

CRANFIELD UNIVERSITY

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Design of redistributed manufacturing networks: a model-based framework

School of Aerospace, Transport and Manufacturing
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PhD thesis
Academic Year: 2017 - 2020

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Associate Supervisor: Dr. Christos Emmanouilidis
October 2020

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This thesis is submitted in partial fulfilment of the requirements for the
degree of Doctor of Philosophy

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ABSTRACT

Throughout the last century, manufacturing has been characterised by mass production conducted in central facilities, benefitting from economies-of-scale. These central facilities supply, and are supplied by sprawling, complex supply chains that are slow to adapt to demand changes and supply disruptions. As production strategies are gradually shifting from economies-of-scale to economies-of-scope to cater for increasingly complex heterogeneous demand and shorter product life cycles, new configurations are required to enable manufacturing systems to accommodate these demand changes efficiently. One area that has the potential to improve the responsiveness of manufacturing systems is redistributed manufacturing (RdM). RdM is a manufacturing paradigm where production is performed in a network of small, autonomous and geographically distributed facilities.

Motivated by the potential opportunities that RdM could bring, this thesis develops a model-based decision-making framework for the design and operation of RdM networks. The framework is context-independent, addresses strategic, tactical and operational decision-making levels and accounts for the interdependence between these decisions in a stochastic environment.

The framework is validated methodically through computational experiments on two case studies of different natures and objectives. Experts opinions were solicited throughout the design stage of this research, the implementation of the case studies and the analysis of the results. Results reveal that even when the objectives of the modelled systems are substantially different, the framework generates consistent outputs. The main takeout from the experiments' results is that the RdM paradigm consistently produces significantly better service level performance, demonstrated by fewer occurrences of unmet demands and shorter lead times. However, although sufficiently close, the RdM paradigm is not as cost efficient as the traditional centralised manufacturing paradigm.

Keywords:

Distributed manufacturing, manufacturing network design, optimisation, simulation, agent-based modelling.

ACKNOWLEDGEMENTS

I would like first to thank my supervisor Prof. Konstantinos Salonitis for all the support and guidance he has provided. I have learnt a lot from Kostas, not only how to conduct research, but more importantly the skills needed to identify and solve problems on my own.

I am also very grateful to my associate supervisor Dr. Christos Emmanouilidis. I would like to thank him for all the support, dedication and valuable feedback that he continued to provide throughout my studies.

I would also like to thank Mr. Richard Glover for all the time and patience he allocated to reviewing my models and enriching them with his decades long industrial experience.

No acknowledgement from a Building 50 student is complete without a special thank you to Mr. John Patsavellas. John has been very kind, supportive and professional and I have learned a lot from him, not only on a professional level, but also on a personal one.

I am also grateful to my good friend Bernadin for all his help and support. Even when he himself had loads of work to do, he was never late to share his exceptional mathematical and programming knowledge to review my work and help me understand new concepts. Finally, and most importantly, I would like to thank my family for everything they have done. My mother, father, brother and sister have always been a great source of motivation, so I hope I never disappoint them.

List of publications

- Haddad, Y. and Salonitis, K., 2018. Design of redistributed manufacturing system networks: Simulation and modelling techniques, *Advances in Transdisciplinary Engineering* 2018, pp. 417-422.
- Haddad, Y., Salonitis, K. and Emmanouilidis, C., 2019. Redistributed manufacturing of spare parts: An agent-based modelling approach, *Procedia CIRP* 2019, pp. 707-712.
- Haddad, Y., Salonitis, K. and Emmanouilidis, C., 2020. Design of emergency response networks: a decision-making framework, *Procedia CIRP* 96(2):151-156.
- Haddad, Y., Salonitis, K. and Emmanouilidis, C., 2020. Design of redistributed manufacturing networks: a decision-making framework, (*Journal paper submitted*)
- Pagone, E., Haddad, Y., Barsotti, L., Gini, D. and Salonitis, K., 2020. Robustness of manufacturing systems: an enhanced evaluation framework, (*Journal paper under preparation*).
- Haddad, Y., Salonitis, K. and Emmanouilidis, C., 2021. A decision-making framework for the design of local production networks under largescale disruptions, *Procedia CIRP* (under review, to be presented at the 30th International Conference on Flexible Automation and Intelligent Manufacturing).

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Notation

Indices:

- i Index for demand nodes ($i = 1, 2, \dots, I$)
- j Index for potential RdM plant locations ($j = \{1, 2, \dots, J\} \subseteq I$)
- p Index for product types ($p = 1, 2, \dots, P$)
- t Index for planning periods ($t = 1, 2, \dots, T$)
- k Index for facility capacity ($k = 1, 2, \dots, K$)

Parameters:

- r_{ipt} Demand at facility i for part p during planning period t
- g_{ij} Distance between demand node i and potential RdM plant site j
- f_{jk} Cost of establishing an RdM plant at potential site j with capacity level k
- a_p Cost of production of one unit of product p
- b_p Cycle time for product p
- h_{pi} Holding cost for product p per unit of time at demand node i
- v_i Inventory amount at the beginning of the first planning period at demand node i
- n Number of available AM equipment
- u Maximum production time per production equipment per planning period
- s Transportation cost per product per unit distance
- u Maximum production time available per AM equipment per planning period
- M Sufficiently large number (big-M)

Decision variables:

$$X_{jk} \begin{cases} 1, \text{ if a plant to be located at potential site } j \text{ with capacity } k \\ 0, \text{ otherwise} \end{cases}$$

$$S_{ijt} \begin{cases} 1, \text{ if demand node } i \text{ is assigned to potential site } j \text{ during planning period } t \\ 0, \text{ otherwise} \end{cases}$$

Y_{jpt} Replenishment amount sent from potential facility site j for product p at the beginning of planning period t to demand node i

Z_{pit} Inventory level for product p at demand point i at the end of planning period t

LIST OF ABBREVIATIONS

ABM	Agent-based modelling
AM	Additive Manufacturing
BPMN	Business Process Model and Notation
CAS	Complex-Adaptive System
CI	Confidence Interval
CNC	Computer Numerical Control
CPS	Cyber-Physical System
DES	Discrete-Event Simulation
DM	Distributed Manufacturing
DMN	Dynamic Manufacturing Network
ICT	Information and Communication Technology
ILP	Integer Linear Programming
IoT	Internet of Things
MCDM	Multi Criteria Decision Making
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non Linear Programming
OEM	Original Equipment Manufacturer
OR	Operational Research
PPE	Personal Protective Equipment
RdM	Redistributed Manufacturing
SAA	Sample Average Approximation
SCOR	Supply Chain Reference Model
SD	System Dynamics
UML	Unified Modelling Language

1 Introduction

1.1 Background

Throughout history, the course of human civilisation has constantly evolved at varying rates. Out of humanity's rich history, two events, commonly referred to as revolutions, have had the most pronounced impacts on the acceleration of the advancement of human civilisation; the agricultural and the industrial revolutions. The former allowed humans, for the first time in history, to establish and dwell in permanent settlements, while the latter provided humans with the means to produce what they needed to advance, beyond their basic survival needs.

The industrial revolution was preceded by a lengthy era of craft production, reliant solely on skilled artisans specialising in various jobs. The era of craft production was characterised by high customisation, high cost and non-scalability due to the inherent localised feature of being geographically constrained and dependent on the skills of few individuals [1]. Those inherent limitations of craft production, along with slow emergence of production philosophies and technologies severely limited the development of manufacturing and, as a consequence, the advancement of human civilisation. Until then, the overwhelming source of wealth generation was agriculture, and almost all production activities were targeting the very basic needs of human survival. Manufacturing, however, drastically changed with the advent of the industrial revolution in mid-18th century Great Britain. The emergence of the industrial revolution is mainly attributed to the invention of machine, such as power looms and efficient steam engines. The industrial revolution made way to the factory system and division of labour, which led to a boom in productivity rates. After the electrification of factories (which set out an era commonly referred to as the second industrial revolution), the assembly line was introduced in the early 20th century. The assembly line had a profound impact on shaping the world as we know it today; it allowed the production of standardised products in abundant quantities (mass production) and at relatively low costs available for the first time to the masses [1,2]. An early example of the impacts that the introduction of the assembly line had is the introduction of the famous Model T by Ford Motors Company, the first affordable car available in mass quantities to the public [1,3].

Mass production had profound impact on human civilisation; much of the advancement of the world could be attributed to the products made available by mass production (e.g. transportation systems infrastructure, automobiles and processed food) [1,2]. However, to mass produce a product, significant capital investment in the form of large factories and several production equipment that are expensive to set up to produce a particular product is required. This led to the centralisation of factories where production, and possibly assembly, take place in a central location, and then finished products are shipped to their respective destinations. This manufacturing paradigm proved highly successful and profitable as considerable cost savings were achieved through economies of scale [4,5]. What also contributed to the success of centralised mass production is the then significantly low transportation rates due to historically cheap fuel rates, along with the lack of awareness and interest in the environmental impacts of transportation activities. This meant that transporting a batch of products from one end of a country to the other did not impose vast cost burdens on manufacturers, nor did it contribute adversely to its environmental performance. For this reason in particular (i.e. historically low transportation costs), manufacturers have long dismissed the idea of decentralising their production activities citing that incurring more transportation cost is way safer than the strategic decision of setting up new plants.

Once markets became saturated and the standardisation of products gave way to customised products tailored to meet continuously growing heterogeneity in demand, and demand became lower than supply, problems with centralised mass production began surfacing. For example, mass production in centralised facilities is often associated with make-to-stock production [2], which inevitably entails potential obsolescence risk and holding cost [6,7]. In addition, centralised mass production is also characterised by long linear supply chains that are slow to respond to the rapidly changing environment and potential disruptions [6].

Then with the development of digital computers, which their application in manufacturing triggered a so-called third industrial revolution enabled by advanced control systems and manufacturing machinery e.g. computer numerical control (CNC) machines, production of varied products at near mass production efficiency became possible. This era is sometimes referred to as the mass customisation era. Mass customisation is achieved

mainly through strategies like modularity and postponement of assembly [8], and it naturally entails some degree of production decentralisation to benefit from the establishment of local presence [9].

Later, the significant advancement in information and communication technologies (ICT), and manufacturing technologies such as additive manufacturing (AM) which is commonly referred to as 3D printing, a so-called fourth industrial revolution (Industry 4.0) is emerging. The emergence of new ICT such as the internet of things, big data analytics, complex adaptive systems and cyber-physical systems [7,10] and advanced manufacturing technologies such as AM is creating valuable opportunities in the manufacturing industry that are yet to be efficiently embraced.

1.2 Redistributed manufacturing

Significant advancements in ICT [10] and manufacturing technologies such as AM [11], along with shorter product lifecycles [12], ever-changing consumption patterns and market dynamics [13], and increasing environmental concerns [14] create both challenges and opportunities for manufacturing enterprises. One candidate that could have the potential to embrace the emerging opportunities and address the ongoing challenges is redistributed manufacturing (RdM). RdM is a manufacturing paradigm that has decentralisation of resources and operations along with autonomy of the distributed production facilities at core. It could be defined as the shift from centralised production with its long, linear and slow to respond supply chains, to smaller geographically dispersed manufacturing facilities, that are interconnected through advanced ICT, and are empowered by advanced manufacturing technologies such as AM [6,15]. Figure 1.1 below demonstrates the basic notion behind RdM where there is a shift from centralised to distributed production.

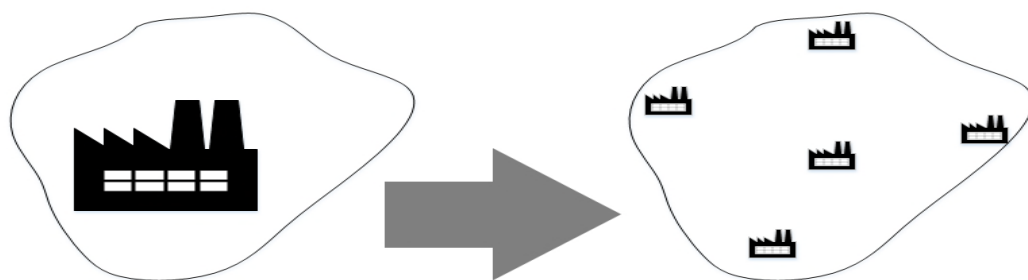


Figure 1.1 The basic notion of RdM

AM is frequently associated with the adoption of RdM as it has the potential to improve the efficiency of manufacturing systems at both the product and system levels [16]. At the product level, AM enables the production of complex parts through topology optimisation [16] and has the potential to produce lightweight products [17]. At the system level, AM results in shorter supply chains as many multi-parts products can be potentially produced as a single part without the need of multi-sourcing of materials, multiple manufacturing processes and assembly.

With regards to the geographical dispersion of RdM facilities, it is important to point out that it is not merely the number of production facilities per a given geographical area that constitutes an RdM system [18], but also the level of autonomy enjoyed by these decentralised facilities [19]. In other words, any number of production facilities located in a given geographical area is a decentralised production system, while a number of autonomous (to certain extents) production facilities dispersed in a given area is an RdM system.

Although the RdM paradigm looks promising on the surface, there are many challenges and barriers associated with its implementation. One common challenge is quality consistency amongst different locations [10,20]. Much like the craft production era of manufacturing, RdM is characterised by localisation; which poses a concern about the viability of replicating a product with the exact same specifications amongst multiple geographically dispersed locations (i.e. inconsistent quality). In addition, the availability of the required knowledge and expertise necessary to run the facilities efficiently could pose a great barrier [15,21]. Sceptics of RdM are also concerned with the environmental impacts of RdM and material consumption, as decades of intensive research on manufacturing technologies and philosophies (e.g. lean manufacturing) have given way to the establishment of production facilities that are highly resource efficient and produce very little waste, and consume minimal energy during manufacturing processes.

The matureness and reliability of the enabling technologies also pose a challenge to the adoption of RdM [10]. Much of the enabling technologies that RdM is powered by is still at the development stage. For instance, AM capabilities enhancements are being introduced at a fast rate, and it has been suggested that RdM's enabling technologies follow Moore's Law in terms of capabilities and price [7,22,23]. Although this means that

the future of RdM is promising, it also means that much of RdM processes and investments could potentially quickly become obsolete.

Moreover, the adoption of RdM is inherently disruptive [6,7,10,24,25]. When manufacturers choose to establish presence in local areas, radical changes to the entire production systems are inevitable. Manufacturers will inevitably have to abandon suppliers that they likely have long-term agreements with, and from whom they benefit from special terms. Manufacturers might then have to establish new (smaller scale) agreements with local suppliers that may, or may not have the capabilities of meeting different requirements and varying demand levels. New warehouses will also have to be built to support the newly established supply chains. Strategic planning here plays a vital role in the successful implementation of RdM. Manufacturing network design which consists of a number of strategic decisions like location of facilities, number of facilities, supplier selection and demand points allocation problems is of particular importance in the successful planning of RdM networks. Manufacturers should also decide upon what should be the basis of their decisions through trade-offs between different conflicting attributes.

In addition to the aforementioned points, there is a scarcity of viable business models and theories that help support, organise and understand the behaviour of RdM systems. There is also an apparent absence of a unified theory in the field of RdM [7] which could hinder the advancement of this manufacturing paradigm. The lack of theory and models is most apparent in the strategic decisions such as supply chain design and network reconfiguration [26]. Most of the effort directed towards understanding and advancing RdM addresses short-term operations problems such as control and scheduling on the product level, while assuming a naturally evolving supply chain. As time progresses, supply chains and manufacturing networks are becoming more dynamic than ever and constantly evolve, but strategic planning decisions that have vital influence on the subsequent tactical and operation decisions have not, yet, caught up with these development. This fragmented knowledge about RdM along with the absence of models and comprehensive simulation packages [27] pose a great barrier towards the adoption of RdM. When a manufacturing enterprise decides upon expansion via the adoption of RdM paradigm, it is faced with a plethora of strategic issues that are critical to its future success.

Such strategic decisions include, but are not limited to, number, location and capacity of the production facilities. Selection of equipment and suppliers and what technology to employ are also crucial elements for the success of the RdM paradigm. In addition, all these strategic decisions have a profound influence on the subsequent tactical and operational decisions. Hence it is particularly important to develop a decision support tool that combines different decision-making levels for RdM network design in order to provide a roadmap for the implementation of RdM.

It is important to note that research in many areas in the field of manufacturing networks and supply chain design, such as the facility location problem is well established [28]. In addition, the traditional tools employed to solve these problems such as operations research and artificial intelligence are also well established by their own rights [29]. Various solutions to the problem of manufacturing network design have been proposed and proved to be efficient in their own right. However, most of the research that proposed model-based solutions (apart from operational level decision models) to the problem, viewed the problem from a traditional manufacturing context. Unfortunately these successful models cannot be simply tweaked to provide efficient solutions to the profoundly different RdM network design problem. The already established models cannot simply incorporate RdM characteristics such as localisation and autonomy, as not all these characteristics were on mind at the time of building the models. In addition, the already established models have different criteria and goals in mind to support the new envisioned production systems. For instance, designing a system geared around cost benefits achieved from economies of scale is profoundly different from a system that is meant to be highly flexible and still be cost efficient. These models also are representations of relatively simple systems – although highly complex by their own right – and are not designed to account for the complexity of RdM systems and the interconnectedness of its different elements. Complexity in this context refers to the high interconnectedness of different heterogeneous elements that is typical in RdM systems. The already developed models, however, provide the basic starting point and serve as a stepping stone for building models and frameworks for RdM network design. It is therefore important to come up with new models or redefine already established models [7] from a higher level perspective and incorporate different RdM characteristics and criteria to support the adoption of RdM at all decision-making levels.

1.3 Research scope

In this thesis, a novel framework for the methodical design and execution of RdM networks is developed. The framework combines two complementing decision-aid tools; namely optimisation and agent-based simulation models, that interact dynamically through a feedback mechanism in a recursive manner within a unifying decision-making framework. The decision-making framework provides decisions at all decision-making levels (i.e. strategic, tactical and operational), accommodates the interdependence between these decision-making levels and incorporates uncertainty.

The framework could be applied to any industrial setting where an original equipment manufacturer (OEM) produces different types of products and distributes them over a given geographical area. It is argued, however, that the development of context-independent general-purpose tools for the design of manufacturing and supply chain networks is unrealistic, due to the many different forms a manufacturing network and its accompanying supply chain can take [30]. However, the work undertaken in this thesis approaches the problem from a modular backdrop; keeping common features, key parameters, interrelationships and entities as core to the framework, and adding the rest, as necessary, to fit the specific problem at hand without loss of generality. Later, to illustrate the applicability of, and to validate, the framework, two distinct case studies are conducted and followed by sensitivity analysis of key parameters.

1.4 Research aim and objectives

The aim of this research is *to develop a model-based decision-making framework for the design of redistributed manufacturing networks*.

The term framework, referred to in the research aim, is the container that houses the lower-level models and orchestrates the operations and feedback between them. To achieve the overall aim of this thesis in a methodical and systematic manner, the research aim has been broken down into smaller individual research objectives; which the realisation of each brings the research closer to successfully achieving the overall aim. The individual research objectives are as follows:

RO 1: To develop thorough understanding of the concept of RdM, and to identify the decision-making tools that have been developed for the design of RdM networks through

a critical analysis of the literature in the field of RdM network design; specifically decision-aid tools.

RO 2: To develop stochastic simulation models that dynamically evaluate the performance of different RdM networks in uncertain environments.

RO 3: To develop facility location optimisation models that feed the simulation models with input parameters' values, and then establish a feedback mechanism between the optimisation and the simulation models in a unified framework.

RO 4: To validate the framework through case studies by comparing the performance of RdM with centralised manufacturing with regards to different conflicting criteria in a methodical process.

In addition to the abovementioned research objectives, this thesis will seek to answer the following key research questions:

- 1- What are the most appropriate decision-support modelling tools that can accommodate the attributes of RdM and can be used in modelling the design of RdM networks?
- 2- How to integrate distinct, complementing, decision-support tools for decision-making in the design of RdM networks?
- 3- What manufacturing system paradigm performs better with regards to cost and service level: centralised or RdM?
- 4- What parameters have the most pronounced impact on the cost and service level of RdM networks?

1.5 Thesis layout

The remainder of the thesis is organised as follows. In Chapter 2, a critical analysis of the literature is conducted. In Chapter 2 the concept of RdM is briefly discussed first, then the manufacturing network design problem in a general sense is explained and discussed. Next, research papers that developed decision-making models and frameworks for the design of RdM systems are analysed. Models and frameworks in RdM network design are grouped in four categories; analytical (optimisation) models, simulation models, optimisation-simulation models and the last category discusses other approaches. Chapter

2 concludes with a discussion of the key findings deduced from the literature review, and the identification of the research gap.

In Chapter 3 the research design and process are presented and discussed. In this chapter the research process, where the methodical steps of conducting the research are presented and discussed with respect to the research's phases and their corresponding research objectives, is laid out and discussed.

In Chapter 4, the decision-making framework is presented and discussed at an abstract high-level. Then the framework's constituent models are presented and discussed at a more detailed level, keeping only the key modules that are shared in all RdM systems.

Chapters 5 and 6 correspond to the framework validation research objective. In these two chapters, the validity of the framework is established through two distinct case studies that demonstrate the applicability of the framework. In Chapter 5, the framework is applied to design an RdM network for the production of spare parts in the aerospace sector. Chapter 6 demonstrates the applicability of RdM for the design of RdM networks for emergency response in the event of pandemic outbreaks. The validation strategy adopted in this research is outlined throughout the chapters as explained in Chapter 3. Sensitivity analysis is also conducted in chapters 5 and 6 to identify the most important parameters, and the impact of the change in their values on the RdM networks' performance.

Finally in Chapter 7 a discussion of the key findings from the preceding chapters is presented. Later the research's limitations and suggested future research directions are provided. Then the key research contributions are presented, and finally the chapter ends with conclusion remarks.

2 Literature Review

2.1 Introduction

In this chapter the contemporary literature will be critically analysed with respect to the overall research aim. First the concept of RdM is discussed, then the literature review will focus strictly on the heart of this research; which is redistributed manufacturing network design and decision making. The literature review will also cover network design decision-making within fields of manufacturing that share close resemblance and key characteristics to RdM. Such fields include research in manufacturing network design that includes decentralisation of production and operations coupled with a certain degree of autonomy in decision-making. Decision-making models and frameworks within RdM – or similar – settings will be reviewed according to the modelling approach employed to investigate and solve the problem. Enablers of RdM will also be reviewed; in particular, the role of additive manufacturing (AM) in enabling RdM will be investigated. Also in the chapter, the applications of RdM will be highlighted in the discussion in order to identify potential case studies to validate the framework.

The literature review chapter will critically analyse the critical elements of this research. In order to do so, a set of themes is explored, which their critical examination will inform the research and lead to the identification of the research gap. The key literature review themes that this chapter will investigate are:

- What constitutes a manufacturing network design problem?
- The extent to which the problem of manufacturing network design addressed specifically from an RdM perspective.
- The decision-making tools and techniques used to solve the RdM network design problem.
- The extent to which the impact of each decision-making level (i.e. strategic, tactical and operational) on other decision-making levels is incorporated.
- The incorporation of uncertainty in RdM network design decision-making models and frameworks.

These themes, which have been identified through a preliminary literature review, constitute the critical elements of this research that inform the research accordingly. These

themes will be critically investigated and analysed throughout the subsequent sections of this chapter.

The relevant papers that are analysed in the upcoming sections were retrieved mainly from Scopus, Web of Science and Google Scholar databases. In addition, papers of interest that were cited in the papers retrieved from the aforementioned databases were also included in the literature review. Two sets of keywords were combined together to search for papers. The first set includes: (re)distributed manufacturing(production), decentralized manufacturing(production), additive manufacturing, manufacturing-as-service, mass customization(personalization), cloud manufacturing(production), cyber-physical system, complex-adaptive system, and product service system. The second set of keywords includes the following terms: manufacturing network(system) design, decision-making, optimization, simulation, optimization-based simulation, agent-based modeling, discrete-event simulation, system dynamics, (non)linear programming, stochastic programming, facility location, and uncertainty. When these two sets of keywords were combined, an excess of 10,000 papers were found by each of the searched databases. To filter the results and narrow them down to papers that directly contribute to the research conducted in this thesis, the results were limited to the subject areas of engineering, mathematics, management and decision sciences. Then the results were narrowed down to include peer-reviewed journal articles, books and conference proceedings. The first screening of the remaining results then included reading the titles of the papers and books. Then the abstracts of those that were deemed related to this research, based on the title only, were read to determine their significance to this research. If the abstract revealed that the paper addresses a critical element of this research, then it is reviewed.

2.2 Redistributed manufacturing

Before embarking on a thorough review on RdM network design, it is useful to provide a more thorough discussion about the term RdM than the one provided in Chapter 1. RdM, as explained earlier, at its most basic level is regarded as the shift from centralised to decentralised production [6]. The term RdM, however, encompasses more than simply the notion of decentralised production. To start with, in the literature the term RdM is often used interchangeably with the term distributed manufacturing (DM). The term RdM

is, however, more appropriate to refer to already established production systems that shifts to a geographically distributed production strategy [31]. To better understand the concept of RdM, the literature review should not be solely confined in previous research that directly addresses RdM. The literature review should rather include areas that are either enabled by the adoption of RdM, or share similar key characteristics with RdM. Such areas of research include, for example, mass customisation [9,32,33] which constitutes the ability to provide end products tailored to the individual needs and preferences of end consumers [34], and dynamic manufacturing networks. The realisation of the goal of mass customisation will require some degree of decentralisation and automation [34] which entails an overlap with RdM where it becomes a means to realise mass customisation. Other areas of research that overlap with RdM include decentralised manufacturing; which overlaps with RdM in the geographical distribution of production, but does not necessarily constitute autonomy enjoyed by decentralised production sites. RdM also shares characteristics with cloud-based design and manufacturing, but differs in that although in cloud-based design and manufacturing resources are distributed over a geographical area, they are centrally orchestrated by a central authority [35]. Other areas of research that share characteristics include complex adaptive systems; which characterise systems that emerge over time and adapt without a central organising authority [36]; which meets the autonomy, and possibly the geographical dispersion characteristics of RdM.

One of the areas that shares much resemblance with RdM is dynamic manufacturing networks (DMN). In particular, DMN, is, at core, a collection of distributed interconnected and largely autonomous production facilities that collaborate to temporarily form a highly flexible virtual enterprise to fulfil a given task [37]. The concept of DMN, its characteristics, perceived benefits, challenges of application and a methodical approach of implementation are presented and discussed in [38]. The difference between RdM and DMN is that RdM is not necessarily always a temporary alliance between different enterprises to perform a specific task, it could be, as in the context of this research, a strategic choice that a manufacturer makes to distribute its own resources and operations. DMN could be therefore thought of as a form of RdM.

The focus of this research is, however, centred around decision-making in the design of RdM networks. Therefore, only research addressing network design problems with an RdM, or similar, setting will be discussed in this chapter. Other popular research streams in RdM, such as its impact on sustainability, the viability of achieving circular economy through RdM and the perceived changes in consumer roles, amongst others, will be excluded from this chapter to keep it dedicated towards contributing to achieve the research's aim.

2.3 Manufacturing system design problem

Prior to reviewing previous work conducted in RdM network design, it would be helpful to provide some relevant definitions first. The terms manufacturing network design and manufacturing system design are often used interchangeably; there is, however, a subtle difference between the two. A manufacturing system is defined by Chryssolouris [29, p.9] as *the combinations of manufacturing equipment and humans, bound by a common material and information flow*. Manufacturing networks, on the other hand, are the collection of manufacturing facilities, that are interconnected, and are located at different geographical locations [39]. It could be deduced therefore that manufacturing networks are a form of manufacturing systems. Subsequently, the design of manufacturing systems could entail the design of manufacturing networks and vice versa. In the latter case, however, the result is a networked manufacturing system. To clarify more, a manufacturing system could be perceived from the plant level where each plant, itself, is a manufacturing system; or from the systems level where the entire manufacturing network is regarded as a networked system. Therefore, for the purposes of this research, these two terms will be used interchangeably with respect to the research's aim.

After clarifying the term *manufacturing system*, the manufacturing system design problem should be defined next. The manufacturing system design problem could be briefly defined as mapping performance measures onto decision variables [29] as depicted in Figure 2.1.

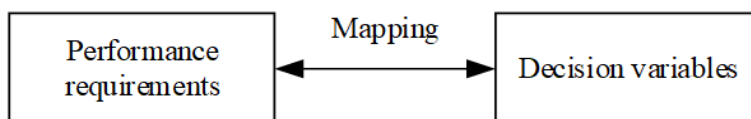


Figure 2.1 The manufacturing system design problem; adapted from [29]

The performance requirements block in Figure 2.1 refer to the desired performance measures expected from the envisioned manufacturing system. Performance measures have been classically divided into four categories; cost, time, quality and flexibility. Recently, however, these four attributes have been expanded to include sustainability decisions [40]. The nature, and number, of performance measures vary from one manufacturing system to another; depending on the particularities of the given manufacturing system [29]. Decision variables, on the other hand, refer numerically to the characteristics of the manufacturing system; such as the number of a given machine, factory layout decisions and locations of plants. The manufacturing system design problem is, in other words, the selection of the values of decision variables so that the envisioned manufacturing system operates in a way that produces the desired performance measures. Given the discussion above, one can naturally deduce that decision-making is at the heart of the manufacturing system design problem.

Decision-making has been classically divided into three levels, with blurry boundaries, according to time horizons namely; strategic, tactical and operational. Strategic decisions refer to those associated with long-term planning decisions such as locations, capacities and other capital investment decisions [28]. These decisions are particularly important due to the high capital investment required, and because decisions are often very costly to reverse. Many studies are dedicated to strategic decisions such as the facility location problem where they provide literature surveys in the contexts of manufacturing and supply chain management [28,41–48]. Tactical decisions are those concerned with medium term planning; usually planning horizons ranging from few weeks to few months constitute tactical decisions. Such decisions include inventory management decisions, routes selection and the determination of the flow of goods and services [28,49]. Finally operational decisions are short-term decisions that span a planning horizon of few hours to few days, such as control and scheduling decisions [50].

These abovementioned levels of decision-making within the manufacturing system design literature have often been addressed separately and the interdependence between them overlooked; which could lead to sub-optimal decisions [51–53]. Therefore the impact of each decision-making level on the others is significant and should not be ignored [54]. Although the norm has been to address each planning level separately,

studies that incorporate more than one decision-making level do exist, and are growing in numbers. In spite of the growing literature dedicated to developing models that incorporate facility location and inventory decisions for specific cases, review papers are scarce. In [55] the author analyses the interdependence between different levels of decision-making (location, inventory and transportation) in distribution network design and proposes a model that accounts for this interdependence. In [56] the authors survey and analyse the literature that incorporates strategic (facility location) and tactical/operational (inventory) decisions. The authors in [56] also provide a general purpose facility-location inventory model that can be adjusted to accommodate various manufacturing system or supply chain design problems. Many other studies also incorporate location and inventory decisions in a single model. In [53] the author surveys the literature in supply chain design that integrates different levels of decision-making. The paper [53], focuses mainly on facility location decisions integrated with inventory and routing decisions. The author also develops a general-purpose facility location-inventory model that incorporates demand uncertainty. Most of these models, however, rely heavily on mathematical programming models which, when incorporating inventory decisions, inevitably become nonlinear [52] and subsequently become much more difficult to solve [57]. Other areas where different levels of decision-making are incorporated in a single model include location-routing problems. There are a number of review papers that survey the literature with regards to facility location-inventory problems such as [58–60]. In these review papers, the authors survey previous research that account for the interdependence between strategic (facility location) and tactical/operations (routes selection) decisions in a single model. In these papers, the authors found, after surveying the literature in combined facility location-routing models, that accounting for more than one level of decision-making leads to better performing systems, particularly with regards to cost.

Most of the abovementioned studies, however, address decision-making with regards to manufacturing system, or supply chain, design from the lens of traditional i.e. centralised manufacturing networks. Nevertheless, the approaches, tools and techniques used in these studies constitute the foundation for any future study with regards to decision-making in a manufacturing system design context. Having briefly visited a selection of the most relevant literature with regards to manufacturing system design in general, this chapter

now delves into a thorough analysis of the literature manufacturing system design in RdM, or similar, settings.

2.4 Overview of RdM system design decision-aid models

In this section, the literature with regards decision-making tools and techniques within RdM system design will be analysed. As stressed earlier in this chapter, RdM as a concept shares some characteristics with other manufacturing systems or research streams. Most important of these characteristics being the decentralisation coupled with a level of autonomy enjoyed, to varying degrees, by the production facilities. Mere decentralisation of production, by itself, does not constitute an RdM. Fox and Alptekin [18] elaborate on this idea and explain that industrial systems that are regarded as *centralised* are in fact *distributed* over the world; meaning that most big manufacturers have multiple production facilities operating in different geographical areas. It is therefore the autonomy in decision-making enjoyed by these distributed production facility is what completes the definition of an RdM system [19].

Although decision-making in manufacturing network design constitutes the three planning levels highlighted earlier; the essence of manufacturing network design has to include strategic decisions. To elaborate more, it was established in the earlier discussion that manufacturing network design revolves around the establishment of a manufacturing system; this could be a new system, or a significant alteration to an already established system. In either case, a new manufacturing system or network emerges; rendering the inclusion of strategic decisions necessary to view a manufacturing-related problem as a system or network design one. For example, scheduling algorithms developed for the flowshop scheduling in distributed production, such as [61,62], account for the operational decisions in an already existent system. These algorithms provide no insights into and tactical strategic decisions, nor the impact that one level of decision-making has on the other levels. Although, on a side note, some models and solution algorithms for operational decisions, particularly scheduling, are questionable with regards to their usefulness [29]. In particular, the ongoing trend of developing heuristic optimisation algorithms to solve a myriad of already solved problems, has been controversial within the academic circles. Interesting discussions on this issue, particularly the perceived novelty of the heuristics used, can be found in [63,64]. This clarification is provided to

guide the classification, which will lead to the identification, of the literature in manufacturing network design and decision making where the majority of the published literature, as will be shown next, deals with operational level decisions.

When searching the literature with regards to RdM network design and decision-aid models, it becomes immediately apparent that the majority of the studies are dedicated to develop models and frameworks for short-term i.e. operational decisions (predominantly control and scheduling). Almost all of the research at the operational level addresses these operational decisions to an already established system; therefore overlooking the impact of strategic and tactical decisions on the operational ones. This preconception, however, does not directly contribute to achieving the aim of this research as it (i.e. this research) aims to design a new RdM network structure. Therefore only operational decisions models and frameworks that account for the interdependence with other decision-making levels, particularly strategic, will be reviewed in this chapter.

To examine a system, whether this system exists or not yet, and make decisions with regards to certain aspects of the subject system, to achieve a certain objective, different approaches exist; as illustrated in Figure 2.2 below [65].

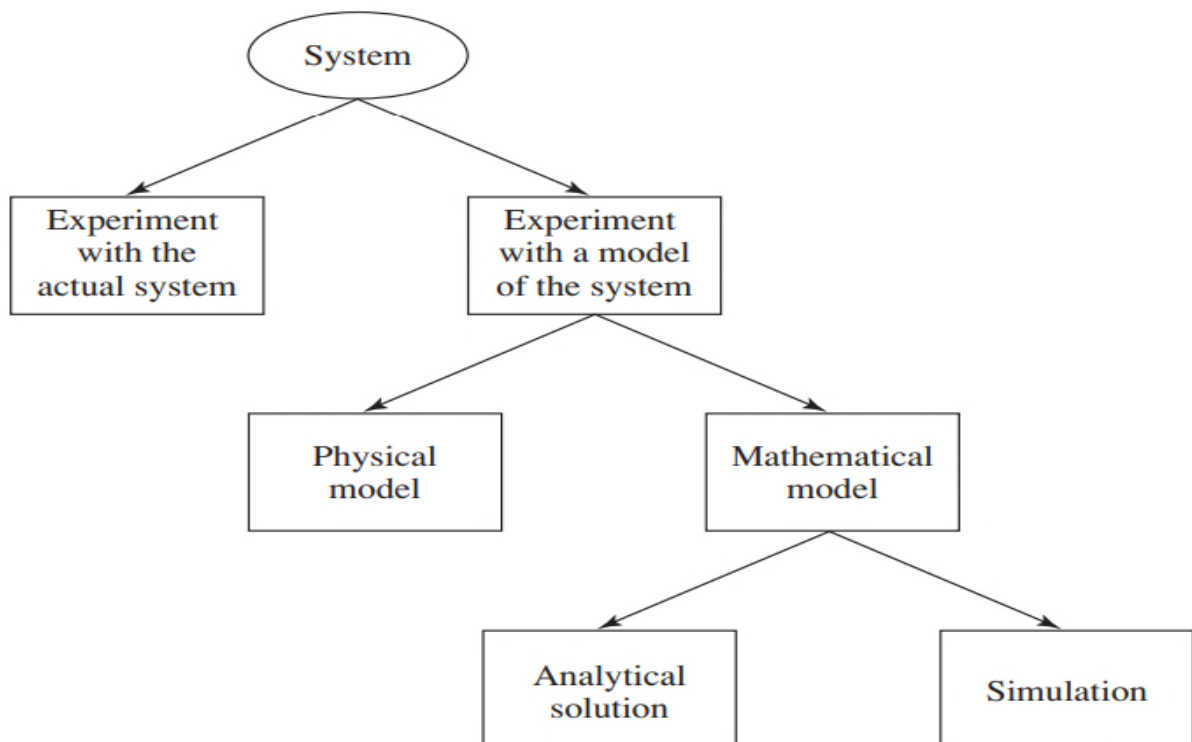


Figure 2.2 Ways to study a system [65]

2.4.1 Analytical models

In the context of studying a system through mathematical modelling, having naturally excluded experimenting with the real system due to the obvious impracticality of designing a manufacturing system and then examining it, two broad approaches exist; analytical solutions and simulation. Analytical solutions refer to modelling a system through a set of closed form mathematical formulae. Analytical solutions include techniques such as mathematical programming [57,66], queuing theory [67], Markov Chains [68] and Petri Nets [69], amongst others. The most widely used approach of the aforementioned approaches in manufacturing network design is mathematical programming. The other approaches, however, are widely used in decision-making, but not as commonly at the design level i.e. strategic decisions. When used at the strategic level, these modelling approaches play, usually, a supportive role to a mathematical programming model. Queuing theory, for instance, has been employed in [70] to establish a shift in manufacturing systems topology from centralised subtractive manufacturing system, to a network of decentralised manufacturing network enabled by additive manufacturing (AM) technology. In their paper, the authors acknowledge an important fact that has been somewhat slightly overshadowed as a result of the hype of AM which is; AM cannot replace traditional manufacturing for all types of products. In this paper i.e. [70] the authors develop a stochastic queuing model as an integer nonlinear programming model and develop a heuristic algorithm to solve the model. The paper provides location-allocation decisions and incorporates uncertainty; however the paper does not incorporate inventory decisions nor accounts for the interdependence between different levels of planning. It is therefore important to review mathematical programming approaches since they are always used in manufacturing network design problems when analytical solutions are employed.

Mathematical programming is the scientific name used in Operational Research to refer to mathematical planning [57]. The term is almost always synonymous with the term *optimisation* which means; maximise or minimise a given value [71]. Optimisation is the most widely used tool in operational research to develop decision-making models [57]. Optimisation models that have been employed in RdM network design problems could be grouped according to different themes such as; stochastic vs deterministic, linear vs nonlinear, or according to each model's objective function (e.g. minimise cost, maximise

profit). In optimisation models, objective function(s) maximising or minimising a given performance metric(s), and a set restrictions (i.e. constraints) in resources are developed using mathematical formulations [57].

The collection of the objective function(s), constraints and the model's assumptions constitute the system being studied. Out of all optimisation techniques, linear programming, in which the objective function(s) and all constraints are linear, is the most predominantly used [71]. Linear programming models can be categorised into either continuous, integer, or mixed integer models. In the continuous case, decision variables can have values of real number while integer programming models have their decision variables restricted to whole numbers. Integer and mixed integer programming models often arise due to some values (such as number of facilities to locate or number of operators to assign to a given job) being restricted to whole numbers.

2.4.1.1 Deterministic mathematical programs

Deterministic programming refers to optimisation models in which all the problem's input parameters are known with certainty. The following discussion will analyse papers that employed integer, mixed-integer, linear and nonlinear mathematical programs for the design of RdM networks.

Integer linear programming has been used in [49] where the authors developed a multi-level framework for the design of a DMN, referred to as integrated electronic supply chains (IESC), which the authors define as a form RdM systems. The framework consisted of three levels encompassing multi-criteria decision making (MCDM) formulated as an ILP model and a simulation model for the evaluation of the resulting network. An MCDM model finds the optimal values for a number of conflicting objectives [72] where a trade-off between these objectives is determined. This work i.e. [49], although relevant to the RdM literature, is more tailored towards the product level rendering strategic decisions to a short one-off order or product specific planning horizon. To explain more, the research in this paper takes advantage of the growing cooperation and sharing of resources between organisations (known as virtual enterprise), and the digitisation of supply chains to establish a unique supply chain for each order/product. Therefore, what is classically categorised as strategic decisions, such as facility location decisions, are scaled down to allocate an existing facility to perform a part (or the entire)

job of producing a product. The work, although incorporates different decision-making levels, is deterministic, and does not introduce nor incorporate the simulation model. After [49], the same authors, in [73] developed two optimisation models (single and multi-objective) for the design of another DMN. In this paper the authors used graph theory to model the manufacturing system and used the optimisation models to generate the optimal network topology minimising cost, energy and CO₂ emissions. In this paper i.e. [73], environmental concerns were embedded into the models. Same as [49], the models are deterministic, but unlike their previous paper, this paper only addressed strategic decisions, omitting shorter planning decisions such as inventory decisions and any potential interdependence on the strategic decisions that might alter the network structure. The same network design problem was then presented in [74] and modelled using fuzzy MCDC, formulated as integer linear program. Similar to [49,73] the models presented in [74] did not incorporate uncertainty. In general, this series of papers i.e. [49,73,74] addressed a network design problem in a sufficiently similar context of RdM, deterministically, but did not account for the autonomy of distributed facilities, and did not incorporate the impact of autonomy on the overall network's emerging behaviour.

Integer linear programming has also been used in [75] to design transportation networks to support distributed manufacturing systems. In this paper the authors developed a deterministic ILP model for the design of transportation networks to support transportation activities in RdM settings. The goal of their model was the selection of the optimal transportation routes between different facilities in RdM systems. The objective function of the optimisation model was to minimise the total weighted distances travelled throughout the transportation network. The authors then developed a heuristic approach, i.e. search algorithm that provides a near-optimal solution, to solve the model. The model however, in addition to being deterministic, does not provide strategic (e.g. facility location) or other tactical or operational decisions (e.g. inventory decisions). In addition, the model presented in the paper i.e. [75] was tailored for a specific case study in the logistics sector which could potentially impact its generalisability to other settings. In particular the applicability to a production setting where the transportation network is part of a manufacturer's supply chain; not merely transportation provider that supports distributed production activities.

A bi-objective mixed-integer linear programming (MILP) model was developed in [76] for the design of regional headquarters, which are largely autonomous bodies that control the operations of distributed manufacturing facilities. Although regional headquarters, as defined by the authors in [76], are not necessarily RdM facilities, they are still decentralised bodies that enable the shift of decision-making from a centralised facilities to decentralised ones. Due to this autonomy that was given to the decentralised regional headquarters, the work done in this paper has been identified as relatively relevant to the research conducted in this thesis. In this paper, i.e. [76], the MILP addresses only location-allocation decisions between production facilities and their assigned decentralised regional headquarters, simultaneously. The model was solved using a memetic algorithm to optimize selecting the best match between different facilities and the fulfilment rate of tasks. In the paper, data envelopment analysis was used to set preference scores which are then maximised. The model was nevertheless deterministic, and did not account for any lower level planning horizon and the impact they can have on strategic decisions.

Another MILP model formulated as a facility location model was used in [77] to assess whether a distributed additive manufactured (AM) powered manufacturing network performs better than a traditional manufacturing network or not. In this paper the facility location MILP was used to quantify the impact of integrating AM, and subsequently decentralisation, on the performance of manufacturing networks by comparing the buy-to-fly ratio between different settings. The MILP model minimises the overall system cost, particularly the cost of opening a new facility and transportation cost. The authors conclude that such RdM is indeed superior to traditional manufacturing approaches, mainly due to better resource utilization and considerable savings in transportation cost. Similar to the papers reviewed in the previous paragraphs, the model in [77] was deterministic, did not address different planning levels and did not account for the dynamic nature of RdM systems (e.g. by incorporating uncertainty or by evaluation through dynamic tools such as simulation).

Similar to the idea behind [49], and borrowing the concept of utilising AM to empower emerging RdM networks which was used in [77], the authors in [78] investigate the notion of a digital supply chain where multiple actors cooperate and share their resources for the

tailored customised production of products. In this paper i.e. [78] the authors develop two mixed-integer linear programming models for the design of RdM networks at the strategic and operational levels. Again, with research that proposes the establishment of *temporary* production network that emerge for individual orders or products, decision-making levels are largely scaled down in terms of time horizons; relative to the lifetime of the product or order-specific production network. Nevertheless, in [78] the first optimisation model was formulated as a facility location model to provide strategic decisions; minimising the total cost incurred from selecting the factories that will process the given order or product. Interestingly, in the strategic model, spatial data such as distances were not included, but rather transportation cost was used as a surrogate for distance. This assumption however, is reasonable, particularly that transportation cost is not always linearly proportioned to the travelled distance. But in some cases, particularly when service level is concerned, this assumption can be limiting. The other optimisation model was formulated to provide operational decisions; minimising the operational cost incurred from selecting the network topology recommended by the first model. Although the work in [78] contained some form of sensitivity analysis where the impact of changing the capacities of the plants and changing the number of processes on the network's performance was done, uncertainty was not further incorporated. Another limitation in this paper is the fact that the two optimisation models were employed in a consecutive manner, and the interdependence between the strategic and operational decisions was not accounted for, which could like, as highlighted earlier, lead to suboptimal solutions. To explain more, the network generated from the first i.e. strategic optimisation model was used as input for the second i.e. operational optimisation model; but whether these operational decisions would impact the strategic decisions was left unexplored. Finally, the dynamism that the paper aims to incorporate, was only incorporated in the operational model through introducing time slices into the optimisation model where several assumptions and simplifications are made. These significant assumptions and simplifications are often necessary in optimisation models as the faithful representation of a complex system almost always contain nonlinearities and complexities that often lead to analytical models with no known solutions [79]. Assumptions and simplifications however are always necessary in modelling, as will be discussed in more detail in the

subsequent chapters, but the discussion here is in relative terms; and in the case of analytical models, they could seriously impact the accuracy of a model's outputs.

Mixed-integer linear programming was used in two papers [80,81] by the same authors to design distributed AM hubs. In [80] the authors develop an uncapacitated and p -median facility location mixed-integer linear programming models for the selection of AM hubs site. P -median facility location models are optimisation models that minimise the total cost incurred by optimally locating a given p number of facilities [47]. The models take into account the important aspect of post-processing in AM production. Similar to [78], the models did not contain distances parameters, but rather used transportation cost as surrogate for the actual distances travelled. The motivation behind the work was the promotion of AM production through the dissemination of post-processing activities by the located AM hubs, which often hinders the integration of AM by smaller manufacturers. In addition to being deterministic, the paper did not include the mathematical formulation for the p -median model, which made it impossible to thoroughly investigate the rather huge difference in the total cost between the two models. The total costs in the paper included the fixed cost of procuring and installing the AM machines at the chosen locations, transportation costs and operational costs. In the p -median model, the total cost of establishing and operating the system was \$40M while in the uncapacitated facility location model the total cost skyrocketed to \$800M. This increase is unclear since, being uncapacitated, the model will naturally assign one AM machine per the selected locations.

In their next paper i.e. [81], the authors developed a capacitated two-stage p -median facility location integer linear programming model for the design of AM hubs network, integrating post-processing activities, particularly heat treatment and machining in order to link already existing heat treatment facilities with future AM hubs. It is worthy to point out here that the two-stage facility location model developed in [81] is fundamentally different from the conventional two (or multi)-stage optimisation models; which are often associated with stochastic models as will be discussed later in this chapter. The two-stage model in [81] in fact merely refers to the *two models* which were developed in the paper. These two models are, similar to [78], for the most part separate from one another and do not communicate in a two-way manner to address the interdependence between the

models' decisions. The first model allocates machine shops (where manufacturing activities are conducted) to heat treatment facilities, and then the second model allocates AM hubs based on the demand at the heat treatment facilities. To explain more, these two paper i.e. [80,81] do not promote the complete substitution of traditional manufacturing activities with AM ones, but rather delegates some activities (or products) to AM production, maintaining these efficient traditional manufacturing activities in place, where efficient. Their models then, in principle, are more realistic than other models that promote the complete shift towards AM, providing little evidence of the efficiency of such fundamental shift in production technologies.

In a series of papers [82–84] the authors addressed the RdM network design problem at the strategic (strictly facility location-allocation decisions) through the solving mixed-integer non-linear programs (MINLP). In the first paper [82] the authors first developed a generalized disjunctive program (non-convex optimisation over disjunctive sets [85]), which was later transformed into a MINLP. The resulting MINLP is a deterministic capacitated multi-facility location model that minimises the total cost associated with establishing a distributed manufacturing system. The total cost constituted of the cost of locating the RdM facilities, transportation cost and raw materials cost. The authors then developed a decomposition algorithm to solve the model, and compare the algorithm's performance with commercial solvers' performance on a case study in the bioethanol supply chains. The algorithm did show significant performance improvement over exact solvers in terms of computational times, but the algorithm's generated solution still was within 7% optimality. For strategic problems like the one presented in this paper, however, it is worth investing extra time and using exact solvers to get provably globally optimal solutions as, solving the model is not a recurring activity that requires fast solutions. In the next paper i.e. [83] the authors introduced the same models and algorithm but introduced a number of randomly generated test cases, ranging from small to large sized problems, to compare the performance of the algorithm with commercial solvers; in which the algorithm demonstrated superiority in terms of search time. In the third and final (to date) paper in this series [84] the authors transform the model into a multi-period to allow the opening and closure of distributed facilities over time. All of these models were, however, deterministic and did not take into account any potential change in parameters; especially that the modelling context was to design a new manufacturing

system. To account for some degree of uncertainty, the papers could have included some sort of sensitivity analysis to account for potential future uncertainties by identifying important parameters. Moreover, these papers located facilities on a continuous two-dimensional plane, where the model will impose the optimal locations of the distributed production facilities by providing their coordinates. These types of facility location models (i.e. continuous ones) can likely recommend locating facilities on locations where it is impossible to do so. For example the model can find the optimal location to be where other facility is already located, in the middle of a river or a lake or mountain [86]. This property severely limits the applicability and the usefulness of continuous facility location models. In addition, although distances were accounted for explicitly, these distances were calculated as the Euclidean distances on a two-dimensional plane, which could likely overlook traffic routes and other important distance related characteristics. Finally, the models did not incorporate shorter planning decisions such as inventory decisions which, as discussed earlier could have large impact on strategic decisions.

Mixed-integer nonlinear programming (MINLP) was used in [87] to select decentralised plants locations for a distributed manufacturing network. The MINLP was formulated as a two-stage capacitated facility location model. The two-stage composition of the model shares similarities with that used in [81] in the sense that two-stage refers to two models (or in the case of [87], two objective functions). Handling the solutions of the models were, however, substantially different from the simplistic approach used in [81]. In [87] the two objective functions were formulated to provide decisions at the strategic (selection of plants locations and opportunity cost resulting from excess capacity assignment) and at the operational (capacity-related operations and transportation) levels. This paper contributed to an important area that was largely overlooked by most of RdM decision-making at the strategic level namely; the independence of decision-making at the strategic and operational levels. To achieve this attribute, the authors employed concepts from Game Theory where the centralised facility (i.e. where systems-level decisions are made) are considered as *leaders* with a complete view of the system; while the distributed facilities are considered *followers* with their own decision-making abilities, but with partial view of the overall system. To account for these characteristics and to solve the model, the authors first transformed the two-level MINLP model to a single-stage MINLP model where the cooperation between distributed and centralised

facilities is accounted for and where the interdependence between strategic and operational levels is also accounted for, simultaneously. The authors then linearised the model in order to solve it optimally using readily available commercial solvers. Through computational experiments, the authors show that incorporating lower-level decisions, made by distributed facilities, indeed results in better overall system performance, with regards to cost. They demonstrate this finding through comparing the results generated by the model when decision-making is centralised versus when distributed facilities are provided autonomy and the interdependence is modelled. The authors in this paper i.e. [87] provide an interesting argument that although their resulting model is NP-Hard (i.e. there is no known algorithm that can solve the problem in polynomial time), the advancement in computational power and the efficiency of commercial solvers render realistic sizes of similar problems solvable by exact algorithms. To explain more, the authors argue that if a realistically sized system (and its corresponding optimisation problem) are not likely to be extremely large, then it is recommended to avoid heuristics and use exact algorithms that provide provably optimal solutions. Although the paper accounts, to a certain degree both strategic and operational decisions, it does so in a highly static environment. To explain more, the model is a single period model; which does not allow a thorough observation of operational decisions and their subsequent impact on strategic decisions. In particular, the model does not allow observing the system's evolution over time; it assumes that all decisions are taken at one moment in time. In addition, being deterministic, the model did not account for potential uncertainties; which are likely to play a big role when providing autonomy to distributed production facilities, particularly that the cost of unused excess capacity is incorporated in the objective functions. Such a cost segment in autonomous decentralized facilities is likely to contain some level of uncertainty that is likely to impact the model's results. Sensitivity analysis, for example, could have been employed to identify important parameters that should be modelled more carefully in order to avoid inaccuracies in the decisions provided by the model.

Two mixed-integer linear programs were developed in [88,89] to design new distributed supply chain networks powered by AM. The models in these two papers were developed for a specific case study in the spare parts sector. In these two papers, the authors investigated the viability of installing AM equipment in selected distribution centres

(determined by the MILP) to produce spare parts on demand. In [88] the authors developed an MILP with an objective function to minimise the new supply chain's cost; which constituted of the cost of installing and operating of AM equipment and stock out costs. Although this paper accounted for uncertainty, in particular demand uncertainty, it is still considered deterministic. The reason behind that is that the value of demand was assumed to follow the normal distribution with a known mean and standard deviation; associated with each different network configuration. This approach is different and less representative of uncertainty than stochastic programming, which will be discussed later in this chapter. In the second paper i.e. [89] the authors develop two MILP models; one formulated as a p-median facility location model that minimises the supply chain's total cost to identify the candidate facility locations. This model's function is only to identify which, out of the networks distribution centres, can serve as a candidate location; it does not select the locations of facilities. It does so by grouping all end customers into clusters based on their demands, distances from the network's distribution centres and potential transportation costs. Then the outputs of this model are used as inputs for another MILP that chooses the optimal number and location of AM facilities and allocates them to demand clusters. The authors then conduct a number of computational experiments with different scenarios; varying the level of demand. Although different scenarios were investigated, the models were deterministic. In this paper i.e. [89] as with [88], the computational results were conducted only to the envisioned distributed network of AM production where the as-is scenario was not included in the papers. These findings might be valuable for the company that the case studies were centred around, but the papers themselves are missing this important comparison that could indicate the suitability of the proposed system and the soundness of the utilised tools. In addition, the models in these two papers were single period ones leaving the dynamics that contributes to the systems emerging behaviour unaccounted for. Moreover, the separation of the models in [89] might very well lead to suboptimal results since the decisions that are made in choosing the facilities and allocating facilities to customers were not included in the first model that chose the potential facilities. Therefore these two sets of decisions could have been integrated in a unified model that takes all the supplied information into consideration while calculating the values for the decision variables.

This section has covered deterministic analytical models (chiefly mathematical programming) that were used for the design of RdM, or similar systems, networks. The next section will briefly cover stochastic analytical modelling techniques and then analyse the papers that use such techniques for the design of RdM, or closely resembling, networks.

2.4.1.2 Stochastic programming

Unlike deterministic linear and nonlinear programs where all the input values are known with certainty, stochastic linear and nonlinear models assume that at least one input parameters is random [90]. This randomness assumption is, however, constrained with the assumption that the random variable follows a probability distribution with known parameters values. In stochastic modelling, the values of the decision variables are revealed at, at least, two stages (i.e. decision variables are grouped into at least two categories). In short, in the first stage decisions are made using the available data, then once more data becomes available (i.e. some uncertainty is revealed) then the decisions associated with subsequent stage(s) are made consecutively. To explain more and make the concept more clear, a very simple example related to the context of this research is provided at a high-level. Consider a manufacturing network design problem that provides strategic and tactical/operational decisions (e.g. facility location, inventory and routing). In real-world applications, it is almost always true that some, if not all, parameters are not known with high certainty. Such parameters, relative to this example, typically include demand level and transportation time/cost for instance. In deterministic programming the values of all the decision variables are determined simultaneously. In stochastic programming however, the value of some decision variables are revealed first; based on the available input data, and then once these variables are revealed, the expected values of the subsequent set of decision variables (typically lower-level decisions that depend of the values of the previous set of decision variables) are determined. Now a question might arise; how are uncertain parameters represented in such formulations? These parameters, as mentioned earlier, have known probability distributions, and their joint distribution constitutes a *scenario* that has a known probability of occurrence.

Two (and multi) stage stochastic programming models are widely used, although to a considerably less extent than their deterministic counterparts, in manufacturing network

design problems. A relatively recent paper [91] reviews the literature in supply chain networks design decision-making under uncertainty and provides a classification of the stochastic approaches that are frequently used to incorporate uncertainty into different modelling context. The authors categorise stochastic optimisation approaches as scenario based; which is another name for the approach briefly described above, chance-constrained programming; which assigns probabilities to constraints with random parameters with a minimum realisation probability [71], robust optimisation; where probability distributions for the uncertain parameters are unknown and the model is then used to provide optimal decisions under *worst-case scenario* [92], and finally fuzzy mathematical programming which uses fuzzy sets to represent uncertainty, or possibility distributions to represent imprecise or vague data [91].

As will become apparent in the following discussion, almost all of the models that were developed for the design of RdM, or similar systems, networks under uncertain environment employed multi-stage stochastic programs. One of the first papers that integrated uncertainty in RdM network design was [93] where the authors developed a multi-period, two-stage stochastic program to assess the viability of production through the deployment distributed AM equipment. In this paper the model considers the uncertainty in throughput time and different cost parameters, and minimises the system's total cost of establishment and operating. To address uncertainty in stochastic modelling, the authors used scenario-based techniques by modelling different potential scenarios, each containing an assortment of stochastic parameters with known probability distribution, and associated with a known probability of occurrence. The first-stage decisions include location decisions for AM and traditional manufacturing facilities, along with warehouses locations. Second-stage decisions include allocation and inventory and flow between facilities and customers decisions. An important characteristic of this paper is that it addresses the problem of developing an entirely new manufacturing system in which the model determines the establishment of the manufacturing system as an either traditional manufacturing network, a distributed AM network or a hybrid network. To identify and evaluate the importance of the various parameters that were used in the stochastic optimisation model, the authors developed a logistic linear regression model to investigate each scenario's outcome. The main findings of this paper was that increased demand favours more centralised traditional manufacturing production paradigm.

Although this finding is in line with other papers, as will be discussed later in this chapter, the authors made an important assumption that traditional manufacturing does not require any capital investment to establish. This assumption holds true in case of already established manufacturing systems where a manufacturer might wish to assess the viability of adopting an AM-powered distributed paradigm. But in the context of this paper, no manufacturing system already existed and therefore intuitively, there should be capital investment associated with the establishment of traditional manufacturing facilities. Interestingly, the authors use the logistic regression model to investigate the impact of jointly decreasing the AM acquisition cost and the filament cost which was determined to be the most important cost factor in adopting distributed AM paradigm, each more than half. The result was that the model still favoured traditional manufacturing due to the high cost of acquiring AM equipment and the filament cost. This finding, particularly regarding AM acquisition cost, was also corroborated by other research in this area as will be discussed later. But this paper still misses the capital investment cost associated with establishing traditional manufacturing facilities which could, in certain manufacturing context, lead to different findings. Finally, being a multi-period model, and providing decisions at both strategic (facility location) and tactical/ operational (allocation and inventory) decisions, the model is able to capture the dynamic of the problem to some extent. Although the dynamisms of the problem and the interdependence of different planning levels were accounted for, to some extent, the assumptions and simplifications that were made to represent the system in closed-form might not capture all key elements of the envisioned system. Therefore the incorporation of a simulation mode, for instance, might be beneficial in modelling some subtle characteristics, complex interrelationships and nonlinearities of the system that cannot be expressed in analytical form. As a result, this might prove beneficial to either corroborate the results or identify unaccounted for facets of the problem.

Another two-stage stochastic program was developed in [94] where the authors approached the problem of distributed manufacturing system design from the system-level through minimising the system-level cost for the entire manufacturing networks; both traditional and distributed. The envisioned manufacturing network in this paper i.e. [94] is powered by AM equipment to produce biomedical implants, locally. In this paper the authors compare the system-level total cost incurred in two scenarios; traditional

manufacturing where the biomedical implants are ordered from an established network of suppliers, and RdM network where the implants are produced on-demand in the location (i.e. hospital in the context of this paper) where the implant is required. In their model, the demand level was assumed to be stochastic while other parameters are assumed to be known. The first stage decisions of the model included the number of AM equipment to install at different hospitals and the production capacity in each location, while the second stage's decisions include routing decisions. Unlike the two-stage model that was presented in [93] where a finite number of scenarios was considered, this paper used a different, although also a scenario-based, approach. The model was solved using a sample average approximation (SAA) algorithm; which uses Monte Carlo simulations to generate several random scenarios and then the value of the objective function is approximated through the sample average of random samples [95]. In addition to including uncertainty in the problem's formulation, the authors also conduct sensitivity analysis to identify the importance of each of the system's parameters on the system-level cost of the manufacturing network. The results of the paper revealed that the relatively high cost of obtaining and running AM equipment is a challenge that faces the adoption of distributed AM production. However, the results also revealed that AM production could be beneficial at centralised facilities when the demand is high. This finding could be attributed to the case-dependency of the model where a relatively small-sized area is considered (the state of Mississippi); hence transportation cost does not have big impact on the configuration decisions, especially that the initial investment of AM equipment is likely to be orders of magnitude more than transportation costs within one state. Although this paper included two decision making levels i.e. strategic and tactical, the interdependence between these decisions was not accounted for; which could provide valuable insights if considered, especially that only a single time period was modelled. The model also was designed for the use in a specific context in a constrained geographical area; rendering the generalisability of the findings and the transferability between different contexts unclear.

A follow-up paper of [94] was presented in [96] where the authors develop a two-stage mixed-integer program for the design distributed AM-powered production network in the biomedical implants sector. In this paper, no comparison with a traditional manufacturing system was made, but it rather investigated the prospect of designing an entirely new AM-

powered distributed manufacturing network. Similar to its predecessor, the paper solves the problem in two stages; first the number, capacities and locations of AM equipment along with allocation between AM facilities and post-processing facilities are determined then, when uncertainty is revealed, next stage decisions are made. These second-stage decisions include production quantities at each AM facility. Uncertainty was only represented in the demand parameter, which is reasonable given the context of the paper where predictability of biomedical implants is difficult to predict. Unlike the previous paper, in [96] post-processing activities were incorporated into the model. To emphasize more, post-processing facilities were modelled as stand-alone facilities, and post-processing activities also constituted a segment of the aggregate throughput time. The uncertainty in the model, which aims to minimise the total AM network establishment and operation cost, was handled through a simple average approximation algorithm same as the previous paper. Interestingly, the results presented from running the model in a similar setting of that in [94] recommended a more distributed AM network topology; contradicting the findings of the first study. This finding, and its contradicting the findings of the previous paper in the series, could be logical due to the differences between the two papers' aims and assumptions. To clarify more, in [94] the goal was to assess the viability of designing a distributed AM network with respect to traditional manufacturing; meaning that the model recommends the establishment of both traditional and AM facilities. To emphasize this point further, the model in [94] might recommend establishing traditional manufacturing facilities where the associated cost and production time of some products are low, while in [96] only AM facilities are established.

A third paper after [94,96] was presented in [97] where a two-stage stochastic model for the design of AM-powered RdM networks was developed. Unlike its predecessors, where the distributed AM network design problem was tackled at the system-level, this paper i.e. [97] approaches the problem from two-angles; the product-level where technical considerations such as layer thickness, and system-level where network design decisions are incorporated in a unified model. The model was formulated as a stochastic two-stage capacitated mixed-integer non-linear multi-period. The nonlinearity in the model's formulation was however easily linearised and well-documented in the paper; rendering the final formulation linear. The modelling setting was however substantially different as the case study presented in [97] departed from the biomedical implants setting and

addressed the production of assembly parts over a larger geographical area that constituted the South Eastern region of the USA. Due to the significantly larger geographical area, the authors solved the resulting model to near-optimality using a heuristic algorithm embedded in the sample average approximation algorithm, and specifically designed to solve the model. The performance of the heuristic was however compared against the results generated from provably optimal algorithms on smaller instances, unlike the case that will be presented in the next paragraph. The results generated from solving the model were indeed interesting, and proves that modelling only one aspect (or planning horizon) in complete isolation from other aspects or planning horizon could lead to considerably different outcomes. This was demonstrated through the incorporation of system-level decisions (facility location and capacity) along with product-level decisions (layer thickness) which both fall under strategic and operations decisions, respectively. To further stress the importance of incorporating product and system level decisions in a single model, the authors conducted sensitivity analyses experiments, varying the layer thickness's parameter value. The results indicated a substantial decrease in the total cost of establishing and running the system when the layer thickness is minimised. Product-level decisions were also found not to have an impact on the AM network topology. Although uncertainty was incorporated in the model, only one parameter was presumed stochastic, which could be insufficient to design a robust system. This was however partially offset through a series of sensitivity analysis experiments that examined the impact that the changes in the values of key parameters can make on the overall system cost. The uncertainty in time parameters (e.g. cycle times and delivery times) were unaccounted for. This could have a significant impact on the overall system, especially that the model incorporates product-level decisions where for instance a decrease in lower layer thickness will lead to an increase in build time, but potentially a decrease in post-processing times. Such increases and decreases in build time for instance could dictate the acquisition (or removal) of AM equipment. In addition, uncertainty in delivery or lead time could potentially reveal the necessity to establish an AM facility in a place that was not identified when the delivery or lead times were deterministic. The model is however multi-period, which better captures the dynamics of the system, especially that inventory (raw materials) decisions are included, and therefore the model

is able to capture the amount left at the end of each time period and add it to the next time period.

Continuing with the theme of AM-powered distributed networks, the authors of [98] developed a multi-period two-level stochastic program for the design of decentralised manufacturing network powered by AM. In this work, uncertainty was incorporated through the inclusion of stochastic and fuzzy parameters; the fuzziness being reserved to inputs that are more difficult to predict. The approach adopted in this paper i.e. [98] to account for different levels of decision-making bears some resemblance to that adopted in [87]. In [98] as in [87] the decision-making authorities at the different planning levels are considered as leaders and followers; which was briefly explained in [87]. Uncertainty was also incorporated through chance-constraint programming in which constraints that contain stochastic parameters have to be met at a minimum probability [71]. In this paper, the objective function was to minimise the total cost of establishing and operating the system; which includes the cost of opening a new facility, production, transportation and holding costs. It is important to point out that this paper was one of the first to account for holding cost in a distributed manufacturing setting. The uncertain parameters were demand which was modelled through a stochastic parameter with a known probability distribution, and the products prices which, the authors established that it is much more difficult to predict and fit in a known probability distribution, was represented through fuzzy numbers. In addition to uncertainty, the paper also included sensitivity analysis to assess the impact of potential prospective changes to demand levels and products price. The model was then solved using a heuristic algorithm that was specifically tailored to solve the particular model formulation. The optimality gap in the results was not clear and no comparison with smaller size instances that can be solved to optimality had been provided. Although the important cost parameters were considered and uncertainty was soundly modelled, the model did not account for production capacity constraints. To explain more, capacity constraints included in the model were storage capacities in plants and distribution centres, measured in cubic meters, but the capacity of each AM equipment production was not included. This constraint is particularly important when modelling an envisioned manufacturing system powered by unconventional means such as AM; especially that the cost of acquisition for AM equipment is quite high, and build time along with pre and post processing could also be lengthy. Therefore, and especially

when minimising cost is the main objective function, AM production capacity could significantly change the results obtained from a model, when considered. A capacitated (in terms of production capacity) version of the model would then further validate the model with respect to its real-world applicability.

The next section will briefly discuss the concept of simulation, the mainstream simulation modelling approaches and analyse papers in the literature that employed simulation-based decision-aid tools for the design of RdM network.

2.4.2 Simulation models

Simulation modelling can be briefly defined as *an imitation of a system* [99, p.2]. Simulation models are typically implemented on computers to take advantage of their high computing capabilities. Simulation modelling aids in decision-making through the investigation of a system in a risk-free environment. Examples of the applicability and usefulness of simulation modelling are plentiful, but in essence it allows the decision-maker to observe a system as it evolves over time, or provides the likely performance metrics that result from certain changes to a system. In short, it allows experimenting with a system in a risk-free environment without the need to disrupt the system itself to realise the potential benefits. Classically, simulation modelling paradigms at the system-level have been classified into three approaches namely; discrete-event simulation (DES), system dynamics (SD) and agent-based modelling (ABM). These three approaches share some similarities, but they share more differences than similarities. The shared attribute between these three approaches is that they are all dynamic tools i.e. they model systems over time. How time advances in each of these approaches is where the similarities end. System dynamics is a continuous simulation approach i.e. time is continuous, more specifically changes to a system can occur continuously [79] (e.g. water flow into a tank). In SD a system is represented by the continuous change in its state variables with respect to time. In DES and ABM time is discrete i.e. the system evolves at discrete points in time where an event is scheduled [99]. These discrete time steps are often unequal where time (represented in the simulation clock) advances to the next scheduled event, regardless of how much time is there between these two events. It is therefore important to consider which time advancement mechanism best represent the system being modelled, keeping in mind that most systems are neither purely continuous nor discrete

[65]. Besides time, other aspects of the nature of the system dictate the choice of the simulation approach such as the abstraction level, heterogeneity of the system's entities and the interrelationships between these entities. System dynamics is usually associated with high levels of abstraction where the individuality of the model's entities is not modelled. In SD the modelled system is represented through stock-and-flow diagrams where the stocks are homogeneous and represent *aggregates* of entities; omitting any individual differences between these entities. This paradigm of modelling (i.e. interactions between aggregates of entities) naturally renders SD a top-down modelling paradigm. Discrete-event simulation on the other hand is fundamentally different. In DES, individualities of the system's entities are accounted for and each of the system's elements, regardless of how much down in the system's hierarchy, can be individually modelled and assigned its own attributes. DES is therefore a bottom-up approach since the system is modelled from the perspective of constituting elements up to represent the entire system. ABM on the other hand is very similar to DES, and all the aforementioned differences between SD and DES are also shared by ABM (in comparison to SD). In fact, ABM is itself a discrete-event simulation paradigm and has been classified as a special case of DES [65]. The subtle, yet important, difference between ABM and DES is in the representation of *behaviour* i.e. the dynamics of the system [100,101]. In DES the behaviour is 'implemented in the model "blocks" that entities pass through' [65, p.695], while in ABM behaviour is encapsulated into the entities themselves. Encapsulation is defined in [102, p.22] as 'the combination of process and data into a single entity'. This particular attribute of ABM makes it an ideal tool to investigate complex, decentralised and autonomous systems [100]. To clarify further how DES and ABM capture the overall behaviour of a system, and how encapsulation plays a key role, a simplistic example is provided. In the often-used model of people entering a facility (e.g. bank or shop) and then potentially join a queue or get served immediately or leave if the queue was too big, a DES model will have people generated from a source block, then each person enters a gateway to determine their next destination (i.e. join a queue or get served or leave), while in ABM people are represented as agents with decision-making capabilities encapsulated inside each one (e.g. if-then rules). In ABM, each person agent determines their next destination based on their own *partial* view of the system, in other words there is no need to pass through an external gateway to determine the next destination. It can be deduced

then that in DES, an entity is passive; it relies on an external unit to decide its destination, while in ABM an entity is active and decides for itself its own destination based on its own logic rule. This was of course a very simplistic example, but it helps in explaining the differences with regards to a model's entities' autonomy and how behaviour emerges in DES and ABM.

Before analysing previous research that employed simulation modelling for decision-making in RdM network design, it is necessary to point out a fundamental difference between simulation models and the previously discussed optimisation models. Simulation modelling is a decision-aid tool that works as an *evaluation* tool [99]; it provides a system's expected performance metrics based on the input values it is fed. These input values are, however, what determine the design of a manufacturing network (e.g. location, inventory and routing parameters). Simulation, by itself, cannot assign optimal values to these parameters and then evaluate the performance of the system unless they were embedded with an optimisation algorithm; which creates a model inside a model. Therefore, the use of simulation in the RdM network design literature was confined in either making comparisons with a traditional manufacturing system, or as a follow-up evaluation tool after some other decision-making model generates a system structure. To explain more, simulation modelling in the manufacturing network design literature works as a decision-aid tool through providing the decision-maker what to expect from a given system structure, not how to establish a system.

At a first glance, the number of research papers that employed simulation modelling in RdM decision-making might seem large. A closer thorough look into these papers will, however, reveal that the vast majority of these papers deals with scheduling and control problem in distributed environments. Another observation about this stream of research is a technical one; when using databases such as Scopus, Web of Science and Google Scholar, amongst others, much of the search results is about *distributed simulation*, not distributed manufacturing. Distributed simulation is a field in computer science that utilises parallel computing to speed up the execution of simulation model, or to link several models together [103], and is not directly related to simulating RdM systems. There is therefore an apparent lack in the number of studies that employ simulation modelling for RdM network design that go beyond scheduling and control focused

studies. To stress this point further, a quick search on Scopus will yield 2,450 papers when the terms (distributed manufacturing AND scheduling AND simulation), while it will yield only 11 papers when scheduling is replaced with (facility location)

System dynamics simulation models have been employed in two studies to investigate the viability of AM deployment for the production of spare parts. In [104] the authors investigated the impact of AM on spare parts supply chains employing system dynamics simulation. They compared three scenarios – traditional, centralized AM and distributed AM. The SD model was used to compare one production location, one with traditional manufacturing and the other using AM. They found that the AM scenario is more cost and carbon footprint efficient. Their study however lacks the inclusion of the distributed scenario, which is vital to achieve the purpose of the study. The model developed in this paper also assumes one OEM, one supplier, one customer, and one distributor; which could yield significantly different results if the complexity of the scenario was expanded to extended distributed manufacturing supply chains. The authors however note that while the distributed setting reduces transportation costs, the initial investment in AM machines and associated labour costs could not be justified.

System dynamics has also been used in [105] where the authors developed SD models to compare the impact of decentralising spare parts production in aerospace supply chains, targeting inventory decisions. The study compared the inventory performance metrics result of the SD simulations in a traditional manufacturing scenario where parts were stocked in centralized locations, with distributed AM spare parts production scenario. The simulation findings revealed that decentralization, enabled by AM technology, could be of profound value when complementing conventional manufacturing of spare parts. They note that decentralized on demand AM production of slow moving spare parts in particular is beneficial. This finding however did not take into consideration the initial investment cost associated with setting up new plants powered by AM equipment. This cost segment i.e. cost of AM equipment, as was discussed earlier, is substantial, particularly when a system already exists and the need to make a paradigm shift in production is not urgent. Therefore this paper captures the impact of decentralisation through AM well, but does so in isolation from other, longer term decisions, which was

discussed earlier in this chapter and shown to potentially result in suboptimality when not incorporating other decision-making levels in a unified model.

Although the choice of SD in these two papers was appropriate for the particularities of the problems studied in these two papers, they offer little in advancing the understanding of RdM networks in a wider perspective. System dynamics, as discussed earlier, is a top-down modelling paradigm that models a system's entities as aggregates of homogeneous entities, which does not account for the individualities of the typically heterogeneous entities constituting a typical RdM network. DES, and especially ABM, were also heavily used in RdM systems modelling, but their applications (predominantly control and scheduling) fall outside the scope of this research.

The previous discussion analysed the use of simulation as a decision-aid tool in the context of RdM. Simulation modelling, on its own, as mentioned earlier does not directly provide answers to system design decisions; it only assesses the performance of a given system topology. Therefore the number of studies that employ simulation modelling, in the context of this research, is significantly lower than studies that employ analytical modelling techniques. It is important however to stress once more that simulation is widely used in the context of RdM, but to evaluate control and scheduling decisions. In the next section, the combined use of analytical and simulation tools in the context of RdM networks design will be investigated.

2.4.3 Optimisation-simulation models

The combined use of simulation and optimisation modelling can be useful in overcoming the limitations of each modelling approach. Optimisation models, being purely mathematical models, do not capture the dynamics, nonlinearities and complex interrelationships inherent in most manufacturing systems and necessary to produce realistic representations of systems [79]. It is in most realistic cases a challenge to incorporate a system's dynamic behaviour and uncertainty, while maintaining the model tractable. Simulation modelling on the other hand offers a solution to these issues, while suffering its own shortcomings. The main shortcoming in simulation modelling as a decision-aid tool in the context of manufacturing system design is its inability to generate answers with regards to the design of the system. The combined use of optimisation and

simulation in a unified framework offers the opportunity to embrace the advantages of each approach while providing a way to overcome each approach's challenges.

When combined together, optimisation and simulation work in a recursive, mostly iterative manner. In this recursive approach, the optimisation model generates a solution, which is then evaluated in a simulation model that passes its assessment of the system back to the optimisation model, which then can produce a more refined solution [106]. Regardless of its great potential as a decision-making tool in the system design literature its use is still limited, although progressively growing. A relatively recent paper surveyed the literature, although the survey was not comprehensive, in optimisation-simulation modelling in supply chain network design under uncertainty found that only 8% of the surveyed papers employed an optimisation-simulation approach to solve the problem [107]. In this same paper i.e. [107] the authors also found that simulation was also scarcely used in network design literature, affirming the findings of this thesis.

To assess the viability of adopting an AM-powered RdM paradigm, an optimisation and a simulation models were developed in [17]. In this paper the authors developed a mixed-integer linear programming model that minimises the cost of establishing an RdM system. The model minimises the production, inventory and transportation costs in RdM setting. In this paper, the authors also developed a process-based cost simulation model which, in essence, is a discrete-event simulation model. The optimisation model is an uncapacitated facility location model with demand allocation and production quantities decisions. The authors argue that the choice of uncapacitated facility decisions is due to the nature of the problem being modelled in the paper, which is spare parts in the aerospace sector. The authors state that in the context of the problem they model, demand at each location is unlikely to surpass the production capacity of a production facility. This assumption however severely limits the transferability of the model between different sectors. More importantly, having no capacity constraints will have a great impact on the outcome of the model when redistribution of production is being contemplated. To clarify this observation, when production capacity is assumed to be unbounded, the model is likely to recommend the establishment of one centralised facility if transportation cost did not constitute a significant cost segment. Moreover, when AM is being considered as the means of production, build time will have no place in the model. When implemented in

real applications, this could cause lengthy queues on each equipment; rendering the model's recommended solution impractical. To explain more, a very simplistic example can convey the importance of capacity constraints when it comes to AM production. If the projected demand at a given facility during a given week is 10 units and the build time for each unit is 10 hours, then an uncapacitated model will likely recommend the acquisition of one AM machine at this given location. If capacity constraints are included in the model, the model then, under the assumption that all demand has to be met within a week, will recommend acquiring two machines (although they will be less utilised). This is an overly simplistic example, but should be sufficient to convey the importance of considering capacity limitations when contemplating paradigm shift in production using new emerging technology. In this paper [17], the authors also assumed that transportation cost is fixed, regardless of distance travelled. This assumption, although well justified for the particular case that the models were developed for, also dismisses an important characteristic of RdM in wider applications: responsiveness and service level improvements. The optimisation model is also single period model, which is reasonable, given that there is a companying simulation model capable of capturing the dynamics of the system. Nevertheless, multi-period optimisation models are better suited to provide inventory-related decisions [71], especially that holding cost is required and hence, a multi-period model can recommend producing more (less) than needed in a given period and move the remaining inventory to the next period. The simulation model in this paper i.e. [17] provides a starting point for the optimisation model where it calculates the values for the input parameters used in the optimisation model. This approach is different to the one highlighted at the beginning of this section as there is no feedback between the two models, and the simulation model's main function is to calculate cost parameters that are then used in the optimisation. Although cost is an important performance metric of most systems, simulation models are far more capable of evaluating the performance of complex systems, far beyond cost. The simulation model in this paper, similar to [80,81,96,97], considered post-processing activities, but accounted only for their costs. The simulation model is then a tool to calculate values for the parameters used in the optimisation model, not to evaluate the optimisation model's solutions. In this paper, the authors investigated three different scenarios with respect to the capabilities of AM technology: the first representing the current state of AM technology (at the time of

publishing i.e. 2019), one with significant improvement in AM capabilities, and a third with the improvements combined with a significant decrease in the cost of AM equipment. The results, which were further supported by investigating the impact of varying different parameters, indicated that even with pronounced improvements in AM technology and cost, the distributed production paradigm is unlikely to be beneficial. They note however, based on the sensitivity analysis demand levels, that distributed production has the potential to be viable when demand is very high. This is mainly due to the significant capital investment in AM facilities (fixed cost) which could be offset if the demand on these facilities is high enough. This observation again has to be substantiated, taking into account localisation in a wider setting, as assuming transportation time and cost to be fixed from and to all locations does not incorporate the characteristics of RdM systems into modelling. The inclusion of post-processing activities draw important remarks with regards to the viability of adopting RdM. The results from the simulation model, which simulated in detail the three post-processing activities mentioned earlier, indicated that distributed AM production could become viable if no hot isostatic pressing was required. This finding could complement the work conducted in [80,81] where separate AM specific post-processing facilities are set up and shared between different manufacturers, thus reducing post-processing-related costs.

Reviewing the literature that employs optimisation and simulation models in a unified framework reveals that this approach has not been widely adopted in RdM networks design yet. In one paper [49], the concept of RdM was modelled as DMN, the models were deterministic and the simulation model was not included in the paper. In the other paper [17], in which the concept of RdM is approached in a way in line with this thesis, the combination of optimisation and simulation was not used in a recursive iterative way that will capture the advantages and offset the limitations of each approach. That is however not to suggest that the approach was used inappropriately, on the contrary, the paper well justifies the approach that it used which is termed simulation-based optimisation. There is therefore a room for further investigation of the combination of optimisation and simulation (optimisation-based simulation) in a unified framework, as will be further discussed at the end of this chapter.

The last set of publications that will be analysed before concluding this chapter and identifying the research gaps is those that used both qualitative and quantitative approaches that do not strictly fall under either analytical (optimisation) nor simulation approaches. These papers mainly use scenario modelling to investigate the viability of adopting RdM production through comparisons between centralised and distributed production scenarios. These papers are reviewed in this research to gain a wider drawn from the outcomes of these papers with regards to the viability of RdM production when compared with the centralised one.

2.4.4 Other approaches

In this section, previous research that investigates the viability of adopting an RdM paradigm employing tools not covered in the previous sections will be analysed. In [108] the authors investigated the viability of distributed AM spare parts production in the aerospace sector. The authors analysed three different scenarios (as-is, centralised AM, distributed AM) using supply chain operation reference model (SCOR). SCOR is a qualitative framework, in particular a reference model, that provides standardised concepts, terminologies and descriptions to processes within a supply chain [109]. The authors devised a hypothetical supply chain and its performance in the three scenarios was analysed solely on the basis of inventory safety stock. Their study, although demonstrated significant reduction in safety stock levels when using AM – both centralized and distributed – did not provide any cost or lead output parameters. Moreover, the costs of decentralisation were not accounted for in the model, rendering the model appropriate as a complementing tool to quantitative strategic decisions models, not to stand on its own as a decision-making tool when the adoption of RdM is being contemplated.

In [110] the authors investigated the viability of spare parts production via AM at both centralised and distributed facilities through conceptual design. In this paper, previously published literature was analysed to develop conceptual models and stimulate a discussion regarding the viability of distributed or centralised AM production. The authors identified three key variables when choosing to produce parts using AM namely material and production costs, distribution and inventory obsolescence costs, and life cycle costs for the user. The findings of this paper, similar to [17], revealed that the

deployment of centralized AM machines is superior to the distributed scenario in terms of cost. However, the authors concluded that with the rapid technological development in AM technologies, and the drop in price, it could become feasible to deploy a distributed spare parts production supply chain. Their study is, however, chiefly qualitative, solely relied on discussing the conceptual designs that the authors developed and lacked an empirical side that could verify their conclusions.

In [23] the authors employed scenario modelling to investigate the viability of spare parts AM production in both centralised and distributed environment. In this paper, the authors modelled four scenarios that explore two AM-powered production paradigms: centralised and distributed. Similar to [17] this study considered a single part in the aerospace sector at a single time period. When devising the scenarios the authors in [23] took into account the possible future improvements in AM technologies that could enable distributed production; a consideration that was also later incorporated in [17]. The scenarios matrix consisted of centralised and distributed production at one side against current and possible future advancement in AM technologies on the other. Similar to most research in this area, total cost was used as the determining factor. The composition of cost in this paper i.e. [23] is more comprehensive than most of the preceding and successive research. Total cost included elements such as annual depreciation of AM equipment, downtime cost, inventory obsolescence and holding costs, amongst others. The paper also introduced and investigated an interesting concept related to the potential advancement in AM technology, this concept is the advancement in automation level which will lead to less personnel cost, and subsequently might enable distributed production. The results generated from calculating the cost of each scenario in [23] were in line with previous [110] and future [17,93,94] studies that also found that centralised AM production is superior to the distributed one. The authors however note that with the perceived decrease in AM acquisition and running costs, distributed production might become viable. All parameters used in each scenario's total cost calculations were deterministic, but sensitivity analysis was conducted to introduce some level accounting for potential uncertainties. This paper, although important and drew much interest in the area of distributed AM production, modelled only *extreme* cases. To explain more, the distributed manufacturing scenarios investigated in the paper presumed an AM equipment at each demand location, which in many cases is unrealistic. A few years after the publication of

[23] the same authors extended the scenarios modelling in [111] where they expanded the number of scenarios to 12. It was not only the number of scenarios that was modified, the authors also modified the AM-related cost and operations parameters to reflect the improvement that had occurred during the period between the two papers' publications ([23] was published in 2014 and [111] in 2018). They added to their comparison of centralised and distributed spare parts supply chains a third family of scenarios which is hub configuration. A hub configuration is a production topology that falls between full centralization and full distribution of the production network. In a hub setting multiple AM powered production units are placed in several locations, each allocated a given number of demand points, establishing zones. The authors also used cost as each scenario's performance metric and found that hub configuration could be the preferable configuration if machine capacities and zones allocation were carefully chosen. The authors identify AM machine automation as the most critical factor for the realization of the distributed scenario. The work in [111] was similar to its predecessor that the inputs to each scenario were deterministic. Moreover, the selection of the hubs locations had been done rather arbitrarily without any evidence with regards to the optimality of the selected location. Basing location decisions, especially in production where raw materials and goods between different facilities exist, using even the simplest optimisation models can have huge impact on cost and service levels [86].

2.5 Discussion and research gap

Given the discussion above, a number of observations regarding the contemporary literature that addresses RdM network design and decision making are made. First, it became apparent that the interest in RdM network design in general, and beyond scheduling and control decisions in particular, began in parallel with the shift in AM application from prototyping to producing final products. Another key observation is that most of the applications that RdM is considered for are characterised by either unpredictable demand or high product customisation. To affirm this observation, almost all of the papers reviewed in this chapter proposed the employment of RdM in either the spare parts or biomedical implants sectors. Each of these two groups follow demand patterns that are difficult to predict, or/and are products characterised by complex geometries that are difficult to manufacture using traditional subtractive manufacturing

efficiently. There are therefore two potential advantages that RdM, when coupled with AM, can bring: high customisation (thanks to AM) and faster response (thanks to localisation). Besides these two points, there are other equally important potential advantages that are being investigated, but not conclusively confirmed. These potential advantages include potential cost and environmental performance improvements due to, to mention a few, more efficient use of raw materials, less transportation and energy savings. These potential advantages are however still debated as was discussed in the Introduction chapter.

Having reviewed and analysed the decision-making models that have been used for the design of RdM networks, it was clear that the most used approach was analytical modelling, in particular optimisation models. Optimisation modelling, as discussed earlier, suffers limitations in capturing a system's dynamic behaviour (i.e. growth over time) and the complex nonlinear interrelationships between its entities. These limitations have their roots in computational complexity where the faithful representation of most real-life systems could entail an exponential growth of the number of variables. Moreover, representing a system mathematically in closed form, as is the case in optimisation modelling, will often quickly become impossible, and the model intractable. Simulation modelling, on the other hand, can capture the dynamic behaviour of a system, and it is often relatively easy to model complex nonlinear relationships of realistically sized systems efficiently. Unfortunately, simulation modelling lacks the optimisation modelling capability of providing values for decision variables. It rather takes these values as given inputs and provides the decision-maker the platform to experiment with the system in a risk-free environment and observe the system's performance. Simulation modelling was, however, scarcely used in RdM network design beyond scheduling and control decisions. The combination of these two tools (i.e. optimisation and simulation) has also been investigated in this chapter, and apart from two studies [17,49] that incorporated them to partially complement each approach's limitations with the other's advantages, combined optimisation-simulation modelling in RdM network design is non-existent. Uncertainty is also an important aspect of modelling, particularly when the viability of a new, non-existing system in the form it is examined, is being considered. With the exception of a few studies that employed stochastic optimisation models

[93,94,96–98], particularly with regards to demand, uncertainty was largely left unexplored.

It is therefore clear that there is a fair number of studies that developed decision-making models for the design of RdM networks. The previous discussion highlighted what each study has accomplished, discussed the appropriateness of the selected tools, and also pointed out what was missing from each study or what could have been done alternatively, all from the lens of this research's aim. A common theme that is shared between all of the research papers that developed decision-making model for RdM network design is that the dynamic nature, along with the distributed decision-making of the distributed facilities have not been accounted for. To explain more, the most widely employed approach i.e. optimisation modelling, as was explained throughout this chapter, is a static tool that models a *snapshot* of the modelled system, and relies heavily on many assumptions and simplifications that does not fully capture individual autonomies and complex and nonlinear relationships. Moreover, much of the research efforts in RdM network design was context-specific (e.g. biomedical implants for a specific geographical area [94,96,112] or spare parts for a specific application [23,111]), rendering generalisability and transferability to other sectors an open concern. It could be deduced then that the research in RdM network design is divided into two separate groups that do not considerably overlap. One group models the problem as a *decentralised* production network, borrowing from the same tools applied for the design of traditional manufacturing networks. The other group accounts for RdM networks characteristics, especially the autonomy of distributed facilities, but does so only at the operational level, control and scheduling, assuming an already naturally occurring existing network. The former group of decision-making models predominantly employs optimisation models, while the latter employs agent-based and discrete-event simulation models. There is then a need to bridge these two areas of research and bring them closer together in a unified framework. The development of such a framework will contribute to a better understanding of RdM systems, and will provide a tool for decision-makers to investigate the viability of adopting an RdM paradigm. Therefore the gap that this research aims to fill is:

- *The lack of context-independent decision-making frameworks for the design of RdM networks that embrace the defining characteristics of RdM systems, address*

different decision-making levels, and account for the interdependence between these decision-making levels in a stochastic environment.

To respond to the abovementioned research gap, a context-independent decision-making framework that consists of optimisation, simulation and database modules is developed. The research gap above corresponds to the first and second research questions. It corresponds since filling this gap will lead to the identification of the most suitable decision-support tools for modelling the design of RdM networks, and after the identification of such; an integration of distinct, yet complementing, decision-support tools is conducted.

In this framework the optimisation and simulation models run successively in an iterative manner, and communicate through a feedback mechanism until the desired performance metrics are realised or the system reaches a steady-state. The framework accounts for all three decision-making levels, and accounts for the impact that each decision has on the entire system performance in an iterative manner. Uncertainty is also incorporated in the framework, and its impact on the entire system's performance is handled in the same way as the interdependence between different levels of decision-making where throughout the successive optimisation-simulation iterations, new values for the parameters and decision variables will be fed from each model to the other. The optimisation model is a multi-period integer linear programming model that provides location-allocation, production and inventory decisions. The simulation model is an agent-based model which, as was discussed earlier in this chapter, an appropriate choice in modelling and capturing the behaviour of complex, decentralised and autonomous systems. In agent-based models, unlike discrete-event and system dynamics, the decentralised entities are themselves autonomous [100] which makes agent-based an appropriate choice for modelling RdM system. The simulation model runs the optimisation model's generated system topology stochastically under varying scenarios, and passes its feedback to the optimisation model where this feedback is translated as refined constraints. The combinations of these two approaches (mathematical programming and agent-based simulation) allows for avoiding oversimplified assumptions, capturing complex-nonlinear interrelationships, and capturing dynamic behaviour (e.g. the emergence of queues) [113]. The framework will be explained and discussed in detail in Chapter 4.

3 Research design

3.1 Introduction

This chapter will present the overall design and process of this research. The chapter will outline the phases of the research process; breaking the research down into four distinct, yet considerably overlapping, phases. The completion of each of the phases contributes indirectly to the realisation of all research objectives, but corresponds directly to an individual research objective.

3.2 Phases of the research design and process

In order to achieve each of the aforementioned objectives, and eventually realise the research's aim, the research design adopted in this thesis is explained in this section; highlighting the processes undertaken to achieve the research objectives, and subsequently the overall aim.

The research process has been divided into four phases that, although are generally successive, they do considerably overlap as will be described in what follows. Each phase of the research is designed to correspond directly to an individual research objective. However, as each phase of the research builds on the previous one, and paves the path for the subsequent phase, each phase then inevitably contributes to all research objectives. To elaborate more on the relationship between the research process and the research objectives, Figure 3.1 depicts the most direct relationship between each research phase and its directly corresponding research objective. It is important to stress again that the work conducted in each phase of this research contributes to all the research objectives, but Figure 3.1 highlights the most direct relationship between the research phase and its corresponding research objective. For example, the literature review phase does not only contribute to the completion of the first research objective, but is rather at the heart of all other objectives. The same principle applies to the framework validation phase; validation is a two-way iterative process in which the models undergo many alterations until they are integrated in the research in their final format. This naturally renders the validation phase, and to varying degrees, all other phases of this research at heart of all research objectives.

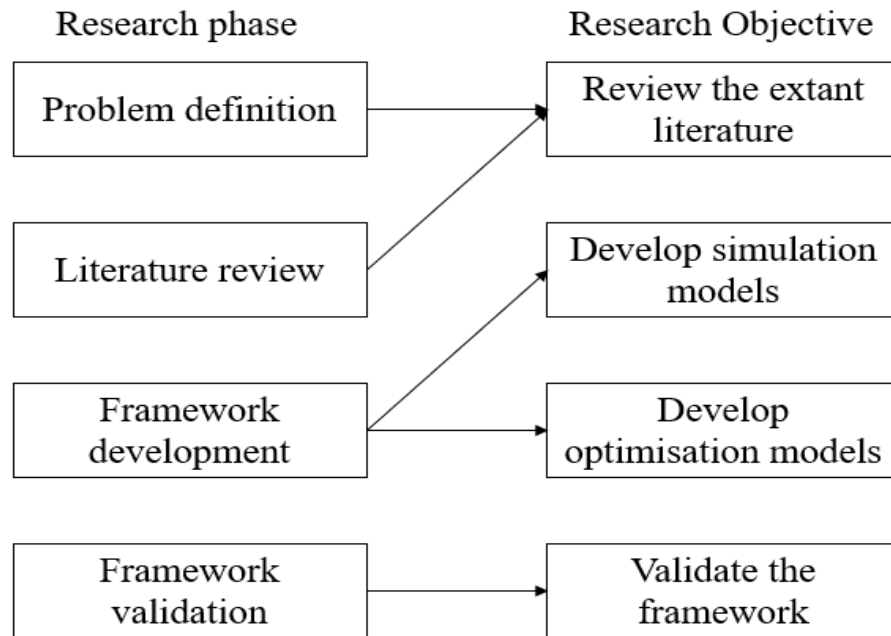


Figure 3.1 Relationships between research process and research objectives

The detailed research process is depicted in Figure 3.2 which shows the logical consequence of the phases, dependencies and methods used in each phase. Each phase of the research is described in detail in what follows.

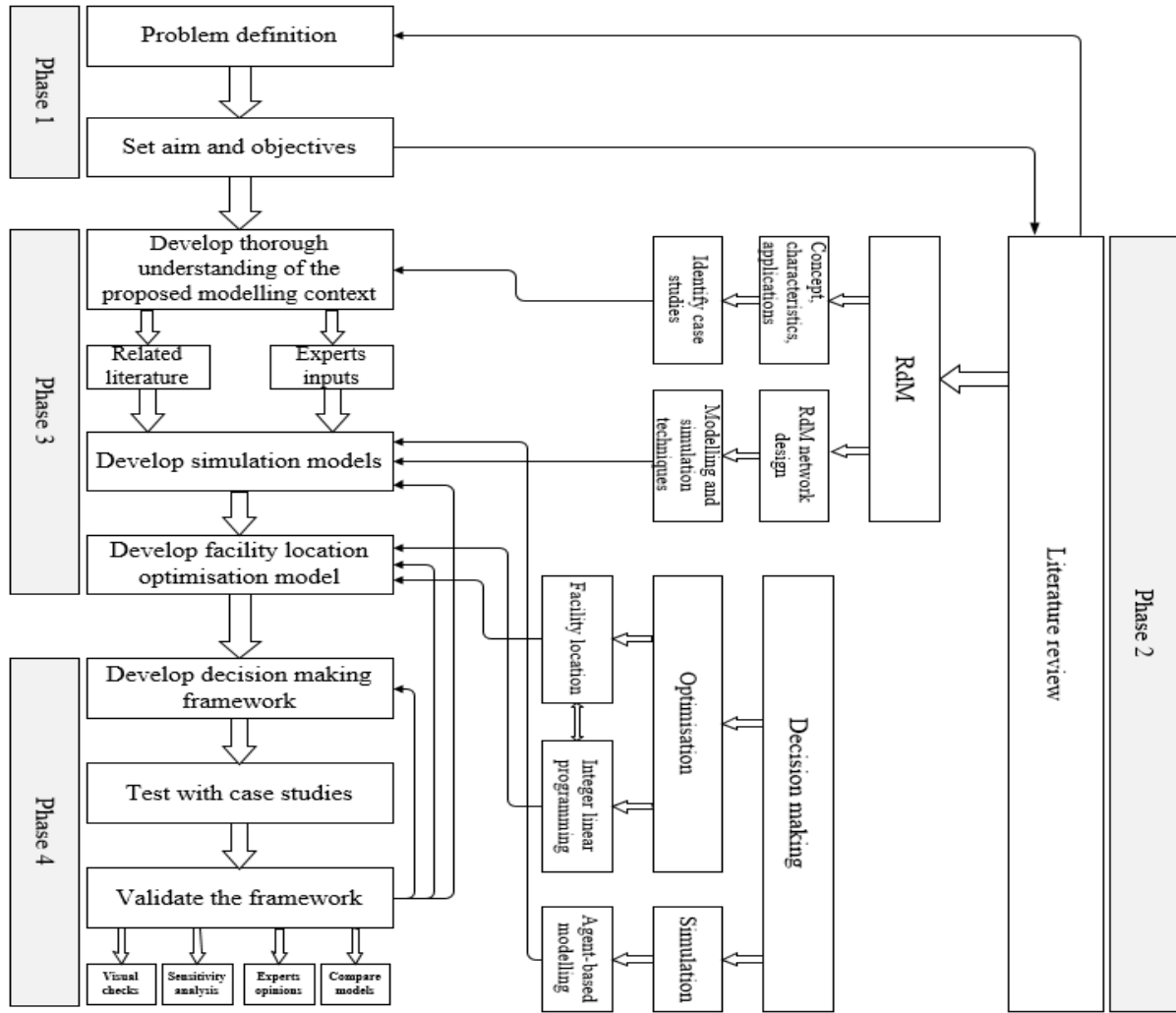


Figure 3.2 Research process

3.2.1 Phase I - Problem definition

The first phase of this research is the problem definition phase. In this phase a preliminary literature review was conducted to define the problem that this research will investigate. This phase of the research is vital as the aim is defined at this stage and then consequently the objectives are devised to achieve the aim.

The preliminary literature review focused directly on the area of redistributed manufacturing (RdM). In RdM multiple streams of research were reviewed; firstly the concept of RdM was thoroughly investigated. This entailed different definitions of RdM from different angles being identified, such as RdM from economical perspective and RdM from manufacturing performance improvement perspective, amongst others. Then the varying defining characteristics of RdM systems were identified. Such characteristics

include localisation of production, digitisation of different facets of production and operations and end consumer involvement, amongst others. Then the drivers that motivate the adoption of RdM were investigated. Such drivers include, but are not limited to, economical, environmental and operational drivers, amongst others. The application of RdM, such as the spare parts, biomedical and emergency response applications were identified from the literature and companies reports.

Undergoing this phase of the research enabled the precise formulation of the research aim and subsequent objectives, which subsequently guided the rest of the research. The findings of this research phase revealed that field of RdM is experiencing increased interest, as was manifested in Chapter 2 of this thesis, but also indicated a lack of decision-support models and framework that incorporates the defining characteristics of RdM into decision-making at the design stage. This finding resulted in formulating the overall aim of the research, which is dedicated to devising a decision-making framework at the design level, and paved the way to conduct a thorough literature review to precisely identify the research gaps and formulate the contribution of this research to align with the overall aim.

3.2.2 Phase II- Literature review

The second phase of this research is the literature review phase. As with the rest of the research phases highlighted in this chapter, this phase significantly overlaps with the rest of the research phases. Literature review was at the core of the preceding phase, and is also at the heart of this stage. The main difference, however, between the first and the second phases is that in the first stage, literature review was at rather a high level, setting the stage and guiding the research for the subsequent phases. While at this phase, literature review is conducted thoroughly at much more depth at the streams of research identified by the preceding phase.

In the literature review phase, two broad streams of research were thoroughly investigated namely: RdM and decision-making. In RdM, the concept, drivers and defining characteristics were investigated thoroughly. In addition to the aforementioned RdM-related topics, RdM network design models and framework were investigated. The second stream of research is decision-making, which is a vast topic in the operational research (OR) literature. In decision-making, which contains a plethora of tools and techniques, two distinct, yet complementing, decision-aid tools were identified as the

most suitable to serve in achieving the research's aim and were subsequently investigated. These tools are namely optimisation and simulation. Similar to their parent field, optimisation and simulation are both vast topics in OR literature. Therefore the literature review at this phase helped identifying the most suitable tools and techniques within the fields of optimisation and simulation that are most appropriate to achieve the research's aim.

In the simulation modeling literature, the three mainstream simulation modelling approaches were investigated, as was demonstrated in Chapter 2, and agent-based modelling (ABM) was identified as the most appropriate tool within the simulation modelling toolbox to serve the research's aim. Equally vast, or even richer, the optimisation literature offers a wealth of tools that have been employed in fields varying from protein structure models for single-cell organisms to spaceships trajectory planning. Therefore the focus on the optimisation literature was limited to facility location linear and nonlinear programming models within a decentralised production environment, as was demonstrated in Chapter 2.

Unlike the first stage which had, although blurry, limits with regards to the commencing and the completion of the research phase, the second phase was a rather ongoing phase as depicted in Figure 3.2 continuing throughout the research process and contributing to all facets of this research. Undergoing this phase of the research has, however, assisted in the upcoming (in many instances rather simultaneously overlapping) phases, and assisted in the identification of case studies for the framework validation.

3.2.3 Phase III- Framework development

The third phase is dubbed as the framework development phase. In this phase, the agent-based simulation models and the facility location integer linear programming optimisation models were developed. It is important to point out here that this phase considerably overlaps with the successive framework validation phase. This is because validation, the term is used here to refer to the processes of verification and validation together (both terms will be explained in the next subsection), is a rather two-way iterative process. Looking at the bigger picture, validation is itself a model development process well intertwined with the rest of model development processes. Validation however is

often addressed separately to distinguish it from other modelling aspects, such as a model's objective and assumptions, amongst others.

In this phase, the optimisation and agent-based simulation models were developed. During the early stages of the models development, experts opinions to develop reasonable assumptions and identify entities and the interrelationships between them. Other sources, mainly the contemporary literature and companies reports, were used to devise the values of the parameters that had to be assumed, and to establish the relationships between variables and entities, and to define the models' internal logic.

Later in this phase, the decision-making framework, which consists of interacting optimisation and simulation models was developed, as will be presented in Chapter 4. At the beginning of the framework development process, the high-level mechanism of the framework was devised as will be shown in Chapter 4. The overall structure of the framework is context-independent and can be used in a wide array of industrial settings such as spare parts, medical equipment and fast moving customer goods. The internal components of the framework are, however, case-dependent and could be changed or adapted to correspond to the case at hand. The framework incorporates uncertainty, provides decisions at all levels of decision-making, and accounts for the interdependence between all levels of decision-making on one another.

The development of the simulation models was done following the object-oriented paradigm to allow the generalisability of the models and their adaptability to different modelling contexts through modularity. The object-orientated paradigm will be described in detail in Chapter 4. It important to point out here that each simulation model consists of a conceptual model and a computerised model. The conceptual model is defined by Robinson [99, p.65] as: *"is a non-software specific description of the simulation model that is to be developed, describing the objectives, inputs, outputs, contents, assumptions and simplifications of the model"*. The conceptual modelling tool used to develop the agent-based simulation models was the Business Process Model and Notation (BPMN) modelling language. The main benefit of conceptual modelling is to clearly define the models' entities and the interrelationships between these entities. These conceptual models were later (after validation) converted to computer models. The optimisation models components of the framework were developed as facility location integer linear

programming models. Conceptual modelling in optimisation models (those represented mathematically) is different from the simulation conceptual models. The difference is that the entities and the interrelationships between them are not represented graphically as in the simulation modelling case, but rather mathematically. In mathematical modelling, the entities and the interrelationships between them are represented through mathematical formulas that define the models' behaviour. It is worth mentioning here that any other modelling approach within the optimisation and simulation toolkits could be used, depending on the study's objective.

To validate the framework (Phase IV), two case studies were employed. The first case study is within the aerospace spare parts sector where a supply chain covering the USA, and supplying its busiest airports with a finite set of spare parts was developed. This case study required the development of a facility location integer linear program with inventory decisions, and a stochastic agent-based simulation model that assesses the performance of the RdM network (generated by the optimisation model) under varying scenarios. The second case study addressed the viability of employing RdM production paradigm in the production of vital goods at times of emergencies. The second case study was inspired by the outbreak of the COVID-19 coronavirus pandemic and used real data published by the UK government to design an RdM production network for the South East of England region. The product of choice to be manufactured was the face shields used by frontline health workers, which was in short supply in many areas around the world. The case studies and the results deduced from them are presented in detail in chapters 5, 6 and 7.

3.2.4 Phase IV- Framework validation

The final phase of this research is the framework validation phase. Although the validation of a framework (mainly through validating its constituent models) is an inseparable activity from the rest of the framework development activities, it is addressed in a separate phase to distinguish it from the rest of the framework development activities. The term validation in this research refers to both the verification, which could be considered a subset of validation [99], and the models' validation itself. Model verification refers to ensuring that the computer model faithfully represents the conceptual model where all the entities, interrelationships and assumptions are

implemented correctly on the computer model as presented in the conceptual model [114]. Model validation on the other hand is establishing that the model is an accurate representation of the modelled system, with respect to the objective of the model [115], and as Balci [116, p.122] adds: “*substantiating that the model, within its domain of applicability, behaves with satisfactory accuracy consistent with the study objectives*”. It is important to point out here that model validation is not only confined to the computer models; conceptual models should be validated as well. Conceptual model validation deals with ensuring that the conceptual model represents the modelled system with reasonable accuracy within the model’s intended purpose, and that the model’s assumptions are reasonable within its intended purposes [117].

The concept of model validation should not be perceived as proving that a model is absolutely correct from all perspectives; this notion is generally dismissed and deemed to be impossible [79,99,115,116]. Model validation is therefore concerned with increasing the confidence that the model is of sufficient accuracy and could be relied upon in decision-making within its domain with regards to the model’s objective [99]. If a model has more than one objective, or if it provides decisions in more than one domain, then each of those objectives and domain-related decisions should be validated [115]. In other words, if a model is valid in one objective or domain, there is nothing to suggest that it is valid in the other objectives or intended domains. To increase the confidence in a model’s behaviour, Sargent [117] suggests there should be conceptual model validation, computerised model verification, operational validation and data validation. Conceptual model validation and computerised model verification were defined earlier in this section, therefore definitions to operational validation and data validation should be provided next to provide a more complete sense of the validation process. Operational validation refers to the process of establishing that the model’s output has sufficient accuracy with respect to the model’s objective and its domain. Data validation on the other hand is concerned with ensuring that all the data used in the model are also sufficiently accurate with regards to the model’s domain and its intended purpose. Different types of data are used at all stages of model building, evaluation and execution. For example, providing quantitative data for the model’s parameters values is one form of data, on the other hand, qualitative or textual data are also used to establish the model’s logic and define interrelationships

between its constituent entities. The framework validation process could be summarised, at a high level, in Figure 3.3 below at its constituent models level.

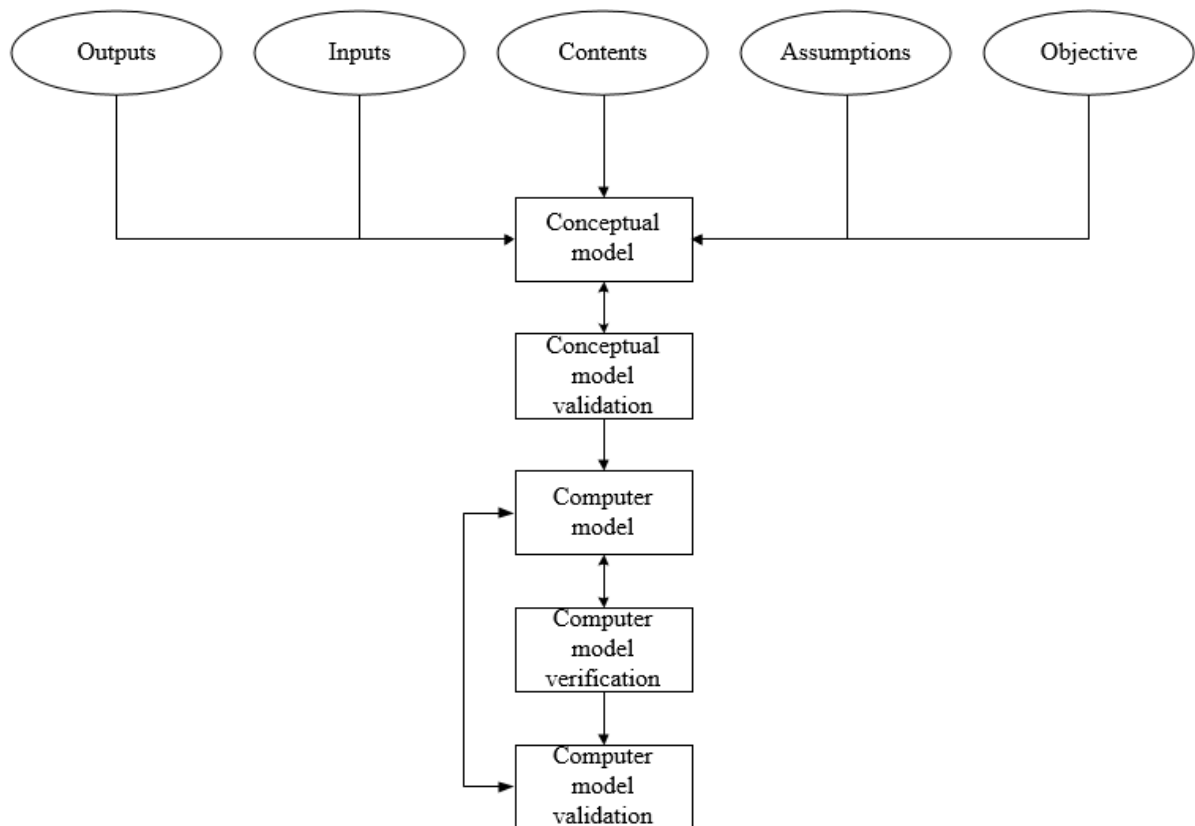


Figure 3.3 Models validation process

As the validation of a framework is a task tightly intertwined with the rest of the framework development activities, it will be described here as a part of its constituent models development process (i.e. at the model level). First, the overall objective of the framework is defined, which in turn defines its constituent models own objectives, assumptions, contents, inputs and outputs, all devised to align with the overall framework objectives, which itself is formulated to achieve the overall aim of this research. As stated earlier, there is no “universal” model validation, therefore the models developed in this study, and the resulting framework are validated before each new application. The main approach employed in this research to validate the framework is through case studies, therefore the framework should be validated before the application of each of this thesis’s case studies. As mentioned earlier, two case studies were employed in this research. The first case study was to design an RdM production network in the aerospace parts sector.

The second case study was to design an emergency response production network for frontline healthcare workers in times of crisis.

In each of the case studies, their models' objectives were defined first. For the simulation models, the objective was to evaluate the performance of different production networks. The optimisation models, however, had different objectives, which are to generate optimal production networks with respect to an objective function. Once the models' objectives were devised, the models' contents (or entities) were then identified. The next step was to identify the models' inputs, such as parameters' values and interrelationships between entities, and to prepare the assumptions list. The assumptions made in the context of this research are of vital importance, particularly that the aim of the overall framework is to design a yet non-existent manufacturing network. Assumptions made to each model were devised based on reviewing the literature and experts opinions. The list of assumptions, along with their impact on the models' outcomes were presented to experts, both academics and industrialists, in the field of manufacturing. A total of five experts were consulted, separately, throughout the development of the models; their details are listed in Table 3.1 below. Their feedback was integrated back into the models. Once the conceptual models were developed, the subject experts were walked through the models where they also provided feedback to improve the models representation of reality. The next step was to develop the computer models. The computer models were then verified through visual checks, experimenting with extreme values and providing a walkthrough of the code to a software architect [118]. Visual checks enable the user to observe whether the model's performance is as it is intended to be or not, and it also allows the user to trace individual entities as they move in the system and establish whether they follow the intended logical paths or not. In addition to visual checks, experimenting with extreme values increases the user's confidence in the computer model's verification. In experimenting with extreme values, the user changes some parameters values to rather unlikely values to enforce some conditions and establish whether the model performs as intended or not. Finally, a software architect experienced in Operational Research and the programming languages used to convert the conceptual models to computer models was provided detailed walkthroughs of the models, and was presented with the models codes. The software architect identified some bugs in the code that could result in system error if the models were run with some specific assortment of parameters values.

Table 3.1 Experts profiles

Expert reference	Academic/ industrial	Job title	Background
Expert 1	Academic	University professor	Manufacturing systems
Expert 2	Academic	Senior lecturer	Computer modelling and simulation
Expert 3	Industrial	Technical services director	Maintenance, repair and operations
Expert 4	Industrial and academic	Manufacturing and technical director	Manufacturing systems
Expert 5	Industrial	Software architect	Operational research, software engineering

Having established the models' validity i.e. increased the confidence in the models as reliable potential decision-aid tools in three of Sargent's [117] validation facets (conceptual model validation, computer model verification and data validation) through the steps detailed in the previous paragraph, the final validation facet i.e. operational validation has to be established next. Operational validation (establishing that the models results are of sufficient accuracy with regards to its intended purpose with its domain), was done through experts opinions, sensitivity analysis and models comparisons. Experts opinions on the models helps in establishing face validity, which is when experts in the field of the model agree that the model's performance and output sufficiently, reasonably and closely resembles that the performance of the envisioned system [115]. The experts reviewed the model's outcomes and all the concerns they raised, which will be discussed in chapters 5, 6 and 7 were discussed thoroughly and later addressed in the models.

Sensitivity analysis was also conducted on the models to help establishing their validity. The main importance of sensitivity in validation is that it allows the identification of

important parameters (those that a small change in their values has big impact on the model's outcome), thus alerting the model developer to carefully assign values to these parameters [119]. The method of sensitivity analysis that was used is to change the values of one parameter at a time, which Gass [119] states that this is the often-used method in models validation. A thorough sensitivity analysis has been conducted to all the optimisation models to identify the important parameters and to compare the impact of the occurrence of varying scenarios on the systems' performance.

Finally, comparison with other models was used to further validate the models. In models comparison, the outputs generated from a model are compared with those generated from another, similar, model. This method is used when there is no real system to compare the model against [99]. Intuitively, comparison with another model only serves the purpose of validation if the other model, which is compared against, is itself valid. As the decision-making framework developed in this research contains two separate models (optimisation and simulation), both models were run (deterministically), and their results were compared against one another. Their outputs were always within close similarity to each other. After investigating the reason for the discrepancy between the models, the reason was attributed to the dynamic nature of the simulation model, which performs calculations on much smaller timescales than the optimisation model. This discrepancy will be further discussed in subsequent chapters. The act of models comparison might not considerably contribute to increasing the validity (confidence) of the framework since both models were developed by the same person, and if a mistake was made in one model, it could be easily replicated in the other. Nevertheless, when combined with the other measures taken to validate the framework's models, models comparison does contribute to the framework's validity in ensuring that each model is valid against the other, which is vital for the successful implementation of the framework.

Finally, it is worth reiterating two points. The first being that validation is not a separate step in model building; it is rather integrated in all model building steps, and is inseparable from any stage of model development. The second point is that regardless of the measures taken to validate a model or a framework, absolute and complete validity is not possible. All the steps taken are only intended to increase the confidence in the framework, and

any extra measures taken will only serve in increasing the confidence, not proving that the framework is 100% correct in all domains.

3.3 Summary

In this chapter, the research design was presented and discussed with respect to how each individual objective was achieved to eventually realise the overall aim. The research process was broken down into four overlapping phases; each contributing to the realisation of all research objectives, but at the same time individually devised to correspond more directly to distinct research objectives. The research starts with the problem definition in which the overall aim and individual objectives are defined. Then the thorough literature review takes place in which the research gaps are identified. In the following phase the decision-making framework's models are developed, and finally in the last phase the framework is validated.

The next chapters present the third and fourth phases of this research namely; the framework development and the framework validation phases. All of the models' development steps are explained in details, and computational studies to the case studies are presented and discussed.

4 RdM network design decision-making framework

4.1 Introduction

In this chapter the decision-making framework for the design of RdM networks will be presented from a high-level perspective, followed by two case studies where the framework is applied to test and validate its applicability.

Optimisation and simulation, as discussed in the Literature Review chapter, each on its own, are among the most widely used decision-aid tools [120,121]. They are, however, different techniques, each serving a different purpose [99]. Optimisation models provide values for the decision variables (e.g. number and location of production plants), while simulation models provide assessment, in the form of performance measures, to different scenarios consisting of varying values of decision variables. In other words, simulation on its own cannot provide values for the decision variables, but can rather efficiently assess whether the examined system performs as desired or not. The optimisation model in the decision-making framework is a multi-period capacitated facility location model formulated as a fixed charge [86] integer linear programming (ILP) model that combines inventory decisions. The simulation model is an agent-based model (ABM) that evaluates the RdM network structure generated by the ILP model and recommends alterations, passed back to the ILP, to gradually improve the performance of the system through several iterations until a steady-state is achieved and certain criteria are met.

The decisions provided by the proposed framework span all planning horizons (i.e. strategic, tactical and operational). Strategic decisions include the number and location of RdM production facilities. Tactical decisions include allocation of demand points to RdM production facilities, production quantities at each RdM plant, inventory levels and inventory replenishment policies. Finally operational decisions include the reallocation of supply decisions in case of unmet demands. The framework is not industry specific; it could be used in different setting and industries where decisions have to be made regarding the distribution of production resources and operations.

In the context of this thesis, a manufacturer (e.g. an original equipment manufacturer OEM), which provides products to demand points that are distributed over a given geographical area, wishes to investigate the viability of adopting an RdM paradigm to

improve some performance measure (e.g. cost or lead time). The proposed setting is to replace the centralised manufacturing of certain products, and move these production activities to local areas closer to the points of demand. It is important to stress here that the replacement of centralised traditional manufacturing to RdM setting is done to only a finite set of the OEM's products offering. In other words, this research follows the findings from previous research that RdM cannot, and will not in the foreseeable future, completely replace traditional centralised production. Such a costly endeavour (i.e. the shift to RdM *for certain products*), however, requires making strategic decisions that are mostly irreversible or prohibitively costly to reverse, and naturally influence both tactical and operational decisions.

Before presenting and discussing the framework and how its constituent models operate, the following sections will present conceptual versions of the optimisation and simulation models at an abstract high-level. The framework's constituents models will typically have different formulations and entities, depending on the context it is applied to. However, the mechanism of the framework itself and how it governs the communication and feedback between its constituent models to achieve performance improvement is the same.

4.2 Optimisation model

The general formulation of the optimisation model is presented below. When the framework is later applied to design RdM networks, the general formulation presented below can be adjusted to fit the specific instance it is developed for. The model is a capacitated multi-period facility location linear programming (ILP) model with inventory decisions. Facility location models are generally employed in manufacturing and supply chain network modelling at the strategic level, especially where production facilities have to be chosen from a finite set of potential locations [86]. The ILP optimisation model provides decisions regarding the number of RdM sites, their locations, allocation of demand points to RdM sites, inventory levels for each product at each demand point and the replenishment amounts for each product at each point.

4.2.1 The model

$$\text{Minimise } Z \quad (1)$$

Subject to (s.t):

$$\sum_{j \in J} Y_{jipt} \geq r_{ipt} \quad \forall i \in I, \forall p \in P, \forall t \in T \quad (2)$$

$$\sum_{i \in I} \sum_{p \in P} Y_{jipt} b_p \leq u \sum_{k \in K} X_{jk} \quad \forall j \in J, \forall t \in T \quad (3)$$

$$X_{jk} \in \{0, 1\} \quad \forall j \in J, \forall k \in K \quad (4)$$

$$Y_{jipt} \in \mathbb{Z}^+ \quad \forall j \in J, \forall i \in I, \forall p \in P, \forall t \in T \quad (5)$$

In the general formulation presented in model (1) – (3) the objective function minimises the chosen objective function (Z). A detailed formulation of the objective function was not presented in the general formulation because each application instance will typically have its unique formulation. The objective function in (1) could be any desired performance measure chosen by the decision-maker. This could be total cost, lead time or any other performance measure. The objective function, however, does not always have to be a minimisation one; it could rather be the maximisation of some value (e.g. profit or total produced units). The objective function can easily be transformed to a maximisation one by simply multiplying both sides of the equation by (-1). Constraints (2) ensure that demand at each demand point for each product type during each planning period is met. This set of constraints also implicitly imply that each demand node is served by at least one RdM facility. Constraints (3) ensure that the appropriate capacity is allocated to each RdM plant by enforcing that the total cycle time in each RdM plant for all parts during each planning period does not exceed the plant's capacity. This constraint however can be converted to reflect the required number of AM equipment in each plant and also to relieve the computational complexity of the model. In doing so, decision variable X will take integer value instead of binary value, and constraints (3) become:

$$\sum_{i \in I} \sum_{p \in P} Y_{jipt} b_p \leq u X_j \quad \forall j \in J, \forall t \in T \quad (6)$$

$$X_j \in \mathbb{Z}^+ \quad \forall j \in J \quad (7)$$

The value that (X_j) takes then will reflect the number of AM equipment to place at potential RdM plant site j . Finally constraints (4) and (5) are the binary and integrality constraints, respectively.

Typically, several parameters (e.g. costs and distances) and decision variables (e.g. remaining inventory at the end of each planning period) have to be added to the general model presented above to reflect the system being modelled. The addition of parameters and decision variables will be explained in Chapter 5 and Chapter 6 where the framework is applied on two case studies.

The above model however, as discussed in Chapter 2, does not take the dynamic nature of the problem into account e.g. it does not capture queues that might emerge in production sites or unexpected delays in lead-time, and is unable to capture nonlinearities and complex interrelationships [113]. The model is also deterministic, and makes a number of assumptions and simplifications that render its output useful only as a starting point for further investigation, or to provide a rough estimate within its intended purpose. These assumptions and simplifications will be discussed along with their impact on the outcome in Chapter 5 and Chapter 6 where the framework is applied on two case studies. The discussion of the assumptions and simplifications is included within each application rather than here in the general formulation because each application is unique, and therefore entails specific assumptions and simplifications. To incorporate uncertainty, dynamic behaviour and complex interrelationships between the system's entity, and to evaluate the performance of the optimisation model's solution under these attributes, the simulation model is incorporated into the framework and presented at a high-level in the next section.

The optimisation model is, as demonstrated in Eqs (1 - 7), targets a single criterion by being a single objective model. In most cases this criterion is cost where the model minimises the total cost establishing and running a manufacturing system. When applying the framework for the design and operation of an RdM network, other criteria might be of equal, if not more, importance to the system. Such criteria are, however, often conflicting, meaning that the improvement in one criterion might lead to a deterioration

in the outcomes of other criteria. Although the simulation model, as will be demonstrated in the next section, allows for the improvement in other criteria, mainly service level targets, doing so to optimality requires different configuration. This can be achieved by either: multi-objective optimisation model, or multi-criteria decision-making (MCDM). In multi-objective optimisation models, the optimal values of the decision variables are demonstrated on a Pareto front, which contains the optimal values of the conflicting decision variables. In multi-objective optimisation modelling, the decision maker chooses a value along the Pareto front that best suits the goals of the manufacturing system. Each point on the Pareto front corresponds to an assortment of decision variables that, if chosen, will lead to a suboptimal solution with regards to a single decision variable. MCDM, on the other hand, can be performed in many different ways. The most common, and used approach in MCDM, is to assign weights to each criterion based on the importance of these criteria to the decision maker. Then, after weights are assigned, the MCDM literature offers a plethora of qualitative tools to determine the most appropriate assortment of parameters' values that, if chosen, is likely to lead to the desired system performance. It should be stressed again that both multi-objective optimisation and MCDM will lead to suboptimal solutions when compared to the approach used in model (1 - 7), but might, if the context dictates, lead to an overall better performance when all conflicting criteria should be improved. In other words, multi-objective optimisation and MCDM are decision-support tools that strike a balance amongst different conflicting objectives while single objective optimisation (the approach used here) minimises only one criterion on the expense of other variables. The next section presents the simulation model, and the approach that is used to improve other system criteria.

4.3 Simulation model

The simulation model employed in the framework belongs to the family of agent-based models (ABM). ABM, as has been discussed in Chapter 2, is a bottom-up modelling approach commonly referred to as individual-centric; meaning that each individual entity, along with its decision-making capability is modelled individually. In addition to being individual-centric, ABM also naturally lends itself to object-orientation [121] as, in addition to encapsulation, object-orientation allows handling complexity by means of modularization where the system is broken down into smaller individual entities (i.e.

objects) that are encapsulated with decision-making capabilities, and interact together to establish a system [102]. To present the ABM at a high-level, Figure 4.1 below represents a class diagram for the ABM. A class diagram is a Unified Modelling Language (UML) diagram, which represents a system's structure by presenting its data (parameters) and processes (functions) that the objects (entities) can perform.

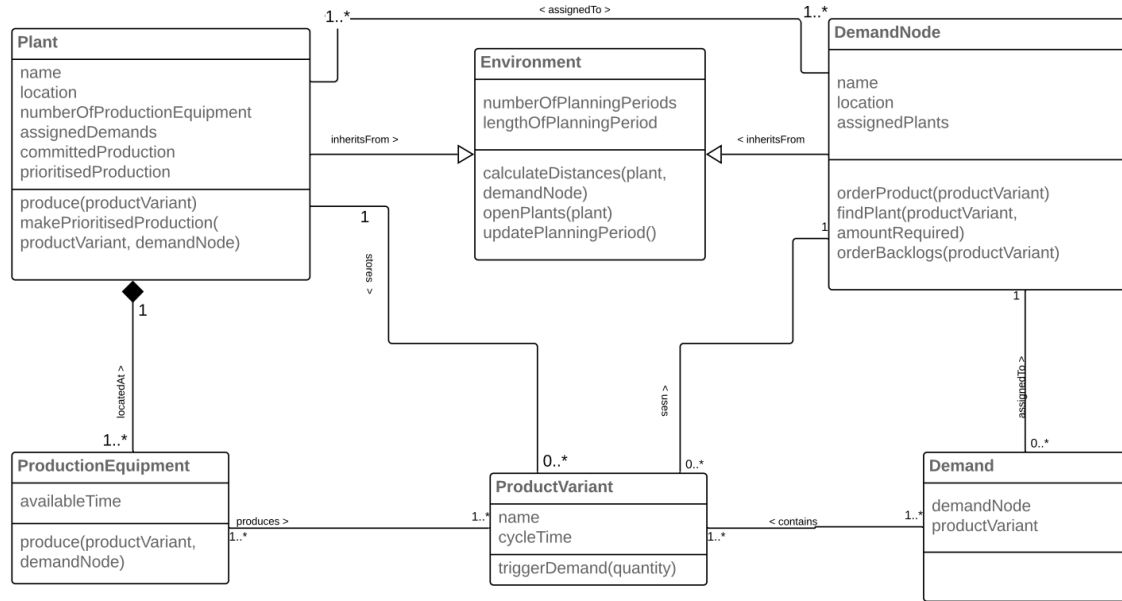


Figure 4.1 High-level generalised UML Class Diagram of the simulation model

To better understand the simulation model it is worthwhile to briefly discuss the concepts of object-orientation, classes and objects. In object-oriented modelling, as the name suggests, objects are the main building blocks of the model. Objects are instances of classes, which are templates that define objects. The ambiguity surrounding the concepts of classes and objects is best alleviated by a simplistic example. A model for example can represent a group of people performing different jobs in a shared environment (e.g. a model of a university). In an object-oriented model, each individual of these people can be modelled separately, and any number of people can be modelled. A *class* in object-oriented modelling acts as a template that stores data and functions of these people. For example, a class in this hypothetical simplistic example could store each person's data such as name and profession. Any individual student is an instance of the class Person. Therefore individual students are objects of the class Person. Using this powerful, and rather intuitive, modelling paradigm, one can include any number of interacting unique entities in a model. Classes can also contain functions, for example a student object can

have a function called: submit thesis. A lecturer can have a function: deliver seminar. Functions can be of any complexity; enabling individual objects to have decision-making abilities. To reiterate the suitability of ABM, powered by object-orientation, it is worthwhile to examine other simulation approaches (i.e. SD and DES) and how they approach the representation of individuality and autonomy. In SD, all individual, regardless of their differences are modelled in one block called *stock*. The individuality of people, in the previous example, is not accounted for. Therefore SD is suitable in modelling people to examine abstract issues such as population growth or decline where individualities (and if the study's goals require so) make little difference on achieving the study's aims. Moving to DES, if ABM is individual-centric then DES is process-centric. DES is appropriate to model processes [101] (blocks that individual objects pass through) therefore allowing observing queues, delays and resources utilisation. If the hypothetical university model is developed as a DES model, the individuals (students and lecturers) can have their own attributes (name and profession) but cannot have function within themselves. The functions (e.g. submit a thesis or deliver a seminar) in DES are integrated into the system, not within each individual. In order for a student to submit a thesis in the hypothetical DES model, then the student entity has to move through the system, and then arrive at a block within the system that performs the function (submit a thesis). To conclude, in ABM the entity (e.g. student) is active and decides for itself based on the functions incorporated in its container class. In DES, the entity is passive and waited for the system to tell it what to do.

Back to class diagrams, class diagrams are a particularly useful tool in presenting and communicating the structure and relationships between entities in object-oriented models [102]. Each block contains three sections, the upper section is the class name, the middle section contains the data (i.e. input parameters) that the class stores (and its objects use), and the bottom section contains the functions that these objects can perform.

To provide a high-level generalised composition of the simulation model, a class diagram is presented in Figure 4.1 above. This class diagram, similar to the general optimisation model formulation presented earlier, is very abstract and contains only the essential entities and relationships within the system. Class diagrams, however, provide a means of modularisation where the most basic entities and interrelation are represented in the

diagram, and then the user can add / subtract entities or relationships to fit the instance being studied. In Figure 4.1, the first class in the class diagram is Plant, which encompasses RdM facilities. The Plant class has parameters (input values) to distinguish each plant (object) from the others, of name, which is the location name where the RdM plant is to be set. Location is stored in the model in the form of latitudes and longitudes. Number of production equipment refers to the number of AM machines installed at this RdM plant. Assigned demands refer to the demand nodes that will receive their inventories from this plant. The functions incorporated in each plant are the production of products, in which the plant sends a production order to its AM equipment. Prioritised production is when the plant produces products for a demand node that experienced a shortage. In prioritised production, the plant temporarily halts the scheduled production and prioritises the production of products to supply to the demand node that experienced shortages. The number on the top-right corner of the Plant class (1..*) states that at least one plant has to exist in the system. The link between the Plant and DemandNode classes with the caption <assignedTo> means that each demand node has to be assigned to at least one plant. The link between the Plant and Environment classes with the caption *inheritsFrom* states that all the attributes (parameters) and functions in the Environment class are also attributes and functions for the Plant class. The Environment class represents the space where all the agents live and communicate, it could be thought of as *the world* or any other scaled-down space that the model entities populate. Finally, the relationship represented by a link with a black blank diamond represents a physical part-of relationship. For example, the ProductionEquipment class is a part of the Plant class; in other words AM equipment are always located at plants.

The remaining classes are ProductionEquipment, ProductVariant and Demand. ProductionEquipment is the class that encompasses the AM machines, it is always contained inside the Plant class (i.e. it inherits all the parameters and functions from its parent class). ProductVariant refers to the product that the AM equipment produce. Demand is a non-physical class that represents the demand requests (e.g. request 10 units of product variant x for demand node y).

Class diagrams are powerful tools to describe the structure of a system and the relationships between its different entities, and to make the model easily reproducible.

Class diagrams are, however, static, and do not represent the dynamic behaviour of a system, as well as the model's internal logic.

When the simulation starts, the parameters' values are imported from the optimisation model's output database. Then the RdM plants are located and are allocated capacities according to the network structure that the optimisation algorithm had already determined. For this part of the simulation, a database containing the coordinates for all the potential RdM plants is typically provided. The simulation model then reads the optimisation model's outcome for each potential site. To illustrate the communication between the two models regarding plants locations and capacities, Figure 4.2 below depicts a simplistic example of seven potential plant sites. The figure shows that two sites were chosen by the optimisation algorithm to set up plants on their location, namely potential sites C and E. The site set up at location C will consist of one AM machine, while the site at E will consist of three AM machines.

A	B	C	D	E	F	G
0	0	1	0	3	0	0

Figure 4.2 Simple illustration of RdM chosen sites communication

After the plants are located and allocated capacities, the model defines the interconnections between the different model's entities, and between the entities themselves and the environment which they populate. These interconnections are first defined implicitly between the plants that were just set up in the previous step, and the demand points that they are assigned. This is done through reading the decision variables Y_{jpt} from the optimisation model's outcome. These decision variables i.e. Y_{jpt} translate to: deliver Y units of product type p from RdM plant j to demand point i at planning period t . Both models (the optimisation and simulation) being multi-period models simply means that the models' parameters and variables change through time; hence the subscript $t \in T$ refers to the decision variable's value at the given planning period. A planning period may span for any length of time from hours to years. The simulation model loops through all values of Y_{jpt} and once it comes across a value that is greater than zero, it immediately establishes a connection between these two model entities.

Then the production schedules are determined (based on the optimisation model's outcome) during the given planning period. These schedules are communicated to the RdM plants through messages (data packets) exchange. Once the production schedules are set for the present planning period, each plant sends messages to the AM machines that are operating in it. AM machines' behaviour and decision making logic are regulated by statecharts; modelling construct based on UML's state machine diagram as shown in Figure 4.3 below.

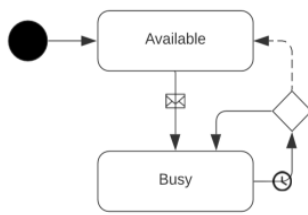


Figure 4.3 Statechart for AM

All AM machines at the start of each simulation replication, automatically enter the “Available” state where they are idle and not processing any production requests. Once a machine receives a message from its respective plant, the “Busy” state becomes active and the machine starts production immediately. Such production triggering messages contain the specifications and the type and number of units to be produced. It is worth mentioning here that the “Busy” state is rarely a standalone state, but is naturally a composite state i.e. a state that contains further states within, such as pre and post processing activities. It is, however, desirable in some cases to aggregate such processes together within a single state so as to maintain the model's complexity at an acceptable level. For the purpose of this research, it is sufficient to aggregate these activities into a single state, as the aim of this research is not to investigate and improve manufacturing processes, but to observe the emerging system-wide performance with regards to cost and service level metrics. It is however possible to incorporate any level of complexity into the model's statecharts.

Each plant's production schedule is determined from two factors: first the optimisation model's outcome, which determines the minimum production for each plant. The second factor is that each demand point, once it experiences inventory shortages sends a request, as will be explained shortly, so that supplies can be delivered as soon as possible. Each

time an AM machine finishes the production of a single unit, which its duration is stochastic and follows a probability distribution, it exits the “Busy” state and the produced unit is added to the respective plant’s inventory. On exiting, the statechart checks whether there are any prioritised production requests, which are given priority over scheduled production. If there are, then the production schedule is put on hold and the AM machine immediately starts production to cover these prioritised production requests. The production for the prioritised production requests follows a first-come-first-serve pulling strategy. If there are not any requests, then the AM machine checks whether the production schedule has been met or not. If it has been met then the machine enters the “Available” state and becomes idle, if not, it continues to produce as scheduled until all units are produced and there are no prioritised requests pending.

Once an inventory shortage occurs, or the re-order point has been reached, the demand point that experienced the shortage calculates the projected amount of demand for this particular product by comparing the demand rate for this particular product against the time left until next inventory replenishment as shown in (8). It should be noted here that the reorder point, or the amount of safety stock is determined by the decision-maker, and is therefore a model input. This has been chosen as a user model input because demand patterns vary greatly amongst different sectors, or even different products within the same sector. Therefore, to maintain the generalisability of the framework, this quantity of safety stock is determined by the model user in accordance with each respective product variant. In Eq (8), e stands for the time left until the end of the current planning period, and u is the number of time units (hours) in each planning period and d_{ipt} is the mean demand for the given product during the current planning period.

$$Order\ amount = \frac{d_{ipt}e}{u} \quad (8)$$

The demand point agent then contacts all plants to enquire about their statuses, it then chooses the plant that can deliver the required amount with the fastest time and sends a message containing the order details for production. The determination of the plant that will perform the production for the backlog is done through a brute-force algorithm as illustrated in Figure 4.4 below. The algorithm begins by creating an empty array with a size that is equal to the number of RdM plants. Then, in each plant’s respective location

in the array, the algorithm calculates the *estimated* time required for each plant to deliver the required products. The algorithm checks the status of each plant, and then calculates the estimated time to receive the requested products as depicted in Figure 4.4 below.

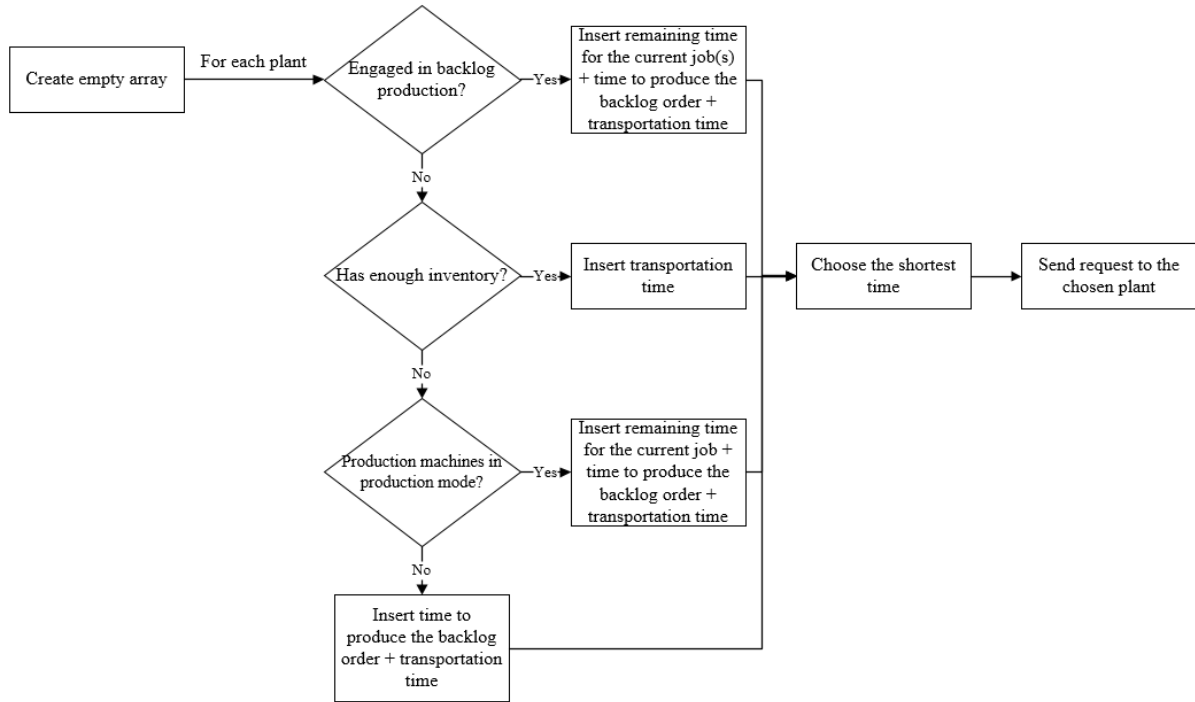


Figure 4.4 Inventory shortages production allocation algorithm

The production request (i.e. the message) is then sent to the chosen RdM plant where its production is prioritised over the set schedule. This prioritised production is inserted into the backlogs database that will be used later to refine the optimisation model's constraints. In the backlogs database, each optimisation-simulation iteration is represented as a column, containing the backlog amount for each product type, at each planning period for each demand point. By the end of each planning period, the products produced at each plant are delivered to their respective demand points. When the simulation time ends, the simulation model stores the values for the desired performance measures. The simulation model then performs several replications and calculates and stores values for the set performance metrics. The number of replications is determined by the confidence interval method as will be discussed in the next section.

The description provided above only describes the shared attributes of the simulation model that are used in all applications. Naturally, each application (i.e.) modelled system

will constitute a unique simulation model development. However, the shared attributes, logic and mechanisms were highlighted in this section. In the subsequent chapters, the simulation model for each application of the framework will be presented separately.

4.4 The unified decision-making framework

The two complementing decision aid tools presented earlier are incorporated in a unified framework where they operate, and communicate, in a recursive manner. To incorporate the real-life dynamic nature of the problem into the decision making process, the output of the ILP is fed into the stochastic individual centric (Agent-based) simulation model that incorporates modelling attributes such as complex interrelationships, nonlinearities and uncertainty into the decision-making environment. The simulation model then executes several replications and calculates key performance measures, such as the total cost of the system, frequency of the occurrence of unmet demands and average lead-times for unmet demands fulfilment. Since the simulation model is stochastic, the results generated from a single run are hardly insightful, therefore several replication of each simulation are performed in order to provide reliable performance measures. To determine the number of simulation replications per each RdM network structure (i.e. per each outcome generated from the ILP), the confidence interval method (CI) is used [99] as shown in equation (9) below. Confidence interval, as used here, provides “a statistical means for showing how accurately the mean average of a value is being estimated” [99, p.154].

$$CI = \bar{X} \pm t_{n-1, \frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}} \quad (9)$$

In equation (9) $\bar{X}$ is the mean of the simulation model’s output for the desired performance metric, $t_{n-1, \frac{\alpha}{2}}$ is the value of the t-distribution with $n - 1$ degree of freedom and a significance level equals to $\frac{\alpha}{2}$ where $0 < \alpha < 1$, finally σ is the standard deviation of the simulation output and n is the sufficiently large number of replications. When using the confidence interval method to determine the minimum number of simulation replications required to provide a sufficient level of accuracy, a significance level (α) is chosen by the decision-maker. The value of the chosen significance level chosen (α) states that the value of the *true mean*, which is the mean value of the chosen performance metric if the

simulation model is run for an infinite number of replications [99], has a probability of $1 - \alpha$ to fall within the confidence interval. To illustrate how the confidence interval method works, a graphical simplistic hypothetical example is provided below in Figure 4.5.

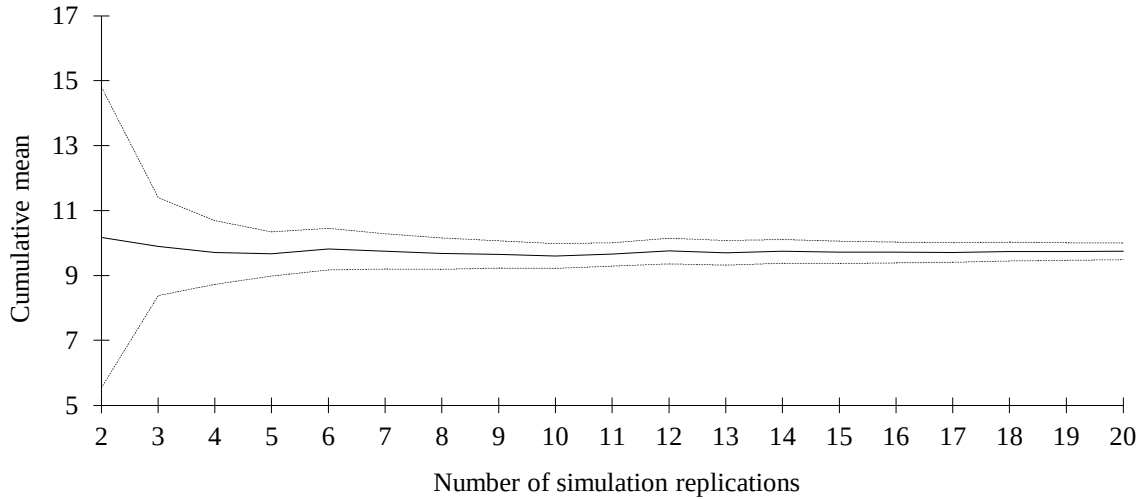


Figure 4.5 Confidence interval graphical example

Figure 4.5 above depicts randomly generated values to represent the simulation output of 20 replications where, in the simulation model, these values will be the values of the desired performance metric. The solid line in the middle represents the *cumulative mean* for the desired performance metric generated from the simulation model, and the dashed lines that bound the cumulative mean are the upper and lower bound of the confidence interval. It could be noticed from Figure 4.5 that the confidence interval narrows as the number of replications progresses. When the confidence interval method is used to determine the minimum number of simulation replications, the decision-maker typically chooses a desired confidence interval (e.g. 95%) and observes when the interval becomes, and remains, sufficiently narrow. In Figure 4.5 for instance, narrows down significantly after the 5th replication, and remains narrowing, but rather slowly, after that. In the example above, for instance, a confidence interval of 95% (based on applying equation 9) is reached after the 8th replication. One last thing to mention before this discussion resumes back to the decision-making framework is that it is not advised to stop right after the desired confidence interval is realised, it is always better to perform a few more replications to ensure that the confidence interval remains narrow. This is because, since

the output values are random, an anomaly in the outcome might slightly widen back the confidence interval, therefore performing extra replications will ensure that the confidence interval remains narrow.

Now back to the decision-making framework, the outcome of the simulation model is then fed back into the ILP where the constraints are refined to more realistically reflect the resulting system's performance. The nature of the constraints refinement depends entirely on the problem being investigated; it could be for instance: produce at least x units of product y at RdM plant z , or any other constraint suitable for the specific problem being modelled. This recursive process is then repeated until certain criteria that the decision maker sets are met as represented in Figure 4.6 below which depicts a high-level schematic of the modelling environment.

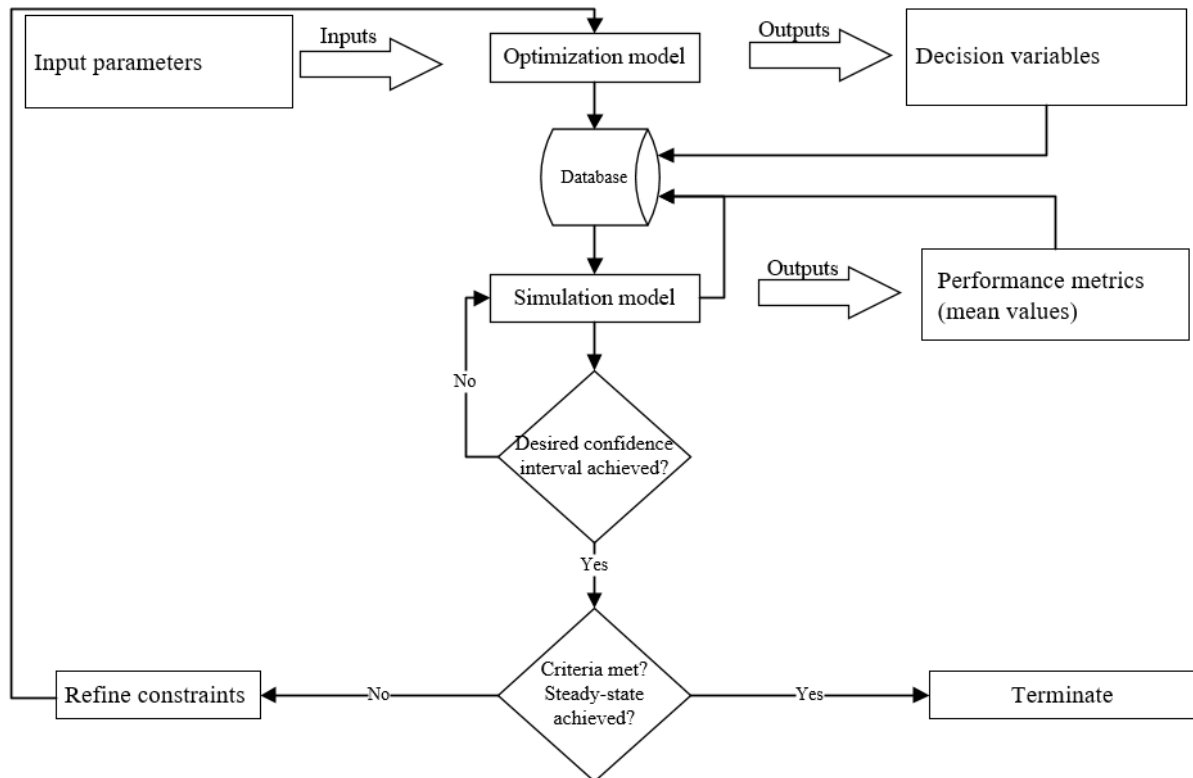


Figure 4.6 High-level schematic of the decision-making framework

It is worth mentioning here that the choice of modelling approaches to include in the framework do not have to be always the same. For example, the ILP model could be replaced with any other optimisation model e.g. nonlinear model. This however does not apply on the choice of the simulation model as the discussion in Chapter 2 showed that

ABM is more suitable to model decentralised autonomous entities (i.e. RdM network). The proposed framework bridges the literature gap, by first being a context-independent tool, where most of the previous research developed models for specific settings, particularly biomedical implants and spare parts. The framework also bridges the gap in the literature by modelling the collective impact of each of the decision-making levels on the rest of decisions recursively in a stochastic environment. The incorporation of optimisation and simulation together, in an RdM setting, results in gradual improvement on the system's performance. In each iteration, the collective impact of all decisions at all three levels of decision-making on one another is evaluated, and subsequently reflected in the system's performance measures. This process will accordingly recommend new values for the system's parameters in each successive iteration; striking a balance between the impact of all decision-making levels to achieve better performance measures in each iteration.

4.5 Summary

In this chapter, the generalised form of the decision-making framework has been presented at an abstract high-level. The shared elements and interrelationships of the framework's constituent models were presented and discussed at a high-level. The dynamics of the framework have also been discussed in this chapter.

To demonstrate the applicability of the framework, and to validate it, as was discussed in Chapter 3, two case studies are presented, applied to the framework and discussed in the next two chapters. Finally, before going through the practical implementation of the framework, it is important to mention that the framework's constituent models will be presented separately for each case study. This is because each of the case studies is considerably different from the other, and therefore requires unique mathematical / logical formulation. This, however, does not adversely impact the applicability of the framework on a wide variety of industrial settings; it just that each case has its own requirements that are different from the other. The essence of the framework i.e. its constituent models, the application process and the feedback mechanism remains the same for all industrial settings.

5 RdM for the production of spare parts- case study I

5.1 Background on the case study instance

The first case study employed in this research to validate the decision-making framework responds to the increased interest in the literature, that was highlighted in Chapter 2, with regards to the production of spare parts using AM technology. The case study was inspired by the work done in [17], which was discussed in Chapter 2, and borrows key parameters values from the paper. In [17], the authors developed an optimisation model on top of a simulation (cost DES model) to assess the viability of AM in the production of jet engine brackets. The paper takes the United States' 48 busiest airports (based on passenger traffic in 2016), which constitute 83% of the total passengers traffic in the USA, as both demand points and potential RdM facilities as shown in Figure 5.1 below. The first case study in this thesis follows the same suit and borrows some input parameters such as locations, demand rate and production lead time. The missing input parameters (and the additional ones) are carefully estimated based on contemporary literature and technical reports.



Figure 5.1 Demand points and potential RdM sites

Demand rate, in line with [17]’s approach, is assumed to be proportional with each airport’s respective traffic. Table 5.1 below summarises the demand points (i.e. airports) key input parameters. In Table 5.1, share of total demand, as the name suggests, refers to each respective airports share of the total demand, which is itself an aggregate input parameter for the framework. For example, if the total demand (for all airports for all types of parts variants) is assumed to be 100,000 parts each year, then ATL airport’s share of the total demand will be 7,310 ($100,000 * 0.0731$). Each airport’s share of demand for each part variant follows the same approach and will be explained shortly. The cost of establishing an RdM facility refers to the total cost associated with placing a facility with capacity level 1 (i.e. one AM equipment). The value for each location’s cost was calculated based on the assumption that the AM equipment used is a direct laser sintering (DLS) machine that costs \$600,000 [17]. The cost associated with each location is proportional to the total traffic (the busier the airport then the more costly it is to establish an RdM facility there), similar to demand share. This assumption has been made because the total cost is an aggregate cost of multiple cost elements, including personnel cost. The cost parameter, as with the cycle time parameter, have been assigned aggregate values in order to make it less detailed as real data regarding these parameters are not available. The cost of establishing an RdM facility is equal to the potential facility’s (airport) share of the total traffic multiplied by a constant and added to the DLS cost. The constant in this instance was chosen to be 5.

Table 5.1 Demand points input parameters

Reference number	Airport name	Three-letter code	Total traffic	Share of total demand	Cost of establishing RdM facility (\$)
0	Hartsfield-Jackson Atlanta International	ATL	46738828	0.0731	821,212
1	Los Angeles International	LAX	36739546	0.0575	774,242
2	Chicago O’Hare International	ORD	34807000	0.0544	763,636

3	Dallas/Fort Worth International	DFW	28892344	0.0452	736,364
4	John F. Kennedy International	JFK	26763037	0.0419	725,758
5	Denver International	DEN	26282242	0.0411	724,242
6	San Francisco International	SFO	23689957	0.0371	712,121
7	McCarran International	LAS	21245433	0.0332	700,000
8	Seattle/Tacoma International	SEA	20180429	0.0316	695,455
9	Charlotte Douglas International	CLT	20003812	0.0313	693,939
10	Phoenix Sky Harbor International	PHX	19558474	0.0306	692,424
11	Miami International	MIA	19056337	0.0298	689,394
12	Orlando International	MCO	18641627	0.0292	687,879
13	George Bush Intercontinental/ Houston	IAH	18402879	0.0288	686,364
14	Newark Liberty International	EWR	18189705	0.0284	684,848
15	Minneapolis-St Paul International	MSP	16827248	0.0263	678,788
16	Logan International	BOS	16384706	0.0256	677,273
17	Detroit Metro Wayne County	DTW	15565642	0.0243	672,727
18	LaGuardia	LGA	13559959	0.0212	663,636
19	Philadelphia International	PHL	13534364	0.0212	663,636
20	Fort Lauderdale-Hollywood International	FLL	13002486	0.0203	660,606

21	Baltimore/Washington International Thurgood Marshall	BWI	11543328	0.0181	654,545
22	Ronald Reagan Washington National	DCA	10571032	0.0165	650,000
23	Chicago Midway International	MDW	10432344	0.0163	648,485
24	Salt Lake City International	SLC	10285694	0.0161	648,485
25	Washington Dulles International	IAD	9749989	0.0152	645,455
26	San Diego International	SAN	9639689	0.0151	645,455
27	Tampa International	TPA	8522772	0.0133	639,394
28	Portland International	PDX	8343693	0.013	639,394
29	Dallas Love Field	DAL	7223271	0.0113	633,333
30	Lambert-St. Louis International	STL	6419698	0.01	630,303
31	Nashville International	BNA	6000123	0.0094	627,273
32	William P Hobby	HOU	5929329	0.0093	627,273
33	Austin - Bergstrom International	AUS	5712783	0.0089	625,758
34	Metropolitan Oakland International	OAK	5560309	0.0087	625,758
35	Louis Armstrong New Orleans International	MSY	5219411	0.0082	624,242
36	Kansas City International	MCI	5086194	0.008	624,242
37	Raleigh-Durham International	RDU	4975665	0.0078	622,727
38	Norman Y. Mineta San Jose International	SJC	4918935	0.0077	622,727

39	John Wayne Airport- Orange County	SNA	4843051	0.0076	622,727
40	Sacramento International	SMF	4631116	0.0072	621,212
41	Indianapolis International	IND	3938248	0.0062	618,182
42	San Antonio International	SAT	3908897	0.0061	618,182
43	Southwest Florida International	RSW	3890676	0.0061	618,182
44	Cleveland-Hopkins International	CLE	3800535	0.0059	616,667
45	Pittsburgh International	PIT	3707037	0.0058	616,667
46	Port Columbus International	CMH	3320485	0.0052	615,152
47	General Mitchell International	MKE	3144797	0.0049	613,636

The authors of [17] chose the aeroplane's engine brackets because the manufacturer of the jet engines, GE, has expressed interest in producing this part using AM technology and, more importantly, the chosen part is a non-critical part. Due to the function they serve, non-critical parts do not contribute to the safety of an aeroplane, and are subsequently subject to less restrictive regulations from approving bodies [17]. In this thesis, two extra parts are added to the assortment of parts that are envisioned to be locally produced using AM technology. This addition of two parts will add a further dimension of complexity to the model (e.g. prioritization of production and the observation of possible emerging queues). In addition, the departure from the single part production facilities will further justify the shift to RdM production in local facilities, as establishing a network for the production of a single part is not always necessarily a realistic choice. The parts variants input parameter data are displayed in Table 5.2 below.

Table 5.2 Parts variants input data

Part reference	Mean cycle time (hours)	Production cost (\$)	Share of demand
Part 1	7.5	577	25%
Part 2	20	806	60%
Part 3	14.5	81	15%

These input data were carefully selected to reflect three classes of possible spare parts variants. These classes are first parts with high cost, and relatively low demand rate and production time (Part 1). Next is parts with high cost, high demand rate and long production time (Part 2). And lastly comes the class of spare parts with low cost and share of demand, and medium production time (Part 3). These three classes of spare parts were devised to reflect different materials and production attributes of spare parts in order to improve the model's representation of reality. The variability of materials used to produce the parts presented in Table 5.2 should be stressed here. This is most apparent in Part 3 where it is noted that Part 3 does not follow suit with Part 1 and Part 2 (i.e. higher cycle time entails higher production cost due to more material used). The significantly lower production cost of Part 3 is due to the different material used to build that part. In this case study, Part 1 and Part 2 are metal parts, while Part 3 is plastic, hence the significantly lower production cost. The characteristics of these three groups of parts variants were thoroughly discussed with the experts that participated with their opinions in this study. Particularly, Expert 3 (Technical services director) suggested these three groups of parts variants to better represent a realistic assortment of spare parts to be produced locally via AM. All other experts (except the software architect who was not involved in the models' assumptions) approved of these values. The cycle time in the simulation model is normally distributed with the mean listed in Table 5.2 above, and the standard deviation being 20% of the mean value. To avoid overly extreme or even negative values, which is a risk when using normal distribution, the truncated form of the normal distribution is used. The truncated normal distribution, when drawing a value simply disregards any values that fall outside the specified upper and lower bounds. The upper and lower bounds

were set to 50% on the lower bound and 150% on the upper bound of the mean production time. The share of demand for each part is its share (rounded to the nearest integer) from each airport's total demand. To explain it clearly, back at the example provided earlier, the annual total demand at ATL airport was determined to be 7,310 parts. Therefore, demand for Part 1 at ATL is equal to 1,828 ($7,310 \times 0.25$), for Part 2 is 4,386 ($7,310 \times 0.6$), and finally demand at ATL for Part 3 equals 1,097 ($7,310 \times 0.15$). Growth in demand is considered in this case study; demand, which is a stochastic parameter is assumed to grow by 5% each year from the precedent year's value. Demand for each part variant at each airport is assumed to follow the truncated normal distribution with the mean calculated as explained in the previous paragraph, and a standard deviation of 20%. The normal distribution of the demand is truncated at the lower bound at 0 to eliminate any, rather unlikely, negative values. It is however unbounded on the upper bound in order to include any extreme demand values that might be generated. Finally, cycle time, same as the cost of establishing an RdM facility, is also an aggregate parameter i.e. it is the entire time taken from transforming raw material into a final functioning product, Inventory holding cost for the stored part, which is an important cost contributor, is assumed to be constant for all parts at all locations at 20% of the part's cost, per year. The holding cost in the simulation model is updated daily ($0.2 \times \text{part cost} / 365$) to provide a more accurate representation of incurred cost. Transportation cost, on the other hand, is calculated differently than [17]. In [17], the authors assume a fixed transportation cost per part regardless of the distance travelled. In this paper, a different approach is used as below;

$$\text{Transportation cost} = g_{ij} \times s \quad (10)$$

Where g_{ij} is the distance in miles between the demand point and the fulfilling site, and s is the fixed cost per part per unit distance. This parameter i.e. s is assumed to be \$0.2 / mile. For example if a part is to be transported to a demand point that is 1,000 miles away, then the transportation cost will be \$200.

5.2 Optimisation model

The optimisation model (ILP) in this case study is formulated as a multi-period capacitated fixed charge facility location model [86] with inventory decisions as explained in Chapter 4. Fixed charge problems belong to the family of discrete facility

location models, where the potential facilities (in this case RdM plants) could only be located at the nodes of a graph, i.e. in predefined potential sites. These potential sites could be predefined by the decision-maker, or they could be a subset of the demand point's locations. This is in contrast to continuous location models where facilities could be located at any point on a graph [86]. The model aims to minimise the overall total cost associated with establishing the proposed manufacturing system. The output of the optimisation model, that will be used later as input for the simulation model, includes the following decisions:

- Number and locations of RdM facilities.
- Allocation of demand nodes to RdM facilities.
- Production amount for each product variant at each RdM facility.
- Quantities of each product variant to be transported from RdM facilities to demand nodes.
- Inventory level and inventory replenishment amounts at each demand node.

Now the optimisation model notation and mathematical formulation will be presented and discussed next.

5.2.1 The model

Total cost =

$$\min \sum_{j \in J} \sum_{k \in K} f_{jk} X_{jk} + s \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} g_{ij} Y_{jipt} + \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} h_{pi} a_p (Y_{jipt} + Z_{pit}) / 2 \quad (11)$$

s.t.

$$\sum_{i \in I} \sum_{p \in P} Y_{jipt} b_p \leq u \sum_{k \in K} X_{jk} \quad \forall j \in J, \forall t \in T \quad (12)$$

$$v_i + \sum_{j \in J} (Y_{jip_{t_0}} - Z_{pit_0}) = r_{ipt_0} \quad \forall i \in I, \forall p \in P \quad (13)$$

$$Z_{pit-1} + \sum_{j \in J} (Y_{jipt} - Z_{pit}) = r_{ipt} \quad \forall i \in I, \forall p \in P, t > 0 \quad (14)$$

$$Z_{pit=T} = 0 \quad \forall i \in I, \forall p \in P \quad (15)$$

$$X_{jk} \in \{0, 1\} \quad \forall j \in J, k \in K \quad (16)$$

$$Y_{jpt}, Z_{pit} \in \mathbb{Z}^+ \quad \forall i \in I, \forall j \in J, \forall t \in T, \forall p \in P \quad (17)$$

Objective function (11) minimises the total cost of establishing and operating the proposed system. The first term of the function minimises the cost of establishing RdM plants at different capacities where production hours cannot exceed the number of products produced multiplied by their respective cycle times. The second term calculates the variable supply weighted cost of supplying parts to demand nodes. The last term minimizes the inventory holding cost for the parts stored at the demand points.

Constraints set (12) guarantees that the maximum capacity of each plant is not exceeded. Constraints sets (13), (14) and (15) are the inventory balance constraints that enforce the inventory left from each previous planning period to be added to the next one. Since enforcing the formal formula of inventory balance to the first planning period (index t_0 is not defined), it is necessary to account for the first planning period in a separate set of constraints, here constraints (13). Constraints (14) enforce the inventory left over from each planning period at each location to be added to the next planning period. Constraints (15) enforce the inventory remaining at each demand node at the end of the last planning period to be zero. Although these constraints (i.e.15) might not be necessary from a practical standpoint, they serve the purpose of providing a more accurate total cost. Inventory balance constraints also ensure that no oversupply of parts that far exceeds demand occurs. Finally, constraints (16) and (17) are the binary and integrality constraints, respectively.

In case of envisioned RdM systems where the bulk of manufactured goods are produced via AM, equation (11) and constraints (12) and (16) could be slightly changed to simplify the model and relieve the computational time required to run the search algorithms. To achieve this simplification, the set of capacities K would be removed, and the binary decision variables X_{jk} (which translate to: locate RdM plant at site j with capacity k) would become integer decision variables X_j indicating the capacity (number of AM machines) in the proposed site. For example, a value of X_j that is equal to 0 indicates that no RdM plant is to be set in potential site j , while a value of X_j that is equal to 3 means: locate an RdM plant at site j and install three AM machines there. Therefore decision variable X_j , equation (11) and constraints (12) and (16) would become, respectively as follows:

X_j Number of AM equipment to locate at potential RdM site j .

$$Total\ cost = \min \sum_{j \in J} f_j X_j + s \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} g_{ij} Y_{jip t} + \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} h_{pi} a_p (Y_{jip t} + Z_{pit}) / 2 \quad (18)$$

$$\sum_{i \in I} \sum_{p \in P} Y_{jip t} b_p \leq u X_j \quad \forall j \in J, \forall t \in T \quad (19)$$

$$X_j \in \mathbb{Z}^+ \quad \forall j \in J \quad (20)$$

Before presenting the optimisation model's assumptions and limitations, it is worth discussing how time (i.e. planning periods) is represented in the model. Since the model is multi-period, several planning periods each consisting of a fixed number of time units are modelled. To explain more, in this case study, the entire planning horizon consists of five years and each planning period (t) corresponds to one year. It is however impractical to model relatively short durations (e.g. cycle time for the production of one unit) as fractions of a year. Therefore the modelling time units has been chosen to be represented in *hours*. Going back to the optimisation model, the parameter u which corresponds to 'maximum production time per production equipment per planning period' is measured, in the instance of the present case study, in hours per planning period. For example, if an AM equipment is assumed to function all year without any breaks or maintenance, then u will be equal to 8,760 (number of hours per day $\times$ number of days per year i.e. 24×365).

It is important to point out that the ILP suffers a number of limitations that allow maintaining a sufficient degree of simplicity in order to keep the model tractable, presentable in closed format and solvable to optimality in reasonable amount of time. One important aspect that should be discussed before presenting the list of the optimisation model's limitations is the depreciation cost of AM equipment. In order to accurately model total costs incurred by a production system, both during setting up and operation, depreciation and end-of-life scenarios should be considered. This is because, as mentioned earlier, AM technologies are relatively new and fast improving, therefore potentially rendering today's AM equipment obsolete within a few years. Therefore, in order to better capture all cost elements of the manufacturing system, an additional cost

element could be added to Eq (18) representing the remaining value of the AM equipment at the end of the modelling period (i.e. the remaining value of the AM equipment will be subtracted in Eq (18)). This term was however not included in the model due to lack of data with regards to the relatively new AM equipment. However, depreciation is presumed linear and is incorporated into the cost of facilities. The rest limitations of the optimisation model are summarized below:

- All parameters are deterministic.
- Depreciation of AM machines is linear and is incorporated into the cost of facilities.
- Production activities (e.g. pre and post processing) are aggregated into the total time of producing a product.
- Holding cost of raw materials is not included in the calculations.
- Raw materials are assumed to be always available.
- Cost of personnel is incorporated into the total facilities' costs.
- Transportation is assumed to be uncapacitated.
- All produced parts are assumed to meet the required specifications (i.e. no rejections).
- Demand is assumed to occur uniformly and products replenishment is instantaneous.
- Backlogs are not allowed.
- AM machines' setting up and maintenance times are aggregated into the production time of each product.

It is clear that some of these limitations could seriously affect the outcome and credibility of the model. Unfortunately, addressing each of the abovementioned limitations in analytical closed form will quickly result in an intractable model. Fortunately, simulation provides a means to efficiently account for these limitations. In cases of system design, where the system does not yet exist in reality, simulation on its own, though useful, is not sufficient to determine values for the envisioned decision variables. Simulation modelling can only evaluate the performance and provide different performance measures. Values for these system's parameters have to come from somewhere, in the case of simulation only, the decision maker or the modeller injects parameters values into the simulation

model based on either instincts, rules of thumb, or some methodical decision making technique. In the case of optimisation, however, these parameters could be determined, sometimes, to optimally using mathematical programming or heuristics.

5.3 Simulation model

The simulation model is triggered to run once the optimisation model has completed running and produced an outcome. The outcome of the optimisation model is then stored in a database that is in turn accessed by the simulation model. The database is a spreadsheet containing the figures for the decision variables including the number and locations of RdM facilities, their capacities (i.e. number of AM machines installed in each plant), and the periodic replenishment amounts of each of the products (parts) that are produced locally via AM.

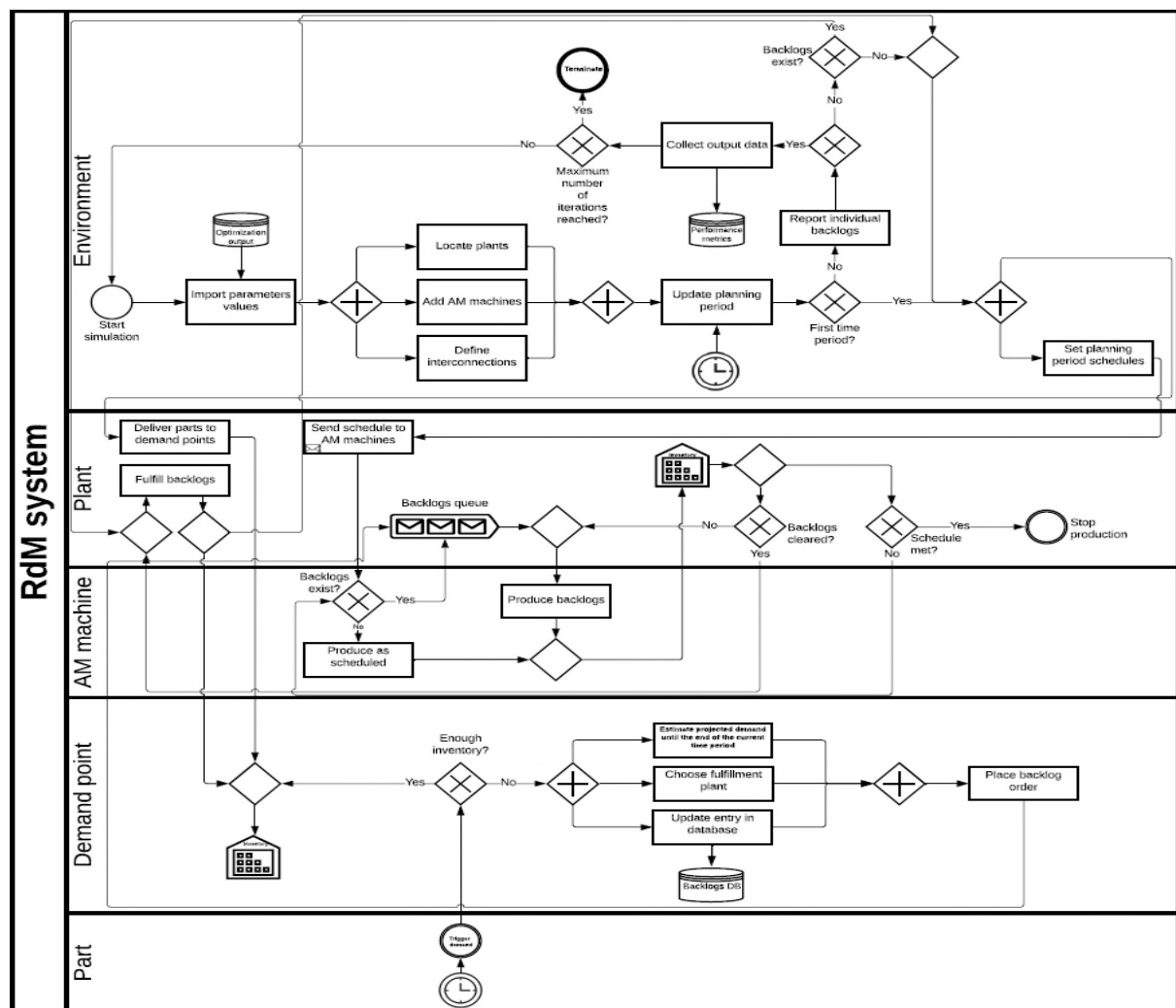


Figure 5.2 Simulation model process map

When the simulation model starts, it imports the parameters' values that were generated by the optimisation model. From these imported values, the simulation model locates RdM plants at the chosen locations, adds AM equipment to the RdM plants and defines the interconnections between the model's entities as was described in Chapter 4.

Once the plants are located and the AM machines added and the interconnections established, a timed function is called to update the value of different parameters and to trigger different other functions. This function, which is named "update planning period" in Figure 5.2 is called at the beginning of each simulation replication, and at the end of each planning period. The end of each planning period is reached once a certain amount of time elapses (i.e. at the end of each year in the case of this case study). This function first checks whether it is called at the beginning of the simulation run or at the end of a planning period. The only difference is that if it is called at the beginning of a simulation run, then there is no possibility of a backlog at any demand point, so the simulation engine immediately skips to set the new planning period's production schedule plans and shares them with their respective plants.

These schedules are then communicated to the RdM plants through messages as was explained in Chapter 4. Once each of the production schedules for the present planning period is determined, each plant sends messages to the AM machines that are operating in it. AM machines' behaviour and decision making logic is identical to that in Figure 4.3.

In this case study, each individual part is modelled individually as an agent, and as time progresses each part triggers demand within itself. The stochastic time interval between demands is calculated through dividing the length of each planning period by each part's projected demand during that planning period. For example, if a planning period consists of 10 hours, and the projected demand is 2 units throughout these 10 hours, then the interarrival time will be the truncated normal distribution for 5 hours. Once demand is triggered (i.e. a part needs replacement), the corresponding part's agent communicates with its respective demand point. The demand point agent checks its inventory of the requested part, if this part exists in inventory then it is replaced from existing inventory and no further escalation is required. If this part was out of stock, or the reorder point has been reached, then the respective demand point agent calculates the projected amount of

demand for this particular part by comparing the demand rate for this particular part against the time left until next inventory replenishment similar to equation (8) in Chapter 4.

The demand point agent then contacts all plants to enquire about their statuses, it then chooses the plant that can deliver the required amount with the fastest time and sends a message containing the order details for production. The determination of the plant that will perform the production and delivery for the backlog is done as was described in Figure 4.4.

The production request (i.e. the message) joins a queue for backlog requests that are prioritized over scheduled production. This backlog is inserted into the backlogs database that will be used later to refine the optimisation model's constraints. In the backlogs database, each optimisation-simulation iteration is represented as a column, containing the backlog amount for each product type, at each planning period for each demand point.

The timed function "update planning period" is automatically called inside the environment agent at the end of each planning period. Since the model has progressed beyond the first planning period, the function checks whether any of the demand points has outstanding backlog requests. If it does find any, it will immediately fulfil the backlog from each demand point's respective plant. Then the process resumes as explained earlier. No production schedules are shared with the plants at the end of the planning period before the last (i.e. t_{T-1}) as this will entail both production and holding costs for a period of time that is not modelled. In simple terms, since the model will run for only a finite amount of time (similar to the one the optimisation had produced results for i.e. 5 years), the output performance measures have to reflect metrics associated only with the modelled time span.

At the end of the last planning period, the simulation model calculates both cost and service level performance metrics and stores them in a database. This database i.e. the simulation model's outcome database contains the performance measures e.g. total cost and total backlogs represented as columns for each iteration. Then statistical calculations are performed on the results, particularly regarding mean values of the service level metrics, are performed and the results stored in a database. This database will later be accessed by the optimisation model. After storing the simulation model's outcome, the

model then calculates the confidence interval, as was shown in Chapter 4 in equation (9). Once a sufficiently satisfactory (usually 95%) confidence interval is reached, the simulation model terminates. It is important to reiterate again that for stochastic models, as is the case with this model, reaching the desired confidence interval is not always sufficient to determine the number of simulation runs [99]. This is due to the fact that relatively extreme simulation outputs could raise the confidence interval above the desired level. To address this issue, the modeller could run the model successively for several further runs to ensure that the mean of the outcome is consistent.

5.4 Recursive optimisation-simulation

After the first optimisation run (the integer programming model), where the outcome is passed to a database, which is then accessed by the simulation model to feed the input parameters values, the simulation model is triggered to run. After completing a number of simulation iterations (determined by the narrowness of the confidence interval), the mean of the service level performance metrics (could be the number of backlogs occurrences or lead time or any performance metric of the decision-maker's choice) is calculated and passed to a database. The mean values of the desired performance metrics are then fed again as either new constraints, or are added to already existing constraints to refine the optimisation outcome.

To provide a meaningful feedback to the optimisation model, at each simulation replication, the frequency of backlogs occurrences at each location, per each part and planning period were recorded in a database. After the specified number of replications is completed, the mean average for the entries in the backlogs database is calculated (q_{ipt}). Then the parameter (q_{ipt}) is passed to the inventory balance constraints as a surplus production stipulation; hence transforming constraints (13) and (14) in the optimisation model to the following:

q_{ipt} Surplus production of part p delivered to demand point i during planning period t .

$$v_i + \sum_{j \in J} Y_{jip t_0} - Z_{pit_0} = r_{ipt_0} + q_{ipt_0} \quad \forall i \in I, \forall p \in P \quad (21)$$

$$Z_{it-1} + \sum_{j \in J} Y_{jip t} - Z_{it} = r_{ipt} + q_{ipt} \quad \forall i \in I, \forall p \in P, \forall t \in T, t \neq 1 \quad (22)$$

To better understand the process, and to test the validity of the framework, a numerical experiment is presented and the output analysed in the next section.

5.5 Numerical experiments' results and discussion

The problem instance discussed in the previous section has been applied to the decision-making framework. The optimisation model was coded in Python and solved using Gurobi 8.1.1, a commercial linear and quadratic solver that implements branch and cut algorithms [122] for integer and mixed-integer programming models. The simulation model was coded in Java and implemented in AnyLogic 7.3.2 University Edition, a Java based commercial simulation modelling platform. The experiments were implemented on a PC with Intel core i5 2.4GHz and 8GB RAM. The communication between the optimisation and the simulation model has been performed manually in this case study (and the one presented in the next chapter). This is due to licensing limitations where the AnyLogic University Edition, which was the platform used to conduct all simulations, does not support exporting models as standalone Java applications. Therefore, it was not possible to call the simulation model automatically from the optimisation model. This process, however, could be automated fairly easily without any human intervention if the simulation model was run as a standalone Java application (which requires a professional license that Cranfield University does not possess).

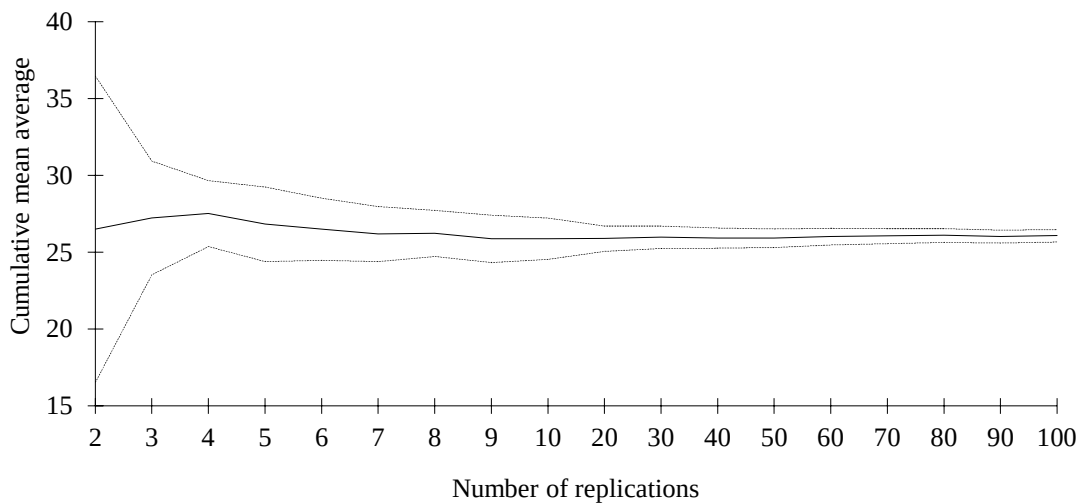
When run, using the parameters provided in the previous section, the optimisation model determined the opening of four RdM plants, all with single capacity as shown in Figure 5.3 below.



Figure 5.3 RdM network topology

It is important to point out, before discussing the optimisation model's outcome, that when all the parameters' values in the simulation model are fixed, the gap between the optimisation and the simulation model outcomes is very close 0%. It is, however, not exactly 0% because, as explained earlier, the cost values are updated on a daily basis (with regards to costs) in the simulation model, while they are aggregated and updated on a yearly basis in the optimisation model. In addition to the difference in the cost values update mechanism in both models, the optimisation model is deterministic, while the simulation model is stochastic. This uncertainty in the simulation model will lead to different cost values in each simulation run due to the existence of stochastic parameters. Before running the simulation model for several replications, it is important first to determine the minimum number of replications required in order to achieve the desired confidence interval, which was set at 95%. In order to do so, first the performance metric that the confidence interval is measured against has to be identified. The lead time along with the frequency of the occurrence of backlogs have been chosen, as will be justified shortly, as the performance measures to be improved. Then, 10 simulation replications were run and the narrowness of the confidence interval for both performance measures was observed. At the 10th replication, the deviation of the cumulative mean from both sides of the confidence interval for the lead time was 5.2%, which indicated a confidence

interval of 94.8%. The next set of replications consisted of 20 replications and the confidence interval was 96.7% then. As for the frequency of the occurrence of inventory shortages, at the 10th replication the confidence interval was 93.33%, while the 20th replication it increased to 95.04%. As a result, and to accommodate for future uncertainty, a total of 100 replications were chosen in order to remain sure that the confidence interval at future iterations will not widen due to increased uncertainty. Each replication only took a few seconds to complete, so the time required for conducting 100 replications was not an issue. A lower number of simulation replications might however suffice, but as the system's performance improves, it will take more replications in order to maintain the narrowness of the confidence interval. This is because as experiments progress (i.e. more optimisation-simulation iterations are made), the performance measures (lead time and frequency of inventory shortages) improves, while the level of uncertainty remains fixed. In other words, the same degree of fluctuation maintains, but within tighter bounds. Moreover, increasing the number of replications to any number will only improve the accuracy of the output (although rather slightly after a certain number of replications). To demonstrate the aforementioned points graphically, Figure 5.4 below depicts the graphical representation for 100 replications for the first and 8th optimisation-simulation iterations against lead time.



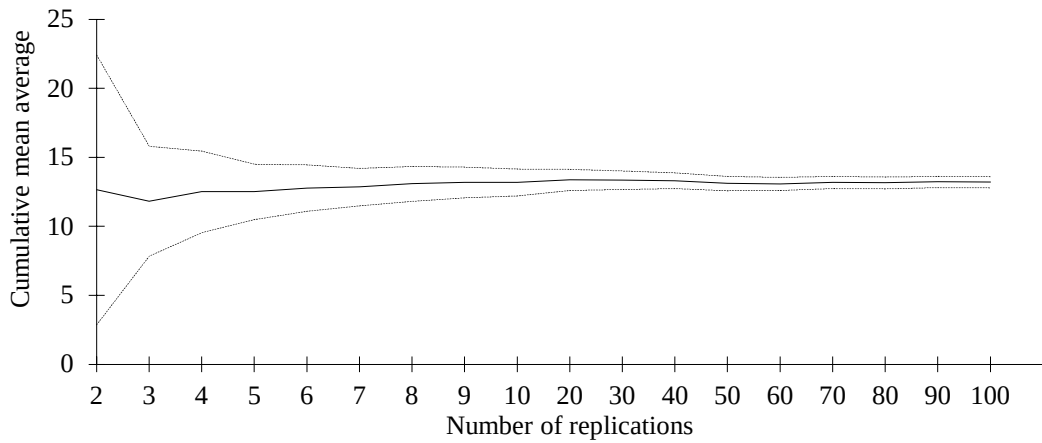


Figure 5.4 Confidence intervals for the first (up) and 8th (bottom) optimisation-simulation iterations against lead time

To illustrate how the confidence interval takes longer to narrow down as the number of optimisation-simulation iteration increases, Figure 5.5 below depicts the later part (from the 10th replication on, with 10 replications increments) of the confidence interval for the simulation replications of the 8th iteration. Figure 5.5 shows that the confidence interval almost ceases to narrow down after the 50th simulation replication. Therefore, in order to generate representative outcome of the system, the simulation model has to be run with random parameters at least 50 times.

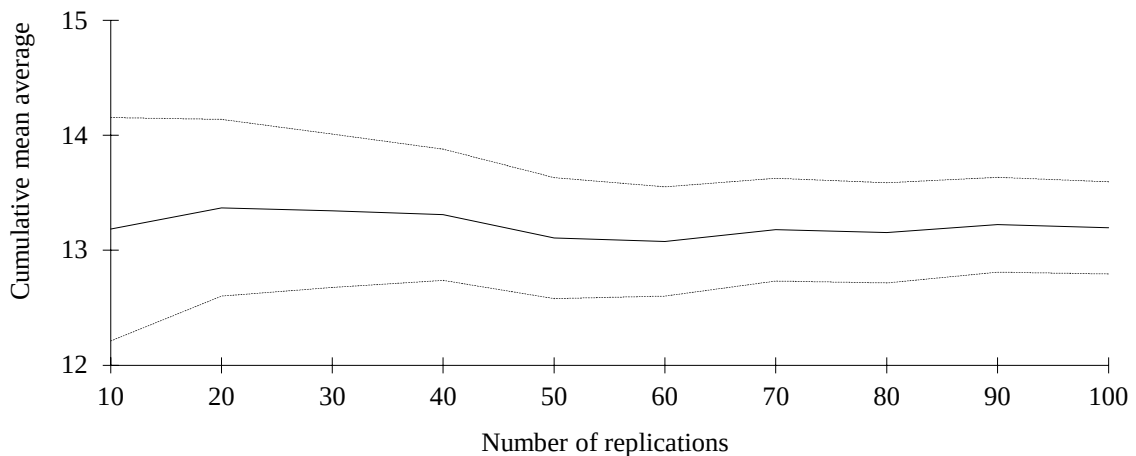


Figure 5.5 Confidence interval for the later replications of the 8th optimisation-simulation iteration against lead time

When the simulation model was run for several replications, using the values generated by the optimisation model, it became clear (as will be shortly demonstrated from the results) that the generated outcome needs further refinement in order to be considered as a valid alternative (or more precisely complementary) approach of manufacturing. As mentioned earlier, lead time and the frequency of the occurrence of unmet demands (or backlogs) were chosen as the performance level metric to improve. This is mainly because these two performance measures in the simulation model were observed to vary widely, as much as 52% between the highest and lowest values between runs for the lead time and 67% for the occurrence of unmet demand. These fluctuations, along with the natural tendency to improve service-level performance measures while minimising cost make these two performance measures appropriate to accurately measure the confidence intervals, and improve their performance. Long lead times and frequent backlogs can also have undesirable impact on the performance of a system, particularly with relation to inventory replenishment and planning.

In order to provide a reference scenario to compare the manufacturing system performance when adopting an RdM paradigm, the same case study is tested on a centralised production system scenario. In order to choose the optimal location for the centralised production facility, the same optimisation model has been used, but with removing the capacity constraints adding an extra constraint to limit the number of RdM locations to one. The location cost in the Centralised scenario is assumed to be half of that (total location cost) in the distributed scenario. This is because of the high cost associated with AM production along with the high operators cost in AM-powered RdM facilities. The extra constraint to enforce the setting up of one production site only is outlined below in equation (23).

$$\sum_{j \in J} X_j = 1 \quad (23)$$

The cycle time in the Centralised scenario is also assumed to be stochastic and is assumed to be the same as of that in the RdM scenario. In reality, however, traditional manufacturing is likely to be faster than AM production. But in this research, cycle time is assumed to be the same in the traditional and RdM scenario because traditional production typically include long setup times, and production is usually performed on

multiple machines in the same job shop, or even production takes place in different places. Transportation between the central production facility and the demand nodes is assumed to be the same as in the RdM facility (a function of distance), which was discussed earlier in this chapter. The production system for the Centralised scenario is illustrated in Figure 5.6 below.



Figure 5.6 Centralised production scenario

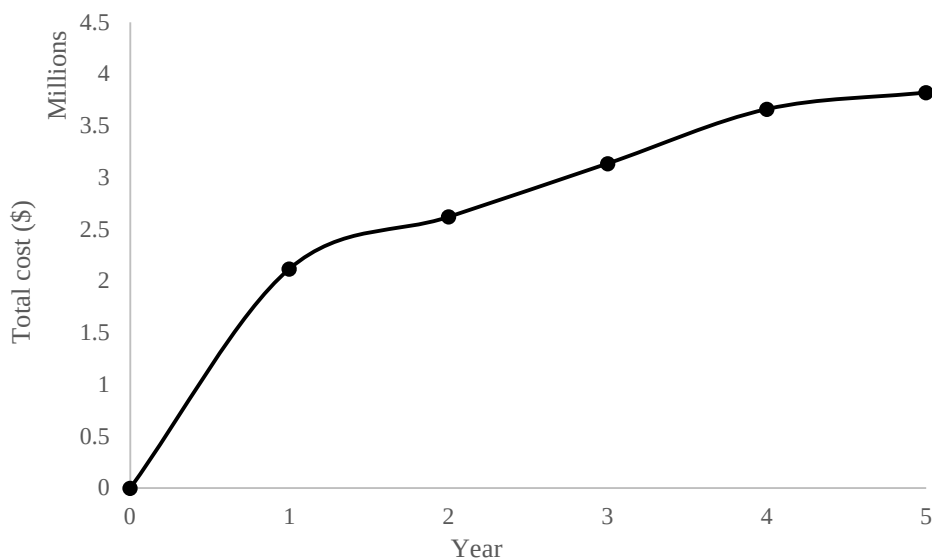
When applying the framework on both the Centralised and RdM scenarios, it took 10 optimisation-simulation iterations for the RdM scenario in order to reach steady state (where no further improvements were achieved), while it took 7 iterations for the Centralised scenario. The mean values for the performance metrics for the first optimisation-simulation run are outlined in Table 5.3 below, where all costs are in US Dollar.

Table 5.3 Mean values for the first optimisation-simulation run

Performance metric	Centralised scenario	RdM scenario
Total cost	3,743,912	3,893,962
Location cost	1,260,606	2,510,606
Inventory holding cost	678,211	674,534

Transportation cost	1,805,095	708,822
Lead time (in hours)	66.8	26.08
Frequency of shortages	131	237

Looking at Table 5.3, one can notice that the total cost of the two scenarios is very close, with a slight advantage to the Centralised scenario. The constituent cost segments are, however, substantially different. The location cost in the Centralised scenario is almost half of that of the RdM scenario; i.e. half the cost of establishing an RdM facility at the central location with 4 AM equipment. This result, as discussed earlier, reflects the costliness of acquiring and operating AM equipment compared to traditional manufacturing equipment and processes [17,111]. To further examine the growth of costs in both scenarios, Figure 5.7 depicts a cumulative cost vs time graph for both the Centralised and the RdM scenarios over time. It could be noticed from Figure 5.7 that the RdM scenario entails a considerable capital investment; which could be noticed from the sharp increase in cost incurred in the first year. Then, after the capital investment (setting up cost) is incurred, the RdM scenario becomes more cost efficient than the Centralised one, bearing in mind that a detailed account of depreciation cost might yield different results.



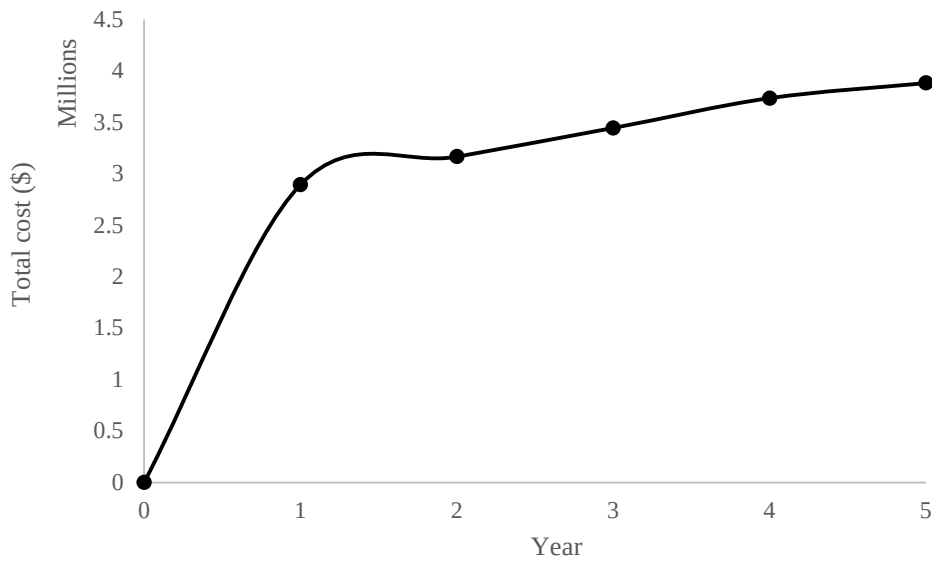


Figure 5.7 The increase in cumulative cost vs time for the Centralised (up) and RdM (bottom) scenarios

Inventory holding cost in both scenarios is very close to one another. This is because demand rate in both scenarios is the same; demand is triggered and therefore inventory level changes at the same (stochastic) rate, hence the close values. Transportation cost is the cost segment where RdM scenario is considerably more cost efficient than the centralised one. It is natural for this performance measure i.e. transportation cost to be much higher in the Centralised scenario. This is because in the RdM scenario, where production takes place closer to the point of demand, deliveries travel much shorter distances, and hence incurs less transportation cost [6,15,17]. In the Centralised scenario, on the other hand, only one production facility serves the entire network, therefore longer distances are travelled, and subsequently higher cost is incurred. Figure 5.8 below depicts the cost segments comparison between the centralised and the RdM scenarios.

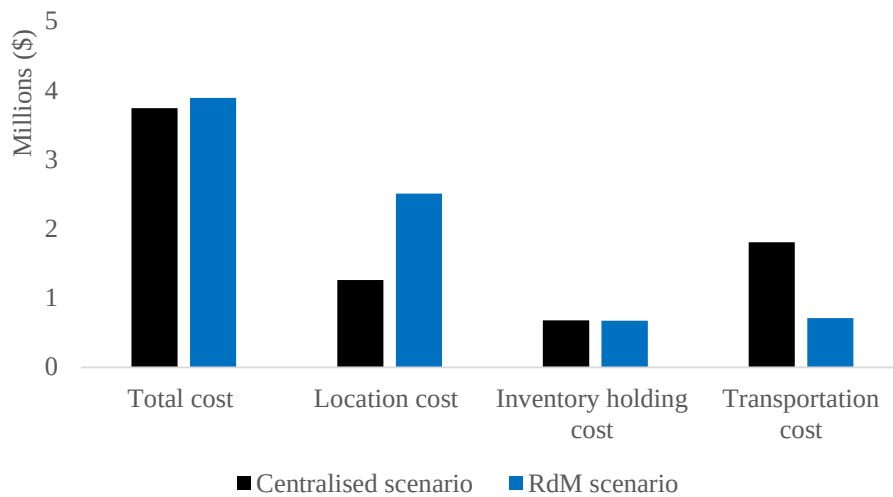


Figure 5.8 Cost segments comparison between the Centralised and RdM scenarios for the first optimisation-simulation run

Service level performance metrics are where the two scenarios differ most considerably. Regarding the delivery lead time, the RdM scenario is much more efficient than the Centralised scenario. This is mainly due to the transportation time differences between the two scenarios. In the RdM scenario, the production facilities are distributed throughout the network as is depicted in Figure 5.3, while in the Centralised scenario, only one facility is located and therefore deliveries, on many instances, will travel for longer distances to reach their final destinations. Finally, the frequency of inventory shortages, which refers to the number of shortages that occurred at the demand points (or unmet demand) during the models run time. In other words, it is the number of times deliveries were made to compensate for shortages at demand points. This value is much higher in the RdM scenario, this is a result of the lead time in the Centralised scenario being much bigger than that of the RdM scenario, which forces the demand points to order more supplies, using the process presented in Figure 4.4. These more supplies ordered in the Centralised scenario might end up as excess or unused inventory that is moved to the next planning period; making the number of inventory units in demand points larger than was had been scheduled. To explain more, a closer look at the frequency of shortages in both scenarios at each planning period, as displayed in Figure 5.9 below, reveals an important finding.

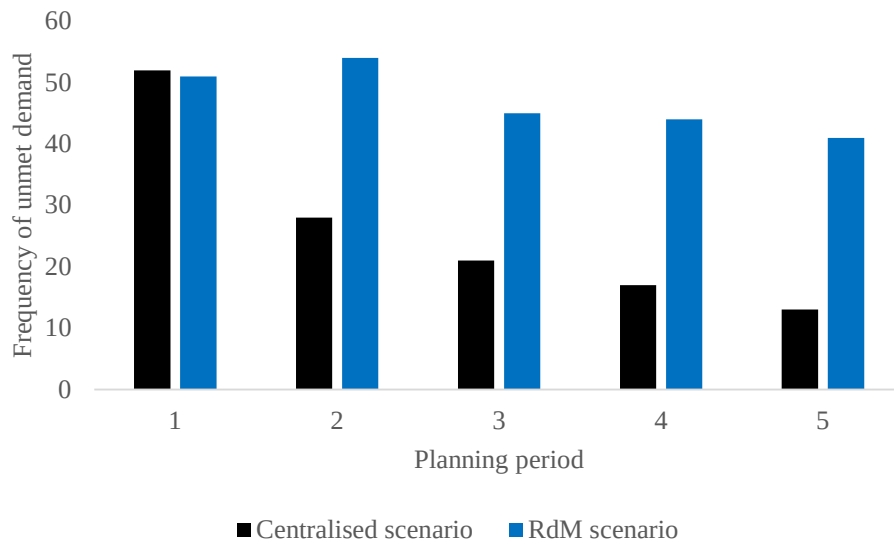


Figure 5.9 Comparison between the Centralised and RdM scenarios with regards to the frequency of inventory shortages in each planning period for the first optimisation-simulation iteration

The main finding that could be drawn from Figure 5.9 is that the frequency of the occurrence of inventory shortages in the Centralised and RdM scenarios in the same planning period is almost identical. In successive planning periods, however, the frequency of inventory shortages (unmet demand) remains consistently high (with slight decrease) in the RdM scenario, while it keeps gradually decreasing in the centralised one. This is because in the first planning period, demand points in both scenarios start with the same number of inventory units, and therefore they are expected to experience a close number of inventory shortages (close not equal because demand is stochastic). However, when inventory shortages occur, and when demand points order parts, which their quantities and the production plants are determined by equation (8) and the process presented in Figure 4.4, respectively, lead time plays an important role. In the Centralised scenario, as shown in Table 5.3, lead time is rather lengthy when compared to the RdM scenario. This, in many cases, results in ordering a larger number of inventory units that are either not fully used, or they arrive after the planning period has elapsed and scheduled inventory replenishment occurred. In both cases, some of the ordered inventory is not used and then moves to the next planning period; creating a larger number of inventory units at demand points. This is also reflected in the slightly larger inventory holding cost value generated by the Centralised scenario. This value (frequency of unmet demand),

however, substantially decreases as the number of optimisation-simulation iteration progresses, as will be demonstrated shortly. Finally, the discrepancies between the values of the outputs of the optimisation model against those of the simulation model were 1.42% for the Centralised scenario and 0.99% for the RdM one for the first optimisation simulation iteration.

Beyond the first optimisation-simulation iteration, the RdM scenario took 8 iterations where continuous gradual improvements were achieved in each iterations. After the 8th iteration, no further improvements were achieved. For the Centralised scenario, it took 5 iterations, after which, no further improvements were achieved. The improvements in the performance measures (lead time and unmet demand), against the increase in cost, for the Centralised and RdM scenarios are illustrated in Figure 5.10 and Figure 5.11, respectively.

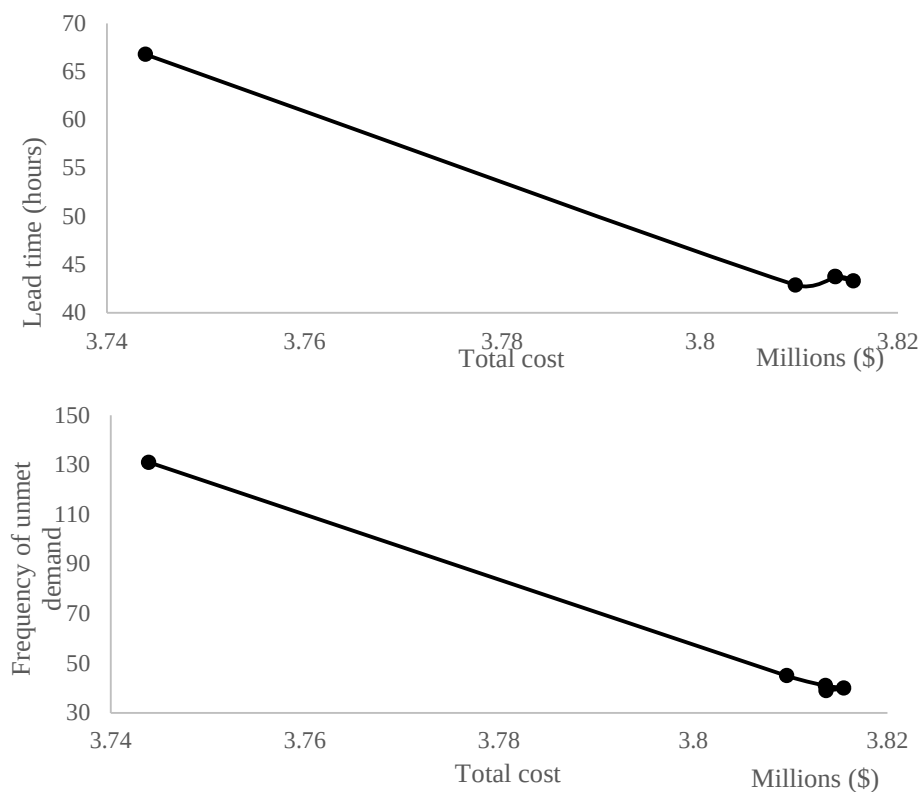


Figure 5.10 Relationship between cost and the improvement in lead time (up) and frequency of unmet demand (bottom) for the Centralised scenario

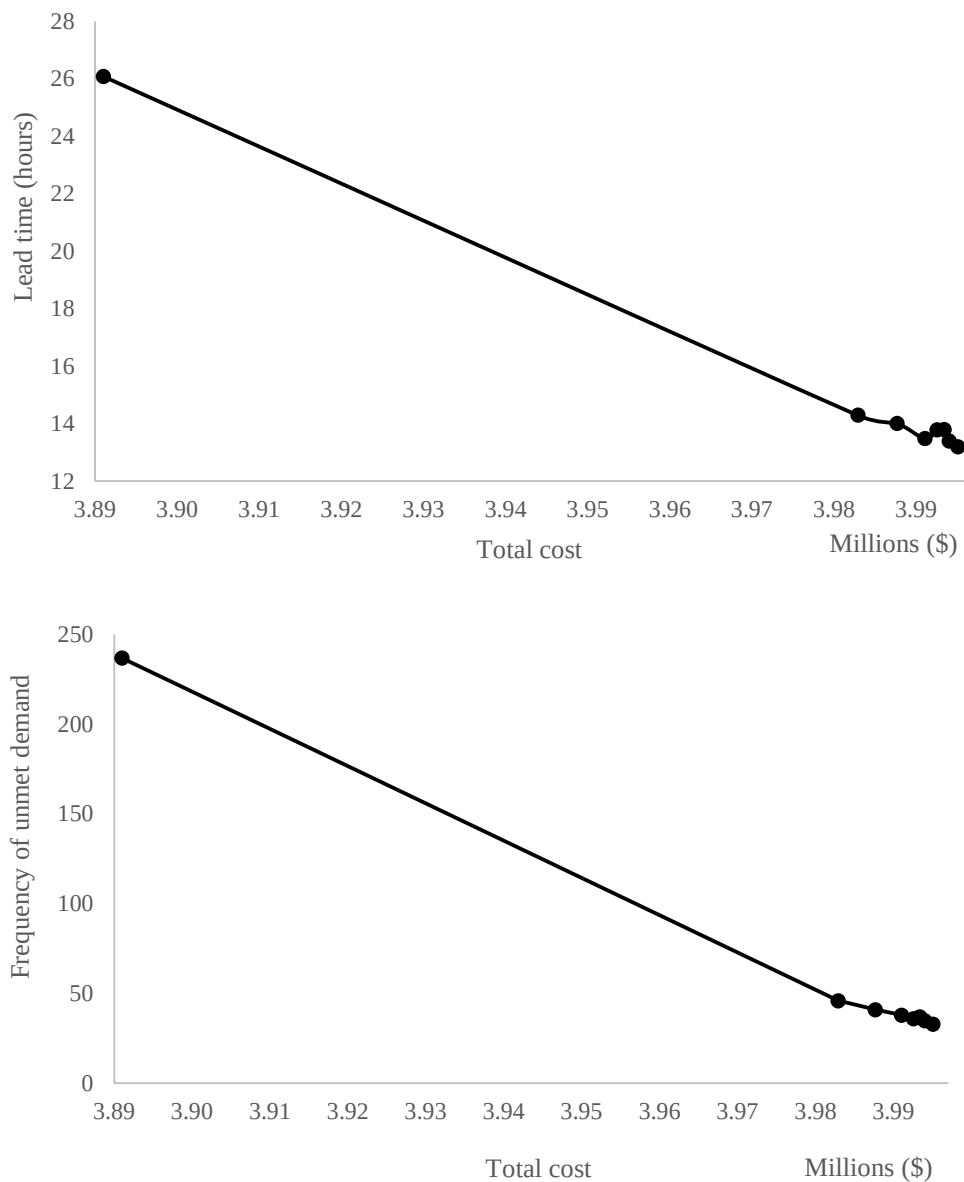


Figure 5.11 Relationship between cost and the improvement in lead time (up) and frequency of unmet demand (bottom) for the RdM scenario

It could be noticed from looking at Figure 5.10 and Figure 5.11 that the most significant improvements in service level performance measures are obtained from the second optimisation-simulation iteration. This implies that the outcome of the optimisation model, by itself, is not very efficient in terms of service levels. Adding uncertainty, through the simulation model, accounted for this issue and improved the performance measure, but at the expense of increased cost. The increase in the total cost, however, is nowhere near as dramatic as that of the improvements in lead time and unmet inventory.

This can be observed in Table 5.4 and Table 5.5 which summarise the main outcomes of the centralised and the RdM scenarios.

Table 5.4 Summary of the outcome of the framework application on the Centralised scenario where all costs are in millions \$

		Total cost (optimisation)	Total cost (simulation)	Gap	Location cost	Inventory holding cost	Transportatio n cost	Lead time (hrs)	Unmet demand
Iteration 1	Value	3.69	3.74	1.42%	1.26	0.678	1.81	66.80	131
	Improvement	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Iteration 2	Value	3.73	3.81	2.15%	1.26	0.732	1.82	42.90	45
	Improvement	-1.03%	-1.75%		0.00%	-7.94%	-0.66%	35.79%	65.65%
Iteration 3	Value	3.73	3.81	2.20%	1.26	0.735	1.82	43.78	41
	Improvement	-0.05%	-0.11%		0.00%	-0.45%	-0.04%	-2.05%	8.89%
Iteration 4	Value	3.73	3.82	2.23%	1.26	0.737	1.8	43.32	40
	Improvement	-0.02%	-0.05%		0.00%	-0.19%	-0.03%	1.03%	2.44%
Iteration 5	Value	3.73	3.81	2.17%	1.26	.0735	1.82	43.75	39
	Improvement	-0.01%	0.05%		0.00%	0.28%	-0.02%	-0.97%	2.50%

Table 5.5 Summary of the outcome of the framework application on the RdM scenario

		Total cost (optimisation)	Total cost (simulation)	Gap	Location cost	Inventory holding cost	Transportatio n cost	Lead time (hrs)	Unmet deman d
Iteration 1	Value	3.86	3.89	0.99%	2.51	0.675	0.709	26.08	237
	Improvement	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Iteration 2	Value	3.91	3.99	2.04%	2.51	0.744	0.731	14.29	46
	Improvement	-1.31%	-2.36%		0.00%	-10.28%	-3.18%	45.20%	80.59%
Iteration 3	Value	3.91	3.99	2.10%	2.5	0.747	0.733	14.01	41
	Improvement	-0.06%	-0.12%		0.00%	-0.40%	-0.24%	1.98%	10.87%
Iteration 4	Value	3.91	3.99	2.14%	2.51	0.749	0.734	13.48	38
	Improvement	-0.04%	-0.09%		0.00%	-0.31%	-0.15%	3.79%	7.32%

Iteration 5	Value	3.91	4.00	2.16%	2.51	0.750	0.735	13.78	36
	Improvement	-0.02%	-0.04%		0.00%	-0.12%	-0.08%	-2.22%	5.26%
Iteration 6	Value	3.91	4.00	2.17%	2.51	0.751	0.735	13.79	37
	Improvement	-0.01%	-0.02%		0.00%	-0.07%	-0.04%	-0.08%	-2.78%
Iteration 7	Value	3.91	4.00	2.17%	2.51	0.751	0.736	13.39	35
	Improvement	-0.01%	-0.02%		0.00%	-0.01%	-0.07%	2.88%	5.41%
Iteration 8	Value	3.91	4.00	2.20%	2.51	0.752	0.736	13.20	33
	Improvement	0.00%	-0.03%		0.00%	-0.15%	0.01%	1.47%	5.71%

Looking at Table 5.4 and Table 5.5 above, one can observe that in each iteration, the total cost calculated by the simulation model increases. However, as the number of iterations increases, the extra incurred cost decreases significantly. For example, the second iteration in the Centralised scenario resulted in a 1.75% increase in total cost, while the fifth iteration only resulted in a decrease by 0.05% over its predecessor. For the RdM scenario, cost increased by 2.36% in the second iteration, while the 8th iteration resulted in no change in the total cost. The gap between the optimisation and the simulation remains below 3%, which is normal, given each model's approach to uncertainty and cost update mechanisms. Holding cost naturally increases as there are more stored in some locations to protect against future possible shortages. Apart from the second iteration, changes to inventory holding cost were minimal. Transportation cost also slightly increased in both scenarios due to more units per deliveries taking place. It can be noticed that both scenarios behave similarly in terms of performance improvement when applying the framework. The RdM scenario, however, although remained more costly and required more optimisation-simulation runs to stabilise, ended up performing better than its centralised counterpart in service level performance measures. It is interesting how the Centralised scenario in the first run was much more efficient in the mean value of unmet demand, but as the modelling progressed the performance of the RdM scenario surpassed the centralised one in this performance aspect. This is due to the distribution of production to several distributed facility rather than only one centralised facility. To explain more, in the RdM scenario the distribution of demand for the whole network is allocated to more than one production facility, resulting in each production facility being dedicated to a

smaller group of demand nodes. In the Centralised scenario, one production facility supplies the entire network, therefore the likelihood of not being able to supply the required amount at the beginning of each planning period increases. In other words, it is easier to adapt to the demand generated from smaller (local) group of demand nodes than having to supply a sprawling network from one facility where conflicting factors affect addressing each group's requirements. To examine the frequency of the occurrence of unmet demand in both scenarios, Figure 5.12 below illustrates the frequency of the occurrence of unmet demands in both scenarios for the first and final optimisation-simulation iterations for demand nodes that experienced the highest amount of unmet demands.

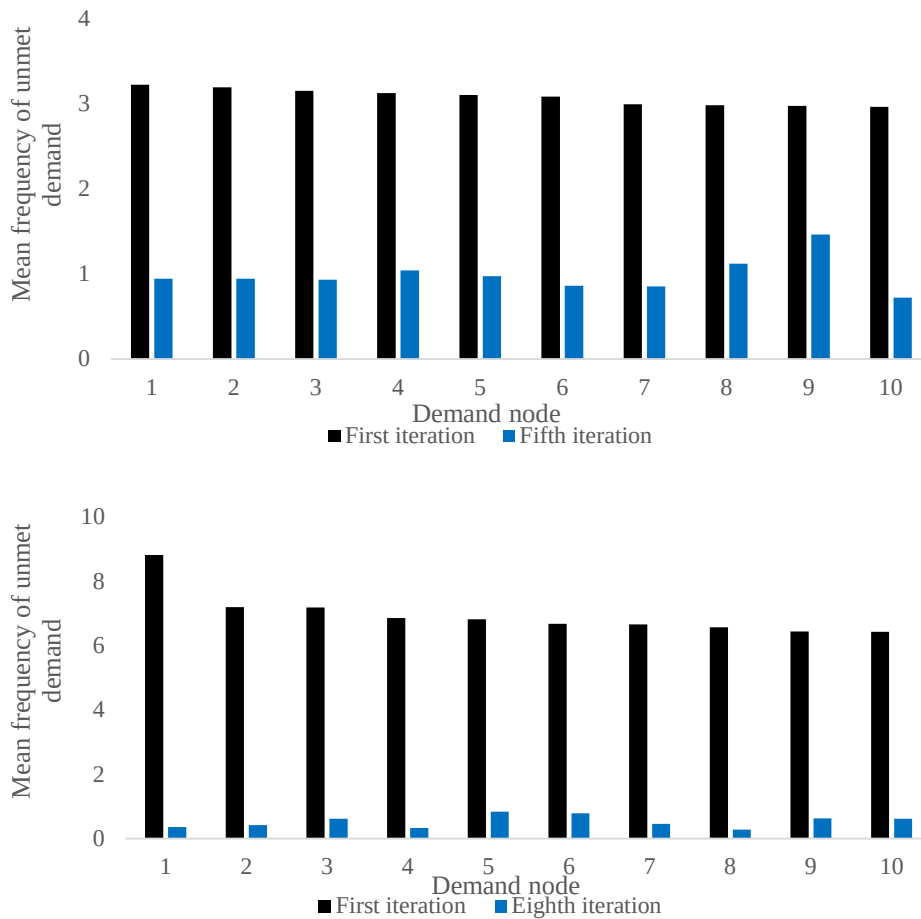


Figure 5.12 Frequency of the occurrence of unmet demand in the centralised (up) and RdM (bottom) scenarios for the 10 demand nodes that experienced the highest numbers of unmet demand

Figure 5.12 above depicts the mean total number of the occurrence of unmet demand for the 10 highest demand nodes. The numbers on the y-axis represent the mean value of the occurrence of unmet demand for the entire modelling duration (i.e. five years) over 100 simulation replications. The Figure above demonstrates that the RdM scenario indeed significantly, and consistently, improves the system's performance in terms of reducing the frequency of the occurrence of unmet demands. After applying the framework on the Centralised scenario, the performance in this aspect also significantly improved, but some demand nodes persisted in experiencing a relatively high number inventory shortages. This result indeed demonstrate that in service-level performance metrics, RdM is superior to the traditional centralised production paradigm.

This section has discussed an application of the decision-making framework for the design of RdM design. To provide a reference for comparison, a centralised counterpart of the production system has also been modelled and compared with the RdM one. Results have shown that the Centralised scenario is more cost efficient, although by a small margin. Cost segments were however not evenly proportional in both scenarios, with location cost favouring the Centralised scenario by a big margin, inventory holding cost being almost equal and transportation cost being much less in the RdM scenario. Service level performance was however different, with the RdM scenario performing better than the centralised one with regards to lead time and the occurrence of unmet demand.

These results indicate that RdM is a viable production paradigm that has potential to improve service offerings if adopted. This conclusion, however, should not be taken in isolation from other factors that are specific for each manufacturer, and other general factors. In general, and as was discussed earlier, RdM is far from replacing centralised manufacturing, and its role is mostly confined as complementary to the traditional, well-established, paradigm. It is therefore important to stress that even if the RdM paradigm can be established at an acceptable cost, other factors and cost segments should be considered as well when applied in different industrial settings. The decision-making framework developed in this research therefore serves as a starting point for manufacturers that contemplates the adoption of RdM.

5.5.1 Sensitivity analysis

Although the uncertainty in the framework is handled through the introduction of the stochastic simulation model, the optimisation model is still deterministic, and hence it has to be examined under some degree of uncertainty. To achieve this aim, sensitivity analysis is introduced in this section.

In spite of the fact that sensitivity analysis does not proactively incorporate uncertainty into modelling, it still remains an indispensable approach to evaluate the robustness of a model, and to better allocate adequate resources into mitigating the uncertainty surrounding these parameters identified by the sensitivity analysis. Sensitivity analysis provides a method to identify important parameters, so that careful planning is used in selecting the value of these parameters. Important parameters in this context refer to input parameters whose relatively small changes in value can have big impact on the overall model outcome.

In this section, key parameters' values were changed, and their impact on the objective function was observed and reported. A base scenario was set (same as the one in the previous section) to benchmark against, and then each parameter's value was increased/decreased in 10% increments/decrements up to 100% of its base value. Figure 5.13 below depicts the impact of the change in the value of key parameters on the overall cost. The sensitivity analysis experiments were conducted only on the RdM scenario in order to explore and identify issues that might emerge after adopting the RdM paradigm. The parameters that were experimented upon are the total demand, cycle time and available time for each AM equipment during each planning period. The available time for each AM equipment is the total time that an AM equipment can operate and produce parts. This parameter is important because it contains important time segments such as setup times and maintenance times. An extreme example, for instance, is if production is presumed to be 24 hours each day with an operator attending by the AM machine, and no maintenance is required throughout each planning period, then this parameter will be equal to 8760 (24×365) i.e. each machine is available for 8760 hour each week. Other parameters such as cost of establishing an RdM facility, holding cost, transportation cost and cost of production per unit were not included because they exhibited a linear relationship with regards to total cost. The outcome collected from the sensitivity analysis

experiments consists of total cost, number and locations of RdM facilities (and subsequently number of AM equipment placed in each location). Table 5.6 below summarises the outcome of the sensitivity analysis where cost is in US Dollar.

Table 5.6 Summary of the sensitivity analysis outcome on total cost (in millions \$), the minimum number of AM equipment required and the locations of RdM facilities

Change in the parameter's value		Total demand	Cycle time	Production availability
-90%	Total cost	0.79	2.93	24.70
	Number of RdM facilities	1	2	16
	Reference of selected locations	42	40, 47	29, 30, 32, 33, 36, 37(2), 38, 39(2), 40(6), 41, 42, 43(2), 44(4), 45, 46(7), 47(2)
-80%	Total cost	1.02	2.93	12.90
	Number of RdM facilities	1	2	12
	Reference of selected locations	42	40, 47	29, 30, 32, 33, 37, 38, 39, 40(3), 42, 44(2), 46(3), 48(2)
-70%	Total cost	1.71	2.93	9.16
	Number of RdM facilities	2	2	11
	Reference of selected locations	40, 47	40, 47	19, 29, 30, 32, 33, 38, 39, 40(2), 44, 46, 48(2)
-60%	Total cost	1.86	2.94	7.28
	Number of RdM facilities	2	2	10
	Reference of selected locations	40, 47	40, 47	19, 25, 30, 32, 38, 40, 41, 44, 46, 48
-50%	Total cost	2.08	3.05	6.06
	Number of RdM facilities	2	2	8
	Reference of selected locations	40, 47	38, 40	19, 30, 32, 40, 41, 44, 46, 48
-40%	Total cost	2.73	3.34	5.44
	Number of RdM facilities	3	3	7

	Reference of selected locations	36, 40, 46	36, 40, 46	19, 30, 38, 40, 41, 44, 48
-30%	Total cost	2.88	3.34	4.89
	Number of RdM facilities	3	3	6
	Reference of selected locations	36, 40, 46	36, 40, 46	19, 30, 40, 41, 44, 48
-20%	Total cost	3.11	3.51	4.37
	Number of RdM facilities	3	3	5
	Reference of selected locations	36, 40, 46	36, 40, 46	19, 30, 39, 44, 48
-10%	Total cost	3.70	3.84	4.34
	Number of RdM facilities	4	4	5
	Reference of selected locations	30, 40, 44, 46	30, 40, 44, 46	26, 30, 40, 44, 48
0%	Total cost	3.86	3.86	3.86
	Number of RdM facilities	4	4	4
	Reference of selected locations	26, 37, 40, 44	26, 37, 40, 44	26, 37, 40, 44
10%	Total cost	4.48	4.34	n/a
	Number of RdM facilities	5	5	n/a
	Reference of selected locations	20, 30, 40, 44, 48	26, 30, 40, 44, 48	n/a
20%	Total cost	4.62	4.36	n/a
	Number of RdM facilities	5	5	n/a
	Reference of selected locations	19, 30, 39, 44, 48	20, 30, 39, 44, 48	n/a
30%	Total cost	5.04	4.40	n/a
	Number of RdM facilities	5	5	n/a

	Reference of selected locations	19, 28, 30, 40, 48	19, 30, 40, 44, 48	n/a
40%	Total cost	5.38	4.89	n/a
	Number of RdM facilities	6	6	n/a
	Reference of selected locations	19, 28, 30, 40, 41, 48	19, 30, 40, 41, 44, 48	n/a
50%	Total cost	5.57	4.91	n/a
	Number of RdM facilities	6	6	n/a
	Reference of selected locations	19, 30, 40, 41, 44, 48	19, 30, 40, 41, 44, 48	n/a
60%	Total cost	6.12	5.10	n/a
	Number of RdM facilities	7	6	n/a
	Reference of selected locations	19, 30, 38, 40, 41, 44, 48	19, 30, 40, 41, 44, 48	n/a
70%	Total cost	6.25	5.44	n/a
	Number of RdM facilities	7	7	n/a
	Reference of selected locations	19, 30, 38, 40, 41, 44, 48	19, 30, 38, 40, 41, 44, 48	n/a
80%	Total cost	6.74	5.46	n/a
	Number of RdM facilities	7	7	n/a
	Reference of selected locations	19, 30, 38, 40, 41, 44, 48	19, 30, 38, 40, 41, 44, 48	n/a
90%	Total cost	7.06	6.05	n/a
	Number of RdM facilities	7	8	n/a
	Reference of selected locations	19, 30, 32, 40, 41, 44, 48	19, 30, 32, 40, 41, 44, 46, 48	n/a
100%	Total cost	7.35	6.05	n/a
	Number of RdM facilities	8	8	n/a

	Reference of selected locations	19, 30, 32, 40, 41, 44, 46, 48	19, 30, 32, 40, 41, 44, 46, 48	n/a
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To better examine the impact of the change in the value of each parameter, the values in Table 5.6 are visualised in Figure 5.13 below. Looking at Figure 5.13, it is apparent that the available time of AM production is the most sensitive parameter. This parameter (i.e. available time for AM production) is, as mentioned earlier, the amount of time per each planning period that an AM equipment can operate. In other words, it refers to the productive time of AM equipment after deducting non-productive time segments, in particular, set-up times, maintenance times and mean time to repair (MTTR) times and times where an operator (if the machine needs to be attended by one) is unavailable. This sensitivity in the parameter, however, only becomes significant with extreme decrease in the availability of AM equipment. However this parameter is still a very important one as it typically encompasses time segments such as setup times, downtimes and maintenance times. The increase in the value of this parameter (i.e. production availability) beyond the base value (available all the time) is not considered in the sensitivity analysis. This is because it is unrealistic to assume that a production equipment can be available beyond all the time.

The second more important parameter, in terms of its impact on total cost, is total demand. Demand rate is typically deemed as one of the most important parameters in the design of production networks under uncertainty [91]. Demand projection drives future decisions at all levels such as capacities of production plants, inventory replenishment decisions and demand fulfilment centres. Sensitivity analysis on the demand rate revealed that the model is quite sensitive to the demand rate. This is expected, as in most supply chains, demand is the trigger of most supply chains' entire operations and subsequently entails considerable contribution to total cost. Total demand considerably impacts the total cost for three reasons; first, increase in total demand will entail an increase of the units produced which, up to a certain level will require the opening of additional RdM facilities. The second reasons is that increase in total demand will also entail increase in supplies delivered to demand points, which also contributes to increase in total cost. Finally, total demand is closely and directly related with the cost of production where more production

will entail more costs, and vice versa. This relationship between total demand and production cost is, however, not as straightforward. This is because cost of production broadly consists of two cost segments: fixed and variable costs [123]. Fixed cost refers to costs that are incurred by the production system regardless of the volume of production, e.g. overhead and administrative costs. Variable costs on the other hand consists of costs that directly result from the production of each unit, e.g. raw material and energy costs. It is common therefore that after a certain threshold (where the fixed cost has been met), increased cost will only contribute by the magnitude of the variable cost per each unit. Fixed and variable costs are, however, much more complex than that. For example, fixed cost will inevitably increase with significant increase in demand as more staff will potentially be required to handle the extra production, and potentially new facilities will have to be opened. In this thesis's decision-making framework, fixed cost is accounted for in the cost of setting up an RdM facility. This cost consists of the cost of acquiring and operating an AM equipment and the cost of establishing and operating the RdM facility.

The implication of total demand is important when making strategic decisions of locating plants and assigning capacities. It is also important at the tactical and operational levels, but decisions at these levels (i.e. tactical and operational) could be reversed, amended or their effects contained with less severe consequences. For example, demand could be expected to grow in the future (e.g. an OEM that recently experienced a growth in the sales of an asset that requires regular future service and parts replacement). The decision-maker can hedge against demand uncertainty by observing carefully the impact of total cost, or any other objective function, with regards to change in demand. In this case study, if the choice of the mean demand was overly conservative, then the sensitivity analysis shows that the number and capacities of RdM plants are sufficient to meet fluctuations in demands. On the other hand, if the mean value of the expected demand underrepresents future demands, then the decision-maker might better add another plant, as recommended by the optimization model, so that it can accommodate consistent fluctuations in demand of up to 20% of the mean value with the addition of one RdM facility.

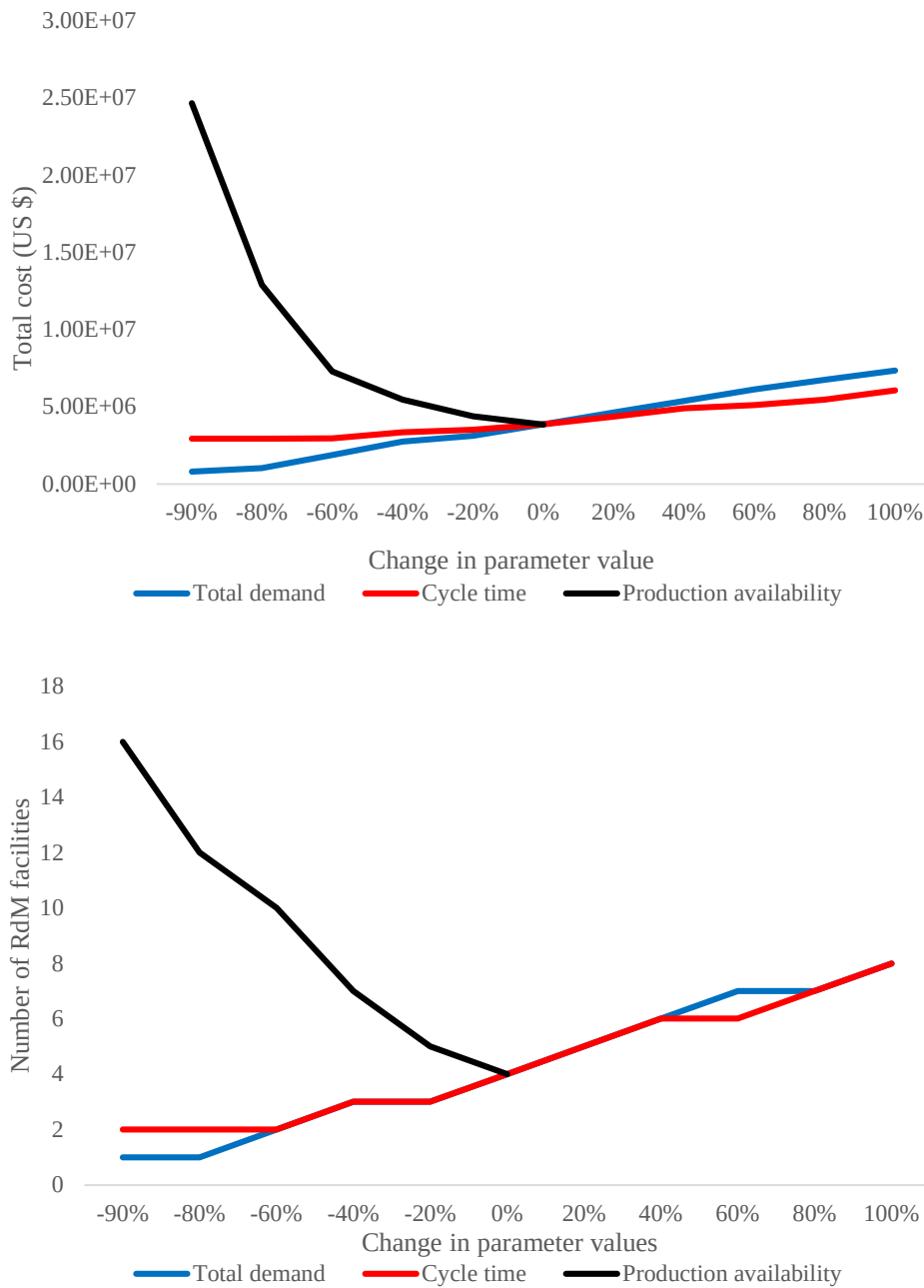


Figure 5.13 The impact of the change in the value of key parameters on total cost (up) and the number of RdM facilities (bottom)

Cycle time per unit is also an important parameter that needs careful investigations. This is because, as with demand, this parameter is stochastic, and is assumed in the optimization model to be an aggregate value of multiple process e.g. pre and post-processing. Another factor contributing to the importance of this parameter is that the modeling setting assumed production via AM machines, which are rapidly improving in many aspects including build time. It is then necessary to acquaint oneself with sufficient

understanding of the impact of the improvement, or even slowing down due to ageing, of AM technology on the performance of the system prior to making strategic decisions. The impact of cycle time on total cost is not, relatively speaking, as pronounced as those of production availability or total demand. This is because the impact of the change in cycle time is only significant when it requires the increase/ decrease in the number of AM facilities. Therefore, the change in demand has more pronounced impact on total cost than cycle time because change in demand does not only potentially entail the addition/ removal of RdM facilities, but also increase/ decrease in transportation cost. Due to the importance of this parameter (i.e. cycle time), it is worthwhile to have a closer look on the impact of cycle time reduction (as a result of improvement in build time) on the total cost.

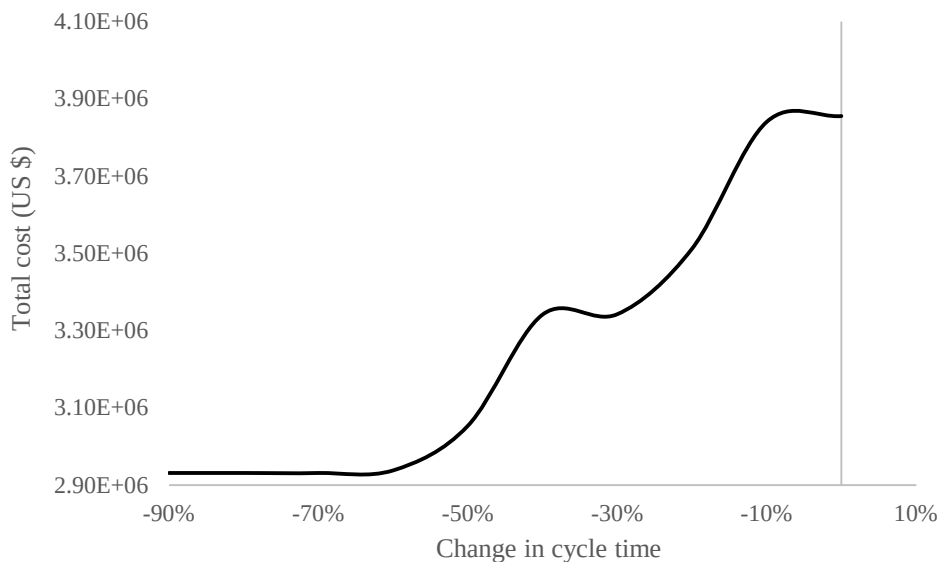


Figure 5.14 The impact of improvement in cycle time on total cost

It could be deduced from Figure 5.14 that the improvement of up to 60% in cycle time will contribute to reduction in the total cost incurred by the system. The slight changes observed when cycle time is reduced from 30% to 40% and again from 0% to 10% are due to the differences in allocations between production sites and demand points, and due to slight increase in holding costs as finished products remain inventoried for slightly longer times. The sharp decrease in cost is, however, due to the removal of entire production sites from the system. After the 60% mark, as in line with [17], this improvement ceases to occur, and the total cost remains constant. This observation carries

important practical insights with regards to the adoption of AM technology to power RdM systems. AM technology has evolved, and is expected to maintain the improvement in terms of build time, therefore many studies (e.g. [17,23,111]) envisioned RdM systems where build time significantly improves, in some instances up to 20 folds [17]. It is then expected that decision-makers, informed by the expectations of considerably faster build time, might want to hold on adopting an AM-powered RdM paradigm. However, looking at the results reported in the sensitivity analysis and visualised in Figure 5.14, the experiments results reveal that reduction in total cost will continue to occur until 60% reduction in cycle time is achieved. Beyond 60% reduction in cycle time, the total cost remains unchanged. This is because beyond 60% reduction in lead time, a minimum of AM equipment are required to fulfil the production requirements.

5.6 Framework validation

As was discussed and reiterated in Chapter 3, frameworks and models validation has to be repeated each time a new problem instance (i.e. case study) is applied. Therefore, to remain in line with the adopted validation methodology, each case study will be validated using the same steps outlined in Chapter 3.

The first step was to validate the conceptual model (process map) of the simulation model and to establish data validity. These two processes are discussed together because they are very closely intertwined. To explain, and as has been discussed earlier, data is not only the values for the input parameters (quantitative data); it also includes other facets such as the interrelationships between the models' entities and the each model's logic. Although the process map is designed specifically for the simulation model, it invariably captures all the system's attributes, relationships and the governing logic. Therefore the experts (A, B, C and D) were presented with a background on the aim of this research, the aim of the decision-making framework and a detailed description of the case study. The meetings were mostly held separately due to logistical and time constraints with the experts. However meetings with Expert A and Expert B were held jointly. Each of the experts was then presented with a detailed walkthrough of the process map. The common feedback received from the experts was that the level of detail included in the model is excessive and is likely to adversely affect the accuracy of the model. The earlier iterations of the process map included physical assets (airplanes) operating and needing parts

replacements. Maintenance engineers were also included in the model. Three of the four experts remarked that the inclusion of these processes and the addition of maintenance engineers are unnecessary and only serve in diverting the framework in achieving its aim. Indeed, the relationship between a model's complexity and its accuracy is an important issue in modelling. To illustrate this relationship, Figure 5.15 below [99], which is only for demonstration purposes and not based on empirical data, provides a visual illustration of this relationship.

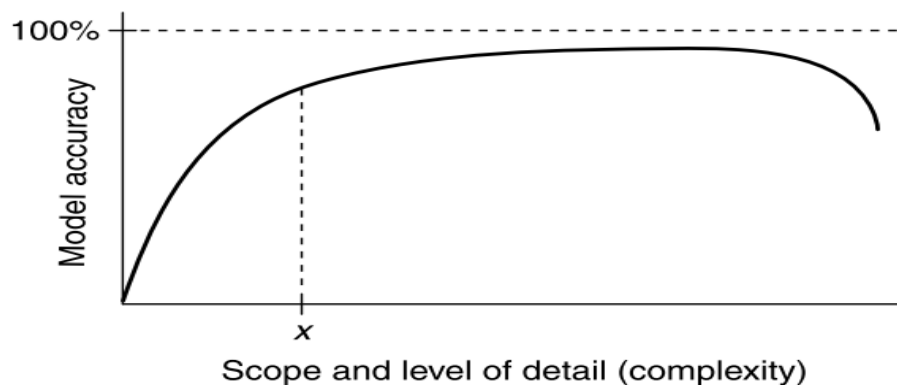


Figure 5.15 The perceived relationship between a model's complexity and its accuracy [99]

Figure 5.15 above demonstrates that most accuracy in a model comes from relatively little complexity. This could be thought of as following Pareto 20/80 rule where 80% of the accuracy in a model comes from 20% of complexity (details), which is represented by the point x in Figure 5.15. Figure 5.15 also demonstrates that little improvement on accuracy is achieved by increasing the model's complexity beyond a certain level (x). Following the x -axis in Figure 5.15, one can notice that incorporating much more complexity (i.e. adding as many details about the system as possible) will result in significant and sharp decrease in the model's accuracy. This is because at some point it will become inevitable that data and information regarding some aspects of the system will be either unavailable or inaccurate. Therefore maintaining sufficient simplicity to incorporate just what directly contributes to the model's *objectives* is key to develop valid models. The experts feedback was incorporated into the model and the entities and processes they identified were removed.

The first version of the model was a single product model. The experts acknowledged that although a single product model provides some insights, but transforming it to a

multi-part model will greatly improve its validity. Although transforming the model to a multiproduct one considerably increases its complexity, the experts cited the need to have different products with different demand rates, costs and cycle times in order to deem the model useful. The model was then developed as a multi-product one based on the experts suggestion. The experts were then presented, separately, with the new process map along with a walkthrough where their feedback was highlighted when providing the walkthrough. The model was then deemed sufficiently representative of the envisioned system.

The second step was to verify the optimisation model by ensuring that the mathematical formulation is correct, and to ensure that the model represent the envisioned system. This step has been accomplished with the help of Expert E (Software architect). Expert E has over 10 year experience in Operational Research and software engineering. The expert was presented with a detailed background about the case study, the optimisation model's objective, inputs, outputs and contents. Then the mathematical formulation of the optimisation model was presented to him. The mathematical formulation was deemed accurate and correct by the expert. The expert was then, in a separate meeting, presented with the Python code of the optimisation model. Being familiar with the optimisation software used (Gurobi) the expert provided feedback that considerably shortened the code. The expert's feedback was integrated into the model in the same meeting, and then multiple instances were tested.

Then after the computerised simulation model was developed based on the conceptual model developed and validated earlier. The computerised simulation model was then presented to Expert E first through a detailed walkthrough in the process map to explain the system being modelled and its corresponding simulation model. After familiarising Expert E with the system being modelled and the process map, the computerised simulation model was presented to him along with another walkthrough, this time of the computer model. The expert identified several bugs in the computer model that indeed could have surfaced in some extreme cases. One of Expert E's concerns was regarding the use of the normal distribution to represent stochastic time durations. He demonstrated that in some cases where the standard deviation is large enough, the simulation model will abruptly stop and show error message due to negative values. The workaround of this

issue was to use the truncated normal distribution which was explained earlier. The computer model was then revised, based on the expert's feedback, and shared back with him. Several instances were run in the simulation model with extreme values, and then the expert determined that the model is technically correct.

The next stage was to compare the models' (optimisation and simulation) outcomes against each other. In order to do so, several instances were tested on both models where all the parameters in the simulation model were deterministic. The outcome of the comparison for the base values of the RdM model are reported in Table 5.7 below.

Table 5.7 Comparison of the models outcome with regards to total cost (\$)

Model	Optimisation model	Simulation model	Difference
Total cost (\$)	3,855,668	3,832,848	-0.59%

Although the values generated from both models are very close to one another, there is a slight discrepancy between their outcomes. This discrepancy has been discussed earlier, but in short it is due to the dynamic nature of the simulation model where it updates cost values on a much shorter time scales than the optimisation model does. In the optimisation model, cost values are updated on each transition to a new planning period (i.e. each year). In the simulation model, however, cost values such as holding cost were updated on a daily basis. Therefore costs in the optimisation model in this application of the framework were updated five times only (because the modelling duration is five years), while in the simulation model they were updated 1,825 times (5×365). Table 5.4 and Table 5.5 also show that even when the simulation model had been stochastic, the discrepancy between the two models remained well below 3%.

Finally the operational validity (establishing the framework's outcome sufficiently represent what is expected from the envisioned system) was established. Separate meetings were held with experts A, B, C and D where the findings were presented to them. There was a consensus amongst the experts that the results sufficiently resembled their expectations. Two of the experts (C and D) however expressed concerns with regards to the feasibility of long-term adoption of AM production. They indicated that the

future of wide scale AM production is still unclear, and factors such as depreciation and fast-paced improvements in AM technology and materials they use might render investment in current technology particularly risky. The experts however agreed that the decision-making framework reflects that its purpose is in the first place for the design of RdM networks, and AM technology comes in the second place. They also added that being not chiefly focused on AM production, but rather AM as an enabler of the distribution of production, contributes to establishing the framework's usefulness and generalisability in different settings. Experts C and D also agreed that since the framework is used for the production of a finite set of products that are in continuous demand, and are not critical to aircrafts safety, then this greatly alleviates their concern about AM production.

5.7 Summary

In this chapter, the framework has been applied to a case study in the aerospace spare parts sector. The objective of the framework application was to minimise the total cost incurred by the setting up and operation of the RdM network. The RdM network's performance has been compared throughout this chapter with that of a centralised counterpart. The results revealed that the total cost incurred in the RdM scenario, although close enough, is more than that of the Centralised scenario. This is mainly due to the significantly bigger capital investment required for setting up an RdM network which entails investment in RdM equipment in multiple distributed locations. The results however revealed that the service level performance, measured by lead time and frequency of unmet demands, is considerably better in the RdM scenario. In the next chapter, the framework will be implemented on a different case with a different objective function; thus establishing validity of the framework's generalisability amongst different cases with varying objectives.

6 RdM for emergency response networks- case study II

6.1 Background

The second case study involves applying the decision-making framework for the design of RdM networks for the production of medical supplies in the event of an emergency. The application of this case study is motivated by the disruptions to production systems that could result from a sudden onset of large-scale emergencies. Such emergencies might be natural disasters such as earthquakes or hurricane or pandemic outbreaks, or manmade such as wars. Typically, all production systems are designed a priori to accommodate disruptions up to a certain level [124]. Nevertheless, hedging against all possible forms of disruption at all levels is deemed an impossible task [125]. This becomes clear when slight fluctuations, in demand for instance, go unnoticed, or cause minimal disruptive consequences. Other disruptions however, such as those caused by unforeseen emergencies, can result in more serious disruption to the production and distribution networks, sometimes rendering them incapable of meeting sudden unexpected spike in demand. In addition to resources and capacity limitations that, in some cases, renders a production system incapable of meeting the sudden unexpected spike in demand levels, supply chains could also become disrupted. Disruption of a supply chain could mean that the required products are available at their point of production, or somewhere else along the chain, but cannot be delivered to the demand point in need [126]. In cases of such disruptions, RdM has the potential to enable meeting the unexpected demand, or localising the supply chain where a sprawling disrupted supply chain is temporarily transformed into a shorter one mostly confined locally [127].

While there is a growing number of decision-making frameworks that are being developed in crises response settings, almost all of these frameworks addresses mostly location and inventory decisions, and omits production processes, assuming that supplies are manufactured earlier in ‘ideal circumstances’. Given the opportunities that AM can provide in enabling the design of RdM networks, and its proven capability of producing medical equipment (as was discussed in Chapter 2, e.g. [97,112]), and as in the previous case study, the RdM network envisioned in this case study will be powered by AM equipment. The application of this case study aims to design a production network for the production of personal protective equipment (PPE), specifically face shields, using AM.

Inspired by the COVID-19 coronavirus pandemic outbreak, which has been affecting the entire world at the time of writing this thesis, this case study applies the decision-making framework for the design of production networks to temporarily produce PPE. During the 2019-2020 coronavirus COVID-19 outbreak, shortages in PPE posed serious danger to frontline healthcare workers [128]. Some countries, such as Italy, experienced a higher rate of mortality among frontline healthcare workers, partly due to the lack of adequate PPE [19]. In this section, the framework is applied to design a production network for the South East England Region, England's most populous region. Data from the UK Government's open data dedicated coronavirus website <https://coronavirus.data.gov.uk/> regarding the region's constituent counties daily new cases were used as inputs to the framework's models. The region's 29 hospitals (those with emergency departments and over 100 beds) were modelled as both demand nodes and potential production sites. The data covered daily new cases in each county in the region from 1 March 2020 till 30 April 2020, aggregated into weekly planning periods. Demand is assumed to be stochastic and follows the truncated normal distribution. Mean demand in each hospital during each planning period is proportional to a percentage (here assumed 10%) of the number of weekly new cases reported in each county with regards to each hospital's proportional capacity (measured by number of beds) with the total county's capacity (i.e. total number of hospital beds in a county). Table 6.1 and Table 6.2 below summarise the key input parameters used in the framework application.

Table 6.1 Input parameters values

Parameter	Value
Number of available AM machines	5
Number of planning periods	9
Production time in hours (μ , σ , min, max)	(2, 0.4, 1.6, 2.4)
Average vehicle speed (mile/hour)	50
Length of each planning period in hours	168 (number of hours in each week)
Demand (μ , σ , min, max)	(demand during planning period as in Table 6.2, demand * 0.5, 0, ∞)

Table 6.2 Mean demand at each hospital during each planning period derived from figured published by the UK Government in <https://coronavirus.data.gov.uk/>

No	Name	Number of beds	County	Planning period								
				1	2	3	4	5	6	7	8	9
1	Heatherwood Hospital	241	Berkshire	0	1	2	4	6	5	8	5	2
2	Royal Berkshire Hospital	813	Berkshire	0	3	5	11	18	17	27	16	5
3	Wexham Park Hospital	650	Berkshire	0	2	4	9	14	13	21	13	4
4	Milton Keynes University Hospital	508	Buckinghamshire	0	2	4	6	8	10	9	7	4
5	Stoke Mandeville Hospital	369	Buckinghamshire	0	2	3	4	6	7	6	5	3
6	Wycombe Hospital	137	Buckinghamshire	0	1	1	2	3	3	3	2	1
7	Conquest Hospital	418	East Sussex	0	0	1	2	5	5	4	3	3
8	Royal Sussex County Hospital	785	East Sussex	0	0	1	4	8	10	6	6	4
9	Basingstoke and North	450	Hampshire	1	1	2	5	7	7	7	5	3

	Hampshire Hospital											
10	Queen Alexandra Hospital	1400	Hampshire	1	3	6	14	21	22	20	16	8
11	Royal Hampshire County Hospital	806	Hampshire	1	2	4	8	12	13	12	9	5
12	Southampton General Hospital	1100	Hampshire	1	3	5	11	16	17	16	13	7
13	St Mary's Hospital	477	Isle of Wight	0	0	0	0	1	2	1	3	2
14	Maidstone Hospital	294	Kent	0	1	1	4	7	9	11	8	2
15	Medway Maritime Hospital	588	Kent	0	1	2	8	0	18	22	15	3
16	Queen Elizabeth The Queen Mother Hospital	388	Kent	0	1	2	6	9	12	15	10	2
17	Tunbridge Wells Hospital	512	Kent	0	1	2	7	12	15	19	13	3
18	William Harvey Hospital	476	Kent	0	1	2	7	11	14	18	12	2
19	Kent and Canterbury Hospital	287	Kent	0	1	1	4	7	9	11	8	2

20	John Radcliffe Hospital	832	Oxfordshire	0	2	5	12	26	31	25	18	5
21	Horton General Hospital	236	Oxfordshire	0	1	2	4	8	9	7	6	2
22	East Surrey Hospital	697	Surrey	0	2	4	9	12	13	13	8	3
23	Epsom Hospital	361	Surrey	0	2	5	12	16	18	17	11	4
24	Frimley Park Hospital	938	Surrey	0	2	5	12	16	18	17	11	4
25	Royal Surrey County Hospital	520	Surrey	0	2	4	9	12	13	13	8	3
26	St Peter's Hospital, Chertsey	550	Surrey	0	2	3	7	9	11	10	7	2
27	Princess Royal Hospital, Haywards Heath	327	West Sussex	0	1	2	4	6	8	7	2	0
28	St Richard's Hospital	430	West Sussex	0	1	2	5	8	10	9	2	0
29	Worthing Hospital	500	West Sussex	0	1	2	5	9	12	10	2	0

6.2 Optimisation model

The optimisation model developed for this case study is a multi-period capacitated facility location model with production quantities and distribution decisions. Unlike the model developed for the previous case study which minimises total cost, the model in this case

study aims to minimise the total supply-weighted distance travelled, which can contribute to speedier response to areas of high demand. It might, however, be argued that in crisis response, all facilities should be considered of equal importance, which is the case when providing to some vital service providers such as public hospitals and fire departments [129]. Such models are usually referred to as minimax models, which minimize the maximum distance travelled between any two facilities [86]. This family of models however fails to prioritize areas that require more dedicated resources to meet high demand [86]. The model developed in this case study, as will be demonstrated shortly, contains constraints that enforce all demand points be served with the required quantities.

6.2.1 The model

Total supply-weighted distance travelled =

Minimise:

$$\sum_{i \in I} \sum_{j \in J} \sum_{t \in T} g_{ij} Y_{ijt} \quad (24)$$

s.t.

$$\sum_{j \in J} X_j \leq n \quad (25)$$

$$c \sum_{i \in I} Y_{ijt} \leq b X_j \quad \forall j \in J, \forall t \in T \quad (26)$$

$$Y_{ijt} \geq r_{it} \quad \forall i \in I, \forall j \in J, \forall t \in T \quad (27)$$

$$\sum_{j \in J} S_{ijt} \leq 1 \quad \forall i \in I, \forall t \in T \quad (28)$$

$$Y_{ijt} \leq S_{ijt} M \quad \forall i \in I, \forall j \in J, \forall t \in T \quad (29)$$

$$Y_{ijt} \geq S_{ijt} \quad \forall i \in I, \forall j \in J, \forall t \in T \quad (30)$$

$$X_j, Y_{ijt} \in \mathbb{Z}^+ \quad \forall i \in I, \forall j \in J, \forall t \in T \quad (31)$$

$$S_{ijt} \in \{0, 1\} \quad \forall i \in I, \forall j \in J, \forall t \in T \quad (32)$$

In model (24) – (32) the objective function (24) minimizes the total supply-weighted distance travelled during all planning periods. Constraint (25) ensures that the total number of AM machines located does not exceed the number of available machines. This constraint i.e. (25) enforces a given number of facilities, or more accurately a given number of AM equipment, to be placed. This was not the case in the first case study where the number of facilities (or AM equipment) was a model output, while in this case study it is a model input. This attribute of the model could be easily changed to make the number of facilities a model output, but in unforeseen emergency response, one usually has to adapt with the available resources (AM equipment) at their disposal particularly in the response, not preparedness stage [130]. Constraints (26) ensure that the available time for each AM machine during each planning period is not exceeded. For example, if the length of each planning period is one week and the cycle time for the production of each unit equals two hours, then this set of constraints stipulates that each AM machine is only allowed to produce up to 84 units per week (number of hours per week / cycle time in hours per unit). If the solution algorithm decides that more than 84 units are required from this location to meet assigned demand, then another AM machine has to be installed in this location. Constraints (27) stipulate that the supply amount at the beginning of each planning period to each demand node should be at least equal to or greater than this period's projected demand. Constraints (28) stipulate that each demand node is served by only one site during each planning period. Constraints (29) and (30) ensure that supply quantity is directed only to those demand nodes assigned to their respective production sites. Finally constraints (31) and (32) specify the types of decision variables.

Before using the model to generate solutions for the current case study, it is important to understand its limitations and assumptions, and their impact on the quality of the final solution. Many of these assumptions and limitations are similar to those in the first case study's optimisation model. First the model is deterministic i.e. all parameters values are known in advance and do not change during the model solution. At a first glance, it might seem that this assumption defeats the model's purpose; being deterministic and requiring specific values for all parameters (the lack of which, contributes to the emergence of crisis situations). Deterministic modelling, however, can provide valuable insights into understanding a problem and therefore provide a starting point for further experimentation; where uncertainty naturally has to be incorporated into the modelling

setting before a reliable solution is generated. As discussed earlier at the beginning of this chapter, uncertainty is introduced through the simulation (ABM) model and incorporated through continuous two-way feedback between the optimisation and the simulation models. The model also assumes that each demand node is assigned to exactly one production facility during each planning period, this assignment however is allowed to change between different time period. The model also assumes road transport where each demand node is responsible for picking up its own supplies at the beginning of each planning period. This assumption was made to suit the modelling setting for the particularity of this case study where it could be faster and more efficient that each demand node (i.e. hospital) collects its supplies, rather than the supplying site dispatching several or single vehicle(s), which is likely to take much longer. Raw materials are assumed to be available at all production sites with no shortages. Pre and post processing of produced units is incorporated into the aggregate cycle time, which helps maintaining some degree of simplicity without compromising the quality of the solution.

It could be noticed from model (24) – (32) that the model in this case study is substantially different from that developed for the case study. A deeper investigation into both models will reveal, however, that at heart they share some degree of similarity. Although the objective function is different (cost in the first case study against distances travelled in this one), they both provide the same decisions; location-allocation, production and deliveries quantities. Both models also belong to the same family of linear programming models i.e. integer linear programming (ILP). The difference in the objective functions was however due to the different objectives of each application of the framework. In the first case study, the objective was to minimise the total cost of designing an RdM network in commercial setting. In this case study, however, cost is less important (although, practically, still important) than having the items delivered with the shortest possible time. Although cost has not been considered in this case study due to the nature of the problem and the need to prioritise speed over cost, cost could be easily integrated into the model. Cost could be included, similar to the previous case study, as the determining objective function, or it could be added as an extra objective function. If the framework has been applied to a context similar to the one presented in this case study, but for long-term planning, then cost should be accounted for. Nevertheless, since the context of this case study is only temporary, and the main goal is to demonstrate that the framework is flexible

with regards to the nature of the objective function, cost has been omitted from the modelling context. In general, if the framework is applied for long-term planning, then cost should be accounted for. This also demonstrates the flexibility and generalisability of the framework where the modeller is not confined with one inflexible model, but can rather alter the models' formulation to best serve achieving the application's objective. The next section will present and discuss the ABM simulation model before discussing the framework's outcome.

6.3 Simulation model

The simulation model, as shown in Figure 6.1 below, consists of three main *agent types*, which are *containers* where the populations of agents live, have their parameters values and functions stored and shared between them. Environment, similar to its explanation in the previous case study, is the encompassing agent where all other agent populations live. Demand nodes and production facilities are the other two agents populations. The simulation model runs once the optimisation model has produced a production network structure, it imports the parameters values from the shared database (where the optimisation model has exported the network structure). Determined by the imported parameters values, the simulation model then adds the production facilities, establishes interconnections between these facilities (i.e. allocates demand nodes to production facilities) and adds delivery vehicles at the demand nodes, simultaneously. Then the planning period is updated, which is a recurrent event that is scheduled at the end of each planning period, and keeps recurring until the simulation is completed. To elaborate more, if the simulation model is to simulate a week's worth of a system's operations divided into 7 days, then at the end of each day the planning period is updated until day 7 is reached. Then, if the current planning period is any, but the last, the production schedule (which was determined by the optimisation model) is shared with all production facilities. If the planning period is not the first, then the model stores each individual demand point's shortages data that were obtained from the previous planning period. Then, if the planning period is not the last one, the production facilities start producing according to the production schedule. After the production of each individual unit, the production schedule is checked inside the production facility agent; if the schedule is met then the production

(for the current planning period) ends and the respective demand points are contacted to collect their supplies.

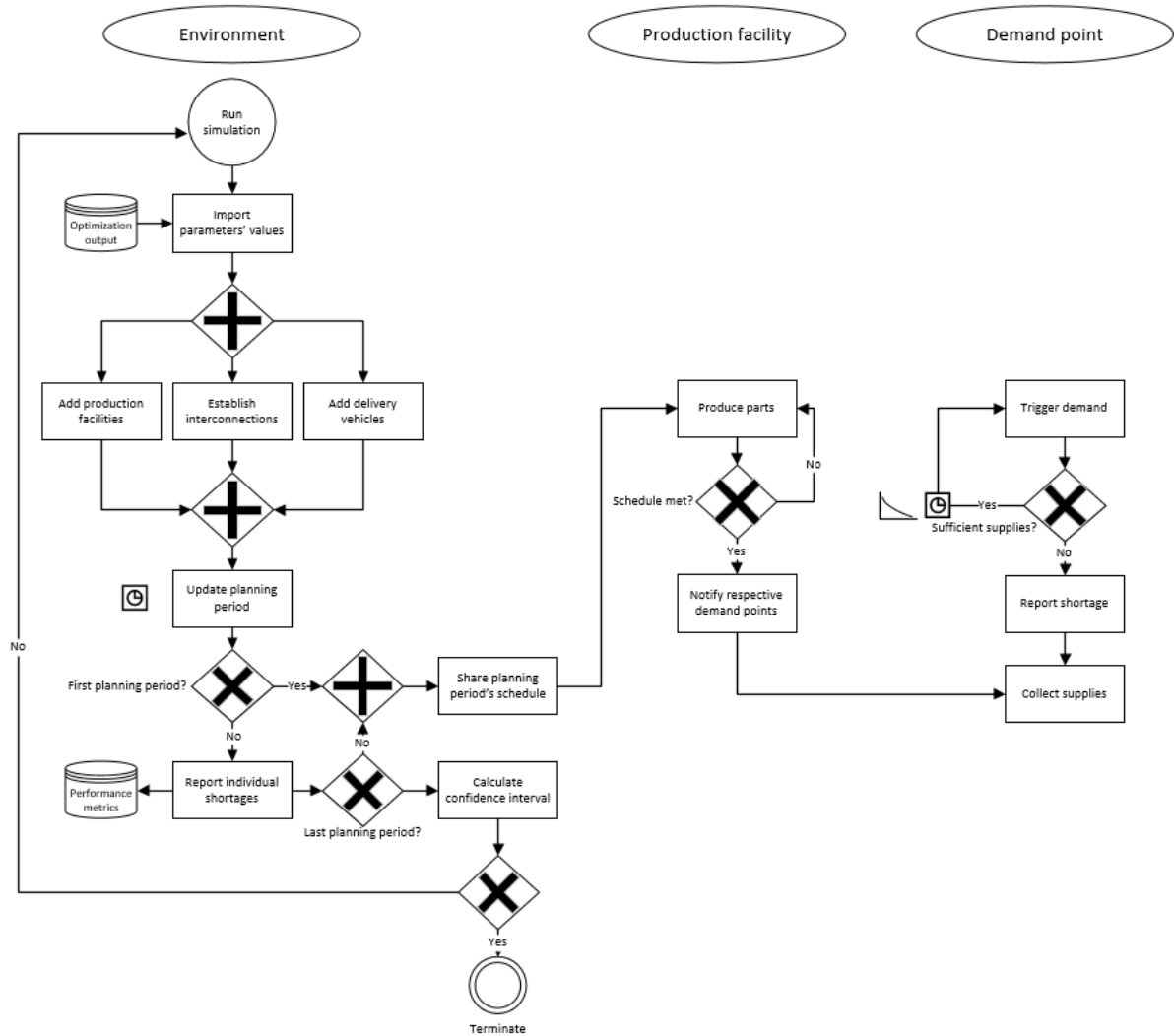


Figure 6.1 Simulation model process map

Inside the demand nodes agent, a stochastically triggered event continuously generates demand several times in each planning period (Table 6.2); if there were not sufficient supplies to meet the demand, then these shortages is reported and the supplies are ordered.

This process keeps going until the last planning period is reached, in which the confidence interval (CI), is calculated as in equation (9). If the desired confidence interval is reached, then the model terminates, otherwise the model performs another replication to add its corresponding values to the cumulative mean of the preceding values until the desired confidence interval is met. Upon the termination of the simulation model the means of

the individual shortages are calculated and passed back to the optimisation model as constraints to devise a new network topology and production plans to meet the observed performance.

6.4 Results and discussion

When the framework was implemented with the parameters values presented in Table 6.1 and Table 6.2, the production network depicted in Figure 6.2 was generated by the optimisation model. Then its performance under uncertainty was evaluated by the simulation model. The performance measures that the simulation model is designed to observe are lead time and the number of PPE shortages experienced by each hospital. It is assumed that PPE replenishments occur on a weekly basis where each hospital is supplied with a projected week's worth of PPE. Since the uncertainty of demand at hospitals is, as is expected in the context of this research, high (with standard deviation being half of the original mean value), a significant number of simulation replications is required to produce a reliable and insightful output. The performance measures chosen to improve, and subsequently the confidence interval measured against, are lead time and the frequency of PPE shortages (i.e. unmet demands). When the confidence interval method, highlighted in equation (9), was used and a desired value of 95% (which indicates that there is a 95% chance that the true mean falls within the confidence interval) was selected, it took 100 replications to achieve the 95% value. This number however increased once the solution improved (i.e. more optimisation simulation iterations were performed) because the performance measures in this instance (lead time and frequency of shortages) gradually decreased while uncertainty remained fixed. In other words the same degree of fluctuation remained but within tighter bounds. Therefore, to ensure that the set confidence interval is met, and that it remains sufficiently narrow, a total of 1000 simulation replications were performed for each optimisation-generated production network. This number of simulation replications is considerably larger than the one chosen for the previous case study, but this is due to the considerably higher uncertainty expected in emergency response settings. Each simulation replication, however, took seconds only to complete; therefore performing 1000 replication was not a computational challenge with regards to time.

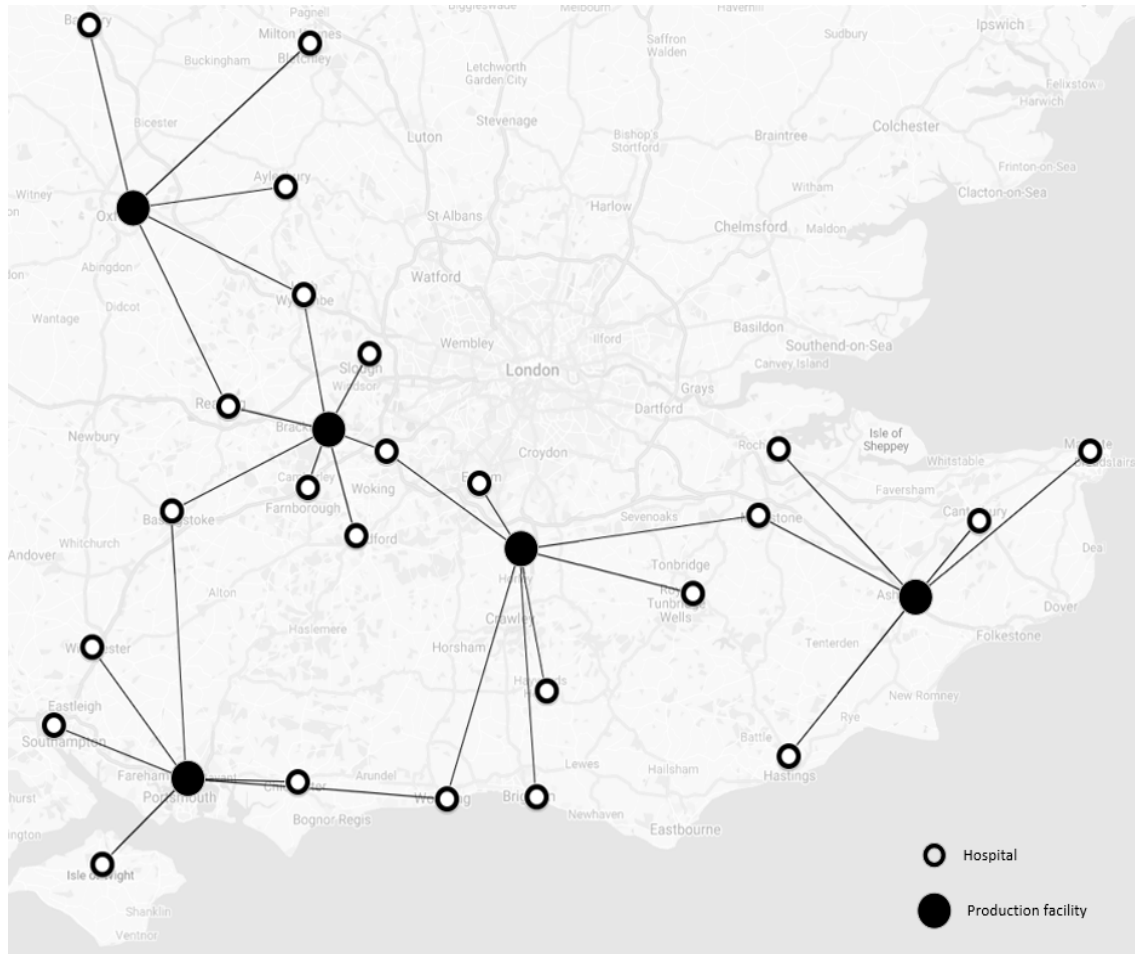


Figure 6.2 RdM network structure from the first iteration

It is clear how in this case study the confidence interval takes much more replications to narrow down to the desired level compared to the previous case study. This is expected given the level of uncertainty incorporated in the simulation model. In particular, demand in all demand nodes and during all planning period has a standard deviation that is half of the mean demand. This rather large value will naturally result in a higher degree of uncertainty, which is necessary to account for when modelling in emergency settings. To demonstrate how more replications are required to achieve the desired confidence interval as the number of optimisation-simulation iterations progresses, Figure 6.3 below depicts the confidence intervals for the first and last (eighth) iterations.

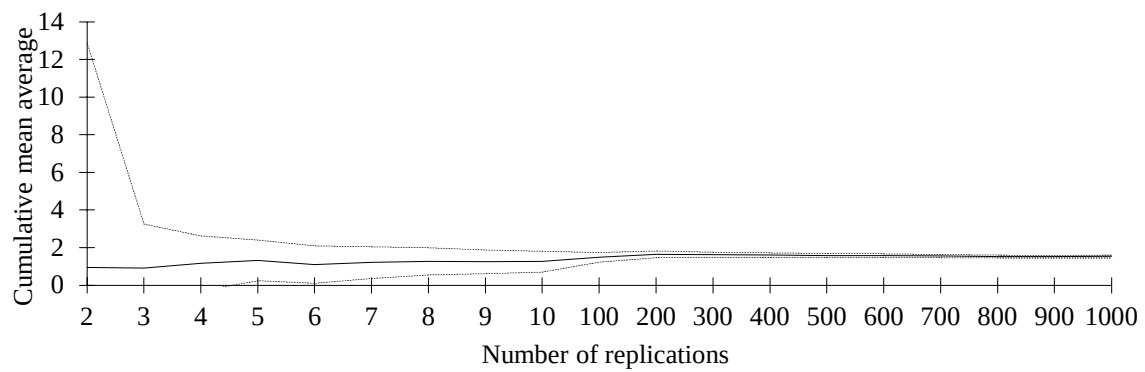
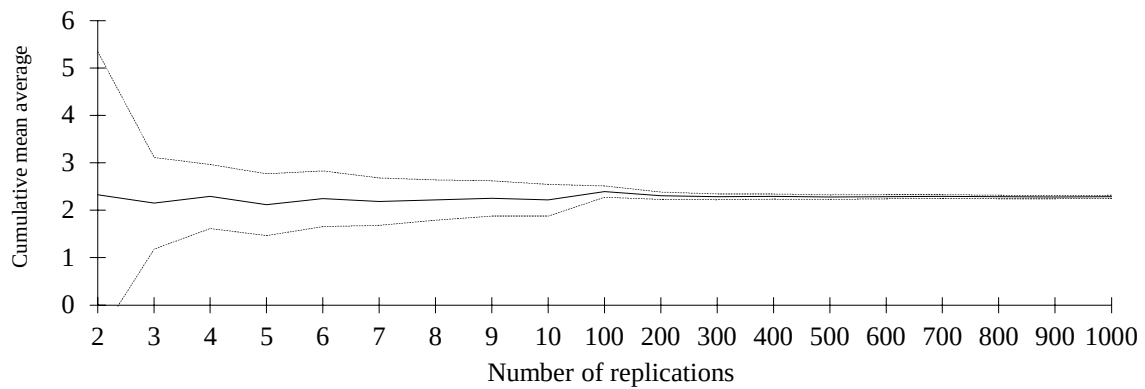


Figure 6.3 Confidence intervals for the first (up) and last (bottom) optimisation-simulation iterations against the duration of lead time for the RdM scenario

A closer depiction of the later replications of the last iteration's confidence interval is provided in Figure 6.4 below where the confidence intervals narrows to 95% and remain around that figure.

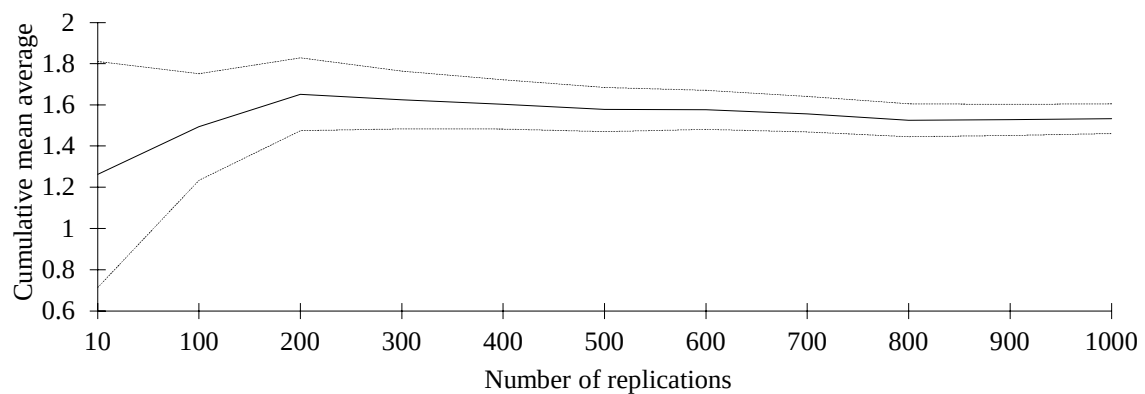


Figure 6.4 Confidence interval for the later replications of the last optimisation-simulation iteration against the duration of lead time for the RdM scenario

feedback (to refine the constraints and achieve better service level performance). It took 8 and 6 optimisation-simulation iterations for the Centralised and RdM scenarios, respectively, of gradual improvements until the framework ceased to identify improvements on the system's performance with regards to lead time and the frequency of the occurrence of unmet demand as shown in Figure 6.6 and Figure 6.7 and Table 6.3 and Table 6.4. Figure 6.6 and Figure 6.7 depict the improvements attained through employing the decision-making framework on the Centralised and RdM scenarios. Figure 6.6 and Figure 6.7 (up) show that the first solution in the Centralised and RdM scenarios had a mean of around 16 and 18 shortages experienced by all the 29 hospitals during all planning periods, respectively. These results could be acceptable in some cases, but in crisis situations it is likely that these numbers are desired to be lower than that. Therefore when the simulation model was utilized, it evaluated the system's performance, observed where most shortages occurred and passed back a number of recommendations to the optimisation model to guide its search for the optimal solution given the new requirements. These requirements include supplying more PPE to hospitals that experienced shortages at the specific planning period that such shortages occurred, and if any, supply less to hospitals that experienced surpluses, although the latter case was not experienced throughout the modelling process. Figure 6.6 and Figure 6.7 (bottom) illustrate the improvement attained from applying the framework with regards to lead time for the Centralised and RdM scenarios, respectively. As the number of optimisation-simulation iterations progressed, both of these service performance measures significantly improved, although to a lesser degree than that experienced in the first case study. This is due to the considerable difference in the length of the planning horizons in each case study, which in turn is due to the nature of each problem. To explain more, the first case study, being strategic in nature where a new manufacturing system is developed to improve long-term goals (cost and service) required a lengthy planning period of one year. While this case study dealt with devising a manufacturing system of temporary nature to deal with a situation of finite duration where the manufacturing system dissolves once the reason that triggered its establishment (pandemic in this case study) is over. Therefore the nature of this case study requires a considerably shorter planning period, which has been set at one week.

However, similar to the first case study the most significant improvement in both scenarios has been achieved from the second iteration. In the Centralised scenario the frequency of unmet demand decreased from 15 to 11, going down to 8 occurrences at the last iteration. Regarding lead time in the Centralised scenario, the duration went down from 3.29 hours in the first iteration to 2.95 hours in the second, and ending up at 2.65 hours in the last iteration. For the RdM scenario, however, the frequency of unmet demand improved from around 18 to around 10 in the second iteration, stopping at around 5 in the last iteration. The mean lead time in the RdM scenario was also significantly better than that of the Centralised scenario where the first iteration yielded a mean lead time of 2.28 hours, improving to 1.83 hours and stabilising at 1.37 hours in the last iteration.

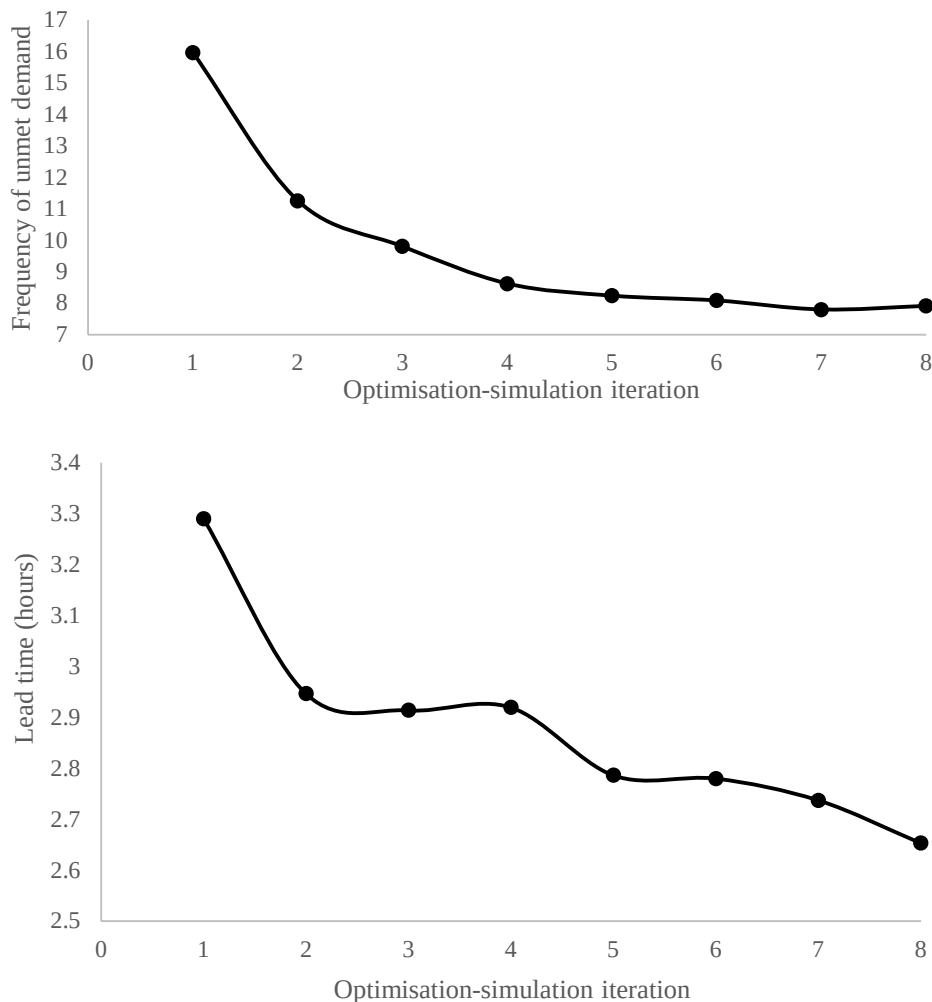


Figure 6.6 Improvement in the occurrence of unmet demands (up) and lead time (bottom) for the Centralised scenario

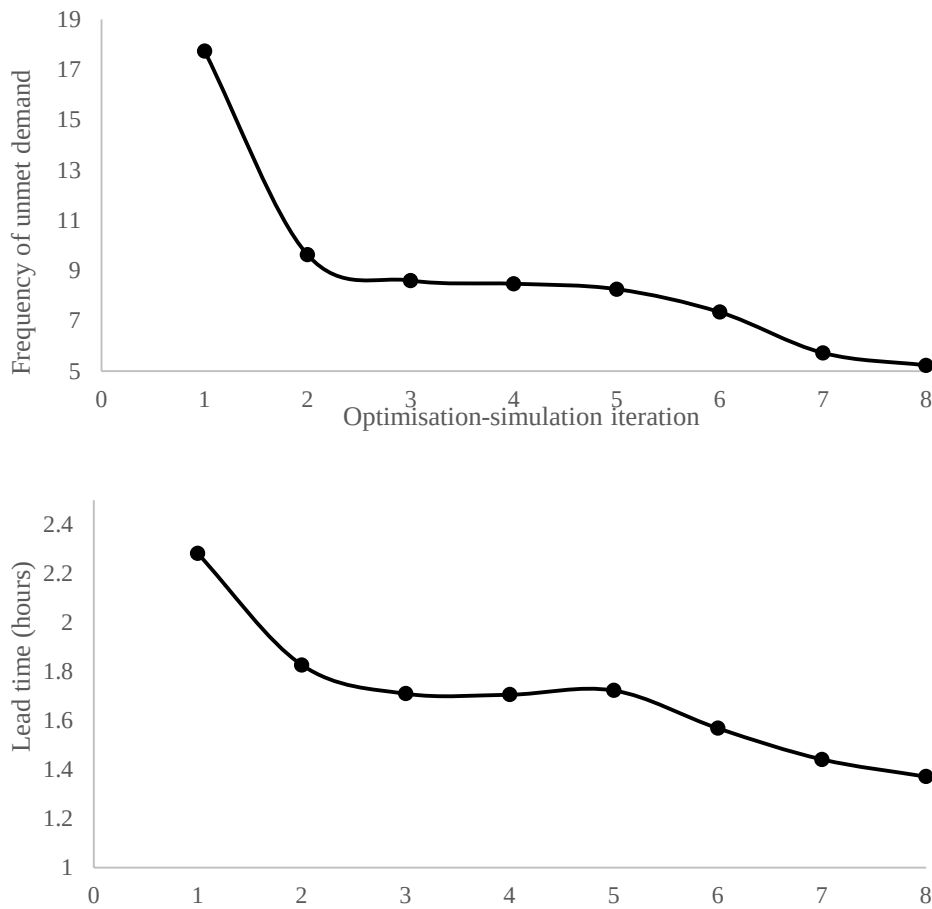


Figure 6.7 Improvement in the occurrence of unmet demands (up) and lead time (bottom) for the RdM scenario

To elaborate more on the improvement attained from applying the framework with regards to the frequency of unmet demand, Figure 6.8 below depicts the frequency of the occurrence of unmet demand for hospitals that experienced the highest degrees of unmet demands. It could be noticed from Figure 6.8 that, similar to the observation made in the first case study, the frequency of the occurrence of unmet demand is lower in the Centralised scenario in the first iteration. This is due to the longer lead time in the Centralised scenario (as a result of longer distances) which results in more supplies, that are moved to the next planning period, stored in each hospital. The results however reveal that by the last optimisation-simulation iteration, both scenarios experienced considerably less occurrence of unmet demands. The RdM scenario however performed slightly better than the Centralised scenario in this aspect, with shorter distances travelled, shorter

maximum distance travelled between any two locations and considerably shorter lead time.

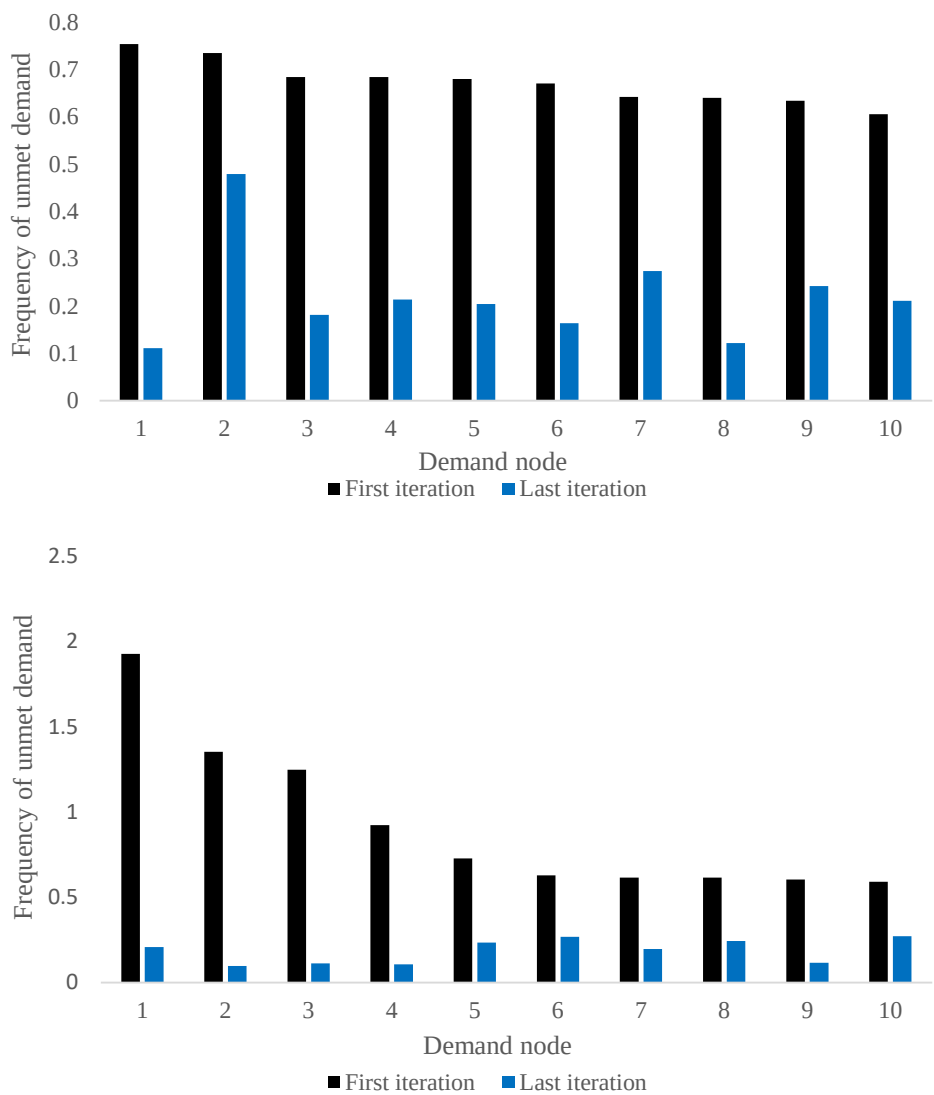


Figure 6.8 Frequency of the occurrence of unmet demand for the 10 highest hospitals in the first and last optimisation-simulation iterations for the Centralised (up) and RdM (bottom) scenarios

Table 6.3 and Table 6.4 below provides the yielded improvements for the Centralised and RdM scenarios for all optimisation-simulation iterations.

Table 6.3 Summary of the framework outcome iterations for the Centralised scenario

		Total distance travelled in miles (optimisation)	Total distance travelled in miles (simulation)	Gap	Maximum distance (miles)	Lead time (hours)	Frequency of unmet demand
Iteration 1	Value	8,235	8,354.08	1.44%	83.09	3.29	15.962
	Improvement	n/a	n/a		n/a	n/a	n/a
Iteration 2	Value	8,392	8,459.71	0.80%	83.09	2.95	11.257
	Improvement	-1.91%	-1.26%		0.00%	11.66%	29.48%
Iteration 3	Value	8,392	8,451.49	0.71%	83.09	2.91	9.806
	Improvement	0.00%	0.10%		0.00%	1.11%	12.89%
Iteration 4	Value	8,392	8,443.36	0.61%	83.09	2.92	8.624
	Improvement	0.00%	0.10%		0.00%	-0.19%	12.05%
Iteration 5	Value	8,392	8,440.23	0.57%	83.09	2.79	8.24
	Improvement	0.00%	0.04%		0.00%	4.56%	4.45%
Iteration 6	Value	8,392	8,438.48	0.55%	83.09	2.78	8.087
	Improvement	0.00%	0.02%		0.00%	0.24%	1.86%
Iteration 7	Value	8,392	8,434.43	-0.05%	83.09	2.74	7.796
	Improvement	0.00%	0.05%		0.00	1.53%	3.60%
Iteration 8	Value	8392.228643	8,435.68	0.52%	83.09	2.65	7.916
	Improvement	0.00%	-0.01%		0.00	3.06%	-1.54%

Table 6.4 Summary of the framework outcome iterations for the RdM scenario

		Total distance travelled in miles (optimisation)	Total distance travelled in miles (simulation)	Gap	Maximum distance (miles)	Lead time (hours)	Frequency of unmet demand

Iteration 1	Value	3,287	3,399	3.40%	37.63	2.28	17.73
	Improvement	n/a	n/a		n/a	n/a	n/a
Iteration 2	Value	3,360	3,399	1.16%	32.97	1.83	9.63
	Improvement	-2.23%	-0.02%		12.37%	24.95%	45.70%
Iteration 3	Value	3,360	3,394	1.00%	32.44	1.71	8.60
	Improvement	0.00%	0.16%		1.62%	6.38%	10.64%
Iteration 4	Value	3,376	3,410	0.99%	40.93	1.71	8.48
	Improvement	-0.48%	-0.47%		-26.19%	0.23%	1.42%
Iteration 5	Value	3,376	3,410	1.02%	40.89	1.72	8.26
	Improvement	0.01%	-0.02%		0.10%	-0.98%	2.59%
Iteration 6	Value	3,376	3,401	0.74%	40.46	1.57	7.35
	Improvement	0.00%	0.28%		1.05%	8.95%	11.03%
Iteration 7	Value	3,376	3,397	0.61%	40.23	1.44	5.73
	Improvement	0.00%	0.13%		0.57%	8.13%	22.07%
Iteration 8	Value	3,376	3,396	0.58%	40.39	1.37	5.24
	Improvement	0.00%	0.03%		-0.39%	4.83%	8.62%

With regards to distances travelled in each scenario, there is a considerable difference between the Centralised and the RdM settings in both total distances travelled and the maximum distance travelled between any two points. This result is natural and intuitive due to the distribution of the production facilities. However, as the modelling progressed, the total distances travelled in the RdM scenario slightly increased when the other performance measures (lead time and frequency of unmet demand) improved. This is similar to the previous case study, where the improvement in service level came at the expense of a slightly higher objective function value (cost). This increase in the total (and maximum distance travelled between any two locations) might at first seem counterintuitive, given the purpose of the framework when applied to the case study. This increase, given the objective function that the optimisation model minimises, is reasonable. This is because what the model minimises is not the total distance travelled,

but rather the supply-weighted distance travelled, which has been explained earlier in this section. The optimisation model might, for instance, allocate a demand node with relatively fewer demand to a farther production facility because the facilities closest to this demand point are fully utilised to supply their neighbouring demand points. Therefore the total supply-weighted distance travelled, not the total distance travelled, is minimised. While if each RdM facility supplied only its closest demand points then the total distance travelled and the maximum distance between any two facilities will be lower, but the objective function will be considerably higher. This observation is very common in facility location modelling, and the weighted distance is often used when busier demand nodes are prioritised [86]. When applying the framework in other contexts, if this property is not desired, then model (24) – (32) could easily be transformed to a minimax problem where the objective function minimises the maximum distance between any pair hospital and its allocated production facility, regardless of the flow between them [47]. Similar to the first case study, the RdM network structure generated by the framework remained fixed throughout the framework application.

6.4.1 Sensitivity analysis

Similar to the first case study, and to further investigate the impact of uncertainty on the framework's outcome and identify the important parameters, a sensitivity analysis is conducted in this section. Important parameters in this context refers to those that a slight change in their value might yield a considerably different outcome. Therefore the sensitivity analysis will examine the relationship between the inputs and outputs of the framework.

The sensitivity analysis experiments are conducted on the RdM scenario only as it is the intended choice of manufacturing paradigm, and the inclusion of the Centralised scenario in the previous sections was only to demonstrate the differences in different performance measures between both scenarios.

The parameters that will be investigated are the demand rate, cycle time and the AM equipment's availability. Each parameter's value will be increased / decreased by 10% increments/ decrements up to 100% of its original mean value. The impact of changing these parameters values will be investigated against the total distances travelled and the number of required production facilities, and consequently the number of AM equipment.

The impact of changing the values of these parameters on lead time and the frequency of unmet demand will not be included in this section. This is because the framework, when applied, exhibits a similar behaviour i.e. these performance measures keep gradually improving until the framework ceases to identify further improvements. Therefore it is unnecessary to report these figures in this section. The outcome of the sensitivity analysis experiments is reported in Table 6.5 below against the total distance travelled and the number of RdM facilities.

Table 6.5 Sensitivity analysis outcome on total distances travelled (in miles), the number of RdM facilities and the locations of RdM facilities

Change in the parameter's value		Total demand	Cycle time	Production availability
-90%	Total distances	4,153	8,235	1,689
	Number of RdM facilities	1	1	14
	Reference of selected locations	26	26	2(4), 3(2), 4(2), 10(4), 11(2), 12(2), 15(4), 16(2), 17(3), 18(4), 20(4), 23(5), 24(4), 29(2)
-80%	Total distances	5,824	8,235	1,692
	Number of RdM facilities	1	1	14
	Reference of selected locations	26	26	2(2), 3, 4, 10(2), 11, 12, 15(2), 16, 17(2), 18(2), 20(2), 23(2), 24(2), 29
-70%	Total distances	5,115	5,783	2,100
	Number of RdM facilities	2	2	13
	Reference of selected locations	14, 24	14, 24	3, 8, 10, 11, 12, 15, 16, 17, 18, 20(2), 22, 23, 24(2)
-60%	Total distances	5,126	5,876	2,091
	Number of RdM facilities	2	2	11
	Reference of selected locations	17, 24	2, 17	2, 3, 8, 10, 12, 15, 17, 19, 20, 23, 24
-50%	Total distances	4,070	4,559	2,367

	Number of RdM facilities	3	3	9
	Reference of selected locations	1, 10, 14	1, 10, 14	2, 8, 10, 12, 14, 19, 20, 23, 24
-40%	Total distances	4,744	4,661	2,562
	Number of RdM facilities	3	3	8
	Reference of selected locations	2, 10, 14	1, 10, 14	2, 10, 12, 14, 19, 20, 22, 24
-30%	Total distances	3,839	3,836	2,581
	Number of RdM facilities	4	4	7
	Reference of selected locations	1, 10, 14, 20	1, 10, 14, 20	2, 10, 14, 19, 20, 26, 27
-20%	Total distances	3,910	3,910	3,068
	Number of RdM facilities	4	4	6
	Reference of selected locations	10, 14, 20, 26	10, 14, 20, 26	10, 17, 19, 20, 23, 24
-10%	Total distances	3,984	4,023	3,357
	Number of RdM facilities	4	4	5
	Reference of selected locations	10, 14, 20, 26	10, 14, 20, 26	1, 10, 18, 20, 22
0%	Total distances	3,287	3,287	3,287
	Number of RdM facilities	5	5	5
	Reference of selected locations	1, 10, 18, 20, 22	1, 10, 18, 20, 22	1, 10, 18, 20, 22
10%	Total distances	3,302	3,309	n/a
	Number of RdM facilities	5	5	n/a
	Reference of selected locations	1, 10, 18, 20, 22	1, 10, 18, 20, 22	n/a
20%	Total distances	3,016	3,016	n/a
	Number of RdM facilities	6	6	n/a

	Reference of selected locations	10, 17, 19, 20, 23, 24	10, 17, 19, 20, 23, 24	n/a
30%	Total distances	3,086	3,093	n/a
	Number of RdM facilities	6	6	n/a
	Reference of selected locations	10, 17, 19, 20, 23, 24	10, 17, 19, 20, 23, 24	n/a
40%	Total distances	2,608	2,608	n/a
	Number of RdM facilities	7	7	n/a
	Reference of selected locations	12, 14, 19, 20, 23, 24, 29	12, 14, 19, 20, 23, 24, 29	n/a
50%	Total distances	2,691	2,808	n/a
	Number of RdM facilities	7	7	n/a
	Reference of selected locations	2, 12, 14, 19, 20, 23, 29	2, 10, 14, 19, 20, 22, 24	n/a
60%	Total distances	3,045	3,132	n/a
	Number of RdM facilities	7	7	n/a
	Reference of selected locations	2, 10, 14, 19, 20, 22, 24	2, 10, 14, 19, 20, 22, 24	n/a
70%	Total distances	2,577	2,611	n/a
	Number of RdM facilities	8	8	n/a
	Reference of selected locations	2, 10, 12, 14, 19, 20, 22, 24	2, 10, 12, 14, 19, 20, 22, 24	n/a
80%	Total distances	2,562	2,601	n/a
	Number of RdM facilities	8	8	n/a
	Reference of selected locations	1, 2, 8, 10, 14, 19, 20, 23	1, 2, 8, 10, 14, 19, 20, 23	n/a
90%	Total distances	2,261	2,261	n/a
	Number of RdM facilities	9	9	n/a

	Reference of selected locations	2, 8, 10, 12, 14, 19, 20, 23, 24	2, 8, 10, 12, 14, 19, 20, 23, 24	n/a
100%	Total distances	2,367	2,367	n/a
	Number of RdM facilities	9	9	n/a
	Reference of selected locations	2, 8, 10, 12, 14, 19, 20, 23, 24	2, 8, 10, 12, 14, 19, 20, 23, 24	n/a

The results reported in Table 6.5 above indicate that there is an apparent relationship between total demand and cycle time. This relationship is identical with regards to the number of RdM facilities where each increment / decrement in each parameter's value resulted in the same change with regards to the number of facilities. This outcome is due to the natural relationship between the number of units produced, which matches demand, and the time required to produce these units. There is therefore a proportional relationship between these two parameters. The reason however why the impact of the change in these two parameters is identical on the number of RdM facilities is that they are both increased / decreased in the same increment / decrements and, more importantly, the observed change in outcome is measured by whole numbers (i.e. integers). To explain more, the change in the number of RdM facilities has to be a whole number; it cannot be a fraction. It is unrealistic, for instance, to have 3.5 facilities; it has to be either 3 or 4 facilities. Therefore, this lack of freedom in the value of the outcome results in the change in both these parameters being identical. This observation could be affirmed by observing the impact of changing these two parameters on the total distances travelled where the outcome is very close, but not exactly identical. This could be noticed from Figure 6.9 below where the lines representing the value of cycle times and total demands against total distances travelled meet for most of the figure but they do not exactly align as in Figure 6.9 (bottom).

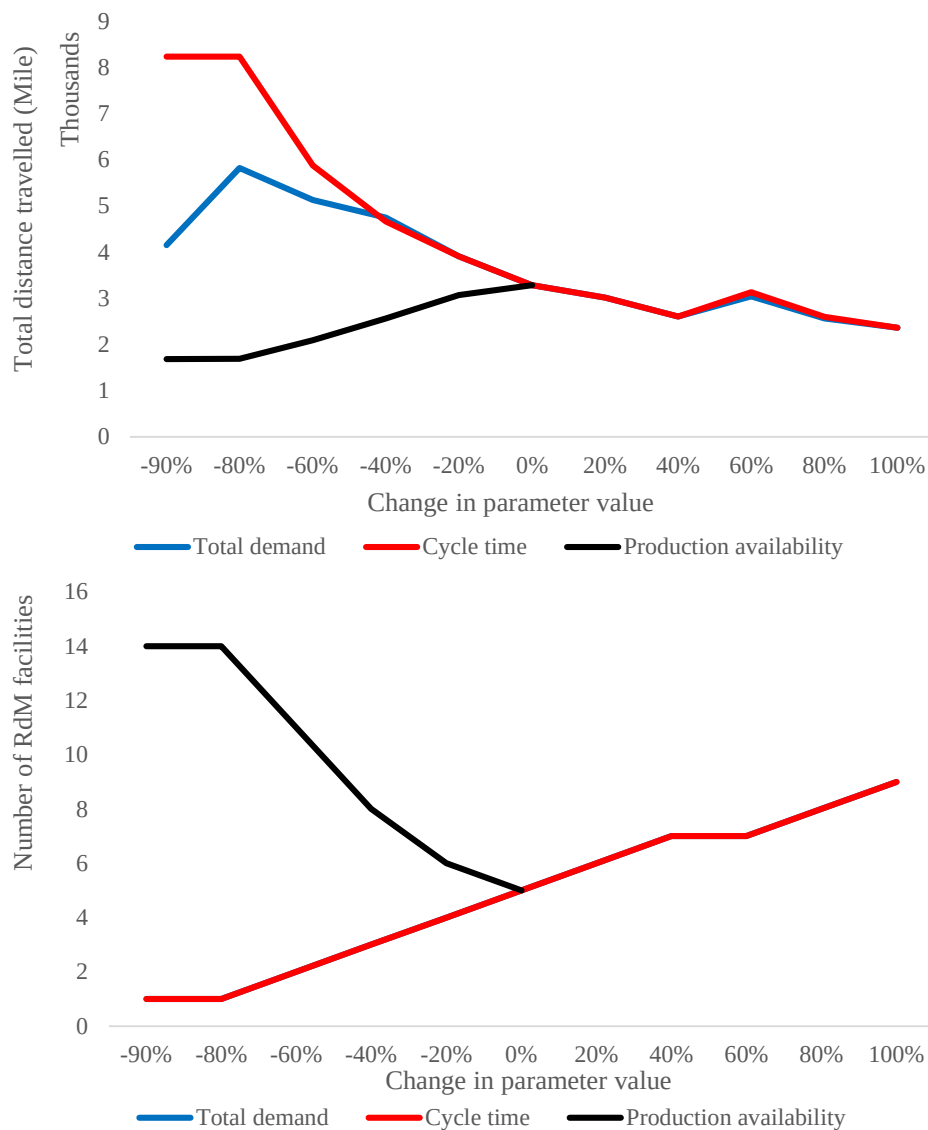


Figure 6.9 The impact of the change in the value of key parameters on the total distance travelled (up) and the number of RdM facilities (bottom)

Looking at Figure 6.9, when the values of total demand and cycle time are considerably reduced, the resulting total distance travelled then differs significantly. When decreasing the total demand, the total distance travelled in turn increases. At a first glance, this might seem counterintuitive, but the explanation for this is rather simple. The longer distances travelled when the demand decreases is due to the decrease in the number of RdM facilities (and subsequently AM equipment required to meet demand level). When a smaller number of RdM facilities is placed in the production network, the network then becomes more *centralised* and therefore these facilities are allocated more (and farther)

demand points. The assumption made in this case study was, however, to have 5 available AM equipment to place anywhere that the optimisation model determines. But the results reported in the sensitivity analysis experiments assumed utilising the minimum number of AM equipment required to fulfil demand. If however the number of AM equipment remained at 5, even though demand could be fulfilled with less than 5 equipment, then the impact of decreasing the demand on the distance travelled will look like Figure 6.10. When the number of AM equipment remained fixed, even though a smaller number can meet demand, and demand decreased, the total distance travelled also decreased with the decrease in total demand. This is because when demand decreases and the number of AM equipment remained fixed, they (AM equipment) will be less utilised and therefore they do not become allocated mainly to their busiest neighbouring hospitals. This point has been discussed earlier in the previous section where the observation was made about the slight increase in the total distance travelled when the performance with regards to lead time and the frequency of unmet demands improves. As a result, each RdM facility is, when demand decreases and production resources remain the same, allocated to its nearest hospitals (i.e. same as if the objective function was to minimise the total distance travelled). Another reason why the total distance travelled significantly decreases when demand decreases is that some hospitals that already have low demand rates will, for certain weeks, not order any PPE. For example, hospital number 6 (Wycombe Hospital) in Table 6.2 (which contains mean demand rates for all hospitals during all planning periods) will not order PPE in the second week if demand decreased by 80%. It should be acknowledged however that such a decrease (80%) in demand is unlikely, but it is still useful to investigate its impact on the manufacturing system.

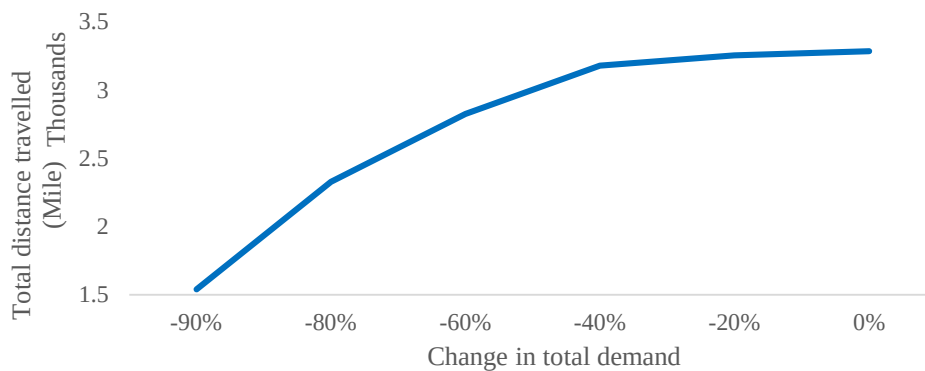


Figure 6.10 The impact of decreasing total demand on the total distances travelled when the number of AM equipment is kept fixed at 5

The impact of the decrease in cycle time on the total distance travelled was, however, more dramatic than that of the total demand. At a first glance, one could deduce that since the number of AM equipment, and consequently the number of RdM facilities, is the same when total demand and cycle time are decreased, then the total distance travelled should be the same in both cases. This principle however applies only on the increase in the values of these two parameters (i.e. total distance and cycle time), and this could be observed from Figure 6.9 (up). The reason, however, why this principle does not apply on the decrease of the values of these two parameters is that, as stated in the previous paragraph, in cases of significant decrease in demand, some hospitals might not order PPE in certain weeks, hence decreasing the total distance travelled. This is however not the case regarding cycle times, if cycle time is decreased even to zero, demand at all hospitals during all weeks remains the same and trips to hospitals, even those with very low demand, will still have to be made and subsequently contribute to the total distance travelled. In other words, if demand decreases, some trips might be eliminated and therefore the total distance travelled also decreases. On the other hand, if cycle time decreases, demand is not affected and all trips still have to be made. In the other case where total demand and cycle time both increase, the total distance travelled increases in almost the same magnitude. This is because in the case of increase, no trips are eliminated from the network, instead quantities of delivered PPE changes, which does not contribute to the total distance travelled. It is appropriate here to point out to an assumption made earlier while developing the framework about PPE delivery which is delivery vehicles have no capacity constraints. This is because each hospital is responsible for collecting its own supplies, the number of weekly required units is relatively low, and finally the sizes of PPE are relatively small. Also with the demand quantities reported in Table 6.2, it is unlikely that more than one delivery vehicle is needed to deliver a week's worth of PPE. This assumption holds when investigating the impact of total demand change on the performance of the system. This is because even if demand doubles, the highest number of PPE to be delivered to one hospital will be 62 PPE (John Radcliffe Hospital in week 6), which can easily fit even in personal vehicles.

Availability of AM production has had a different impact on both total distance travelled and the number of RdM facilities. First, availability of AM production in the decision-making framework refers to the number of available hours for each AM equipment. For

example, if AM equipment were always available and there was always an operator available then the production capacity will be 168 ($24 * 7$) hours per week. This figure (168 hours), however, assumes that there is no time between the production of two consecutive units, and that there is always an operator available to operate the AM equipment. As the availability of AM equipment decreased, total distance travelled also decreased with it. This is because as the availability decreases, more equipment are needed to fulfil demand, resulting in a more distributed RdM network that subsequently contributes to shorter travelled distances. Conversely, when availability increases, the number of AM equipment decreases resulting in a more centralised production network where typically longer distances are travelled. The impact of increasing the availability of AM production beyond 168 hours per week was, similar to the first case study, not included because it is unrealistic to assume that a week has a number of hours more than it contains. The decrease in production availability had a pronounced impact on the number of RdM facilities (and the minimum number of required AM equipment). this impact significantly increased as the availability of AM machines further decreased. For example, when the AM equipment availability decreased from 100% availability to 90% of the time being available the number of AM equipment remained at 5. While when availability decreased from 50% to being available only 40% of the time, the number of AM equipment increased from 11 to 15, respectively. This is partly because when first, the availability gradually slightly decreases, the available AM equipment can accommodate this decrease in availability from already existing surplus capacity. To explain more, the AM equipment when full availability is assumed are not fully utilised, therefore when availability decreases, the number of required AM equipment is little affected. Later on, however, when all the machines are fully utilised, extra AM machines will be required to compensate for the lost availability. To further clarify the impact of machine utilisation on slight reduction in AM availability, Figure 6.11 below depicts the AM equipment's utilisation in each RdM facility.

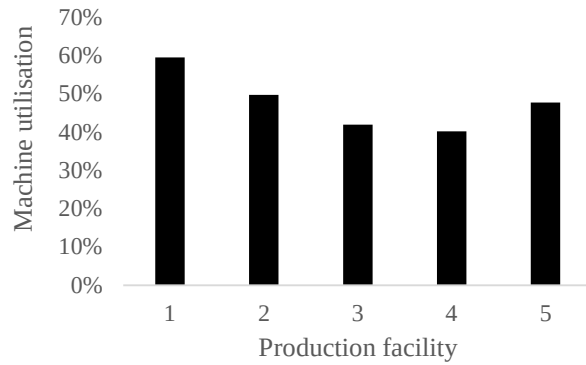


Figure 6.11 AM equipment utilisation for the first optimisation-simulation iteration for the RdM scenario

The other reason behind this observation is an intuitive one which is, the more availability decreases the less units are produced. To explain more, when availability decreases by 20%, each AM equipment can operate for 134.4 hours each week. While when availability decreases by 60%, each AM equipment can operate for 67.2 hours each week. When the cycle time is 2 hours, in case of the 20% decrease each AM equipment can produce 67 units per week, while in the case of 60% reduction in availability, each AM equipment can produce only 33 units per week. For example, considering the busiest week from Table 6.2, 364 units are demanded from all hospitals during week 7. In case of only 20% reduction in availability, six AM equipment ($\frac{634 \times 2}{134.4}$) are required, while 60% reduction in availability will result require 11 AM equipment ($\frac{634 \times 2}{67.2}$). The demand rate is multiplied by 2 (cycle time for one unit) to reflect the entire production time required to produce all the chosen week's demand.

The observations made from the sensitivity analysis outcome can have a number of practical implications. First the sensitivity analysis experiment results reveal that the framework in most cases tends to generate a more distributed production network rather than centralising production equipment in one location. In all cases, except when the availability of AM equipment was extremely reduced, the framework located one AM equipment at each location, and spread the allocation of equipment into the network.

In addition to confirming that RdM is the preferred setting for the efficient production and distribution in crisis scenarios, sensitivity analysis can also identify not only important (or sensitive) parameters, but can also identify important potential RdM

locations. For example, prior to placing the AM equipment in the chosen sites, the decision-maker might want to investigate any future potential spike of demand on the locations, number of required AM equipment and hospitals that are frequently selected to host AM equipment. It could be noticed, for instance, that when demand and cycle time increase, and availability of AM equipment decrease, hospital number 20 (John Radcliffe Hospital) is always chosen to host AM equipment. This hospital (i.e. 20) has a relatively high demand compared to other hospitals, which is one reason why this hospital is always chosen when demand is high or cycle time is high. This is, however, not the case when demand or cycle time is low as the location of hospital 20 is rather far from the rest of the network (in Figure 6.2 it is the RdM facility located in the upper left corner of the figure). As a result, when demand is low, it is no longer efficient to prioritise this hospital by placing an AM equipment in it, or in a neighbouring hospital.

6.5 Framework validation

As has been discussed several times before, each new application of the framework has to be validated separately all over again according to the steps outlined in Chapter 3 and implemented previously in Chapter 4. After the data were collected, experts A and B were presented with a background about the framework application and were presented with the data. Experts A, B and D were presented with the objective of each model, its inputs, outputs and contents. The experts were then presented with a detailed walkthrough of the conceptual model. The meetings conducted with the experts took place remotely using web calls due to the coronavirus pandemic. At this point, the experts were familiar with the framework and its model, and they expressed that the conceptual model reflects what was conveyed to them regarding the system being modelled.

The optimisation model verification was conducted with Expert E who determined that the mathematical formulation is correct and reflects the envisioned system as it was described to him. The next step was to verify the computerised simulation model with Expert E. The expert ran the model on different instances with different assortments of values and indicated that it represents the conceptual model that was presented to him.

After all the experiments were conducted, experts A, B and D were presented with the results. The general consensus was that the context of this application greatly helps in proving that the framework could indeed be utilised in different settings. Expert D

acknowledged that this case study indeed proves that the framework could be used in varying settings, but raised concerns about the outputs of this case study when compared to the one presented in the preceding chapter. The expert's major concern was that the output generated from the optimisation model exhibited a relatively satisfactory performance in terms of unmet demands when compared to the results from the first case study. The other concern was that the improvement attained from the framework in this case study is less pronounced than the one in the previous one. The expert was then presented with an explanation to this observation which had been discussed earlier. In short the reason is that this case study has a much shorter planning period (one week as opposed to one year), mean cycle time (2 hours as opposed to a minimum of 7 hours) and lower demand. The expert however agreed that the implementation of this case study proves that the applicability of the framework is transferable amongst varying contexts.

6.6 Summary

In this chapter, the framework has been implemented to design an RdM network for the production of personal protective equipment after the sudden onset of emergencies. The objective of this instance of the framework application has been to minimise the supply-weighted total distances travelled between production sites and demand points. This objective has been chosen because minimising the distances between production sites and demand points will generally result in speedier delivery of products. The application of the framework on this instance helped in further validating the framework, in particular with regards to its generalisability within different sectors and objectives. Similar to Chapter 5, the performance of the RdM network has been compared with that of a Centralised counterpart. The results revealed that the RdM scenario performs significantly better with regards to lead time. The frequency of the occurrence of unmet demands has also been demonstrated to be lower in the RdM scenario. In the next chapter, a general discussion of the results and concluding remarks are presented.

7 Discussion and conclusion

This chapter will discuss the key findings deduced from conducting this research, findings of the numerical experiments presented in the preceding chapters and their implications. Then the framework will be evaluated in terms of its usefulness and generalisability. The contributions of this research will be then laid out, and its limitations and future work will be discussed.

7.1 Key findings, discussion and generalisability

The literature review chapter revealed that although there is a growing interest in the field of RdM network design, demonstrated by the growing number of papers dedicated to developing decision-making models and frameworks in the field, most of the contemporary studies focus on short-term operational decisions. Most of these models and frameworks addresses the operational time horizon of the problem, assuming an already existing naturally evolving production network of distributed resources and processes. Therefore most of the contemporary research efforts are mainly dedicated to devising coordination (tactical and operational) decisions, rather than configuration (strategic) ones. Research efforts that diverted from this prevailing stream of research and addressed configuration decisions, did so mainly in isolation from coordination decisions. The remaining research efforts that integrated multiple decision-making levels in one model or framework, did not account for the interdependence between these decisions in a dynamic manner under uncertainty. Apart from modelling the RdM network design problem, one of the most important findings from the literature is that RdM should, at least in the foreseeable future, not be considered as a replacement to traditional manufacturing. RdM should be considered as a complementing production paradigm that has the potential to improve the performance of certain production systems in certain areas. This approach has been emphasised in this research where the assortment of product variants that are produced via RdM are only a subset of the complete assortment of products that a manufacturer produces following the findings in [68, 78, 79].

The decision-making framework developed in this thesis has been applied on two distinct case studies to test and validate it. The two case studies, although considerably different in context, demonstrated that the framework could be generalised to, and applied in

different industrial settings such as biomedical implants, fast moving customer goods and highly customised end products, amongst others. Although the objectives of the framework's constituent models were different, the application of the two case studies demonstrated that the framework's behaviour is consistent with regards to devising, evaluating and improving the performance of RdM networks. In both case studies, a centralised scenario had been developed to provide a reference to compare the RdM scenario against with regards to performance measures. With regards to total cost in the first case study that dealt with the production of spare parts, the total cost incurred by the centralised version of the production network is slightly lower than that of the RdM system. This finding confirms the growing consensus that, with the current state of technology, centralised production is more cost efficient than AM-powered RdM one [23, 17, 91, 92, 102, 108]

Although the difference in total cost is rather low, it is not evenly distributed amongst all cost segments, and there are other factors that could further widen this discrepancy in cost. The first cost segment that had considerable difference between Centralised and RdM scenarios is the location cost (front end capital investment cost). Centralised production, having less locations and therefore less setting up and operating costs, will typically contribute to lower contribution to total cost in terms of location than that contributed by an RdM setting. This finding is in line with the literature findings with regards to the capital investment required for setting up RdM networks posing a real challenge with respect to cost [17, 91, 92, 102]. In addition, the cost of AM equipment depreciation is still not fully understood due to the relatively recent introduction of AM into wide scale production, and the rapid introduction of new models. Since AM is the proposed means of empowering the RdM network, it is important to consider to what extent the cost of depreciation can contribute to the total cost of establishing and operating an RdM network on the long run. If depreciation cost proves to be significant, then it is likely that the difference in the total cost between the Centralised and the RdM scenarios will be much more than what has been reported.

The other cost segment that had a large difference between the Centralised and the RdM systems is transportation cost, which is in line with the findings in [75]. It is likely that transportation cost will remain favouring the RdM paradigm, however if the fuel prices

keep falling in the long-run and electric and hybrid vehicles become more widespread within the logistics sector, then the gap in the transportation cost between the two production settings is likely to narrow.

Given the results reported in the first case study, if cost was the sole factor to determine the adoption of RdM or not, then it is unlikely that RdM is the most efficient paradigm to adopt. If service level was, however, an important determining factor then RdM carries a promising potential. This has been demonstrated from the results generated from the agent-based model where the RdM scenario exceeded the performance of the Centralised scenario in lead time and the frequency of unmet demand in both case studies. The localisation of production demonstrated to have an impact on reducing both lead time and the frequency of unmet demand. Lead time was considerably shorter in the RdM scenario for two reasons. First, the distribution of facilities means that less demand points are assigned to each local RdM facility, therefore it is less likely to take long time to respond to a supply request. The second intuitive reason is that RdM facilities are located closer to demand points, and less distances travelled will entail shorter travel times. This has been demonstrated and reported in the second case study, where speedy response was the most important element, and subsequently total distances travelled were the determining factor in the allocation of RdM facilities.

As for the frequency of the occurrence of unmet demand, the advantage of the RdM scenario in this aspect is due to the autonomy enjoyed by the RdM facilities, demonstrated by the agent-base model. In the agent-based model, the RdM facilities determined how much supplies to produce, and made contact with their assigned demand nodes. Demand nodes also contacted RdM facilities in case of inventory shortage; they did not only contact their assigned RdM facilities, but rather contacted all RdM facilities in the network and determined which one can provide the needed supplies faster. In the Centralised scenario, the communication between demand nodes and the centralised production facility was not as efficient due to the large number of demand nodes assigned to the same production facility.

The sensitivity analysis revealed that adopting an RdM production paradigm should be approached with caution. This has been more pronounced when observing the impact of demand and AM equipment uncertainty on the system's performance. This is in line with

the findings in [17, 23] where the impact of the change in demand was thoroughly investigated and determined to be of significant affect. This finding is, however, directly related to the mode of production in the RdM facilities (i.e. AM production). To explain more, the capacity of AM equipment played a key role in resulting in a high impact of demand and production availability uncertainty on the system's performance. In reference to the first case study, demand demonstrated a considerable impact on the total cost of the system. While with regards to the second case study, where the availability of production resources (i.e. AM equipment) was constrained, a change in demand beyond 10% of its mean value will result in an infeasible model. Infeasibility occurs from having a limited number of AM equipment (5 machines) that cannot produce the total number of demand. This infeasibility could result in either 1) some demand being unmet or 2) the setting up of new RdM locations or increasing existing locations capacity by adding additional AM equipment. This high impact of demand is because higher demand will result in the need of more AM equipment to be installed and operated. Higher demand, similarly, might also result in more production equipment being required in a production facility in traditional manufacturing. But production in traditional manufacturing in a typical job shop requires the produced product moved along different processes performed by several machines. Therefore the application of an efficient scheduling algorithm in traditional manufacturing is potentially likely to require less resources than those required in AM (i.e. better utilisation of capacity). In AM production, multiple manufacturing processes are aggregated and conducted in the same equipment, as a result there will typically be less room for scheduling different processes optimally in order to optimise throughput.

The impact of the availability of AM production on the system's performance also indicates important implications. This availability is governed by several factors; the availability of qualified operators to attend to the production, setup times, breakdowns and maintenance, amongst others. The implications of these factors, particularly breakdowns and maintenance, on AM-powered RdM systems are still not entirely clear. First the need for qualified operators to operate the AM equipment could drastically change in the future due to the anticipated increased autonomy in AM equipment. Indeed, in [23,111] it has been suggested that the need to less human involvement in the operation of AM equipment, up to 15 equipment becoming operated by a single individual, will largely result in favouring redistributed production over centralised one. As for

breakdowns and regular maintenance, the widespread adoption of AM production needs to mature more in order to have a clearer picture. This is because, as mentioned earlier, the advent of AM production in industrial setting to produce end products is still relatively new and immature. Therefore there is not enough historical data to identify breakdown patterns, maintenance, time duration for these breakdowns and maintenance operations, and finally the impact that ageing of AM equipment could have on the quality of the final products and build times.

The impact of cycle time on the system's performance has demonstrated a relatively similar behaviour to that of total demand. The impact of the change in cycle time on the number of RdM facilities was almost identical to that of total demand. This observation however differed between the first and the second case studies. This is due to the considerably longer cycle times in the first case study. In the second case study, where the produced products were relatively simple to build and thus required relatively short build time, significant reduction in cycle time resulted in the need to only one RdM facility powered by one AM equipment to supply the entire network. While in the first case study, where the produced products were more complex and required longer build time, even a reduction of 90% of the original build time still needed at least two RdM facilities to supply the entire network. The observation of the change in cycle time provides insights, as discussed earlier, on the potential adoption of AM-powered RdM production. Since AM is often characterised by long cycle times [78], examining the impact of shortening this time encourage potential future adopters if they observe that shorter cycle times could result in better performance. Examining the impact of shortening the cycle time is also important as it shows that after a certain threshold, shorter cycle times will lead to no improvements.

The quality of the framework and the solutions obtained from applying it have been established through following the research process outlined in Chapter 3. The development of the framework and its constituent models, the identification of entities and the interrelationships between them, the models' objectives, input, outputs, assumptions and data collection were all performed methodically and in an iterative manner with close consultation with experts in the field. Although the models inside the framework differed in their objectives, and each case study constituted unique objectives

and set of assumptions, the methodical implementation of the framework development and application were all done with the purpose of achieving the aim of this thesis.

The applicability range of the framework has been demonstrated throughout this research in several ways. First, from the onset of this research, the framework has been intended to be context-independent and therefore applicable to a wide array of industrial settings. Therefore the research process has been devised, as outlined in Chapter 3, to keep the framework and its constituent models free of any particular elements that are context-specific. At an abstract high-level, the framework consists of two distinct interrelated models and a shared database. At the models level, only the relevant modules / entities and relationships are included so that, through the object-orientation approach, any system up to any level of complexity and down to any level of detail could be modelled by adding/ removing relevant entities. The framework also demonstrated consistent behaviour and similar, relative to its domain of application, results. The experts consulted throughout conducting this research also agreed that the outcomes obtained from applying the framework in two different settings conform to their expectations of the systems' performance. Finally, although the framework is applicable in different varying settings, its applicability is mainly confined within individual original equipment manufacturers (OEM)s. This means that the framework is not for use in instances where RdM facilities are shared amongst different actors; a paradigm growing in popularity.

7.2 Key research contributions

The main contribution of this research is the development of a context-independent model-based decision-making framework for the design of RdM networks at the design stage and during the operation of the system. The novelty of this work is threefold: firstly, it addresses a research area (demonstrated in the research gap identified in Chapter 2) that has not been explored before with respect to this thesis's aim. Secondly, the combination of the methods used in this thesis have not been employed before to address a similar problem with the same context of this thesis's aim. Thirdly, the results presented in this thesis, particularly the frequency of unmet demands and lead time performance in cases of backlogs fulfilment, have not been examined before from the lens of RdM.

A number of sub-contributions have emerged during the course of this research, which are:

- A reconfigurable agent-based model that retains the characteristics of RdM systems behaviour. The agent-based model, which evaluates the performance of the RdM network has been designed from an object-oriented backdrop where entities and relationship can be added / removed to represent the system. The agent-based model, however, retains the defining characteristics of RdM networks, particularly autonomy. In addition, all the communication protocols are defined in the agent-based model. Therefore when the agent-based model is used in different contexts (as has been demonstrated on applying it on two distinct instances), it is only necessary to add facilities down to the desired level of detail with no need to define communication protocols.
- A methodical approach to incorporate uncertainty and the impact of each decision-making level on the others in an iterative manner. This has been accomplished through the feedback between the framework's constituent models. when applying the framework, the agent-based model evaluates the impact of strategic decisions at the operational level. Then it passes back information, based on the performance at the operational level, through the framework so that a next set of strategic decisions are generated. These new strategic decisions, having incorporated feedback of their performance at the operational level, result in gradual improvement in the system's performance. This also addresses the problems of making unrealistic assumptions and oversimplifications in analytical models (i.e. optimisation models) as the complexity is moved to the agent-based model and then only the *impact* of this added complexity is moved back to the analytical model. The same principle applies regarding handling uncertainty where uncertainty is represented and handled by the agent-based model, and only its impact, demonstrated by the persistent behaviour of undesirable effects, is moved back to the analytical model.
- Enhanced familiarity and understanding of RdM, and the identification of key factors that determine the suitability of the RdM paradigm. The literature review revealed that contemporary studies on RdM network design either developed models for the design of RdM networks from a cost perspective, or developed models for optimised system performance of already established naturally

evolving (i.e. not based on methodical decision-making tools) RdM networks. In this research both of these areas were addressed in a unified framework, and both cost and service level performances were addressed simultaneously in a recursive manner. The practicality of the long-term adoption of RdM has also been examined where the impact of further uncertainty that might emerge in the future has been investigated.

7.3 Limitations of the work and future research directions

Due to time and other resources constraints, there are a number of limitations associated with this research that give way to future research directions and opportunities. First, the applicability of the framework has been validated with two in-depth case studies instead of several ones with less depth. Collecting data, assigning values to missing data, validating data with experts, validating the conceptual models, verifying the conceptual models and validating the models and then the encompassing framework over multiple iteration with several experts in the field is a very time-demanding process. Therefore the time constraints of this PhD did not allow for more case studies to be explored. Nevertheless, it has been argued that even one in-depth case study can provide insightful and generalisable outcomes [131].

Another limitation is that the sensitivity analyses experiments used the one parameter at a time method, which overlooks the impact of the collective change in a number of parameters on the framework's outputs. The one parameter at a time method still provides valuable insights, and is generally acceptable, and is the often used method [132]. Therefore future studies that examine the collective impact of several parameters on the system's performance will provide great insight into the applicability of the RdM paradigm under long-term uncertainty. The sensitivity analysis has also been only examined over the first iteration of each objective function; not throughout all the optimisation-simulation iterations. Over few random samples throughout the sensitivity analysis, the iterative process of models' feedback and gradual improvements exhibited similar behaviour to those reported in the case studies. However, a complete application of the framework iteratively over all parameters values and a close examination of the outputs might reveal some emerging unforeseen behaviour of the system. This will,

however, require hundreds of optimisation-simulation iterations and tens of thousands of simulation replications.

The work conducted in this thesis could be extended in different research directions. First, the optimisation model incorporated in the framework has been solved to optimality in all instances in a reasonable amount of time (less than 30 minutes for all instances) using a branch-and-cut algorithm. Exact algorithms can provide optimal solutions to moderately sized problems, which even in extreme cases in the context of this research can still be solved to optimality and no suboptimal algorithms are required [87]. It will be interesting, however, to integrate a heuristic algorithm, such as genetic algorithm or tabu search or simulated annealing, in the decision-making framework to solve a more complex and detailed optimisation model. As mentioned earlier, most of the complexity, uncertainty and details were passed to the agent-based model which performed all complex operations and passed back the key observations to the optimisation model, iteratively. Therefore, examining the framework's output when both the optimisation and the agent-based models are complex and detailed, and comparing it with the outputs presented in this study will be an interesting area of research.

In addition, cost considerations could be incorporated into the framework application introduced in Chapter 6. Although it has been argued that cost, in the context of onset largescale unforeseen disruptions, might not be the foremost important factor in developing makeshift production networks, future studies can integrate cost in the objective function(s). Cost could be incorporated in the framework through either multi-objective programming or through multi-criteria decision making. In either case, cost considerations will lead to deterioration in the values of service-level variables. Therefore, future studies could conduct in-depth analysis on the relationship between cost and service-level, and develop a decision-support tool that determines the balance between cost and service-level considerations based on each application of the framework.

Finally, a number of assumptions made earlier could be relaxed, and the impact of removing these assumptions could be observed. For example, transportation deliveries could become capacitated. Another assumption that could be relaxed is to allow multiple

inventory replenishments per each planning period, which will reflect many real-life scenarios.

7.4 Conclusion

This research aimed to develop a context-independent model-based decision-making framework for the design of RdM networks. To achieve this aim, a number of objectives have been developed to systematically realise the overall aim. This research has achieved all its objectives and subsequently realised the overall aim outlined in Chapter 1 as follows. The first objective which has been to develop thorough understanding of the concept of RdM, and to identify the decision-making tools that have been developed for the design of RdM networks. This objective has been met through carrying out a critical literature review focused on RdM and decision-making as outlined in Chapter 2. In order to capture the complete set of modelling tools used in decision-making to model attributes of RdM systems, particularly decentralisation and autonomy, other manufacturing paradigms that share these attributes were also reviewed. The literature review helped in identifying the decision-making models and frameworks that have been used in the design of RdM networks, and consequently the identification of the research gap where facets of the problem were not investigated. The literature review revealed that there is a lack in decision-making models and framework for the methodical design and implementation of RdM networks that account for the interdependence between different levels of decision-making in a stochastic environment. Therefore this objective has been met by the identification of the research gap, and by the familiarity and knowledge acquired about RdM network design and decision-making that served as a stepping stone to realise the subsequent objectives and consequently the overall aim.

The second objective has been to develop stochastic agent-based models to dynamically evaluate the performance of different RdM networks. This objective has been systematically achieved as has been laid out in chapters 4, 5 and 6. The generalisability of the framework has been accomplished through the object-oriented approach adopted for building the models. Through object-orientation, the key characteristics of RdM (e.g. behaviour and communication protocols) were embedded into the model so that it can accommodate a wide array of RdM settings while maintaining its key characteristics transferable to varying contexts. This general agent-based model was then adapted to

model the two systems presented in chapters 5 and 6 by adding the systems' entities (RdM facilities and demand points) and establishing the interconnection between them.

The third objective has been to develop the decision-making framework by first developing an optimisation model that, when run, will generate input parameters values for the agent-based model, and then to establish feedback between the framework's constituent models. This objective has been achieved as demonstrated in Chapter 4 where first the optimisation and agent-based models were developed at high-level and the interaction between the models presented. The framework, which acted as a container orchestrating the operability of its constituent models and the feedback between them, has been developed at this stage at high-level.

The final objective has been to validate the framework through case studies. To achieve this objective, two different case studies have been selected to apply to the framework and generate and observe the performance of the resulting RdM network with comparison to a Centralised counterpart. The realisation of this objective has been achieved systematically as demonstrated in chapters 5 and 6 as per the research process presented in Chapter 3. First, the case studies were identified based on two factors: the suitability of conforming to the RdM paradigm, and second to be different enough from the other case study in order to demonstrate the generalisability of the framework. Then the data collected and those assumed were validated by experts in the field from both academia and industry. The conceptual and computerised models were then verified and validated through experts opinions in an iterative manner until all experts were satisfied with the accuracy of the models within their intended domain of applicability. Sensitivity analysis experiments on key parameters were then conducted to further validate the framework. Sensitivity analysis increases validation by allowing the observance of the most sensitive parameters so that the importance is conveyed to the experts and values are chosen very carefully. Finally the outputs of these two case studies were presented to the experts who eventually all agreed that the results resemble what they would have expected from a similar system.

The research conducted in this thesis also sought to answer the four research questions highlighted in Chapter 1. The first question, which sought to identify the most appropriate decision-support tools to model RdM networks, has been answered through the literature

review related to RdM network design. The literature review revealed that, with regards to the key attributes that define an RdM network, a combination of mathematical (optimisation) and simulation (agent-based) modelling is appropriate to both generate RdM network topologies, and to capture the dynamics, complexity and uncertainty surrounding these networks.

The second research question, which is about the integration of the methods defined in the first research question in a unified framework, has been answered through the development of the feedback mechanism between the framework's constituent model. The models in the framework communicate through a shared database that is accessed by both of the framework's models, and it supplies both models with their input data. Therefore, the shared database contains both models' outputs and inputs that are interchanged between the models throughout the models runtime.

The third research question, which seeks to investigate which production paradigm (RdM or centralised) performs better in terms of cost and service-level, and the fourth question, which seeks to identify the parameters with the most pronounced impact on RdM networks, have been answered through the numerical experiments in chapters 5 and 6 as discussed earlier in this section.

In conclusion, this research presents a methodical and systematic approach for the design and operation of RdM systems. The agent-based model could also be used after an RdM system has been established where it can provide decisions with regards to fulfilling unmet demands. The applicability of the framework demonstrated that OEMs and emergency response providers can benefit from the this work. OEMs can benefit in faster response to spares replacement where, if an RdM is adopted, then this could mean that some machines could have their lifetime extended through the tailor production of obsolete spare parts locally. Emergency response, or healthcare organisations, could benefit by quickly establishing localised production networks in the events of unforeseen disruption.

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