A Feature-based Comparison of the Centralised versus Market-based Decision Making under Lens of Environment Uncertainty: Case of the Mobile Task Allocation Problem

A Thesis submitted for the degree of
Doctor of Philosophy
by

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January 2012

To the one who I miss so…

To my family…

To my country…

Declaration

I declare that, to the best of my knowledge, no portion of the study referred to in this thesis has been submitted in support of an application for another degree, or qualification, to any other university, or institution of academic learning.

The thesis conforms to the British Standard BS 4821: 1990, the 'British Standard Recommendation for the Presentation of the thesis and Dissertations', and follows the Harvard referencing system.

Karim Al-Yafi

Acknowledgement

I would like to express my sincere gratitude and thanks to all those who have offered help, support, and advice over those years of enduring doctoral research. It is recognised that research activity is a collaborative effort in nature, and the research presented in this thesis is no exception. The support of a number of individuals: supervisors, Brunel Business School staff members, friends, and family are gratefully acknowledged.

I would like to express my gratitude to my supervisors Dr. Habin Lee and Dr. Afshin Mansouri for their great help, support, advice, patience, encouragement, and constant energy for ideas sharing throughout the research effort. I would like also to present my warmest gratitude to Professor Zahir Irani for his invaluable advice and support.

My sincerest thankfulness goes to my family who, despite the distance, was always beside me morally and gave me unlimited support at hard moments and shared with me the good ones. I particularly address all my love and respect to my teachers of life: my parents, Nassib and Ginette. Special thoughts and unforgettable love, gratitude, and memories are all towards my teacher of all times and all subjects of life, my uncle Wahib (May God bless his soul and rest in peace) who left us a short while ago. I'll never ever forget you Wahib!

Last but not least, all my thanks go also to my officemates, PhD colleagues, and friends with whom I shared an important episode of my life.

Thank you all!

Karim

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List of Abbreviations

AI	- Artificial Intelligence
AR	- Arrival Rate
C	- Centralised
CEO	- Chief Executive Officer
CFP	- Call For Proposals
CNP	- Contract Net Protocol
DES	- Discrete Event Systems
DMT	- Decision Making Time
DoD	- Degree of Dynamism
DPF	- Dynamism Priority Factor
DRAP	- Distributed Resource Allocation Problem
DSS	- Decision Support Systems
DU	- Distance Unit
FAMA	- Framework for the Adoption of the Market-based Approach
FCFS	- First Come First Served
FIPA	- Foundation for Intelligent Physical Agents
GUI	- Graphical User Interface
ICT	- Information and Communication Technology
IS	- Information Systems
LK	- Local Knowledge
LKDR	- Local Knowledge Delays Reduction

MAS	- Multi-Agent Systems
MB	- Market-Based
MIS	- Management Information Systems
MOP	- Market-Oriented Programming
MTAP	- Mobile Task Allocation Problem
MTAP-MaSim	- Mobile Task Allocation Problem- Multi-agent Simulator
MTMCP	- Multiple Tour Maximum Collection Problem
m-TSP	- multiple Travelling Salesmen Problem
OP	- Orienteering Problem
OR	- Operational Research
RAM	- Random Access Memory
RAP	- Resource Allocation Problem
RPD	- Relative Performance Difference
TAP	- Task Allocation Problem
TOP	- Team Orienteering Problem
TSP	- Travelling Salesman Problem
UR	- Update Rate
VRP	- Vehicle Routing Problems

Abstract

Decision making problems are amongst the most common challenges facing managers at different management levels in the organisation: strategic, tactical, and operational. However, prior reaching decisions at the operational level of the management hierarchy, operations management departments frequently have to deal with the optimisation process to evaluate the available decision alternatives. Industries with complex supply chain structures and service organisations that have to optimise the utilisation of their resources are examples.

Conventionally, operational decisions used to be taken centrally by a decision making authority located at the top of a hierarchically-structured organisation. In order to take decisions, information related to the managed system and the affecting externalities (e.g. demand) should be globally available to the decision maker. The obtained information is then processed to reach the optimal decision. This approach usually makes extensive use of information systems (IS) containing myriad of optimisation algorithms and meta-heuristics to process the high amount and complex nature of data. The decisions reached are then broadcasted to the passive actuators of the system to put them in execution.

On the other hand, recent advancements in information and communication technologies (ICT) made it possible to distribute the decision making rights and proved its applicability in several sectors. The market-based approach is as such a distributed decision making mechanism where passive actuators are delegated the rights of taking individual decisions matching their self-interests. The communication among the market agents is done through market transactions regulated by auctions. The system's global optimisation, therefore, raise from the aggregated self-oriented market agents. As opposed to the centralised approach, the main characteristics of the market-based approach are the market mechanism and local knowledge of the agents.

The existence of both approaches attracted several studies to compare them in different contexts. Recently, some comparisons compared the centralised versus market-based

approaches in the context of transportation applications from an algorithm perspective. Transportation applications and routing problems are assumed to be good candidates for this comparison given the distributed nature of the system and due to the presence of several sources of uncertainty. Uncertainty exceptions make decisions highly vulnerable and necessitating frequent corrective interventions to keep an efficient level of service.

Motivated by the previous comparison studies, this research aims at further investigating the features of both approaches and to contrast them in the context of a distributed task allocation problem in light of environmental uncertainty. Similar applications are often faced by service industries with mobile workforce. Contrary to the previous comparison studies that sought to compare those approaches at the mechanism level, this research attempts to identify the effect of the most significant characteristics of each approach to face environmental uncertainty, which is reflected in this research by the arrival of dynamic tasks and the occurrence of stochasticity delays.

To achieve the aim of this research, a target optimisation problem from the VRP family is proposed and solved with both approaches. Given that this research does not target proposing new algorithms, two basic solution mechanisms are adopted to compare the centralised and the market-based approach. The produced solutions are executed on a dedicated multi-agent simulation system. During execution dynamism and stochasticity are introduced.

The research findings suggest that a market-based approach is attractive to implement in highly uncertain environments when the degree of local knowledge and workers' experience is high and when the system tends to be complex with large dimensions. It is also suggested that a centralised approach fits more in situations where uncertainty is lower and the decision maker is able to make timely decision updates, which is in turn regulated by the size of the system at hand.

Chapter 1. Introduction

This chapter is aimed at providing research's background and overview. The main definitions, concepts, and motivation of this research are provided along with the research question and research aim. This chapter concludes with the research scope before presenting the thesis structure.

1.1. Background and Motivation

Resource Allocation Problems (RAPs) are a classical application in operations management (Korhonen and Syrjanen, 2004). The main goal of addressing such problems is to reach decisions for optimising the utilisation of limited resources, and yet to attain high output performance. In Distributed RAPs (DRAPs), resources are physically and/or temporally separated from the decision maker, and direct monitoring of resources tends to be infeasible. In large organisations, such distributed decision making problems are frequently faced. A common DRAP faced at the operations management level of organisations is the allocation of tasks to distributed workforce (Lesaint et al., 2000; Chevalier and Schrieck, 2008; Castillo et al., 2009; Dohn et al., 2009; Sabar et al., 2009; Sun et al., 2012). This variation of DRAP is referred to in this study as the Task Allocation Problem (TAP).

The real world phenomenon of uncertainty considerably complicates distributed decision making problems since it turns decisions vulnerable and short-lived (Gendreau *et al.*, 1996; Gendreau and Potvin, 1998; Ichoua *et al.*, 2000; Sun *et al.*, 2012). In order to cope with uncertainty and minimise its negative impact, organisations have either to forecast future exceptions in their initial decisions or to frequently update their allocations according to the new changes. Including uncertainty anticipation in decisions imposes compromising performance for stability as it is the case with, for instance, deploying slack resources. On the other hand, updating decisions in response to exceptions may relatively preserve performance but requires an information updating mechanism coupled with timely decision making processes. When organisations follow the latter approach to deal with uncertainty in decision making, it is crucial to collocating global up-to-date information with the decision making rights (Hayek, 1945). This can be implemented either: a) by moving information to the central decisive point in the organisation, or b) by lowering and distributing the decision making rights to where information is generated. These two alternatives are referred to as the Information System (IS) solution and the Organisation Redesign, respectively (Jensen and Meckling, 1992; Nault, 1998).

Conventionally, organisations address DRAP by adopting the centralised IS solutions. Decisions are therefore made by ISs implementing relevant algorithms proposed by the stream of Operational Research (OR). This implementation results in obtaining Decision Support Systems (DSS) that are aligned with the hierarchical structure of the organisation. The IS solutions are therefore adapted and coupled with the centralised and procedural decision making of the organisation.

As an alternative to the centralised IS solutions, market mechanisms provide decision makers with an appropriate framework for distributing decision making rights over entire organisation (Tan and Harker, 1999; Dias et al., 2006). A market-based approach borrows price concepts from the field of micro-economics and employs them to efficiently allocate resources among the agents in artificial market places. These agents are mainly classified into resource providers and consumers with private utilities and knowledge and acting in the market to maximise their individual utilities. The solution for the corresponding DRAP then dynamically emerges from the market equilibrium as a consequence of the interactions between seller and buyer agents. This corresponds to Adam Smith "*invisible hand*" metaphor for the self-regulating markets in real economies.

Recent advancements in ICT enabling the implementation of market-based solutions motivated several studies to compare the centralised and the market-based approaches. These comparisons covered several DRAPs contexts and concentrated on different perspectives. For instance, the market-based approach proved its competitiveness against centralised approaches for allocating energy resources in buildings (Ygge and Akkerman, 1999), the allocation of computational grid resources among competing clients when demand is stochastic (Pourebrahimi *et al.*, 2006; Caramia and Giordani, 2008; Stößer et al., 2010), and in managing teams of rover robots when the problem size is large and direct monitoring is unfeasible (Dias and Stentz, 2003b; Dias et al., 2006; Vig and Adams, 2006). However, similar comparisons are scarce in the organisation context and the adoption of market-based solutions is limited in the literature, notably when it comes to address TAPs in the presence of uncertainty (Al-Yafi and Lee, 2009). This is mainly attributed to the reflexive choice of IS solutions belonging to the centralised approach and directly addressing such optimisation problems by the OR stream.

Despite the centralised approach dominance for addressing the TAP and other similar routing applications, a few studies address the issue of comparing traditional OR techniques against market-based solutions in the context of Vehicle Routing Problems (VRP) with uncertainty (Mes et al., 2007; Máhr et al., 2010); proving efficacy of the market-based approach. However, such comparisons are incomplete as they are limited to the algorithmic level and do not consider elements such as timeliness of decision making in terms of scalability and local knowledge of the agents, which are imperative in order to evaluate the suitability of a particular approach over the other when it comes to implement them in real-world settings. For instance, in large and complex problem settings, instantaneous reactions by a central solver turn unfeasible, notably as environment uncertainty increases the need for frequent solution updates. Therefore, corrective recourses are taken periodically (Lesaint *et al.*, 2000; Voudouris *et al.*, 2007), which may cause centralised performance deterioration as the time separating these updates increases. On the other hand, agents' local knowledge and incentives are attractive features of the market-based approach to instantly react in face of uncertainty when properly employed in a suitable market mechanism. This market-based feature, along with other features emerging from distribution, may significantly compete with centralised approaches based on periodical updates and on global information.

This study is dedicated to compare the market-based and the centralised approaches in a specific TAP application to incorporate environmental uncertainty, referred to as the Mobile Task Allocation Problem (MTAP). The MTAP consists of efficiently assigning a set of geographically distributed tasks to teams of mobile workers (Al-Yafi and Lee, 2009). An allocation is considered efficient when the maximum level of customer satisfaction is achieved through the execution of tasks, while minimising the operational costs mainly reflected by the travel costs. As well as scheduling the predefined set of tasks, solving MTAP instances requires the allocation of tasks entering the system dynamically during plans execution. Travel delays are also a main source of exceptions that the solving mechanism needs to address. The comparison is not based merely on the technical aspects of each approach; instead, it takes into account the features of each approach, such as timeliness of central decision making and agents' local knowledge in the market-based approach, and evaluates them in the context of environmental uncertainty during the decision making process. This is motivated by the recent technical advancements in mobile computing and communication that would support the adoption of a distributed decision making approach, like the market-based approach, for distributed resource allocation problems, notably those related to the allocation of tasks to mobile teams of workers (Psaraftis, 1995; Adler *et al.*, 2005; Davidsson *et al.*, 2005; Bhuiyan *et al.*, 2010a; Chen and Cheng, 2010).

1.2. Research Question

According to Tan and Harker (1999), technology and communication costs hindered the implementation of market-based solutions due to communication reliability issues and technology cost overhead. Nevertheless, recent advancements in ICT and the propagation of advanced mobile computers connected to web services solved these issues to a great extent, and therefore promoted the adoption of distributed approaches for distributed applications like the MTAP. A potential reason for still rejecting the market-based approach in operations management might be the limited understanding of its features and their potential advantages when applied to distributed decision making applications at the personnel management level, this problem gets magnified when incorporating uncertainty. Therefore, this research addresses the following question: How to comprehensively compare the centralised and the market-based approaches and evaluate their suitability for distributed decision making applications regarding task allocation among teams of mobile workers, more specifically in the presence of uncertainty? Furthermore, how do the features of each approach affect their relative preference, notably when the timeliness of centralised decision making and the local knowledge of distributed agents are incorporated as main features of the centralised and market-based approaches, respectively?

1.3. Research Aim and Objectives

The aim of this research is to propose a theoretical framework for comparing the centralised and the market-based approaches and perform an evaluation for the suitability of an approach over the other based on its key features. Notably, to investigate the role of the timeliness of decision making and agents' local knowledge in the comparison of these approaches to address the MTAP in the presence of uncertainty.

In order to achieve this research aim, the objectives of this research are:

1. Conducting a comprehensive review of the related literature. The main topics to be reviewed are related to the decision making process in the organisation, particularly regarding optimisation problems and the relationship between the decision making procedures, the organisation structure, and the environmental uncertainty. Other centralised versus market-based approaches should also be revisited, even if conducted in other fields than human organisations. Finally, given that this research targets a task allocation problem related to routing problems, related literature in the field of operational research should be reviewed, particularly where environmental uncertainty is involved.
2. To have a conceptual model highlighting the relationship between uncertainty and the comparative performance of the centralised and the market-based approaches. This relationship is suggested to be moderated by different factors

identifying key features and limitations of each approach. These factors are identified from the literature review.

3. To formally define the Mobile Task Allocation Problem (MTAP) as a target problem to be modelled and simulated in order to test the propositions suggested in the conceptual model. Modelling and simulation include the representation and implementation of the target environment with its uncertainty as well as the moderator constructs from the conceptual model.
4. To secure a suitable simulation system for the comparison of the two approaches to MTAP with the presence of uncertainty.
5. To have the features for the comparison verified through simulation experiments
6. To evaluate the suitability of the market-based approach for the distributed decision making applications regarding task allocation in the presence of uncertainty and propose a theoretical framework based on the conceptual model and informed by the results of the experiments.

1.4. Research Scope

Theoretically, this study can be framed into two main contexts. The first one is the organisation theory, given that this research concentrates on comparing two divergent coordination structures, and the second is the stream of OR and optimisation theory since the target problem is directly linked to the optimisation literature.

Organisation theory widely discusses coordination structures in human organisations. It also devotes special interest in studying the effects of environmental uncertainty on the achieved performances exposed by organisation following different structures. On the other hand, operations research mainly concentrates on optimising decision making in RAPs by suggesting computational tools such as algorithms. Since this study targets an operations management problem with transportation applications, OR is considered crucial as it delivers deep insights on the different ways and methods employed to tackle such problems. It is also worth mentioning that OR has also investigated uncertainty in optimisation problems.

The practical boundaries of this work can be delimited by focusing on service organisations facing the problem of task assignments to distributed workforce. The reason for considering these types of applications is flexibility of the schedule. Such scheduling applications are widely faced by service and maintenance companies having to manage their engineering teams and equipment in order to efficiently fulfil technical tasks while keeping high customer satisfaction. Sales companies having to manage their sales teams may also benefit from the outcomes of this research.

1.5. Thesis Structure

This thesis is structured as following:

- Chapter 1: This chapter presents the rationale for this research by introducing a background and the motivation of this research. It also highlights the research problem and identifies the aim of this research and the objectives in order to accomplish that aim.
- Chapter 2: Revisits the inherent theoretical body of literature and attempts to relate the aim of this research to existing work. Besides reviewing the existing centralised versus market-based comparison studies, the review is essentially based on two axes: the organisation theory and the OR and optimisation theory. More specifically, the organisation theory review focuses on related topics about coordination structures, decision making procedures, and environment uncertainty. The OR review attempts to relate the proposed MTAP to existing problem families.
- Chapter 3: Consolidates the concepts making up the major features of both approaches identified in the previous chapter in a conceptual model. This model forms the conceptual framework around which the comparison is conducted.
- Chapter 4: In this chapter, the research method is presented in order to demonstrate the propositions suggested in chapter 3. The use of simulation methodology is justified for this research as well as a detailed description of the simulation model and verification processes are provided.

- Chapter 5: The simulation experiment design, basic model and validation, and results are presented in this chapter.
- Chapter 6: The discussion of the obtained results is presented in this chapter. The main findings are highlighted and linked with the existing literature. This chapter also formulates the major theoretical and managerial contributions of this study.
- Chapter 7: This chapter concludes by summarising the whole work conducted in this research and by describing the main limitations of this work. It also suggests future directions of research to complement this work.

Chapter 2. Review of Prior Studies on Centralised and Distributed Resources Allocation

2.1. Introduction

Addressing Resource Allocation Problems (RAPs) mainly consists of optimising the decisions made in order to reach efficient allocations as a solution for the problem at hand. That is, several solutions may exist for a given RAP, and an optimisation decision is made in order to select the best alternative among all the available solutions according to a specific criterion. In regard to this, Task Allocation Problems (TAPs) can be perceived as decision problems (i.e. finding feasible sets of task allocations) with optimisation (i.e. efficiently allocating tasks incurring minimum costs).

Starting from the point that this research aims at contrasting two different decision-making approaches, namely the centralised against the market-based approaches, on one hand; and their application in an optimisation decision making problem on the other, the review of this study covers two different aspects in the theoretical body of literature. Therefore, this chapter aims at presenting a critical review of the literature discussing and comparing the centralised and market-based approaches for decision making, and of the operational research (OR) and optimisation theory for the problems related to the Mobile Task Allocation Problem (MTAP).

Firstly, the review starts by defining and contrasting the centralised and the market-based approaches as techniques for resource allocation decision making problems in organisations. The organisation theory literature is reviewed with a particular focus on the organisation design and decision making procedures in light of uncertainty. Thereafter, a comprehensive and critical review of existing comparisons across several management applications is undertaken. This covers the comparison studies conducted in a wide range of fields that are not necessarily directly related to the domain of this study, which then concludes with the comparison studies done in the field of operations management, logistics, and transportation applications for their relevance with this research.

Secondly, this review is then moved to focus on the OR and optimisation literature in order to link the target MTAP with related existing well-known optimisation problems. Given that this study does not focus on developing new or improving existing solutions; the review concentrates on problems formulations, versions (e.g. static vs. dynamic), related assumptions and constraints, and on the approaches used to address them.

In both phases of the review, a particular emphasis is devoted to the environmental uncertainty given it is the main criterion of this comparison study. The purpose of this specific focus is to review how uncertainty has been perceived, discussed, and handled in the literature, from both the organisation theory and OR perspectives.

This chapter concludes by identifying the research gap intended to be addressed in this work and properly places it within the existing theoretical literature.

2.2. Decision Making Perceived by the Organisation Theory

This study addresses an optimisation decision making problem regarding the efficient allocation of resources. Even though these types of problems basically lay in the realm of OR and optimisation theory (as it will be discussed later in this chapter), the fact that this problem is considered in human organisations with tasks executed by human resources, it is thought imperative to revisit the organisation theory literature regarding coordination structures and the specific features of the human factors in optimisation problems.

According to the definition proposed by Daft, "*organisations are (1) social entities that (2) are goal-directed, (3) are designed as deliberately structured and coordinated activity systems, and (4) are linked to the external environment*" (Daft, 2009, p. 11). According to Anderson (1999), organisations are treated as "open systems" since the sixties of the previous century. They are "open" since they exchange resources with their environments, hence the importance of properly dealing with the surrounding environment and its accompanying uncertainty, and "systems" given the interconnectivity of its components working together to achieve a goal that is impossible to realise by individual components (e.g. a person). The important points to note here is that organisations exist because of their human capital, hence the social structure. Organisations are goal-oriented and deliberately structured, hence the need of close management and monitoring to assess its performance in terms of goal convergence. Lastly, organisations are linked to their environments, hence the importance to adapt to it.

When considering the market-based approach as a resource allocation mechanism in human organisations, the "design and the coordinated activity system" are the main targeted features from the organisation definition presented above. These two main characteristics particularly stand out when compared to the traditional centralised organisation structures. They can be interpreted as the coordination structure and the decision making procedure of the organisation. These topics were thoroughly discussed in the organisation theory literature, notably in light of external uncertainty.

From an organisation point of view, this study can be regarded as a comparison of two coordination structure extremes to address a distributed resource allocation decision making problem in light of environmental uncertainty. This can also be considered as a comparison of two organisation structures accompanied by two different decision making procedures in an organisation facing environmental threats. More specifically and according to the organisation theory paradigm, the centralised versus market-based approaches explored in this study can be mapped to the procedural hierarchy versus experiential market-based flat structure approaches, respectively. Furthermore, this study particularly focuses on service organisations facing decision making at the operations management level in order to schedule and plan the activities of distributed mobile workforce facing environmental uncertainty (Tsang and Voudouris, 1997; Lesaint *et al.*, 2000; Voudouris *et al.*, 2006).

Even though this combination has not been explicitly addressed, organisation theory is probably the field that most thoroughly investigated different organisation and coordination structures, assessed their performance according to different metrics, and considered environmental uncertainty an important factor affecting decision making processes and performance outcomes.

Organisation Structure and Decision Making Procedure

Organisations are complex open systems addressing particular concerns to uncertainty. This is mainly due to their constant interaction with the surrounding environment (Thompson, 1967; Aldrich and Pfeffer, 1976; Aldrich and Marsden, 1988; Aldrich, 2007). While the external environment has many characteristics, a particular feature putting pressure on organisations to adapt to the changing environment is its degree of uncertainty (Joyce *et al.*, 1997; Lin, 2006). Environments with low degrees of uncertainty exhibits more stability with longer validity for decisions made (Aldrich, 2007). While on the other hand, environments with higher degrees of uncertainty lead to lower decision making performance (Lin, 2006), higher needs to information exchanges (Galbraith, 1974), and impose organisations to take timely and appropriate actions to limit negative impacts and costly errors (Eisenhardt, 1989). Therefore, higher information transfer and processing coupled with decision updates are crucial in order to minimise the impact of high degrees of uncertainty.

Given the importance of environmental uncertainty, research in organisation theory and design has been investigating how organisations can actively structure and redesign themselves to reach better decision making schemes and face external threats. In respect to this, two key elements stand out: the organisation structure and the decision making procedure itself (Lin, 2006).

From an organisation structure point of view, the complexity of organisation structures and the choice of centralisation versus decentralisation of organisations activities have been addressed in many studies in this field (Galbraith, 1977; Huber and McDaniel, 1986; Malone and Smith, 1988; Jensen and Meckling, 1992; Kung and Marsden, 1995; Joyce *et al.*, 1997; Tan and Harker, 1999; Vagstad, 2000; Harris and Raviv, 2002; Horling and Lesser, 2004; Lin, 2006; Christensen and Knudsen, 2010). According to Lin and Carley (1997), the relationship between the organisation structure and the external uncertainty, and their effect on the organisation performance, was regarded from different perspectives.

Institutionalists claim there is a significant relationship between the organisation and the environment it is operating in (Scott, 1987; Powell and DiMaggio, 1991). Given this, structural theorists affirm that the organisation internal and external structure closely determines its performance (Huber and McDaniel, 1986) meanwhile, contingency theorists (Hofer, 1975; Feldman, 1976; Van de Ven and Drazin, 1985) stress on the match or fitness of the organisation and its environment is what actually determines its performance rather than each aspect separately. Following this approach, ecologists complimented this claim further to argue that the match between the organisation structure and its surrounding environment is "vital" (Hannan and Freeman, 1977; Betton and Dess, 1985).

Despite the fact that researches seeking for best structures to face uncertainty overlaps sometimes and are controversial in many cases; they all converge towards the fact that there is no single structure that can be generalised for all cases and activities (Lin *et al.*, 2006). Furthermore, it can be concluded that the match between organisation's structure, activity, and its surrounding environment is crucial for its performance.

On the other hand, information process theorists suggest a more micro level vision on organisation's performance. They argue that organisation's performance highly relies on the behaviour of intelligent agents at the individual level, and on the information system adopted (Lin *et al.*, 2006). That is, the performance of the organisation is tightly coupled with the level of training or knowledge individuals are having in the organisation on one hand, and on the information system they have access to on the other (Lin and Carley, 1997). This leads to the decision making procedure the organisation should adopt for facing external threats.

From the decision making procedure perspective, organisations tend to either follow institutionalised or experiential procedures for decision making according to the definition of Lin (2006). Institutionalisation procedures impose rigid rules on individual members limiting the usage of their past experience or personal knowledge, like in military organisations (Roberts *et al.*, 1994). This is mainly followed when members are required to be objective, unbiased, and there is high risk of moral hazard (Eisenhardt, 1989). On the other hand, experiential decision making procedure enables individuals to use their own knowledge and past experience of performing similar tasks to reach new decisions (Carley, 1992). This results in giving more proactive roles to individuals at lower levels of hierarchical structures in the decision making process.

Finally, it is worth noting to the importance of the timeliness of decision making in dynamic environments. When organisations face highly dynamic external crisis, they have to respond both accurately and rapidly to limit the negative effects of such exceptions. Therefore, it can be stated that "time pressure" becomes an important factor affecting organisations performance in face of uncertainty (Perrow, 1984).

Given these different indicators affecting organisation's performance, Lin and Carley (1997) and Lin (2006) conducted studies consolidating all these indicators categorised by: organisational structure, decision making procedure, and environment uncertainty in a computational model. It is argued that time pressure, training individuals within the organisation, organisation structure complexity, and organisation environment are of high effect on its performance; and are higher determinants than the match between the organisation and environment, as claimed by institutionalists (Lin and Carley, 1997). In another study (Lin, 2006), it is argued that complex structures are favourable under high uncertainty and with an experiential procedure while operational procedures are preferred when coupled with simple structures.

These results might be attributed to the nature of the tasks and activities an organisation is operating. In the previous examples, all tasks were modelled as complex and requiring all individuals to participate in acquiring partial information leading to global decisions made by a central manager. In other words, individual agents are not autonomous in taking actions upon their perception of dynamic changes. This is due to the assumption that individual members don't have access to enough information to take final decisions. This cannot be generalised for cases where organisation's global goal can be decomposed into sub tasks.

It is worth also noting that most of the previously mentioned studies (Lin and Carley, 1997; Carley *et al.*, 1998; Lin *et al.*, 2006; Lin, 2006) focused on the effect of external uncertainty on the performance of hierarchically structured organisations; contrasting simple versus complex hierarchies. Even though the team decision making structure was considered distributed in some cases; however, final decisions were always made by a "leader" acting as a decisive point located on top of other team members; eliminating the consideration of flat structures coordinating through market transactions.

Despite the differences between the target problems discussed in the previous studies and the case of the MTAP regarded in this research, there are some major concepts from the organisation literature to be retained at the operational level. From the model suggested by Lin and Carley (1997) summarising the main constructs described in the organisation literature, the "time pressure", "type of training", and "opportunities to review" constructs are of particular interest for optimisation decision making problems. It is agreed in the literature that "opportunities for review" improves the performance given that reviewed decisions would lower the risk of erroneous decisions (Lin and Carley, 1997; Lin, 2006). However the opportunity for review is directly governed by the other two variables. First variable is the "Time pressure" – which is mainly related to the temporal dimension of the decision making process. In other words, more dynamic and uncertain environments result with higher time pressure leaving less time to review a decision, and therefore lowering the obtained performance. The second variable is the "type of training" – which determines workers' roles according to their knowledge and experience type. Thus, when coupled with the decision making procedures, workers may either rely on institutional procedures in executing their activities, relaxing the value of individual knowledge and personal experiences, or rather employ their own knowledge and decision rights in experiential procedures reducing the opportunities for review. The impact of such knowledge on the organisation performance is debated in the theoretical literature (Lin, 2006).

In the case of this study however, members are working in parallel on independent tasks that can be accomplished by individual workers. This is similar to the white-collar scenario described by Tan and Harker (1999). The main difference here is not only limited to the type of tasks or decision making (collective versus individual), but also spans to address that, in the context of uncertainty, whether composition of decisions based on local knowledge (market-based) are comparable to the decisions based on global information (centralised). For this purpose, the market-based coordination mechanism is taken as a representative for the distributed decision making approach.

Before proceeding in the description of the centralised and market-based approached to decision making, it is worth defining the terms global information and local knowledge as used by the centralised and the market-based approaches, respectively.

Global information mainly refers to the collection of information reported by lower levels in the management hierarchy to their next higher levels. The term global indicates the availability of all information that can be possibly gathered. Such information, therefore, is only available at the highest level of the hierarchy. Generally, global information is an aggregation of partially processed information that cannot guarantee consistency among all the reported data. Furthermore, this type of information often follows specific presentation schemes that follow a certain bureaucratic or business process routine. Therefore, such information is processed at each level and is interpreted prior decisions are made at the top level of the hierarchy. Information processing may turn to be long and complicated when global information tends to be large, complex, and dynamically arriving at a fast rate. For instance, the operations management department in an organisation may have access to different types of reports and figures and decision support systems deployed in such departments use such information as their main input.

On the other hand, local knowledge refers to the knowledge acquired by each individual executing tasks. Such knowledge is acquired on the long run by the combination of one or more elements including the perception of the surrounding environment, level of education and personal learning, skills, and experience. Such knowledge is considered local as it is acquired and held privately by each individual. Furthermore, this knowledge is often tacit making it unfeasible to be represented in a standard scheme for communication with others. A good example of local knowledge is the private utilisation preferences of a market participant towards different commodities available.

The next section revisits comparison studies explicitly conducted to compare hierarchically centralised structures versus market-based settings.

2.3. Approaches to Address Resource Allocation Problems

This section provides a description for the centralised and the market-based decision making approaches to address resource allocation problems. The structure, communication scheme, decision making process, and tools for each approach are described.

2.3.1. The Centralised Approach to Decision Making

Conventionally, the centralised control scheme is considered as a reflexive choice for addressing decision making problems in different applications (Lin, 2006; Tan and Harker, 1999; Dias and Stentz, 2003a; Dias and Stentz, 2003b); and decisions related to RAPs are no exception. The term "centralised" is used to denote that all solutions and decisions are generated by a single entity. This can be a central computing unit for computational and logical problems, or an organisation's top-management board for organisation-related decisions.

Centralized structures tend to be hierarchical with the omniscient central decisive point located at the top (Lin, 2006; Harris and Raviv, 2002; Huber and McDaniel, 1986). At the lower level, information is collected to flow up as a snapshot of the system's global state. After being processed by higher level decision makers, new information flows down the hierarchy as instructions to be disseminated to processors, that is, action executors.

In organisation theory, the centralised design is mainly characterised by its hierarchical structure (Lin, 2006; Christensen and Knudsen, 2010). That is, the centralized approach mainly relies on a central decision making point located at the top of the management pyramid. In order to reach decisions, global information is collected from lower levels, partially processed at intermediate levels, turned into decisions and actions at the top level of the management hierarchy before being spread down again. This results in assigning a passive role to intermediate managers and agents responsible for executing orders.

In cases where decisions are to be taken repetitively over a longer time horizon, the central decision making point updates its perception of the global information at regular periods of times to be processed and then turned into solutions upon the use of decision support tools, such as decision analysis software, decision support systems, advanced algorithms, and met-heuristics.

For instance, in the centralised organisation design where the final decisions are taken at the top management board (e.g. CEO level); managers at different levels are limited in their decision making initiatives (Harris and Raviv, 2002). Many studies in the literature investigated and evaluated different forms of centralised control (Malone and Smith, 1988; Harris and Raviv, 2002; Christensen and Knudsen, 2010). Hierarchical structures are identified to have considerable variations in the number of levels and the set of grouped activities. Product hierarchies (also known as divisional hierarchies, multi-divisional, or M-Form), functional hierarchies (also known as unitary or U-Form), matrix organisations, and flat structures are the most common designs adopted by an organisation (Malone and Smith, 1988; Harris and Raviv, 2002). However, in all these structures, the final decision making is still done at the top level of the hierarchy (e.g. CEO). The main difference between these organisation forms is the communication scheme and/or the contents of information.

Particularly in operations management, decisions making problems regarding the allocation of available resource come with the need to conduct some optimisation processing. This is faced in the field of industrial engineering (Johnson *et al.*, 1976; Ramesh and Cary, 1989; Fortemps, 1997), supply chain management (Dolgui *et al.*, 2005), service chain management (Voudouris *et al.*, 2007), and transportation applications (Crainic *et al.*, 2009). When the centralised approach is used to address such problems, the centralised decision making point periodically gathers all relevant global information. Such information contains data about the availability of resources, demands, and the surrounding environment conditions. The process of collecting this information (or part of it) may be direct, through direct interaction with the source of information, or indirect, passing through mediators organised in a hierarchical structure. The central decision making point then heavily relies on optimisation techniques to process the input information and transform them into efficient actions. These techniques, all assisted by computer software and algorithms, are mainly borrowed from the field of operations research (OR) and artificial intelligence (AI).

Hence, it can be said that the quality of the decisions achieved by the centralised approach heavily depends on the accuracy and timeliness of the reported global information and on the decision making tools.

2.3.2. The Market-based Decision Making Approach

Emerged from the field of economics, markets have a long history behind the allocation of welfare and resources in societies. In modern economics and according to Adam Smith in his famous “Wealth of Nations” publication, markets form the “invisible hand” power leading to the best benefit a society can accumulate from its available resources. This is achieved through the market interactions of its consisting agents who are solely driven by their own self-interests. The aggregation of the individual optimal allocations would lead to the global equilibrium, which in turn reflects the optimality of allocations over the society.

In a given economic society, agents are endowed with initial resources (e.g. initial amount of currency or quantities of goods) along with some production capabilities specifying their types. They also have private evaluation for each good, or bundle of goods, which specify the utility function of each agent. These differences in types and utility functions make the market agents heterogeneous with their individual goals. Through trade transactions that take place in the market place, agents’ ultimate objective is to maximise their own utility with the available resources in the market. This generally creates “demand-supply” problems reflecting the inequality of resource allocations among the agents. Pricing of goods is the main strategy to face the problem of demand-supply. When the demand of a certain good, or resource, exceeds the supply, its price is increased to seek a balance referred to as the "market equilibrium". When market equilibrium is attained in a perfect market with no external influences, it is implied that the total demand for the good equals the total of its supply. In other words, there is neither shortage nor surplus in the society. This would lead to a "fair" allocation of goods that can be interpreted as efficient (Wellman, 1993; Walsh *et al.*, 1998).

Thus, with prices, each agent has reservation prices for the goods it plans to acquire or sell that match its own utility. Therefore, the reservation price denotes the maximum price an agent is willing to pay for a good if the agent is a buyer. Similarly, the reservation price for a selling agent is the lowest price it accepts for selling a good it owns. From a buyer's perspective, the reservation price can be denoted as the price at which the buying agent is "*indifferent between and not buying the product, given the consumption alternatives available*" (Jedidi and Zhang, 2002, p. 1352)

When prices of goods are adjusted to reach equilibrium, agents with reservation prices that are not within the boundaries of the new price withdraw from the auction implying that allocating these goods to these agents would not be efficient. This automatic outcome of allocations is referred to as the "invisible hand" according to Smith. When perceiving these market outcomes as a solution to a RAP, it is said that this allocation problem was solved in a market-based fashion (Wellman, 1995).

In comparison with the centralised control for addressing optimisation decision making problems, the market-based approach can be distinguished from the centralised approach in several points:

- **Distributed control**: The market-based approach is mainly characterised to operate in Multi-Agent Systems (MAS) (Huberman and Clearwater, 1995; Ygge and Akkermans, 1999) where agents in the market interchange buyer and seller roles to accomplish transactions. In such settings, there is no central control to coordinate agents' activities, but rather, agents autonomously decide when, what, and at what price goods should be sold or bought. The emerging equilibrium of these trade transactions triggered by self-oriented individual decisions reflects the efficiency and optimality of supply and demand. In terms of resource allocations, markets equilibrium implies optimum solutions for the resource allocation problem instances (Wellman, 1993).

- **Flat structure**: oppositely to the hierarchical organisation structures the centralised approach tends to have, agents in the market-based approach are all located in the same level of control with equally distributed decision rights (Malone, 1987; Malone and Smith, 1988). Even though formed markets are regulated and cleared by auctioneers' decisions, however the role of auctioneer is shared, granting all agents the right to become auctioneers in their turn. Furthermore, multiple markets may run simultaneously in parallel.
- **Nature of information**: Central decision making authorities require global vision of the system it manage in order to reach practical decisions. In the market-based approach, such availability of information is not available to the trading agents (Ygge and Akkermans, 1999; Tan and Harker, 1999). They rather privately depend on their own local knowledge (e.g. environment perception and experience) and interests (e.g. evaluation and utility) when taking decisions reflected in the bids they submit/evaluate.
- **Incentives**: Given that agents in market-based settings are self-oriented with individual goals, it is crucial to align these goals with the system's global objectives. Price theory and game theory make of markets a good infrastructure to decompose resource allocation problems and to be solved among trader agents. However, expected outcomes are only achievable as long as agents report their evaluations and current status truthfully through their bids (Varian, 1995; Tan and Harker, 1999). This cannot be guaranteed by all agents in all circumstances resulting with the need for "incentive compatible mechanisms" to avoid probable agency problems (Eisenhardt, 1989a; Bester and Strausz, 2000; Peters, 2001). Therefore, the revelation principle (Epstein and Peters, 1999; Bester and Strausz, 2000; Peters, 2001) and algorithmic mechanism designs (Nisan, 1999; Kfir-Dahav *et al.*, 2000; Nisan and Ronen, 2001) are employed to ensure incentive compatibility among agents in the market and yet to align their private interests with the global objective.

- **Communication**: The trade transactions carried out between the auctioning and bidding agents to exchange information (and goods) require a considerable number of messages. The number of exchanged messages in the market-based approach is generally higher than it is in the centralised approach (Malone, 1987; Malone and Smith, 1988; Tan and Harker, 1999). This is mainly due to the different types of messages (e.g. call for proposals, bids, and proposal accepted) involved in each auction round. Therefore, a market-based structure may only be attractive if the communication technology is relatively cheap and reliable (Tan and Harker, 1999). However, the inferior number of exchanged messages in the centralised approach is arguable and may be affected by several factors, like the organisation structure complexity, level of uncertainty, and information update mechanisms.

Given these characteristics, the market-based approach attracted many scholars and practitioners to adopt it and was investigated in different contexts, notably in optimisation decision making problems incorporating distributed entities and/or resources. For instance, it was employed in different applications for the allocation of computing resources among prospective users e.g. (Pourebrahimi *et al.*, 2006; Caramia and Giordani, 2008; Stößer *et al.*, 2010). Similarly, market auctions were employed in robotics (Dias and Stentz, 2003b; Gerkey and Matarić, 2004; Stentz *et al.*, 2004; Lin and Zheng, 2005; Dias *et al.*, 2006; Vig and Adams, 2006; Zlot and Stentz, 2006), communication networks management e.g. (Thomas *et al.*, 2002; Haque *et al.*, 2005; Edalat *et al.*, 2009), power management e.g. (Akkermans *et al.*, 1996), coordination of distributed supply chains (Fan *et al.*, 2003), and transportation applications (Zeddini *et al.*, 2008; Bhuiyan *et al.*, 2010; Robu *et al.*, 2011) among other applications.

When the market-based approach is employed to tackle optimisation decision making problems, there is a major choice to be done by the mechanism designer that is the one of auction type. According to Klemperer (1999), there are four main types of auctions: i) ascending-bid auction (also known as the English auction); ii) descending-bid auction (also known as the Dutch auction); iii) first-price sealed bid auction; and iv) second-price sealed bid auction (also called the Vickery auction). The main difference between the first two auction types and the latter two is that English and Dutch auctions are multiple-round and open bidding auctions. That is, bidders generally have to submit more than one bid for the auction to clear. Furthermore, the submitted bids are made public in the market so all bidders know the valuation of all other bidders. On the other hand, the first- and second-price sealed bid auctions are mainly referred to be “single-shot” with bids held private from other participants.

Another important design issue of auctions is the count of items being exchanged in a single transaction (single vs. multiple items) and the bid structure (sequential vs. combinatorial). According to this classification, auction design ranges from the sequential single-item as its simplest form to the combinatorial multiple-items as the most complex design. In computational markets, sealed bid auctions were modelled and implemented through the contract net protocol (CNP) suggested by Smith (1980) and was employed in many applications among the examples presented above, notably in robotics and transportation applications. On the other hand, Wellman (1993) suggested the market-oriented programming to frame combinatorial auctions, and other related concepts adopted from the microeconomics theory, as a programming paradigm. Meanwhile combinatorial auctions tend to be more efficient in allocating items where agents’ valuation depends on the structure of bundles rather than the additive utility of items individually, bids are harder to compute by the bidders and the problem of winner(s) determination is very complicated as well (de Vries and Vohra, 2003). Actually, the complexity of problems accompanying combinatorial auctions, notably the winner determination problem faced by the auctioneer, is considered NP-hard and need in its turn sophisticated algorithms and heuristics to be solved (Sandholm, 2002; Bichler *et al.*, 2009). Therefore, combinatorial auctions are not considered attractive for allocation problems where the bundles’ size and the number of available commodities are high (Dias and Stentz, 2003b; Dias *et al.*, 2006). Instead, auctions with single item bids are employed, like the CNP that became a standard interaction protocol in agent-based programming according to the Foundation for Intelligent Physical Agents (FIPA).

The following table summarises and compares the main features of the centralised and the market-based approaches when employed to address decision making problems, notably those incurring optimisation.

	Centralized	**Market-based**
Structure	Centralized, hierarchical.	Distributed, flat.
Decision making authority	Central decision making point.	Parallel actuators (i.e. workers).
Information & knowledge location	Global.	Local.
Decision making instruments	Heuristics, AI, Integer programming, etc.	Combinatorial markets, auctions and negotiations.
Communication	Lower	Higher
Solution quality in deterministic and static settings	Optimal, near optimal.	Sub-optimal.
Information update mechanism	Real-time for moderate problem size. Periodical for large-scale problem instances.	Real-time.

Table 2-1. Feature-based C vs. MB analogy

2.4. Centralised versus Market-based Decision Making Structures

The existence of the two divergent centralised and market-based approaches to address RAP's, attracted many researchers to explore the pros and cons of each approach. These comparisons were conducted in different fields and on a wide variety of applications. However, they all contribute in better understanding the potential of the emerging market-based approach where the centralised approach is considered to be best suited. This section illustrates the comparison between the two approaches considering four areas or domains: 1) robotics; 2) energy management; 3) coordination structures within organisations; and 4) routing applications. The last two areas are most relevant to this research due to the nature of the discipline.

2.4.1. Market-based Task Allocation in Robotics

In the field of robotics, the market-based approach has been adopted for managing and coordinating teams of robots in many applications e.g. (Dias and Stentz, 2003b; Gerkey and Matarić, 2004; Stentz *et al.*, 2004; Lin and Zheng, 2005; Dias *et al.*, 2006; Vig and Adams, 2006; Zlot and Stentz, 2006). The market-based approach attracted robotics scholars for many reasons. The ability to manage teams of robots on missions in a distributed manner, delegating coordination decisions to autonomous robots, computational tractability, and avoiding the communication bottlenecks and reliance on a single computing unit; are some of the reasons to consider the market-based approach.

Three different coordination mechanisms for teams of robot agents were studied and contrasted by Dias and Stent (2003b). The aim of this study was to compare the fully centralised, the fully distributed behavioural, and the market-based coordination approaches. On one side of spectrum, the centralised approach was assumed to produce optimal coordination plans by depending on a single leader planner. While on the other extreme, the distributed behavioural approach relies on the local information and available actions of each team member independently. Each robot (agent) would autonomously make decisions and take actions as if they were the only entity in the team, suppressing any kind of cooperation among the team members. However, the market-based approach acted as an approach located in between the two previous extremes. Despite the reliance on individual and local decision making based on local knowledge, team members would use economic and market protocols to trade tasks. This is observed as a way of coordinating global actions through maximising marginal utilities of individual self-interested rational robots during market transactions.

The study was conducted along two dimensions: the number of robots (agents) and the degree of heterogeneity within the team. The dependent performance indicator taken into consideration was the total operational costs (expressed by travel distance) and the computation time. Dias and Stents (2003b) concluded the comparison by judging the market-based approach favourable as the team size increases; and positively comparable with the optimal solution observed in the centralised approach in terms of costs. On the other hand, the market-based also compared favourably with the behavioural approach in terms of computation time.

Another important observation from the previous study, as well from other similar comparisons (Dias and Stentz, 2003a; Gerkey and Matarić, 2004), is the vulnerability of the centralised approach. Despite the optimality of generated solutions by central solvers, the centralised approach is prone to the single point of failure problem, slow response to dynamic uncertainty, intractability of computation as problem size increases, and inappropriateness of maintaining constant active communication between the central point and all team members.

What can be retained from the robotics review is that optimisation decision making can turn intractable when addressed centrally in distributed scenarios, notably when the problem size and complexity increases and when communication turns unfeasible. Furthermore, the comparison studies reviewed in the field of robotics revealed that the market-based approach seems to be promising. Mostly based on the simple contract-net protocol, positive results were demonstrated in different dynamic task allocation scenarios. The primary concern of these researches is to optimise the limited resources a robot agent has (battery life, for example), reduce communication with central control units (control station on Earth, for instance), and to best utilise its local sensory capabilities to achieve the designated global goal as active members of a larger team.

While problems related to managing robotic resources may have similar objectives as human organisation at the operational level, like reducing travel costs or energy consumption, findings applied on robotics are hardly justifiable to be directly applied on human organisations. Dissimilarities arising from human factors like intelligence, preferences, and senses make human organisations different. Similarly, dealing with human resources imposes respecting limited working hours, personal experience, and preferences may differentiate human organisations from teams of robots. Nevertheless, the technical observations, like the vulnerability of the centralised approaches as problems increase in size and complexity can still be retained for human organisations' optimisation problems such as task allocations.

2.4.2. Market-based Resource Allocation in Energy Management

The market-based approach, also viewed as Multi-Agent Systems (MAS), has gained considerable interest in the field of power and energy management, e.g. (Huberman and Clearwater, 1995; Akkermans *et al.*, 1996; Clearwater, 1996). It proved to be an efficient way to manage energy resources in large-scale applications. Given the number of studies conducted to support the adoption of the market-based approach in RAP's related to the allocation of power and energy resources, Ygge and Akkermans (1999) conducted a rigorous comparison study between the centralised and the market-based approaches. This study aimed at further exploring the claims of Clearwater and Huberman (1994) which implied the superiority of the distributed market-based paradigm in thermal control applications. Ygge and Akkermans argued the findings of Clearwater and Huberman claiming that the observed superiority was not solely due to auctions in the market-mechanism, but rather due to the availability of global information to every sensory agent. This lead to the reach of optimal distributed decisions composing a global optimal solution. This assumption contradicts with the main feature of local knowledge characterising the market-based approach, as well as all distributed approaches.

Subsequently, Ygge and Akkermans (1999) developed a market-based approach relying on the limited local knowledge of distributed sensory agents. The market design followed the combinatorial auction mode borrowed from the Market-Oriented Programming (MOP) (Wellman, 1993). In such a setting, market participants submit bids evaluated according to a bundle of goods rather than for single goods. Their observed results lead to important findings implying that the market-based approach can at most reach the performance of an equally-sophisticated centralised approach. Another interesting finding formulated that "*distributed local knowledge + market communication = global control*".

Despite the important contribution of Ygge and Akkermans (1999), their outcomes cannot be guaranteed on the wide spectrum of decision making applications. Their application of thermal control by allocating cool air resources to homogenous offices in a static building environment does not cover the cases of dynamic environments. Furthermore, combinatorial auctions turned to be a suitable market-based technique given the limited size of the problem at hand; however, the calculation of bids may grow exponentially as goods making up bundles increases and market equilibriums cannot be guaranteed in all cases (Dias et al., 2006).

2.4.3. Decision Making Procedures and Organisations' Structures

Managers seeking to reach an optimal organisation structure between the centralised and distributed schemes to reach excellence in decision making (Kung and Marsden, 1995) motivated researchers in the field to explore different structures viewed from different perspectives. Notably, different studies directly contrasted the classical centralised control to the emerging market-based approach in different decision making applications faced by human organisations, following different methodological approaches, and concluding with different outcomes.

Advancements in Information and Communication Technology (ICT) highly contributed to flexibly design organisations' Information Systems (IS). Current ICT allows the design of any form of IS allowing the collocation of information along with decision making rights, either by transferring information to where decisions are taken, referred to as the MIS solution, or through pushing decision making rights down to where information is perceived, referred to as the organisation redesign solution (Jensen and Meckling, 1992). In both scenarios, such a collocation scheme is vital for effective and efficient decision making (Hayek, 1945). As a result, the technological progress observed during the last few decades influenced many researchers to affirm that the organisation structure is tightly coupled with the design of its IS, which is in its turn regulated by the ICT (Robey, 1981; King, 1983; Malone, 1987; Malone and Smith, 1988; Fiedler *et al.*, 1996; Nault, 1998; Tan and Harker, 1999).

The study by King (1983) is among the first concrete comparisons, yet theoretical, which addressed the debate of centralisation versus decentralisation of decision making in organisations from a computing perspective. The study addressed the dilemma of choosing centralised or decentralised computing in the organisation. The comparison stems from Hayek (1945) theoretical debate of locating decision making rights with where decisions are actually enacted. King grounded this theorem on organisations' IS taking into consideration the locus of decision making within the organisation, its physical structure, and its functional composition. The study concludes that no global best solution can be generalised. However, it is argued that centralisation would support the stability of organisation's operations given that all decisions are made at the top level, but would separate decision making from where information is sourced (i.e. surrounding environment). On the other hand, whilst decentralisation delegates decision rights to lower levels, problem arises when lower level decision makers suffer from incompetence or held unaccountable. This problem of rights delegation in decentralised settings is further accentuated when agency problems arise due to conflict of interests and information asymmetry (Eisenhardt, 1989a).

Nault (1998) also advocates the importance of collocating information and the decision making rights. In respect to centralised and distributed organisation designs, the two ways to achieve the collocation proposed by Jensen and Meckling (1992), that is the MIS and the organisation redesign solutions, are applied to a local versus global investment decision faced by an organisation with several branches and where information asymmetry arises. It is concluded that a hierarchical centralised decision making mechanism is less profitable than the markets when inefficiency resulted from information asymmetry is high. However, collocating decision rights and information in a form that require high coordination for global decision making may not be the correct strategy when coordination costs are significant; costs that are falling in price as ICT advances.

While the previous studies compared the centralised and the distributed (market) approaches from a structural feasibility and performance-based perspectives, other comparison studies contrasted different organisation designs from a quantitative cost perspective, and mapped these taxonomies to their corresponding IS structures (Malone, 1987; Malone and Smith, 1988; Tan and Harker, 1999).

Malone and Smith (1988) presented a quantitative model contrasting four generic structures for product organisations and mapped them to their corresponding computer systems. These are: the product hierarchy, the functional hierarchy, the centralised market, and the decentralised market; with two sub categorisations for the functional hierarchy and the centralised market in order to cover the cases of small-scale and large-scale processors. Hierarchical structures in the functional hierarchy and in the centralised markets are assumed to have a “functional manager” layer between the product manager at the top and the task processors at the lower level. In such settings, products managers aim at assigning tasks to processors either directly, like in the case of product hierarchies and decentralised markets, or through the mediation of the functional manager. This comparison was based on the term “coordination structure” as a pattern of decision making and communication between actors executing tasks to achieve global goals. Costs incurred by each coordination structure in order to make decisions about task assignment were the main comparison criteria. Three dimensions are considered to evaluate these costs, these are: production costs, coordination costs, and vulnerability costs. Production costs refer to the operational costs to process a task and are proportional to the waiting time a task spends in the system, given that tasks are served on the First-Come-First-Served (FCFS) queuing model. As for the coordination costs, they refer to the cost of communication and are proportional to the number of messages exchanged in order to assign a task to a processor. Finally, vulnerability costs reflect the extra costs incurred to reassign a task caused by a failure of a functional manager or disruptive processors.

Following the studies led by Malone (1987) and Malone and Smith (1988), Tan and Harker (1999) conducted a relevant comparison study where they extended the cost-based comparisons by concentrating on contrasting two of the coordination structures.

These are the functional hierarchy coordination structure representing the centralised approach and the decentralised market structure standing for the market-based approach. The comparison is conducted in the context of a workflow coordination framework where the application described is exemplified through coordinating the work of white-collar employees in a small business loan processing unit. As opposed to Malone and Smith (1988) assumption of the ability to directly monitor workers' status, assigning a task to a worker requires the selection of an available worker. The selection is done by a random sampling process assuming all workers are skills-wise homogeneous. The sampling process is considered by Tan and Harker (1999) as "monitoring costs" given the assumption of the large pool of workers and different production activities taking place in different locations makes the direct monitoring of workers unfeasible. In other words, the sampling costs are added to the coordination costs since they are proportional to the number of query messages to check the workers' status. On the other hand, the market-based approach relies on the contract-net protocol (Smith, 1980). Auctions are initiated by broadcasting a "call for bids" message to all workers. Workers respond with a bid containing their ability to perform the task according to their preferences and local information. This is dependent on the time the task will wait in the system before the worker can execute it. The product manager decides to assign the task to the best bidding worker with least waiting.

Using mathematical analysis techniques and concepts borrowed from the queuing theory, Tan and Harker quantitatively contrasted both approaches from a cost perspective using the same cost dimensions as proposed by Malone (1987) and Malone and Smith (1988); that is: production, coordination, and vulnerability costs. It is concluded that the coordination costs attached to the market-based approach are relatively high; nevertheless, recommendations were concluded to adopt the market-based approach. The market-based approach is recognised to be attractive for implementation when: workers are less prone to failures and reveal their true local status, when there's a decreasing number of workers involved in the auction, when the failure rate of functional managers increase in the centralised approach, when workers are hard to be monitored, when task inter-arrival rate increases, and when coordination messaging technology is cheap.

While the studies mentioned above remarkably contributed to the comparison literature of organisation and coordination designs, apart from Tan and Harker (1999), they were mainly based on the strategic and tactical management aspect of the organisation. There is still little evidence, however, of their direct application to more operational scenarios which are prone to quick changes and directly facing the external environment. Furthermore, even though failures and vulnerability costs were addressed in the comparison criteria, this uncertainty can be categorised as internal and dependent on the individual skills, competence, and/or machinery reliability. External and environmental uncertainty was not directly included in the comparisons. How the environment dynamism and exceptions may affect the decision making process has not been investigated for cases where quick response to dynamic changes is crucial for the quality of decisions.

2.4.4. Market-based Coordination in Routing Applications

Decision making regarding routing and transportation applications are very common in production and service organisations. It mainly deals with scheduling and planning the activities of fleets of vehicles and/or teams of mobile workers to serve customers at different locations through a certain planning horizon. These applications are commonly addressed in a centralised way by the planning and operations department of such organisations.

Traditionally, these scheduling and planning problems are addressed by a centralised approach (Mes *et al.*, 2007; Máhr *et al.*, 2010). The “centralised” approach mainly refers to the methods where complex algorithms or meta-heuristics are employed by a central computing unit to solve these, generally, NP-hard problems. Despite the clear dominance of the centralised solutions, there have been considerable efforts to apply the multi-agent market-based approach to different traffic management and transportation applications based on the vehicle routing problem (VRP). (Davidsson *et al.*, 2005) and

(Chen and Cheng, 2010) provide comprehensive reviews on the use of agent-based techniques for transportation and traffic applications. Contrary to centralised solutions, the market-based approach deals with such optimisation problems by decomposing them into smaller problems, delegating the decision making to different agents involved in the market settings. The combination of the sub-solutions obtained by agents via market transactions forms the global solution.

Despite the application of both approaches on routing and transportation planning, very few studies compared the centralised and market-based approaches in the context of routing and transportation applications (Mes et al., 2007) and further comparisons in different applications are necessary for practically adopting market-based solutions (Davidsson *et al.*, 2005). Apart from the comparisons by Mes et al. (2007) and Máhr et al. (2010), nothing much has been done in this area.

In their study, Mes et al. (2007) compared a hierarchically structured centralised approach with a hierarchical market setting based on combinatorial Vickery auctions (Vickrey, 1961). This was done in the context of a real-time multiple-vehicle pickup and delivery routing problem with time windows and the presence of dynamic tasks. The simulation model was applied on unmanned vehicles operating on a rail network. The findings suggest the superiority of the market-based techniques in all cases, i.e. low and high dynamism. This can be attributed to the hierarchical market-based structure. With such a structure, global information is available to all agents in the market; whereas, a basic constraint in distributed markets is to solely rely on local information (Ygge and Akkermans, 1999). Furthermore, even if combinatorial auctions result in better performance if an equilibrium is reached (Wellman, 1993), they can lead to local bottlenecks as the problem size increases and gets more complicated (Dias *et al.*, 2006). Most importantly, given that the simulation model assumed that the vehicles were unmanned and operating automatically on a rail network, no travel delays were considered. Only service time was prone to delays. That is, if rescheduling is needed, then changes may only affect schedule entries following the active task. This considerably limits the flexibility of the application and cannot be generalised to other routing problems where en-route deviations are possible. Furthermore, should any change affect a vehicle schedule, this change only takes effect after the current task is completed giving an extended period of time for a sophisticated algorithm to compute solutions. In other words, despite decisions may be taken in real-time upon the arrival of a dynamic task or in response to a perceived delay, a respective reaction is not carried out instantaneously.

Another comparison study appears in (Máhr et al., 2010) applied on a dynamic drayage problem with service time uncertainty. The comparison approach is very relevant to this study since it was comparing both approaches in transportation application with the presence of delays and arrival of new dynamic jobs. However, the comparison was conducted on a variation of the VRP referred to as “truck load pick-up and delivery problem with time windows”. In such problems the flexibility of changing schedules and reacting to the changes at any time is limited. This is due to the fact that loaded trucks cannot change their destinations before they unload at customers’ locations. The main finding of this paper is that the market-based approach, represented by a market based on second-price Vickery single-round sealed bid auctions, can perform competitively with the centralised algorithm, represented by an online SIMPLEX algorithm for solving mixed integer problems. It is found that the agent-based approach outperforms the centralised algorithm for cases where service times are highly uncertain. The opposite was concluded for the case of arrival of dynamic jobs. When both uncertainties are applied, the centralised approach was leading in cases of high rates of combined uncertainties. The market-based approach, however, was claimed to outperform in cases of moderate rates of combined uncertainties.

Despite the relevance and importance of the previous comparison study; the observed results cannot be generalised for problems where flexibility is higher. It is meant by flexibility, the ability to react to the necessary changes done to schedules, due to uncertainty, as soon as they occur. Another important point worth noting is the problem size. All simulated instances contained the problem of scheduling a fleet of 40 trucks. Such a problem size is manageable with an online algorithm running on modern hardware. However, since scheduling problems are NP-Hard hard, then maintaining an online algorithm operating in real-time to manage large problem instances within a highly uncertain environment seems inappropriate. Most importantly, these comparisons were based on comparing the performance achieved by two algorithms without covering the vulnerabilities of each approach in light of the experienced uncertainty.

As a conclusion of the reviewed comparisons addressing the centralised and market-based approaches, the following table summarises the most relevant studies.

Author(s)	Context	Centralized Structure	Market-based Structure	Environment Uncertainty	Comparison Criteria	Study Outcome
Malone and Smith (1987)	Organisation and IS structures.	Product hierarchy, functional hierarchy	Decentralized market, centralized market.	Low (based on processors failures).	Production, coordination, and vulnerability costs.	Analogy between organization structures and future IS architectures.
Tan and Harker (1999)	Organisation and IS structures.	Functional hierarchy.	Decentralized market (CNP).	Low (based on processors and functional management failures).	Same as Malone and Smith (1987).	A set of corollaries prescribing when an approach is more suitable than the other according to multiple variables.
Ygge and Akkermans (1999)	Energy management.	Standard engineering thermal control.	Multi-agent system with combinatorial market.	None.	Performance measured as standard deviation of the optimal solution.	Local knowledge + market communication = Global control.
Fan *et al.* (2003)	Supply chain organisations	Linear program.	Combinatorial auction.	None.	Resource allocation costs.	Proposing a combinatorial auction market with incentive alignment providing goal congruence in the organisation.
Mes *et al.* (2007)	Operations management (VRP).	Local dispatch and serial scheduling heuristics.	Hierarchical market structure with Vickery auctions.	Dynamic arrivals of orders.	Costs incurred by vehicle utilization, and service level.	Market-based approach always yields higher performance.
Màhr *et al.* (2010)	Operations management, drayage problem (variant of VRP).	Online mixed integer program	Vickery auction	Dynamic arrival of new orders and stochastic waiting times at customers' locations.	Operation costs caused by travels, travel of empty containers, and penalties of rejecting orders.	- MB outperforms when service time is highly uncertain and when delays and arrival uncertainties are moderate. - C outperforms under dynamic arrival of new orders and when both uncertainties are high.

Table 2-2. Most relevant Centralised vs. Market-based comparison studies summary.

This study complements the existing comparisons in routing and transportation by investigating the centralised and market-based approaches from a different perspective than just a heuristic comparison. Regardless of the performance indicators studied in previous comparisons, they were all limited to compare algorithms. Whereas and according to organisation design literature, deciding upon the centralisation or distribution of decision making depends not only on the available decision support tools, but also includes other factors affecting the whole decision making process such as the organisation environment, organisation activity, and information structure (Galbraith, 1974; Lin, 2006; Lin, 2007; Daft, 2009). The following table summarises the relevant arguments from the reviewed literature in different fields and that are suggested to have significant impacts on the performance difference between both approaches in distributed applications involving optimisation decision making.

Field	Argument	Authors
Organisation Theory.	Workers' skills, level of training, and use of personal and local knowledge are crucial for experiential decision making procedures.	(Huber and McDaniel, 1986; Jensen and Meckling, 1992; Jensen and Meckling, 1994; Lin and Carley, 1997; Lin and Hui, 1997; Lin and Carley, 1997; Nault, 1998; Lin, 2006; Lin et al., 2006; Lin, 2007)
Organisation Theory, real-time optimisation in operational research in face of uncertainty.	Quick responses are essential to face uncertainty and to update running solutions resulting in time pressure on the decision maker which affects the solution quality in its turn.	(Lin and Carley, 1997; Shen, 2002; Lin, 2006; Lin et al., 2006; Mes et al., 2007; Máhr et al., 2010)
Operational Research.	Optimisation problems are NP-Hard making the relationship between the problem size and computation time (decision making time) nonlinear.	(Fan *et al.*, 2003; Dias *et al.*, 2006)

Table 2-3. Observed arguments with potential effect on Centralised versus Market-based performance

From the previous table, three main arguments stand out from the reviewed literature. These are the: i) the importance of workers' experience, skills and ability to demonstrate their local knowledge in experiential decision making procedures in an organisation, ii) timely reactions are essential in order to minimise the negative impacts of uncertainty, notably in scenarios requiring real-time reactions, and iii) problem size is a main hurdle facing quick responses for optimisation problems given the extended computation time. These arguments are adopted and conceptualised to be included in the conceptual model, as it will be discussed in chapter 3.

2.5. The Mobile Task Allocation Problem as an Optimisation Problem

The MTAP is an optimisation decision making problem facing many real world organisations; notably service organisations with teams of mobile workers operating on geographically dispersed tasks (Voudouris *et al.*, 2006; Lesaint *et al.*, 2000; Azarmi and Smith, 2007; Castillo *et al.*, 2009; Sun *et al.*, 2012).

Managing mobile workforce is a challenging and complex problem consisting of multiple sub-problems. From an organisation's operational point of view, operations carried out in order to deliver services to customers should be efficient cost-wise and effective to maximise customers' satisfaction. Therefore, on one hand the management problem faced here is a combination of routing optimisation, to minimise travel costs, and scheduling, to maximise the utility of the working time horizon (Lesaint *et al.*, 2000; Voudouris *et al.*, 2007). On the other hand, there are some special considerations related to the human side of the workforce. These problems have to be addressed to ensure the organisation is meeting the required health and safety standards. These problems can be related to shifting and rostering management e.g. (Ernst *et al.*, 2004; Bester *et al.*, 2007), scheduling working breaks and duty rules e.g. (Powell, 1996), and annual leaves and holidays planning. The latter category of problems can be considered as parts of human resources management problems. In this study, only the operations management aspect is considered. Therefore, the routing and scheduling problem of mobile workforce is considered in the MTAP.

2.5.1. The Mobile Task Allocation Problem & Static Routing Problems in OR

The MTAP consists of efficiently allocating a set of geographically dispersed tasks to teams of mobile workers over a limited working time horizon. A solution for such a problem is a set of schedules, one per worker per day, where the global performance measurement is optimised. The measured performance in the MTAP can be described as an objective function with a goal of maximising a weighted summation of a customer satisfaction metric minus the incurred operational costs. Customer satisfaction is modelled by a score attached to tasks that is obtained by the worker whom successfully service them. Operational costs are estimated by the travel costs which are in function of the travelled distance. Despite that MTAP can be addressed for extended time periods, this study only considers, for the sake of simplicity, a time horizon of a single working day.

Considered as a routing problem, the MTAP can be attributed to the family of Vehicle Routing Problems (VRP). (Toth and Vigo, 2002) provides a comprehensive review of the VRP family of problems along with the most common algorithms and heuristics used to solve them.

Several well-known routing problems derived from the family of VRP are commonly described in the operational research literature. The Travelling Salesman Problem (TSP) and its variations (Gutin and Punnen, 2002) is one of the most famous routing problems (Zhang and Korf, 1996). In the TSP, a single mobile agent, referred to as a salesman (or worker), has to visit a set of vertices exactly once starting and ending at an initial location according to the shortest path connecting these vertices. These vertices are referred to as cities or customers, and the initial location is called the home vertex. This kind of tours, where all cities should be visited exactly once, is called a Hamiltonian path. With the distances between any two vertices are given, the goal is to find a Hamiltonian path with the shortest travelled distance.

Many variations of the TSP with several scenarios were discussed in the literature and different algorithms and heuristic were suggested. For instance, the asymmetric traveling salesman problem is a derivative of the standard TSP having the cost of traversing an arc connecting two vertices dependent on the travel direction (Kanellakis and Papadimitriou, 1980; Zhang and Korf, 1996; Cirasella *et al.*, 2001; Altinel *et al.*, 2009; Majumdar and Bhunia, 2011; Chen *et al.*, 2011). The orienteering problem (OP) (Tsiligirides, 1984; Golden et al., 1987; Chao et al., 1996; Vansteenwegen et al., 2011) is another generalisation of the TSP with particular resemblance to the target MTAP addressed in this research. The OP is also known in the routing optimisation problems literature under several synonyms (Vansteenwegen *et al.*, 2009). Among these synonyms are the multi objective vending problem (Keller, 1989), the selective traveling salesman (Laporte and Martello, 1990), the traveling salesman with profits (Dejax et al., 2005), and the bank robber problem (Arkin et al., 1998). In the OP, and its matching problems, each vertex of the target graph is assigned a score (e.g. bonus points) and the objective is to build a path, limited in length, that visits a subset of vertices and maximises the total sum of the collected scores.

The particularity of the TSP and its variations is the number of tours considered to optimise. There is only one tour to be optimised for one travelling agent (i.e. salesman). The multiple TSP (m-TSP) (Bektas, 2006) is a generalisation of the TSP involving a team of m salesmen. Each salesman has to visit a subset of the vertices. The sets of the visited cities by each salesman are mutually exclusive, that is, each city is visited exactly once by one of the salesmen. The m-TSP basically resembles to the MTAP from the fact that it addresses the problem of optimising the total travel distance of a team of mobile workers. However, all vertices have the same importance and they all have to be visited; a situation that cannot be handled in real life scenarios given that demand exceeds the available resources. Furthermore, standard objective functions and constraints of the m-TSP are not including the travel and task execution durations and constraints about working time horizon.

The multiple tour maximum collection problem (MTMCP) defined by Butt and Cavalier (1994) is a generalisation of the selective traveling salesman described above where there is $m > 1$ travelling agents. Similarly, the Team Orienteering Problem (TOP) proposed by Chao et al. (1996) is a generalisation of the OP where $m > 1$ tours have to be optimised to satisfy the objective function of maximising the total collected score. In that sense, the TOP can best match the MTAP. In the TOP, m team members start from a specific point, referred to as the depot, and have to visit a subset of n "control points". Each of the control points i is coupled with a bonus score S_i obtained by the team when a member visits that point. If each control point is assumed to represent a task, then the bonus score can reflect the importance or urgency of that task. All members have to reach a final point within a time limit T_{max} which can be fixed as the ending time of a working day. Because the time limit doesn't allow the team members to visit all locations, members have to select a subset of control points to visit in order to maximize the total bonus score collected by the team, and to reach the end point by T_{max}. The final score can reflect the level of customers' satisfaction. Therefore, the TOP is the generalisation of the OP with $m > 1$. Given that the OP is a special case of the TOP where $m = 1$ and which has been proven to be NP-hard (Golden *et al.* 1987), it can be concluded that the TOP is NP-hard as well.

The TOP was addressed by different studies in the literature suggesting new solutions; however, all the proposed solutions were based on the centralised heuristic approach and none examined the market-based alternative. Chao *et al.* (1996) used a heuristic employing a set of simple procedures to produce good solutions with relatively small computation costs. Later, Tang and Miller-Hooks (2005) proposed a tabu search heuristic to solve the TOP. Thereafter, Vansteenwegen *et al.* (2009) suggested a guided local search meta-heuristic which reduces computation time compared to other techniques and still produce good solutions. The main criteria used to compare the different solutions were the obtained objective function score and the computation time.

It is worth noting that despite the resemblance between the TOP and the MTAP, the TOP formulation cannot be directly adopted given that it doesn't include a constraint to consider service time at the control points; furthermore, the objective function does not reflect the travel costs. For these reasons, a new formal representation for the MTAP is suggested in Chapter 4. Furthermore, none of the previously mentioned studies considered uncertainty in TOP heuristics. This study serves as first step suggesting the necessity to consider stochasticity and dynamism in such problems.

The MTAP is a real-world optimisation problem that can be faced in different business organisations. Service companies having teams of maintenance workers using the company's vehicles and starting their working days from their home locations are examples of such organisations. Product and marketing companies are also candidates for similar scenarios. Despite the direct objective of each organisation may differ, but they all essentially stress on the optimisation of their operational costs (essentially travel costs in these cases) and on preserving customer satisfaction over a certain threshold. Customer satisfaction may be measurable in several ways.

The following table lists the most relevant routing problems in operational research and compares them to the MTAP.

Problem	Objective Function	Main Constraints	Agents
Vehicle Routing Problem (VRP)	Varied, most popular are: - Minimise travel costs. - Minimise the number of deployed vehicles. - Minimise makespan.	Visit a subset of locations. A location is visited only once by an agent. A visited location by an agent cannot be visited by another agent. All agents' subset are mutually exclusive and their union is the set of all locations. All agents start and end at the same initial location. Vehicles capacity, time windows, pickup& delivery constraints are sometimes present.	m
Travelling Salesman Problem (TSP)	Minimize travel costs, finding shortest path.	Visit all locations exactly once. Start and end at the initial location.	1
Multiple Travelling Salesman Problem (mTSP)	Minimize travel costs by the group of travelling agents. Minimize the sum of travelled distances.	Each agent visits a subset of locations. A location is visited only once by any agent. A visited location by an agent cannot be visited by another agent. All agents' subset are mutually exclusive and their union is the set of all locations. All agents start and end at the same initial location.	m
Orienteering Problem (OP)	Building a path, limited in length, that visits a subset of scored vertices and maximises the total sum of the collected scores.	Similar to mTSP except that the path is limited in length. This length can be expressed as duration (e.g. travel duration).	1
Team Orienteering Problem (TOP)	Maximize the sum of collected points from visiting a subset of locations.	Each location is visited at most once by an agent in the team. All agents start, have to visit locations, and return to start point within time T_{max}. Travel times are considered. T_i is the time needed to visit location i.	m
Mobile Task Allocation Problem (MTAP)	Maximize the sum of collected points from visiting a subset of locations taking incurred costs in consideration.	Each location is visited at most once by an agent in the team and requires time to spent on site. Agents start at different locations and end at the last visited location. Travels and visits duration do not exceed T_{max}. Travel and processing costs may differ between agents.	m

Table 2-4. Comparison of the MTAP with the relevant well-known OR routing problems

2.5.2. Uncertainty & Routing Problems in OR

All problems described above can be categorised as static and deterministic. In the static version of optimisation problems, all input data is available prior the search of a solution. This means that input data is time-independent and new data cannot be introduced to the problem as time progresses (Berbeglia et al., 2010). On the other hand, a problem is stated to be deterministic when all data is fixed and not prone to any random changes during solutions execution (Ghiani *et al.*, 2003).

The operations research literature has not been limited to consider only static and deterministic versions of the routing problems; but many VRP variations were addressed in dynamic and stochastic contexts too. (Gendreau *et al.*, 1996; Larsen *et al.*, 2002; Ghiani *et al.*, 2003; Flatberg *et al.*, 2007; Berbeglia *et al.*, 2010) provide detailed surveys on different classes of routing problems with different sources of stochasticity and dynamism while listing different methods to embed uncertainty as a main characteristics in their solutions.

Generally, stochasticity, as opposed to determinism, refers to the uncertainty about information which may be known a-priori but are prone to random changes in function of time. In other words and according to Gendreau *et al.* (1996), stochastic VRP arises "*when some elements of the problem are random*". VRP with stochastic service and travel times, e.g. (Bertsimas and Van Ryzin, 1991; Bertsimas and Van Ryzin, 1993; Fischer et al., 1996; Chang et al., 2009), stochastic customer demand, e.g. (Mendoza *et al.*, 2010; Pandelis *et al.*, 2012), or vehicle breakdowns, for example (Li *et al.*, 2009), are all sources of stochasticity.

On the other hand and as opposed to static problems, dynamic problems refer to the arrival of new input to be taken in consideration in the actual solution as time progresses. According to Powell *et al.* (1995), a dynamic problem is one which has one or more parameters in function of time. Similarly, dynamic applications have underlying models which are solved repeatedly as new information enters the system. As a result, considerable computational resources are needed. From a VRP point of view, dynamic problems include VRP with dynamic demand when new requests have to be served after operations have started. This is a typical and widely studied problem. In such settings, new customers with random demands enter the system and expect to be considered while the previous solution is being executed.

According to Psaraftis in (Psaraftis, 1988) and (Psaraftis, 1995), the dynamic version of the VRP can be mainly differentiated from its static counterparts in 12 points:

1- **Time dimension is essential**: The time dimension in static problems may not be of high importance. However, in dynamic versions of the VRP at least the location and actual information of the vehicles should be available to the solver in order to include new requests.
2- **The problem may be open-ended:** Given that in static situations the process time is known in advance, therefore the conventional VRP aims at constructing Hamiltonian tours starting and ending at the initial depot location. Such tours cannot be guaranteed in dynamic settings. Instead, open paths are constructed and altered as time progresses.
3- **Future information may be imprecise or unknown:** In contrast to real-life dynamic situations where the future is almost unknown, in static problems all information is known with certainty and would not change in the future.
4- **Near-term events are more important: A**s opposed to static settings where there is no input information updates, in dynamic settings the solving dispatcher should not focus on long term requirements since they may change dramatically in function to new input.
5- **Information update mechanisms are essential:** Given that a major part of input information is constantly changing in the dynamic VRP, it is essential to design a proper information update mechanism and integrate it with the solving process. Such update mechanisms are not relevant in static contexts.
6- **Re-sequencing and reassigning decisions may be warranted:** As new input enters the system, previous solutions may turn outdated and suboptimal forcing the solver to reroute or reassign vehicles in response to the new changes. In static

versions, no changes on the solution are to be made once the optimal solution is found.

7- **Faster computation times are necessary:** In static settings, it is possible to wait for intensive computational operations of advanced algorithms seeking for high quality and optimal solutions. However, when dynamism is introduced, it is inappropriate for the dispatcher to run long time-consuming algorithms, especially that solutions are to be updated within minutes or seconds.

8- **Indefinite deferment mechanisms are essential:** This refers to the possibility of not servicing some demands when it clearly saturates the available resources. This is particularly true in highly dynamic settings or when certain demand is located in an unfavourable geographical location. This problem can be alleviated by considering time windows or introducing some penalty expression in the objective function in case of excessively delaying servicing a demand.

9- **Objective function may be different:** In traditional static objective functions the aim was to minimize the whole travel distance or costs. This may not be directly applicable in case dynamic problems where the process is open-ended and future input is unknown. Instead, optimising the problem at hand with available information may turn to be a sound approach to follow. However, if future input can be forecasted or estimated then these should be included in the objective function as well.

10- **Time constraints may be different:** For VRP with time windows, time constraints may be hard for static versions of the problem. In dynamic settings, time constraints tend to be softer. This is due to the fact that, despite the probable incurred penalty costs, delaying an immediate demand may still be more attractive than denying it because its time constraints cannot be met.

11- **Flexibility to vary vehicle fleet size is lower:** In VRPs having to minimise the number of deployed vehicles in their objective functions, an alternative to delay a demand might be by deploying new vehicles at a certain cost. Given that in static versions of such problems the time between planning and execution of plans is relatively long, such extra optimisation can be done. This extended period of time is not present in dynamic versions; therefore the flexibility in limiting the number of used vehicles is lower.

12- **Queuing considerations may become important:** If the arrival rate of customer demands exceeds a certain limit, the system turn to be congested and not all requests may be addressed during the time constraints. Therefore, algorithms used in static settings are bound to produce low quality results in such settings.

Following this differentiation, Psaraftis (1995) provided a taxonomy characterising the attributes of the information forming problems' input and ways VRPs are solved. This are listed as following:

- **Evolution of information:** In static versions of the VRP all input data remain stable and unchanged. Such information can be the number of vehicles and demand locations. However in dynamic settings, new information and input are gradually revealed as time passes. So given that dynamic demands enter the system according to a Poisson process with parameters μ and λ, which remain fixed, the time of a new demand, its location, its service time, and locations of vehicles at that time are all, nevertheless, revealed dynamically.
- **Quality of information:** In dynamic VRP, information may be deterministic implying that it will not change when revealed, probabilistic following a certain probability random model, known with uncertainty and depends of forecasts, or totally stochastic and cannot be accurately determined beforehand.
- **Availability of information:** Information is either local or global. Local information refers to agents' local knowledge and may depend on the agents' perception of the surrounding context. Global information is formed when all local information is gathered at one decisive point, like the customer demands dispatcher.
- **Processing of information:** Information can either be processed in a centralised or in a distributed way. In the centralised approach, global information is concentrated at a single solving point. On the other hand, some of the information can be processed by the agents in a distributed manner. It is worth noting that distributed approach allows for the parallel processing.

In order to tackle optimisation problems involving uncertainty, operational research employs different techniques and methods for decision making. Some of these techniques are straightforward and based on re-optimising the initial solution whenever new uncertain information is revealed (Berbeglia et al., 2010). Re-optimisation can be done by solving the whole problem from scratch combining the new information to the already known parameters, or by applying updating strategies that are adapted heuristics to operate on smaller amount of input data in order to consume less time. While the first method is easier to setup, it does not guarantee its feasibility for online problems where real-time reactions are needed. Using updating strategies requires the decision maker to solve the static problem only once followed by applying the necessary changes through insertion/deletion heuristics or by swapping moves. These strategies ensure quick and feasible updates for dynamic real-time problems.

While the previous simple techniques are widely used to tackle dynamic VRP's, they do not consider the use of information related to future uncertainty. The knowledge about the probability distributions of future events may be employed at the planning time to anticipate future events in the form of scenarios. "*Stochastic programming*" is among the most popular approaches to include uncertain variables in the objective functions of optimisation problems (Kall and Wallace, 1994; Archibald *et al.*, 1997; Birge and Louveaux, 1997; Archibald *et al.*, 2006). By using stochastic programming with recourse techniques, the decision maker takes decisions at two stages. The first stage requires the decision maker to decide upon the variables and their values prior the occurrence of uncertain parameters. Such decisions are made assuming that the uncertain parameters can be modelled as random variables with known distributions. Once uncertain parameters are realised and all information becomes available, recourse actions are taken at the second stage to correct any probable infeasibility. Usually such corrections are made at a certain cost that is aimed to be minimised from the planning phase. Sahinidis (2004) provides a comprehensive review on optimisation under uncertainty when information regarding future exceptions is available at planning time. Another method for using a-priory information about future uncertainty is the "*fuzzy mathematical programming*". Contrary to the stochastic programming, where uncertainty is modelled through probability functions, random parameters are considered as fuzzy numbers and constraints as fuzzy sets (Bellman and Zadeh, 1970). That is, the degree of satisfying a constraint in linear program is defined as a membership function of the constraint fuzzy set.

Essentially and regardless of the way uncertainty is handled by the problem solver, it can be seen that operational research techniques to tackle uncertainty in optimisation decision making problems are systematic and quite similar to how centralised organisations perceive and contains uncertainty. This is mainly realised by obtaining initial decisions (feasible static solution) that is executed until exceptions occur and more information is revealed to take better decisions. The central solver then uses the employed techniques (update heuristics or second-stage recourse) to decide upon the corrective actions. The newly obtained solution is then executed until new exceptions happen to repeat the correction cycle. Furthermore, these techniques mainly rely on the global availability of real-time information about uncertainty and the ability to instantaneously process the amount of information generated by exceptions, which greatly depends on the problem size and complexity of the studied uncertainty.

Given the particularity of the VRP family in its distributed nature facing myriad types of uncertainty and due to technological advancements in ICT, the market-based approach is recently considered as a convenient approach to handle uncertainty in a distributed fashion and to process uncertain information locally. The studies by Mes *et al.* (2007) and Màhr *et al.* (2010) are the most outstanding examples.

2.6. Conclusions

This chapter started by describing the centralised and the distributed market-based approaches for addressing decision making problems related to resource allocations. Given the divergence of structures and decision making procedures between these approaches, the organisation theory perspective is reviewed to outline the importance and methods of insuring the collocation of information and decision making rights, notably under uncertain environments. The chapter then continued to review the existing comparisons contrasting both approaches in different fields concerned with the managerial issue of resource allocation. Each field distinguished several arguments making an approach favourable over the other in different contexts. In the second part of this chapter, the MTAP is briefly defined and placed among the related problems from OR literature which are also reviewed. A particular focus is dedicated to the differentiation between static versus dynamic and deterministic versus stochastic problem settings. Different techniques of handling these problems with uncertainty are also reviewed.

The following list of conclusions was drawn from the previous review:

- Resource allocation problems (RAPs) are critical decision making problems faced in organisations and often require optimisation processing. Task allocation problems (TAPs) are a variance of RAPs addressing the best utilisation of the available workforce by optimising the appropriate tasks assignment and workforce schedules. The mobile TAP (MTAP) is a variance of the TAP characterised by its distributed and mobile workforce.
- Uncertainty has a significant impact on the initial allocation decisions and the adaptation to such environments in crucial for maintaining performance minimum thresholds.
- Two main approaches exist to address general RAPs. These are the centralised and the distributed, which is often represented by the market-based (or agent-based) approach. Generally, the centralised approach is adopted by default to address RAPs and produces better performance in static settings. However, the market-based approach has been applied in its turn to several distributed applications (e.g. transportation and routing problems) since it allows a natural distribution of optimisation decision making.
- The organisation theory gives particular interest to the relation between the organisation structure, decision making procedure, and the surrounding environment. According to this perspective, the collocation of information and decision making rights are crucial for facing the dynamic surrounding

environment. This is either done by information transfer (centralisation) or by lowering the decision making rights to where information is generated (distribution). The centralised versus market-based comparison can stand for the comparison of these two modes of information-decision rights collocation.

- Several centralised versus market-based comparisons were conducted in different fields leading to arguments of preference of an approach over the other. However, few comparisons compared the centralised and market-based approaches in the context of routing problems and none for the applications of task allocations to mobile resources.
- The mobile task allocation problem (MTAP) best matches the team orienteering problem (TOP) from the family of routing problems in the OR literature. However, the TOP has not been explicitly addressed with the presence of uncertainty; neither has it been addressed by the market-based approach.
- Two main sources of uncertainty for routing problems have been widely considered in the OR literature, these are dynamism (i.e. arrival of new requests to be served during execution) and stochasticity (i.e. travel and/or tasks execution delays). Problems involving such uncertainties are mainly handled centrally by the use of advanced techniques as stochastic programming with recourse. Routing problems with uncertainty were categorised according to the evolution of information, quality of information, availability of information, and processing of information criteria.
- The main outcome of this chapter is the categorisation of the arguments characterising each approach identified in the reviewed literature of organisation theory and operational research. These arguments are defined and linked in a conceptual model, as will be described in chapter 3.
- Finally, it is concluded that the prior studies on the comparison of the two approaches to routing problems have the theoretical gap of being limited to the algorithm level employed by both approaches and do not include the features characterising each approach, like the timeliness of central decision making and the usage of distributed local knowledge for the market-based approach.

Therefore, this study intends to compare both approaches in light their respective features in the context of the MTAP in the presence of uncertainty.

Chapter 3. Conceptual Model

3.1. Introduction

Derived from the literature review in the previous chapter, this chapter aims at describing, operationalising, and consolidating in a conceptual model the relevant arguments assumed to affect the performances of the centralised and the market-based approaches to address the MTAP.

In the previous chapter, notably in the review of the operational research literature, it is discussed that the main differences between deterministic static optimisation problems and their stochastic dynamic counterparts are the nature of the input information needed for the decision making, the way this new information is processed over time, and also on the objective function which may differ (Psaraftis, 1988). Given that in stochastic and dynamic problems the input information is neither available in its entirety nor in its perfect accuracy at any given moment, the quality of generated solutions heavily depends on the degree of dynamism, the rate of randomness, and, supposedly, the mechanism used to handle this uncertainty (Psaraftis, 1988; Psaraftis, 1995; Gendreau *et al.*, 1996; Gendreau and Potvin, 1998; Flatberg *et al.*, 2007). Therefore, different approaches to handle such uncertainty may in turn be moderated by external factors characterising the given approach. Therefore, different approaches for solving such problems may lead to different solutions with different performance throughput.

As mentioned earlier, this research does not consider the development of a new solution or solving mechanism leading to better solutions for the MTAP, but rather to develop a theoretical framework enabling comprehensive comparison of the centralised and the market-based approach when applied on the MTAP in the presence of uncertainty. This comparison is mainly based on the key characteristics of both approaches in the sense of structure, type of input information, decision making procedure, and achieved performances.

Given that this research compares two decision making approaches for the MTAP in the presence of uncertainty, the key construct of this study is formulated around the difference between the performances achieved by both approaches. The individual performance achieved by each approach on its own is of limited meaning unless compared with its counterpart from the other approach under similar uncertainty conditions.

The seminal work (Psaraftis, 1995) categorises input information and the ways of processing this information in the presence of dynamism and stochasticity in VRPs. This categorisation reflects some core features characterising the centralised and the market-based approaches like the availability of information (global vs. local) and the processing of information (central vs. distributed). Hence, this research aim would also contribute at extending the taxonomy in the work of Psaraftis (Psaraftis, 1995) by further investigating how the key features (or limitations) of each approach may aid (or hurdle) the centralised (local) processing of global (local) information, and therefore affect their performances. These features are adopted from different fields reviewed in the literature presented in chapter 2. These are the timeliness of decision making, the problem size and complexity, and the degree of local knowledge and workers' experience. The four key constructs are elaborated in the following sections, and a conceptual model is presented, which would form basis for the theoretical framework of this research.

3.2. Research Constructs

3.2.1. Dynamism, Stochasticity, and the Performance Difference Constructs

In the context of the MTAP, which is represented as an integer program as it will be depicted in the next chapter, the performance achieved by each approach is measured by the value of the objective function realised at the end of the operation time horizon. This can be for instance comparing the total incurred travel costs of the vehicles at the end of a working day. To obtain the performance difference between both scores, the arithmetical subtraction can be used according to the following formula:

$$PD_t = P_t(C) - P_t(MB)$$

Where:

PD_t: The performance difference between this of the centralised and the market-based approaches over a time horizon t.
$P_t(C)$: The performance achieved by the centralised approach over the time horizon t.
$P_t(MB)$: The performance achieved by the market-based approach over the same time horizon t.

In static and deterministic settings, PD_t tends to be a positive value given that a distributed market-based approach can at most perform as good as the centralised approach (Ygge and Akkermans, 1999). However, it cannot be affirmed that this difference would remain constant as the nature of the input information is prone to uncertainty. As reviewed in Chapter 2 many factors favouring the centralised approach become absent as an optimisation application becomes dynamic and stochastic. The extended time for running advanced decision support tools such as algorithms and sophisticated heuristics, the availability of the whole information with perfect accuracy prior processing at high frequency rates, are some of these affected factors when the degree of uncertainty increases (Psaraftis, 1988; Psaraftis, 1995; Gendreau *et al.*, 1996; Gendreau and Potvin, 1998; Flatberg *et al.*, 2007).

In addition to the previous factors, the distributed nature of the MTAP, like other routing and transportation problems, makes the process of collecting updated information more complicated for the centralised approach. For instance, direct monitoring of resources turns to be unfeasible for a central controller as the number of the distributed workers increases (Tan and Harker, 1999) and as uncertainty gets higher since this may result in severe bottlenecks (Dias and Stentz, 2003a; Dias et al., 2006).

While it is assumed that the degree of uncertainty affects the performance difference, this influence can be perceived from two perspectives: stochasticity and dynamism. While stochasticity is considered to have a negative impact on the performance achieved by both approaches, dynamism has a positive effect. This is attributed to the assumption that dynamic tasks are of higher importance than static tasks. As a consequence, timely trade-offs of tasks with low importance and scheduling more dynamic tasks leads to better solutions. In both cases of uncertainty the performance difference measurement can assess the quality of reaction of both approaches. If the value of PD_t increases, this would reflect that the centralised approach is more appropriate to handle uncertainty. Oppositely, if it decreases then it reflects the convergence of both performances. Finally, if the value of PD_t becomes negative then this means that the market-based approach reached the point of outperforming the centralised approach.

The relationships between both dimensions of uncertainty, that is, stochasticity and dynamism, and the performance difference are further assumed to be moderated by the effects of other factors. These are: “timeliness of decision making” affected in its turn by the “problem size” and the workers’ “degree of local knowledge”.

3.2.2. Timeliness of Decision Making

Timeliness of decision making is regarded as the appropriateness of the time at which decisions are made and within the time constraints. If decisions are to be made in response to uncertainty, then generally the time separating the moment when uncertainty exceptions occur, the times at which decisions are made, and corresponding actions are taken are of particular importance since they determine the timeliness of reaction (Ichoua *et al.*, 2007). In cases where uncertainty is high enough to cause changes in the initial plans and unexpected in the sense that it cannot be forecasted beforehand, the faster new decisions are made and new actions are taken the lower is the negative impact of such uncertainty. This is similar the concept of time pressure in the organisation theory. Therefore and in ideal situations, uncertainty perception, decision making, and appropriate reaction should be achieved in real time. However, due to practical restrictions, instantaneous reaction turns to be impossible, especially if the resources prone to exceptions are numerous and are not directly monitored due to a distributed operating environment (Dias and Stentz, 2003a), such as in the MTAP. Instead, periodical updates are carried out to capture the latest information of the system and update the actual decisions accordingly. Therefore, it is crucial for the central decision making authority to determine when to perform these updates as well as their frequency.

From here stems the term "timeliness of decision making" rather than organisation's "time pressure". Timeliness of decision making is intended to reflect both dimensions of the temporal aspect of decision making, these are when decisions are taken and the time separating consecutive updates. Furthermore, these dimensions are clearly reflected in Psaraftis's (1988) differentiation of dynamic VRP's from their static counterparts. Notably when mentioning the importance of the time dimension and information update mechanisms. In order to reflect both perspectives, the term "timeliness of decision making" is employed in the model.

The time separating successive updates should be balanced in order to be short enough to timely react upon exceptions occurrence while sufficient to avoid bottlenecks and extra communication overhead, resulting with extra costs (Malone, 1987; Malone and Smith, 1988; Tan and Harker, 1999). Furthermore, timeliness of decision making has a particular importance in cases where decision outcomes may take effect at any moment of time. This assumption is frequently relaxed in operations research problems or in fast environments. For instance, changes in the schedule of a machine in a factory cannot be applied before it terminates the current job, or changes in a vehicle destination are not considered for the current route in transportation problems, e.g. (Larsen et al., 2002). Therefore, to magnify the effect of timeliness of decision making, the MTAP allows route deviations at any moment as described in (Ichoua *et al.*, 2000). The route deviation assumption allows travelling vehicles to change their destinations if it becomes unreachable without delays or unattractive due to the arrival of a new task with significant higher importance. Given this, the sooner the decision of changing a route towards a new destination is made, the lower sunk costs occur on the original route.

Such flexibility may lead to considerable costs savings, especially if travel costs are high.

Centralised decision making structures perceive uncertainty through global information updates. In hierarchical structures, these information updates are obtained from the agents located at the lower levels and which are in direct contact with the external environment. When an updated global view is made available at the decision making point, it is compared with the actual plans. In case of divergence, new plans are processed as corrective recourse to contain exceptions at lowest costs and performance deterioration. When the number of resources facing uncertainty increases and the rate of uncertainty goes higher, more information flows to and from the decision making point are necessary and, therefore, decisions should be updated at a faster pace. However, after a certain threshold, the process of capturing global snapshots and producing new solutions to face endured uncertainty becomes more complicated and time consuming. Therefore, such updates are done periodically based on a push-query protocol. As stated previously, the time period separating consecutive updates should be balanced to leave adequate time room for new solutions to be processed but also short enough to perceive exceptions as soon as possible after their occurrence. The update period can be expressed by the following inequality:

$$UP \geq min\left[\max_{n \in N}(U_n), MAX\right] + DMT + BT$$

Where:

UP: Update period.

n: Resource identifier.

N: The number of resources.

U_n: Time needed for resource n to report its current status.

MAX: Timeout for query response.

DMT: Decision making time.

BT: Time for broadcasting new decisions to resources.

In settings where communication is assumed to be perfectly reliable and taking place instantaneously, the first and last elements of the previous inequality may be ignored for their insignificance. Therefore, the most influencing factor is the decision making time and the communication costs. The decision making time factor in its turn is in function of the tools used to assist the decision makers, the problem size and complexity, and the required accuracy. While communication costs highly depends on the employed technology (Tan and Harker, 1999) and its reliability.

Resources operating according to a market-based approach are responsible of taking their own decisions and maintaining their respective schedules. Therefore, actions to be taken in face of uncertainty are directly delegated to resource agents. Based on their local knowledge and on their individual decision making, plans are updated in a completely distributed and parallel mechanism as soon as exceptions are perceived. Plans' update process may require the initiation or participation in one or multiple market auctions where information about the new changes can be interpreted through exchanged bids. In such settings, agents facing uncertainty are basically facing two kinds of decision making which depend on the role of the agent in the market: initiator (auctioneer) or participant (bidder). Auctioneer agents initiating markets following their own local decisions have to decide about the winning bidder. This follows a winner resolution rule. Bidding agents on their side have to decide about the bid they submit. So according to this, the decision and reaction time needed to face an exception can be modelled as follows:

$$DMT = \begin{cases} EPT + LDMT + CFPT + WBDT + MCT: agent\ is\ auctioneer \\ BDT + MCT: agent\ is\ bidder \end{cases}$$

Where:

DMT: The decision making time upon the occurrence of a single exception.
EPT: Exception perception time. That is, the time needed for an agent to perceive uncertainty.
$LDMT$: Local decision making time. Which is the time needed for the perceiving agent to adjust its schedule according to the experienced exception.

$CFPT$: Time needed to initiate an auction and call for participants.

BDT: Bid decision time. The time needed for participants to decide about the value of the bid. This process is done locally in parallel and is independent of the number of participants.

$WBDT$: Winning bid decision time. The time needed for the initiator agent to decide upon the winning bid(s).

MCT: Market conclusion time. The time bidders wait till the initiator (auctioneer) informs the winning agent(s) and close the market. This time includes the $WBDT$ needed by the auctioneer (WBDT <= MCT).

Based on the same assumption that communication is reliable and instantaneous, $CFPT$ and MCT can be ignored. Furthermore, it is assumed that the time for perceiving uncertainty by agents is null given they are in direct contact with the external environment. Local decision making time as well as bid decision time depend on the decision making mechanism used locally and only on the size of schedule. If proper decision making algorithms are designed in order to run in real-time with limited computational resources, then the DMT can be reduced to null. This implies that decision making in response to uncertainty in the market-based approach is in real-time and close to be instantaneous.

3.2.3. Problem Size and complexity

Decision making problems regarding the efficient allocation of scarce resources are hard problems. Particularly, that those concerned with the allocation of mobile resources in routing applications are NP-hard problems (Cordeau *et al.*, 2002; Gutin and Punnen, 2002; Larsen *et al.*, 2002; Toth and Vigo, 2002; Eksioglu *et al.*, 2009). According to the computational complexity theory, this class of problems complexity implies a nonlinear relationship between the problem size and the time required in order to reach the optimal solution (Gendreau *et al.*, 1996; Dias *et al.*, 2006). In other words, the processing time for obtaining the optimal decisions about the allocations may increase exponentially in function of the size of the input information.

In this context, the problem size can viewed as the number of workers and tasks to be allocated. However, when it comes to solve MTAP instances, the properties of the input information is not limited to the number of input, but also ranges from the status of the available workers to the nature of the demand to be fulfilled.

With the presence of uncertainty, these input elements are prone to changes of which their frequency and magnitude are in function of the severity of uncertainty. These changes can be expressed in the variation of their initial values, like the stochasticity of travel times, and/or in the revelation of additional information, like the arrival of dynamic demands (Psaraftis, 1988; Psaraftis, 1995; Gendreau *et al.*, 1996; Larsen *et al.*, 2002). In both cases, modified and new input information have to be included in the subsequent decisions by updating the existing solution (decision). These solution updates are mainly done either by i) completely resolving the decision problem from scratch or by ii) applying recourse strategies as it is with stochastic programming (Sahinidis, 2004; Berbeglia *et al.*, 2010; Máhr *et al.*, 2010). In both ways, such updates can be challenging and time consuming as the problem size increases given the original problem complexity. Furthermore, centralised solutions may face severe bottlenecks as higher levels of uncertainty are affecting this growing size of input information (Fan *et al.*, 2003). Therefore, the frequency of such update mechanisms is strongly bound by the decision making time needed in order to process the new input (i.e. decision making time) which strongly depends on the problem size.

By returning to the construct "timeliness of decision making" discussed earlier, the update rate variable (UR) is defined as a function of the decision making time variable (DMT). This construct, "decision making problem size", suggests that the DMT variable is further in function of the problem size. Therefore, it is proposed that the problem size is affecting the relationship between the performance difference of both approaches and uncertainty, mediated by the timeliness of decision making construct.

$$DMT = f(n, t)$$

Where:

n: Refers to the number of workers to be managed.

t: The number of tasks to be scheduled.

Following this description of the problem size construct, it can be concluded that it mainly affects the centralised approach given that it deals with the collection of global information and process this bulk of input in order to reach global decisions. On the other hand, this construct is of marginal effect to the market-based approach given that all decisions are taken in parallel.

3.2.4. Degree of Workers' Local Knowledge

As mentioned in chapter 2, the main difference between the centralised approach and the distributed approach, such as the market-based, is their structures and the locus of the decision making rights (Jensen and Meckling, 1992; Nault, 1998). Therefore, the difference between both the decision making processes mainly resides in the location and type of information used for this decision making. While the centralised approach benefits from the global knowledge collected from the lower levels of the hierarchy and processed centrally, the market-based approach relies on the distributed local knowledge in order to reach individual decisions. This categorisation matches "*availability of information*" and "*processing of information*" elements in the taxonomy proposed by Psaraftis (1995).

By focusing on the concept of the agents' local knowledge, it can be interpreted in several ways and at different levels. Unlike the other two constructs mentioned above that are more tangible and quantifiable, local knowledge is highly subjective and tends to be more human oriented. Human senses and basic logical reasoning that a person benefits from form the first level of local knowledge when taking any decision (Eraut, 2000; Brockmann and Anthony, 2002). For instance, a human worker would be able to judge the occurrence of an exception (e.g. traffic jam) and therefore try to avoid it. This aspect of local knowledge is very basic but crucial and is eagerly sought to be improved when the entities to be managed are not naturally endowed with such senses, like machinery in a factory or robots in spatial missions. For instance, the market-based approach proved its suitability to manage teams of rover robots during interplanetary missions in the field of robotics (Dias and Stentz, 2003b; Stentz et al., 2004); however, the quality of the autonomous decisions made by the robots highly depends on their ability to accurately recognise the surrounding environment, foresee future events, and act accordingly. This is achieved by equipping them with advanced sensors and processors to process and understand the surroundings.

Another important aspect of local knowledge is the individual experience an agent possesses for making decisions. An agent's personal experience is acquired through time and in different circumstances that form, along with the basic senses, the tacit knowledge of that agent. As opposed to the explicit type of knowledge, tacit knowledge is hard to transfer or to directly communicate (Osterloh and Frey, 2000; Brockmann and Anthony, 2002) and is yet of high importance to sustain the organisation performance if such a knowledge is crucial to attenuate the negative impacts of uncertainty when first perceived by upfront workers. Therefore, the degree of local knowledge and experience

The degree of local knowledge is regarded in this research as the level of knowledge an agent can accumulate explicitly based on its own perception of the surrounding environment, personal experience, and skills. This construct particularly affects the performance achieved by the market-based approach and is marginal for the centralised approach. This is due to the experiential decision making procedure followed in the market-based approach enabling the workers to be proactive in the decision making process, while workers in the centralised approach are considered as passive and reactive entities following the procedural orders dictated from the central decisive authority.

In light of this definition of local knowledge and with respect to the bounded-rationality of individual agents, it is proposed that different levels of local knowledge would lead to different decision qualities when an experiential decision making procedure is adopted as it is the case for the market-based approach. However, it is strongly constrained that no isolated local knowledge can equal to a global awareness of the system. This assumption matches its equivalent in the study by Lin (2006) and forms the essence of the term “*local*”.

3.3. Conceptual Model

In order to consolidate all the studied relationships described previously, Figure 3-1 presents a model conceptualising the focal construct entitled “Performance Difference”.

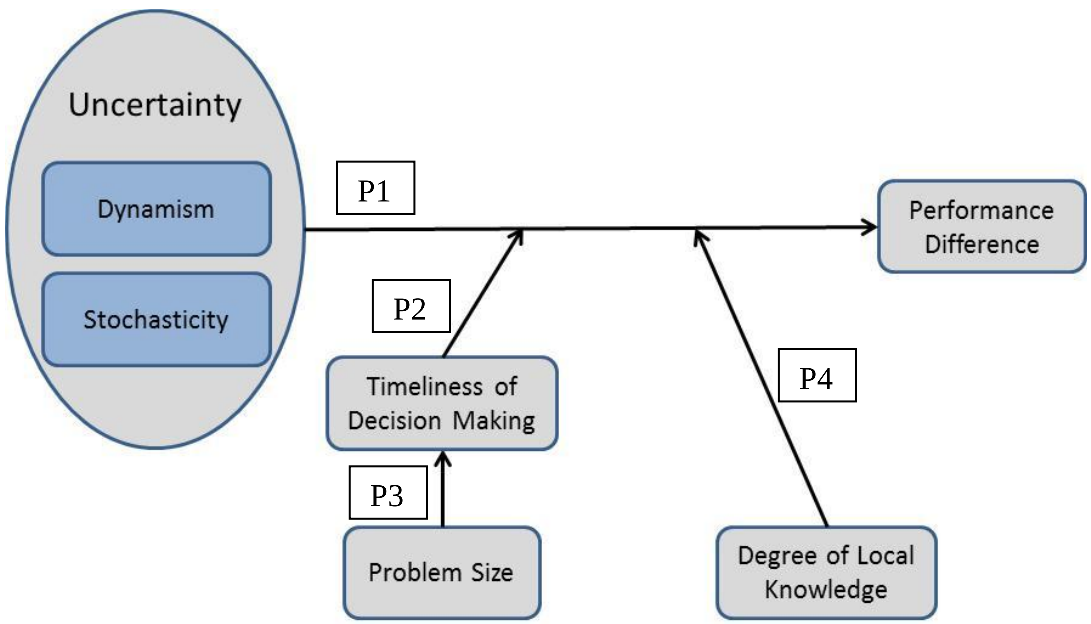

Figure 3-1. Research conceptual model

As depicted in Figure 3-1, uncertainty is considered from two main perspectives: dynamism, which is the ad hoc arrival of new tasks; and stochasticity, which is the distortion of information revealed. These perspectives were considered due to their significance as reported in the literature. Performance difference is the key construct that evaluates the suitability of an approach over the other; this construct is calculated by the performance of each approach that considers impact of the moderator constructs. Moreover, Figure 3-1 illustrates three moderator constructs, where the degree of local knowledge is independent and timeliness of decision making is dependent on the size of the problem. This conceptual model would be used in Chapter 6 to compile the proposed theoretical framework.

3.4. Research Propositions

According to the conceptual model in Figure 3-1 and following the above description of the constructs studied in this research, the relationships connecting these constructs can be described in terms of propositions. The following derived propositions are suggested in order to be tested and validated through simulation experimentations, as it will be described in subsequent chapters and are listed as follows:

P1: Uncertainty has a negative impact on the performance difference. This proposes that the higher the dynamism rate gets, the lower is the difference between the performances exhibited by both approaches**.** Starting with a superior performance in favour of the centralised approach in static settings, the inappropriateness of executing long processes to include new tasks imposes on the centralised approach to trade off superior accuracy in decision making for faster processing. This is notably true for the centralised approach to keep pace with new changes as the rate of new tasks' arrival increases. On the other hand, since reaction occurs in real-time for the market-based approach, the lower performance achieved from distributed markets may catch up with this of the centralised approach starting from a dynamism threshold decreasing the performance distance.

P2: Timeliness of decision making has a significant moderating role on the relationship between uncertainty and the performance difference. This proposition suggests that the time between the moments a new task enters the system and at which it is scheduled affects the influence of dynamism on the performance difference. In the case of the market-based approach, this construct is of no value given that decisions are made in real-time. On the other hand, this construct directly affects the centralised approach due to its periodical decision making recourses. The longer the update period, the later new dynamic tasks are scheduled, resulting in higher probability of sunk costs given that route deviation is permitted in the MTAP. On the other hand, the update period cannot be lower than a minimum limit to keep a certain performance quality.

P3: Problem size has a significant impact on the timeliness of decision making, which further affects the relationship between uncertainty and the performance difference. This proposition relates to the previous one by suggesting that the timeliness of decision making is controlled by the decision making time, which is in turn in function of the problem size. The effect of the problem size is accentuated as uncertainty increases affecting large parts of the current allocations, the more the complexity of the problem is (expressed in terms of constraints), and the finer the results are required. This proposition is basically related to the centralised approach given that it centrally runs decision support systems to generate global solutions for every entity. On the other hand, the problem size does not affect the market-based approach since global decisions emerge from the distributed solutions obtained in parallel solely by processing local information on individual problem instances. This distribution significantly reduces the problem complexity and size, and therefore results in much simpler and smaller local problem instances. This is similar to reducing a single mTSP instance of n salesmen and m cities to n TSP instances, each with an average city set size of m/n, solved in parallel. The exact city set is determined by market transactions among the salesmen.

P4: Degree of local knowledge has a significant moderating role on the relationship between uncertainty and the performance difference. This proposition is mainly related to the market-based approach and is of limited influence on the centralised approach. Since the market-based approach follows an experiential decision making scheme relying on proactive individual participations, new decisions are produced through workers' own ability to perceive their surrounding environment and to react according to their previous experience. Therefore, the level of experience and knowledge of a certain worker is crucial for the quality of the newly reached decisions. This is notably true when it is assumed that workers are rational and there is no collusion to improve their own decisions and increase their individual performance levels. As for the centralised approach, decisions are made based on a procedural scheme where workers are considered reactive to decisions made at higher levels of the management hierarchy giving limited importance to the individual knowledge or experience of workers. So from a degree of knowledge point of view, the decisions quality of the centralised approach depends on the global knowledge formed by the reported states of individual workers. As with the market-based approach, it is assumed that workers do not collude or misreport their actual states when requested by the decision maker.

3.5. Conclusions

This chapter aimed at highlighting the main concepts observed in from chapter 2 by identifying four key constructs and suggests a conceptual model linking their potential effects on the performance difference between the centralised and market-based approach in light of uncertainty. These concepts were defined, explained, and formally described in terms of theoretical constructs in order to clarify their expected influences on the focal construct of this research. The derived relationships were consolidated in a theoretical model as a tentative to produce a framework prescribing the suitability of the centralised and the market-based approaches for addressing the MTAP under different conditions of uncertainty. Following the conceptual model, a set of propositions is identified in order to be verified according to the simulation methods adopted for this research.

The following lists the main conclusions of this chapter:

- The taxonomy proposed by Psaraftis (Psaraftis, 1995) covers two main features of the centralised and the market-based approaches. For the centralised approach the features are: global nature of the information and the centralised processing; for the market-based approach the features are: local nature of the information and the distributed processing. However, it does not describe how the characteristics of each approach affect its performance under different uncertainty settings. This chapter highlighted four key constructs and linked them into a conceptual model.

- Given that this research compares the performance of the centralised and the market-based approaches, the focal construct in the proposed conceptual model is the performance difference.
- Timeliness of decision making is a characteristic of the centralised approach given the periodical update mechanism to correct the uncertainty impact on performance. It is proposed therefore that the higher the update frequency the better the reactions are, assuming a perfect costless communication condition.
- The problem size is a challenging issue for the centralised approach given that the decision making time increases non-linearly as the problem grows in size. The problem size is mainly assessed by the amount of input information needed at each corrective update, like the number of workers and tasks. Therefore, it is proposed that the problem size directly affects the timeliness of decision making by imposing a lower bound on the update period, which in turn affects the performance as uncertainty increases.
- Following that the market-based approach employs an experiential decision making procedure, it is the workers' responsibility to process their local knowledge to obtain distributed individual decisions. Therefore, it is proposed that the degree of local knowledge and workers' experience has a positive impact on the performance achieved by the market-based approach, compared to the centralised approach, as uncertainty increases.
- The conceptual model suggested in this chapter incorporates the previous propositions in a way that can be computationally modelled for validation through simulation experimentations; the conceptual model is one of the contributions of this research, which forms the basis for a theoretical framework for comprehensive comparison described in Chapter 6.

Chapter 4. Research Methodology: Formal Model and Simulation of the Mobile Task Allocation Problem

4.1. Introduction

Having presented the conceptual model of this research in the previous chapter, the purpose of this chapter is to describe the research methodology used in order to examine the propositions put forward by the model. This chapter describes the research method adopted for this study. Then it introduces the definition of computer simulation as a research methodology along with the justification of selecting simulation for conducting this research. This chapter also defines the MTAP as a representative and target problem to be modelled and simulated in order to validate the proposed conceptual model. This is done by introducing the MTAP scenario and defining it formally as a linear program. Moreover, this chapter describes how the studied sources of uncertainty, namely dynamism and stochasticity, are introduced in the simulation model along with their settings to be incorporated in the simulation system. This section also provides how the moderating variables from the theoretical model are modelled and simulated. Also, this chapter describes two basic solutions used to model the centralised and market-based approaches. These are: A simple greedy insertion heuristic and a market mechanism based on the Contract Net Protocol (CNP) (Smith, 1980; Davis and Smith, 1983), respectively. Having the previous elements explained, this chapter continues to describe the simulation system, MTAP-MaSim, employed as the main instrument of this research method and justifies the choice of multi-agent simulation among other alternatives. Finally, the last section of this chapter is dedicated to the verification processes of the simulation system.

4.2. Research Methodology

This research was initiated by researching and scoping of the problem area; and then by conducting literature reviews in the area of resource allocation problems in the organisation, specifically, task allocation under uncertainty to mobile workers. The research methodology process is shown in Figure 4-1. Several search engines, relevant databases and journals have been searched.

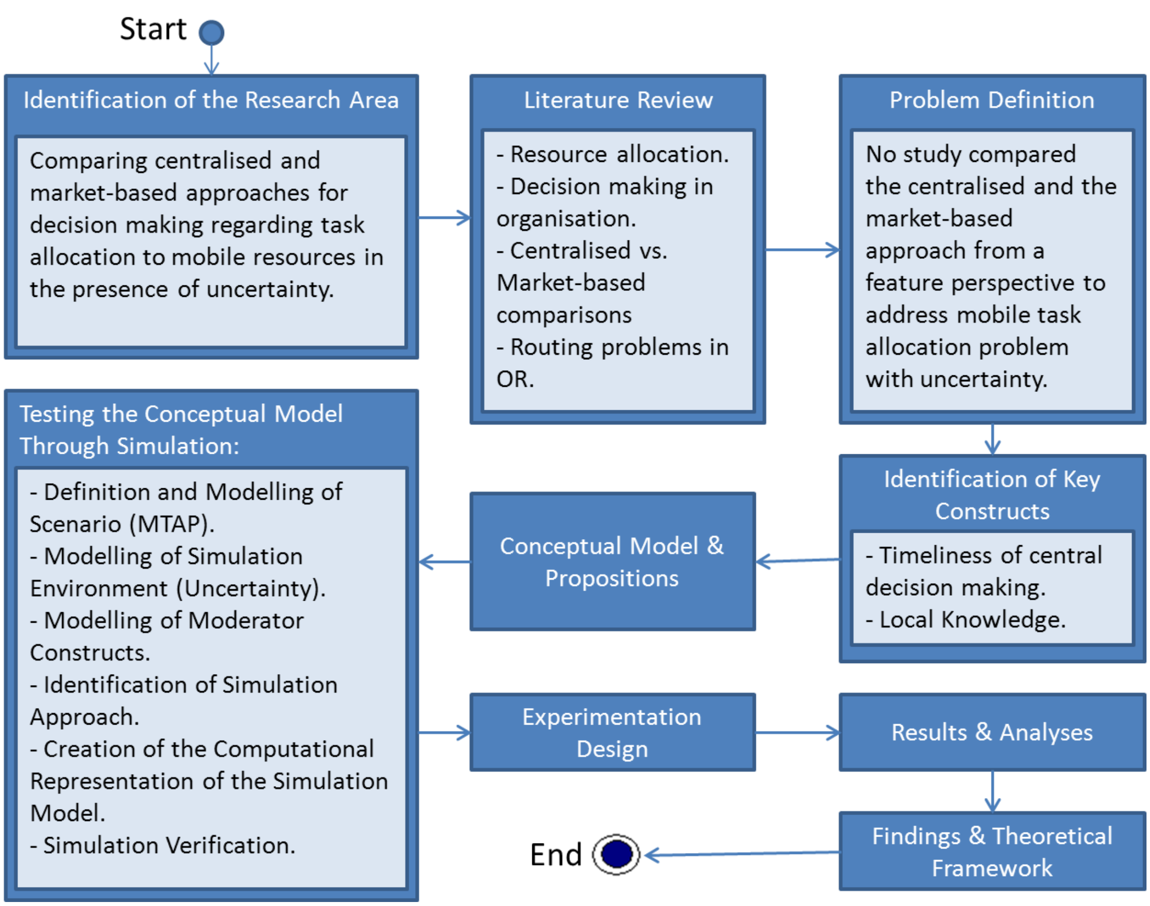

Figure 4-1. Research Methodology Process

Following the identification of the area of this research, which is investigating the centralised and market-based approaches for the decision making problems regarding the allocation of mobile resources in service organisations, several research studies were reviewed and analysed in Chapter 2. These reviews were mainly focused on the field of decision making regarding the allocation of resources perceived by the organisation theory, notably the effect of the organisation environment, structure, and uncertainty on the quality of the allocations. Similar centralised versus market-based approach comparisons were also revisited in the review process covering also those conducted in different fields. Based on the descriptive and critical reviews of previous studies and analytical comparisons, it was established that there is limited research in the area of comparing the conventionally-adopted centralised approach against the market-based approach in the context of task allocation to mobile workers in human organisations, notably a comparison based on the key features of each approach, which favour, or hinder, its adoption for such applications. This leads to a systematic aim for investigating this limitation in the realm of operations management and operational research literatures, and to clear research objectives, which are stated in Chapter 1. Following the review, various arguments were identified characterising the key features of both the centralised and the market-based approaches. These features, the timeliness of central decision making and agents' local knowledge in the market-based approach, are consolidated as moderator constructs affecting the relationship between uncertainty and the performance difference of both approaches in the conceptual model presented in Chapter 3.

In the next step, simulation is adopted as a method for testing the suggested conceptual model by modelling a formal description of the Mobile Task Allocation Problem (MTAP), uncertainty (dynamism and stochasticity), the moderator constructs, and two representative solutions for the centralised and the market-based approaches. The reason for choosing of simulation techniques to test the proposed conceptual model is detailed later in this chapter, but is mainly attributed to the ability of controlling the degree of uncertainty as well as replicating scenarios to obtain fair comparisons of both approaches. The modelling and design of the agent-based simulation system to comprehensively include the aspects of the MTAP as well as the compared approaches are also further detailed in this chapter.

The motivation of this research emerges from the recent advancements in mobile computing and communication technologies that would support the adoption of a distributed decision making approach, like the market-based approach, for distributed resource allocation problems, notably those related to the allocation of tasks to mobile teams of workers. Conventionally, techniques belonging to the centralised approach are employed for these applications, though the market-based approach successfully addressed other allocation problems. This research then aims at evaluating the suitability of the market-based approach for real world mobile task allocation problems by comparing its features with those of the centralised approach and to consolidate this assessment in a theoretical framework.

4.3. Simulation as an Experimentation Technique

In order to test the propositions suggested in the previous chapter, computer modelling and simulation is adopted as the scientific methodology for this research. Modelling and computer simulation are powerful research methods for confirming and exploring new aspects of a theory in complex behaviours and systems (Harrison *et al.*, 2007).

Computer simulation has been defined in the scientific research methodology literature in different contexts. According to Lave and March (1975), computer simulation involves the creation of a simplified representation of the world including some of its characteristics. Simulation has also been defined as the use of computer software for modelling real-world processes, system behaviours, or events (Kelton and Law, 2000). Following these main definitions, computer simulation is about reproducing parts of the real-world phenomena of interest in virtual experiments (Carley, 2001). Harrison *et al.* (2007) perceive computer simulation as two distinct concepts; first, the computational model that consists of the systems constructs (variables) to be studied and the set of processes that governs the changes of the constructs over time; and second, the implementation and execution of the model according to an experimental design. Considering these definitions, computer modelling and simulation is regarded in this research as the process of creating virtual experimentations by running a computerised scheme that models a real-world system and mimics its behaviour, internal processes, and interaction with the external environment, which all determine its state at a given moment of a time dimension.

In addition to the theoretical analysis and empirical analysis, also referred to as deduction and induction approaches, respectively, simulation is suggested to another way of doing science (Axelrod, 1997; Davis *et al.*, 2007; Harrison *et al.*, 2007). Generally, the main advantage of simulation over theoretical deduction is that it overcomes the problem of analytic intractability when dealing with large systems. Instead, simulation handles complex mathematical relationships using numerical methods (Harrison *et al.*, 2007). On the other hand, simulation also fills the gap of data availability and accessibility that is often faced by empirical methods. Simulation methods are applied on their own input data, which may be adopted from real world datasets or synthetically produced to generate output according to the modelled processes. Therefore, simulation is proposed as a practical methodology not only for theory validation, but also for theory development. Davis *et al.* (2007) provides a detailed roadmap for employing simulation as a process for the development of new theories.

Besides the advantages of simulation methods over the conventional deduction and induction methods mentioned above, the virtual nature of simulation provides many benefits that are of particular interest for this research. These are as follows:

- Simulation provides the ability to observe complex theoretical relationships among variables, particularly when empirical limitations exist on such data (Zott, 2003).
- The ability to study real-world phenomena that are unfeasible or even impossible to reproduce in reality. This advantage is crucial in the study of MTAP in general and the effects of environmental uncertainty on it in particular. It is unfeasible to try two different approaches for managing the task allocation process on real teams of workers as this requires particular access to service organisation, which is not available, and would impose high costs on setting up new settings to investigate the effects of each construct presented in the conceptual model.

- Stochastic simulation permits the introduction of some probabilistic elements when simulating a system (Harrison et al., 2007). The degree of stochasticity can be controlled according to the conducted experiment. When simulating the MTAP in presence of uncertainty, two main elements were regarded as stochastic; these are the introduction of new random tasks (defined previously as dynamism) and the distortion of travel durations (referred to as stochasticity). The severity of these types of uncertainty is controlled according to the experiment design.
- Scenario replication: It is possible to reproduce a given simulation round or experiment in its finest details if required, even with the same sequence of random input or stochastic uncertainty. This is particularly useful for this research given that it is based on comparing two approaches in light of different settings of uncertainty and other factors. Therefore, it is crucial to be able to reproduce the same scenarios for both approaches as part of a single experiment. For instance, the introduction of a new task at a specific moment should be identical for both approaches when observing their behaviours in function of dynamism.
- There are also advantages provided by the computational tools that prove to be useful through the experimentation process. For instance, time scaling allows simulating the studied system at an accelerated pace. That is, simulating the operations of an 8-hours working can be done in a few minutes. Another feature is the ability of logging all the changes and events that are taking place during the simulation process. This is useful during the verification process. Organising output data and the automatic representation of results.

According to the comprehensive roadmap proposed by (Davis *et al.*, 2007) for using simulation as a methodology to develop new theory, there are several steps before reaching the point of designing and conducting simulation experimentation, which are detailed in Chapter 5.

Step 1: ***Identifying a scenario for simulation***

The first step requires the definition of the phenomenon to be studied, which also contain the research question to be addressed. This step should also identify a "*simple theory*" or proposition that addresses that phenomenon in question and is yet a platform to be further investigated and developed. As defined by the same authors, a simple theory is:

"*…undeveloped theory that involves a few constructs and related propositions with some empirical or analytic grounding but that is limited by weak conceptualization, few propositions, and/or rough underlying theoretical logic. Simple theory may also include concepts and basic processes from well-known theories… especially when the research focus is on their vaguely (if at all) understood interactions.*" (Davis *et al.*, 2007, p. 484)

Following this and with regard to this research, different concepts were identified in the reviewed literature that would form a simple theory. It was found that uncertainty has a significant impact on the achieved performance of an organisation as well as the organisation structure should match its environment (Psaraftis, 1995; Lin and Carley, 1997; Lin *et al.*, 2006; Larsen *et al.*, 2002). It was also claimed that a distributed mechanism can at best perform as good as centralised mechanisms (Ygge and Akkermans, 1999). However, it is not obvious how the competing centralised and market-based approaches are behaving when these two propositions are combined, notably when compared according to their characterising features.

Step 2: ***Choosing a suitable simulation approach***

The second step is to choose a suitable simulation approach, though this step is thought to be better placed after the creation of the computational model since it is believed that it affects the simulation approach choice to a great extent. The simulation approach adopted for this research is agent-based simulation. The reason for this choice is described in subsequent sections after modelling the target MTAP and constructs of interest.

Step 3: ***Creating the simulation model***

Thereafter and most importantly, the creation of the simulation model (or computational representation) consists of formally representing the system to be simulated which incorporates in its turn the simple theory. This involves: i) operationalizing the constructs, ii) designing the processes affecting the theoretical constructs through well-defined algorithms, and iii) identifying the assumption bounding the theory and obtained results.

Step 4: ***Verification of the simulation model and computational implementation***

Following the design and implementation of the simulation model, the verification process of the resulting simulation system should be done appropriately. This done to ensure the correctness of the programming code and to avoid any bugs that would cause simulation errors resulting in unreliable results. The verification process of the simulator built for this research is discussed by the end of this chapter.

Step 5: ***Designing and running experimentations***

This is the main step for doing experimentation using simulation as the outcome of this step is the actual results to be further analysed. Prior the execution of any experimentation, it is designed and setup according to the assumptions. There are several issues to be considered during the experimentation design. These are deciding upon the initial stages of the simulation rounds, the number of repetitions (rounds), the simulation time horizon, and the experimented construct value variation (Harrison *et al.*, 2007). This step is further detailed in the context of the experiments conducted for this research in Chapter 5.

Step 6*: Validation of experimentation results*

This step implies the comparison of the results obtained from simulation with existing empirical data in order to confirm the correctness and reliability of these results. While the importance of this step is controversial in the simulation literature, some argue that it is marginal and limits the central feature of simulation in developing new interesting theory e.g. (Weick, 1990; Van Maanen, 1995). According the Davis *et al.* (2007), the importance of validation strongly depends on the simple theory that is the core of the simulation model. If the simple theory is based on empirical evidence, then validation becomes less important as long as the obtained results match that simple theory. This was the case of the simulation results of Knight *et al.* (2011) where validation was substituted by detailed and comprehensive walk-through verification process.

This step, along with the design and run of experimentation, are described in Chapter 5 before conducting the actual experimentations and presenting the results.

4.4. Formulation of the Mobile Task Allocation Problem

In this research, the Mobile Task Allocation Problem (MTAP) is taken as a representative for the family of DRAPs with distributed resources facing environmental uncertainty. The MTAP can be considered as an optimisation problem which is a variance of the general Vehicle Routing Problem (VRP), which is a well-known problem family in the operational research and optimisation literature as discussed in chapter 2.

Service organisations which provide on-site services to customers such as telecommunication equipment installation, after-sale maintenance, mail delivery, police patrols, taxi services, or marketing demonstrations for products by salesmen are faced with the problem of efficiently allocating tasks to the available workforce. Such optimisation is mainly based on maximising the customer satisfaction while reducing the operational costs incurred of such activities. Given the limited resources modelled here as the available time and equipment used by the workforce, appropriate schedules and work plan are necessary to be employed. Generally, such work plans are prepared by specific tools in light of the available information about the problem context such as the available resources, tasks' requirements, and cost thresholds among other elements needed for the planning. The output of the planning process is a set of static schedules satisfying the input constraints and optimising the intended outcome. However, environment uncertainty significantly complicates the planning process as plans may need considerable changes based on the exceptions faced. For instance, delays occurring during travels or task execution may result in the need for rescheduling the initial plans. Similarly, the arrival of emergency or high-priority tasks may need to be included in the planned schedules to be addressed as soon as possible. These sources of uncertainty impose different mechanisms to contain the faced exceptions and minimise the negative impact. Therefore, schedules are either re-planned by the solver or local actions might be taken. Derived from these real world scenarios, the MTAP is formulated to contain all these specifications and considers uncertainty as a main feature to be included in the solving mechanisms. These are summarised in the Table 4-1.

Problem Feature	**Feature Description**
Time Element	A time element refers to the entity representing the timespan any activity may require to be completed. This can be the travel duration between two locations or the time needed to complete a task.
Schedules	The ordered list of time elements assigned to the owner of the schedules. This can be the listing of tasks to be executed by the respective worker and travel times. Schedules generally specify the times at which each time element is approximately supposed to start as well as its duration.
Initial Schedules	The schedules generated during the planning phase prior being executed by the workers. These plans may consider some robustness to face certain degree of uncertainty, but generally are not as it is the case in this study.
Delays Uncertainty	This type of uncertainty refers to unplanned and unexpected delay exceptions faced by workers in any scheduled time element causing it to end later than initially planned.

Dynamic Arrival of Tasks	This uncertainty denotes that not the entire set of tasks is known during the planning phase and that additional tasks are gradually revealed during schedules execution as time progresses. In scenarios where tasks have different priorities, those with higher priorities should be considered dynamically in the schedules.
Update Rate	The update rate is the time separating two consecutive schedule updates to contain uncertainty faced during this period. During schedule updates, new tasks are inserted as well as unfeasible tasks are replaced or removed according to the changes.
Operational Costs	Represent the costs incurred by the operation activities to fulfil the scheduled tasks. These costs are met by the organisation, which aims at minimising. Such costs may be different per workers and/or equipment.
Customer Satisfaction	From service organisations' perspective, customer satisfaction refers to the contentment of the customer requiring the service by providing it as agreed beforehand. It may also serve as a priority indicator showing that important customers should always be kept with a minimum satisfaction of the offered service.
Route Deviation	Route deviation happens when a worker changes the planned destination for another. This mainly happens when a task is cancelled while the worker is on its way or when plans have the flexibility to reorder tasks during the travel. Some application may not consider the latter case, such as taxi services.

Table 4-1. MTAP features' description

The MTAP consists of planning a team of mobile workers to serve a set of geographically-dispersed tasks. Since each task is coupled with a degree of customer satisfaction reflected by its priority indicator and requires travelling, the global objective is to minimise the travel costs, which is proportional to the travelled distance, while keeping a high customer satisfaction by completing a maximum number of high-priority tasks.

Based on this definition of the MTAP, the MTAP can be compared to different applications belonging to the same VRP family of problems corresponding to the real life scenarios mentioned before. For instance, taxi services, inventory replenishment, maintenance teams, and mail delivery all plan routes for their drivers or workers in a way to satisfy all customers as well as optimise the costs. For taxi service companies, tasks can be represented as the pickup, driving, and drop off of customers at different locations. The satisfaction criteria can be arrival time, cost, and journey delays. As for inventory replenishment and maintenance operations, service occurs at the customers site and satisfaction criteria is reflected by the timeliness of servicing high priority failures. Despite the fact that these applications are also faced by different levels and types of uncertainty, the reaction may differ depending on the nature of that application. Taxi services, for example, may not be able to drop off a customer in a location other than the planned destination. On the other hand, uncertainty handling may turn more flexible for the case of mail delivery given that the delivery of parcels can have large time windows to contain unexpected delays.

The studied MTAP matches best the scenario of planning the operations of maintenance teams. Workers are equipped with different equipment, travel and service customers on site, do not have strict time windows, and their schedules are changeable without having to consider specific constraints such as trips to the repository. The major restriction, though, is the assumption that a worker cannot cancel a task once started while this is possible during travel. The following table lists the main features of MTAP and how they apply to different service types and scenarios.

Service Type	MTAP Features
Engineering & maintenance teams	All features are highly considered.
Salesmen teams	All features are highly considered.
Equipment delivery and installation	Initial schedules, delays uncertainty, dynamism is rarely applicable, operational costs, customer satisfaction is very important, route diversion is applied only if delivery vehicle is loaded with multiple items to be delivered to different customers.
Taxi services	Initial schedules are relatively short, delays uncertainty, dynamic tasks can be considered only when driving empty (without customer on board), operational costs differ from vehicle type to another, customer satisfaction is important and measured in different ways (e.g. timely pickup, arrival to destination on time, and driver's driving behaviour), and route deviation is not applicable.
Inventory replenishment services	Initial schedules are short to medium size, prone to delays uncertainty, dynamic tasks are important to consider, operational costs differ from vehicle type to another, customer satisfaction is important and measured in different ways (e.g. timely replenishment and customer type), and route deviation is highly applicable.
Mail delivery services	Initial schedules contain all tasks, prone to delays uncertainty, dynamic tasks are not

	applicable, operational costs differ from vehicle type to another, customer satisfaction is more flexible, and route deviation is highly applicable when delivery tasks are reordered.
Police patrols	None or short Initial schedules, delays uncertainty not very apparent, dynamic tasks are important to consider, operational costs differ from vehicle type to another but not very important, customer satisfaction is important and measured in different ways (e.g. timeliness), and route deviation is not applicable.

Table 4-2. MTAP features corresponding to some practical service scenarios

To formally describe the MTAP, the problem was modelled in the form of an integer program as it was assumed that all numerical values are integers and fractions are not allowed. This mathematical representation is suitable to solve the static version of the problem. That is, during the planning phase when all the relevant information is available (like the number of workers, tasks, and their respective locations) no exception is allowed while a solution is being produced. Travel costs are modelled as a function of the travelled distance rather than the duration since travel durations are already deducted from the workers' time budget. Each task is coupled with a bonus score to reflect its priority or importance. This metric can serve as a customer satisfaction measurement. For the service organisation to measure the achieved performance, the objective function is represented as the total collected bonus score from executed tasks by all workers.

In mathematical terms, the MTAP considers the assignment of n independent and geographically dispersed tasks to m mobile workers ($m < n$). Each worker d starts journey from an initial location l_d and has a schedule length (or time budget) T_{max} e.g. 8

hours of working time. Every task i has a processing duration T_i and a bonus score S_i. Traveling from task i location to task j location costs c_{ij} and has a travel duration t_{ij}. For the particular case when task i is the first task scheduled for worker d, which is denoted as $ft_d = i$, travel costs and durations to the location of that task from the worker's initial location are $c_{l_d i}$ and $t_{l_d i}$, respectively.

It is assumed that each task needs only one worker to be processed and that every worker finishes his journey at the location of the last scheduled task. The objective function is given by maximizing the net weighted benefit of the service organisation, that is, the total collected score minus the total incurred travel costs.

To formally describe the static MTAP, a mathematical formulation of the quasi-similar TOP (Vansteenwegen *et al.*, 2009) is adopted and modified to reflect the particularity of MTAP. The objective function of the MTAP integer programme aims at maximising the total net benefit achieved by servicing the maximum number of tasks within the available time limit. This net benefit is obtained by subtracting the operational costs from the collected bonus score achieved by servicing the tasks. The main constraint in this programme is to ensure that all time elements are within the time limits. This is modelled as following:

$$\max \sum_{d=1}^{m} \left[\sum_{i=1}^{n} \left(\alpha_d S_i y_{id} - \beta_d \left(\sum_{\substack{j=1 \\ j \neq i}}^{n} c_{ij} x_{ijd} + c_{l_d i} x_{l_d id} \right) \right) \right]$$

Subject to:

$$\sum_{d=1}^{m} y_{kd} \leq 1\,; \qquad \forall k = 1,\ldots,n \tag{1}$$

$$\sum_{i=1}^{n} \left(T_i y_{id} + \sum_{j=1}^{n} t_{ji} x_{jid} + t_{l_d i} x_{l_d id} \right) \leq T_{max}; \tag{2}$$

$$\sum_{i=1}^{n} x_{ikd} = \sum_{j=1}^{n} x_{kjd} = y_{kd}; \qquad \forall k \in \{1,\ldots,n\} \wedge k \neq ft_d \wedge k \neq lt_d \tag{3}$$

$$x_{l_d id} = 1; \;\; i = ft_d \tag{4}$$

$x_{ijd}, y_{id} \in \{0,1\}; \quad \forall i, j = 1,\ldots,n; \quad \forall d = 1,\ldots,m.$

Where:

α_d, β_d are normative factors for worker d making the evaluation of a task importance and the incurred costs of allocating it comparable values. α_d represents the importance of customer satisfaction at the worker's level. This is particularly viable for cases where workers have to attain a certain threshold of tasks within a time limit (e.g. month). Therefore, the value of a task becomes higher as the deadline approaches and the worker still has tasks to be assigned to reach the threshold. On the other hand, β_d reflects the costs incurred to fulfil a task by a given worker. This value is uniform for cases where tasks are completed by workers with same wages and using similar equipment. However, β_d may take different values if, for instance, workers use different types of vehicles with different operational costs (i.e. a truck consumes more energy than a small car).

$x_{ijd} = 1$ if a visit of task i is followed by a visit to task j in the schedule of worker d, 0 otherwise.

$x_{l_d id} = 1$ if task i is the first scheduled task for worker d, 0 otherwise.

$y_{id} = 1$ if task i is visited by worker d, 0 otherwise.

ft_i and lt_i are the first and the last scheduled tasks in worker i's schedule, respectively.

u_{id} is the position of task i in the schedule of worker d. $u_{id} \in \{1, \ldots, n\}$

Constraint (1) ensures that each task is visited once at most. Constraint (2) ensures the total travel time plus the scheduled-tasks execution times are within the limits of the schedule length. Constraint (3) ensures that, apart from the first and last scheduled tasks in schedule d, each visited task has only one arc entering it and exactly one exiting it, this constraint is assumed to prevent routes disruptions.

This representation of the MTAP is convenient to be implemented and solved by either exact algorithms e.g. SIMPLEX or heuristics e.g. Tabu Search.

4.5. Simulation of the Mobile Task Allocation Environment

The previous formal representation of the MTAP provides a straightforward model to be interpreted into simulation software. However, and in order to comply with the main aim of this research, many elements accompanying the implementation and execution of MTAP instances on a computer are yet needed to simulate the whole target system. Given that environmental uncertainty is regarded as the major aspect of this research, this should also be properly modelled in order to be included in the simulation process. The same is also applicable for the moderator variables as shown in the conceptual model in chapter 3.

This section presents the formal models used to incorporate dynamism and stochasticity as the main sources of uncertainty in the simulation model at hand. It also describes how the other variables; namely the degree of local knowledge, timeliness of decision making, and problem size, are modelled.

4.5.1. Simulation of the Environmental Uncertainty

As previously discussed in the literature review chapter, optimisation decision making problems can be considered dynamic, as opposed to static, and/or stochastic, contrary to deterministic. These characteristics in a problem impose the ability to consider such uncertainty when designing a solution. The introduction of new input information and distortions in existing solutions, due to information updates, are referred to in this study as “environmental uncertainty”. In other words, environmental uncertainty encompasses to all sources of exceptions entirely originated from the external environment and out of stakeholders’ control. Exceptions such as unexpected travel delays, unavailability of worker or task, and arrivals of new dynamic tasks can fall in this class of uncertainty.

These exceptions are particularly numerous in a distributed and mobile environment where causes of plan distortions are arbitrary and most probably are location- and/or time-dependent. In some cases, other factors can play considerable roles in expecting and/or forecasting the severity of those exceptions. For instance, the weather can be an antecedent to some exceptions causing delays or disruptions of service, like floods, and can generally be predicted beforehand. Such forecasting information systems are basically used when fuzzy and a-priory optimisation solutions are generated.

Given that this study covers only the comparison of online real-time optimisation approaches, delays and dynamic task arrivals are only considered upon their occurrence. Therefore, it is assumed in this study that both approaches being compared do not rely on any forecasting system or may obtain any information about probable future exceptions. This implies for the case of delays that the workers are the actual upfront line perceiving the endured delays and are the only ones who may best evaluate its importance. Similarly, when new dynamic tasks enter the system, for the centralized approach to produce best decisions, the central decision making point must obtain an updated picture of the system. This requirement can only be fulfilled via direct communication with the workers so that the workers report their current location and state.

4.5.1.1. Modelling the Arrival of Dynamic Tasks

As mentioned in Chapter 2, decision making problems with dynamism uncertainty refer to those problems where some elements are in function of time and the complete set of information is not available when the solution is being processed, but is gradually disclosed as time progresses (Psaraftis, 1988; Powell *et al.*, 1995; Gendreau *et al.*, 1996; Gendreau and Potvin, 1998; Larsen *et al.*, 2002; Thomas *et al.*, 2011). Therefore, initial solutions are prone to frequent updates as new information is revealed. In order to include the new information updates in the current solution, dedicated strategies should be setup to handle the changes. In this study, dynamic tasks fall within the type of dynamism uncertainty.

In this research, it is meant by the term “dynamic tasks” the arrival of new random tasks at the time when previous solutions (i.e. planned schedules) are being executed. Similar problem has widely been investigated in the OR literature, for example (Powell *et al.*, 1995; Gendreau *et al.*, 1996; Powell, 1996; Gendreau and Potvin, 1998; Ghiani *et al.*, 2003; Berbeglia *et al.*, 2010). Larsen *et al.* (2002) provided the degree of dynamism measure as a mean to classify dynamic vehicle routing problems. By definition, the degree of dynamism is the ratio of the number of dynamic requests (or tasks) over the total number of requests, including the advanced demands from the planning phase. This can be expressed as:

$$dod = \frac{n_{imm}}{n_{tot}}$$

Where:

n_{imm}: is the number of immediate requests, which here can correspond to the number of MTAP dynamic tasks.

n_{tot}: is the total number of requests. This can further be given by $n_{tot} = n_{adv} + n_{imm}$ where n_{adv} is the number of advanced requests, that is, the tasks considered during the planning phase of an MTAP instance.

Despite the fact that the dod measure may describe the dynamism level of a system, however, it does not take into account the times at which the dynamic demands arrive into the system. For instance, given two systems where requests are fulfilled during a limited time horizon (i.e. like the MTAP) and where dynamic requests arrive early in the schedule horizon as compared to the second system where dynamic requests occur late during the day. If the total number of dynamic and static requests is equal for both systems, then they have a similar dod. However, the decision maker would prefer the first scenario since information is revealed earlier, giving more time to react. For this reason, Larsen *et al.* (2003) extended the simple dod to include the notion of time at which dynamic information is revealed. This measure is defined as the effective degree of dynamism $edod$ and denoted:

$$edod = \frac{\sum_{i=1}^{n_{imm}} \left(\frac{t_i}{T}\right)}{n_{tot}}$$

Where:

T: is the end of the schedule horizon that starts at scheduling time 0.

t_i: is the time the ith request is intercepted. $0 \leq t_i \leq T \; \forall \; 0 \leq i < n_{imm}$

According to this measure, any system may have $0 \leq edod \leq 1$ where $edod = 0$ represents a static.

Even though these measures characterise the dynamism of a system through the number of dynamic over the number of static tasks and the arrival time of dynamic tasks, however, they do not describe the impact of such dynamism on the solution. That is, how a given solution is updated in response to this dynamism. Furthermore, the authors of these measures did not point the impact of different values of these measures on free schedules, where the initial solution would dramatically change upon the arrival of new tasks, versus the case where all schedules in an initial solution are busy. The term *busy* schedule refers here to schedules that are loaded with tasks leaving very limited free schedulable time to insert additional tasks. On the other hand, *free* schedules refer to those having relatively large amount of schedulable time to contain future tasks.

These issues mainly arise in the suggested measures as they do not consider the importance or priority of the dynamic tasks over those at the planning phase, or the tasks that has already been scheduled. Particularly, tasks' priority is of considerable importance in situations where all the schedules in a solution are already full when a new task has to be scheduled. In such situations, the decision maker would use the dynamic task's priority as a major criterion to improve the actual solution by replacing less important scheduled tasks with more attractive dynamic ones.

Nevertheless, it is argued that busy schedules are less likely to be altered when all dynamic tasks are of quasi-equal importance of those scheduled, even if the system is highly dynamic with a dod close, or equal, to 1. So for a dynamic task to be included in the solution, it should be of higher importance than some of the scheduled tasks to be considered in the next round of solution update.

Given that this research is observing the behaviour of each approach in reaction to frequent changes of the solution, neither the dod nor the $edod$ measures are sufficient to describe the dynamism of the simulated environment. Therefore and in order to stimulate the effect of dynamic tasks and to serve the maximum number of dynamic tasks by frequently updating busy schedules, the Dynamism Priority Factor (DPF) parameter is introduced. The DPF is used to amplify the impact of dynamic tasks on the reaction behaviour of the decision makers in both approaches. By the use of the DPF, dynamic tasks are assigned with higher priority than the advanced tasks by DPF. Therefore, to make all dynamic tasks of higher importance than their advanced tasks counterpart the value of the DPF is set greater than one.

Generally, the priority of each task i, which is represented by its bonus score S_i, is randomly generated and is in function of the task duration. This is mainly to keep a consistent ratio of importance over duration among tasks. Therefore, during the generation of dynamic tasks, the generated priority score is multiplied by the DPF. This potentially results with major changes in the solution upon the arrival of dynamic tasks if the DPF is assigned a high value. Thus, the higher the DPF is, the most likely the actual solution is subject to change after each update. This may result at the end of execution in obtaining a completely different solution than the one generated from the planning phase.

As for the mechanism governing the arrival of dynamic tasks, the simulation system used in this study generates dynamic tasks in time according to a homogenous Poisson process with intensity λ. That is, by definition, that λ denotes the expected number of dynamic tasks entering the system in a time period equals to one time unit. In other words, there is a new task entering the system every $1/\lambda$ time unit. Poisson distribution function is given by:

$$f(\lambda) = \lambda e^{-\lambda}$$

Where e is the base of the natural logarithm.

In order to apply different levels of dynamism in the system, different values are assigned to λ. Thus, to increase the dynamism rate in the system, a higher value is given to λ.

According to this and in order to express the impact of dynamism on a given solution, dynamism in this study is mainly evaluated according to two parameters. The first is the DPF and the second parameter is the arrival rate of dynamic tasks λ. However, when the DPF is assigned a sufficiently high value, dynamism is assumed to have a significant impact on initial solutions, regardless whether the schedules are empty or full.

4.5.1.2. Modelling of the Stochastic Travel Delays

Contrary to deterministic problems where all input information is known for the decision maker with certainty, stochasticity in stochastic problems refers to the fact that some input information may not be accurate, but only known within certain bounds, at the time the solutions are being produced. The actual value of these stochastic parameters is only unveiled at the time they happen. Stochasticity in transportation applications, like the VRP family of problems, can be observed in travel and service time uncertainty. Furthermore, some VRP applications considered the availability of customers at servicing time as a stochastic variable denoting that the customer request remains uncertain until a servicing vehicle is at the customer location. According to this, it is worth noting the distinction between stochastic customers and problems with the arrival of new dynamic requests, which has been described in the previous section.

Given that this research mainly focuses its interest on studying the effect of uncertainty on the centralised and market-based approaches, stochasticity is obviously considered in the target MTAP. Among the sources of stochasticity mentioned above, the MTAP incorporates stochasticity through delay exceptions. Delays in MTAP instances may appear during travel, during tasks execution (i.e. servicing delays), or both types of delays can be considered simultaneously.

Delay exceptions are considered to be totally random and unknown to the decision maker before they happen. This randomness covers the main properties of each delay, which are:

- The instant at which the delay exception occurs.
- The severity of the delay, which is reflected by its duration.

- The number of times it is likely for delays to occur on the same time element. It is referred by a time element as any activity requiring an extended period of time to be accomplished, like travelling on the same route or executing a task.
- Finally, the decision maker's awareness of any of the previous properties before the end of the time element.

To formally describe the previous properties; and assuming t_{ij} is the travel duration taken by a worker agent to travel from task i to task j, and that this travel duration is prone to n delay exceptions d, each of duration Dur_d; then the instant at which the kth ($k \leq n$) delay occurs on route t_{ij} can be given as: $I_{d_k,t_{ij}}: 0 < k \leq n$

The actual travel duration experienced by the travelling worker agent at the time it reaches destination can be given by:

$$t`_{ij} = t_{ij} + Delay_{t_{ij}}: Delay_{t_{ij}} = \sum_{k=1}^{n} Dur_{d_k}$$

A similar representation can be employed to reflect delay exceptions occurring during tasks execution.

It is worth noting that the last property of the studied delays refers to that the instant $I_{d,t_{ij}}$ at which delay d occurs, its duration Dur_d, and the number of these delays on the same time element is considered unknown to the decision maker.

However, the local knowledge and personal experience of worker agents may contribute in reducing the effect of the faced delay exceptions. Although it is strongly constrained that this knowledge would not contribute prior to the occurrence of the delay at instant $I_{d,t_{ij}}$. For instance, an agent worker may endure traffic jam and consequently decides to alter its original route to alleviate the delay, but the agent would not be able to make such a decision before it faces the congestion delays. Such a decision to change the original route would mainly depend on two factors. The first factor is the decision making procedure followed by the organisation, which determines the degree of freedom delegated to the agents. The second factor is the agent's local knowledge and its ability to make correct decisions. The agent's familiarity with the region in which it operates greatly enhance the quality of such decisions.

As an example of the previously-described model to represent delays in the MTAP, let's assume that the travel duration of an agent travelling from task i to task j at a constant speed is 30 minutes. Travel delays in this case are expressed as additional amounts of time extending the original duration happening at random instants during the travel. The instant at which the first delay starts is at minute 12 from the beginning of the travel and with a severity of 10 minutes. That is: $I_{d_1,t_{ij}} = 12$ and $Dur_{d_1} = 10$ minutes. This would result, so far, with total travel duration of 40 minutes. Another delay happens at instant $I_{d_2,t_{ij}} = 30$ from the beginning of the travel (that is 8 minutes after resuming the travel from the first delay) with $Dur_{d_2} = 12$ minutes. The occurrence of these two delays results in total travel duration of $t'_{ij} = 30 + (10 + 12) = 52$ minutes to reach destination, instead of 30 minutes initially planned. Now if it is assumed that the travelling agent is aware of a deviation that would shorten the second delays (e.g. by taking a shortcut) by 5 minutes and chooses to do so at instant 38 from the beginning of the travel (which is after $I_{d_2,t_{ij}} = 30$ and before the end of the delay), the resulting total travel duration would be 47 minutes.

In order to include the effect of such delay exceptions in this study, delays affecting a time element of duration t are modelled as random positive-value variables drawn from normal random distributions. These distributions are set with the mean equals to zero and a standard deviation equals to the time element duration multiplied by a value $0 \le \sigma^2 \le 1$ reflecting the severity of the applied uncertainty, as given by equation (1). For the ease of implementation, delays are generated by a dedicated component in the simulation system at the time a new time element is started. Afterwards, the generated delay amount is partitioned to a random number $n \ge 1$ of smaller durations, as given by equations (2), (3a), and (3b). Each generated duration Dur_{d_k} is then randomly spread at random instants $I_{d_k,t}$ during the time element, as given by equation (4), noting that a delay exception cannot be applied when a previous exception is still active.

$$Delay_t \sim N(0, t * \sigma^2) : \ \sigma^2 \in \{10\%, 20\%, \ldots, 100\%\} \quad (1)$$

$$n \sim Un(1, \frac{Delay_t}{min}) \quad (2)$$

$$Dur_{d_k} \sim Un\left(min, Delay_t - \sum_{x=1}^{k-1} Dur_{d_x}\right) : Delay_t - \sum_{x=1}^{k-1} Dur_{d_x} > min \quad (3a)$$

$$Dur_{d_k} = Delay_t - \sum_{x=1}^{k-1} Dur_{d_x} : Delay_t - \sum_{x=1}^{k-1} Dur_{d_x} \leq min \quad (3b)$$

$$I_{d_k,t} \sim Un\left(I_{d_k,t,earliest}, t_{end}\right) : I_{d_k,earliest} = \begin{cases} 0 : \ k = 1 \\ I_{d_{k-1}} + Dur_{d_{k-1}} + 1 : otherwise \end{cases} \quad (4)$$

Where:

$Delay_t$: is the total duration of the generated delay for the time element t.

min: is the minimum duration of the applied delay. Throughout the simulation process of this research, this parameter is set to 5.

$I_{d_k,t,earliest}$: is the earliest time delay $d_k$can be applied on the time element t.

t_{end}: is the end time of time element t.

As previously noted, delays are faced in any activity requiring time to be achieved. In the MTAP, delays are faced during travels and tasks execution. Whereas, it is assumed that all communications in the system are made in real-time and no delays are faced to deliver messages among the agents. This assumption is mainly retained given that the time of message delivery can be ignored compared to other time elements in MTAP instances.

Spreading delays in such a way allows modelling random events causing unexpected delays in a realistic way. Having the delays duration in function of the time element length implies that workers are more prone to delays when the travels are longer. Furthermore, when delays are spread along the time element it prevents the decision maker to make one off decisions towards delays faced on a given time element. For instance, if total delays duration of 60 minutes is applied at once, schedules may change differently from applying the same amount gradually along the time element. Shorter and more frequent delays require more decisions to be taken and therefore accentuate the accuracy of the comparison of the centralised versus market-based decision making processes.

4.5.2. Simulation of the Moderating Variables

From the theoretical model described in the previous chapter, it is suggested that three moderating variables may affect the relationship between the difference of the demonstrated performance of both approaches and sources of uncertainty. Each of these moderating variables mainly reflects a characteristic of an approach. For instance, timeliness of decision making refers to when decisions are taken. Since decisions are taken in parallel and in real-time by the workers in the market-based approach, this construct is mainly related to the centralised approach in the sense of how timely the central solver takes new decisions when exceptions take place.

4.5.2.1. Modelling the Centralised Update Rate

As described earlier, the central solver may operate in two modes. When the periodical mode is adopted, as it is often the case for transportation applications (Mes et al., 2007; Máhr et al., 2010), the central decision maker updates its global vision at regular intervals by broadcasting query messages to the workers in the system. This is simulated via a timer held by the central solver agent regulating these updates. Different values of timeliness of decision making can be reflected through varying the timer's value. Real-time monitoring is achieved when the timer value is set to 1. That is updates are done every simulated minute, which is the smaller time unit.

4.5.2.2. Simulating Workers' Local Knowledge

The local knowledge refers to any kind of information that is only locally available and cannot be transmitted perfectly. This can be the experience workers may have previously acquired, the perception of the surrounding environment, and personal preferences when making individual decisions.

Starting from this definition, local knowledge turns to be a broad subjective term and not straightforward to be operationalized. However it may also considerably contribute when it comes to face uncertainty in the context of the MTAP.

For instance, personal preferences and valuations about dynamic tasks and self-efficacy at performing them can be attributed to local knowledge since no one other than the worker may know these preferences. Another important situation is the perception of the surrounding environment and acting in real-time. Following this perception, a correct assessment of the surrounding environment coupled with experience and ability to react may dramatically reduce the negative impacts of stochasticity. Such situations might be mapped to real-world situations when an individual is familiar with an area and knows how to avoid probable traffic jam by taking shortcuts. In that sense, avoiding travel delays on time can also be attributed to local knowledge. For instance, a travelling worker may perceive traffic congestion before getting involved and decides to take another route to avoid the delay.

In this research and for simplicity, only the latter case will be covered to express and experiment the effect of local knowledge. That is, how workers' knowledge improves their ability to reduce the severity of the faced delays.

This is modelled for the simulation process as a random variable LKDR (acronym for Local Knowledge Delays Reduction) sampled from a normal distribution determining the amount of a potential delay a worker can get rid of. When delays on a time element are revealed to the worker, it is assumed that the worker has the ability, to a certain extent, to evaluate this delay and react on it resulting with LKDR minutes reduced from the original value. The following pseudo-code shows the LKDR value generation process:

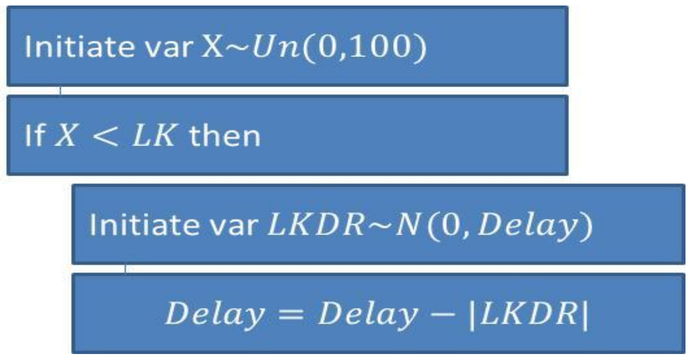

Figure 4-2. Process of LKDR value generation.

Where LK is an input parameter representing the average degree of the worker's local knowledge and $Delay$ is the amount of encountered delay which is known by the worker agent.

4.5.2.3. Simulation of Solutions' Computation Time

The centralised algorithm proposed in this research is considered simple and quick when processing datasets of reasonable size and running on modern hardware. Therefore, it is possible to assume in the basic model (as it will be described later) that corrections on initial decisions can be done in real-time by the central solver. However, as the problem dimensions increase and the target problem becomes more complex, the computation time can dramatically grow exponentially, and therefore affect the timeliness of decision making. The problem size and complexity construct in the theoretical model is therefore mainly represented by the computation time it takes to adjust a solution upon the arrival of new input.

Given that long and non-trivial process of defining a new more complicated MTAP and then developing new heuristics to tackle it, computation time is simulated through the injection of artificial computation time that would match the experiment measurements.

It worth pointing again here to the relationship between computation times needed by the central solver and the update rate it uses to maintain an updated view on the system. The update time interval should at least be as long as the computation time, as it is described in Chapter 3.

4.6. Simulation Model of the Mobile Task Allocation Problem Solution Approaches

Having setup the ground for simulating MTAP, the next subsections explains how the approaches to be compared are modelled and implemented in the MTAP-MaSim. As previously mentioned, this research does not intend to propose a new or improve an existing algorithm or heuristic to obtain better optimisation results for the problem at hand, but rather to compare both approaches according to some of their features in light of uncertainty. A simple greedy insertion heuristic is suggested as a representative for the centralised approach. Similarly, a basic market mechanism based on the CNP is delegating the market-based approach.

4.6.1. The Centralised Approach Simulation Model

Centralized approaches usually use well-defined algorithms running on powerful computation equipment. The heuristic used in this study is a greedy heuristic mainly based on the best insertion strategy. The greedy insertion algorithm was proposed by Solomon (1987) and is widely used as a *constructive* method to produce initial solutions to then be improved by *improvement* methods that depend on the meta-heuristic used (Cordeau *et al.*, 2002; Máhr *et al.*, 2010). Figure 4-3 summarizes the steps followed in the greedy insertion heuristic used to build feasible solutions to the MTAP as modelled earlier.

It’s worthwhile to note that such greedy algorithms are polynomial-time and linear in function to the number of schedules to build, i.e. workers, and number of tasks to assign. This feature is pretty important for real-time situations where solutions are to be re-generated quickly in reaction to uncertainty (Ghiani *et al.* 2003).

The centralised approach running such algorithms has two modes of operating: event-based and periodical. In the event-based mode, workers report to the central point about their status and information regarding any change upon the occurrence of exceptions. This approach heavily depends on workers’ incentives and motivation to reveal every event they face, if possible at all. Furthermore, the central solver may face bottleneck problems with a growing number of workers and the levels of uncertainty increase. On the other hand, periodical update mode implies the central decision maker to explicitly probe workers about their status at regular time intervals, and therefore integrating a batch of changes in the solution, rather than individually as it is the case for the event-based mode.

In both cases and upon the reception of new information, the central solver runs the algorithm with the updated information as new input data, finds new solutions, and then broadcasts updates to the affected schedules. In order to create correct updates, it is crucial for the central solver to have accurate information about workers’ state, new tasks to be scheduled, and general knowledge about the environment. For the periodical updates mode, the update rate is a main parameter to be set by the central decision maker. Since the central solver benefits from a global view of the system prior solving the problem and taking decisions accordingly, it is possible then to run the simple greedy heuristic several times during the planning phase with different orders of input data and keeping the best solution. This is a main advantage compared to the market-based approach given that markets are run only once. This is supposed to give extra performance in favour of the centralised approach during the planning phase.

Figure 4-3. Pseudo-code for greedy insertion heuristic to solve the MTAP.

4.6.2. The Market-based Approach Simulation Model

As mentioned in chapter 2, when it comes to considering the design of a market-based solution, there are several aspects to be addressed. The market solution should take into account the structure of the market (e.g. direct or via delegates), the actors (e.g. who are the buyers and sellers), their incentives, the form of transactions (e.g. single versus bundles of items), contract conditions (e.g. considering de-commitments), and the market mechanism where the auction bidding process is designed.

The following subsections are covering the relevant parts of the proposed simple market-based solution to address the MTAP. Similar to the case of the centralised approach, the suggested market is not intended to perfectly tackle the MTAP, but to reflect the main features a market solution is ought to have so it can be compared to its centralised counterpart.

4.6.2.1. Markets, Incentives, and Mechanisms

In the market-based approach, complete information to make global decisions for all workers and to maximise the global score is not available. Instead, privately-held local information is used at the individual level for decision making. The local information of each agent (worker) is communicated among other agents according to a market protocol. This exchange of information would assist agents in taking individual and self-interested decisions to maximise their own benefits. Therefore, it is crucial to align agents' private goals with the global objective function of the whole system. Such an alignment arises from the communication protocol used to exchange information among the agents, and their willingness to reveal their private information. In the case of market-based protocols, information is exchanged according to buying and selling transactions, which is achieved through auctions. As for the willingness to reveal participants' true private information, a proper incentive mechanism should be designed and deployed to govern the auction process. According to the formulation of Hurwicz (1973; 1977), a mechanism is a system of communication where participants exchange messages among each other that jointly determine the outcome. These messages may contain private information, such as an individual's willingness to pay for a public good. Based on this system, each agent attempts to maximise its utility and may, therefore, disclose misleading or false information.

In this study, the market-based approach is intended to be designed as a mechanism in which workers in the MTAP are turned into autonomous and self-interested agents able to actively communicate and perform trade transactions. This includes buying and selling tasks rather than direct exchanges with other agents. Each worker would buy and sell tasks in order to increase its own utility regardless of others' or of the global state. The utility of each worker is privately computed according to a defined utility function. The difference of the mechanism in this study from the one followed in (Mes et al., 2007) and in (Máhr et al., 2010) is that this research intends to use market negotiations to allocate tasks among workers holding private information with no assumption to openly share this private information with others, which is a core feature of the market-based approach.

Since each agent holds private information about its preferences and current state, referred to as its "type", and tends to act selfishly; this situation leads to a case known in the Game Theory literature as a "*Bayesian-Nash Equilibrium*", e.g. (Gairing et al., 2008; Van Zandt, 2010) . As described by Harsanyi (1967), a Bayesian-Nash equilibrium, contrary to the dominant strategy, can be described as a game of incomplete information where each agent adopts a strategy as the best response to other players' strategies. On the other hand, the dominant strategy is the optimal strategy an agent may take regardless of other agents' choices. Furthermore, when the dominant strategy is to truthfully report the private information then the mechanism is referred to as incentive compatible (Myerson, 1979; Walker, 1981; Mookherjee and Reichelstein, 1992).

For addressing the MTAP in a market-based way, the design of a mechanism where a dominant strategy exists is required in order to align the workers' individual goals with the system global objective. This is mainly due to the fact that agents are unaware of other agents' strategies during task assignments given that they are submitting their decisions through sealed-bids in single-round auctions. According to the "*Revelation*

Principle", which basically states that any mechanism able to produce equilibrium outcomes can be replicated by a direct mechanism that is also incentive compatible (Epstein and Peters, 1999; Bester and Strausz, 2000; Peters, 2001), it is possible to achieve such a mechanism to produce align workers' incentives with global goal of the system.

In addition to the need of aligning agents' individual incentives with the MTAP's global objective function through a mechanism with a dominant strategy; it is crucial for the agents to interact in real time to face uncertainty. These requirements lead to the necessity to design a mechanism where workers can not only participate to auctions, but are also able to initiate new auctions. For the agents participating in auctions, the mechanism should allow the agents to evaluate and report their private information in their bids and schedule assigned tasks in real time. The same requirements are also for the initiator agents. Agents initiating auctions should be able to call for bids, evaluate replies, and resolve best bidder(s) in real time and yet satisfying the incentive requirements. These requirements can be interpreted as the need of a mechanism where agents' decisions are computationally tractable and made within reasonable amount of time while being incentive compatible. The design of such mechanisms has been the subject of the field of "*algorithm mechanism design*" proposed by Nisan and Ronen (2001), which is out of the scope of this research.

Motivated by the promising features provided by the revelation principle and by the algorithm mechanism design, the design of the market-based mechanism for this research is centred on a single-round first-price sealed-bid auction with allowed de-commitment and tasks' re-allocation. It is referred by first-price that the items are sold at the price submitted by the highest bidder, as opposed to the Vickery second price auctions. And it is meant by single-round that the auction determines the winner of the auctioned item following only one round of bids submission and evaluation. The mechanism is managed by the contract-net protocol (CNP) (Smith, 1980; Davis and Smith, 1983) to coordinate the exchange of bid messages.

Sealed-bid auctions are a practical way to keep private information hidden from other participants throughout the whole execution time; therefore each agent would only be aware of his own allocations and utility. The use of first-price auctions in this research is mainly to simplify the comparison with the performance achieved by the centralised approach. Instead of designing an artificial currency for the market transactions, the market mechanism in this research will employ the same performance metrics as a way to describe the agents' marginal utilities when bidding and evaluating those bids.

4.6.2.2. Breach of Contracts

Breaching a contract, or a contracted item, refers to the ability for a contractor agent to retreat from the commitment agreed in the contract in exchange of a penalty from not complying with obligations stated in that contract (Sandholm and Lesser, 2001). In the context of the market mechanism employed in this research to tackle the MTAP, breaching a contract happens when a worker cancels the execution of a scheduled task. This cancellation is only possible before the task execution is started. This breaching option provides more flexibility to better adapt in face of probable uncertainty and better adjust resource allocations. As an example of breaching a contracted task in face of stochasticity is when severe delay exceptions face a worker with a busy schedule. In such cases, the worker may opt to resell those scheduled tasks to other workers given that it cannot perform them anymore due to hard time constraints. Similar breach may occur when dynamic tasks enter the system. If the worker's schedule is full and a new task is more attractive than one (or more) scheduled task(s), the new task may be scheduled instead of the less beneficial one(s). This results in the worker cancelling and reselling one (or more) scheduled tasks in order to improve its utility.

When a worker agent retreats from the execution of a scheduled task, it is possible for that worker to resell it to other prospective agents through initiating an auction as an attempt to reschedule the task before dropping it. To ensure that agents resell their de-committed tasks, the employed mechanism should incorporate a proper incentive mechanism to ensure such behaviour. This can be achieved by paying off the selling worker a commission for successfully reselling the task to another agent. The amount of the commission can be a fixed rate (regardless of the type of task being auctioned), a percentage of the task value, a value in function of task-related and other external factors, or simply to drop the incurred penalty costs from this breach. Establishing the details of such transaction costs can be borrowed from the literature of the transaction cost theory, e.g. (Williamson, 1981; Williamson, 1995). In this research, the latter strategy is assumed to be sufficient to motivate the workers to sell breached tasks, that is, by voiding the penalties. Further transaction costs/rewards for reselling tasks are out of the scope of this study and are suggested for future research.

4.6.2.3. A Basic Market Mechanism for Solving the MTAP

The market-based mechanism designed for this research is intended to be basic, not too sophisticated computationally, but yet to include the distributed markets characteristics. It is designed to operate in the same way for both phases of the MTAP, which are: the planning phase, where all information is static and deterministic; and the execution phase where plans from the previous phase are put to execution under varying levels of uncertainty. In both phases, each worker, represented by an individual trading agent, has the ability to adopt the role of a buyer, as well as a seller when de-committing from a previously planned task.

During the planning phase, the main seller in the system is the tasks dispatcher, who sequentially auctions tasks one-by-one to all worker agents by broadcasting call for proposal (CFP) messages. Upon the receipt of a CFP, each worker calculates and replies with a bid if the task is of any positive utility; otherwise, the CFP is simply discarded. $B_{i,d}$ is the generated bid for task i by worker d. It represents the marginal utility obtained from including the task in the actual schedule. This is evaluated by the following utility function:

$$B_{i,d} = \alpha S_i - \beta \min\{C_{i,d,p} : 0 \leq p \leq |sched_d|\}$$

Where:

α, β: are normative operands for the auctioned task score and incurred travel costs, respectively.

$C_{i,d,p}$: is the cost of scheduling task i in worker's d schedule, at position p. This is calculated as:

$$C_{i,d,p} = \begin{cases} dist(d_{il}, i_l): |sched_d| = 0; \\ dist(d_{il}, i_l) + dist(i_l, t_p) - dist(d_{il}, t_p): p = 0; \\ dist(t_{p-1}, i_l) + dist(i_l, t_p) - dist(t_{p-1}, t_p): 0 < p < |sched_d|; \\ dist(t_{|sched_d|-1}, i_l): otherwise; \end{cases}$$

Where:

$dist(a, b)$: is the travel distance from location a to location b. For simplicity, in the simulation model this distance is calculated according to the Euclidean distance equation assuming that workers are operating on tasks located in a 2-dimension Cartesian plane. That is:

$$dist(a, b) = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2}$$

d_{il}, i_l, t_p: are worker's d initial location, task i location on the plane, and the location of the task positioned at p in the schedule, respectively.

$sched_d$: is the schedule maintained by worker d and $|sched_d|$ is the length of the schedule. The first scheduled task has a p value of 0 and the last task a p value of $|sched_d| - 1$.

During the execution phase worker agents can, in addition to participate to auctions, turn into sellers by initiating auctions for selling tasks. Decisions regarding buying, discarding, and selling tasks to face uncertainty are based on the adopted exception handling strategy the agent uses.

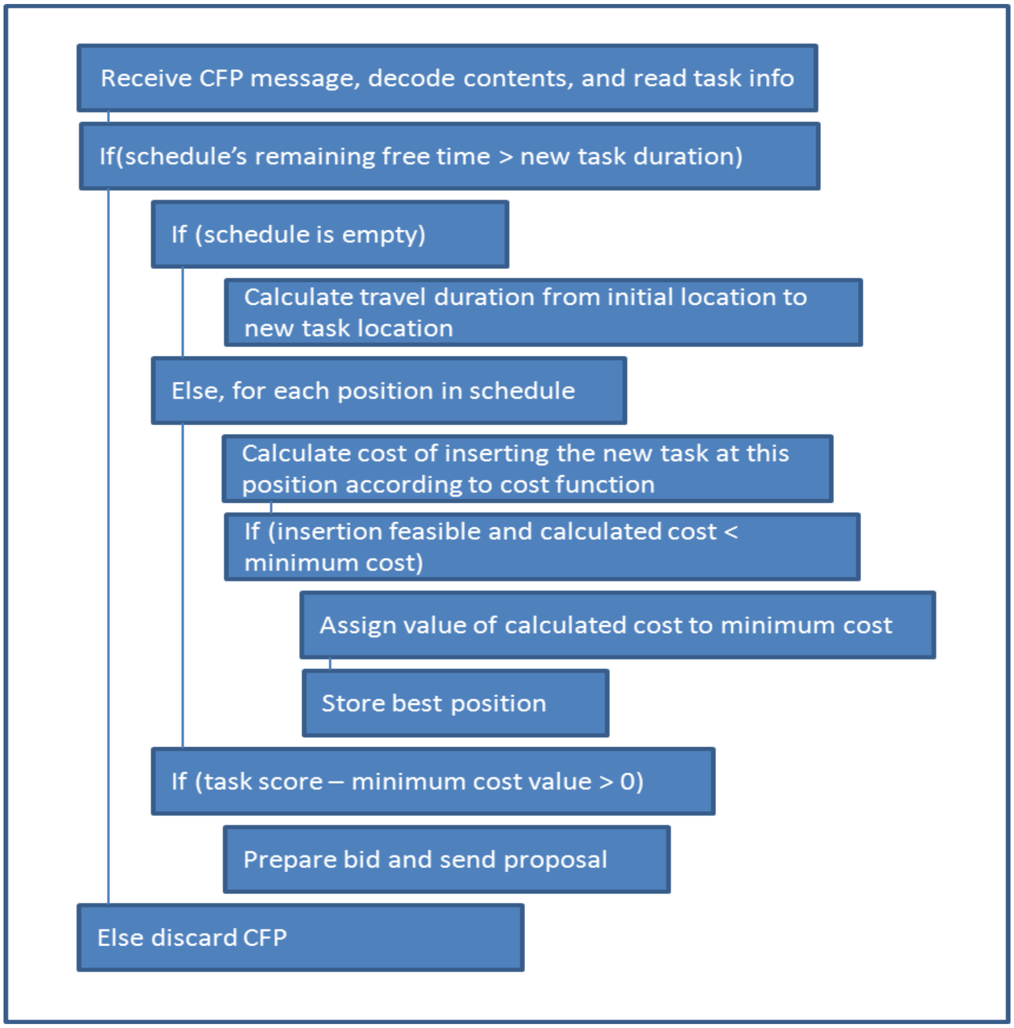

Figure 4-4. Pseudo-code of the operations flow for worker agents participating in task auctions during the planning phase.

In dynamic environments where new tasks are scheduled during execution, worker agents may frequently initiate auctions. This happens in scenarios when the agent's schedule is full and a dynamic task of higher importance than an unexecuted scheduled one is auctioned, the worker agent would maximize his own marginal utility by trading off the new task with an already scheduled one; resulting in bidding for the new task and auctioning the most appropriate one simultaneously. The selection criteria of the task(s) to be disposed and auctioned to other agents may vary. In this research and for simplicity, an agent can only replace one scheduled task at a time. The selected task to auction is this with the minimum marginal utility. If the new task fits in the schedule after taking out the task with least marginal utility, then the worker agent would bid for the new task. If its bid is accepted and the task is successfully scheduled, the worker then initiates an auction to sell the disposed task.

Similarly, worker agents can sell scheduled tasks they cannot execute due to delay exceptions. Such sell transactions are frequent when workers' schedules are full and delays are severe. When a worker agent faces delays during the travel or execution time of a task, all subsequent travel and task starting times are shifted by the amount of the delay (if known). The worker agent would discard those tasks it cannot execute anymore, due to hard schedule time exceeding constraints, according to an exception handling strategy. As mentioned previously, the criteria of the task(s) to be eliminated from the schedule depends on the strategy. In this research and for simplicity, discarded tasks due to delays are chosen according to their marginal utility. Sequentially and until the schedule is feasible, tasks with the least marginal utility are discarded from the schedule and auctioned to other worker agents.

4.7. The MTAP Multi-agent Simulator (MTAP-MaSim)

After formally representing the MTAP, the solutions used by both approaches, and how the environmental uncertainty is modelled in the previous sections, this section describes the simulation system developed specifically as the main instrument to address the main objective of this study, which is the comparison of the centralised and the market-based approach in the presence of the environmental uncertainty. This comes according to the third step of Davis *et al.* (2007) roadmap followed in this research. The MTAP multi-agent simulation system is introduced along with justifying the adoption of a multi-agent approach. In the next subsections, the main elements making up the simulator are described as well as the main process followed by the simulation programme for running subsequent experimentations.

4.7.1. Conceptual Definition of MTAP-MaSim

MTAP-MaSim stands for the Mobile Task Allocation Problem Multi-agent Simulator. Whilst the name of the MTAP-MaSim suggests that it is an agent-based simulation system (also known as agent-based models), it also incorporates some features borrowed from the Discrete Event Systems (DES), particularly when it comes to simulate uncertainty through the creation of exception events (Pidd, 1986; Macal et al., 2010). However and as opposed to pure DES simulation systems, MTAP-MaSim updates the system at every tick of the clock instead of only at events occurrence, therefore it can be said that it is a continuous time-based simulator where the global clock is employed to coordinate the system's global status. This is mainly due to the nature of the MTAP where the internal state of agents is constantly changing and need updating.

Agent-based simulation is based around modelling the behaviours and interactions of autonomous artificial entities, referred to as agents, to form a social system (Macy and Willer, 2002; Harrison et al., 2007; Macal and North, 2010). The global behaviour of the system then emerges from the aggregation of these individual behaviours and interactions (Bonabeau, 2002). Therefore it can be concluded that agent-based modelling is mainly a suitable approach when it comes to simulate systems following a bottom-up approach. With a bottom-up approach, the system is easier to understand and to design since the design of the simulation model starts at the entity-level of the system instead of the whole system. This is mainly a suitable approach to model complex systems with significant numbers and types of interactions which make the design of the whole system behaviour unclear and prone to errors (Macal et al., 2010). The simulation of people-centric systems in a society is a good, if not the best, type of systems to be simulated by agent-based simulation (Macal et al., 2010; Siebers et al., 2011). For this research, two main concepts are perceived to belong to this category of systems; these are the organisation and the markets.

According to Davidsson (2001), agent-based simulation is advantageous in comparison to DES since it simplifies the modelling of proactive behaviours, support of distributed computation in a straightforward way, implementation of agents' communication protocols, and it is more appropriate to simulate time-driven systems. All these features are internally incorporated in the MTAP model as presented earlier. The goal of the model is to investigate the proactive behaviour of the communicating worker agents in centralised organisations and in distributed markets, with the presence of uncertainty exceptions happening at any moment.

Besides the previous reasons and those highlighted by (Bonabeau, 2002; Macal et al., 2010; Siebers et al., 2011) for which an agent-based simulation system may be preferred over a DES simulator, the reason for using a continuous time-based approach to simulate the MTAP can be addressed on the following points:

- The high number of simulated agent entities: The number of simulated worker agents in the MTAP is intended to be relatively high (>25), each with individual state updates in function of time. That is, each agent updates its own status (e.g. location, activity) at every clock tick. This is efficiently implemented in MTAP-MaSim since each agent is assigned a dedicated thread responsible of continuously updating the agent's state and reacting upon a change of the actual state. This approach makes it easier to manage the simulator coordination engine, which in its turn controls the global clock. So rather than having a large single queue of events governing the simulation clock, as it is the case in DES, MTAP-MaSim maintains a single global clock according to which each agent autonomously updates its status and responds to events, if any.
- Time consistency across all agent entities: given that each agent is an autonomous entity and independent from other entities in the system, the coordination and synchronisation of agents is hard to maintain with the absence of a reference global clock regulating the pace at which each agent should perform a status update. For example, if an instance of the MTAP was simulated using DES, then all involved agents are implemented as being passive entities and the events causing a status change in every agent should be queued in a single event list. Upon the occurrence of an event, the corresponding agent entity may start/end an activity and trigger new events for other agents causing changes in their status. Such changes should therefore be reflected in the main event list.

As the event list grows, due to the problem size and degree of applied uncertainty, managing such changes and keeping an updated and consistent event list is not an easy task. If, however, the 3-A (Pidd, 1986) methodology is used to build the DES then at any time the length of the event list would at most equal the number of the simulated worker agents (i.e. for each agent, each event, apart from the initial ones, are generated after the previous event takes place). Thus, if a change in a certain agent's status would lead to change(s) in others status too, then a dedicated component should be designed and implemented to monitor the status of each agent prior the new change(s) and manage the list of events to reflect these changes and keep time consistency.

- Ease of debugging and simplifying the verification process: When agents are updated at regular time intervals, it is easier to monitor their behaviour and ensure the correct flow of status changes, notably upon their reaction to uncertainty. For example, MTAP-MaSim has a graphical component representing the mobile worker agents. At every tick of the global clock, the location (represented by two-dimensional coordination) of each worker is updated drawing the path of the workers. The more frequent the clock ticks are the more accurate the path is rendered. When a route deviation happens, such a graphical representation makes it easy to verify that the correct behaviour and status updates have been correctly implemented (e.g. travel durations, smooth route deviations without odd hops, etc…).
- Convergence of the DES behaviour to a continuous system as the number of entries in the events list highly increases (i.e. number of agents and environment uncertainty exceptions' frequency).

Following the previous points, the multi-agent with continuous time-based approach was chosen for being simpler to implement than a pure DES for simulating MTAP instances. It is not claimed that a pure DES cannot be employed to achieve a similar target, as proclaimed, but it is definitely more challenging to implement, especially during the debugging and verification stages.

Nevertheless, some characteristics of the DES are implemented in the MTAP-MaSim. This is the usage of lists of events to store future events to be pushed in the system. With the use of lists of events, uncertainty exceptions are modelled as events happening at random moments during schedules execution time. These events are stored in lists indicating when they should be applied. The entity managing these events depends on the type of uncertainty: dynamism or stochasticity.

For the case of dynamic tasks, the task generator agent (as will be described later) generates dynamic tasks according to the mechanism described in the previous chapter at arbitrary time intervals. When one, or more, dynamic task(s) is generated and pushed in the system, the time interval to wait before generating the next dynamic task is also generated indicating the task generator when to next push the dynamic task(s) in the system. So rather than statically generating all dynamic tasks prior simulation execution, dynamic tasks, along with when they enter the system, are dynamically generated. This approach gives more flexibility to experimentations as to when and what type of dynamic tasks to generate. For instance, some dynamic tasks may arise as a result of a certain decision made by an actor in the system that cannot be predicted beforehand; by this approach, this concept can easily be modelled.

As for the case of stochastic delays affecting time elements in the system, delay exceptions are also considered as events happening at random moments specifying the start of delay. These events are stored in specific lists until they are due. However and as opposed to the case of dynamic tasks, the list of delay events are not centrally preserved by a single agent (the task generator agent for dynamic tasks list), but rather maintained by the worker agents themselves. As described in the previous chapter, when a time element is started and stochastic delay uncertainty is studied, delays affecting this time element are generated as a single “bulk” amount of delay. These delays are then spread throughout the whole time element at random intervals. When the total amount of delays is broken down to several shorter delay segments, each of these segments is modelled as an event and stored in the delay-start event list of the owner of the affected time element.

Even though the delays event list is maintained by worker agents, they are designed so that worker agents are unaware of future delays until they are due. This distributed design and implementation of delay event lists avoids the necessity of having a centralised controller to manage the occurrence of delays, but to encapsulate them as part of the worker agents' structure and ensuring synchronisation and parallel execution.

4.7.2. MTAP-MaSim Simulation Entities

In order to create a simulation model for the MTAP scenario as it is described above; there are several elements to be identified. The most important elements are the actual agents representing the mobile workers, the nature of tasks, and the surrounding environment of the whole system with the time dimension reflected by the simulation clock.

4.7.2.1. Simulation Actors

In multi-agent simulation, the main elements in the simulation process are the actors that are represented by computerised agents. Agents are defined as being autonomous entities behaving in the system according to a set of behaviours and strategies. At any simulation moment, each agent is characterised by its own internal state that specifies, for instance, the activity of the agent and its location. Through its life cycle, an agent interacts with other agents and has its internal state that is either changed internally (e.g. the worker agent's location is a state that changes due its own movement) or in response to an external stimulus (e.g. a worker agent changing its schedule due to the arrival of a new task). Agents communicate among each other and with the environment by the mean of formatted messages.

There are four main agent types interacting in an MTAP-MaSim round. These types are:

- **Worker**: The main actors in the MTAP scenario are the worker agents. Each worker is planned to be executing a set of tasks according to a planned schedule. Agents of this type are very dynamic, having their internal states frequently updated, and constantly involved in extensive communication with other agents in the system. As independent entities, each worker agent is responsible to update its status according to the global clock, its schedule, and other internal settings when applicable (e.g. exception handling strategies in the market-based approach). The lifecycle of worker agents starts at the beginning of each simulation round when they are created by the "Simulation Controller" agent. At the end of the simulation round, each worker agent outputs its schedule along with its achieved score on a dedicated file in the output folder structure (as it will be described later).

- **Central Solver**: The central solver agent is only used during the simulation of the centralised approach since it models the role of the centralised decision maker. Only a singleton instance of this agent type is created when simulating the centralised approach. The central solver agent actively communicates with worker agents to obtain recent updates and to broadcast updated schedules. It also receives messages from the "Task Generator" agent containing the dynamic tasks to be scheduled. The central solver agent is created by the "Simulation Controller" agent at the beginning of centralised simulation rounds and after the creation of worker agents.
- **Task Generator**: This agent is the source of tasks in any simulation round. In addition to the generation of random dynamic tasks, the task generator agent is responsible of reading input files and run sequential auctions during the planning phase of market-based simulation rounds (as it will be described below). It also determines when to start the execution phase following the completion of the planning phase of any simulation round. This is determined when all worker agents successfully outputs their planning phase scores for the market-based approach, and when the "Central Solver" agent completes solving and broadcasting schedules to worker agents for the centralised approach.
- **Simulation Controller**: This is the main controller of the simulation process. The simulator controller agent does not have a dedicated role in MTAP simulation scenarios neither it has a direct impact on the obtained results. However, each MTAP-MaSim instance should have a singleton simulator controller agent to create other agents and to govern the execution sequence of

experiments, measurements, and simulation rounds according to the contents of the experiments and general settings files. The simulation controller agent is created at the start-up of an MTAP-MaSim instance and remains active until the simulation instance is shut down.

4.7.2.2. Simulating the Mobile Tasks

Mobile tasks are randomly generated as described above in section 4.3.1.1. Each task is however characterised by the following attributes:

- **ID**: A unique name to identify the task.
- **Location**: The coordinates of the task.
- **Duration**: The expected on-site service time.
- **Score**: The task's score reflecting its priority, and hence the customer satisfaction attached to this task.

4.7.2.3. Simulation of the Environment and the Time Clock

As previously mentioned in this chapter, the MTAP-MaSim is a continuous time-based multi-agent simulation system. That is, there should be an independent timing mechanism governing the simulation process. In MTAP-MaSim, this mechanism is defined as the global clock. Since the global clock represents the notion of time used by all the actor agents to synchronise their actions and manage their activities, there is only one global clock for any MTAP-MaSim instance. There are two main attributes for the global clock element; these are the tick value and the current time. The current time determines the time status of the simulated system, while the tick value reflects the time scale used for the simulated clock. For instance, if the tick value is set to 200 this means that each simulated minute corresponds to 200 milliseconds of the real time. This value obviously controls the simulation speed. For example, if schedules of 8-hours working-horizon are being simulated then it would take 96 seconds to complete with a clock tick value set to 200 milliseconds ($0.2 * 60 * 8 = 96$ seconds).

4.7.3. Simulation Process

Basically, MTAP-MaSim was created in order to conduct experimentations and comparing the exposed performance of the centralised and market-based approach in different settings and scenarios of the MTAP. According to the conceptual model presented in Chapter 3, it can be seen that there are two main settings for uncertainty an MTAP instance can have, these are stochasticity and dynamism. These two sources of uncertainty have been detailed in Chapter 2, 3, and previously in this chapter. Within these two settings, several scenarios may rise due to the effect of the moderating variables: timeliness of decision making affected by the problem size and complexity and the degree of local knowledge. For example, within different degrees of stochasticity, we want to know the impact of different levels of local knowledge on the exposed performance. In order to organise such experimentations, MTAP-MaSim defines three elements:

- Experiment (E).
- Measurement (M). This matches the term "*number of sets*" employed by Davis *et al.* (2007).
- And, simulation round (R). This maps to the term "*number of runs*" also employed by Davis *et al.* (2007).

The relations between these elements can be expressed in a tree structure, as depicted in the next figure. Each MTAP-MaSim instance can automatically and sequentially run several experiments (z experiments in the figure); each experiment is conducted with several measurements, that can also be expressed as observations (n measurements in the figure); and finally, the retained value for each measurement is taken as the average result of x simulation rounds run on different inputs. This is also expressed as experiment replications. If the experimentation is applicable for both approaches, then each round is repeated twice; once for each approach.

Decisions about the number of measurements for an experiment belong to the experimenter. However, a higher number of measurements provide a better fine-grain observation of how changes occur in the system. Thus, it leads to smoother graphical representations of outcomes in graphical representations of results and a higher potential to understand the causalities among the system elements being studied. As for the number of simulation rounds to execute, more repetitions lead to lower marginal errors, lower bias, and higher probability of generality. In statistical terms, the number of simulation rounds x represents the sample size for a certain random experiment.

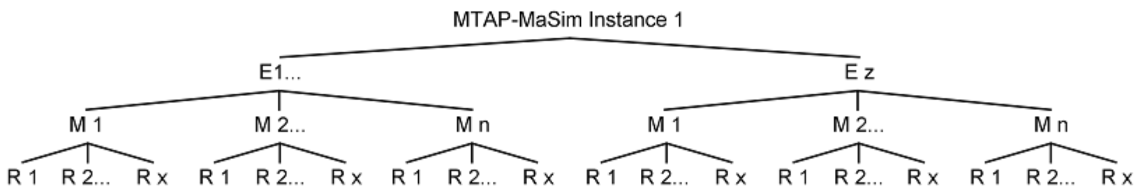

Figure 4-5. MTAP-MaSim experiment-measurement-round tree structure

The previous tree structure describing the experiments to be executed by the MTAP-MaSim instance is stored in the “experiments.xml” file. As a simulator instance starts, it reads and parses the “experiments.xml” file to represent the tree structure in a set of nested Java objects. The order of execution of these experiments corresponds to a *depth-first-search* of the tree with *preorder-traversal sequence* as described in the pseudo-code presented in the next figure.

The simulation process of the MTAP consists of two major phases: the planning and the execution phase. During the planning phase, initial solutions are generated based on the parameters settings and the input data assuming that no change can affect these data. These input data are therefore the actual determinants of the initial state of the simulation round. Both approaches go through the planning phase prior the execution of these. During the planning phase of the centralised approach, the central solver agent collects all the relevant data about the tasks and workers and then employs its solving mechanism (e.g. heuristic) to generate the solution. On the other hand, the market-based approach deals with the planning phase by having a task generator agent acting as the main auctioneer in this phase. This auctioneer agent sequentially organises market auctions to assign input tasks and its role is terminated with the end of the planning phase.

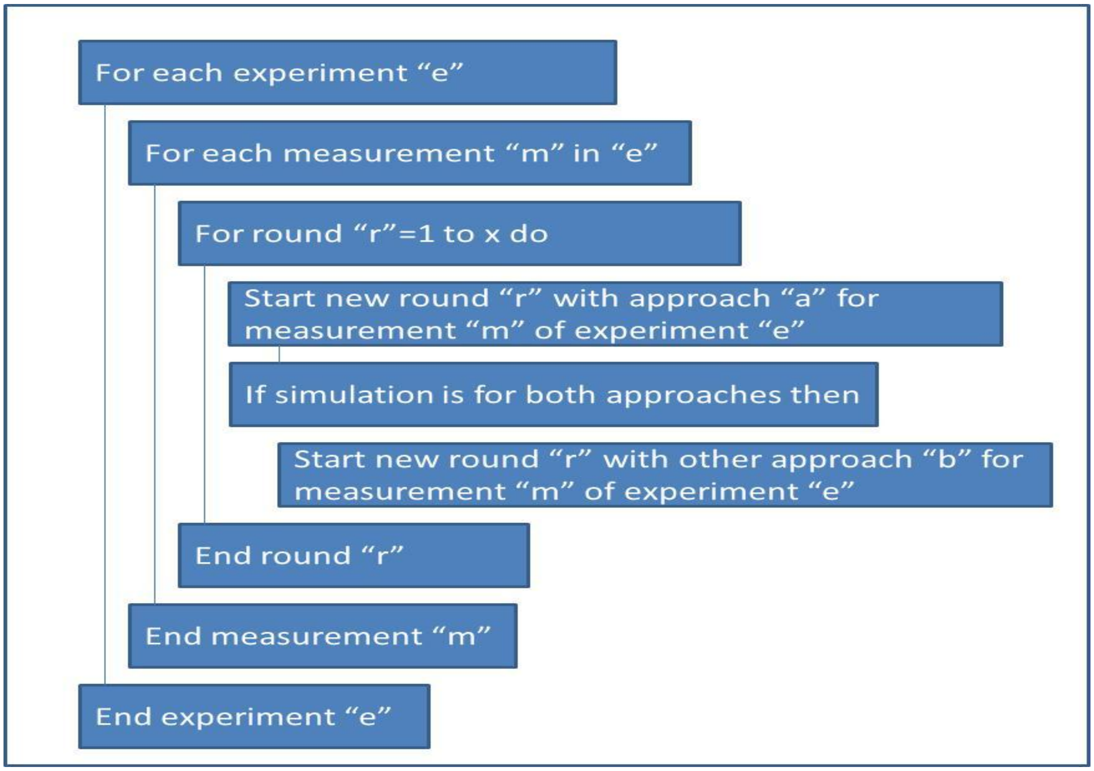

Figure 4-6. MTAP-MaSim execution order of experiments.

As the planning phase is completed and the execution initial states are defined, the results of this phase are recorded before proceeding to the second phase where the generated schedules are executed. During execution, uncertainty is introduced and corrective actions are taken by both approaches to handle the faced exceptions. This is conducted till the end of the simulation time horizon (one working day for the experiments conducted in this research). The flowing figure summarises the simulation process with the major steps run by the MTAP-MaSim. When the execution phase completes, it is considered that a simulation round has completed.

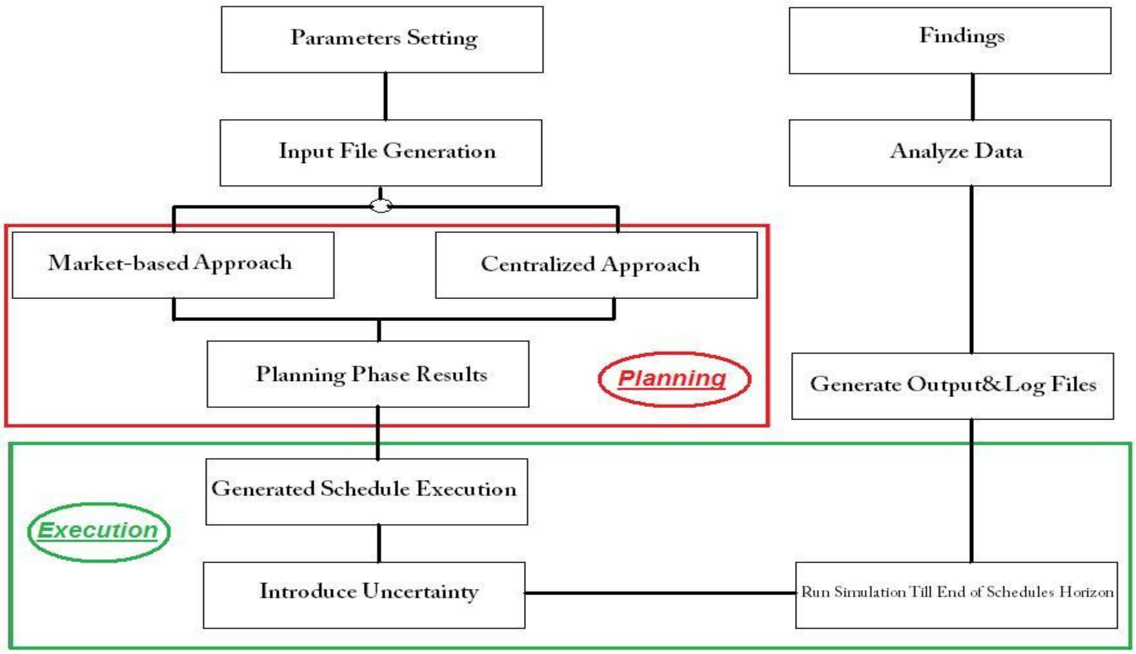

Figure 4-7. MTAP-MaSim simulation process

As shown in the previous figure, the output generated by simulation rounds is stored in well-organised output and log files. The file tree structure is similar to the tree structure presented earlier as shown in the next figure. The next figure shows the tree structure of a single MTAP-MaSim instance running 3 experiments on 4 input files (datasets). Each measurement has 4 rounds executed for both approaches.

While the only files of interest are those holding the simulation results, other log files are essential for verification purposes as it will be described in the next section.

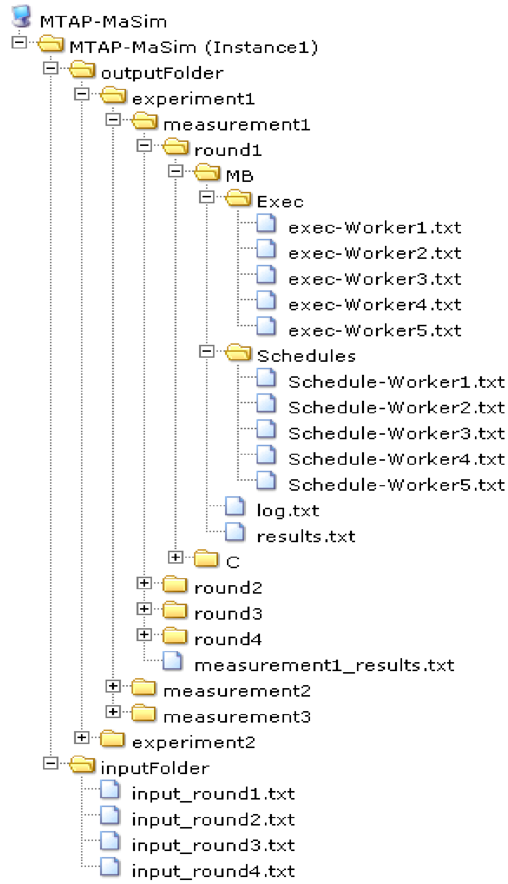

Figure 4-8. MTAP-MaSim file structure.

4.8. Verification of the Simulation System

The model verification process is the last step of the simulation model design and implementation before proceeding to experimentation according to the followed roadmap of Davis *et al.* (2007). According to Chung (2004), the verification process can be considered as “building the model correctly”. In other words, it is meant by verification the process of ensuring the technical correctness of the code that is implementing the simulation model. In addition to addressing obvious and hidden code syntax error, ensuring the code correctness involves optimising the written code and ensuring it properly does what it is supposed to be doing. This is progressively done from the very initial stages by debugging, looking for inconsistencies in the interpretation of the model to programming code, and verifying execution flows and calculations. Third party tools are of great benefit at his stage of verification. For instance, syntax error highlighting in integrated development environments (IDE) ensure the code is properly written before proceeding in compiling and running the faulty code. Another example is the use of the debugger and testing units to test the implemented logic and calculations via test cases. However, it is still a tedious effort to ensure that all aspects of the simulation system are covered by suitable test cases, especially if the simulation system is built from scratch.

For MTAP-MaSim, the verification process was mainly conducted by carefully checking the correctness of calculations and execution flows by outputting intermediary results and comparing them with logical and independently computed results (e.g. by hand or using a reliable source) for the same case. This is mainly done for simple and tractable scenarios. When these tests pass, it is considered that the concept at hand is correctly implemented and reliable for larger scale cases. However, for more complicated and longer cases, MTAP-MaSim is set to run in the debugging mode where log files are created to record fine-grain details about the activity and behaviour of each simulated entity during the simulation process. An example of such log files is the outcomes of iterated market transactions along with all the changes following this transaction.

Another way to verify that the model has been implemented realistically, dedicated graphical user interfaces (GUI) were created in order to graphically represent the simulated system and its underlying dynamics. The next figure is showing a screenshot of a running instance of an MTAP-MaSim simulation round. Agent workers are redrawn at every clock tick and different colours are used for each task status. This allows a real-time monitoring of agents' activity switching and how they are moving to new locations during travel. This GUI was of particular benefit when debugging the worker agents moving behaviour, notably when deviating from an original route to a new task location. Many mistakes (e.g. workers abnormally jumping from one location to another) were identified and thus leading to correct such bugs. Resolving this bug is believed to be crucial for the correctness and validity of results, and yet, it is believed that it could not have been identified otherwise.

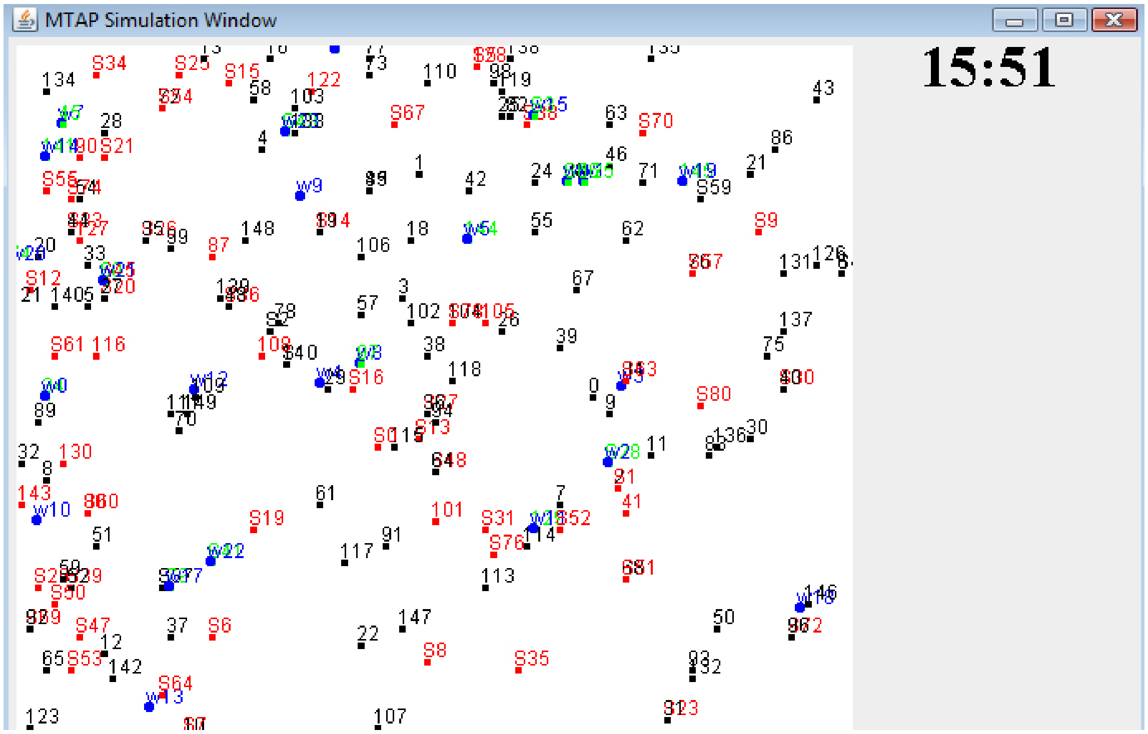

Figure 4-9. MTAP-MaSim execution window

For each measurement, graphs of the simulation rounds results are also shown in the GUI to ensure the correct execution flow of simulation. This is considered helpful to ensure successful transitions between simulation rounds and avoiding (or diagnosing) the occurrence of severe irregularities.

4.9. Conclusions

This chapter aimed to describe the research methodology and presented the simulation model and the agent-based simulation system employed in this research. It introduced with defining simulation methods and justifying its adoption as a methodology for this research along with the roadmap proposed by Davis *et al.* (2007), which is followed in this study. This chapter also presented a formal model for the MTAP along with two solutions representing the centralised and the market-based approaches. Environmental uncertainty and the moderating variables from the conceptual model described in Chapter 3 were also described and modelled for simulation.

The main conclusions of this chapter can be listed as follows:

- This research adopts simulation methods as its methodology in order to verify the propositions in Chapter 3. Simulation methods are particularly advantageous for this research given the ability to virtually represent real-world MTAP scenarios with varied levels of uncertainty. It also permits the direct control over the studied moderating constructs and the reproduction of experimentation scenarios for fair and comprehensive comparisons of the studied approaches under similar conditions.
- Multi-agent simulation is adopted as a simulation approach for its ability to model a system based on its agents' behaviours and communication rather than system-wide complex processes. This simplifies the design and simulation of the MTAP solution approaches and provides natural and more realistic system behaviour, notably at simulating workers' individual states and reactions to uncertainty.
- The MTAP is an optimisation problem which can be formally defined as an integer program. This is done by adapting the formulation of the TOP provided by Vansteenwegen *et al.* (2009).
- Environmental uncertainty affecting the MTAP lays in defining dynamism and stochasticity processes that controls the arrival of dynamic tasks and the occurrence of travel delays, respectively. The dynamic arrival is modelled by a Poisson process and delay values are obtained from a Normal random distribution function.
- The centralised approach is represented by a greedy heuristic operated by a central solver agent that initially finds initial solutions, which are then periodically adjusted according to update recourses as new global information is revealed. These updated solutions are then broadcasted to worker agents to react in face of uncertainty.

- The market-based approach is represented by a direct first-price single-round sealed-bid auction market mechanism regulated by the contract net protocol. The utility function of each worker is based on the best insertion algorithm, which resembles to the greedy heuristic employed by the central solver but on a smaller scale. This eliminates the technical differences of the employed heuristics by both approaches and ensures that the differences in the achieved performances are based on the effects of the moderating variables.
- The MTAP multi-agent simulator (MTAP-MaSim) is technically introduced as the simulation system specifically developed to correspond to this research requirements and to incorporate all the necessary concepts of the target MTAP and other studied phenomena such as uncertainty.
- MTAP-MaSim is verified through multi-stage code debugging and GUI components in order to ensure the simulated behaviour correctness of the system.
- The main outcome of this chapter is that the agent-based simulation instrument is employed in order to test the suggested propositions, as will be detailed in Chapter 5.

Chapter 5. Experimentations & Simulation Results

5.1. Introduction

Returning to chapters 3, which was mainly dedicated to describe the conceptual constructs observed from the reviewed literature and aimed to be addressed in this research, these were expressed in a theoretical model from which a set of propositions were suggested and to be tested with a suitable methodology.

Chapter 4 then provided an additional layer on top of the conceptual model by defining the simulation model used in this research. The simulation model consisted of the definition and formulation of the target problem employed in this research, which is the MTAP. It also covered how the suggested propositions would be included in simulation scenarios by operationalizing uncertainty and the other moderating variables: timeliness of decision making, problem size, and the degree of workers' local knowledge. A detailed description of the implemented simulator MTAP-MaSim was also provided.

This chapter aims at describing the experimentation settings used with the mobile task allocation problem multi-agent simulator (MTAP-MaSim) and at presenting the results obtained from the simulation experimentations. It starts with discussing how the input datasets were randomly generated and lists the values used for the main settings. This chapter then presents the set of experiments conducted for this research. The scenario of each experiment is intended to cover one, or more, proposition from the theoretical model. Therefore, each scenario is described in a dedicated section concluding with the results and graphical representations of the experiments.

5.2. Experimentation Design

Due to the lack of real world data to be used as input for MTAP-MaSim, synthetic data is produced and used instead. Input datasets were randomly generated by a dedicated component, part of MTAP-MaSim. Each file contains a single instance of the generated datasets and represents one simulation round per approach. That is, each input file is simulated twice, once by each approach, where applicable. The next figure shows how input datasets (files) are generated via the input file generator window of the MTAP-MaSim. In the implementation followed in this research, the problem size of an MTAP instance is determined by the number of workers to manage and the number of planning tasks.

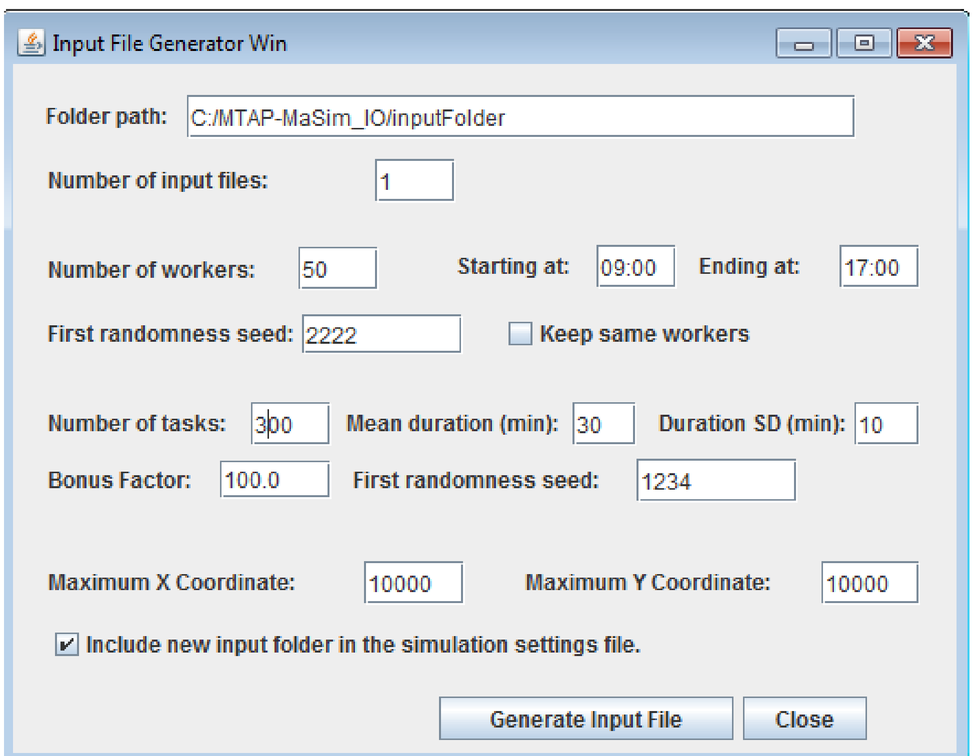

Figure 5-1. MTAP-MaSim window for generating new input files.

The details of the simulated workers and planning tasks are formatted in text files as shown in the next figure. Each input files has the number tasks and number of workers as a header, then each line in the file starts with a prefix “Tsk” or “Wrk” to define the initial status of a task or a worker, respectively. This is given in the following format for defining a task:

Tsk:Task_id,x-coord,y-coord,earliest_start_time,latest_end_time,duration,score;

Similarly, workers are defined according to the following format:

Wrk:worker_id,start_time,end_time,initial_x-coord,initial_y-coord,travel_speed;

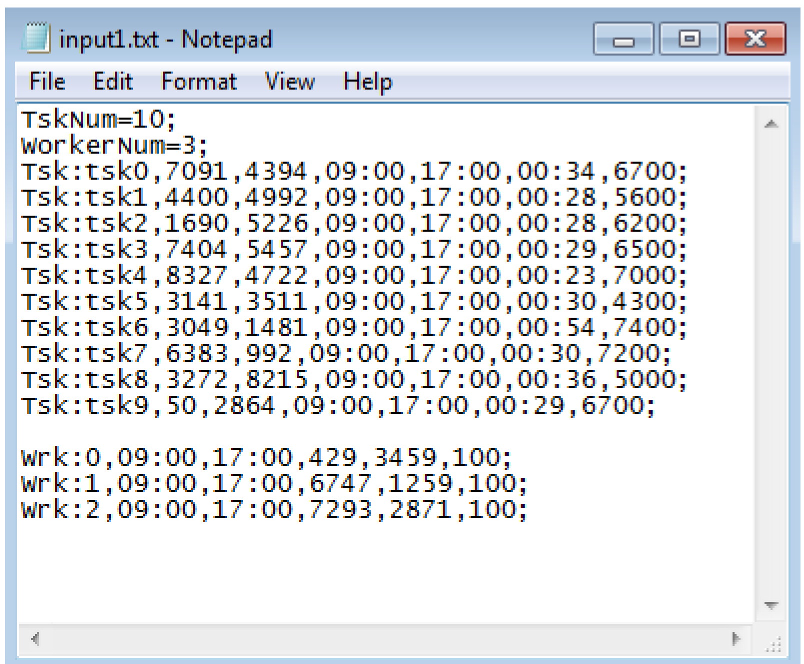

Figure 5-2. MTAP-MaSim Input file with 10 tasks and 3 workers.

As for the experimentation designs followed in the research, the number of input files for each experiment was fixed at 50 files. Each file contains a dataset of 50 workers and 300 planning tasks. This results with a total number of 2500 schedule per experiment per approach, which is believed to be sufficiently large samples to generalise the findings. During experimentation, the seed values of random generators are updated between rounds (i.e. simulating the execution of the next input file) according to a known pattern. These values are reset for the following measurements. This ensures diverse randomness among rounds in the same measurement and preserves consistency of random patterns among measurements within the same experiment.

These dataset dimensions were borrowed from the problem size faced by the centralised algorithm deployed by British Telecom to solve their constrained optimisation model for the allocation of tasks among their workforce (Lesaint *et al.*, 2000), of which MTAP is a simplified version of the problem. The count of simulation rounds was also fixed to 50 which is higher than the comparison experiments conducted by Mes et al. (2008) and the datasets larger than those experimented in (Mahr et al. 2010), which simulated 40 trucks in their VRP application.

In all scenarios, it is assumed that the workers start their working day at 9:00, finishes at 17:00, and operate in square-shaped 2-dimensional areas with a side length of 10,000 distance units (DU). When travelling among tasks, workers move at a regular travel speed of 100 DU per simulated minute. Tasks are randomly generated with their duration values sampled from a normal distribution with a mean $\mu = 30$ minutes and $\sigma^2 = 10$ minutes, and location coordinates sampled from a uniform distribution with the minimum parameter value of 0 and maximum value of 10,000.

All communications among the agents are assumed to happen in real-time. Computation times are also assumed to take 1 simulated minute at most, except when differently stated in particular experiments.

Experiments were conducted on a machine equipped with the Intel Xeon Quad Core processor running at 2.40GHz with 12MB of cache and a total of 12GB of RAM. The hosting operating system is Microsoft Windows 7 (Professional Edition) running the latest stable version of the Java virtual machine, which is version 1.6 at the time of experimentations. With these hardware specifications, it was possible to safely run the simulation with a global clock tick value of 50 milliseconds.

5.3. Experimentation Results

This section provides the simulation results for the different types of experimentations conducted in order to verify the proposed theoretical model. All the experiments were executed with the settings described in the previous section. Prior presenting the obtained results, experiment scenarios are introduced along with the particular settings values.

5.3.1. Experimentation of the Basic Models

Basic model experiments refer to replicate those scenarios where the dependent variable, namely the performance difference, is only affected by the independent constructs, which is uncertainty. These experimentations are conducted without the influence of the moderator constructs on the relationships of the former two constructs. That is, the basic model explores how the difference between the performances exposed by both approaches is affected by the studied sources of uncertainty, regardless of the particular features of a given approach.

The importance of the basic model is twofold:

1- Comply with the relevant literature, which also ensures the simulation model validity. Since there is no empirical data to compare with the simulation results of the different scenarios of the MTAP, simulation validation is done by confirming the simple theory on which the simulation model was based on (Davis *et al.*, 2007). This way of validation, coupled with a thorough verification process, is similar to Knight (2011).

2- Create a benchmark model that will serve at observing the changes caused by the effects of the moderating variables.

This research has two basic models, one per source of uncertainty. The basic model experiments are as follows:

5.3.1.1. *Dynamism Basic Model*

In the dynamic basic model experiment, dynamic tasks are introduced with different arrival rates determining the degree of dynamism. The measured values range from very low rate of dynamism with an arrival rate $\frac{1}{\lambda} = 60$ minutes to very dynamic with $\frac{1}{\lambda} = 5$ minutes. The measurement value $\frac{1}{\lambda} = \infty$ refers to a completely static environment, which is the result of the planning phase results.

In order to amplify the effect of dynamism, the dynamism priority factor is set to 2. That is, on average, the importance of a dynamic task is twice as much as this of a planning task. The following table presents the obtained results conducted with the experiments settings described before.

	5	**10**	**20**	**40**	**60**	∞
MB	69286433	46892616	33917711	26757449	24239844	19581405
C	72535518	50014416	36265289	28664151	25835546	20851422

Table 5-1. Dynamism basic model experimentation results

The following graph plots the values of the previous table in a regular line chart.

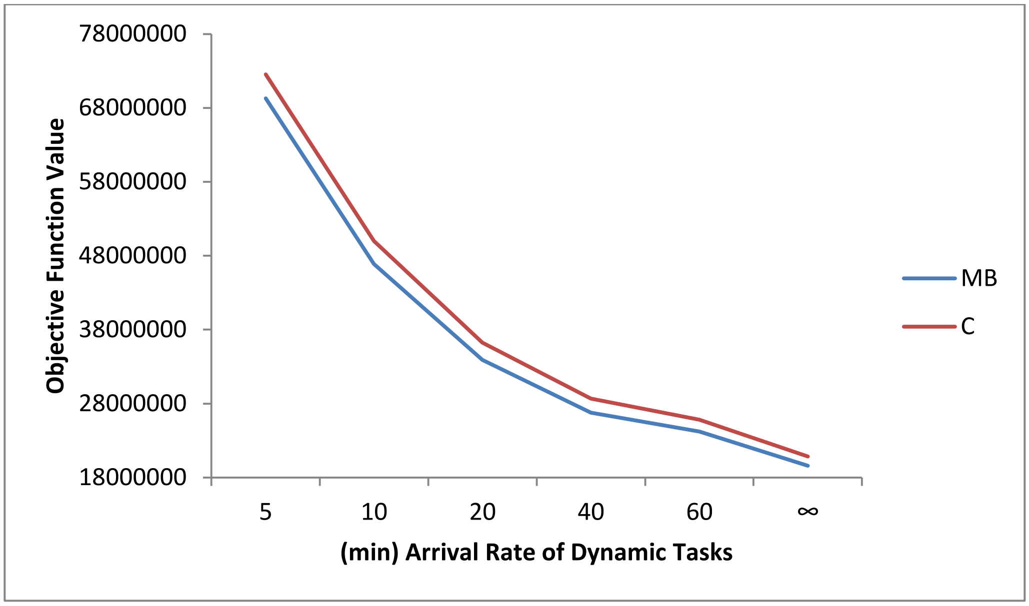

Figure 5-3. Line chart of the dynamism basic model showing the achieved results of both approaches in function of the degree of dynamism.

Starting with a slight advantage in favour of the centralised approach, it can be seen that dynamism has a further positive effect on the performances difference. Despite the difference with the studied objective functions of the simulated problem, these results comply with those of Máhr *et al.* (2010). Furthermore, it can be noted from this basic model that the market-based approach could never outperform the centralised performance. In its turn, this matches the claim of Ygge and Akkermans (1999).

In regard with the simple theories, which the simulation model of the MTAP-MaSim is based on, the results of the dynamism basic model correspond with both of them. Firstly, uncertainty had an impact on the performance. Even if it is a positive impact, this is due to the insertion of additional tasks, with higher priority, to be scheduled. Secondly, the performance of the market-based approach could not, in any condition, to overcome the one of the centralised approach. This matching with the simple theories advances the credibility and validation of the MTAP-MaSim simulation model and implementation.

5.3.1.2. Stochasticity Basic Model

The second experiment for the basic model consists of observing the effect of travel delays on the achieved performances. In this experiments (as it is the case for this research), only travel delays are considered for the stochastic type of uncertainty. This can be explained due to the assumption that delays during tasks execution and those occurring during travels can be handled similarly by both approaches. This choice was also made to increase the probability of decision changes during travels, which may result in route deviations and highly depends when decisions are adjusted, and to cover the type of delays not discussed in the work of Máhr *et al.* (2010).

For this experiment, 5 measurements are taken by varying the degree of travel delays between 0, for the case of a fully deterministic environment, to 100%, for the case of extreme stochasticity. The following table lists the obtained results:

	0%	**20%**	**40%**	**60%**	**80%**	**100%**
MB	19829805	18887183	18257390	17807957	17372845	16858478
C	20903961	19247952	18671132	18204918	17659059	17296239

Table 5-2. Experimentation results of the Stochastic travel delays basic model

The following figure shows the graphical representation of the experiment outcomes. It can be seen that both approaches are vulnerable to travel delay exceptions. However, the initial centralised outperformance tends to converge to the performance exposed by the market-based approach, before a slight gap reforms for the last measurement. Again, these outcomes match with those from the corresponding experiment of Máhr *et al.* (2010), which focused on the effect of service time delays. This in turn also ensures the validity of the simulation model regarding the delays as the second source of uncertainty.

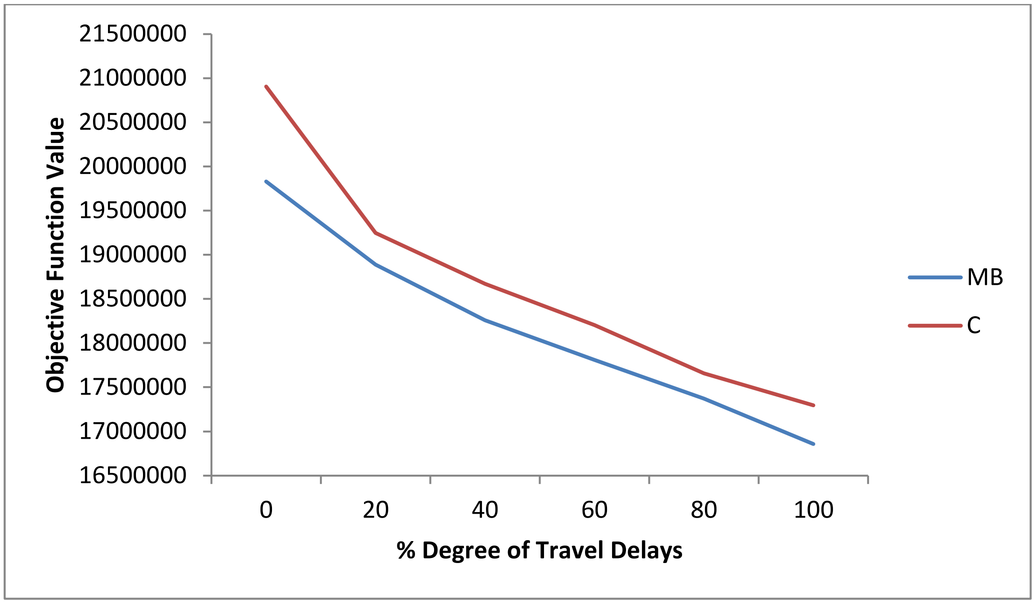

Figure 5-4. Line chart of the stochastic basic model showing the achieved performances of both approaches in function of the degree of travel delays.

It can be seen from the graph that the centralised approach is always overcoming the market-based approach. However, the initial solution of the centralised approach shows more vulnerability by just introducing moderate degree of uncertainty. The reason for such a steep slope comes from the centralised approach seeking for an optimal solution by utilising the maximum schedulable time of workers' plans. This results by obtaining busy schedules with less robustness against any delays. This is why slight delay exception would result in the cancellation of some tasks, and therefore decreasing performance, to reach a similar performance of worse solutions. A practical way for the centralised approach to avoid such sharp performance deterioration is to consider time cushions to ensure minimum flexibility as a trade off against performance. The remaining question, though, is to decide about the degree of flexibility, which requires some forecasting information about future uncertainty. This is not considered in this research.

5.3.2. *The Effect of Timeliness of Decision Making*

In the previous experiments of the basic models, the effect of the moderator variables on the relationship between uncertainty and performance difference was nullified. Therefore, it was assumed that the central solver has the capability to update its global view of the system in real-time and react to the new changes instantly. This experiment attempts to observe the effect of timeliness of decision making by varying the update rate at which the central solver catches a global view of the system. At each update, the solver broadcasts messages to query the workers about their locations and current activities. It is assumed that all workers respond truthfully and in real-time. That is, no collusion is allowed and the communication is always reliable without delays. When all response messages are intercepted, the solver updates the actual solution instantly and broadcasts the changes to the respective worker agents.

This experiment is not related to the market-based approach since it does not have a central solver needing global view updates. Instead, workers in the market-based approach takes their own decisions independently in real-time upon the occurrence of uncertainty exceptions. Therefore, this experiment is only conducted for the centralised approach and then to compare its outcomes with the corresponding market-based score taken from the basic model.

The effect of timeliness of decision making is examined under both sources of uncertainty, dynamism and stochasticity. The next experiment investigates the case of dynamism.

For this experiment, 9 measurements are taken over 5 settings of dynamism. The measurements are the rates at which the central solver updates the solution. These are varied from 90 minutes (very low) to 1 minute (real-time), whereas the settings are the degrees of dynamism (i.e. arrival rate of dynamic tasks AR), which are varied, according to the basic model, between 60 minutes (very low dynamism) to 5 minutes (very high dynamism).

The next table lists the obtained results:

	1	5	10	20	30	40	50	60	90
AR5	72535518	72470280	71419636	69635740	68586048	66519868	65219456	63030502	58092135
AR10	50814416	49927712	49721309	48816139	47872952	47201980	46392445	45098611	41583884
AR20	36265289	36231758	36169809	35961116	35246460	34634677	33809496	33084127	31060400
AR40	28664151	28434987	28433757	28084531	27919869	27947240	27579282	27051603	25784818
AR60	25835546	25644291	25644230	25635066	25660896	25425992	25406722	25451697	24538966

Table 5-3. Results of the central update rate experimentations.

In the next figure, each line plots the performance changes in function of the update rates. It can be seen that the centralised update rate has a significant impact on the achieved performance. This effect reaches its peak in the very high-dynamism setting (i.e. AR5) with a gradually “smoother” effect as the settings apply lower rates of dynamism. It is also worth noting from the graph that a centralised update rate with a value inferior to the average arrival rate of dynamic tasks does not achieve a higher performance. Therefore, it can be asserted that in less dynamic environments, real-time communication with agents does not make a system better off. Therefore, a lower bound for the centralised update rate can be fixed to the average dynamism rate. On the other hand and even though communication costs are not considered in this research, slower update rates may save costs on the communication between the central solver and the workers (costs), but it dramatically drops the performance for cases of high and very high dynamism.

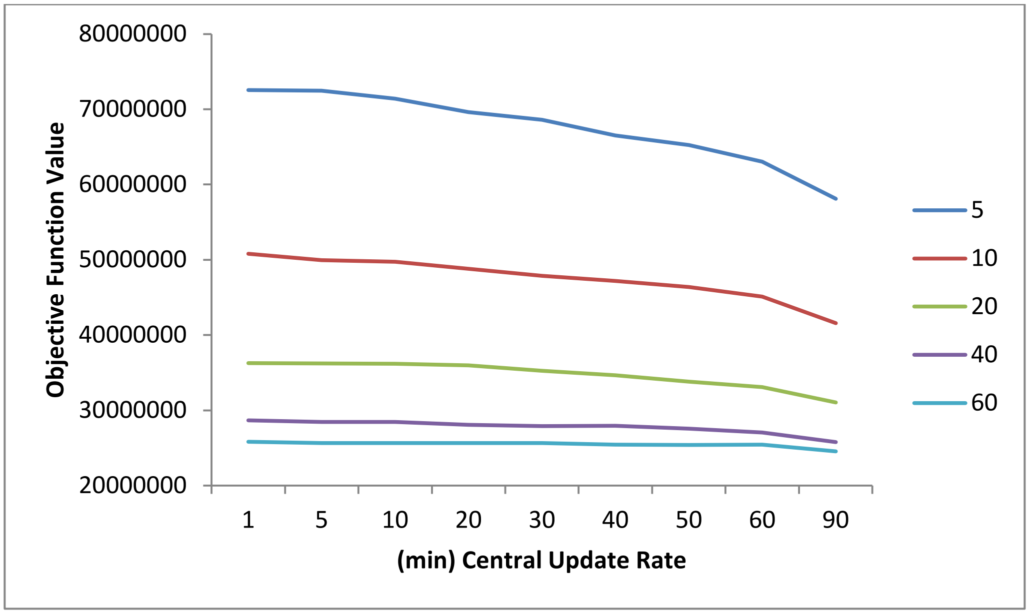

Figure 5-5. Line chart showing the centralised approach performance in function of central update rate with different dynamism settings.

To better understand the effect of the moderating variable of the timeliness of centralised decision making, reflected by the central update rate, the following figure shows how the basic model is altered due to the influence of the update rate moderating variable.

From Figure 5-6, the line 1 represents the dynamism basic model benchmark for the centralised approach. It is noted that this line is totally covered by line 5 stemming the fact that a 5-minutes update rate is sufficient for monitoring and successfully updating the extremely highly-dynamic system. As dynamism goes down, the lines converge to express the lower importance the central update rate has as the system approaches a static settings. In other words, if there are no dynamic tasks introduced in the system then regular central updates are of lower importance, if not useless.

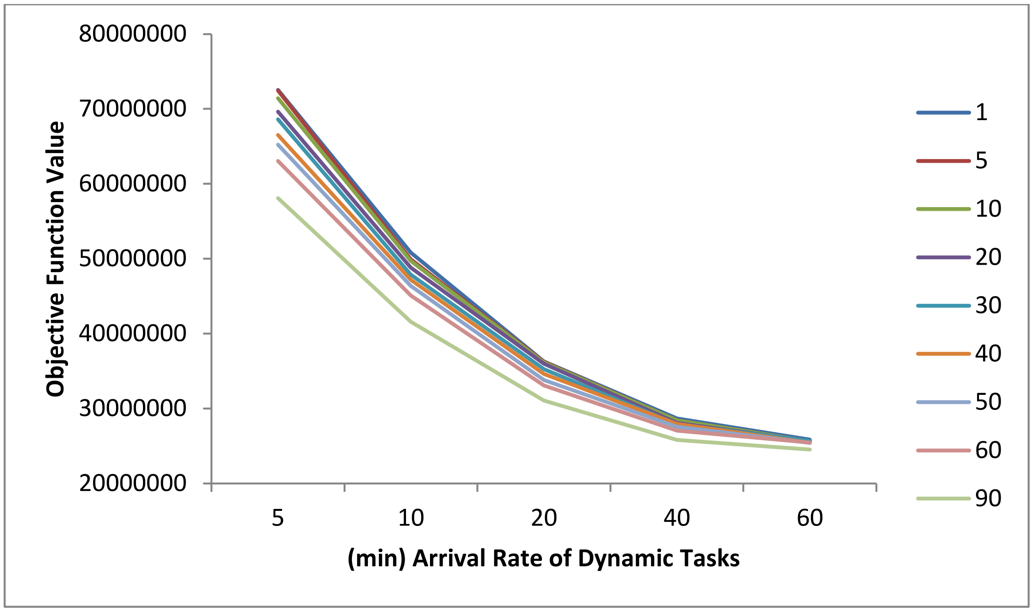

Figure 5-6. Line chart showing the performance in function of the system's degree of dynamisms and central update rates

Figure 5-7 shows the relative performance difference of the centralised approach compared to the market-based performance taken from the dynamism basic model.

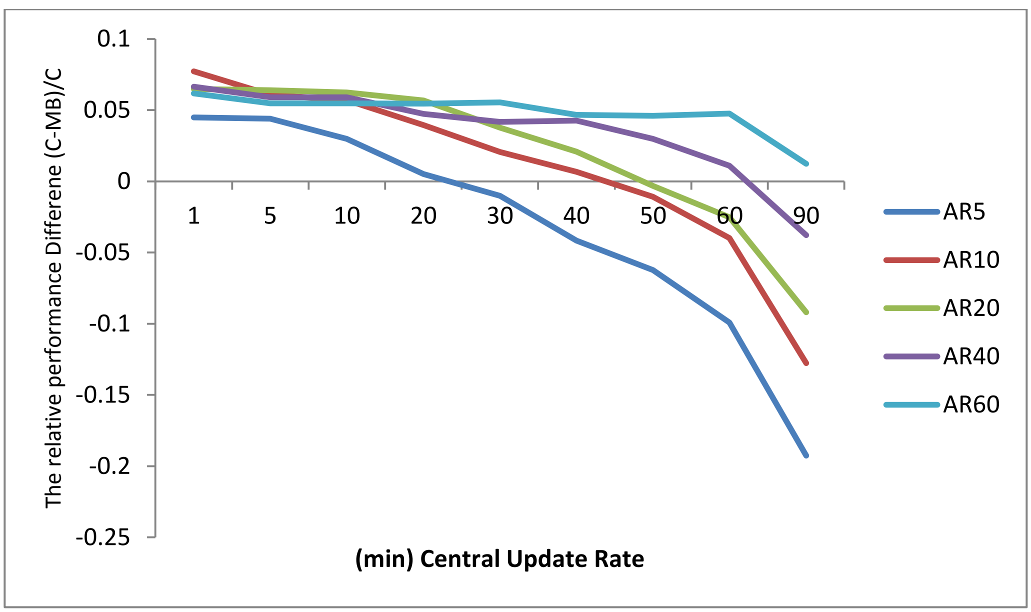

Figure 5-7. Line chart of the relative performance difference in function of dynamism and central update rates

The Relative Performance Difference (RPD) is obtained by the following equation and serves as an indicator to express the centralised performance changes in comparison with the market-based approach. C and MB stand for the performance of the centralised and the market-based approaches, respectively.

$$RPD = (C - MB)/C$$

The positive values of RPD stand for the centralised approach being performing better than the market-based approach under the same conditions of dynamism and central update rate.

The next experiment is conducted in a similar way to the previous one but for the case of stochasticity. The following table lists the obtained results, which are also represented in the line chart below.

	1	**5**	**10**	**20**	**30**	**40**	**50**	**60**	**90**
100	17126377	17101417	17272604	17233641	17182904	17210833	17162650	17162657	17249731
80	17549073	17482562	17455489	17472653	17514268	17432587	17396725	17425769	17504732
60	18210642	18178536	18087625	18200369	18098625	18204586	18298657	18256487	18178962
40	18765241	18836587	18905874	18799652	18962548	18896254	18796534	18888624	18875632
20	19302569	19268745	19205498	19198625	19278625	19298635	19300568	19287654	19186532
0	20903961	20903961	20903961	20903961	20903961	20903961	20903961	20903961	20903961

Table 5-4. Results of the central update rate experimentations.

It is noticed from *Figure 5-8* that the central update rate has a marginal effect on the centralised performance change in the same stochasticity settings. That is, securing quick updates about stochastic uncertainty does not affect the centralised reaction since there is no way to reduce stochastic delays once they are applied. For instance, if a worker is stuck in a long traffic jam that would delay the operations of that worker by an hour, then it makes no difference if the central solver knows about the exceptions immediately or after 30 minutes given that the worker is stuck anyway and the changes to the workers' schedule will not take effect until the delays are over, that is after an hour.

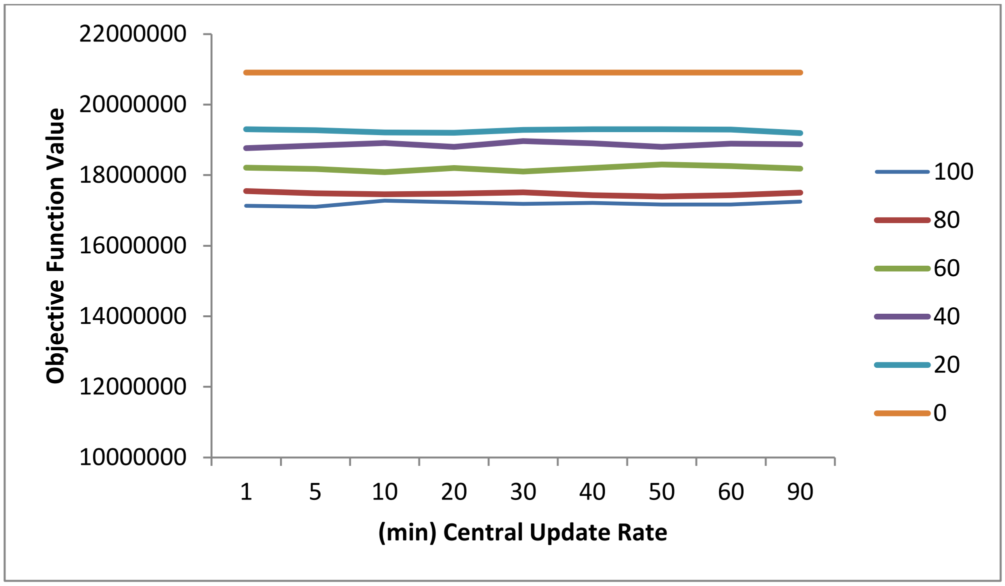

Figure 5-8. Centralised approach performance in function of central update rates with different stochastic settings

5.3.3. The Effect of Problem Size and Complexity:

All the previous experiments, including those for the basic models, were conducted on datasets with dimensions similar to those described in the experimentation design section at the beginning of this chapter. It is also assumed that these experimentation settings, when applied to the MTAP, are suitable to demonstrate the differences between the studied approaches and to test the proposed conceptual model. However, operations management departments dealing with real life problem instances are often faced with larger datasets with much more complex problems. For example, British Telecommunication Plc. (BT) has to manage the schedules of over 50,000 members of its mobile workforce over a 15-day time horizon. Furthermore, the scheduling problem faced by BT includes a large and complex set of constraints that require powerful algorithms and meta-heuristics to run on powerful hardware to accomplish the scheduling task within a reasonable period of time (Lesaint et al., 2000).

Even though the use of sophisticated hardware to run algorithms and heuristics with optimised code may significantly reduce computation times, however, this throughput relationship is not always linear. This is particularly valid for solving NP-hard problems, which is the case for almost all scheduling and routing problems.

It is shown Chapter 3 that the central update rate is in function of different factors fixing a lower bound to it. The decision making time is one of these factors, which is dependent on the problem size and complexity. Therefore, it can be said that the problem size and complexity affects the timeliness of decision making. Moreover, the particularity of computation time is that it affects schedulable time given the delays needed to compute a solution. For instance, if the time separating between the information collection process (i.e. broadcasting status query messages to workers) and the moment the updated solution is sent back and received by the workers is x minutes, then the central solver cannot include these x minutes in the solution. This results by reducing the schedulable time of each schedule by $T - x$, where T is the schedule horizon (e.g. 8 hours), and therefore further reduce performance.

This experiment explores the effect of computation time needed by the central solver to update a solution on the performance. It is only conducted for the centralised approach given that computations of the market-based approach are done independently in parallel among workers, which is a main feature of the distributed market-based approach. Centralised computation time may increase due to different sources. Collecting an updated view of the system, filtering processes prior the execution of computations, algorithms execution time, and broadcasting the new updates to all workers are all examples of time-consuming activities which depend on the problem size and complexity.

This experiment simulates the computation time the central solver needs to update a solution in different dynamism settings. Only the case of dynamism was experimented assuming that dynamism cause larger changes to the initial schedules and it is harder to insert dynamic tasks in busy schedules than simply eliminating tasks from infeasible schedules due to delays. Furthermore, the previous experimentation showed limited effect of the central update rate on the relationship between stochasticity and performance difference.

The experiment was conducted in 5 settings with 4 measurements for each. The measurements taken ranges from 5 minutes to 20 minutes in the 5 dynamism settings of the basic model. The next table lists the obtained results.

	5	10	15	20
AR05	62887899	58409890	51966479	42554764
AR10	43917374	39978861	37308572	32621990
AR20	32808087	30999811	27785478	25952035
AR40	26411034	24785731	23615381	22434304
AR60	24210272	23326363	22224051	21324977

Table 5-5. Centralised computation time experimentation results.

It can be seen from the graph plotting the obtained results how the computation time has a significant impact on the achieved performances. Even though computation times of 15 to 20 minutes seem very long for modern hardware equipment, fair computation times of 5 minutes seem to still have an important negative impact on the performance in settings of high and very high dynamism. This can be explained similarly to the effect of delays on performance given that the computation time can be viewed as delays too, but on the solver’s side rather than the workers’. The reason for such degradation is due to the lack of robustness in the schedules initially produced by the central solver in the planning phase. The negative impact of the computation delays is further amplified by the central update rate, which increases with higher computation times.

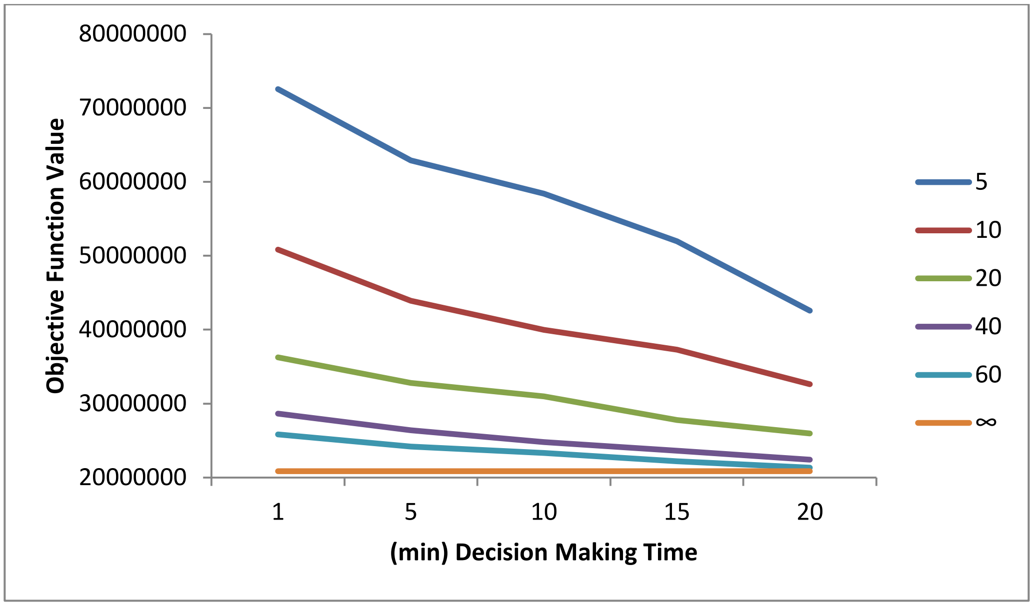

Figure 5-9. The effect of central computation time on performance with different dynamism settings

The following graph shows the achieved performances for different computation times in comparison with the basic model, where computations were done in real-time.

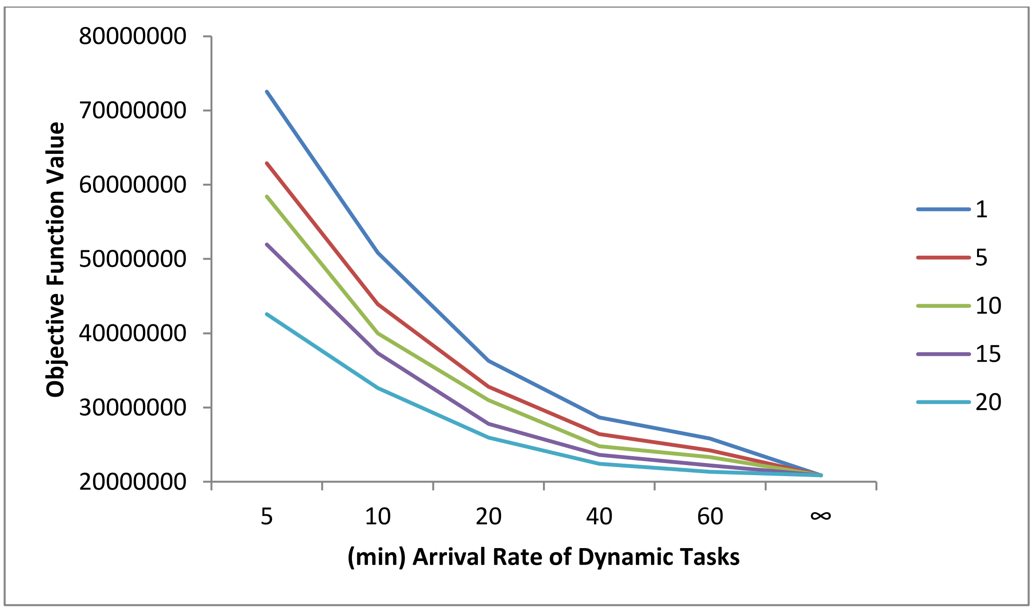

Figure 5-10. Line chart comparing the centralised basic model with the performance achieved with different central computation times. Line 1 is the basic model score

Figure 5-11 shows the relative performance difference between the centralised approach performances compared with those of the market-based approach under the same conditions of dynamism taken from the dynamism basic model.

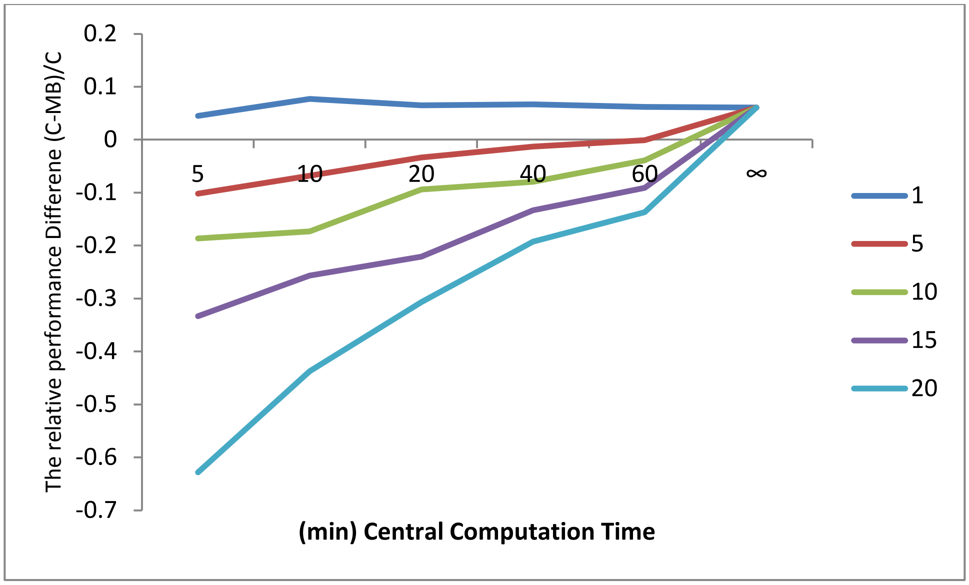

Figure 5-11. Line chart of the relative performance difference in function of dynamism and central computation time

The relative performance difference is calculated in a similar way to the one for the experiment of the effect of timeliness of decision making. That is, negative values refer to the market-based approach superiority.

5.3.4. The Effect of the Degree of Local Knowledge

This experiment explores the effect of workers' local knowledge, which is a main feature of the market-based approach, on the impact of travel delays. In this scenario, workers are assumed to have certain knowledge about some geographical areas they operate in. This knowledge can be gained from personal experience that would then contribute in reducing the severity of the encountered delays. In this experiment, local knowledge is modelled as described in Chapter 4 and is considered as measurements for 5 environmental settings. Each setting reflects a degree of stochasticity (i.e. severity of travel delays) within which 6 measurements of local knowledge are taken. Travel delays settings are set to range from 0% standing for a deterministic environment to 100% for the extremely stochastic case. The local knowledge measurements are varied from 0% for total workers' unfamiliarity with their operating region and inability to anticipate traffic jams to 100% for perfect knowledge of all workers about all areas and perfect perception of the environment, which allows the workers to anticipate delay exceptions shortly before they happen and, therefore, reduce their severity.

Given that this experiment examines the quality of workers self-oriented decisions based on their personal knowledge, perception of the environment, and experiences, it is only applied for the market-based approach. This stems from the fact that workers in the centralised approach obtain their plans from the central solvers in a procedural way, without any personal intervention. This situation can also serve as a model for potential incentive issues. When workers are dictated with their communicated plans in the centralised approach, they tend to follow the plan without any motivation to improve it. While on the other hand, workers tend to more participate when they should take their own decisions, even if the source of such a motivation may just be intrinsic.

The next table lists the experiment results and plot them on the following chart.

	0	**20**	**40**	**60**	**80**	**100**
TD0	19829805	19826598	19826598	19826598	19826598	19826598
TD20	18887183	18888198	18899407	18941610	19088541	19201729
TD40	18257390	18345903	18467657	18564336	18741959	18863602
TD60	17807957	17842237	17928282	18121761	18376101	18544593
TD80	17372845	17557611	17666878	17869152	18076124	18236977
TD100	16858478	16949901	17208568	17481406	17785175	18143855

Table 5-6. Experimentation results of the effect of local knowledge on performance in function of travel delays.

It can be noted from the chart the how the workers' experiences positively affect the achieved performance. Despite that a perfect knowledge would never totally eliminate the negative impact of stochastic exceptions, but it significantly improves the overall performance, notably in cases of extreme stochasticity.

In order to better understand the effect of the moderating "local knowledge" variable, Figure 5-12 plots the obtained result along with the basic model. Since it was assumed in the basic model that workers do not possess any additional local knowledge, the basic model line is represented by Line 0 in the graph.

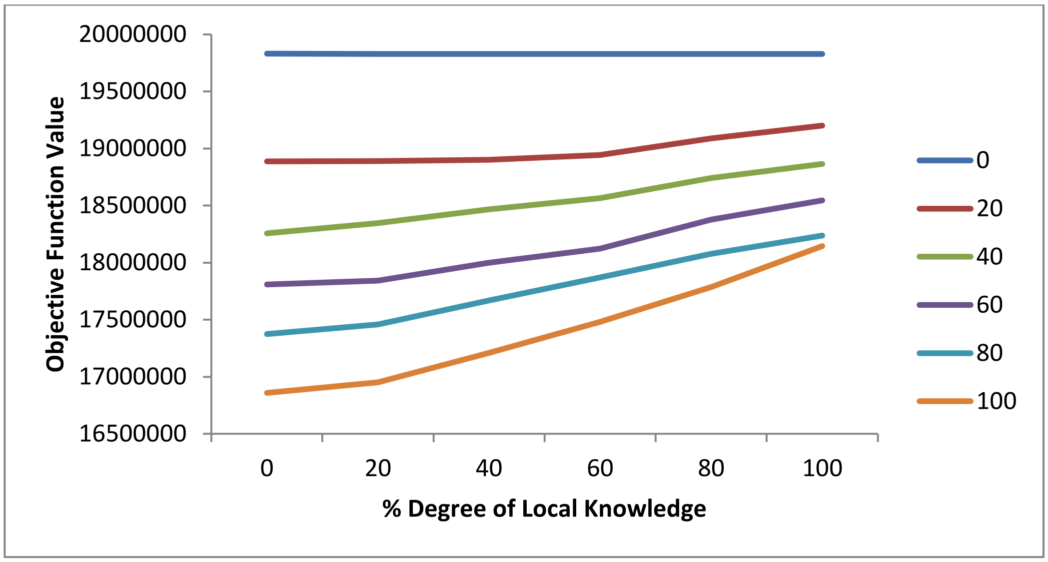

Figure 5-12. The effect of local knowledge on performance with different stochasticity settings

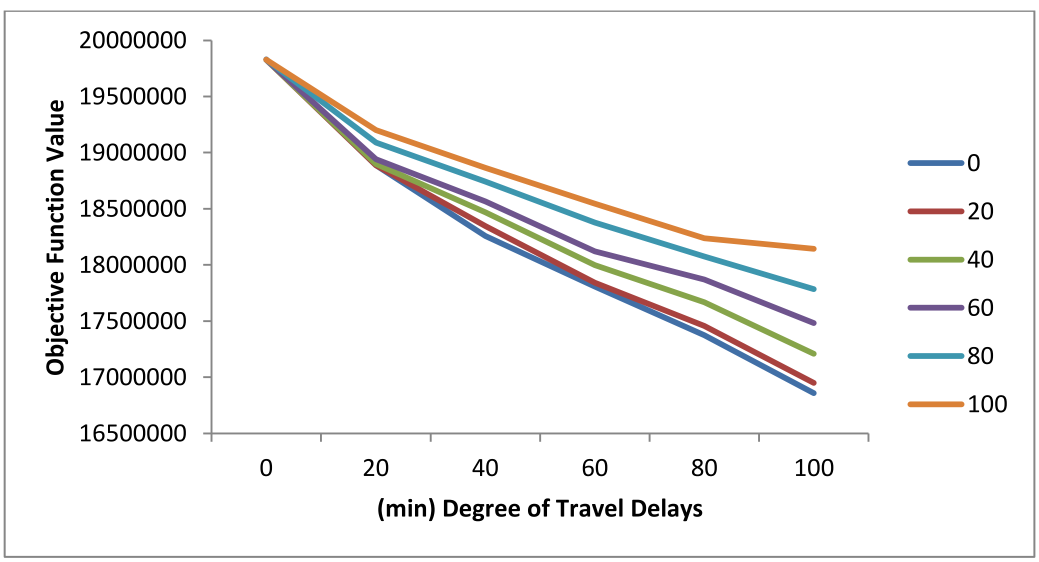

Figure 5-13. Line chart comparing the MB basic model with the performance achieved in presence of different levels of local knowledge. Line 0 is the basic model score

Figure 5-14 shows the relative performance difference between the market-based approach performances compared with those of the centralised approach under the same conditions of stochasticity taken from the stochasticity basic model

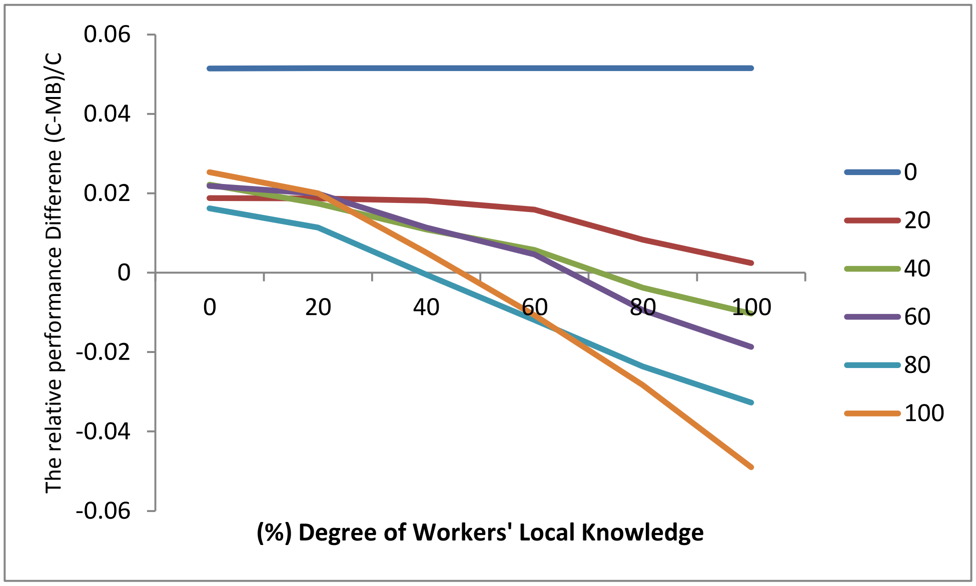

Figure 5-14. Line chart of the relative performance difference in function of stochasticity and workers' degree of local knowledge

Again, the relative performance difference is calculated in a similar way to the one for the experiment of the effect of timeliness of decision making. That is, negative values refer to the market-based approach superiority

5.4. Conclusions

After presenting the conceptual model that formulates the main aim of this research in Chapter 3, describing the target problem and simulation model to test the conceptual propositions in Chapter 4, and introducing MTAP-MaSim as the simulation system used to run the experiments in Chapter 5, this chapter presented the results from conducting the necessary experiments to test the hypotheses in the context of the MTAP. After running the basic models experimentations, each experiment was described as a scenario reflecting one of the moderating variables of the theoretical model. Obtained results were listed in tables and represented in line charts. After each experiment, a comparison graph is provided to demonstrate the effect of the new variable on the basic model.

The main conclusions of this chapter can be listed as follows:

- The first set of experiments was dedicated to test the basic model for both types of uncertainty, namely dynamism and stochasticity. The basic model design assumed a centralised real-time monitoring and reaction time. As for the market-based approach, the basic model did not include any type of workers' local knowledge.
- The results obtained from basic model did not show a significant impact on the performance difference of both approaches. Therefore, the effect of pure uncertainty with the assumptions of the basic model did not recommend the adaption of the market-based approach.
- The next simulated scenario introduced the effect of the moderator construct defined as the timeliness of decision making. This experimentation is mainly addressed to observe the impact of different rates of update rates in light of dynamism and stochasticity. The results suggested that the timeliness of decision making plays a major role in dynamic scenarios but is limited for stochasticity cases.
- Given that the problem size has a direct effect on the centralised decision making time, different scenarios of problem sizes were simulated, and therefore affecting the construct of timeliness of decision making. The results suggested the vulnerability of the centralised approach in scenarios of large problem sizes.
- The last set of experimentations was aimed at observing the impact of the workers' local knowledge to reduce the negative effects of stochastic uncertainty. The results suggested that higher degrees of experience and workers' local knowledge dramatically increase the robustness of the market-based approach to face travel delays exceptions.
- Derived from the observed results, it can be concluded that:

- The centralised approach is favourable to be implemented for the mobile task allocation problem in static and deterministic environments where uncertainty has a limited impact on the initial allocations.
- The market-based approach is favourable to be implemented for DRAPs in the presence of higher uncertainty when distributed entities' local knowledge is high and the problem size is large.

The main novelty in this categorisation lays in the integration of the main advantage of the market-based approach, which is employing the local knowledge of the distributed entities in the decision making process. This advantage is mainly obtained from the experiential decision making procedure followed in such a distributed structure, assuming that the market mechanism is incentive compatible as opposed to the procedural centralised decision making in the centralised approach.

Another observed factor is the limitation of the centralised approach when it comes to deal with high levels of uncertainty and large problem instances. The limitation of the centralised approach can be attributed to two main reasons. Firstly, the ability to timely collect global information from the distributed entities requires a large amount of information exchange. Secondly, the central decision making entity has to deal with this large amount of data and to process it accordingly, which may turn to be a very time-consuming process. This processing time greatly depends on the problem size and complexity, and since uncertainty increases complexity, the central decision making entity may have to deal with bottleneck issues. On the other hand, the market-based approach is not affected by the problem size given that markets are run in parallel.

Next chapter is dedicated to further discuss these results and to reflect on the findings in a proposed theoretical framework based on the conceptual model introduced in Chapter 3. It will also discuss the findings implied by the results and map them to the existing literature. The theoretical, as well as practical, implications of the findings lead by these results will also be described in the following chapter.

Chapter 6. Discussion

6.1. Introduction

Following the results obtained from the simulation experimentations presented in the previous chapter, this chapter aims at discussing the concluded findings and reflecting on the outcomes based on the proposed theoretical framework.

This discussion will start by depicting the outcomes of the basic model and explain the behaviour of both approaches. Thereafter, the effect of each moderating variables from the theoretical model is investigated.

6.2. Findings

As summary of the experimentation results, it is observed that the centralised approach is favourable in cases where it can operate in real-time. That is, when the central solver is able to instantly monitor the activities, locations, and exceptions encountered by all the workers in the system and updates their schedules accordingly without facing bottlenecks problems. However, these conditions are hardly met as the problem increases in size and complexity. Therefore, periodical updates are necessary and, consequently, the centralised approach becomes vulnerable as the problem size increases resulting in longer reaction times, notably for the case of dynamism. On the other hand, the market-based approach is favourable as the degree of workers' local knowledge increases, notably in cases of high stochasticity, and is indifferent towards the problem size given the parallel processing as a main advantage of distributed decision making.

Following these results obtained from the experiments described in Chapter 5, the main findings can be highlighted according to the sequence of conducted experiments and in light of the proposed conceptual model presented in Chapter 3.

In the basic case, where uncertainty affects the performance difference without considering the moderator variables, the impact of uncertainty on the performance difference is experimented from two distinct viewpoints, once with the presence of dynamism, where dynamic tasks enter the system, and again with the presence of stochasticity, which is reflected by the travel delays. These basic experimentations are mainly conducted in order to ensure the simulation model validation against the previous results concluded by other comparison studies observing the same sources of uncertainty (Mes et al., 2007; Máhr et al., 2010). While the performance difference is not affected by dynamism, it is significantly affected by the introduction of relatively slight degree of stochasticity. Thereafter, the performance difference remains relatively constant under higher levels of stochasticity, as it is discussed and explained in Chapter 5.

Therefore, it can be concluded from the basic model experimentation that the market-based approach is not capable of competing with the centralised approach with just the effect of uncertainty. This is mainly attributed to the performance advantage the centralised approach is benefiting initially from the planning phase, due to global information (Ygge and Akkermans, 1999), and to the similarity of the uncertainty handling mechanisms employed by both approaches, in the basic model. However, the basic model is considered as the ideal operating conditions for the centralised approach since monitoring is done in real-time, that is global information is available instantly, and the solving mechanism is able to process that amount of information accordingly. On the other hand, the market-based approach in the basic model does not benefit from its key feature, which is the exploitation of the workers' local knowledge. Subsequent experimentation introduced the effect of the moderator constructs reflecting the realistic features of both approaches.

As the effect of timelines of decision making of the central solver is experimented, it is shown that the higher the dynamism rate, the quicker the central update should be. In order to keep a quick central update rate, factors like the problem size and the efficiency of the employed heuristics implemented in the deployed decision support systems should be taken into consideration with regards to highly dynamic environments. In extreme cases of dynamism and huge problem size instances, e.g. tasks have to be allocated to over 50,000 mobile workers in British Telecommunications PLC. (Lesaint *et al.*, 2000), it may be mandatory for the centralised approach to divide the main problem into several sub-problems and address these separately. A sector-based strategy may be an example (Larsen *et al.*, 2002). This implies the division of the whole area into multiple sub-areas which are then managed independently. A main disadvantage of such strategies is that they reduce the advantage of using the full advantage of global information. Another way to overcome the computational resources of the centralised approaches is to use grid or cloud computing with, virtually, unlimited resources. However, these methods require extensive communication bandwidth, resulting in probable delays, in addition to other issues related to the confidentiality and security of the organisation's operations data may not be trivial to resolve.

While the effect of the timeliness of decision making of the central solver is significant for the case of dynamism uncertainty, experiments shows it is of marginal effect when uncertainty is limited to stochasticity. This is mainly due to the assumption that when a worker faces traffic jam, there is nothing to be done but to wait the end of this exception. This is a realistic assumption and turns the pace of the system evolution slower. In other words, the central solver does not necessarily need to know about the occurrence of delay exceptions instantly since it will not benefit from this timely information as no corrective reaction is possible but waiting for the end of the delay. This reduced pace of the system evolution makes the value of timely global information less important, and therefore, the problem size is not a major concern for the centralised approach when the only source of uncertainty is stochastic delays.

The other moderator construct considered in the conceptual model and tested in the experimentations in Chapter 5 is the degree of workers' local knowledge. In the basic model experiments, it is assumed that the workers act as passive entities in regard with their own private knowledge and only use their location information for bidding. The market-based approach is, therefore, only considered as another heuristic for solving routing problems benefiting only from the feature of distributed computation. This assumption made the comparisons by Mes *et al.* (2007) and Máhr *et al.* (2010) limited to the algorithm level. The introduction of local knowledge as a main feature to be exploited in the market-based approach dramatically changes the centralised vs. market-based preference balance. In the experimentation where the effect of workers' local knowledge is tested, it is shown that higher degrees of experience and local knowledge dramatically improve the decisions made by individual workers. This is notably demonstrated in the experimentation testing the effect of local knowledge in the presence of stochasticity as source of uncertainty. It can be seen how the negative impact of travel delays are reduced with higher levels of local knowledge. This is due to employing the real feature of the market-based approach enabling the workers to use their own perception of their surrounding environment and act accordingly and timely. For instance, the worker is able to foresee coming traffic jams and therefore to change its original route to minimise the exception amplitude.

A main issue to consider when seeking exploiting the experience and local knowledge of the workers is to provide a suitable incentive mechanism that would motivate the workers to act actively and refuse to collude. These requirements need to be carefully addressed in the employed market mechanism design and auction protocol. Otherwise, the market-based approach may be prone to several agency problems like moral hazards and adverse selection (Eisenhardt, 1988; Eisenhardt, 1989) and loses its main advantage of positively employing workers' knowledge in alignment with the global goal of the organisation.

This research regarded workers' local knowledge just as personal experience and ability to use the basic human senses to perceive the surrounding environment. For this reason, the degree of local knowledge is only tested in regard with stochasticity and is not considered for the case of dynamism. This is mainly due to the assumptions made in the simulation model to keep it tractable and simple for this research. However, human knowledge is not limited to these two types of awareness. Personal preferences and memories also form a major part of a human worker's private knowledge, on top of the acquired tacit knowledge (Eraut, 2000; Osterloh and Frey, 2000; Wilson, 2005). For instance, workers' preferences, task types, and workers' activity history may play a significant role on how the dynamic tasks would be allocated among workers bidding to meet their preferences. This scenario is not covered in this research, even if it is included in the framework for illustration as shown later in this chapter. However, it is definitely a promising venue for future research in order to confirm its moderating role on the relationship between different types of uncertainty and the adoption of the market-based approach.

6.3. Theoretical Framework

Based on the conceptual model proposed in Chapter 3, the results obtained from the simulation experimentations conducted in Chapter 5, and the findings discussed in the previous section, this section describes the theoretical framework for the adoption of market-based approach. This framework is considered theoretical given that it is based on a conceptual model that has been tested in a simulated environment with synthetic data and has not been empirically tested in real-world settings.

As depicted in the conceptual model in Chapter 3, the key construct is performance difference which is controlled by uncertainty. The relationship between the key construct and uncertainty is further controlled by the effect of the moderator variables reflecting the key features of the approaches. However, the impact of each of the moderator variable was not detailed and assumed a uniform impact of each moderator variable on both types of uncertainty. Therefore, this section elaborates the conceptual model in accordance to the suitability of adopting the market-based approach to address distributed task allocation problems or applications.

Figure 6-1 illustrates the Framework for the Adoption of the Market-based Approach (FAMA) which considers uncertainty in two perspectives: dynamism and stochasticity, in order to evaluate the suitability of a particular approach. This framework also details the effect of each moderator variable on both perspectives of uncertainty. For instance, it can be clearly seen that the dynamism-performance difference relationship is affected by delays of the centralised decision making which is not the case with stochasticity-performance difference relationship. On the contrary, high degree of local knowledge has significant effect on the stochasticity-performance difference relationship and has partial effect on the dynamism-performance difference relationship.

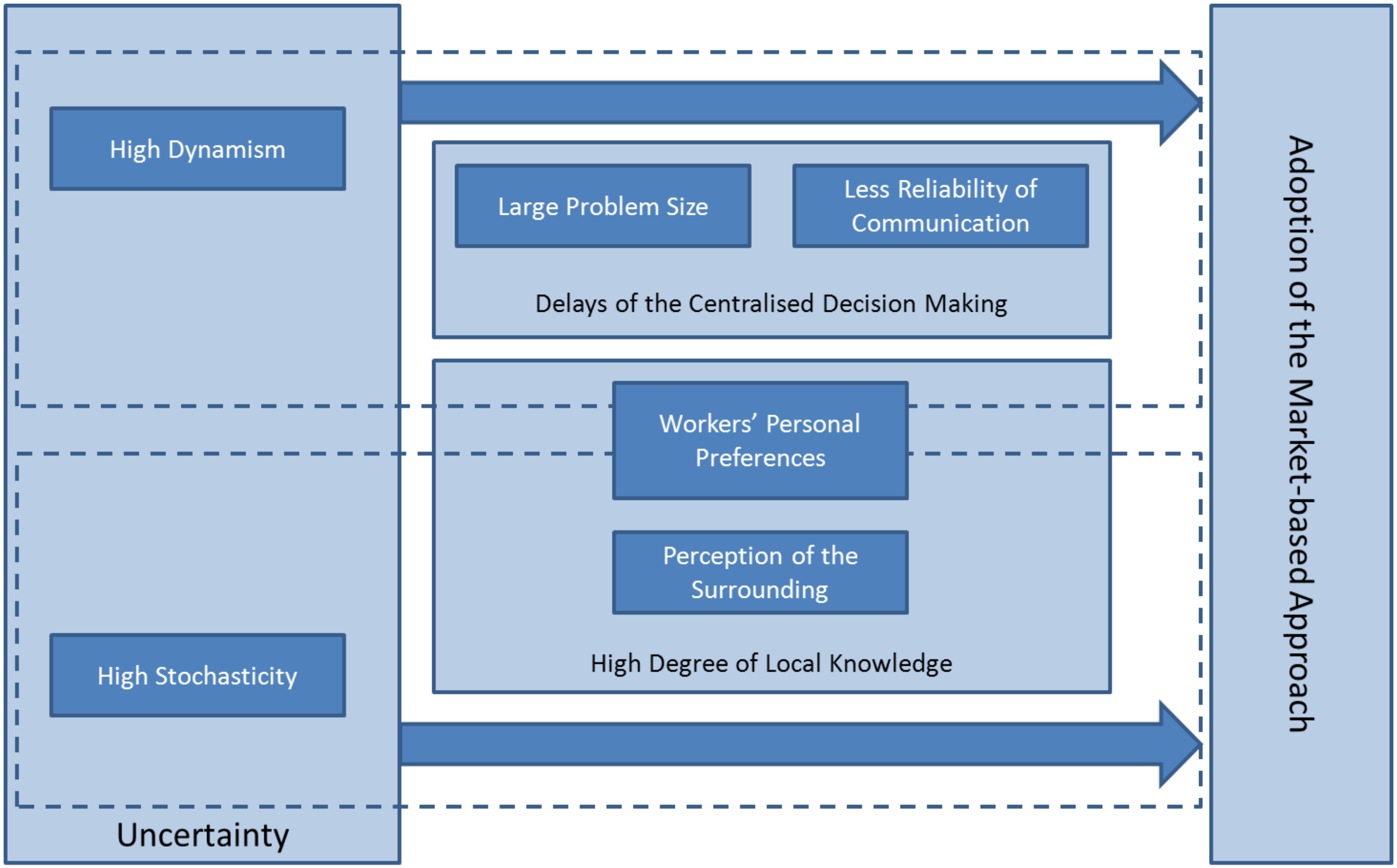

Figure 6-1. FAMA - Framework for the Adoption of Market-based Approach

FAMA aims at consolidating different types of uncertainty and relevant key factors, represented as features or moderator variables, which may lead to the adoption of the market-based approach.

Uncertainty is considered a generic construct in FAMA and can, therefore, be broken down to several constructs that would define more precisely different sources of uncertainty. Given that this research only considers two types of uncertainty, namely dynamism and stochasticity, these are shown as parts of the uncertainty construct and each of these uncertainty types directly affect the preference for adopting a market-based approach for distributed decision making problems like the mobile task allocation problem.

Between the uncertainty construct and the construct standing for the adoption of the market-based approach lay the moderator variables explored in this research and tested in the previous experimentations. These moderator variables affect, at different levels, the relationship governing the adoption of the market-based approach in light of a respective type of uncertainty. For instance, problems related to delayed decision making endured by the centralised approach moderates the adoption of a market-based approach in cases of high dynamism.

The moderator variables may also be composite and therefore be further detailed to define secondary constructs under these composite variables. For instance, delays of the centralised decision making are affected by the problem size and by the communication reliability. Having high values for these two directly increases the impact of the composite variable and, consequently, reinforcing the moderating effect to the adoption of the market-based approach when the environment consists of high levels of dynamism. Similarly, high degree of local knowledge mediates the effects of the perception of the environment and workers' personal preferences, leading to an accentuated moderator effect to adopt a market-based approach when high levels of stochasticity are present.

Furthermore, FAMA groups the types of uncertainty with the respective moderator variables (or features) that lead to the adoption of the market-based approach. This is expressed in the figure depicting the framework by dotted frames. In this research, two such groups are identified. The first group contains the high dynamism, as the source of uncertainty, and the delays of the centralised approach reflected by the problem size and less reliability of communication. Despite the reliability of communication has not been tested in this research, it has been a main issue in the field of robotics when managing teams of robots in spatial remote missions and it is included in the framework as an illustration of how the framework can be extended to include additional moderator variables. The second group investigated in this research contains high stochasticity and high degree of local knowledge. Local knowledge consists of the perception of the surrounding, which was shown, through experimentation, to be favourable to the adoption of the market-based approach and the workers' personal preferences. The latter construct has not been tested in this research due to the simplifying assumptions about workers and tasks characteristics, as explained earlier in the findings section. However, it has been integrated in the framework to show that a moderator construct may belong to more than a single group.

The proposed FAMA can be extended in three different ways:

- The addition of new types (perspectives) of uncertainty, e.g. "Breakdowns".
- Adding new moderator variables affecting existent, or newly established, relationships between uncertainty and the adoption of the market-based approach. This also covers the case of adding constructs to composite moderator variables. For instance, "workers' personal preferences" is added to the composite variable "high degree of local knowledge".
- Creating new groups to contain the type(s) of uncertainty and the moderator variables that would lead to the adoption of the market-based approach. This research identifies two such groups and the framework may be extended to include more groups as the previous two ways of framework extension are more elaborated.

Lastly, FAMA is considered to be a generic framework that is not limited to a particular problem or application. Though its creation followed the study and analyses of the mobile task allocation problem, it can be applied for other decision making problems where the market-based approach can be adopted, notably the family of distributed routing problems. This flexibility of FAMA enhances its potential to be extended and, probably, adopted for future comparison studies.

6.4. Reflection and Contribution to the Theory

In addition to the resulting FAMA discussed earlier, the findings of this research contribute to the different streams of the related literature. In order to emphasis the theoretical contribution of the findings described earlier, this section attempts to link them to the key concepts of the theoretical backgrounds from which the propositions of this research were deducted.

Given that this research mainly addressed a comparison study between the traditional centralised and the market-based approach, the primary contribution of the obtained outcomes joins the stream of similar comparisons. Among the existing comparison studies, this research compares itself the most to the prominent work of Tan and Harker (1999). Despite the divergence in the comparison criteria and the target application employed by both researches, the conceptual comparison in (Tan and Harker, 1999) matches this research in the sense of not limiting the comparison to the technical details of algorithms, but rather on the task allocation mechanisms. This research therefore complements the propositions of (Tan and Harker, 1999) in several ways.

Firstly, the target application in this study includes the management of mobile workers which implies that the workers' status continuously changes according to their locations and activities. This imposes on the central decision maker the necessity to constantly track the activities of the workers before any assignment decision is made, as it is the case in (Máhr et al., 2010). Though Tan and Harker (1999) relax the assumption of direct monitoring, it is assumed that polling workers for their status is event-based when new tasks enter the system. This updating mechanism tends to be unfeasible in higher cases of uncertainty, particularly when the problem instance is large and decision making is relatively long. Alternatively, the adoption of a time-based updating mechanism requires the decision maker to increase communication and according to the comparison criteria of Tan and Harker (1999), this would significantly increase the communication costs and therefore prefer the centralised approach. In this study, as well as in other recent comparisons (Mes et al., 2007; Máhr et al., 2010), these communication costs are ignored due to the accepted assumption of technological progress. When such costs are ignored, then the proposition by Tan and Harker (1999) stating the preference of adopting the market-based approach as the tasks arrival rate is faster is still supported in this study. This would further support the proposition of adopting a distributed market-based approach for dynamic scenarios.

Secondly, ignoring the coordination costs in this study inverses the proposition of Tan and Harker (1999) stating the preference of implementing a market-based approach as the number of workers participating in the auction decreases. The simulation results showed a noticeable vulnerability of the centralised approach as the problem size increases. Therefore, it can be concluded that the market-based approach is preferable as the problem grows in size and complexity. And given that all decisions are made by individual workers in parallel, therefore the market-based approach is unaffected by the number of workers involved in the market auctions.

Thirdly, a conceptual, yet very important, proposition of Tan and Harker's (1999) study suggests the implementation of the market-based approach when the workers are hard to monitor. In the case of the MTAP, the difficulty for the centralised approach to monitor the workers rises in their mobility and distributed geographical locations. Therefore, the centralised approach has to increase the frequency of monitoring messages. Given that communication costs are ignored, increasing the number of messages becomes marginal; however, the processing a large amount of messages at short time intervals becomes complicated as new input originating from uncertainty has to be considered.

Among the other relevant comparison studies conducted by Mes *et al.* (2007) and Máhr *et al.* (2010), this research is distinguished by its comparison perspective. While the mentioned studies are comparing the same approaches addressed in this study, their comparisons are mainly based on the algorithm level, and the market-based approach is therefore only regarded from the OR lens as just another family of algorithms for tackling optimisation decision making problems. Despite the importance of such comparisons to advance the employed algorithms by both approaches, they tend to neglect the main advantages and features sought by a distributed approach. Implementing the market-based approach to solve any RAP requires considerable efforts for decomposing the main problem and defining a suitable market mechanism to generate plausible global solutions. This process for adopting the market-based approach is non-trivial and goes beyond regarding it just as an algorithm. Adopting a market-based solution should be based on specific requirements necessitating the autonomous self-management of the resource entities, like for instance the inability of controlling the distributed resources to be allocated as it is the case for managing teams of robots in remote missions where communication turns infeasible (Dias and Stentz, 2003b).

This study also contributes to the OR and optimisation stream by linking the proposed framework for the adoption of the market-based approach. The proposed framework is also applied to the MTAP as an initial attempt for comparing the addressed approaches in light of uncertainty. Furthermore, the framework theoretically corresponds to the taxonomy defined by Psaraftis (1995) as described in this table:

Psaraftis Taxonomy (1995)	**Proposed Framework: FAMA**
Evolution of information	Dynamism uncertainty dimension
Quality of information	Stochasticity uncertainty dimension
Availability of information	Central global knowledge vs. Distributed private and local knowledge
Processing of information	Centrally Vs. Market-based (locally + auctions)

Table 6-1. Proposed framework and Psaraftis taxonomy

In addition to the mapping of the proposed FAMA with the taxonomy provided by Psaraftis (1995), the FAMA includes a temporal dimension for the decision making. In that respect, it is proposed to add an additional attribute for characterising the information of routing problems with uncertainty. This attribute is the "the timeliness of information" as it can either be "instantaneous" (i.e. real-time) upon the change of information occur, or "periodical" where all the new information is collected in batch at regular periods.

Another theoretical link comes to relate this study with the relevant work in the field of organisation theory, notably in the stream of comparing different organisation designs and decision making procedures. This study's contribution to that field comes in terms of proposing an additional distributed coordination structure based on markets in the existing comparisons. Despite the existence of several comparison studies dedicated to contrast different organisation structures (Roberts *et al.*, 1994; Joyce *et al.*, 1997; Lin and Carley, 1997; Nault, 1998; Lin, 2006; Lin *et al.*, 2006; Christensen and Knudsen, 2010), these were all relying on the concept of centralisation of the organisation, whereas the market-based approach allows the fully distributed scheme of knowledge exploitation and individual decision making.

It is also worth mentioning that the target MTAP discussed in this research has some unique features that have not been explored in the organisation theory at the level of operations management. This feature of MTAP is the ability to fully distribute the problem to be completely addressed by distributed workers without the explicit need of a centralised decision making authority to reach the final decisions. In previous comparisons of organisation designs, pioneered by Lin and Carley (1997), Lin (2006), and Lin *et al.* (2006), the target problem was modelled around the idea of hierarchy of control where the final decision is made at the top of the hierarchy. The criteria of the different structures were the number of the vertical and horizontal layers as well as the decision making procedure.

Finally, the findings of this research may comfortably be linked to the contingency theory under the larger umbrella of the organisation theory. The findings deducted from the experiments results infer to the fact that there is no ideal global solution to match all problem scenarios. However, it is prescribed that the adoption of a procedural centralised approach is more beneficial in cases of uncertain DRAPs when the problem size is manageable and the local knowledge and experience of the distributed entities is limited (or uncertain). On the other hand, a market-based approach is desirable to be implemented when the problem size and complexity increase and the degree of local knowledge and experience of the distributed entities is leveraged, at the condition of designing an incentive compatible market mechanism to ensure the convergence of the individual and the global goal.

6.5. Practical Implications

The practical interpretation of the obtained findings may mainly be addressed to the IS decision makers in organisations having to manage distributed workforce. Nowadays, mobile workforce is mainly managed centrally and linked to the central decision making point by the use of handheld devices, on-board computers, and other means of communication. These devices are reliably connected with the central control unit and the communication costs have dramatically decreased, making this approach quite convenient to schedule and manage the activities of the workforce. However, it must be thought that these distributed mobile devices are increasing in computational power and may considerably participate in the solving scheduling decision making problems that overwhelms the central control units as the problem bursts into size, complexity, and uncertainty avoidance.

This study therefore demonstrated, to some extent, the possibility of employing the distributed computational power as a major part for solving local optimisation issues and enabling a proactive role to the workforce members to participate in the decision making process. Adopting such a distributed approach has a twofold benefit. Firstly, it maximises the utilisation of the mobile computation equipment, which is deployed and only used for communication purposes in the centralised control scheme, and thus, saving the costs of expensive sophisticated computation hardware and software operated by the central controller. Secondly, it would provide an intrinsic motivation to workers given that they are able to make their own decisions in the context of a market and where they are enabled to use their local knowledge and personal experience to expect a maximum outcome of that market.

Reflecting back to the practical examples discussed in chapter 2 and 4 where features of the MTAP are applicable, it is seen that most of the operation scenarios conducted by service organisations are prone to face uncertainty. Despite that the nature of the business implies different types of uncertainty at different degrees. Conducted experimentations clearly demonstrated the negative impact uncertainty may have on initial plans and how the characteristics of each approach affect the reaction quality. For instance, quick response and timeliness of decision making were shown to be essential to actively face high rates of dynamism, particularly for cases where the problem tends to be large and complex. These features can be practically tangible during failure crises where urgent customers reporting serious equipment failures at a high rate should be serviced. Similarly, police patrols are highly affected by dynamism. High rates of dynamic tasks may commonly arise in cities with large population density when hosting big events (e.g. Olympic Games or carnivals). For those scenarios, the degree of agents' awareness may also play a significant role, as also shown in the experiments. The private knowledge a worker acquires with experience would dramatically improve the decisions at different levels. A worker knows best its own ability to perform a task as well as how to reach it when familiar with the area he operates in. For instance, the awareness of taxi drivers about the area of their potential customers would form a clear advantage when navigation systems are lacking.

Given that nowadays GPS navigation systems are commonly used in service vehicles (even using a centralised decision making approach), the local knowledge of workers about places might be highly assisted in avoiding traffic jams. However, the ability for a certain worker to change the working plan is definitely more straightforward in the market-based approach than it is in the centralised. This feature is regarded particularly useful in cases when delays are perceived by the worker (case of stochasticity) or when a given worker opts for a new task and modifies the plan accordingly (case of dynamism).

Obviously, shifting to a market-based approach is a non-trivial objective since it requires the design of the proper incentive mechanism and a matching rewarding system to keep the correct incentive and motivation among the workers. This can be, for instance, organising monthly rewards for the best worker who managed to reallocate the maximum number of tasks in response to perceived uncertainty.

6.6. Conclusions

This chapter aimed at discussing the findings revealed by the experimentation results obtained in Chapter 5. It also presented a proposed theoretical framework for the adoption of the market-based approach (FAMA). This chapter also reflected with findings back to relevant theoretical literature in order to link the findings with the existing theory. Finally, the practical implications of this work were highlighted.

The main conclusions of this chapter can be listed as follows:

- The findings of the experimentation results suggest that there is no significant impact of uncertainty on preferring the adoption of a market-based approach when none of moderator variables is introduced. This is attributed to the fact that such a basic model assumes the ideal conditions for the centralised approach and abstracts the market-based approach from its main feature, which is the exploitation of workers' local knowledge.
- As the timeliness of decision making moderator variable is introduced, the centralised approach suffers from keeping pace with high degrees of dynamism, notably with large-size problem instances. Therefore, the market-based approach becomes more attractive to be adopted since it is not affected by problem size.
- Timeliness of decision making is of limited impact on performance deterioration of the centralised approach when stochasticity is the only type of uncertainty. This is attributed to the fact that when delay exceptions occur, no strategy can be

followed but waiting till the end of the delay. This slows down the system evolution and therefore instantaneous information is of less importance.

- Introducing the exploitation of workers' local knowledge leads to considerable advantages for the market-based approach to face stochasticity. This is mainly due to the use of workers' perception of the surrounding environment and motivation to minimise the negative impact of delays when perceived before the occurrence of exceptions.
- The impact of workers' local knowledge on the performance in the presence of dynamism was not investigated given the simplification assumptions of the simulation model. However, it is assumed that such an effect exists, especially when workers' preferences and tasks characteristics are considered. This is suggested for future work.
- Based on the experimentation results and concluded findings, a theoretical framework (FAMA) is suggested for the adoption of the market-based approach in the context of the mobile task allocation problem.
- This chapter also related the observed findings back to the relevant theoretical body of literature highlighting the contribution of this research to different streams of literature on which this research is based.
- The practical implication of this work was also discussed in this chapter.

Chapter 7. Conclusions, Limitations & Suggested Future Work

7.1. Introduction

This chapter is aimed at concisely packing the work conducted along this research and to reflect on the major steps described in this thesis. Therefore, this chapter provides a summary of the thesis and the conclusions from the research carried out. Moreover, the novelty of this research, its limitations, and avenues for future research are discussed.

7.2. Research Summary

This research focused on comparing two distinct approaches for the optimisation decision making problems to address resource allocations in the presence of uncertainty. These approaches, namely the centralised and the market-based, are compared in the context of a task allocation problem often faced by service organisations dealing with the scheduling of mobile workforce, e.g. maintenance engineers and salesmen teams. The comparison criteria are based on the features and characteristics provided by each approach to face environmental uncertainty, reflected by the arrival of dynamic tasks during execution and stochastic delay exceptions.

This research basically relates itself to two bodies of theoretical literature: the organisation theory and the operational research (OR) and optimisation theory. The relationship between the organisation structure, decision making procedures, environmental uncertainty, and decisions quality is a topic of the organisation theory that is of particular relevance to this research given the divergence in the structure and the decision making procedures of the centralised and the market-based approaches addressed in this research. Given the nature of the mobile task allocation problem addressed in this research, it is closely related to the family of routing problems, which is widely discussed in the OR literature, notably those addressing the aspect of dynamism and stochasticity as sources of environment uncertainty.

Based on the literature reviewed in the fields described earlier, as well as to the existing centralised versus market-based comparison studies in other fields, a conceptual model is proposed to express the preference of adopting an approach over the other in function of uncertainty and the moderating constructs identified from the observed arguments in the review of the relevant literature.

The set of propositions suggested in the conceptual framework are then tested in a multi-agent simulation system. The employed simulation system comprehensively implemented a formal definition of the mobile task allocation problem, a basic greedy insertion heuristic-based centralised solution, a simple adapted single-item sealed-bid auction market-based mechanism, simulation environments containing dynamism and stochasticity as sources of uncertainty, and the identified features of each approach.

The concluded findings from the experimentation results suggest the preference for adopting a market-based approach for scenarios involving higher rates of uncertainty, high levels of local knowledge and workers' experience, and as the problem size and complexity grows. The centralised approach, on the other hand, demonstrates some vulnerability when it is faced to such scenarios. However, it is noticed that the effects of uncertainty alone could not favour the adoption of the market-based approach given the assumption of ideal operating conditions for the centralised approach and the market-based approach being deprived of its features. This balance is altered gradually as higher levels of the moderator variables, reflecting the features of both approaches, are applied.

Based on the conceptual model, the results obtained from the experimentations, and the concluded findings, a theoretical framework for the adoption of market-based approach (FAMA) is proposed as the main output of this research. The theoretical framework consolidates the relationships between different sources of uncertainty and the adoption of the market-based approach, along with the factors moderating this relationship. The FAMA is intended to be flexible in order to enable the integration of additional sources of uncertainty and moderator factors that would lead to the adoption of the market-based approach.

7.3. Research Novelty

This research distinguishes itself from previous centralised versus market-based comparisons in the sense that in considers the features, as well as vulnerabilities, of each approach rather than being limited to the algorithm or mechanism level. In the previous comparison studies, the centralised approach is always assumed to operate in ideal conditions where global information is available instantly and decision making is done in real-time. However, these assumptions are constrained in real applications by the inability of ensuring such timeliness of information availability and reaction. This is notably true as the decision problem grows in complexity and size. This research observed the role of these features and how the centralised performance is highly affected by these features that are taken for granted in similar studies.

As for the market-based approach, the employment of workers' local knowledge is a main feature. Local knowledge is demonstrated in other studies as the explicit type of knowledge that is basic, and most importantly transferable. However, in real world applications, the knowledge of workers' extends to include the tacit knowledge and preferences, which are of great benefit if a correct incentive mechanism is employed to motivate workers to properly use their knowledge in line with the organisation goal. This study investigated both approaches with these features taken into consideration and therefore provides a more comprehensive comparison to identify the strengths and weaknesses of each approach when it comes to implement them in distributed task allocation to mobile resources. Consequently, this research sheds the light on the importance of the features of each approach and to take them in full consideration when comparing a centralised solution to a market mechanism for resource allocations in the organisation. Thus, the divergence between both approaches is definitely not limited to the technical aspect of the decision making process (i.e. algorithm) but spans to how the features of an approach would affect the success, or failure, for adopting a given approach. For instance, assessing a centralised approach is not limited to evaluate the sophistication of the employed decision support system or solving heuristic, but should also consider the other factors like the ability of collecting and processing global information in a timely way to meet the real-time requirements of the application.

Similarly, the market-based approach is highly affected by the degree of workers' knowledge and their incentives to actively participate in the decision making process. Therefore, assessing a market-based approach should consider the human aspect of the managed resources by providing proper incentive market mechanisms, along with efficient technical solutions such as bid calculations and winner determination algorithms.

Conclusively, this research revealed that a proper understanding of the features of each approach and including them in any comparison is crucial for a realistic comparison that would reflect practical issues when it comes to implement these approaches in real world organisations.

7.4. Research Outcomes

The output of this research can be categorised into three main categories: theoretical, methodology, and practical contributions. These are detailed as follows:

Theoretical Contributions

In addition to the contribution to the already existing comparisons of the centralised versus market-based approaches, as well as other organisation forms, as mechanisms for decision making towards resource allocations, the major outcome of this research consists of proposing a theoretical framework for the adoption of the market-based approach (FAMA). Following the findings concluded from the results of simulation experimentations, the proposed framework is intended to contain these findings and to intuitively highlight the effect of the moderator constructs, representing the features/vulnerabilities of a given approach, on the relationship between uncertainty preferences for adopting a market-based decision approach.

Even though the FAMA is built based upon the dynamic and stochastic mobile task allocation problem, it is flexible to include additional types of uncertainty and moderator constructs as framework extension. It is also not limited for the specific application of the mobile task allocation problem and may be applied for other decision making problems where the market-based approach stands as an alternative decision making mechanism.

Methodology Contributions

This research contributes methodologically to the simulation literature by proposing an agent-based simulation system for simulating the target MTAP with presence of two types of uncertainty, dynamism and stochastic delays. The simulator is designed and implemented in a flexible manner to be extended and simulate other related routing problems with the ability to integrate different heuristic-based centralised solutions as well as market-based mechanisms.

Practical Implications

This research presented an alternative approach to manage mobile workforce in organisations through the adoption of the market-based mechanism. The distributed nature of the market-based approach is a promising candidate for the operations management of mobile teams given its distributed nature too. The recent technological advancements in portable computing and mobile communication break the barrier hindering the implementation of such a distributed solution. Furthermore, these technologies are also deployed by the centralised approach, but only used for communicating local information to the central solving unit. Given the increasing power of handheld computing devices, the market-based approach enables the computation power of these devices to engage in solving the global problem of efficient task allocation. Moreover, it enables the workforce to actively participate in decision making by using their tacit knowledge and preferences, as long as the market mechanism is properly designed and incentive compatible.

As a result of adopting a distributed market-based solution, the usage of mobile technology would be enhanced for a better utilisation than just as a mean of communication. It would, furthermore, reduce the deployment of expensive sophisticated centralised scheduling systems, and therefore achieve considerable savings on the purchasing, operating, and maintenance costs.

7.5. Research Limitations

This study was conducted in light of some assumptions that result in some research limitations listed as follows:

- It is believed that employing more advanced mechanisms to represent both approaches worth to be investigated in future research. This can be sophisticated meta-heuristics like simulated annealing and tabu search for the centralised approach, and combinatorial auctions for the market-based approach.
- Another limitation of this research is the consideration of perfect incentive match between individual workers' and the global objective. Though this was thoroughly explained in this study, however it has not been considered in the simulation model. Therefore, the investigation of different incentive mechanisms may provide further insight into the features of the market-based approach and its suitability to tackle operations management problem in real organisations.
- This research only investigated the comparison of the centralised and market-based approach in a simplified version of the mobile task allocation problem where all tasks are of similar types and workers' skills, preferences, and memory are not included.

7.6. Avenues for Future Research

Departing from the identified limitations in the previous section, the following list suggests future avenues for research that would extend this study:

- Compare the centralised and the market-based approaches with respect to the best heuristic and market mechanism to solve the MTAP, respectively.
- Study the effect of different incentive mechanisms and observe the effect of these on the adoption of the market-based approach.
- Introducing other types of uncertainty like breakdowns, communication failures, and the dynamic addition of workers.

- Extend the target MTAP to include more details in the simulation model. For instance, defining types for tasks with minimum execution skills required and include more properties for workers like preferences, skills, and equipment.

These suggested future works may integrate their findings in the FAMA suggested in this research as a way of generalising it.

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Appendix A: MTAP-MaSim Programming Libraries

MTAP-MaSim is an open source project hosted on Google Code repository under the GPL licencing scheme. It has been fully implemented using Java™ 1.6 Standard Edition and has made use of different open source class libraries that cover specific functionalities consumed by the simulation core engine. These are:

- **A-Globe**: An open source multi-agent programming framework (http://agents.felk.cvut.cz/projects/aglobe). Even though there are several similar class libraries, A-Globe is a light-weight, yet very effective, class library that ships with different utilities such as timer-based behaviours and pre-implemented communication protocols (e.g. CNP) and an advanced event-based directory service to manage the subscription and retrieval of registered agents. Furthermore, A-Globe follows an event-driven model for managing the message flows among agents. That is, each agent is explicitly notified as a new message is received. This is opposed to some other libraries where messages are delivered to the recipient mailbox and on whom falls the responsibility to retrieve the delivered messages, e.g. Jade (http://jade.tilab.com/). A-Globe has also been successfully employed for implementing advanced GIS agent-based simulation systems with scenarios resembling that of the MTAP.
- **Colt**: An open source class library that provides high performance and efficient scientific and technical computing (http://acs.lbl.gov/software/colt/). Colt provides a wide range of mathematical and computing utilities that is widely used in scientific simulation systems, notably its package for generating random numbers sampled from different random distribution functions. MTAP-MaSim only uses the random number generator and random sampling package of Colt. Therefore, Colt is considered in MTAP-MaSim as the main random generator to efficiently produce random input datasets and also for generating uncertainty exceptions at random time intervals during the execution phase.

- **JFreeChart**: An open source class library for creating a wide range of graphs and charts types (http://www.jfree.org/index.html). This library is used by the MTAP-MaSim to dynamically plot the results obtained from rounds of a given simulation experiment and to graphically represent experimentation results in bar charts and line chart, respectively.

In addition to these third-party class libraries shipped and consumed in the form of external jar files, it is worth mentioning that MTAP-MaSim makes extensive use of built-in Java libraries; notably for IO operations, XML parsing, and working with text regular expressions (RegEx).

A main functionality commonly expected from multi-agent simulation systems is the ability to distribute the simulation across different hardware machines. This eliminates the potential bottlenecks and lack of resources of the hosting machine as well as ensuring high scalability for cases of large-scale experiments. These features of distributed and parallel execution of MTAP instances are incorporated in the MTAP-MaSim. Given this, it is possible to run experimentations on large datasets including hundreds or thousands of tasks and workers with complex decision making mechanisms. The credits for enabling these features are attributed to A-Globe, which transparently provides the basic and necessary implementation to enable the execution and migration of agents among distributed containers running in parallel on a network of hardware computers. This is achieved since all method calls between agents and message exchanging mechanisms are based on Java Remote Method Invocation (RMI). This technology allows distributed components to run and invoke each other on distributed and different platforms.

Appendix B: MTAP-MaSim Package Structure and Resource Files

Starting from the fact that MTAP-MaSim is designed and implemented according to the OO methodology, the source code is organised into packages, classes, interfaces, and sets (i.e. enum in the jargon of Java). These packages are listed in the following table:

Package Name	Description
actors	Contains all agent classes. A detailed description of each agent is provided in the next section.
centralSolvingTools	Contains classes and interfaces used by the central solver agent to centrally solve MTAP instances. These classes contain data structures as well as the implementation of the centralised heuristics. This package is only used with the centralised approach.
elements	The main core of MTAP-MaSim. It contains classes implementing the basic data structures and the simulation engine code.
elements.exceptionHandling	A sub-package of the "elements". Contains an interface to be implemented by every class implementing exception handling strategies. At least one instance of this interface should be used by both approaches.
elements.exceptionHandling.centralized	A sub-package of the previous package containing the exception handling strategies for the centralised approach.
elements.exceptionHandling.marketBased	Similar to the previous package, but

	containing exception handling strategies for the market-based approach.
elements.utilityFunctions	A sub-package of the "elements". Contains interfaces and classes implementing utility functions to be used by worker agents in the market-based approach. There should be at least one utility function instance per worker agent in the market-based approach.
gui	Contains all the graphical aspects of the MTAP-MaSim. This includes execution GUI and result graphs.
utils	Contains utilities used by the MTAP-MaSim. These utilities are not essential for running an instance of MTAP-MaSim. These utilities include a random input file generator and schedule validator.
utils.experiments	Contains utility classes to manage the automatic run of series of experimentations and measurements.

In addition to the source code files contained in the previous packages, there are additional mandatory file resources. These files are:

File Name	**Description**
simSettings.txt	The text file that contains the global settings to control the simulation process. This file is updated either manually prior the start of simulation experiments or automatically by the simulation engine before starting a new simulation measurement. The latter case is particularly useful when changing parameter values between measurement rounds. For example, in the

	stochasticity experiment, different values are automatically assigned to the degree of delays parameter after a measurement is done. These automatically-settable values are defined in the experiments.xml file.
experiments.xml	An xml file containing a node list of experiments to be executed by this MTAP-MaSim instance. Each experiment contains a node list of measurements, each with a list of settings to be replicated in subsequent simulation rounds. The settings listed in this file, along with their values, are updated in the simSettings.txt prior the start of a new measurement. This is due to that each setting in this file has a corresponding setting in the simSettings.txt file, which in its turn holds the global settings the MTAP-MaSim instance reads before executing a new round.

Appendix C: MTAP-MaSim Data Structures

The basic elements are data structures and objects used by any MTAP-MaSim simulation round. Getting back to the MTAP formulation in Chapter 4, solving an MTAP consists of building multiple schedules, one per worker, to optimise a weighted objective function including bonus score and travel costs elements. During the execution phase, the produced schedules endure different types of uncertainty necessitating constant changes in the initial solution. To programmatically implement these requirements, the following classes represent the basic and most important data structures used in MTAP-MaSim:

Location2D: An objects instance of the Location2D class represents a 2-dimensional point defined in a regular Cartesian plane. Given that MTAP-MaSim assumes all operations take place on 2-dimensional planes, any object or agent having location attributes has an instance of this class. The main properties of this class are the x-coordinate and y-coordinate of the given point. The main methods are to calculate the distance between the point represented by this object and another point, and a method to calculate the travel duration according to a speed argument. Task and worker status objects make extensive use of Location2D objects.

Task: Task objects represent the tasks to be assigned in workers schedules. Each task has a unique identifier, earliest and latest start time, execution duration, bonus score reflecting its importance, and a Location2D object.

TaskScheduleEntry: Objects instances of this class represent wrappers for scheduled tasks. In other words, each schedule contains a list of schedulable entities; TaskScheduleEntry objects are entities holding scheduled tasks with other information related to the task entry in the containing schedule. The main attributes of this class are a task object instance, start and end time, travel duration to reach the task, obtained utility by scheduling this entry, starting location, redundant travel distance and duration.

The starting location attribute typically takes the value of either the initial location of a worker if this entry is the first scheduled, or the location of the previous scheduled task. However, this is not the case if a task is scheduled while a worker is travelling to another one. This causes a route deviation and the starting location of the newly-added entry holds the value of where the deviation took place. Similarly, redundant travel distance and duration reflects the travelled distance and time to a task before this entry was scheduled. Generally, these values are zero for initial solutions produced during the planning phase and holds positive values only when route deviation happens due to scheduling this entry.

Schedule: Schedule objects are the main building blocks of an MTAP solution. Given that an MTAP solution consists of producing a set of schedules, the schedule data structure can be seen as a list of schedulable entries, i.e. a list of TaskScheduleEntry objects, in addition to some attributes. The main attributes of the Schedule data structure are the list of scheduled task entries, start and end time of schedule working horizon, initial location of the owning worker, travel speed of worker, total score, and the extra travel duration and costs. Extra travel duration and costs occur when a worker travels to his last scheduled task but it gets cancelled on the way due to uncertainty. These values are zero for schedules produced in the planning phase and scenarios without stochastic uncertainty.

IExceptionHandlingStrat: The centralised and the market-based approaches have two different philosophies for handling uncertainty upon its occurrence. For the market-based approach, worker agents react immediately according to individual decision making based on given strategies. On the other hand, worker agents in the centralised approach wait for solution updates after the central solver agent has updated its vision of the system and adapted the existing solution according to a predefined strategy in case of uncertainty.

In both approaches, uncertainty is handled according to predefined strategies, however, the owner of these strategies differ. That is, worker agents in the market-based approach, and the central solver agent in the centralised approach, should have a strategy (or set of strategies) to handle the faced uncertainty. In programming terms, these agents should have access to such objects implementing these strategies. Therefore, IExceptionHandlingStrat is a programming interface to be implemented by any class providing uncertainty handling strategies. Given that the current implementation of MTAP-MaSim is only considering dynamic tasks and stochastic delays as sources of uncertainty, the IExceptionHandlingStrat interface has two methods, handleDynamicTask() and handleDelay(), to be implemented by concrete uncertainty-handling classes.

GlobalClock: MTAP-MaSim is a time-based multi-agent simulation system. That is, there is an independent timing mechanism governing the simulation process. The global clock is a singleton object that provides this timing functionality by simulating a real clock. Since the clock represents the notion of time used by all the actor agents to synchronise their actions and manage their activities, there is only one global clock for any MTAP-MaSim instance; the reason why the "singleton" pattern is applied for objects instantiated from the GlobalClock class. The two main attributes of the GlobalClock are the tick value and the current time. The tick value reflects the time scale of the simulated clock. For instance, if the tick value is set to 200 this means that each simulated minute corresponds to 200 milliseconds of the real time. This value obviously controls the simulation speed. For example, if schedules of 8-hours working-horizon are being simulated then it would take 96 seconds to complete with a clock tick value set to 200. It is important to note that minimising the clock tick value depends on the hardware hosting the MTAP-MaSim instance. Exceedingly small value may cause bottlenecks on some resources (i.e. cpu and/or file system) resulting with thrown exceptions. GlobalClock has two main static methods: the startClock() method is called at the beginning of simulation, and the getTime() method called by any entity needing the current time.

The data structures described above are applicable for any MTAP-MaSim instance regardless of the simulated approach, centralised or the market-based. However, the centralised approach has, in addition to the above data structures, particular objects used by the central solver agent while generating an MTAP solution. These additional data structure are the following:

ISolver: ISolver is a programming interface to be implemented by any class containing the code of an algorithm or heuristic to solve MTAP instances. The main methods defined in this interface are those to search for the best solution, obtaining a handler to the object holding the generated best solution, and a method to output the solution.

GreedyHeuristic: GreedyHeuristic is the class that contains the implementation of the greedy insertion heuristic described in Chapter 4. This class implements the ISolver interface to be usable by the central solver agent.

MtapSolution: Starting from the fact that the centralised approach depends on the central solver agent to produce MTAP solutions and manage workers' updates, solution produced by centralised algorithms and heuristics are stored in MTAPSolution objects. This data structure is also internally used by the employed algorithm to store temporary solutions. The main attributes of an MtapSolution instance is a list of workers' schedules and some characteristics about the produced solution. These characteristics are the score achieved by this solution, the total number of scheduled tasks, the total duration of travelling and processing times.

WorkerCurrentState: During the execution phase, the central solver periodically updates its global view of the system by probing workers about their actual status and activity. According to the received responses, the MTAP solution is adapted to the new changes, if necessary. Therefore, objects from the WorkerCurrentState serve as holders of the data workers communicate to the central solver upon receiving its update queries. The main attributes of this data structure is the location (i.e. a Location2D object) and the activity of the worker. In the current implementation of MTAP-MaSim, the supported activities a worker can have are: travel, task, or idle.

PositionScore: PositionScore objects are temporary data structures internally used by the centralised algorithm to evaluate the score of inserting a new entry in a given schedule at a certain position. The main attributes held in this data structure are the identifier of a schedule, the position at which the entry is to be positioned in the schedule, and finally the score achieved from placing the entry in this schedule at this position.

SimpleCentralizedExcpetionHandlingStrat: This class implements the IExceptionHandlingStrat interface and provides the functionalities of the basic strategy described in the Chapter 4 to deal with uncertainty. Given that the central solver agent manages workers' schedule updates, it therefore owns an object instance of the SimpleCentralizedExceptionHandlingStrat.

Similarly to the centralised approach, the market-based approach also makes use of particular data structures to solve MTAP instances according to distributed market communications. Besides the basic elements described above, the market-based approach uses two main data structures: utility functions, and a basic implementation of the IExceptionHandlingStrat interface that fits with the distributed nature of decision making. Details about agents' communication protocols and the structure of exchanged messages are not part of MTAP-MaSim implementation, thanks to the A-Globe multi-agent framework that provides all these low-level details.

IUtilityFunction: As described in Chapter 4, each worker agent acts independently and autonomously when it comes to decision making in the market-based approach. Decisions are assessed and taken according to well-defined private utility functions. The IUtilityFunction interface should be implemented by any class to be used as a utility function. This interface defines two methods: getMarginalUtilityValue() and doSchedule(). The first method should calculate the marginal utility of adding a given task to the actual schedule, and the second method is to actually schedule the task when the market ends in favour to the owning worker agent.

AgentInsertUtilityFunction: This class is the basic utility function by the worker agents in MTAP-MaSim instances in this research. It implements the previous interface and provides the functions described in Chapter 4.

SimpleMBExceptionHandlingStrat: This class implements the IExceptionHandling interface to provide the worker agents with the basic exception handling strategies when uncertainty is faced. This class is quite similar to its centralised counterpart, except that objects instantiated from it are held by worker agents.