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ON MONITORING AND INTELLIGENCE IN AN INTEGRATED MANUFACTURING SYSTEM

by

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Dissertation presented for the
Degree of Doctor of Philosophy (Engineering)
at the
University of Stellenbosch

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April 2003

Declaration

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

Abstract

Some concepts of manufacturing on their own play a decisive role in manufacturing like Integration, Intelligence and Remote Monitoring. They have been tried and tested with great success in various applications in manufacturing. However, very little has been written on the synergy that is created when all three is deployed in one system. It is the aim of this work to survey the attributes of each of these key concepts, to compare them on the grounds of applicability and to study the effects when combined into one system. Final conclusions are made after the hypotheses have been validated with the aid of an experimental model.

The first objective of this work is to show how many techniques such as expert systems, fuzzy logic, neural networks and genetic algorithms are used to enable systems to perform intelligently. It is accepted that the competitiveness, growth and profitability of a company in future may depend on the level of its system intelligence. This is so because an intelligent system is able to act appropriately under rapidly changing conditions of customer customisation and demands on quicker throughputs.

A further objective of this work is to show how integration adds the element of synergy to a system. This is done by showing several ways of achieving integration by non-technological means like departmental consolidation, plant consolidation, product rationalisation, more flexible working practices, etc. There are as many options for integration by technical means as well, ranging from group technology to process or transfer lines, and from flexible automation such as robots through to hard automation using special-purpose machinery and transfer lines.

The third objective is to show how remote monitoring enhances the capabilities of manufacturing systems by synergising with the other two key concepts.

With the technology of intelligent manufacturing and integration, larger and more complex manufacturing systems are becoming a reality. However, the danger exists that the shop floor machine tools remain isolated islands of automation. Plant machinery needs to be networked

into the enterprise-wide information system. The ability to monitor a variety of process parameters and alert plant staff to changing conditions can greatly reduce downtime. This lack of connectivity therefore represents a huge constraint as far as productivity is concerned. For this reason, there is a great interest to study remote monitoring, analysis and diagnostic systems for application in modern manufacturing.

The major contribution of this work is to study the synergy that is created by combining the three key concepts into one system and to validate the findings with the aid of the experimental model. The meaning of *validation* is to make legally valid; to grant official sanction to; to confirm the validity of something or to declare something as true. To *validate* is to support or corroborate a theory on a sound or authoritative basis by experiments designed to show a hypothesis as being true.

The components of the validation model are a neural network, a simulator, a decision evaluator or critic, and a teacher. The neural network is used to make the decisions. Its inputs are the system parameters and its outputs are a vector of values between 0 and 1, the highest value indicates the decision being made (winner takes all). The simulator executes the decision it obtains from the network and thus changes the state of the system. The evaluator looks at how the system changed due to the decision made by the network and decides whether it was a good or a bad decision. The teacher then adjusts the output of the network accordingly and trains the network with the adjusted outputs.

The results of the validation experiments show that intelligence is used to train the model, integration is achieved by combining the elements of the model with the mobile robot and remote monitoring is done by the model to analyse the condition of the system and to react accordingly. The main objective of this work is clearly met in that synergy was shown to be created by the three key concepts.

Opsomming

Aspekte soos Integrasie, Intelligensie en Afstandsmonitering speel 'n deurslaggewende rol in vervaardiging en is al op hulle eie met groot sukses in vele toepassings gebruik. Daar is egter nog nie veel aangeteken oor die sinergie wat ontstaan wanneer hulle tesame in een stelsel gebruik word nie. Dit is die doel van hierdie werk om die kenmerke van elk van hierdie sleutel aspekte na te vors, dit op grond van toepaslikheid met mekaar te vergelyk en die uitwerking te bestudeer wanneer hulle in een stelsel saamgevoeg word. Nadat die hipoteses met behulp van 'n eksperimentele model gevalideer is, word finale gevolgtrekkings gemaak.

Die eerste doelwit van hierdie werk is om aan te toon dat verskeie tegnieke soos genetiese algoritmes en neurale netwerke gebruik word om stelsels meer kundig te laat optree. Dit word aanvaar dat die toekomstige mededingendheid en groei van ondernemings mag afhang van die stelsel intelligentheidsvlak. Dit is omdat intelligente stelsels gepas kan optree onder snel-veranderende omstandighede.

'n Verdere doelwit is om aan te toon hoe integrasie sinergie kan toevoeg tot 'n stelsel. Dit word gedoen deur verskeie metodes te bespreek van hoe om integrasie op 'n nie-tegniese vlak te bewerkstellig. Die tegniese metodes van integrasie word ook bespreek en sluit tegnieke soos groeptegnologie, aanpasbare outomatisasie en robotika in.

Die derde doelwit is om aan te toon hoe afstandsmonitering as sleutel aspek die ander twee sleutel aspekte kan versterk.

Die tegnologië van intelligente vervaardiging en integrasie maak die skepping van groter en meer kompleks vervaardigingstelsels nou moontlik. Die gevaar bestaan egter dat hierdie masjiene slegs eilande van outomatisasie sal bly indien hulle nie met behulp van netwerke in die onderneming se inligtingstelsel opgeneem word nie. Die vermoë om prosesveranderinge te monitor kan lei tot verminderde staantyd van masjiene en kan dus produktiwiteit verhoog. Om hierdie redes is die toepassing van afstandsmonitering en –diagnosering belangrik vir toepassing in vervaardiging.

Die belangrikste bydrae van hierdie werk is die studie van die sinergie wat ontstaan wanneer die drie sleutel aspekte in een stelsel gekombineer word en om die bevindinge te valideer met behulp van 'n eksperimentele model. Om te *valideer* beteken om iets geldig te verklaar of om die geldigheid van iets te bevestig. Dit beteken verder om 'n teorie te ondersteun of te staaf op 'n grondige en deskundige basis met behulp van eksperimente.

Die validasie model bestaan uit 'n neurale netwerk, 'n simulator, 'n besluitevalueerder of beoordelaar, en 'n onderwyser (terugvoerder). Die neurale netwerk neem die besluite met die stelselparameters as inset en die uitset 'n vektor met waardes tussen 0 en 1. Die simulator voer die besluit uit en verander so die toestand van die stelsel. Die evalueerder bepaal hoe die stelsel verander het as gevolg van die besluit en bepaal ook of dit 'n goeie of slegte besluit was. Die onderwyser verstel dan die uitset van die netwerk dienooreenkomstig en lei die netwerk op met die verstelde uitsette.

Die resultate van die validasie eksperiment toon aan dat intelligensie gebruik word om die model op te lei, integrasie behaal word deur die elemente van die model te kombineer met die mobiele robot en afstandsmonitering toegepas word deur die toestand van die stelsel te monitor en te analiseer. Die hoofdoelwit van hierdie werk word dus duidelik behaal deur die beskrywing van die sinergie wat ontstaan deur die kombinasie van die drie sleutel aspekte.

Acknowledgements

The completion of this body of work was not an easy task. It would not have been possible without the assistance from a number of people, who I thank with great appreciation.

In particular I would like to thank:

> Prof. Zvi Katz, my supervisor, my mentor and my friend for his infinite wisdom and endless patience, without whom this work would never have been finished.
>
> My wife, Hérine and my children for their love and support and for never losing faith in our abilities.

My departmental chairman, Prof. Niek du Preez, and my colleagues for giving me the opportunity and support to complete this work.

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Glossary

The following acronyms are used in this document:

Acronym	*Description*
AGV	Automated Guided Vehicle
AI	Artificial Intelligence
AMH	Automated Material Handling
ANN	Artificial Neural Network
AS/RS	Automated Storage and Retrieval System
CAD	Computer Aided Design
CADD	Computer Aided Drafting
CAE	Computer Aided Engineering
CAM	Computer Aided Manufacturing
CAP	Computer Aided Planning
CAPM	Computer Aided Production Management
CAPP	Computer Aided Production Planning
CAQC	Computer Aided Quality Control
CIM	Computer Integrated Manufacturing
CM	Cellular Manufacturing
CNC	Computer Numerical Control
DDMIS	Data Driven Management Information System
FMS	Flexible Manufacturing System
GT	Group Technology
IT	Information Technology
MAP	Manufacturing Automation Protocol
MIS	Management Information System
MRP	Materials Requirement Planning
NC	Numerical Control
TOP	Technical Office Protocol

CHAPTER 1

RESEARCH OBJECTIVES

Chapter Overview: The work presented in this chapter attempts to suggest an original approach to the validation of the synergy created between intelligence, integration and remote monitoring in manufacturing systems. The synergy could result in an improved enterprise adaptivity to market variations. The adaptiveness is enhanced by the combination of the various key factors. Details on the thesis objectives, contribution to the knowledge in this field and originality of the work are exhibited in a condensed form in the Abstract.

1.1 The importance of the proposed work

The relevant areas of investigation are as included in the title of the thesis: "On Monitoring and Intelligence in an Integrated Manufacturing System". The three key concepts of this research focus therefore are Intelligence, Integration and Remote Monitoring.

While considering the importance of the synergy between the key concepts of integration, intelligence and remote monitoring, the individual contribution made by each of these concepts is discussed. The extent of how they will enhance and support each other when teamed together in the same system is evaluated. An original validation procedure is also suggested.

The individual aspect and influence of each area is discussed in terms of their respective contribution.

1.1.1 Intelligence and Intelligent Systems.

In an attempt to evaluate and validate the contribution of intelligence in a manufacturing system, the first objective is to fully discuss and debate the origin, characteristics and role of intelligence. The important contribution made in this section is the similarities drawn between human and artificial intelligence and how these similarities can be implemented to validate the concept of intelligence.

In the past, two of the critical fields in manufacturing were *organisational theory* and *information technology* [1]. The prevailing paradigm was the command and control paradigm with major characteristics of economy of scale, deep hierachical structures, clear lines of command/reporting, limited span of control, division of labour (including the division between thinking and doing), functional organisational units and a competitive relationship with suppliers. These however, along with many other previously accepted norms in manufacturing, have been experiencing some very fundamental changes. The new paradigm consists of very different principles like flexibility, responsiveness, shallow hierarchies, devolution of decision-making, multidisciplinary teams, process-oriented organisational units and global partnerships.

In the manufacturing system, conventional or fixed automation is presently considered to be too rigid. Aspects like precision and repeatability (i.e. a robotic system) are now considered to be insufficient because of the inability to cope with unexpected events. Under the new paradigm, sensors and artificial intelligence enable the development of intelligent systems capable of making decisions under conditions of uncertainty.

1.1.2 System Integration.

A further objective of this work is to show how integration adds the element of synergy to a system. This is done by showing several ways of achieving integration firstly by non-technological means like departmental consolidation, plant consolidation, product rationalisation, more flexible working practices, etc. There are as many options for integration by technical means as well, ranging from group technology to process or transfer lines, and from flexible automation such as robots through to hard automation using special-purpose machinery and transfer lines. These aspects are discussed in Chapter 2 and Chapter 4.

The following are some of the advantages of integrated systems that may be expected in the manufacturing environment:

- A complete flow of production and management information throughout the entire organisation at all levels.
- Universal communication links with interfacing between all hardware and software.
- The standardisation of software packages, achieving the transferability of information from engineering applications to commercial modules and vice versa.
- The ability to respond quickly, both in quantity and type, to customer demands.
- Greater volumes of output with a reduction in work force, but maintaining and enhancing quality levels.
- The minimisation of stock levels, inventories and work in progress.

It is however evident that in order to initiate, plan and implement such integration, new problems could be created:

- The lack of technical knowledge at middle and top management levels.
- Poor integration and flow of information between management and their various departments.
- Insufficient knowledge of market requirements and integration of the company's product/products in the market.
- Lack of personal esteem, leading to unwillingness to share information or collaborate with others.
- Insufficient evaluation at the appraisal stage of implementing CIM, due to over-enthusiasm and lack of detailed knowledge.
- Underestimation of the time scale required for full implementation of the integrated system.
- The change of technology, resulting in obsolescence of equipment.

1.1.3 Remote monitoring of systems

The third objective is to show how remote monitoring enhances the capabilities of manufacturing systems by synergising with the other two key concepts.

With the technology of intelligent manufacturing and integration, larger and more complex manufacturing systems are becoming a reality. However, the danger exists that the shop floor machine tools remain isolated islands of automation. Plant machinery needs to be networked into the enterprise-wide information system. The ability to monitor a variety of process parameters and alert plant staff to changing conditions can greatly reduce downtime [2]. This lack of connectivity therefore represents a huge constraint as far as productivity is concerned. Furthermore, such manufacturing systems depend heavily on trouble-free operations of all the component parts [3]. The state of the system needs to be monitored and analysed to ensure a high level of productivity. For this reason, there is a great interest to study remote monitoring, analysis and diagnostic systems for application in modern manufacturing.

The action of monitoring is usually used to detect faults, while diagnosis includes fault tracing, identification and recovery procedures. The action of analysis includes the investigation of information in order to reach certain conclusions about that information.

The design requirements of a remote analysis and diagnosis system will depend on the information that is to be analysed. From this, the required data signals that can best describe the manufacturing operations, can be selected. Sensors are typical methods of capturing these data signals. The data capturing must be done in-time and be non-complex in order to facilitate quick response for analysis. The response speed is of course dependant on the level of expertise of the human operator of the system and can have a detrimental effect on the effectiveness of it. Remote monitoring is discussed in more detail in Chapter 4.

1.2 Synergy of the proposed systems

One of the further objectives of this work is to show how some of the above problems can be alleviated by the synergy created through the combination of the key concepts. In essence, these three concepts should enhance one another when used together in a manufacturing environment. They should in fact cancel out or at least improve on the disadvantages/limitations that each key concept generates when it is used individually.

1.2.1 Intelligent systems

A major strength of a conventional manufacturing system such as a robotic system, is its precision and repeatability. A major weakness of such a system is its inability to respond to unexpected events.

As an example, consider the case of a welding robotic system on an automobile assembly line performing a number of spot welds on the chassis. The robot is not equipped with any form of intelligence to enable it to make decisions. If the chassis is positioned in the correct position, the robotic system will perform the required number of spot welds on a continuous basis. However, if the chassis is incorrectly positioned, the welds will be made in the wrong locations. If the robot was equipped with intelligent capabilities, it would have been able to overcome such unexpected occurrences.

The main advantage in building intelligent systems is in their ability to cope with uncertain conditions. There is, however, usually a financial limit to the amount of system intelligence that can be incorporated at the expense of human intelligence. This condition can be explained by using the standard break-even graph as shown in Fig. 1.1.

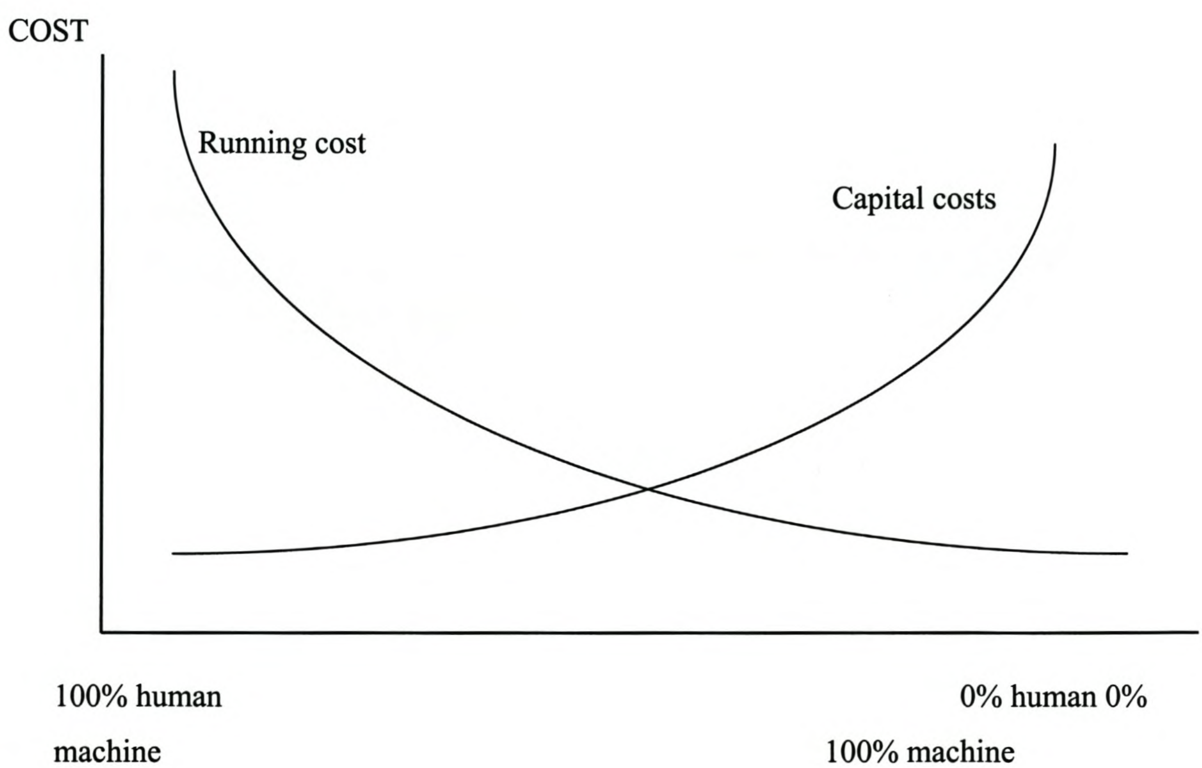

Fig. 1.1: Break-even cost graph of system intelligence vs. human intelligence

1.2.2 Combination of Intelligence and Remote Analysis with Integrated systems

When using an integrated system with intelligent features and having a remote analysis capability, the following improvements to the problems created by non-integrated systems can be expected (see also paragraph 1.1.2):

- The lack of technical knowledge can be greatly reduced by using expert systems and decision support systems. This will enable users of technologies to use the systems without extended prior knowledge of the systems.
- Poor integration and flow of information can be improved by using data mining in conjunction with neural networks together with instant remote analysis.
- Insufficient knowledge of market requirements and integration of the product can be improved by using expert systems to match market requirements with product development.
- The problems arising from insufficient planning and scheduling of integrated systems can be solved and indeed improved by using various intelligent scheduling techniques equipped with neural networks, data mining and neuro-fuzzy systems. Further enhancement is possible if the information is presented in a remote manner, enabling instant analysis and corrective measures.
- The response speed of the remote analysis system can be dramatically improved when employing intelligent analysis like neural networks, neuro-fuzzy systems and data mining.

1.3 Summary

When considering the issues presented above, it becomes clear from this work that synergy can be created between an integrated system, intelligent features and remote monitoring. The main contribution of this work is to investigate the key concepts individually and as a combination and to show how the adaptability of a manufacturing system can be improved at various levels of the production systems. An original method of validating the three key concepts is also presented and forms the core of the unique contribution of this work.

CHAPTER 2

INTRODUCTION

Chapter Overview: The main objective of this chapter is to investigate the current outlook on aspects of intelligence and integration in manufacturing from a psychological and a manufacturing perspective. From the psychological perspective, different views on intelligence and integration are discussed. These include the psychometrical approach, the information processing approach and the different theories on integration. Creativity and intelligence tests are discussed as well. To gain a manufacturing perspective, a variety of definitions of intelligence and integration in manufacturing are given and briefly discussed. Where applicable, similarities between human and machine intelligence are drawn.

2.1 Introductory Ideas on Intelligence

The main objective of the discussion on intelligence is to show that the study of human intelligence has developed to a high level and that many theories have been postulated in order to define the concept of intelligence. A further objective is to indicate the similarities between these theories and to show that these similarities can also be drawn between human and system intelligence. This leads to the derivation of a group of characteristics that are true for human as well as for system intelligence. This should then make possible a structured study of system intelligence because similar analyses as for human intelligence can be applied. The contribution of this group of characteristics is unique and could not be found anywhere in literature.

Most people think of intelligence as cleverness or the ability to exhibit cleverness [4]. It is said that it is versatility in solving novel problems.

Foresight or the ability to think proactively is also said to be an essential aspect of intelligence. Foresight can however only be mastered after a good deal of experience (or learning). It is therefore based on previous knowledge of specific circumstances.

It is further said that creativity is also an outcome or product of intelligence: the amount of creativity increasing as the level of intelligence increases. It implies that intelligence is a prerequisite for creativity.

Higher life forms exhibit a highly developed form of survival-oriented response to changes in the environment [5]. This developed form is referred to as a variability to respond to environmental challenges and has led to the development of what is called "intelligence". In general, psychologists agree that intelligence involves the speed with which a living organism or system is able to effectively analyse data provided to it by its sensory organs. This ability has ensured survival of many species.

This last thought can also be seen in an evolutionary context which states that intelligence is the ability to analyse data about the surrounding environment, relate this to the past experience of the organism (or system) and to promote reactive behaviour which will promote the survival chances of the organism. This is probably more evident in the case of mobile organisms (animals) whose environment changes more rapidly and offer frequent and often sudden threats to survival.

These mobile organisms have often developed "built-in" reactions like alertness to noise. It is however true that intelligence will lead them to react in far more sophisticated ways including the devising of tools to assist in getting food or protecting their young. In doing so, an element of proactive behaviour is evident based on the knowledge obtained from the environment.

In modern technologically advanced societies, it is only modern man that has become particularly dependent on intelligence for survival [5]. As a species, hominids have moved away from prime dependence upon physical attributes for survival to survival through the ability to solve problems.

From the above preamble, it is evident that there exist many theories and approaches to the study of intelligence. It is therefore important to follow a structured approach to the study of intelligence simply because if intelligence is to be applied to a specific discipline like manufacturing, the correct approach must be adhered to.

2.2 Different views on Intelligence

The understanding of intelligence increased over the years, leading to the evolution of different theories explaining human intelligence. The psychometrical approach, the information processing approach and the theory of multiple intelligence are discussed [6]. Where applicable, an attempt is made to find some relationship between these theories and the application of intelligence in manufacturing. The reason for this is that the rules that apply for human intelligence should be just as applicable to manufacturing intelligence and could follow a structured approach as well.

2.2.1 The psychometrical approach

Supporters of the psychometrical approach on intelligence analyse the results of intelligence tests to describe the structure of information. The technique used is called factor analysing. Specifically they try to answer the question of whether intelligence is a single ability, or whether it is rather a property combined from several abilities. When applied to more practical systems like manufacturing, it would seem more appropriate to assume that it is a property combined from several abilities, giving it the advantages of being a modular system. The different abilities can be built into the manufacturing system as the situation changes.

Following is an introduction to the important theories in the category of psychometrical approach.

2.2.1.1 The Two-Factor Theory of Spearman

Spearman's theory, introduced at the beginning of the twentieth century, came to the conclusion that intelligence can be seen as a function of two factors or abilities. These are:

- *General intelligence:* This factor is a fundamental intellectual ability that is common to all forms of intellectual behaviour. A person with a high degree of general intelligence will be more likely to be successful in any performance activity.
- *Specific intelligence:* Performance in any task or test is not a function only of general intelligence. Alongside the general intelligence is also a specific intelligence. Performance in something like accounting is thus the combined result of general intelligence as well as accounting ability. The relative contribution of the general and specific intelligence depends on the nature of the task at hand. Relating to manufacturing, this could involve the system intelligence on the general level and applicable process intelligence on the specific level.

Further research led to the conclusion that the two previous factors are not necessary independent of each other, but that overlapping may exist. This overlapping was called a group factor. A group factor will play a role in specific activities, but will play no role in other specific activities. Activities that starts off by requiring general intelligence, but later become automatic (e.g. driving), are such because the general intelligence required declines until only the specific intelligence is needed for the successful execution of the activity.

2.2.1.2 Thurstone's theory of primary intelligence ability

Thurstone followed on Spearman's work and came to the conclusion that the total intellectual ability is dependent on seven primary group factors. These factors are:

- *Verbal understanding:* The understanding a person shows for words. In terms of manufacturing intelligence, this will refer to the ability of a system to communicate and understand specific programming commands.
- *Word fluency:* The ability to express yourself fluently in words. In manufacturing intelligence, this is the ability of a sub-system to communicate its machine state to the control program (as with remote analysis).
- *Spatial ability:* The ability to make visual-spatial representations and to manipulate them. In a manufacturing system, this would refer to some form of visual aid with the ability to capture digital images and an intelligent algorithm to interpret and manipulate the digital image.
- *Numeric ability:* The ability to work with numbers. This will relate to the manufacturing system's computing capability.
- *Memory:* The ability to store and recall information, relating to the memory storage and retrieval abilities of a manufacturing system.
- *Reasoning:* The ability to plan and to solve problems according to rules, principles and experience. In a manufacturing system, this will refer to the artificial intelligent module (neural network, genetic algorithm) with the ability to manipulate knowledge to solve problems.
- *Observation speed:* The speed with which objects are accurately observed and compared. A manufacturing system equipped with digital cameras and image recognition programmes would be able to accurately observe its environment and react accordingly.

Initially, Thurstone thought that these abilities are relatively independent of each other, but further research showed a high correlation between different groups of abilities. This correlation implies the existence of a general factor that is mutual to the group factors. There is thus not much difference in the final form of Spearman and Thurstone's views.

In a manufacturing system, its intelligence would also display some correlation between different groups of abilities. The ability to observe and rapidly communicate (observation speed and verbal understanding) specific information relating to a system's environment, to manipulate and compute relevant algorithms (numeric ability) and to use neural networks to solve problems (reasoning), is all related in an integrated and intelligent manufacturing system.

2.2.1.3 Guilford's three dimensional theory

Guilford debated the notion of a general factor. He differentiated between three dimensions of intellectual functioning: *operations* (the way in which intellect operates), *contents* (the material wherein the intellect operates) and *products* (the results of the intellectual process).

(a) Different intellectual operations

- *Memory:* The retention of information.
- *Cognition:* The awakening, identification and understanding of information.
- *Convergent reasoning:* The ability to use information already known for new ideas or solutions.
- *Divergent reasoning:* The ability to use given information for new ideas or solutions.
- *Evaluation:* The ability to evaluate ideas critically and decide on its correctness and applicability.

(b) Types of contents

- *Figure content:* Concrete stimuli that must be structured and organised.
- *Symbolic content:* Stimuli with no inherent meaning (e.g. numbers, letters and words).
- *Semantic content:* The verbal ability in vocabulary and reading comprehension.
- *Behaviour content:* The behaviour as it shows with interaction with other people.

(c) Responses classified according to products

- *Units:* The identification of certain units of information like words or numbers.
- *Classes:* The grouping of items according to a common property.
- *Relationship:* The identifying of relationships between items.
- *Systems:* The organising or structuring of items in patterns.
- *Transformations:* The transformation of excising information into new ideas and solutions.
- *Implications:* The use of excising information in planning and forecasting.

Thus, intelligence consists of 120 different factors (4 content factors x 5 operation factors x 6 product factors) with at least one factor from every category present in any intellectual activity. Guilford emphasised the interdependency of intellectual factors, the complexity of intelligence and the reliability of intelligence on personality.

2.2.1.4 The hierarchy models of intelligence

The hierarchy models of intelligence try to combine the ideas of a single general factor, group factors and specific factors and show the underlying relationship. According to Vernon's model the general intelligence factor is the fundamental factor, and 40% of all intellectual behaviour can be explained with it. Two primary group factors (verbal-numeric-educational and practical-mechanical-spatial-physical) develop from the general factor. Each of these primary group factors branches into secondary group factors. These factors form a hierarchical pattern and represent smaller elements of the previous factor in each new branch.

2.2.2 The information processing approach

The psychometric approach dominated research into intelligence. With the emergence of cognitive psychology and the accompanying focus on information processing, a new approach called information processing gained popularity. Information processing can be described as the process where information is changed or brought in relation with information that is already available to produce new information. While the psychometric approach tries to explain intelligence in terms of factors, the information processing approach sees intelligence as the result of certain cognitive processes that is working while we are busy with intelligent behaviour. Some of the processes examined are the influence of processing speed, short-term memory and attention on intelligent behaviour.

When considering a manufacturing system, this approach to information processing is valid as well. It is important to note that information flow can be considered as the one major component of intelligence as well as integration. None of these characteristics would be possible without the presence of information. In a well-designed manufacturing system, various types of information will exist [7] and can generally be categorised into planning information, control information and historical information. It will include information on parameters such as materials, order status, quality levels, inventory levels, and so on. This represents the obtainable information and will be matched with information that is already available to produce a result.

The most important theory in the information processing approach is Sternberg's triarchy theory, according to which intelligence must be examined as a multi-dimensional property consisting of componential intelligence, experience intelligence and contextual intelligence.

2.2.2.1 Componential intelligence

Componential intelligence describes the traditional concept of intelligence and consists of three processes:

- *Metacomponents*: Also called executing processes because they give direction to the two other components. Metacomponents includes abilities like the identifying of a problem and making strategic decisions.
- *Performance components:* Execute the actions planned from the metacomponents. Performance components are relevant with the deciphering of stimuli information and recycling of information from memory.

- *Knowledge learning components:* Relevant with the learning and storing of new information.

2.2.2.2 Experimental intelligence

Experimental intelligence refers to the ability to master new tasks and execute complex tasks automatically. Writing and reading are examples of complex tasks automatically executed by intelligent people. In manufacturing, it would refer to the system's ability to use neural networks or case-based reasoning together with reinforcement learning to learn from past experience how to master new tasks and solve novel problems automatically.

2.2.2.3 Contextual intelligence

Contextual intelligence is the ability to adapt to the environment. More specifically it refers to the ability to function efficiently in practical situations. An example is the ability to stay out of trouble. Contextual intelligence cannot be learned formally, but is extremely important to make a success of life.

The most import aspect of this theory is that people can be intelligent in different ways and that practical-general intelligent behaviour is an important part of intelligence. While Sternberg's theory gets lots of attention from psychologists, all its assumptions cannot be accepted without reserve before the necessary research and evaluation is done.

The use of reconfigurable manufacturing based on biological systems and the use of adaptive control are relevant examples taken from the manufacturing environment.

2.2.3 Gardner's Theory of multiple intelligence

Gardner suggests that intelligence is not a unique entity, but that different kinds of intelligence exist. Gardner identified seven different kinds of intelligence:

- *Linguistic intelligence:* The ability to communicate through language, either written or spoken.
- *Logic-mathematical intelligence:* The ability to solve problems on a logical and analytical way.
- *Spatial intelligence:* The ability to manipulate the location, form, size and orientation of objects in the mind.
- *Musical intelligence:* The ability to evaluate, analyse and compose music, or play a musical instrument.
- *Body-kinetic intelligence:* The ability to control body motions.
- *Intra-personal intelligence:* The ability to know yourself and your behaviour.
- *Inter-personal intelligence:* The ability to understand and show sensitivity for other people.

The seven kinds of intelligence operate independently from each other, but there are interactions between them. Some kinds of inheritance will be stronger in certain people because of inheritance and/or training. There is a strong correlation between this theory and Spearman's original theory of general intelligence (inheritance) and specific intelligence (training). Activities will first require general intelligence but will later become automatic because the specific intelligence will increase as training is effected.

These theories find their application in manufacturing through the effective use of neural networks, genetic algorithms and case-based reasoning using reinforcement learning. By using past experiences as a learning tool, the system is increasingly able to act independently (automatically) while having to depend less and less on fixed instructions (general intelligence). This could ultimately lead to the emergence of very responsive cell systems planned and controlled by teams of autonomous intelligent agents capable of making decisions under conditions of uncertainty. Fig. 2.1 shows the evolution of manufacturing systems with the current transition from rigid, fully automated production lines to multi-agent teams.

Fig. 2.1: Evolving manufacturing systems.

2.3 Creativity

It has been said that creativity is the creation of the new and the rearranging of the old in new and different ways. It means bringing into being something that was not there before. However, creativity has been called the "ugly stepsister" of intelligence [6]. This is because society does not rate creativity as high as intelligence. Furthermore there is still a serious debate surrounding creativity, because some psychologists see it as an integral part of intelligence, while others see it as an isolated and separate ability. Certain abilities has been isolated that are associated with creativity and are adaptability, originality and unique ideas. Current research shows that creativity can be distinguished from intelligence, but cannot be separated.

When considering creativity from a manufacturing point of view, it becomes important to decide if creativity can be implemented in a system. It is obvious that creativity can be a tremendous advantage in increasing the competitiveness of a system.

According to Sternberg and Williams creativity consists of the application and melding of three types of thinking, all of which they contend can be learned or enhanced. They feel that creativity is a balance between these three forms of thinking:

- Synthetic ability - This obviously includes divergent thinking, as it is the ability to think of or generate new, novel, and interesting ideas. But it is also the ability to spontaneously make connections between ideas, or groups of things -- ones that often go unnoticed, or undiscovered by others.
- Analytical ability - Again, this includes the ability to think convergently in that it requires critical thinking and appraisal as one analyzes and evaluates thoughts, ideas, and possible solutions. This type of thinking is key in the realm of creative work because not all ideas are good ones, some need to be culled. Creative people use this type of thinking to consider implications and project possible responses, problems, and outcomes.
- Practical ability - The world is full of people who have good ideas, as well as ones who can pick ideas apart. However, the basic key to creative work must include the ability to use practical thinking. This is the ability to translate abstractions and theories into realistic applications. It is the skill to sell or communicate one's ideas to others, to make others believe that ideas or products are valuable, different, useful, innovative, unusual, or worthy of consideration.

From reading and research on the concept of creativity, one aspect of practical thinking in creativity needs to be added, namely the component of persistence. It is not enough to just have ideas, or to be able to appraise them critically, or to sell, translate, or market them. What separates truly creative greats from those who are less creative is the aspect of persistence.

To bring the concept of creativity into a manufacturing context, the requirements for creativity can now be listed and the abilities of manufacturing systems measured against these requirements:

- Adaptability
- Originality
- Unique ideas
- Ability to synthesise
- Ability to critically analyse
- Ability to use practical thinking
- Ability to persevere

Modern machine intelligence is able to make a system more adaptable (reconfigurable systems), it can enable the elements of the system to synthesise, to make connection between ideas (genetic algorithms), it can enable the system to critically analyse problems and generate solutions (neural networks) and it can be made to use practical thinking (expert systems). However, it is difficult to conceive a system that is able to create new and original ideas from nothing, or to display the ability to persevere.

2.4 Intelligence Tests

It is generally accepted that intelligence tests started in 1904 in France, when the French government ordered Alfred Binet (director of the first psychology laboratory in Paris) to separate intellectually normal children from intellectually inferior children to place the latter in special schools [6]. To ensure the best results of tests, they must be correct and good. The main properties of a good test are reliability, validity, objectivity and standards.

2.4.1 Reliability

A test is reliable when the result is the same count by the same individual at different occasions. The measure results thus have to be repeatable. The reliability of a test can be determined by the following methods:

- *The test- retest method:* This method, the most simple, means that the test is done on a group and then after some time, again on the same group. If the individuals' counts are the same for both tests, the test can be regarded as reliable.
- *The equal form method:* With this method, two equivalent forms of the same test are prepared. If an individual's count is the same for both forms, the test is reliable.
- *The halving method:* With this method the test is divided into two equal parts. If the two counts agree, the test can be thought of as reliable.
- *Internal consistency methods:* These methods determine the homogeneity of tests, which is the extent to which different items measures the same property. This is done with statistical formulas.

In manufacturing, the term reliability means "repeatability" or "consistency". A system is considered reliable if it would give the same result over and over again.

2.4.2 Validity

A test is valid if it measures what it is supposed to measure. Thus an intelligence test must measure intelligence and not something else (e.g. interest). It can be very difficult to measure the validity of abstract properties, so they are evaluated on these different kinds of validity.

- *Content validity:* This implies that the items of the test must be representative of the property being measured.
- *Forecasting validity:* This form of validity shows the efficiency of the test to forecast future behaviour.
- *Overlapping validity:* The test is evaluated by comparing its results with those of another test that is already proved reliable.
- *Construct validity:* This shows the extent to which a test is able to measure a theoretical construct.

2.4.3 Objectivity

The word "objectivity" refers to the view that the truth of a thing is independent from the observing subject. The notion of objectivity means that certain things exist independently from the mind, or that they are at least in an external sphere. Objective truths are independent of human wishes and beliefs. The notion of objectivity is especially relevant to the status of various ideas.

With reference to intelligence tests, it means that the examiners' subjective preference or feelings should not influence the evaluation of the test. Different able examiners must give the same result to the same individual's test.

2.4.4 Standards

A test result on its own has no practical value. The result only gets meaning when it is interpreted with standards. Standards are a value or group of values describing the normal or general performance of a group with which an individual can be compared.

2.5 Intelligence from a manufacturing perspective

From the discussions in previous sections and other sources, it is evident that there exist countless theories and approaches to the study of human intelligence. In order to gain insight into the properties of intelligence in manufacturing, a brief summary of these major theories serves as a basis [8]:

- Intelligence is the ability to exhibit "cleverness".
- Intelligence is the versatility in solving novel problems.
- Intelligence is the ability to think proactively (foresight).
- Creativity is an outcome of intelligence.
- Intelligence results in a highly developed form of survival-oriented response to changes.
- Intelligence involves the speed with which a living system is able to effectively analyse data provided to it via its sensory organs.
- Analyse data about the surroundings, relate this to past experience and promote reactive behaviour.
- Intelligence ensures survival through the ability to solve problems about the environment.

To lend validity to the comparisons, manufacturing intelligence must first be defined. There is not a singular, accepted definition of intelligence in the context of manufacturing. The following definitions are given to demonstrate some of the ideas behind intelligence in manufacturing.

- Intelligence is the ability of the manufacturing system to reconfigure the production system, including machines, purchasing, inventory control and factory layout, in response to changing market demands for various types of products [9]. To have intelligence, the system must make correct decisions based on rules or principles.
- Intelligence is the ability of a system to act appropriately in an uncertain environment to increase the probability of success of the system given the criteria of success [10].
- Intelligence is the capability of a system to achieve a goal or sustain desired behaviour under conditions of uncertainty [1]. Intelligence is a property that enables the system to operate effectively when available information is incomplete or inadequate. The ability to recognise partially specified patterns is the key to intelligent behaviour.

The preceding descriptions illustrate the scope and diversity of the definition by leaders in the field and explain why it is not possible to have a conclusive definition. It is interesting to note that the common property of all the above definitions is the intelligent systems' adaptivity to changing situations in order to achieve success.

When considering the discussions on manufacturing intelligence in the context of the similarities between it and human intelligence, many concepts become important.

The first concept of importance is the many similarities between human and machine intelligence:

- Intelligence is a property combined from several abilities. (The 7 group factors of Thurstone and Gardner)
- Intelligence is the ability to represent knowledge using data as input
- Intelligence is the ability and versatility in solving novel problems
- Intelligence leads to proactive action based on survival
- Intelligence places importance on the speed of response to changes

The second important concept is that there does not exist sufficient proof to claim that creativity can be built into machine intelligence. This remains the exclusive domain of the human being.

2.6 Integration

The objective of this discussion on integration is to show what integration is, how it became an indispensable aspect of systems and how it contributes to the synergy that is created in systems.

2.6.1 Integration definition

Integration is defined as follows:

- To form, co-ordinate or blend into a functioning or unified whole
- To unite with something else
- To incorporate into a larger unit
- To bring into equal membership in a system

A system on the other hand is defined as follows:

- A regularly interacting or interdependent group of items forming a unified whole
- A group of devices or artificial objects or an organisation forming a network especially for distributing something or serving a common purpose like manufacturing or assembly

It is therefore evident that the action of system integration is related to the combination of various aspects of a system or business into a functioning whole.

2.6.2 Technology changes leading to the need for integration

The futuristic dream of most industrialists and indeed that of most researchers was the complete automation of manufacturing processes [11]. Then, decision-makers came to realise that the present-day consensus on the "Factory of the Future" is different. It seems that this realisation has not come about as a result of technology not living up to its capability: it is rather due to a fundamental change in the rules of the market during the 70's.

Productivity used to be the all-important objective that influenced most manufacturing decisions. This however gave way to other objectives that were more concerned with flexibility and quality in the workplace. As a result of this new climate, a different mode of industrial organisation developed, that aimed at increasing the responsiveness and thus the flexibility of the company. This is done by reducing the human involvement in manufacturing, control and management, and introducing automated systems. This is not to be confused with the concept of equipment automation, which has been around for some time already: it is the automation of *all* aspects of manufacturing.

At the same time, manufacturing organisations globally found themselves under intense competitive pressures because of changes experienced with respect to resources, markets, manufacturing processes and product strategies [12]. As a result of such international competition, companies came to realise that only the most responsive and cost-effective industries could become globally competitive.

Another factor that played a major role in the evolution of the manufacturing scene, was the concept of manufacturing as a means of creating wealth. The energy-triggered recession of the late 70's and 80's brought a renewed emphasis on operating efficiencies and thereby prodding many firms to shed some of the excess weight they had built up during the prosperous years [13]. This resulted in firms being genuinely leaner and fitter and forced companies, academics and consultants to take a fresh look at the neglected art of production. An old idea in a new form thus gained ground: manufacturing should not be regarded as just another cost centre but as a source of competitive strength.

The last, and probably the most important variable to play a role in the change, is information. It has now become as important as all the other factors put together. Information has always been important to the manufacturer: manufacturing know-how, management know-how and market intelligence. It is however not this role that has brought about the changes. It is the dramatic development of information related technology (IT) itself that brought information within the grasp of every single person in a company. This led to the automated and integrated use of production factors, the use of artificial intelligence and also the ability to control and monitor processes by remote means.

In summary, these are some of the major influences that changed the face of manufacturing:

- Change of focus from pure productivity to quality and flexibility in the workplace.
- New improved manufacturing technologies.
- Global competition.
- Manufacturing's new role.
- Dramatic changes in information related technologies.

2.6.3 The drive towards integration

One of the factors that changed the concept of manufacturing, was the need to become more flexible, and thus more competitive. Consequently, many firms invested in the physical tooling, computer hardware, and control software of flexible manufacturing without understanding how these systems require a redefining of information flows, knowledge use and organisation structure [14]. Smooth implementation and growing competence in applying advanced manufacturing and information technologies depend on the company's cultivation of organisational practices that encourage continuous organisational learning and knowledge-creating activities. However, competitive advantage is likely to result only when managers understand the need to redesign their organisations to exploit the full benefits of the new technology. By *integrating* new technology with innovative and more flexible organisation designs, manufacturing firms may be able to create and sustain levels of strategic flexibility and customer responsiveness that competitors will find difficult to imitate and customers will find difficult to abandon. In turn, it is believed that this will lead to more sustainable competitive advantage.

It is important to note that in this new competitive and integrated climate, the key variables which make the difference between manufacturing success and failure is not only technology, which is potentially the same everywhere. It is also not the low cost of labour because at 5-10% of total cost, it hardly matters. What does make a difference are concepts like product design and process management, in other words, how information is used. It has become apparent that manufacturing is as much about collecting, handling, modifying and acting upon data as it is about processing material and producing products. It is the ability to deploy these data manipulating skills that is determining cost competitiveness.

In the wake of this important realisation, came the explosion of vendors attempting to deliver the means to reach the goal. Computer aided design (CAD) and computer aided manufacturing (CAM) were the first attempts at integrating certain aspects of design and manufacturing while computer aided production planning (CAPP) and computer aided production management (CAPM) were developed at the same time as attempts to integrate the manufacturing support services. Meanwhile, numerical control (NC) of machine tools gave way to computer numerical control (CNC), some making use of manufacturing automation protocol (MAP) to enable them to be combined in networks. In this way, information technology (IT) became an indispensable building block in modern manufacturing technology.

Because of this crucial importance of information technology, some discussion is required. Defining its role in manufacturing is a problem in itself. It may be useful to think first of the four functions of manufacturing, as shown in Fig. 2.2. Using this model, IT in the factory breaks down into four categories.

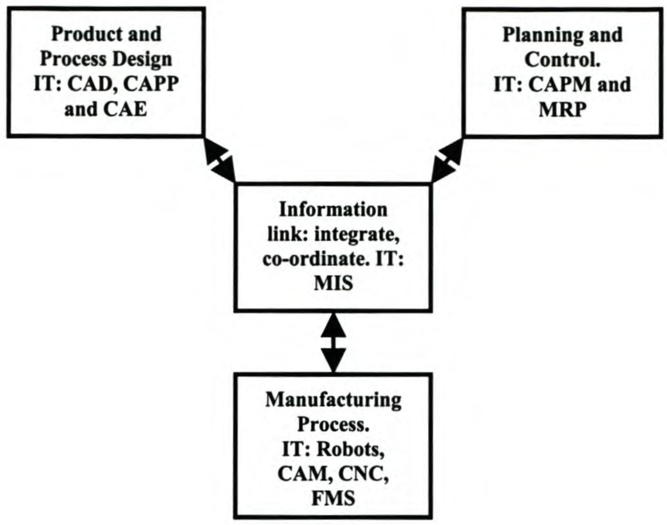

Fig. 2.2: IT in the factory [13].

As the drive toward integration continued, it was only natural that the next and at that stage, ultimate step was to integrate most of the aspects of manufacturing and thus computer integrated manufacturing (CIM) was born. CIM is the shorthand for the attempt to run an entire manufacturing business by computer. It presupposes a high degree of automation and integration and it includes all the rest of the individual computer aided functions. A graphical description is presented in Fig. 2.3.

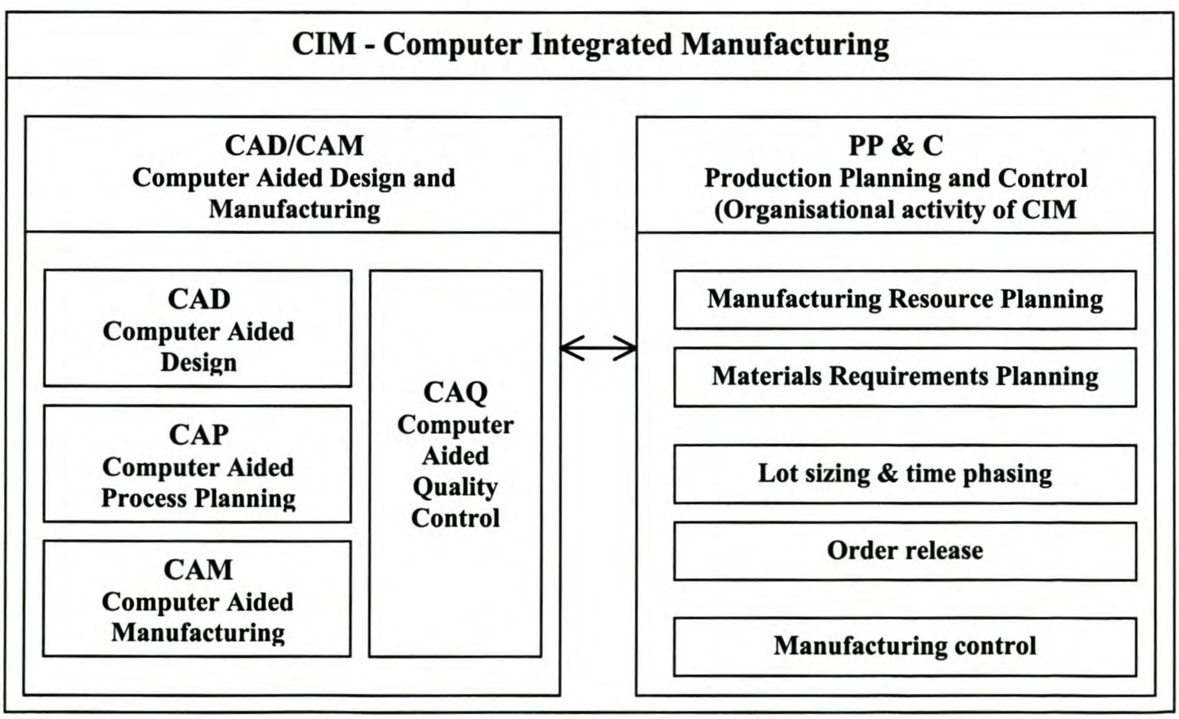

Fig. 2.3: CIM activities [15].

The above description represents the traditional view of integrated systems. There are many other views representing different strategies and to understand the importance of integrated systems, two other views are discussed as well. The first view emphasises the data-handling capabilities, while the other looks at the system itself as well as two special techniques implemented for integration.

In the first view, an integrated system is considered to refer basically to the data-handling capabilities of the manufacturer [16]. It is a sophisticated system for gathering, tracking, processing, and routing information that links purchasing, distribution, marketing and financial data with design, engineering and manufacturing data to expand and speed up the knowledge available to employees and managers. Integrated systems will use interactive data bases and hierarchical control systems coupled to advanced CAD systems, modelling and simulation systems, computer-aided engineering (CAE) systems, production process planning systems, computer-integrated manufacturing systems and/or hard automation processes, material handling systems, and automated inspection/quality assurance systems. In essence, the integrated system will allow teams of design, process and manufacturing engineers to design and manufacture products quickly in response to market demand, product innovations or input price changes. The essential difference between conventional machines and the automated production inherent in integrated systems, is the integration of all information technology required to design, produce and deliver the product. The different integrated components are structured in the following way:

- Computer-Aided Design (CAD)
    - Computer-Aided Design (CAD)
    - Computer-Aided Drafting (CADD)
    - Computer-Aided Engineering (CAE)
- Computer-Aided Manufacturing (CAM)
    - Robots

- Machine vision
- Numerically Controlled (NC) machine tools
- Flexible Manufacturing Systems (FMS)
- Automated Materials Handling (AMH) and Automated Storage and Retrieval Systems (AS/RS)

- Tools and strategies for Manufacturing Management
  - Data-Driven Management Information Systems (DDMIS)
  - Computer-Aided Planning (CAP)
  - Computer-Aided Process Planning (CAPP)

In the second view, integrated systems are used to describe the structures that ensure the correct working of a facility for manufacturing a variety of products using computers to initiate, control and monitor all activities [17]. Ideally this structure uses networked computers to initiate, control and monitor all activities including management, financial systems and outside influences to produce a totally automated factory as shown in Fig. 2.4.

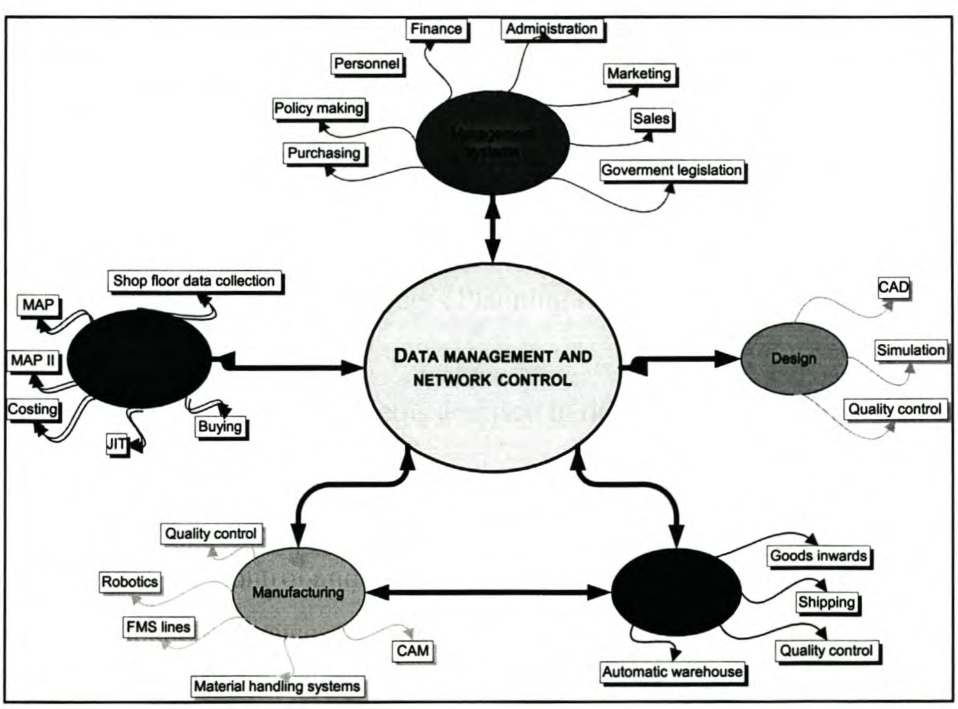

Fig. 2.4: The integrated structure using integrated systems as description [17].

This structure is not easily achieved therefore the following two special techniques are suggested for implementing integration:

- *Databases:* Databases are the heart of integrated systems, since it receives, processes and outputs information/data needed for all manufacturing and administration functions. This includes the control of data flow to machine tools, material handling equipment and stores, scheduling of operations, component design and management functions.
- *Interfacing*: All the systems within the integrated environment must be able to communicate with each other. This includes CNC machine controllers, programmable logic controllers, robots, and sensors, AGV's, screen monitors, databases and so on. The International Standards Organisation (ISO) and Open Systems Interconnection (OSI) models define specifications for standards for communications networks. Two standard systems which are based on the ISO/OSI format is MAP (Manufacturing Automation Protocol), developed by General Motors, and TOP (Technical Office Protocol). Although these are communications systems, it does not necessarily follow that the devices communicating with each other actually understands the data being transmitted. Although they share the same protocol, their languages may be different.

It is of importance to note that CIM is largely a technology-pushed rather than a customer-pulled solution. At present, it did not prove to be applicable and did not spread within the manufacturing environments.

2.7 Remote monitoring

Large scale integration and use of manufacturing intelligence as described in the previous sections, leads to more efficiency and flexibility in meeting production schedules and can potentially lead to lower cost and higher quality products. This is what is demanded from modern manufacturing systems. However, these systems are very dependent on trouble-free operation of all its component parts. When a failure occurs it is critical to isolate the causes as quickly as possible and to take appropriate corrective action. In line with the use of intelligence to drive the integrated systems, monitoring systems also need to be equipped with intelligence to keep up with the main systems. This is usually achieved by employing some form of knowledge bases like expert systems with symptom-based functional reasoning.

The representation of a remote monitoring and diagnostic model can be described from a variety of viewpoints which depends on the underlying hierarchical system [18]. A typical example is broken up into three levels: physical control, coordination and executive. A block diagram of this example is shown in Fig. 2.5.

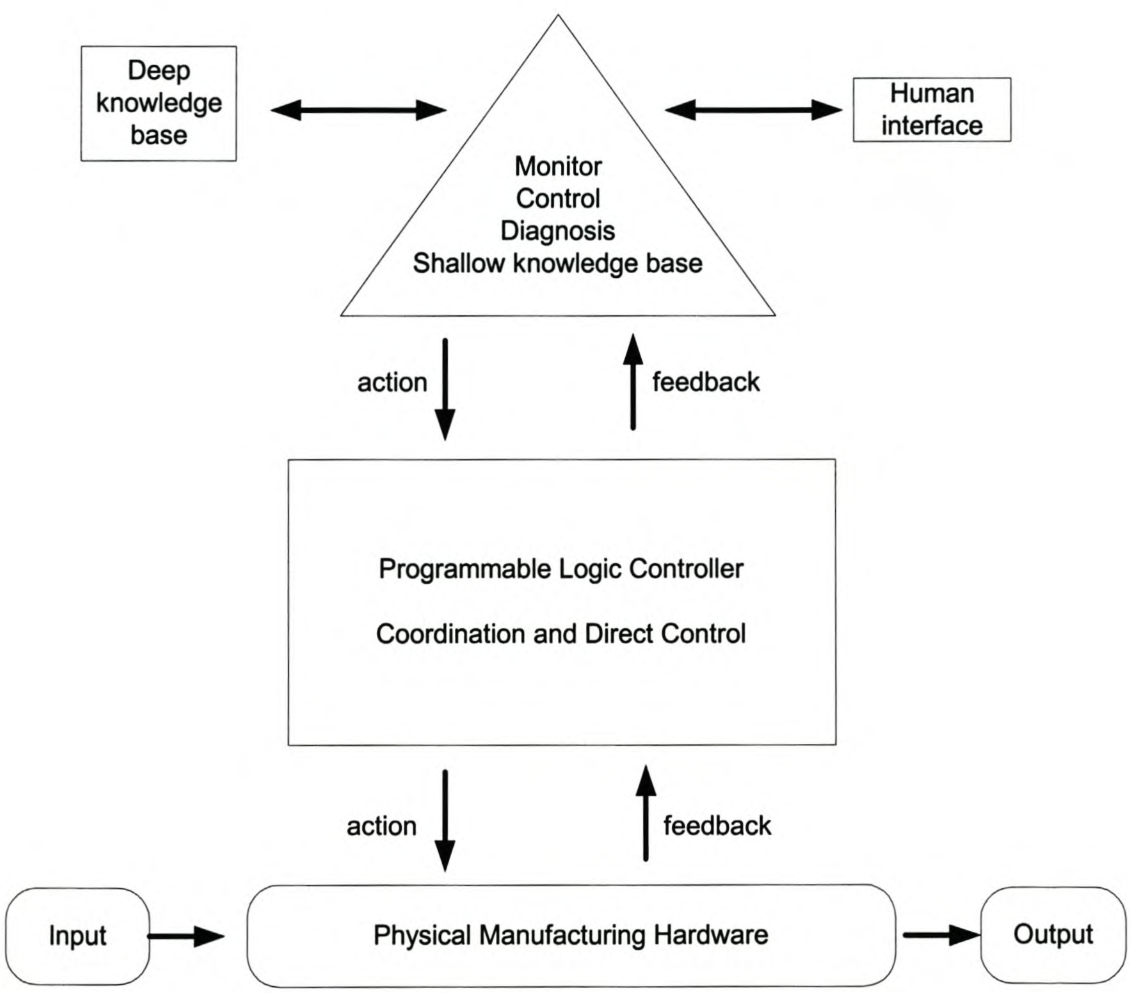

Fig. 2.5: CIM System with Monitoring and Diagnosis [18].

2.8 Summary

This chapter presents the three important aspects of manufacturing, namely intelligence, integration and remote monitoring. It is shown that there exist many similarities between human and manufacturing related intelligence. This creates a sound platform from which manufacturing intelligence will be analysed in chapters 3 and 4. The reasons for and the elements of integration are also presented from different viewpoints. Remote monitoring is briefly discussed and its importance to productivity improvement is shown.

The discussion of these three key concepts show that individually each can contribute to the improvement of the performance of manufacturing systems. It is however suggested that these improvements are not individually sufficient to ensure market leadership and global competitiveness. It is further suggested that the three concepts will, when implemented in combination in a system, exhibit a final result, which will prove to be synergeous and result in improvements exceeding that of the three individual results. The investigation into this suggestion will form a major part of this work.

CHAPTER 3

A FRAMEWORK FOR SYNERGY IN A MANUFACTURING ENVIRONMENT

Chapter Overview: The focus of this chapter is on the synergy between integrated systems and intelligent manufacture. The external behaviour of systems is examined to determine whether they show programmed, semi-intelligent or intelligent behaviour. The specific features of intelligent behaviour of systems are discussed. The outline for a general theory on manufacturing intelligence is formulated.

3.1 External behaviour of Manufacturing Systems

The external behaviour of manufacturing systems can be classified according to their ability to handle uncertain conditions [1]. The following three broad categories are identified: programmed behaviour, semi-intelligent behaviour and intelligent behaviour.

Programmed behaviour is exhibited by manufacturing systems capable of achieving specified goals or sustaining desired behaviour but only under predictable conditions. The manufacturing wealth of the past was built on production lines and automated manufacturing systems exhibiting programmed behaviour and characterised by precision and repeatability. However, it is now becoming increasingly difficult and expensive to construct rigid, deterministic operational environments for manufacturing systems (such as a mass production factory) and as a consequence, conventional automated manufacturing systems are being phased out.

Semi-intelligent behaviour is exhibited by manufacturing systems capable of achieving specified goals or sustaining desired behaviour under well-defined variable conditions. The term semi-intelligence is used here to describe self-regulation, the most elementary behaviour that may appear externally as intelligent. It denotes the capability of a system to achieve and sustain the desired behaviour when working in an environment that changes in time in a limited way. The characteristics that change, the range of measurable changes, and the way in which the system should respond to any particular change are known in advance. Only the timing and the magnitude of changes (within a given range) are unpredictable. For purposes of self-regulation, a manufacturing system may monitor one or several measurable physical characteristics, called variables, such as position on work table, distance of cutting tool from the work piece, direction of spindle movement, spindle speed, acceleration and deceleration, cutting fluid pressure, liquid level of cutting fluid, thickness and composition. Whatever the variable or the set of variables, the mechanism of self-regulation is always the same via the feedback loop.

Demands for semi-intelligent manufacturing systems are increasing. Sensors are now being built into a variety of manufacturing systems that were previously programmed to behave in a strictly predictable fashion. These sensors provide the required feedback loop and enable the manufacturing systems to function in a semi-intelligent manner.

Intelligent behaviour is exhibited by manufacturing systems capable of achieving specified goals or sustaining desired behaviour under conditions of uncertainty. Intelligent manufacturing systems can operate even in poorly structured environments, i.e. the environments in which variable characteristics are not measurable, where several characteristics change simultaneously and in unsuspected ways, and where it is not possible to predict in advance how the system should respond to every combination of events. An example of this would be a situation where a mobile robot must distinguish between a person and a piece of furniture in a workshop in which it operates.

3.2 Features of intelligent behaviour

When attempting to describe intelligent behaviour in manufacturing systems, a list of features is proposed [1]. This exhibits a strong resemblance to the seven kinds of intelligence proposed by Gardner as discussed in Chapter 2. At present there is no strong demand for comprehensive intelligent behaviour, in other words, behaviour that would encompass all the feature described in this list. As the ability to design intelligent behaviour improves, that demand would no doubt change. The implication is that ways should be found of adding features of intelligent behaviour incrementally. This is also true for the validation model described in Chapter 4. The model has many features of those listed below but will not include the full list. Where a feature is included, reference to the model in Chapter 4 will be made.

3.2.1 Adaptability

This feature implies that the system is capable of changing its behaviour to accommodate unpredictable changes in its environment, e.g. a vehicle which is capable of spotting an unexpected obstacle and, in spite of its presence, will still reach its given destination. This system is considered to be adaptable.

Another example which is more in line with the system under discussion, can be called manufacturing adaptability. This may be defined as the number of different types of operations that a machine can accept without requiring major operation changeover cost and/or long operation changeover times. This may be measured in terms of a percentage value and then applied in calculating an overall system intelligence.

As a first order example, the following is suggested with reference to time:

$$System\ \ Adaptability = 1 - \frac{Avg.\ setup\ \ time}{Avg.\ time\ \ of\ \ production\ \ run} \quad \ldots\ldots\ldots\ldots(3.1)$$

When considering cost as basis, the equation could be written as follows:

$$System\ \ Adaptability = 1 - \frac{Idle\ \ Cost\ \ of\ \ equipmeny}{Cost\ \ of\ \ output\ \ of\ \ production\ run} \quad \ldots\ldots\ldots(3.2)$$

This of course is a simplification of the complexity of the total system by referring only to the manufacturing equipment as the main contributor to the equation. Various other types of adaptability like material handling adaptability, routing adaptability and volume adaptability have equal importance and can also be used to assign an analytical magnitude to system adaptability.

In the case of the validation model discussed in Chapter 4, adaptability is evident in the manner with which the neural network that controls the mobile robot is able to adapt to the happiness state of the machines that it services. When the machines are "happy", in other words supplied with material, the systems adapts to that state and learns to make decisions that maintains this state of happiness.

3.2.2 Self maintenance

The system is capable of maintaining its own state of operational readiness by means of self-diagnosing, preventive self-maintenance and self-repair by reconfiguration, e.g. a machine tool that identifies a faulty component and reconfigures itself by replacing the faulty part with a stand-by component is deemed capable of self-maintenance.

A self-maintaining system requires:

- A robust platform that provides online self-testing and self-analysis of its hardware and software.
- Easy incremental scalability when existing resources stop providing desired quality of service.
- Rapid detection of anomalous behaviour and changes in the system environment.
- Fast and flexible reaction to detected conditions.
- Flexible specifications of conditions that trigger adaptation.

When studying the latest trends in self-maintaining systems [19], self-maintenance can roughly be divided into two components: Reactive self-maintenance and Proactive self-maintenance. Reactive self-maintenance implies dynamic reaction to exceptional system events and has self-diagnosing and self-monitoring hardware, software monitoring and problem detection and automatic reaction to detected problems. Proactive self-maintenance means the system can carry out continuous online self-testing and self-analysis and this is done by automatic characterisation of system components, in situ fault injection, self-testing and exercising rarely-taken application code paths before they are used.

The effectiveness of a self-maintenance system can be measured as follows:

$$\gamma = \frac{T_T - T_D}{T_T} \qquad \text{..(3.3)}$$

Where: $\boldsymbol{\gamma}$ = Effectiveness of self-maintenance system

$\boldsymbol{T_T}$ = Total available productive time

$\boldsymbol{T_D}$ = Downtime on self-maintenance system

The model discussed in Chapter 4 does not have the feature of self-maintenance but could very easily be added in the form of an expert system capable of following a decision-tree reasoning structure to self-analyse and self-maintain its subsystems.

3.2.3 Communication

The system is capable of exchanging information with other systems via a communication network with a view to exercise control over, to report to, to receive instructions from, to engage in competition or to collaborate with other systems. Machines or systems may be designed to operate in collectives, in which every constituent element obeys precisely defined rules of collaboration, or in societies in which artificially intelligent agents negotiate collaborative or competitive arrangements among themselves.

A communication network can be considered as the backbone of an intelligent system. Networks help companies to link all their computerised devices irrespective of their physical location. Through these networks, the whole enterprise can be integrated, including suppliers and customers. To provide these facilities, well-developed enterprise networks on three distinct levels are necessary [20]:

- Device-level subnetworks on the shop floor that connect individual devices such as robots and numerical control machines.
- Plant-wide networks that connect cells and other departments.
- Enterprise-wide networks that can globally link various plants/sites and interconnect corporations through electronic data interchange.

When selecting the appropriate network technology, a number of factors should be considered like communication medium, network topology, medium access control methods and signalling method. Some of the popular network topologies are shown in Fig. 3.1.

The validation model in Chapter 4 makes use of a device-level subnetwork that links the mobile robot to the main computer.

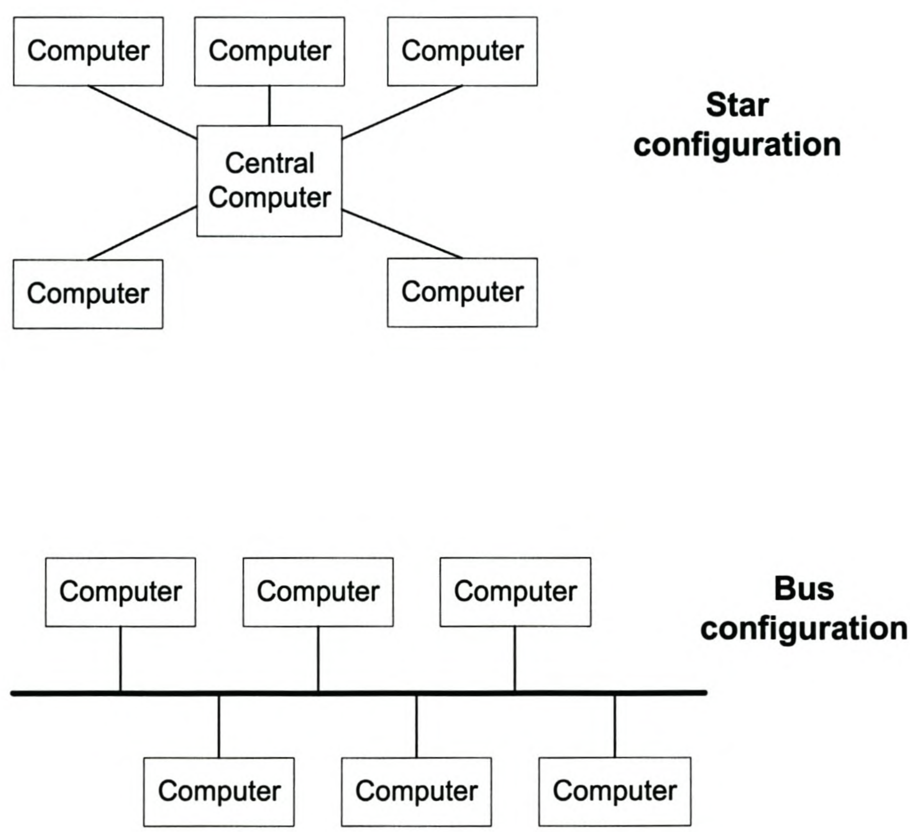

Fig. 3.1: Some network topologies

3.2.4 Autonomy

The system is capable of acting independently from other systems, including human operators. Autonomous manufacturing systems are capable of operating only in well-defined environments such as the environment of a factory.

Autonomous manufacturing is based on the creation of a manufacturing holon [21]. A holon is defined as an autonomous and cooperative building block of a manufacturing system for transforming, transporting, storing and/or validating information and physical objects. Autonomy is further defined as the capability of an entity to create and control the execution of its own plans and/or strategies.

Recent research has shown that a further entity is required to fully deploy the concept of autonomy. This entity is known as an agent and is defined as a computing system that can autonomously react and reflexively respond to the impacts from the environment in accordance with its given goals [22]. This leads to the possibility of defining the degree of autonomy of a system, which is defined as the number of decisions made by local decision makers (agents) divided by the total number of potential strategies. This shows that autonomy is related to the agent's capability to handle decisions. By following this concept, the following equation gives an analytical definition for agent autonomy.

$$\alpha_i = \theta_i / \Theta \qquad \text{.........................(3.4)}$$

Where: α_i = Degree of autonomy for agent $\boldsymbol{i}$

θ_i = Number of strategies that agent $\boldsymbol{i}$ can adopt

$\boldsymbol{\Theta}$ = Total number of potential strategies in an agent-based manufacturing system

The neural network of the validation model can be classified as an agent acting autonomously from the rest of the system and is able to arrive at a number of strategies independently from the main system. The degree of autonomy could therefore be calculated.

3.2.5 Learning

The system is capable of being trained to carry out certain tasks. Learning not only implies memorising, but also correct interpretation of context-dependant meanings. It can be said that an accounting program has learned something if it can recognise that the pattern of characters "petrol" means a category of travel expenses.

In nature, experience changes the state or an organism in such a way that the new state enables it to do better in subsequent situations. The classical name for this process is learning. An important parameter in the classification of learning strategies is the degree of inference required on the part of the learner. A widely accepted classification scheme spanning the spectrum from no inference required to a great deal is:

- Rote learning
- Learning by instruction
- Learning by deduction
- Learning by analogy
- Learning by induction

Rote learning is the lowest level of both human and machine learning. In machine learning it corresponds to knowledge being represented directly in the system by programming or simple database systems. No further processing or transformations on the data are required in order to use it. The performance of systems employing rote learning may be enhanced by selectively forgetting knowledge that is rarely used or proves to be incorrect.

In **learning by instruction**, knowledge is acquired from a teacher or textbook and is transformed by the learning system into an internal representation applicable to the problem at hand. The primary responsibility of structuring and representing knowledge remains with the teacher, but the learner must perform some inference in order to transform the knowledge into a readily usable representation. The learner's role in this mode of learning may be considered to be that of performing a syntactic reformulation of the knowledge provided by the primary source.

Learning by deduction shifts even more responsibility for transforming knowledge into a usable form from the teacher to the learner. The constraints on knowledge representation from the source are relaxed. The learner draws deductive inferences from the knowledge and reformulates it in the form of useful conclusions that preserve the information content of the original data. Deductive learning includes knowledge reformulation, compilation and organisational procedures.

The mode of learning known as **learning by analogy** combines deductive and inductive learning. The first step is the inductive inference required to find the common substructure between the problem domain and one of the analogous domains stored in the learner's existing knowledge base. The next step is to map the solution from the selected analogous domain to the problem domain using deductive logic.

Inductive learning is the classification of a set of experiences into categories or concepts. The concepts to be learned are given by the teacher or emerge as similarities in experience are noticed. From one or more instances in which a particular action was the appropriate action in at response to a situation, it is inferred that a generalised form of this action is appropriate in response to this general situation type.

Reinforcement learning is learning what to do so as to maximise a numerical reward. It is a learning technique that encourages actions that reap the most reward. The distinguishing factor of reinforcement learning is the emphasis on learning by the individual from direct interaction with its environment. This is the learning technique that is used by the validation model in Chapter 4. The model is implemented in a simulated manufacturing environment. The neural network controls a mobile robot that has to deliver material from a storeroom to a number of machines. Each machine has a state of "happiness" which is determined by the amount of material it has. The further a machine's material level deviates from the optimum, the lower the state of happiness is. The entire systems state is the sum of every machine's state.

It is up to the neural network to maintain the best possible state for the system. Every decision it makes is evaluated to see whether it improved or worsened the system state. Depending on whether a decision was good or bad, a teacher "rewards" the neural network so as to encourage it to make good decisions and discourage it from making bad decisions.

Such a model requires a critic that evaluates the decisions. The critic uses a benchmark that divides good decisions from bad decisions. Any decision that causes the state to increase above the benchmark is considered bad whereas a decision that causes the state to drop below the benchmark is considered good.

3.2.6 Self-improvement

The system is capable of improving its own future performance based on past performance combined with learning from other agents or human operators. Self-improvement requires collecting information from its own behaviour, analysing it, deconstructing established behavioural patterns and constructing new ones that are likely to be more effective.

The validation model is not equipped with the feature of self-improvement.

3.3 Outline for a theory on manufacturing intelligence

The discussion of the features of intelligent behaviour in manufacturing in the previous section shows that intelligence can be built into a manufacturing system. However, these are only the features and now the question arises of how these features can be represented in a manufacturing system and how they can contribute to the synergy of the system. This leads to the study of the theories used to define and limit the field of manufacturing intelligence. The objective of this section is therefore to describe a model through which intelligent behaviour in a system can be explained. This in turn leads to the building of a validation model which is the main theme of Chapter 4.

The study of intelligent manufacturing systems and the neurosciences are both extremely active fields [23]. Much time and money is spent on computer-integrated manufacturing, robotics and intelligent manufacturing systems for a wide variety of military and commercial applications. Around the world, researchers in the neurosciences are searching for the anatomical, physiological and chemical basis of behaviour. Progress is rapid and there exists an enormous and rapidly growing amount of literature in the different fields.

As mentioned above, an attempt is made to formulate the broad outlines of a general model of intelligence to tie all the separate features of intelligence into a unified framework. The ultimate goal is a general theory of intelligence that encompasses both biological and manufacturing systems. This theory will then form the basis of the proposed validation model as discussed in Chapter 4.

The model is described in terms of definitions, axioms, theorems, hypotheses, conjectures and arguments in support of them. A short redefined overview of the core parts of the model is now given.

3.3.1 Definition of intelligence

Although various definitions of intelligence have been given in previous chapters, it serves a purpose to repeat some of the key concepts and to add some new ideas on intelligence. This is done to align the concepts of machine capabilities with those of intelligence.

In this sense, a useful definition of intelligence should span a wide range of capabilities, from those that are well understood, to those that are beyond comprehension as well as both biological and machine embodiments. With this in mind, intelligence can be re-defined as:

> *Intelligence is the ability of a system to act appropriately in an uncertain environment, where appropriate action is that which increases the probability of success, and success is the achievement of behavioural subgoals that support the system's ultimate goal.*

Both the criteria of success and the system's ultimate goal are defined external to the intelligent system. For an intelligent machine system, designers, programmers and operators typically define the goals and success criteria. For intelligent biological creatures, the ultimate goal is gene propagation and the processes of natural selection define success criteria.

> *Theorem: There are degrees, or levels of intelligence, and these are determined by:*
>
> 1) *the computational power of the system's brain (or computer),*
> 2) *the sophistication of algorithms the system uses for sensory processing, world modelling, behaviour generating, value judgement and global communication, and*
> 3) *the information and values the system has stored in its memory*

Intelligence can be observed to grow and evolve both through growth in computational power and through accumulation of knowledge of how to sense, decide and act in a complex and changing world. In artificial systems, growth in computational power and the accumulation of knowledge derives mostly from human hardware engineers and software programmers. In natural systems, intelligence grows, over the lifetime of an individual, through maturation and learning and over intervals spanning generations, through evolution. Learning is not required in order to be intelligent, only to become more intelligent as a result of experience. Learning is defined as consolidating short-term memory into long-term memory and exhibiting altered behaviour because of what was remembered.

3.3.2 The function of intelligence

> *Theorem: Natural intelligence, like the brain in which it appears, is a result of the process of natural selection.*

The brain is primarily a control system. Its primary function is to produce successful goal-seeking behaviour in finding food, avoiding danger, competing for territory, etc. All brains that ever existed, even those of the tiniest insects, generate and control behaviour. Some brains produce only simple forms of behaviour, while others produce very complex behaviours. Only the most recent and highly developed brains show any evidence of abstract thought.

Theorem: For the individual, intelligence provides a mechanism for generating biologically advantageous behaviour.

Intelligence improves an individual's ability to act effectively and choose wisely between alternative behaviours. All else being equal, a more intelligent individual has many advantages over less intelligent rivals. Higher levels of intelligence produce capabilities in the individual for thinking ahead, planning before acting and reasoning about the probable results of alternative actions.

Theorem: For groups of individuals, intelligence provides a mechanism for co-operatively generating biologically advantageous behaviour.

The intellectual capacity to simply congregate into flocks, herds, schools and packs increases the number of sensors watching for danger. The ability to communicate danger signals improves the survival probability of all individuals in the group. Communication is most advantageous to those individuals who are the quickest and most discriminating in the recognition of danger messages and most effective in responding with appropriate action.

3.3.2.1 Communication and language

Definition: Communication as the transmission of information between intelligent systems and language as the means by which the information is encoded for purposes of communication.

Language has three basic components: vocabulary, syntax and semantics. Vocabulary is the set of words in the language. Words may be represented by symbols. Syntax, or grammar, is the set of rules for generating strings of symbols that form sentences. Semantics is the encoding of information into meaningful patterns or messages. Messages are sentences that convey useful information. Communication requires that information be:

1) encoded
2) transmitted
3) received
4) decoded and
5) understood

Communication may be either intentional or unintentional. Intentional communication occurs as the result of a sender executing a task whose goal it is to alter the knowledge or behaviour of the receiver to the benefit of the sender. Unintentional communication occurs when a message is unintentionally send, or when an intended message is received and understood by someone other than the intended receiver.

Theorem: In any species, language evolves to support the complexity of messages that can be generated by the intelligence of that species.

Depending on its complexity, a language may be capable of communicating many messages, or only a few. More intelligent individuals have a larger vocabulary and are quicker to understand and act on the meaning of messages.

Theorem: To the receiver, the benefit, or value, of communication is roughly proportional to the product of the amount of information contained in the message, multiplied by the ability of the receiver to understand and act on the information, multiplied by the importance of the act to survival of the receiver. To the sender, the benefit is the value of the receiver's action to the sender, minus the danger incurred by transmitting a message that may be intercepted by, and give advantage to, an enemy.

Greater intelligence enhances both the individual's and the group's ability to analyse the environment, to encode and transmit information about it, to detect messages, to recognise their significance and act effectively on information received. Greater intelligence produces more complex language capable of expressing more information, i.e. more messages with more shades of meaning.

Among humans, primitive forms of communication include facial expressions, cries, gestures, body language and pantomime. The human brain is, however, capable of generating ideas of much greater complexity and subtlety than can be expressed through cries and gestures. In order to transmit messages commensurate with the complexity of human thought, human languages have evolved grammatical and semantic rules capable of stringing words from vocabularies consisting of thousands of entries into sentences that express ideas and concepts with exquisitely subtle nuances of meaning. To support this process, the human vocal apparatus has evolved complex mechanisms for making a wide variety of sounds.

3.3.2.2 Human intelligence and technology

In recent millennia, human levels of intelligence have led to the use of fire, the domestication of animals, the development of agriculture, the rise of civilisation, the invention of writing, the building of cities, the practice of war, the emergence of science and the growth of industry. Intelligence has thus made modern civilised humans the dominant species on the planet.

3.3.3 The elements of intelligence in a system

> *Theorem: There are four system elements of intelligence: sensory processing, world modelling, behaviour generation and value judgement. Input to, and output from, intelligent systems are via sensors and actuators.*

3.3.3.1 Actuators

Output from an intelligent system is produced by actuators that move, exert forces and position arms, legs, hands and eyes. Actuators generate forces to point sensors, excite transducers, move manipulators, handle tools, steer and propel locomotion. An intelligent system may have hundreds or even millions of actuators, all of which must be co-ordinated in order to perform tasks and accomplish goals. Actuators are muscles and glands. Machine actuators are motors, pistons, valves, solenoids and transducers.

3.3.3.2 Sensors

Input to an intelligent system is produced by sensors, which may include visual brightness and colour sensors; tactile, force, torque, position detectors; velocity, vibration, acoustic, range, smell taste, pressure and temperature measuring devices. Sensors may be used to monitor both the state of the external world and the internal state of the intelligent system itself. Sensors provide input to a sensory processing system.

3.3.3.3 Sensory processing

Perception takes place in a sensory processing system element that compares sensory observations with expectations generated by an internal world model. Sensory processing algorithms integrate similarities and differences between observations and expectations over time and space so as to detect events and recognise features, objects, and relationships in the world. Sensory input data from a wide variety of sensors over extended periods of time are fused into a consistent unified perception of the state of the world. Sensory processing algorithms compute distance, shape, orientation, surface characteristics, physical and dynamical attributes of objects and regions of space. Sensory processing may include recognition of speech and interpretation of language and music.

3.3.3.4 World model

The world model is the intelligent system's best estimate of the state of the world. The world model includes a database of knowledge about the world, plus a database management system that stores and retrieves information. The world model also contains a simulation capability that generates expectations and predictions. The world model thus can provide answers to requests for information about the present, past and probable future states of the world. The world model provides this information service to the behaviour generating system element, so that it can make intelligent plans and behaviour choices, to the sensory processing system element, in order for it to perform correlation, model matching and model based recognition of states, objects and events and to the value judgement systems element in order for it to compute values such as cost, benefit, risk, uncertainty, importance, attractiveness, etc. The world model is kept up-to-date by the sensory processing systems element.

3.3.3.5 Value judgement

The value judgement system element determines what is good and bad, rewarding and punishing, important and trivial, certain and improbable. The value judgement system evaluates both the observed state of the world and the predicted results of the hypothesised plans. It computes costs, risks, and benefits both of observed situations and of the planned activities. It computes the probability of correctness and assigns believability and uncertainty parameters to state variables. It also assigns attractiveness, or repulsiveness to objects, events, regions of space, and other creatures. The value judgement system thus provides the basis for making decisions-for choosing one action as opposed to another, or for pursuing one object and fleeing from another. Without value judgements, any artificially intelligent system would soon be disabled by its own inappropriate actions.

3.3.3.6 Behaviour generation

Behaviour results from a behaviour generating systems element that selects goals and plans and executes tasks. Tasks are recursively decomposed into subtasks, and subtasks are sequenced so as to achieve goals. Goals are selected and plans generated by a looping interaction between behaviour generation, world modelling, and value judgement elements. The behaviour generating system hypothesises plans, the world model predicts the results of those plans and the value judgement element evaluates those results. The behaviour generating system then selects the plans with the highest evaluations for execution. The behaviour generating system element also monitors the execution of plans and modifies existing plans whenever the situation requires.

Each of the above system elements of intelligence is reasonable well understood. The phenomenon of intelligence, however, requires more than a set of disconnected elements. Intelligence requires an interconnecting system architecture that enables the various system elements to interact and communicate with each other in intimate and sophisticated ways.

A system is what partitions the system elements of intelligence into computational modules and interconnects the modules in networks and hierarchies. It is what enables the behaviour generation elements to direct sensors and to focus sensory processing algorithms on objects and events worthy of attention, ignoring things that are not important to current goals and task priorities. It is what enables the world model to answer queries from behaviour generating modules and makes predictions and receives updates from sensory processing modules. It is what communicates the value state-variables that describe the success of behaviour and the desirability of states of the world from the value judgement element to the goal selection subsystem. It is through the incorporation into a system that enables intelligence to create the synergy. It enhances the features of an integrated manufacturing system.

3.3.4 A proposed architecture for a combined intelligent and integrated system

A comprehensive description of an integrated system was given in Chapter 2. The proposed system architecture for an intelligent system organises the elements of intelligence so as to create the functional relationships and integrated information flow as shown in Fig. 3.2.

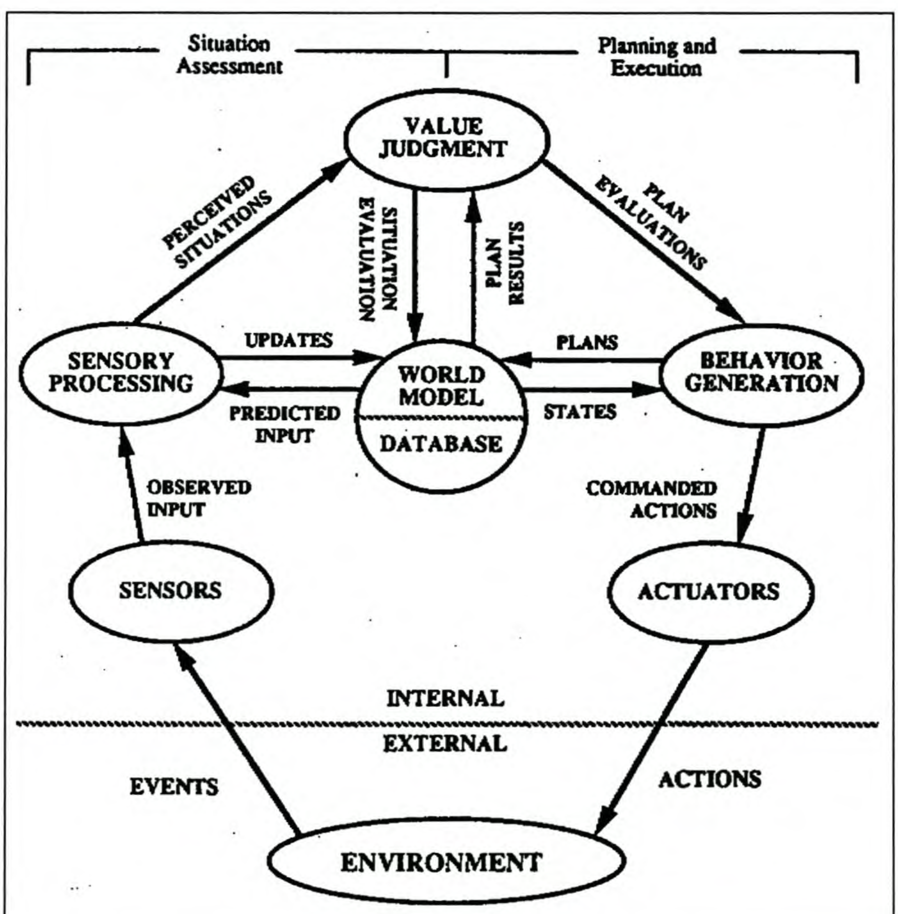

Fig. 3.2: Elements of intelligence and the functional relationships between them [23]

In all intelligent systems, a sensory processing system processes sensory information to acquire and maintain an internal model of the world of the external world. In all systems, a behaviour generating system controls actuators so as to pursue behaviour goals in the context of the perceived world model. In systems of higher intelligence, the behaviour generating system element may interact with the world model and value judgement system to reason about time and space, geometry and dynamics, and to formulate or select plans based on values such as cost, risk, utility and goal priorities. The sensory processing system element may interact with the world model and value judgement system to assign values to perceived entities, events and situations.

3.3.5 Behaviour generation

> *Definition: Behaviour is the result of executing a series of tasks*
>
> *Definition: A task is a piece of work to be done, or an activity to be performed*
>
> *Axiom: For any intelligent system, there exists a set of tasks that the system knows how to do.*

Each task in this set can be assigned a name. The task vocabulary is the set of task names assigned to the set of tasks the system is capable of performing. For creatures capable of learning, the task vocabulary is not fixed in size. It can be expanded through learning, training or programming. It may shrink from forgetting or program deletion. Typically, a task is performed by one or more actors on one or more objects. The performance of a task can usually be described as an activity that begins with a start event and is directed to a goal event. This is illustrated in Fig. 3.3.

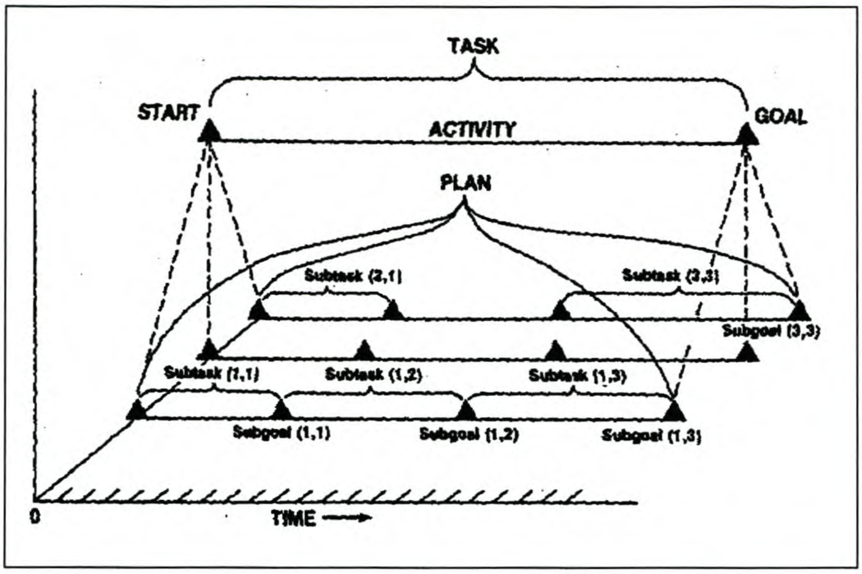

Fig. 3.3: Illustration of tasks, start and goal events and subtasks [23]

Definition: A goal is an event that successfully terminates a task. A goal is the objective toward which task activity is directed.

Definition: A task command is an instruction to perform a named task. Task knowledge is knowledge of how to perform a task, including information as to what tools, materials, time, resources, information, and conditions are required, plus information as to what costs, benefits and risks are expected.

Task knowledge may be expressed implicitly in fixed circuitry, either in the neuronal connections and synaptic weights of the brain, or in algorithms, software and computing hardware. Task knowledge may also be expressed explicitly in data structures, either in the neuronal substrate or in computer memory.

Definition: A task frame is a data structure in which task knowledge can be stored.

In systems where task knowledge is explicit, a task frame can be defined for each task in the task vocabulary. Fig. 3.4 shows an example of a task frame.

TASKNAME	name of the task
type	generic or specifi
actor	agent performing the task
action	activity to be performed
object	thing to be acted upon
goal	event that successfully terminates or renders the task successful
parameters	priority
	status (e.g. active, waiting, inactive)
	timing requirements
	source of task command
requirements	tools, time, resources, and materials needed to perform the task
	enabling conditions that must be satisfied to begin, or continue, the task
	disabling conditions that will prevent, or interrupt, the task
	information that may be required
procedures	a state-graph or state-table defining a plan for executing the task
	functions that may be called
	algorithms that may be needed
effects	expected results of task execution
	expected costs, risks, benefits
	estimated time to complete

Fig. 3.4: An example of a task frame [23]

Explicit representation of task knowledge in task frames has a variety of uses. For example, task planners may use it for generating hypothesised actions. The world model may use it for predicting the results of hypothesised actions. The value judgement system may use it for computing how important the goal is and how many resources to expend in pursuing it. Plan executors may use it for selecting what to do next.

Task knowledge is typically difficult to discover, but once known, can be readily transferred to others. Task knowledge may be acquired by trail and error learning, but more often it is acquired from a teacher or from written or programmed instructions.

In most cases, the ability to successfully accomplish complex tasks is more dependent on the amount of task knowledge stored in task frames (particularly in the procedure section) than on the sophistication of planners in reasoning about tasks.

3.3.6 Knowledge representation

The world model knowledge database contains both a priori information that is available to the intelligent system before action begins, and a posteriori knowledge that is gained from sensing the environment as action proceeds. It contains information about space, time, entities, events, and states of the external world. The knowledge database also includes information about the intelligent system itself, such as values assigned to motives, drives and priorities; values assigned to goals, objects, and events; parameters embedded in kinematic and dynamic models of the limbs and body; states of internal pressure, temperature, clocks and blood chemistry or fuel level.

Knowledge about space is represented in maps. Knowledge about entities, events, and states is represented in lists or frames. Knowledge about the laws of physics, chemistry, optics and the rules of logic and mathematics are represented as parameters in the functions that generate predictions and simulate results of hypothetical actions. Physical knowledge may be represented may be represented as algorithms, formulae, or as IF/THEN rules of what happens under certain situations, such as when things are pushed, thrown, dropped, handled or burned.

The correctness and consistency of world model knowledge is verified by sensory processing mechanisms that measure differences between world model predictions and sensory observations.

3.3.7 Value judgements

Value judgements provide the criteria for making intelligent choices. Value judgements evaluate the costs, risks and benefits of plans and actions and the desirability, attractiveness and uncertainty of objects and events. Value judgement modules produce evaluations that can be represented as value state variables. These can be assigned to the attribute lists in entity frames of objects, persons, events, situations and regions of space. They can also be assigned to the attribute lists of plans and actions in task frames. Value state variables can label entities, tasks and plans as good or bad, costly or inexpensive, as important or trivial, as attractive or repulsive, as reliable or uncertain. Value state-variables can also be used by the behaviour generation modules both for planning and executing actions. They provide the criteria for decisions about which course of action to take.

> *Definition: Priorities are value state-variables that provide estimates of importance.*

Priorities can be assigned to task frames so that planners and executors can decide what to do first, how much effort to spend, how much risk is prudent and how much cost is acceptable, for each task.

> *Definition: Drives are value state-variables that provide estimates of need.*

Drives can be assigned to the self-frame, to indicate internal system needs and requirements. In biological systems, drives indicate levels of hunger, thirst, etc. In mechanical systems, drives might indicate how much fuel is left, how much pressure is in a boiler, how many expendables have been consumed or how much battery charge is remaining.

3.3.8 Final remarks on the theory of intelligence

The theory of intelligence presented here is only an outline. It is far from complete. Most theorems have not been proven. Much of what has been presented is hypothesis and argument from analogy. Many important issues remain uncertain and many aspects of intelligent behaviour are unexplained.

Yet, despite its incomplete character and hypothetical nature, the suggested theory explains a lot. It brings together concepts from a wide variety of disciplines into a single conceptual framework. Intelligent systems research is seriously impeded because of the widely accepted theoretical framework. Even a common definition of terms like this one would present a major step forward.

The model presented here only suggests how the neural substrate could generate intelligence, and how computer systems might be designed so as to produce intelligent behaviour in manufacturing systems.

3.4 Final thoughts on the synergy between intelligence and the system

From the previous discussions, it becomes clear that there are several points of intersection between intelligence and its existence in an integrated system. It is these commonalities that explain the fact that intelligence becomes more powerful when functioning in a system and also that a system will perform at a higher level of effectiveness when it has some form of intelligence.

The next step is to use the framework as discussed in this chapter and construct a model of an integrated manufacturing system into which the features of intelligence is incorporated and to use this model as validation of the synergy of the key concepts of intelligence, integration and remote monitoring. This model forms the core of the next chapter.

CHAPTER 4

VALIDATION THROUGH EXPERIMENTAL APPROACH

Chapter Overview: This chapter attempts to present validation procedures for the principles of Integration, Intelligence and Remote Monitoring in certain manufacturing systems. An attempt is made to show how they are validated in a specific experimental procedure, independently as well as in an interactive manner.

4.1 Introduction

This chapter attempts to present a validation procedure for the principles of Integration, Intelligence and Remote Monitoring in advanced manufacturing. It shows how they could be validated in a specific experimental procedure, independently as well as in an interactive manner.

The meaning of *validation* is to make legally valid; to grant official sanction to; to confirm the validity of something or to declare something as true. To *validate* is to support or corroborate a theory on a sound or authoritative basis by experiments designed to show a hypothesis as being true. For a hypothesis to be true, it must be supported by objective truth or generally accepted authority. In its turn, *sound* implies a basis of flawless reasoning or of solid grounds with a power to overcome doubt, opposition or reluctance to accept.

Experimentation and data collection are the tools of science for validating theories [24]. The classical scientific method depends upon theory formation, followed by experimentation and observation of the results. This provides a feedback loop to validate, modify and improve on the theory. Most of these concepts developed in the so-called "theoretical sciences" like physics and chemistry where experiments are relatively simple to design and control. However, it is just as true for the more "practical sciences" like engineering (manufacturing), where the design of an experiment may involve more planning and data collecting.

The goal of an experiment is to collect enough data from a sufficient number of cases in order to obtain a statistically significant result on the attribute under observation. When developing an experiment, there are three aspects of data collection [25]:

- Replication: The most important attribute of the scientific method is to be able to replicate the results of an experiment to permit other researchers to reproduce the findings. In the experimental model, replication is made possible by the use of a commercially available software program with standard operating procedures. The neural network model is fixed and will produce standardised results with every repetition of the experiment.

- Local control: Refers to the degree to which the experiment can be modified locally. The experimental model allows for local control via the computer on which the model is running.
- Factorial design: Refers to the manner in which all possibilities are covered, thus if there are three factors to evaluate and each has two possible values, then six experiments have to be run. The experimental model has six parameters that determine its learning capabilities and each of these parameters are examined to determine its unique contribution. These parameters are the benchmark against which the critic evaluates the decisions, the reward at which the teacher adjusts the outputs, the greedy function, the number of epochs the network is trained, the maximum number of decisions the network is capable of differentiating and the network architecture (the number of layers and neurons). Refer to section 4.6 for more detail on the experimental set-up.

When designing the experiment to validate the principles of integration, intelligence and remote monitoring, the experimental category that is best suited uses a *controlled* method which provides for multiple instances and statistical validity of the results. This is the more classical concept of experimental design allowing for methods like replication, synthetic environment, dynamic analysis and simulation.

4.2 Validation of the key principles

In order to experimentally validate the three key principles, each principle is discussed in terms of the validation parameters.

4.2.1 Intelligence

As discussed in Chapter 1, one of the characteristics of manufacturing intelligence is the ability of a system to act appropriately in an uncertain environment to increase the probability of success of the system given the criteria of success. To validate this key principle, it is important to show through experimentation that a manufacturing system can act intelligently under uncertain conditions and thus increase the productivity of the system as measured against an appropriate benchmark.

When considering conventional manufacturing equipment such as robots, it is true that their main advantage is their precision and repeatability. However, the major weakness of such machines is its inability to handle unexpected occurrences. This requires efforts toward the building of "intelligent " machines because they are capable of overcoming unexpected problems. Consider the case of a welding robot on a car production line, programmed to perform a number of welds on the chassis. If the chassis is available and if it is correctly positioned, then the robot will be able to perform its task without interruption and with precision. If however the chassis is incorrectly positioned or not the correct type of chassis, an "unintelligent" robot would be unable to perform. An intelligent robot, on the other hand, could observe the unscheduled events, use artificial intelligence to determine an alternative process plan based on optimal output and then execute the plan.

Conventional control systems are generally able to cope with disturbances and changes like load changes, schedule changes and planned stoppages. However, a higher form of intelligent behaviour is required to handle an "unstructured" environment with unexpected changes. The system in this case must have the ability to use information and knowledge to "reason", thereby creating intelligence. The knowledge could include:

- Knowledge about goals and tasks.
- Knowledge about own capabilities.
- Knowledge of the environment in which the system is operating.

An intelligent machine is capable to achieve a goal or sustained behaviour under conditions of uncertainty [26]. Many techniques such as expert systems, fuzzy logic, neural networks and genetic algorithms are used to enable systems to perform intelligently. It is accepted that the competitiveness, growth and profitability of a company in future may depend on the level of its system intelligence. This is so because an intelligent system is able to act appropriately under rapidly changing conditions of customer customisation and demands on quicker throughputs.

Among the techniques mentioned above, *expert systems* have been around the longest and for this reason are probably the most mature. Expert systems are computer programs that are capable of storing knowledge about a narrow domain for solving problems in that domain. The system usually consists of three main elements: a knowledge base, an inference mechanism and a user interface. The domain knowledge is contained in the knowledge base and can be expressed as any combination of "IF – THEN" rules, factual statements, frames, objects, procedures and cases. The so-called inference engine is that part of an expert system that manipulates the stored knowledge to produce solutions to problems. Manipulation of knowledge is done by various methods like the use of inheritance and constraints, the retrieval and adaptation of case examples or the application of inference rules (forward chaining or backward chaining). The application of expert systems is extremely user-friendly because of the development of programs known as "shells". These are essentially ready-made expert systems complete with inferencing, knowledge storage and user interface but without the domain knowledge. Once the domain knowledge has been extracted and entered into the shell, the process of building the system is relatively easy. The ease with which expert systems can be developed in this way, has led to a large number of applications. In manufacturing, applications can be found for a variety of tasks including selection of materials, machine elements, tools, equipment and processes, signal interpretation, condition monitoring, fault diagnosis, machine and process control, machine design, process planning, production scheduling and system configuring.

One of the disadvantages of the ordinary rule-based expert systems is that they are unable to handle new or unknown situations which are not covered by the knowledge captured in their knowledge bases. This refers specifically to the conditions not fitting exactly those described in the "IF" parts of the rules. These systems are unable to formulate conclusions under uncertain conditions and are therefore considered as "shallow" systems which fail in a rather abrupt manner in comparison to human experts who would show a gradual reduction in performance when faced with increasingly unfamiliar problems. Because of this limitation, expert systems are not considered as truly "intelligent" systems as they cannot increase the performance of a system under uncertain conditions.

To overcome the inability of a system to handle unfamiliar problems, the use of fuzzy reasoning was suggested. *Fuzzy reasoning,* also referred to as *fuzzy logic,* is an application of fuzzy set theory. In classical crisp set theory, any element in the domain under discourse is either a member of a set or not a member of that set [27]. From this follows that a particular element fully belongs to a particular set (with a membership value of 1) or does not belong to that set at all (with a membership value of 0). No in-between values are possible. Contrary to this definition, fuzzy set theory states that a particular element can also partially belong to a given set, in other words have an in-between value. The degree to which that element belongs to the set is expressed in terms of the membership value having a value between 0 and 1.

This concept is illustrated in Fig. 4.1

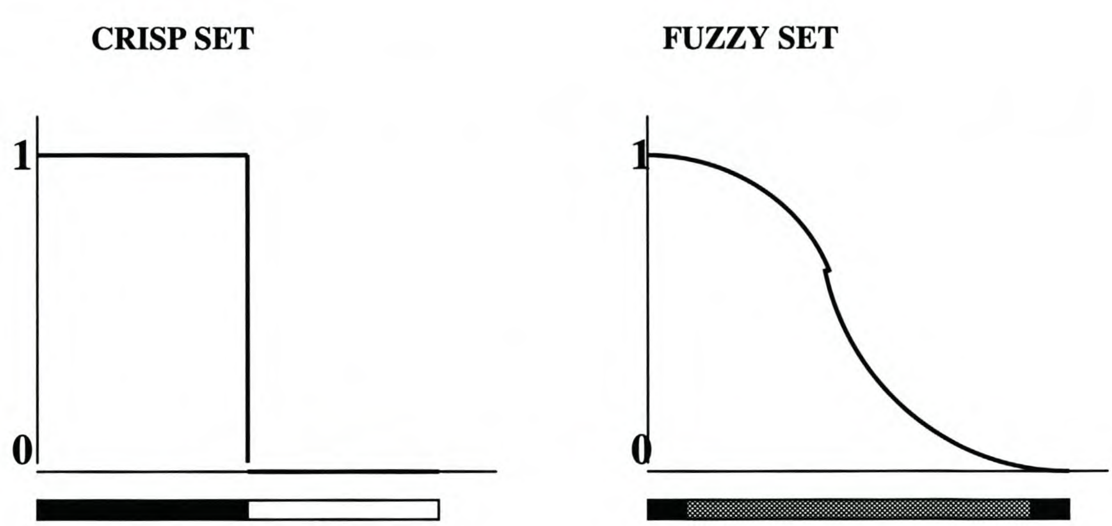

Fig. 4.1: Crisp Set vs. Fuzzy Set

In crisp set theory the transition of an element from belonging to a given set (membership = 1) to not belonging to that set (membership = 0) is described in terms of a step function. In fuzzy set theory, this transition is not necessarily a step function but rather a gradual change from belonging to a set to not belonging to that set. The function that describes this transition is referred to as the membership function.

With the above explanation in mind, the principle of fuzzy logic becomes clear. It differs from classic logic in the sense that it can use graded statements and not be limited by statements that can only be true or false. It can therefore operate in the grey area between true and false, and still produce a logical answer. This method of reasoning is very close to human reasoning. By using fuzzy set theory, linguistic terms can be translated into a format which can be directly interpreted by computer programs. This means that terms like "near", "far", "large" or "small" can now be defined as having a specific membership function and as such be recognised by a computer program like an expert system. These linguistic terms can be regarded as fuzzy terms. By using and qualifying these terms, human-type reasoning can be implemented for use by computers.

Fuzzy logic has the potential to be used in many manufacturing areas where the domain knowledge is usually imprecise. These include applications in areas of process control, machine control, object recognition and mobile robot control. In the last case, a typical control rule may be: "If the robot is *near* a corner, then turn *left*". The linguistic terms "near" and "left" is given membership functions, enabling the computer program to directly interpret this rule and act upon it.

The acquisition of domain knowledge to build into a knowledge base is usually complex and may take a lot of time. For this reason, automatic knowledge acquisition techniques have been developed to assist researchers and engineers in this task. *Rule induction* and *neural networks* are just two of these techniques.

Neural networks can capture domain knowledge from examples. However, on their own they cannot store the acquired knowledge in explicit form like rules and decision trees and therefore need some additional and artificial algorithms to do this.

Artificial neural networks (ANN's) are biologically inspired computer programs designed to simulate the way in which the human brain processes information [28]. These networks collect their knowledge by detecting patterns and relationships in information and are then trained to react through experience and not through programming. An ANN is formed from hundreds of single units, artificial neurons or processing elements, connected with coefficients (or weights) which then make up the neural structure.

Once the structure of the network has been established, the power of neural computations comes into play and is because of the fact that the neurons (or processing elements) are connected in a network. Each processing element has weighted inputs, a transfer function and one output. The behaviour of a neural network is determined by the transfer functions of its neurons, by the learning rule, and by the architecture itself. Two types of architecture are identified according to the use of feedback or not. These two types are feedforward and feedback and are shown in Fig. 4.2.

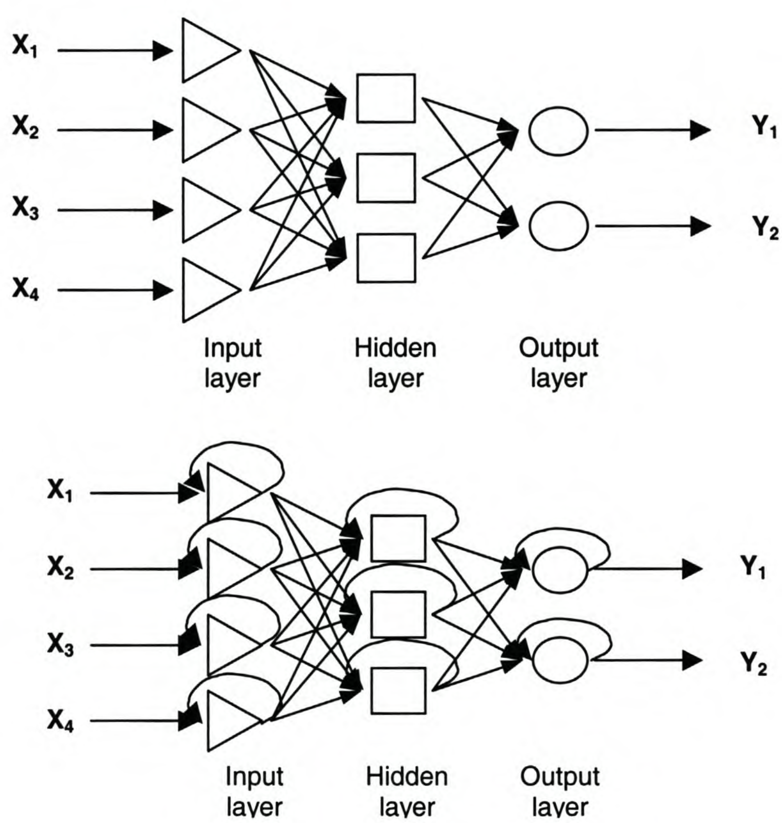

Fig. 4.2: Feedforward and feedback networks [28].

The weights are the adjustable parameters and, in that sense, a neural network is a parameterised system. The weighed sum of the inputs creates an activation signal which is passed through transfer functions to produce a single output of the neuron. This can be illustrated as shown in Fig. 4.3.

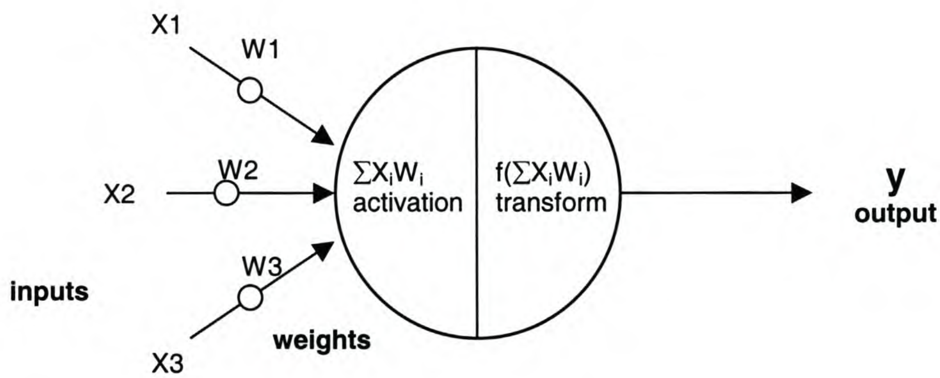

Fig. 4.3: Model of an artificial neuron [28].

Domain "knowledge" can now be built into the neural network by training it. Some neural networks can be trained by being presented with typical input patterns and the corresponding expected output patterns. The error between the actual and the expected results is used to modify the strengths (or weights) of the connecting parameters between the neurons. In this way, the inter-unit connections are optimised until the error in predictions is minimised and the network reaches the specified level of accuracy. This level of accuracy can also be some sort of benchmark against which the output is measured.

Once the network is trained and tested it can be given new input information to predict the output. Artificial neural network represents a promising modelling technique, especially for data sets having non-linear relationships. In terms of model specification, artificial neural networks require no knowledge of the data source but, since they often contain many weights that must be estimated, they require large training sets. In addition, artificial neural networks can combine and incorporate both literature based and experimental data to solve problems.

In the case of the validation model described in section 4.5, the neural network is a multilayer feedforward network that uses the backpropagation training method. It is used to schedule the distribution of material to a number of machines. The state of machine loading is used as input parameters to the neural network, which then makes a decision on how to carry on with the scheduling. If a good decision is taken, the network learns to repeat the pattern, if a bad decision is taken, the network learns to avoid similar decisions. In this manner, the neural network is trained to use "intelligence" to make good decisions. The model is thus used to validate the concept of intelligence.

Another artificially intelligent technique that is used in manufacturing is *genetic algorithms.* They are optimisation techniques based on evolution or rules of natural selection [29] and can yield the global optimum solution in a complex multimodal search space without requiring specific knowledge about the problem to be solved. In this technique, the population of the domain is the set of all possible solutions. Each individual (or solution) of this population is represented by a string of numbers (usually binary) called chromosomes. The possibilities of survival of each chromosome are evaluated by the cost function (function to be optimised). For a genetic algorithm to work, there must be a means of determining the goodness or fitness of each chromosome.

The genetic algorithm operates on a group or population of chromosomes at a time, repeatedly applying genetically-based operators such as cross-over and mutation to produce fitter populations containing better solution chromosomes. Fig. 4.4 illustrates a simple genetic algorithm flowchart.

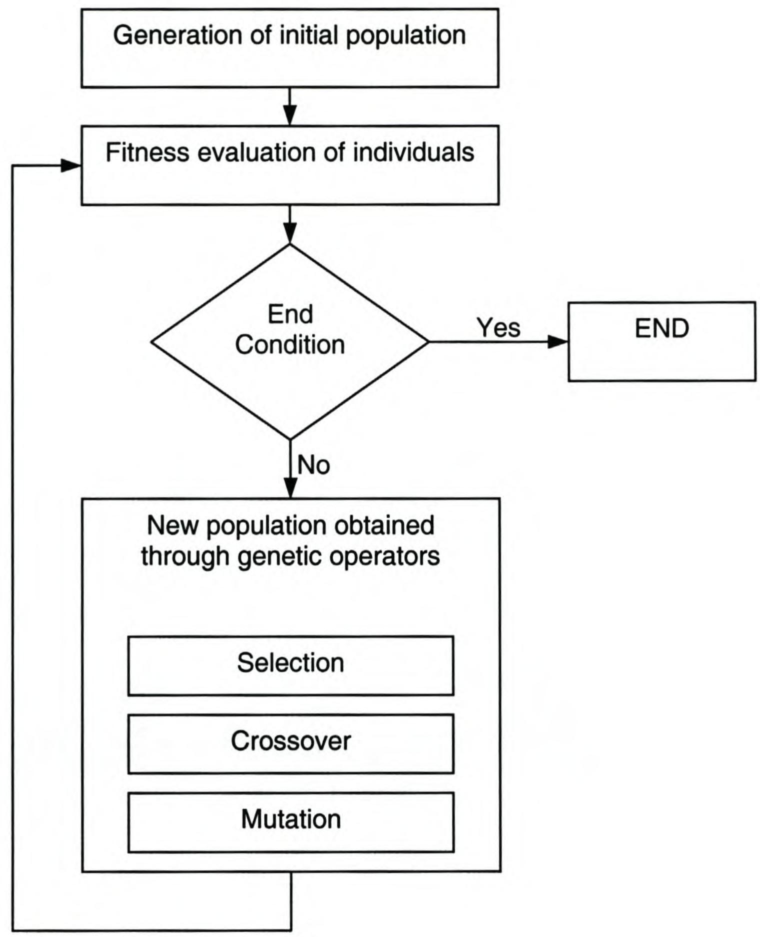

Fig. 4.4: A simple genetic algorithm flowchart.

The algorithm usually starts by generating an initial population (strings of numbers) using a random number generator. Each individual (chromosome) is then evaluated for fitness. If the condition is to be continued, a new population is obtained through the genetic operators (selection, crossover or mutation). The new population is again evaluated for fitness, and so the process is repeated until the user is satisfied with the solution.

There are many examples in manufacturing where genetic algorithms have been applied with success, especially problems involving complex combinations or multi-parameter optimisation [30]. Some recent applications include workstation design to minimise handling efforts of workers, path planning for mobile robots and fault diagnoses on complex systems.

4.2.2 Integration

The practical implementation of a manufacturing system's intelligence would not be possible without some form of system integration. Integration adds the ability to consolidate the various sub-systems of a system and to allow manufacturing data, information and knowledge to be collected, created, used and distributed.

To fully understand the role that integration plays in systems, it is of importance to comment on the progression of facts from data to intelligence.

Data is defined as: "… *factual information used as a basis for reasoning that includes both useful and irrelevant or redundant information and must be processed to be meaningful.*" This first of all implies that data is collected and then processed to generate information which is meaningful as well as useful. In an integrated manufacturing system it means that data is captured at shop floor level in numerical or digital format, transmitted via the local area network to the process control unit and then processed to generate manufacturing information.

Information is described as the communication or reception through which processed data is transformed into knowledge or intelligence. It is clear that knowledge cannot be created without the input of information. It is however of absolute importance that the available information is relevant to the specific domain. When sufficient information pertaining to the relevant manufacturing domain is available, knowledge can be created.

Knowledge can be seen as human understanding of a field of interest that has been acquired through education and experience [31], in this case the field of interest being the domain of the manufacturing system. Manufacturing knowledge therefore implies learning, creating awareness and familiarity with one or more domain subjects. This domain knowledge is made up of ideas, concepts, facts and figures, theories, procedures, relationships among these, and ways to apply these to practical problem solving within the manufacturing domain. However, in most manufacturing applications the kind of knowledge that works best and proves to be the most valuable is *heuristic* knowledge.

Heuristic knowledge refers to practical real world understanding of a given domain. It includes all of those tricks of the trade, rules of thumb and gimmicks that an expert uses to solve problems. Heuristic knowledge is not textbook or classroom knowledge, but instead it is that kind of knowledge that has been acquired through years of experience and exposure to a wide variety of manufacturing problems and situations. Heuristic knowledge lets experts solve problems quickly primarily because they know what works and what doesn't work in a given situation.

The final step in the integration process of facts is the transition of knowledge into intelligence. As discussed in chapter 2, there are many similarities between human intelligence and the use of artificial intelligence in manufacturing. The major similarities are:

- The ability to represent knowledge
- The ability and versatility to solve novel problems
- Proactive action based on survival
- Speed of response ensures competitiveness
- Creativity

Taking these similarities as background, some definitions of intelligence in manufacturing systems can be re-stated (with reference to chapter 2):

Manufacturing intelligence is the ability of a system to act appropriately in an uncertain environment to increase the probability of success of the system [10].

Property which enables a system to operate effectively when available information is incomplete/inadequate [1].

Adaptive ability on pseudo-decision making of a manufacturing system in an integrated environment [32].

These definitions clearly point to the fact that intelligence comes into being only when conditions are uncertain and only in an integrated environment.

The transition of facts from data to intelligence can now be represented as shown in Fig. 4.5:

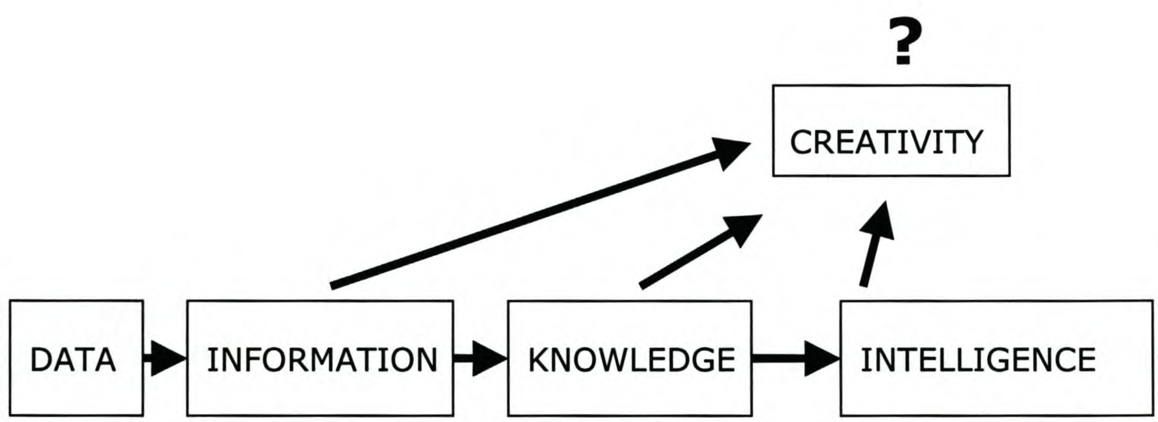

Fig. 4.5: Transition of facts from data to intelligence

Data about the manufacturing system is collected from the shop floor or from specifications or drawings. It is then collated and organised in a specific manner to form information. When this information is now grouped, reformatted and mined (information mining), relevant knowledge "nuggets" is created for use in a specified environment. If these nuggets are now used correctly to solve novel problems, intelligence comes into being. It remains a topic of discussion at which stage creativity comes into play and whether it can be recreated in an artificial manner.

From this discussion, it becomes clear that manufacturing intelligence is created from data through a transitional process and can only be done when all the relevant sub-systems are integrated in such a manner as to allow the bits and bytes of data to flow unimpeded through the system.

With reference to the validation model described in section 4.5, the flow and integration of data can be explained. The data on the machine states is collected by the counting sensors located at each machine. This data is transformed into information by the collating computer connected to (integrated with) the machines. The information is sorted and the present state of each machine is determined. This information is made available to the neural network in the form of selected bits of information (say, one specific machine), which uses this knowledge to generate a decision according to the feedback given by the reinforcement learning module. It learns to take only good decisions and thereby becomes intelligent. The whole process is made possible only by the fact that all elements of the system are connected (integrated) and that data is used as input with intelligence as a final result.

There are several ways of achieving *integration of technological sub-systems* in manufacturing. Some of these techniques are group technology, cellular manufacturing and flexible manufacturing.

Group Technology (GT) provides a higher level of integration by creating a link between design and manufacturing in such a way that product costs and lead times are reduced. GT is a philosophy that implies the notion of recognising and exploiting the design and processing similarities that exist among the parts to be processed in a manufacturing system [33]. The similarity in the characteristics of similar parts suggests that benefits can be obtained by classifying and coding these parts into families of parts. It is not unusual for a factory that produces 10 000 different parts to be able to group most of these parts into 20 to 30 part families. In each part family the processing steps are similar. When these similarities are exploited in manufacturing, operating efficiencies are improved. The improvements are typically achieved by organising the production facilities into manufacturing cells.

Cellular manufacturing (CM) is an application of group technology in manufacturing in which all or a portion of a company's manufacturing system has been converted into cells [20]. A manufacturing cell is a cluster of machines or processes located in close proximity and dedicated to the manufacture of a family of parts. Each cell is designed to produce one part family or a limited number of part families, thereby following the principle of specialisation of operations. The cell includes special production equipment and custom-designed tools and fixtures, so that the production of that part family can be optimised. This means that in effect, each cell becomes a factory within a factory. Integration is achieved by initially connecting two or three cells, thereby creating islands of integration. The interconnectivity is then extended to include more islands until the whole domain is integrated.

A flexible manufacturing system (FMS) is a highly automated GT machine cell, consisting of a group of processing stations, interconnected by an automated material handling and storage system, and controlled by an integrated computer system [34]. The FMS is capable of processing a variety of different part styles simultaneously at the different workstations. As with cellular manufacturing, FMS's rely on the principles of group technology and cannot therefore be completely flexible. In other words, an FMS is capable of producing a single part family or a limited range of part families.

To qualify as being flexible, a manufacturing system should satisfy several criteria. The tests of flexibility in an automated manufacturing system are the capability to:

- process different part styles in a non-batch mode;
- accept changes in a production schedule;
- respond optimally to equipment malfunctions and breakdowns in the system;
- accommodate the introduction of new part designs;
- act in an integrated manner with its components and other systems;
- allow for the use of machine intelligence.

By integrating these new technologies with innovative and flexible organisational designs like agile manufacturing, supply chain management and concurrent engineering, manufacturing firms are able to create and sustain levels of strategic flexibility and customer responsiveness. This will ultimately lead to more sustainable competitive advantage.

The term agile manufacturing came into common usage with the publication of the report 21st Century Manufacturing Enterprise Strategy by the Iacocca Institute [35]. The Iacocca Institute report had three key points:

- A new competitive environment is emerging, which is acting as a driving force for change in manufacturing.
- Competitive advantage will accrue to those enterprises that develop the capability to rapidly respond to the demand for high quality, highly customized products.
- To achieve the agility that is required to respond to these driving forces and to develop the required capability, it is necessary to integrate flexible technologies with a highly skilled, knowledgeable, motivated, and empowered workforce.

Agile manufacturing stresses the systems approach, integrating technology, organization and people [36]. Therefore, in a company, continuous change, rapid response, quality improvement, and social responsibility are implemented under the unifying umbrella of agile manufacturing. Agility and flexibility are closely related. In its most restricted form, flexibility refers to adaptability and versatility while agility is related to the speed that a system adapts. Flexibility is therefore a necessary condition for agility. The term agility stresses the importance of time-based competition and flexibility, and therefore agile manufacturing is seen as a new paradigm in manufacturing strategy.

The central idea of supply chain management is to apply a total system approach to managing the flow of information, materials and services from raw material suppliers through factories and warehouses to the end customer [37]. Recent trends like outsourcing and mass customisation are forcing companies to find flexible ways to meet customer demand. This ties in very well with the previous demands for agility and flexibility. The focus here however is on optimising core activities to maximise the speed of response to customer demands, which change continuously. As with agile manufacturing, the successful implementation of a supply chain management system depends on the level of integration in a company.

Concurrent engineering is one of the newer techniques to help achieve the objectives of reduced costs, better quality and improved delivery performance [20]. The U. S. Institute of Defense has defined concurrent engineering as follows:

Concurrent Engineering is a systematic approach to the integrated, concurrent design of products and their related processes, including manufacturing and support. This approach is intended to cause the developers, from the outset, to consider all elements of the product life cycle from conception to disposal, including quality, cost, schedule and user requirements.

The evolution of the product and the associated manufacturing and repair capabilities are treated as a single integrated activity from concept to delivery. This idea is in contrast with the current industry standard which dictates that a sequential engineering technique be followed with the associated restrictions on flexibility and agility.

It is clear from the above that there are many similarities among these managerial principles, the major similarity being that integration is a prerequisite to a sustainable competitive advantage.

4.2.3 Remote monitoring and diagnostics

With the increased complexity of manufacturing systems, it becomes more important to ensure trouble-free operation of all the sub-systems. For this reason companies are continuously seeking strategies to lower costs while boosting system performance and ensuring faster customer response. A solution which improves system reliability and performance at a lower cost is remote monitoring and diagnostics because it increases the transparency and reliability of decision-making in production control.

Monitoring and diagnostics are performed through utilisation of online sensing devices. It increases the transparency and reliability of decision-making in production control [38]. The required information on the present production system condition is periodically collected (monitored) using a variation of sensors such as force, vibration and acoustic emission. This data is then collated into information matrices or tables for transmission to the remote control centre for calculating the characteristic key figures for the production process. Graphics are normally used to display these results. In particular, a comparison is made between the various levels in the planned and actual conditions of the processes. Some form of artificial intelligence like neural networks can be used to perform this procedure.

Remote diagnosis systems can be designed for the installation on a company's WWW-server and thus gives the operator and expert worldwide access. The essential components and features of the system are installed on the server and consist of the information systems with the description of the failure-cause structures for a type of production systems, the knowledge-based diagnostics strategies incorporating a neural network, as well as a means of communication. The system has an integrated structure and uses the skills and knowledge of both the operator and the knowledge base. At first the operator applies the remote diagnosis system for trouble-shooting. He/she then has the possibility to consult the neural network to get instructions when the problem cannot be resolved. Finally the neural network can provide certain methods for restricted remote control of the manufacturing system by the neural network with assistance of the operator.

The structure of a remote monitoring and diagnostic system needs to be integrated with the manufacturing system. It therefore becomes clear that the three key elements of <u>intelligence,</u> <u>integration</u> and <u>remote monitoring</u> must be incorporated into a manufacturing system to enhance the capabilities of each. Manufacturing intelligence can only be implemented when the sub-elements of the system are integrated and will have no value if it is deployed in isolation. The same applies to remote monitoring, as seen from the previous discussion.

4.3 Practical requirements for experimental validation

In order to validate the respective concepts, an experimental model is constructed that presents the concepts in a specific application and generates results that are recorded and analysed. The model also allows various adjustments to be made to it so that different inputs such as number of decisions or number of machines can be experimented with.

To validate the concept of <u>intelligence,</u> the techniques based on fuzzy logic and neural networks are used to analyse the system data and generate a solution that can be seen as the best solution for a given set of inputs. It is important to note that in order to validate the use of intelligence, the solution should not be generated by using a fixed decision-making tree or hierarchy like an expert system, which is not a true form of artificial intelligence.

The validation of integration is demonstrated by the use of several items of equipment in a system which shares information in a digital format.

Remote monitoring is demonstrated by a method in which the status of the system is transmitted from the system to the remote control centre via the Internet or a dedicated local area network. Furthermore, it is also demonstrated by the manner of diagnostic and rectification of the system from a remote location. The use of intelligence is also a part of the analysing process.

4.4 Design of the experimental model

4.4.1 Background and model objectives

The objective of the model is to validate the respective concepts of Integration, Intelligence and Remote Monitoring as applied in a manufacturing system.

In an automated manufacturing environment, neural networks are effective in a large number of applications. Neural networks learn from data that is collected from a real world system, or a simulation thereof. The neural network acquires the knowledge that exists outside of itself. However, if this knowledge does not exist, and therefore no relevant data can be captured, neural networks cannot be employed in their usual way.

The developed model uses an artificial neural network in conjunction with reinforcement learning techniques to develop a decision-making system that is capable of learning from experience. In a simulated environment the model is used to control a mobile robot that transport material to machines. States of 'happiness' are defined for each machine, which are the inputs of the neural network. The output of the neural network is a decision of which machine to service next. After every decision a critic evaluates the decision and a teacher 'rewards' the network to encourage good decisions and discourage bad ones.

This specific application was chosen because it shows clearly how the three relevant concepts are validated. Manufacturing intelligence in the form of the neural network is used to optimise the performance of the mobile robot scheduling. This is validated by the manner in which the system output converges when measured against the benchmark, showing that the scheduling system is capable of teaching itself and thereby exhibiting intelligence.

The concept of integration is validated as well, because optimisation would not have been possible if the sub-systems were not integrated. The neural network receives information from the mobile robot and also transmits information back to the robot. The various machines to be serviced are also integrated with the neural network and the mobile robot, making the exchange of information possible.

The output of the neural network that results in a decision being taken which changes the state of the system, validates the concept of remote monitoring, showing clearly that an integrated system can be monitored and controlled in a remote manner.

Before the experimental set-up of the validation model is explained, each of the techniques that drive the model will be discussed with reference to the model.

4.4.2 **Artificial Neural Networks**

The artificial neural network (ANN) approach to machine intelligence is based on the study of the brain and its emergent properties while AI's symbolic approach is centred upon the study of the mind, independent of the structure and functioning of its physical support [39]. AI uses dedicated symbols (local representation) to represent each concept and these symbols are manipulated by chains of inference or rules, usually under a centralised control. ANN systems, using distributed representations, reach their conclusions by applying evolutive rules to numerical values. They lack centralised control in the classical sense; all local units are simultaneously working. While every rule in an AI system has a precise, pre-assigned meaning, it is common that several neurons in an ANN model have no pre-defined meaning.

They evolve and/or specialise during learning in manner that is often difficult for a human observer to predict.

Artificial neural networks (ANN) are systems that simulate the function of the human brain. By using the same architecture, but on a smaller scale, artificial neural network systems work in a similar way. ANN's learn through association. They require large amounts of data, which trains them to associate certain inputs with outputs. Through the process of generalisation, they are able to identify relationships, and thus acquire knowledge that is inherent in the data. They have been successfully used as predictors and classifiers.

A neural network can learn by changing its response as the inputs change. Neural networks learn by association, that is, they learn that pairs of things go together. For example, red goes with stop and green goes with go. The learning rule determines how the weights are adjusted as the neural network gains experience.

As an example, consider the case of the mobile robot used in the validation experiment that moves materials from a storeroom to five machines on the shop floor. This system can be simplified into a problem of making six decisions. On further simplification, it can be considered as an assignment problem where resources (in this case the mobile robot), would have to be assigned to one of six possibilities, namely five possibilities of bringing material to one of the five machines and a sixth possibility if doing nothing. If a human forklift driver would have been used, he would know the current levels of materials at every machine, the rate at which they transform these materials and the batch size of the material to be delivered. From this knowledge he can estimate at which point it becomes necessary to take material to which machine. This is a skill the operator must have learned from experience. He might have been explicitly told at what minimum level of material the next batch should be delivered but through experience he learned to become more efficient and take more parameters into consideration (like for example if two machines are near their minimum level, material should be delivered earlier). These decisions might seem obvious to a human but now the forklift operator is replaced by a mobile robot and these considerations become important. Consequently, if the operator was replaced by a neural network, the system parameters coupled with the decisions made by the operator, could be documented over a long time. Then the neural network is trained with the system parameters (inventory levels, etc.) being the inputs and the operator decisions being the outputs. If this network trains well, the knowledge of the operator is captured in the network and in theory the system should function as it always did. Should however, the demand of one machine suddenly change, the network is no longer capable of making the right decisions and the intelligence of the system breaks down. In this case one would have to reinstate a human operator capable of adapting to change, and start the whole process of gathering data and training the network again. This is not an attractive option if the goal is to create an automated manufacturing environment, especially if the conditions of the system change regularly.

This is where the idea of a self-training neural network model originated, a model that generates its own training data and trains the network without any human intervention. If successful, it will clearly validate the concept of intelligence in a manufacturing system. It will also show that the system elements must be integrated to enable the neural network to be trained and to be used for remote analysis.

4.4.3 Neural Network Design

A neural network is designed to fit a specific application. There are no clear rules for the best design for a certain application. The number of input and output neurons is equal to the number of input items and answers in a training fact. However, the exact number of hidden layers and hidden neurons is largely dependent on the complexity of the problem being solved. One rule of thumb allows the use the average of the number of input neurons and the number of output neurons. Another suggests using the smaller of the two. Yet another method suggests to start with a small number of neurons and adding another hidden neuron whenever the training stops progressing. The disadvantage of having too many hidden layers and hidden neurons is that the network may end memorising the facts rather than learning to generalise about them.

A neural network consists of layers of neurons which are connected to each other. The details of how the neurons interconnect represent some of the more important choices to be made when building a neural network. Some of the neurons communicate with the outside world and some of the neurons communicate only with other neurons. They are hidden neurons.

The neurons in a neural network are usually organised in three layers: input, hidden and output (see Fig. 4.2). The input layer consists of neurons that receive their inputs from the outside environment. The information then flows through any number of hidden layers consisting of neurons connected only to other neurons. From here the information flows to the output layer that consists of neurons whose output provides us with the neural network's response of the input data. The meaning of each output neuron's response is interpreted by the way the network is defined in the first place.

To ensure proper integration of all the neurons, connections are required. A connection is a unique line of communication that goes from one sending neuron to one receiving neuron. There can be two types of connections going to a neuron: excitatory and inhibitory. Inhibitory connections tend to prevent firing of the neuron. Excitatory connections tend to cause firing of the neuron. The network structure may involve inhibitory connections from one neuron to the rest of the neurons in the same layer. This is called lateral inhibition. Sometimes a network has such strong lateral inhibition that only one neuron in a layer, usually the output layer, can be activated at a time. This effect of minimising the number of active neurons is one type of competition.

The way in which the neurons are connected to each other has an important effect on the operation of the network. Specifying the connections determines the type of processing that will occur. Sometimes connections go from the output of one layer to the input of a previous or same layer. This is known as feedback. The most common type of feedback model connects every neuron to every other neuron.

Building a network may require the specification for the type of transfer functions and their range, the learning rate and the smoothing factor. The learning rate determines the size of the correction to the network when the output is wrong during training. The smoothing factor determines the extent to which recent past corrections are considered when new corrections are made.

4.4.4 Reinforcement Learning

The previous discussion shows that neural network can be trained if explicit examples from a supervisor are available (supervised learning) or if learning samples can be generated but the system itself (unsupervised learning). However, such a set of learning examples is not always available or can be derived.

Reinforcement learning is learning what to do – how to map situations to actions – so as to maximise a numerical reward signal. It represents the problem faced by an agent that must learn behaviour through trial-and-error interactions with a dynamic environment [40]. The learner must discover which actions yield the most reward by trying them. In some cases the action does not only affect the immediate reward but the subsequent rewards as well. After the action is implemented, the learning system receives a feedback or reinforcement signal from the environment to indicate the results of its actions [41].

One of the challenges that arise in reinforcement learning and not in other kinds of learning (or to a much lesser degree) is the trade-off between exploration and exploitation. To obtain a lot of reward, a reinforcement learning agent must prefer actions that it has tried in the past and has found to be very rewarding. But to discover such actions, it must try actions it has not tried before. The agent has to *exploit* what it already knows in order to obtain reward, but it also has to *explore* in order to make better action selections in the future. The dilemma is that neither exploration nor exploitation can be pursued exclusively without failing at the task [42].

In the case of reinforcement learning with neural networks, the only information is a scalar signal which indicates how well the neural network is performing. This "reinforcement" signal is characterised by the fact that it is less informative than a set of examples (only a correct-false judgement is given) and that it is often delayed: The success or failure signal which is given at a certain moment is a result of a series of network outputs in the past.

The validation model makes use of a reinforced learning module (also referred to as the "teacher") to adjust the outputs from the neural network according to the type of decision made by the network (Good or Bad). If it was a "Good" decision, in other words if the state of the system was improved and the machine material level was improved, then the teacher increases the value of that output by a specified reward and decreases the values of the other outputs. This ensures that the network is more likely to make the same correct decision next time the same inputs are encountered. If it was a "Bad" decision in other words when the overall machine material level has deteriorated, then the teacher decreases the value of that output by a specified reward and increases the value of the other outputs. This again ensures that the network is less likely to make the same mistake the next time the same outputs are encountered. In this way, the neural network is "trained" with the adjusted outputs as targets by using the back propagation training method.

The distinguishing factor of reinforcement learning is the emphasis on learning by the individual from direct interaction with its environment.

4.4.5 Generalisation

The concept of generalisation is an important one to be considered in any machine learning applications. The power of neural networks lies in their ability to generalise.

Generalisation in psychology is the tendency to respond in the same way to different but similar stimuli. Learning, on the other hand, may be considered as a balance between generalisation and discrimination (the ability to respond to differences among stimuli).

Learning methods can be described as data-intensive and knowledge-intensive. In data-intensive, the learner is shown a large number of related examples and is required to identify their similarities and generalise the embedded concept. This is an inductive process where a large number of observations are taken into account. In contrast, knowledge-intensive methods rely on domain-specific methods. The learner analyses a single training example using domain knowledge and the concept under study to produce a generalisation of the example. This is a deductive process where the knowledge gained from one instance in a certain domain is generalised to a wider field.

Neural networks use the data-intensive learning method of generalisation. It is therefore important that the data sufficiently captures the concepts the learner has to learn. This poses a special problem in neural network reinforcement learning because the system creates it's own learning data. In order for the network to learn, the data has to be representative but in order for the data to become more representative the network must learn. A convergence between the data and the network will have to occur [43].

4.5 The Experimental Set-up

4.5.1 Description of the set-up

The proposed model to validate the concepts of intelligence, integration and remote monitoring uses a set-up of a neural network to make decisions and the technique of reinforcement learning to train the neural network.

The model is implemented in a simulated manufacturing environment of a material handling scheduling problem. Because the model is used in a new domain, it has to be trained using data created by a simulator. Once the model is implemented, the simulator will be replaced with the real-world system. The neural network controls a mobile robot that has to deliver material from a storeroom to a number of machines. The model consists of N number of machines equally spaced from the storeroom. The set-up is shown in Fig. 4.6.

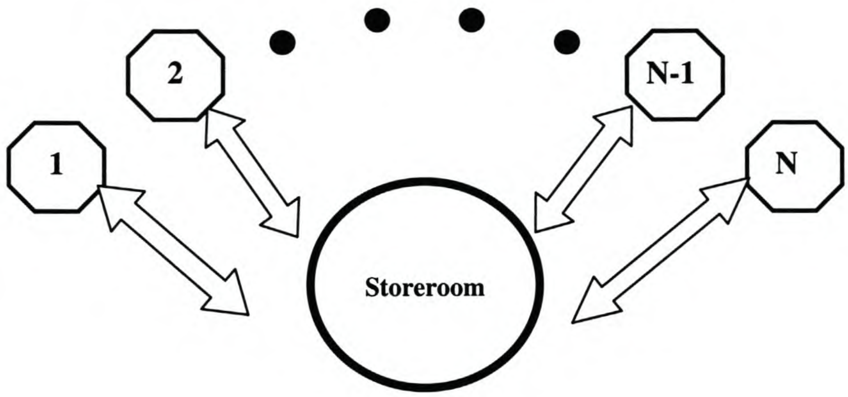

Fig. 4.6: Simulated environment of experimental set-up

Every trip is of equal time (t). For every time unit the mobile robot either delivers the raw material or does nothing. During that time unit, each machine processes an amount of raw material. Each machine has its own parameters that will be different according to the type of machine. The different parameters are:

- Maximum inventory
- Batch size
- Inventory level
- Average usage
- Standard deviation of usage

Each machine has a state of "happiness" which is determined by the amount of material it has. The further a machine's material level deviates from the optimum, the lower the state of happiness is. The entire systems state is the sum of every machine's state.

The components of the decision making model are a neural network, a simulator, a decision evaluator or critic and a teacher with reinforcement learning. It is up to the neural network to maintain the best possible state for the system. The neural network is therefore used to make the decisions. Its inputs are the system parameters and its outputs are a vector of values between 0 and 1, the highest value indicates the decision being made (winner takes all). The simulator executes the decision it obtains from the network and thus changes the state of the system. The evaluator looks at how the system changed due to the decision made by the network and decides whether it was a good or a bad decision. The teacher then adjusts the output of the networks accordingly and trains the network with the adjusted outputs. A graphic depiction of the model is shown in Fig. 4.7.

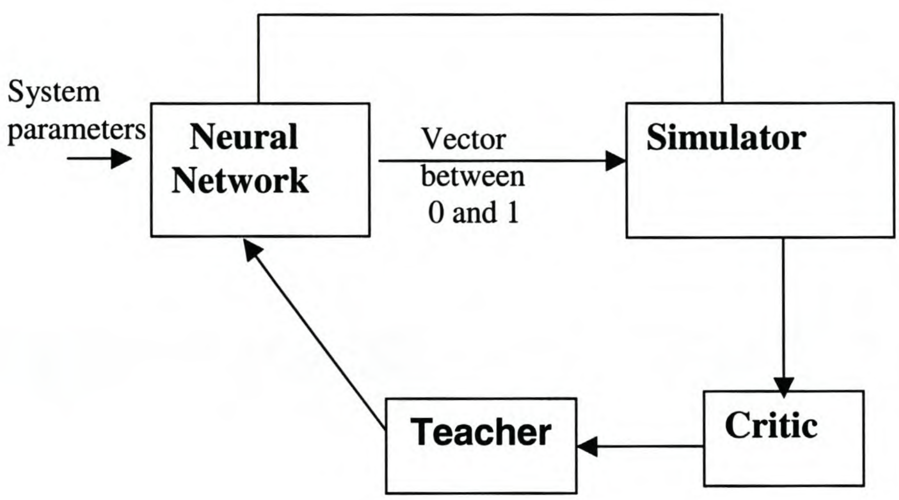

Fig. 4.7: Graphic representation of the model

4.5.2 Neural Network Structure

The neural network consists of a multi-layer feedforward neural network that uses the back propagation reinforced learning method. The number of input neurons, N_i, and output neurons, N_o, is equal to the number of machines in the system plus one. N_o is equal to the number of different decisions that can be made plus the decision to do nothing. An optional feature of the network that was attempted, was the addition of a hidden layer with the same number of neurons as the input layer.

The input range is from –1 to 1. The transfer function of the input neurons is a Tan-Sigmoid function, which allows for non-linear relationships between inputs and outputs. The transfer function of the output neurons is Log-Sigmoid that limits the output between 0 and 1. For a graphical explanation, see Fig. 4.8.

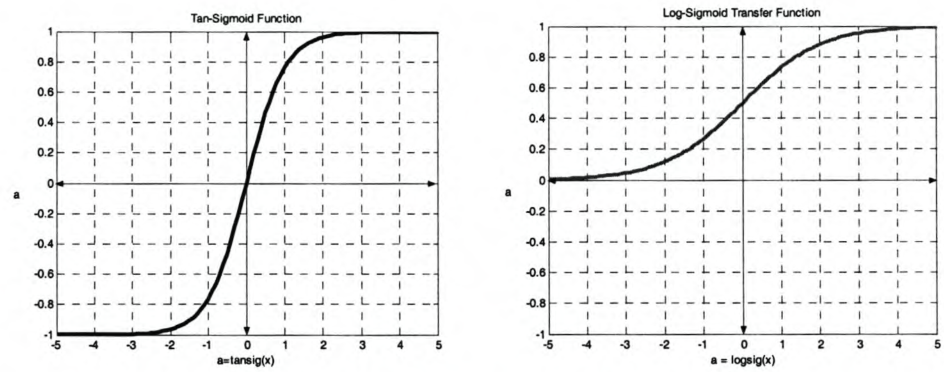

Fig. 4.8: Tan-Sigmoid and Log-Sigmoid Transfer Functions

4.5.3 The Greedy Function

The neural network is trained to exploit its learned knowledge for immediate reward, which is to select that decision which it has learned to be good. This method spends no time at all sampling apparently inferior options to see if they might really be better. A simple alternative is to select random options, every once in a while, say with probability ε. This is called the ε-greedy method. At the beginning stages of learning, the probability ε should be relatively large in order to explore all possible options for given inputs. As learning commences, ε should decrease in order to exploit the learned knowledge of the network. A typical greedy function for a learning run of 1000 iterations is shown in Fig. 4.9.

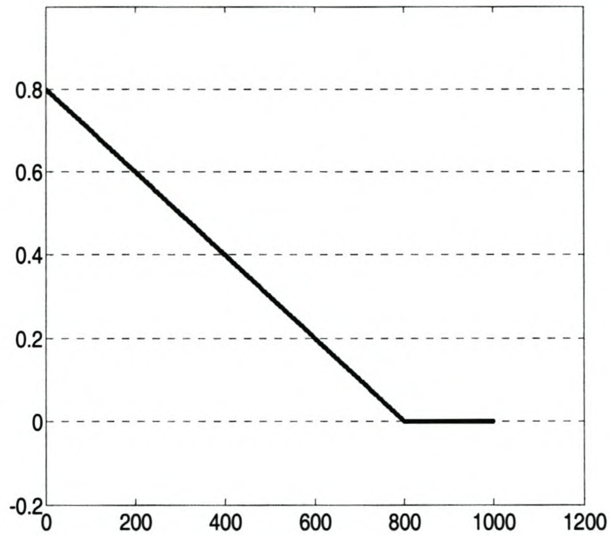

Fig. 4.9: A greedy function for a learning run of 1000 iterations.

At the beginning of learning, 80% of the decisions are random and after 800 iterations the network purely exploits the learned knowledge.

The greedy function operates much like mutation in the genetic algorithm that ensures variety and diversity in the population. It ensures that the system does not settle on a sub-optimum answer by randomly selecting one of the given options instead of the winning decision. The greedy function is a linear declining value that starts at 0.8 and drops down to 0 after half of the simulation has completed.

$$G = \frac{2*k}{d+0.8} \text{...............(1)}$$

where;

k = the current iteration in the simulation,

d = the total number of iterations.

This means the mutation will be large at the beginning of the simulation to explore all possible options for the given inputs, and drop down to exploit the learned knowledge of the system. The experimental set-up makes use of the above formulation to determine the greedy function. The effect of the function is also tested by omitting it during one experiment.

4.5.4 The Critic

The critic determines whether the decision that has been made was a good decision or a bad decision. In order to evaluate the decision it has to have a reference to base the decision on. Measuring the state of the machines can do this. One factor of the state is determined by the probability of having no material and therefore being unused. The less material a machine has available, the higher the probability of running out of material. The relationship is exponential as shown in the expression (2) below.

$$state(i) = -e^{\frac{-inv(i)}{mean(i)}} + \frac{inv(i)}{\max inv(i)} \quad \ldots\ldots\ldots\ldots\ldots(2)$$

The other factor of the state is determined by the cost of having in-process material. This is a linear relationship with the coefficient being equal to the inverse of the maximum allowable inventory for every machine. Some machine states are shown in Appendix A.

The state is compared with a benchmark of the system to evaluate the decision. The benchmark for the current state is simply the sum of all the states of the machines. The benchmark for the system is the moving average over a certain window period. The rationale behind this decision is explained in section 4.6.1. Different window sizes will be used to adjust the sensitivity of the system to changes and is also discussed in section 4.6.1. With each experiment, the benchmark is determined to show its effect.

4.5.5 The Reinforced Learning module

As discussed in section 4.4.4, the Reinforced Learning Module or "teacher" adjusts the outputs of the network according to the type of decision made (Good or Bad). If it was a **good** decision, the teacher increases the value of that output by a specified reward and decreases the values of the other outputs by Reward/N. This ensures that the network is more likely to make the same correct decision next time the same inputs are given. If it was a **bad** decision, the teacher decreases the value of that output by a specified reward and increases the values of the other outputs by Reward/N. This ensures that the network is less likely to make the same mistake next time the same inputs are given.

Good decision: $output(i) = output(i) + Reward$

$output\ (N\text{-}i) = output\ (N\text{-}i) - Reward/N$

Bad decision: $output(i) = output(i) - Reward$

$output(N\text{-}i) = output(N\text{-}i) + Reward/N$

4.5.6 The Simulation module

The model also contains a simulation to execute the decisions faster. The model can be trained from data gathered from a real world system if it is available and can then continue learning once implemented. The experimental model is simulated on a Matlab program; the program codes are given in Appendix B and the start-up procedures in Appendix C.

4.6 Experimental Results

4.6.1 Experimental set-up

In order to test the decision-making capabilities of the neural network, it is put to the test in several hypothetical environments. The purpose is to examine the influence of the model parameters on the generalisation and learning capabilities of the network. The model parameters that were examined are the benchmark against which the critic evaluates the decisions, the reward at which the teacher adjusts the outputs, the greedy function, the number of epochs the network is trained, the maximum number of decisions the network is capable of differentiating and the network architecture (the number of layers and neurons).

The critic relies on a benchmark, which is in some way related to the state of the overall system over a certain time period.

During experimentation, several approaches are taken. The first approach is to fix the time span over the whole learning time. A 3-time unit window proved to be good at the first stages of learning when the decisions where still largely random. However, once the network started generalising and converged to an ordered decision pattern, the benchmark contains too little historical knowledge to assist the network in distinguishing between good and bad decisions effectively. This results in the network often unlearning what it had learned because the benchmark does not sufficiently represent the general ability of the network and the critic and therefore could not distinguish effectively between good and bad decisions.

The second approach is to calculate the benchmark as the average of all the states of the system from the beginning of learning. This is an approach similar to basic quality function learning in reinforcement learning techniques [42]. This approach is unsuccessful because the benchmark becomes very *rigid* even in the beginning and is therefore unable to react fast enough to changes in the decision making pattern The network mostly fails to converge at all.

The final approach, which proves to be rather successful, is to start the learning process with a benchmark determined by the average of the last three states. As learning progresses, the moving average window of the states increases linearly to include about fifty to a hundred states. This ensures that the critic is at first very responsive to good or bad decisions and later uses a benchmark that is a true representation of the decision making capability. There is however a problem that arises once the network has converged to an optimum decision making pattern. At this stage the benchmark reaches a minimum and being the average of the past states, half the current states are above the benchmark and half below. The critic has been told that any decision that causes the state of the system to go above the benchmark, is a bad decision; therefore the critic decides that half the decisions are bad which is of course not true. One way to overcome this problem can be by using statistical process control to find an upper control limit of good decisions. This means that the benchmark is the average of the past states plus a factor of the standard deviation of the past states.

An element that is added to the critic is that if the network decides to allocate material to a machine, which would increase the machine's inventory level above the maximum inventory level, that decision would immediately be classified as bad.

The ultimate aim of the experiments is to validate the hypothesis that manufacturing intelligence can be created in an integrated system equipped with remote monitoring.

4.6.2 Experimenting with the Neural Network

The simulated environment contained 5 machines. This translates into six possible options the neural network can choose from (1 option of servicing each machine and one option of doing nothing). The characteristics of the five machines are summarised in Table 4.1.

	Machine 1	Machine 2	Machine 3	Machine 4	Machine 5
Maximum inventory	400	400	500	600	600
Beta-value	50	50	60	80	80
Batch size	60	60	80	120	120
Starting inventory	50	50	60	80	80
Mean usage	10	10	12	15	15
Standard deviation of usage	2	2	2.5	3	3

Table 4.1: Machine characteristics of five machines

The maximum inventory and beta-value determine the state function of each machine. A graphical representation of the state curves is included in Appendix A.
The network is trained over 2000 iterations. The benchmark is a moving average function of the overall system state. The window size for the moving average is set to 3 initially but it increases linearly to 103. The greedy function starts with 80% random decisions but decreases linearly to 0% after 1600 iterations.

(a) Experiment 1:

For the first training run a single 6-neuron layer network is used (with no hidden layers). A log-sigmoid transfer function is used. This network differentiates the input space into six possible outputs.

The reward is set at 0.1 and the network is trained for 3 epochs (repetitions of training). A graph of the benchmark and the machine inventory levels is shown in Fig. 4.10 and Fig. 4.11 respectively.

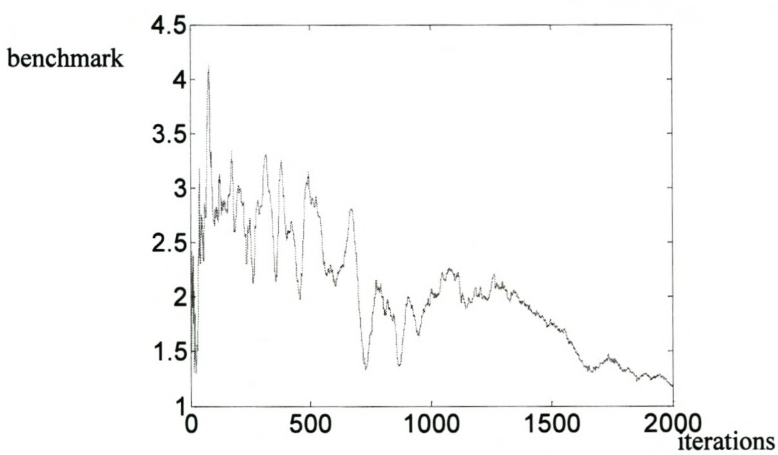

Fig. 4.10: Experiment 1: Benchmark performance

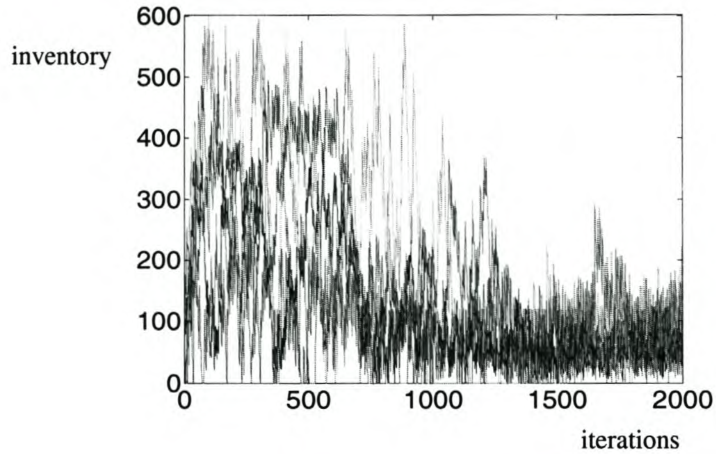

Fig. 4.11: Experiment 1: Inventory levels

It is apparent from the plot of the benchmark that the overall state of the system improves over the test run. The plot of the machine inventory levels also shows that the system starts stabilising. It is evident therefore that the neural network learns. The fact that the system only converges after about 1000 iterations can be partially ascribed to the greedy function. The greedy function is active until 1600 iterations. Fig 4.11 indicates that at about 1700 iterations the inventory level of one machine suddenly shot up. The reason is that once the network converged the benchmark is no longer an attainable target and many good decisions are classified as bad. Thus the network unlearns what it has learned and functions less effectively.

Fig. 4.12 shows the results of the same model without the greedy function. It can also be seen that the network converges but one machine is running idle constantly. The network converged into a decision making pattern that ignored one machine totally (bold line).

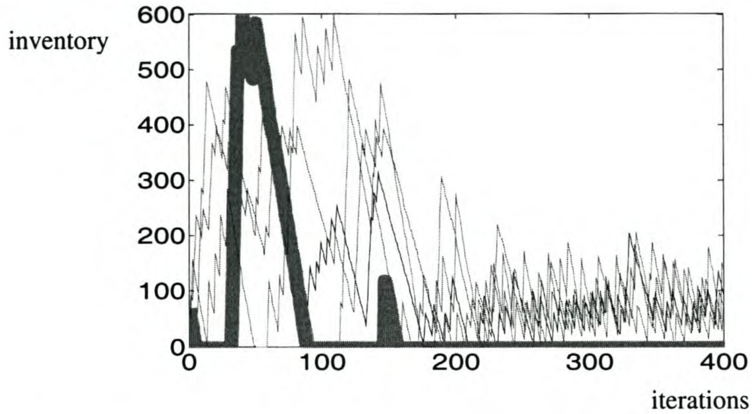

Fig. 4.12: Experiment 1: Inventory levels (without greedy function)

(b) Experiment 2:

To investigate the effect of the network architecture on the learning capability, the network architecture is changed to a 2-layer feed forward network with 6 input neurons and 6 output neurons. The transfer function is tan-sigmoid for the input layer and log-sigmoid for the output layer. The graph of the benchmark is shown in Fig. 4.13. The minimum benchmark is remarkably lower than for the single layer network. It is evident that the 2-layer network is much better at making decisions. This can be ascribed to the interrelationships that can be created between the inputs and outputs in a multi-layer network.

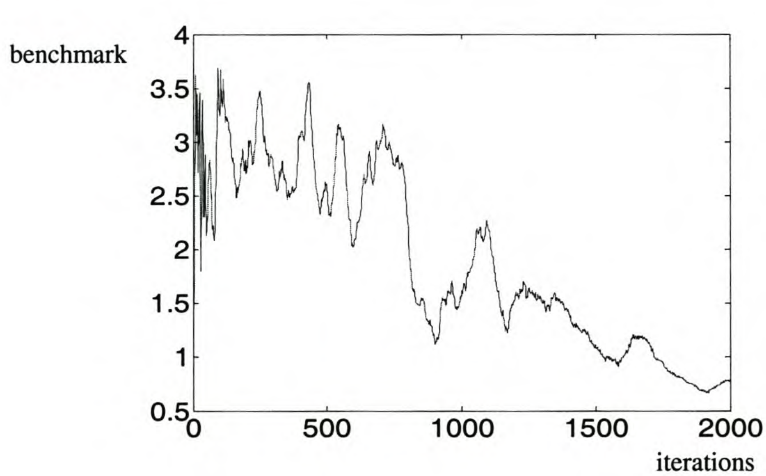

Fig. 4.13: Experiment 2: Benchmark performance

(c) Experiment 3:

The network architecture is now changed to a 3-layer feed forward network with 10 input neurons, 6 hidden neurons and 6 output neurons. The transfer function is tan-sigmoid for the input and hidden layer and log-sigmoid for the output layer. Being a more complex network than the previous two, it is trained over 10000 iterations. Even with five times more training, it is evident from Fig. 4.14 that the network does not converge. After 8000 iterations the greedy function is at 1 and the network fully exploits its knowledge, but yet it can't sustain sensible inventory levels. A network with too many layers does not generalise effectively thus it can be concluded that a 2-layer network is most suited for this training method.

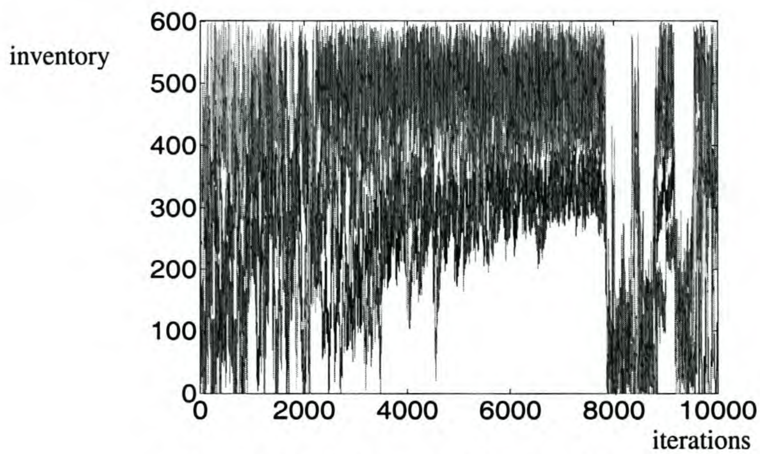

Fig. 4.14: Experiment 3: Inventory levels

(d) Experiment 4:

Heaving concluded that a 2-layer network is best suited; the last variable to be examined is the transfer function. The first layer has to have a sigmoid function to ensure that non-linear relationships can be learned. The second layer can have either a sigmoid or linear transfer function. In the previous experiments a log-sigmoid function was used. This experiment was conducted using a linear transfer function. The other parameters are the same as in experiment 2. As Fig. 4.15 suggest, a linear transfer function at the output layer does converge but not as fast as a log-sigmoid function. It reached a minimum benchmark of only 1.5 compared to the benchmark of 0.7 achieved in experiment 2

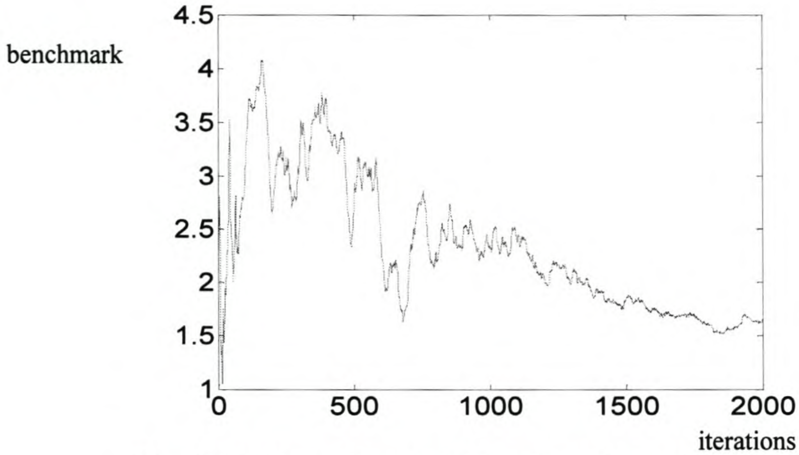

Fig. 4.15: Experiment 4: Benchmark performance

(e) *Summary of the results of the experiments with the multilayer perceptron (neural network):*

EXPERIMENTING WITH MULTILAYER PERCEPTRON

	Experiment 1	Experiment 2	Experiment 3	Experiment 4
Benchmark	Moving avg.	Moving avg.	Moving avg.	Moving avg.
Window size	3 - 103	3 – 103	3 – 103	3 – 103
Greedy function	80% - 0%	80% - 0%	80% - 0%	80% - 0%
Layers	1	2	3	2
Neurons: Input	6	6	10	6
Neurons: Hidden			6	
Neurons: Output		6	6	6
Transfer func:Output		log-sigmoid	log-sigmoid	Linear
Learning meth.	GDR	GDR	GDR	GDR
Reward	0.1	0.1	0.1	0.1
Epochs	3	3	3	3
Iterations	2000	2000	10000	2000
Benchmark End value	1.2	0.7		1.5
Inventory end	10 - 190		100 - 600	
Converge	Yes	Yes	No	Yes

GDR = Generalized Delta Rule

Table 4.2: Summary of neural network experimental results

From the results in table 4.2, it is clear that the variables chosen for experiment 2 result in the best performance if measured against the benchmark (a happiness state of 0.7). A 2-layer network will therefore be used as a reference network for further experiments.

4.6.3 Experimenting with the critic

The critic uses the benchmark to evaluate any decision against. If a decision improves the state of the system beyond the benchmark, the decision is classified as good. A true estimate of the benchmark is therefore of utmost importance. The greedy function interferes with a true estimate of the neurons capacity because it forces random decisions that usually deteriorate the state of the system. Therefore to find a good estimate of the benchmark the greedy function will be excluded from the experiment. To prevent the network from converging to a local minimum, a rule set is added. This rule states that if a system is idle, the decision to do nothing will be classified as bad. Only if all machines have material can the decision to do nothing be classified as good. Similarly, should a decision cause a machines inventory level to go above the maximum, that decision will also be classified as bad. The other system parameters remain as in experiment 2 as explained in 4.6.2 (e) .

(a) Experiment 5:

The first experiment in this series of experiments uses the average of the past 4 states as the benchmark. Due to the short *memory* of the benchmark the critic is very responsive and the network converges relatively fast. The network is trained for only 500 iterations. The graph of the benchmark is shown in Fig.4.16.

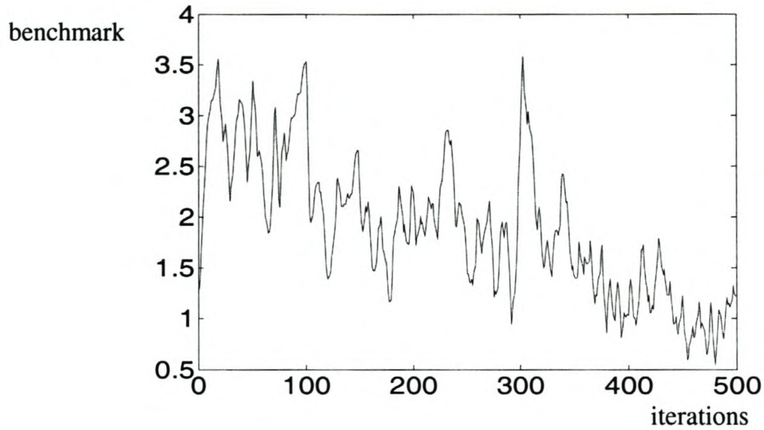

Fig. 4.16: Experiment 5: Benchmark performance

(b) Experiment 6:

For the second experiment in this series, the benchmark is the average of the past 50 states. Because the benchmark does not respond quickly to the current state of the system, the critic is much less responsive and it takes much longer for the network to learn. From Fig. 4.17 it is evident that even after 2000 iterations the network has not been able to find a good decision-making pattern.

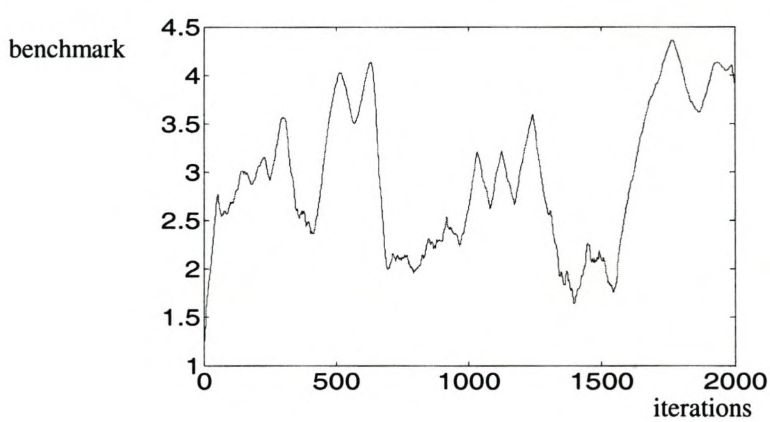

Fig. 4.17: Experiment 6: Benchmark performance

(c) Experiment 7:

In this experiment, the benchmark is the moving average of the states starting with a window size of 1 and increasing linearly to a window size of 100 after 5000 iterations, i.e. after every 50 iterations the window size will increase by 1. Without the effect of the greedy function, the network converged to an overall best benchmark after only 400 iterations. After that the benchmark becomes increasingly unstable. The red line in Fig. 4.18 is the current state of the system and the superimposed blue line indicates the benchmark. What can be clearly seen is that even during good intervals, like at about 1000 iterations, the current critic still classifies roughly half the decisions as bad, which obviously is not the case. Therefore the network unlearns good decisions and becomes sporadically unstable.

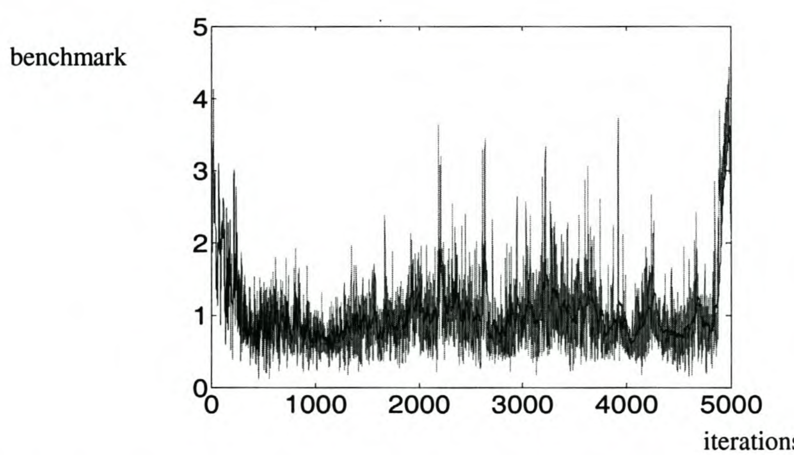

Fig. 4.18: Experiment 7: Plot of benchmark and current state

(d) Summary of the results of the experiments with the critic

EXPERIMENTING WITH CRITIC

	Experiment 5	***Experiment 6***	***Experiment 7***
Benchmark	Avg. past 4 states	Avg past 50 states	Moving avg. of
			states from wndow
			size 1 to 100
Window size	3 - 103	3 - 103	1 – 100
Greedy function	80% - 0%	80% - 0%	80% - 0%
Layers	2	2	2
Neurons: Input	6	6	6
Neurons: Hidden			
Neurons: Output	6	6	6
Transfer func:Output	log-sigmoid	log-sigmoid	log-sigmoid
Learning meth.	GDR	GDR	GDR
Reward	0.1	0.1	0.1
Epochs	3	3	3
Iterations	500	2000	5000
Benchmark end	0.6	4	4.5
Inventory end			
Converge	Yes	No	No

GDR = Generalized Delta Rule

Table 4.3: Summary of critic experimental results

The above results were obtained with the use of the reference system parameters as fixed in experiment 2. The only parameter that was changed, was the value of the moving benchmark. The best result was obtained when using a benchmark based on the average of the past 4 states of the machines. This parameter will again be used a reference value for the later experiments.

4.6.4 Experimenting with the teacher

The teacher has two variable parameters that can influence the network's ability to learn. The first parameter is the learning rate, which has been held constant at 0.1 previously. The second is the training parameter determining the number of epochs the network should be trained after each decision.

(a) Experiment 8:

To examine how the learning rate influences the performance of the network, the learning rate is set to 0.2 and the performance is compared to the model used in experiment 2. All other parameters are kept the same. What is interesting in the graph of the benchmark (Fig. 4.19) is that the system faired much better during the first 500 iterations but after that it deteriorated to level out at about 3.3. Three of the machines were not serviced at all in the last 700 iterations. The graph of the inventory levels (Fig. 4.20) suggests that the network generalised towards a local optimum of servicing only 2 machines.

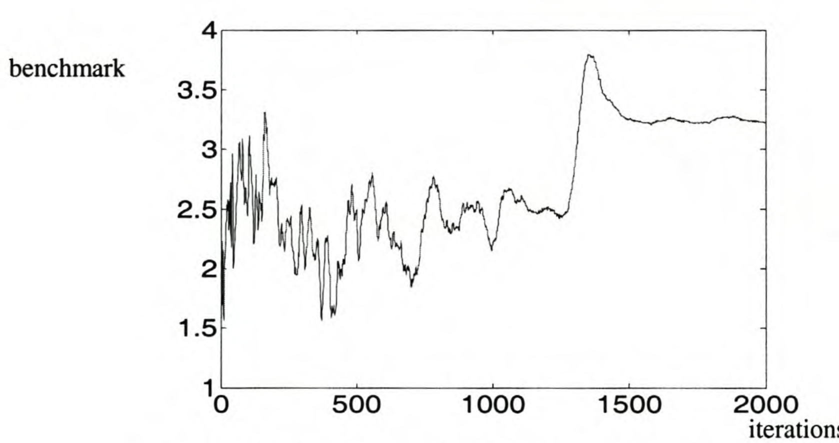

Fig. 4.19: Experiment 8: Benchmark performance

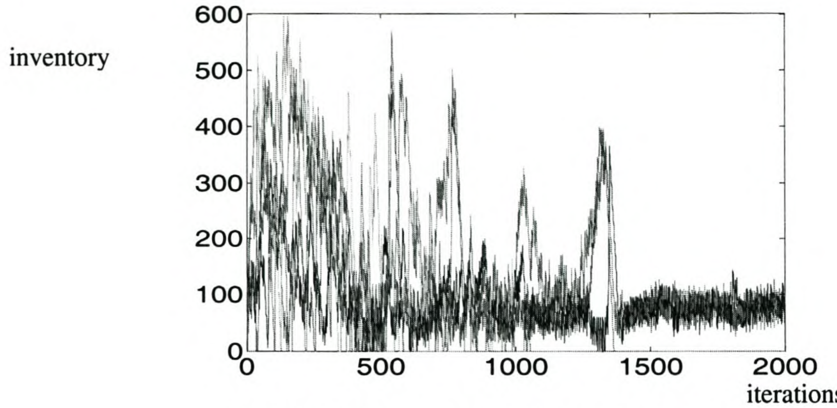

Fig. 4.20: Experiment 8: Inventory levels

(b) Experiment 9:

In the second experiment in this series, the learning rate will be set to 0.05 while the other parameters remain constant. The result is that machine one had no inventory for the last part (Fig. 4.21) of learning and the best benchmark was around 1.9 (Fig. 4.22).

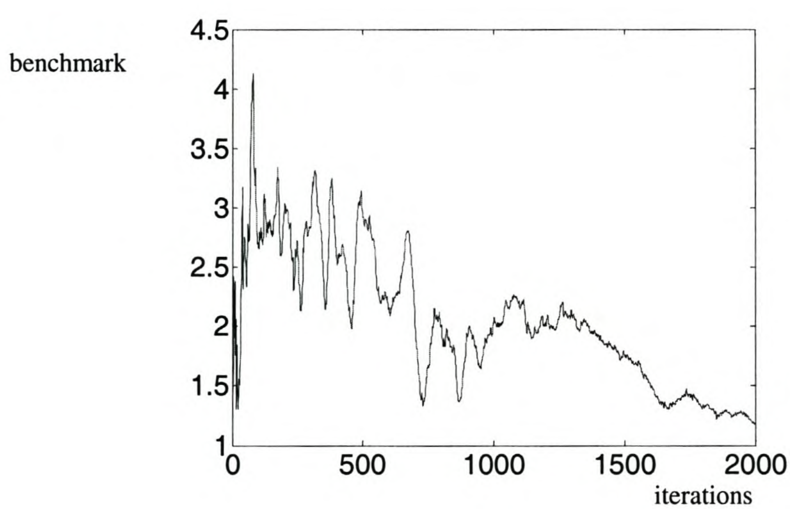

Fig. 4.21: Experiment 9: Benchmark performance

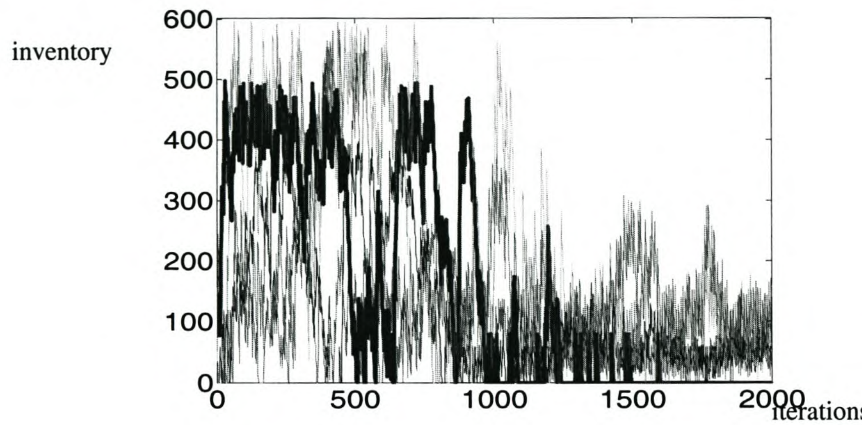

Fig. 4.22: Experiment 9: Inventory levels

(c) Experiment 10:

In this third experiment of the series, an experiment is made with a reward as shown in the Fig. 4.23. The results indicate no improvement of learning with the adjusting learning rate as can be seen by the representation of the benchmark in Fig. 4.24.

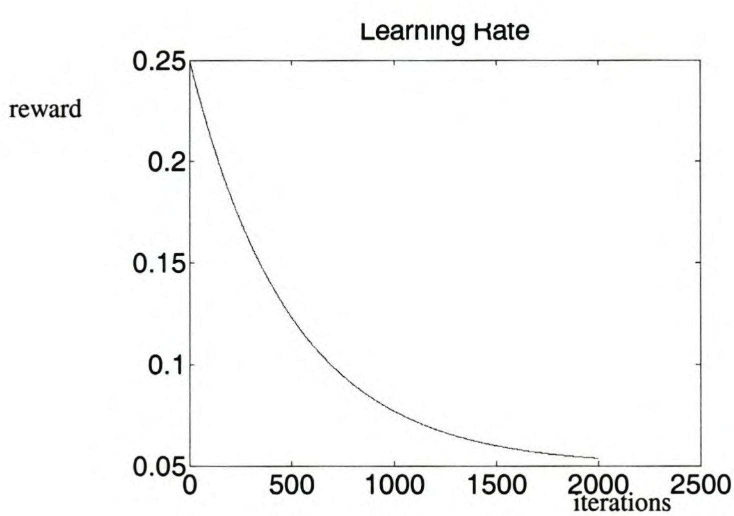

Fig. 4.23: Experiment 10: Reward

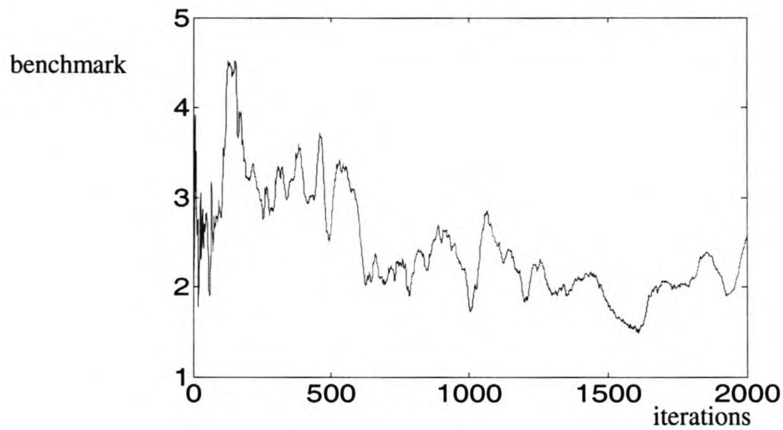

Fig. 4.24: Experiment 10: Benchmark performance

(d) Experiment 11:

The final experiment involves different learning rates for good and bad decision. The learning rates are also dependant on the benchmark. The benchmark if defined as the previous state of the system. A decision is therefore only criticised on whether it improved the current state compared to the last one or not. The reward is dependent on the benchmark as is shown in Fig. 4.25. The red line represents the reward for a bad decision and the blue line for a good decision. The benchmark is on the horizontal axis and the reward on the vertical axis. If the benchmark is close to the maximum, which indicates a bad state, the reward for a good decision tends towards zero while the reward for a bad decision tends toward 0.2. The argument is that while the state is bad, a decision that improves the state is not necessarily a very good decision, hence the small reward, whereas a decision that worsens the state is necessarily a very bad decision, hence the large reward. Alternatively, while the state is good, it is inevitable that a decision will worsen the state although it might not be a bad decision, hence the small reward, whereas a decision that improves the state is necessarily a good decision, hence the large reward.

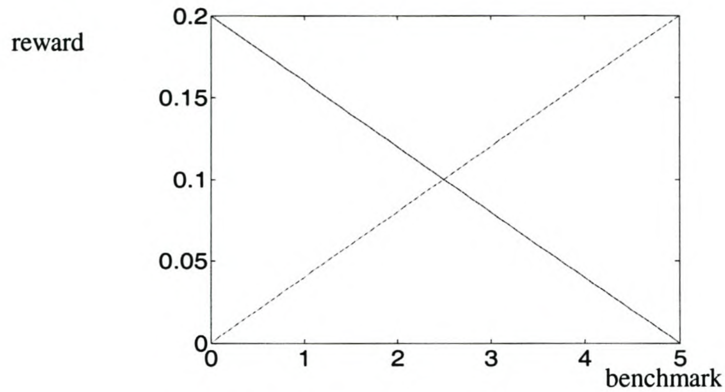

Fig. 4.25: Experiment 11: Plot of reward

The results in Fig. 4.26 indicate that the network converged within 400 iterations and was able to maintain a consistently good state. The red line superimposed indicates the average benchmark of the last 1600 states.

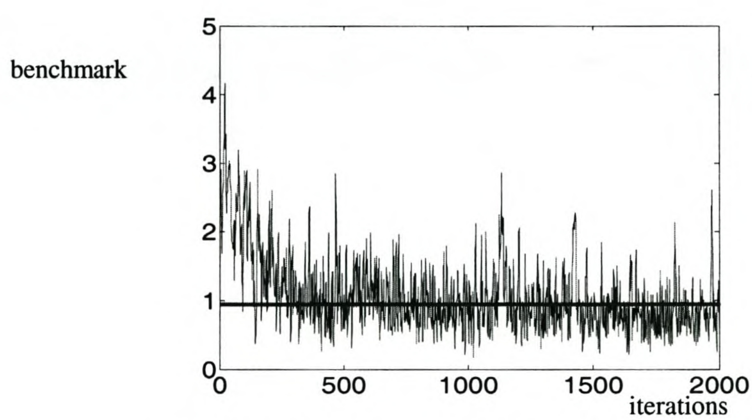

Fig. 4.26: Experiment 11: Plot of benchmark

(e) *Experiment 12:*

To test the effect of the number of epochs the network is trained on the adjusted outputs, the same model as in experiment 2 is used with the number of epochs set to 5 and 10 respectively. The result is shown in Fig. 4.27.

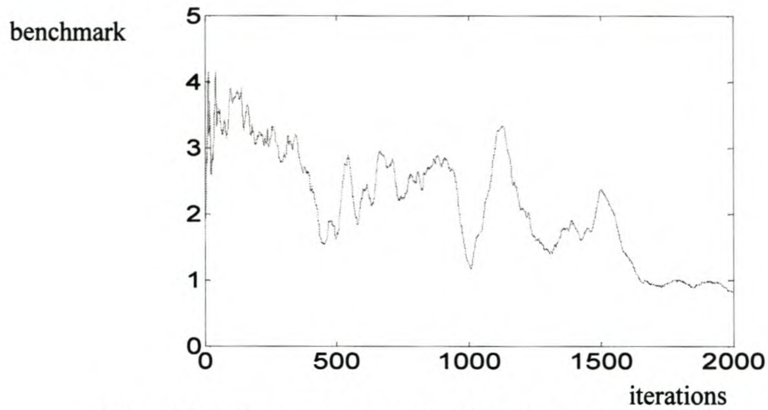

Fig. 4.27: Experiment 12: Benchmark performance

(f) *Summary of the results of the experiments with the teacher*

EXPERIMENTING WITH TEACHER

	Experiment 8	*Experiment 9*	*Experiment 10*	*Experiment 11*
Benchmark	Moving avg.	Moving avg.	Moving avg.	Moving avg.
Window size	3 - 103	3 – 103	3 – 103	3 – 103
Greedy function	80% - 0%	80% - 0%	80% - 0%	80% - 0%
Layers	2	2	2	2
Neurons: Input	6	6	6	6
Neurons: Hidden				
Neurons: Output	6	6	6	6
Transfer func:Output	log-sigmoid	log-sigmoid	log-sigmoid	log-sigmoid
Learning meth.	GDR	GDR	GDR	GDR
Reward/learning rate	0.2	0.05	Decreasing	Differ good/bad
Epochs	3	3	3	3
Iterations	2000	2000	2000	2000
Benchmark end	3.3	1.9	2.5	1
Inventory end	100	150		
Converge	No	Yes	No	Yes

GDR = Generalized Delta Rule

Table 4.4: Summary of teacher experimental results

The summary in table 4.4 shows that the best result was obtained with the parameters as chosen for experiment 11. It shows that a learning rate (reward) based on the benchmark as explained in *(d)* , will cause the quickest convergence of the machine states.

The result of experiment 12 is not included in the table.

4.6.5 Testing the limit

After experimenting with the variables that influence the models performance, the most successful results are used to test how many possible decisions the model is capable of incorporating in an effective way. The two best results are used, namely the configurations of experiment 2 with the adjusting benchmark and the configuration of experiment 11 with the adjusting learning rate. Ten machines are to be serviced in this experiment, which results in 11 possible decisions the network, has to differentiate. The machine characteristics are shown in Table 4.5.

	Mach 1	Mach 2	Mach 3	Mach 4	Mach 5	Mach 6	Mach 7	Mach 8	Mach 9	Mach 10
Maximum inventory	400	400	400	400	500	500	600	600	600	600
Beta-value	50	50	50	50	60	60	80	80	80	80
Batch size	60	60	60	60	80	80	120	120	120	120
Starting inventory	50	50	50	50	60	60	80	80	80	80
Mean usage	5	5	5	5	6	6	8	8	8	8
Standard deviation of usage	1	1	1	1	1	1	1	1	1	1

Table 4.5: Machine characteristics for ten machines

The results of the experiment using the adjusting benchmark configuration are shown in Fig. 4.28. The blue line is the benchmark superimposed on the system states. A 10^{th} degree polynomial fit is also shown. It is evident that the network did not converge over 4000 iterations and there is no indication that it will. Whereas the results for the second experiment, as depicted in Fig. 4.29, show that the network converged very effectively. A 10^{th} degree and 3^{rd} degree polynomial fit is also shown. It is interesting to see that the system states resonate around the general convergence. This seems to indicate that apart from the general trend of learning, the network periodically unlearns its knowledge but consistently to a lesser degree.

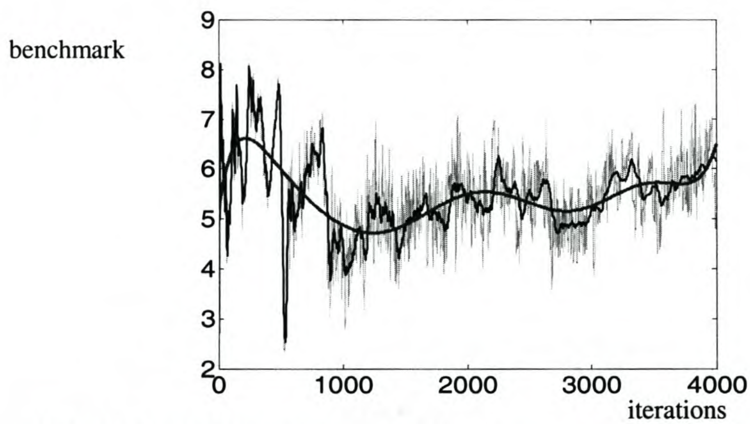

Fig. 4.28: Testing the limit: Benchmark performance (Exp. 2)

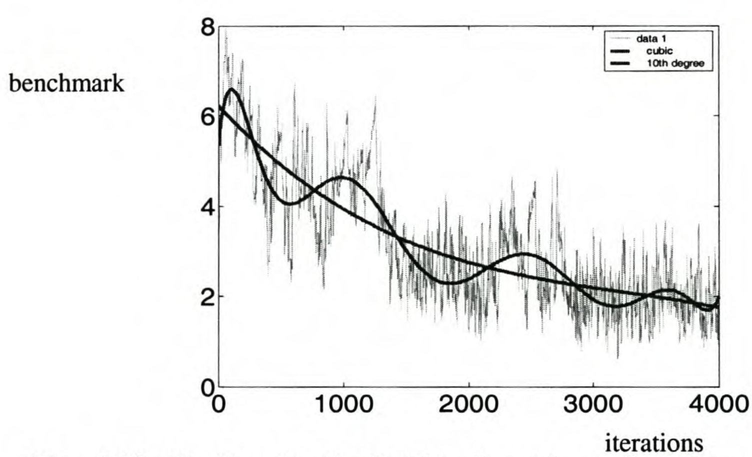

Fig. 4.29: Testing the limit: Benchmark performance (Exp. 11)

4.7 Evaluation of experimental results

When the model was designed, one of the major objectives was to enable easy manipulation of the model variables. This proved to be invaluable during the experimental stages as different model variables could be tested for best results.

The best results were found using a 2-layer feed forward network with 6 input neurons and 6 output neurons. The transfer function is tan-sigmoid for the input layer and log-sigmoid for the output layer. Further experiments showed that using an adjustable learning rate and evaluating the decision only against the last state of the system again proved to be successful. The initial attempt to improve learning by adjusting the benchmark did not show significant results because a true representation of the network's ability is not achieved; thus the critic cannot adequately evaluate the decision. The idea behind adjusting the learning rate is thus an attempt to minimise the damage done by evaluating a decision wrongly.

From the above, it is evident that the validation model is capable of learning from past experience to improve its decision-making ability. If every machine's state as well as the overall state of the system can be precisely represented, the network learns to make the right decisions so as to improve the overall state of the system. The network functions as a classifier to partition the input space into output decisions.

In order to train the model, considerable preparations is needed. Apart from defining the machine states the environment also has to be simulated. If the simulation is not a sufficient predictor of the real world system, the model will not perform sufficiently although it has the capability to refine its knowledge once implemented in a real world system. This poses the question whether it is advisable to use such a model for the purpose intended. If a simulation of the system is available, it could be linked to the real world system and the possible decisions would be simulated with the best one being executed. This would be a deterministic approach containing no machine learning or intelligence. However the strength of the proposed model lies in its ability to adapt to changes, hence the claim that it uses intelligence to make good decisions.

The model furthermore is successful only because of the fact that all the components of the set-up are interconnected and can only yield results when integrated in this manner. The data on the machine states is collected by the counting sensors located at each machine. This data is transformed into information by the collating computer connected to (integrated with) the machines. This process is carried out in a remote fashion and does not have to be in close proximity with the machines. The information is sorted and the present state of each machine is determined (monitored). This information is made available to the neural network in the form of selected bits of information (say, one specific machine), which uses this knowledge to generate a decision according to the feedback given by the reinforcement learning module. It learns to take only good decisions and thereby becomes intelligent. The whole process is made possible only by the fact that all elements of the system are connected (integrated) and that data is used as input with intelligence as a final result.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

Chapter Overview: In this final chapter, the relevance of the experimental results in terms of validation of the three key concepts is discussed. A final conclusion on the synergy of intelligence, integration and remote monitoring is made while some recommendations are discussed.

5.1 Relevance of experimental results in terms of validation of the three key concepts

5.1.1 Integration

As stated in Chapter 1, integration is:

- To form, co-ordinate or blend into a functioning whole
- To unite with something else
- To incorporate into a larger unit
- To bring into equal membership in a system
- To create an interaction among a group of devices or objects thereby forming a network and serving a common purpose.

The various units of the validation set-up like the neural network, the teacher and the simulator were incorporated and blended into a larger unit or system with the common purpose of scheduling the mobile robot to optimise the happiness state of a group of machines. Communication takes place and feedback is created by the rewards that the teaching unit feeds back to the neural network. The validation model therefore clearly shows that integration did take place.

5.1.2 Intelligence

The validation of the concept of intelligence will be true if it can be shown that intelligence was created by the validation set-up.

Three degrees of intelligence is defined and is determined by [10]:

- The computational power of the system
- The complexity of the algorithm used by the system of processing sensory input and sophistication of the system

- The information and values the system has stored in the memory

Intelligence can be observed to grow and evolve through the growth in computational power and accumulation of knowledge of how to behave in uncertain conditions. Based on these statements, four system elements of intelligence can be defined:

- Sensory processing
- World model
- Value judgement
- Behaviour generation

These elements also characterise elements of intelligent manufacturing systems, as they are valid for any system.

With reference to the validation model, the requirements of an intelligent system are clearly met. The simulation component embodies the world model of the system although the neural network also implicitly learns this world model. The critic component takes on the role of the value judgement element. The neural network is the behaviour generation and the sensory processing is the communication, in this case between the simulation and the other components. The model shows learning capabilities in an environment where rules are not explicitly stated and therefore has the capacity to adapt to changes.

It was thus clearly shown that the validation model exhibits intelligence in the manner with which the model used a neural network in combination with a reinforcement learning module to train the model to take good decisions. It was furthermore shown that integration is required to create the intelligence network. Without integration, the validation model will not be possible.

5.1.3 Remote monitoring

As discussed in section 4.2.3, some of the characteristics of a remote monitoring system are:

- On-line sensing devices
- Transmission of information to control centre
- Collation of information into characteristic key figures
- Graphic displays
- Comparison between planned and actual performance
- Generation of intelligent response to optimise system

The validation model with the simulator is equipped with sensors which indicate the present states of each machine. This information is then transmitted to the central computer where the happiness states of the machines are calculated. This knowledge is then transmitted to the neural network (or control centre) for analysis by the critic and a reward is fed back to the neural network by the teacher. The overall happiness state for all the machines is collated and analysed and the results are given in the form of the convergence graphs. The machine state is compared with the benchmark as indicated on each graph. This procedure shows that the model is able to validate the concept of remote analysis.

5.1.4 The three concepts in unison

Consider the concept of intelligence in the validation model on its own. If the elements of the model like the machines, the neural network, the simulator, the critic and the teacher were not connected (integrated), the neural network would not have been able to be trained and would not have been able to make intelligent decisions. The same argument is true for remote monitoring: it would not have been possible without integration. The reverse argument is true as well: the contribution of integration on its own does not guarantee decision making under variable and uncertain conditions. It is only when the neural network is integrated into the system that the ability to make good decisions is created.

When the three concepts of integration, intelligence and remote analysis are therefore considered together in the system, the validation model clearly shows that any one of the three concepts on its own does not contribute as it would if deployed in unison with the other two. The validation model is therefore considered to be successful in showing the synergy among the three key concepts.

5.2 Final Conclusion

The three manufacturing concepts of intelligence, integration and remote monitoring are recognised as key contributors to successful modern manufacturing systems and are individually responsible for increasing the competitiveness of global competitors. This is the first time that these key concepts are considered as making a collective contribution and that a validation model is used to validate this hypothesis. The model shows that the three concepts enhance and support each other when teamed together in the same system.

5.3 Recommendations

Further testing with the model is necessary to investigate its functionality. A more representative simulation of a manufacturing environment must be used to investigate if it can learn in a more complex environment. This can include the testing of the ability of the system to handle catastrophic events such as the sudden loss of inventory or different levels of uncertainty with regard to running out of inventory. Events such as these will probably have an effect on the overall happiness state of the machines and will force the neural network to make choices under unnatural conditions.

Further research into the model parameters is also necessary to improve its learning capacity. The learning rate and the benchmark are two critical components that determine the performance of the model. Other techniques of reinforcement learning should also be tested on the model.

Although the validation of the three concepts were done successfully on a qualitative basis, further research into the quantitative aspects would serve to classify systems according to the numerical value of its I-I-R factor (Intelligence-Integration-Remote monitoring). The features of intelligent behaviour as discussed in section 3.2 could serve as starting point while aspects of integration and remote monitoring could be added in accordance with their contribution to the performance of the manufacturing system.

The issue of "non-synergy" should also be investigated. This can perhaps be simulated by excluding one by one of the key concepts from the model and evaluating the effect of the exclusion on the performance of the neural network.

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Appendix A: Plots of various machine states.

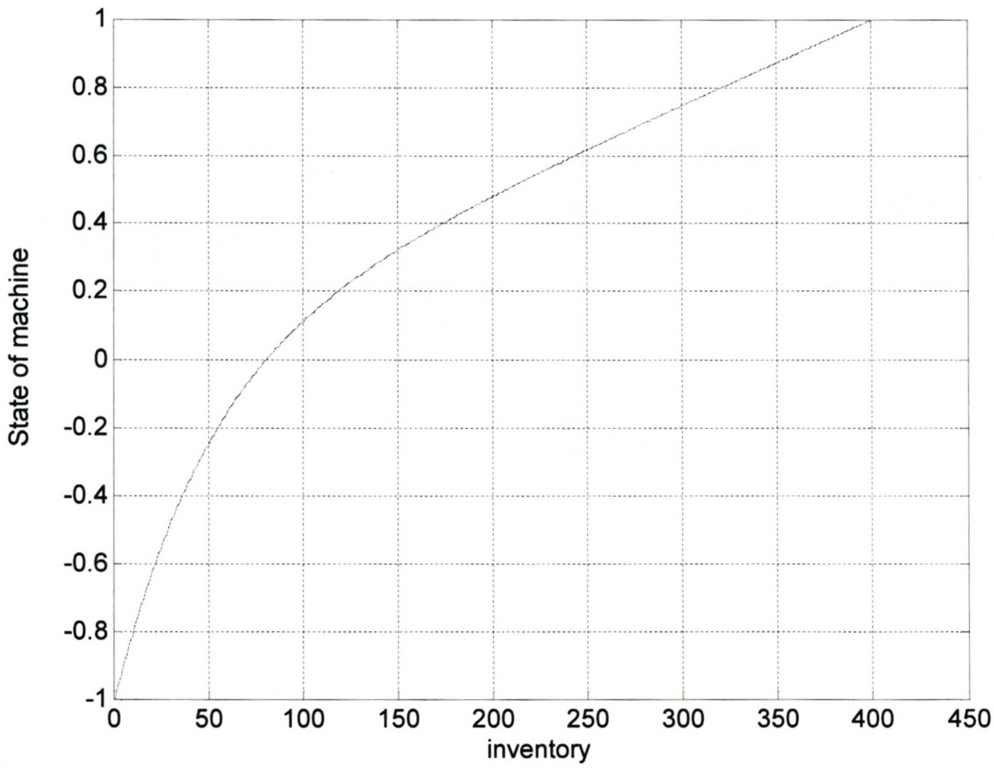

Figure A.1: Plot of state for machine 1 and 3

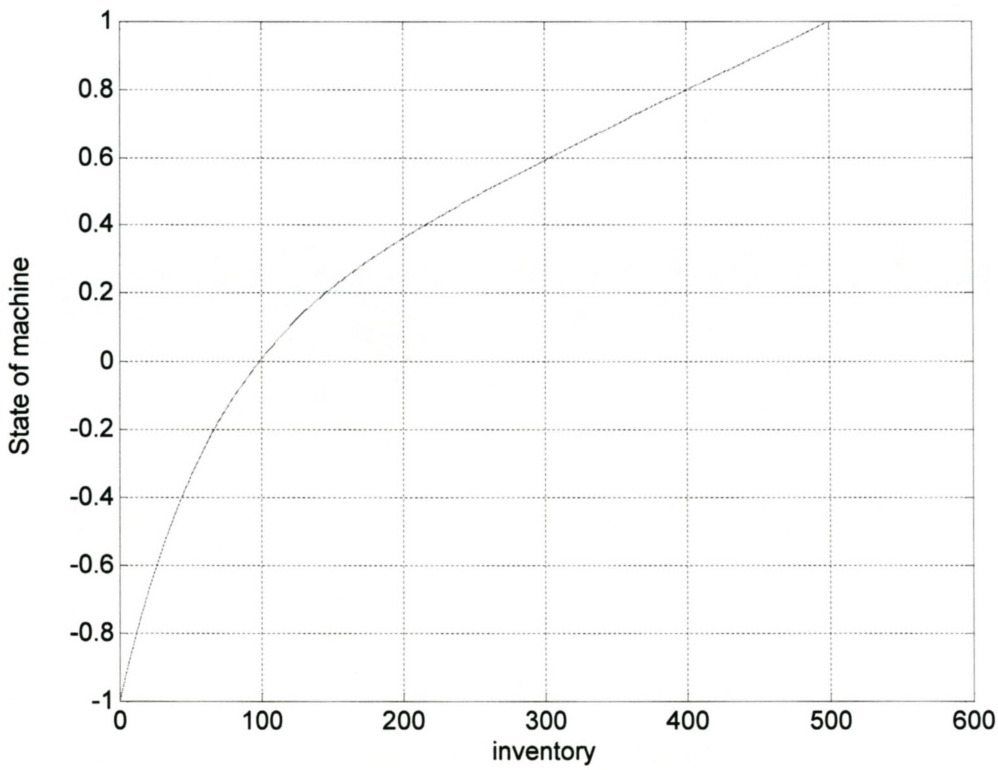

Figure A.2: Plot of state for machine 3

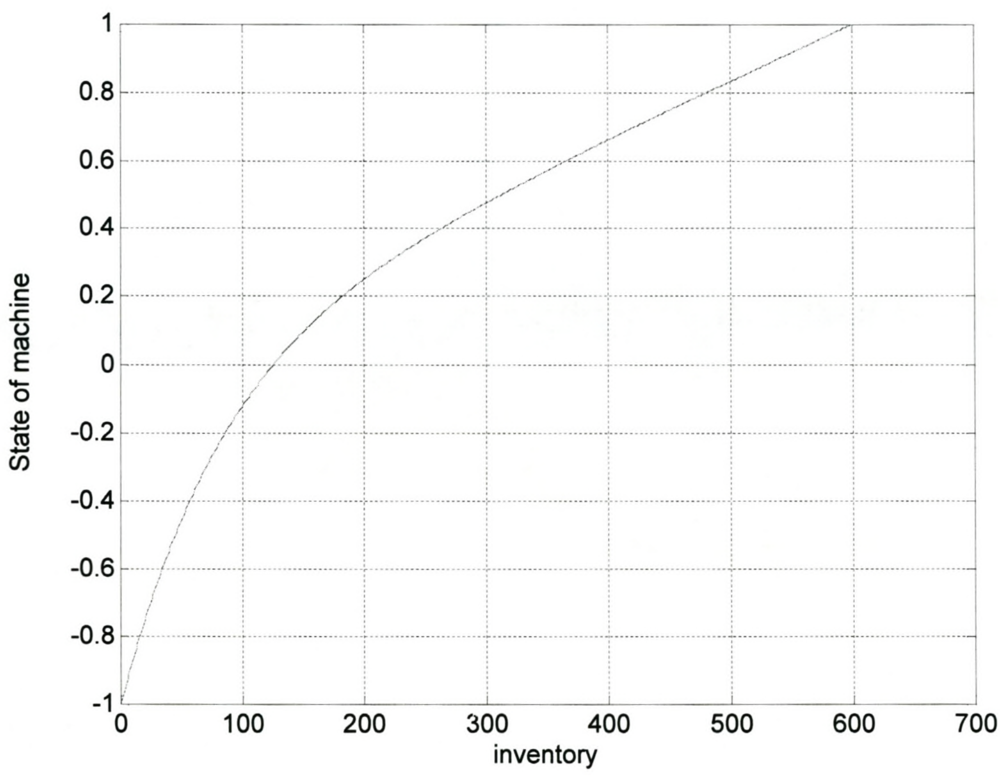

Figure A.3: Plot of states for machines 3 and 4

Appendix B:

Source Code for MATLAB Program.

All the registries and variables are cleared and other programs are closed.

```
Clear all
Close all
```

Here you can select how many machines you want in the system.

```
num_mach = 5;
```

All the system parameters in the tables are read into the program automatically so you don't have to type them in every time.

```
maxinv(1) = 400;
maxinv(2) = 400;
maxinv(3) = 500;
maxinv(4) = 600;
maxinv(5) = 600;
inv(1) = 50;
inv(2) = 50;
inv(3) = 60;
inv(4) = 80;
inv(5) = 80;
mean(1)=50;
mean(2)=50;
mean(3)=60;
mean(4)=80;
mean(5)=80;
usage_mean(1) = 10;
usage_mean(2) = 10;
usage_mean(3) = 12;
usage_mean(4) = 15;
usage_mean(5) = 15;
batch(1)=60;
```

```
batch(2)=60;
batch(3)=80;
batch(4)=120;
batch(5)=120;

for i = 1:num_mach,
   usage_std(i) = 2.5;
end
```

The alternative coding is in order to let the user type in the system parameters when the program is running is given here:

```
Num_mach = input ('How many machine will be served?: ')
For I = 1:num_mach,
  Maxinv(i) = input ('What is the maximum inventory level? : ')
  Inv(i) = input ('What is the starting inventory?: ')
  Mean(i) = input ('What is the average amount of stock at the machine?: ')
  Usage_mean(i) = input ('What is the average usage of the machines per cycle?: ')
  Batch(i) = input ('What is the batch size brought to the machine?: ')
End
```

The new system is defined, newff (Matlab r12) creates a feed-forward back-propagation network.

The first brackets are a matrix of min and max values for input elements. The second brackets are the size of the *i*th layer, for the **n** number of layers.

```
network = newff([-1 1;-1 1;-1 1;-1 1;-1 1],[6 6],{'tansig' 'logsig'});
```

Initialise the state of the system. The state of the system is defined by the probability of running idle plus the cost of having in-process material

```
for i = 1:num_mach,
   State(i) = -exp(-inv(i)/mean(i)) + inv(i)/maxinv(i);
   end
```

The state is then displayed on the monitor.

```
State
```

The benchmark is calculated as the sum of the individual states of the machines.

```
benchmark = sum(abs(state));
% var1 = benchmark;
% var2 = var1;
% var3 = var2;
% bench = [var1 var2 var3];
```

The moving average of three is calculated; this is one option for calculating the moving benchmark.

```
% bench = zeros(1,50);
% for i = 1:50,
%     bench(i) = sum(abs(state));
% end
% benchmark = MEAN(bench);
```

The moving average of fifty is calculated; this is another option for the moving benchmark.

The user is asked to enter the number of iterations needed to train the network.

```
d = input (' enter number of iterations : ');
```

The variables to store the inventory levels and benchmark in are defined.

```
data = zeros(d,num_mach);
datab = zeros(d,2);
```

The Training Program is started here, it will loop for as many times as was defined above:

```
for k = 1:d,
```

The verdict is set to one so the system can be initialised after every iteration.

```
 verdict = 1;
```

The greedy function is defined.

```
greed = 2*k/d + 0.8
```

The input into the simulation model is the current state of the system.

```
input = state;
```

A decision is made by using a random number, if the number is smaller than the greedy function number; the decision (of which machine to serve next) goes to the machine with the highest vector.

```
if rand(1) < greed,
   m_state = state';
```

```
    output1 = sim(network,m_state);
    output = output1';
    [dummy1,j] = sort(output);
    decision = j(num_mach + 1);
```

If the number is bigger than the greedy function number, the decision of which machine to serve next is randomly selected, thus bringing mutation in the system to ensure diversity and not settling on a sub-optimum answer.

```
else
    m_state = state';
    output1 = sim(network,m_state);
    output = output1';
    decision = randint(1,1,[1,6]);
end
```

This is the element of the critic that classifies doing nothing as bad if any machine is idle.

```
if decision == (num_mach+1),
    for i=1:num_mach;
        if inv(i) == 0,
            verd = 0;
        end
    end
end
```

This part simulates the system processing the raw material with a certain standard deviation. The machine that was chosen before with the worst state has raw material added according to the system parameters.

```
for i=1:num_mach,
    inv(i) = inv(i)-fix(normrnd(usage_mean(i),usage_std(i),1,1));
    if inv(i) < 0,
        inv(i) = 0;
    end
end
```

```
if decision ~= (num_mach+1),
    if maxinv(decision) > (inv(decision) + batch(decision)),
        inv(decision) = inv(decision) + batch(decision);
    else
        verd = 0;
    end
end
```

The inventory levels of all the machines is displayed on the screen.

```
Inv
```

The inventory levels are logged in the data stores.

```
data(k,:) = inv;
```

The new states of the system are calculated after simulation.

```
for i = 1:num_mach,
    state(i) = -exp(-inv(i)/mean(i)) + inv(i)/maxinv(i);
end
```

The states are displayed on the screen.

```
State
```

The new benchmark is calculated and compared with the old benchmark.

Now the critic evaluates if the decision made was a good or bad decision.

```
current_state = sum(abs(state));
if verd == 1,
    if current_state < benchmark,
        verdict = 1;
    else current_state >= benchmark,
        verdict = 0;
    end
else
    verdict = 0;
end
```

The different types of benchmark are all updated.

```
% var4 = var3;
% var3 = var2;
% var2 = var1;
% var1 = current_state;
% benchmark = (var1 + var2 + var3 + var4)/4
```

The moving average window of four.

```
% mm = fix((100*k)/(d))+1;
% % maxm = min([mm 50])
% bench(mm) = current_state;
% for n = 2:mm,
% bench(n-1) = bench(n);
% end
% benchmark = MEAN(bench);
benchmark = current_state;
```

Dynamic growing moving average window of 1 to 100.

```
% for n = 2:50,
% bench(n-1) = bench(n);
% end
% bench(50) = current_state;
% benchmark = MEAN(bench);
```

The moving average window of fifty.

The benchmark is logged in the data stores.

```
datab(k,:) = [benchmark current_state];
```

These are the three different reward systems, the programmer must chose one system before running the program.

```
RewardGood = 0.2*exp(-k/500)+0.05;]
RewardBad = 0.2*exp(-k/500)+0.05;]
RewardGood = ((num_mach-benchmark)/num_mach)*0.2;
RewardBad = (benchmark/num_mach)*0.2;
RewardGood = 0.1;
RewardBad = 0.1;
```

The three different types of reward systems. Choose one pair.

The following variables are shown on the screen so the user can monitor the progress of the training.

```
display = [decision verdict benchmark current_state RewardGood RewardBad k]
```

The outputs have to be adjusted according to the rewards just calculated.

```
if verdict == 1,
   for i = 1:(num_mach + 1),
      if i ~= decision,
         output(i) = output(i) - RewardGood/(num_mach);
      else
         output(i) = output(i) + RewardGood;
      end
      if output(i) < 0,
         output(i) = 0;
      elseif output(i) >= 1,
        output(i) = 1;
      end
   end

elseif verdict == 0,
   for i = 1:(num_mach + 1),
      if i ~= decision,
         output(i) = output(i) + RewardBad/(num_mach);
      else
         output(i) = output(i) - RewardBad;
```

```
        end
        if output(i) < 0,
            output(i) = 0;
        elseif output(i) >= 1,
            output(i) = 1;
        end
    end
end
```

Train the neural network with adjusted output.

```
    network.trainParam.epochs = 3;
    input1 = input';
    output1 = output';
    network=train(network,input1,output1);
end
```

Appendix C:

User Instructions for MATLAB Program.

1. When running the ANN program:

- Open the Matlab environment with the icon on the screen or through the start menu.

- Change the path to read from the A drive if the program is on disk.
    1. Click on File > Set Path …
    2. Click on Browse and select the A: drive
    3. Close the window
- In the command line in the Matlab Environment type: **NN_IS** and press enter.
- The program will prompt you to type in the number of iterations that you as user think is necessary to achieve successful training. 2000 iterations are usually sufficient.
- The program will now automatically start running till the number of iterations is completed.

2. When editing the program

- The file name is **NN_IS**.
- The Matlab program has to be installed on the computer to be able to edit and compile the ANN program
- The Matlab program does not has to be running at the time of editing.
- The writing in green is the comments and the writing in black is the actual programming.
- The number of machines and their parameters can be adjusted to the company's specifications in the programming section.
- The Program has the optional setting to read in these variables while the program is running. The program is set by default to read the parameters already in the program.