International Journal of Computer Integrated Manufacturing

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tcim20

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To cite this article: Yousef Haddad, Konstantinos Salonitis & Christos Emmanouilidis (2021) Design of redistributed manufacturing networks: a model-based decision-making framework, International Journal of Computer Integrated Manufacturing, 34:10, 1011-1030, DOI: 10.1080/0951192X.2021.1946860

To link to this article: https://doi.org/10.1080/0951192X.2021.1946860

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Published online: 06 Aug 2021.

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INTERNATIONAL JOURNAL OF COMPUTER INTEGRATED MANUFACTURING
2021, VOL. 34, NO. 10, 1011–1030
https://doi.org/10.1080/0951192X.2021.1946860

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Design of redistributed manufacturing networks: a model-based decision-making framework

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ABSTRACT

In this paper, a decision-making framework for the design of redistributed manufacturing (RdM) networks is developed. Redistributed manufacturing, a manufacturing paradigm greatly empowered by the Industry 4.0 toolset, is the shift in production towards geographically dispersed interconnected facilities. The framework is context independent, accounts for the collective impact of all decision-making levels on one another in an iterative manner, and incorporates uncertainty. The framework has been applied to a case study in the aerospace spare parts production sector. Results indicated that the RdM paradigm demonstrated considerable improvements in service level when compared with a traditional centralized counterpart, while it was not as competitive with regards to total cost. This paper contributes to the literature on model-based distributed manufacturing systems design under uncertainty, and enables informed decision-making regarding the redistribution of resources and decentralization of decision-making. The novelty of this paper is the approach employed to handle complexity, nonlinear interrelationships and uncertainty, within the domain of RdM network design. These computationally demanding attributes are handled through simulation, and only their impact is passed back to an analytical model that generates the RdM network.

ARTICLE HISTORY
Received 27 October 2020
Accepted 19 May 2021

KEYWORDS
Distributed manufacturing; manufacturing network design; optimization-based simulation; facility location; agent-based modelling

Introduction

Manufacturing systems have evolved, and continue to evolve, in order to adapt to the consequences of varying changes, such as changes in consumption behaviour and the emergence of new manufacturing technologies (Mourtzis and Doukas 2014). In the unfolding era of post-industrial economy, marked by fast moving ideas and high uncertainty (Doll and Vonderembse 1991), manufacturing systems have to continue to adapt in order to accommodate such attributes. This, in turn, could entail adjustments, or even transformation to the design of manufacturing systems.

Significant advancements in information and communication technologies (ICT) (Srai et al. 2016a) and manufacturing technologies such as direct digital manufacturing (DDM) (Chen et al. 2015), along with shorter product lifecycles (ElMaraghy et al. 2013), ever-changing consumption patterns and market dynamics (Colledani et al. 2016), and increasing environmental concerns (Oztemel and Gursev 2020) create both challenges and opportunities for manufacturing systems. One candidate that that has the potential to embrace the emerging opportunities and address the ongoing challenges is redistributed manufacturing (RdM). RdM is a manufacturing paradigm that has decentralization of resources and operations along with autonomy of the distributed production facilities at core. It could be defined as the shift from centralized production with its long, linear and slow to respond supply chains, to smaller geographically dispersed manufacturing facilities, that are interconnected and empowered by Industry 4.0 toolset offerings through advanced ICT, such as the internet of things, and manufacturing technologies, such as additive manufacturing (AM), respectively (Srai et al. 2016b; Kohtala 2015). It is important to point out, however, that it is not merely the number of production facilities per a given geographical area is what distinguishes an RdM system (Fox and Alptekin 2018), but also the level of autonomy enjoyed by these decentralized facilities (Leitao 2009).

Motivated by the conflicting research findings in the fields of RdM in general, and AM-powered RdM

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in particular, and the scarcity of decision-aid tools in the area of RdM networks design, this research develops a novel framework for the methodical design of RdM systems. The framework combines two complementing decision-aid tools namely optimization and simulation, 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 (Thanh, Bostel, and Olivier 2008). However, this paper 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.

To illustrate the applicability of the framework, a case study in the aerospace spare parts sector is conducted and followed by the sensitivity analysis of key parameters. The computational results reveal that implementing the framework can indeed significantly improve the service level with minimal impact on the total cost of establishing the RdM network.

The rest of this paper is organized as follows. Section 2 briefly reviews the literature in the area of decision-making in RdM systems design. Section 3 introduces the framework, its constituting models and the recursive feedback mechanism. Section 4 presents a case study to demonstrate and validate the framework, followed by numerical experiments and discussion on the results, then sensitivity analysis experiments are conducted. Finally the concluding remarks and recommendations are discussed in Section 5.

Literature review

Decision-making in manufacturing systems design has been the subject of much interest in the contemporary literature, hence this section will focus strictly on decision-making tools for redistributed manufacturing, or closely related, systems. Closely related manufacturing systems that share close resemblance to RdM include, but are not limited to, dynamic manufacturing networks (DNM), cloud manufacturing (CM), cyber-physical systems (CPS) and mass customization (MC). In particular, DNM shares the most common characteristics with RdM as DNM 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 (Papakostas, Georgoulias, and Koukas 2013). The concept of DMN, its characteristics, perceived benefits, challenges of application and a methodical approach of implementation are presented and discussed in (Papakostas et al. 2015). 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 defining features of RdM, decentralization and autonomy, can be realized through exploiting the Industry 4.0 toolset (Oztemel and Gursev 2020). Particularly, advanced ICT, which provides the necessary infrastructure to established a connected environment for the RdM facilities, enables decentralization of resources and decision-making (Durão et al. 2017).

In (M. Dotoli et al. 2005), the authors developed a multi-level framework for the design of integrated electronic supply chains (IESC), a form of DMN which the authors define as 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. The work, although incorporates different decision-making levels, is deterministic, and does not introduce nor incorporate the simulation model. Similar to (Dotoli et al. 2005), the works in (Dotoli, Fanti, and Mangini 2007; Mariagrazia Dotoli et al. 2006) develop models for the design of IESC networks using graph theory. Their work, along with the works of (Doukas, Psarommatis, and Mourtzis 2014; Mourtzis, Doukas, and Psarommatis 2015; Woo, Kulvatunyou, and Cho 2008; Do Chung, Kim, and Lee 2018), produce models for DNM design where the concept of RdM is

utilized to enhance manufacturing systems' flexibility by developing dynamic manufacturing networks that use shared resources. In (Moghaddam, Nof, and Menipaz 2016), the authors develop a framework for the design of distributed, largely autonomous, regional headquarters that manage RdM facilities. Although their work does not entirely fall under the RdM realm, it still addresses the problem of designing a network of autonomous entities in a manufacturing context. To achieve their goal, a deterministic bi-objective mixed integer program was formulated and solved using a memetic algorithm to optimize selecting the best match between different facilities and the fulfilment rate of tasks. To assess whether an AM powered RdM paradigm is superior to a traditional manufacturing one, the authors in (Barz, Buer, and Haasis 2016) develop a facility location model to design a manufacturing network and compare the buy-to-fly ratio between different settings. They conclude that RdM is indeed superior to traditional manufacturing approaches, mainly due to better resource utilization and considerable savings in transportation cost. Their work, however, used a deterministic optimization model, which requires a number of simplifications and assumptions that could be limiting. The model was also deterministic and did not take into account possible variation in different parameters. Moreover, the resulting networks structures were not evaluated in a dynamic way where the performance of the systems could be observed over time.Continuing with the theme of AM powered RdM networks, an agent-based simulation model for the production of spare parts was developed in (Haddad, Salonitis, and Emmanouilidis 2019). In (Haddad, Salonitis, and Emmanouilidis 2019) the performance of an RdM and a centralized spare parts production networks were compared through an agent-based simulation model. The results revealed that the RdM paradigm has slight advantage over the centralized one, but service demonstrated significant improvement in the RdM setting. The work, however, does not provide a methodical approach for the strategic decision-making, but rather provides a tool to evaluate performance of already established RdM networks.

To assess the viability of adopting an AM-powered RdM paradigm, an optimization and a simulation models were developed in (Roca et al. 2019). In this paper, the authors developed a mixed integer linear programming model that minimizes the cost of establishing an RdM system and a discrete-event simulation model to generate inputs for the optimization model. The model minimizes the production, inventory and transportation costs in RdM setting. The optimization model is an uncapacitated facility location model with demand allocation and production quantities decisions. The optimization model being uncapacitated, will likely result in assigning one facility at each of the selected locations, thus overlooking AM production capacity. Also, although this paper, i.e. (Roca et al. 2019), integrates optimization and simulation models, the models do not operate in an iterative manner, therefore limiting the exploitation of each model's advantages. The models were also developed to minimize overall costs, leaving service-level measures unexplored.

One of the first papers to incorporate uncertainty in RdM networks design is (Emelogu et al. 2016) where the authors develop a two-stage stochastic cost model in the biomedical implants sector. The model was solved using a sample average approximation (SAA) algorithm determining the number of RdM facilities and the inventory replenishment amounts. Although this paper included two decision-making levels, i.e. strategic and tactical, the interdependence between these decisions was not modelled, which could provide valuable insights if considered. The model also was designed for the use in a specific context in a constrained geographical area, rendering its transferability between different sectors unclear. An SAA to solve a two-stage stochastic model was also developed in (Chowdhury et al. 2019) where the algorithm provides the optimal locations of RdM facilities with respect to sustainability. Another stochastic model for the design of RdM networks was developed in (Mac Gregor and Kerbache 2017) where the authors used queueing theory to provide location and allocation decisions through a stochastic mixed integer nonlinear program (MINLP) in RdM settings. A fuzzy multi-period two-stage stochastic mixed integer linear program (MILP) for strategic and tactical decisions in RdM systems was developed in (Nourifar et al. 2018) where the model was solved using a heuristic algorithm.

Deterministic uncapacitated facility location models were developed in (Strong et al. 2018) where the authors envision a hybrid distributed manufacturing network where AM facilities will provide inputs for the traditional manufacturing facilities for post-

processing activities. Similar to (Strong et al. 2018), the authors of (Strong et al. 2019) develop a two-stage ILP facility location model which optimizes the cost of establishing RdM facility in already established heat treatment facilities. In (Lara et al. 2019) the authors formulated a deterministic multi-period MINLP that was solved through a bi-level decomposition algorithm. Their work, however, placed RdM on the optimal location on a continuous 2-D plane, which does not factor in matters such as land price or the existence of premises such as schools or parks (Daskin 2013).

In this paper, a decision-making framework for the design and operating of RdM systems is developed. There is a gap in the literature, to the best of the authors' knowledge, in decision-support tools in RdM settings that incorporate uncertainty, are reusable in different industrial settings, address different decision-making levels and account for the interdependence between different planning horizons in a unified framework. Additionally, most of the contemporary literature uses analytical techniques, i.e. optimization models, which require many assumptions and simplifications that could have serious direct impact on the quality of the solutions. Accordingly, there is a need to either use alternative techniques, or incorporate different complementing techniques that can address these assumptions in a dynamic manner. This paper contributes to the manufacturing systems design literature through the development of a novel context-independent decision-making framework for the design of RdM systems that can be used both prior to RdM system design and during the operation of the system. Another contribution to the field of manufacturing systems is the ABM which is designed modularly and can accommodate a wide array of industrial settings, maintaining the autonomy of individual facilities at its core. Finally, the feedback mechanism between the framework's constituent models which addresses the problems of making unrealistic assumptions and oversimplifications in analytical models, along with accounting for the impact of different decisions making levels on one another in a recursive manner until a steady state is reached and the desired performance criteria are met, is another contribution this work makes.

Decision-making framework

The optimization model in this paper is a multi-period capacitated facility location model formulated as a fixed charge (Daskin 2013) 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 decision include allocation of demand points to RdM production facilities, inventory levels and inventory replenishment policies. Finally operational decisions include the reallocation of supply in case of backlogs. The framework is not industry specific; it could be used in different setting and industries were decisions have to be made regarding the distribution of production resources and operations.

In the context of this paper, a manufacturer (e.g. an original equipment manufacturer OEM), which provides services to demand points that are distributed over a given geographical area, wishes to investigate the viability of adopting an RdM setting to reduce costs and improve their service offerings. The proposed setting is to replace the centralized manufacturing of certain products, and move these production activities to local areas closer to the point of demand. Such a costly endeavour however requires making strategic decisions that are mostly irreversible or prohibitively costly to reverse, and naturally influence both tactical and operational decisions.

To address this problem, and to bridge the gap in the literature highlighted in the previous section, the two complementing decision aid tools mentioned earlier are incorporated in a unified framework where they operate in a recursive manner. The ILP optimization model provides decisions regarding the number of RdM sites, their locations, allocation of demand points to RdM sites, inventory level for each product at each demand point and replenishment amount for each product at each point. The ILP however 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 (Nikolopoulou and Ierapetritou 2012). 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, number of backlog occurrences and average lead times for backlogs fulfilment. 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.

This recursive process is then repeated until certain criteria that the decision maker sets are met as represented in Figure 1 below which depicts a high-level schematic of the modelling environment. 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 (Emelogu et al. 2016; Khajavi, Partanen, and Jan 2014). 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. The novelty in this work is the way the framework's constituent models work together with regards to the collective interdependence between the different decision-making levels and the handling of uncertainty and complex nonlinear interrelationships. In the framework, only the impact of these attributes, which cannot be modelled analytically in closed form, is passed back to the optimization model. The incorporation of optimization 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 under uncertainty, and 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.

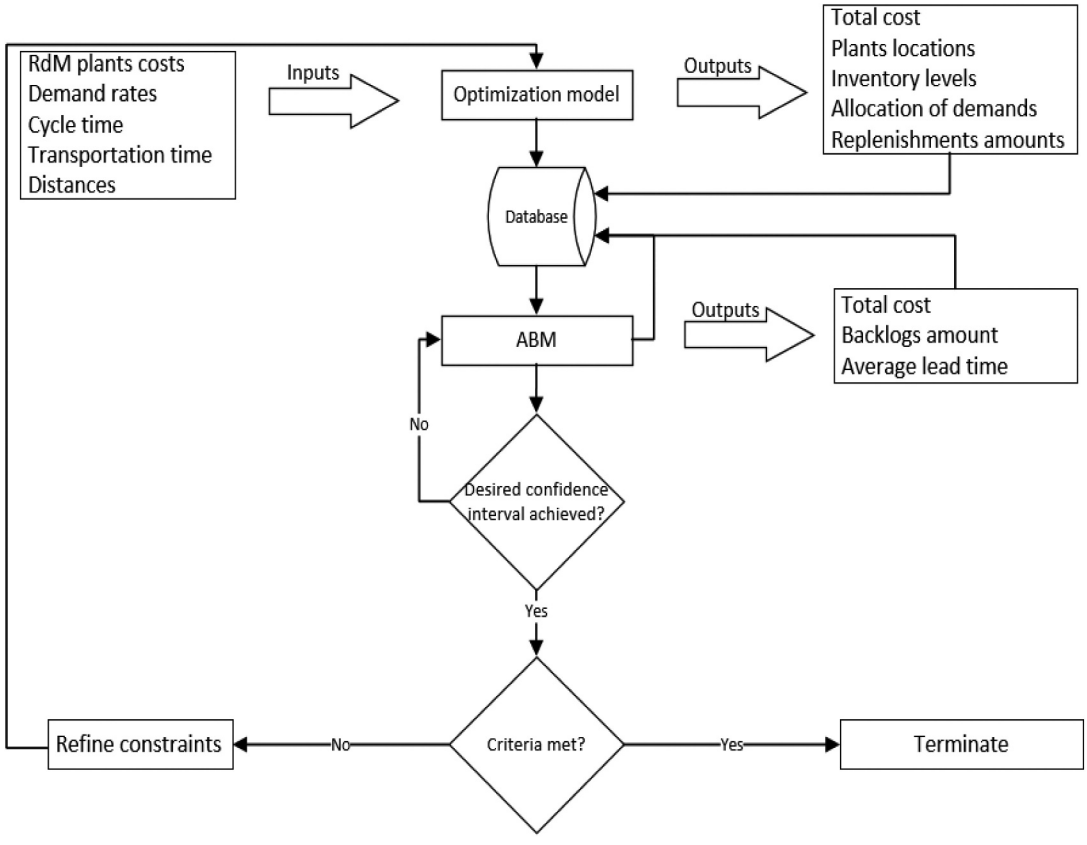

Figure 1. High-level schematic of the framework.

The models presented below are developed for the case of spare parts replacement from an OEM's perspective. RdM plants consists of additive manufacturing (AM) machines that produce a subset of replacement parts that an OEM offers. This subset of parts typically consists of parts that meet certain criteria to be manufactured using AM. However, both models can easily accommodate any different industry within a similar setting.

In the following sections a more detailed description of the models and the interactions between them is presented.

Optimization model

The optimization model (ILP) in this research is formulated as a multi-period capacitated facility location model with inventory decisions. The model aims to minimize the overall total cost associated with establishing the proposed manufacturing system.

Notation

Indices:

i Index for demand nodes ($i = 1, 2, \ldots, I$)

j Index for potential RdM plant locations ($j = \{1, 2, \ldots, J\} \in I$)

p Index for product types ($p = 1, 2, \ldots, P$)

t Index for planning periods ($t = 1, 2, \ldots, T$)

k Index for facility capacity ($k = 1, 2, \ldots, K$)

Parameters

c_{jk} Cost of establishing an RdM plant at potential site j with capacity level k

d_{it} Demand at facility i during planning period t

g_{ij} Distance between demand node i and potential RdM plant site j

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

u Maximum production time per production equipment per planning period

s Transportation cost per product per unit distance

Decision variables

X_{jk} $\{1,$ if a plant to be located at potential site with capacity k$0,$ otherwise.

Y_{jipt} Replenishment amount 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

The model

$$Total\cos t = \min \sum_{j\in J}\sum_{j\in K} c_{jk}X_{jk} + s\sum_{i\in I}\sum_{j\in J}\sum_{p\in P}\sum_{t\in T} g_{ij}Y_{jipt} + \sum_{i\in I}\sum_{j\in J}\sum_{p\in P}\sum_{t\in T} h_{pi}a_p(Y_{jipt}+Z_{pit})/2 \quad (1)$$

s.t.

$$\sum_{i\in I}\sum_{p\in P} Y_{jipt}b_p \le u\sum_{k\in K} X_{jk} \qquad j\in J,\quad t\in T \quad (2)$$

$$V_i + \sum_{j\in J}(Y_{jipt_0} - Z_{pit_0}) = d_{it_0} \qquad i\in I,\quad p\in P \quad (3)$$

$$Z_{pit-1} + \sum_{j\in J}(Y_{jipt} - Z_{pit}) = d_{it} \qquad i\in I,\quad p\in p, t>0 \quad (4)$$

$$Z_{pit=T} = 0 \qquad i\in I \quad (5)$$

$$X_{jk}\in\{0,1\} \qquad j\in J, k\in K \quad (6)$$

$$Y_{jipt}, A_{it}, Y_{ijt} \ge 0 \qquad i\in I,\quad j\in J,\quad t,\quad p\in P\in T \quad (7)$$

Objective function (1) minimizes the total cost of establishing and operating the proposed system. The first term of the function minimizes the cost of establishing RdM plants at different capacities where production hours cannot exceed the number of products produced multiplied by their respective production 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 (2) guarantees that the maximum capacity of each plant is not exceeded. Constraints sets (3), (4) and (5) 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 $_{t0}$ is not defined), it is necessary to account

for the first planning period in a separate set of constraints, here constraints (3). Constraints (4) enforce the inventory left over from each planning period at each location to be added to the next planning period. Constraints (5) enforce the inventory remaining at each demand node at the end of the last planning period to be zero. Although these constraints (i.e. (5)) 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 (6) and (7) are the integrality and non-negativity constraints, respectively.

In case of envisioned RdM systems where the bulk of manufactured goods are produced via AM, equation (1) and constraints (2) and (6) 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 equation (1) and constraints (2) and (6) would become, respectively as follows:

$$Total\cos t = \min \sum_{j\in J}\sum_{j\in j} c_j X_j + s\sum_{i\in I}\sum_{j\in J}\sum_{p\in P}\sum_{t\in T} g_{ij} Y_{jipt} + \sum_{i\in I}\sum_{j\in j}\sum_{p\in P}\sum_{t\in T} h_{pi} a_p (Y_{jipt} + Z_{pit})/2 \quad (8)$$

$$\sum_{i\in I}\sum_{p\in P} Y_{jipt} b_p \le u X_j \qquad j \in J, \quad t \in T \quad (9)$$

$$X_j \in \mathbb{Z}^+ \qquad \beth \in \mathbb{J} \quad (10)$$

It is important to point out that the ILP suffers a number of limitations that allow to be the model tractable, presentable in closed format and solvable to optimality in reasonable amount of time. These limitations are summarized below:

- All parameters are deterministic.
- Depreciation of AM machines is linear and is incorporated into the cost of facilities.
- Post-processing activities are not included.
- 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.
- 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 unaccounted for.

It is clear that some of these limitations could seriously affect the outcome and credibility of the model. Unfortunately, addressing each of the above-mentioned limitations in analytical closed form will quickly result in an intractable model. Fortunately, simulation provides a means to efficiently account for each one of these limitations. The next subsection will present and discuss the simulation model.

Simulation model

The simulation model is triggered to run once the optimization model has completed running and produced an outcome. The outcome of the optimization 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. After the simulation starts, the parameters' values are imported from the optimization model's output database. Then, the experiment setup code is executed. In the experiment setup, the RdM plants are located and are allocated capacities according to the network structure that the optimization algorithm had already determined. For this part of the simulation, a database containing the coordinates for all the potential RdM plants is typically provided. Then the simulation model reads the optimization model's outcome for each potential site. To illustrate the communication between the two models regarding plants locations and capacities, Figure 3 below depicts a simplistic example of seven potential plant sites. The figure shows that two sites were

chosen by the optimization 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.

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.

Once the plants are located, 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 2 is called at the beginning of each simulation run, and at the end of each planning period. The end of each planning period is reached once a certain amount of time elapses (e.g. at the end of each year if each planning period corresponds to one year). This function first checks whether it is called at the beginning of the simulation run or if it is called 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 each respective plant.

These schedules are communicated to the RdM plants through messages (data packets) exchange. Once each plant receives its production schedule for the present planning period, it sends messages to the AM machines that are operating in it. AM machines' behaviour and decision-making logic are regulated by statecharts, which are modelling constructs based on UML's state machine diagram as shown in Figure 4 below.

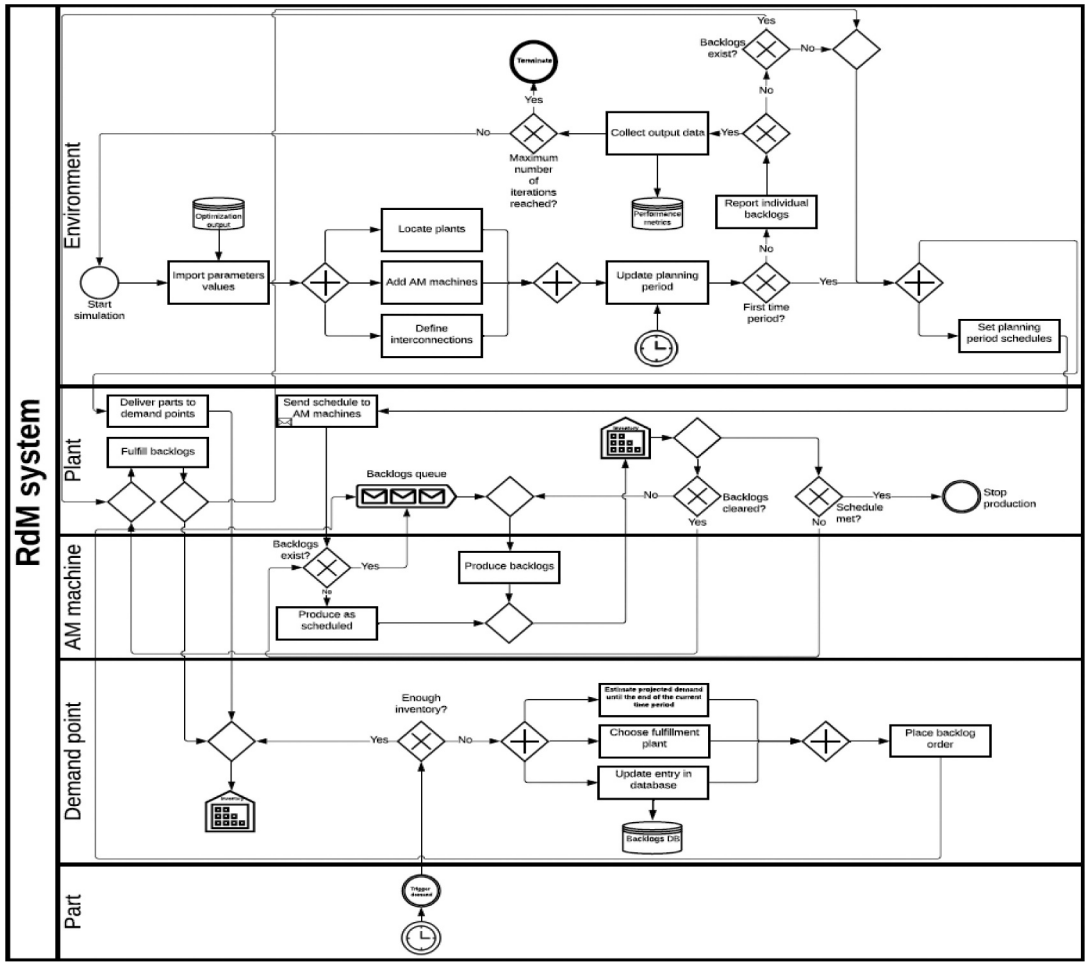

Figure 2. Simulation model.

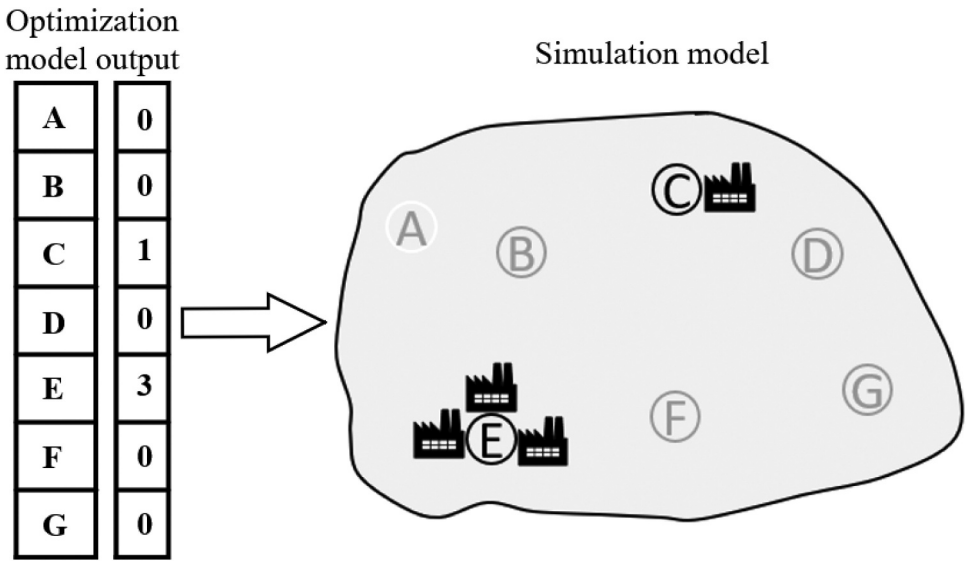

Figure 3. Simple illustration of RdM chosen sites representation.

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 number of units to be produced.

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 backlog 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 the backlogs. If there are not any backlogs, then the AM machine checks whether the pre-set 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 backlog requests pending.

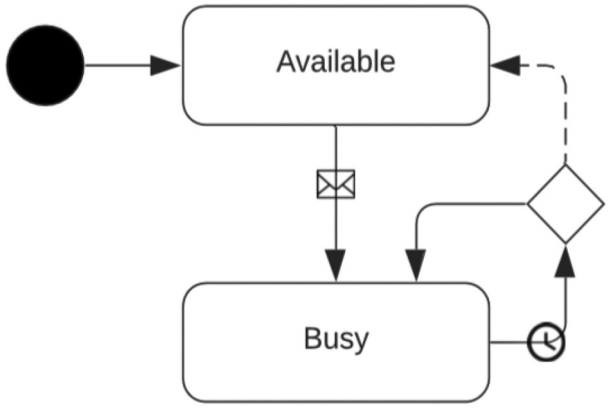

Figure 4. Statechart for AM.

As the model time progresses, demand nodes stochastically trigger demand. Since the modelling approach used in this study is individual centric, each part (e.g. spare part that periodically requires replacement) at each demand node is modelled individually. 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 a certain safety stock (which is a model input) is 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. The demand point agent then contacts all plants to enquire about their statuses, it then chooses the least busy plant and send a message containing the order details for production. This 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 optimization model's constraints. In the backlogs database, each optimization-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.

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 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, in particular frequency of backlogs and lead times, are performed and the results stored in a database. This database will later be accessed by the optimization model. After storing the simulation model's outcome, the model then calculates the confidence interval (as in (Robinson 2004)), compared with previous model runs outcomes.

The determination of the confidence interval is key in stochastic models as the outcome varies with each run and once simulation run is very likely to be unrepresentative. Once a sufficiently satisfactory (usually 95%) confidence interval is reached, the simulation model terminates.

Recursive optimization-simulation

After the first optimization run has completed and generated an RdM network, the simulation model is triggered. After completing a number of simulation replications (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 optimization outcome. 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.

Computational experiments

Background on the problem instance

To test and validate the framework, a problem instance is investigated in this section. The problem instance is to design an RdM system for a number of demand nodes that are dispersed over a given geographical area. Input data followed the suit adopted in (Bonnín Roca et al. 2019) where the authors developed an optimization model, on top of a simulation model to assess the viability of AM in the production of jet engine brackets. The full input values can be found in the supplementary material accompanying this paper. This paper borrows some input parameters such as locations, demand rate and production lead time. Data regarding product variants were hypothesized to reflect a wide range of products with regards to cost, cycle time and demand rate. These values, which will be discussed shortly and presented in Table 1, were carefully devised in collaboration with four experts in the fields of manufacturing and technical support.

Briefly, this study will model the 48 busiest airports in the United States, and will assume a demand rate in each airport proportional to the number of departures. Each of the 48 airports will serve as a demand point, as well as a potential RdM production facility site. Figure 5 below shows the demand nodes on the contiguous United States map.

The authors of (Bonnín Roca et al. 2019) chose the engine brackets because the manufacturer of the jet engines, GE, has expressed interest in producing the parts using AM technology and, more importantly, the chosen part is a noncritical part. Due to the function they serve, noncritical parts do not contribute to the safety of an aeroplane, and are subsequently subject to less restrictive regulations from approving bodies (Bonnín Roca et al. 2019). In this paper, 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 (prioritization of production and the observation of possible

Table 1. Parts input data.

Part reference	Cycle time	Production cost	Share of demand
Part 1	7.5	577	25%
Part 2	20	806	60%
Part 3	14.5	81	15%

emerging queues). In addition, the departure from the single part production facilities will further justify the shift to RdM production in local facilities. Table 1 below summarizes the input data for the manufactured parts.

Table 2. Summary of the outcome of the framework application on the Centralized scenario where all costs are in millions $

		Total cost (optimization)	Total cost (simulation)	Gap	Location cost	Inventory holding cost	Transportation 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 3. Summary of the outcome of the framework application on the RdM scenario.

		Total cost (optimization)	Total cost (simulation)	Gap	Location cost	Inventory holding cost	Transportation cost	Lead time (hrs)	Unmet demand
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%

Figure 5. Demand nodes and potential RdM sites [22].

These input data were hypothesized to reflect three classes of possible spare parts. These classes are first parts with high cost, high demand rate and long cycle time. Next is spare parts with high cost, and relatively low demand rate and cycle time. And lastly comes the class of spare parts that consists of low cost materials, low share of demand and medium cycle time. These three classes of spare parts were devised to reflect different production attributes of spare parts in order to improve the model's representation of reality. A batch size of one part is assumed The cycle time in the simulation model is normally distributed with the mean listed in Table 1 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.

Demand rate is also stochastic, and is assumed to grow over time at a growth rate of 5% each planning period. A total demand of 10,000 parts is assumed (increasing by 5% each planning period). As indicated in the share of demands column in Table 1 above, part 1 will have a mean demand of 2,500 instances, part 2 will have 6,000 demand instances and part 3 will trigger 1,500 demand instances on average. Demand for each part at each demand point (i.e. airport in this paper), as indicated earlier, is calculated proportionally to its respective departure of flights (i.e. the busiest the airport the more parts will need replacement). Demand rate, as with cycle time, is stochastic and follows the normal distribution with means (for the first planning period), and standard deviation of 20% of the mean. The normal distribution for demand rates is only truncated at the lower bound tail at zero to eliminate, any rather unlikely, negative values. The stochastic time intervals between demands is calculated through dividing the length of each planning period by each part's projected demand during that planning period.

Demand nodes, i.e. airports, are considered as potential RdM sites. The cost of setting up RdM varies from one location to another, and is assumed to increase proportionally, as with demand rate, with the airport's passenger traffic. The costs of RdM facilities, are for one capacity level (i.e. one AM machine per location is equal to one capacity level), and are all between 500,000 USD and 700,000. For example, if setting up a facility at a certain location costs 500,000, USD then this figure represents one capacity level only. If, for instance, the optimization model determined that a capacity of level two is to be installed at that location, then setting up the RdM facility will cost 1,000,000 USD It should be noted here that this assumption of capacity levels (each corresponding to one AM equipment) could become inappropriate if there are limited post-processing resources. To explain more, adding extra AM equipment could double the number of units produced, but will likely cause a bottleneck at post-processing, if no adequate resources are available. Therefore, the availability of adequate post-processing resources are a prerequisite for the capacity assumption to remain valid.

The duration of the each planning period in the experiments is assumed to be one year, and a total of five planning periods (i.e. planning horizon of five years) is modelled. The model time units was set to be hours, so each planning period consisted of 8,760 hours (365 $\times$ 24). So each RdM plant of capacity one can produce for a maximum of 8,760 hours. If the production assigned to this site exceeds 8,760 hours, then this site will be assigned a higher level capacity; with careful consideration of post-processing activities.

The holding cost for the stored part 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 $\times$ part cost/365) to provide a more accurate representation of incurred cost. Since parts have a relatively high cost, and could incur high holding cost, and demand is relatively low (given that each planning period spans one year), safety stock has been set at 1 unit, where a replenishment is required when inventory level drops to one unit. If safety stock is set higher, although backlogs will drop, cost will in turn increase.

In this paper, the transportation cost for parts is calculated differently than (Bonnín Roca et al. 2019). In (Bonnín Roca et al. 2019), the authors assume a fixed

transportation cost per part regardless of the distance travelled. In this paper, a different approach is used as below:

$$\text{Transportation } cost = g_{ij} \times s \tag{11}$$

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 20%. 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 USD

Numerical results and discussion

The problem instance described in the previous section was solved using the proposed approach in Section 3. The optimization model was coded in Python and solved using Gurobi 8.1.1, a commercial linear and quadratic solver that implements branch and cut algorithms for integer and mixed-integer programming models. The simulation model was coded in Java and implemented in AnyLogic 7.3.2, a Java based commercial simulation modelling platform. The experiments were run on a PC with Intel core i5 2.4 GHz and 8 GB RAM. The interaction between the optimization and the simulation model was performed manually in this case study due to limitation in the software licenses obtained. This interaction, however, can easily be performed automatically without any manual intervention with the Professional software licence from AnyLogic, where the simulation model can be exported as a standalone Java application. This property, however, is not available in the University education license available for this research.

When run using the parameters overviewed in the previous section, the optimization model determined the opening of four RdM plants, all with single capacity, as shown in Figure 6. It is important to point out that when all the parameters' values in the simulation model are fixed, the gap between the optimization and the simulation model outcomes is very close 0%. It is, however, not exactly 0% because the cost values are updated on a daily basis in the simulation model, while they are aggregated and updated on a yearly basis in the optimization model. When the simulation model was run, using the values generated by the optimization model, it became clear that the generated outcome needs further refinement in order to be considered as a valid alternative (or more precisely complementary) approach of manufacturing. The frequency of the occurrence of unmet demands (or backlogs) and lead time were chosen as the performance level metrics 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

Figure 6. RdM network topology.

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.

Since the RdM network design literature does not contain model-based frameworks, or any other decision-support tools, that span all decision-making levels uncertainty, it is difficult to compare the outcome of the framework with that of the published literature. Therefore, and to provide a reference to compare the performance of the proposed RdM system against, a centralized counterpart has been also modelled. Input values for the Centralized scenarios are the same as the RdM one, except for location cost, being half of that for RdM (since only one location houses all resources and operations.). To determine the optimal location for the Centralized scenario, the same model has been used, but with the addition of constraint 13.

$$\sum_{j\in J} X_j = 1 \tag{13}$$

To provide a meaningful feedback to the optimization model, at each simulation replication, the frequency of backlogs occurrences at each location, per each part and planning period were recorded. After the specified number of simulation replications is completed (determined by the confidence interval), the mean average for the frequency of the occurrence of backlogs is calculated (q_{ipt}). Then the parameter (q_{ipt}) is passed to the inventory balance constraints in the optimization model as a surplus production stipulation, hence transforming constraints (3) and (4) in model (1–7) to the follows:

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

$$v_i + \sum_{j\in J} Y_{jipt_0} - Z_{pit0} = d_{it_0} + q_{ipt0} \qquad i \in I, \quad p \in P \tag{14}$$

$$Z_{it-1} + \sum_{j\in J} Y_{jipt} - Z_{it} = d_{it} + q_{ipt} \qquad i \in I, \quad p \in P, \quad t \in T, t\neq 1 \tag{15}$$

It took 5 and 8 optimization-simulation iterations for the Centralized and the RdM scenarios, respectively, to achieve a steady-state, meaning that no further improvements could be attained within the available resources. Tables 2 and 3 present key outcome figures for the Centralized and RdM scenarios, respectively.

It can be observed from Tables 2 and 3 that in each iteration the total cost calculated by the simulation model increases, while as the number of iterations progresses, the increase in total cost becomes minimal, or completely halts. For example, the second iteration in the Centralized 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 optimization 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 optimization-simulation runs to stabilize, ended up performing better than its centralized counterpart in service level performance measures. It is interesting how the centralized scenario in the first run was much more efficient with regards to the frequency of unmet demands, but as the modelling progressed the performance of the RdM scenario surpassed the centralized one in this performance aspect. This is due to the distribution of production to several distributed facility rather than only one centralized 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 centralized 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 7 illustrates the frequency of the occurrence of unmet demands in both scenarios for the first and final optimization-simulation iterations for demand nodes that experienced the highest amount of unmet demands.

Figure 7 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 centralized scenario, the performance in this aspect also significantly improved, but some demand nodes consistently experienced a relatively high number inventory shortages. This result indeed demonstrate that in service-level performance metrics, RdM is superior to the traditional centralized production paradigm.

The computation time for all experiments is presented in Table 4. It could be noticed that the first iteration in all instances took considerably longer to complete. This is because the framework loads all databases that contains all the models inputs in the first iteration, and then they are kept in the computer memory. Moreover, the software packages used also keep the previous experiment's data in memory, therefore they execute the experiments considerably faster in subsequent runs.

The results indicate that the Centralized scenario is more cost efficient, although by a small margin. Cost segments were however not evenly proportioned in both scenarios, with location cost favouring the Centralized 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 centralized one with regards to lead time and the frequency of backlogs.

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 traditional centralized manufacturing, and its role is mostly confined as complementary to the traditional, well-established, paradigm.

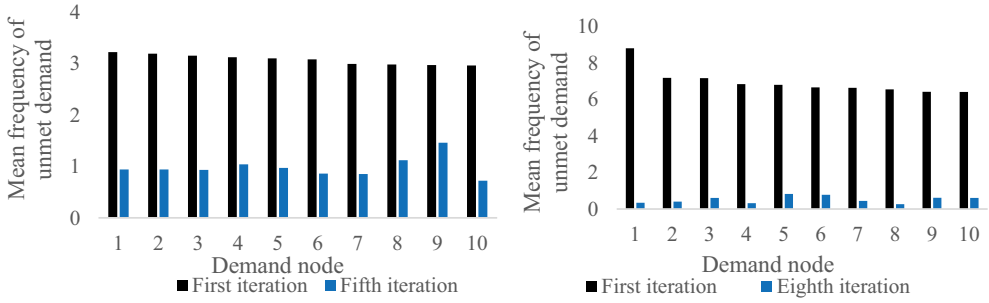

Figure 7. Frequency of the occurrence of unmet demand in the centralized (left) and RdM (right) scenarios for the 10 demand nodes that experienced the highest numbers of unmet demand.

Table 4. Computation time (in seconds).

	Centralized		RdM	
	Computation time in seconds (optimization)	Computation time in seconds (simulation)	Computation time in seconds (optimization)	Computation time in seconds (simulation)
Iteration 1	25	295	1,496	303
Iteration 2	18	125	649	105
Iteration 3	15	119	608	109
Iteration 4	14	120	693	109
Iteration 5	16	115	662	92
Iteration 6	N/A	N/A	670	105
Iteration 7	N/A	N/A	300	94
Iteration 8	N/A	N/A	390	83

Sensitivity analysis

Although uncertainty in the framework is handled through the stochastic agent-based simulation model, the optimization 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.

Although sensitivity analysis does not proactively incorporate uncertainty into modelling, it still remains a valuable approach to evaluate the robustness of a model. Sensitivity analysis provides a method to identify important parameters, so that careful planning is used when allocating resources for 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 8 below depicts the impact of the change in the value of key parameters on the overall cost. The sensitivity analyses 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. 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 examined the impact of change on total cost and the number of RdM facilities as shown in Figure 8.

Looking at Figure 8, it is apparent that the available time of AM production is the most sensitive parameter. 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, among others. 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 actual time.

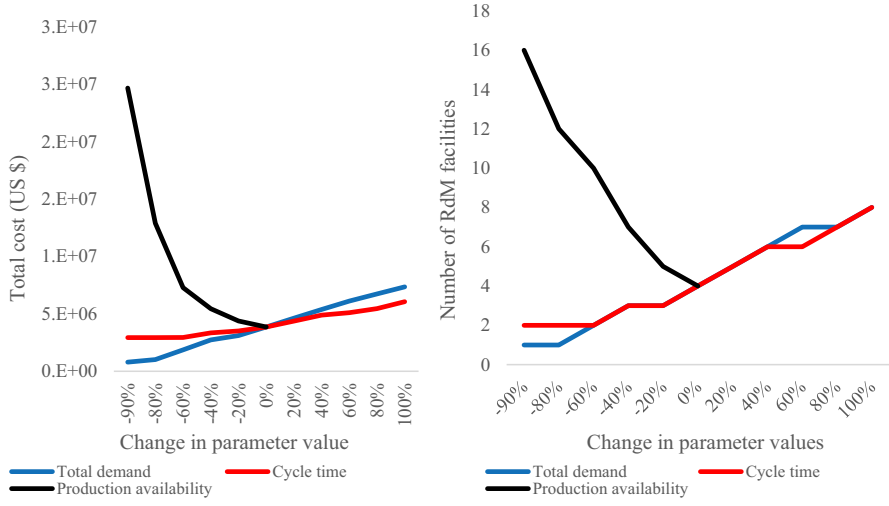

Figure 8. The impact of the change in the value of key parameters on total cost (left) and the number of RdM facilities (right).

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 (Govindan, Fattahi, and Keyvanshokooh 2017). 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.

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 careful observation of the impact on 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.

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 modelling 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 the anticipated improvement in build time) on the total cost.

It could be deduced from Figure 9 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 (Bonnín Roca et al. 2019), 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. (Khajavi, Partanen, and Jan 2014; Khajavi, Holmström, and Partanen 2018; Bonnín Roca et al. 2019)) envisioned RdM systems where build time

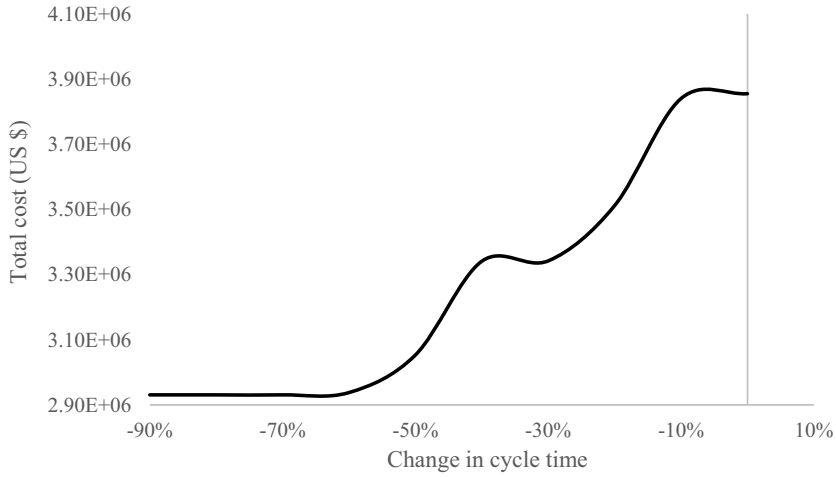

Figure 9. The impact of improvement in cycle time on total cost.

significantly improves, in some instances up to 20 folds (Bonnín Roca et al. 2019). 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 visualized in Figure 9, 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.

Conclusion

This paper presents a decision-making framework for the design of AM-powered redistributed manufacturing networks. The framework, and its constituent models, employ modularity in order to establish its applicability and adaptability to a wide array of industrial settings. Modularity has been achieved through keeping the key common components, interrelationships and communication protocols of the framework's models fixed, and then adding and removing these elements as necessary to model the desired production system. The framework handles complex nonlinear interrelationships and uncertainty through the simulation model where only their *impact* is passed back to the optimization model.

The framework has been applied to a case study in the aerospace sector in order to test and validate it where the performances of two production systems, distributed and centralized, were compared. Results were in line with previous research in that in terms of total cost, an RdM production network is unlikely to compete efficiently against the more established traditional centralized production. This is further exacerbated by the rapid improvement of RdM enabling technologies, particularly AM equipment, which constitutes a considerable risk when making investment in these technologies. Moreover, the advent of AM production in largescale industrial settings 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. With regards to service level performance, the performance of the RdM network, measured by the frequency of the occurrences of backlogs and lead time far surpassed that of the centralized scenario. The reason for improvement in performance in these two performance measures is due to the decentralized property of the RdM production system. To explain more, having several production facilities strategically located in local areas, each assigned to a small set of demand nodes, will improve the production facilities' responsiveness to variations in local demands and other disturbances. In the case of the centralized scenario, one location serves a sprawling networks of demand nodes, which can adversely impact its ability to respond efficiently to

backlogs (e.g. long queues might emerge). As for lead time, the obvious reason why it was much shorter in the RdM setting is because less distances, and therefore shorter times, are travelled between local production facilities and demand nodes.

One of the main challenges that constitutes a further area of investigation is the obsolescence cost associated with RdM enabling technologies, particularly AM production. Future research that addresses this challenge could employ a techno-economic assessment model to capture the values of key cost performance indicators. A techno-economic assessment model could inform the decision maker whether the considerable initial investment required for setting up RdM plants and equipping them with the necessary production equipment is financially viable or not, thus mitigating potential risk. A future research direction could also be to consider the environmental performance, in addition to those of cost and service level. Indeed, environmental performance of RdM networks, with comparison to that of traditional centralized production is still unclear. This is because clustering all resources in a single location, along with production using traditional subtractive methods could greatly improve resources utilization, energy consumption and waste reduction, while resource utilization is likely to be sub-optimal in RdM settings. To address this issue, an environmental impact assessment model could be developed to compare different environmental measures in both centralized and RdM settings.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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2021-08-06
Taylor & Francis
https://doi.org/10.1080/0951192X.2021.1946860
Haddad Y, Salonitis K, Emmanouilidis C. (2021) Design of redistributed manufacturing systems: a model-based decision-making framework. International Journal of Computer Integrated Manufacturing, Volume 34, Number 10, 2021, pp. 1011-1030

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