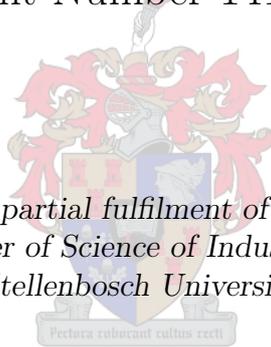


Determining Tactical Operations Policies for an auto carrier using discrete–event Simulation

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the degree of Master of Science of Industrial Engineering at
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Declaration

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Abstract

Passenger cars are either imported to or assembled in South Africa, and then distributed to the customer. An important part of the supply chain is formed by the auto carrier companies who do this distribution. The basis of this thesis is a study that was executed in collaboration with a South African auto carrier company, and the objective was to improve the long-distance auto carrier fleet management through improved tactical operational policies. These policies focus on application of the fleet by assigning transportation vehicles to routes, as well as the business rules that must be followed at pick-up and drop-off locations.

Several rules were developed during this study, which, together with specific transportation vehicle (carriers) assignments, form operational scenarios. The quality of each scenario was evaluated using discrete event simulation over a six month time-span, and considering four decision parameters simultaneously. These parameters are 1) useful kilometres travelled by the long-distance carriers, 2) empty kilometres travelled by the same long-distance carriers, 3) the expected number of cars waiting to be transported and 4) the expected time it takes to deliver a car to its destination.

A high level of uncertainty prevails in these transportation operations, while fluctuating demand calls for the dynamic allocation and management of carriers in order to sustain an acceptable service level in a cost-effective manner. The best tactical policies should maximize the number of cars delivered on time at the lowest cost. Major constraints considered are staff- and maintenance schedules.

While searching for the best of several scenarios, multiple, conflicting criteria had to be evaluated, as mentioned above. Two multi-criteria decision analysis (MCDA) methods were used namely SAW and TOPSIS, while the Mahalanobis distance method was also applied as an evaluation technique. These methods were used to rank scenarios. Additionally, the application of Portfolio theory and the efficient frontier was investigated for applicability to the problem studied. An analogy to the efficient frontier providing an additional means for scenario selection and evaluation was developed.

The result of this study provides the decision maker of the auto carrier company with a tactical decision aid, consisting of the MCDA and Mahalanobis scenario rankings, a cost-benefit graph and a fleet portfolio efficient frontier, to aid long-distance carrier management. Additionally, a sensitivity analysis was also done for strategic planning concerned with the sufficient long-distance carrier fleet size.

The first part of this thesis comprises a study of literature in which freight operations, auto carrier studies and the auto carrier context in South Africa are investigated. The problem is formulated and a suitable formulation and solution tool identified. Multi-criteria decision analysis is also investigated in order to enable scenario evaluation.

The solution development phase consisted of the simulation model concept development, acquisition of input data, model verification and validation, scenario construction, simulation execution, and analysis of results.

Opsomming

Die vragvervoerbedryf ondervind baie onsekerhede in hulle besigheidsumgewing waarin vraag na diens gedurig wissel. Om 'n aanvaarbare vlak van diens op ekonomiese wyse te lewer word dinamiese aanwending en bestuur van afleweringervoertuie verlang.

Hierdie studie handel oor die ontwikkeling van bedryfsbeleide op taktiese beplanningsvlak vir 'n motorvervoeronderneming. Hierdie soort onderneming versprei passasiersmotors vanaf Suid-Afrikaanse hawens en plaaslike monter-aanlegte na landwye motorhandelaars deur van gespesialiseerde vragmotors gebruik te maak. Die doel van die studie is om te bepaal watter getal vragmotors in die vloot vas aan roetes toegedeel moet word, terwyl die res as swerwende hulpbronne moet werk. 'n Swerwende hulpbron is nie gebonde aan roetes nie en mag enige roete volg om motors te versprei. Saam met die toedelingbesluit is reëls bepaal om aan vragmotorhulpbronne voor te skryf wat om by op- en aflaaibestemmings te doen ten opsigte van watter motors gelaai moet word, en hoe die volgende bestemming gekies moet word. Belangrike beperkings wat geld is vragmotorbestuurder- en diensskedules wat nagekom móét word.

Verskeie scenarios vir taktiese beplanning en bestuur is ontwikkel en die waarde van elk is met diskrete, stogastiese simulاسie evalueer. Hierdie evaluاسie het egter vereis dat uiteenlopende kriteria in ag geneem moes word, derhalwe is multikriteria-besluitnemingtegnieke soos SAW en TOPSIS aangewend om tussen scenarios te onderskei. 'n Verdere metode, naamlik die Mahalanobis-afstandmetode, is ook toegepas vir die ordening van scenarios. 'n Analogie tot die *efficient frontier* uit die portefeuljeteorie is ook ontwikkel en toegepas om die belegging in vaste en swerwende hulpbronne (die vlootsamestelling) te ondersoek.

Die resultaat van die studie voorsien die besluitnemer by die motorvervoer-onderneming met verskeie hulpmiddels vir taktiese besluitneming en bestuur. Die multi-attibuutontledings en Mahalanobis-afstande toon watter soort bedryfs-reëls effektief sal wees vir 'n gegewe vlootsamestelling en 'n gegewe wisselende vraag. 'n Koste-winsontleding asook die analogie tot portefeuljebestuur is verdere hulpmiddels wat vir besluitneming gebruik kan word. 'n Sensitiwiteits-

analise, wat meer strategies van aard is, is ook gedoen deur te bepaal hoeveel aflewingsvoertuie nodig is om in die huidige vraag te voorsien, asook in groeiende toekomstige vraag.

Die eerste gedeelte van die tesis word gewy aan 'n literatuurstudie. Algemene tegnieke wat potensieel gebruik kon word om die probleem mee te bestudeer word kortliks genoem en oppervlakkig uiteengesit, terwyl die werking van vragvervoer asook motorvragvervoer ondersoek word. Die formele probleemstelling word bespreek en die moontlike metodes om die probleem mee te formuleer. Die modelkonsep word uiteengesit, gevolg deur scenario-ontwikkeling, 'n bespreking van die data gebruik en die verkryging daarvan, modelverifikasie en -validasie, en die resultate verkry en die gevolgtrekkings wat daaruit volg. 'n Aanbeveling word laastens aan die motorvervoeronderneming gemaak ten opsigte van hulle vlootsamestelling en taktiese beplanning en bestuurreëls.

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Glossary

Mode	Means of transportation.
Intermodal	Inter-connectivity between various modes of transportation.
Consolidation	The combination of many small loads into one.
Carrier	A means of transporting goods from origin to destination.
Motor carrier	Using a truck to transport goods from origin to destination.
Auto carrier	A truck transporting vehicles; the business entity that provides vehicle transportation using trucks.
D RTP	Dynamic Resource Transformation Problem.
Terminal	A station where transport passengers or goods are unloaded.
Capacitated	Restricted capacity.
Commodity	Articles of commerce, a good or service that is exchanged for money.
Multi-commodity	Multiple types of articles or goods are involved.
LTL	Less than Truckload.
Vertex	The point at which two line segments/ lines, meet.
Long-haul	A drive over a long distance, generally performed with tractor-trailers.
Solution space	A framework for conditions which describes all valid solutions of a problem instance.
SN DP	Service Network Design Problem.
AC	Auto Carrier.
DM	Decision Maker.
IP	Integer program.
stevedoring	The action of loading and unloading cargo of a ship.
MCDA	Multi-criteria Decision Analysis.
MADM	Multi-attribute Decision Making.
MODM	Multi-objective Decision Making.
Portfolio	A collection of investments (usually stocks or shares) held by an institution or individual; a list of such investments.

VRP	Vehicle Routing Problem.
Freight	Refers to the cargo that is being transported.
Dispatching	The scheduling and control of a truck picking up and delivering items.

Chapter 1

Introduction

This chapter comprises a short background on the problem with which this study is concerned, the thesis objectives and an overview of the layout of this document.

1.1 Problem background

Delivering cars, trucks or vans to auto dealerships is a unique problem in the routing and scheduling problem class. Vehicles are collected at their point of import or at the manufacturer, and then have to be transported to dealerships. This important link in the supply chain is facilitated by auto carriers and rail operations. The focus of this study is on the former.

Car dealerships initiate the vehicle distribution process by placing orders at the manufacturer. The manufacturer then contracts an auto carrier company to pick up the vehicles and distribute them to the car dealers. Vehicles are collected at the manufacturers by the auto carriers and transported to the auto carrier branches from where regional deliveries are made to car dealers from the local auto carrier branch. A time-frame for order delivery exists.

This study was done in collaboration with a South African auto carrier company which distributes most of the major car brands in South Africa. This auto carrier company has branches in all the major cities where they can store the cars temporarily, and facilitate loading and unloading of regional and long-distance carriers. Since the orders of individual car dealers are usually small, smaller carriers (regional) are used for these regional deliveries. Car dealerships are grouped together in a cluster of three or less, and serviced by an auto carrier.

The scheduling of the long-distance carriers is currently done at a scheduling depot in Bellville. The scheduling depot receives information from the individual branches and some manufacturers, and constructs a schedule according to which long-distance carriers are employed on the fixed long-distance routes.

This schedule has to accommodate different factors. South African labour and traffic regulations require that truck drivers rest a certain number of hours per day, and after 14 work days drivers have to be home for two consecutive days. Carriers also receive maintenance and service in Bellville.

The core function of an auto carrier company is to apply auto carriers effectively and efficiently to meet manufacturers' requirements. The efficiency of dispatching carriers determines to a great extent the success of the company. Usually some trade-offs have to be made, e.g. cost-effectiveness vs. service level.

Policies that would increase predictability in an uncertain environment would enable greater efficiency regarding auto carrier functioning. Currently, long-distance carriers scheduled and assigned to specific routes, may be employed otherwise to constitute a bee-hive effect which means that carriers attend to unexpected events or peaks in the demand. Uncertainty in the system is therefore high as branch managers do not always know which carrier and what load to expect when. However, the auto carrier company needs to be flexible and dynamic in order to stay in business.

To accommodate peaks in the demand while reducing uncertainty in the auto carrier system, two types of carrier fleets are identified. The long distance carriers may either be employed as fixed or roaming, where fixed carriers persist with the prescribed schedule, and roaming carriers follow dynamic decision making, which sends them to where they are needed most at a specific point in time.

The question is therefore how many long-distance carriers to use as fixed and how many as roaming. Apart from determining the most suitable fleet composition for the current demand, rules/operational policies may also be identified, dictating how these carrier fleets should operate.

This study intends therefore, to improve dispatch, scheduling and fleet operations by investigating fleet composition and other operational policies of the carrier fleet on a tactical level.

Variation and uncertainty in this specific area, in terms of varying demand sizes and types, when orders arise and when they are to be delivered, as well as when cars are ready for pick-up at the manufacturer, add to the complexity of routing, scheduling and overall fleet management. Efficient management of the auto carrier fleet is of great importance to enable better scheduling and task assignment.

1.2 Project objectives

The project objectives were identified to encompass the following aspects:

- To develop and evaluate policies on a tactical level that will reduce uncertainty in an unpredictable environment, enabling better long-distance carrier fleet management.
- To develop an effective tactical decision support tool for the auto carrier company.

1.3 Chapter overview of this study

This chapter provided background information and an introduction to the problem addressed, and the objectives of this study. In Chapter 2 some background information on transportation problems is presented, whereas freight transportation operations and related literature are discussed in Chapter 3. Chapter 4 involves information on the motor carrier industry, while general auto carrier functioning, auto carrier studies found in literature, and specific functioning of the auto carrier company with which this study is concerned, are discussed in Chapters 5 and 6. Chapter 7 focuses on the particular problem and the problem objectives. The appropriate method for this project is then investigated in Chapters 8, 9, 10 and 11. Subject matters covered include different analytical modelling possibilities such as the transportation problem, integer programming, resource allocation and assignment, the service network design problem, stochastic programming, and computer simulation. In Chapter 12, performance measures for evaluating scenarios are identified, and then MCDA evaluation techniques are explored as well as the Mahalanobis distance approach. Financial modelling and portfolio theory are also investigated. A road-map of the literature study done is shown in Figure 1.1.

The solution strategy is then provided in Chapter 13, which introduces the solution development phase of this study, presented in Chapters 14 to 18. The scenario development is presented in Chapter 14, after which the conceptual development is discussed in Chapter 15. Chapter 14 encompasses the examination of the scenarios constructed and the policy rules developed which characterise these scenarios. Chapter 15 explains model functioning, input and output requirements. A graphical concept model is also included. Chapter 16 presents the data requirements and information acquired. Validation and verification matters investigated are discussed in Chapter 17, to ensure that the simulation models are correct and valid. The scenario results and the analysis thereof are included in Chapter 18. Scenario output is shown, as well as the analysis results. In conclusion, the developed decision support is provided and discussed.

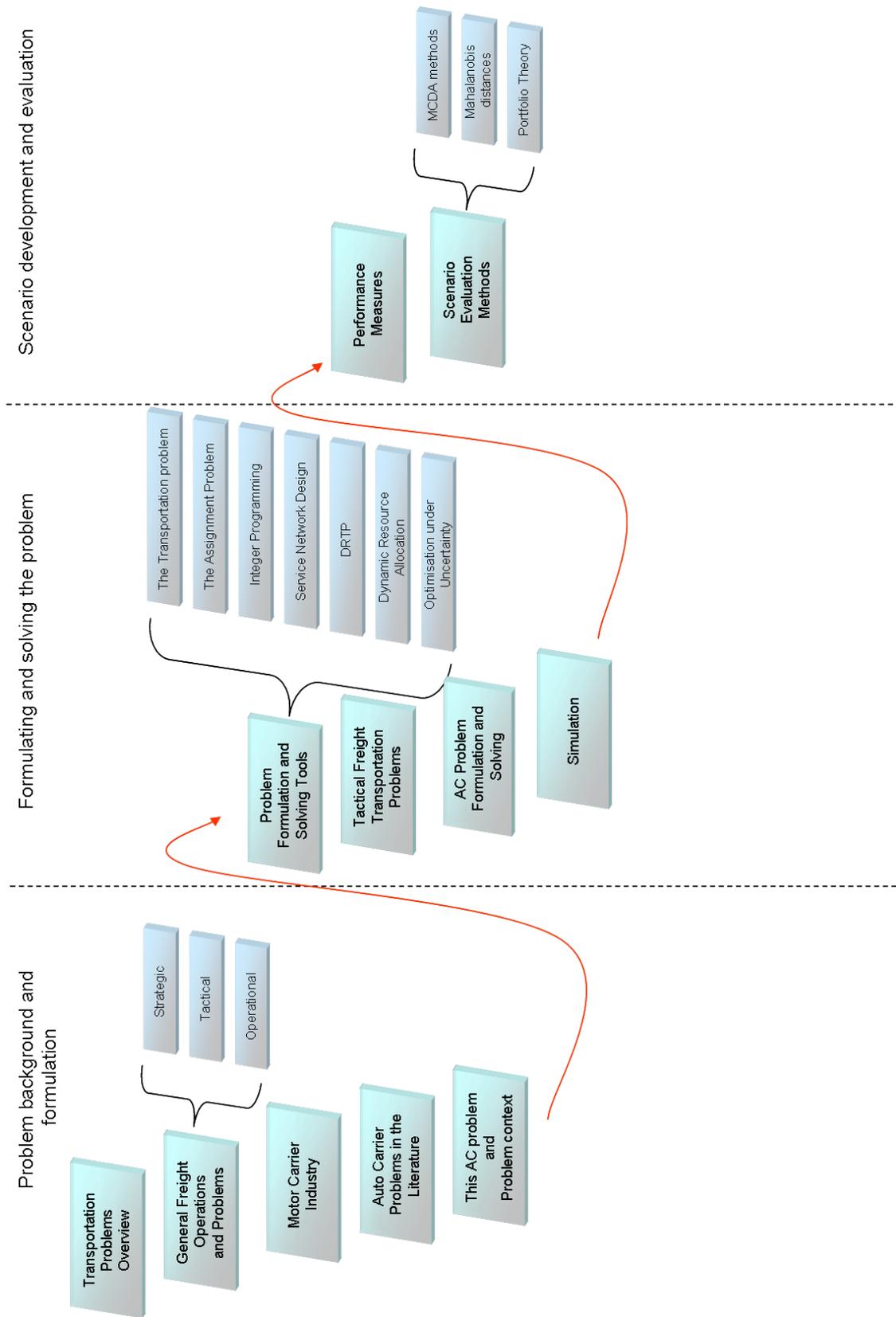


Figure 1.1: Roadmap of the Literature Study

Chapter 2

Transportation Problems

Transportation can be defined, according to Powell & Topaloglu (2003), as “the business of moving things so that they are more useful”. Transportation systems may be seen as complex systems, involving a great deal of human and material resources, and requiring numerous trade-offs among policies and various decisions. Different types of players in the transportation field may be identified. The major role players according to Crainic & Laporte (1996) are the producers (often called shippers), the carriers and the government. Where the producers of goods determine the demand for transportation, the carrier (railways, shipping lines, motor carriers) performs the transportation, and the government usually provides a large part of the infrastructure. In this chapter typical transportation problems and uncertainty in a transportation system are explained to illustrate the complexity of transportation in general.

2.1 Transportation sample problems

A variety of problems in transportation exists. Some main problem classes of application are:

- Product distribution: A typical problem is to determine what quantity of product to ship from a plant to intermediate warehouses before it arrives at the retailer. Decisions must be made on where to, and how much to ship, before the customer demand is known. Variations of this problem include:
 1. Separability of the distribution process: customers may (often the case) be served by one specific warehouse although substitution among warehouses may occur.
 2. Multiple product types with substitution: Multiple products may be produced, and when one type is sold out, customers would be willing to purchase alternative products.

3. Demand backlogging: When a specific demand is not satisfied in one time-period, the demand can be assumed to be either lost or backlogged.
- Fleet management/Container management: Containers represent a reusable resource, changing the state of the system when satisfying the customer demand. When fulfilled, customer demands disappear from the system, but the container does not. Problem variations include:
 1. Single commodity problems: These problems occur when all containers are the same, or where no substitution is allowed between different container types.
 2. Multi-commodity problems: Different container types may exist and customers may choose between them.
 3. Time windows and demand backlogging: It is usually the case that customer orders can be delayed or be delivered within an agreed-upon time window. The most common models, however, represent customer orders which are lost when not served/serviced at a specific point in time.
 4. Trans-shipment and relay points: The most simple models represent a demand as the need to move from i to j , representing a single decision. More complex circumstances have to deal with relays or transshipment points where containers have to move from one mode to another.
 - Managing complex equipment: Complex equipment may include different aircraft or classes of locomotives. The complexity is due to the large number of characteristics/attributes that needs to be taken into account. It may be necessary to distinguish between different trucks in terms of size, axles, or where their home depot is.
 - People and crews: People are required to drive the trucks and operate equipment. When humans are of concern, a complex set of operational attributes is often the case. Attributes may include current location, home base, level of skill, and hours driven.

All these problems are some kind of resource allocation problem, involving the assignment of a set of reusable resources to tasks. These tasks are usually performed over a period of time, and therefore require the dynamic assignment of resources.

2.2 Uncertainty in transportation

According to Powell & Topaloglu (2003), “uncertainty arises whenever we need to make a decision based on information that is not fully known”.

Three scenarios of uncertainty regarding information can be defined as follows:

- The information is not yet known.
- The information is known to a particular person who is not the decision maker.
- Incomplete information: The information will never be known.

Conventionally, uncertainty can be defined as the unpredictability that is present in a system, due to arrival of information over time, as decision-making is often required when information is still incomplete or not yet known.

Problems in transportation and logistics are typically characterised by highly dynamic information processes. Three basic classes of dynamic information processes can be identified to facilitate a means of evaluating uncertainty in a system: the resource being managed, the physical processes which facilitate the evolution of the system over time, and the decisions that are implemented in the system as controls. These classes are briefly discussed below.

2.2.1 The resources being managed

Resources in this context include all information classes that are actively managed, and can be defined as “endogenously controllable information classes which constrain the system” (Powell & Topaloglu (2003)). Here not only the conventional resources such as trucks, trains and planes are included, but also customer orders. Dynamic information processes for resources may include:

- Information about new arrivals in the system: usually the arrival of new customer orders, but can also be the arrival of a product, people, or equipment (for example, the hiring of new drivers at a trucking company).
- Information about resources leaving the system.
- Information regarding the state of a resource: the breakdown of a truck or a driver on leave.

An important concept regarding the modelling of resources is the difference between ‘knowability’ and ‘actionability’: A customer order that was booked in advance becomes known right now, but effective only when it arrives at some future point in time.

2.2.2 Physical processes

Processes include information about parameters that govern the evolution of the system over time. The three most important classes that contribute to uncertainty include: The time required to complete a decision, the cost of a decision, and parameters that determine the attributes of a resource after a decision (Powell & Topaloglu (2003)).

2.2.3 Controls for decision making

In real problems a distinction can be made between decisions that are planned and those that are actually made. When modelling the decision making process, it is often observed that the actual physical system does not evolve as planned, due to unavailability of information required by the model, or the fact that decisions made by a model are not detailed enough. Decision makers may also simply prefer to use a different problem solving approach when making the decisions (Powell & Topaloglu (2003)).

2.3 Concluding remarks: Chapter 2

It is argued in this chapter that real-life transportation problems are usually not trivial. A lot of uncertainty is present in transportation systems and different kinds of complexities need to be considered.

The field of transportation has to cope with a vast spectrum of problems. The focus of the literature study progressively narrows in order to create a context and facilitate better understanding of the auto carrier industry and this study problem. A basic illustration of the narrowing literature study focus is provided in Figure 2.1.

In the next chapter, general freight problems which form a subset of transportation problems, are introduced. An overview is given on particular freight problems found in the literature, with particular emphasis on *tactical planning problems*. Appropriate formulation possibilities and solution techniques are also introduced and briefly discussed.

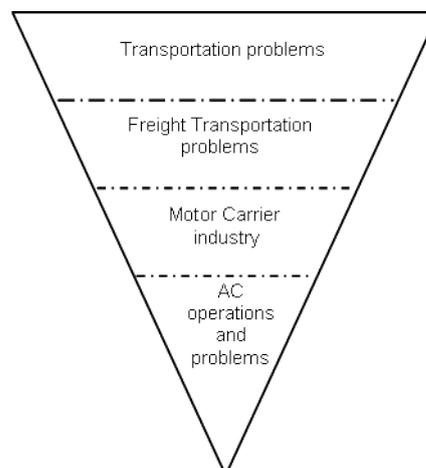


Figure 2.1: Literature study focus

Chapter 3

General Freight Problems

In the previous chapter the nature of transportation problems was discussed following a general approach. This chapter focusses more on on-land freight operations, typical problems that are encountered and problem modelling techniques for improved decision making.

Freight transportation is one of the most important activities in an economy, affecting almost all sectors of society, where transport costs make up a significant part of the cost of a product (Crainic & Laporte (1996)). Freight transportation has to adapt to changes in political, social and economic trends. Since a transportation company has to be profitable to sustain itself and simultaneously compete in an open and competitive market, where cost of a given quality and service level is of concern, the freight transportation industry has to achieve high performance levels in economic efficiency and service quality. There is an increasing emphasis on the quality of service offered, where quality control of the entire logistics chain, driven by the customer demands and requirements, demands high service standards of the transportation industry in terms of total delivery time and service. It is therefore important that planning and decision making processes related to freight operations are efficient and improved continuously.

Trucking, rail and other types of transportation networks share a common characteristic of moving equipment and crews between spatially separated terminals in order to accommodate the transportation of goods or people. The result is temporal and reveals spatial imbalances in freight flows. Methods to measure these flow imbalances and randomness on the transportation networks are developed and applied. Hall (1999) defined an associated imbalance cost.

According to Caramia *et al.* (2007) freight distribution may be addressed from two perspectives:

- From the delivery and pick-up viewpoint, delivery itineraries need to be considered, taking into consideration the delivery capacities and times of the operations.
- From the transportation and city planners' viewpoint, the 'distribution capacity' of the Central Business District (CBD), cost of distribution routes, total number of stores and routes are coordinated simultaneously.

In the article by Caramia *et al.* (2007), both these mentioned viewpoints are addressed by determining delivery itineraries available, balancing them while respecting time windows and capacity constraints.

According to Crainic & Laporte (1996), freight transportation planning may be classified as: strategic, tactical and operational.

Strategic policy guidelines determine the decisions taken on a tactical level, which in turn establish the operational rules and policies. Data flows in the opposite direction/the reverse route; each level of planning provides essential information for decision making at a higher level. Therefore, different model formulations are required to address specific problems at specific decision-making levels (Crainic & Laporte (1996)).

Figure 3.1 illustrates an overview of the freight transportation problem classes introduced and briefly discussed in this chapter, where more attention is paid to tactical planning. Tactical freight transportation problems in particular and specific solution techniques are discussed in more detail at a later stage.

3.1 Modelling freight problems on strategic level

Strategic planning at a company involves decisions about general development policies over relatively long time horizons, involves the top level of management and usually requires large capital investments. Strategic planning takes place at the international, national and regional levels, and involves holistic perspectives and more general policies. It may include the design and changes of a physical network, location of main facilities, resource acquisition, and tariff policies. State transportation departments, consultants and international shippers would typically be involved on this level of decision making. Strategic planning can be done according to Crainic & Laporte (1996) using location models, network design models and regional multimodal planning. These are subsequently discussed.

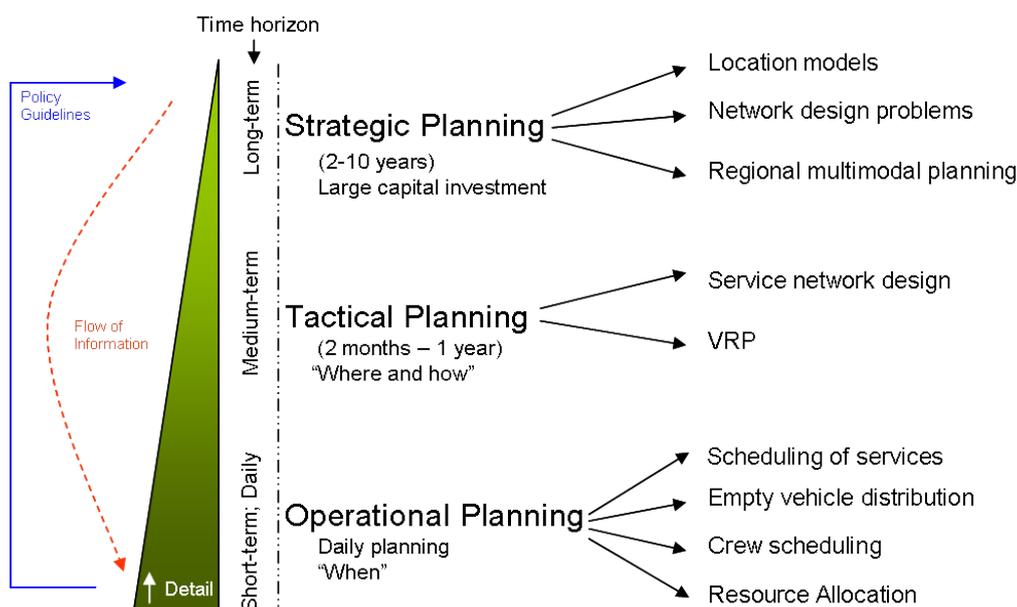


Figure 3.1: Overview of Freight Problems and Planning levels

3.1.1 Location problem models

Location problems involve 'where' a facility must be placed. A facility is usually positioned in such a way as to assist in the movement of goods along the network, therefore facilities are usually at vertices of a network. In the classical location problem, the customer demand is fixed. According to Crainic & Laporte (1996) one may distinguish between covering models, centre models and median models.

Covering models are typically associated with the location of public facilities such as post offices, shopping centres or schools. Facilities are located so that they lie within a given distance from vertices where the objective would be to minimise the locating cost and/or maximize demand covered by the facilities, subject to constraints. Centre models are associated with emergency services, aiming to minimize the maximum distance between a vertex and a facility. Median models are concerned with locating p facilities at vertices on the network and allocating demands to these facilities with the objective of minimizing the total weighted distance between facilities and demand points. The value of p determines whether the problem is an Uncapacitated Plant Allocation Problem, a so-called p -median problem, or a Capacitated Plant Location Problem. Other than the uncapacitated version, the capacitated plant location requires a fixed and finite capacity. Median problems are especially relevant to freight transportation and distribution.

Lim & Kim (1999) studied the dynamic plant location problem, where the location problem becomes a multicommodity uncapacitated location problem. Gendron *et al.* (2003) also developed the multicommodity version of the capacitated location problem. An overview on strategic location problems may be found in the review by Owen & Daskin (1998). More complex instances of this problem class include the multicommodity, multi-plant, capacitated version (Pirkul & Jayaraman (1998)). Some current state-of-the-art contributions on this subject matter are given in a review by Klose & Drexl (2005).

3.1.2 Network design models

Network design problems can be defined on graphs with nodes or vertices, and links. Links are typically directed and represented by arcs in the network. Without direction they are represented by edges. Some vertices are then origins and other are destinations for the traffic (Crainic & Laporte (1996)).

The simplest version of this problem may be identified as the *Shortest Spanning Tree Problem* (SSTP). The aim is to determine the minimal length tree linking all vertices of an undirected graph. The most general formulation of network design problems may be found in Magnanti & Wong (1984). The capacitated SSTP and an applicable algorithm is addressed in Sharaiha *et al.* (1997). However, the problems arising in transportation operations and planning are often more complex. Gendron & Crainic (1994) and Gendron & Crainic (1996) also contributed research to this field of problems.

3.1.3 Regional multimodal planning

Strategic planning must also address questions regarding the evolution of a particular transportation system. Three such issues would be the impact of infrastructure changes on the system's performance, the impact of government or industry policies, and system utilization changes due to demand changes in terms of volume, composition and special distribution. The focus of regional multimodal planning is on the specific representation of several transportation modes, the corresponding inter-modal transfer operation, the various criteria to determine the movement of freight, and the associated traffic distributions over the transportation system. For this type of planning, the class of network models is generally considered appropriate (Crainic & Laporte (1996)).

In the regional modelling framework, a node is a means of transportation with its own characteristics such as vehicle type, capacity, and particular cost measures. The base network is described by the nodes, links and modes that represent all possible physical movements on the available infrastructure. A

product is any commodity, passenger or good that generates a link flow. This formulated network model facilitates a detailed representation of the transportation infrastructure, facilities, services, and the simultaneous assignment of multiple products to multiple nodes (Crainic & Laporte (1996)).

Lingaitiene (2005) considers network models that allow for the prediction of multicargo flows in a multimodal network for the detailed modelling of a physical network on regional level.

3.2 Tactical freight problems

According to Crainic (2000), tactical planning of operations involves “interrelated decisions that aim to ensure an optimal allocation and utilization of resources to achieve the economic and customer service goals of the company”. It therefore involves the successful allocation and utilization of resources. Trade-offs are often necessary, such as the trade-off between operating cost and service performance.

Tactical planning is done over a medium-term horizon and involves efficient and effective allocation of resources with the aim of improving the whole system. On this level the data used for decision making is a bit more aggregated and although sensitive to variation, does not include all the day-to-day detailed operational data.

The transportation system can be divided into long distance distribution and regional traffic. The long distance distribution decisions are usually made concerning the design of the network designed by Wieberneit (2008). Tactical decisions are mainly concerned with route choices, type of services, general operating policies, rules regarding work allocation among terminals and repositioning of resources. A *transportation plan* is produced, according to which day-to-day policies are established that guide system operations, and planning on this level may therefore be seen as an important link in the planning process of a freight transportation carrier. A tactical transportation plan may also enable the evaluation of ‘what-if’ questions identified on the strategic level.

A distinction can be made between the *producers* of the goods and the *carriers* performing the transportation. From a planning point of view there may further be distinguished between the operations concerned with long distance movements of goods, such as rail operations and Less-than-Truckload (LTL) operations, and those transportation operations concerned with several pick-ups and deliveries, mainly by truck and over relatively short distances.

The first case is often referred to as the *service network design problem* and the latter as a *vehicle routing problem* (Crainic & Laporte (1996)). These two cases are now discussed.

3.2.1 Service network design for intermodal transportation

The goal of service network design formulations, according to Crainic (2000), is to plan services and operations to satisfy demand and ensure profitability of the firm. The objectives of a service network design formulation are quite complex, and includes the lowest possible operating cost while offering high quality of service in terms of reliability and flexibility. The best trade-off between the operating cost and service performance is usually of significance, and is one of the major concerns on the tactical level.

Crainic (2000) presents a review of service network design modelling and mathematical programming developments for network design. A classification of service network design problems and formulations is also introduced. According to Crainic & Laporte (1996), main decisions made at the tactical level concern the issues such as:

- Service network design: the selection of routes (origin, destination, physical route and intermediate stops), of services in terms of service characteristics and in particular their frequency.
- Traffic distribution: routing specifications for traffic of each origin-destination pair.
- Terminal policies: the efficient work allocation among terminals and general rules for each terminal regarding the consolidation type to perform.
- Empty balancing: repositioning of empty vehicles in order to fulfil forecasted demands.
- Crew and motive scheduling: allocation and repositioning for the next planning period according to the transportation plan. These decisions are strongly interconnected and have network-wide impacts, often requiring trade-offs.

Some important tactical planning decisions involve consolidation matters of intercity freight carriers. Logistic service providers consolidate freight in a network of hubs and terminals, and facilitate services required (Wieberneit (2008)). The design of these services involves decisions about the particular mode, frequency, routes and of course the scheduling and routing of the freight. Consolidation operations may include the grouping of vehicles and the movement of services (Crainic (2000)). Consolidation type operations, in contrast to ‘door-to-door’ transportation operations, are central to tactical planning issues.

Crainic (2000) illustrates the complexity of tactical decisions/planning in the context of an inter-modal system. When a shipment arrives at the terminal, it must be routed/ distributed according to strategies which may include:

- Consolidation of the shipload with other shipments, and use a ‘direct’ service (no stops involved).
- No consolidation with other shipments, but a service is used that stops at one or several intermediate terminals to drop-off and pickup load.
- The consolidation of a particular load at an intermediate terminal.
- No consolidation, but a ‘dedicated’ service, truck or direct train is used (when the freight volume is sufficient, and the customer contract allows it).

The ‘best’ option requires the simultaneous evaluation of all traffic, the level of service on each route, and the terminal costs and characteristics.

Most service network designs result in fixed cost, capacitated, multi-commodity network design formulations, which may be static or dynamic, and deterministic (Crainic (2000)).

For the deterministic dynamic service network design, a time dimension is introduced into the formulation by representing the system operations over a number of time periods, using a space-time network. Dynamic or time-dependent service network design (DSND) arises therefore when the schedule is a function of time. Due to the time dimension, this network formulation results in significantly large graphs. The size of the dynamic network as well as the additional constraints required makes this type of problem much harder to solve than a static one (Crainic (2000)).

Farvolden & Powell (1994) present a dynamic service network design model for LTL transportation. Although it allows for several departures at once, only a simpler 0, 1 version could be solved. Attempts to incorporate other constraints and additions include combining empty car distribution with the train

routing problems by Haghani (1989), and the integration of various service network design aspects into a scheduled operating plan by Gorman (1998). More recently, Dall’Orto *et al.* (2006) focus on a particular version of the dynamic service network design (DSND) problem where a single-terminal dispatches services to a number of customers and other terminals.

A distinction can be made between frequency and dynamic service network design models (Crainic (2000)). Frequency service network design concerns questions such as What services to offer, How often over the planning horizon, What traffic itineraries to operate, and Terminal policies and workloads. The frequency service may be further classified as decision or output, according to the role that service level plays in the formulations. The output of frequency service network design models is a load plan or transportation plan, facilitating day-to-day policies that guide the system operations, also enabling ‘what if’ questions.

Powell & Sheffi (1983) contributed to the frequency service network. The load planning problem for less-than-truckload motor carriers is formulated by Powell (1986) as a fixed charge network design problem. Service level constraints are represented heuristically by a set of minimum frequencies on links. The frequency of services also plays an important role in railroad freight transportation (Jeong *et al.* (2007), Mancuso & Reverberi (2003)).

3.2.2 The vehicle routing problem

According to Caramia *et al.* (2007), there are many freight distribution models for national level problems, including multi-modal transportation. For medium-size to small customer deliveries, models focus on the vehicle routing problem (VRP) and its variants, and try to design routes that minimize either the number of vehicles or the total distance travelled. When time-window constraints are introduced, VRP models are applied to address problems concerned with the timely distribution of goods.

VRP models typically involve the distribution of goods at the local or regional level, comprising activities such as pick-up and delivery. In essence, according to Crainic & Laporte (1996), VRPs involve the design of pick-up and delivery routes from one or more central depot to a set of customers with different geographical locations. Different versions of this problem may be identified to include:

- Pick-up, delivery or pick-up and delivery.
- Distribution from a single or multiple depots.

- How many vehicles involved? Is the number fixed? Associated capacity, speed, operating costs of the vehicles.
- Driver work conditions?
- Known demand? Or is the demand revealed dynamically?
- How often and when are customers to be visited?

Caliskan & Hall (2006) address the optimization of equipment and crew movements on a tactical level in long-haul trucking networks with the strict time constraint of getting the crew home in time. Static routes are produced by means of a column generation algorithm. Caliskan & Hall (2003) present a dynamic formulation for generating route sets, but on an operational level. Skitt & Levary (1985) and Bodin *et al.* (1983) study a problem in which demands are expressed as truckloads and the objective is to minimize total distance travelled. Apart from Caliskan and Hall, Powell (1996) and Crainic & van Roy (1992) also address the issue of returning drivers home. The basic formulation of the VRP and different problem classes are discussed in the next section.

3.2.2.1 VRP classes

The classical VRP basically consists of finding m vehicle routes of minimal total cost where each vehicle route starts and ends at the depot, and each vertex (physical location in a transportation network) is visited at least once by exactly one vehicle. The total duration of each vehicle route should not exceed the present limit T_{max} (this restriction is often discarded) (Toth & Vigo (2002a)). When the homogeneous fleet of vehicles delivering goods from a single depot to various customers have restricted capacity Q , the classical VRP becomes a capacitated vehicle routing problem (CVRP) (Toth & Vigo (2002a)). A limit may be imposed on the distance travelled by each vehicle. The problem then becomes a distance constrained VRP, the DVRP (Toth & Vigo (2002a)). This may also be imposed on the CVRP, resulting in a CDVRP.

Time windows are introduced when customers impose restrictions on the delivery times of goods. Time windows may be hard or soft. Hard time windows implies that no delivery is allowed (the solution is regarded as infeasible), when service time does not fall within the time window. In the soft case, however, time windows may be violated, but a penalty is incurred (Toth & Vigo (2002b)).

The multiple-depot VRP (MDVRP) describes the case where a company has more than one depot from where it may provide services to different customers (Giosa *et al.* (2002)). Possible fleet constraints include the limitation on the number of vehicles, heterogeneous fleet (homogeneous fleet is usually

assumed where vehicles have the same capacity, speed and transit cost), or a finite fleet size (Lau *et al.* (2003), Renault & Boctor (2002), Gendreau *et al.* (1999)).

Time windows may be introduced to particular fleet specifications in combination with other capacity constraints. The VRP with time windows and a limited number of vehicles is therefore known as the m-VRPTW, and the heterogeneous fleet (also known as fleet size and mix) in combination with time windows would be FSMVRPTW (Renault & Boctor (2002)).

The VRP with pick-ups and deliveries (VRPPD) is a variation of the VRP in which a heterogeneous set of vehicles, based at multiple depots, have to complete requests, where these requests consist of a pick-up and delivery point and a volume to be transported. An important aspect is that the goods do not move through a depot. A well-known example of the VRPPD is the Dial-a-ride problem (Toth & Vigo (2002c)). The VRP with backhauls (VRPB) requires that a set of customers is divided into line haul customers, each requiring delivery of goods, and backhaul customers requiring pickup of goods by the vehicles.

There are other VRP types as well, where customers may be served more than once by more than one vehicle, or where vehicles do not have to return to the depot. However, these and other additional VRP problems are not discussed here. The simple illustration in Figure 3.2 gives a basic overview of how VRP problem cases may be constructed. In real-life applications, there is usually some degree of uncertainty and randomness present, and dynamic information only becomes known as routes are carried out.

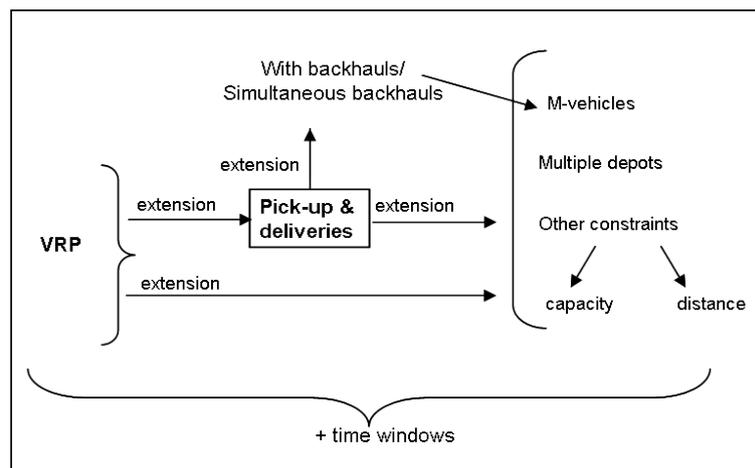


Figure 3.2: Overview of VRP problem classes

3.2.2.2 The probabilistic VRP, dynamic and stochastic VRP

The Probabilistic VRP was developed to address customer demands which vary in a known or predictable way. This class of VRP is however also static since the change in demand is still known in advance and thus predictable.

The Dynamic VRP (DVRP) can be defined, according to Larsen (2001), as having the following attributes:

1. *Not all information relevant to the planning of the routes is known by the planner when the routing process begins.*
2. *Information can change after the initial routes have been constructed.*

The DVRP can be seen as a ‘richer’ problem than the conventional static VRP, since it calls for on-line algorithms functioning in real-time. Psaraftis (1988) also stated that the choice of suitable solution techniques is highly dependent on whether a VRP is dynamic or static. He defined twelve methodological points by which a dynamic VRP can be distinguished. He also proposed a taxonomy used for characterizing attributes of the information forming the input for the VRP. Powell *et al.* (1995*b*) distinguishes between the dynamism within a problem, a dynamic model and the dynamic application of a model.

Larsen (2001) developed a measure for establishing the degree of dynamism of a system in order to be able to measure the performance of specific algorithms under certain conditions. The Degree of Dynamism measure, considers the number of immediate customers (arising while the planned route is executed, thus after the planning period is finished) in relation to the total number of customer orders (immediate and known in advance). DVRP real-life application examples as identified by Larsen (2001) include Courier service, Heating oil, Dial-a-ride problem, Taxi cab service and Emergency service.

The Stochastic VRP, according to Larsen (2001), has one or more stochastic elements. These usually encompass uncertain travel durations, unknown demands or unknown existence of customers. The Stochastic VRP may also be seen as a generalization of the Probabilistic VRP. The PVRP deals with demands which are probabilistic in nature since the demands vary in a known and predictable way. Stochastic VRP (SVRP) can be either static or dynamic.

Six categories of stochastic application can be distinguished, according to Larsen (2001), of which three are relevant to this study. They are:

- VRPSD: Vehicle Routing Problem with stochastic demands
- VRPSC: Vehicle Routing Problem with stochastic demands
- VRPSCD: Vehicle Routing Problem with stochastic customers and demand

A relationship between the PVRP, SVRP and DVRP according to dynamism, is shown in Figure 3.3.

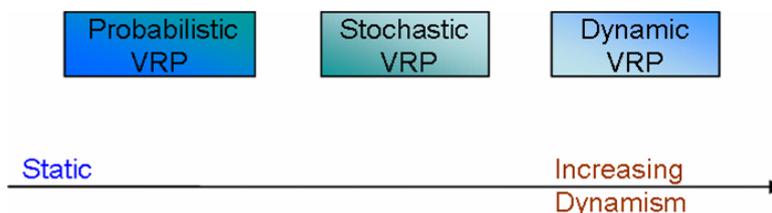


Figure 3.3: The scale of dynamism of VRPs

3.2.2.3 Overview of VRP solution techniques

Algorithms used to solve vehicle routing problems may be divided into three categories: exact methods, heuristics and metaheuristic methods.

Exact methods may be formulated as vehicle flow formulations, commodity flow and set partitioning formulations usually solved using branch-and-bound algorithms, branch-and-cut algorithms or set partitioning methods.

Heuristics are flexible; they seldom return an optimal solution but are computationally efficient. Well-known algorithms include the sweep algorithm, petal algorithms, savings-based algorithms, matching-based saving algorithms, ‘cluster first, route second’ or ‘route first, cluster second’ and route improvement algorithms.

Metaheuristics identify good solutions, often also including heuristic algorithms. The well-known and widely applied metaheuristics include the ant colony optimization algorithm, genetic algorithms, the tabu search, and simulated- and deterministic annealing.

3.2.3 Tactical planning models

Tactical planning models may be classified according to Crainic & Laporte (1996) into two main groups: network simulation and optimization models.

According to Crainic & Laporte (1996), simulation models have been used for a long time in the context of rail operations. Movements of trains and cars through the rail network are simulated, adhering to operating policies and schedules. Results may include detailed cost information, a measure of facility occupancy, and estimations of transit traffic times. Certain policies may be evaluated by means of these indications.

Network optimisation models are less detailed, but may aid the evaluation and selection of integrated network-wide operation strategies with respect to some objective function which could involve both operating costs and service criteria.

3.3 Operational freight problems

Operational planning or short-term planning is done by local management and in a highly dynamic environment. Time plays an important role, as well as the detailed representation of facilities, vehicles and operations/activities. Such decisions may include maintenance schedules, crew and service schedules, routing and dispatching of vehicles and crews, and resource allocation.

For day-to-day operational decisions, the time factor plays a significant role and today's decisions may have a significant impact on future decisions and performances. Most models used in transportation planning, use static input data, although the real world in which they are implemented is continuously changing. Demand may be higher than predicted and traffic more than expected. The stochasticity of a system also adds to the dynamic aspect of operations. These characteristics are incorporated more and more into the models.

Tactical planning is concerned with the 'where' and 'how' issues, including the selection of service types and traffic routes between locations. Operational planning is concerned with 'when'- when to start and end a service and/or when the vehicle arrives at the location/destination.

3.3.1 Main operational problems

Problems most often seen in operations planning and management may include the following (Crainic & Laporte (1996)):

- Scheduling services: a tactical load plan would indicate what service to offer, and the frequency to run it during the planning horizon. Services are offered according to a schedule indicating departure and arrival times and intermediate stops. This schedule may be fixed, or of a more dynamic nature.
- Empty vehicle distribution and repositioning: An imbalance between freight demand and supply is often the case. A particular terminal may have a surplus number of transportation vehicles at a certain point in time; while suffering from a shortage at a later stage. The repositioning of empty vehicles/carriers is then necessary. Empty vehicle distribution is a central part of planning and operations of many transportation firms, particularly in the rail, container and LTL motor carrier industries. Other studies addressing the empty vehicle distribution and repositioning, include Turnquist (1994). The problem with the repositioning of empty vehicles does not generate any 'real and immediate' revenues, but the expenses incurred now may increase future revenue. It is thus necessary to consider the total planning horizon with the objective of maximizing the total system profit in mind. The major difficulty with this is that decisions made 'now' are based on 'unsure' data with great uncertainty regarding future demands and performing the operations (Crainic & Laporte (1996)).
- Crew scheduling: In order to support the planned operations, crews have to be assigned to vehicles/carriers. It appears, according to Crainic & Laporte (1996) that dynamic resource allocation may be of value in this context.
- Allocation of resources: Many operational problems require the dynamic allocation of resource to tasks. The problem of allocating limited resources to requests and tasks can be seen as one of the most critical issues in the context of transportation systems. This is an extremely rich field for research and for applications, and is discussed in more depth at a later stage.

Common characteristics of these problems may be identified as follows (Crainic & Laporte (1996)):

- Although there is unpredictability regarding requests, some future demands may be known.
- Majority of requests materialize in real-time and requires action within a relatively short time period.

- As soon as a resource is committed to an activity, it is unavailable for a certain period of time.
- Once the resource becomes available again it is usually in a different location than the initial one.
- The value of an additional resource unit at a location greatly depends on the sum of resources available and the current demand.

Another problem instance is concerned with the empty container allocation problem which occurs in the context of land distribution and transportation management. Crainic *et al.* (1993) investigate the single and multi-commodity cases, which are formulated dynamically and deterministically.

3.3.2 Dynamic and stochastic modelling for operational planning

A classical modelling approach for these problem classes is to maximise the total profit by looking at the entire planning horizon. Consequently, a major difficulty is that the uncertainties regarding future demand and uncertainty related to performance have to be considered when decisions are taken ‘now’ for future periods. Decisions are therefore not based on ‘sure’ data but on estimations.

Two approaches may be identified according to Crainic & Laporte (1996), to address stochasticity in transportation planning and in particular VRP: A priori optimization and real-time optimization. In a priori optimization, the problems are formulated in two stages. During the first stage a planned/priory solution is designed, and during the second stage a recourse action is taken.

When modelling a problem, random variables are used to represent the stochastic elements and decisions. The objective function then becomes a very complex recursive stochastic equation. To incorporate this complexity, the model may take on the form of a recursive formulation. Powell addresses the simple recourse model, nodal and network recourse (Powell & Frantzeskakis (1994), Powell & Cheung (1994)), and the issues regarding stochastic formulations (Powell (1996)). The basic dynamic service design network is briefly discussed by Crainic & Laporte (1996).

Powell *et al.* (1995a) introduced the Logistics Queuing Network methodology which is an interesting framework for addressing different real-world problems. The basic idea of the LQN methodology is that in order to evaluate the gain of allocating a vehicle/carrier to a loaded movement, the operating costs, load price and value of the vehicle to the destination should be evaluated.

Powell & Carvalho (1998) present the first LQN formulation of a dynamic fleet management problem, where the problem of managing a homogeneous fleet of vehicles over time is considered with time window constraints. The solution approach starts with the classical linear programming formulation, and is then reformulated as a recursive dynamic program. An apparent advantage of the LQN approach is the fact that it allows for several real-world details that cannot be modelled into a linear program, including load priorities and labour regulations. The LQN approach typically mimics a decentralised decision environment.

3.4 Concluding remarks: Chapter 3

In this chapter, the findings of a literature survey on operational, tactical and strategic freight planning problems as well as techniques for modelling these problems, were presented. An overall trend towards larger, more integrated and more efficient transportation systems is noticeable, and hence create the need for better planning on the strategic, tactical and operational levels. Computational development also enables more realistic and powerful models and more user-friendly interfaces.

In the next chapter, issues regarding the motor carrier industry are discussed briefly. This industry is a subset of freight transportation, narrowing the focuss of the literature study.

Chapter 4

The Motor Carrier Industry

In this chapter some issues concerning the motor carrier industry is discussed. A motor carrier is an enterprise that offers a transport service by means of motor carriage. From the literature investigated, some industry-related aspects could be identified and are included here. The issue concerned with applicability and effectiveness of real-time optimization in the motor carrier context is also examined.

4.1 General information on the motor carrier industry

The motor industry is highly influenced by the freight movements of the country as trucking revenues will rise and fall according to these movements. Total domestic freight shipments move along with trends in the national gross domestic output (Fox *et al.* (2006)). With the increase in economic activity, freight shipments will induce an increase in motor carrier revenues. Conversely, business downturns will have the opposite effect. Motor carrier revenues decrease when the economy declines, but benefit from economic growth. An imbalance between demand and supply of trucking capacity is often the result of changes in economic growth (Fox *et al.* (2006)). Fuel prices also have a direct influence and effect on the motor carrier industry.

Using other transportation modes, such as rail for longer distances, may address the unbalanced flow of ‘demand’ on the routes, i.e. from Station *A* to Station *B* the demand may be higher than the demand from Station *B* to Station *A*. Therefore more carriers are required to drive from *A* to *B* than from *B* to *A*, and the optimal allocation of carriers may be problematic.

Incorporating rail would also assist in alleviating driver-hour restrictions and fuel costs. There is only one rail operator in South Africa, and it has become unpopular since the 1990s, except for transporting bulk like ore and coal. Currently motor carriers are preferred for transportation by many South African industries.

A major trend which may continue to plague the motor carrier industry is the drivers. Driver turnover, and replacing drivers can be a significant cost burden. The most significant labour regulation which plays a crucial role in the scheduling of carrier operations in South Africa requires that a driver must be at home for 2 days after 14 days away. Other constraints include the servicing of carriers (Fox *et al.* (2006)).

4.2 Real-time optimization in the motor carrier industry

The implementation of online models for real-time operations planning may induce some issues and may be a daunting task. Powell *et al.* (2002) did a study to investigate the implementation hurdles of implementing a real-time dispatch system by investigating the simple problem of assigning drivers to loads (the load-matching problem). The most significant obstacle appeared to be the lack of available information which the model requires.

Optimisation models offer the promise of a powerful technology for processing information as fast as it arrives. However, they often struggle in real-life operations. According to Powell *et al.* (2002), there are numerous motor carriers that would benefit from an online dispatching tool. But they found that only a few have actually implemented these systems with mixed success. The important finding was that they suffer from a lack of information.

There is, according to Powell *et al.* (2002), a long and extensive history of trying to implement operational models for vehicle routing and scheduling. Modern technologies make the use of optimization algorithms even more attractive. The most common approach in engineering practice, when confronted with dynamic problems, is to solve sequences of static, largely myopic, assignment problems.

The load-matching problem is concerned with the assignment of drivers to loads: finding the *right* driver for the *right* load. The most obvious objective is to minimize *empty kilometres*, which entails the distance a truck has to move empty or with a load less than its capacity. But there are usually a few competing goals that a carrier has to combine since loads must be picked up and

delivered within time windows while being cost-effective. Challenging difficulties are the problem of getting the drivers home within 14 days, servicing of carriers and when the load is non-homogeneous.

Challenges with which the dispatcher is confronted, are greatly due to the highly dynamic environment: shippers may announce requests one or two days in advance, but sometimes make requests for the same day. Also, shippers may announce shipments for a particular day, and the shipments then arrive only the next day. Drivers in the process of moving loads have an estimated arrival time, after which they will become available again. These times may, however, be uncertain due to travel time fluctuations and often because of loading and unloading delays. A planner would typically pre-assign a driver to a region, but makes contingencies if the driver does not become available as was expected. The volume of information to be handled seems to require a computerised decision support system. However, a significant difference exists between information known to the dispatcher, the data in the computer system, and the information known to the person concerned with the customers. Powell *et al.* (2002) found in their study that the dispatcher would typically override the outcome of the model up to 40% of the time. This may be due to the fact that there is missing information or information that only becomes available at a very late stage. There is also a difference between what the human knew and what the computer knew. Consequently, discrepancies between model recommendations and actual decisions are the case.

A challenge encountered specifically in the motor carrier industry involves the balancing of competing objectives from different perspectives. Motor carriers have to minimise costs (total empty kilometres), maximise customer service (picking up and delivering loads on time), and manage drivers effectively. Three perspectives mentioned in Powell *et al.* (2002), comprise: the model (which requires that all issues be quantified into a single cost function), management (with the focus on a series of statistics measuring performance, and management goals), and the dispatcher (who uses its own rules and patterns of behaviour to make decisions). These perspectives were then used to measure the success of the load-assignment model implementation, from the user point of view (dispatcher happiness/willingness to execute model decisions), management goals, and the minimization of costs and maximisation of benefit.

According to Powell *et al.* (2002) the information system struggled from a lack of information. A lot of information was not only in the head of the dispatcher, but also in the head of the driver. Another challenge for introducing and implementing an information system is to overcome the established patterns of planner behaviour, in other words: a human's resistance to change. While it might be argued that these patterns encompass 'bad' practices, it is not necessarily the case. An identified frustration, however, is the lack of

information due to ineffective communication. When combining competing measures, the particular mix of measures and the differences in how these measures are calculated and weighted depend on the dispatcher. Discrepancies in results would then not only be the case for different dispatchers, but also when the computerised dispatching system is introduced.

4.3 Concluding remarks: Chapter 4

In this chapter, issues and concerns related to the motor carrier industry in particular, were investigated, which help provide a context and framework for the auto carrier problem. In the next chapter the auto carrier problem is explored with reference to general auto carrier functioning in South Africa and auto carrier problems found in the literature.

Chapter 5

Auto Carrier Operations and Literature

In the previous chapter the focus was on the motor carrier industry in particular, where typical industry-related issues were discussed and the topic of real-time optimization in this context investigated. This chapter discusses aspects of auto carrier functioning in South Africa and AC problems identified in the literature.

Delivering cars, trucks or vans to auto dealerships is a unique and specialised problem in the routing and scheduling problem class, and it may be viewed as one of the more interesting problems in transportation. Vehicles are collected at their point of import or at the manufacturer, and then have to be transported to auto dealerships distributed throughout a geographical area. This important link in the supply chain is facilitated by auto carriers. An auto carrier may be defined as a truck with a tractor and a trailer, a special tractor-trailer rig, which present upper and lower loading planes (Tadei *et al.* (2002)).

There are two types of carriers/trailers: those used for regional delivery, and those used for long distance work. The regional trucks transport three to four vehicles each, whereas the long distance trucks can carry a load of seven to eleven vehicles each. The latter carrier type transports the largest number of vehicles per month.

A dealership sells cars to the public and order these from the local or overseas manufacturers. The manufacturer then contracts an auto carrier company to pick up the cars and distribute them to the dealers. Each order, as it is placed at an auto carrier, has specific attributes including type, release date, destination, origin and latest delivery date of a car. When the cars are delivered late (after the specified delivery date), a penalty cost may be incurred

and/or the manufacturer loses confidence in the service offered and may contract another auto carrier company.

Cars are collected at the manufacturers by the auto carriers and transported either directly to a car dealership, or to the auto carrier depot (see Figure 5.1). Cars first transported to the depot are then distributed to dealers (direct delivery is less common). Smaller dealers are grouped together in a cluster of three or less, and serviced by an auto carrier. There exists a lead time or time window for delivery. Long distance carriers are used for inter-branch distribution whereas regional deliveries to individual dealers are done with smaller carriers.

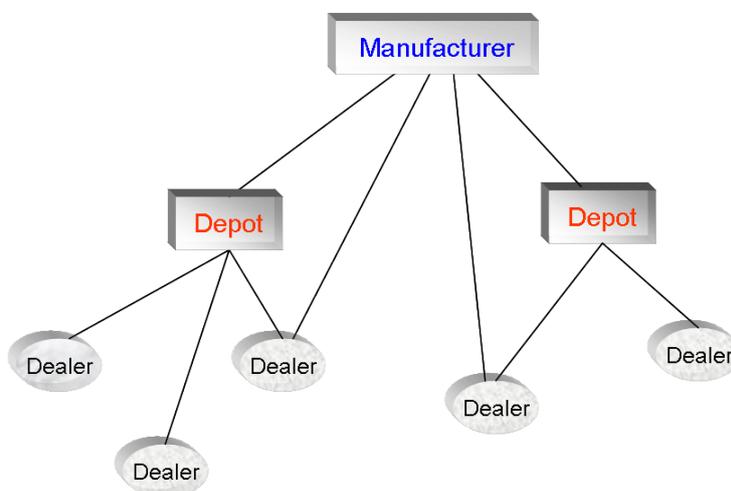


Figure 5.1: Distribution of cars

South African labour and traffic regulations require that the drivers rest for a specified number of hours every day, and that the drivers have to be home for two consecutive days after 14 days of work. Two drivers may be used to drive a long distance carrier; however, there are specific reasons for not encouraging that.

From the auto carrier viewpoint, two types of demand may be identified: the cars waiting at the manufacturer to be collected by the auto carriers, and the need for certain cars (collected from the manufacturers) to be delivered to the individual motor dealers. If four cars of type X are ready at the manufacturer N to be picked-up and there is a need for four cars of type Y to be delivered to dealer M , there are in total 8 cars to be moved at that specific point in time.

Different subproblems of delivering cars to auto dealerships may be identified. One subproblem is that of loading cars onto an auto carrier (equipment used are specially designed for this purpose). Another problem involves the allocation of cars to the loading equipment, usually done by means of trial and error and heuristic methods. Then the carriers need to be dispatched in a cost-effective way while being on time: this may include inter-branch deliveries and deliveries to dealers. Whereas inter-branch deliveries would generally require carrier dispatches on fixed routes, smaller local deliveries to dealerships can induce a VRP for daily deliveries among individual dealerships. Long-distance carriers may vary in size, constituting a non-homogeneous fleet. Since the load on an auto carrier truck is also not homogeneous and each vehicle specification varies according to destination, current location and arrival time/due date characteristics, carrier dispatches are directly dependent on the particular load involved. The 'loading problem' therefore also has to take carrier dispatches and routing aspects into consideration.

To the best knowledge of the author, auto carrier-specific studies in the literature are very limited, mainly involving planning and scheduling on an operational level. Heuristics, algorithms and/or software are developed to aid the loading and/or routing aspects of the auto carrier problem. The loading problem is significant since deliveries to dealerships usually require that the cars of only one dealer are placed on a single auto carrier. Additionally, the cost of reloading can be significant. The driver has to be paid for a reload, and the risk of damaging the cars during handling is increased. Loading equipment involved is also then underutilized.

The loading problem is addressed in a study by Agbegha *et al.* (1998), where the main focus of their work is the formulation and solution of the loading problem. They define the Auto Carrier Problem (ACP) as the problem of allocating cars to spaces/slots on the carrier, where the physical characteristics of the auto carrier give this problem its unique combinatorial nature. The complexity of this problem is due to the fact that when a trailer is used to deliver cars to more than one dealer, the cars should be loaded in a sequence that minimizes the unloading of some cars in order to gain access to others. Cars also vary in size and height, and they have to be assigned to slots in a configuration that will not violate the space restrictions. Figure 5.2 illustrates how different car types can influence the carrier loading possibilities. Agbegha *et al.* (1998) formulates a loading algorithm, but also stresses the importance of properly interfacing the loading of cars with the vehicle-routing/ dispatching aspect of auto carriers.

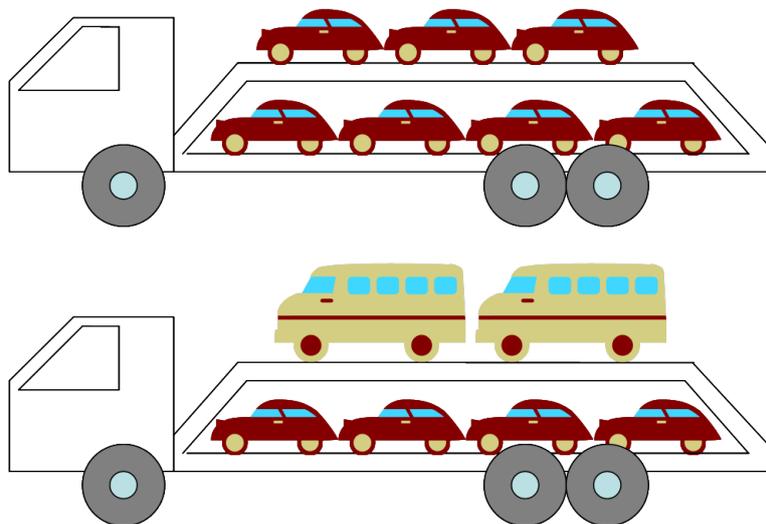


Figure 5.2: Carrier capacity is determined by the vehicles that are loaded

Tadei *et al.* (2002) developed a three-step heuristic procedure, strongly based on integer programming, to aid loading, vehicle selection and routing aspects of auto carrier functioning. Whereas Agbegha *et al.* (1998) only address the loading methodology without considering unloading stops and routing aspects, Tadei *et al.* (2002) developed a mixed integer program that considers both loading and scheduling aspects, to ensure good auto carrier fleet routing and functioning. The proposed model outperformed manual solutions by about 3%.

Marx (2006) developed heuristics and solution algorithms addressing scheduling auto carrier problems. A software tool was developed that defines instances of a generic problem and solves the problem approximately by means of a number of algorithms. Simulation is also incorporated in order to assess these algorithms.

To summarize, the limited literature found on AC problems was found to involve solution development on an operational level, mainly focussing on the loading problem. General auto carrier functioning in South Africa was also discussed. In the next chapter, the specific auto carrier functioning with which this study is concerned, is provided.

Chapter 6

Characteristics of the AC Company Operations

The core function of an auto carrier business is to apply auto carriers effectively and efficiently, in order to meet manufacturers' requirements and be cost-effective. The efficiency of dispatching carriers determines the success of a company to a great extent. Usually some trade-offs have to be made, e.g. cost-effectiveness vs. service level. This chapter is concerned with the auto carrier functioning related to this study. Some background information is given and the distribution network is provided. Uncertainty in the auto carrier context is also discussed, as well as the auto carrier functioning and scheduling process and some current performance indicators.

6.1 Auto carrier company background

The specific Auto carrier company (AC company) distributes all the major brands of cars sold in South Africa. The technology that the AC company employs encompass a GPS/Cellular phone tracking system and radio barcode scanners to provide real time information regarding the status of carriers/trucks (in terms of geographical location). The AC company also provides other services such as storage facilities, stevedoring of import and export cars at the ports of Durban and East London, and upfitment of cars.

6.2 Distribution network, assignment of carriers and physical flow

Since the AC company is contracted to transport cars from manufacturers and harbours to AC company branches and then to individual branches, carriers travel between all major cities in South Africa. These include Johannesburg, Cape Town, East London, Port Elizabeth, Durban and Bloemfontein. The long-distance routes connecting the branches are considered fixed since there are hardly feasible alternative connecting routes.

Depots/branches are therefore established in these major cities, especially where the manufacturers and harbours are situated. Long distance carriers are then employed to distribute cars between auto carrier branches, so that cars can be delivered at the closest depot to a particular dealer. Smaller regional carriers are employed for local deliveries to individual dealerships.

The carrier trucks have slots of various sizes and types onto which cars may be loaded. Certain cars can only fit into particular spaces. The Mercedes A-Class motor car is, for example, too high for the lower deck of a trailer and the Mercedes C-Class motor car too high and too long for a single slot on the lower deck. Carriers differ in number of slots, slot configuration, speed and travelling costs.

Carriers are fitted with GPRS and GPS devices to enable their tracking. The auto carrier company can therefore determine the location of a carrier at any point in time. The GPRS device enables the monitoring of carriers regarding the correct loading and unloading of cars at the correct location, also allowing the company to monitor the carrier schedule. Drivers also have mobile phones and can be contacted at any time when they are on the road.

The AC company branches constitute the ‘nodes’ of the distribution network. Regional deliveries to dealers are the responsibility of the individual branches. Regional carriers are used for these deliveries, on internal short-distance routes. These internal routes are not scheduled by the dispatcher.

The scheduling of operations is done at a central depot situated in Bellville. The result is a ‘master plan’ which is distributed to the branches on a daily basis. This schedule takes into consideration the needs of the branches (in terms of cars to be moved) and allocates long-distance carriers to fixed long-distance routes accordingly. It is to some extent computerized but due to uncertainties and incomplete information, depends strongly on the human scheduler/dispatcher. The auto carrier long-distance routes in South Africa, on which long-distance carriers are employed, are indicated in Figure 6.1.

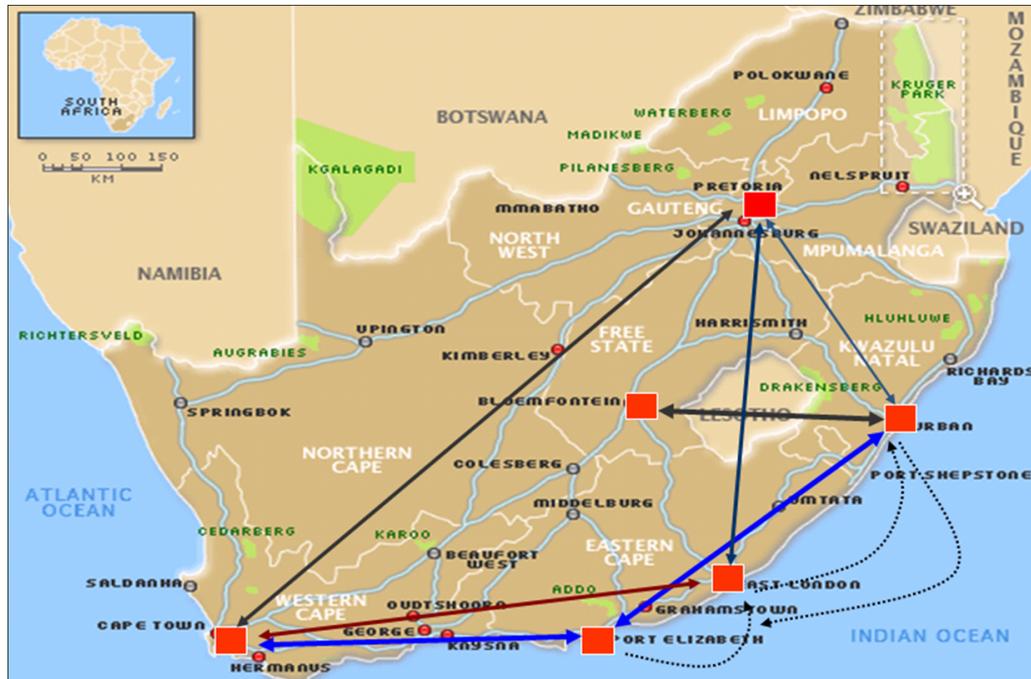


Figure 6.1: AC company distribution network

The locations of the AC company branches are indicated by the red blocks in the picture. The long-distance routes, connecting the branches are then:

- CT-PE-DBN-PE-CT
- DBN-PE-EL-DBN
- EL-CT-EL
- DBN-BFN-DBN
- EL-JHB-EL
- CT-JHB-CT
- DBN-JHB-DBN

where the above acronyms are as follows:

- JHB: Johannesburg auto carrier branches
- CT: Bellville depot
- DBN: Durban auto carrier branches

- PE: Port Elizabeth auto carrier branches
- EL: East London depot
- BFN: Bloemfontein

These routes are fixed, but the number of carriers assigned to the routes varies. Carriers may be employed on these long-distance routes as fixed or roaming. When a carrier is fixed between A and B, the carrier may not deviate from this route and only carries freight between those two branches, in both directions. Roaming carriers, however, may go to any destination on the distribution network. They may be employed according to different rules and policies and effectively create a ‘bee-hive’ effect, which implies that carriers are like a swarm of bees that attend to crises in the operations by going to where they are needed most.

Currently, the carriers are all scheduled as though they are fixed on the identified routes, and then, when peaks arise or work accumulates at branch i at some point in time t , a number of carriers are then used as roaming fleet. The problem is that branch managers can never be certain as to how many carriers they will have at their disposal. Another result of this action is that by using fixed carriers on particular routes I, J, K and roaming fleet on other routes F, G, H where demand is temporarily higher, demand on routes I, J, K accumulates and constitutes another crisis at time $t + \Delta t$. Carriers are thus forced to operate more and more in a crisis environment, while uncertainty in the system is increased.

6.3 AC variability and uncertainty

A problem context is said to be dynamic when one or more of its parameters are a function of time. It involves dynamic data that change constantly and time-dependent data which are known in advance (Larsen (2001)).

Parameters changing over time in the auto carrier context include deviations in dispatch plans (due to the dispatcher) before execution, changes during execution, demand, carrier status, position, destination and load, cars (units) to be loaded and carrier status. Constant/Fixed parameters include the time window for vehicle delivery, the number of available carriers which is a strategic long-term decision and running cost (including driver wages) which would typically not vary on a daily basis. Some factors facilitating changes in the system by influencing the mentioned parameters may be identified. An overview of the time-dependent parameters and constant parameters, as well as the identified factors affecting these parameters, are illustrated in Figure 6.2.

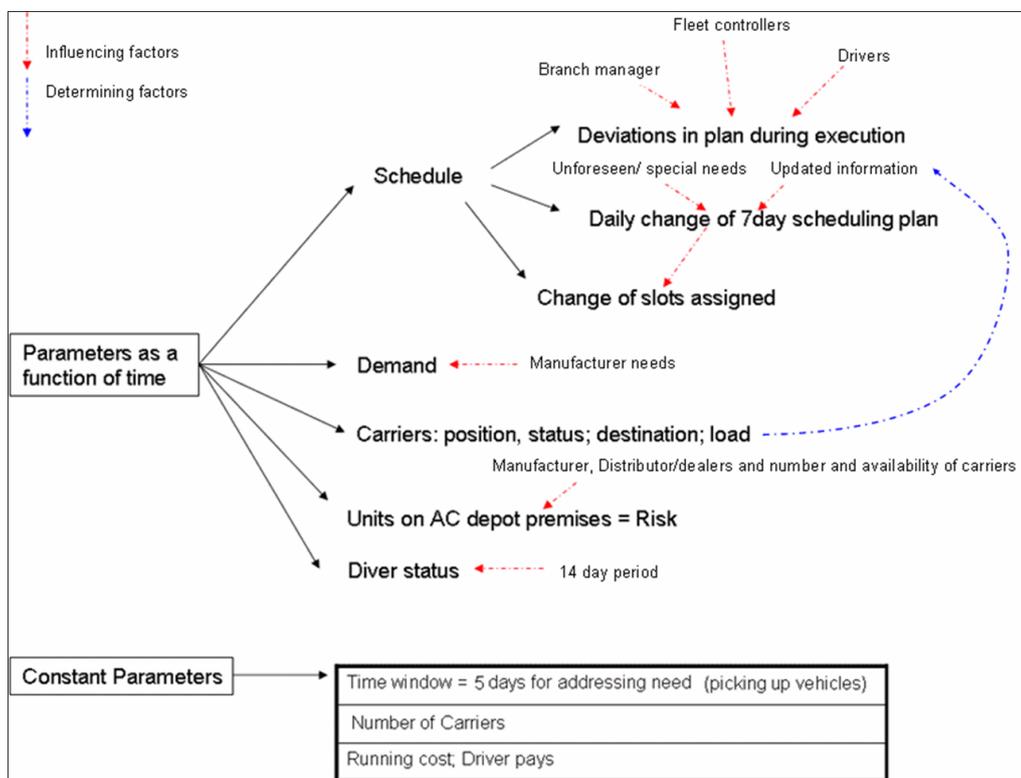


Figure 6.2: Variability and AC uncertainty

Changes in the scheduling plan are to a great extent due to the changes made by the dispatcher when reacting to peaks in the demand (as informed by individual branch managers) and unforeseen events. These changes of plan and carrier assignment increase the uncertainty in the system as branch managers do not know what carriers they may count on and what load to expect when. Some manufacturers may provide the AC company with a prediction of the next two to four days' production. However, this is not a reliable source of information since it is prone to change and often-times incomplete. An auto carrier company is therefore required to be dynamic in nature in order to accommodate the uncertainty.

6.4 Flow of information and physical flow

The scheduling plan is generated at the scheduling depot in Bellville, and is developed on a daily basis and distributed to the individual branches. Long-distance carriers are then employed accordingly on the long-distance routes. Cars are collected at the manufacturer and transported by means of long-distance carriers to the AC destination branches. From there regional short-distance carriers are used for local distributions to the car dealers. Figure 6.3

presents a basic representation of the physical and information flow.

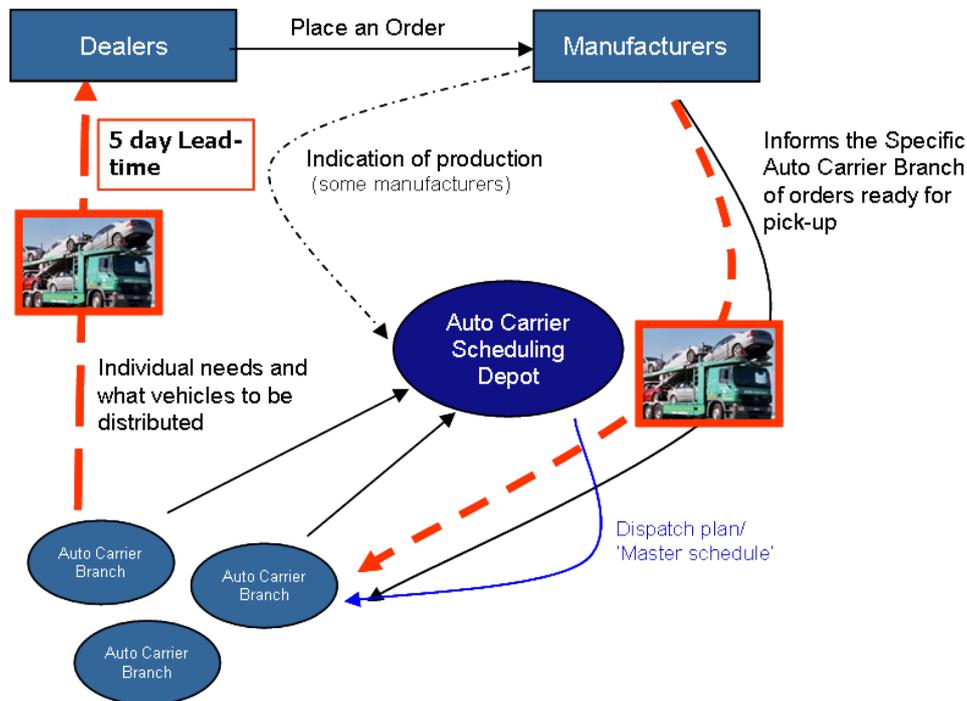


Figure 6.3: Physical flow and flow of information

The manufacturer provides the local AC branch with information. The branches inform the AC scheduling depot of their particular needs. Additionally, some manufacturers may provide the AC scheduling depot with a prediction of production. The dispatch plan is then constructed and sent to the individual branches where long-distance carriers are employed accordingly. The AC company has a lead time of effectively five days for distributing cars to car dealerships.

6.5 AC operational processes

The AC company operational processes include the scheduling and dispatching of carriers according to a dispatch plan. This is a scheduling process where the long-distance carriers are of concern, and these carriers are allocated to routes as needed. The dispatcher receives information from the branches, incorporates it into this schedule, calculates the effectiveness of the schedule; change it accordingly, and when satisfied, sends it to all the branches. The dispatcher takes into consideration factors such as the 5-day lead-time period

for order delivery, the 14 day driver schedule, the service schedule, the needs and requests of individual branches and the fact that a working day for an auto carrier driver is from 05:00 to 23:00. This schedule provides the branches with an indication of how many carriers and cars can be expected for that day and how many carriers and what cars should be dispatched or are needed at another branch. At the scheduling branch, carriers may be tracked according to the schedule.

The loading and unloading of carriers are done at each depot between 05:00 and 23:00, for 7 days a week. The dispatcher at the scheduling branch keeps track of the servicing of carriers which happens at the Bellville branch after a certain number of kilometres has been driven, depending on the carrier type and size. A 14 day schedule is also formulated by the dispatcher to facilitate the on-time arrival home of the driver after 14 days on the road. This driver schedule is also distributed to the branches on a regular basis. The branches are then responsible for the drivers involved and for realising their particular schedule.

The AC scheduling process may be described using IDEF0 notation. The IDEF0 notation is used to distinguish between the *Inputs*, *Outputs*, *Controls* and *Mechanisms* of the process. The notation may be explained according to Figure 6.4. The *Inputs* are transformed or consumed to produce outputs, the *Controls* specify conditions to produce correct outputs, the *Outputs* are the data or objects produced and the *Mechanisms* are the means that support execution.

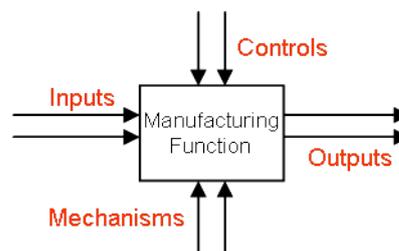


Figure 6.4: IDEF0 notation

A detailed representation of the AC scheduling process is illustrated in Figure 6.5, using IDEF0 notation.

Deviations from the schedule may incur some complications such as:

- Branch managers are uncertain: uncertainty in the system increases when the number of carriers (and load) scheduled for, do not arrive as expected.
- 14 day working period of drivers: drivers may not arrive home by the end of the 14th work day as prescribed.
- Servicing: The 'master schedule' takes into consideration when carriers are due for service and their routes are scheduled accordingly. Deviating from the dispatch plan may then directly affect the on-time servicing of carriers.
- Time and effort: fleet controllers and the dispatcher have to find a carrier in terms of current route, new destinations, load and rescheduling is therefore necessary.
- Training: training of drivers is different for different types of carriers, and is done at Bellville depot, situated in Cape Town. Training cannot be done on a specific carrier type when none are available in Cape Town. Vehicle loading training is also affected by changes. Training is planned according to the dispatch plan, and deviations regarding this schedule therefore directly affect training.

6.6 Typical AC measures and performance indicators

The following evaluation measures are used by the AC company to obtain an indication of performance. These include:

- Lateness of vehicle deliveries is defined as a function of the availability of manufacturer produced cars and the number of carriers.
- Efficiency is currently measured in terms of kilometer/operating hours. This is used as a measure of driver performance. The average is 46 km/operating hours, determined by taking the kilometres driven and dividing it by the working hours. Therefore, if the average speed of a truck is 60 km/h on the road and it has to stop for lunch and supper, the daily average would be about 46 km/operating hours.
- There are two components to the cost measure:
 1. Running cost for a carrier to be on the road, and
 2. Revenue/car (can also be seen as a risk for the AC company implied by the cars loaded). Penalty cost seems to play a negligible role.

- There is also a KPI for evaluating branch managers, which incorporates different factors.

6.7 Concluding remarks: Chapter 6

Since the core function of an auto carrier business is to apply auto carriers to address demand in such a way as to incur a minimum cost and deliver cars on time, the efficiency regarding carrier dispatching can to a great extent determine the success of a company. Scheduling and task assignment is therefore of great importance to enable better management of an auto carrier fleet.

In this chapter, specific characteristics of the AC operations were discussed with which this study is concerned. This enables/facilitates the problem formulation for the purpose of this study and provides a context for the AC problem of concern. The next chapter provides the AC problem description and objectives of this study.

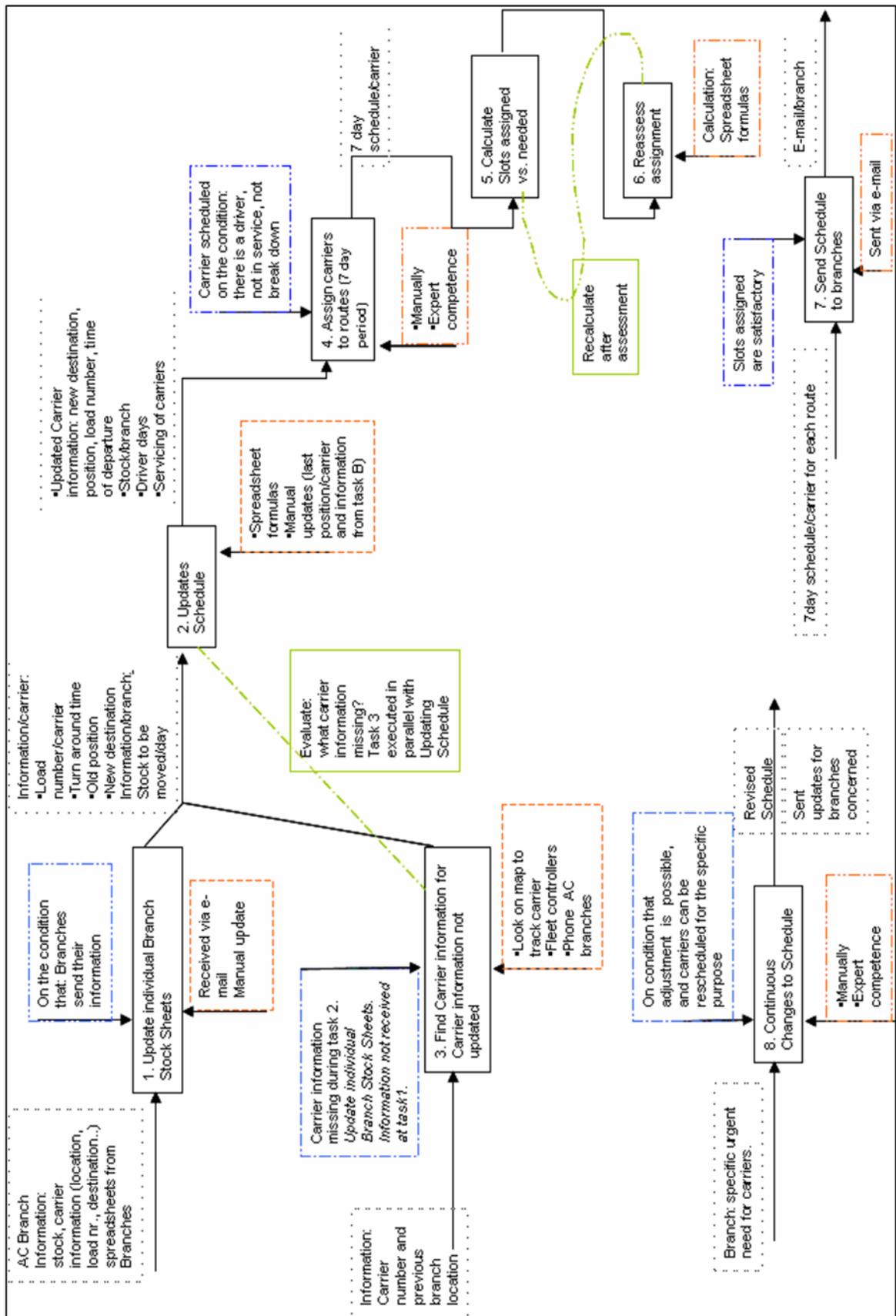


Figure 6.5: AC Scheduling process

Chapter 7

Objectives of this Study

Considering the high importance of dispatching, routing, scheduling and overall management in this field of vehicle transportation and delivery, improvement possibilities are important to an auto carrier company and have to be considered continuously. In the motor carrier industry an imbalance between capacity and demand is often the case. Peaks and valleys in the demand call for the effective allocation and management of carriers in order to maintain an acceptable service level in a cost-effective manner, while adhering to regulations.

Policies that would increase predictability in an uncertain environment enable greater efficiency regarding the scheduling and allocation of demands as well as auto carrier assignment to tasks. This study intends therefore to improve dispatch, scheduling and fleet operations by investigating fleet composition and other operational policies regarding the carrier fleet.

Variation and uncertainty in this specific area, in terms of varying demand sizes and types, when orders arise and when they are to be delivered, as well as when cars are ready for pick-up at the manufacturer, add to the complexity of routing, scheduling and overall fleet management. Efficiency regarding the management of an auto carrier fleet is therefore of great importance to enable better scheduling and task assignment.

7.1 This particular problem

This study was done in collaboration with a South African auto carrier company. The company had a particular need for *tactical decision-making policies* regarding the employment of their long-distance auto carriers. The long-distance routes are fixed and the focus is on tactical policies to utilize the long-distance carriers on these routes, by employing carriers as roaming or fixed. The question at hand is concerned with what the best fleet composition would be, i.e. what number of the limited carrier resource should be roaming and fixed in order to incur the most benefit and the least costs and penalties. ‘Fixed’ involves that carriers persist on predefined routes, whereas roaming carriers rely on dynamic decision making, providing service where needed, if possible. The fixed carriers and roaming carriers operate according to specific policies and rules dictating and prescribing carrier behaviour. Certain operational policy rules may be combined, and for a particular combination of policy rules the most suitable fleet composition may be identified. Different combinations of policies and fleet compositions can therefore be evaluated by means of multiple criteria, in order to decide on the best combination of fleet policies and fleet composition.

7.2 The main objectives of the study

The main objectives of this study were identified as follows:

- Defining and improving the efficiency of fleet management.
- Developing effective tactical decision support that will provide suggestions regarding:
 - Ideal fleet composition (how many carriers to employ as roaming and how many as fixed).
 - Some operational policies concerning the dispatch and functioning of roaming and fixed fleet.
- To develop and evaluate operational policies on a tactical level that will provide the AC company with a tool, aiming at reducing uncertainty in an unpredictable environment, enabling better scheduling and carrier assignment.

7.3 Concluding remarks: Chapter 7

The problem with which this study is concerned has now been identified and will from now on be referred to as the "AC problem". The corresponding objectives were also identified. However, what would the method be? Keeping this particular auto carrier problem in mind, the following chapters investigate formulation and solving tools for the purpose of this study.

Chapter 8

Possible Formulation and Solution Techniques

Real life transportation and freight problems have to deal with a great amount of uncertainty and complexity. However, generic mathematical formulations are largely deterministic and ‘fixed’ in nature, and do not readily accommodate uncertainty. It is not easy to bridge the gap between the generic mathematical formulations and real life problems (Powell & Topaloglu (2003)). In this chapter, possible analytical formulation and solving tools are investigated for applicability in addressing the AC problem.

According to Powell & Topaloglu (2003), transportation modelling usually involves factors such as:

- Time staging of information where information arrives over time.
- The lagging of information: A customer order is placed at time t but only served at time $t + \Delta t$.
- Resource attributes are often complex and therefore induce particular difficulties in the stochastic context since resource types and characteristics determine the number of constraints.
- Integrality: The network structure of a transportation problem (which makes it easier to produce integer or near-integer solutions) can easily be destroyed when uncertainty is incorporated in a system.
- Travel times: In transportation problems the movement from one location to another requires some time. In deterministic models it is merely a minor issue, whereas it can introduce major difficulties in stochastic models.
- Multi-agent control: Different agents may control specific dimensions of a large transportation system.

- Implementation: The difference between the planned and executed decisions is in itself also a source of uncertainty.

The above mentioned issues in transportation modelling can significantly affect the complexity of developing an appropriate model (Powell & Topaloglu (2003)).

Freight transportation problems have classically been modelled as large scale linear or integer programs (Powell & Topaloglu (2003)).

In searching for a suitable modelling/formulation framework and solution technique for this AC problem, linear programming, integer programming, service network design, dynamic resource allocation, the dynamic resource transformation problem (DRTP) framework, dynamic and stochastic programming are investigated. Firstly, integer programming is discussed, then the transportation problem and assignment formulations are introduced, followed by the the service network design (SND) model, dynamic resource allocation formulation, the DRTP, and lastly dynamic and stochastic programming. A roadmap of the operations research formulating frameworks and solution aids investigated are illustrated in Figure 8.1.

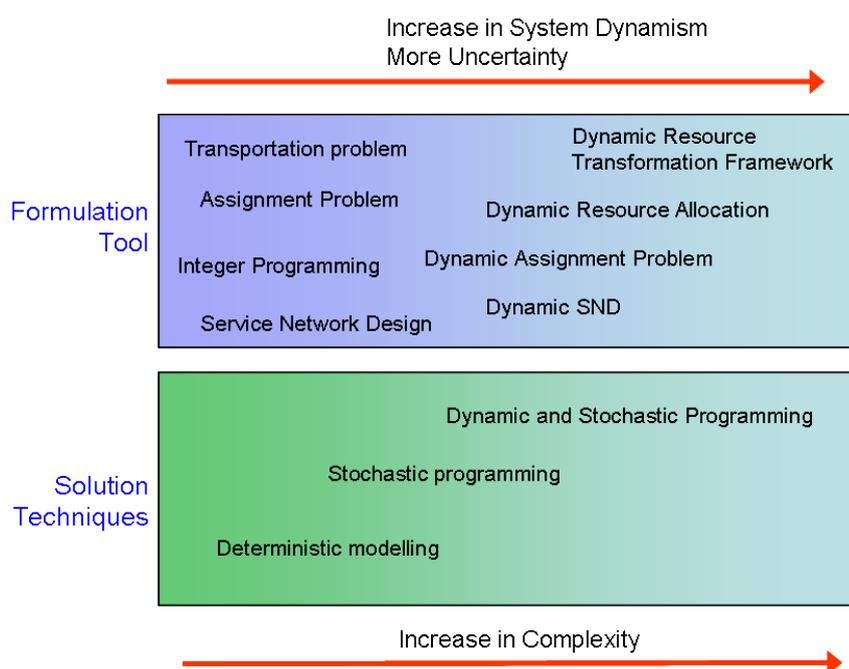


Figure 8.1: Formulating and Solution techniques investigated

8.1 Integer Programming

It is often necessary to assign vehicles/people/equipment to activities in integer quantities. An important application of integer programming is problems concerned with ‘yes’ or ‘no’ decisions. The mathematical formulation of an integer program is a linear programming model with the additional constraint/restriction that variables must have integer values.

In the most simplistic form the objective function consists of decision variables, representing the alternatives considered. It is usually in the form:

$$Z = ax_1 + bx_2 + cx_3 \quad (8.1.1)$$

where the x_i 's are decision variables and the function Z is either maximised or minimised (Hillier & Lieberman (2005a)).

Linear programming problems may be expressed in canonical form as follows:

Maximize:

$$\mathbf{c}^T \mathbf{x} \quad (8.1.2)$$

Subject to:

$$A\mathbf{x} \leq \mathbf{b} \quad (8.1.3)$$

where $\mathbf{x} \geq \mathbf{0}$ represent a vector of variables, \mathbf{c} and \mathbf{b} are vectors of coefficients and A is a matrix of coefficients.

8.1.1 Some Integer Programming applications

Some integer programming applications according to (Hillier & Lieberman (2005a)) include investment decisions, site selection, designing a distribution network, dispatching shipments, airline applications and crew scheduling. The applications included here are discussed according to the level of abstraction. A differentiation is made between strategic problems and operational and/or tactical decisions.

8.1.1.1 Integer Programming for strategic decisions

On a strategic level, decisions regarding transportation investments, site location and the distribution network are needed. On this level the nature of the problem is long-term and the effect of decisions on the profitability of the company lasts for years. Therefore the use of optimization may be of great value and hold great saving potential.

For investment analysis and decisions, the question is whether or not to invest in a certain project/investment. The objective may be to maximise the long-term return of the portfolio, or the minimization of transactions when rebalancing an existing portfolio.

In site selection the objective is to select the site of a new facility as to minimize the total cost of the new facilities.

Designing a production and distribution network, typically involves questions such as: “Should a certain site be selected for a new plant/distribution centre?” “Should a certain plant/distribution centre remain open?” “Should a distribution centre remain open?” “Should a certain site be selected for a new distribution centre?” A ‘yes’/‘no’ decision could also be concerned with the question of whether a particular distribution centre should be assigned to serve a certain market area.

The network design problem is formulated by Powell & Sheffi (1989). Special cases of the network design problem according to Holmberg & Hellstrand (1998) include the fixed charge network problem (where there is only one commodity), the simple plant location problem (SPLP) and the travelling salesman problem (TSP).

Some interesting applications of integer programming on strategic level in freight transportation are found in the literature. Allahviranloo & Afandizadeh (2008) formulate an investment optimization problem where cargo operation, investment costs, cargo-handling capacity, cargo transportation network, and maritime fleet constraints are included. Integer-programming is used to identify the optimum investment regarding port development for national investment potential. An investment planning model was developed for North-Central Railway in Brazil by Petersen & Taylor (2001). Although this problem may be modelled as a large mixed integer programming problem, they used nested dynamic programming to implement a traffic assignment problem as a recursive model to calculate the system state benefits. A second dynamic programming problem calculates the optimal expansion path for the system.

Beamon & Fernandes (2004) address decisions such as: which warehouses and collection centres should be open, which warehouses should have sorting capabilities and how much material should be transported between pairs of sites.

8.1.1.2 Integer Programming for tactical and operational planning

When the distribution network is in place, and strategic decisions made, route selection, scheduling and other operations are of concern.

Dispatching Shipments (Route selection): In selecting a shipment route, a ‘yes’/‘no’ decision is required with the objective to minimize the total cost of all the deliveries.

Many of the problems faced in the airline industry also arise in other segments of the transportation industry. Therefore many of the airline Operations Research applications may be applicable or extended to other transportation problems.

Airline scheduling applications involve fleet scheduling and crew scheduling. With several different types of airplanes available, the airline fleet assignment problem requires the right assignment of airline type to each flight leg in the schedule in order to maximise the total profit (from meeting the schedule). A specific trade-off is that when a too small aircraft is assigned to a flight leg, potential customers may be lost whereas a too large airplane may incur a loss. For each combination of airplane type and flight leg, there is a ‘yes’/‘no’ decision to be made. The decision variable is then 1 if yes, and 0 if no (Hillier & Lieberman (2005a)). An overview on assignment concepts, models and algorithms is given by Sherali *et al.* (2006).

For the airline crew scheduling problem sequences of flight-legs are assigned to crews of pilots or attendants. The objective is to minimize the total cost of providing crews that cover each flight leg in the schedule, where the decision variable determines whether a certain sequence of flight legs should be assigned to a particular crew (Hillier & Lieberman (2005a)). In a survey on airline crew scheduling, Gopalakrishnan & Johnson (2005) discussed state-of-the-art solution methods.

Scheduling in general may involve the scheduling of inter-related activities and the scheduling of asset divestitures (Hillier & Lieberman (2005a)).

Inter-related activities involve decision making that is time dependent and also depends on task precedence. The decision variable would then determine whether a certain activity should begin in a certain time period or not. Kim & Lee (2007) address the routing and scheduled delivery and pickup of freight by trucks between branches and depots. A mixed-integer programming model is suggested as well as three different heuristics. Only the scheduling aspect of regional transportation is addressed.

Regarding freight transportation, Kuo & Nicholls (2007) developed a mixed integer linear program (MILP) to determine the least-cost plan of allocating locomotives to yards and moving light engines between yards for a scheduling and routing problem of Conrail. The aim is to indicate how locomotives

should be allocated from yard to yard and how unloaded engines should be repositioned to ensure that trains have sufficient locomotive power at the lowest possible cost. The mixed-integer objective function tries to minimise the fixed and variable cost of shifting light engines from yard to yard while adhering to constraints. Maintenance downtime is not accounted for in their model, nor is the impact of service disruptions. Engines are also considered to be homogeneous. Train patterns and engine power requirements are assumed to be constant, despite the fact that the tonnage moved varies from train to train and that the train schedule changes periodically. Additionally, other factors which may also affect railroad operations, such as train delays, crew shortages, derailments or road accidents, are excluded as well.

Asset divestitures is in effect another example of inter-related activities, although the activities in this case involve the selling of assets to generate an income. The assets may be physical or financial, and the question is whether or not to sell a certain asset in a certain time period.

8.1.2 Solving Integer Programs

The exponential growth ‘fallacy’ of the integer programming method implies that for binary problems with n variables, there are 2^n solutions to be considered. Because of this, even the best algorithms cannot be guaranteed, depending on their characteristics, to solve a relatively small problem within an acceptable time frame (Hillier & Lieberman (2005a)).

8.2 The transportation problem

This problem formulation is an application of linear programming. Although it involves determining how to optimally transport goods, many of the major applications actually have nothing to do with transportation. Here only the most basic form of this problem class is introduced (Hillier & Lieberman (2005b)).

The transportation problem may be described as being concerned with the distribution of any commodity from any group of suppliers (sources) to any group of receiving centres (destinations), in such a way as to minimise the total distribution cost (Hillier & Lieberman (2005b)). The so-called ‘parameter’ table for the transportation problem is illustrated in Table 8.1.

Table 8.1: Transportation parameter table

Cost/Unit Distributed						
Destination						
Source	1	2	3	...	n	Supply
1	c_{11}	c_{12}	c_{13}	...	c_{1n}	s_1
2	c_{21}	c_{22}	c_{23}	...	c_{2n}	s_2
...
m	c_{m1}	c_{m2}	c_{m3}	...	c_{mn}	s_m
Demand	d_1	d_2	d_n	

The c_{ij} resemble the distribution cost from Source i to Destination j .

Assumptions regarding the demands and supplies include the requirement assumption, feasible solution property and the cost assumption (Hillier & Lieberman (2005b), Winston (1994)).

According to the requirement assumption:

- Each source has a fixed supply of units, and the entire supply must be distributed to the destinations.
- s_i denotes the number of units being supplied by source i .
- Each destination has a fixed demand for units, d_i , and
- The entire demand must be met by receiving units from the sources.

The feasible solutions property requires that

$$\sum_{i=1}^m s_i = \sum_{j=1}^n d_j. \quad (8.2.1)$$

However, in the case of over- or under- supply, dummy nodes are introduced.

The cost assumption requires that the cost of distributing units from any particular source to any particular destination is directly proportional to the number of units distributed. Therefore, the cost is just the unit cost of distribution multiplied by the units distributed.

Any problem may be said to fit the model if it can be described completely in terms of a parameter table as illustrated previously, and if it satisfies the cost- and requirements-assumption. The model parameters are the supplies, demands and unit costs.

In the transport problem the objective is to

minimize

$$Z = \sum_{i=1}^m \sum_{j=1}^n c_{ij}x_{ij} \quad (8.2.2)$$

subject to

$$\sum_{i=1}^m x_{ij} = s_i \quad \text{for } i = 1, 2, \dots, m, \quad (8.2.3)$$

$$\sum_{j=1}^n x_{ij} = d_j \quad \text{for } j = 1, 2, \dots, n, \quad (8.2.4)$$

$$x_{ij} \geq 0 \quad \text{for all } i \text{ and } j. \quad (8.2.5)$$

$$(8.2.6)$$

In solving the transportation problem, the simplex method, encompassing the North-west corner rule, Vogel's and Russell's approximation methods may be used.

Generalisations of the Transportation Problem include (Hillier & Lieberman (2005b)):

- The minimum cost flow problem
- The transshipment problem which does not impose upper limits.

Powell & Sheffi (1989) apply the transportation problem in the decomposition of the load problem for motor carriers. Different subproblems are constructed, and the empty routing subproblem is formulated as a transshipment problem where the re-optimization of the routing of shipments involves finding the path of least cost.

8.3 The assignment problem

The assignment problem may be described as being a special type of integer programming problem, and a special type of transportation problem, where assignees are assigned to perform tasks. These assignees may refer to people, machines, vehicles or plants (Hillier & Lieberman (2005b)).

Recent applications of the assignment problem found in literature range from personnel assignment (Toroslu & Arslanoglu (2007)), vehicle routing

(Imai *et al.* (2007)), communication networks (Clementi *et al.* (2004), Salcedo-Sanz *et al.* (2004)), (comparative) genomics (Chen *et al.* (2005)), to the formulation for cellular lay-out (Solimanpur *et al.* (2004)).

The network representation of the assignment problem is shown in Figure 8.2.

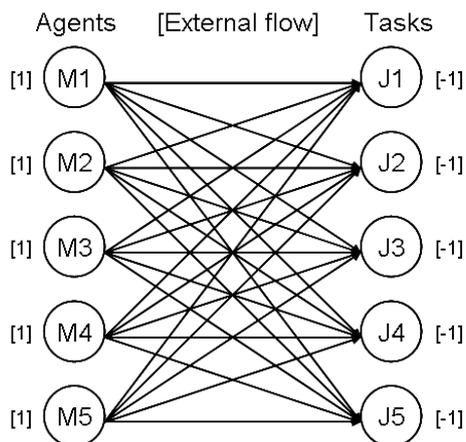


Figure 8.2: Assignment problem network representation for $n = 5$.

The network model is very similar to the transportation model, except that the external flows are all $+1$ or -1 . The only relevant parameter for the assignment model is arc cost (not shown in the figure), where all other parameters should be set to default values. The arrows between the nodes represent arcs.

In the most basic form, the assignment problem requires the following assumptions (Hillier & Lieberman (2005b), Winston (1994)):

1. The number of assignees and the number of tasks are the same (denoted by n).
2. Each assignee is to be assigned to exactly one task.
3. Each task is performed by only one assignee.
4. There is a cost c_{ij} associated with assignee i where $(i = 1, 2, \dots, n)$ performing task j where $(j = 1, 2, \dots, n)$.
5. The objective is to make assignments in such a way as to minimize the total cost.

All problems that can satisfy the assignment assumptions may be solved by efficient algorithms designed for the assignment problem, such as the Hungarian algorithm (Hillier & Lieberman (2005*b*)). Other algorithms applicable include the successive shortest path algorithm and the cost scaling algorithm, of which the most efficient is a modification of the cost scaling algorithm (Corry & Kozan (2005)).

The assignment problem model may be formulated according to Hillier & Lieberman (2005*b*) by defining the decision variables

$$x_{ij} = \begin{cases} 1 & \text{if assignee } i \text{ performs task } j \\ 0 & \text{otherwise} \end{cases} \quad (8.3.1)$$

and minimizing

$$Z = \sum_{i=1}^n \sum_{j=1}^n c_{ij} x_{ij} \quad (8.3.2)$$

subject to

$$\sum_{i=1}^n x_{ij} = 1 \quad \text{for all } i = 1, 2, \dots, n, \quad (8.3.3)$$

$$\sum_{j=1}^n x_{ij} = 1 \quad \text{for all } j = 1, 2, \dots, n, \quad (8.3.4)$$

$$x_{ij} \in [0, 1] \quad \text{for all } i, j = 1, 2, \dots, n. \quad (8.3.5)$$

Spivey & Powell (2004) formulated the Dynamic Assignment Problem. Corry & Kozan (2005) developed a dynamic assignment model for the dynamic load planning of intermodal trains. Because of uncertainty, solving the model over a rolling horizon is required. The objective is to minimize excess handling time and to optimize the weight distribution of the train in the assignment of two handling equipment. Service time is considered to be constant and homogeneous load is assumed.

Powell (1996) developed a stochastic formulation of the loadmatching problem that arises in long-haul truckload trucking, which requires the assignment of drivers to loads on a real-time basis.

Applications of the transportation and assignment problem tend to require a very large number of constraints and variables. Although some coefficients in the constraints may be zero, a straightforward computer program may still not be sufficient (Hillier & Lieberman (2005*b*)).

8.4 Network flow problems

Network representations are widely used for problems in sectors as diverse as distribution, project planning, facilities location, resource management and financial planning. A network representation can be a very helpful visual tool to aid conceptual understanding of a problem. Software is available for standard network problems that have to be solved routinely (Hillier & Lieberman (2005c)).

Many network problems are actually special types of linear programming problems, for example the transportation problem and the assignment problem. Commodity Network Flow Problems are addressed by Barnhart & Sheffi (1993).

An illustration of a basic network representation is shown in Figure 8.3.

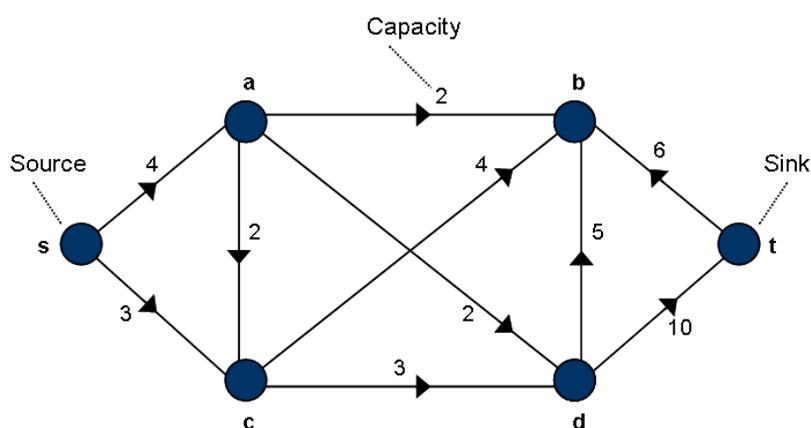


Figure 8.3: A basic network representation (Graph Theory)

In Figure 8.3, a , b , c and d are transshipment nodes, s is the supply node and t is the demand node. Each arc is described by a particular arc capacity. Specific network problems may be identified as:

- The shortest path problem, often used in the field of VRP (Desrochers *et al.* (1992), Ribeiro & Soumis (1994), Kallehauge (2008)).
- Minimum spanning tree problem: Formulations of the general minimum spanning tree problem are addressed and compared by Feremans *et al.* (2002).
- Maximum flow problem: Typical applications include maximising flow of vehicles through a transportation network or the flow of products through a company's distribution network (Hillier & Lieberman (2005c)).

- Minimum cost flow: Many problems and applications may be formulated as a minimum cost flow network. The minimum cost flow problem is described in Hillier & Lieberman (2005c). Special cases of the minimum cost flow problem are the Transportation problem, Assignment problem, Transshipment problem, The Shortest-path problem and the Max flow problem. Holmberg & Hellstrand (1998) formulated a multi-commodity minimum cost network flow problem. Holmberg & Hellstrand (1998) make use of the multi-commodity minimal cost network flow problem with fixed costs on the arcs in the modelling of a network design. An exact solution method is developed based on Lagrangian relaxation.

According to Wieberneit (2008), tactical freight transportation planning problems found in the literature mainly involve service network design problems (SNDP). In dynamic service network design problems the decision regarding the scheduling of the services is of concern. These problems tend to cover the tactical and/or operational point of view.

8.5 The service network design problem

In a SNDP, decisions regarding service selection and transport distribution are addressed. Aspects of empty balancing and vehicle and crew planning may sometimes also be included. (Also refer to Chapter 3.) Although the SNDP may be explained by the node-arc and the tree formulation as in Kim & Barnhart (1999), the generic SNDP is described in the path formulation form.

For the path formulation SNDP model as described by Wieberneit (2008), the decisions involve selection of services, service routes, and traffic distribution (i.e. on which available routes and terminals will an order be transported). The objective of the SNDP is to minimize the costs (fixed and variable), of all relevant decisions. A graph $G = (N, A)$ is provided with a set of nodes N and a set of arcs A , representing the physical transportation network. A commodity $k \in K$ is defined by an origin $o(k)$ and a destination $d(k)$ with customer service type $s \in S$. S is defined as a set of all customer service types. The demand d^k has to be shipped from origin to destination within a particular time frame of its customer service type. A certain fleet $f \in F$ is available and every fleet type has a specific capacity u^f . The given set of service routes available is represented by R , and P resembles the set of paths from the origin to destination throughout this network.

There are two types of decision variables. The integer variable y_r^f , also called the design variable, models the decision as to how many vehicles of type $f \in F$ are in use on the service route $r \in R$. R^f represents the routes which are serviced by the fleet of type f . The variable x_p^k (also known as the shipment flow variable) models the flow of commodity $k \in K$, transported via path $p \in P$. The indicator α_{ij}^r indicates whether arc (i,j) is part of route r ($=1$) or not ($=0$). β_i^r is 1 if route r starts from i and -1 if route r ends in i .

The fixed cost of running the service route r with vehicle type f is defined by h_r^f , and c_p^k is the shipment flow cost or variable cost of handling goods per unit flow of k along path $p \in P$. The objective is then to

$$\begin{aligned} &\text{minimize} \\ &\sum_{f \in F} \sum_{r \in R^f} h_r^f y_r^f + \sum_{k \in K} \sum_{p \in P^k} c_p^k x_p^k \end{aligned} \quad (8.5.1)$$

subject to

$$\sum_{k \in K} \sum_{p \in P^k} x_p^k \leq \sum_{f \in F} \sum_{r \in R^f} w^f y_r^f \alpha_{ij}^r, \quad (i,j) \in A, \quad (8.5.2)$$

$$\sum_{p \in P^k} x_p^k = d^k, \quad k \in K, \quad (8.5.3)$$

$$\sum_{r \in R^f} \beta_i^r y_r^f = 0, \quad i \in N, f \in F, \quad (8.5.4)$$

$$x_p^k \geq 0, \quad k \in K, p \in P, \quad (8.5.5)$$

$$y_r^f \geq 0, \quad \text{and integer}, r \in R^f, f \in F. \quad (8.5.6)$$

The expression in (8.5.1) is the objective function of minimizing all costs. The constraint (8.5.2) is the capacity restriction of flow. The constraint (8.5.3) ensures that demand is satisfied for each commodity and constraint (8.5.4) represents the balancing of assets for different fleet types. Furthermore, design variables need to be positive integer values. For the dynamic SNDP, the planning horizon is considered in a discrete manner by replicating the physical network for each period. Nodes in these models represent locations in time and space, while arcs and links provide the physical movements. The SNDP and its applications are examined in Chapter 9.

8.6 Modelling of complex real-life problems in uncertainty: stochastic and dynamic problems

Stochastic, dynamic problems in the context of complex operational applications such as freight transportation and logistics have traditionally been formulated as large-scale mixed integer optimization problems with the primary emphasis and goal of finding an algorithm. Strong simplifications are then needed to represent the problem successfully. When representing the problem in a general way, much richer modelling issues arising in the dynamic setting can be captured (Powell & Topaloglu (2003)).

Modelling languages can take two general forms: algebraic modelling systems which are high level code or data generators for lower level systems, and conceptual representations. An identified challenge regarding the development of a representational system is the trade-off between scope of application (generality) and ease of application (requiring domain specific features). According to Powell & Shapiro (1999), other general modelling approaches are difficult to apply to the stochastic, dynamic problems in complex fields such as freight transportation.

Some of the most complex and largest operational problems can be found in the management of logistics systems and specifically in the design and control of freight transportation operations. The challenge of such problems appears to specifically involve the mathematical formulation of a model which captures not only the system dynamics but also the complex problem rules. Classical mathematical paradigms appear to be insufficient and a constraining modelling language for these problems under uncertainty with a large amount of complexities. Most models do not capture the flow of information in an organization and always assume a single decision-maker. Consequently, the most dynamic models in the literature are either found to be myopic or deterministic.

Due to problems characterised by complex operations, different lines of research can be found presenting models that are unique to a particular industry. Some industry specific problem classes include: airline fleet management, railroad car distribution problems, the load matching problem of truckload trucking, routing and scheduling problems in less-than-truckload trucking, the flow management in air traffic control and management of containers. Within each industry, there can be distinguished between distribution of goods, resource management and crew scheduling. As a result the possibility of learning from similar problems in different industries is greatly reduced (Powell & Topaloglu (2003)).

The mathematical formulation of stochastic, dynamic problems proves to be difficult. Therefore, more attention is usually given to the solution technique formulation and development than to the proper problem formulation. These solutions are then often found to be for a particular type of problem only and very context specific. According to Powell & Shapiro (1999), modelling a stochastic, dynamic problem proves to be quite a challenge and extremely difficult.

The dynamic resource transformation problem modelling framework was developed (and is the first paradigm of this kind to the author's knowledge) to accommodate the richness of stochastic, dynamic problems which arise in practice, as opposed to classical, more rigid, modelling techniques. The DRTP also provides a means of distinguishing important dimensions of stochastic, dynamic problems.

8.6.1 The dynamic resource transformation problem: A representational paradigm

Transportation problems typically involve highly dynamic information processes where decision making is often required when information is not yet known or incomplete, which induce uncertainty into the system (see Chapter 2). The DRTP offers a new vocabulary for the representation of complex problems in uncertain and dynamic settings. Subclasses of this problem include the dynamic resource allocation problems, and more broadly dynamic resource management.

The focus of the DRTP is particularly on developing a relatively context-free vocabulary for stochastic and dynamic problems, also free from algorithmic strategies. Stochastic and dynamic problems have, according to Powell & Shapiro (1999), received very little attention in the large-scale optimization context.

The DRTP elements may be organized according to three major/primary dimensions and ten subdimensions. This representation is also believed to be the first to focus on the information content in decisions for multi-agent systems, along with a characterization of information.

The resource layering concept appears to be newly introduced in the literature by Powell & Shapiro (1999), as well as the transfer/modify function, and the modelling of information sub-problems.

The Dynamic Resource Transformation Problem can be found in a variety of settings characterised by the transformation of one or more types of resources in a way that incurs a benefit and generates a cost of transformation. A central concept of the problem class is the layering of resources. A problem comprising more resource layers implies that it is more difficult to solve than problems with fewer layers.

8.6.1.1 Classifications of DRTP applications

Applications can be classified according to the number of resource layers involved (Powell *et al.* (2003)):

- One layer problems
 - Classical Inventory planning (with no demand backlogging).
 - Distribution problems with stochastic demands but no backlogging.
 - Dynamic Travelling Repairman Problem.
 - Machine scheduling (with no setups).
 - Airline crew scheduling problems (fixed times or flights).
 - Truckload fleet management I: managing the flows of trucks over a set of loads with fixed departure and arrival times.
 - Less-than-truckload trucking I: the traffic assignment problem (routing shipments).
 - Rail operations I: distributing box cars to customers with no demand backlogging.
- Two layer problems
 - Vehicle routing problems.
 - Machine scheduling with setups.
 - Personnel planning.
 - Fleet management (vehicles and loads or customers to be moved).
 - Truckload fleet management II: optimizing the assignment of drivers to loads, may be served over a time period (with time windows).
 - Less-than-truckload trucking II: routing shipments and trailers.
 - Rail operations II: Scheduling locomotives to move trains.
- Three layer problems
 - Truckload fleet management III: simultaneously managing drivers, tractors and trailers.
 - Machine scheduling (with setups) with operators (jobs, machines and people).

- Less-than-truckload trucking III: routing shipments, trailers and drivers.
- Rail operations II: Scheduling locomotives and crews to move trains.
- Four layer problems
 - Routing and scheduling: managing driver, tractor, trailer and product.
 - Multiple Machine scheduling (with setups) with operators (jobs, two types of machines and people).
 - Less-than-truckload trucking IV: routing shipments, tractors, trailers and drivers.
 - Rail operations IV: Scheduling locomotives, crews and boxcars to satisfy external demands with backlogging.

The DRTP identifies various physical processes which cause the change of attributes over time. These may include:

- Temporal processes: They determine the duration of an operation, and includes travel times, unload/loading time, task execution time.
- Economic processes: The generation of costs, revenues, and service levels as a result of a transformation.
- Discrete classification processes: This may be seen as the location/state/level of skill of a resource which may change.
- Aging and replenishment processes: Resources may comprise of a dimension that needs replenishing, or an aging factor, such as deterioration or fuel consumption.
- Arrival and departure processes: Entities may arrive at, or depart from a system.
- Information processes: Describing the arrival of data into the system for the use of decision making. These processes are the means by which a DRTP can be controlled.

The most complex systems are run by more than one decision maker and can be referred to as multi-agent control systems. Classical optimization models usually imply a single-agent structure (Powell & Shapiro (1999)).

8.6.1.2 A conceptual overview

The dynamic transformation problem, as defined by Powell *et al.* (2003), facilitates a framework for describing problems according to three main dimensions: knowledge, processes and controls. Knowledge in this case, is the exogenously supplied data, and a set of inference functions used to estimate data elements that are not currently known to the system. The processes resemble the laws determining how the system changes over time, physical constraints and the evolution of information. Controls describe the ‘what’, ‘who’, ‘when’ and ‘how’ of decision making within the system.

Notation for the identification of DRTP is derived from queuing theory and is proposed by Powell *et al.* (2003), as *Knowledge || Processes || Controls*, where each element can be replaced by a series of descriptive abbreviations, describing the nature of the element. In Powell & Shapiro (1999), the first category was referred to as Information. In this literature, the term Knowledge is used, although it does not really matter which one is used as the meaning and application remain the same.

When the decision maker is considering a problem where the management of resources is of concern, implying that the information of concern is about the resources, the notation may become *Resources || Processes || Controls*. Each of the three main DRTP dimensions and associated subelements are subsequently discussed.

1. DRTP element: Knowledge

A distinction can be made between data knowledge and functional knowledge, where the first dimension consists of the attributes of the resource being managed. These two dimensions may each be explained according to Powell *et al.* (2003).

Data knowledge: data used by/in the system that is exogenously supplied to the system. These exogenous data may include:

- Data about resources to be managed, resource classes and vector attributes.
- Data about parameters, governing the physical operations of the system, such as travel times and costs.
- Data about ‘plans’ that have been made previously, used to influence future decisions. These plans may be aggregated forecasts of future decisions, forecasts based on historical behaviour, and policies that make up the rules that govern how decisions are to be made.

Functional knowledge: the functions that enable obtaining information about data elements which cannot be deduced directly. Functional knowledge may involve:

- Functions that provide information not directly obtainable, such as inventory level.
- Aggregation functions, allowing knowledge about certain parts of a group by grouping the data.
- Forecasting functions.

Data classes may furthermore broadly be defined as static or dynamic.

- Static classes comprise data that will never change within the context of the model.
- Dynamic classes encompass data that change over time, describing ‘how’ attributes of an object change as a result of exogenous or endogenous processes.

Powell *et al.* (2007) focus on modelling the evolution of information of dynamic models for freight transportation. Information describing resources is of particular interest, as resources are the data elements which make up the system (Powell *et al.* (2003)). The concept of resources may be explained according to Powell *et al.* (2003) by the following definitions:

A resource is an endogenously controllable information class which constrains the system over time. An **active** resource resembles a resource with attributes that can be endogenously modified without necessarily being coupled with other resources, whereas a **passive** resource layer is one that can only be coupled or uncoupled with other resources. Active resources are the resources being managed, and passive resources enable the active resources to perform their function.

A **persistent** resource is a resource that remains in the system over the planning horizon, and a **transient** resource is one that may enter and/or leave the system during the planning horizon (also referred to as perishable). A **recurrent** resource is a persistent resource that cyclically needs to go back to a specific base state. A **strongly recurrent** resource is described by the return to a base state in a fixed time period. A **weak recurrent** resource has the incentive to cycle back, and **nonrecurrent** resources, such as trucks, usually move aimlessly around in the system with no returning constraint.

Point resources have a single point of entry and exit. **Path-based** resources have different single entry and exit points. **Tree-based** resources have

a single point of entry and multiple exit points. **General** transient resources are described by multiple entry and exit points.

A **primitive** resource is an elementary, indivisible resource with fixed attribute types and predefined behaviour, whereas a **composite** (compound) resource is formed by the joining of two or more resources in different classes to form a combined set of attributes. The **bundling** of resources occurs when two resources from the same object class are joined, and **coupled** joined resources are resources from different classes. A resource **layer** is a set of attributes from one or more resource classes. A **primitive** layer is a resource layer with attributes drawn from a single class and a **composite** layer has attributes from more than one class.

Most applications comprise a resource layer which may be viewed as a task, demand or customer. If a customer order may be satisfied over some time interval, the strictest definition of a passive resource is then satisfied: it is an information object which is endogenously controllable and it constrains the system. A clear distinction between customer orders and customers is that orders are endogenous ‘resources’ and customers are typically exogenous.

A compound resource can be found in many settings, in the form of teams (grouped people where one person is a resource) or compound portfolios (where resources are financial assets).

2. DRTP element: Processes

Process elements may be distinguished according to Powell *et al.* (2003) as follows:

- Information processes impact the transformation of a resource, and can be classified as:
 - Exogenous information processes, representing information updates from outside the system.
 - Endogenous information processes which are the sequence of decisions made within a system.
- System dynamics, representing the physical laws, dictates the changing of a system over time. Three subelements can be distinguished:
 - The modification of attributes.
 - Economics of a transformation: the generation of costs and rewards.
 - The transfer time required for a transformation.

- Two classes of constraints, restricting the ability to transform a process, can be identified:
 - The conservation of mass, which prevents a resource from being in two places at the same time or from being destroyed.
 - The rate of process transformation, specifically applicable where multiple resources have to be modified. Identified classes of rate transformation constraints include:
 - * Technology constraints: computational implications and limitations.
 - * Exogenous controls: may include factors such as policies from higher management levels.
 - * Market demands.

Almost all physics of a real problem are referred to as system dynamics and are contained within a group of equations called constraints. Time windows would typically be modelled as part of the cost function or through rules governing allowable transformations.

3. DRTP element: Controls

Five subdimensions may be identified (Powell *et al.* (2003)):

- Types of controls: defining the way in which the system is controlled.
- Control structure: who owns what decision.
- The information set: what information is available when a decision is made.
- Decision function: how decisions are made, and with what information.
- Measurement and evaluation: how decisions are compared.

A primitive decision is an elementary action which cannot be represented as a sequence of other decisions, modifying the system (Powell *et al.* (2003)). Controls can furthermore be defined as being direct or indirect. Direct controls induce change of the resource attributes, while indirect controls can be changed endogenously, having an effect on the outcome of a direct control. Decision variables, such as moving the truck or managing inventories, would typically be direct controls. In a dynamic system, these decisions are state dependent and are made as the system evolves. The indirect controls represent an ‘everything else’ category.

Direct (primal) controls may further be described by four dimensions (Powell *et al.* (2003)):

- The control structure: within a multi agent system the ‘who owns what decision’ needs to be specified.
- The information set specifies what information is available when a decision is made.
- The decision function determines how decisions are made and with what information.
- Measurement and evaluation specifies how decisions are compared.

Furthermore, decisions can be seen as being primitive or composite (tactic). A primitive decision is an elementary action, whereas a composite decision or tactic is a sequence of two or more decisions which may be executed with the same set of information.

Three classes of primitive controls are identified according to Powell *et al.* (2003) as:

- Coupling of resources: where different resource layers are put together.
- The uncoupling of resources: such as taking the driver out of the truck.
- Modification: where the driver is used to take the truck to a different location.

According to Powell *et al.* (2003), the only way a DRTP can be controlled endogenously is by employing the three fundamental decisions (which include couple, uncouple and modify). Special modification cases can be identified as hold (do nothing), move (a resource from a special location to another), entry (a resource is allowed to enter a system) and exit. Powell & Shapiro (1999) and Powell *et al.* (2003) developed a notation for describing problems within the DRTP framework. They also developed a notation for problem formulation.

8.6.1.3 Identification of transportation problems within the DRTP framework

Within this modelling framework, problem classes arising in transportation are identified, according to Powell & Topaloglu (2003), within each of the three major dimensions previously defined as information about resources, processes and controls. Problems may be described by means of the three DRTP dimensions.

1. Problem identification: resources

The characteristics of a resource can be described by a resource specific attribute vector a_r , where $r \in R_c$ and c denotes a particular resource class.

Six major problem classes are mentioned here in terms of the attribute vectors:

- Basic inventory problems: $a = \{\text{no attributes}\}$.
- Multi-product inventory problems: $a = \{k\}$ where $k \in K$ is a product type.
- Single commodity flow problems: $a = \{i\}$, where $i \in I$ is a state variable.
- Multi-commodity flow problems: $a = \{i, k\}$, where i is a state variable such as location and k denotes a commodity class.
- Heterogeneous resource allocation problems: $a = \{a_1, a_2, \dots, a_N\}$. This is a more complex problem class, where it is possible to divide the attribute vector into static and dynamic attributes, therefore $a = \{a^s, a^d\}$.
- Multilayered resource allocation problem: $a = \{a^1|a^2|\dots|a^L\}$, where a^c is the attributes of the resource class c .

Resource allocations can further be classified as single-, two-layer and multi-layer problems. A two-layer problem would typically consist of an active resource layer representing people or equipment, and a passive layer representing customer orders.

2. Problem identification: System dynamics

System dynamics may be described by Powell & Topaloglu (2003) according to these elements:

- Time staging of information, with two major problem classes:
 - Two-stage problems
 - Multi-stage problems
- Travel times (also defined as ‘decision completion times’)
 - Single period times
 - Multi-period times
- Measurability of the modify function.

The modify function can be defined as $M(K_t, a, d)$ which captures the impact of a decision d involving resource attributes a , where K_t is the knowledge base

at time t . $M(K_t, a, d)$ then produces (a', c, τ) with a' as the transformed attributes, c the contribution and τ the time to completion. According to Powell *et al.* (2003) problems can be defined in terms of the measurability of the modify function, as being either measurable or not.

3. Problem identification: Controls

Two broad classes may be identified according to Powell & Topaloglu (2003) as:

- Single agent control, where the entire system/company is modelled as being controlled by a single agent, and
- Multi-agent control where multiple control units/agents exist in one system.

Most of the transportation problems can be formulated as dynamic resource allocation problems, a subset of the dynamic resource transformation problem class.

Powell & Topaloglu (2003) then also describe the four classes of algorithms that can be built on these information sets:

- The classic myopic model: $I_t = (K_t)$.
- The classic rolling horizon procedure: $I_t = (K_t, \hat{\Omega}_t)$ if $|\hat{\Omega}| = 1$.
- Making decisions according to what we know now, but using plans to guide decisions: $I_t = (K_t, x_t^p)$.
- The information set $I_t = (K_t, Q_t)$ results in dynamic programming formulations, Bender's decomposition and other approximations.

The information state is described by I_t , K_t resembles the exogenous data that have been provided to the system, $\hat{\Omega}_t$ is the set of future events forecasted at time t , x_t^p represents the vector of decisions, and Q_t implies the forecasts of the impact of decisions now on the future.

Classical mathematical paradigms appear to be insufficient and a constraining modelling language for complex stochastic problems under uncertainties with a large amount of complexities. The different lines of research are often found to present models that are unique to a particular industry where more attention is generally given to the solution technique development. The DRTP offers a formulation framework for describing and formulating these problems. The identification of transportation problems within this framework was discussed.

Powell & Shapiro (1999) and Powell *et al.* (2003) also developed notation for formulating problems. Since transportation and freight transportation problems are often very complex in nature, concerned with dynamic information processes and uncertainty, the DRTP is particularly applicable in this context. As a formulation framework, the DRTP provides a means for distinguishing important dimensions of stochastic dynamic problems. Most of the transportation problems are concerned with or can be formulated as dynamic resource allocation problems, which is a subset of the DRTP.

8.6.2 The dynamic resource allocation (DRA) problem

Dynamic resource allocation problems involve the assignment of a set of reusable resources to tasks that occur over time. The arrival of tasks is only known through a probability distribution. The assignment of a resource to a task induces a reward and removes the task from the system while modifying the state of the resource (Topaloglu & Powell (2006)).

These problems may be found in many aspects of freight transportation. Some of the most prominent studies include dynamic fleet management (Topaloglu & Powell (2006)), (Powell & Carvalho (1998)), (Godfrey & Powell (2002a)), (Godfrey & Powell (2002b)), product distribution (Bassok & Ernst (1995)), and personnel management (Walton *et al.* (2007)).

8.6.2.1 Dynamic resource allocation problem formulation

The dynamic resource allocation problem may be formulated according to Powell & Van Roy (2004). Consider the state of a system which evolves in discrete time over T periods. At each time $t = 0, \dots, T$, the state of the system can be described by a state variable R_t , which describes a single resource class, where

$$\begin{aligned} a &= \text{Attribute vector describing a single resource,} \\ A &= \text{The set of possible attributes,} \\ R_{ta} &= \text{The number of resources having attribute } a \text{ at time } t, \\ R_t &= (R_{ta})_{a \in A}. \end{aligned}$$

When multi-resource classes exist, different resource classes C^R have to be defined. A_c then defines the attribute space for the resource class $c \in C^R$, and R^c then resembles the resource vector for class c .

At each time $t = 0, \dots, T - 1$, a decision is made regarding what to do with each resource. A set of actions D_a can be defined for each resource which includes actions that can be applied to that resource. The collection of actions

applied can be referred to as $x_t = (x_{tad})_{a \in A, d \in D_a}$ where x_{tad} denotes the number of resources with attribute a for which action d is applied to. Each decision variable x_{tad} has to be a nonnegative integer and the decision variables must satisfy flow conservation constraints of the form

$$\sum_{d \in D_a} x_{tad} = R_{ta}, \quad a \in A. \quad (8.6.1)$$

The above formulation can be written more compactly as $A_t x_t = R_t$ where A_t is a linear operator. Other constraints on the decision variable are assumed to be linear, and of the form:

$$U_t x_t \leq u_t. \quad (8.6.2)$$

U_t is a linear operator in the above formulation, mapping the decisions to R^{nt} for some n_t . The change of the state R_t , caused by the decision made, is defined by $(\Delta_t x_t)_a$, which denotes the number of resources that result in attribute a given the decision vector x_t . The resource vector which can be acted on during time period t is known as the *pre-decision state vector*, whereas the *post-decision state vector* describes the resource vector after the resources have been acted on.

The dynamics of the system can be explained by the simple recurrence

$$R_{t+1} = \Delta_t x_t + \hat{R}(R_t^x, w_{t+1}), \quad (8.6.3)$$

where $\hat{R}(w_t)$ is the exogenous arrivals to the system during time interval t , not dependent on the state of the system.

At each time, a feasible action x_t must be selected, where

$$x_t = X_t^\pi(R_t) \in \chi_t(R_t). \quad (8.6.4)$$

The feasible set of decisions is referred to as $\chi_t(R_t)$, where a decision is made according to a function $X_t^\pi(R_t)$ that maps out each state R_t to a feasible action.

The contribution generated during each period t , can be described by the linear function $C_t x_t$ of the decision x_t as

$$\max_{\pi \in \Pi} E \left[\sum_{t=0}^{T-1} C_t X_t^\pi(R_t) \right]. \quad (8.6.5)$$

The objective is to select a policy which would maximise the expected contribution over the horizon T .

8.6.2.2 Curses of dimensionality

In principle, the dynamic resource allocation problem can be addressed via dynamic programming. However, when dealing with practical problems three computational obstacles prevail (Powell & Van Roy (2004)):

- The number of possible state vectors grows very quickly with the number of possible attributes, resulting in unmanageable computation. Exact computation of the expectation is infeasible since the number of possible outcomes becomes enormous as the attributes grow.
- An exhaustive search over χ_t is required to find an optimal decision x_t .

Powell & Van Roy (2004) developed some algorithms to address large-scale dynamic resource allocation problems, which are iterative and incorporate integer programming, stochastic approximation, and function approximation. Dynamic programming approximations appear to be useful in solving large stochastic dynamic resource allocation problems (Topaloglu & Powell (2006)).

Many resource allocation problems are found in the field of freight transportation. Dynamic resource allocation considers the changes of a system state as it evolves over time by investigating the effect of decisions on resources.

The aim is then to decide on a feasible action at each point in time. The contribution generated for all time periods is considered. Multi-resources classes are also accommodated. For complex stochastic problems the attribute vectors are often required to be large, resulting in an enormous solution space and infeasibility. However, approximations appear to aid in the solution of large stochastic dynamic resource allocation problems (Topaloglu & Powell (2006)).

8.7 Optimizing under uncertainty

As of this writing, the field of large-scale resource allocation problems in transportation and logistics is governed by algorithms developed within the mathematical programming community (Powell & Van Roy (2004)). Approaches to optimization under uncertainty have followed a variety of modelling philosophies, including expectation minimization, minimization of deviations from goals, minimization of maximum costs, and optimization over soft constraints (Sahinidis (2004)).

Main approaches to optimization under uncertainty may be identified (Sahinidis 2004) as stochastic programming (recourse models, robust stochastic programming and probabilistic programming), fuzzy programming (flexible and possibilistic programming) and stochastic dynamic programming.

8.7.1 Deterministic modelling

The most common modelling and algorithmic strategy is to formulate the problem deterministically and then to use classical mathematical programming to solve the resulting model. Deterministic models, however, can exhibit fundamental weaknesses from a practical point of view, ignoring uncertainty and other more complex real-world dynamics completely.

According to Powell & Topaloglu (2003), the most basic model in engineering practice is the myopic model, which implies that decisions are made based on what is known and computable. A strength of the myopic model is that it is simple to formulate and solve, using commercial solvers. It is also easily understandable. Possibly the most overlooked limitation of very sophisticated solution techniques is that the solutions produced are hard to understand.

The myopic model is, however, limited by the fact that resources will only be assigned to known demands, and it is not possible to send vehicles to intermediate/regional depots. Consequently, an idle vehicle, having nothing to do, would therefore be left idle and would not be sent to a location where there is a high probability of future demand. The model might move a vehicle to the next booked order location, whereas it could have been moved to a much closer location where there probably will be an order. Also, in the case where more vehicles than orders are present in the system, the model provides almost no assistance in positioning vehicles in anticipation of future orders (Powell & Topaloglu (2003)).

8.7.2 Stochastic programming

Stochastic programming is another subfield of mathematical programming, an extension of deterministic mathematical programming which accommodates uncertainty. In transportation modelling, stochastic programming is of significance due to the high amount of uncertainty usually present. Deterministic models assume that all orders are known in advance, taking into consideration only the known orders, whereas stochastic models assume that customer demand is not known until it actually arrives (Powell & Topaloglu (2003)). Markov decision processes may be seen as an extension to stochastic system models that incorporates optimization (Powell & Van Roy (2004)).

According to Powell & Van Roy (2004), two algorithmic stochastic programming strategies can be identified:

1. Scenario methods use an explicit future representation of decisions for a finite set of scenarios, and
2. Bender's decomposition, which employs a strategy for approximating the downstream impact of decisions.

A key difficulty in optimization under uncertainty is the fact that an uncertainty space is huge and frequently leads to very large-scale optimization models. Decision making under uncertainty is often further complicated by the presence of integer decision variables in modelling a multi-period or multi-stage problem.

8.7.2.1 Two-stage modelling and solution techniques

In the context of transportation, a simple recourse model basically involves vehicles which are assigned and sent to particular customers or locations rather than to specific orders (Powell *et al.* (2003)). This implies that the model may send more or fewer vehicles than required, to a customer location at time t , incurring a penalty or cost when learning the outcome. Decisions are made before orders become known. It is assumed in this simple recourse model that when a car is sent to customer c , it cannot at a later stage be sent to another customer. The major weakness of this model is that it does not have the ability to send a load to a regional intermediate depot to wait until the last minute before servicing the customer.

The *first-stage* variables are those that have to be decided before the actual realisation of the uncertain parameters. The *second-stage* variables are interpreted as corrective measures or recourse against infeasibilities arising due to the realization of uncertainty (Sahinidis (2004)).

This problem is usually reduced to piecewise linear or concave functions characterising the value of a load at a location. The concave functions can be estimated by means of Monte Carlo methods. In order to deal with ‘intermediate depots or classification yards’, the two-stage stochastic program with network recourse is introduced (Powell *et al.* (2003)).

According to Sahinidis (2004) the stochastic linear program for the two-stage formulation is formulated by Kall and Wallace in 1994. This two-stage formulation can easily be extended to a multi-stage setting by modelling the uncertainty as a filtration process (Sahinidis (2004)).

More recently, Hingle & Sen (2000) and Sherali & Fraticelli (2002) proposed algorithms concerned with Bender-like decomposition approaches. A finite branch-and-bound scheme was developed by Ahmed *et al.* (2004) for a class of stochastic integer programs. Most of the algorithms developed for stochastic linear programming carry over to the non-linear case, but non-linearity may induce convexities and local optima.

Robust stochastic programming was introduced to capture the notion of risk in stochastic programming, introducing a variability measure. A highly

undesirable property, however, is the result of suboptimality. Takriti & Ahmed (2003) proposed conditions on the variability measure to remedy this problem.

The recourse-based approach requires the decision maker to assign a cost to resource activities that are taken to ensure feasibility of the second-stage problem. In essence, probabilistic programming focuses on the reliability of the system/the ability of the system to meet feasibility in an uncertain environment (Sahinidis (2004)).

According to Powell & Topaloglu (2003) surprisingly little work compare different stochastic programming approaches for two-stage and multi-stage problems in particular. Algorithmic strategies developed in the context of stochastic programming may be identified to include scenario methods, Bender's decomposition, stochastic linearization techniques, nonlinear functional approximations and the incorporation of substitution. Bender's decomposition is a very appealing algorithm that replaces very large problems posed in scenario optimization with sequences of relatively small problems. The issue with Bender's algorithm, however, is the slow rate of convergence and the need for integer solutions.

Stochastic linearization techniques are identified according to Powell & Topaloglu (2003), as the simplest to employ and attractive for transportation applications, since they retain the structure of the original problem. They are unfortunately unlikely to work effectively in practice because of the lack of stability.

In transportation the goal is usually to solve multistage problems. It is important to study algorithms for two-stage problems since algorithms which work for two-stage problems might also be appropriate in a multi-stage problem context, whereas an algorithm which does not work for a two-stage problem would not work for a multi-stage problem either. But the best algorithm for a two-stage resource allocation problem remains an open question (Powell & Topaloglu (2003)).

8.7.2.2 Multi-stage resource allocation problems

In multi-stage problems it is necessary to capture the sequential decision-making process as information that evolves over time. For transportation problems the issue of the reusability of resources is usually encountered. It implies that once a vehicle has moved a load, it is ready to move the next load.

Different real-life applications of the Multi-stage Resource Allocation problem are identified by Powell & Topaloglu (2003), and are as follows:

- Fleet management for truckload trucking: Truckload trucking is characterised by the movement of an entire freight load from origin to destination. Uncertainty in this context is caused by the fact that loads can take anything from one to four days to be delivered, and customers may call in and request the use of trucks two days or one day beforehand, or even the same day. As it is explained here, this problem class may reject loads (in contrast to rail). This can be seen as a classic problem of decision-making under uncertainty.
- Driver management for long-haul less-than-truckload motor carriers: This problem class involves timing the movement of loads which requires careful management of drivers.
- Management of jets in a so-called ‘fractional ownership industry’: Individuals own a fraction of a jet which gives them access to the whole fleet. Requests may arrive not long beforehand, and after the flight the pilot will move the jet to another location.
- Routing and scheduling transport aircraft of the United States air mobility command (AMC): The AMC is basically like a large trucking company and is typically involved in emergency situations.

8.7.2.3 Multi-period travel times

An important and annoying characteristic of transportation problems is the property that it takes time to complete a decision. This is referred to as ‘multi-period’ travel times. More generally, problems incorporating this characteristic would be referred to as having ‘multi-period transfer times’.

The implication of multi-period travel times is that, after attending to a resource at time t , it is committed to an activity in time period $t + \Delta t$ and cannot be acted upon. The resource can also not be ignored since it will eventually complete the movement and has to be taken into account regarding decisions in the time period $t + \Delta t$.

The problem with multi-period travel times is unique to multistage stochastic models (Powell & Topaloglu (2003)). Multi-stage problems are much harder to solve than two-stage problems, but are generally solved as sequences of two-stage problems. Sahinidis (2004) suggests stochastic dynamic programming in addressing multi-stage problems.

8.7.2.4 Dynamic programming

Dynamic programming was introduced by Bellman in 1957 in order to deal with a dynamic environment and uncertainty. The assumption is that the present state in period k of a system, can fully be determined by its recent history:

$$x_k = f_{k-1}(x_{k-1}, u_{k-1}, w_{k-1}), \quad k = 1, \dots, N. \quad (8.7.1)$$

Here u_{k-1} is selected with the knowledge of the present state from a set of allowable control actions, and the uncertainty w_{k-1} follows some distribution that depends only on the current state and control action.

When a cost function is minimized over an entire time horizon, the tail subproblem of the final stage in the time horizon is solved first. And step by step, all tail subproblems are solved, based on the previous solution. Suitable algorithms are needed to solve the tail problems such as non-linear and other stochastic programming methods (Sahinidis (2004)). The result, however, is a computationally very intensive procedure which suffers from the curse of dimensionality previously introduced. Approximation strategies through simulation or heuristics such as neuro-dynamic programming (Bertsekas & Tsitsiklis (1995)) were developed to address this difficulty.

The algorithmic strategy for solving multistage problems as Powell & Topaloglu (2003) propose is based on techniques from approximate dynamic programming. Powell & Topaloglu (2003) suggest the use of nonlinear functional approximations and also the use of an augmented state variable as a standard solution for problems of this type. However, practical implementation thereof may be problematic.

Powell *et al.* (2005) proposes an approximate dynamic program methodology for highly-dimensional discrete resource allocation problems, based on the use of continuous separable value function approximations with a post-decision state variable. This method appears to be useful for particular problems. It is, however, stressed that even simple resources can become surprisingly complicated, resulting in huge state spaces. They also only consider a single resource class, and not different resource attribute spaces. An overview on approximate dynamic programming is given by Powell *et al.* (2007).

8.7.2.5 Motivations for applying stochastic models

Powell & Topaloglu (2003) highlighted a few aspects for applying stochastic models:

- The newsvendor effect: Stochastic models can over-allocate or under-allocate, depending on the availability of the resource, whereas deterministic models will never allocate more than the point forecast.

- Robust allocation: A truck might be needed at location A or B, but since it is not exactly sure, it is sent halfway to C where it will wait until the last minute to respond to the demand.
- Advance information: Stochastic models can accommodate the staging of information over time.
- Forecasts and discrete items might be needed.
- Deterministic viewpoints might produce problems that are larger and more complex than needed, whereas models which incorporate ‘here and now’ as well as future uncertainty could be smaller and more compact.

8.8 Concluding remarks: Chapter 8

In this chapter different mathematical formulation and solution methods for the AC problem were investigated. Freight transportation problems have traditionally been modelled as large-scale linear programs or integer programs. When introducing uncertainty and other real-world factors, techniques for optimization under uncertainty have to be investigated. The DRTP framework is identified as a method which facilitates the formulation of complex and stochastic real-world freight transportation problems, but is in itself not a solution tool. Stochastic programming and stochastic dynamic programming have proven to be useful and applicable as solution techniques in the contexts of some real-life freight transportation problems, but the richness of problems encountered in freight transportation in particular, involves some issues which appear to be not yet addressed by the stochastic programming community (Powell & Topaloglu (2003)). Some of these issues include:

1. Random travel times.
2. Advance information: customers place orders in advance.
3. Demand backlogging: the ‘now’ vs. ‘later’ problem: if the demand is not attended to now it remains in the system in the next time period. In freight transportation it is usually necessary to manage trucks and locomotives, boxcars/load and crew over a long/extensive time horizon.
4. The problem of multiple, reusable resources, which is probably the most challenging problem in the presence of multiple resource layers. The simplest example of this sort arises with backlogging demands.
5. User non-compliance: An important and mostly overlooked dimension is that what is being planned, is not necessarily what is implemented.
6. Multi-agent problems: breakdown of large problems.

7. Data errors.
8. Incomplete information: Random variables can be said to arise when information not known now, becomes measurable at a later stage.
9. In real problems it is usually found that the attribute vectors are much more complex than the attribute vectors modelled.

In order to address the curses of dimensionality, Powell & Van Roy (2004) present approximation algorithms. These algorithms incorporate the reformulation of the dynamic programming recursion, simulation-based stochastic approximation techniques, and continuous approximation techniques which facilitate integer programming solutions to decision optimization sub-problems. The effectiveness of these identified algorithms on general multistage problems appears to be not exactly known due to a lack of computationally tractable competing algorithms. There are many unanswered questions, although this line of investigation could be promising for freight transportation.

Typical modelling approaches which are commonly used in practice are simulation models, and deterministic optimization and algorithms. Simulation models are mostly used for planning purposes where the need exists to understand the behaviour of a system which evolves over time. Deterministic optimisation models and algorithms are usually employed to obtain computer-based recommendations. In engineering practice it is often found that deterministic optimization models are considered as ‘good enough’, since stochastic models often lack practical problem-solving tools, and are mathematically much harder to understand and interpret.

In the next chapter, tactical freight transportation problems and possible formulation and solution techniques, as identified in the literature, are discussed, after which the applicability and validity of these methods as presented in this and the next chapter are considered and evaluated for the AC problem.

Chapter 9

SNDP Freight Transportation Problems

Tactical problems may be classified as VRP or Service network design problems (refer to Figure 3.1). According to Wieberneit (2008) a system can often be divided into long distance distribution and regional traffic, where the long distance distribution is usually concerned with the service network. Considering that the goal of service network design formulations is to plan services and operations on a tactical level in order to achieve a satisfactory service level, while ensuring profitability of the firm, this chapter is devoted to different tactical service network problems in the literature which are also encountered in practice. More attention is paid to on-land freight applications. Applicable solution techniques for these problems are also explained.

9.1 Identified SNDPs encountered in practice

Five tactical problems encountered in practice were identified by Wieberneit (2008):

- The express shipment delivery problem.
- Flight network for lettermail.
- LTL operations in North America.
- LTL operations in Europe on a Multi-modal Network.
- LTL operations in Europe on a Rail Network.

A brief overview of these service network design (SNDP) problems is included here, as well as contributions found in the literature regarding suitable formulation and solution techniques.

9.1.1 The express shipment delivery problem

This problem is concerned with packages that have to be expedited by air transport, because they cannot be shipped in time using overland transport. The problem formulation involves that:

- Products are treated as homogeneous.
- Time-windows are associated with airports for pick-up and delivery in order to meet service requirements.
- Some airports are used as hubs.
- Due to complexity, this problem is decomposed into an air network and on-land ground (feeder) network, which are planned separately.
- Transportation from shipment centres to airports and vice versa is not considered (Wieberneit (2008)).

9.1.2 Flight network for lettermail

Letters are collected either from the customer or mailboxes and delivered to letter centres where letters are sorted according to their destination. This problem is concerned with letters that need to reach their destination within one night, requiring aircraft transportation. The optimization of the lettermail network involves different modes of transport and is therefore too complex to consider as a whole. A decomposition heuristic distinguishes between the inner network (the flight network) and the outer service network (long-haul road transporters). Since the inner network incurs by far the highest costs, the focus is on the flight network. Transportation to and from the airport is not considered.

One aim of this particular problem is to design the inner service network. Another matter is how to assign orders to routes and also the decision of whether empty flights (ferry flights) should be conducted. The objective is to find a combination of routes and ferry flights so that the sum of all costs for the routes, ferry flights and the feeder transports, is minimal (Wieberneit (2008)).

9.1.3 LTL operations in North America

The type of goods loaded on intercity trucks may vary in size, weight and other characteristics, although homogeneity is assumed. Carriers have to consolidate shipments using terminals and hubs. The planning horizon consists of different time periods, and shipments with low volume may pass through several hubs before reaching their end destination. Some services between the

terminals and closest hub have to be offered at least once a day, whereas other services may be offered once a week. The problem is characterised furthermore by a large geographical area. In this planning problem, services between terminals, routes of the goods as well as the hubs, need to be determined. Unlike the general SNDP, imbalances of empty trailers may occur. Any additional restrictions are not considered here.

The aim of this model is to determine which of the services from the possible set of services should be established and how the freight should be transported across these services. The result is a load plan. A so-called minimal load plan may then be obtained which incorporates costs for the services and delays (Wieberneit (2008)).

An overview of some contributions to this problem class may be summarised, according to Wieberneit (2008), as in Table 9.1:

Table 9.1: Literature Contributions to LTL Operations in North America

Formulating and Solving contributions	Authors
Operational problem development. Stochastic and Dynamic characteristics are considered. Real time information is incorporated.	Cheung and Muralidharan (2000)
Development of a local heuristic, dropping and adding links from the network of the shipment routing problem. Powell (1986) extended this work.	Powell and Sheffi (1983) Powell (1986)
Development of shipment routing algorithms to solve the shortest path problems. The shipment routing problem with practical requirements is considered.	Koskosidis and Powell (1992)
Decomposition strategy for the SNDP. The planner is incorporated into the optimization process where constraints and trade-offs are of concern.	Powell and Sheffi (1989)
A subgradient method to solve SNDP for LTL applications is developed. It is based on the dynamic SNDP, only considering capacity and flow balance constraints. For this algorithm shipments take the minimal cost path until an arc is saturated and the remaining shipments are routed over the next minimal cost path. Only a small percentage of shipments are split.	Farvolden and Powell (1994)

9.1.4 LTL operations in Europe on a multi-modal network

A national transportation system is considered. Orders with different delivery-time requirements can be shipped together, and each order is given in contained quantities with a mode preference. Containers may be shipped by truck or train. Legal and social requirements have to be taken into consideration in the planning process. The truck driver and truck is considered as one unit. Travel time restrictions also have to be considered. Each truck departs from its home terminal and has to return at the latest after five days. Jansen *et al.* (2004) lowers this requirement/constraint in a multi-modal transportation study for the Deutsche Post World Net in Germany, in that a truck can return to any home terminal, i.e. the depot in the vicinity of where the driver lives. Only direct routes are considered since consolidation is not needed.

Empty transports are also sometimes needed due to an imbalance in demand. The number of stops on a route is not restricted, although a route should require a feasible period of time and distance. Two drivers may be allowed on a route to decrease possible travel time. Other constraints include sorting capacities at the terminals and the repositioning of empty containers. The aim of this planning model is to provide a cost-minimized set of services and empty transports by taking into account all orders with pick-up time in the particular planning horizon, although planning itself is repeated every day. This implies then that the focus is in effect operational.

Jansen *et al.* (2004) implemented a decomposition algorithm consisting of different subproblems. The first is a ‘Modality Choice sub-problem’ for all orders to be transported by train, assigning orders to specific trains. The second step solves the repositioning of containers, modelled as a minimum cost network. The third step is the ‘Order Planning’ problem, which tries to assign combinations of orders to routes. Routes are generated and orders assigned. The order and route-orientated planning approach may be set up in two types of loops: the outer loops define what orders are allowed to routes/vehicles and what kind of routes is allowed. The assignment itself is conducted in the inner loops. The last subproblem is the ‘Planning Improvement’ which attempts to improve the plan by moving a route’s orders and services around by means of three local search algorithms.

9.1.5 LTL operations in Europe on a rail network

According to Wieberneit (2008), this problem is based on the road network in Germany considered by Wlcek in 1998, where a homogeneous fleet of long-haul carriers transport containers. Pick-up and delivery time windows at the terminals are provided. Consolidation is often needed since order quantities are

too small for direct road-traffic. Consolidation approaches include: container consolidation, additional cargo and consolidation using hubs. In addition to the generic SNDP, another decision has to be made: the assignment of quantities to containers. Direct and hub routes are considered, and empty transports may be required. The objective is to provide a cost-minimized set of services and a transportation plan for orders. Transport costs, non-linear in quantity, and freight handling costs have to be considered.

The solution approach developed by Wlcek for a carrier network is more strategic in nature, although his methodology is extended to the tactical planning framework. The solution algorithm is a sequential decomposition in sub-problems with two consolidation steps and one route generation.

The first consolidation is the grouping of ‘rest quantities’ (quantities that do not fill a container fully). The heuristic creates an initial solution which is improved by a local search. The second consolidation is the grouping of containers according to the services required by means of an algorithm almost like the first. In the third sub-problem, the ‘Route Generation’, services are planned according to routes with the aim to find a minimal-cost schedule for the routes under the restriction that all services have to be assigned. Routes and the corresponding services are generated using a heuristic column generation approach. A genetic algorithm is then used to improve the solution (Wieberneit (2008)).

9.2 SNDP solution techniques

Wieberneit (2008) provides a comparison of different modelling and solution approaches for these tactical planning problems and important problem characteristics.

It proved to be possible to analyze problems concerned with scheduling according to the mentioned solution techniques when simplifications can be implemented. Time-space networks appear not to be beneficial, unless reduction techniques may be included in the solution approach. Decomposition and submodels are especially needed when different transportation modes are of concern and the planning problem has to be decomposed. When decomposition is necessary, it should be executed iteratively and should incorporate operational characteristics. Local search heuristics are implemented to improve initial solutions (Wieberneit (2008)).

9.3 Concluding remarks: Chapter 9

In this chapter different SNDPs in the literature (Wieberneit (2008)), which may also be found in practice, were investigated and discussed. The SNDP is considered to be concerned with tactical decision making (see Chapter 3, Section 3.2.1). The on-land freight problems examined in this chapter appear to lack a truly tactical nature. Attempts are made in the literature to achieve a tactical focus. But, as Wieberneit (2008) points out, LTL operations in Europe are either addressed in a strategic manner by Wlcek or from an operational perspective (Jansen *et al.* (2004)).

Wieberneit (2008) explores different modelling and solution techniques for SNDPs. Issues of concern include that Farvolden & Powell (1994) only modelled flow conservation and capacity constraints, as required by the SNDP, without taking additional constraints into consideration. All products are assumed to be homogeneous, which is not always realistic, especially for LTL operations. Real-world practice, also in the case of the AC problem, may require that any load or order cannot always be loaded on to any truck. It seems that the SNDP problems investigated generally only focus on a particular part of the whole tactical planning problem. Additionally, the problems usually also consider a service time period of 24 hours only (Wieberneit (2008)).

The problems identified in the literature, formulation and solution techniques investigated in this chapter and Chapter 8, now facilitates the identification of formulation and solution tools applicable in addressing the AC problem. The validity of different formulation and solution methods, with regards to the AC problem, is discussed in the next chapter.

Chapter 10

Auto Carrier Problem Formulation and Solution Possibilities

Different formulating and solution techniques were investigated in Chapter 8 and 9. The applicability of these tools in the AC context can now be determined. This chapter is concerned with identifying suitable formulation and solution tools for addressing the AC problem.

10.1 The AC problem: A transportation problem

The AC problem can be classified as a freight transportation problem, where cars are transported from the manufacturers and harbours to the AC branches. It is therefore concerned with the distribution of goods by means of motor carriers. The AC company has to deal with highly dynamic information processes and decisions often have to be made with some information incomplete. Additionally, information known to the individual branch managers might not be known to the dispatcher. Factors that need to be accommodated include:

- Information arrives over time.
- An order arriving at time t is only serviced at time $t+1$ or $t+2, \dots$ up to $t+5$ or $t+6$ depending on decisions made previously at time t , $t-1$, $t-2, \dots$, $t-6$ and even before that. Note that t advances in discrete units of days.
- Complex resource attributes: a carrier is described by at least 11 static and dynamic attributes, where each attribute may have one of a number of possible values/options.
- There is a difference between planned and executed decisions.

- Variation in travel time is induced by a number of factors. The distance a carrier travels depends on the departure location and the next destination. Additionally carriers drive only between 05:00 and 23:00 and the time on the road is therefore dependent on when the carrier departs. Carrier loading time depends on the particular location, also influencing departure time. When a carrier departs 06:00 and travels for 6 hours, it arrives at 12:00, whereas a carrier departing at 22:00 in effect travels for 12 hours due to the compulsory rest period from 23:00 until 05:00.

10.2 The focus of this AC study

Cars have to be transported from the manufacturer or harbour to the auto carrier branches and from there to individual car dealerships. Individual branches are responsible for regional deliveries, whereas a scheduling depot manages the long distance carriers on the long-distance routes. In comparison to the regional/local deliveries, long-distance deliveries and dispatches induce the greatest risk or potentially the highest revenue, considering *distance travelled multiplied by cars transported*. The focus of this study is then on the larger, long-haul carriers.

The long-haul routes are fixed, and whereas regional deliveries to car dealerships may require finding the optimal route/shortest path for each carrier and the scheduling of door-to-door delivery services, there is only one optimal route between (for instance) Cape Town and Johannesburg. In Figure 10.1, the difference between local deliveries and long-distance dispatches is shown. The fixed routes are indicated in red, connecting regional auto carrier branches marked 'B'. For local deliveries (the responsibility of individual branch managers) the routes change daily and selecting the best routes may be of concern. The focus of this study, however, is on the long-distance dispatches.

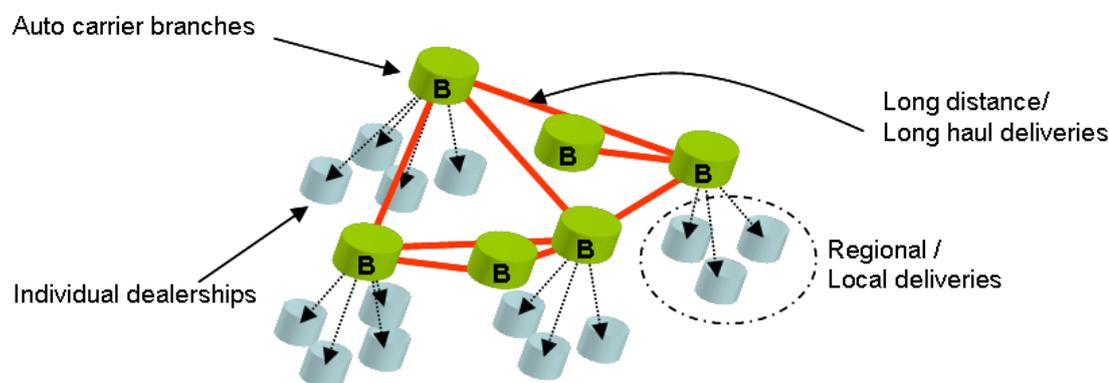


Figure 10.1: AC problem focus

10.3 The AC problem: Tactical planning

Tactical planning of operations involves decisions that aim to ensure optimal resource allocation and utilization to realize a sufficient service level and be cost effective. Tactical planning is done over a medium-term horizon and involves efficient and effective allocation of resources with the aim of improving the whole system (see Section 3.2). Operational policies and fleet composition decisions are not daily operational choices but more tactical in nature, and a tactical decision support tool is of concern in addressing the AC problem.

As identified by Crainic & Laporte (1996) (refer to Chapter 3), tactical problems and models are mainly concerned with service network design and vehicle routing. Although the AC problem is concerned with pick-up and deliveries, it is not a vehicle routing problem, as the objective is not to find vehicle routes of minimal total cost. Long-distance routes and the fleet size are already a given.

The goal of service network design formulations, according to Crainic (2000) (refer to Section 3.2), is to plan services and operations to satisfy demand and ensure profitability of the firm. The objectives of a service network design formulation are quite complex, and include the lowest possible operating cost while offering high quality of service in terms of reliability and flexibility. Service network design problems as addressed by Wieberneit (2008) and explained in Chapter 9, attempt to integrate the strategic and operational decisions to some extent. These SNDPs (presented in Chapter 9) are also very problem specific in nature. Additionally, restrictions are required. Homogeneous loads are assumed, while a relaxation (when included) is that carriers are allowed to return to any node in the network for the rest period, and a service period of only 24 hours is generally considered.

The AC problem requires tactical planning, aiming at achieving resource allocation and utilization that will realize a high quality of service at the lowest possible cost. Although the AC problem requires the planning of services in terms of fleet composition (type) and Fixed and Roaming operations and functioning, it does not suit the service network design formulations which have been presented and discussed (see Chapter 3 and 9).

10.4 Dynamic and stochastic decision making

The allocation of fixed carriers to the fixed routes is static in nature. Decisions are made at the beginning of a time period and are not a function of time. Roaming carriers, however, are concerned with dynamic decision making, as carriers are directly influenced by the demand at a specific point in time at a particular location. The system state at time t is the result of previous decisions, i.e. the queue of orders (cars) waiting for carriers at Durban may be 100 at time t whereas it could have been 10 if 10% of the carriers were not sent to East London at time $t-1$ but to Durban. Since the auto carrier fleet consists of a total of 140 carriers, and the contractually agreed time-frame for order delivery is 5 days, it is virtually impossible to decide what all the possibilities may be at time t .

The fact that roaming carrier operations involve dynamic decision-making implies a dynamic system where the decisions and the outcome are uncertain and unpredictable. The sequence of previous decisions which determines the system state at time t , and the large number of resource attributes make planning decisions even more complex.

10.5 AC problem formulation

The applicability of tools that have been investigated previously, is discussed here for particular use in addressing the auto carrier problem.

10.5.1 The transportation problem

Regarding the AC problem, the focus is on the distribution of cars between AC company branches. There is therefore not a distinction between ‘source’ and ‘destination’ since a node is both a source and a destination. The load consists of individual units (cars) with different attributes. When Branch A , for instance needs Volkswagen (VW) and Nissan but has only Mercedes-Benz available, one or more carriers may collect VW and Nissan cars at Branch C and deliver them to Branch A . As Branch C in turn needs Mercedes-Benz, the carrier may pick up Mercedes-Benz cars at Branch A and transport the cars back to Branch C .

The transportation problem requires that the load on a truck is of homogeneous nature, e.g. tins of peas. Neither does the truck-load differ for different trucks (in terms of the load composition/nature). The distribution cost of units from any particular source to any destination is therefore directly proportional to the number of units distributed, and may be quantified by

multiplying the unit cost of distribution by the units distributed.

In the AC problem, however, the load composition may differ/vary in size as well as in load attributes (referring to the specific type of cars loaded, delivery date, and destination, in particular). Since the service level is of great concern, the lateness of individual cars loaded should be penalised, inducing a virtual cost. This lateness factor might then be incorporated together with the actual distribution cost in a cost function.

The distribution cost of a load of non-homogeneous cars with varying delivery dates and other complicating load attributes and factors would be exceedingly hard to quantify convincingly while still being applicable and valid. Additionally, there are different performance measures that need to be incorporated, measured in different units (kilometres, hours, cars). Due to varying load compositions (in terms of size and type), and the introduction of a virtual cost, the ‘direct proportionality’ assumption of the cost factor can hardly be called valid for the AC problem.

The requirement assumption is not applicable since many of the parameters, which are taken as ‘known’ and ‘fixed’ for the transportation model, are unknown and unsure in the AC problem context. Demand may only be known at a very late stage, sometimes only after the assignment of resources has been done.

It is said, according to Hillier & Lieberman (2005*b*), that a problem fits the transportation model if it can be completely described by the source, destination and cost parameters. In the case of the AC problem, this would require the introduction of major simplifications which might interfere with the solution validity.

10.5.2 The assignment problem

The assignment problem requirements were discussed in Chapter 8. The assignment of carriers to routes, in the AC problem context, involves the following:

- Sources may also be sinks and sinks are also sources.
- Demand is destination- and source-specific and individual units (orders) have particular specifications which include release date, destination, and origin. This complication changes the decision completely: For the AC problem the decision does not involve the ‘optimal quantity’ to be transported from each source to each destination, as this is fixed. The question is how to employ the carriers to satisfy the demand.

- The objective function has to allow for conflicting multiple criteria, where these criteria are measured in different units and are not cost-based only.
- The evaluation parameters (cost/benefit) in the AC problem give an indication of the performance of the system in non-financial terms, which is a result of decisions made regarding the resource allocation and operations. ‘Task-costs’ are therefore not dependent on the particular assignee and task (as the assignment formulation requires).

Additionally, the effective and successful conversion/transformation of the demand on these routes into tasks is highly questionable. Truckload quantities are dependent on the specific units to be loaded as well as the type of carrier (the assignee) involved. It is therefore not viable to change demand on routes into individual tasks. In the AC case, it would be impractical and infeasible to formulate it so that one assignee performs one task, and that a single task is performed by a single carrier.

10.5.3 Integer Programming

In order to model the AC problem as an integer program strong simplifications would be needed and the validity of the formulation and the result thereof would be highly questionable. Multiple evaluation factors would also contribute to the problem complexity.

The integer program objective function requires that a benefit/cost is associated with each of the decision variables which may either be yes or no. This is clearly not applicable or possible in the Auto Carrier problem context.

Additionally, the curses of dimensionality are also of great concern: The exponential growth fallacy of some integer programming methods implies that with n variables, there are 2^n solutions to be considered (Hillier & Lieberman (2005a)). This can be a serious obstacle in addressing real-world transportation and freight transportation problems, as mentioned previously in Chapter 8.

10.5.4 The AC problem is concerned with resource allocation

Although the AC problem as it is identified for the purpose of this study, has more aspects to it than just the allocation of carriers to routes, it may be considered as a resource allocation problem where the auto carriers are the resources. Decisions regarding the employment of the carriers are then required.

Each resource has a set of possible attributes including idle/busy, carrier type, home station, capacity (as a function of the current location and the carrier type), the utilisation of a carrier at time t , distance travelled, servicing, current location, destination and the driver schedule (influencing the carrier destination). At each time t , a decision about what to do with each resource is made. A feasible action must be selected and a corresponding contribution is the result. The objective is to find a policy that will induce the greatest expected contribution over a time horizon T . The resource allocation is, however, usually more operational in nature and concerned with short-term decision making.

As in the case of integer programming, an important aspect of the dynamic resource allocation problem investigated is the curses of dimensionality. Due to the curses of dimensionality, the multi-criteria evaluation and the tactical nature of this problem, the resource allocation problem is not a preferable choice. The attribute vector of the auto carriers has to include at least 11 different attributes of which the majority are dynamic in nature. An attribute, such as capacity, may be any integer between 7 and 11, and location and destination may respectively be any of the six possibilities. An additional complication is that the carriers and the load are of a non-homogeneous nature where the capacity of each carrier not only depends on the type of carrier, but also on the particular cars loaded. Each of the 140 carriers is described by an individual attribute vector, changing over time. The attribute possibilities are therefore vast and dynamic in nature. An exact computation of the expected return is therefore impossible.

10.5.5 Identifying the AC problem within the DRTP framework

The auto carrier problem as identified for the purpose of this study, may be described according to the DRTP framework developed by Powell *et al.* (2003), accommodating stochastic and resource complexity. The problem is here described by means of resource information, system dynamics and controls.

10.5.5.1 AC problem: Knowledge of resources

- The AC problem is heterogeneous because a distinction may be made between static and dynamic attributes. The attribute vector for an auto carrier includes dynamic attributes such as capacity, utilisation, location, destination, distance driven, carrier idle/busy, as well as static attributes, including Home station and the carrier type, while the carrier capacity is dependent on the carrier type as well as the cars loaded. Each attribute

may also assume one of a few possibilities, for instance the current location of a carrier may be one of 6 possible places.

- The AC problem is a three-layer problem: the two active resource layers represent the fixed and the roaming auto carrier fleets (where the carrier and the driver are modelled as one entity and the driver's attributes form part of the carrier attributes), while the orders form the passive layer.

10.5.5.2 AC problem: System dynamics

The system dynamics of the AC problem are characterized by:

- Multi-period travel times apply.
- Multi-stage problem: sequential decision-making as information evolves over time. Two services are required: Pick-up and delivery of cars, however, the servicing of orders generally requires more than a single time period.
- The modify function is hardly measurable, where the modify function captures the impact of decisions on resources over time (see Chapter 8, Section 8.6.1.3).

10.5.5.3 AC problem: Controls

Multi-agent control is needed in the modelling of the AC problem where roaming carrier decisions are made locally at a particular location and point in time, as routes are not predefined.

10.6 AC problem: Solution methods

Algorithms and solution methods available are found to be inadequate in addressing real-world problem characteristics/constraints such as those that the AC problem requires:

- Returning the drivers home after 14 work days.
- Servicing of carriers.
- Incorporating sleeping time and partial travelling.
- Incorporating varying service periods of different hour lengths and often more than one day.
- Non-homogeneous load and carriers, where the carrier capacity is also dependent on the particular cars loaded.
- Particular Fixed and Roaming characteristics.

Additionally, the backlogging of orders and the 4-day order delivery time frame cannot be accommodated sufficiently by existing mathematical modelling tools. The current status and state of the system is dependent on all previous decisions made during previous time periods since orders remain in the system until they are delivered. At times, large order quantities are released (typically in the range of 400 cars), and it may take more than 5 days to deliver the cars, depending on the decisions made regarding the resources (of which there are 140) before the orders were released, at time t when the orders are released in the system, and during the next 5 days.

Another complexity in modelling the AC problem is the combination of local and central decision making required. Roaming carriers need to make decisions locally and dynamically at a particular location based on the system state at that time, whereas fixed carriers abide by central decisions and rules. Since carrier status and attributes change dynamically and the system state accordingly, information cannot always be known at the time of decision making.

10.7 Concluding remarks: Chapter 10

Since the AC problem is a complex transportation problem (also noticeable from the DRTP formulation framework), the curses of dimensionality are of concern for analytical formulation and solution techniques. The AC problem complexity is induced by requirements such as sending drivers home after 14 work days, servicing of carriers, non-homogeneous load and carriers, incorporating the compulsory rest period each day and backlogging of unlimited time periods.

Validity becomes questionable when trying to use the mathematical modelling tools, and although the auto carrier problem may be described according to the DRTP dimensions, the DRTP is only a formulation framework and does not provide a solution technique. The algorithms and appropriate solution techniques found in the literature appear to be unsatisfactory for the purpose of addressing this auto carrier problem.

The AC problem might benefit more from investigating scenarios that enables ‘what-if’ questions and provide decision support of a more tactical nature, rather than a day-to-day operational solution of which the validity may be doubtful since incomplete information is used and major simplifications and assumptions must be made. In the next chapter, simulation as a possible solution tool is evaluated.

Chapter 11

Simulation

Simulation is a tool that mimics the behaviour of an existing or conceptual process or sub-process, on which experiments can be done to evaluate the corresponding outcomes. The assumption is that the behaviour of the model is a reliable enough prediction of the real system's behaviour under particular circumstances. Simulation is therefore a powerful problem-solving tool, allowing for the analysis of 'what-if' scenarios and aiding systems design.

Simulation is generally considered applicable when a system proves to be complex, and is therefore a tool that is used in numerous sectors, for instance business and manufacturing processes, the simulation of transport systems and queuing systems.

11.1 Simulation modelling

Simulation models are a representation of reality, and a distinction can be made between different types of simulation. A simulation model comprises different components, as described below.

Concerns about the system to be analysed may be identified (Kelton *et al.* (2004), Borschev & Filippov (2004a)):

- Availability of information concerning the system to be modelled.
- The method for acquiring this information: Is it readily available and harmless to gather the information?
- Distinguishing between fundamental system characteristics and insignificant negligible system attributes.
- Assumptions and mathematical relationships needed to reduce modelling complexities.

- The validity and integrity of the simulation results: whether the outcomes of the simulation provide an acceptable account of the real system and evaluating whether results are consistent for subsequent simulation runs.

A system may also be classified according to the level of abstraction. According to Borschev & Filippov (2004b), the decision made regarding this classification directly affects the modelling method chosen and how well the system is modelled and simulated.

The different levels of abstraction are as follows (AnyLogic (2008)):

- Strategic level: The aim is to identify and analyse strategic organizational issues. Less detail is required for modelling on this level. Typical applications would include: study of advertising strategies, the estimation of disease speed dynamics and obtaining adequate measures.
- Operational level: Systems are usually modelled on this level when tactical decision making is needed. More detail is required here than on the strategic level. The reason for modelling on the operational level may be to investigate problems such as minimisation of work in progress inventory, balancing of production lines and locating bottlenecks by measuring process performance.
- Physical level: The physical level may be seen as the ‘detail level’ where the behaviours of individual objects with exact description in terms of size, speed and timings are relevant. Problem instances include subway stations, congestion and flow on roads, junctions, evacuation process simulation and sign positioning.

The classification of different applications may be illustrated on an abstraction level scale graph (Borschev & Filippov (2004b)), as shown in Figure 11.1.

11.1.1 Simulation modelling approaches

According to Kelton *et al.* (2004), traditional modelling approaches may be identified according to three main dimensions:

1. Models may be classified as static or as dynamic. A static model describes the system at a given instant in time and in an assumed state of equilibrium. It can be perceived as a snapshot of a particular system at a specific point in time. A dynamic model describes the time-spread phenomena (dynamic processes) in a system, conveying the essence of changes in a system over time. Most operational models can be said to be dynamic.

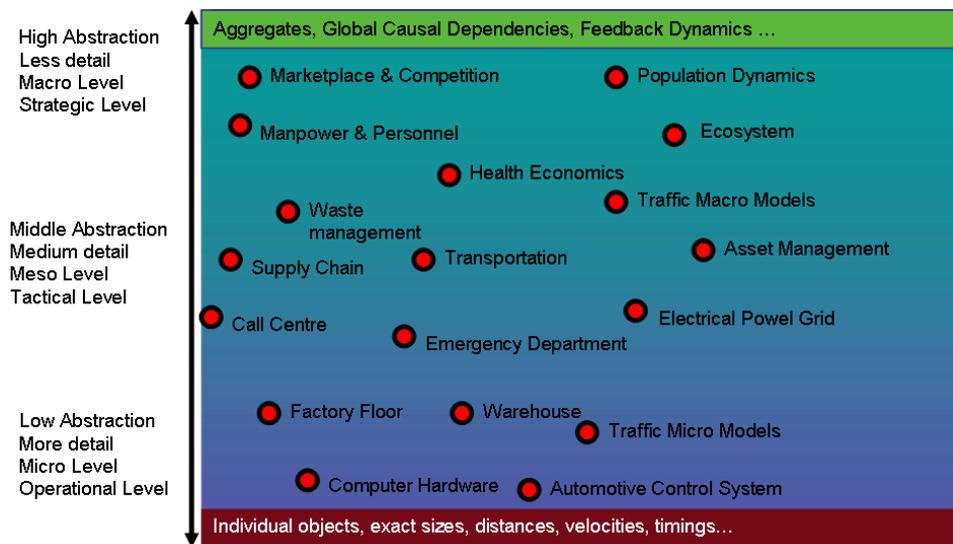


Figure 11.1: Abstraction level scale graph

- Another distinction between model types would be stochastic models, which incorporate probabilities, versus deterministic models that do not. Deterministic models have no random input, whereas stochastic models have at least one random input.
- Models can furthermore be classified as being continuous or discrete. A continuous model is subject to continuous change over time. In a discrete model change can occur only at separate points in time. Mixed continuous-discrete models consist of both elements of change.

11.1.2 Topical approaches

A contemporary way of distinguishing between simulation approaches is to consider the following four modelling types (AnyLogic (2008)):

- System dynamics modelling:** From a business process perspective, it may be seen as a tool for investigating how the organisational structure interacts with other factors to influence the success of the enterprise. In practical terms a system dynamics model is developed and implemented by using causal loops and stock-flow diagrams, representing relationships between the variables in a system dynamics model.
- Discrete Event Modelling:** In discrete event simulation, state changes within the model occur at a set of discrete points in time, which are usually randomly spaced. Events in discrete event simulation take place

as a result of activity times and delays and entities competing for system resources. Discrete Event simulation typically finds its application in industries such as service-centred processes, logistics, manufacturing, business and call centres (Banks *et al.* (2005)).

- **Dynamic ‘Physical’ Systems Modelling:** Dynamic systems modelling can be seen as the modelling of actual control systems consisting of complex objects, described by a set of algebraic-differential equations (Glebovsky *et al.* (2006)). Dynamic systems models would typically rely on the use of graphical modelling languages like Matlab-Simulink, where the underlying mathematical model would be described by means of several physical state variables and a variety of algebraic-differential equations inherent to block diagrams (Borshev & Filippov (2004a)).
- **Agent-Based Modelling:** Agent-Based modelling and simulation form part of the network in computational science of Agent-based systems. Agent-based simulation is a special type of discrete and typical stochastic simulation that does not necessarily rely on a model with underlying mathematical or differential equations. It entails the modelling and simulation of systems that consist of autonomous, interacting individual agents.

These modelling types may differ in elemental structure and application, although some elements may be present in more than one approach. These types are suitable for different abstraction levels, although integration may also occur.

A tabular comparison of modelling paradigms, based on research of Glebovsky *et al.* (2006), Reynolds (2007) and Borshev & Filippov (2004b) is shown in Figure 11.3.

11.1.3 The composition of a simulation model

In order to apply simulation in modelling a system, it is important to know what a simulation consists of. Following is a brief discussion on each of the basic features of a simulation model.

11.1.3.1 System state variables

The System state variables resemble all information required to define the events within a system at a specific point in time. The nature of the study determines the state variables. Therefore it may be possible that the state variables differ for two systems with the same physical nature. Given the system state variables, a distinction can be made between continuous and discrete-event models.

11.1.3.2 Entities and attributes

An entity represents an object which requires clear definition and can either move through the system and be dynamic, or be static in the sense that it ‘serves’ other entities. Each entity may have attributes of which the values characterise that specific entity and belongs to that entity alone.

11.1.3.3 Resources

A resource can be described as being a type of entity that is of use to one or more dynamic entities. It provides service to one or more dynamic entities and can operate as a parallel server. More than one unit may therefore be requested from the resource. In the case where the resource entity refuses service to the requesting entity, the dynamic entity takes some action, such as waiting in a queue. The resource comprise many possible states, of which the most basic states are idle and busy.

11.1.3.4 List Proceedings

Lists are used to represent queues, into which entities are placed. These entities allocate themselves to resources, by attaching them to event notices, thereby placing them into an ordered list. Lists are processed according to particular disciplines such as FIFO (first-in-first-out) or LIFO (last-in-first-out).

11.1.3.5 Activities and delays

An activity has a predefined duration during which it is executed. This may be a service time of constant nature or a random value from a probability distribution. The beginning and ending of an activity create events. A delay, on the other hand, has an indeterminate duration which is subject to a combination of system conditions. This can be illustrated by the queuing of an entity at a resource. The duration of waiting time is initially unknown, as the queuing time is dependent on other events that may occur.

Discrete-event simulations consist of activities that cause time to advance. Most discrete-event simulations also contain delays causing entities to wait.

11.1.3.6 Modelling structures

Four simulation modelling structures may be identified (Banks (1998)). They are briefly explained here:

1. Process-interaction method: The concept is that the computer programme imitates the flow of an object through the system. This movement describes the sequence of all the states the object can have in the system.

2. Event-Scheduling: This structure involves the advance in time to when something next happens. A resource is usually released, and an object or entity is allocated where it can participate.
3. Activity Scanning: This structure produces a simulation programme that consists of independent modules, waiting to be executed. Activity scanning is similar to rule-based programming, implying that when a condition is met, a rule is activated and an action taken.
4. Three-phase method: As the name implies, this structure covers three phases: Time advance, release of resources according to schedule at the particular time, and starting activities.

11.1.3.7 Steps in a simulation study

The simulation study is initiated by a problem which should be analysed. When simulation is chosen as the appropriate tool to apply in the analysis, the following steps would be required to model the problem (Banks (1998), Law & Kelton (2000)):

1. Problem formulation and definition: The importance of establishing a clear understanding of the problem, as well as defining the goals, purposes, limitations and objectives of the study, is essential in the study of any problem.
2. Planning: Project planning is a crucial factor of the simulation study, and includes the planning for time and cost resources involved.
3. Define the Study Boundaries: The scope of a simulation project necessitates the importance to define boundaries, as boundaries determine what is included and excluded from the model. Two boundaries are of concern: The boundary that separates the system from the world, and the boundary that separates the system from its environment. Boundaries are defined in terms of the system and its context. Additionally, the level of detail in the study should also be taken into account.
4. Conceptualisation: The proposed model is constructed in terms of pseudo code and/or in block diagram format. This is necessary to better understand the problem, and to establish model requirements, the level of detail and assumptions.
5. Preliminary experiment: This stage is concerned with the determination of the confidence level of confidence intervals, model time span, input variables, parameters to be studied, definition of entities, attributes and resources.

6. Investigation of parameters: From the preliminary experiment stage, the parameters to be studied in obtaining the desired information, can be selected.
7. Input data requirements: During the conceptualising stage the data required are identified, and are obtained and processed in this step.
8. Translation of the model to a simulation language: In this step the model is computerised.
9. Verification: The main objective is to debug the simulation model, ensuring that the model works correctly. Verification includes evaluation of the syntax and logic used in the model, as well as testing of various data sets, and conducting 'walk throughs'.
10. Validation: Here the model is evaluated in its context, to determine whether the right model has been built in terms of real system representation, data correspondence and the confidence in output. The validation can be said to be determined from three different perspectives: The analyst, technical evaluator and decision maker. From these three perspectives, the design, technical and model significance, are evaluated. Reasonableness of the model is required in the form of output continuity according to input variance, and consistency in terms of repeatability: "similar runs of the model should reflect similar results". Corresponding reflectance of resource decrease and the handling of absurd conditions are also required.
11. Rework: Verification and validation expose problems and subsequently rework is required. Rework is therefore almost always necessary, after which the model is again verified and validated. This is a continuous process to filter out problem areas and refine the model to ensure it is an adequate representation of the real-world system it imitates.
12. Initial run: Preliminary confidence intervals are determined with the initial run, and are necessary to generate output data.
13. Statistical Analysis is conducted and the production runs executed.
14. Documentation: This process is a concurrent process, as it is better practice and easier to document the study from the start. Alterations and additions are then made along the way.
15. Implementation, maintenance and monitoring: The designer should make sure that implementation is maintained. Feedback is also a necessity in evaluation of the study.

11.2 Reasons for using simulation

Some advantages of using simulation may be identified (Banks (1998), Craig (2006)) as follows:

- One of the primary advantages of simulators is that they are able to provide users with practical feedback when designing real world systems. This allows the designer to determine the correctness and efficiency of a design before the system is actually constructed. Consequently, the user may explore alternative designs without actually physically building the systems or having to commit any resources and capital, except for the capital required for simulation.
- Another benefit of simulation is that system designers are permitted to study a problem at several different levels of abstraction. By approaching a system at a higher level of abstraction, the designer is able to better understand the overall behaviour and interactions of the system. This prevents the system designer from becoming mired by detail and losing focus.
- Simulation can be used as an effective means for illustrating or demonstrating concepts. This is particularly true of simulation models that incorporate computer graphics and animation.
- By compressing and expanding time, simulation allows the speeding up or slowing down of time in order to aid the investigation of phenomena.
- The question ‘Why?’ is addressed, as simulation enables a microscopic examination of the system to determine the reason for the occurring phenomena.
- The typical cost of a simulation study is substantially less than the total amount being expended for the implementation of a design or redesign. Since the cost for modification to a system after installation is so large, simulation could be a wise option.
- Simulation can be used to specify requirements for a system design.

11.3 Drawbacks of simulation

Despite the advantages of simulation presented above, simulation and simulation models do have their drawbacks. Computationally intensive processing is sometimes required for simulation. As a consequence, the results of the simulation may not be readily available after the simulation has started. An event that may occur instantaneously in the real world may actually take hours to mimic in a simulated environment, and be costly. The delays may be due to

an exceedingly large number of entities being simulated, or due to the complex interactions that occur between the entities within the system being simulated. Consequently, restrictions such as limited hardware capacity may not meet the computational demands needed. With the development of hardware and improvement in simulation techniques, this problem is becoming less of a concern.

One of the ways to overcome the above mentioned restrictions is to use simplifying assumptions or heuristics when simulating. While this technique can dramatically reduce the simulation time, it may also give its users a false sense of security regarding the accuracy of the simulation results. Another means of dealing with the computational complexity is to employ the hierarchical simulation approach so as to permit the designer to operate at a higher level of design. However, this technique may introduce its own problems as well. By operating at too high an abstraction level, the designer may tend to oversimplify or even omit some of the lower level details of the system (Banks (1998), Reynolds (2007)).

11.4 Simulation in the context of on-land freight transportation

Freight transportation usually forms part of a supply chain or is the link between other role-players. The contracting of services is therefore of significance. A simulation model was developed by Tavasszy *et al.* (1998) to address the contracting of freight carrying services in a supply chain, and the effectiveness of the contracting system is evaluated by means of real-time simulations. Different bidding behaviours of carriers are investigated.

Salling *et al.* (2007) developed a decision support system for a transport system. This system was developed to aid the evaluation and appraisal of different large infrastructure projects by evaluating scenarios and performing a cost-benefit analysis.

In a recent contribution by Powell (2007), the integration of simulation and optimization was examined concerning the dynamic resource allocation problem in particular in the context of transportation.

The problem is that resources have to be managed by assigning them to tasks over time in the presence of different types of uncertainty, resulting in dynamic assignment problems. The decision involves ‘what resource would be best for each task’, where a task occupies a resource for a period of time and changes the resource attributes. The wide range of problems concerning dynamic resource allocation with respect to simulation and optimization, are

addressed by Powell (2007).

Optimisation and simulation is merged to produce a technology that handles the randomness and complexities of simulation with the intelligence of optimisation. It requires formulating a decision function which may be myopic (rule- or cost-based) or may use two forms of adaptive learning where the first form of adaptive learning uses approximate value functions so that decisions now may incorporate at least an approximate estimation of future impacts. The second part introduces low-dimensional patterns to replace the imperfections of cost-based objective functions. These patterns are iterative since they are mostly static, to adjust for time-dependent behaviour.

Implementing these models in practice made it apparent, according to Powell (2007), that cost-based models often do not produce desired behaviours, whereas these patterns help retain some flexibility, telling the model what to do. It appears to be favourable to combine both simulation and optimisation in addressing dynamic resource allocation problems.

11.5 Simulation in the context of freight transportation

Different applications of simulation in the field of freight transportation may be identified to include:

- Simulation may be used for evaluating effectiveness of methods, i.e. evaluating the applicability of hub-and-spoke networks for use in truck-load trucking (Taha & Taylor (1994)), or the evaluation of partitioning method for a letter and parcel pick-up and delivery problem (Langevin & Soumis (2002)).
- Simulation is applied in network design, to select the appropriate inter-modal routes on a multimodal and transcontinental freight transportation network (Southworth & Peterson (2000)), and the evaluation of bus routes (Fan & Machemehl (2006)).
- Real-time simulation in freight transportation has been demonstrated by van Duin *et al.* (2007).
- Simulation as a tool to optimise the transportation system in a coal mine (Adenso-Diaz *et al.* (2004)).
- Simulation may also be a powerful planning tool for merging branches (Duman (2007)) or for terminal capacity planning (Garcia (2005)).
- Simulation has been used to compare different transportation systems (Duinkerken *et al.* (2006)).

- Simulation has been applied in the context of Intermodal Transfer (Southworth & Peterson (2000)).

11.6 The use of simulation for the AC problem

Optimization, simulation, freight operations and the particular AC problem are discussed as motivation for using simulation modelling.

11.6.1 Optimization and simulation

Simulation strives to model operations, often using rule-based logic. Optimization strives to find a best possible solution, minimizing costs or maximising profits. Simulation is used to study the AC problem because it can easily handle uncertainty in the modelling of complex system dynamics, and it accommodates the curses of dimensionality. Optimization models typically ignore the future impact of decisions made now on the future.

According to Powell (2007), the property that the behaviour of simulation is guided by user-specified rules is often overlooked, whereas the behaviour of an optimization model is determined by a cost function and constraints. Where tuning/fine-tuning of an optimization model is difficult and not always possible, a simulation model can relatively easily be adjusted/alterd. Simulations that involve solving sequences of optimization models have been widely used in engineering practice as well as in the research literature.

As previously mentioned, Powell (2007) argues that optimization and simulation can be integrated. The objective is to solve the optimization problem by identifying policies that make good decisions, not only for now but also over time. The transformation of rule-based policies into cost-based policies is attempted.

Powell (2007) also mentions that cost based models with cost-based policies cannot capture all the complexities of real-world problem operations, and may often in such instances not produce desired forms of behaviour.

For the AC problem, the aim is to investigate tactical policies by examining different rules that dictate how carriers operate, as well as fleet compositions. The rule-based logic and modelling of operations are therefore particularly of concern. The AC problem is complex in nature, involving large resource attribute vectors. Additionally, the AC problem is concerned with developing and comparing scenarios for tactical decision making, rather than finding an optimal answer(s). Since simulation easily accommodates model dynamics and complexities, relying on rule-based logic and allowing model tuning, it was identified as a suitable tool to model and investigate the AC problem.

11.6.2 Simulation in freight transportation and the AC problem

Simulation provides an analysis framework that is difficult to achieve with other methods. Many system interactions and timings can be represented to determine infrastructure accurately, assess capacity increases, and quantify the level of service and potential operating cost savings. It also enables sensitivity analysis while considering impacts of real-world variables. Simulation may be seen as an invaluable tool to evaluate and understand performance capabilities, which can also accommodate real-world demand requirements (Garcia (2005)).

The focus of the AC problem is not to know what particular resource is assigned to which load, in order to provide a load-planning schedule, as the assignment problem facilitates. The incorporation of possible future outcomes as a result of current decisions and dynamic programming is definitely essential to this AC problem. Resource vectors, problem complexity and the time-frame for order delivery within 5 days are of such nature that the solution space can become intractable and analytical computation impractical.

The aim is to develop a Tactical Planning Tool in the context of transportation, for which discrete-event simulation may be identified as an appropriate tool on the tabular comparison of modelling paradigms, Figure 11.1 is repeated here for convenience.



Figure 11.2: Abstraction level of transportation modelling

11.6.3 Choice of simulation language

The simulation language Arena (Rockwell (2008)) will be used in this study. It supports discrete-event processes, as identified to be applicable in this context, and the user-knowledge and support of this language is available in the Department of Industrial Engineering at Stellenbosch University.

11.7 Concluding remarks: Chapter 11

For the real-world auto carrier problem, it is not possible to transform all rule-based policies into cost-based policies. Additionally, as previously identified, the complexity of this problem makes it extremely hard to formulate and solve analytically. The aim is not to optimize but rather to investigate scenarios for tactical planning purposes. Simulation is therefore a desirable and applicable tool for this particular AC problem, and is therefore adopted for the study. In the next chapter, parameters for evaluating the simulated scenarios are identified.

Modelling approaches				
	Discrete event	System dynamics	Dynamic systems	Agent-based
Origin	General Purpose Simulation Systems; Introduced in 1961 by International Business Machines Corporation	Developed by J.W. Forrester at MIT in late 1950s; started with the modelling of industrial dynamics	Roots in Analogue modelling with analogue electronic computers in the 1950s	Roots in Von Neumann machines; first application in 1990s
Abstraction Level				
Chief Domains of Application	service-centred processes, manufacturing processes, business processes, logistics	urban and industrial dynamics, economics, management skills, ecologies	mechatronics, physics, automation, electronics, signal processing, engineering	Ecology & biology, industrial engineering, social science, business & economics
Main modelling aspects	Top-down: Entities, Resources, Control Elements; Flowchart blocks and/or transportation networks	Top-down: Levels (aggregates), Stock-flow diagrams, Feedback loops	Bottom-up: Physical state variables; Block diagrams and/or algebraic-differential equations	Bottom-up: Agents (active objects), Environment, Agent characteristics, Behavioural rules, Direct and/or indirect interaction
Existing Simulation Tools	Arena, Extend, PROMODEL, SimProcess, AutoMod, FlexSim	Vensim, IThink, PowerSim, ModelMaker	Matlab, LabView, VisSim, EasySim	Mostly academic software (Swarm, Repast, NetLogo), Agentsheets

Figure 11.3: Simulation modelling paradigms

Chapter 12

Performance Measures and Evaluation Methods

The quality of a proposed tactical operations plan must be determined, and one or more performance measures are thus required. In practical situations, the decision maker requires that as many as possible performance measures be considered to make planning realistic and efficient. This may result in conflicting performance measures that are often measured in different dimensions. In this chapter, the performance measures identified for the purpose of this study are discussed, as well as the evaluation methods applicable.

12.1 Performance measures

A vast number of performance measures may be used to evaluate a proposed tactical policy, including general factors such as on-time pick-up analysis, on-time delivery, dispatch performance, equipment utilization and load revenue kilometres.

Some specific measures of significance in the auto carrier context, which are conflicting in nature, are mentioned by Tadei *et al.* (2002). They include the quantity of cars loaded, contributing to the revenue, number of unloading stops and total vehicle tardiness (a lateness measure) incurring a cost. Their problem is more operational in nature and focuses on deliveries to dealerships; the number of unloading stops also has to be taken into consideration. The performance measures deemed most relevant to this study are shown in Table 12.1.

Some of the selected attributes are competing in nature. Maximising cost effectiveness (less empty kilometres relative to more useful kilometres) may imply that orders have to wait longer before delivered. The kilometre measures are summed over the duration of the simulation run, and each slot (empty or

Table 12.1: Description of the performance measures

Performance Measure	Explanation	Unit of measurement
Average Queue Length	The time-weighted average of the queue at each location. It was aggregated for all locations to determine a single figure that reflects a country-wide situation.	# cars
Empty km	The accumulated value of empty slots on each carrier times the distance the carrier travelled with each of the un-filled spaces.	Kilometres
Useful km	The accumulated value of loaded cars on a carrier times the distance travelled by that carrier.	Kilometres
Average time	The average time an order spent in the system: the time that a vehicle waits from arriving in the system until delivered.	Hours

filled) appropriately contribute to these measures.

Since multiple conflicting measures with different units have to be considered, an appropriate method needs to be employed to combine them in order to evaluate the different scenarios. Multi-criteria decision analysis (MCDA) is introduced as a means to evaluate the generated scenarios by integrating the four performance measures.

Multi-criteria decision analysis is discussed, together with the multi-attribute decision making (MADM) methods applicable, as well as the Mahalanobis distance method. Additionally, Portfolio theory is also investigated for its applicability in this context. The literature on MCDA in finance and multiple attributes in financial modelling is consulted, followed by a discussion on the construction of fleet portfolios and the selection of portfolios by applying an analogy to the efficient frontier.

These evaluation methods will be used to determine, according to the values of these four performance measures identified, which scenario(s) is (are) most desirable, and are discussed subsequently.

12.2 Multi-criteria decision analysis

A problem may be said to have a multi-criteria nature when the analysis is not merely an optimisation procedure where a particular quantity has to be maximised or minimized. Instead, what is optimal, depends on the different criteria, and how they are weighted. It also therefore accommodates the subjective element of decision making. MCDA acknowledges the fact that the world is multi-dimensional and cannot be reduced to a single dimension. In dealing with actual problems, these dimensions may include several socio-economic, monetary, or performance measures (Drechsler (2004)).

MCDA involves making decisions when multiple conflicting criteria are present, and is required when the following problem characteristics are of concern (Agrawal *et al.* (1991)):

- Multiple objectives/attributes: In the case of a selection problem where many attributes are to be considered, or in a design problem where many objectives are the case.
- Conflict among criteria: When multiple criteria are in conflict, where a particular option may score a high criterion value in one category but a low value for another criterion.
- Incommensurable units: Each criterion has different unit measurements, which complicates the direct comparison between criteria values.
- Design/selection: Solutions to these problems are either to design the best alternative, or to select the ‘best’ among a finite number of alternatives.

Some applications of MCDA include areas such as evaluations of technology investment (Boucher *et al.* (1993)), water and agriculture management (Ozelkan & Duckstein (1996), Raju & Pillai (1999)), and also energy planning (Pohekar & Ramachandran (2004)).

12.2.1 Overview of MCDA methods

A brief discussion on the weighted sum method, weighted product method, Analytical hierarchy process, PROMETHEE, ELECTRE, TOPSIS, CP and MAUT according to Pohekar & Ramachandran (2004) is included here.

12.2.1.1 Weighted sum method (WSM)

This is the most commonly used approach, especially in single dimensional problems, and can be described as follows. If there are M alternatives and N criteria, the best one would be the one that satisfies the expression

$$A_{WSM}^* = \max_i \sum_j^N a_{ij} w_j, \quad i = 1, 2, 3, \dots, M. \quad (12.2.1)$$

Here A_{WSM}^* is the *WSM* score of the best alternative, a_{ij} is the actual value of the i^{th} alternative in terms of the j^{th} criterion, and w_j is the weight of importance of the j^{th} criterion where $\sum w_j = 1$, $w_j \geq 0$.

12.2.1.2 Weighted product method (WPM)

The WPM is very similar to the WSM with the main difference that, instead of addition in the model, there is multiplication. The alternatives are compared with each other by multiplying a number of ratios, one for each criterion. Each ratio is raised to the power of the relative weight of the corresponding criterion. The product

$$R(A_K/A_L) = \sum_{j=1}^N \left(\frac{a_{Kj}}{a_{Lj}} \right)^{w_j}, \quad (12.2.2)$$

is obtained in the comparison of the alternatives, where N is the number of criteria, a_{ij} is the actual value of the i^{th} alternative in terms of the j^{th} criterion, and w_j is the weight of importance of the j^{th} criterion (for $w_j \geq 0$). If $R(A_K/A_L)$ is greater than 1, then it means that the alternative A_K is more desirable than alternative A_L (in the maximization case), and the best alternative is then the one that is better than or at least equal to all the other alternatives.

12.2.1.3 Analytical hierarchy process (AHP)

The essence of the AHP is the decomposition of a complex problem into a hierarchy with the objective at the top, criteria and sub-criteria at levels and sub-levels of the hierarchy, and decision alternatives at the bottom of the hierarchy. Elements at given levels of the hierarchy are compared in pairs to assess their 'relative preference' in respect to each of the elements at the next higher level. The method compares and aggregates eigenvectors until the final vector for weight coefficients is obtained. The final vector then reflects the relative importance of each alternative with respect to the goal stated at the top hierarchy (see Saaty (1980)).

12.2.1.4 Preference ranking organization method for enrichment evaluation

The PROMETHEE method uses the outranking principle in the ranking of alternatives. It compares alternatives pair-wise in order to rank them with respect to a number of criteria J . The method uses the preference function $P_j(a, b)$, which is a function of the difference d_j between two alternatives a and b for a particular criterion j . There are an indifference threshold q' and a preference threshold p' which both depend on the type of criteria function. This implies that two alternatives may be different for criterion j as long as d_j does not exceed the indifference threshold, and if d_j becomes greater than p' , there is a strict preference. A multi-criteria preference index $\pi(a, b)$, a weighted average of the preference functions $P_j(a, b)$ may be defined as

$$\pi(a, b) = \frac{\sum_{j=1}^J w_j P_j(a, b)}{\sum_{j=1}^J w_j}. \quad (12.2.3)$$

The outranking index of a is $\phi^+(a)$, and the outranked index of a in the alternative set A is $\phi^-(a)$, where $\phi(a)$ is the net ranking of a . These expressions are as follows:

$$\phi^+(a) = \sum_A \pi(a, b), \quad (12.2.4)$$

$$\phi^-(a) = \sum_A \pi(a, b), \quad (12.2.5)$$

$$\phi(a) = \phi^+(a) - \phi^-(a). \quad (12.2.6)$$

Here w_j is the weight assigned to the criterion j . The maximum value of $\phi(a)$ is considered as the best. It can then be said that a outranks b if $\phi(a) > \phi(b)$, and a is indifferent to b if $\phi(a) = \phi(b)$.

12.2.1.5 The elimination and choice translating reality (ELECTRE)

This is a method which can accommodate both quantitative and qualitative discrete criteria, and provides complete ranking/ordering of alternatives. The problem needs to be formulated so that it chooses alternatives which are preferred according to most of the criteria in order to prevent an unacceptable level of discontent. Concordance, discordance and threshold values are determined and evaluated. Graphs are developed for the strong and weak relationships, based on the indices. The index of global concordance,

$$C_{ik} = \frac{\sum_{j=1}^m w_j c_j(A_i A_k)}{\sum_{j=1}^m w_j}, \quad (12.2.7)$$

supports the concordance among all criteria, where w_j is the weight associated with the j^{th} of m criteria. The ELECTRE method yields a whole ‘system’ of binary outranking relations between the alternatives. Since this ‘system’ is not necessarily complete, the ELECTRE method is sometimes unable to identify the most favoured alternative, but only provides a score of ‘leading’ alternatives.

12.2.1.6 The technique for order preference by similarity to ideal solutions (TOPSIS)

This method was developed as an alternative to the ELECTRE method by Hwang & Yoon (1981). The basic concept of this method is that the selected alternative should have the shortest distance to the ‘ideal solution’ in a geometric sense. This is discussed in more detail later on when introducing Multi Attribute Decision Making.

12.2.1.7 Compromise programming (CP)

This method defines the best solution in the set of efficient solutions, where the best option is closest to the ideal point. The distance measure in this case is the family of L_p metrics and is given as

$$L_p(a) = \sum_{j=1}^j w_j^p |f_j^* - f(a)| / |M_j - m_j| \quad (12.2.8)$$

where $L_p(a)$ is the L_p metric for alternative a , $f(a)$ is the value of criterion j for alternative a , M_j is the maximum (ideal) value of criterion j in set A , m_j is the minimum (anti ideal), w_j is the weight of criterion j , p is the parameter reflecting the attribute of the decision maker with respect to the compensation between deviations, and f_j^* is the ideal value of criterion j .

12.2.1.8 Multi-attribute utility theory (MAUT)

Multi-attribute Utility Theory takes into consideration the decision maker’s preferences by defining a utility function over a set of attributes. The utility value may be determined by means of single attribute utility functions. The verification of preferential and utility independent conditions and the derivation of multi-attribute utility functions are also considered. The different utility functions can be additively or multiplicatively separable with respect to the single attribute utility. The multiplicative form of the utility equation is

$$1 + ku(x_1, x_2, \dots, x_n) = \prod_{j=1}^n (1 + kk_j u_j(x_j)), \quad (12.2.9)$$

where j is the index of the attribute, k is the overall scaling constant and $k \geq -1$, k_j is the scaling constant for attribute j , $u(\cdot)$ is the overall utility

function operator and $u_j(\cdot)$ is the utility function operator for each attribute j .

12.2.1.9 Multi-attribute decision making vs multi-objective decision making

The class of MCDA methods can further be divided into multi-objective decision making (MODM) methods and Multi-attribute decision making (MADM) methods. The difference between MADM and MODM may be summarized according to Agrawal *et al.* (1991) in Table 12.2.

Table 12.2: MADM vs MODM

	MADM	MODM
Criteria	Attributes	Objectives
Objectives	Implicit	Explicit
Attribute	Explicit	Implicit
Constraint	Interactive (incorporated into attributes)	Active
Alternatives	Finite in number and discrete	Infinite in number and continuous (emerging)
Interactive with DM	Not so much	Mostly
Usage	Selection/evaluation	Design

The MODM consists of a set of conflicting goals that cannot be achieved simultaneously, and it concentrates on continuous decisions. Mathematic programming techniques may often be of great help in solving a MODM (Yang *et al.* (2007)).

According to Yang *et al.* (2007) MODM generally involves:

1. preferences in accordance to the DM's objectives.
2. relationships between objectives and attributes.

MADM deals with the problem of choosing among a set of alternatives that are characterized in terms of their attributes. It is a quantitative approach due to the existence of criteria subjectivity, and requires information about the preferences of an attribute among a group of possibilities as well as preferences across the existing attributes (Yang *et al.* (2007)). MADM refers to a problem solving approach for problems involving selection from among a finite number of alternatives, and is a procedure that specifies how attribute information is to be processed in order to arrive at a choice. It also supports decision making when multiple, conflicting criteria are present.

12.2.2 Multi-attribute decision making

MADM refers to a problem solving approach for problems where the selection from among a finite number of alternatives is of concern. MADM is a procedure which specifies how attribute information is to be processed in order to arrive at a choice (Agrawal *et al.* (1991)). In a multi-attribute decision making (MCDM) problem, a decision maker has to rank and select alternatives associated with conflicting attributes.

MADM problems may be found in many real-world contexts such as: the dynamic operator allocation problem (Yang *et al.* (2007)); robot selection problem (Agrawal *et al.* (1991)); measuring operational performance of different production units (Parkan & Wu (1997)); urban transport decision making (Tudela *et al.* (2006)); sustainable energy (Pohekar & Ramachandran (2004)), and manufacturing strategy selection (Chiadamrong (1999)). According to Hwang & Yoon (1981) all MADM problems may be said to encompass the following three main characteristics:

- Each problem has multiple attributes and the decision-maker must generate relevant attributes for the problem under consideration.
- Multiple criteria involved in the problem are usually conflicting in nature.
- Each attribute may have a different unit of measurement.

Three main aspects of a MADM approach may be identified as (Yang *et al.* (2001)):

- Identifying the assessment hierarchy consisting of criteria, subcriteria, etc.
- Determining the relative weights of the elements of hierarchy.
- Comparing the various alternatives according to the identified criteria and ranking them in order of preference.

An MADM problem can be classified into three categories according to different forms of preference information given by the decision maker (Fan *et al.* (2002)):

1. The approaches without preference information given by the decision maker.
2. The approaches with information on attributes.
3. The approaches with information on alternatives.

Current approaches for MADM problems with preference information on alternatives include the interactive simple additive weighting (SAW) method, multidimensional scaling (MDS) with ideal point, and linear programming techniques for multidimensional analysis of preference (LINMAP) (Fan *et al.* (2002)).

12.2.2.1 MADM formulation

The MADM can be explained by the following notation (Fan *et al.* (2002)):

- The alternatives are known: Let $S = S_1, S_2, \dots, S_m$ denote a discrete set of $m \geq 2$ possible alternatives.
- Attributes are known:
Let $P = P_1, P_2, \dots, P_n$ denote a set of $n \geq 2$ attributes.
- Weights of attributes are known:
Let $w = (w_1, w_2, \dots, w_n)^T$ be the vector of weights, where $\sum_{j=1}^n w_j = 1, w_j \geq 0, j = 1, \dots, n$, and w_j denotes the weight of attribute P_j .
- The decision matrix is known:
Let $A = [a_{ij}]_{m \times n}$ denote the decision matrix where $a_{ij} \geq 0$ is the consequence with a numerical value for alternative S_i with respect to attribute P_j , $i = 1, \dots, m, j = 1, \dots, n$.

12.2.2.2 Normalisation of attributes

In the decision matrix A , every a_{ij} is an objective value between 0 and 1 which allows each attribute to have the same measurement range. In order to achieve this, the elements in the matrix A have to be normalized into a corresponding element in matrix $B = [b_{ij}]_{m \times n}$. The following method may be used (Ma *et al.* (1999)):

For benefit attributes:

$$b_{ij} = \frac{a_{ij} - a_j^{\min}}{a_j^{\max} - a_j^{\min}}, \quad i = 1, \dots, m; \quad j = 1, \dots, n. \quad (12.2.10)$$

For cost attributes:

$$b_{ij} = \frac{a_j^{max} - a_{ij}}{a_j^{max} - a_j^{min}}, \quad i = 1, \dots, m; \quad j = 1, \dots, n, \quad (12.2.11)$$

where

$$a_j^{max} = \max\{a_{1j}, a_{2j}, \dots, a_{mj}\}, \quad (12.2.12)$$

$$a_j^{min} = \min\{a_{1j}, a_{2j}, \dots, a_{mj}\}. \quad (12.2.13)$$

According to Yang *et al.* (2007), this method is applicable when the differences in performance measures are not significantly large. The decision maker can then choose $M < m$ most preferred alternatives S^* from the set S , $S^* \subset S$ (Ma *et al.* (1999)).

An alternative normalisation approach that is widely accepted is the vector normalisation

$$b_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^m a_{ij}^2}}, \quad i = 1, \dots, m; \quad j = 1, \dots, n. \quad (12.2.14)$$

12.2.2.3 Selection of an alternative using the SAW method

The simple additive weighting method is one of the most commonly known and widely used MADM methods (Hwang & Yoon (1981), Ma *et al.* (1999)). The overall value of an alternative, according to the SAW method, can be expressed according to Ma *et al.* (1999) as

$$\varphi(S_i) = \sum_{j=1}^n w_j b_{ij} \quad i = 1, \dots, m. \quad (12.2.15)$$

The chosen alternative, S^* is then of such nature that $\varphi(S^*) \geq \varphi(S_i)$ for all i .

12.2.2.4 The TOPSIS method of selection

Hwang & Yoon (1981) developed the *Technique for Ordered Preference by Similarity to the Ideal Solution* (TOPSIS) method. This method is based on the concept that the chosen alternative should have the shortest distance from the positive ideal solution and the longest distance from the negative ideal solution. It forms part of the ELECTRE methods, relying on outranking relations to rank a set of alternatives (Wang & Triantaphyllou (2008)).

Three TOPSIS methods may be identified: the Manhattan distance, Euclidean distance, and the Tchebycheff distance (Méndez *et al.* (2006)). The Euclidean distance is found most relevant, and is therefore discussed in more

detail. This method is presented in Jahanshahloo *et al.* (2006), with reference to Hwang & Yoon (1981). The TOPSIS procedure may be explained according to the following series of steps.

Step 1: Calculate the normalised rating for each element of the decision matrix as

$$n_{ij} = x_{ij} / \sqrt{\sum_{i=1}^m x_{ij}^2}, \quad i = 1, \dots, m; \quad j = 1, \dots, n, \quad (12.2.16)$$

where there are m alternatives and n different attributes. Here x_{ij} is the element in row i and column j .

Step 2: Calculate weighted normalised ratings

$$v_{ij} = w_j n_{ij}, \quad i = 1, \dots, m; \quad j = 1, \dots, n, \quad (12.2.17)$$

where w_j is the weight associated with the j^{th} attribute or criterion, and $\sum_{j=1}^n w_j = 1$ for $w_j \geq 0$.

Step 3: Identify positive ideal (A^*) and negative ideal (A^-) solutions. These solutions are defined in terms of the weighted normalized values as

$$A^* = \{v_1^*, v_2^*, \dots, v_n^*\} = \{(\max_i v_{ij} | j \in I), (\min_i v_{ij} | j \in J)\}, \quad (12.2.18)$$

$$A^- = \{v_1^-, v_2^-, \dots, v_n^-\} = \{(\min_i v_{ij} | j \in I), (\max_i v_{ij} | j \in J)\}, \quad (12.2.19)$$

where I is associated with benefit criteria, and J is associated with the cost criteria.

Step 4: Calculate the Euclidean distances as separation measures: The positive ideal is given by

$$d_i^* = \left\{ \sum_{j=1}^n (v_{ij} - v_j^*)^2 \right\}^{\frac{1}{2}}, \quad i = 1, \dots, m, \quad (12.2.20)$$

and the negative ideal by

$$d_i^- = \left\{ \sum_{j=1}^n (v_{ij} - v_j^-)^2 \right\}^{\frac{1}{2}}, \quad i = 1, \dots, m. \quad (12.2.21)$$

Step 5: Calculate similarities to the ideal solution as

$$R_i = \frac{d_i^-}{d_i^* + d_i^-}, \quad i = 1, \dots, m. \quad (12.2.22)$$

Step 6: With this index, values and thus alternatives, can be ranked in decreasing order, with the best alternative at the top of the list.

The TOPSIS method then not only gives a solution which is closest to the hypothetically best, but also the farthest from the hypothetically worst. This is illustrated in Figure 12.1 (only considering two attributes).

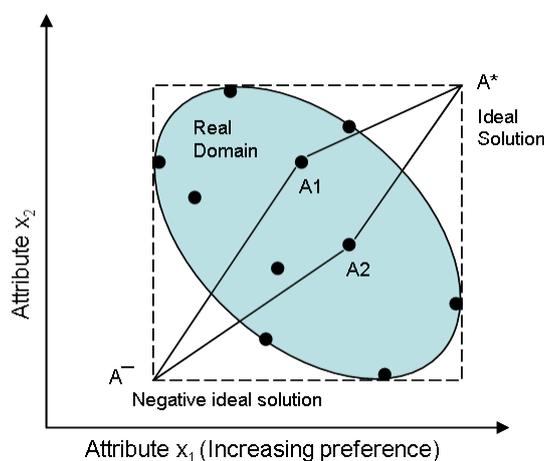


Figure 12.1: TOPSIS method

The black dots in Figure 12.1 represent R_i values. When comparing $A1$ to $A2$, $A1$ is better since the distance to A^- is longer and $A1$ is also closer to the positive ideal (Agrawal *et al.* (1991)).

The TOPSIS method, using the Euclidean distance alternative, was applied in a dynamic operator allocation study by Yang *et al.* (2007), where different performance measures had to be taken into consideration and simulation was used as an evaluation tool.

12.2.3 Ranking irregularities

Often times, different multi-criteria methods may yield different answers to the same problem, which is a potential drawback. The ELECTRE family of MCDA, strongly relying on outranking methods, may also provide different rankings (Wang 2008). There exist different evaluation techniques and comparisons to decide on the ‘best’ multi-criteria method. Three test criteria may be established to test the relative performance of various MCDA methods (Wang & Triantaphyllou (2008)). These methods were, however, not exploited in any more detail for the purpose of this study.

12.2.4 The matter of weighting in MADM

The crucial problem in MADM is to assess the relative importance of attributes. Different criteria, or performance measures in this case, are assigned weights in order to express preference/importance. The result of the multi-criteria decision analysis will most likely depend on the weighting. Weighting is done according to preference and is therefore subjective. If several decision makers are involved, it is most likely that there will be differences about the weights assigned to the criteria. However, by performing a sensitivity and robustness analysis (Drechsler (2004)) it is possible to reduce the subjectivity of the weight selections.

Subjective and Objective approaches may be used. Subjective approaches select weights based on the preference information of attributes given by the decision maker. Objective approaches include principal element analysis, the entropy method and multiple objective programming. An integrated approach of both Objective and Subjective information is provided by Ma *et al.* (1999).

12.3 Mahalanobis distance method

For this study, an alternative approach for selecting among alternatives, is introduced. The Mahalanobis distance method is incorporated in this study as a MADM approach, which allows for oblique positioning of an ‘elliptic envelope’ within a multi-dimensional attribute space (Farber & Kadmon (2003)). The Mahalanobis distance approach differs from the TOPSIS Euclidean distance, as it accommodates different measuring units while taking into account correlations among the variables.

The Mahalanobis distance technique introduces multivariate statistics, encompasses the multivariate mean and co-variance matrix. In this context, the multiple decision criteria attributes resemble the multiple variants.

The Mahalanobis distance method is generally used to compute the distance between two centroids. For this study, an ideal scenario option may be constructed as consisting of the highest value of a ‘benefit’ criterion and the lowest value of the ‘cost’ criterion within the four dimensional attribute space. It is then possible to determine the relative distances for each of the generated scenarios from this optimal solution. The scenario closest to the optimum in this multi-dimensional space is then the best.

As a multivariate statistical method, concerned with the distance between multivariate populations, the Mahalanobis distance may be formulated according to Manly (2005) as follows.

Suppose that two or more populations are available, and the multivariate distributions in these are known for p variables, X_1, X_2, \dots, X_p . Let the mean of the variable X_k in the i^{th} population be μ_{ki} , and assume that the variance of X_k is V_k in all the populations. The Mahalanobis distance is then

$$D_{ij}^2 = \sum_{r=1}^p \sum_{s=1}^p (\mu_{ri} - \mu_{rj}) v^{rs} (\mu_{si} - \mu_{sj}), \quad (12.3.1)$$

where v^{rs} is the element in row r and column s of the inverse of the population covariance matrix, for the p variables.

This quadratic form can also be written as:

$$D_{ij}^2 = (\vec{\mu}_i - \vec{\mu}_j)' V^{-1} (\vec{\mu}_i - \vec{\mu}_j), \quad (12.3.2)$$

where $\vec{\mu}_i$ is the population mean vector for the i^{th} population, and V is the population covariance matrix. This formulation requires that V is the same for all populations.

The Mahalanobis distance between a vector x and a set of vectors (matrix S) is defined by Farber & Kadmon (2003) as

$$D^2 = (\vec{x} - \vec{m})^T C^{-1} (\vec{x} - \vec{m}), \quad (12.3.3)$$

where \vec{m} is the mean vector and C is the covariance matrix of S with the T superscript the transpose operator (Clark *et al.* (1993)). The vector \vec{m} represents then the 'optimum' attributes, and \vec{x} is a vector indicating the attributes of a particular scenario option (Farber & Kadmon (2003)).

12.4 Scenario evaluation and selection methods for the AC problem

The SAW, TOPSIS and Mahalanobis distance methods are selected for the purpose of this study. Ranking irregularities may occur, as these methods imply different methodologies in selecting a possible option.

The SAW method is a well known and commonly accepted method. This method is also very applicable and used in the AC problem case due to its simplicity. The TOPSIS method is found applicable in the case of dynamic resource allocation problems (Yang *et al.* (2007)), where the outcome of different attributes are used to measure overall performance. The AC problem is a dynamic allocation problem, where a finite number of scenarios are evaluated by means of simulation. The aim is to evaluate performance by considering several attribute criteria.

As previously mentioned, the TOPSIS method not only gives a solution that is closest to the hypothetically best, but also the farthest from the hypothetically worst. Due to its conceptual simplicity and applicability in this context this method is selected as a multi-attribute decision aid for the AC problem scenario evaluation.

For the SAW and TOPSIS methods, weighting of the different criteria is needed, which introduces subjectivity. The issue of assigning weights may be seen as a study field by itself, and to a large extent subjective. The performance measures for the AC problem, as defined for the purpose of this study, are assigned equal weights. A sensitivity analysis may be performed by adjusting/varying the importance of the criteria. Additionally, the AC company may be consulted to provide insight into their real-world preferences.

The Mahalanobis distance method proves to be appropriate as it accommodates different units of measuring, taking into account correlations of the data set. The decision maker is then able to obtain the relative distances of each option from the most ideal option in a multi-dimensional space. It is appropriate for this study, as it takes the different measuring units (kilometres, cars, time) into account, and enables the four-dimensional evaluation of options.

The TOPSIS and SAW methods are also justifiable according to the MADM 'choice rule' flowchart (Agrawal *et al.* (1991)). Although only one method will usually be used, the three methods mentioned will all be used due to research curiosity.

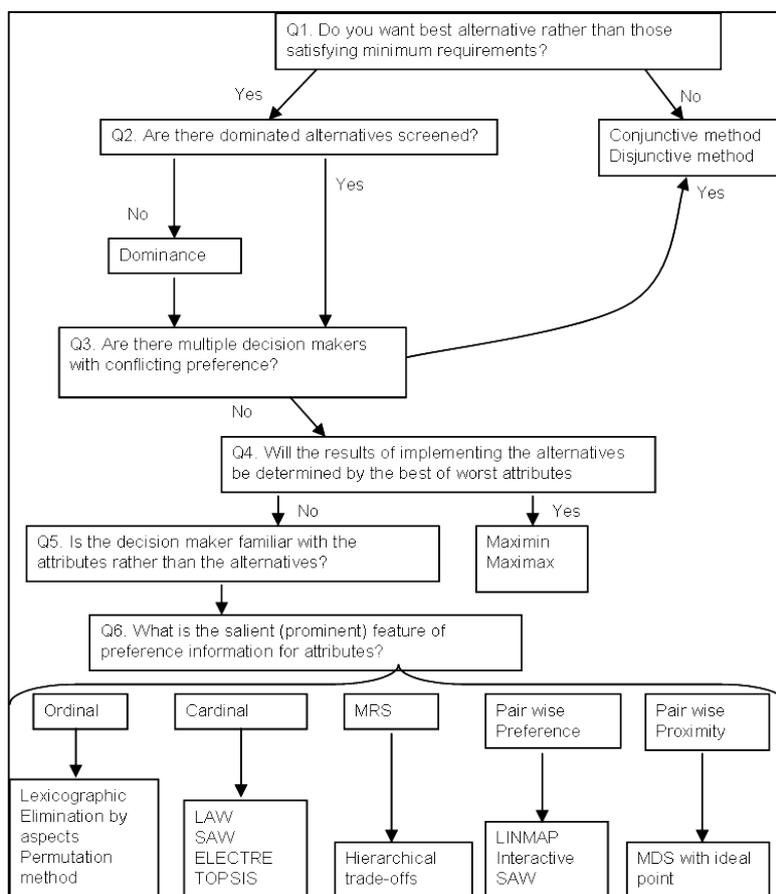


Figure 12.2: MADM ‘choice rule’ flowchart

12.5 MCDA and financial modelling

In finance, investors often make use of diversification as a risk-management technique that facilitates the incorporation of a variety of investments within a portfolio. When considering the AC problem, the 140 long-distance carriers may be seen as resources that have to be ‘invested’ in either ‘Fixed’ or ‘Roaming’. The question is *how many* carriers to employ as Roaming and Fixed respectively in order to maximize the return. However, the option with the highest return may not be without a risk of obtaining that expected outcome. The risk associated with each fleet composition is therefore also of concern and requires investigation.

From the viewpoint that MCDA methods only consider the expected return for the different attributes in order to establish a ranked order of preference for the different alternatives, financial modelling and portfolio theory was investigated in search of a way to also incorporate a ‘risk’ associated with obtaining

the expected return for the individual possibilities.

In this section MCDA in financial modelling is briefly discussed, as well as portfolio theory, as introduced by Markowitz (1952), and Multiple attributes in portfolio selection.

12.5.1 Financial modelling

According to Spronk & Hallerbach (1997) the term ‘financial modelling’ is often used very broadly for a quantitative-analytical description of the financial system or parts of the system, the empirical estimation of relationships, the testing of hypotheses and the development of quantitative-analytical tools supporting financial-economic decision making. It may be seen as tools which support firms and investors in their financial-economic decision making.

Three roles of financial modelling, as identified by Spronk & Hallerbach (1997), are:

- To provide a better idea of the set of alternative decision strategies, in order to get better insight regarding the feasibility of different strategies and possibly to generate new ideas.
- To clarify relations between decision alternatives and the possible results.
- To help identify the suitable stream of decision alternatives.

Financial modelling may therefore be seen as not only involving ‘hard core’ optimization and econometrics, but also softer techniques such as simulation, heuristics, decision support techniques and problem structuring methods.

The investment decision involves not only the investors’ preferences but also investment opportunity characteristics. Most models used for portfolio management focus on the ‘average’ investor since the assumptions needed in this regard are often adequate. The mean-variance framework, introduced by Markowitz (1952), is the traditional and also most popular approach to the investment decision problem (Spronk & Hallerbach (1997)).

12.5.2 Portfolio and investment theory as introduced by Markowitz

Modern portfolio theory principles have long been familiar to society. Investors are often warned against putting all their eggs in one basket. Portfolio selection and assessment methods were developed, and the effects of investing in assets with correlated risks were investigated. A portfolio of assets can be simply described as a collection of items owned by an individual or group. Such

items may include tangible objects or non-tangible assets. There may be very practical reasons for investing in certain assets; however, the decision regarding possible combinations of assets (portfolios) when investing in the financial markets, may not be trivial. Portfolio theory was developed as an aid to the process of decision-making under risky circumstances (Prattley *et al.* (2007)).

Markowitz (1952) formulated the portfolio selection problem as a choice of the mean-variance of a portfolio of assets, which is still the cornerstone of modern portfolio theory. The fundamental theorem of mean variance portfolio theory implies holding constant the variance while maximising the expected return, and holding constant the return, minimizing the variance. These two principles led to the formulation of the *efficient frontier*. From the *efficient frontier* the investor is able to choose the preferred portfolio, depending on individual risk-return preferences. The essence of this theory is that investments cannot be selected when only considering the characteristics unique to that particular security. It is of importance to consider the interaction of investments. As a result, a portfolio with less risk can be constructed. Mean variance theory was developed to find an optimal portfolio when considering the mean and variance over a time period (Elton & Gruber (1997)).

The risk of an individual asset may be measured and expressed as the standard deviation, measuring the average spread of the observations of return. It is the square root of the variance, which may be calculated, over time period T , as

$$\hat{\sigma} = \sqrt{\frac{1}{T} \sum_{t=1}^T [R_t - \bar{R}]^2}, \quad (12.5.1)$$

where R_t is the return of the investment at time t , and \bar{R} is the mean return over the time period (Goetzmann (1997)). The benefits of using the standard deviation include: it is simple, allows for the quantification of asset returns by risk, and also provides the basis for investor decisions about portfolio choice.

Markowitz's contributions regarding investments may be summarized by three measures: the mean return, the standard deviation of the returns and the correlation with other assets' returns. The mean and variance may be used to plot the relative risk and return of any selection of investments.

It is usually the case that stocks with the potential of providing the highest return, also imply the highest risk, and the expected return of a low risk stock would also be low. With the construction of a portfolio (and not only selecting one single stock), the diversification across a number of different investments is possible. By means of diversification it is possible to reduce risk and increase the return. The key to diversification lies in the correlation across investments.

The correlation in the case of two investments A and B are calculated as

$$\rho_{A,B} = \frac{1}{T} \sum_{t=1}^T \frac{(R_{A,t} - \bar{R}_A)(R_{B,t} - \bar{R}_B)}{\sigma_A \sigma_B} \quad (12.5.2)$$

(Goetzmann (1997)), which may be written as

$$\rho_{A,B} = \frac{\sigma_{AB}}{\sigma_A \sigma_B}. \quad (12.5.3)$$

The standard deviation of the portfolio, which is composed of different mixtures of A and B , would then be

$$\sigma_P = \sqrt{W_A^2 \sigma_A^2 + W_B^2 \sigma_B^2 + 2\rho_{A,B} W_A W_B \sigma_A \sigma_B} \quad , \quad (12.5.4)$$

where W_A and W_B are weights.

The expected return is then simply the weighted average of the means of the two assets,

$$mean_p = W_A R_A + W_B R_B, \quad (12.5.5)$$

where $W_A + W_B = 1$, $W_A > 0$ and $W_B > 0$. These weights are the percentage invested in the particular asset, e.g. 20% in A and 80% in B .

More assets may be included in the portfolio. Portfolio weights as well as asset combinations may be varied to create a set of portfolios.

The expected return E_p and standard deviation σ_p of a portfolio composed of more than two assets, can be calculated as

$$E_p = \sum_{i=1}^n W_i \bar{R}_i, \quad (12.5.6)$$

$$\sigma_p = \sum_{i=1}^n \sum_{j=1}^n W_i W_j \sigma_{ij}, \quad (12.5.7)$$

where $\sum_{i=1}^n W_i = 1$ and $W_i \geq 0$, $i = 1, 2, \dots, n$, (Markowitz (1952)). There are n investments, and an associated weight W_i , \bar{R}_i is the expected return for security i and σ_{ij} is the covariance between investments i and j .

Within the set of portfolios there will be portfolios providing the lowest level of risk for each level of return, and the highest level of return of each level of risk. The efficient frontier is then the set of portfolios which, for any level of risk, identifies a point that is the portfolio with the highest return for a particular risk associated, extending from the maximum return portfolio to the minimum variance portfolio (Goetzmann (1997)). A basic representation

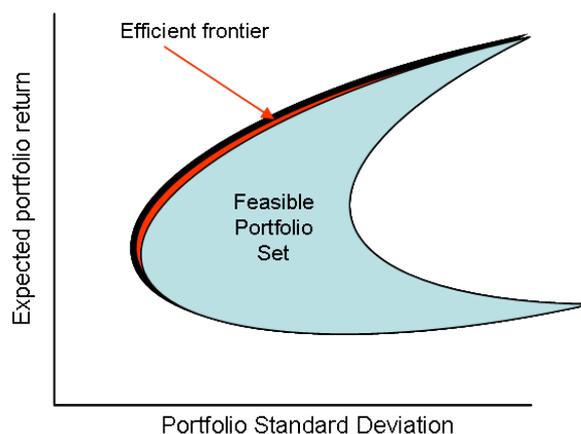


Figure 12.3: The efficient frontier

of the efficient frontier is shown in Figure 12.3.

This concludes the brief introduction to portfolio theory. Since the AC problem requires four different performance measures, MCDA in finance was investigated.

12.5.3 Multi-criteria in finance

MCDA techniques may be employed in finance when more than three criteria are of concern. Additionally, it was found that a multi-attribute approach is also sometimes applied to portfolio selection. This section is devoted to a brief discussion on MCDA and multi-attributes in finance.

Finance has traditionally recognised the two-objective situation of risk versus return, the efficient frontier and the trade-off of risk against return to achieve a final solution. The risk-return aspects have been extensively studied with a single criterion and parametric solution techniques. According to Hallerbach *et al.* (2004), extensions to the mean-variance model were proposed where the uni-dimensional risk measure variance can be replaced by a set of multi-dimensional risk parameters/measures. These risk measures comprise higher order statistical moments of the return distributions or may be based on a multi-factor risk model. There may be new ways identified of looking at financial problems when three or more criteria exist. If more than two criteria are incorporated, the efficient frontier is no longer a frontier but becomes a surface. The 'efficient surface' cannot be parameterised like the frontier. This then leads to the introduction of MCDM techniques, attempting to intelli-

gently probe and sample the efficient set so that they may converge (Steuer & Na (2003)).

According to Steuer & Na (2003) main methods applied in finance include Goal programming, Multiple Objective Programming, Multi-Attribute Utility Analysis (MAUT), MCDA (ELECTRE) for outranking and the analytical hierarchy process (AHP). Zopounidis & Doumpos (2002) provides a summary of applications of multi-criteria in the financial field, which includes bankruptcy and credit risk assessment, portfolio evaluation and selection, corporate performance evaluation, and investment appraisal.

In the context of financial theory, an attribute's ability to contribute to the explanation of cross-sectional return, appears to be a convincing criterion for the selection of relevant attributes (Hallerbach *et al.* (2004)). In general, the multi-attribute framework proposed by Spronk & Hallerbach (1997) consists of two stages: formulation of a multi-attribute representation of investments and the portfolio selection process. The multi-attribute representation enables the investor to select a set of security attributes that he considers relevant. When buying a security, an investor is actually buying an exposure to various attributes. Multi-attribute portfolio selection is therefore concerned with balancing the attributes of individual investments on the portfolio level.

Two types of attributes may be distinguished: those directly related to the return, consisting of (explicit) expected return and risk measures, and those attributes which are indirectly return related. In the first case where attributes are directly return related, the return is usually made up of a joint distribution of their returns. The risk dimension, however, proves to be problematic in its complexity. When it seems that all relevant information is not captured by explicit return and risk attributes, indirect return related attributes apply (Spronk & Hallerbach (1997)).

12.5.4 Portfolios applied in other contexts

A tool portfolio of a plant refers to the makeup, in quantity and type, of processing machines in the plant. This is determined by taking into consideration the future process and technology trends and forecasts of product evolution and product demands. Tool portfolio planning in this context is strongly dependent on manufacturing efficiency, and also involves multi-criteria decision making. This is applied in a study for Semiconductor Manufacturing (Wu *et al.* (2001)).

Another application involves the selection of projects for a project portfolio: In the context of R&D project portfolios (Linton *et al.* (2002)), or for the prioritization of transportation projects (Joshi & Lambert (2007)).

12.6 AC portfolio selection

The principles of portfolio theory will now be applied to the AC problem to establish an additional means for deciding among possible scenario alternatives.

In this context, ‘Fixed’ and ‘Roaming’ carriers are two investments, while there are only a limited number of carriers to ‘invest’ in either Fixed or Roaming fleet. The number of carriers would therefore be the ‘capital’ invested. Consequently, a ‘fleet portfolio’ may be constructed, consisting of Fixed and Roaming investments. It would be of interest to know the optimal fleet composition, i.e. what percentage of the available carriers to employ as fixed and what percentage as roaming.

Scenarios would typically be described by the percentage fixed and roaming carriers (where Fixed + Roaming = 100%). A fleet portfolio may thus be constructed as illustrated in Figure 12.4. The expected outcome for each scenario may be obtained by applying the SAW, TOPSIS or Mahalanobis distance method to obtain a non-financial ‘expected return’ value. It would be valuable to also investigate risk associated with the outcome that can be expected for each scenario alternative.

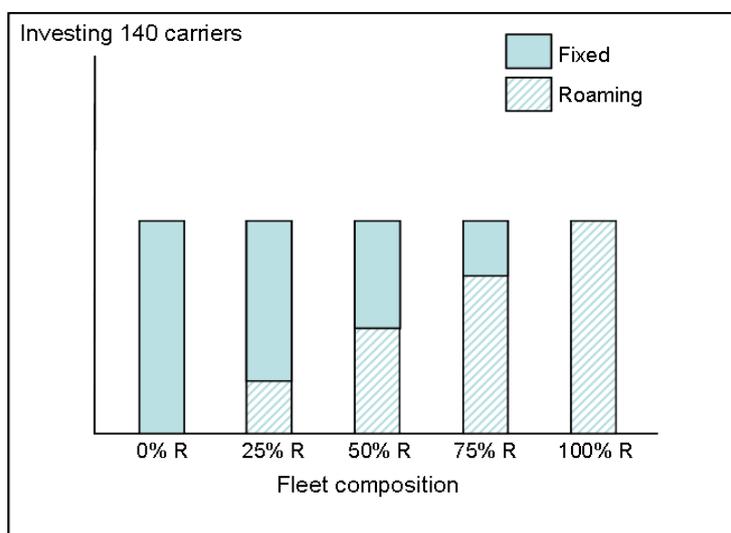


Figure 12.4: AC fleet portfolio construction

Because the *non-monetary* performance measures are in different units, the standard deviations cannot readily be integrated into a single risk factor. Instead of using the direct standard deviations, the integrated effect of deviation, as portrayed by the spread in the expected outcome for different fleet

compositions, is utilized as an indication of the associated ‘risk’. An efficient frontier analogue may then be constructed to facilitate fleet portfolio selection, portraying the deviation or spread in expected outcome for a particular Roaming/Fixed investment. This concept is explained in Figure 12.5.

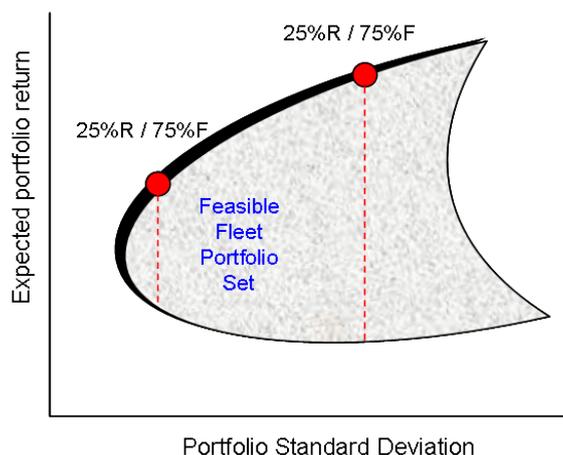


Figure 12.5: AC efficient frontier analogue

The range of expected return values possible for the 25% Roaming investment is much smaller than the spread of 75% Roaming investment return values. The variation in outcome may be viewed as a ‘risk’ associated in attaining the expected return.

The application of portfolio construction and the fleet portfolio efficient frontier in the AC problem context is discussed and explained when analysing the results in Chapter 18.

12.7 Concluding remarks: Chapter 12

The AC problem performance measures were identified and presented at the beginning of this chapter. In order to facilitate the proper evaluation of different scenarios, the AC problem performance measures, which are conflicting in nature and measured in different units, need to be incorporated into a single measure. MCDA and Mahalanobis distance methods were investigated for this purpose, where two different MADM approaches, SAW and TOPSIS, are considered suitable and applicable to the auto carrier problem in this study.

An additional scenario evaluation method was identified by exploring portfolio theory and the efficient frontier from the financial sector. MCDA in fi-

nance and multiple attributes in financial modelling were studied and were briefly discussed in this chapter. Finally, the application of portfolio construction and selection is extended to the AC problem context, where a fleet composition is considered a portfolio, and an efficient frontier analogy is incorporated to select (a) suitable portfolio(s) by viewing the variation in outcome as potential risk.

The application and results of the SAW, TOPSIS and Mahalanobis distance analysis, as well as fleet portfolio selection and the efficient frontier analogy are discussed in Chapter 18.

Chapter 13

Solution Method

The literature study facilitated the identification of the problem context, the formulation of the problem and investigating a suitable solution tool. The auto carrier problem exists in the freight transportation context, and the aim is to provide tactical policies regarding long-distance auto carrier fleet management.

From the literature investigated it is apparent that the AC problem is a unique problem class. The AC problem as identified and addressed in the literature, involves different sub-problems where the loading problem generally receives more attention. The limited literature on auto carrier specific studies mainly involves planning and scheduling on an operational level. Heuristics and algorithms are developed to aid the loading and/or routing aspects of the problem.

There seems to be a lack of information on truly tactical medium-term planning in the freight transportation literature. Simplifications are usually needed, which include assumptions such as homogeneous load, homogeneous carriers, and one day service period. There is also relaxation of constraints, e.g. trucks may return to any terminal when off-duty and not necessarily to their specific 'home' depot.

The AC problem in this case is concerned with

- Pickup and deliveries, although it is not a VRP problem.
- The allocation of resources.
- Cars (units) have to be transported from one destination to another.
- The system has to function in a flexible dynamic manner, accommodating uncertainty and constraints over a longer planning window.

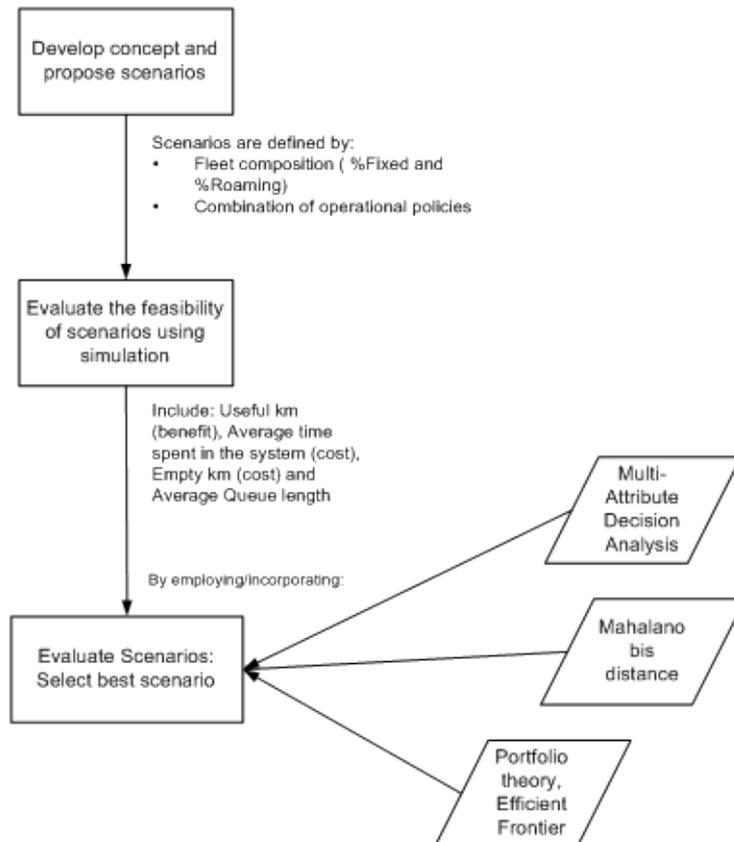
The AC problem of this study suits neither the assignment model, nor the transportation or resource allocation formulations. Stochastic programming may be helpful and has proven to be applicable in the case of many freight transportation problems. However, the real-world constraints, uncertainty and dynamics that have to be taken into consideration for this AC problem includes sending drivers home after 14 work-days, servicing carriers (scheduled maintenance), accommodating sleeping hours between 23:00 and 5:00 as well as back-logging of unlimited time-periods. Therefore, simulation was investigated for its applicability. Additionally, the analytical models are optimization techniques, ideal for daily operational planning. But for this study, the need exists to compare and analyse different scenarios with a more tactical focus.

The DRTP notation framework enables the formulation of the AC problem, whereas simulation was identified as an applicable tool to employ in this regard. The solution strategy for the AC problem comprises the development and proposal of tactical operational scenarios, followed by evaluation and analysis using simulation. The fleet composition (%Fixed and %Roaming) varies for each scenario.

The objective is to establish support to improve decisions regarding long-distance carrier fleet management. The Multi-attribute analysis techniques, SAW, TOPSIS, as well as the Mahalanobis distance method are used to evaluate these scenarios. Portfolio theory is also investigated as a research question to determine whether or not it could assist with fleet composition decision making.

A representation of the suggested solution strategy is illustrated in Figure 13.1. The following chapters will elaborate on the solution development steps followed in order to achieve useful and valid results. The analysis and outcome then provide the applicable decision support developed.

In the next chapter scenario construction is discussed, describing the different operational rules developed and the construction of policies. The chapter on scenario development precedes the explanation of the simulation model concept, as the operational rules, characterising the scenarios, make out an integral part of the model logic and functioning.

**Main Processes:**

1. Define and construct scenarios: specific policies and aspects.
2. Develop the scenarios.
3. Simulate scenarios and obtain evaluation parameter values.
4. Evaluate scenarios by employing MADM and other techniques.

Main Tools:

1. Simulation
2. MADM
3. Mahalanobis distance.
3. Portfolio theory and Efficient Frontier.

Decisions:

1. A post- evaluation will be done.
2. Four measuring factors are required to evaluate scenarios properly.
3. Scenarios will be characterized by the fleet composition (%Fixed;%Roaming), and the combination of operational policies used.

Figure 13.1: Solution Strategy Overview

Chapter 14

Scenario Construction

The author developed several operational rules that will dictate carrier functioning. A number of these rules are combined into an operational policy. The composition of these rules, and a given fleet composition (Fixed, Roaming) forms a scenario. The different policy classes which were developed, and the construction of scenarios are explained in this chapter.

The different operational policies may be classified into 2 major classes: 1) Roaming order picking, and 2) Waiting policies. Waiting policies may further be divided into: 1) Waiting at the beginning of a station for work, and 2) Waiting until full enough before departure.

Roaming order picking policies are of concern since the next best destination for roaming carriers is only decided on when picking up orders at the current location. A scenario is therefore composed as shown in the Figure 14.1. The detail of each policy is described next.

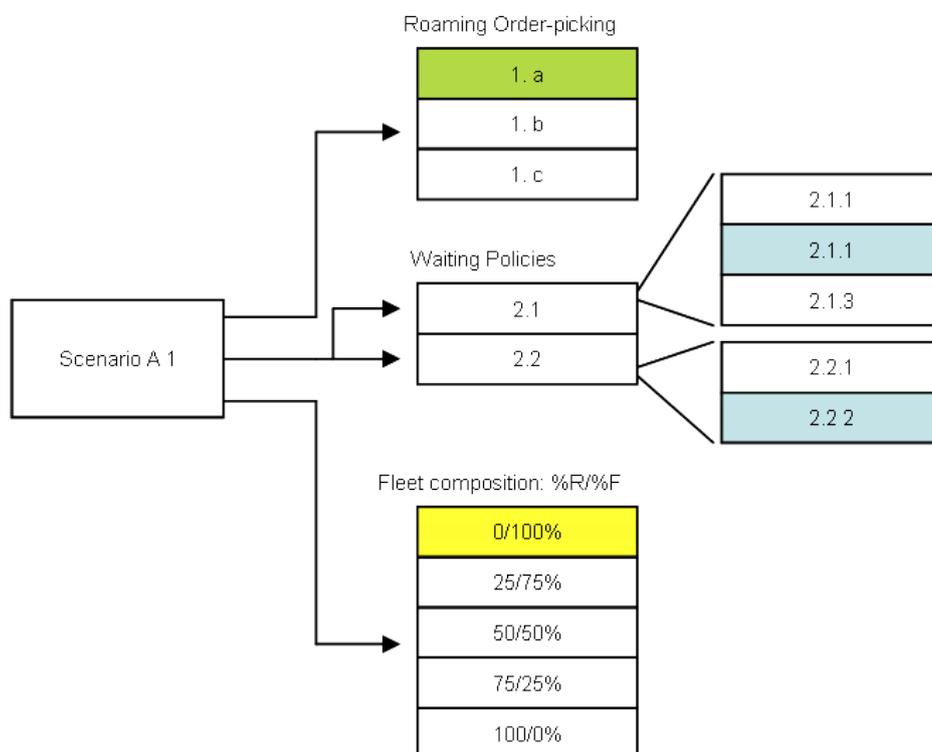


Figure 14.1: Scenario composition

14.1 Operational policy description

The policy classes developed consist of the rules in Table 14.1:

Table 14.1: Scenario description

Policy	Sub-class	Operational Rule	Description
1	a	Pick orders with destination where majority of orders have to go to.	Roaming carriers at current location i , select orders from queue i with destination j , where the majority of orders in queue i have to go to j .

Table 14.1 – continued from previous page

Policy	Sub-class	Operational Rule	Description
	b	Pick orders with highest priority.	Roaming carriers at current location i select orders from queue i with destination j , where the orders have the highest rank in the queue, and the additive sum of the <i>Waiting time</i> is the greatest for a particular destination j .
	c	Pick orders where majority of orders have to go to closest destination.	Roaming carriers at the current location i select orders from queue i with destination j , where the majority of orders have to go to the same destination and the selected destination is closest to the current location.
2.1	1	Roaming: no wait policy.	When there is no work at the current location, roaming carriers may depart empty and select the next best destination by investigating the amount of work at each destination.
2.1	2	Roaming and Fixed: no wait policy.	If the current location i has no work, fixed carriers simply depart for the next planned station in their sequence and roaming carriers depart for the next best destination (station with most work).
2.1	3	No wait at Cape Town / East London.	Fixed and roaming carriers may depart empty from East London and Capetown and do not wait for work at these stations, since the need for cars is usually greater at Cape Town and East London than the need for cars to be collected.
2.2	1	Carriers do not wait until completely filled.	Carriers depart from location i no matter how many slots occupied.
2.2	2	Carriers	Carriers wait until at least 75%

Table 14.1 – continued from previous page

Policy	Sub-class	Operational Rule	Description
		depart when sufficiently filled.	full/occupied before they may depart.

An operational rule from each policy class may be combined to constitute a policy. For instance: Roaming carriers do not need to wait for work at any location (2.1.1); but if there is work, the roaming carriers pick orders according to rule 1.b. Additionally, all carriers are allowed to depart from a given location no matter how many slots are occupied (2.2.1). These rules, and the functioning/execution thereof are now explained.

14.1.1 Explanation of Policy rule 1.a

This Roaming order picking rule may be explained and illustrated using Figure 14.2 and subsequent pseudo code.

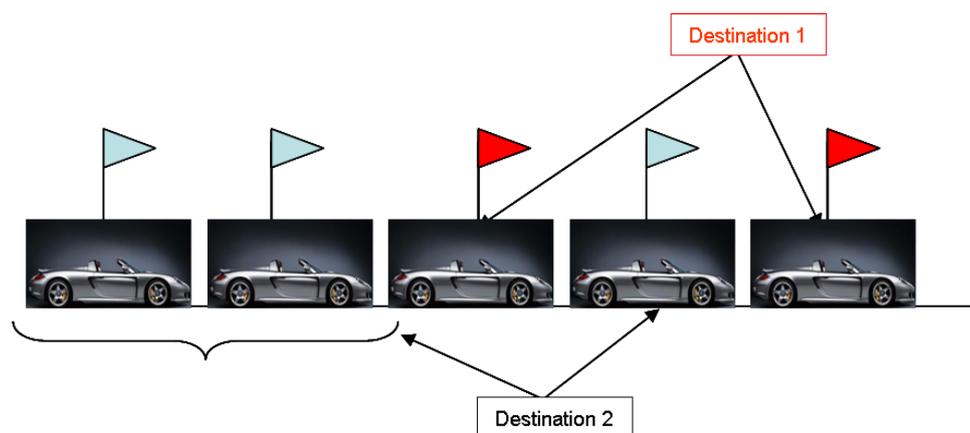


Figure 14.2: Order layout for illustrating Policy rule 1.a

Orders in the queue at station i are evaluated for their destination j : at station i , three cars have to go to destination 2 and two to destination 1 (marked with the red flags). The destination with the most work is selected as the next destination for the roaming carrier. The individual position of the orders in the queue (the rank) is not taken into account, and the next destination in the picture would be destination 2 (the blue destination) at time t .

The pseudo code for Policy rule 1.a is as follows:

```

1:  $r \leftarrow$  carrier current location locationNOW
2:  $k \leftarrow$  associated order queue length at  $r$ 
//  $d \in 1,2,3,4,5,6$  (possible branch destinations )
3: counter [1..6]  $\leftarrow 0$ 
4: For Each order  $j$  In  $k$ 
5:    $d_j \leftarrow$  destination of order with rank  $j$ 
6:   counter( $d$ ) = counter( $d$ ) + 1 where  $d = d_j$ ;  $d \neq r$ 
7: End For
8: Carrier Dest  $\leftarrow$  Index of Max(counter(1..6))

```

14.1.2 Explanation of Policy rule 1.b

A roaming carrier arrives at a location and when unloaded and not due for off duty or for service, investigates the queue of orders for a next best destination. For this policy, the rank and waiting time of the queuing orders are examined for each destination.

The combined priority factor is found by evaluating the order rank in the queue and the arrival time in the system. The priority factor of the first order would be greater than the second order priority in the queue. It may be found that the priority factor decreases as the order arrival time and rank increase.

For each destination the normalised values of the order priorities are added, and different possible destinations evaluated accordingly. This policy takes into account the relative priority (the rank and relative waiting time) of each order, as well as the additive sum of 'work' due for the different destinations. The pseudo code for Policy rule 1.b is shown on the next page.

```

1:  $r \leftarrow$  carrier current location locationNOW
2:  $k \leftarrow$  associated order queue length at  $r$ 
   //  $d \in 1,2,3,4,5,6$  (possible branch destinations)
3:  $Tnow \leftarrow$  Current simulation time
4:  $t_L \leftarrow$  the arrival time of the oldest order in the queue at  $r$ 
5:  $P [1..6] \leftarrow 0$ 
6: For Each order  $j$  In  $k$ 
7:    $d_j \leftarrow$  destination of order with rank  $j$ 
8:    $t_j \leftarrow$  arrival time of order with rank  $j$  in the queue at  $r$ 
9:   If  $(Tnow - t_L) > 0$  Then
10:     $P(d) = P(d) + 0.5 \times \frac{Tnow-t_j}{Tnow-t_L} + 0.5 \times \frac{k-j}{k}$  where  $d = d_j$  ;  $d \neq r$ 
11:   Else
12:     $P(d) = P(d) + 0.5 \times \frac{k-j}{k}$  where  $d = d_j$ ;  $d \neq r$ 
13:   End If
14: End For
15: Carrier Dest  $\leftarrow$  Index of  $\text{Max}(P(1..6))$ 

```

The value $P(d)$ consists of three terms. The first is simply the previous value of $P(d)$ and is included to calculate the additive sum of all priorities for each destination d . The second and third terms are both an individual value between 0 and 1. The two factors are multiplied by 0.5 to obtain a combined priority value for each element j between 0 and 1. The second term resembles the time period order j spent in queue k (time spent waiting by order j), relative to the order with longest waiting time $Tnow - t_L$ (the oldest order in the queue).

The second term describes the relative rank of each order j in queue k . The priority of an element j in queue with length k , is thus a function of the relative time spent in the system and the rank in the queue.

When considering Figure 14.3, this rule may be explained by means of a simple example. Suppose $Tnow = 30$. Then for the first order in the queue, which is destined for location 1, the value $P(d = 2)$ would be:

$$P(1) = 0.5 \times \frac{30 - 10}{30 - 10} + 0.5 \times \frac{5 - 1}{5} \quad (14.1.1)$$

The ‘priority’ score for destination 1, $P(1)$, would then be the sum of the first and third order priorities. The order in the queue for which $j = k$, has arrived last. Consequently, the term $\frac{k-j}{k}$ does not contribute to the $P(d)$ value, and the last order arrival is assigned the lowest priority.

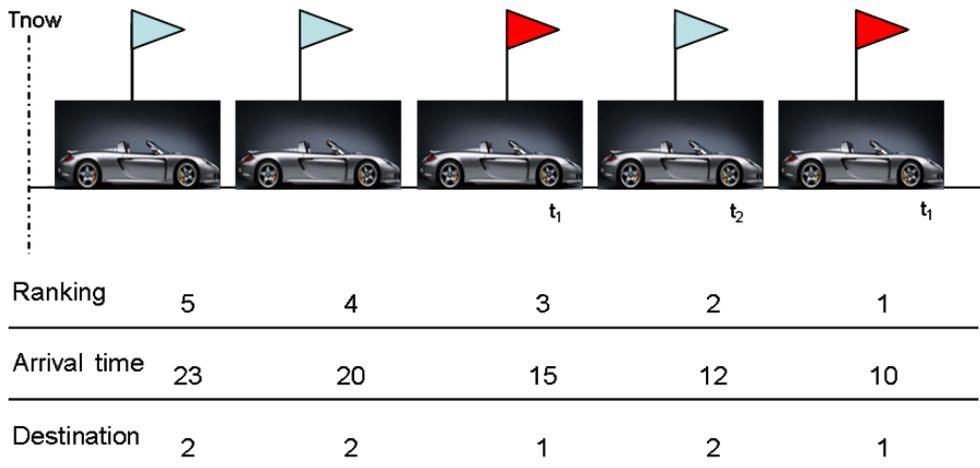


Figure 14.3: Order layout for illustrating Policy rule 1.b

14.1.3 Explanation of Policy rule 1.c

Roaming carriers select a destination by evaluating the amount of work for that destination and the distance from the current location to that destination.

This policy can be explained referring to Figure 14.4 and the pseudo code.

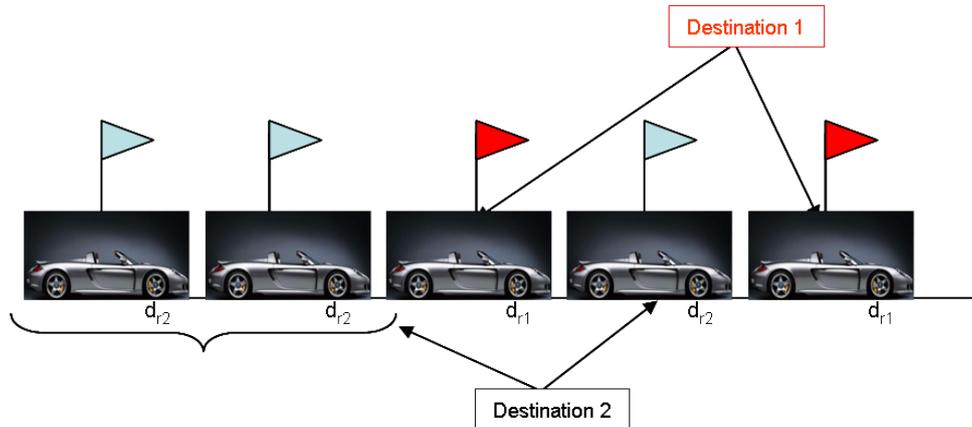


Figure 14.4: Order layout for illustrating Policy rule 1.c

The pseudo code for Policy rule 1.c is as follows:

```

1:  $r \leftarrow$  carrier current location locationNOW
2:  $k \leftarrow$  associated order queue length at  $r$ 
   //  $d \in 1,2,3,4,5,6$  (possible branch destinations)
3: counter [1...6]  $\leftarrow 0$ 
4: distance[1...6]  $\leftarrow 0$ 
5: work[1...6]  $\leftarrow 0$ 
6: For Each order  $j$  In  $k$ 
7:    $d_j \leftarrow$  destination of order with rank  $j$ 
8:   counter( $d$ )  $\leftarrow$  counter( $d$ ) + 1 where  $d = d_j$ ;  $d \neq r$ 
9:   distance( $j$ )  $\leftarrow$  distance from location  $r$  to destination  $d_j$ 
10: End For
11: For all  $d \in 1,2,3,4,5,6$ 
12:   If distance( $d$ ) > 0 Then
13:     work( $d$ )  $\leftarrow$  counter( $d$ )/distance( $d$ )
14:   End If
15: End For
16: Carrier Dest  $\leftarrow$  Index of Max(work(1...6))

```

A possible destination is therefore in effect rewarded for the amount of work or the number of orders going there, and penalised for the distance from the current location to that destination. In Figure 14.4, destination 1 would score a value of $3/d_{r1}$ and destination 2 a value of $5/d_{r2}$ where r is the current location of the carrier. Ties are arbitrarily broken.

14.1.4 Explanation of Policy class 2.1

This policy class is concerned with the decision to keep carriers waiting at a location i when there are no orders waiting at location i . The basic principle that one would naturally like to follow is that carriers are only allowed to depart when there are orders in the queue at that location, i.e. work at the location.

The problem with this may be that, especially because demand is not equally distributed and an imbalance in flow is often the case, carriers are kept waiting at location i where there is no work, whereas there are many orders waiting to be distributed at location j .

When this principle was followed initially in the simulation model, it was found that the lateness of orders and the queue lengths of work at locations became problematic, although empty kilometres were kept low and carrier utilization high. Carriers are kept waiting at some locations with no work, and are then unable to attend to work elsewhere. As a result, the orders in the

system accumulate to unacceptable levels.

When carriers are allowed to depart empty from a location when there is no work, an increase in empty kilometres and decrease in utilization may be expected. But carriers are then able to get to where they are needed, and an improved level of service is then possible. This principle has been redefined and three different Waiting rules were identified within this policy class. These are discussed below.

14.1.4.1 Explanation of Policy rule 2.1a

Roaming carriers are allowed to depart from a location when there is no work there, while fixed carriers are kept waiting for work before they are allowed to depart.

14.1.4.2 Explanation of Policy rule 2.1b

There is no 'hold' for fixed or roaming carriers at any location, and any carrier may depart empty from any location when no work is available there.

14.1.4.3 Explanation of Policy rule 2.1c

Carriers are allowed to depart empty only from East London (EL) and/or Cape Town (CT) when no work is available there, since the demand for cars to be delivered to EL and CT is usually much higher than the demand for cars to be collected. By retaining carriers at these stations when there is no work, a build-up of entities occur at other locations and resources are underutilized. Roaming and fixed carriers are then allowed to depart from CT and EL when there is no work available.

14.1.5 Explanation of Policy class 2.2

In order to reduce empty kilometres, a policy rule may be implemented that will prevent the departure of carriers from a station if they are less than 75% occupied. This number of 75% is arbitrarily selected, and a sensitivity analysis could be done in future. It was implemented by including a decision block in the model as space control point to decide whether a carrier may depart or remain at a location and wait until it can load more cars. Since carrier capacity is a function of the carrier type and the current location, the utilization would be a relative measure of capacity occupied relative to the capacity available. Requirements of Policy 2.2 are now discussed.

14.1.5.1 Explanation of Policy rule 2.2a

This policy allows the departure of carriers regardless of the carrier utilisation, and carriers are allowed to depart from a location no matter how many slots

(spaces) are occupied (their utilisation), i.e. how many cars they have picked up.

14.1.5.2 Explanation of Policy rule 2.2b

In this case carriers would only be allowed to depart from a station when they are at least 75% full.

14.1.5.3 Implementation of Policy class 2.2

With the implementation of this policy, it became apparent that the retention of carriers is not a viable option. Orders very quickly build up in the system which results in operational inefficiency. At some locations this may not be a problem, as carriers are usually fully loaded upon departure, whereas at Cape Town, for instance, carriers have to be able to depart with only one or two / a few slots occupied.

This policy class was eventually discarded (including the 75% occupied rule), and in all generated scenarios, carriers were allowed to depart irrespective of how many cars loaded.

14.2 Combining operational policy rules

The Roaming order-picking and Waiting policy 2.1 rules were combined to construct nine different options, as illustrated in Figure 14.5.

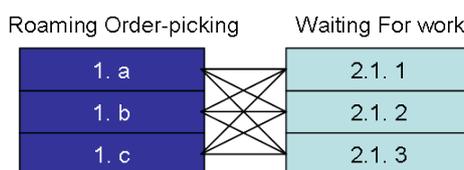


Figure 14.5: Possible policy combinations

For each of the nine policy combinations, different fleet compositions are possible.

14.3 Fleet composition

The 140 available long-distance carriers may be used as either fixed or roaming. The fixed carriers follow a predefined course of actions and a predetermined sequence of stations/destinations applies. Roaming carriers are used where needed, and attend to peaks in the demand. The question would then be how big the roaming and fixed carrier fleets should be, in other words how many

of the available carriers should be used as roaming and how many as fixed. In order to investigate this, different fleet compositions were examined for each policy combination.

14.3.1 Fleet compositions investigated

Five different fleet compositions, %Roaming carriers and %Fixed carriers were identified for this purpose:

- 0% Roaming, 100% Fixed (where a 100% implies 140 carriers)
- 25% Roaming, 75% Fixed
- 50% Roaming, 50% Fixed
- 75% Roaming, 25% Fixed
- 100% Roaming, 0% Fixed

Fixed carriers, once determined, have to be assigned to the fixed routes. When the fleet composition is e.g. 25% Roaming, the remaining 105 carriers are employed as Fixed and have to be allocated to a fixed sequence of destinations. The selection of these fleet compositions results in 5 variations, and combined with the nine policy combinations in Section 14.4, lead to 45 scenarios.

14.3.2 The assignment of fixed carriers to fixed routes

In the assignment of fixed carriers to the routes, operations research methods investigated include the assignment problem and the transportation problem. However, the assignment of fixed carriers to fixed routes for this AC problem requires that:

- Sources may be sinks also and sinks are also sources.
- Demand is destination- AND source- specific: individual units (orders) have particular specifications including release date, destination, and origin. This complication changes the decision completely: For the AC problem the decision does not involve the ‘optimal quantity’ that each source provides a destination with, as this is fixed. The question is how many of the available fixed number of carriers to allocate to each fixed route where each route has a demand.
- The objective is therefore not to minimize distribution cost- the assignment of fixed carriers to fixed routes does not change the cost of transporting the non-homogeneous cars.

- A serious complication is the assignment of carriers to routes with more than 2 nodes, i.e. CT–PE–DBN–PE–CT.

Given the above, carriers were simply assigned proportionally based on the 75th percentile of demand on the routes as described below. If the flow of cars is considered for July - December 2007, the total demands between nodes are as indicated in Table 14.2.

Table 14.2: Total number of cars on long-distance routes considered

From	To					
	CT	DBN	EL	GP	PE	BFN
CT	-	983	186	2329	345	115
DBN	10701	-	2009	12118	16310	2152
EL	1173	3694	-	2511	402	7
GP	7552	7183	1524	-	1644	1510
PE	139	12618	2501	574	-	34

BFN is only a destination. The maximum demand between two nodes is highlighted in each case: the need for cars to be transported from DBN to CT is much higher than the demand for cars from CT to DBN.

The direction of demands is in all cases taken into consideration. For the CT–PE–DBN–PE–CT route, the total CT→DBN demand is less than the total number of cars to be transported along direction DBN→CT. Therefore demand is considered for DBN→CT. Since there is a separate route for CT–DBN–CT, the direct demand between DBN and CT is not incorporated in the CT–PE–DBN–PE–CT route. The 75th percentile for maximum demands may then be calculated, as well as the associated proportion of carriers for each route. As a result, Table 14.3 is obtained for the different routes. Carriers assigned to routes with more than two nodes are also allowed to load cars for the subsequent destination if they have available capacity, after picking up orders at the current location.

Table 14.3: Example proportional assignment of fixed carriers to long-distance routes

Routes	75% of Max Demand	Proportion	Number of fixed carriers assigned
CT-GP-CT	54.00	13.1%	18
DBN-BFN-DBN	17.25	4.2%	6
DBN-GP-DBN	92.75	22.5%	32
EL-GP-EL	30.50	7.4%	10
EL-CT-EL	5.00	1.2%	2
CT-PE-DBN-PE-CT	100.00	24.3%	34
DBN-PE-EL-DBN	112.25	27.3%	38
Total		100%	140

14.4 Concluding remarks: Chapter 14

Several operational scenarios were developed and described in this chapter. These scenarios each consists of operational rules and a given proposed fleet composition (%Fixed, %Roaming). The scenarios are intended to improve the efficiency of the AC company operations. The various contributions of operational rules and combinations resulted in 45 scenarios. The quality of each scenario was evaluated by means of simulation, and the results are presented in Chapter 18. In the next chapter the simulation model concept, facilitating the execution of the developed scenarios, is discussed.

Chapter 15

Concept development of the Simulation Model

A concept model was constructed to understand the long-distance carrier functioning. From this conceptual formulation, the input data needed and output required were identified, and the model logic was established to enable the realisation of the developed scenarios. In this chapter, the simulation model concept is discussed, facilitating model creation in the simulation software Arena (Rockwell (2008)).

15.1 The concept model

A concept model was constructed to create a logical representation of the AC system and functioning thereof. A concept model is of great help in developing a better understanding of the problem, identifying input data needed and the output desired.

15.1.1 Description of the concept model

The concept model aids and supports the simulation model construction. This study is concerned with determining the long-distance fleet composition (% Fixed and % Roaming) and combination of operational policies that would maximise the number of cars delivered on time and at the lowest cost. The model therefore basically entails:

- The AC distribution network: There are 6 nodes (branches), and fixed routes connecting these AC branches. Five of the six nodes may be origins and destinations, and all 6 nodes are possible destinations.
- Orders are released in the system. These orders are described by the time of release, the associated origin and destination.

- Long-distance carriers attend to these orders according to particular policies, abiding certain rules.
- These carriers are created once-off at the beginning of each simulation run, and then operate continuously.
- Fleet composition: Carriers may be employed as fixed or roaming, where fixed implies static decision making, pre-defined course of actions, pre-determined routes and destinations. Roaming involves dynamic decision making and that the next best destination is only decided on at the current location just before picking up orders. The specific number of roaming and fixed carriers is specified by the decision maker at the start of each simulation run.
- The combinations of policies according to which the carriers operate, were described in Chapter 14. The concept model representation illustrates where the policies are of concern.
- Model restrictions include:
 - Carriers are inactive between 23:00 and 05:00, because the drivers of the carriers have to sleep. If they are travelling, they have to stop to rest and may only resume after six hours.
 - Carriers have to be serviced at the Bellville depot. An 11 slot carrier has to be serviced every 22 500 kilometres, and any other type of carrier has to be serviced every 20 000 kilometres.
 - Drivers have to be home for two consecutive days after 14 days on the road. This implies that carriers have to go the specific driver's home station in time, so that a driver arrives home at least on the 14th day. A carrier is reassigned to another driver from that 'home station', and resumes work again. It will be delayed longer if it is at Bellville depot and needs to be serviced.
- Carrier attributes assigned from the start include:
 - For each fixed carrier a particular sequence (one of the 7 pre-defined fixed routes) is assigned. The assignment of fixed carriers to these routes has previously been discussed in Chapter 14.
 - The 'Home Station' to which each carrier belongs, where that carrier has to return to after 14 days of work, is assigned. For fixed carriers, this attribute is assigned according to a discrete probability function which depends on the fixed route to which the fixed carrier belongs. For roaming carriers, their 'Home Station' is one of the possible carrier 'home' destinations, with a particular probability.

- In order for carriers to take leave at different times, carriers are assigned different work-schedule days according to a discrete probability function, to start their work on, at the beginning of each simulation run.
- The specific Carrier Type is assigned. A long-distance carrier capacity may range between 7 - 11 slots, where a slot is equivalent to a single vehicle space. Carrier Type is assigned according to a discrete empirical function, based on data obtained from the AC company:

$$f(x) = \begin{cases} 0.73 & x = 11 \\ 0.03 & x = 10 \\ 0.13 & x = 9 \\ 0.02 & x = 8 \\ 0.09 & x = 7 \end{cases} \quad (15.1.1)$$

- As the carriers attend to the orders, travelling from one destination to another, picking-up and dropping off orders, additional attributes are assigned. These attributes may change from one point in time to another, and include distance travelled, whether servicing is needed, how many consecutive days a driver has spent away from ‘home’, whether the carrier is loaded or not, the number of cars loaded, the available carrier capacity, travel time, the current location and the next destination.

The concept model gives an overview of basic model logic, when a carrier arrives at a particular location, where operational policies apply and which policies and conditions apply, attributes assigned and how these attributes change.

15.1.2 Input data needed

In order to create the model, input data was needed. The identified input data necessary for this model include the following:

- Daily order releases.
- Information regarding the AC distribution network:
 - The fixed long distance routes currently scheduled for.
 - The location of the AC branches and distances between them.
- Other operational information:
 - Carrier operational speed.
 - Work schedule: 14 days of work, followed by two days spent at home.

- Servicing of carriers: Target distance travelled, and duration of service.
- The fleet currently consists of 140 carriers.
- Home station for each carrier.
- The Carrier Type of each carrier (e.g. 73% of the carrier fleet have 11 slots)
- How the available carrier capacity varies according to the particular types of cars loaded.
- The expected delay or idle time at each station, resulting mainly from unloading and loading.

The data acquired and the data analysis are explained in more detail in the next chapter.

15.1.3 Simulated system boundaries

Boundaries are important in the simplification of a simulation study so as to reduce the amount of detail. The boundaries define what is included and excluded from the model. Two boundaries can be defined (Law & Kelton (2000), Banks (1998)).

- The Environmental Boundary: In this study, the aim is to determine how to employ the long-distance carriers in terms of fleet composition and the particular operational policies identified. Only the operational policies as identified for the purpose of this study are investigated, and only fleet composition in terms of Roaming or Fixed. Long distance routes and the sequences according to which fixed carriers operate, are considered as already adequate. The focus in this study is tactical and not operational in nature. Driver schedules (two days at home after 14 days of work), sleeping hours and servicing of carriers are included in this study. However, operational detail involved in the servicing of carriers, driver issues, maintenance and/or other factors are excluded.
- The Physical boundary: Two physical boundaries may be identified: The first boundary separates the AC company from the supply chain it belongs to. The AC company is concerned with the distribution of cars to individual car dealerships. The second physical boundary: This study is only concerned with the transportation of cars between AC branches and does not consider the local deliveries to individual motor dealerships. If a system boundary is constructed around the long-distance carriers and long-haul dispatches, all cars enter the system as orders and leave the system again when they are delivered to the destination branches. The two physical boundaries are depicted in Figure 15.1. The arrows indicate the flow of cars into and out of the system.

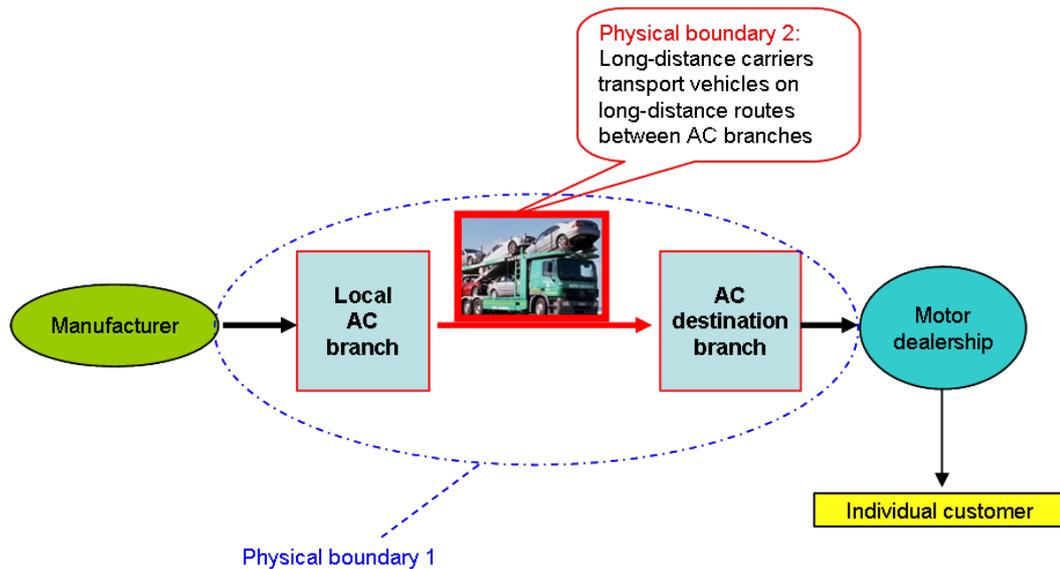


Figure 15.1: Representation of physical boundaries

15.1.4 Model logic of when a carrier arrives at a location

The concept model representation (Figure 15.2 and Figure 15.3), illustrates the following logic executed when a carrier arrives at a particular location, the latter being an AC branch:

1. As the carrier arrives at a branch, the distance driven from the previous branch to the current branch is added to the total distance travelled.
2. These assigned values then determine whether or not it is time for the carrier to drive home, and whether the carrier needs to be serviced or not.
3. If the carrier is a fixed carrier, following a particular sequence of destinations, the next destination is assigned as being the next planned branch in the sequence.
4. If the carrier has to be unloaded, all orders with a destination corresponding to the current carrier location, are unloaded. For each vehicle unloaded, the available carrier capacity is increased by an equivalent slot. The time it takes a carrier to unload is dependent on the current location of that carrier. Unloading times differ for each AC branch.
5. After the carrier is unloaded, the carrier status is evaluated for an imminent break or service due. If the carrier needs to be serviced and the carrier is currently at Bellville depot, the carrier is serviced, and therefore out of service for one day, after which it is returned to the work

pool. If the carrier needs to be serviced and is currently not at Bellville depot, the next destination (for roaming and fixed carriers) is assigned as Bellville. For a carrier to return home, due to the required break of two days, the next destination assigned, is that of the carrier home station. However, if the current location is the carrier home station, and no service is required, the carrier is returned to the work pool. When the driver takes leave for two days, the carrier is assigned to the next best task and keeps on working. It is assumed that there are always drivers available.

6. Before the loading process commences, the carrier capacity is adjusted according to the nature of the cars that must be loaded at the particular branch.
7. The ‘Waiting for work’ policies discussed in Chapter 14 include:
 - Only fixed carriers are retained when no work is available, and roaming carriers may depart empty to the next best destination.
 - Roaming and fixed carriers do not wait for work at a station if there are no cars to pick up.
 - Fixed and roaming carriers are free to depart empty from Cape Town and East London stations, as the demand for cars is generally much higher at these locations than the demand for cars to be collected.
8. The next best destination for a roaming carrier is only identified when picking up orders at that particular location. The roaming destination may be selected according to the following identified Roaming order-picking rules:
 - Picking Orders with the destination where the most work have to go to.
 - Selecting Orders with the highest priority in the queue at a given location.
 - Picking orders where the most orders have to go to the closest destination.

The policy options (7 and 8) are scenario specific. The scenarios and associated policies were described in more detail in Chapter 14.

9. Orders are then loaded according to the Fixed and Roaming loading policies. This implies that a fixed carrier may also load cars for the second destination in the sequence (when applicable) and roaming carriers pick up cars from the queue, according to the next best destination as identified by the particular Roaming order-picking policy. The time it takes

to load a carrier is dependent on the current location of that carrier, as loading times differ for each AC branch.

10. Carrier attributes are updated, and expected travel time to the next branch is also specified.
11. For roaming carriers with no cars loaded (if there is no work at the current location) the most attractive location in terms of cars waiting to be collected, is assigned as the carrier destination.
12. Before departure, the carrier travel time is evaluated at the current point in time. If the driver of a carrier is required to sleep before it reaches the proposed destination, a partial travel time is assigned. Else, the carrier travels the specified required time. For partial travelling, the remaining travel time is re-evaluated after the partial travel time and compulsory sleeping period are over. This process repeats itself until the required number of hours have been spent travelling, while the compulsory sleeping hours have been respected.
13. As the carrier arrives at its destination, this destination becomes the current location, and the model logic repeats itself from step 1.

The concept model illustrates the model logic, assignments made and basic functioning of the system. The sleeping rules and loading policies are also included in Figure 15.2 and 15.3 for clarity, and the policy dependent processes/aspects are also indicated.

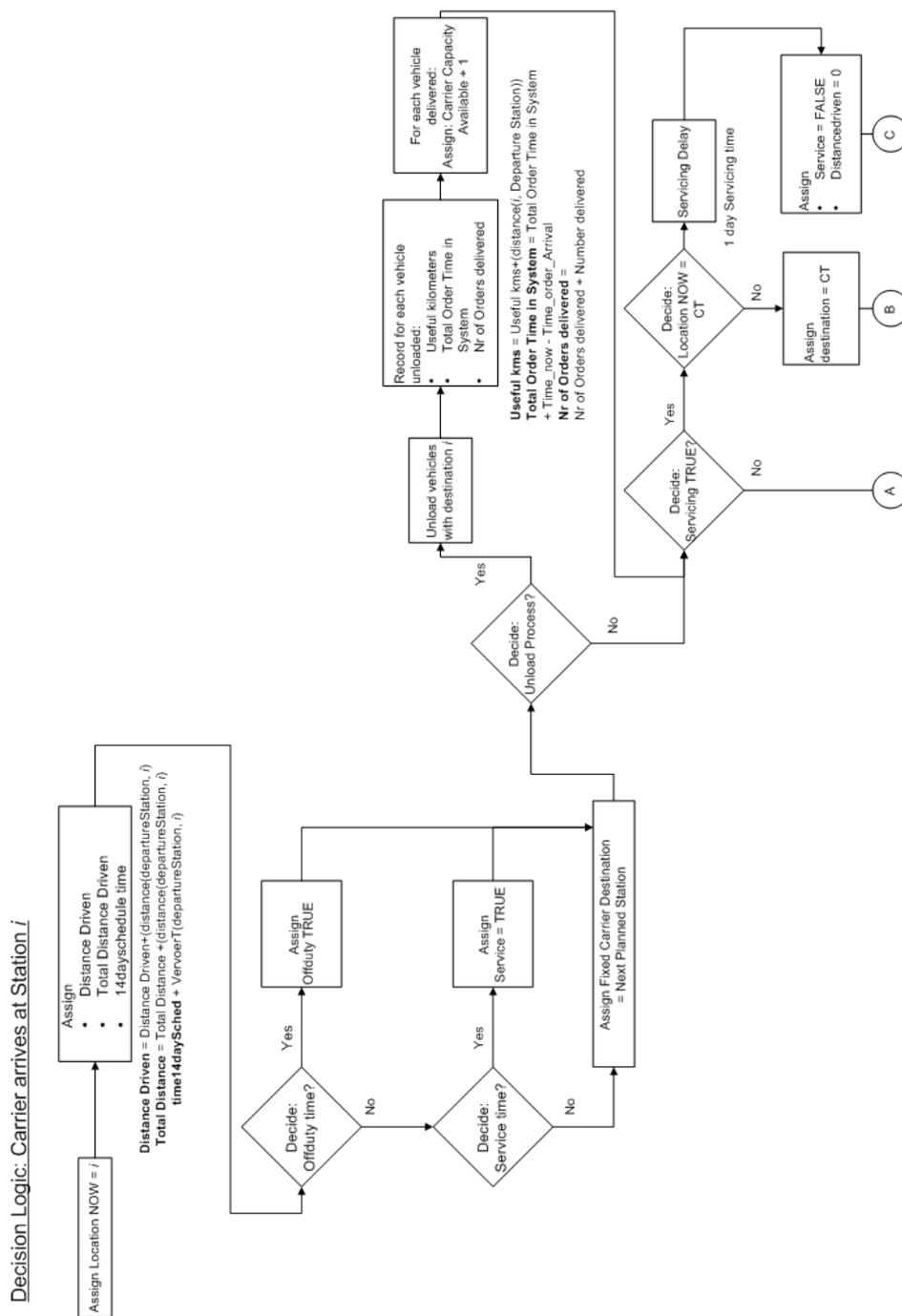


Figure 15.2: Concept model (Part A)

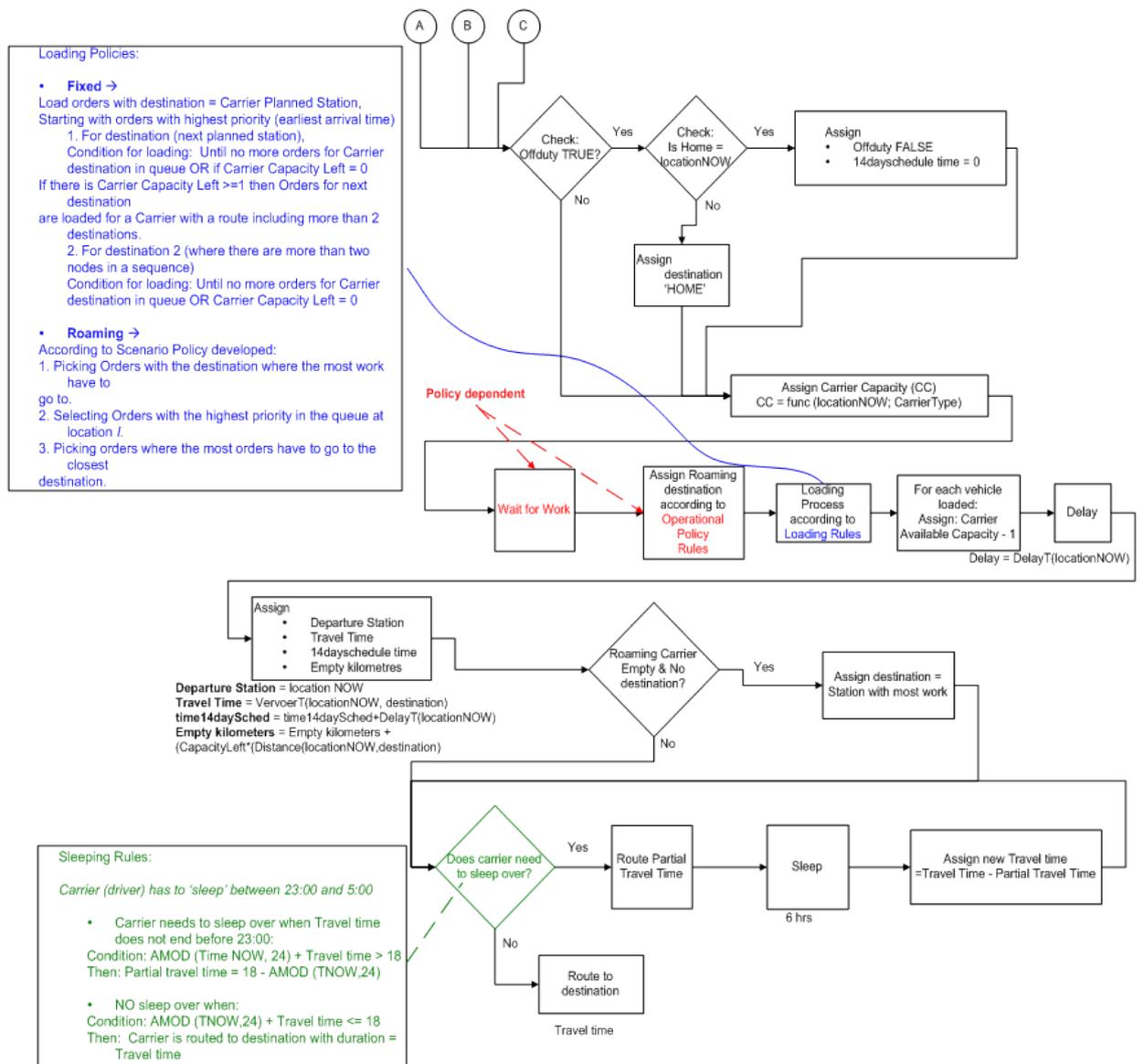


Figure 15.3: Concept model (Part B)

15.1.5 Output analysis

The AC operations constitute a non-terminating system, because the system is as a rule never left empty or at rest. Orders arrive on a daily basis and the carriers remain in the system to attend to these orders.

System describers can be perceived to be the system characteristics which have measuring significance, and portray how the system reacts. Describers include expected values, minimum and maximum values, n^{th} percentiles and proportions. For the purpose of this study, the focus is on the outcome of expected values.

The performance measures were described in Chapter 12, and are briefly repeated here:

- Mean number of cars waiting to be distributed.
- Useful kilometres covered by the carriers.
- Empty kilometres travelled by the carriers.
- Mean time that an order spent in the system.

The Replication/Deletion approach was used in order to obtain statistically independent observations (see Law & Kelton (2000)). The simulation model starts empty with resources idle, and is allowed to pass through a transient time period to reach a steady state. The responses in this steady state are collected as model output observations. Point estimates and 95% confidence intervals were determined for each parameter according to the procedure for constructing a confidence interval for multiple performance measures, as described in Law & Kelton (2000).

15.2 Concluding remarks: Chapter 15

The model concept and basic model functioning were considered in this chapter. A graphical concept model is also included, from which the input needed and the required system output could be identified. The concept development facilitated scenario realisation in Arena. An overview of a simulation model which portrays basic functioning of fixed and roaming carriers, picking-up and dropping-off orders, is included in Appendix A. The creation of orders on a daily basis, the once-off creation of carriers, and the logic executed at each AC station is illustrated. In order to investigate the quality of the developed scenarios (in Chapter 14), valid and useful data were required. In the next chapter the acquired input data, as identified by means of the concept model, is discussed.

Chapter 16

Input Data for the Simulation Model

In a simulation study, the results and recommendations obtained from the model are dictated by the quality of the model and its inputs. The validity and applicability of the input data directly affect the confidence in the results generated, and is therefore of great importance. In this chapter the data acquired from the AC company are discussed.

Data can be obtained from historical records, observations, similar systems, operator estimates, vendors' claims, designer estimates or theoretical considerations. When no data are available, vendor and designer claims or estimates can be applied, as they usually comprise a mean value and a tolerance deviation. If data are available, one of two approaches can be followed. One approach is to sample directly from the available empirical distribution whereas the other approach samples from a theoretical distribution that fits the data. Historical data may also be used directly as input for the simulation model.

For this AC study, the AC company provided real business data which included historical order releases.

16.1 Data requirements for the simulation model

The data required included:

- Daily releases of orders in the system: Data on when each vehicle was released in the system, including its origin and destination.

- The number of long-distance carriers (140 carriers) and the associated carrier capacities (carrier types). A long-distance carrier may be a 7, 8, 9, 10 or 11 slot carrier. The current number of carriers for each type is as depicted in Table 16.1.

Table 16.1: Fleet composition in terms of carrier type

Carrier type	7	8	9	10	11
Number of carriers	7	3	10	4	10

- Depending on the particular cars loaded, the number of cars a carrier can accommodate may change, due to the size and shape of the particular load. Some cars do not fit on the lower deck of the trailer, and/or may occupy more than one slot (vehicle space). The carrier capacity at a particular location is therefore a function of the carrier type (original carrier capacity) and the current location. An 11 slot carrier may become a 10 slot carrier at a location, due to the types of cars generally distributed from there. The non-homogeneity of the load and the carriers are therefore accommodated by defining Carrier Capacity (CC) as a function of the particular type of carrier and the current location: $CC = f(\text{CarrierType}; \text{CurrentLocation})$.
- The most probable delay times associated with pick-up and delivery at the different locations.
- Servicing of carriers: For an 11 slot carrier, servicing is due every 22 500 kilometres, while other types of carriers need a service every 20 000 kilometres.
- The location of the ‘home’ stations for the different drivers: Where carriers have to be sent to after 14 days of work, to enable drivers to spend 2 days at home.
- The travelling times could be deduced by dividing the distances between AC branches by the average carrier operational speed of 46km/h.
- The current important fixed long distance routes as scheduled for, include:
 1. CT–PE–DBN –PE–CT
 2. DBN–PE–EL–DBN
 3. EL–CT–EL
 4. CT–JHB–CT

5. DBN–BFN–DBN
6. DBN–JHB–DBN
7. EL–JHB–EL

The AC company provided business data covering a period of six months, from July 2007 to December 2007.

16.2 Nature of daily order releases (Demand)

An example of daily releases of orders in the system, as received from the AC company, is shown in Table 16.2.

Table 16.2: Example of order releases

Job Number	Branch	NAAMSA	Release date	Load release date
00003955	04	MOZ	21/10/2007	21/10/2007
00003955	04	N01	09/10/2007	13/10/2007
00004589	04	N01	09/10/2007	13/10/2007
00004590	04	N01	09/10/2007	13/10/2007
0000590202	07	N01	30/10/2007	03/11/2007
0000732974	04	C05	05/10/2007	09/10/2007
0000736622	03	N01	30/10/2007	01/11/2007
0000776170	03	N02	30/10/2007	01/11/2007
...

For a particular month, each vehicle to be delivered has a *Job Number*. The *Branch Code* indicates the depot dispatching the unit, and *NAAMSA* (*National Association of Automobile Manufacturers in South Africa*) Codes show the regions to which the cars must be distributed. The *Release date* is the actual date an order entered the AC system.

From these data, the simulation model inputs were prepared by accumulating the individual releases for each station of origin to all possible destinations (accumulating and considering the relevant NAAMSA regions) for six months. Table 16.3 illustrates the order releases at Durban to all destinations for a given day.

Table 16.3: Input data example: releases at Durban

Day	From DBN			To	
	BFN	CT	EL	JHB	PE
1	1	88	17	2	37
2	17	41	9	349	372
3	0	88	12	72	97
4	4	65	7	62	76
5	3	134	3	101	114
6	3	78	12	69	103
7	0	6	2	0	6
8	0	29	2	1	6
9	6	24	9	75	91
10	3	116	20	433	488
11	1	61	14	21	59
12	2	158	12	138	172
13	11	81	19	201	246
14	0	47	9	125	147
15	0	20	0	1	1
...

These data, obtained from the AC company, were crucial in the construction of a valid simulation model. Orders are released in the system, and directly affect the movements of carriers, i.e. how and where carriers are required. Significant variation is present in the data and an imbalance in flow is evident, as indicated in the Figure 16.1 (Bloemfontein is not included in the picture since it is only a possible destination.)

For this study, the past is repeated by directly using the historical data of six months' order releases as input for the simulation model. It is assumed that the data are sufficient. For the benefit of the simulation model, the data have been arranged in MS-Excel, from where it can be read directly.

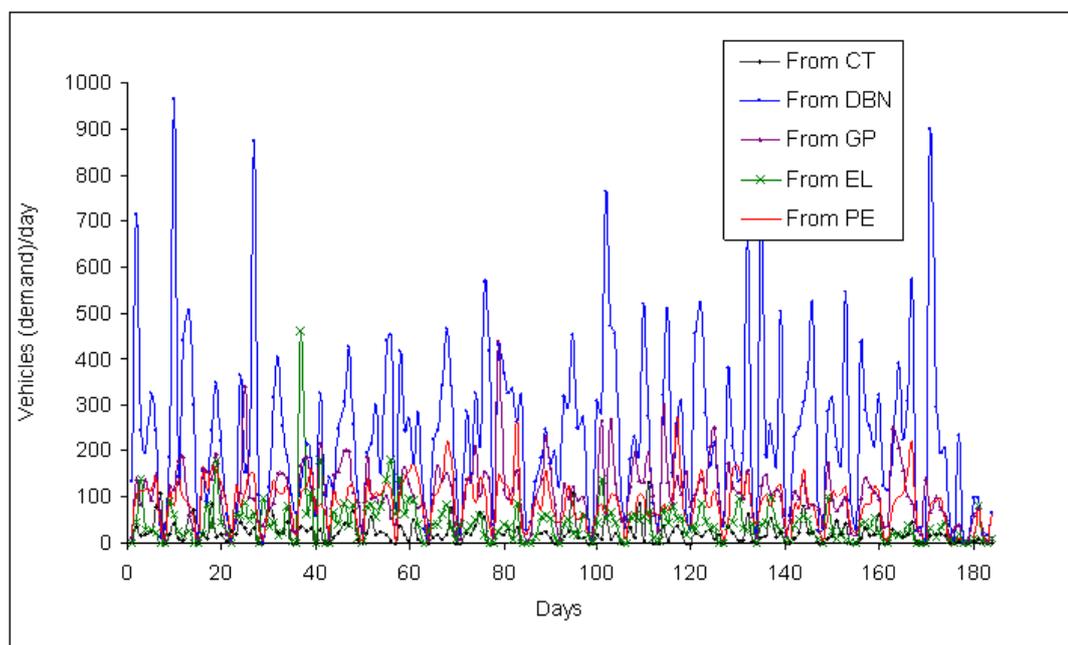


Figure 16.1: AC demand data on long-distance routes

16.3 Concluding remarks: Chapter 16

The input data required for simulating the developed scenarios were discussed in this chapter. Six months' historical data were obtained from the AC company, indicating when each vehicle was released in the system, and its origin and destination. The other information regarding the AC distribution network and functioning, as mentioned in this chapter, was also acquired and used for model construction. In the next chapter simulation validation and verification issues are discussed.

Chapter 17

Validation and Verification

As part of the simulation study steps previously discussed in Chapter 11, the application of validation and verification is discussed in this chapter. Verification focuses on the correctness of the model and includes actions such as inspecting logic, correcting syntax errors, and correcting run-time errors, whereas validation can be defined as asking the question: “Was the right model built?” i.e. is the model an adequate representation of the real-world system? The verification and validation issues investigated here are based on the work of Law & Kelton (2000) and Banks (1998). Validation and verification was done continuously during the simulation model construction and scenario development phases. The validation and verification aspects explored here, were considered for each of the simulated scenarios.

As illustrated in Figure 17.1, verification and validation go hand-in-hand. With the investigation of validation, model verification is also addressed. Validation and verification are therefore discussed jointly in this chapter.

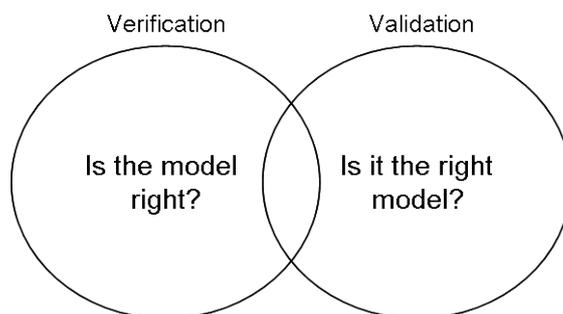


Figure 17.1: Validation and Verification

17.1 Validation and verification approaches followed

In order to have confidence in the simulation model, the following approaches were followed:

- Trying to ‘crash’ the model: Different input data were used to try and uncover potential model errors. Two extreme cases were considered: very low demand, where one or two orders were introduced, while extremely high demands for carriers were induced. The effect of a higher demand in the event of employing only a few carriers, was also inspected. The case of carriers having a capacity of one slot only was also considered. The results obtained, portrayed these changes as had been expected. In the worst cases, the model could not run to completion, due to the build-up of too many entities (orders) in the system.
- The incorporation of outside ‘doubters’ in this study included the involvement of an AC company subject matter expert (SME).
- The model was executed with a single carrier, two and three carriers, with only a few orders. This was done in respect of both fixed and roaming carriers. The correctness of the model was investigated by monitoring the functioning of these few carriers throughout the system. The purpose of this procedure was to investigate whether the model logic is executed correctly for a roaming and a fixed carrier respectively.
- The model was executed with certain parameters which are set to certain values: When carriers have a capacity of one slot, the results reflected the change. When carriers attend only to selected stations/destinations, following specific sequences only, the effects of these actions were as anticipated and were reflected in the outcome. With a carrier capacity of only one slot, orders build up in the system very quickly, resulting in infeasibility. When carriers visit specific destinations only and not all branches, some orders are never picked up and delivered, whereas other orders are delivered steadily.
- Animation: Basic animation was employed to facilitate visual investigation of the model execution.

17.2 Validation factors applied in this study

Conceptual and operational factors were investigated to ensure model validity. Conceptual validity evaluates the adequacy with which the model represents the real world system. A summary of the face validation issues investigated is given later in Table 17.1.

Operational validity: The historical data received from the AC company were processed in order to obtain the information needed in the correct format needed. The AC company verified the processed input data, and the data (orders released in the system) generated by the model was compared to the historical data by means of face validation.

17.3 Model reasonableness

The model behaviour and output were examined for a realistic portrayal of changes made to the model and model input by investigating the following factors.

- Continuity: The difference in input is reflected in the output, and the model showed good continuity. With an increase in demand, the time that cars spend in the system also increases. Additionally, an increase in the average queue length of cars waiting to be distributed, is also noticeable. When there is a decrease in demand, carriers incur more empty kilometres, although the time average that the cars spent waiting, was drastically reduced.
- Consistency: Runs using different random numbers were found to produce similar results.
- Degeneracy: The reduction and addition of active carriers to the system were reflected in the output, by a corresponding increase or decrease in queue length, the empty kilometres driven and the overall time that a vehicle spent in the system.
- Absurd conditions: Extreme conditions investigated, were included in the face validation table. The results portrayed the extremities. With excessive high demand and/or only a few active carriers in place, the model could not run to completion due to the number of orders building up in the system.

17.4 Face validation of the simulation model

Face validation is not a scientific means of validation, but can identify problems in terms of model logic and functioning, as well as correctness by means of inspection and experimentation (Banks (1998)). Included here, is a summary of the face validation matters investigated. In most cases the correctness of functioning was considered for fixed and roaming carriers respectively, since different rules and functioning apply.

Table 17.1: Face validation issues

Carrier Function	Criteria	Fixed	Roaming
Loading	Correct number of orders loaded according to carrier capacity?	✓	✓
	Correct orders loaded for correct destination, and at the correct place?	✓	✓
	Do Carrier Capacity and Capacity Left decrease incrementally as supposed to?	✓	✓
Unloading	Correct orders dropped at correct destination?	✓	✓
	Correct quantity dropped?	✓	✓
	Does Capacity Left increase incrementally as supposed to?	✓	✓
Following route sequences correctly	For route 1, 2, 3, 4, 5, 6 and 7 (see Section 16.1).	✓	NA
Correct assignment of destination(s)	Fixed (for 2 and 3 destination Sequences) carriers: Is destination assigned to carrier the next planned station in sequence.	✓	✓
	Fixed (3 destination sequences): Is destination 2 also assigned correctly?	✓	✓
	Roaming: Is destination assigned correctly according to selected policy?	✓	✓

Continued on next page

Carrier Function	Criteria	Fixed	Roaming
Correct Overall functioning	Correct station capacity assigned to carrier?	✓	✓
	Does carrier wait where it is supposed to?	✓	✓
	Does carrier follow correct logic?	✓	✓
	Are the correct attributes assigned?	✓	✓
14 day Schedule	Is 'Offduty' assigned appropriately?	✓	✓
	Carrier goes to 'Home' station and takes leave correctly?	✓	✓
	Carrier takes leave when unloaded?	✓	✓
Carrier servicing	Carrier departs for CT station when Servicing is due, and when carrier is unloaded.	✓	✓
	After 1 day, carrier departs from CT for the planned destination.	✓	✓
Correct Input Data	Data from the Auto Carriers is Correct and Valid.	✓	✓
	Data is read correctly from Excel into Arena.	✓	✓
	Data is converted correctly into entities (cars) in model?	✓	✓
Other System state variables	Changes in queue lengths: does it make sense?	✓	✓
	Change in the number of carriers on individual routes: correct system response?	✓	✓
	Increase/decrease in available carriers: correct system response?	✓	✓
	Carrier occupation and utilisation levels acceptable.	✓	✓
	Order disposal count.	✓	✓
'Sleep' state of system	Operations stop between 23:00 - 05:00?	✓	✓
	Correct partial travelling.	✓	✓

Continued on next page

Carrier Function	Criteria	Fixed	Roaming
Extreme situations	Only 3 carriers, 10 orders.	✓	✓
	200 Carriers and a few orders.	✓	✓
	Carriers with a capacity of one vehicle space and a high number of orders.	✓	✓
	Tuning the input data: extremely high demand, and excessively low demand.	✓	✓

17.5 Concluding remarks: Chapter 17

In this chapter, verification and validation matters of the simulated model (per scenario) were explored. Verification and Validation go hand in hand, supporting the adequacy of the model in functioning and portraying the real-world problem. The issues mentioned here were investigated in order to develop useful scenarios and to have confidence in the results generated.

Validation and verification were done continuously during the model development phase for each of the scenarios. With confidence in the simulation model functioning, meaningful results could be generated. In the next chapter, the scenario results and the analysis thereof are presented.

Chapter 18

Results and Analysis

The quality of the 45 scenarios were evaluated by estimating the expected values of each of the four performance measures described in Chapter 12, using simulation. The results and subsequent MCDA are presented in this chapter.

For each of the 45 scenarios 10 independent simulation runs were found to provide a sufficient 95% confidence interval per performance measure. These performance measures are used to assess the quality of the generated scenarios. The different performance measure values were acquired during each simulation run to calculate average output values for each scenario.

First the simulation results are shown, followed by the MCDA methods previously identified for evaluating and ranking the scenarios. The outcome of the different MCDA methods is compared and the most favourable scenario characteristics can then be identified. The decision maker is then provided with decision support tools: the SAW, TOPSIS and Mahalanobis rankings, a Cost-Benefit analysis, Fleet portfolio selection by means of an analogy to the efficient frontier, and a sensitivity analysis for strategic planning in terms of the sufficient number of long-distance carriers.

18.1 Scenario results

The notation used to describe the scenarios is shown in Table 18.1.

Table 18.1: Scenario description notation

Policy rule	Description
1.a	Roaming order-picking: Most Work in Queue: Destination where majority of the orders have to go to.
1.b	Roaming order-picking: Priority of Orders.
1.c	Roaming order-picking: Distance: Most work and closest destination.
2.1.i	Waiting policy: Roaming carriers do not wait for work; Fixed carriers wait for work at a location.
2.1.ii	Waiting policy: Fixed and Roaming carriers do not wait for work.
2.1.iii	No waiting at CT and EL.

The results obtained from the simulation runs for each scenario are shown in Table 18.2.

Table 18.2: Summary of simulated scenario results

Scenario Description				Scenario Output			
Label	Policy 1	Policy 2.1	%R/%F	Avg QL	Useful Km (/1000)	Empty Km (/1000)	Avg t (h)
A12	a	iii	25/75	776	76704	47617	286
A11	a	iii	0/100	1196	64322	49105	266
A14	a	iii	75/25	253	85696	40490	116
A13	a	iii	50/50	403	83400	43280	167
A15	a	iii	100/0	240	86619	39401	105
B15	b	iii	100/0	241	86368	38788	106
B12	a	iii	25/75	780	76443	47474	293
B14	b	iii	75/25	263	85224	39706	122
B13	b	iii	50/50	382	83124	42795	162
B11	b	iii	0/100	1253	64100	50265	285
A4	a	i	75/25	3450	42487	10027	1168
A5	a	i	100/0	3866	39480	7807	1233
A1	a	i	0/100	1234	64602	49993	284
A2	a	i	25/75	1786	57937	27797	548
A3	a	i	50/50	2577	50335	13843	874
A10	a	ii	100/0	210	88316	55561	88
A9	a	ii	75/25	233	87753	52087	99

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Scenario Description				Scenario Output			
Label	Policy 1	Policy 2.1	%R/%F	Avg QL	Useful Km (/1000)	Empty Km (/1000)	Avg t (h)
A8	a	ii	50/50	447	85063	47462	178
A7	a	ii	25/75	859	76163	48292	294
A6	a	ii	0/100	1267	64007	50140	272
B6	b	ii	0/100	1267	64007	50140	287
B8	b	ii	50/50	424	85651	47473	180
B9	b	ii	75/25	237	88155	52633	106
B10	b	ii	100/0	198	88222	56421	86
B7	b	ii	25/75	904	76156	47776	323
C1	c	i	0/100	1105	65286	49527	242
C3	c	i	50/50	1867	58271	16021	611
C2	c	i	25/75	1315	64030	30331	424
C5	c	i	100/0	2714	49450	9633	804
C4	c	i	75/25	2235	52562	11974	734
C11	c	iii	0/100	1179	64635	49467	260
C12	c	iii	25/75	822	75882	46923	296
C13	c	iii	50/50	520	80580	40625	199
C14	c	iii	75/25	553	81491	35512	215
C15	c	iii	100/0	616	81692	33912	227
B1	b	i	0/100	1105	65343	49465	243
B2	b	i	25/75	1588	58122	26613	506
B3	b	i	50/50	2241	53266	15883	776
B4	b	i	75/25	2980	46171	12771	1057
B5	b	i	100/0	3352	44071	10832	1061
C10	c	ii	100/0	147	88650	55984	71
C6	c	ii	0/100	1179	64635	49467	260
C9	c	ii	75/25	177	88391	50891	87
C8	c	ii	50/50	336	85358	47566	154
C7	c	ii	25/75	758	76804	46704	282

The Bonferroni inequality states that for k performance measures, the probability that all the confidence intervals cover the respective true means simultaneously is given by (Law & Kelton (2000))

$$P(\mu_k \in I_k, k = 1, 2, \dots, n) \geq 1 - \sum_{k=1}^n \alpha_k. \quad (18.1.1)$$

For each of the four performance measures in this case, and $\alpha = 5\%$, there is a confidence of 95% that the confidence intervals cover their true means. The Bonferroni inequality suggests that there is a reduced confidence of at least 80% that the confidence intervals cover their true measures simultaneously. However, the estimated means are assumed to be correct.

18.2 Analysis of results

The results will now be analyzed. First, the nature of the performance measures, introduced in Chapter 12, is discussed. Then the MCDA and Mahalanobis rankings are shown, after which a Cost-Benefit analysis is considered, as well as the fleet portfolio efficient frontier. Additionally, a sensitivity analysis is also included for strategic analysis.

18.2.1 Investigation of the performance measures

The performance measures used to evaluate the different scenarios are measured in different units. The time spent in the system is measured in hours, the average queue length represents the physical number of cars waiting to be distributed, and the other two measures are expressed in kilometres. The different units of measure implies incomparable ranges of possible values: where the average queue length ranges between 148 and 3 867 cars, the useful kilometres range between 39 481 and 88 650 kilometres.

While *Useful kilometres* is a benefit, *Empty kilometres*, *Average time in the system* and *Queue Length* are costs. These performance measures are conflicting in nature. If only *Empty* and *Useful kilometres* are considered, it is apparent from Figure 18.1 that with an increase in benefit (*Useful km*) there is also an increase in cost. Each point on the graph follows from a scenario.

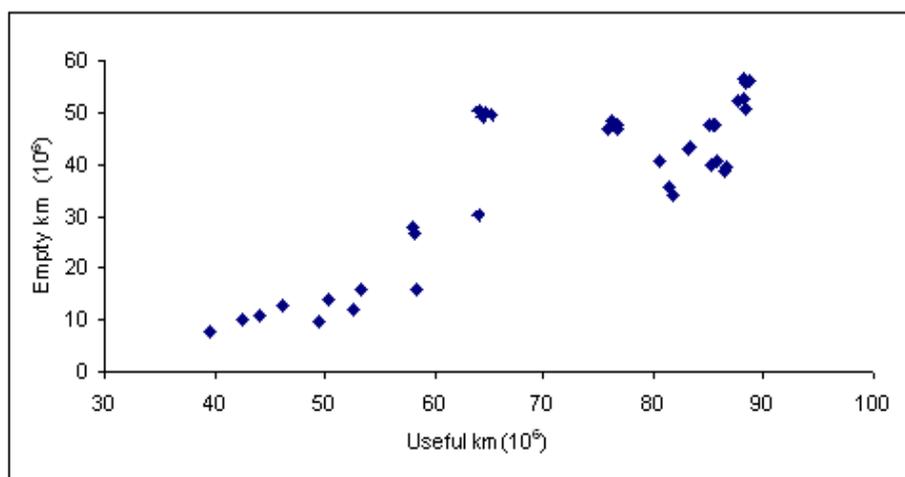


Figure 18.1: Empty km vs. Useful km

When examining *Average time* in the system and *Empty kilometres*, both cost measures should ideally be kept at a minimum. However, from Figure 18.2 fewer *Empty kilometres* is associated with an increase in *Average time* that an order spent in the system and a quick order throughput implies excessive *Empty kilometres*.

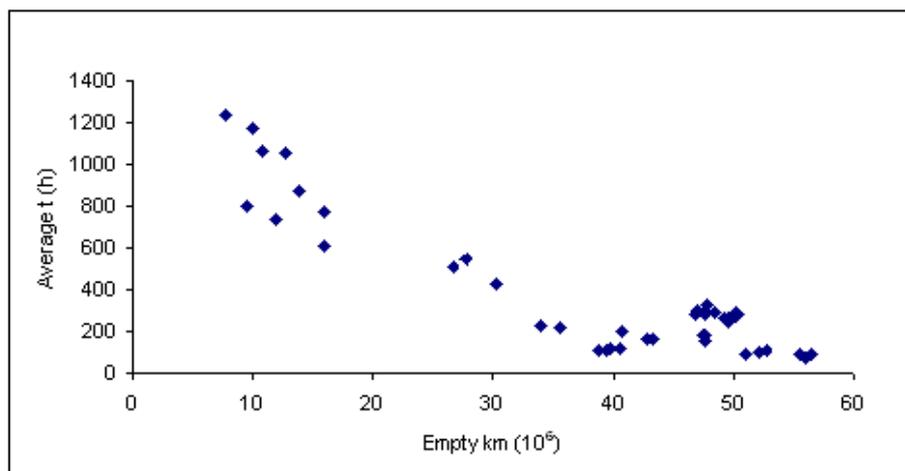


Figure 18.2: Average time vs. Empty kilometres

In order to evaluate the scenarios, taking into consideration the four performance measures which are conflicting in nature and measured in different units, multi-criteria decision analysis is used.

18.2.2 Scenario analysis: MCDA methods and the Mahalanobis distance method

MCDA methods were introduced and investigated earlier in the literature study, where two different multi-attribute decision making methods, namely SAW and TOPSIS, were identified as suitable in this context. The Mahalanobis distance method was also identified as suitable for relative comparison of the 45 scenarios, as it allows for oblique positioning of an ellipsoid within a multi-dimensional attribute space. The Simple Additive Weighting method (SAW) is the most basic MCDA method. TOPSIS comes from the same family, but determines the Euclidean distance for each scenario from the ideal solution. The Mahalanobis distance method differs from TOPSIS, as it accommodates different units of measure, in unnormalized form, while taking into account correlations of the data set.

These three methods were used, due to research curiosity to combine the four performance measures into a single measure. The different rankings could be compared and general tendencies/trends in terms of suitable policy combinations and/or fleet compositions could be identified.

The SAW and TOPSIS methods both require the assignment of weights to the attributes according to the various relevancies. The Mahalanobis distance method takes the performance measures as equally important. For the SAW and TOPSIS ranking results shown in Table 18.3, the four performance measures were given equal weights so that *Average Queue length*, *Time in the system*, *Empty* and *Useful kilometres* had equal effect on the outcome. For the Mahalanobis distance method the scenarios closest to the ideal are best. The Mahalanobis, SAW and TOPSIS rankings are shown in Table 18.3.

Rank reversals are noticeable, which is often the case with some MCDA methods (Wang & Triantaphyllou (2008)). The top scenarios are generally ranked in the same category, but exceptions do occur.

Table 18.3: SAW TOPSIS and Mahalanobis results

Output Mahalanobis			SAW results		TOPSIS Analysis	
Rank	Scenario	MH dist	Scenario	$\varphi(S_i)$	Scenario	R_j
1	C5	0.7005	B15	0.8153	B15	0.8215
2	B15	0.7054	A15	0.8138	A15	0.8188
3	C15	0.7063	A14	0.8002	B14	0.8144
4	A15	0.7176	B14	0.7998	A14	0.8119
5	C14	0.8127	C9	0.7717	C14	0.8008
6	B14	0.8338	C15	0.7653	C15	0.8002
7	A14	0.8359	C14	0.7628	B13	0.7893
8	C3	0.8622	B13	0.7567	A13	0.7854
9	C4	0.9920	A9	0.7561	C13	0.7837
10	C13	1.0614	B9	0.7536	C8	0.7723
11	B13	1.0917	A13	0.7530	C9	0.7714
12	A13	1.0974	C10	0.7522	B8	0.7648
13	A2	1.2084	C8	0.7484	A8	0.7639
14	C2	1.2104	A10	0.7448	A9	0.7638
15	C9	1.2297	B10	0.7412	B9	0.7608
16	A8	1.2586	B8	0.7387	C10	0.7531
17	C8	1.2927	C13	0.7376	A10	0.7516
18	B8	1.2933	A8	0.7346	B10	0.7488
19	A9	1.2989	C7	0.6533	C7	0.7226
20	B2	1.3396	A12	0.6462	A12	0.7169

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Output Mahalanobis			SAW results		TOPSIS Analysis	
Rank	Scenario	MH dist	Scenario	$\varphi(S_i)$	Scenario	R_j
21	B9	1.3548	B12	0.6437	B12	0.7152
22	B5	1.3816	C12	0.6402	C12	0.7129
23	A3	1.4047	A7	0.6326	A7	0.7057
24	B3	1.4304	B7	0.6259	B7	0.6964
25	B1	1.4499	C2	0.6047	B1	0.6854
26	A6	1.4511	C3	0.5714	C1	0.6854
27	C6	1.4513	B1	0.5658	C11	0.6746
28	C11	1.4513	C1	0.5654	C6	0.6746
29	C1	1.4521	B2	0.5576	A11	0.6725
30	A11	1.4531	C11	0.5538	C2	0.6672
31	A10	1.4599	C6	0.5538	A1	0.6620
32	C10	1.4697	A11	0.5516	A6	0.6610
33	B10	1.5225	A1	0.5419	B11	0.6588
34	A1	1.5289	A6	0.5386	B6	0.6573
35	B6	1.5303	B11	0.5365	B2	0.6096
36	B11	1.5441	B6	0.5353	A2	0.5685
37	A7	1.6562	A2	0.5282	C3	0.5582
38	C7	1.6652	C4	0.5120	C4	0.4778
39	C12	1.6826	B3	0.4863	B3	0.4557
40	A5	1.7133	C5	0.4611	C5	0.4096
41	A12	1.7161	A3	0.4381	A3	0.3915
42	B7	1.7439	B4	0.3560	B4	0.3066
43	B12	1.7729	B5	0.3293	B5	0.2841
44	A4	1.8900	A4	0.2959	A4	0.2634
45	B4	2.0926	A5	0.2500	A5	0.2486

When examining the Mahalanobis, SAW and TOPSIS results, it seems that a 50% to 100% Roaming fleet is more favourable, and the policy which specifies that carriers do not wait for work at CT and EL, appear in general to be beneficial. Although more attractive policies of fleet compositions may be identified, it is nevertheless evident from the results that the outcome for each scenario depends not only on one policy or on the fleet composition alone, but on the particular combination of policy decisions and the specific fleet composition. Other than the SAW and TOPSIS, which are MADM methods, the Mahalanobis distance method is in essence a different approach, taking into account the covariances between parameters. This may be a reason for some significant differences in results: Scenario C5 is considered as the best for the Mahalanobis distance method.

In Figure 18.3 the SAW results for the different policy decisions of Policy class 1 are provided. For each policy there is a range of possible results, depending on the particular waiting policy in combination with the fleet composition selected.

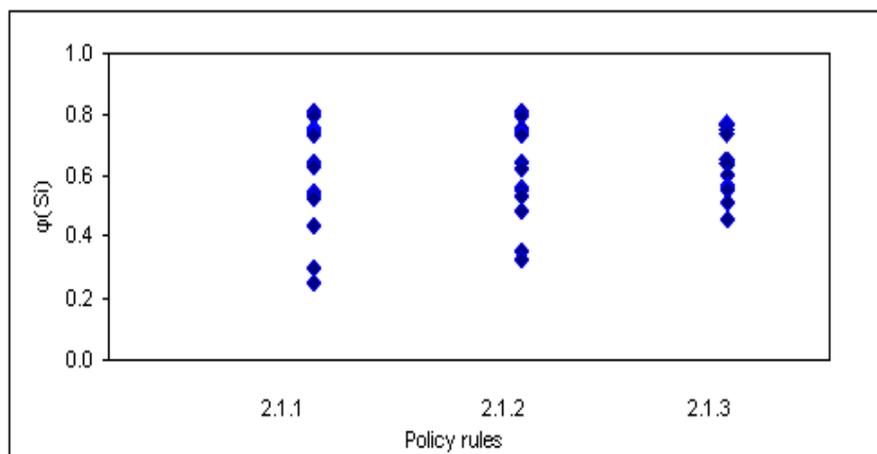


Figure 18.3: Return for Policy class 2.1 rules

Also evident from this figure, is the fact that less variation in outcome is present where the *No wait at CT or EL* policy (policy 2.1.3) applies, whereas the *Roaming do not wait* policy (policy 2.1.1) may be quite undesirable, with a result of 0.25, when combined with Roaming order picking policy 1.a, despite a fleet composition of 75-100% Roaming carriers.

18.2.3 Assigning different weights

When considering the implications and importance of high fuel expenses and the possibility of future price increases, more emphasis on *Empty kilometres* might be required. The *Empty kilometres* evaluation measure is a cost which reflects a lost opportunity caused by a given policy.

To investigate the impact of more emphasis on the *Empty kilometres* cost, the TOPSIS analysis was done for a weight factor of 0.5 associated with the empty kilometres cost factor, and equal weights for the other three measures (where all weights add up to 1).

The results were as follows: the Roaming order-picking policy which also considers the distances from the current location to possible destinations as a penalty (Policy 1.c) in combination with a fleet of 50% - 100% Roaming, is found to be more beneficial. The top scenarios are C3, C15, C4 and C14, after which B15 follows. These results also reflect the importance of empty kilometres with regards to the Waiting policy. The policies which appear most favourable, encompass the retention of Fixed carriers (Policy 2.1.i) and where carriers wait for work, except at CT and EL. Scenario C3, with rank 1, comprises a 50% Roaming fleet in combination with the Waiting policy which stipulates that Fixed carriers wait for work, as to limit *Empty kilometres* cost as much as possible.

18.2.4 Tactical decision support tools

The decision maker (DM) may use the SAW, TOPSIS or Mahalanobis rankings to select a preferred fleet composition and combination of policies, or for identifying more desirable and less desirable tendencies. However, additional visual aids may also be consulted to gain more insight regarding the fleet management of long-distance auto carriers. A cost-benefit analysis reveals some interesting information. Additionally, the fleet portfolio efficient frontier, an analogy to the efficient frontier from investment theory, provides the decision maker assistance, especially with respect to fleet composition.

18.2.4.1 Cost-benefit analysis

The cost benefit graph was constructed as an additional means to evaluate the quality of the different scenarios. A Cost-Benefit analysis is a method used to aid decision making by appraising different options or scenarios. The process involves weighting total expected costs against total benefits, to facilitate the identification of the most favourable option or group of options.

The three costs were integrated into a single measure by applying SAW, where each cost was equal in importance. Note that the analysis could also be done using TOPSIS or Mahalanobis. SAW is arbitrarily used to illustrate the principle.

From the Cost-Benefit analysis shown in Figure 18.4, it is apparent that, although more useful kilometers may be obtained at the cost of more empty kilometres, scenario B15 implies least costs at almost the same benefit and might be most favourable. The family of most desirable scenarios as identified by means of the Cost-Benefit analysis, indicated in blue in the picture, include scenarios: B15, A14, B14, A15, A13, A15, B13, A10, A9, A8, B8, B9, B10, C13, C14, C15, C10, C9, C8.

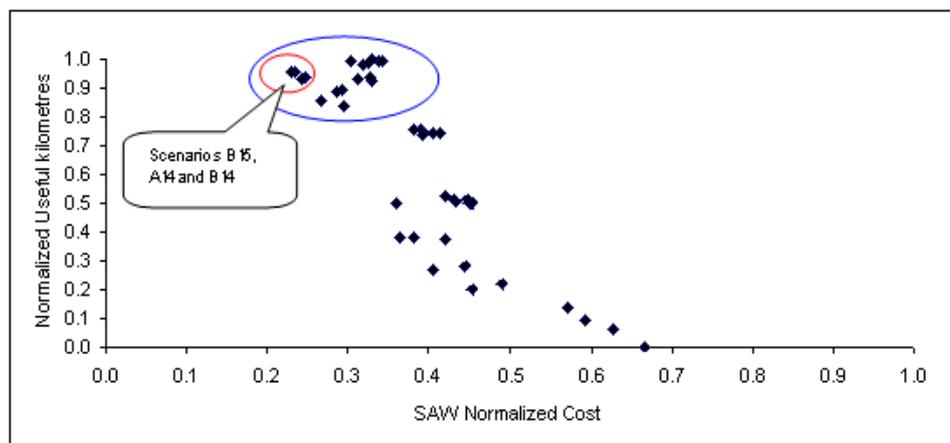


Figure 18.4: Cost-Benefit graph

The results from this graph support the MCDA results: a larger Roaming fleet of 50 - 100% Roaming appears to be beneficial. The most desirable scenarios B15, A14 and B14 also appear in the top seven positions of the SAW, TOPSIS and Mahalanobis rankings. The Cost-Benefit graph also seems to favour the *Fixed and Roaming No Wait* and *No CT/EL Queues* Waiting policies in general.

In general it seems that a fleet composition of 0-50% Roaming does not provide desirable results. However, introducing the method of portfolio selection in this context provides a different view on the effectiveness of fleet composition.

18.2.4.2 Fleet portfolio selection and the fleet portfolio efficient frontier

When concerned with deciding on the most suitable or preferable fleet composition, a 'fleet portfolio' may be selected by introducing an analogy to the efficient frontier. This fleet portfolio is constructed in Figure 18.5 as discussed previously.

In the AC problem, it is worthwhile to investigate and take into consideration the risk associated with the return of a particular 'investment'. In this context the variation for an investment (the specific %R and %F carrier fleet) may be viewed as the 'risk' associated with attaining an expected outcome for that investment.

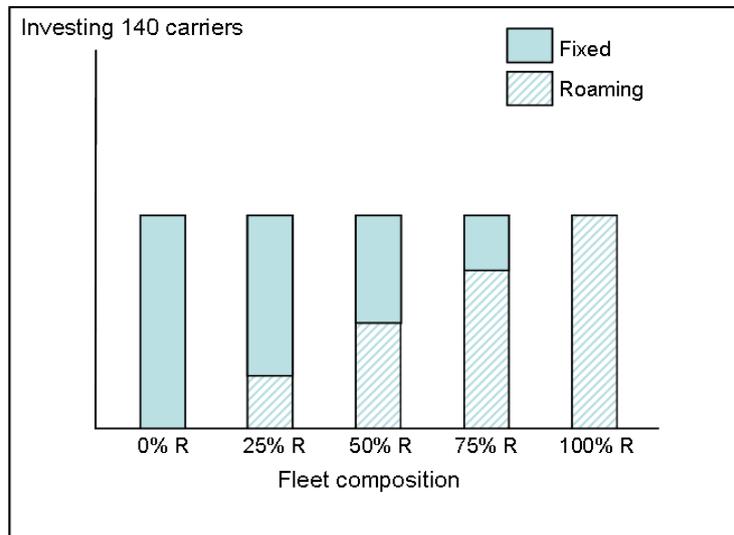


Figure 18.5: Fleet portfolio construction

The expected return of each scenario may be determined by means of the MCDA techniques. The graph in Figure 18.6 is similar to the efficient frontier introduced previously in Chapter 12. In Figure 18.6 the data points resemble the SAW results of the 45 scenarios.

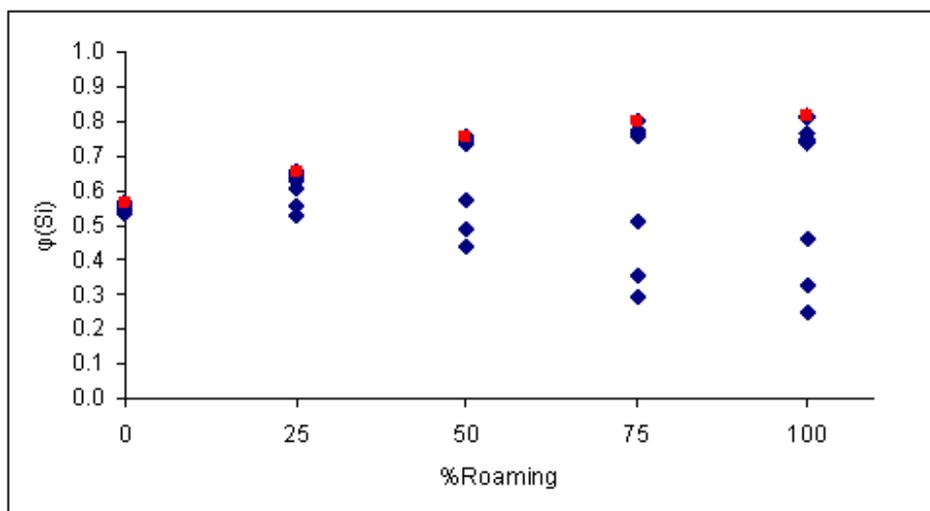


Figure 18.6: Fleet portfolio efficient frontier

It may be noticed that with an increase in roaming carriers, a greater overall return may be expected, although the variation in the outcome is also greater. Therefore, the risk of not getting the expected return, is higher when greater return may be expected. The possible return is evidently much more policy-dependent for a greater Roaming fleet than for no roaming carriers.

Fewer roaming carriers may bring 'surer' return for any operations policy, although not as high as expected that a greater roaming fleet should achieve. A risk-averse decision maker might favour no roaming carriers or a 25% Roaming fleet, whereas a risk seeker could be interested in a 75% - 100% Roaming investment.

The fleet portfolio efficient frontier also indicates which policy combinations are most suitable for each fleet composition. These are shown in Table 18.4.

Table 18.4: Best fleet portfolios

% Roaming	$\varphi(S_i)$	Scenario
100	0.8153	B15
75	0.7998	B14
50	0.7567	B13
25	0.6533	C7
0	0.5658	B1

The roaming order-picking policy 1.b, which considers the order priority in the queue when deciding on a next best destination, in combination with no waiting for work at CT and EL, outperforms the other scenarios for a fleet composition of 50 - 100% Roaming.

When there are no roaming carriers, the roaming order-picking policies do not play a role, and although B1 appears to be most favourable (included in Table 18.4), the results of scenarios B1, A1 and C1 are very close to each other (refer to Table 18.3), and C1 is almost the same as B1 with a $\varphi(S_i)$ value of 0.5654.

18.2.5 Strategic decision aid

For more strategic planning, the required number of carriers might be of interest for current and possible future demands. A sensitivity analysis was done for scenario B15 (the scenario considered best by the SAW and TOPSIS rankings), by generating the SAW results for 120, 140, 160, 180 and 200 carriers for current demand, and repeating it for a 10% increase in demand. TOPSIS analysis also provided a similar outcome. The results are shown in Figure 18.7.

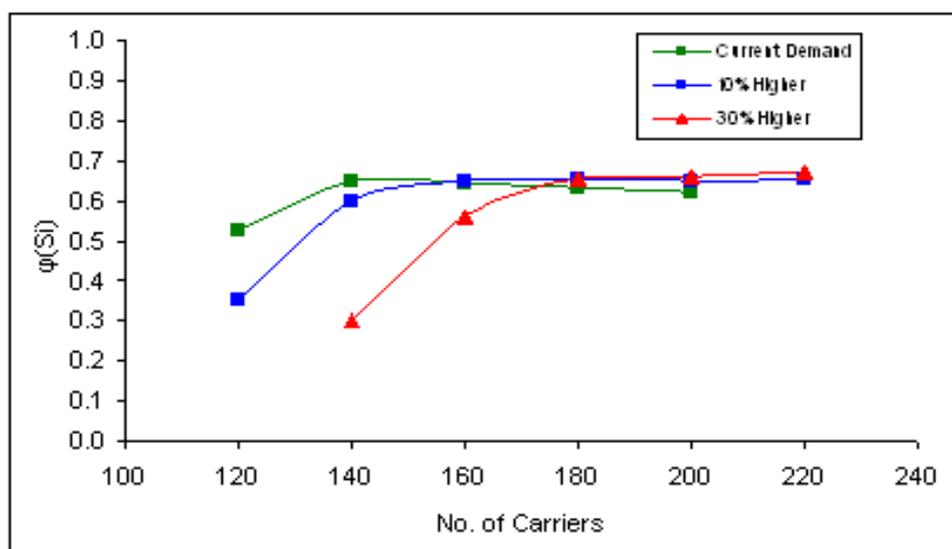


Figure 18.7: Sensitivity Analysis: The required number of carriers

From this graph it is evident that a fleet of 140 carriers would suffice for current demand, while following the requirements of scenario B15. For a 10% increase in demand, an additional 20 carriers will be required, and another 20 carriers for a 30% demand increase.

This graph may be interpreted as an indication of when to acquire additional carriers, and how many carriers, if scenario B15 is followed.

Although the sensitivity analysis for only one scenario, B15, is included here, it may be performed for any other scenario. These results are also dependent on the particular performance measures used. Factors such as carrier maintenance, space needed to accommodate the carriers, driver training and pay, and other costs were excluded.

18.3 Recommendations to the AC company

It is recommended that the AC company adopt a tactical operations policy where 75% of the carriers are allowed to roam, while roaming carriers pick orders according to priority in the queue or most work in the queue, and fixed and roaming carriers do not wait at CT or EL (Scenarios B14 and A14).

The motivation for this recommendation is as follows: The analysis of results indicated that a greater Roaming fleet may induce higher expected return for specific policies when the four performance measures are equally weighted. However, a mixed fleet is suggested where a number of fixed carriers are employed to constitute a sure fleet component. For a 75% Roaming fleet, the 25% fixed carriers ensure some predictability in the system, while the greater Roaming fleet facilitates a high return when employing operational rules 2.1.iii in combination with 1.b, or 2.1.iii in combination with 1.a. The 25% Fixed carriers also have to be assigned to routes as indicated in Table 18.5.

Table 18.5: Assignment of Fixed Carriers for a 25% Fixed fleet

Routes	75% of Max Demand	Proportion	Number of fixed carriers assigned
CT-GP-CT	54.00	13.1%	5
DBN-BFN-DBN	17.25	4.2%	1
DBN-GP-DBN	92.75	22.5%	8
EL-GP-EL	30.50	7.4%	3
EL-CT-EL	5.00	1.2%	0
CT-PE-DBN-PE-CT	100.00	24.3%	9
DBN-PE-EL-DBN	112.25	27.3%	9
Total		100%	35

18.4 Assessment of study results and recommended policies

Since the service level is of particular concern in this industry, the possible benefit of this study for the AC auto carrier company was investigated by comparing the developed scenarios with the actual six month average (July to December 2007) time that an order spent in system.

A greater weight was assigned to the Average time performance measure, and the scenarios could be ranked again according to the TOPSIS analysis. The ten winning scenarios could be compared to the AC company average time in Figure 18.8.

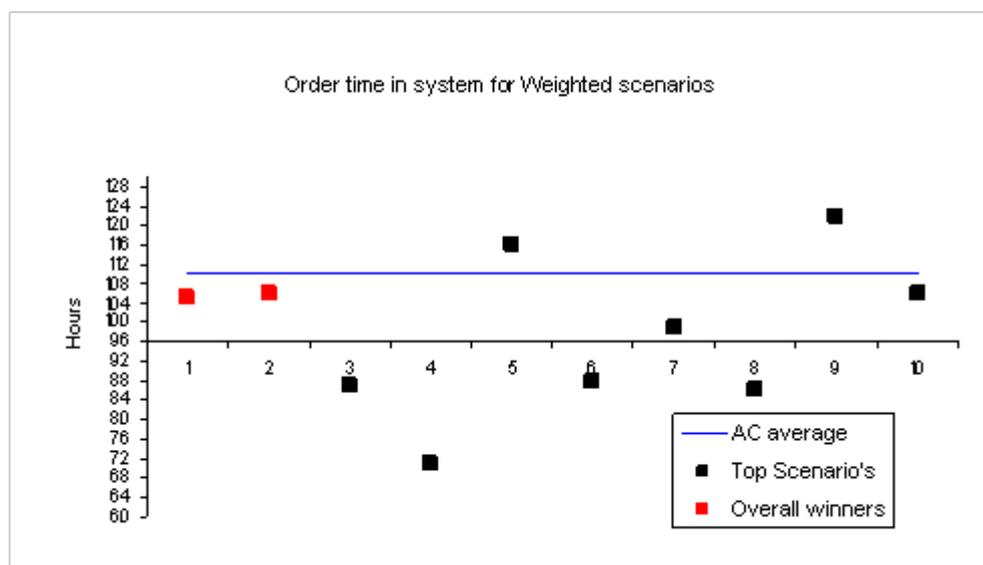


Figure 18.8: Average order time in system

It is evident that the majority of the ten winning scenarios outperform the actual Average time that an order spent in the system. The two red data points represent the overall winners: A15 and B15, which corresponds to the overall winning scenarios for a 100% Roaming fleet from previous analysis. Scenario A14 and B14 are also included in the top ten scenarios.

From this assessment, it is clear that the AC company may benefit from employing a greater roaming fleet in combination with the identified policy rules.

18.5 Response of the AC company

The outcome of this study, and the decision making guidelines introduced were presented to top management at the AC company. They were realistically pleased with the results of this study and the following could be identified as of particular interest:

- They were particularly interested in the suggested greater Roaming fleet. There appears to be conflict across different levels of management between different schools of thought: Fixed vs. Roaming. Branch managers want all carriers fixed, as they feel that this could increase the predictability in the system. But it seems that they are ignorant about the variation and unpredictability of demand on the long-distance routes, as depicted in Figure 16.1. This requires the auto carrier company to be

flexible and agile to some extent. This study explores the fleet composition matter, clearly pointing out the advantages and success of a greater roaming fleet. As a result they want to discuss the results of this study at their strategic board meeting.

- They greatly appreciated the investigation of the demand on their long-distance routes, as shown in Figure 16.1, as this was never before explored. The apparent spikes and uncertainty present were of particular value to them.
- They also approved of, and found the operations policy rules developed as applicable to auto carrier functioning.
- They were also pleased with the *No wait at EL and CT* operations policy rule performing well since this supports their current functioning and operations.
- The sufficient number of carriers was also of interest, since they expect their market share to increase. They expect their demand to increase with a possible 30%.

18.6 Concluding remarks: Chapter 18

Analysis of scenarios and the results were presented in this chapter, in order to provide the decision maker with decision support tools. The tactical planning tools developed involve MCDA with the SAW, TOPSIS and Mahalanobis distance methods, a Cost-Benefit analysis and an analogue to the efficient frontier from portfolio theory. For more strategic decision making regarding the long-distance carrier fleet size, a sensitivity analysis was done for current demand and possible future demands, based on specific scenarios.

When considering the MCDA rankings, results appear to be counter-intuitive as a greater Roaming fleet appears to be more beneficial and keeping carriers waiting seems in general unfavourable. A family or group of best scenarios may be identified by investigating the rankings as well as the Cost-Benefit analysis. By considering the outcome of the 45 scenarios from a different perspective, the Cost-Benefit graph also facilitates the identification of the most desired scenario/scenarios or policy characteristics. The group of best scenarios appear in essence to remain the same for the different MCDA methods, Mahalanobis distance method and Cost-Benefit analysis. As a result, more confidence is gained in the top scenarios presented.

The Mahalanobis distance method enables the evaluation of scenarios in a multi-dimensional attribute space, taking into account correlations of the dataset, and therefore proves to be applicable and a truthful evaluation method

in this context. However, when one or some of the performance measures are more important than the other, the SAW and TOPSIS methods may be helpful as these methods allow the assignment of different weights to the respective attributes.

Another tactical tool was developed by investigating the possibility of applying a portfolio theory perspective to the selection of a suitable fleet composition. A fleet portfolio efficient frontier analogue provided interesting findings, and enables the decision maker to make a choice according to preference. With an increase in roaming carriers, a greater overall return may be expected, although the variation in the outcome is also greater.

The sensitivity analysis showed that 140 carriers appear to be sufficient for current demand if scenario B15 is followed, whereas additional carriers may be required when demand increases are experienced. It was shown how many carriers for a given percentage increase in demand will be required for scenario B15.

Although the Cost-Benefit analysis and the sensitivity analysis for strategic decision making were done for a specific scenario or only selected MCDA ranking results, these analysis tools may be applied to any scenario desired. Different weights may also be assigned to the performance measures when differentiation among attribute importance is required.

The top scenarios identified, showed improved *Average order time in system* over six months when compared with the actual AC data. The results and recommendations were presented to the AC company management, who were realistically pleased with the outcome of this study.

When the AC company decide to implement and execute the identified preferred policy rules and fleet composition, it will also be necessary to train employees to understand and accept these policies. As the market demand grows or flows on the long-distance routes changes, the analysis should be repeated to adopt the appropriate operational policies. This study provides them with the means to do so.

Chapter 19

Conclusion and Project Summary

For the purpose of this thesis, a simulation study was done in collaboration with a South African auto carrier company, with the aim to improve current carrier fleet management. The objective was to develop a tactical decision aid tool that will provide insight regarding the best fleet composition for particular operational policy combinations by means of simulation.

A literature study was done to investigate what has been done in terms of auto carrier specific studies, general freight operations and tactical freight operations. From the literature possible formulation and solution tools were investigated for applicability in the Auto Carrier problem context.

The Auto Carrier problem, as formulated for the purpose of this study, could be described and identified according to the DRTP formulation dimensions. Simulation was identified as a suitable tool for addressing the real-world dynamics, constraints and uncertainty of this problem, including problem-specific requirements like nonhomogeneous carriers and cars, sending drivers to their specific home bases after 14 days of work, the servicing of carriers and the backlogging of unlimited time periods.

The solution development phase involved acquiring data, concept modelling, developing the simulation model, developing scenarios, verification and validation of the simulation models, generating results per scenario and analysis of results.

The performance measures found relevant to the evaluation of this problem were identified as average queue length of cars waiting to be distributed, average time that orders spent in the system, the useful kilometres a carrier travelled and the empty kilometres. Six months' data were obtained from the

AC company, and was used as input for the simulation model.

45 scenarios were evaluated with simulation and results generated. The SAW, TOPSIS and Mahalanobis distance methods were applied to rank scenarios. Investment theory and portfolio selection were examined, and an analogy to the efficient frontier was applied to address fleet composition decisions in particular.

In analysing the results, different tactical decision aid tools could be developed. The decision maker may use the different MCDA rankings, a Cost-Benefit analysis and/or the fleet portfolio efficient frontier to decide on more beneficial operational policies and fleet compositions. Additionally, a sensitivity analysis was done to facilitate strategic planning regarding the sufficient number of carriers for current and possible future demands.

The results and analysis revealed that:

- A greater Roaming fleet is, in general, more beneficial.
- However, more variation in the outcome may be expected for a greater Roaming investment, and the results may be said to be more policy-dependent.
- Retention of carriers appears to be, in general, not beneficial. The intuitive idea that carriers may only depart for the next destination once they are full, was proven to be ineffective.
- With more emphasis on the cost of empty kilometres, the Roaming order-picking policy which takes the distance between destinations into consideration, appears to be more favourable.
- The *No wait at CT and EL* Waiting policy rule appeared to perform well.
- Results are not dependent on one policy only, but depend on the combination of policies and specific fleet composition.
- 140 carriers appear to be sufficient for current demand and a given scenario, and possibly a different scenario and/or higher demand in the future may require additional carriers.

The particular value of this study was confirmed when the outcome and the findings of this work were presented to the AC company. They were very interested in the results, as this study addressed matters of conflict across different levels of management. This study also provided more insight into the dynamics of auto carrier functioning and operations. The greater roaming fleet was of particular interest, as well as the *No wait at CT and EL* policy rule.

The tactical and strategic decision support developed in this study presents the decision maker with the opportunity to make medium-term and longer-term decisions concerned with auto carrier fleet management on a once-off and on a continuous basis.

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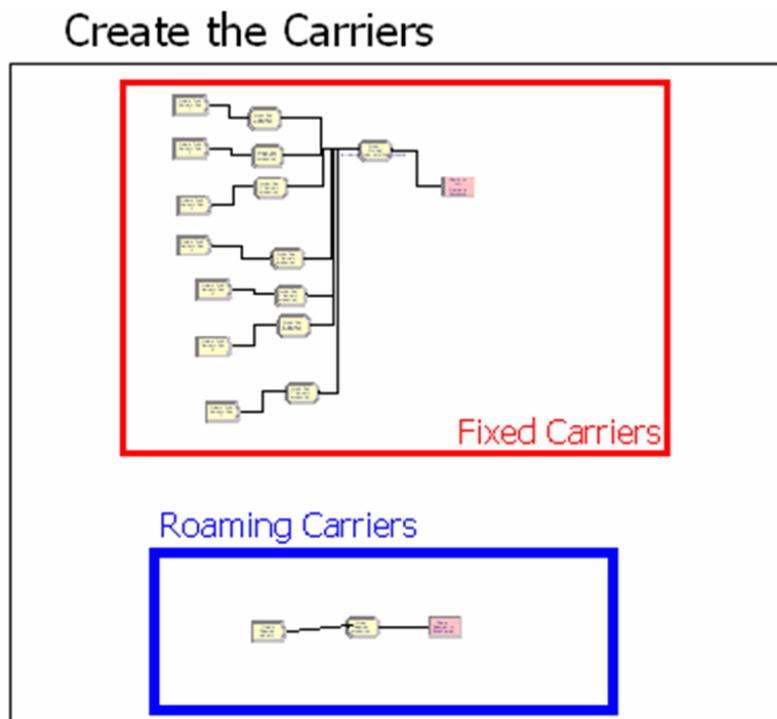
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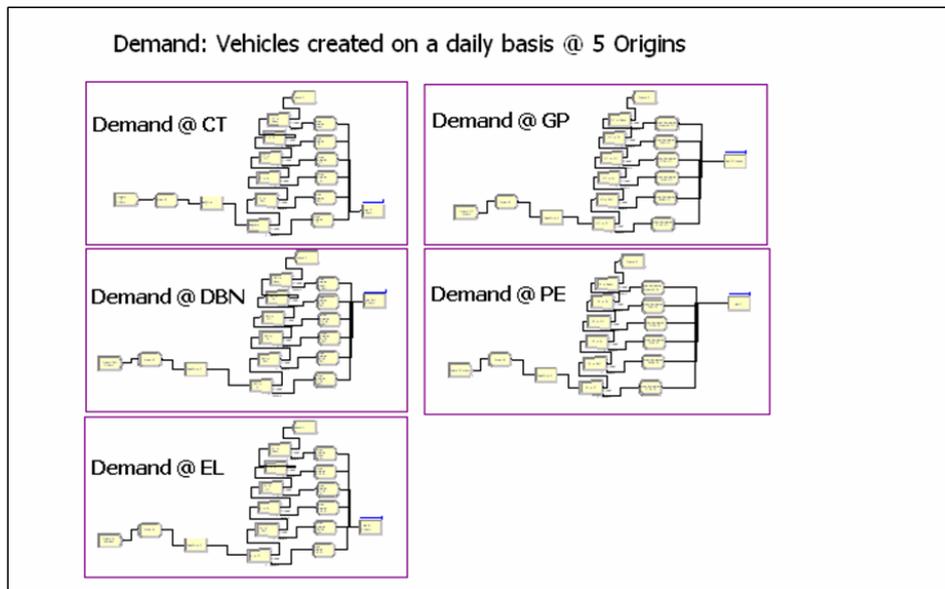
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Overview of model logic in Arena

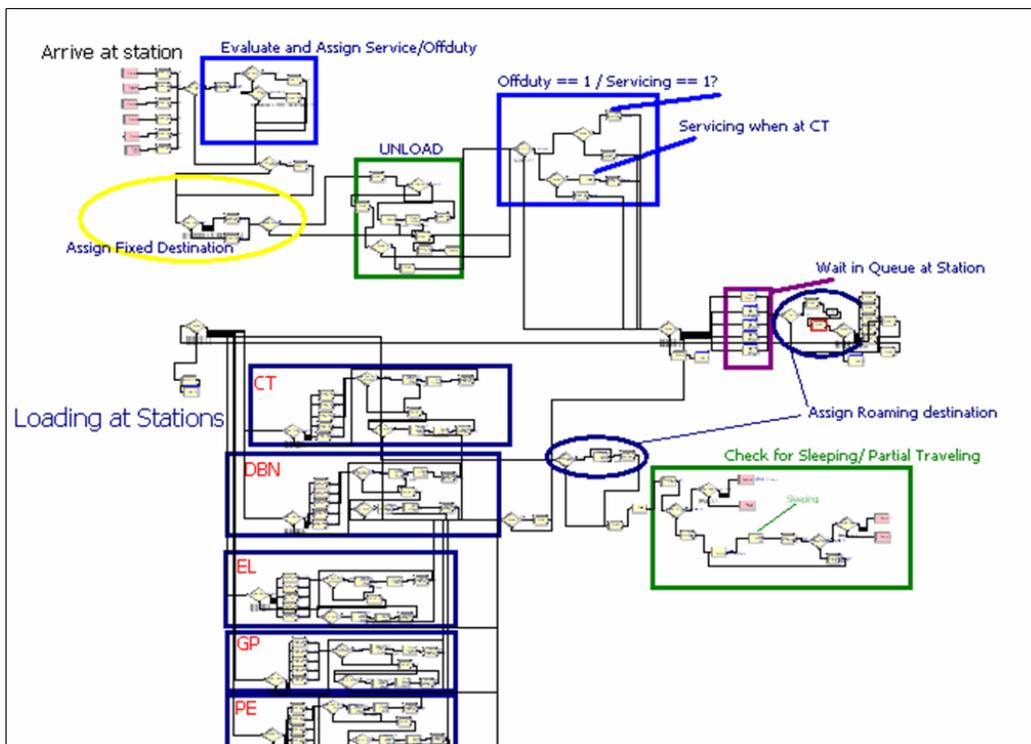
A few snapshots of the simulation model implementation in Arena are shown below. The purpose is to show implementation on a high level without elaborating on the detail coding.



Carriers are created once-off at the beginning of each simulation run and remain in the system, whereas orders arrive in the system on a daily basis and leave the system when delivered.



The model logic, executed when a carrier arrives at a location, is shown below.



Scenario Output

The detail model output of the 45 scenarios generated with the Arena simulation models are included on the following pages.

	A12	1.a	2.1.iii	25R/75F		A14	1.a	2.1.iii	75R/25F
	Roaming order-picking policy: Most work in Q Waiting policy: NO CT/EL queue 10 reps; 2week warmup					Roaming order-picking policy: Most work in Q Waiting policy: NO CT/EL queue 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system		QL ave	Useful KM	Empty KM	Ave t in system
	736	78304	48964	274		247	86019	40743	114
	749	78010	47016	281		258	85753	40156	117
	727	77821	48154	271		272	85408	40140	124
	774	76917	47622	286		215	85762	41704	106
	811	75499	48026	285		245	86138	41289	107
	764	76841	49255	291		270	85648	40240	121
	868	74261	45977	316		253	85377	39968	119
	833	75117	45646	301		264	85058	39123	124
	709	78178	48517	271		264	86070	41179	115
	791	76096	47002	285		245	85735	40365	116
Mean of means	776.1	76704.4	47618.0	286.1		253.2	85697.0	40490.7	116.4
Standard deviation	50.0	1416.6	1205.5	14.1		16.9	340.4	753.2	6.1
Halfwidth	29.0	821.1	698.8	8.1		9.8	197.3	436.6	3.5
Confidence Interval	747.2	75883.3	46919.2	278.0		243.4	85499.7	40054.1	112.9

	A11	1.a	2.1.iii	0R/100F	A13	1.a	2.1.iii	50/50
	Roaming order-picking policy: Most work in Q Waiting policy: NO CT/EL queue 10 reps; 2week warmup				Roaming order-picking policy: Most work in Q Waiting policy: NO CT/EL queue 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	1209	63836	48888	256	465	83013	42067	179
	1197	63907	48942	274	446	83157	42355	178
	1255	63079	48078	290	371	83793	43943	158
	1103	66319	51043	235	294	84164	45223	132
	1241	63782	49899	277	366	83274	43884	163
	1126	66637	50309	237	376	83203	43226	160
	1238	63076	47413	286	553	82632	41148	214
	1250	63313	48849	293	462	83249	43193	185
	1208	64233	48561	272	326	83876	43942	144
	1133	65041	49072	243	381	83646	43828	164
Mean of means	1196.0	64322.2	49105.5	266.3	404.0	83400.7	43280.7	167.7
Standard deviation	55.7	1277.5	1064.0	21.9	76.7	459.6	1164.4	22.6
Halfwidth	32.3	740.5	616.8	12.7	44.5	266.4	674.9	13.1
Confidence Interval	1163.7	63581.7	48488.7	253.6	359.5	83134.3	42605.8	154.6

	A15	1.a	2.1.iii	100R/0F	B12	1. b	2.1.iii	25R/75F
	Roaming order-picking policy: Most work in Q Waiting policy: NO CT/EL queue 10 reps; 2week warmup				Roaming order-picking policy: Priority Waiting policy: NO CT/EL queue 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	234	87144	40602	100	815	77041	47987	302
	241	86851	39290	105	677	78270	47547	263
	237	86626	39644	106	693	78323	48433	259
	240	86261	39271	105	816	76032	46528	305
	235	86800	39649	105	790	75891	48119	288
	240	86471	39488	104	783	76421	48821	302
	242	86489	38981	105	901	73377	45908	342
	255	86146	38277	112	792	76087	46157	292
	253	86484	39143	108	715	77601	48175	278
	232	86919	39666	101	821	75397	47068	304
Mean of means	241.0	86619.1	39401.2	105.1	780.3	76443.9	47474.3	293.5
Standard deviation	7.8	309.3	594.2	3.2	67.9	1478.4	1008.6	23.9
Halfwidth	4.5	179.3	344.4	1.9	39.4	856.9	584.6	13.8
Confidence Interval	236.4	86439.8	39056.8	103.2	740.9	75587.0	46889.6	279.7

	B15	1. b	2.1.iii	100R/0F	B14	1. b	2.1.iii	75R/25F
	Roaming order-picking policy: Priority Waiting policy: NO CT/EL queue 10 reps; 2week warmup				Roaming order-picking policy: Priority Waiting policy: NO CT/EL queue 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	248	86323	38646	105	263	85242	39780	120
	252	85801	37596	112	267	85274	39840	124
	231	86979	39692	100	264	85133	39843	118
	232	86486	39103	103	246	85305	40442	114
	225	86747	39862	100	260	85516	39831	120
	225	87096	39865	97	249	85414	40267	122
	229	86037	38585	107	279	84954	38722	131
	255	85850	37768	113	283	85096	38389	133
	263	86026	38013	120	259	85705	40627	116
	251	86340	38753	107	269	84610	39321	129
Mean of means	241.1	86368.6	38788.2	106.4	263.9	85224.7	39706.2	122.4
Standard deviation	14.1	457.0	840.2	7.1	11.6	305.0	716.0	6.4
Halfwidth	8.2	264.9	487.0	4.1	6.7	176.8	415.0	3.7
Confidence Interval	232.9	86103.7	38301.2	102.3	257.2	85048.0	39291.2	118.7

	B13	1. b	2.1.iii	50R/50F	A4	1. a	2.1.i	75R/25F
	Roaming order-picking policy:Priority Waiting policy: NO CT/EL queue 10 reps; 2week warmup				Roaming order-picking policy:Most Work in Q Waiting policy: Roaming No WAiT 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	420	83034	41922	170	3450	43113	10432	1140
	473	82631	40825	191	3508	42162	9936	1237
	375	83809	43985	158	3334	43191	10798	1110
	283	83723	44457	130	3183	44220	11008	1096
	350	83257	43660	152	3637	39837	8052	1213
	350	83141	43627	157	3768	41420	9595	1233
	408	82474	41351	172	3512	43508	10580	1169
	478	82784	42066	192	3067	42636	10250	1069
	336	83365	43014	147	3596	43830	10660	1209
	350	83026	43045	154	3454	40957	8968	1206
Mean of means	382.5	83124.2	42795.3	162.3	3450.9	42487.5	10027.9	1168.2
Standard deviation	62.3	435.0	1201.4	19.3	209.8	1389.2	924.6	60.7
Halfwidth	36.1	252.1	696.4	11.2	121.6	805.3	535.9	35.2
Confidence Interval	346.4	82872.1	42098.9	151.1	3329.2	41682.2	9491.9	1133.0

	B11	1. b	2.1.iii	0R/100F	A5	1. a	2.1.i	100%R/0F
	Roaming order-picking policy: Priority Waiting policy: NO CT/EL queue 10 reps; 2week warmup				Roaming order-picking policy: Most Work in Q Waiting policy: Roaming No WAiT 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	1302	63858	51577	300	3710	39832	8301	1209
	1182	64373	49874	261	3625	41449	8534	1222
	1316	62153	49190	297	3425	41248	8862	1116
	1127	66193	50919	260	3725	41239	8615	1222
	1273	64299	50282	300	4226	39044	7404	1277
	1222	66525	52086	262	4239	39223	7933	1297
	1269	62184	48857	296	3998	37648	6488	1260
	1255	62559	49617	298	4021	38450	7204	1276
	1280	65281	50484	298	3842	37751	7003	1249
	1310	63577	49766	283	3856	38923	7734	1209
Mean of means	1253.6	64100.3	50265.1	285.6	3866.7	39480.7	7807.7	1233.7
Standard deviation	60.5	1561.3	1025.9	17.5	260.1	1421.9	779.7	51.6
Halfwidth	35.1	905.0	594.7	10.2	150.7	824.2	451.9	29.9
Confidence Interval	1218.6	63195.3	49670.5	275.5	3716.0	38656.5	7355.8	1203.8

	A1	1. a	2.1.i	0R/100F	A3	1. a	2.1.i	50R/50%F
	Roaming order-picking policy: Most Work in Q Waiting policy: Roaming No WAiT 10 reps; 2week warmup				Roaming order-picking policy: Most Work in Q Waiting policy: Roaming No WAiT 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	1153	65357	51334	233	2522	50440	13973	845
	1191	65396	50264	271	2616	52151	14516	897
	1160	62556	50322	283	2885	48184	13002	975
	1278	64823	49882	305	2380	52639	14900	824
	1394	62197	48422	325	2723	51541	14311	943
	1188	64559	48709	299	2629	50784	13964	881
	1346	64601	48759	297	2782	48644	13370	942
	1163	64948	50725	247	2356	50443	14020	806
	1211	67555	52349	276	2787	46281	11995	898
	1264	64035	49170	309	2095	52253	14382	732
Mean of means	1234.7	64602.8	49993.6	284.6	2577.6	50336.0	13843.3	874.3
Standard deviation	83.4	1504.9	1264.8	28.5	242.7	2051.8	849.1	73.5
Halfwidth	48.3	872.3	733.2	16.5	140.7	1189.3	492.2	42.6
Confidence Interval	1186.4	63730.5	49260.4	268.0	2436.9	49146.6	13351.1	831.7

	A2	1. a	2.1.i	25R/75%F	A10	1. a	2.1.ii	100%R/0F
	Roaming order-picking policy: Most Work in Q Waiting policy: Roaming No WAiT 10 reps; 2week warmup				Roaming order-picking policy: Most Work in Q Waiting policy: Roaming + Fixed No WAiT 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	1488	58457	28414	491	215	88656	55676	82
	2033	57063	23979	615	195	87820	55163	90
	1771	59170	28344	538	207	88567	54760	94
	1597	58679	28262	514	147	87607	56671	77
	1882	57266	28950	575	215	88160	57652	85
	1788	58762	29257	572	181	88527	56941	81
	1982	58587	30934	571	284	88832	53910	113
	1987	57726	28216	598	199	88437	53516	94
	1634	57215	25625	486	248	88006	56053	86
	1705	56454	25990	527	215	88548	55274	88
Mean of means	1786.8	57937.8	27797.1	548.7	210.6	88316.1	55561.7	88.9
Standard deviation	183.5	908.4	2025.9	44.1	36.9	398.3	1314.5	10.0
Halfwidth	106.4	526.5	1174.3	25.5	21.4	230.9	761.9	5.8
Confidence Interval	1680.5	57411.3	26622.8	523.1	189.2	88085.2	54799.7	83.1

	A9	1. a	2.1.ii	75%R/25F	A7	1. a	2.1.ii	25%R/75F
	Roaming order-picking policy: Most Work in Q Waiting policy: Roaming + Fixed No WAiT 10 reps; 2week warmup				Roaming order-picking policy: Most Work in Q Waiting policy: Roaming + Fixed No WAiT 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	232	87942	51386	100	842	76471	48099	290
	208	87841	51295	100	912	76379	46891	304
	294	88181	52835	111	892	76725	49729	311
	209	88108	51135	97	794	75892	50001	265
	203	87237	54197	86	683	76595	49455	239
	221	88050	51259	89	711	77429	48961	250
	236	87138	52151	104	1049	73394	45361	352
	177	86478	51864	83	998	74977	47647	327
	259	88127	53632	105	781	77329	48985	281
	292	88434	51117	118	935	76442	47801	326
Mean of means	233.2	87753.8	52087.2	99.2	859.6	76163.2	48292.9	294.4
Standard deviation	38.5	606.9	1110.7	10.9	119.5	1194.1	1434.2	36.2
Halfwidth	22.3	351.8	643.8	6.3	69.2	692.2	831.3	21.0
Confidence Interval	210.9	87402.0	51443.4	92.9	790.4	75471.0	47461.6	273.4

	A8	1. a	2.1.ii	50%R/50F	A6	1. a	2.1.ii	0R/100%F
	Roaming order-picking policy: Most Work in Q Waiting policy: Roaming + Fixed No Wait 10 reps; 2week warmup				Roaming order-picking policy: Most Work in Q Waiting policy: Roaming + Fixed No Wait 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	583	86073	46896	207	1302	63858	51577	285
	342	84776	47538	149	1182	64373	49874	249
	473	85715	48839	180	1316	62153	49190	279
	561	85149	49457	205	1216	66101	49976	255
	329	83217	47027	139	1273	64299	50282	286
	567	85627	46789	220	1222	66525	52086	248
	360	83350	46737	161	1316	61346	48554	291
	399	84944	46921	156	1255	62559	49617	281
	485	86297	47673	196	1280	65281	50484	282
	379	85483	46750	175	1310	63577	49766	268
Mean of means	447.6	85063.1	47462.6	178.8	1267.2	64007.2	50140.5	272.2
Standard deviation	98.6	1049.3	955.3	27.6	47.1	1679.7	1049.8	16.3
Halfwidth	57.1	608.2	553.7	16.0	27.3	973.6	608.5	9.5
Confidence Interval	390.4	84454.9	46908.9	162.7	1239.8	63033.6	49532.0	262.7

	B6	1. b	2.1.ii	100%F/0R	B9	1. b	2.1.ii	75%R/25F
	Roaming order-picking policy: Priority Waiting policy: Roaming + Fixed No Wait 10 reps; 2week warmup				Roaming order-picking policy: Priority Waiting policy: Roaming + Fixed No Wait 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	1302	63858	51577	300	267	88311	52017	114
	1182	64373	49874	261	249	88231	51712	117
	1316	62153	49190	297	203	88184	52770	94
	1216	66101	49976	268	234	87453	52612	96
	1273	64299	50282	300	203	87230	56711	86
	1222	66525	52086	262	193	88281	52774	95
	1316	61346	48554	308	264	88325	50756	114
	1255	62559	49617	298	229	88213	52651	100
	1280	65281	50484	298	242	88371	52769	116
	1310	63577	49766	283	288	88954	51563	126
Mean of means	1267.2	64007.2	50140.5	287.6	237.1	88155.2	52633.5	106.0
Standard deviation	47.1	1679.7	1049.8	17.7	31.1	484.4	1584.1	13.2
Halfwidth	27.3	973.6	608.5	10.3	18.0	280.8	918.2	7.6
Confidence Interval	1239.8	63033.6	49532.0	277.3	219.1	87874.4	51715.3	98.4

	B8	1. b	2.1.ii	50%R/F	B10	1. b	2.1.ii	100%R
	Roaming order-picking policy: Priority Waiting policy: Roaming + Fixed No Wait 10 reps; 2week warmup				Roaming order-picking policy: Priority Waiting policy: Roaming + Fixed No Wait 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	294	85489	50289	132	191	88647	56867	88
	530	85788	47419	213	211	88172	56112	106
	457	86281	48297	191	172	88216	55328	81
	461	85192	47108	193	173	88327	56823	75
	412	84799	46953	185	210	88167	58869	87
	321	85629	47651	158	216	87891	58144	94
	417	84876	45948	184	179	88676	54451	88
	431	85671	46812	188	214	88417	54059	80
	444	86323	48129	182	188	88443	56256	81
	478	86465	46132	183	226	87265	57308	87
Mean of means	424.5	85651.3	47473.7	180.9	198.2	88222.2	56421.8	86.8
Standard deviation	70.6	586.3	1248.8	21.8	19.6	410.4	1523.4	8.8
Halfwidth	40.9	339.9	723.9	12.6	11.4	237.9	883.0	5.1
Confidence Interval	383.6	85311.4	46749.8	168.3	186.8	87984.3	55538.7	81.7

	B7	1. b	2.1.ii	25%R	C8	1.c	2.1.ii	50F/50%R
	Roaming order-picking policy: Priority Waiting policy: Roaming + Fixed No Wait 10 reps; 2week warmup				Roaming order-picking policy: Distance Waiting policy: Roaming No Wait 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	966	75733	48186	332	2039	57342	15541	645
	821	76024	48308	315	1779	62301	18508	581
	825	76398	46999	296	1901	58337	15996	631
	1068	76961	47760	368	1772	56867	15655	585
	880	76909	48332	312	1798	59251	16783	611
	748	77208	48319	278	1989	57583	15570	635
	1212	73734	45489	416	1796	56558	14670	588
	1005	76040	47707	352	1849	59837	17130	597
	808	76969	48797	300	1844	56799	14683	622
	715	75591	47867	263	1911	57837	15681	626
Mean of means	904.6	76156.6	47776.3	323.2	1867.8	58271.1	16021.7	612.0
Standard deviation	155.9	1024.0	939.7	45.6	91.3	1771.8	1168.9	23.0
Halfwidth	90.4	593.6	544.7	26.4	52.9	1027.0	677.6	13.4
Confidence Interval	814.3	75563.0	47231.6	296.8	1814.8	57244.1	15344.1	598.6

	C6	1.c	2.1.ii	100F/0%R		C7	1.c	2.1.ii	75F/25%R
	Roaming order-picking policy: Distance Waiting policy: Roaming No Wait 10 reps; 2week warmup					Roaming order-picking policy: Distance Waiting policy: Roaming No Wait 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system		QL ave	Useful KM	Empty KM	Ave t in system
	1152	64582	49082	253		1411	62313	28078	447
	1097	65767	49659	230		1177	66796	32385	382
	1186	63148	47906	283		1258	63940	29419	407
	1052	66958	51868	219		1162	67287	35503	404
	1122	64483	50144	258		1281	63780	30851	413
	1058	66241	48795	240		1343	63487	29581	424
	1184	62500	46647	261		1401	62677	29244	453
	1128	65448	48998	257		1415	62270	28639	454
	1021	67358	51792	209		1331	63213	28960	419
	1057	66382	50383	221		1375	64541	30657	439
Mean of means	1105.7	65286.6	49527.4	243.0		1315.3	64030.3	30331.7	424.3
Standard deviation	58.1	1596.3	1622.0	23.3		93.1	1745.8	2204.6	23.9
Halfwidth	33.7	925.3	940.2	13.5		54.0	1011.9	1277.9	13.8
Confidence Interval	1072.0	64361.3	48587.2	229.5		1261.3	63018.4	29053.8	410.4

	C10	1.c	2.1.ii	0F/100%R		C11	1.c	2.1.iii	100F/0%R
	Roaming order-picking policy: Distance Waiting policy: Roaming No Wait 10 reps; 2week warmup					Roaming order-picking policy: Distance Waiting policy: No CL/EL Q 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system		QL ave	Useful KM	Empty KM	Ave t in system
	2700	49267	9077	803		1206	63916	49249	255
	2611	50339	9720	781		1189	64314	49006	265
	2817	51030	10544	821		1246	63409	48224	283
	2562	51926	10781	754		1101	66208	50966	233
	2636	49588	10047	814		1215	63933	49987	268
	2925	47617	8683	835		1091	66879	50932	226
	2717	50822	10148	791		1203	63517	48118	278
	2711	46432	8128	805		1201	64172	49291	277
	2738	50552	10559	786		1191	64923	49275	267
	2730	46930	8650	854		1149	65081	49624	247
Mean of means	2714.8	49450.4	9633.8	804.5		1179.4	64635.2	49467.3	260.1
Standard deviation	103.2	1867.3	936.4	28.8		50.1	1148.7	965.1	19.4
Halfwidth	59.8	1082.4	542.8	16.7		29.0	665.8	559.4	11.3
Confidence Interval	2655.0	48368.0	9091.0	787.8		1150.4	63969.4	48907.9	248.8

	C9	1.c	2.1.ii	25F/75%R		C12	1.c	2.1.iii	75F/25%R
	Roaming order-picking policy: Distance Waiting policy: Roaming No Wait 10 reps; 2week warmup					Roaming order-picking policy: Distance Waiting policy: No CL/EL Q 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system		QL ave	Useful KM	Empty KM	Ave t in system
	2238	54069	12363	740		889	76562	46686	326
	2014	54659	12563	690		886	76957	46080	306
	2163	52838	11703	710		834	74687	46448	312
	2068	52169	11967	714		670	76713	47834	249
	2390	51438	11157	773		710	78041	48931	248
	2511	50644	11337	828		737	74240	47425	282
	2352	52049	12106	735		912	74255	46056	333
	2367	52772	12443	742		813	75053	45381	297
	2140	52811	11813	710		915	76231	48198	306
	2115	52180	12293	705		863	76082	46195	304
Mean of means	2235.8	52562.9	11974.5	734.8		822.9	75882.2	46923.4	296.2
Standard deviation	162.2	1171.7	472.5	40.6		88.4	1273.4	1124.9	28.8
Halfwidth	94.0	679.1	273.9	23.5		51.2	738.1	652.1	16.7
Confidence Interval	2141.8	51883.8	11700.6	711.3		771.7	75144.0	46271.4	279.5

	C13	1.c	2.1.iii	50F/50%R		C14	1.c	2.1.iii	25F/75%R
	Roaming order-picking policy: Distance Waiting policy: No CL/EL Q 10 reps; 2week warmup					Roaming order-picking policy: Distance Waiting policy: No CL/EL Q 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system		QL ave	Useful KM	Empty KM	Ave t in system
	551	81700	41414	195		751	82088	34867	257
	471	81117	41186	185		762	83619	36805	300
	417	80067	39893	172		298	79882	35660	150
	505	79635	41242	183		603	75922	30416	263
	435	80241	40387	198		423	84320	38159	148
	591	82393	41674	205		714	82601	34622	268
	478	78461	38279	174		432	81634	36554	189
	560	81058	40111	229		506	82925	36212	163
	616	78975	38968	241		612	80212	34978	268
	581	82154	43100	217		434	81716	36852	152
Mean of means	520.5	80580.1	40625.4	199.9		553.6	81491.9	35512.6	215.9
Standard deviation	69.0	1328.1	1400.4	23.3		159.1	2391.7	2096.1	60.5
Halfwidth	40.0	769.8	811.7	13.5		92.2	1386.3	1215.0	35.0
Confidence Interval	480.5	79810.2	39813.6	186.4		461.4	80105.6	34297.6	180.8

	C15	1.c	2.1.iii	100%R	B1	1.b	2.1.ii	100%F
	Roaming order-picking policy: Distance Waiting policy: No CL/EL Q 10 reps; 2week warmup				Roaming order-picking policy: Priority Waiting policy: Roaming No Wait 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	796	84385	35603	266	1117	65177	49124	236
	376	81047	32567	179	1108	65775	49651	232
	608	83037	34402	206	1103	64310	47947	259
	259	81326	34776	125	1091	66428	51061	238
	1215	68647	26132	470	1124	64488	50097	258
	677	80789	33279	268	1057	66248	48791	240
	572	85997	35684	165	1234	61872	46540	283
	799	81391	33300	286	1130	65568	49490	259
	366	86603	37073	126	1020	67255	51797	212
	493	83704	36308	188	1074	66315	50159	222
Mean of means	616.1	81692.5	33912.5	228.0	1105.9	65343.5	49465.8	243.8
Standard deviation	277.5	5026.4	3088.1	102.5	56.3	1516.7	1503.0	20.9
Halfwidth	160.8	2913.5	1790.0	59.4	32.6	879.2	871.2	12.1
Confidence Interval	455.3	78779.0	32122.6	168.6	1073.3	64464.3	48594.6	231.7

	B2	1.b	2.1.ii	75/25%R	B4	1.b	2.1.i	25/75%R
	Roaming order-picking policy: Priority Waiting policy: Roaming No Wait 10 reps; 2week warmup				Roaming order-picking policy: Priority Waiting policy: Roaming No Wait 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	1611	57988	27381	516	3356	44272	11759	1193
	1571	58989	26615	515	2695	48536	13662	998
	1792	54624	22716	567	3016	48137	14189	1009
	1530	58318	26963	476	2748	49270	14405	950
	1838	54355	23177	564	2772	46191	13232	1000
	1462	57741	25961	476	3023	43664	11311	1038
	1439	60515	28989	458	2713	48349	13534	982
	1495	60128	28138	488	2748	46806	13506	999
	1489	58708	28546	466	3277	44663	11473	1197
	1660	59859	27647	539	3456	41833	10646	1208
Mean of means	1588.7	58122.4	26613.2	506.6	2980.4	46172.0	12771.6	1057.5
Standard deviation	137.5	2121.1	2132.1	40.0	291.0	2476.6	1340.2	100.5
Halfwidth	79.7	1229.5	1235.8	23.2	168.7	1435.6	776.8	58.2
Confidence Interval	1509.0	56892.9	25377.4	483.4	2811.7	44736.4	11994.8	999.3

	B3	1.b	2.1.i	50/25%R	B5	1.b	2.1.i	100%R
	Roaming order-picking policy: Priority Waiting policy: Roaming No Wait 10 reps; 2week warmup				Roaming order-picking policy: Priority Waiting policy: Roaming No Wait 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	2370	52587	15941	761	3732	41799	9931	1202
	2424	52612	15177	861	3096	42901	9690	1013
	2234	54277	16158	787	3039	48419	13056	933
	2111	55380	17139	749	3412	43039	10130	1116
	1958	53718	16118	714	3220	45615	11536	964
	2462	53112	15804	859	3580	42140	10060	1094
	2318	51179	14480	804	3244	45857	11646	1004
	1892	56726	18832	653	3379	43025	10708	1139
	2099	52995	15415	725	3086	45646	11431	989
	2547	50084	13774	848	3742	42271	10141	1163
Mean of means	2241.5	53266.9	15883.7	776.1	3353.0	44071.1	10833.0	1061.9
Standard deviation	220.4	1918.9	1396.3	69.0	261.7	2176.1	1062.4	92.5
Halfwidth	127.8	1112.3	809.3	40.0	151.7	1261.4	615.8	53.6
Confidence Interval	2113.7	52154.6	15074.4	736.1	3201.3	42809.7	10217.2	1008.3

	C10	1.c	2.1.ii	100%R	C9	1.c	2.1.ii	25/75%R
	Roaming order-picking policy: Distance Waiting policy: Fixed + Roaming No Wait 10 reps; 2week warmup				Roaming order-picking policy: Distance Waiting policy: Fixed + Roaming No Wait 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system	QL ave	Useful KM	Empty KM	Ave t in system
	149	88730	56389	71	172	88321	52002	84
	153	88642	55343	72	195	88475	48844	96
	148	88628	55338	73	185	88426	50298	90
	145	88611	56621	71	174	88382	50093	85
	146	88532	58502	70	148	88272	54363	73
	137	88655	57102	69	172	88387	52079	83
	144	88748	55164	71	195	88483	48445	99
	157	88691	53639	75	187	88359	49970	91
	153	88595	56017	72	158	88324	52737	79
	145	88671	55732	72	192	88489	50080	94
Mean of means	147.8	88650.1	55984.7	71.7	177.7	88391.7	50891.1	87.5
Standard deviation	5.7	64.2	1300.6	1.9	16.0	75.2	1849.0	8.2
Halfwidth	3.3	37.2	753.9	1.1	9.3	43.6	1071.8	4.7
Confidence Interval	144.5	88612.9	55230.8	70.6	168.5	88348.1	49819.3	82.7

	C6	1.c	2.1.ii	100%F		C8	1.c	2.1.ii	50/50%R
	Roaming order-picking policy: Distance Waiting policy: Fixed + Roaming No Wait 10 reps; 2week warmup					Roaming order-picking policy: Distance Waiting policy: Fixed + Roaming No Wait 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system		QL ave	Useful KM	Empty KM	Ave t in system
	1206	63916	49249	255		358	84977	47038	164
	1189	64314	49006	265		334	85406	47452	153
	1246	63409	48224	283		295	86031	49637	137
	1101	66208	50966	233		348	85286	47203	156
	1215	63933	49987	268		283	86161	49694	135
	1091	66879	50932	226		295	85924	48266	139
	1203	63517	48118	278		404	84354	44816	177
	1201	64172	49291	277		403	84268	45633	180
	1191	64923	49275	267		291	86068	48556	136
	1149	65081	49624	247		355	85108	47364	163
Mean of means	1179.4	64635.2	49467.3	260.1		336.7	85358.3	47566.0	154.1
Standard deviation	50.1	1148.7	965.1	19.4		45.1	693.9	1565.3	17.0
Halfwidth	29.0	665.8	559.4	11.3		26.1	402.2	907.3	9.9
Confidence Interval	1150.4	63969.4	48907.9	248.8		310.5	84956.1	46658.7	144.2

	C7	1.c	2.1.ii	75F/25%R
	Roaming order-picking policy: Distance Waiting policy: Fixed + Roaming No Wait 10 reps; 2week warmup			
	QL ave	Useful KM	Empty KM	Ave t in system
	792	76676	47338	297
	790	76320	45283	294
	761	76490	46712	281
	752	77170	47144	280
	708	77548	48007	268
	678	77467	47668	252
	839	75549	44213	308
	762	76517	46587	284
	691	77865	48723	256
	815	76443	45374	303
Mean of means	758.7	76804.4	46704.9	282.4
Standard deviation	53.3	698.2	1386.7	19.0
Halfwidth	30.9	404.7	803.8	11.0
Confidence Interval	727.8	76399.6	45901.1	271.4