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A decision-making framework for the design of local production networks under largescale disruptions

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Abstract

In this paper, a model-based decision-making framework for the design of localized networked production systems under largescale disruptions is developed. The framework consists of optimization and agent-based simulation models that run successively in an iterative manner, gradually improving the performance of the perceived system. The framework integrates uncertainty, provides decisions at different decision-making levels and embeds an algorithm that allows for communication between demand nodes and production sites once inventory shortages occur. The framework has been applied on a case study for the design of localized production and distribution networks, powered by additive manufacturing (AM), in South East England during the early stages of the COVID-19 pandemic outbreak. Results revealed that implementing the framework indeed results in performance improvements to AM-powered production networks, particularly with regards to inventory shortages and lead time.

Keywords: localized production; additive manufacturing; agent-based modelling

1. Introduction

Manufacturing systems are typically designed to accommodate, and adapt to, varying degrees of uncertainty and potential disruptions, to enhance the robustness of manufacturing systems. Methods to handle uncertainty and potential disruptions could be incorporated at the design stage of a manufacturing system i.e. passive or proactive robustness [1] (e.g. allocating redundant capacities that allow the accommodation of increased unplanned production). The other approach to handle uncertainty and disruptions is the reactive approach where the manufacturing system reacts to uncertainty and disruptions through its existing resources [2] (e.g. efficient flexible scheduling algorithm coupled with modular production to react to changes in the nature of demand). These disruptions, if not handled properly, could have adverse consequences on the manufacturing system, potentially significantly deviating it from achieving its intended targets. However, regardless of the nature and number of measures taken to boost robustness, hedging against all possible disruptions is usually deemed as an impossible task [3].

Disruptions are, however, not confined within the boundaries of a manufacturing system [4], they can rather occur anywhere along the supply chain. For example, a manufacturing system can be equipped with an additional machine tool (e.g. a late or milling machine) to cope with a sudden spike in demand. It can, however, still face disruptions due to, for instance, shortage of supply of raw materials, stemming somewhere else along the supply chain where the manufacturing system has no control, rendering additional resources (or capacities) or other measures ineffective. This case of disruptions occurs in wide scale emergencies where supplies (finished goods or raw materials) could be readily available in their point of origin or somewhere else along the supply chain, but disruptions outside the control of the manufacturing system make it impossible to deliver to their point of demand at the required time. In such cases of disruptions, localised production, and subsequently localised

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supply chains could provide a means to mitigate the adverse consequences of such disruptions.

Recent advancements in manufacturing technologies, particularly unconventional methods such as additive manufacturing (AM) have the potential to enable the prospect of localised production to meet urgent needs [3]. AM, which is steadily moving from prototyping, to a means to produce final products [5], can bring advantages such as less need for tooling, the production of complex optimised geometries and shorter lead times [5,6]. The opportunities that AM provides can be exploited in situations of largescale disruptions (e.g. sudden onset of disasters) where localised impromptu production sites can be established to temporarily compensate for shortage of supplies (provided that the required products conform to AM production capabilities). The collection of these localised production sites constitute a networked manufacturing system that is distributed over, and supplies to, a given geographical area. The design of efficient localised networked manufacturing systems, in response to largescale disruptions, entails several decisions. Decisions, in this context, means assigning values to decision variables (e.g. location/ allocation, capacities, production/ distribution schedules etc..).

Research into the area of manufacturing systems design, mostly through the development of decision-support tools, is well-established in its own right where it borrows heavily from the field of operational research (OR). Most of this research, however, is conducted from the lens of commercial production, enabled by highly efficient conventional means of production. Research into manufacturing systems design, in the context of largescale disruptions, is mostly conducted from the lens of supply chain design, assuming that production itself is uninterrupted, but the movement of products is interrupted [3], rendering this body of research tailored towards the preparedness phase of disruptions handling [7]. A growing body of research exists in the area of supply chain design, to meet urgent needs, in the event of largescale disturbances. A number of survey papers that review and analyse the state-of-the-art in the decision-support tools for the design of largescale disturbances response networks can be found in [8–11]. Apart from review papers, most other papers in this area develop optimisation models for the preparedness phase of largescale disturbances. In particular, these papers develop models and frameworks for the strategic prepositioning of supplies, in preparation for response to disturbances. In [12], a facility location-inventory model is developed to maximise the covered area assigned to prepositioned distribution centres. The model developed in [12] handles uncertainty through experimenting with different scenarios, each with an associated probability of occurrence. This approach to handle uncertainty, although provides insight into possible scenarios, can only cover a limited number of scenarios, leaving many facets of the problem unexplored. In [7], a two-stage stochastic model for the design of relief chains in times of emergencies is developed. Similar to the work in [12], the model developed in [7] handles uncertainty through modelling a limited number of scenarios, but employed fuzzy numbers to model the stochastic parameters. In this paper, [7], the first stage decisions consisted of location/ allocation decisions, while the second stage decisions, which are determined after the uncertainty is revealed and minimise travel times and costs, and provide inventory and routing decisions. Centralized and distributed production paradigms have been discussed and modelled in [13,14] where in [14] the authors investigated the idea of decentralization of healthcare production in the UK. In [3], the authors developed a framework consisting of interacting optimisation and agent-based simulation models for the design of localised distributed production networks in times of largescale crises. In their paper, the authors proposed the use of additive manufacturing, distributed over a given geographical area, and applied the framework on a case study to produce personal protective equipment (PPE) during the early stages of the COVID-19 pandemic outbreak.

Although there has been an increased attention dedicated to AM production and response to largescale disruptions, studies that develop quantitative decision-support tools for the design of production networks in response to largescale disruptions at the system-level are almost non-existent. It should be noted however, that there is a considerable body of research that investigates the viability of AM production in largescale disruptions, but such research is almost entirely confined in technical aspect of production at the product level, overlooking the system-level production network. Apart from [3], all research that addresses response to largescale disruptions, from production and logistical contexts, either does so at the system-level assuming that products have already been produced without interruptions and stored in prepositioned distribution centres, and only designs a logistical network to deliver these products, or at the product-level. Research at the product-level, utilising AM, is mostly directed towards identifying and investigating the conformance of different products to AM production, and the impact of AM production on affected communities.

This work builds in the work conducted in [3] where the authors developed a model-based decision-making framework for the design of AM-powered production and distribution networks for crises response. The framework developed in [3] consisted of interacting optimisation and simulation models that provide decisions at the strategic, tactical and operational levels of decision-making, accounts for the interdependence between different levels of decision-making and incorporates uncertainty. The models inside the framework run consecutively in an iterative manner, where the performance of the production system gradually improves as will be explained in detail in the next section. In this paper, uncertainty is further integrated into the framework through sensitivity analysis, and the simulation model is embedded with a brute-force algorithm that allows instant communication between different facilities in case of inventory shortages. Similar to [3], the framework developed in this paper is a complementing tool that incorporates production activities through AM, in situations where the supply of goods that can be readily, safely and reliably produced via AM is disrupted.

The rest of the paper is organised as follows; the next section presents the overall decision making framework, its constituent models and the mechanism of its operations. Section 3 presents a case study application for the production of PPE during the early stages of the COVID-19 pandemic outbreak in South East England, and numerical experiments to test and validate the framework. Finally, Section 4 presents concluding remarks and discusses future research directions.

2. Decision-making framework

The decision-making framework consists of two decision-support tools that operate successively to generate production networks and then evaluate their performance in the following manner as depicted in Fig. 1. The optimisation model, which is a multi-period capacitated integer linear program (ILP), generates the production network's topology and the production and distribution plans. The decisions provided by the ILP are location-allocation decisions; placing the available AM equipment at strategic sites to minimise the total supply-weighted distances travelled. The choice of this objective function (i.e. supply-weighted distances travelled) is made to prioritise demand locations with the highest projected demand rates. This objective function, however, can be easily transformed to minimise or maximise any other attribute deemed necessary to serve the overall aim of the framework's application. For example, cost could be minimised to operate with minimal costs, or the maximum distance between any two facilities could be minimised (maximal covering model [15]). Nevertheless, it has been deemed appropriate, for the purpose of this modelling setting (i.e. supplying demand nodes in times of largescale disruptions), to prioritise areas with high demand.

Since the ILP is deterministic, meaning that all inputs are known with certainty, it is necessary to account for some degree of uncertainty. Although the subsequent agent-based simulation model is stochastic, and in turn incorporates uncertainty into the overall framework, it is still necessary to account for uncertainty in all modelling stages. To do so, sensitivity analysis experiments are performed on the optimisation model before passing the production network's parameters to the simulation model. 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.

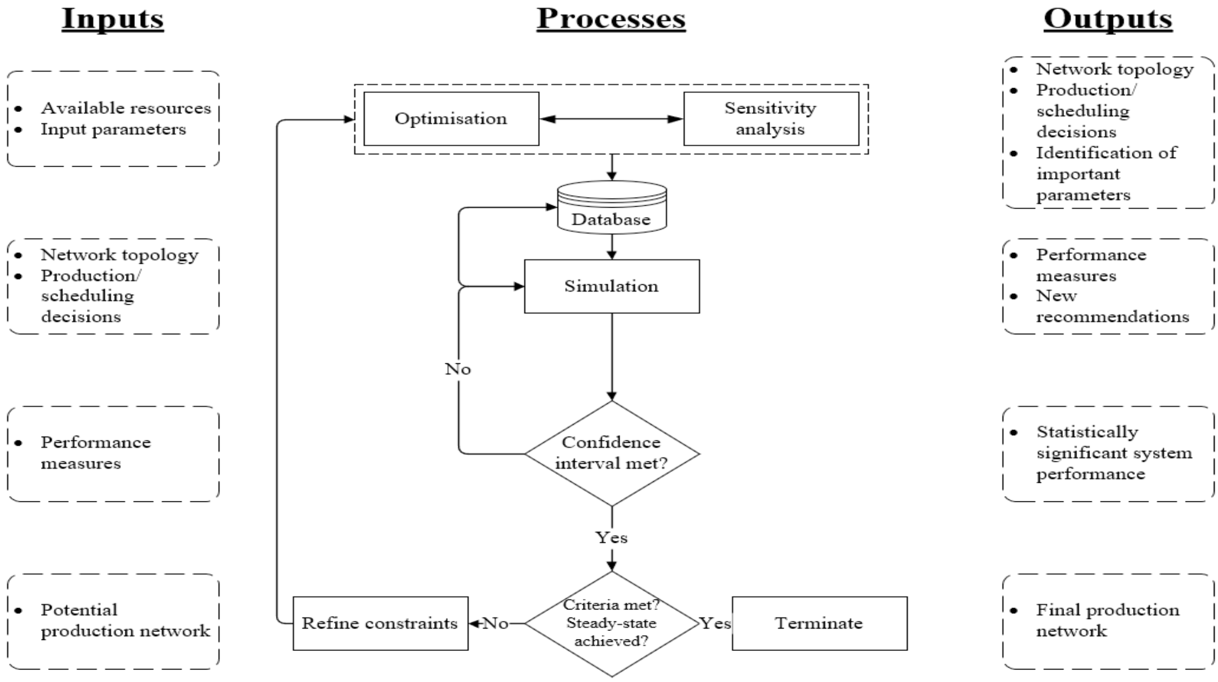

Figure 1 Decision-making framework

After the sensitivity analysis experiments reveal impact of uncertainty in each parameter on the outcome of the model (i.e. location-allocation and production-distribution decisions), these values are stored in database which is then accessed by the agent-based simulation model. The role of the simulation model then is to evaluate the performance of the production network under further uncertainty. In short, the inputs of the simulation model are the outputs of the optimisation model, and vice versa. Since the simulation model is stochastic, containing several stochastic parameters to reflect the instance being modelled, the outputs of one simulation run are hardly insightful. Therefore, to produce statistically significant results that reliably provide an insight into the performance of the perceived production network, the mean output of several simulation replications is required. To determine the minimum number of simulation replications required to produce statistically significant observations, the confidence interval method, which indicates how accurate the mean outputs are [16], has been used.

After the minimum number of replications has been determined, as highlighted above, the framework checks whether the desired criteria have been met, or a steady-state is achieved, or not. In this step, the mean output of the simulation replications for the desired performance measure is checked whether it meets target performance measure or not. For example, the target performance measure could be to have no more than 10 instances or inventory shortages, or less than 24 hours lead time, or any other measure. Steady-state, in the context of this research, is when the framework ceases to improve on the performance of the system without adding extra resources. For example, in order to improve the performance of the system in one aspect, say significant reduction in travel time, the framework might locate and allocate facilities in strategic locations to minimise travel time down to a certain threshold, after which, it becomes necessary to add more facilities along the network to further decrease travel times.

2.1. Optimization model

The optimisation model is a multi-period capacitated facility location model with production and distribution decisions. The model is formulated as integer linear program and its objective function minimises the total supply-weighted distances travelled. The model notation and formulation are as follows:

Indices

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

j Index for potential production sites ($j = \{1, 2, \ldots, J\} \subseteq I$)

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

Parameters

n Number of available AM equipment

c Cycle time for the production of one unit

u Maximum production time per production equipment per planning period

q_{it} Demand at demand node i during planning period t

d_{ij} Distance between demand node i and potential production facility site j

M Sufficiently large number (big-M)

Decision variables

X_j Number of AM machines to place at potential production site j

Y_{ijt} $\begin{cases} 1, \text{if demand } i \text{ is assigned to site } j \text{ during } t \\ 0, \text{otherwise} \end{cases}$

S_{ijt} Supply quantity from potential production site j to demand node i at the beginning of planning period t

The model

Total supply-weighted distances travelled =

Minimise:

$$\sum_{i\in I}\sum_{j\in J}\sum_{t\in T} d_{ij}S_{ijt} \quad (1)$$

s.t.

$$\sum_{j\in J} X_j \le n \quad (2)$$

$$c\sum_{i\in I} S_{ijt} \le uX_j \qquad \forall j\in J, \forall t\in T \quad (3)$$

$$S_{ijt} \ge d_{it} \qquad \forall i\in I, \forall j\in J, \forall t\in T \quad (4)$$

$$\sum_{j\in J} Y_{ijt} \le 1 \qquad \forall i\in I, \forall t\in T \quad (5)$$

$$S_{ijt} \le Y_{ijt}M \qquad \forall i\in I, \forall j\in J, \forall t\in T \quad (6)$$

$$S_{ijt} \ge Y_{ijt} \qquad \forall i\in I, \forall j\in J, \forall t\in T \quad (7)$$

$$X_j, S_{ijt} \in \mathbb{Z}^+ \qquad \forall i\in I, \forall j\in J, \forall t\in T \quad (8)$$

$$Y_{ijt} \in \{0, 1\} \qquad \forall i\in I, \forall j\in J, \forall t\in T \quad (9)$$

In model (1) – (9) the objective function (1) minimises the total supply-weighted distances travelled during all planning periods. Constraint (2) ensures that the number of allocated production facilities (and implicitly the number of assigned AM machines) does not exceed the number of the available ones. It should be noted here that the number of production facilities (or more accurately the number of AM machines) is a model input rather than a model output. This is because in cases of largescale disturbances, one has to adapt with the available resources at their disposal, especially that the objective of the framework is to assist in the response phase of disturbances, not the preparedness phase. Nevertheless, this modelling attribute can be easily changed to make the number of production facilities (and AM equipment) a model output. Constraints (3) ensure that each AM machine's production capacity is not exceeded. Constraints (4) stipulate that the supply amount received by each demand node at the beginning of each planning period has to be at least equal to its projected demand during that planning period. Constraints (5) impose a condition that each demand node at each planning period is served by exactly one production site. Constraints (6) and (7) ensure that demand nodes are only supplied from their assigned production sites. Finally, constraints (8) and (9) specify the types of the decision variables (integers and binary).

It is important to discuss the model's assumptions and limitations, and their impacts on the quality of the framework's outcome, before presenting the remaining components and processes of the framework. First, model (1) – (9) is deterministic. This might at first glance, especially in the context of this research which deals with largescale disturbances, seem to severely limit the usefulness of the framework. This is, however, not the case as the uncertainty is integrated into the overall framework and also into its constituent models. Uncertainty, more precisely its impact, is integrated into the optimisation model through the sensitivity analysis experiments, as depicted in Fig. 1. Later in the framework, as will be explained in the following section, uncertainty will be further introduced into the framework through the stochastic agent-based simulation model. The model also assumes road transport, where travel times are proportional to distances. Also, the model assumes no shortages of raw materials al all production facilities. Finally, the model assumes that pre and post production activities are aggregated within the cycle time. This assumption, as with all other assumptions, is made to maintain some degree of simplicity in the optimisation model without affecting the quality of its solutions. Relative simplicity (or more accurately less complexity) is necessary in optimization models as the computation time can grow exponentially, rendering a model practically unsolvable.

2.2. Simulation model

The simulation model, which is depicted in Fig. 2 below, is an agent-based model developed from an object-oriented backdrop. Object-orientation allows building modular models, greatly facilitating their transferability to different contexts by adding/ removing classes and objects. Classes in object-oriented models refer to the containers that store the parameters and functions of objects that define their characteristics and behaviour. To explain more, the model depicted in Fig. 2 below contains three main classes, which in agent-based models represent agent populations. Each of these classes (agents) can contain any number of objects (entities) that are defined by the parameters values stored in their corresponding classes, and their behaviour governed by the functions which are also stored in the classes. For example, the Demand node agent in Fig. 2 refers to the population of all demand nodes that populate the model. Their parameters include key information that distinguish each individual one from the rest of the population (defines each demand node's individuality). Such parameters are location (latitude and longitude for each demand node) and demand rate, amongst others. The functions they perform are, for example, triggering demand, and communicating with all production facilities agents to request supplies in instances of inventory shortages. The Environment agent is the space where all agents populate. It could be thought of as the world, scaled down to contain only the given model's setting.

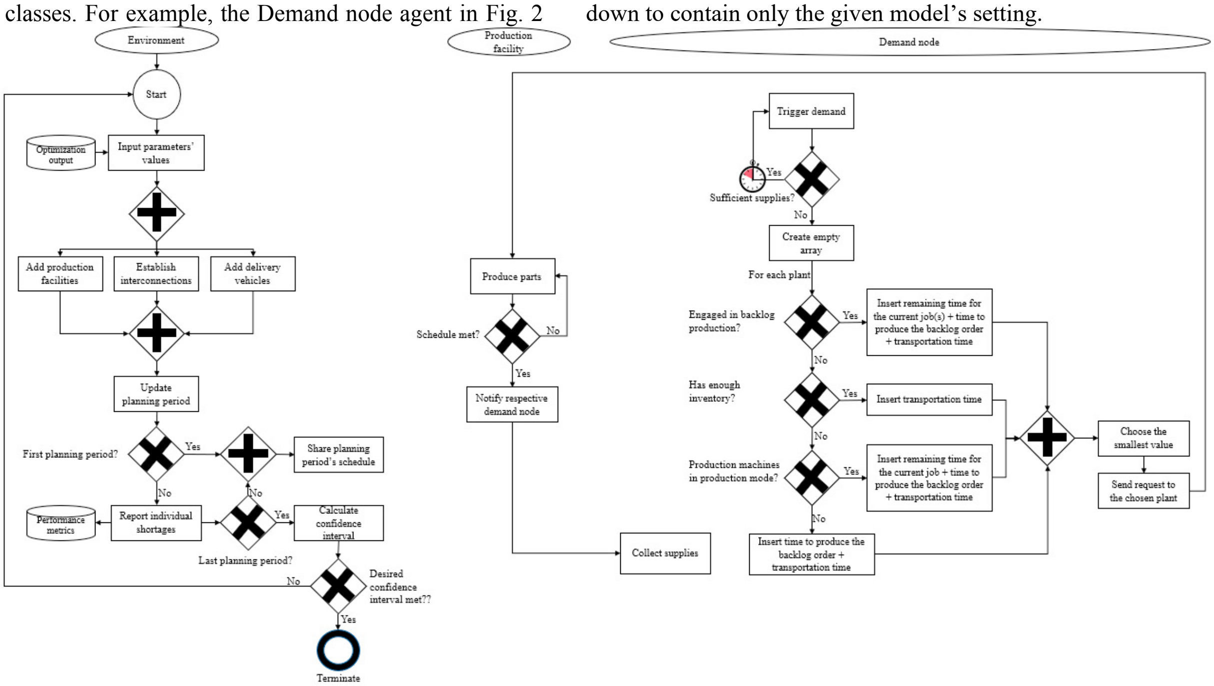

Fig. 2. Agent-based simulation model

The simulation model runs once the optimisation model has found an optimal solution and stored it in the database. The simulation model accesses the database, imports the parameters values (in this case the production network topology and the production and distribution schedules) and builds the model according to these parameters values. The simulation model begins by adding demand nodes and production facilities on a map where the demand nodes locations are provided by the user and the production facilities are provided by the outcome of the optimisation model. Then the model establishes interconnections between demand nodes and their assigned production facilities, which could differ in each planning period. The model then adds delivery vehicles, where each demand node is responsible for the collection of its deliveries at the beginning of each planning period. The aforementioned processes are conducted simultaneously, and after performing these processes, the model updates the planning period. Update planning period is a timed function that is triggered by the simulation model when the time of each planning period elapses, and keeps recurring until the entire simulation time has elapsed. To explain more, if the model is to simulate a week's period of operations, and each planning period corresponds to one day, then the Update planning period function is called at the end of each day until the final (seventh) day. Then, if the new planning period is not the first one, the model reports the individual shortages, if any, that were experienced by each site. The selection of inventory shortages has been made to serve the aim of the framework to supply all demand nodes with their required products, and, when inventory shortages occur, to fulfil the backlogs. Then, the production and distribution schedules (which were determined by the optimisation model) are shared with the respective production sites. After each production facility receives its production and distribution schedules, it begins immediately producing the assigned quantity. After the production of each individual unit, the production facility agent checks if the schedule has been met or not. If the set schedule has been met, then the production facility contacts each of its assigned demand nodes to inform them that their share of products is available for collection. Then each contacted demand node sends a delivery vehicle to collects its share of supplies.

Inside each demand node's agent, a random event triggers demand throughout the simulation time. Once the event occurs, the model checks if there are sufficient supplies to cover demand at the demand node's own inventory stock. If there are enough units to cover this demand instance, then no further escalation occurs, if not then a brute-force algorithm, embedded inside the simulation model contacts all production sites and determined which one can supply the required units with shortest time. Once an inventory shortage occurs, the demand node that experienced the shortage calculates the projected amount of demand by comparing the demand rate against the time left until the next scheduled delivery as shown in (10), where e stands for the time left until the end of the current planning period, and u is the number of time units in each planning period and d_{it} is the mean demand during the current planning period.

$$Order\ amount = \frac{d_{it}e}{u} \quad (10)$$

The demand node agent then contacts all production sites to enquire about their statuses. It then chooses the production site that can deliver the required amount with the fastest time and sends a message containing the order details for production. The algorithm begins by creating an empty array with a size that is equal to the number of production sites. Then, in each production site's respective location in the array, the algorithm calculates the estimated time required for each production site to deliver the required products. The algorithm checks the status of each production site, and then calculates the estimated time to receive the requested products and chooses the production site that can deliver with the shortest amount of time.

The model keeps running as explained above until the last planning period is reached and the simulation time has completed. The model then calculates the confidence interval for the performance metric that the user wishes to improve. This performance measure could be any performance measure such as service level improvement or cost reduction, or any other performance measure that is in line with the overall framework's objective. If the desired confidence interval (which is defined by the user) is met, then the model terminates. Otherwise the model performs extra replications and adds their outputs to the cumulative mean of the previous replications until the desired value is met. After the desired confidence interval is met and the simulation model terminated, the model calculates the means of the individual shortages for each demand node at each planning period, and passes them to the optimisation model as new constraints to generate new production network. This interchange then between the optimisation and simulation models keeps occurring iteratively as discussed at the beginning of this section.

3. Computational experiments

3.1. Case study background

To test and validate the framework, and to demonstrate its applicability in its intended domain, a case study for the design of localised networked production system for the production of PPE, in particular face shields, is conducted in this section. The domain of the case study was inspired by the outbreak of the COVID-19 pandemic where much of the world experienced severe disruptions that it was unprepared for, particularly at the early stages of the pandemic outbreak. During early stages of the pandemic many healthcare providers around the world experienced severe shortages in PPE, which constituted a serious risk factor to frontline healthcare workers [17]. Some countries, such as Italy, experienced relatively high mortality rate amongst frontline healthcare workers, in part due to inadequate supplies of PPE. In this paper, following suit with [3], the framework is applied to design a localised production network for the region of South East England; England's most populous region. The same data set that was used in [3], which was retrieved from the UK Government's open data dedicated COVID-19 website (https://coronavirus.data.gov.uk/). In short, the case study takes the South East England's region hospitals as demand nodes that require face shields for healthcare workers. Demand at each hospital is proportional to the number of daily new confirmed cases in the respective hospital's catchment area from 1 March 2020 until 30 April 2020. Hospitals also served as potential locations for production sites. Further details about the case study's data can be found in [3]. However, Table 1 below presents key values for the parameters used while applying the framework.

Table 1 Key parameters values

Parameter	Value
Number of available AM machines	5
Number of planning periods	9
Cycle 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 (hrs)	168 (number of hours in a week)
Demand rate (μ, σ, min, max)	(demand during planning period, demand * 0.5, 0, ∞)

3.2. Numerical experiments

The experiments were performed on a PC with Intel core i5 2.4GHz and 8GB RAM, the optimisation model was coded in Python and run using Gurobi 8.1.1, while the simulation model was coded in Java and developed using AnyLogic 7.3.2 University Edition..

When the framework was applied using the data in Table 1 and [3], the production network depicted in Fig. 3 was generated by the optimisation model. The resulting production network was then evaluated under uncertainty by the simulation model. The stochastic parameters in the simulation model are demand rate, cycle time and transportation time.

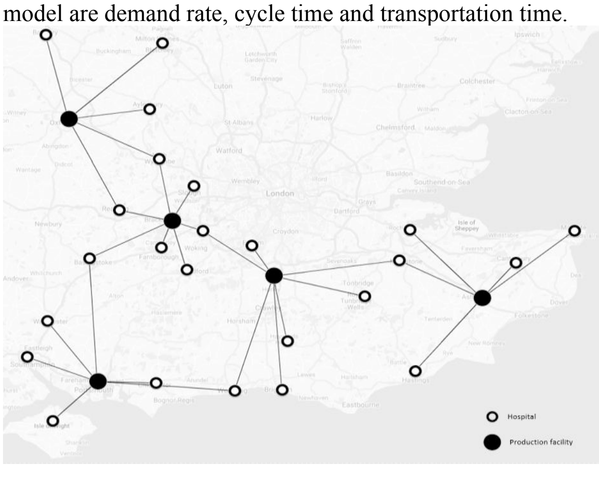

Fig. 3. Production network generated by the optimisation model

After the optimisation model generated the production network, the next step is to run sensitivity analysis experiments on key parameters to examine their impact on key performance measures. The key parameters that were changes are demand rate, cycle time and the available time for each AM equipment. Their impact has been investigated on the total distances travelled. Fig. 4 demonstrates the impact of changing these parameters on the aforementioned performance metric. Looking at Fig. 4, it can be noticed that when total demand decreases, total distances travelled increases to a certain point and then they start decreasing. This is because as demand decreases, less production facilities are required to meet the decreasing demand, resulting in fewer production facilities and therefore more distances travelled. After the 80% decrease threshold, however, total distances start decreasing as well. This is because as demand significantly decreases, many demand nodes (i.e. hospitals) will not request any deliveries for several planning periods, resulting in fewer delivery trips and subsequently shorter distances travelled. The decrease in cycle time also leads to an increase in total distances travelled as shorter cycle times will also eventually lead to fewer production facilities to fulfil demand. The impact of the increase in demand rate and cycle time is almost identical more demand, or cycle time, will entail more production sites, which results in shorter distances. As for production time available for each AM equipment, the decrease in its value leads to shorter distances travelled. This is because less availability for each equipment will mean more AM equipment have to be distributed to supply demand, resulting in shorter distances travelled. The impact of the increase in production availability was not included because it is unrealistic to assume that a machine can operate beyond its time capacity.

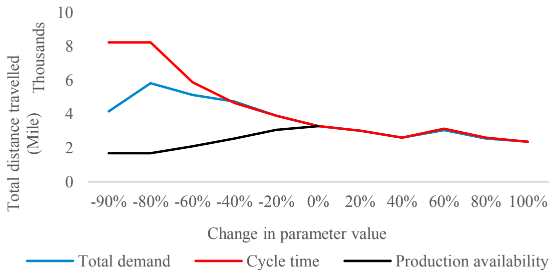

Fig. 4 The impact of the change in key parameters on total distances travelled

After the sensitivity analysis experiments, the performance under uncertainty was evaluated over several replications by the simulation model. The performance measures that the simulation model is designed to observe is the number of face shield shortages experienced by each hospital and lead time. Lead time is the time duration from an inventory shortage instance until receiving the required amount. It is assumed that face shields deliveries occur on a weekly basis where each hospital is supplied with the projected period's supplies of face shields. Since some parameters have high uncertainty, particularly demand, a significant number simulation replications has to be performed to generate statistically significant outputs. After running several replications and observing the confidence interval, a total of 1000 simulation replication has been determined sufficient.

The production network generated by the optimisation model should ideally be optimal in a highly certain environment. This is however not the case in most real life scenarios, particularly during largescale disturbances. Therefore, when the simulation model was run, incorporating uncertainty in the form of key stochastic parameters for the required number of replications, the simulation outcome revealed that the performance could be further improved with regards to the frequency of face shield shortages (unmet demands) and lead time. The modelling then resumed similar to the mechanism depicted in Fig. 1 in order to feed the optimisation model with feedback (to refine the constraints and achieve better service level performance).

It took 8 optimisation-simulation iterations of gradual improvements until the framework ceased to identify improvements to the system's performance with regards to the frequency of the occurrence of unmet demand and lead time as shown in Fig. 5. Fig. 5 shows that the first optimisation-simulation iteration had a mean of around 18 shortages experienced by all the 29 hospitals during all planning periods, while the mean lead time was around 2.28 hours.

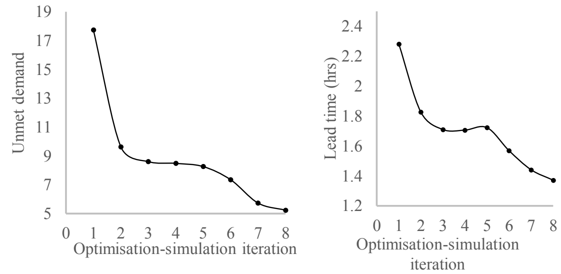

Fig. 5. Improvement in unmet demands (left) and lead time (right)

These outcomes could be acceptable in some cases, but in crisis situations it is likely that these values are desired to be lower than that. Therefore when the simulation model was run, 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 face shields to hospitals that experienced shortages at the specific planning period that such shortages occurred, and if any, supply less to hospitals that experienced surpluses.

It could be noticed from Fig. 5 that the most significant improvement has been achieved from the second iteration. The frequency of unmet demand improved from around 18 to around 10 in the second iteration, stopping at around 5 in the last iteration. Regarding improvement in lead time, 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. To elaborate more on the improvement attained from applying the framework to improve the frequency of unmet demand, Fig. 6 below depicts the frequency of the occurrence of unmet demand for hospitals that experienced the highest degrees of unmet demands for the first and last optimisation-simulation iterations. The results reveal that by the last optimisation-simulation iteration, demand nodes experienced significantly less occurrence of unmet demands.

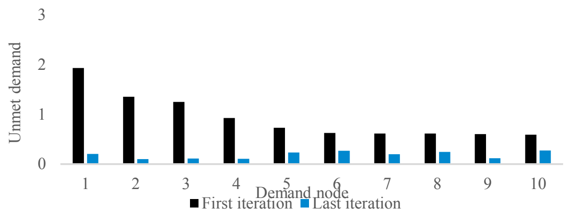

Fig. 6. Frequency of the occurrence of unmet demand for the 10 highest hospitals in the first and last optimisation-simulation iterations

4. Conclusion

In this paper, a model-based decision-making framework for the design of localised networked production systems in times of largescale disruptions has been developed. The framework improves on the one developed in [3] by adding sensitivity analysis to pass the impact of potential uncertainty in certain parameters to the deterministic section of the framework, and embeds an algorithm that handles backlogs into the simulation model. The performance with regards to lead time has been observed in addition to the frequency of inventory shortages. The sensitivity analysis revealed interesting insights, particularly with regards to the relationship between the impact of the change in the values of demand and cycle time. The key characteristic of the framework is that it can generate production networks from the optimisation model under uncertainty, where only the impact of uncertainty is passed to the model. This approach to handle uncertainty and complexity in optimisation model is useful as the optimisation model can still be simple enough to be presented in closed form and solved to optimality, while at the same time including the perceived impacts of uncertainty and complexity into its solutions. In other words, uncertainty and complex interrelationships are handled by the simulation model, while their impact is passed back to the optimisation model.

This research can be extended in a number of directions. First, the cost of establishing the system could be considered by adding an extra cost minimisation objective function to the model. It will also be interesting 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. 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.

CRediT author statement

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