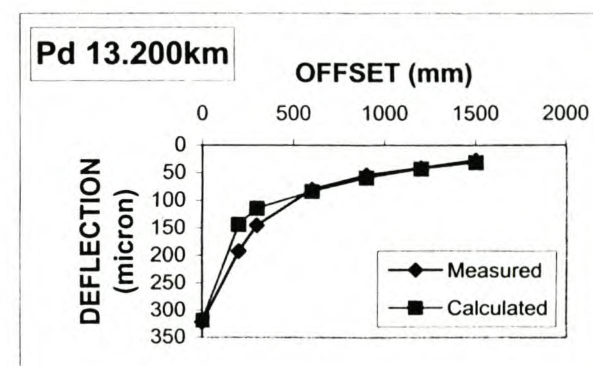




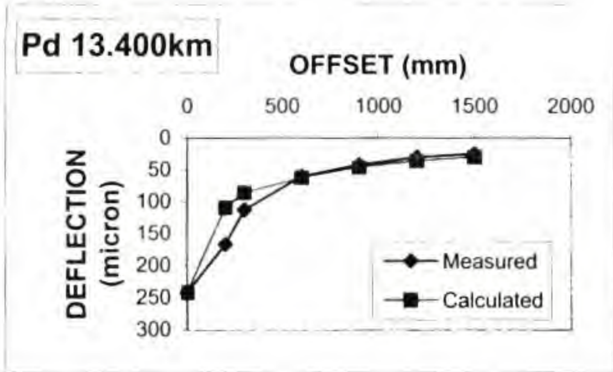


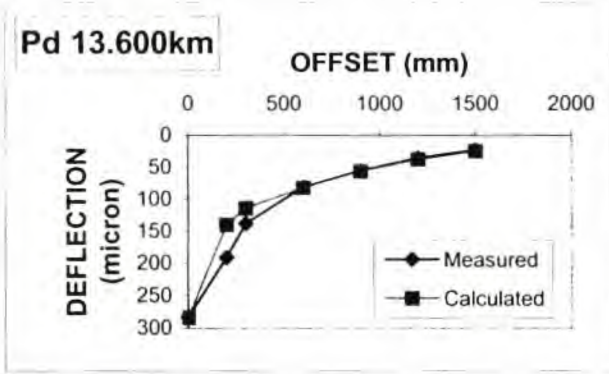


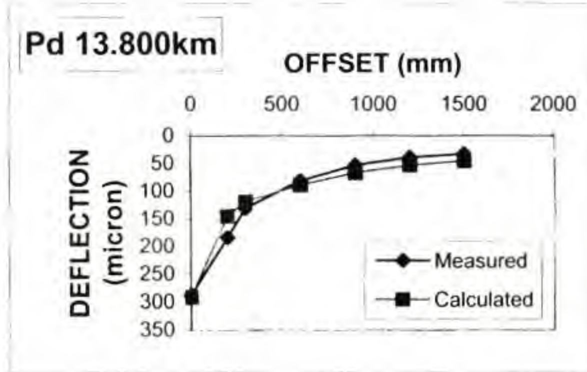


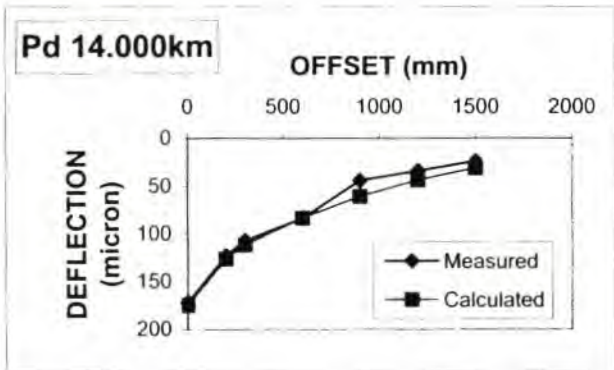


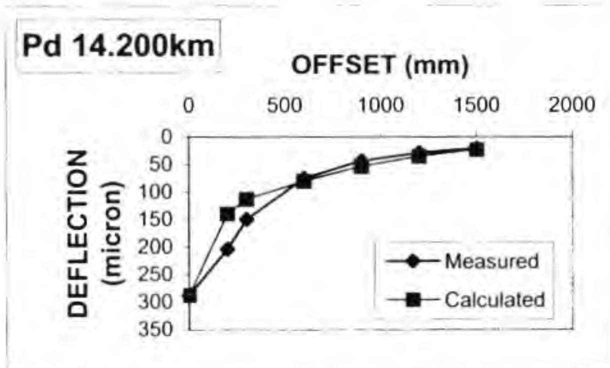
MR188: MEASURED vs CALCULATED DEFLECTIONS BY MODCOMP

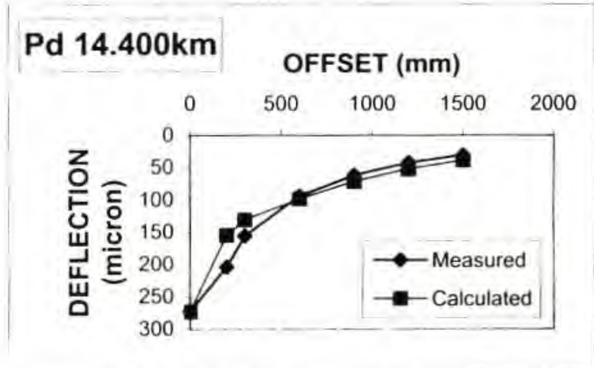


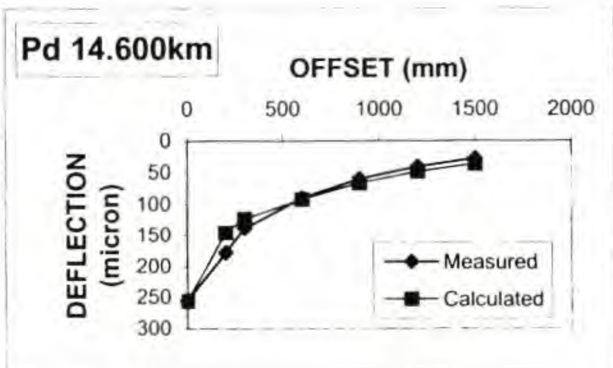


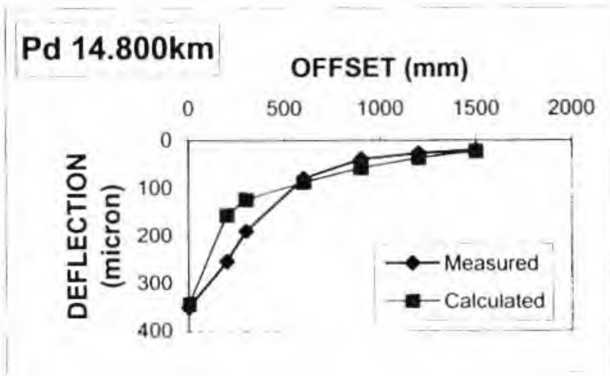


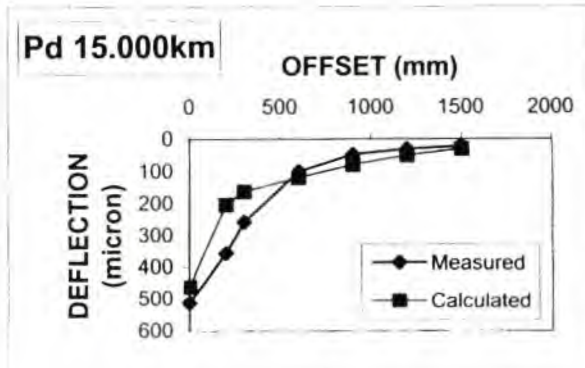




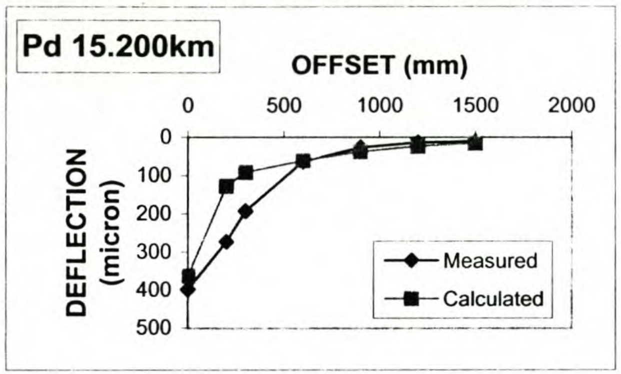


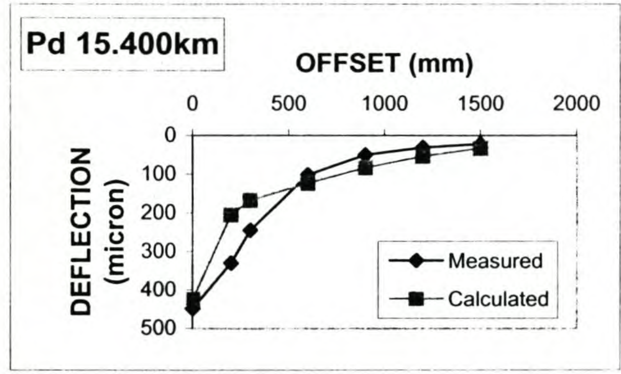


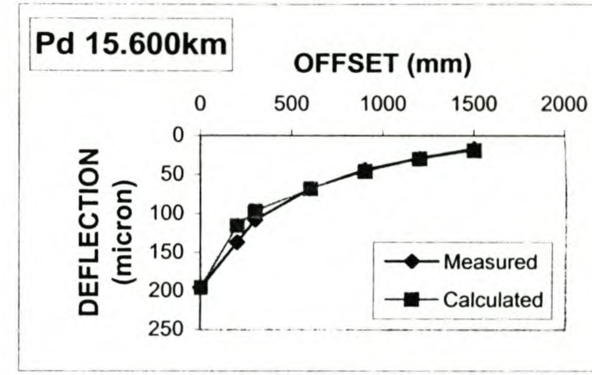


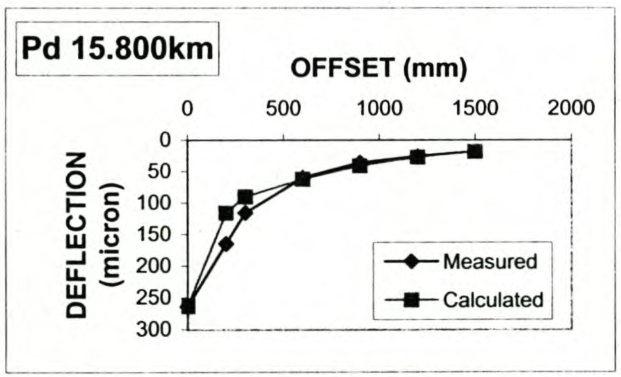


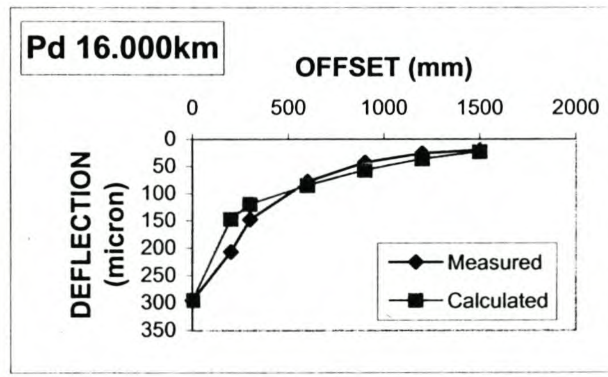
MR188: MEASURED vs CALCULATED DEFLECTIONS BY MODCOMP

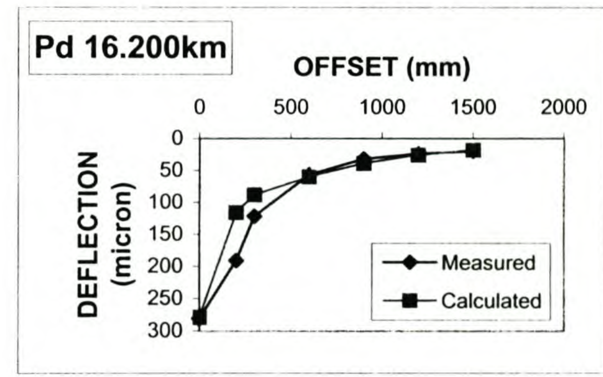


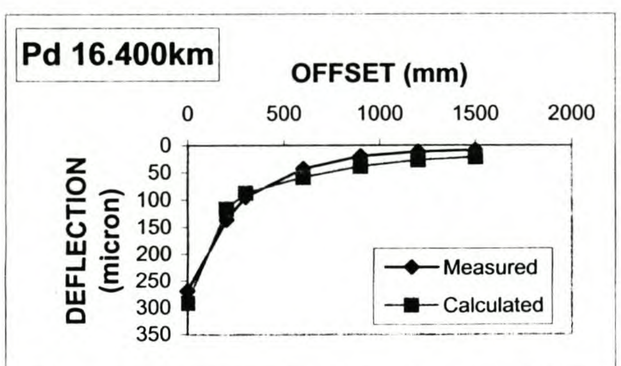


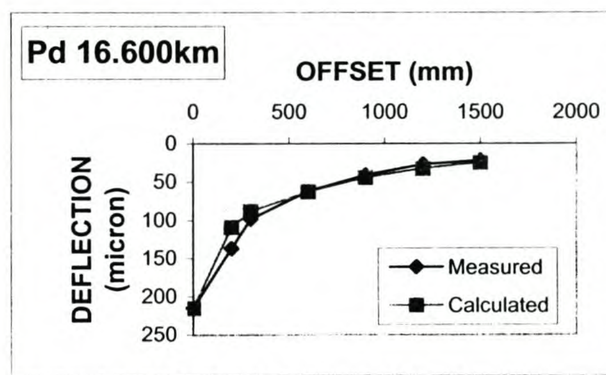


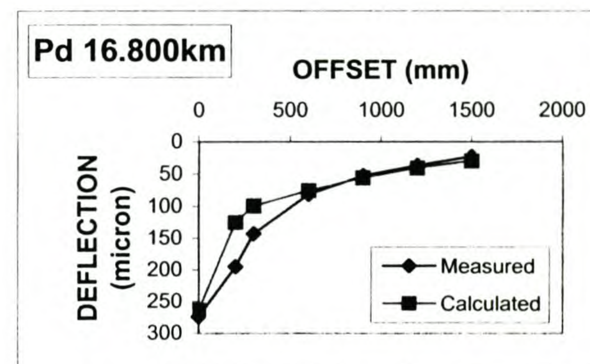




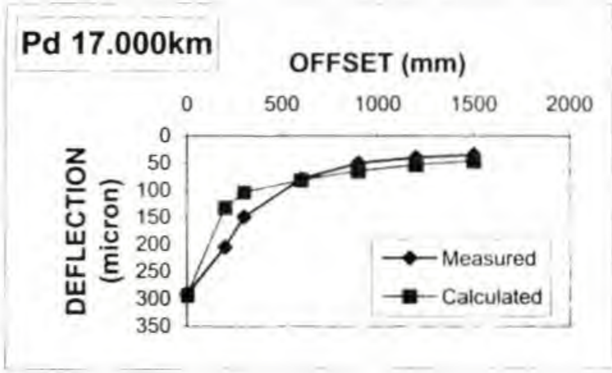


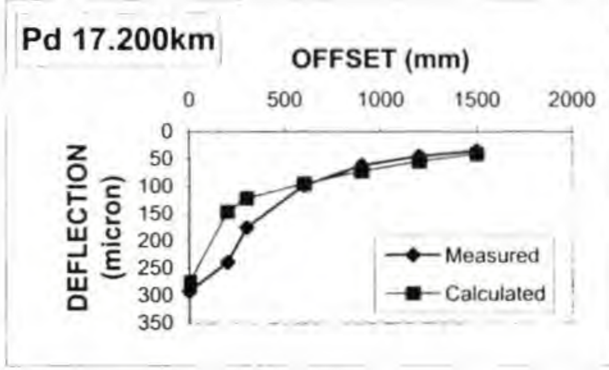


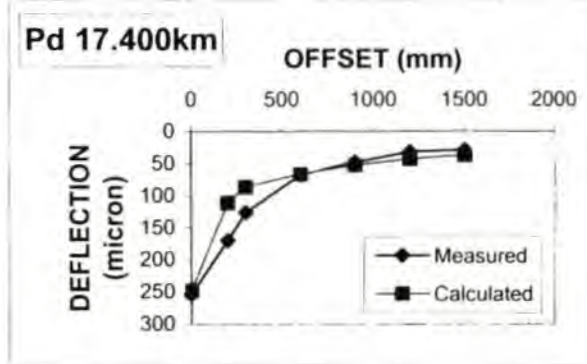


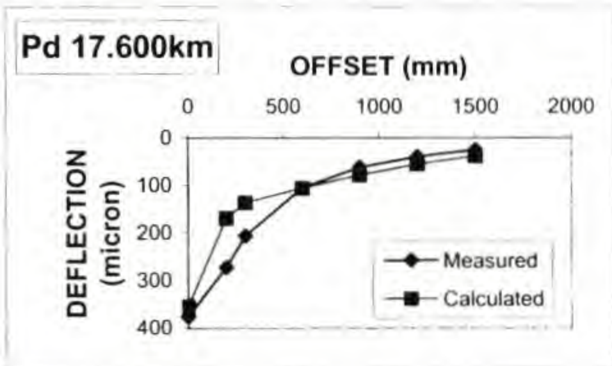


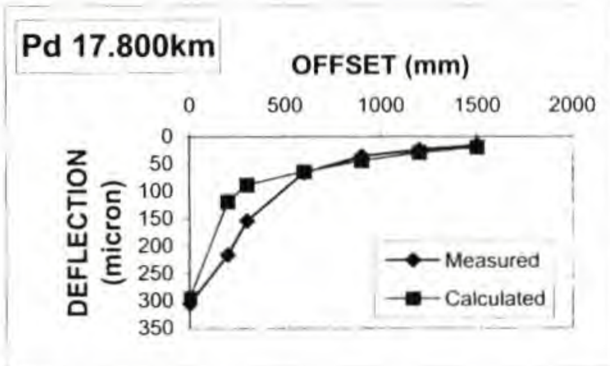
MR188: MEASURED vs CALCULATED DEFLECTIONS BY MODCOMP

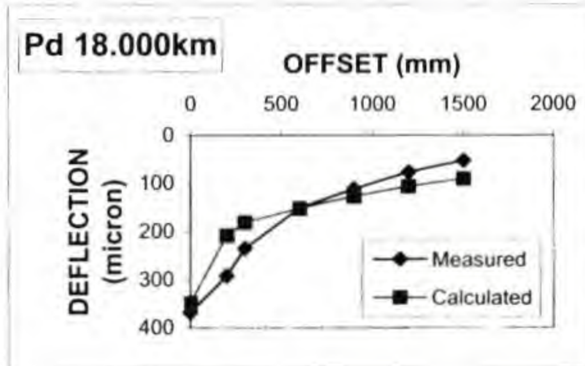


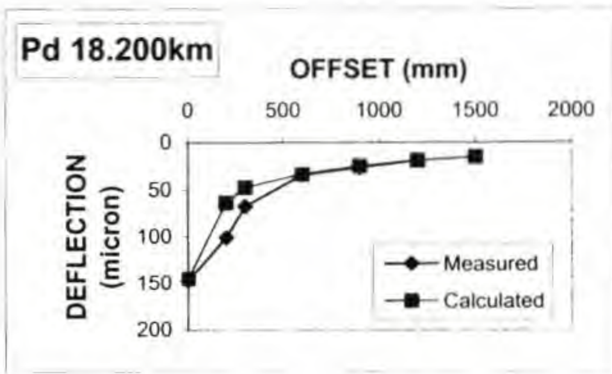


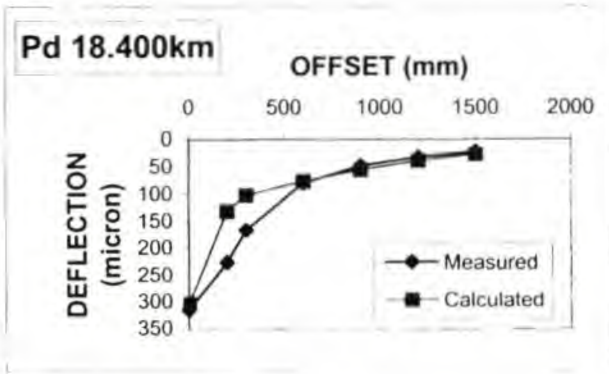


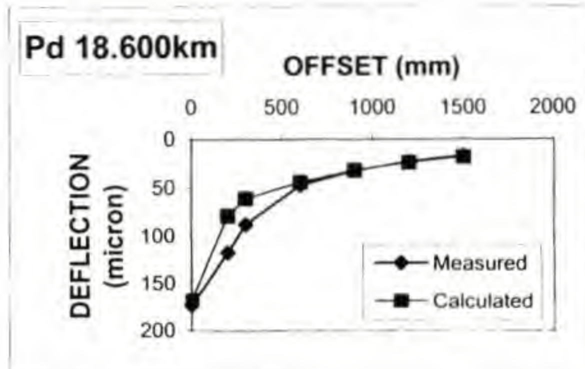












MR188: COMPARISON OF MEASURED AND CALCULATED DEFLECTIONS BY MODCOMP

Pos (Km)	Offset (mm)	0	200	300	600	900	1200	1500	RMSE(%)
18.000	Measured	251	192	133	65	44	31	24	19.56%
	Calculated	251	116	92	66	46	34	26	
18.200	Measured	323	222	154	80	54	38	28	19.09%
	Calculated	319	143	113	83	59	43	33	
18.400	Measured	330	269	182	86	58	42	33	21.62%
	Calculated	326	151	121	90	64	46	34	
18.600	Measured	253	172	125	79	47	30	20	9.82%
	Calculated	253	137	113	79	51	31	18	
18.800	Measured	271	193	140	84	58	43	38	19.89%
	Calculated	275	142	118	89	68	55	48	
19.000	Measured	397	244	164	73	45	30	25	22.51%
	Calculated	361	143	109	78	52	35	25	
19.200	Measured	198	141	95	50	30	21	16	15.38%
	Calculated	198	95	75	50	33	22	15	
19.400	Measured	211	155	108	75	54	38	32	12.77%
	Calculated	207	118	99	74	56	44	37	
19.600	Measured	322	192	145	80	54	41	27	14.39%
	Calculated	318	143	114	83	59	42	31	
19.800	Measured	242	167	113	60	42	30	25	19.12%
	Calculated	241	109	86	62	46	36	30	
20.000	Measured	283	191	138	81	55	35	23	12.60%
	Calculated	284	140	114	82	56	37	24	
20.200	Measured	288	184	131	81	53	39	33	24.16%
	Calculated	291	145	119	89	67	53	46	
20.400	Measured	172	123	107	84	44	34	24	20.87%
	Calculated	175	126	111	83	61	43	31	
20.600	Measured	288	204	150	75	44	29	21	19.76%
	Calculated	288	139	112	80	54	35	23	
20.800	Measured	273	204	156	94	62	43	31	17.93%
	Calculated	273	155	131	98	72	52	39	
21.000	Measured	256	178	139	90	60	41	28	16.48%
	Calculated	256	146	123	92	67	49	37	
23.000	Measured	351	254	190	79	39	27	20	30.29%
	Calculated	344	155	123	87	57	36	23	
23.200	Measured	513	357	257	100	48	31	22	43.81%
	Calculated	461	203	162	118	79	50	31	
23.400	Measured	398	273	193	64	27	14	11	43.69%
	Calculated	362	128	91	61	38	23	15	
23.600	Measured	449	330	245	102	50	31	22	46.45%
	Calculated	425	204	167	123	84	53	33	
23.800	Measured	196	137	108	68	44	29	17	8.54%
	Calculated	196	115	96	68	46	30	19	
24.000	Measured	264	165	116	60	36	26	18	15.04%
	Calculated	263	116	90	62	41	27	18	
24.200	Measured	296	207	148	78	43	26	20	24.30%
	Calculated	295	147	120	85	57	36	23	
24.400	Measured	281	191	122	57	32	24	20	20.59%
	Calculated	279	116	88	60	39	26	18	
24.600	Measured	269	136	95	43	20	12	9	81.85%
	Calculated	292	117	87	59	38	27	22	
24.800	Measured	215	137	98	62	41	27	22	12.71%
	Calculated	215	109	88	62	44	32	25	
25.000	Measured	274	195	143	81	53	37	23	21.58%
	Calculated	264	125	99	75	56	41	30	
25.200	Measured	292	205	149	79	50	40	35	26.82%
	Calculated	293	132	103	81	64	53	46	
25.400	Measured	292	239	175	98	62	45	35	22.14%
	Calculated	276	146	121	95	72	54	41	
25.600	Measured	254	170	126	68	48	32	29	24.52%
	Calculated	248	111	86	66	52	43	37	
25.800	Measured	376	272	206	105	62	40	25	32.85%
	Calculated	354	169	136	106	78	55	38	
26.000	Measured	305	216	154	66	36	24	16	27.68%
	Calculated	295	118	88	64	44	29	19	
26.200	Measured	299	221	164	70	38	26	21	28.34%
	Calculated	289	122	93	68	48	34	23	
26.400	Measured	368	292	235	152	112	77	53	33.90%
	Calculated	349	208	181	153	127	106	91	
26.600	Measured	147	101	67	34	26	19	15	18.35%
	Calculated	145	63	47	33	24	19	15	
26.800	Measured	315	226	166	79	48	32	22	25.32%
	Calculated	304	131	101	76	55	39	27	
26.980	Measured	173	118	88	47	32	23	17	17.56%
	Calculated	168	79	61	44	32	24	13	

APPENDIX C.6 : MR188

Comparison of back-calculated E-moduli between Case (b) and ModComp for MR188

POSITION (Km)	METHOD	BACK-CALCULATED E-MODULI (Mpa)					RMSE (%)
		E1	E2	E3	E4	E5	
18.00	Case (b)	1199.7	187.8	899.9	329.6	10000.0	28.32
	ModComp	528.0	3000.0	118.0	317.0	261.0	19.56
18.20	Case (b)	1199.7	200.6	899.9	281.7	10000.0	32.05
	ModComp	395.0	3000.0	82.7	254.0	216.0	19.09
18.40	Case (b)	1199.7	185.6	899.9	288.4	10000.0	38.43
	ModComp	397.0	3000.0	78.7	217.0	671.0	21.62
18.60	Case (b)	1199.7	237.0	899.4	152.8	10000.0	21.76
	ModComp	632.0	3000.0	27.9	310.0	110000.0	9.82
18.80	Case (b)	1199.7	223.8	899.9	198.9	10000.0	24.43
	ModComp	542.0	3000.0	45.6	604.0	9.3	19.89
19.00	Case (b)	1192.8	456.8	899.9	245.9	10000.0	32.31
	ModComp	314.0	3000.0	65.2	267.0	1820.0	22.51
19.20	Case (b)	1199.7	204.2	899.9	342.4	10000.0	24.61
	ModComp	715.0	3000.0	108.0	403.0	5020.0	15.38
19.40	Case (b)	1199.7	261.4	899.9	216.0	10000.0	30.99
	ModComp	840.0	3000.0	97.4	370.0	30.6	12.77
19.60	Case (b)	928.9	539.3	844.5	189.0	10000.0	12.96
	ModComp	396.0	3000.0	93.5	227.0	689000.0	14.39
19.80	Case (b)	1199.7	204.9	899.9	335.0	10000.0	27.06
	ModComp	537.0	3000.0	113.0	481.0	40.9	19.12
20.00	Case (b)	1199.7	322.8	899.9	233.5	10000.0	24.88
	ModComp	495.0	3000.0	85.2	186.0	689000.0	12.6
20.20	Case (b)	1199.5	326.8	863.6	155.9	10000.0	24.23
	ModComp	486.0	3000.0	38.6	712.0	10.2	24.16
20.40	Case (b)	1015.5	6999.4	100.1	896.8	10000.0	57.53
	ModComp	1830.0	3000.0	28.6	279.0	689000.0	20.87
20.60	Case (b)	1199.7	219.5	899.9	195.0	10000.0	26.58
	ModComp	479.0	3000.0	53.0	241.0	2970.0	19.76
20.80	Case (b)	1199.7	222.6	899.9	175.7	10000.0	30.66
	ModComp	617.0	3000.0	53.2	209.0	233.0	17.93
21.00	Case (b)	1199.4	395.2	899.2	132.5	10000.0	23.26
	ModComp	670.0	3000.0	65.2	210.0	272.0	16.48
23.00	Case (b)	1199.7	188.9	877.9	242.8	10000.0	35.00
	ModComp	368.0	3000.0	30.7	286.0	689000.0	30.29
23.20	Case (b)	1199.7	187.7	899.9	202.5	10000.0	47.70
	ModComp	263.0	3000.0	18.3	205.0	689000.0	43.81
23.40	Case (b)	1199.7	182.5	899.9	242.7	10000.0	28.08
	ModComp	289.0	3000.0	47.2	484.0	689000.0	43.69
23.60	Case (b)	1199.7	178.8	899.9	174.2	10000.0	40.74
	ModComp	312.0	3000.0	16.8	189.0	145000.0	46.45
23.80	Case (b)	1199.6	383.3	899.8	171.2	10000.0	19.58
	ModComp	963.0	3000.0	67.4	236.0	513000.0	8.54
24.00	Case (b)	1199.2	338.3	899.7	233.7	10000.0	18.20
	ModComp	479.0	3000.0	85.0	316.0	5760.0	15.04
24.20	Case (b)	1199.7	181.0	899.5	153.9	10000.0	19.70
	ModComp	480.0	3000.0	39.0	236.0	4420.0	24.3
24.40	Case (b)	1199.7	190.2	899.9	360.1	10000.0	24.00
	ModComp	429.0	3000.0	67.6	402.0	131000.0	20.59

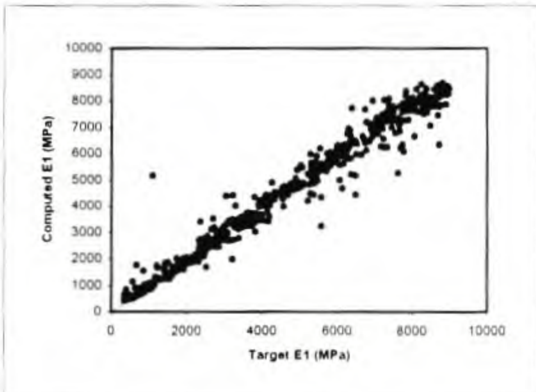
24.60	Case (b)	685.5	1018.3	102.8	768.7	10000.0	16.98
	ModComp	397.0	3000.0	32.3	68900.0	26.2	81.85
24.80	Case (b)	1199.2	521.3	899.9	204.9	10000.0	21.34
	ModComp	690.0	3000.0	104.0	362.0	227.0	12.71
25.00	Case (b)	1199.7	205.4	899.9	258.9	10000.0	30.17
	ModComp	532.0	3000.0	82.9	204.0	773.0	21.58
25.20	Case (b)	1199.7	204.0	899.9	210.5	10000.0	15.51
	ModComp	452.0	3000.0	37.7	934.0	8.5	26.82
25.40	Case (b)	1199.7	192.8	899.9	221.3	10000.0	37.98
	ModComp	575.0	3000.0	39.4	193.0	98100.0	22.14
25.60	Case (b)	1198.7	457.4	899.9	224.4	10000.0	23.84
	ModComp	535.0	3000.0	75.4	599.0	16.9	24.52
25.80	Case (b)	1199.7	205.8	899.9	229.7	10000.0	45.09
	ModComp	392.0	3000.0	26.0	147.0	3880.0	32.85
26.00	Case (b)	1199.7	197.0	899.9	323.6	10000.0	26.38
	ModComp	411.0	3000.0	53.1	283.0	10900.0	27.68
26.20	Case (b)	1199.7	203.1	899.9	213.0	10000.0	29.52
	ModComp	437.0	3000.0	44.5	314.0	689000.0	28.34
26.40	Case (b)	1199.7	205.9	899.9	166.0	10000.0	47.08
	ModComp	528.0	3000.0	28.6	172.0	40.8	33.9
26.60	Case (b)	1199.7	215.5	899.9	389.3	10000.0	43.79
	ModComp	938.0	3000.0	435.0	571.0	350.0	18.35
26.80	Case (b)	1199.7	201.3	899.9	286.7	10000.0	33.07
	ModComp	422.0	3000.0	56.6	219.0	1780.0	25.32
26.98	Case (b)	1199.7	313.6	899.9	282.0	10000.0	19.28
	ModComp	860.0	3000.0	192.0	421.0	571.0	17.56

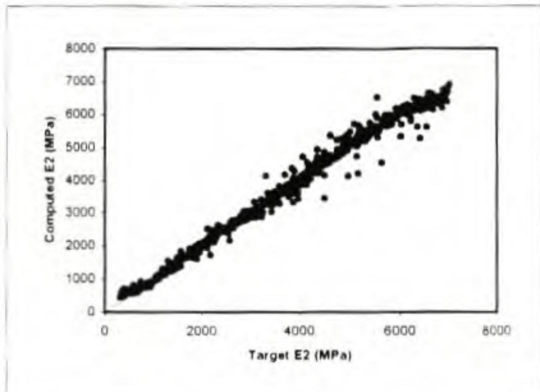
Appendix C.7

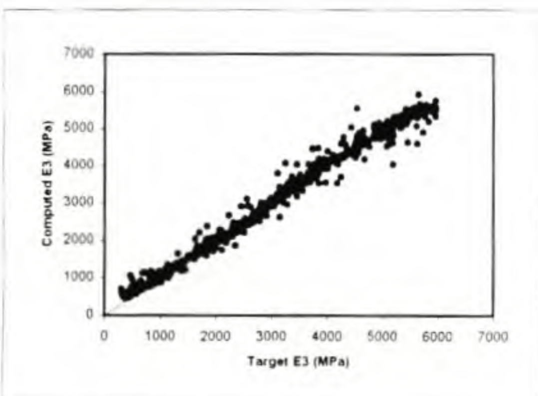
Results of Back-calculations for Type 4 pavements (TR901)

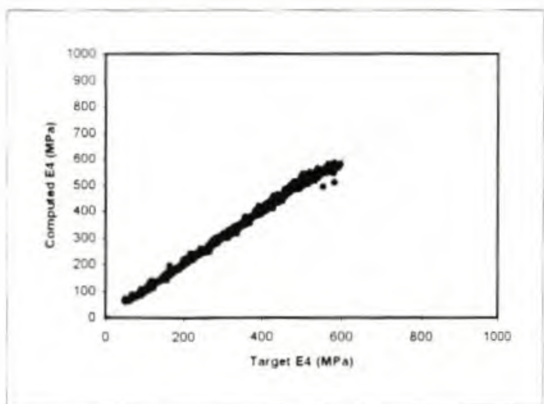
APPENDIX C.7: TR901 CASE (a)

RESULTS OF BACK-CALCULATIONS (E-MODULI LAYER 1-4 FROM DEFLECTIONS) OF A TYPICAL SOUTH AFRICAN PAVEMENT: BITUMINOUS BASE/CEMENTED SUBBASE WITH A THIN SURFACING : CASE (a): DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000MPa









TR901: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (a)
DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
0.00	364	291	233	139	86	61	45	131	94	53	84.6	G1	3.43	6.1	1085	358108	0.9
0.20	265	218	174	120	80	58	47	91	54	40	91.5	G1	4.37	10.7	1085	2737173	6.1
0.40	432	368	290	158	87	57	34	142	132	71	82.4	G1	2.64	3	1085	142403	0.4
0.60	141	105	92	72	52	40	30	49	20	20	97.4	G1	6.09	25	1085	30734637	37
0.80	242	205	174	130	92	65	45	68	44	38	94.9	G1	4.18	5.8	1085	3163511	6.9
1.00	190	150	126	101	74	53	44	64	25	27	95.4	G1	5.3	15.3	1085	20486267	29.1
1.20	192	158	118	92	66	50	37	74	26	26	94.1	G1	5.56	25	1085	29029280	35.8
1.40	119	89	71	62	41	30	24	48	9	21	97.5	G1	6.33	25	1085	88197763	61.3
1.60	107	86	70	55	39	29	24	37	15	16	98.7	G1	6.56	25	1085	45541185	45.5
1.80	115	90	71	55	46	34	28	44	16	9	97.9	G1	6.5	25	1085	42892071	44.1
2.00	233	182	149	110	72	47	36	84	39	38	92.6	G1	4.32	7.9	1085	3958647	8.4
2.20	379	303	259	178	114	72	41	120	81	64	86.6	G1	2.94	3	1085	285586	0.7
2.40	157	132	114	85	57	41	28	43	29	28	98.1	G1	5.93	25	1085	37557165	41.2
2.60	109	85	71	62	46	38	33	38	9	16	98.6	G1	6.69	25	1085	73099168	56.7
2.80	136	96	83	63	44	32	24	53	20	19	96.9	G1	6.03	25	1085	24468759	32.4
3.00	203	148	121	93	65	49	38	82	28	28	92.9	G1	5.42	25	1085	19366443	28.1
3.20	326	232	157	70	39	29	16	169	87	31	76.7	G1	4.48	25	1085	3647003	7.9
3.40	139	114	93	78	53	41	30	46	15	25	97.7	G1	6.17	25	1085	50966559	48.1
3.60	166	124	104	79	61	46	37	62	25	18	95.7	G1	5.82	25	1085	32771298	38.3
3.80	354	273	210	128	78	51	30	144	82	50	82	G1	3.27	5	1085	708342	1.7
4.00	281	215	159	86	49	35	25	122	73	37	86.3	G1	4.74	25	1085	7376308	14.1
4.20	181	154	141	119	96	79	60	40	22	23	98.4	G1	6.14	23.5	1085	49492378	47.4
4.40	167	124	108	84	64	49	37	59	24	20	96.1	G1	5.86	25	1085	26417167	33.9
4.60	192	144	118	85	59	42	31	74	33	26	94.1	G1	5.48	25	1085	20775683	29.4
4.80	152	121	101	81	58	45	30	51	20	23	97.1	G1	6.01	25	1085	41860895	43.6
5.00	347	269	201	109	60	40	30	146	92	49	81.6	G1	3.91	11.9	1085	2067320	4.7
5.20	139	104	89	72	55	42	30	50	17	17	97.2	G1	6.19	25	1085	16971225	25.8
5.40	249	163	117	77	54	41	30	132	40	23	84.4	G1	4.94	25	1085	6903265	13.4
5.60	494	359	270	144	86	59	39	224	126	58	63.4	G1	2.79	4.6	1085	231267	0.6
5.80	245	193	163	117	83	61	45	82	46	34	92.9	G1	4.55	10.8	1085	3546473	7.7
6.00	188	155	136	105	70	51	37	52	31	35	97	G1	5.32	15.8	1085	9915188	17.7
6.20	214	170	145	102	69	48	42	69	43	33	94.8	G1	4.94	14.5	1085	7796097	14.7
6.40	326	266	217	137	93	70	66	109	80	44	88.6	G1	4.02	10	1085	2249145	5.1
6.60	233	190	165	129	92	65	8	68	36	37	94.9	G1	3.94	3.8	1085	1981081	4.5
6.80	436	389	325	201	113	67	42	111	124	88	88.2	G1	2.73	3	1085	202571	0.5
7.00	211	159	136	109	81	63	35	75	27	28	93.9	G1	5.16	16	1937	13538976	14.4
7.20	236	192	173	141	105	81	60	63	32	36	95.6	G1	4.62	7.9	1937	5563858	6.8

TR901: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (a)
DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

NEURAL NETWORK: BACKCALCULATED E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	60	150	150	9795	364	291	233	139	86	61	45	8999.1	540.2	761.4	129.8	10000.0
0.20	60	150	150	8868	265	218	174	120	80	58	47	8999.0	715.5	5974.2	85.2	10000.0
0.40	60	150	150	11162	432	368	290	158	87	57	34	8999.1	476.8	622.7	149.1	10000.0
0.60	60	150	150	6066	141	105	92	72	52	40	30	4276.3	2047.0	5968.1	168.0	10000.0
0.80	60	150	150	8801	242	205	174	130	92	65	45	8999.1	795.7	3635.6	80.3	10000.0
1.00	60	150	150	7225	190	150	126	101	74	53	44	8999.1	1178.5	5999.4	103.1	10000.0
1.20	60	150	150	7023	192	158	118	92	66	50	37	8998.9	885.5	5999.5	90.0	10000.0
1.40	60	150	150	6417	119	89	71	62	41	30	24	8999.0	1267.6	5999.6	166.1	10000.0
1.60	60	150	150	5435	107	86	70	55	39	29	24	8999.0	1127.4	5999.6	193.9	10000.0
1.80	60	150	150	4186	115	90	71	55	46	34	28	8998.9	1132.7	5999.6	202.4	10000.0
2.00	60	150	150	8958	233	182	149	110	72	47	36	8999.2	1069.9	3127.4	98.4	10000.0
2.20	60	150	150	12654	379	303	259	178	114	72	41	4908.2	1040.2	642.8	91.0	10000.0
2.40	60	150	150	7323	157	132	114	85	57	41	28	8999.1	2538.0	1301.2	120.0	10000.0
2.60	60	150	150	5507	109	85	71	62	46	38	33	8999.0	1266.2	5999.6	183.1	10000.0
2.80	60	150	150	5892	136	96	83	63	44	32	24	2561.8	1967.4	5947.9	207.3	10000.0
3.00	60	150	150	7344	203	148	121	93	65	49	38	8998.6	1137.8	5995.4	123.1	10000.0
3.20	60	150	150	6661	326	232	157	70	39	29	16	8999.0	590.0	5442.5	230.9	10000.0
3.40	60	150	150	7057	139	114	93	78	53	41	30	8999.0	1107.1	5999.6	124.9	10000.0
3.60	60	150	150	5655	166	124	104	79	61	46	37	8998.8	1194.8	5998.8	146.3	10000.0
3.80	60	150	150	9726	354	273	210	128	78	51	30	8999.1	638.7	4715.3	114.4	10000.0
4.00	60	150	150	7828	281	215	159	86	49	35	25	8999.1	599.0	5204.3	169.6	10000.0
4.20	60	150	150	6561	181	154	141	119	96	79	60	8997.6	2561.6	5922.5	85.7	10000.0
4.40	60	150	150	6008	167	124	108	84	64	49	37	5099.2	1463.9	5939.4	144.0	10000.0
4.60	60	150	150	6888	192	144	118	85	59	42	31	8999.1	1090.5	3996.9	132.7	10000.0
4.80	60	150	150	6596	152	121	101	81	58	45	30	8999.0	1158.6	5999.6	125.9	10000.0
5.00	60	150	150	9197	347	269	201	109	60	40	30	8999.1	550.5	2653.8	158.0	10000.0
5.20	60	150	150	5585	139	104	89	72	55	42	30	8997.9	1726.4	5999.5	146.1	10000.0
5.40	60	150	150	6265	249	163	117	77	54	41	30	8998.8	964.4	5999.6	173.6	10000.0
5.60	60	150	150	9402	494	359	270	144	86	59	39	8998.2	519.3	390.8	174.3	10000.0
5.80	60	150	150	8002	245	193	163	117	83	61	45	8999.0	1183.1	1150.9	99.2	10000.0
6.00	60	150	150	8604	188	155	136	105	70	51	37	8995.4	2820.5	1569.5	103.6	10000.0
6.20	60	150	150	7899	214	170	145	102	69	48	42	8997.7	2130.4	781.8	116.9	10000.0
6.40	60	150	150	8762	326	266	217	137	93	70	66	8999.1	579.9	2360.0	101.7	10000.0
6.60	60	150	150	8853	233	190	165	129	92	65	8	8432.2	1326.5	3259.2	89.2	10000.0
6.80	60	150	150	15140	436	389	325	201	113	67	42	8999.1	506.4	600.5	99.5	10000.0
7.00	60	150	150	7366	211	159	136	109	81	63	35	7316.5	1067.4	5992.5	104.1	10000.0
7.20	60	150	150	8776	236	192	173	141	105	81	60	4081.5	1673.6	5276.5	80.4	10000.0

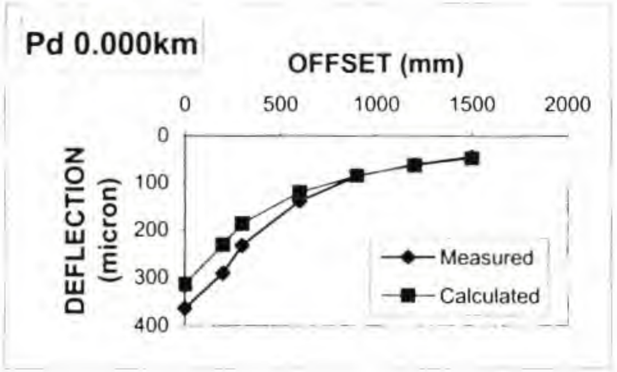
TR901: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (a)
DEPTH TO STIFF LAYER CALCULATED WITH RHODE WITH E5 = 10000 Mpa

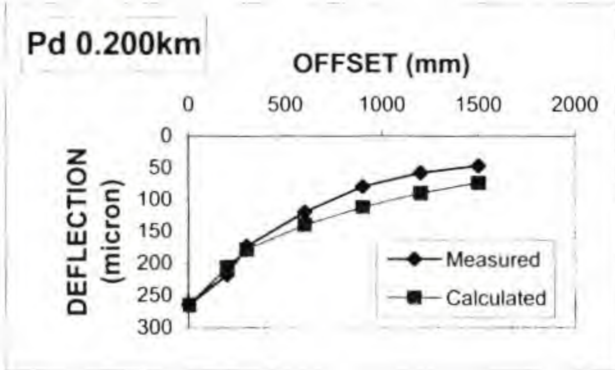
Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

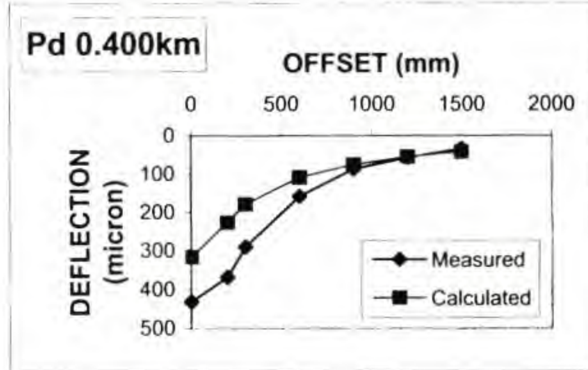
WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

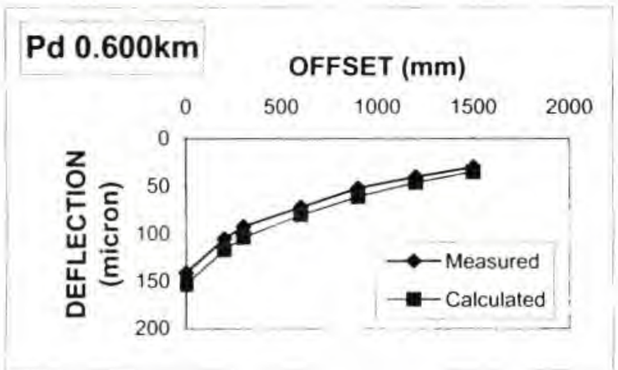
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	60	150	150	9795	314	231	187	120	85	62	48	8999.1	540.2	761.4	129.8	10000.0
0.20	60	150	150	8868	265	206	179	141	113	90	74	8999.0	715.5	5974.2	85.2	10000.0
0.40	60	150	150	11162	316	227	179	109	75	55	42	8999.1	476.8	622.7	149.1	10000.0
0.60	60	150	150	6066	153	117	104	80	61	46	35	4276.3	2047.0	5968.1	168.0	10000.0
0.80	60	150	150	8801	281	223	195	153	122	97	78	8999.1	795.7	3635.6	80.3	10000.0
1.00	60	150	150	7225	207	163	144	115	92	74	58	8999.1	1178.5	5999.4	103.1	10000.0
1.20	60	150	150	7023	238	186	163	129	103	82	65	8998.9	885.5	5999.5	90.0	10000.0
1.40	60	150	150	6417	161	120	103	78	60	46	36	8999.0	1267.6	5999.6	166.1	10000.0
1.60	60	150	150	5435	155	111	93	67	50	38	29	8999.0	1127.4	5999.6	193.9	10000.0
1.80	60	150	150	4186	149	105	87	62	45	33	24	8998.9	1132.7	5999.6	202.4	10000.0
2.00	60	150	150	8958	241	192	169	131	103	81	64	8999.2	1069.9	3127.4	98.4	10000.0
2.20	60	150	150	12654	352	279	241	173	127	96	74	4908.2	1040.2	642.8	91.0	10000.0
2.40	60	150	150	7323	206	172	154	116	87	66	51	8999.1	2538.0	1301.2	120.0	10000.0
2.60	60	150	150	5507	153	112	95	70	53	40	31	8999.0	1266.2	5999.6	183.1	10000.0
2.80	60	150	150	5892	149	107	94	71	52	39	29	2561.8	1967.4	5947.9	207.3	10000.0
3.00	60	150	150	7344	193	149	129	101	79	63	50	8998.6	1137.8	5995.4	123.1	10000.0
3.20	60	150	150	6661	187	123	95	63	45	33	25	8999.0	590.0	5442.5	230.9	10000.0
3.40	60	150	150	7057	193	148	128	99	78	61	49	8999.0	1107.1	5999.6	124.9	10000.0
3.60	60	150	150	5655	172	129	111	84	65	49	38	8998.8	1194.8	5998.8	146.3	10000.0
3.80	60	150	150	9726	249	186	156	117	90	71	56	8999.1	638.7	4715.3	114.4	10000.0
4.00	60	150	150	7828	212	148	118	83	61	46	36	8999.1	599.0	5204.3	169.6	10000.0
4.20	60	150	150	6561	189	161	149	125	103	84	68	8997.6	2561.6	5922.5	85.7	10000.0
4.40	60	150	150	6008	176	133	117	90	69	53	40	5099.2	1463.9	5939.4	144.0	10000.0
4.60	60	150	150	6888	198	151	130	98	75	58	45	8999.1	1090.5	3996.9	132.7	10000.0
4.80	60	150	150	6596	188	145	126	97	76	60	47	8999.0	1158.6	5999.6	125.9	10000.0
5.00	60	150	150	9197	243	172	138	93	68	51	40	8999.1	550.5	2653.8	158.0	10000.0
5.20	60	150	150	5585	155	121	106	83	64	50	38	8997.9	1726.4	5999.5	146.1	10000.0
5.40	60	150	150	6265	173	124	104	76	57	43	34	8998.8	964.4	5999.6	173.6	10000.0
5.60	60	150	150	9402	307	217	168	95	63	45	34	8998.2	519.3	390.8	174.3	10000.0
5.80	60	150	150	8002	274	220	192	141	106	81	62	8999.0	1183.1	1150.9	99.2	10000.0
6.00	60	150	150	8604	216	184	167	130	102	79	61	8995.4	2820.5	1569.5	103.6	10000.0
6.20	60	150	150	7899	236	195	172	125	92	69	52	8997.7	2130.4	781.8	116.9	10000.0
6.40	60	150	150	8762	293	221	186	134	102	78	61	8999.1	579.9	2360.0	101.7	10000.0
6.60	60	150	150	8853	241	196	176	140	112	89	71	8432.2	1326.5	3259.2	89.2	10000.0
6.80	60	150	150	15140	380	291	241	160	116	87	67	8999.1	506.4	600.5	99.5	10000.0
7.00	60	150	150	7366	218	169	148	117	93	74	59	7316.5	1067.4	5992.5	104.1	10000.0
7.20	60	150	150	8776	246	203	186	154	125	101	81	4081.5	1673.6	5276.5	80.4	10000.0

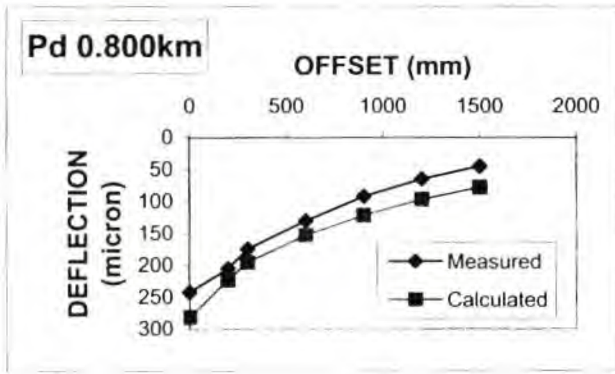
TR901: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)

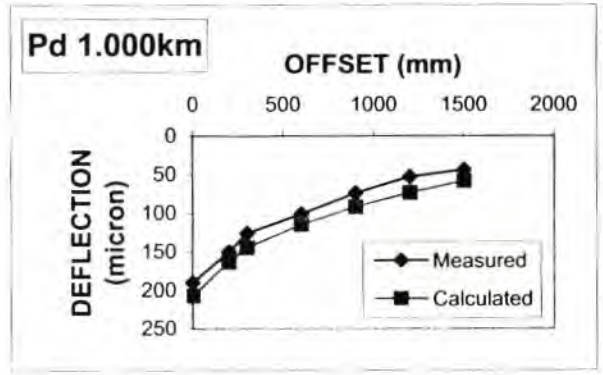


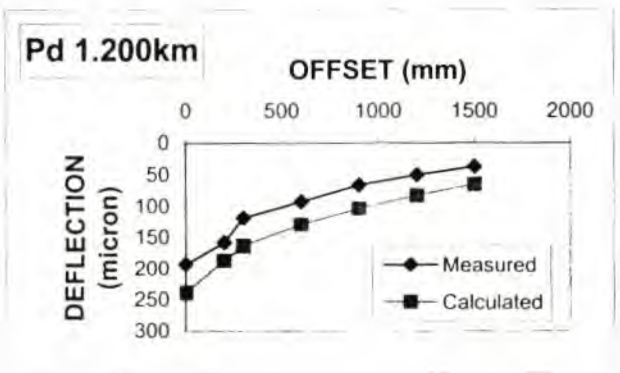


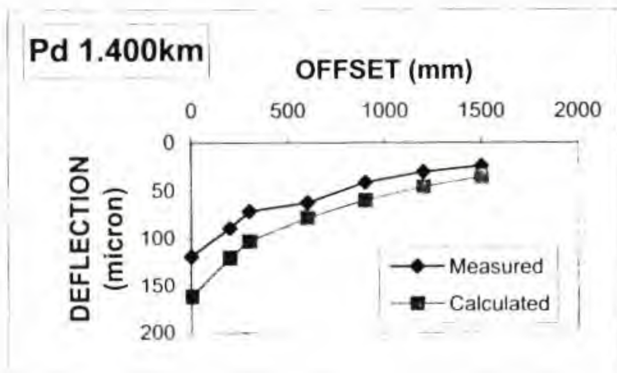


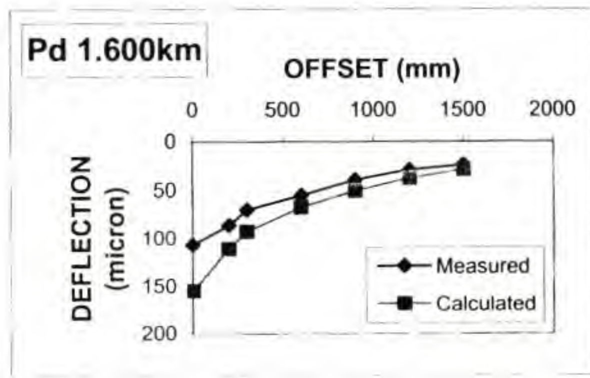




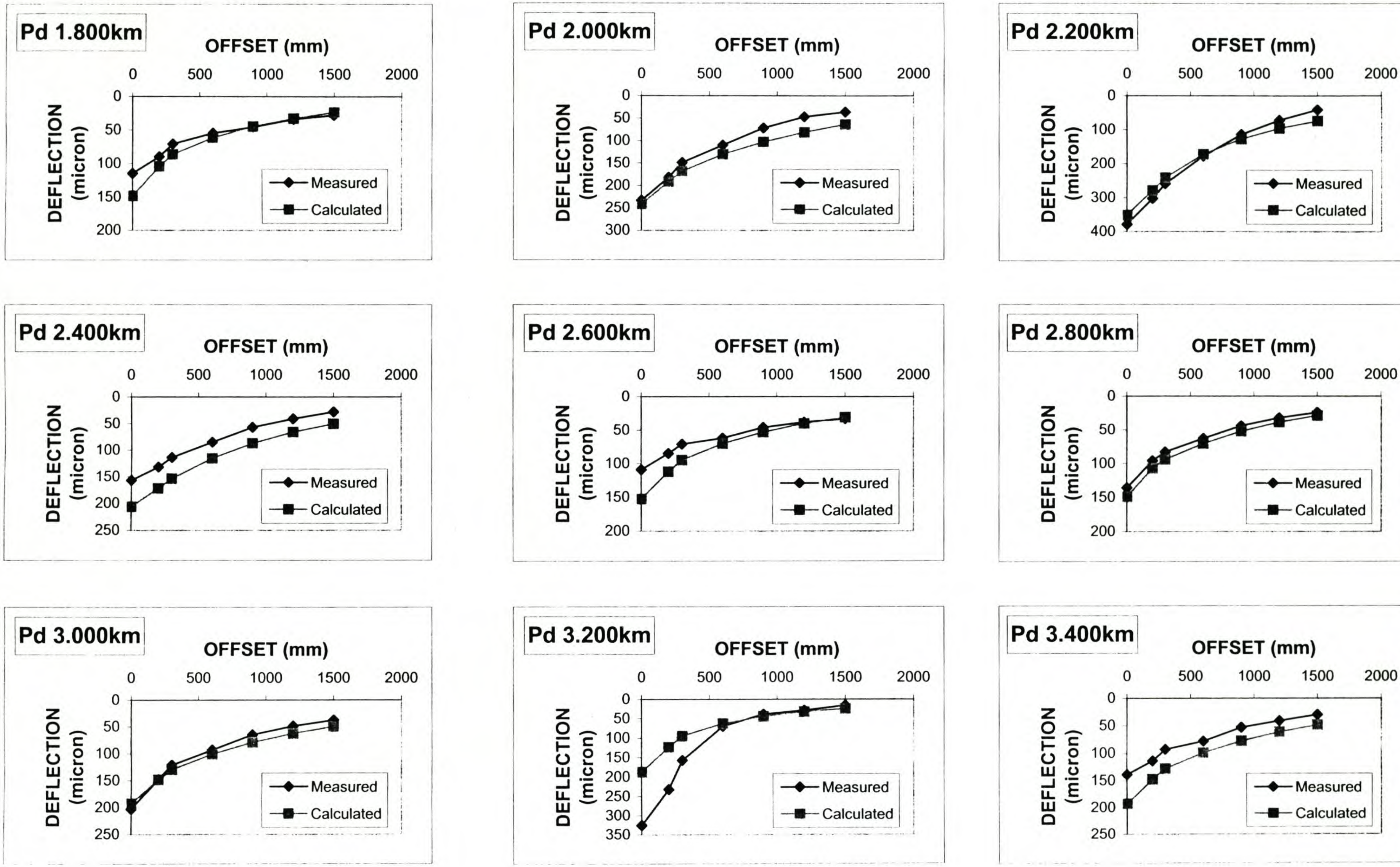




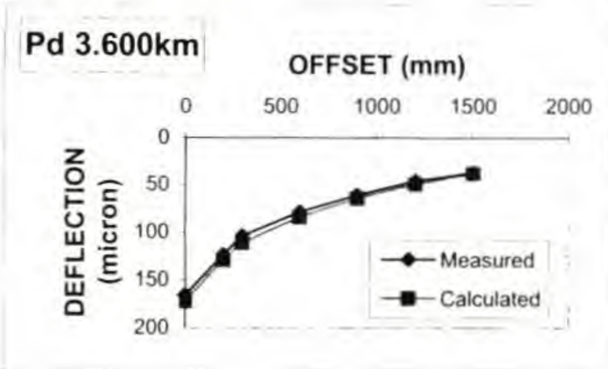


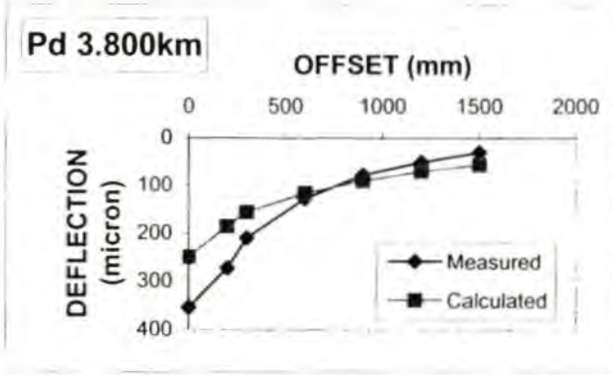


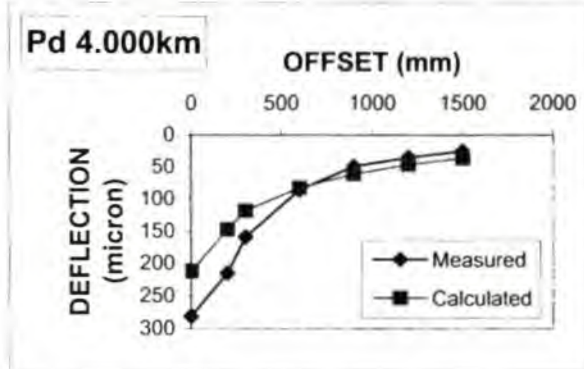
TR901: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)

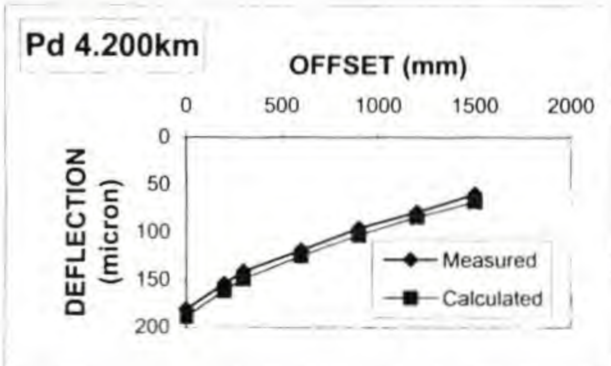


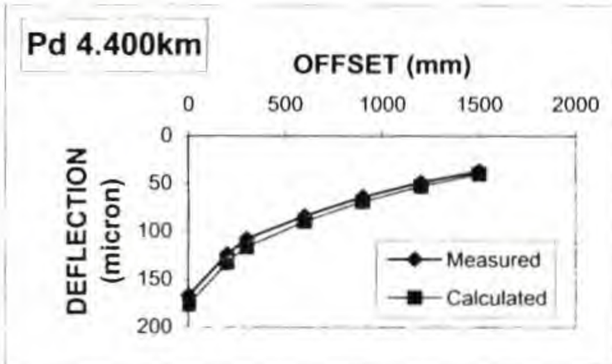
TR901: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)

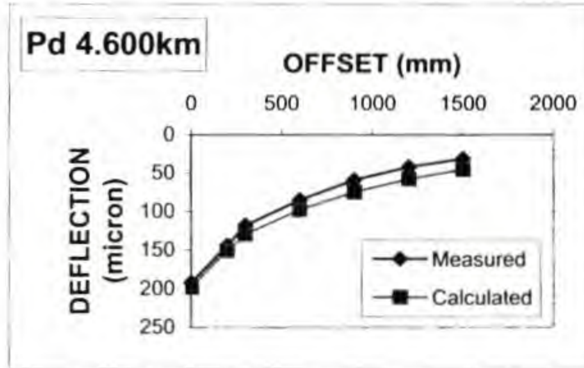


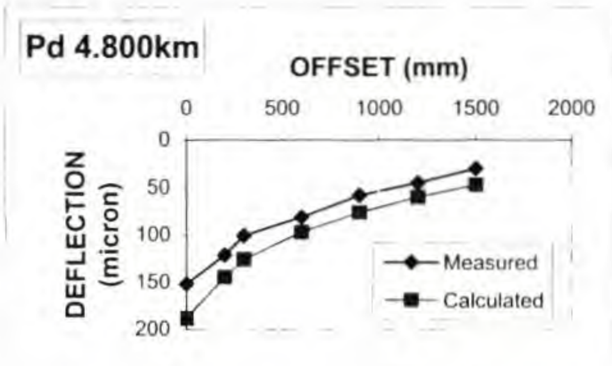


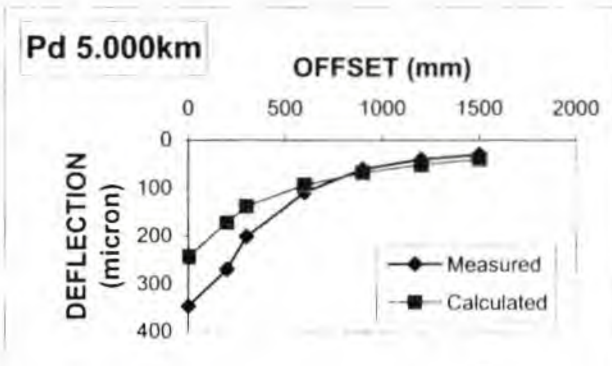


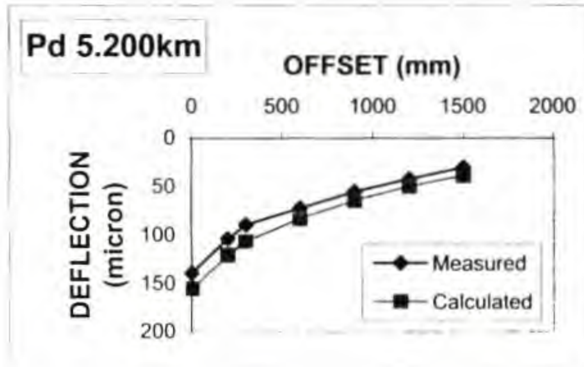




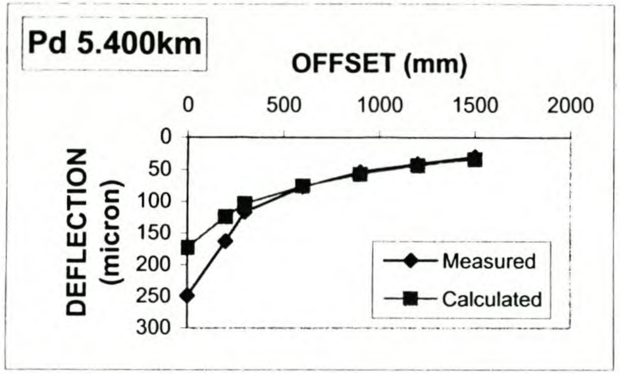


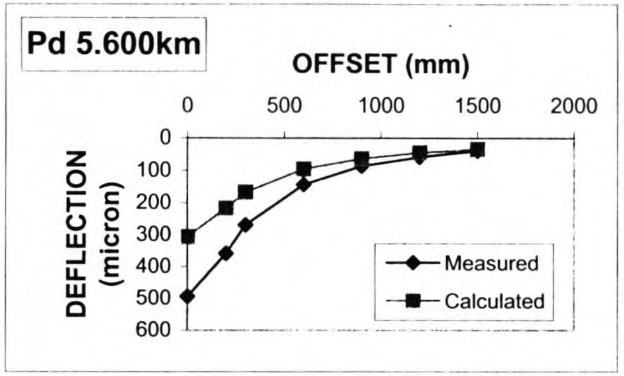


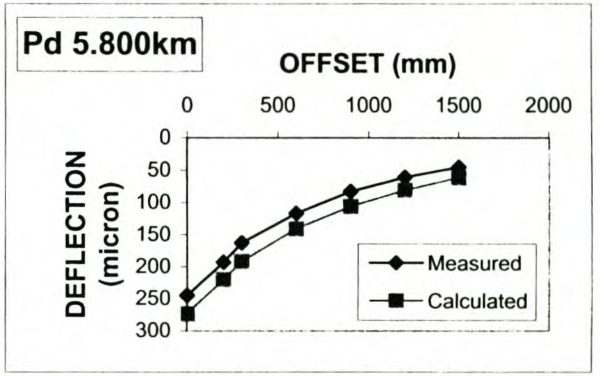


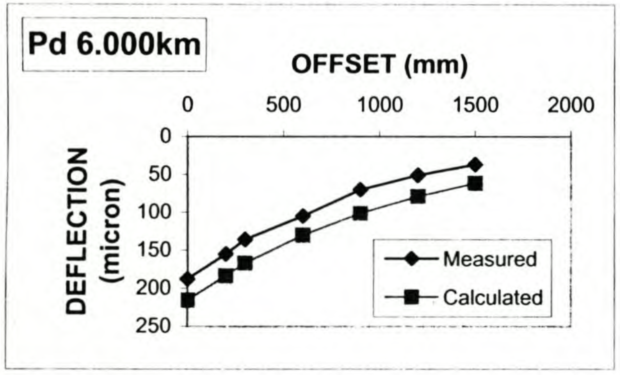


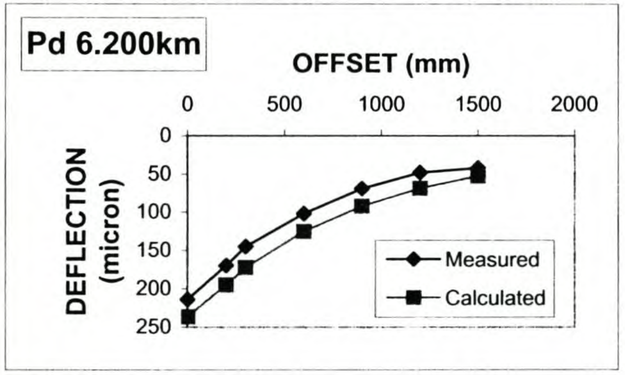
TR901: MEASURED vs CALCULATED DEFLECTIONS: CASE (a)

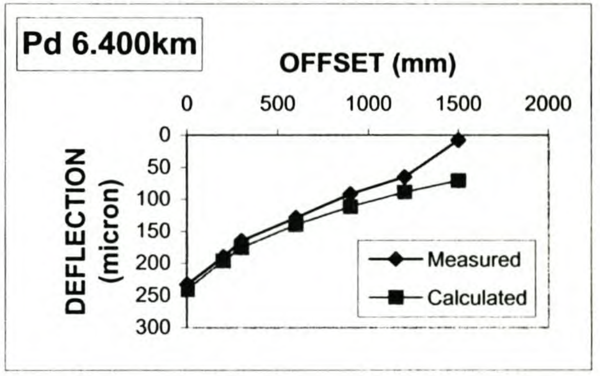


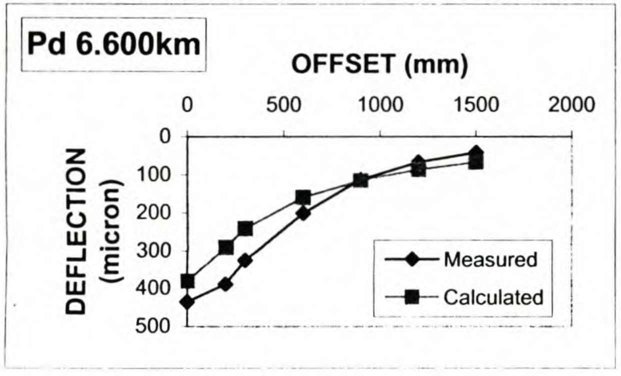


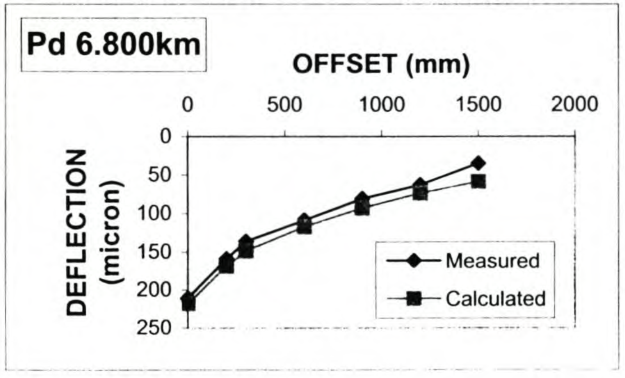


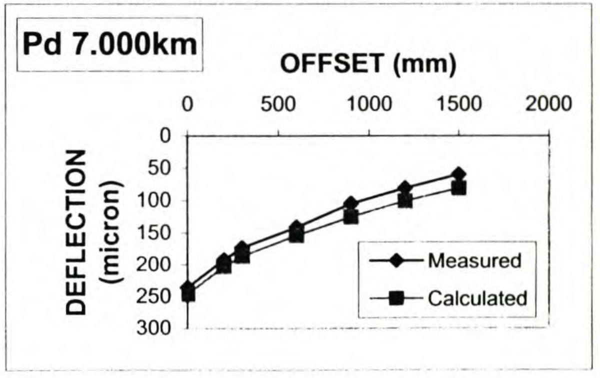










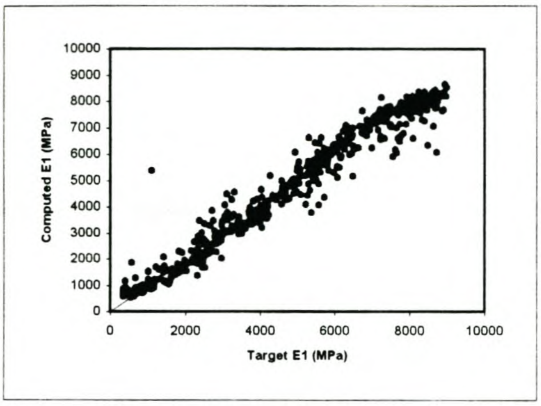


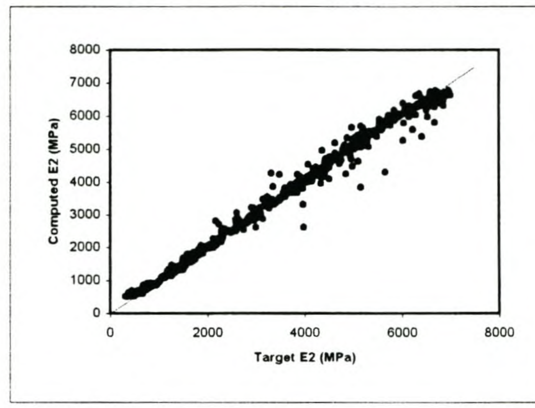
TR901: COMPARISON OF MEASURED AND CALCULATED DEFLECTIONS: CASE (a)

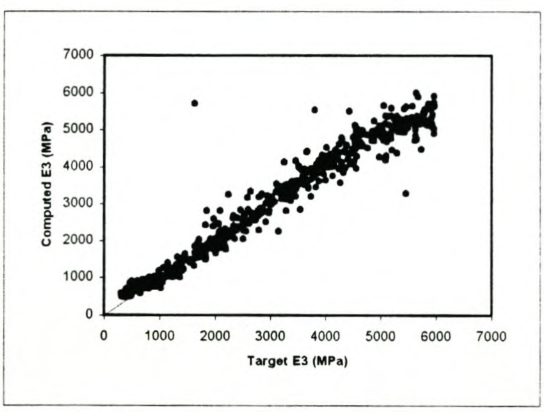
Pos (Km)\Offset (mm)		0	200	300	600	900	1200	1500	RMSE (%)
0.000	Measured	364	291	233	139	86	61	45	13.20%
	Calculated	314	231	187	120	85	62	48	
0.200	Measured	265	218	174	120	80	58	47	34.55%
	Calculated	265	206	179	141	113	90	74	
0.400	Measured	432	368	290	158	87	57	34	27.75%
	Calculated	316	227	179	109	75	55	42	
0.600	Measured	141	105	92	72	52	40	30	13.59%
	Calculated	153	117	104	80	61	46	35	
0.800	Measured	242	205	174	130	92	65	45	37.22%
	Calculated	281	223	195	153	122	97	78	
1.000	Measured	190	150	126	101	74	53	44	23.12%
	Calculated	207	163	144	115	92	74	58	
1.200	Measured	192	158	118	92	66	50	37	49.16%
	Calculated	238	186	163	129	103	82	65	
1.400	Measured	119	89	71	62	41	30	24	41.88%
	Calculated	161	120	103	78	60	46	36	
1.600	Measured	107	86	70	55	39	29	24	30.39%
	Calculated	155	111	93	67	50	38	29	
1.800	Measured	115	90	71	55	46	34	28	17.02%
	Calculated	149	105	87	62	45	33	24	
2.000	Measured	233	182	149	110	72	47	36	44.28%
	Calculated	241	192	169	131	103	81	64	
2.200	Measured	379	303	259	178	114	72	41	33.78%
	Calculated	352	279	241	173	127	96	74	
2.400	Measured	157	132	114	85	57	41	28	49.98%
	Calculated	206	172	154	116	87	66	51	
2.600	Measured	109	85	71	62	46	38	33	24.63%
	Calculated	153	112	95	70	53	40	31	
2.800	Measured	136	96	83	63	44	32	24	15.73%
	Calculated	149	107	94	71	52	39	29	
3.000	Measured	203	148	121	93	65	49	38	18.46%
	Calculated	193	149	129	101	79	63	50	
3.200	Measured	326	232	157	70	39	29	16	35.89%
	Calculated	187	123	95	63	45	33	25	
3.400	Measured	139	114	93	78	53	41	30	43.00%
	Calculated	193	148	128	99	78	61	49	
3.600	Measured	166	124	104	79	61	46	37	5.71%
	Calculated	172	129	111	84	65	49	38	
3.800	Measured	354	273	210	128	78	51	30	41.17%
	Calculated	249	186	156	117	90	71	56	
4.000	Measured	281	215	159	86	49	35	25	28.86%
	Calculated	212	148	118	83	61	46	36	
4.200	Measured	181	154	141	119	96	79	60	7.39%
	Calculated	189	161	149	125	103	84	68	
4.400	Measured	167	124	108	84	64	49	37	7.65%
	Calculated	176	133	117	90	69	53	40	
4.600	Measured	192	144	118	85	59	42	31	25.43%
	Calculated	198	151	130	98	75	58	45	
4.800	Measured	152	121	101	81	58	45	30	32.31%
	Calculated	188	145	126	97	76	60	47	
5.000	Measured	347	269	201	109	60	40	30	27.79%
	Calculated	243	172	138	93	68	51	40	
5.200	Measured	139	104	89	72	55	42	30	18.50%
	Calculated	155	121	106	83	64	50	38	
5.400	Measured	249	163	117	77	54	41	30	16.30%
	Calculated	173	124	104	76	57	43	34	
5.600	Measured	494	359	270	144	86	59	39	31.64%
	Calculated	307	217	168	95	63	45	34	
5.800	Measured	245	193	163	117	83	61	45	24.73%
	Calculated	274	220	192	141	106	81	62	
6.000	Measured	188	155	136	105	70	51	37	39.80%
	Calculated	216	184	167	130	102	79	61	
6.200	Measured	214	170	145	102	69	48	42	26.17%
	Calculated	236	195	172	125	92	69	52	
6.400	Measured	326	266	217	137	93	70	66	11.24%
	Calculated	293	221	186	134	102	78	61	
6.600	Measured	233	190	165	129	92	65	8	297.48%
	Calculated	241	196	176	140	112	89	71	
6.800	Measured	436	389	325	201	113	67	42	30.25%
	Calculated	380	291	241	160	116	87	67	
7.000	Measured	211	159	136	109	81	63	35	27.70%
	Calculated	218	169	148	117	93	74	59	
7.200	Measured	236	192	173	141	105	81	60	18.69%
	Calculated	246	203	186	154	125	101	81	

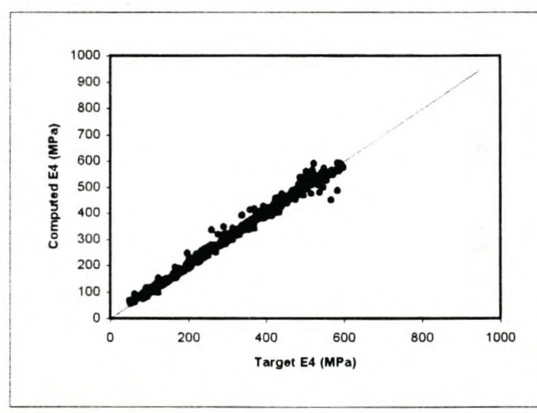
APPENDIX C.7: TR901 CASE (b)

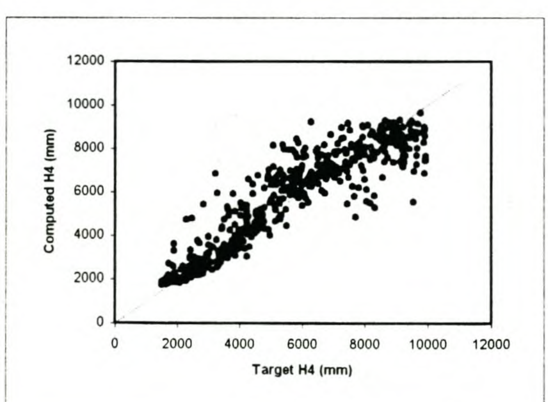
RESULTS OF BACK-CALCULATIONS (E-MODULI LAYERS 1-4 FROM DEFLECTIONS) FROM TEST SET OF A TYPICAL SOUTH AFRICAN PAVEMENT: BITUMINOUS BASE/CEMENTED SUBBASE WITH A THIN SURFACING : CASE (b): DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000MPa











TR901: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (b)
DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
0.00	364	291	233	139	86	61	45	131	94	53	84.6	G1	3.43	6.1	1085	358108	0.9
0.20	265	218	174	120	80	58	47	91	54	40	91.5	G1	4.37	10.7	1085	2737173	6.1
0.40	432	368	290	158	87	57	34	142	132	71	82.4	G1	2.64	3	1085	142403	0.4
0.60	141	105	92	72	52	40	30	49	20	20	97.4	G1	6.09	25	1085	30734637	37
0.80	242	205	174	130	92	65	45	68	44	38	94.9	G1	4.18	5.8	1085	3163511	6.9
1.00	190	150	126	101	74	53	44	64	25	27	95.4	G1	5.3	15.3	1085	20486267	29.1
1.20	192	158	118	92	66	50	37	74	26	26	94.1	G1	5.56	25	1085	29029280	35.8
1.40	119	89	71	62	41	30	24	48	9	21	97.5	G1	6.33	25	1085	88197763	61.3
1.60	107	86	70	55	39	29	24	37	15	16	98.7	G1	6.56	25	1085	45541185	45.5
1.80	115	90	71	55	46	34	28	44	16	9	97.9	G1	6.5	25	1085	42892071	44.1
2.00	233	182	149	110	72	47	36	84	39	38	92.6	G1	4.32	7.9	1085	3958647	8.4
2.20	379	303	259	178	114	72	41	120	81	64	86.6	G1	2.94	3	1085	285586	0.7
2.40	157	132	114	85	57	41	28	43	29	28	98.1	G1	5.93	25	1085	37557165	41.2
2.60	109	85	71	62	46	38	33	38	9	16	98.6	G1	6.69	25	1085	73099168	56.7
2.80	136	96	83	63	44	32	24	53	20	19	96.9	G1	6.03	25	1085	24468759	32.4
3.00	203	148	121	93	65	49	38	82	28	28	92.9	G1	5.42	25	1085	19366443	28.1
3.20	326	232	157	70	39	29	16	169	87	31	76.7	G1	4.48	25	1085	3647003	7.9
3.40	139	114	93	78	53	41	30	46	15	25	97.7	G1	6.17	25	1085	50966559	48.1
3.60	166	124	104	79	61	46	37	62	25	18	95.7	G1	5.82	25	1085	32771298	38.3
3.80	354	273	210	128	78	51	30	144	82	50	82	G1	3.27	5	1085	708342	1.7
4.00	281	215	159	86	49	35	25	122	73	37	86.3	G1	4.74	25	1085	7376308	14.1
4.20	181	154	141	119	96	79	60	40	22	23	98.4	G1	6.14	23.5	1085	49492378	47.4
4.40	167	124	108	84	64	49	37	59	24	20	96.1	G1	5.86	25	1085	26417167	33.9
4.60	192	144	118	85	59	42	31	74	33	26	94.1	G1	5.48	25	1085	20775683	29.4
4.80	152	121	101	81	58	45	30	51	20	23	97.1	G1	6.01	25	1085	41860895	43.6
5.00	347	269	201	109	60	40	30	146	92	49	81.6	G1	3.91	11.9	1085	2067320	4.7
5.20	139	104	89	72	55	42	30	50	17	17	97.2	G1	6.19	25	1085	16971225	25.8
5.40	249	163	117	77	54	41	30	132	40	23	84.4	G1	4.94	25	1085	6903265	13.4
5.60	494	359	270	144	86	59	39	224	126	58	63.4	G1	2.79	4.6	1085	231267	0.6
5.80	245	193	163	117	83	61	45	82	46	34	92.9	G1	4.55	10.8	1085	3546473	7.7
6.00	188	155	136	105	70	51	37	52	31	35	97	G1	5.32	15.8	1085	9915188	17.7
6.20	214	170	145	102	69	48	42	69	43	33	94.8	G1	4.94	14.5	1085	7796097	14.7
6.40	326	266	217	137	93	70	66	109	80	44	88.6	G1	4.02	10	1085	2249145	5.1
6.60	233	190	165	129	92	65	8	68	36	37	94.9	G1	3.94	3.8	1085	1981081	4.5
6.80	436	389	325	201	113	67	42	111	124	88	88.2	G1	2.73	3	1085	202571	0.5
7.00	211	159	136	109	81	63	35	75	27	28	93.9	G1	5.16	16	1937	13538976	14.4
7.20	236	192	173	141	105	81	60	63	32	36	95.6	G1	4.62	7.9	1937	5563858	6.8

TR901: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (b)
DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

NEURAL NETWORK: BACKCALCULATED E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	60	150	150	1919.5	364	291	233	139	86	61	45	8999.4	657.4	486.9	60.2	10000.0
0.20	60	150	150	1514.1	265	218	174	120	80	58	47	8999.4	895.7	5998.1	55.2	10000.0
0.40	60	150	150	1519.1	432	368	290	158	87	57	34	8999.4	871.0	5999.6	51.3	10000.0
0.60	60	150	150	2913.6	141	105	92	72	52	40	30	1149.0	2580.4	5999.6	194.4	10000.0
0.80	60	150	150	1507.0	242	205	174	130	92	65	45	8999.4	957.7	5883.0	55.6	10000.0
1.00	60	150	150	1513.6	190	150	126	101	74	53	44	8999.4	1966.5	5999.7	71.2	10000.0
1.20	60	150	150	1506.0	192	158	118	92	66	50	37	8999.4	1136.1	5999.7	55.3	10000.0
1.40	60	150	150	1507.4	119	89	71	62	41	30	24	8999.4	1358.7	5999.7	75.0	10000.0
1.60	60	150	150	1554.6	107	86	70	55	39	29	24	8999.4	2535.4	5999.7	147.5	10000.0
1.80	60	150	150	1794.1	115	90	71	55	46	34	28	8999.4	1778.8	5999.7	147.4	10000.0
2.00	60	150	150	1508.0	233	182	149	110	72	47	36	8999.4	1526.9	5999.6	67.5	10000.0
2.20	60	150	150	1515.9	379	303	259	178	114	72	41	8999.4	1457.5	486.2	60.7	10000.0
2.40	60	150	150	1522.5	157	132	114	85	57	41	28	8999.4	2213.5	524.6	75.7	10000.0
2.60	60	150	150	1594.9	109	85	71	62	46	38	33	8999.4	1982.3	5999.7	135.0	10000.0
2.80	60	150	150	2694.6	136	96	83	63	44	32	24	561.0	2313.2	5999.5	226.5	10000.0
3.00	60	150	150	1529.3	203	148	121	93	65	49	38	8999.4	2146.7	5999.7	94.3	10000.0
3.20	60	150	150	6654.3	326	232	157	70	39	29	16	8999.4	1279.7	5999.6	291.6	10000.0
3.40	60	150	150	1505.9	139	114	93	78	53	41	30	8999.4	1362.4	5999.7	61.1	10000.0
3.60	60	150	150	2837.1	166	124	104	79	61	46	37	8998.9	1656.1	5998.1	145.2	10000.0
3.80	60	150	150	1522.8	354	273	210	128	78	51	30	8999.4	1144.7	5999.5	70.9	10000.0
4.00	60	150	150	1865.4	281	215	159	86	49	35	25	8999.4	1304.5	5999.6	116.7	10000.0
4.20	60	150	150	1621.3	181	154	141	119	96	79	60	8999.2	3458.0	5999.6	79.5	10000.0
4.40	60	150	150	4603.1	167	124	108	84	64	49	37	3523.1	1451.1	5964.7	150.9	10000.0
4.60	60	150	150	1531.2	192	144	118	85	59	42	31	8999.4	1332.5	5872.2	88.3	10000.0
4.80	60	150	150	1511.4	152	121	101	81	58	45	30	8999.4	2063.5	5999.7	76.5	10000.0
5.00	60	150	150	1691.5	347	269	201	109	60	40	30	8999.4	1156.2	5999.6	75.2	10000.0
5.20	60	150	150	1602.2	139	104	89	72	55	42	30	8999.0	2968.0	5999.7	133.5	10000.0
5.40	60	150	150	1755.8	249	163	117	77	54	41	30	8999.4	1444.9	5999.7	167.9	10000.0
5.60	60	150	150	1732.5	494	359	270	144	86	59	39	8999.4	562.9	316.6	68.6	10000.0
5.80	60	150	150	1552.3	245	193	163	117	83	61	45	8999.4	1050.1	730.8	67.8	10000.0
6.00	60	150	150	1513.4	188	155	136	105	70	51	37	8999.4	2353.8	2611.7	69.7	10000.0
6.20	60	150	150	2540.6	214	170	145	102	69	48	42	8999.4	1988.4	453.1	105.6	10000.0
6.40	60	150	150	8185.3	326	266	217	137	93	70	66	8999.4	1304.6	5999.3	71.8	10000.0
6.60	60	150	150	1508.3	233	190	165	129	92	65	8	8999.2	3847.5	5999.7	59.1	10000.0
6.80	60	150	150	1534.7	436	389	325	201	113	67	42	8999.4	949.9	5999.6	51.4	10000.0
7.00	60	150	150	1520.0	211	159	136	109	81	63	35	8999.0	2288.5	5999.7	77.1	10000.0
7.20	60	150	150	1579.7	236	192	173	141	105	81	60	8905.6	1771.1	5992.9	69.8	10000.0

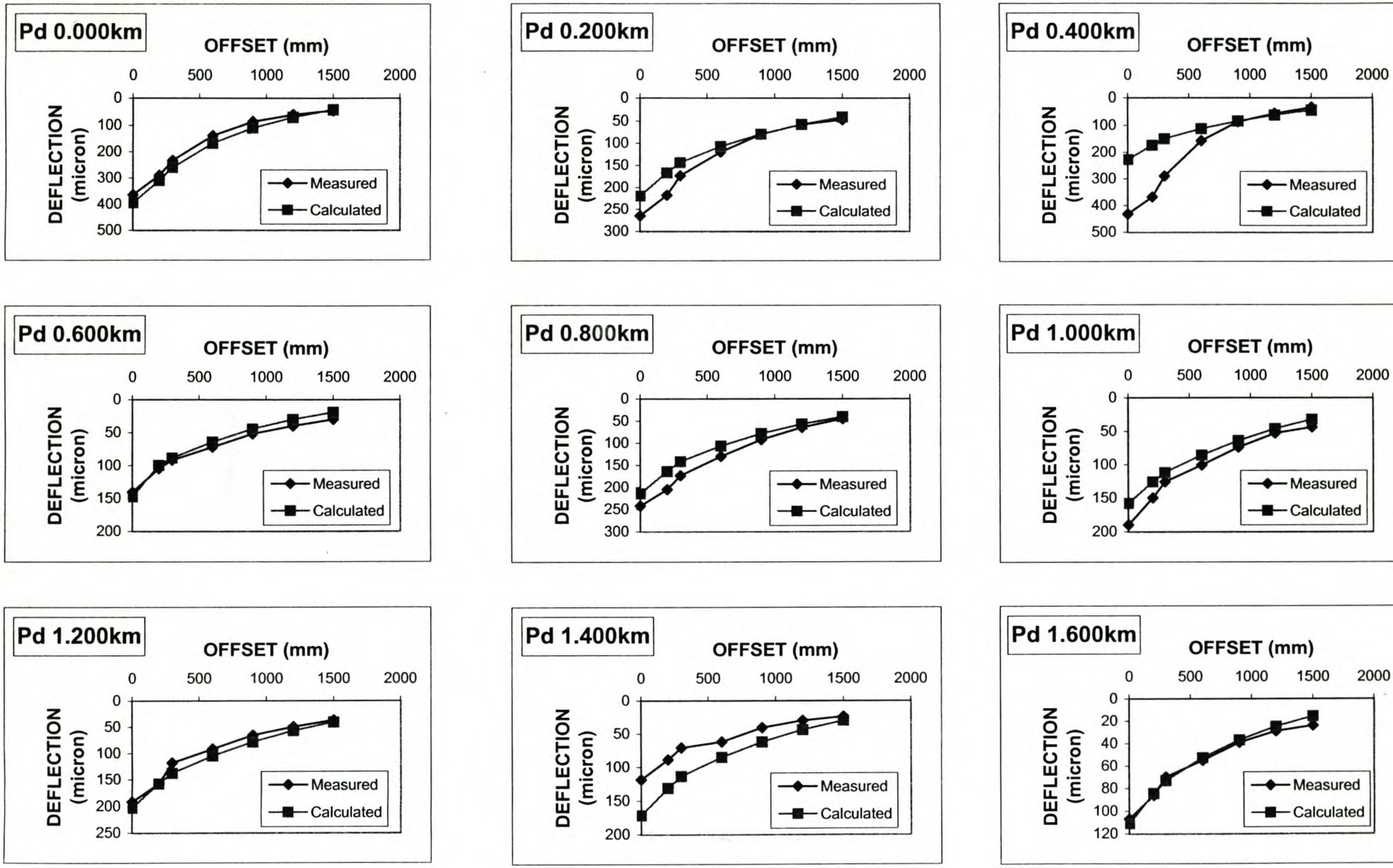
TR901: E-MODULI BACK-CALCULATED WITH NEURAL NETWORK: CASE (b)
DEPTH TO STIFF LAYER CALCULATED WITH NEURAL NETWORK WITH E5 = 10000 Mpa

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

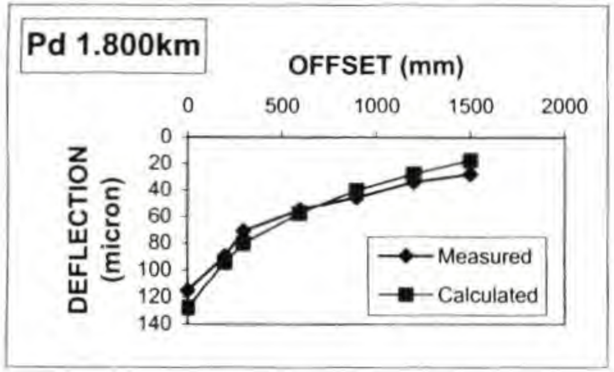
WES5: DEFLECTIONS FROM NEURAL NETWORK E-MODULI

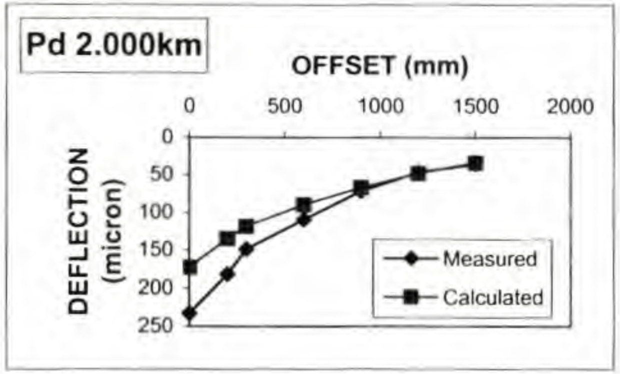
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	60	150	150	1920	395	310	261	168	110	70	42	8999.4	657.4	486.9	60.2	10000.0
0.20	60	150	150	1514	219	167	144	107	80	58	41	8999.4	895.7	5998.1	55.2	10000.0
0.40	60	150	150	1519	227	174	150	113	84	62	44	8999.4	871.0	5999.6	51.3	10000.0
0.60	60	150	150	2914	148	100	88	64	44	30	19	1149.0	2580.4	5999.6	194.4	10000.0
0.80	60	150	150	1507	214	164	142	106	79	57	40	8999.4	957.7	5883.0	55.6	10000.0
1.00	60	150	150	1514	158	126	112	86	64	46	32	8999.4	1966.5	5999.7	71.2	10000.0
1.20	60	150	150	1506	203	158	138	105	78	57	41	8999.4	1136.1	5999.7	55.3	10000.0
1.40	60	150	150	1507	172	132	114	85	62	44	30	8999.4	1358.7	5999.7	75.0	10000.0
1.60	60	150	150	1555	111	84	73	53	37	25	16	8999.4	2535.4	5999.7	147.5	10000.0
1.80	60	150	150	1794	128	94	80	58	40	28	17	8999.4	1778.8	5999.7	147.4	10000.0
2.00	60	150	150	1508	173	135	119	90	67	48	34	8999.4	1526.9	5999.6	67.5	10000.0
2.20	60	150	150	1516	308	251	218	146	95	59	34	8999.4	1457.5	486.2	60.7	10000.0
2.40	60	150	150	1522	248	204	178	120	77	47	27	8999.4	2213.5	524.6	75.7	10000.0
2.60	60	150	150	1595	124	93	80	58	40	27	17	8999.4	1982.3	5999.7	135.0	10000.0
2.80	60	150	150	2695	164	92	81	57	38	24	18	561.0	2313.2	5999.5	226.5	10000.0
3.00	60	150	150	1529	138	108	95	72	52	37	25	8999.4	2146.7	5999.7	94.3	10000.0
3.20	60	150	150	6654	127	87	70	50	36	27	21	8999.4	1279.7	5999.6	291.6	10000.0
3.40	60	150	150	1506	185	145	127	97	72	53	37	8999.4	1362.4	5999.7	61.1	10000.0
3.60	60	150	150	2837	144	109	94	70	52	38	28	8998.9	1656.1	5998.1	145.2	10000.0
3.80	60	150	150	1523	186	141	121	90	65	46	32	8999.4	1144.7	5999.5	70.9	10000.0
4.00	60	150	150	1865	156	115	97	71	51	35	24	8999.4	1304.5	5999.6	116.7	10000.0
4.20	60	150	150	1621	135	112	102	80	61	45	31	8999.2	3458.0	5999.6	79.5	10000.0
4.40	60	150	150	4603	176	129	113	85	64	47	34	3523.1	1451.1	5964.7	150.9	10000.0
4.60	60	150	150	1531	164	123	106	77	56	38	26	8999.4	1332.5	5872.2	88.3	10000.0
4.80	60	150	150	1511	151	120	107	82	61	43	30	8999.4	2063.5	5999.7	76.5	10000.0
5.00	60	150	150	1692	186	142	122	91	67	48	34	8999.4	1156.2	5999.6	75.2	10000.0
5.20	60	150	150	1602	112	87	77	57	41	28	18	8999.0	2968.0	5999.7	133.5	10000.0
5.40	60	150	150	1756	130	92	76	53	36	24	15	8999.4	1444.9	5999.7	167.9	10000.0
5.60	60	150	150	1732	412	316	259	153	93	54	31	8999.4	562.9	316.6	68.6	10000.0
5.80	60	150	150	1552	295	232	197	130	85	53	32	8999.4	1050.1	730.8	67.8	10000.0
6.00	60	150	150	1513	182	149	133	99	72	50	33	8999.4	2353.8	2611.7	69.7	10000.0
6.20	60	150	150	2541	245	199	172	115	76	49	32	8999.4	1988.4	453.1	105.6	10000.0
6.40	60	150	150	8185	243	201	183	152	126	104	86	8999.4	1304.6	5999.3	71.8	10000.0
6.60	60	150	150	1508	147	125	115	93	72	54	39	8999.2	3847.5	5999.7	59.1	10000.0
6.80	60	150	150	1535	222	171	148	112	84	62	44	8999.4	949.9	5999.6	51.4	10000.0
7.00	60	150	150	1520	147	118	105	81	60	43	30	8999.0	2288.5	5999.7	77.1	10000.0
7.20	60	150	150	1580	166	132	117	90	67	49	34	8905.6	1771.1	5992.9	69.8	10000.0

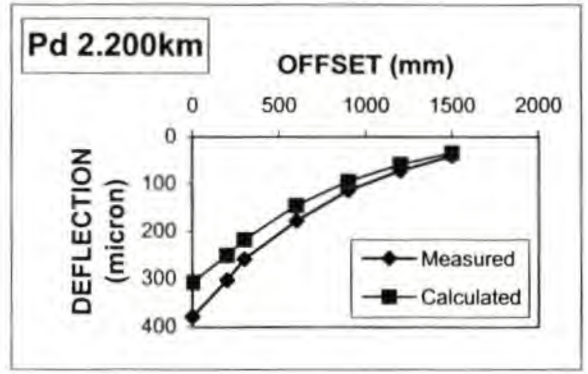
TR901: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

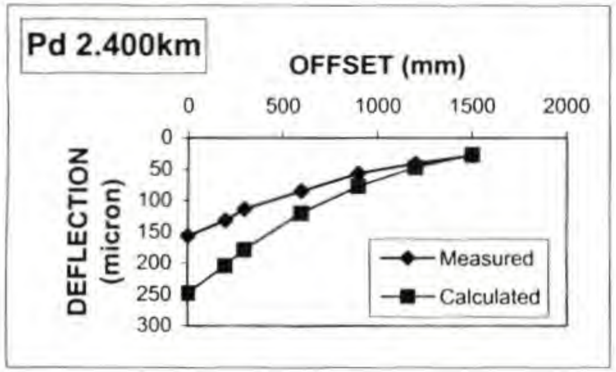


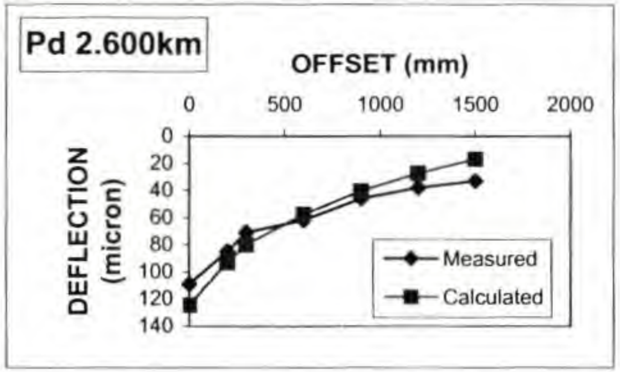
TR901: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

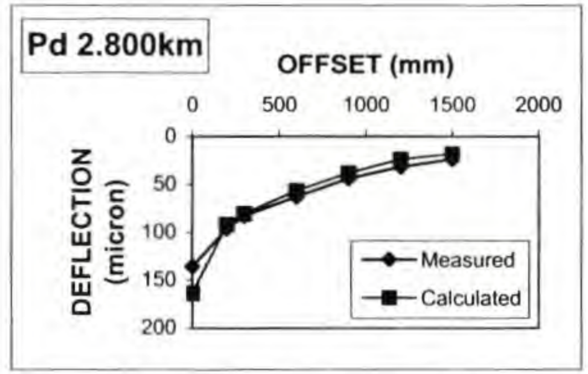


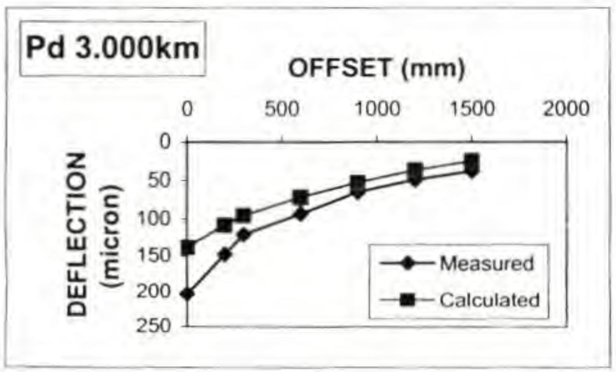


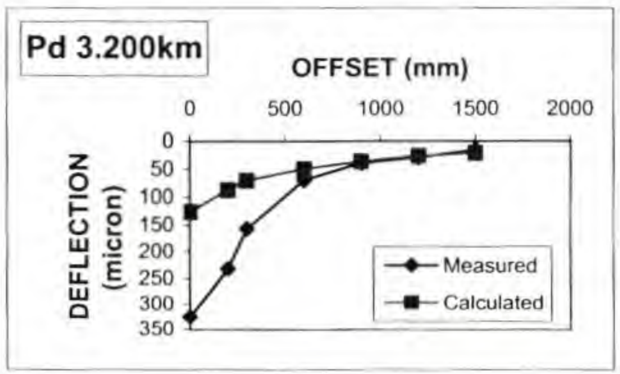


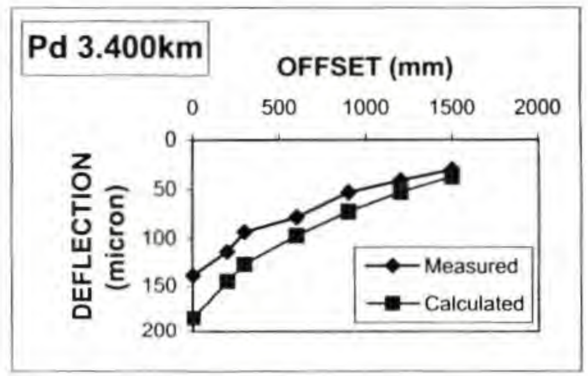




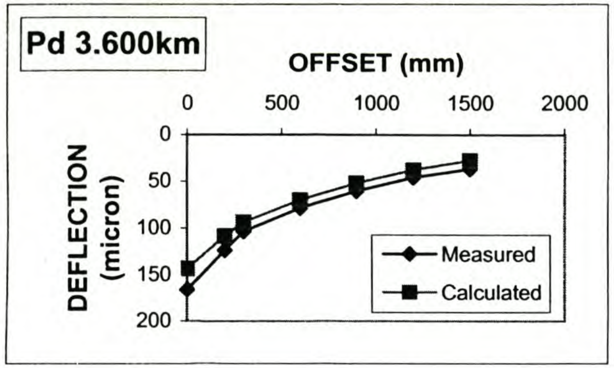


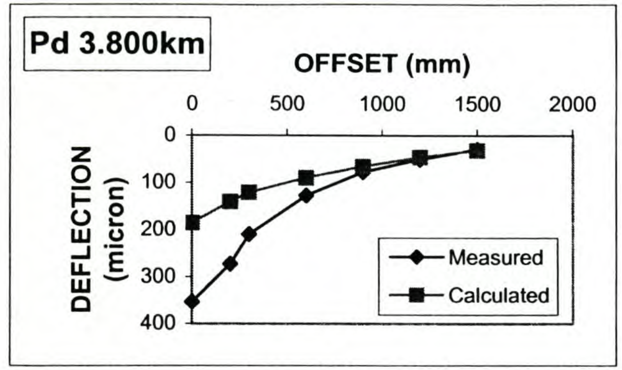


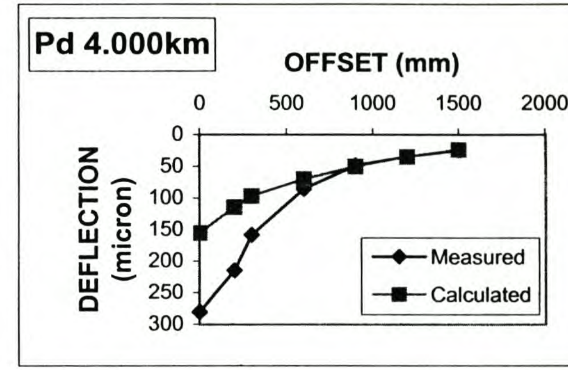


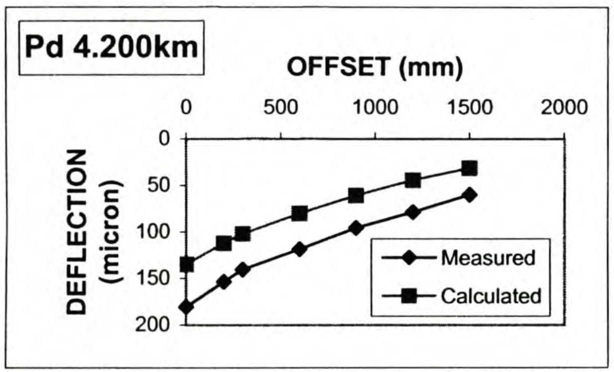


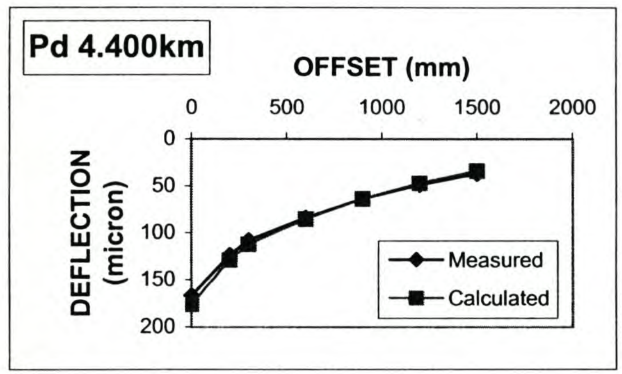
TR901: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

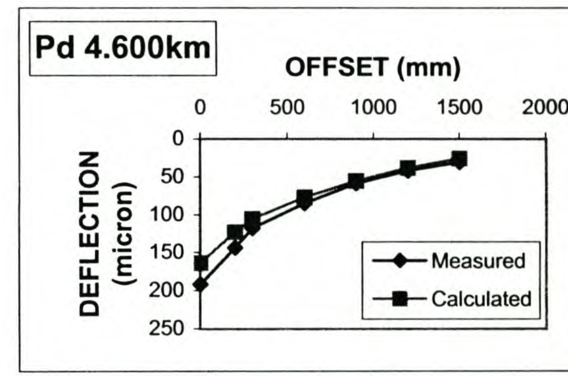


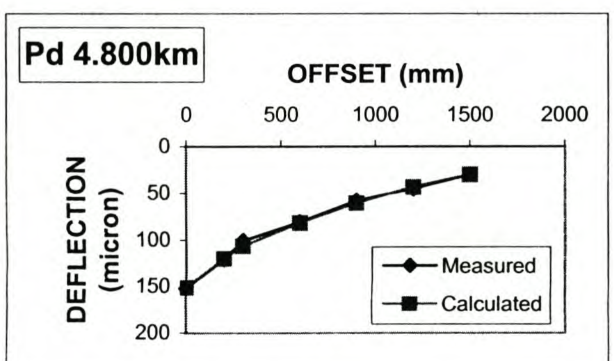


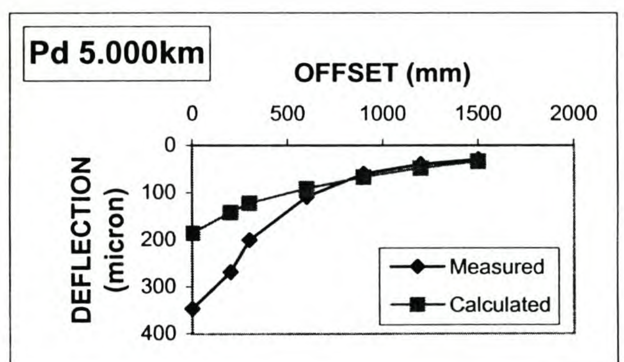


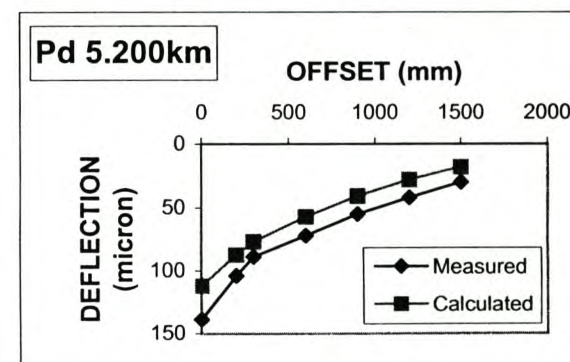




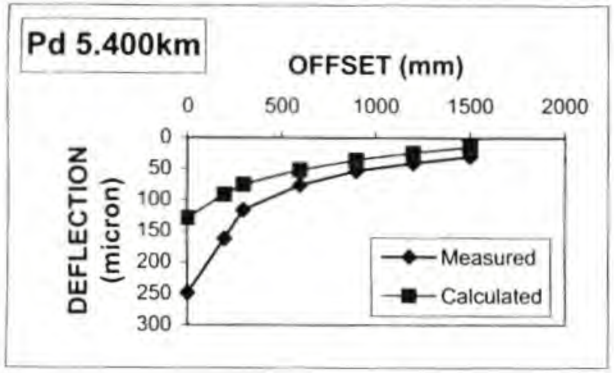


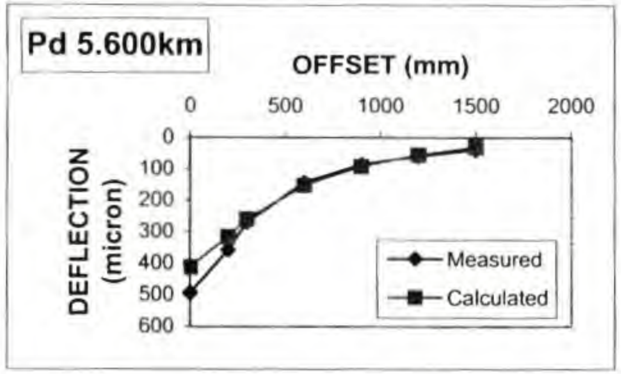


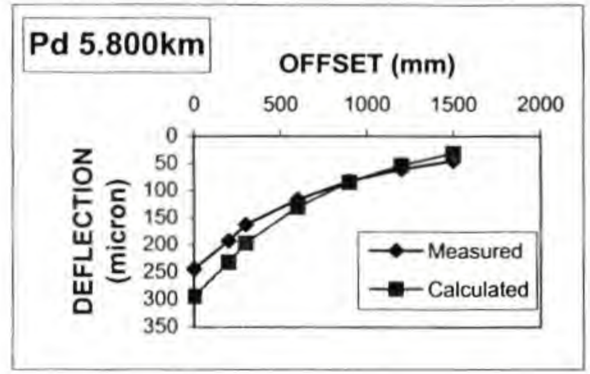


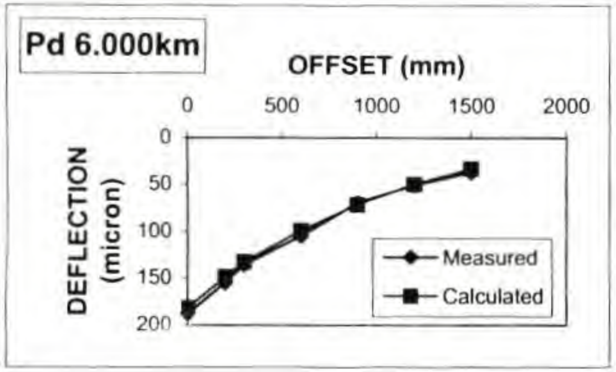


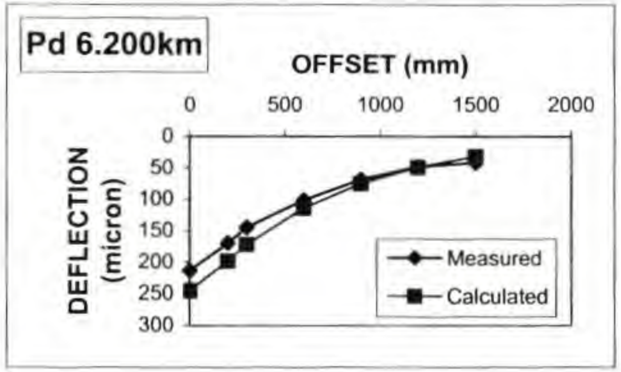
TR901: MEASURED vs CALCULATED DEFLECTIONS: CASE (b)

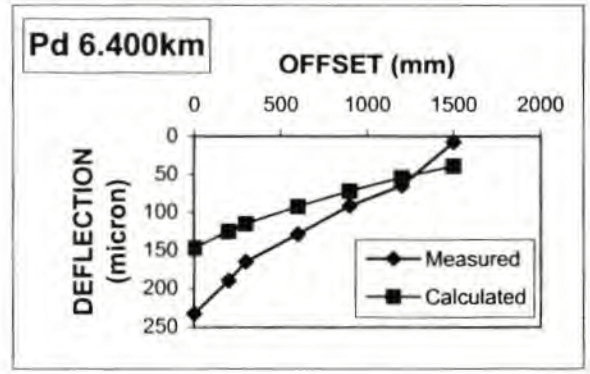


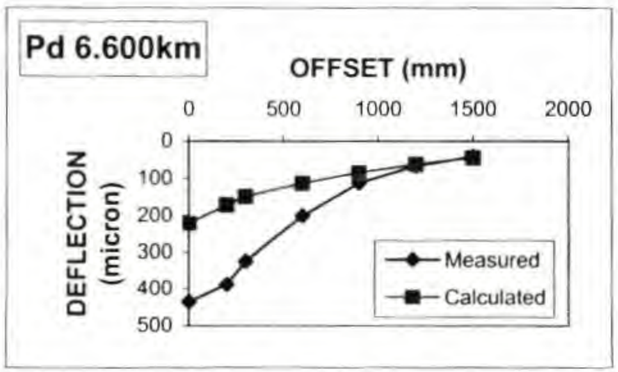


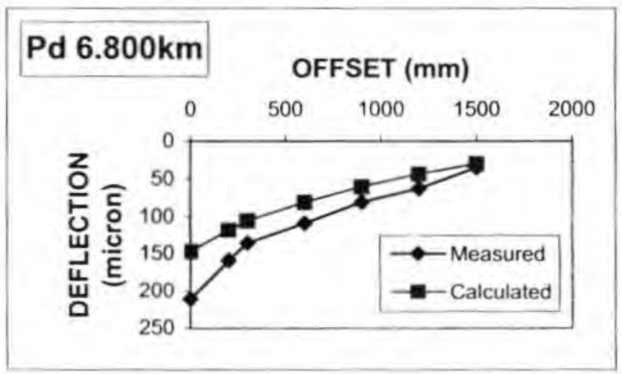


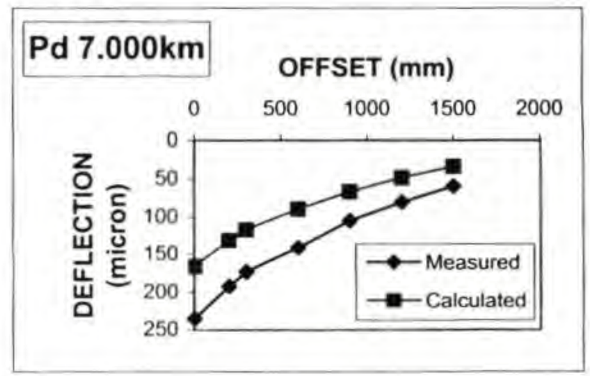












TR901: COMPARISON OF MEASURED AND CALCULATED DEFLECTIONS: CASE (b)

Pos (Km)\Offset (mm)		0	200	300	600	900	1200	1500	RMSE (%)
0.000	Measured	364	291	233	139	86	61	45	15.73%
	Calculated	395	310	261	168	110	70	42	
0.200	Measured	265	218	174	120	80	58	47	14.25%
	Calculated	219	167	144	107	80	58	41	
0.400	Measured	432	368	290	158	87	57	34	35.98%
	Calculated	227	174	150	113	84	62	44	
0.600	Measured	141	105	92	72	52	40	30	18.14%
	Calculated	148	100	88	64	44	30	19	
0.800	Measured	242	205	174	130	92	65	45	15.43%
	Calculated	214	164	142	106	79	57	40	
1.000	Measured	190	150	126	101	74	53	44	16.70%
	Calculated	158	126	112	86	64	46	32	
1.200	Measured	192	158	118	92	66	50	37	12.96%
	Calculated	203	158	138	105	78	57	41	
1.400	Measured	119	89	71	62	41	30	24	45.75%
	Calculated	172	132	114	85	62	44	30	
1.600	Measured	107	86	70	55	39	29	24	14.72%
	Calculated	111	84	73	53	37	25	16	
1.800	Measured	115	90	71	55	46	34	28	17.88%
	Calculated	128	94	80	58	40	28	17	
2.000	Measured	233	182	149	110	72	47	36	17.65%
	Calculated	173	135	119	90	67	48	34	
2.200	Measured	379	303	259	178	114	72	41	17.50%
	Calculated	308	251	218	146	95	59	34	
2.400	Measured	157	132	114	85	57	41	28	42.64%
	Calculated	248	204	178	120	77	47	27	
2.600	Measured	109	85	71	62	46	38	33	23.10%
	Calculated	124	93	80	58	40	27	17	
2.800	Measured	136	96	83	63	44	32	24	16.18%
	Calculated	164	92	81	57	38	24	18	
3.000	Measured	203	148	121	93	65	49	38	26.49%
	Calculated	138	108	95	72	52	37	25	
3.200	Measured	326	232	157	70	39	29	16	42.59%
	Calculated	127	87	70	50	36	27	21	
3.400	Measured	139	114	93	78	53	41	30	30.58%
	Calculated	185	145	127	97	72	53	37	
3.600	Measured	166	124	104	79	61	46	37	15.52%
	Calculated	144	109	94	70	52	38	28	
3.800	Measured	354	273	210	128	78	51	30	33.10%
	Calculated	186	141	121	90	65	46	32	
4.000	Measured	281	215	159	86	49	35	25	29.32%
	Calculated	156	115	97	71	51	35	24	
4.200	Measured	181	154	141	119	96	79	60	35.23%
	Calculated	135	112	102	80	61	45	31	
4.400	Measured	167	124	108	84	64	49	37	4.57%
	Calculated	176	129	113	85	64	47	34	
4.600	Measured	192	144	118	85	59	42	31	11.84%
	Calculated	164	123	106	77	56	38	26	
4.800	Measured	152	121	101	81	58	45	30	3.10%
	Calculated	151	120	107	82	61	43	30	
5.000	Measured	347	269	201	109	60	40	30	31.33%
	Calculated	186	142	122	91	67	48	34	
5.200	Measured	139	104	89	72	55	42	30	25.75%
	Calculated	112	87	77	57	41	28	18	
5.400	Measured	249	163	117	77	54	41	30	41.10%
	Calculated	130	92	76	53	36	24	15	
5.600	Measured	494	359	270	144	86	59	39	12.33%
	Calculated	412	316	259	153	93	54	31	
5.800	Measured	245	193	163	117	83	61	45	18.63%
	Calculated	295	232	197	130	85	53	32	
6.000	Measured	188	155	136	105	70	51	37	5.06%
	Calculated	182	149	133	99	72	50	33	
6.200	Measured	214	170	145	102	69	48	42	15.49%
	Calculated	245	199	172	115	76	49	32	
6.400	Measured	326	266	217	137	93	70	66	29.72%
	Calculated	243	201	183	152	126	104	86	
6.600	Measured	233	190	165	129	92	65	8	149.55%
	Calculated	147	125	115	93	72	54	39	
6.800	Measured	436	389	325	201	113	67	42	39.96%
	Calculated	222	171	148	112	84	62	44	
7.000	Measured	211	159	136	109	81	63	35	25.50%
	Calculated	147	118	105	81	60	43	30	
7.200	Measured	236	192	173	141	105	81	60	35.79%
	Calculated	166	132	117	90	67	49	34	

TR901: E-MODULI BACK-CALCULATED WITH MODCOMP

Date: Jul-96
Load: 40 kN
Temp: 17 deg C

MEASURED DATA

Pos (Km)	D0	D200	D300	D600	D900	D1200	D1500	BLI	MLI	LLI	SI	Base	SN	CBR	E80	Res. E80	Res. Life
0.00	364	291	233	139	86	61	45	131	94	53	84.6	G1	3.43	6.1	1085	358108	0.9
0.20	265	218	174	120	80	58	47	91	54	40	91.5	G1	4.37	10.7	1085	2737173	6.1
0.40	432	368	290	158	87	57	34	142	132	71	82.4	G1	2.64	3	1085	142403	0.4
0.60	141	105	92	72	52	40	30	49	20	20	97.4	G1	6.09	25	1085	30734637	37
0.80	242	205	174	130	92	65	45	68	44	38	94.9	G1	4.18	5.8	1085	3163511	6.9
1.00	190	150	126	101	74	53	44	64	25	27	95.4	G1	5.3	15.3	1085	20486267	29.1
1.20	192	158	118	92	66	50	37	74	26	26	94.1	G1	5.56	25	1085	29029280	35.8
1.40	119	89	71	62	41	30	24	48	9	21	97.5	G1	6.33	25	1085	88197763	61.3
1.60	107	86	70	55	39	29	24	37	15	16	98.7	G1	6.56	25	1085	45541185	45.5
1.80	115	90	71	55	46	34	28	44	16	9	97.9	G1	6.5	25	1085	42892071	44.1
2.00	233	182	149	110	72	47	36	84	39	38	92.6	G1	4.32	7.9	1085	3958647	8.4
2.20	379	303	259	178	114	72	41	120	81	64	86.6	G1	2.94	3	1085	285586	0.7
2.40	157	132	114	85	57	41	28	43	29	28	98.1	G1	5.93	25	1085	37557165	41.2
2.60	109	85	71	62	46	38	33	38	9	16	98.6	G1	6.69	25	1085	73099168	56.7
2.80	136	96	83	63	44	32	24	53	20	19	96.9	G1	6.03	25	1085	24468759	32.4
3.00	203	148	121	93	65	49	38	82	28	28	92.9	G1	5.42	25	1085	19366443	28.1
3.20	326	232	157	70	39	29	16	169	87	31	76.7	G1	4.48	25	1085	3647003	7.9
3.40	139	114	93	78	53	41	30	46	15	25	97.7	G1	6.17	25	1085	50966559	48.1
3.60	166	124	104	79	61	46	37	62	25	18	95.7	G1	5.82	25	1085	32771298	38.3
3.80	354	273	210	128	78	51	30	144	82	50	82	G1	3.27	5	1085	708342	1.7
4.00	281	215	159	86	49	35	25	122	73	37	86.3	G1	4.74	25	1085	7376308	14.1
4.20	181	154	141	119	96	79	60	40	22	23	98.4	G1	6.14	23.5	1085	49492378	47.4
4.40	167	124	108	84	64	49	37	59	24	20	96.1	G1	5.86	25	1085	26417167	33.9
4.60	192	144	118	85	59	42	31	74	33	26	94.1	G1	5.48	25	1085	20775683	29.4
4.80	152	121	101	81	58	45	30	51	20	23	97.1	G1	6.01	25	1085	41860895	43.6
5.00	347	269	201	109	60	40	30	146	92	49	81.6	G1	3.91	11.9	1085	2067320	4.7
5.20	139	104	89	72	55	42	30	50	17	17	97.2	G1	6.19	25	1085	16971225	25.8
5.40	249	163	117	77	54	41	30	132	40	23	84.4	G1	4.94	25	1085	6903265	13.4
5.60	494	359	270	144	86	59	39	224	126	58	63.4	G1	2.79	4.6	1085	231267	0.6
5.80	245	193	163	117	83	61	45	82	46	34	92.9	G1	4.55	10.8	1085	3546473	7.7
6.00	188	155	136	105	70	51	37	52	31	35	97	G1	5.32	15.8	1085	9915188	17.7
6.20	214	170	145	102	69	48	42	69	43	33	94.8	G1	4.94	14.5	1085	7796097	14.7
6.40	326	266	217	137	93	70	66	109	80	44	88.6	G1	4.02	10	1085	2249145	5.1
6.60	233	190	165	129	92	65	8	68	36	37	94.9	G1	3.94	3.8	1085	1981081	4.5
6.80	436	389	325	201	113	67	42	111	124	88	88.2	G1	2.73	3	1085	202571	0.5
7.00	211	159	136	109	81	63	35	75	27	28	93.9	G1	5.16	16	1937	13538976	14.4
7.20	236	192	173	141	105	81	60	63	32	36	95.6	G1	4.62	7.9	1937	5563858	6.8

TR901: E-MODULI BACK-CALCULATED WITH MODCOMP

Date: Jul-96
Load: 40 kN
Temp.: 17 deg C

MODCOMP: BACK-CALCULATED E-MODULI

Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	60	150	150	6900.0	364	291	233	139	86	61	45	8000.0	1310.0	344.0	78.7	14100.0
0.20	60	150	150	15000.0	265	218	174	120	80	58	47	8000.0	1490.0	806.0	115.0	192.0
0.40	60	150	150	3300.0	432	368	290	158	87	57	34	8000.0	1620.0	260.0	48.8	223000.0
0.60	60	150	150	3000.0	141	105	92	72	52	40	30	8000.0	1410.0	11000.0	134.0	8820.0
0.80	60	150	150	5300.0	242	205	174	130	92	65	45	8000.0	1730.0	1130.0	102.0	41700.0
1.00	60	150	150	15000.0	190	150	126	101	74	53	44	8000.0	1020.0	2720.0	320.0	6.9
1.20	60	150	150	15000.0	192	158	118	92	66	50	37	8000.0	1210.0	2080.0	189.0	51.0
1.40	60	150	150	15000.0	119	89	71	62	41	30	24	8000.0	1730.0	7370.0	245.0	689000.0
1.60	60	150	150	15000.0	107	86	70	55	39	29	24	8000.0	2940.0	4070.0	281.0	689000.0
1.80	60	150	150	15000.0	115	90	71	55	46	34	28	8000.0	2260.0	3680.0	281.0	689000.0
2.00	60	150	150	5000.0	233	182	149	110	72	47	36	8000.0	1810.0	299.0	357.0	18.5
2.20	60	150	150	3000.0	379	303	259	178	114	72	41	8000.0	817.0	533.0	67.2	689000.0
2.40	60	150	150	5500.0	157	132	114	85	57	41	28	8000.0	3390.0	2150.0	145.0	7370.0
2.60	60	150	150	15000.0	109	85	71	62	46	38	33	8000.0	2470.0	7370.0	245.0	689000.0
2.80	60	150	150	9500.0	136	96	83	63	44	32	24	8000.0	1870.0	2840.0	230.0	689000.0
3.00	60	150	150	15000.0	203	148	121	93	65	49	38	8000.0	799.0	1750.0	373.0	6.9
3.20	60	150	150	15000.0	326	232	157	70	39	29	16	8000.0	1980.0	23.5	212.0	689000.0
3.40	60	150	150	15000.0	139	114	93	78	53	41	30	8000.0	2140.0	4480.0	186.0	689000.0
3.60	60	150	150	15000.0	166	124	104	79	61	46	37	8000.0	1690.0	1880.0	232.0	51.0
3.80	60	150	150	3200.0	354	273	210	128	78	51	30	8000.0	550.0	436.0	104.0	689000.0
4.00	60	150	150	6200.0	281	215	159	86	49	35	25	8000.0	1480.0	177.0	146.0	689000.0
4.20	60	150	150	15000.0	181	154	141	119	96	79	60	8000.0	2090.0	4040.0	238.0	6.9
4.40	60	150	150	15000.0	167	124	108	84	64	49	37	8000.0	1770.0	2170.0	214.0	51.0
4.60	60	150	150	7100.0	192	144	118	85	59	42	31	8000.0	1430.0	1630.0	154.0	3120.0
4.80	60	150	150	15000.0	152	121	101	81	58	45	30	8000.0	2020.0	3220.0	178.0	689000.0
5.00	60	150	150	5200.0	347	269	201	109	60	40	30	8000.0	1280.0	154.0	109.0	487.0
5.20	60	150	150	11500.0	139	104	89	72	55	42	30	8000.0	1920.0	3800.0	200.0	689000.0
5.40	60	150	150	13600.0	249	163	117	77	54	41	30	8000.0	671.0	835.0	188.0	689000.0
5.60	60	150	150	4200.0	494	359	270	144	86	59	39	8000.0	236.0	235.0	103.0	9620.0
5.80	60	150	150	9400.0	245	193	163	117	83	61	45	8000.0	2520.0	211.0	373.0	6.9
6.00	60	150	150	7700.0	188	155	136	105	70	51	37	8000.0	4600.0	378.0	617.0	6.9
6.20	60	150	150	15000.0	214	170	145	102	69	48	42	8000.0	1770.0	529.0	314.0	6.9
6.40	60	150	150	15000.0	326	266	217	137	93	70	66	8000.0	1730.0	116.0	186.0	6.9
6.60	60	150	150	15000.0	233	190	165	129	92	65	8	8000.0	1600.0	2360.0	95.3	689000.0
6.80	60	150	150	2900.0	436	389	325	201	113	67	42	8000.0	1700.0	21.7	83.3	689000.0
7.00	60	150	150	15000.0	211	159	136	109	81	63	35	8000.0	1140.0	2830.0	121.0	16300.0
7.20	60	150	150	15000.0	236	192	173	141	105	81	60	8000.0	1530.0	2230.0	177.0	6.9

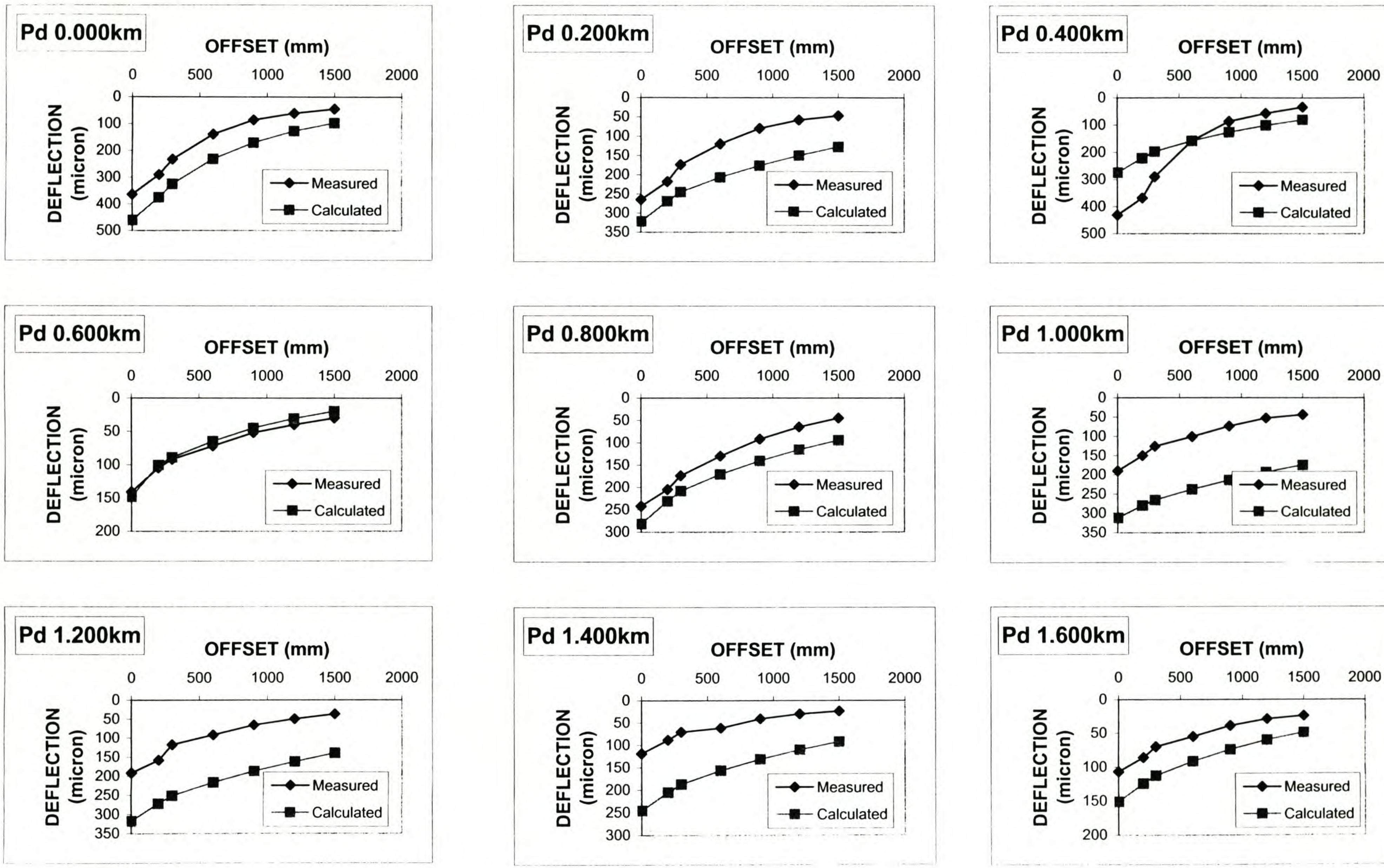
TR901: E-MODULI BACK-CALCULATED WITH MODCOMP

Date: Jul-96
Load: 40 kN
Temp: 17 deg C

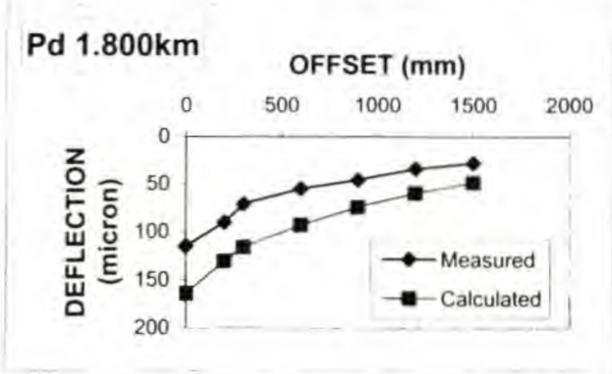
MODCOMP: DEFLECTIONS FROM BACK-CALCULATED E-MODULI

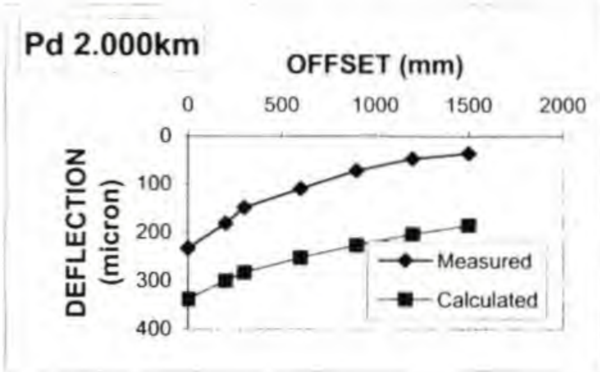
Pos (Km)	H1	H2	H3	H4	D0	D200	D300	D600	D900	D1200	D1500	E1	E2	E3	E4	E5
0.00	60	150	150	6900	461	375	326	232	171	127	97	8000.0	1310.0	344.0	78.7	14100.0
0.20	60	150	150	15000	322	269	245	207	176	150	128	8000.0	1490.0	806.0	115.0	192.0
0.40	60	150	150	3300	275	221	197	158	127	101	80	8000.0	1620.0	260.0	48.8	223000.0
0.60	60	150	150	3000	148	101	89	65	45	31	20	8000.0	1410.0	11000.0	134.0	8820.0
0.80	60	150	150	5300	282	231	208	171	141	115	95	8000.0	1730.0	1130.0	102.0	41700.0
1.00	60	150	150	15000	312	280	265	238	214	193	175	8000.0	1020.0	2720.0	320.0	6.9
1.20	60	150	150	15000	318	272	252	217	187	162	140	8000.0	1210.0	2080.0	189.0	51.0
1.40	60	150	150	15000	246	205	187	157	132	110	93	8000.0	1730.0	7370.0	245.0	689000.0
1.60	60	150	150	15000	151	124	113	92	74	60	49	8000.0	2940.0	4070.0	281.0	689000.0
1.80	60	150	150	15000	164	130	116	93	74	60	49	8000.0	2260.0	3680.0	281.0	689000.0
2.00	60	150	150	5000	338	300	283	253	227	204	186	8000.0	1810.0	299.0	357.0	18.5
2.20	60	150	150	3000	354	296	263	189	134	94	65	8000.0	817.0	533.0	67.2	689000.0
2.40	60	150	150	5500	308	264	238	177	132	97	73	8000.0	3390.0	2150.0	145.0	7370.0
2.60	60	150	150	15000	167	136	122	99	80	65	53	8000.0	2470.0	7370.0	245.0	689000.0
2.80	60	150	150	9500	179	108	96	72	52	40	31	8000.0	1870.0	2840.0	230.0	689000.0
3.00	60	150	150	15000	269	239	226	201	179	161	146	8000.0	799.0	1750.0	373.0	6.9
3.20	60	150	150	15000	131	91	75	54	40	31	25	8000.0	1980.0	23.5	212.0	689000.0
3.40	60	150	150	15000	273	232	214	182	155	132	111	8000.0	2140.0	4480.0	186.0	689000.0
3.60	60	150	150	15000	183	147	133	109	90	75	64	8000.0	1690.0	1880.0	232.0	51.0
3.80	60	150	150	3200	221	176	156	124	97	75	57	8000.0	550.0	436.0	104.0	689000.0
4.00	60	150	150	6200	187	146	129	101	80	63	50	8000.0	1480.0	177.0	146.0	689000.0
4.20	60	150	150	15000	275	253	242	219	198	179	162	8000.0	2090.0	4040.0	238.0	6.9
4.40	60	150	150	15000	205	158	141	114	92	75	63	8000.0	1770.0	2170.0	214.0	51.0
4.60	60	150	150	7100	217	176	158	128	104	84	68	8000.0	1430.0	1630.0	154.0	3120.0
4.80	60	150	150	15000	223	192	178	152	128	108	91	8000.0	2020.0	3220.0	178.0	689000.0
5.00	60	150	150	5200	239	194	175	142	116	94	77	8000.0	1280.0	154.0	109.0	487.0
5.20	60	150	150	11500	152	127	117	96	78	63	52	8000.0	1920.0	3800.0	200.0	689000.0
5.40	60	150	150	13600	162	124	108	84	66	52	42	8000.0	671.0	835.0	188.0	689000.0
5.60	60	150	150	4200	462	365	308	200	137	95	67	8000.0	236.0	235.0	103.0	9620.0
5.80	60	150	150	9400	501	438	403	333	284	248	221	8000.0	2520.0	211.0	373.0	6.9
6.00	60	150	150	7700	399	366	350	314	284	258	236	8000.0	4600.0	378.0	617.0	6.9
6.20	60	150	150	15000	355	308	281	223	183	156	137	8000.0	1770.0	529.0	314.0	6.9
6.40	60	150	150	15000	331	290	271	240	214	193	174	8000.0	1730.0	116.0	186.0	6.9
6.60	60	150	150	15000	235	213	203	179	155	134	114	8000.0	1600.0	2360.0	95.3	689000.0
6.80	60	150	150	2900	261	210	187	150	119	94	74	8000.0	1700.0	21.7	83.3	689000.0
7.00	60	150	150	15000	218	189	176	150	127	107	91	8000.0	1140.0	2830.0	121.0	16300.0
7.20	60	150	150	15000	320	286	270	242	217	196	177	8000.0	1530.0	2230.0	177.0	6.9

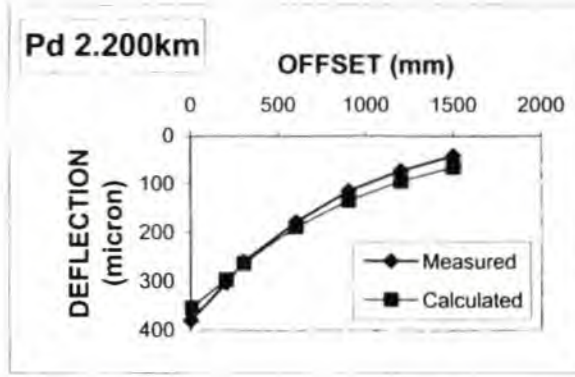
TR901: MEASURED vs CALCULATED DEFLECTION BASINS BY MODCOMP

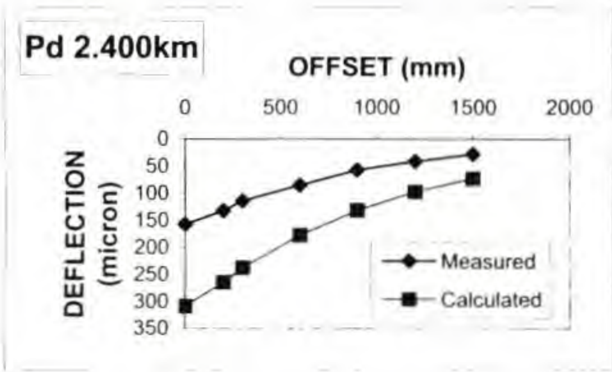


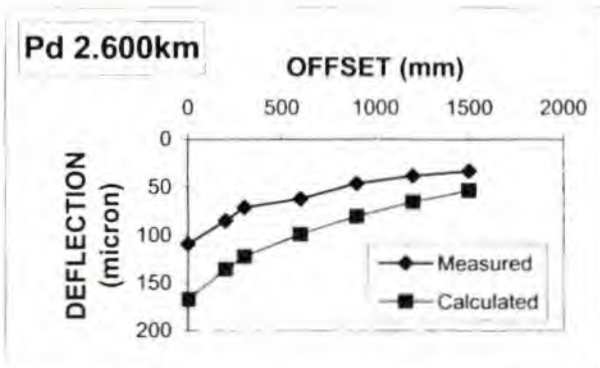
TR901: MEASURED vs CALCULATED DEFLECTION BASINS BY MODCOMP

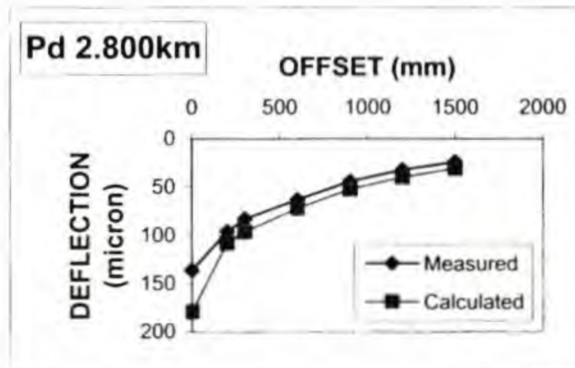


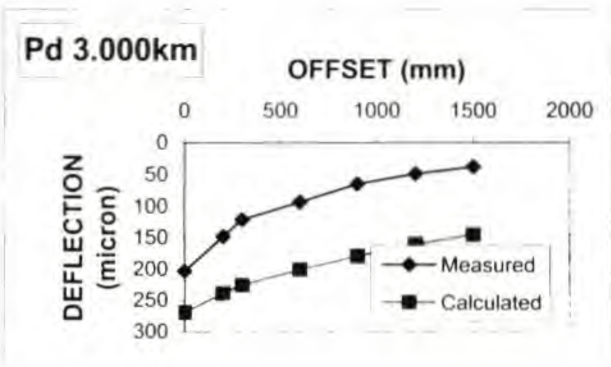


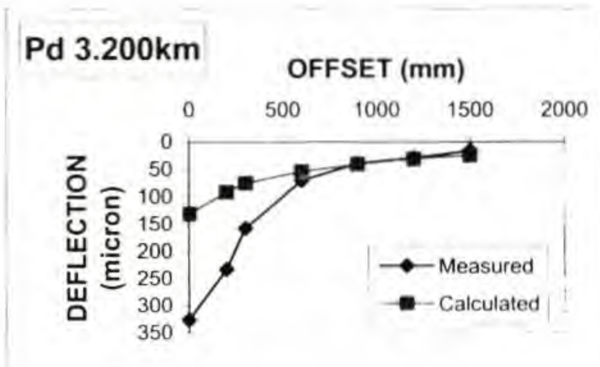


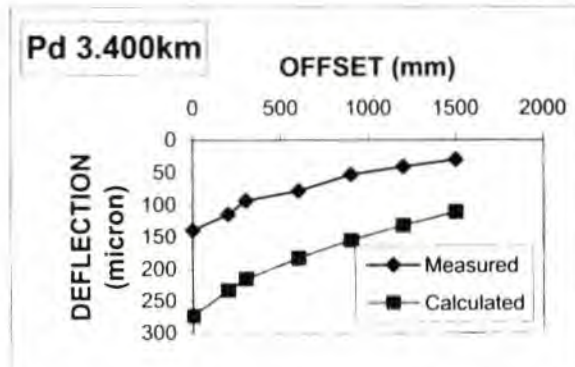




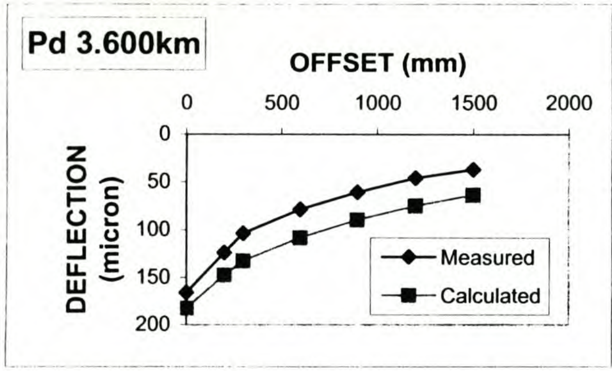


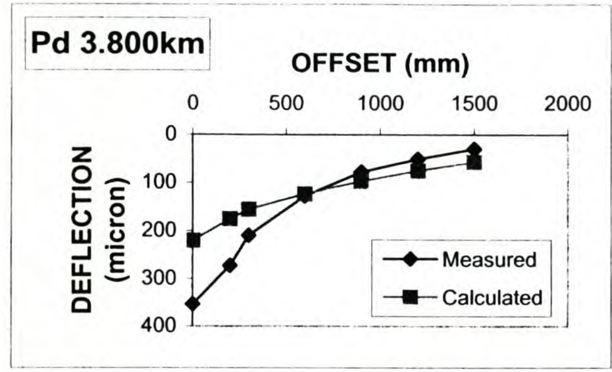


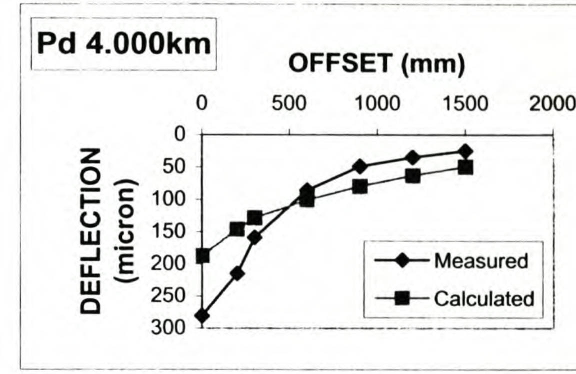


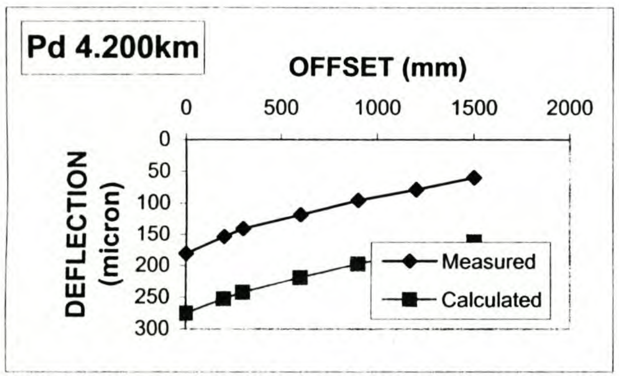


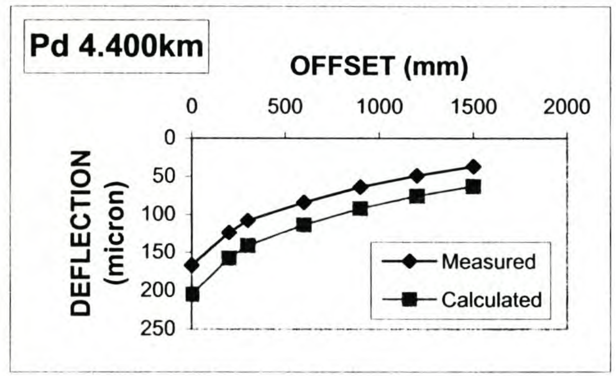
TR901: MEASURED vs CALCULATED DEFLECTION BASINS BY MODCOMP

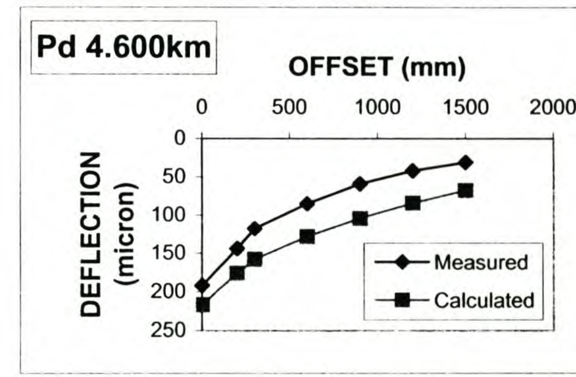


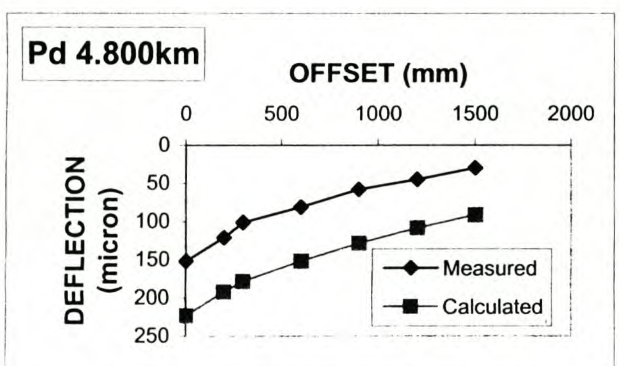


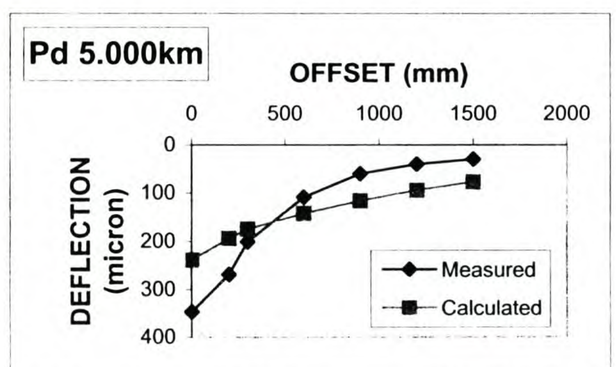


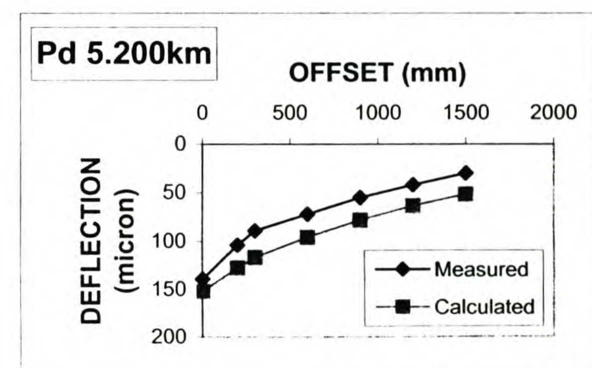




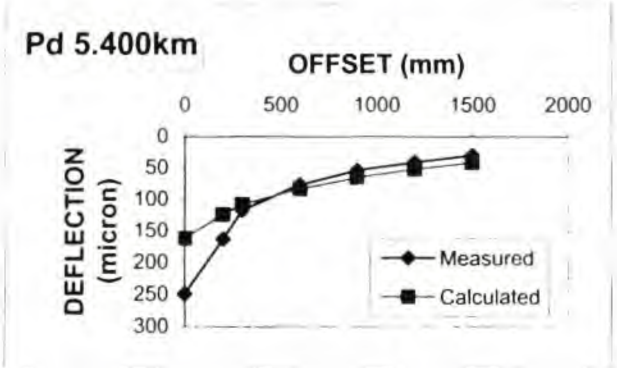


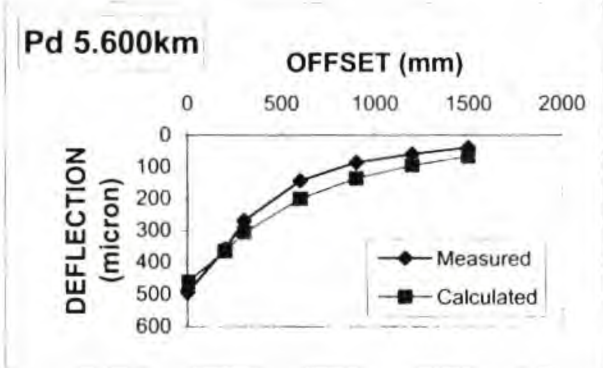


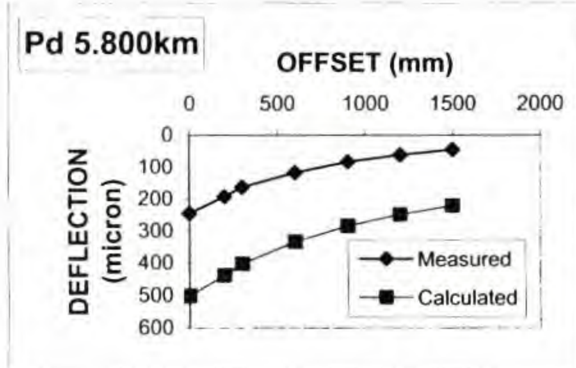


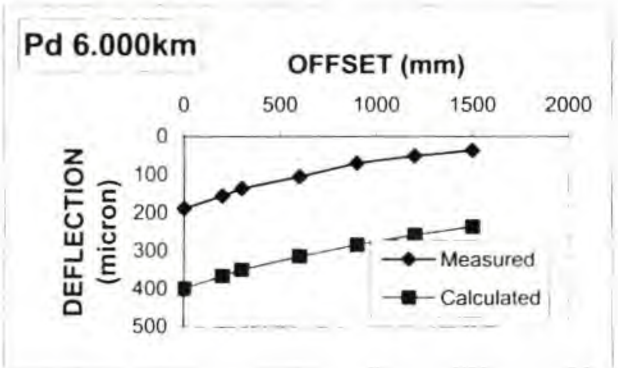


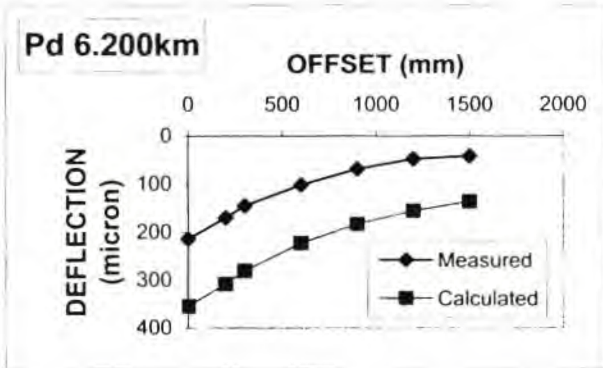
TR901: MEASURED & CALCULATED DEFLECTION BASINS BY MODCOMP

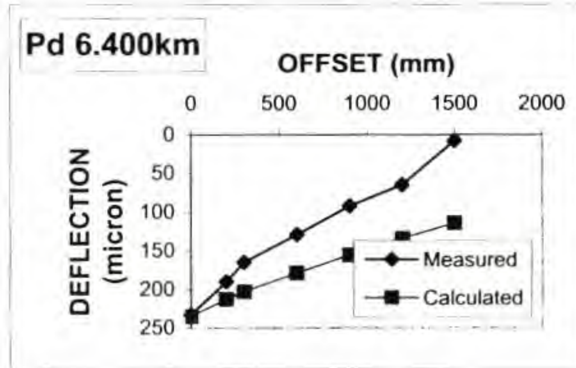


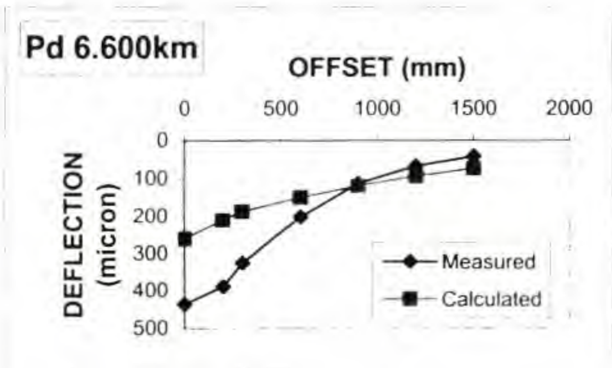


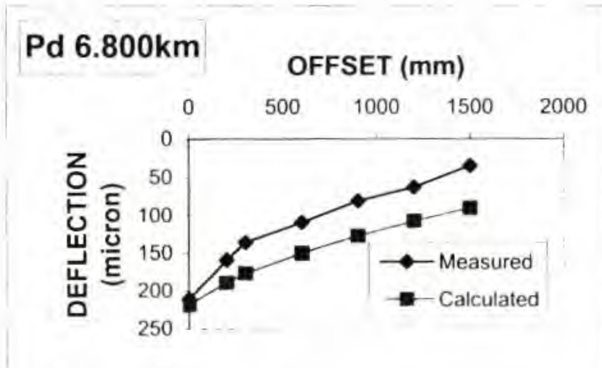


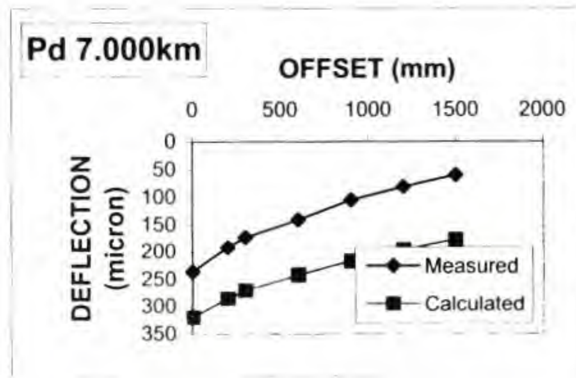












TR901: COMPARISON OF MEASURED AND CALCULATED DEFLECTIONS BY MODCOMP

Pos (Km)\Offset (mm)		0	200	300	600	900	1200	1500	RMSE (%)
0.000	Measured	364	291	233	139	86	61	45	78.10%
	Calculated	461	375	326	232	171	127	97	
0.200	Measured	265	218	174	120	80	58	47	104.88%
	Calculated	322	269	245	207	176	150	128	
0.400	Measured	432	368	290	158	87	57	34	66.23%
	Calculated	275	221	197	158	127	101	80	
0.600	Measured	141	105	92	72	52	40	30	17.10%
	Calculated	148	101	89	65	45	31	20	
0.800	Measured	242	205	174	130	92	65	45	57.06%
	Calculated	282	231	208	171	141	115	95	
1.000	Measured	190	150	126	101	74	53	44	183.59%
	Calculated	312	280	265	238	214	193	175	
1.200	Measured	192	158	118	92	66	50	37	170.05%
	Calculated	318	272	252	217	187	162	140	
1.400	Measured	119	89	71	62	41	30	24	200.72%
	Calculated	246	205	187	157	132	110	93	
1.600	Measured	107	86	70	55	39	29	24	77.59%
	Calculated	151	124	113	92	74	60	49	
1.800	Measured	115	90	71	55	46	34	28	63.01%
	Calculated	164	130	116	93	74	60	49	
2.000	Measured	233	182	149	110	72	47	36	227.85%
	Calculated	338	300	283	253	227	204	186	
2.200	Measured	379	303	259	178	114	72	41	26.14%
	Calculated	354	296	263	189	134	94	65	
2.400	Measured	157	132	114	85	57	41	28	122.15%
	Calculated	308	264	238	177	132	97	73	
2.600	Measured	109	85	71	62	46	38	33	65.15%
	Calculated	167	136	122	99	80	65	53	
2.800	Measured	136	96	83	63	44	32	24	21.80%
	Calculated	179	108	96	72	52	40	31	
3.000	Measured	203	148	121	93	65	49	38	164.55%
	Calculated	269	239	226	201	179	161	146	
3.200	Measured	326	232	157	70	39	29	16	43.89%
	Calculated	131	91	75	54	40	31	25	
3.400	Measured	139	114	93	78	53	41	30	174.55%
	Calculated	273	232	214	182	155	132	111	
3.600	Measured	166	124	104	79	61	46	37	44.97%
	Calculated	183	147	133	109	90	75	64	
3.800	Measured	354	273	210	128	78	51	30	45.68%
	Calculated	221	176	156	124	97	75	57	
4.000	Measured	281	215	159	86	49	35	25	57.52%
	Calculated	187	146	129	101	80	63	50	
4.200	Measured	181	154	141	119	96	79	60	103.59%
	Calculated	275	253	242	219	198	179	162	
4.400	Measured	167	124	108	84	64	49	37	43.38%
	Calculated	205	158	141	114	92	75	63	
4.600	Measured	192	144	118	85	59	42	31	70.07%
	Calculated	217	176	158	128	104	84	68	
4.800	Measured	152	121	101	81	58	45	30	116.79%
	Calculated	223	192	178	152	128	108	91	
5.000	Measured	347	269	201	109	60	40	30	88.41%
	Calculated	239	194	175	142	116	94	77	
5.200	Measured	139	104	89	72	55	42	30	41.69%
	Calculated	152	127	117	96	78	63	52	
5.400	Measured	249	163	117	77	54	41	30	26.00%
	Calculated	162	124	108	84	66	52	42	
5.600	Measured	494	359	270	144	86	59	39	44.85%
	Calculated	462	365	308	200	137	95	67	
5.800	Measured	245	193	163	117	83	61	45	235.79%
	Calculated	501	438	403	333	284	248	221	
6.000	Measured	188	155	136	105	70	51	37	303.36%
	Calculated	399	366	350	314	284	258	236	
6.200	Measured	214	170	145	102	69	48	42	152.49%
	Calculated	355	308	281	223	183	156	137	
6.400	Measured	326	266	217	137	93	70	66	107.50%
	Calculated	331	290	271	240	214	193	174	
6.600	Measured	233	190	165	129	92	65	8	504.55%
	Calculated	235	213	203	179	155	134	114	
6.800	Measured	436	389	325	201	113	67	42	44.02%
	Calculated	261	210	187	150	119	94	74	
7.000	Measured	211	159	136	109	81	63	35	72.00%
	Calculated	218	189	176	150	127	107	91	
7.200	Measured	236	192	173	141	105	81	60	107.90%
	Calculated	320	286	270	242	217	196	177	

APPENDIX C.7: TR901

Comparison of back-calculated E-moduli between Case (b) and ModComp for TR901

POSITION (Km)	METHOD	BACK-CALCULATED E-MODULI (Mpa)					RMSE (%)
		E1	E2	E3	E4	E5	
0.00	Case (b)	8999.4	657.4	486.9	60.2	10000	15.73
	ModComp	8000	1310	344	78.7	14100	78.1
0.20	Case (b)	8999.4	895.7	5998.1	55.2	10000	14.25
	ModComp	8000	1490	806	115	192	104.88
0.40	Case (b)	8999.4	871	5999.6	51.3	10000	35.98
	ModComp	8000	1620	260	48.8	223000	66.23
0.60	Case (b)	1149	2580.4	5999.6	194.4	10000	18.14
	ModComp	8000	1410	11000	134	8820	17.1
0.80	Case (b)	8999.4	957.7	5883	55.6	10000	15.43
	ModComp	8000	1730	1130	102	41700	57.06
1.00	Case (b)	8999.4	1966.5	5999.7	71.2	10000	16.7
	ModComp	8000	1020	2720	320	6.9	183.59
1.20	Case (b)	8999.4	1136.1	5999.7	55.3	10000	12.96
	ModComp	8000	1210	2080	189	51	170.05
1.40	Case (b)	8999.4	1358.7	5999.7	75	10000	45.75
	ModComp	8000	1730	7370	245	689000	200.72
1.60	Case (b)	8999.4	2535.4	5999.7	147.5	10000	14.72
	ModComp	8000	2940	4070	281	689000	77.59
1.80	Case (b)	8999.4	1778.8	5999.7	147.4	10000	17.88
	ModComp	8000	2260	3680	281	689000	63.01
2.00	Case (b)	8999.4	1526.9	5999.6	67.5	10000	17.65
	ModComp	8000	1810	299	357	18.5	227.85
2.20	Case (b)	8999.4	1457.5	486.2	60.7	10000	17.5
	ModComp	8000	817	533	67.2	689000	26.14
2.40	Case (b)	8999.4	2213.5	524.6	75.7	10000	42.64
	ModComp	8000	3390	2150	145	7370	122.15
2.60	Case (b)	8999.4	1982.3	5999.7	135	10000	23.1
	ModComp	8000	2470	7370	245	689000	65.15
2.80	Case (b)	561	2313.2	5999.5	226.5	10000	16.18
	ModComp	8000	1870	2840	230	689000	21.8
3.00	Case (b)	8999.4	2146.7	5999.7	94.3	10000	26.49
	ModComp	8000	799	1750	373	6.9	164.55
3.20	Case (b)	8999.4	1279.7	5999.6	291.6	10000	42.59
	ModComp	8000	1980	23.5	212	689000	43.89
3.40	Case (b)	8999.4	1362.4	5999.7	61.1	10000	30.58
	ModComp	8000	2140	4480	186	689000	174.55
3.60	Case (b)	8998.9	1656.1	5998.1	145.2	10000	15.52
	ModComp	8000	1690	1880	232	51	44.97
3.80	Case (b)	8999.4	1144.7	5999.5	70.9	10000	33.1
	ModComp	8000	550	436	104	689000	45.68
4.00	Case (b)	8999.4	1304.5	5999.6	116.7	10000	29.32
	ModComp	8000	1480	177	146	689000	57.52
4.20	Case (b)	8999.2	3458	5999.6	79.5	10000	35.23
	ModComp	8000	2090	4040	238	6.9	103.59
4.40	Case (b)	3523.1	1451.1	5964.7	150.9	10000	4.57
	ModComp	8000	1770	2170	214	51	43.38
4.60	Case (b)	8999.4	1332.5	5872.2	88.3	10000	11.84
	ModComp	8000	1430	1630	154	3120	70.07

APPENDIX C.7: TR901

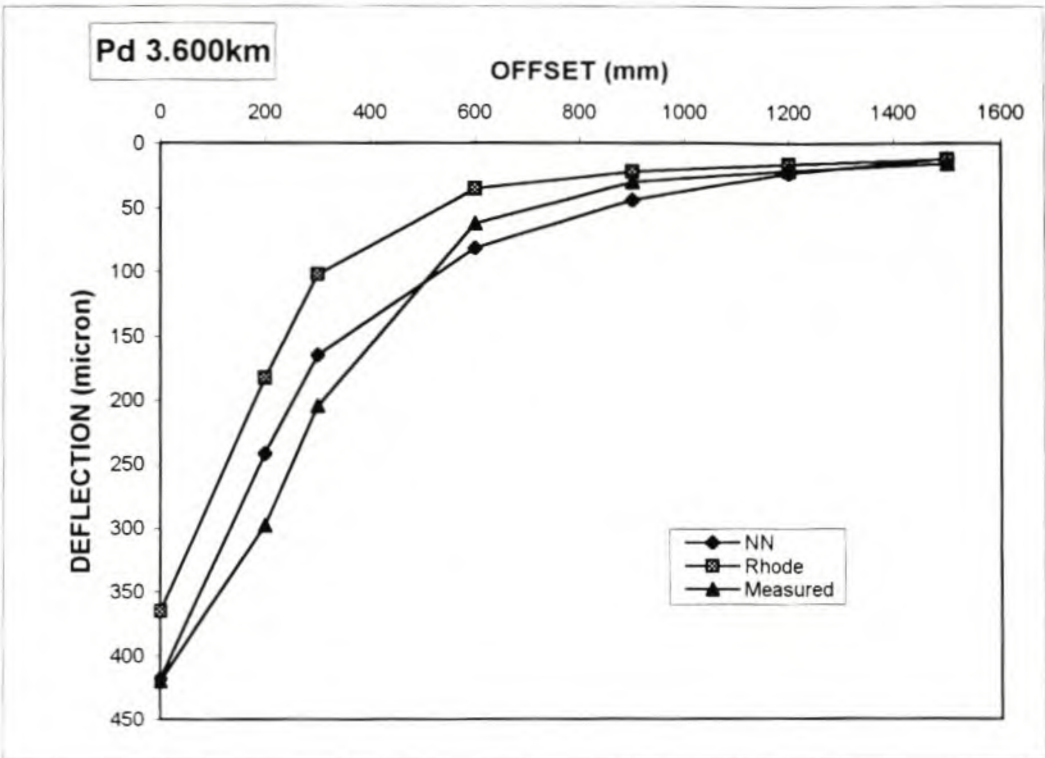
Comparison of back-calculated E-moduli between Case (b) and ModComp for TR901

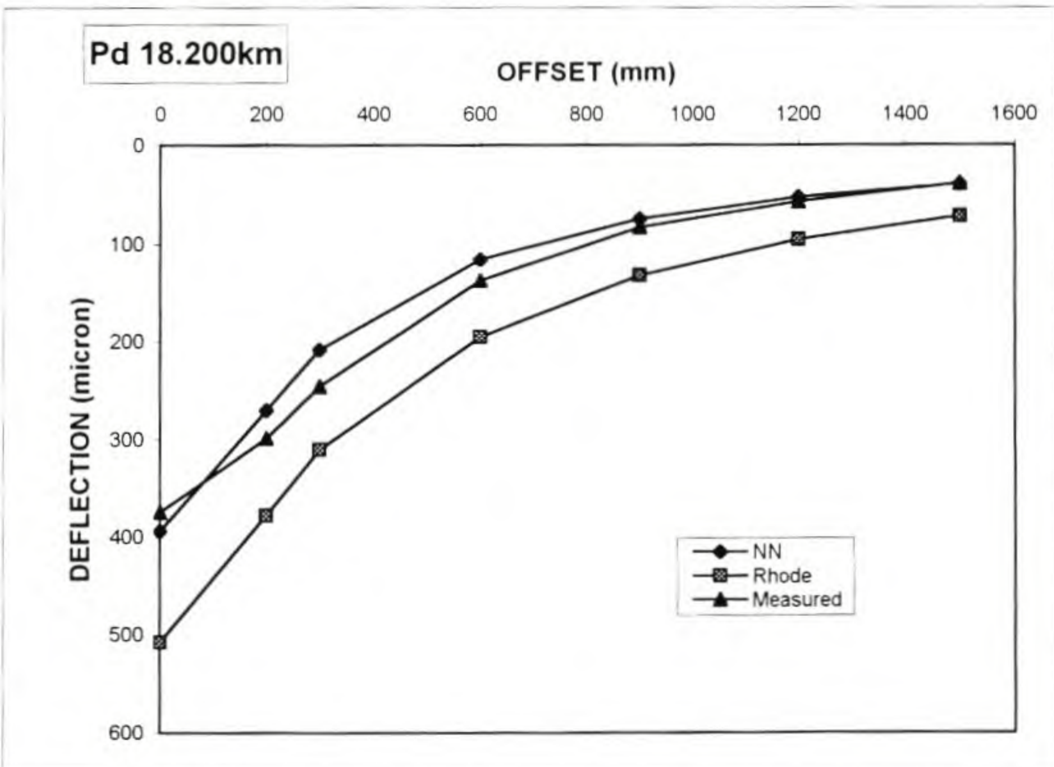
4.80	Case (b)	8999.4	2063.5	5999.7	76.5	10000	3.1
	ModComp	8000	2020	3220	178	689000	116.79
5.00	Case (b)	8999.4	1156.2	5999.6	75.2	10000	31.33
	ModComp	8000	1280	154	109	487	88.41
5.20	Case (b)	8999	2968	5999.7	133.5	10000	25.75
	ModComp	8000	1920	3800	200	689000	41.69
5.40	Case (b)	8999.4	1444.9	5999.7	167.9	10000	41.1
	ModComp	8000	671	835	188	689000	26
5.60	Case (b)	8999.4	562.9	316.6	68.6	10000	12.33
	ModComp	8000	236	235	103	9620	44.85
5.80	Case (b)	8999.4	1050.1	730.8	67.8	10000	18.63
	ModComp	8000	2520	211	373	6.9	235.79
6.00	Case (b)	8999.4	2353.8	2611.7	69.7	10000	5.06
	ModComp	8000	4600	378	617	6.9	303.36
6.20	Case (b)	8999.4	1988.4	453.1	105.6	10000	15.49
	ModComp	8000	1770	529	314	6.9	152.49
6.40	Case (b)	8999.1	579.9	2360.0	101.7	10000.0	29.72
	ModComp	8000	1730	116	186	6.9	107.5
6.60	Case (b)	8999.4	1304.6	5999.3	71.8	10000	149.55
	ModComp	8000	1600	2360	95.3	689000	504.55
6.80	Case (b)	8999.4	949.9	5999.6	51.4	10000	39.96
	ModComp	8000	1700	21.7	83.3	689000	44.02
7.00	Case (b)	8999	2288.5	5999.7	77.1	10000	25.5
	ModComp	8000	1140	2830	121	16300	72
7.20	Case (b)	8905.6	1771.1	5992.9	69.8	10000	35.79
	ModComp	8000	1530	2230	177	6.9	107.9

Appendix C.8

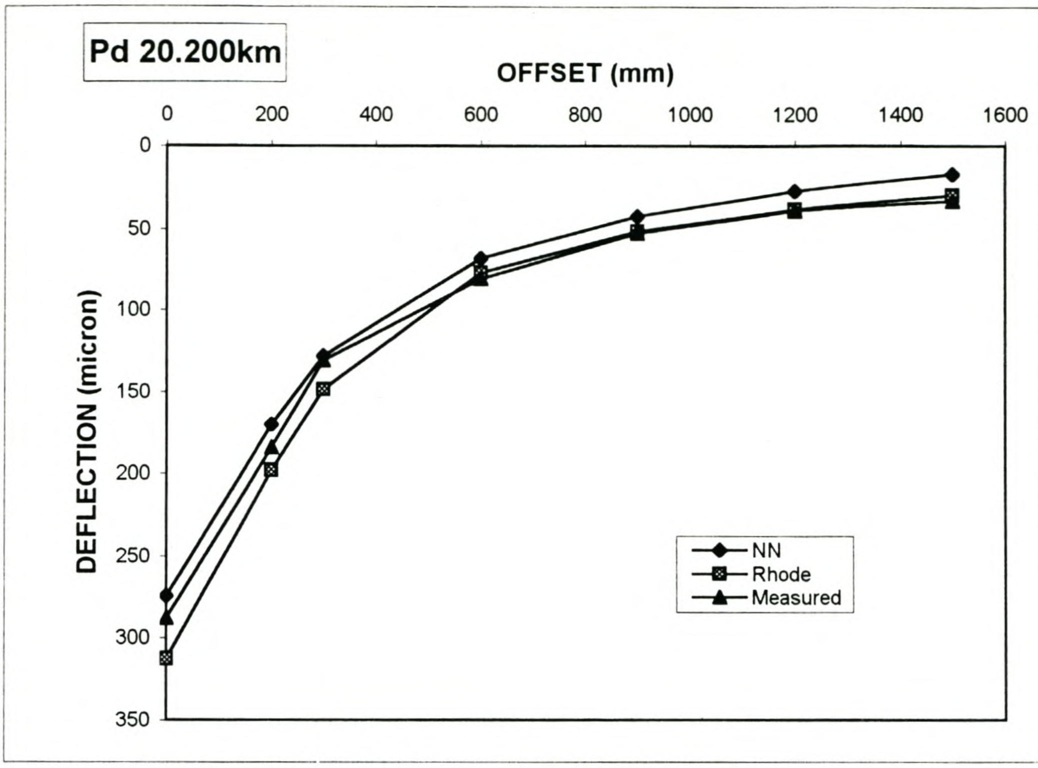
Comparison of Back-calculation results for six Deflection Basins: Depth to stiff layer calculated with Rohde's method vs Neural Network

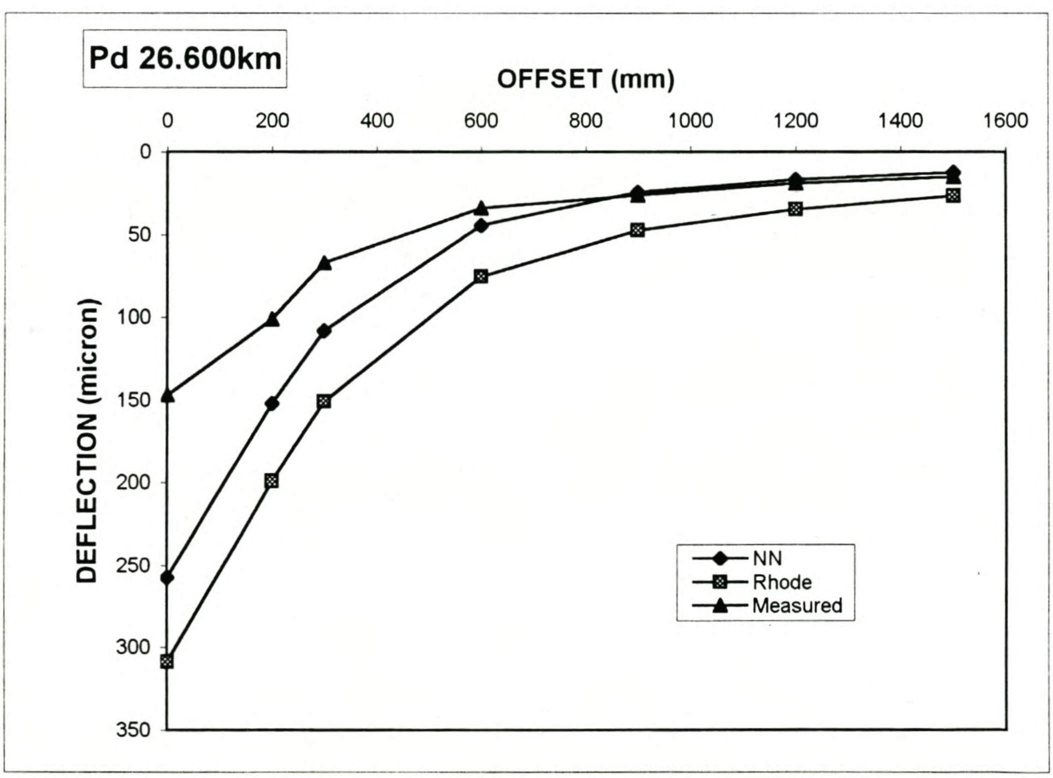
TR1102: AC35: MEASURED vs CALCULATED DEFLECTIONS: CASE (a) vs CASE (b)



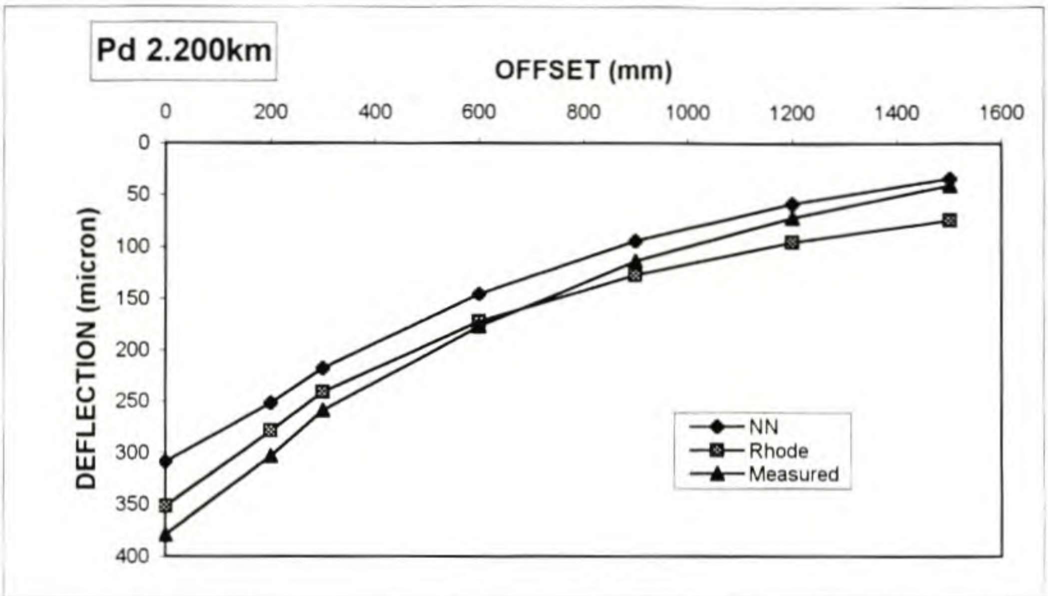


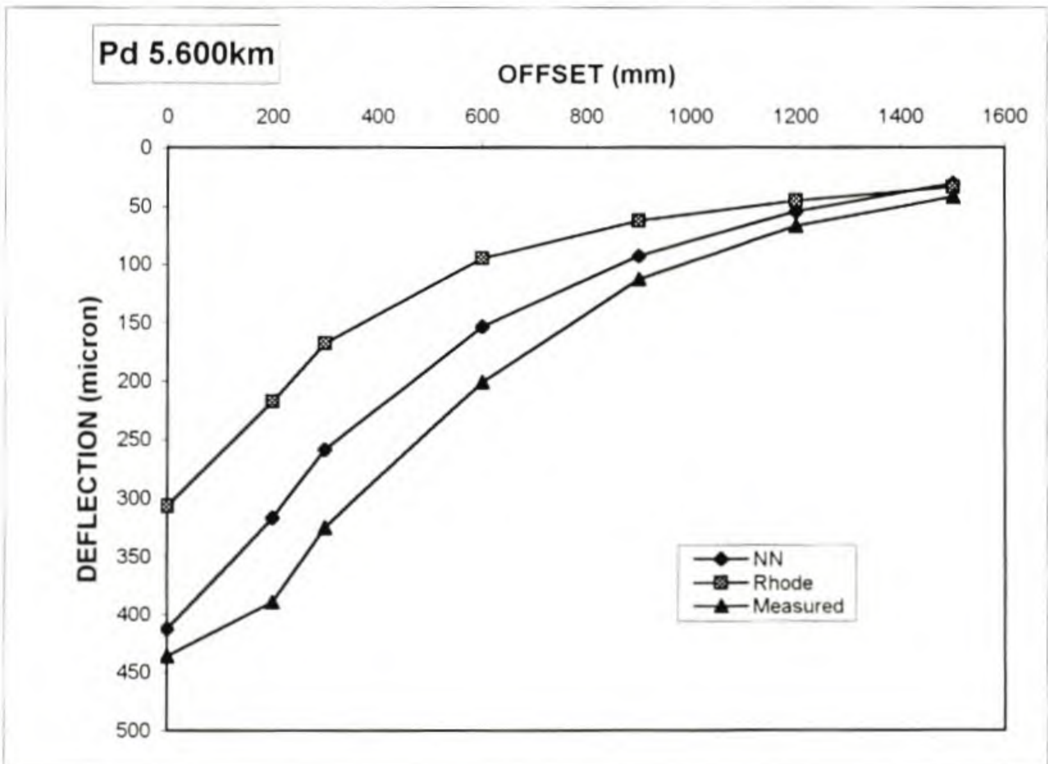
MR188: MEASURED vs CALCULATED DEFLECTIONS: CASE (a) vs CASE (b)





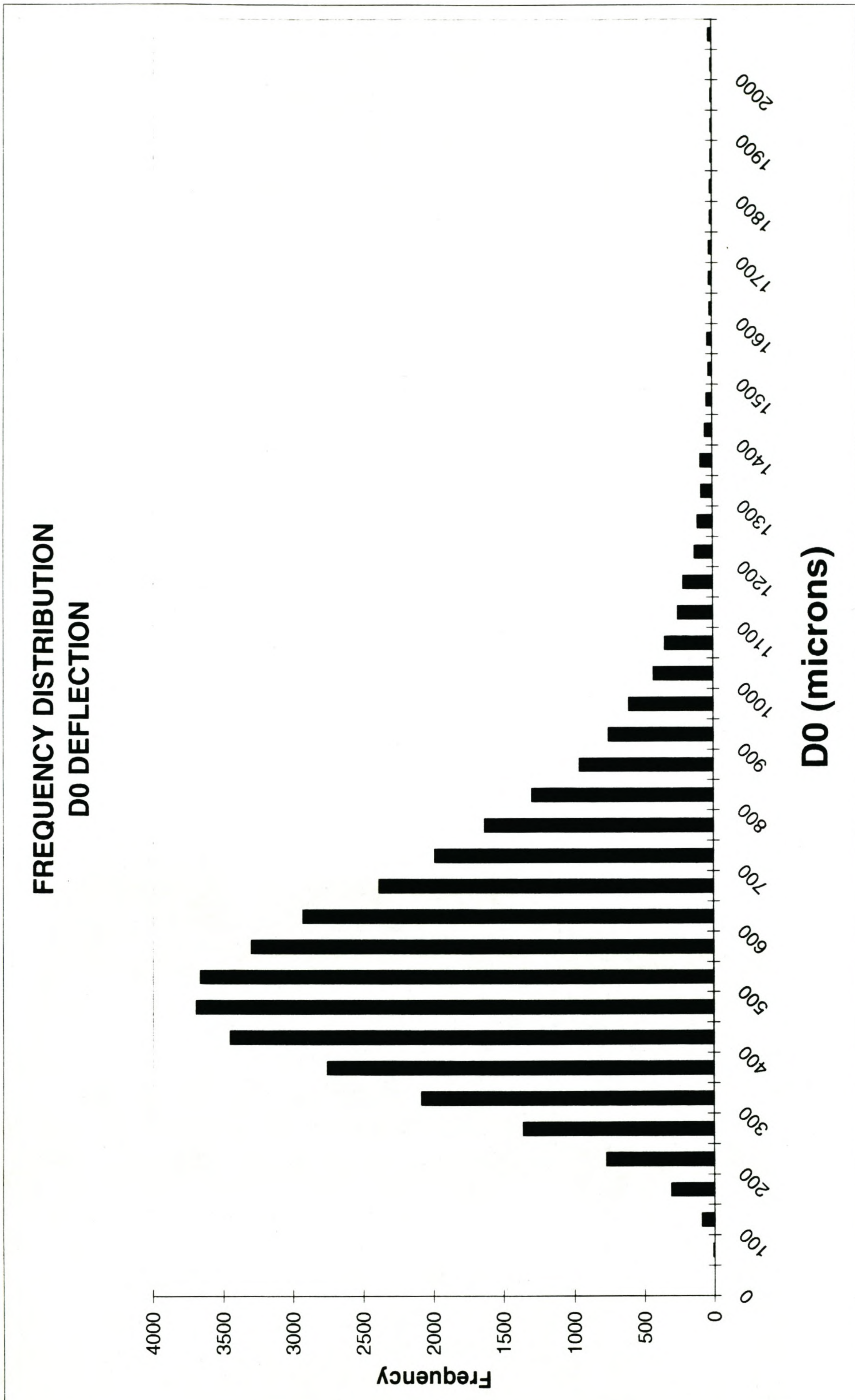
TR901: MEASURED vs CALCULATED DEFLECTIONS: CASE (a) vs CASE (b)

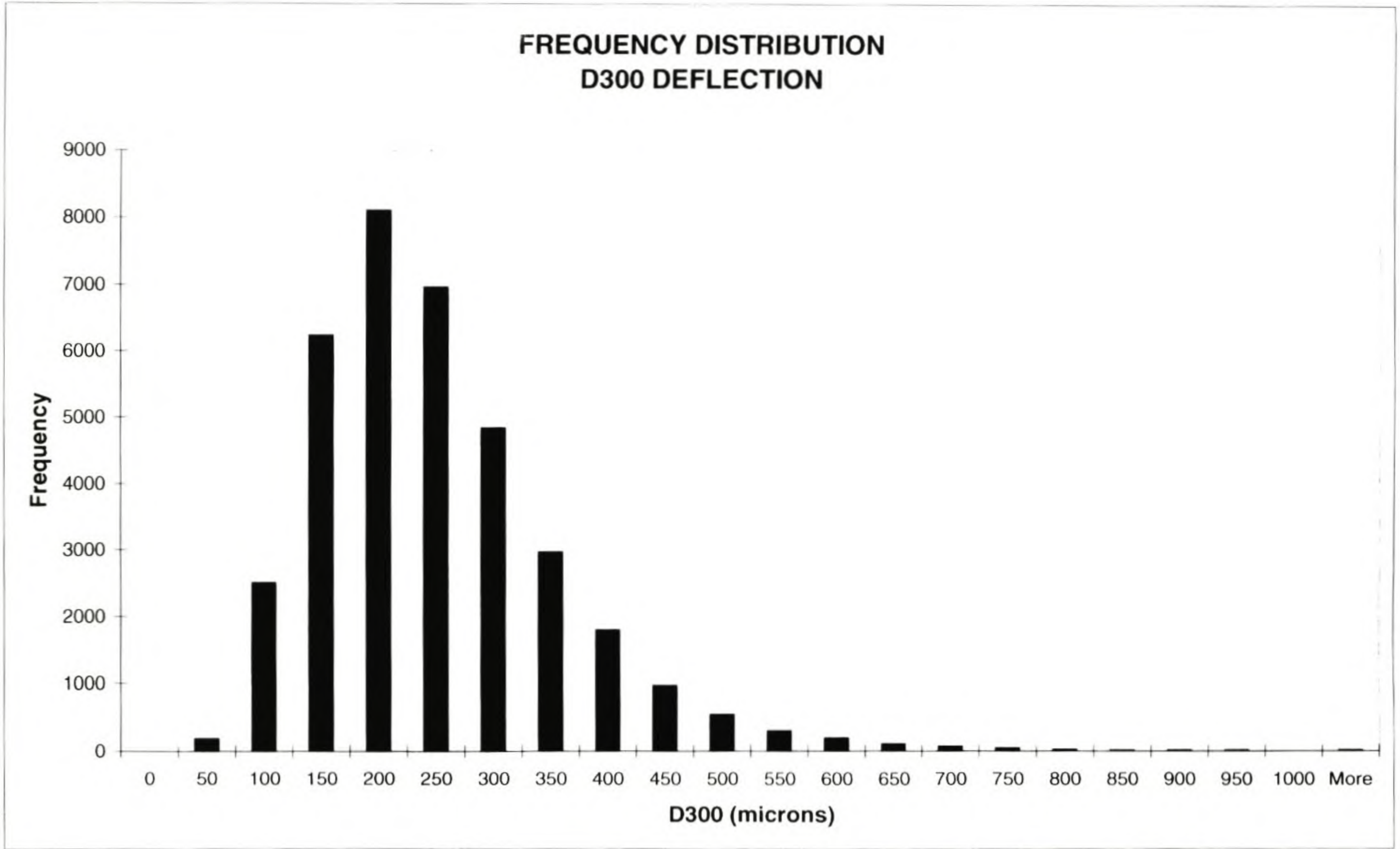


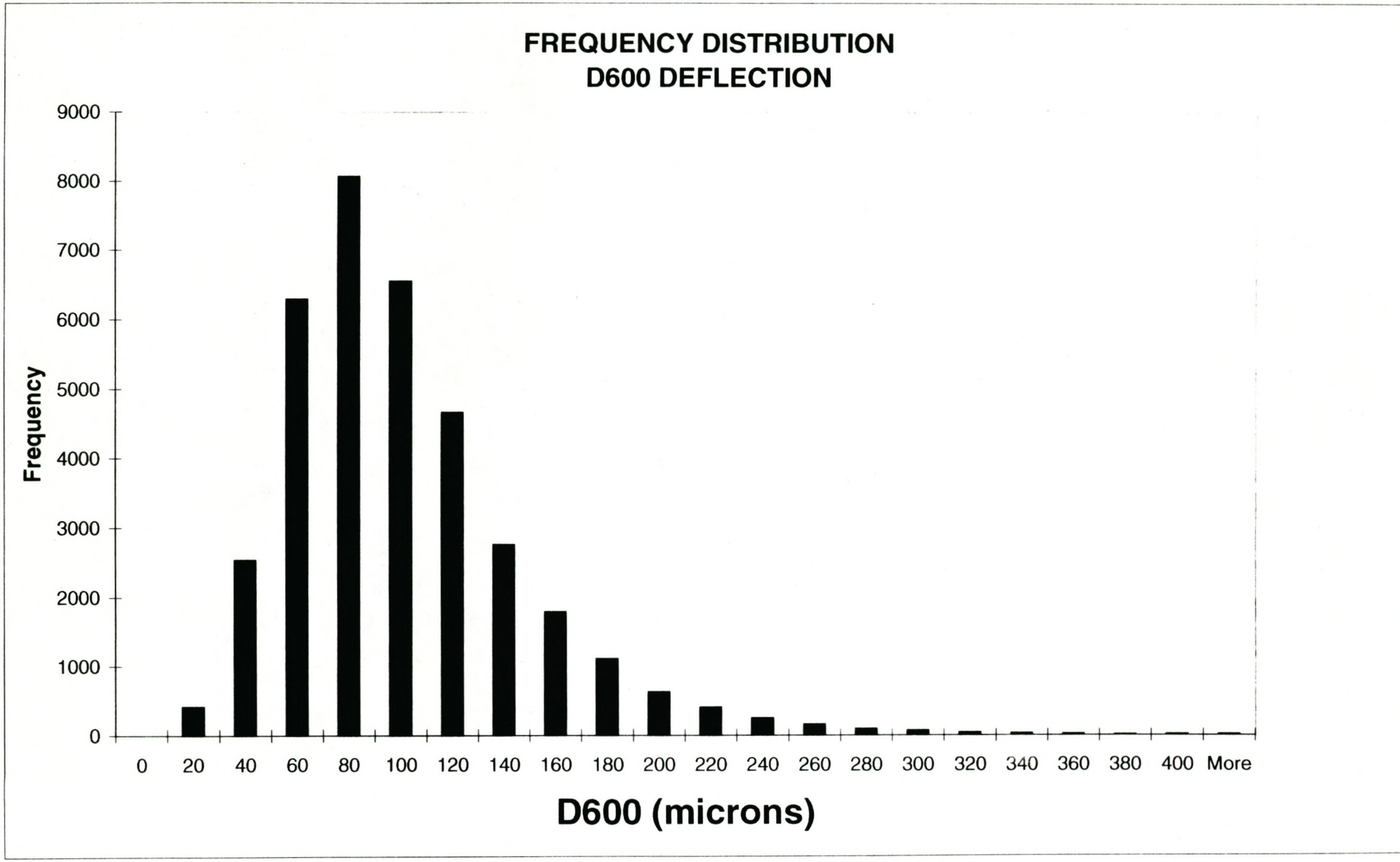


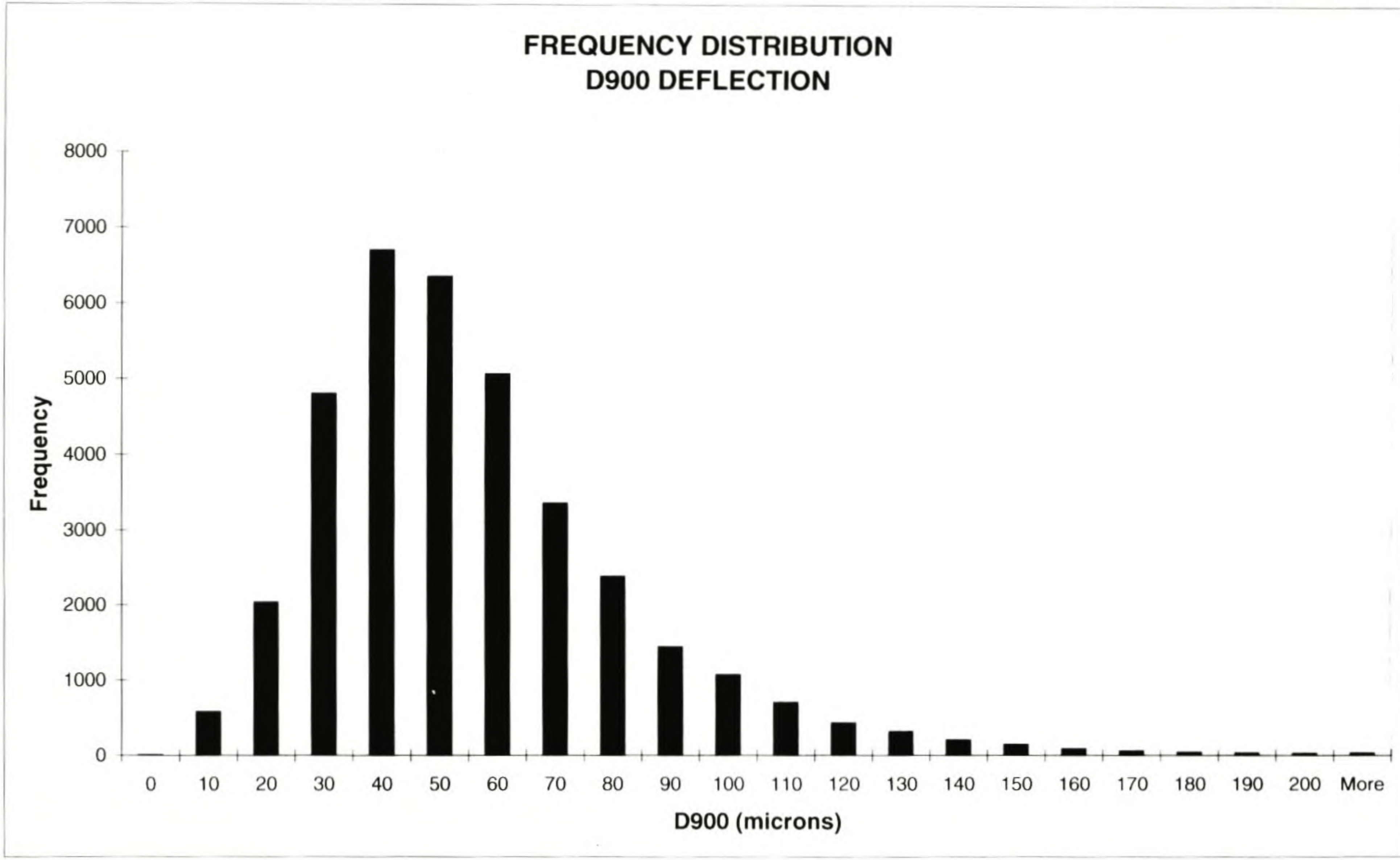
Appendix C.9

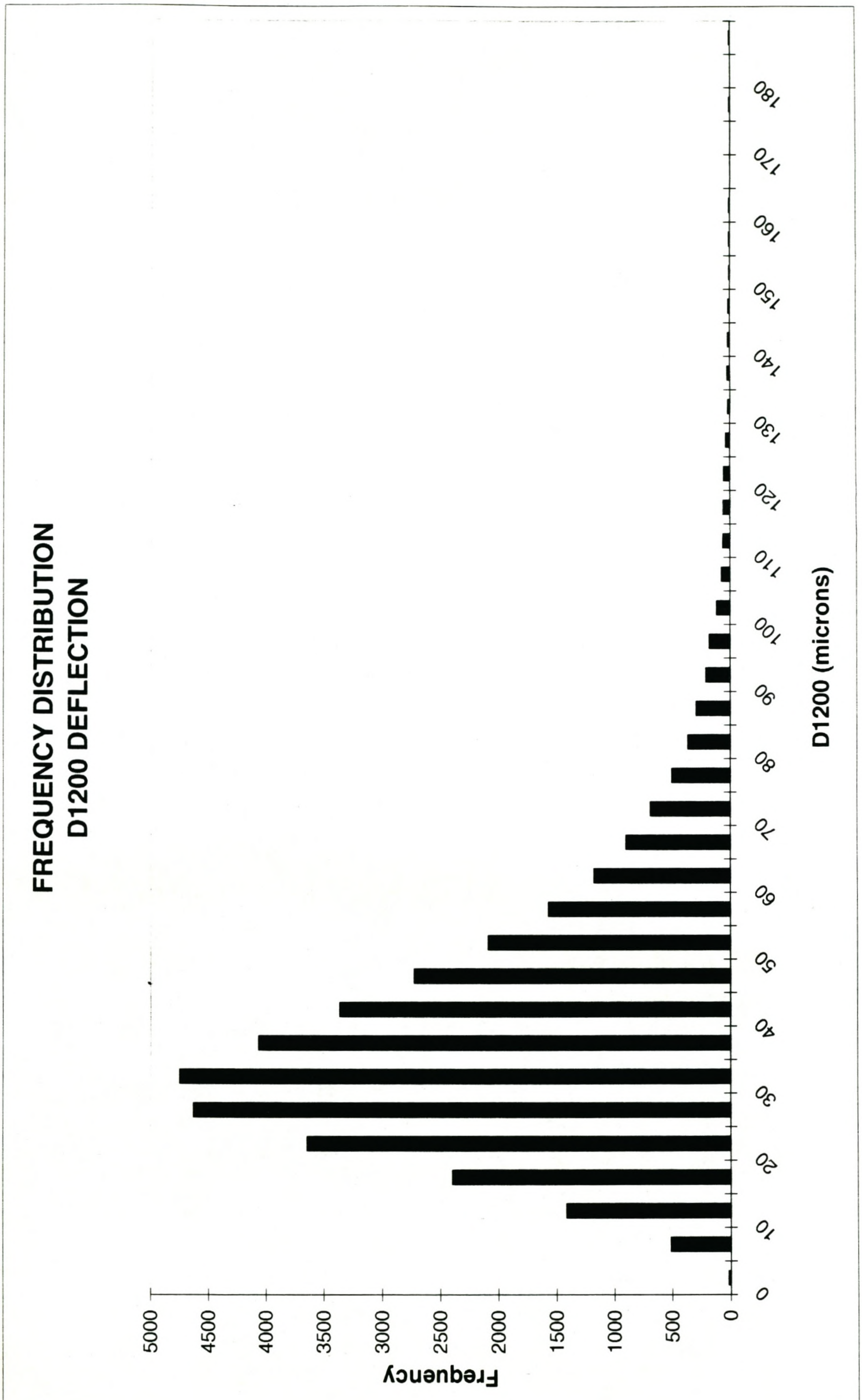
Frequency Distribution of Deflections at each geophone, from PAWC PMS Database

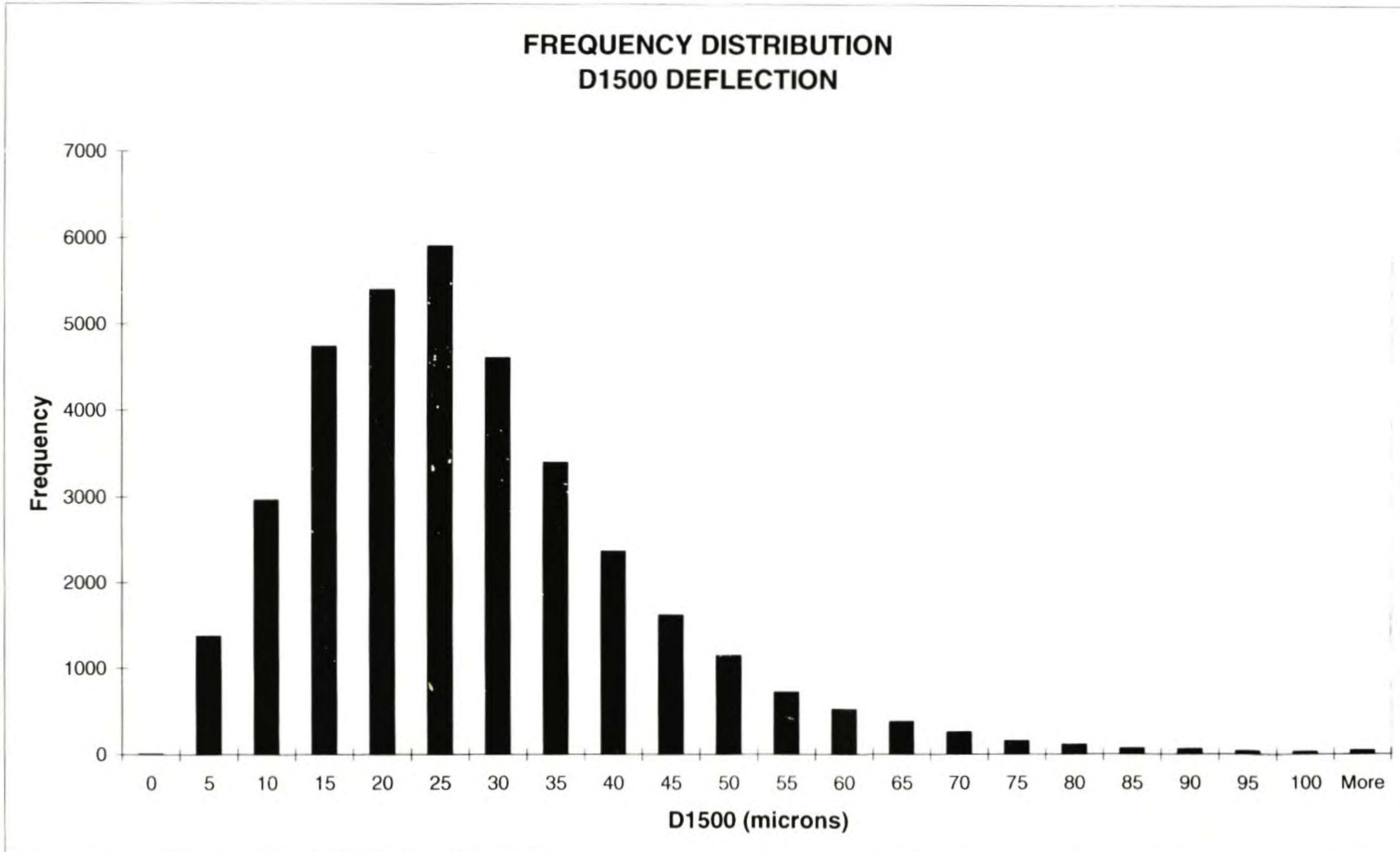

FREQUENCY DISTRIBUTION
D0 DEFLECTION
Frequency
4000
3500
3000
2500
2000
1500
1000
500
0
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
1300
1400
1500
1600
1700
1800
1900
2000
D0 (microns)


FREQUENCY DISTRIBUTION
D300 DEFLECTION
Frequency
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
0
50
100
150
200
250
300
350
400
450
500
550
600
650
700
750
800
850
900
950
1000
More
D300 (microns)


FREQUENCY DISTRIBUTION
D600 DEFLECTION
Frequency
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
0 20 40 60 80 100 120 140 160 180 200 220 240 260 280 300 320 340 360 380 400 More
D600 (microns)


FREQUENCY DISTRIBUTION
D900 DEFLECTION
Frequency
8000
7000
6000
5000
4000
3000
2000
1000
0
0
10
20
30
40
50
60
70
80
90
100
110
120
130
140
150
160
170
180
190
200
More
D900 (microns)


FREQUENCY DISTRIBUTION
D1200 DEFLECTION
Frequency
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
0
10
20
30
40
50
60
70
80
90
100
110
120
130
140
150
160
170
180
D1200 (microns)


FREQUENCY DISTRIBUTION
D1500 DEFLECTION
Frequency
7000
6000
5000
4000
3000
2000
1000
0
0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100 More
D1500 (microns)