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Design of emergency response manufacturing networks: a decision-making framework

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Abstract

In times of large-scale crises, seemingly streamlined supply chains could become prone to unforeseen disruptions, leading to interruption in the provision of vital supplies. This could lead to severe consequences if such interruptions include vital products, such as lifesaving medical supplies or healthcare workers' protective gear. Shortages of vital supplies could occur due to unexpected sharp spike in demand, where manufacturers are unable to produce the necessary quantities required to meet the unusual demand. They could also be the result of a disruption in the product's supply chain, originating in another country, or even continent, worse affected by the crisis. In either case, localized production, enabled by efforts and resources of local establishments and individuals, could provide a contingency means to produce such vital products to serve local needs, temporarily. Motivated by the growing availability of advanced manufacturing technologies, in particular additive manufacturing (AM), this paper aims to develop a decision-making framework for the design of AM enabled local manufacturing networks in times of crises. The framework consists of complementing interrelated optimization and simulation models that operate iteratively in an uncertain environment, until a local production network, producing the desired performance targets, emerges. Finally, a case study inspired by the shortages of medical supplies, and healthcare workers' personal protective equipment (PPE), during the worldwide 2020 outbreak of the COVID-19 coronavirus is employed to demonstrate the applicability of the framework.

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1. Introduction

Although production and distribution networks typically incorporate measures to adapt to certain levels of disruptions a priori [1]; designing systems capable of handling all types and degrees of disruption is regarded as an impossible task [2]. This becomes clear when slight fluctuations in, demand for instance, go unnoticed, or cause minimal disruptive consequences. Other disruptions however, such as those caused by unforeseen emergencies, can result in more serious disruption to the production and distribution networks, sometimes rendering them incapable of meeting the sudden unexpected demand. Other than production systems being incapable of producing the required quantities on time, sometimes the supply chain

itself is disrupted; and goods (or raw materials), even if they are readily available somewhere, cannot be transported to the desired demand point(s) [3]. In cases of severe disruptions, localized production has the potential to provide a means to meet the unexpected demand, and/ or, localize disrupted supply chains [4]. Recently, the advent and growing widespread use of advanced flexible manufacturing technologies, in particular additive manufacturing (AM), have made the prospect of localized production networks a reality.

Design of production and distribution networks has received considerable attention from academics and practitioners alike over the past few decades. Historically, production and distribution network design problems have been tackled through decision-aid tools borrowed from the field of

operations research (OR). Decision-making has been historically classified at three overlapping levels, with blurred boundaries, according to time horizons; namely strategic, tactical and operational [5]. Since decision-making, lies at the heart of the production network design problem (e.g. where to locate facilities, how much to produce, what is the optimal inventory level), it is pivotal that careful and well-informed decisions are made beforehand, so that the envisioned system is more likely to behave the way it is intended to. While decision-making models and frameworks in crises response settings have gained increased attention, literature in production and distribution network design for such settings addresses mostly location and inventory decisions, and omits production processes, assuming that supplies are manufactured earlier in ‘ideal circumstances’.

A number of survey papers that review models and frameworks for emergency response network design are reported in [6–8]. Few studies have developed optimization models for the prepositioning of supplies needed in crises times. In [9] the authors developed a facility location model which maximizes the covered demand with inventory decisions for the prepositioning of life-saving supplies. The model incorporates uncertainty through a limited number of scenarios; each with an associated probability of occurrence. Uncertainty modeling through scenarios however, can only handle a modest number of scenarios [10]; leaving many possibilities unexplored. In [11] the authors developed a two-stage stochastic model for the design of relief chains. They formulated the first stage to provide location and allocation decisions, while the second stage consisted of a multi-objective model minimizing travel times and costs. Although similar to [9] in the use of scenarios to represent uncertainties, they used fuzzy numbers to represent stochastic parameters within each scenario.

Given the increasing attention that AM and crises response are experiencing, both jointly and separately, one can guess that an increasing number of studies employing quantitative tools for informed decision-making in this area has been developed. However, reviewing the literature, it was somewhat surprising not to find any study that uses quantitative methods to design a production network powered by AM.

Motivated by the lack of quantitative tools, a model-based decision-making framework for the design of AM-powered production and distribution networks for the response to crises situations is developed in this paper. The framework incorporates uncertainty and accounts for the interdependence between different levels of decision-making. It is worth mentioning here that the production network envisioned in this paper is temporary, could be for example borrowing AM equipment from existing manufacturers; diverting their productions, and therefore the levels of decisions-making are largely scaled down. In other words, strategic decisions in the particular context of this paper are not those that span years; but rather refer to the longest spanning decisions, which are naturally the location decisions. The framework consists of interacting optimization (facility location-inventory mathematical program) and simulation (agent-based) that run consecutively in an iterative manner; gradually improving the performance of the system in each run through two-way feedback.

The framework is not intended for use as a tool for the preparedness phase [11] of a crisis response, but rather as a tool

for the design of temporary response network after the occurrence of a crisis. The approach that this paper takes differs from most of the existing studies in this area (those excluding production activities) where most papers develop decision-aid tools as a part of a preparedness plan for any anticipated crisis. One might argue that it is unnecessary to develop such tools since decision-aid tools already exist, and many life-saving supplies are strategically prepositioned in carefully selected locations around the globe based on these tools. The framework presented in this paper, however, is intended to be a complementing tool, incorporating 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 organized as follows; the next section introduces the decision-making framework along with its constituent models. Section 3 presents an application of the framework through a case study inspired by the 2019-2020 coronavirus global pandemic outbreak where a production network for personal protective equipment (PPE) is designed for the region of South East England. Finally, Section 4 offers concluding remarks and possible future research directions.

2. Decision-making framework

The framework encompasses two distinct, yet complementing, decision aid tools; namely optimization (mathematical programming) and simulation (agent-based modeling). The framework is geared towards the design of temporary production and distribution networks for crisis response in pursuit of fast response.

The models run successively in an iterative manner as depicted in Fig. 1. where first the optimization model is fed the parameters’ values such as the number of available additive manufacturing equipment, their locations, cycle times, distances and transportation times.

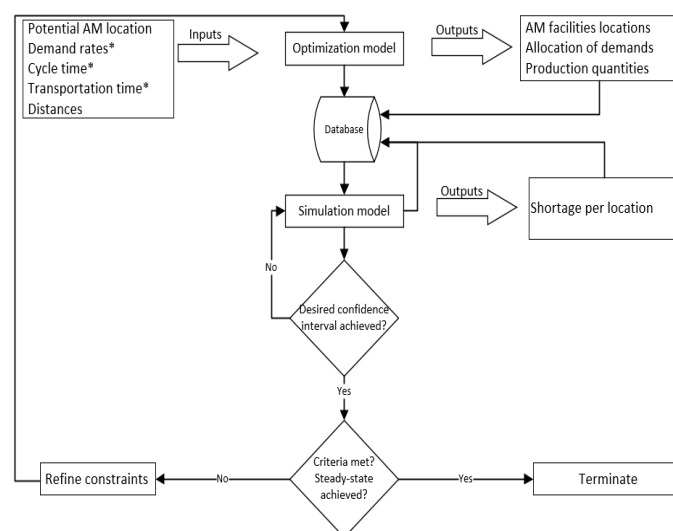


Fig. 1. Decision-making framework

The optimization model generates an optimal production network structure along with production and distribution plans. These are entered into a database that is then accessed by the simulation model, which constructs the production network based on the optimization model’s solution. In other words, the optimization model generates the parameters values for the

simulation model. The simulation model then runs a succession of replications constituting varying stochastic scenarios. The uncertainty is modelled through the incorporation of stochastic parameters which take their values from user-defined probability distributions. For the purpose of this research, the stochastic parameters are those indicated with an asterisk, but in reality any parameter could be stochastic.

Multiple replications are necessary as, being a stochastic model, the outputs generated from a single model run are hardly insightful. Therefore, several replications are required to produce meaningful, statistically significant outputs.

To determine the minimum number of replications required to produce statistically significant results, the confidence interval method is utilized [12].

2.1. Optimization model

The optimization model developed in this paper is a multi-period capacitated facility location model with production scheduling and distribution decisions. The model aims to minimize the total supply-weighted distance travelled, which can contribute to speedier response to areas of high demand. It might be, however, argued that in crisis response, all facilities should be considered of equal importance, which is the case when providing to some vital service providers such as public hospitals and fire departments [13]. Such models are usually referred to as minimax models, which minimize the maximum distance travelled between any two facilities [14]. This family of models however fails to prioritize areas that require more dedicated resources to meet high demand [14].

2.1.1. Notation

Indices

i	Index for demand nodes ($i = 1, 2, \dots, I$)
j	Index for potential facility location ($j = 1, 2, \dots, J$)
t	Index for planning period ($t = 1, 2, \dots, T$)

Parameters

n	Number of available AM equipment
c	Cycle time per unit
p	Number of time units per planning period
q_{it}	Demand quantity at demand node i during planning period t
d_{ij}	Distance between demand node i and potential facility site j
M	Sufficiently large number (big-M)

Decision variables

X_j	Number of AM machines to locate at potential site j
Y_{ijt}	$\begin{cases} 1, \text{ if demand node } i \text{ is assigned to potential site } j \\ \text{during planning period } t \\ 0, \text{ otherwise} \end{cases}$
S_{ijt}	Supply quantity from potential site j to demand node i at the beginning of planning period t

2.1.2. The model

The model aims to suggest a network topology that minimizes the total supply weighted distance travelled during all planning periods. On that basis, mathematically it can be described by the following set of equations (eq (1) – (9)).

Minimize total supply-weighted distance travelled =

$$\sum_i \sum_j \sum_t d_{ij} S_{ijt} \quad (1)$$

$$\text{s.t.} \quad \sum_j X_j \leq n \quad (2)$$

$$c \sum_i S_{ijt} \leq p X_j \quad \forall j \in J, \forall t \in T \quad (3)$$

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

$$\sum_j Y_{ijt} \leq 1 \quad \forall i \in I, \forall t \in T \quad (5)$$

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

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

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

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

The objective function (1) minimizes the total supply-weighted distance travelled during all planning periods. Constraint (2) ensures that the total number of AM machines located does not exceed the number of available machines. Constraints (3) ensure that the production capacity for each AM machine during each planning period is not exceeded. For example, if the length of each planning period is one week and the cycle time for the production of each unit equals two hours, then this set of constraints stipulates that each AM machine is only allowed to produce up to 84 units per week (number of hours per week / cycle time in hours per unit). If the solution algorithm decides that more than 84 units are required from this location to meet demand, then another AM machine has to be installed in this location. Constraints (4) stipulate that the supply amount at the beginning of each planning period to each demand node should be at least equal to or greater than this period's projected demand. Constraints (5) stipulate that each demand node is served by only one site during each planning period. Constraints (6) and (7) ensure that supply quantity is directed only to those demand nodes assigned to their respective production sites and link the decision variable Y_{ijt} to the rest of the variables. Finally constraints (8) and (9) specify the types of decision variables.

Before using the model to generate solutions for real world problems, it is important to understand its limitations and assumptions, and their impact on the quality of the final solution. First the model is deterministic i.e. all parameters values are known in advance and do not change during the model solution. At a first glance, it might seem that this assumption defeats the model's purpose; being deterministic and requiring specific values for all parameters (the lack of which, contributes to the emergence of crisis situations). Deterministic modeling, however, can provide valuable insights into understanding a problem and therefore provide a starting point for further experimentation; where uncertainty naturally has to be incorporated into the modeling setting before a reliable solution is generated. Uncertainty in this paper is introduced through the simulation model and incorporated through continuous two-way feedback between the optimization and the simulation models. The model also assumes that each demand node is assigned to exactly one

production facility during each planning period, this assignment however is allowed to change between different time period. The model also assumes road transport where each demand node is responsible for picking up its supplies at the beginning of each planning period. This assumption was made to suit the modeling setting in this paper where it could be faster and more efficient that each demand node (for example hospital) collects its supplies. Raw materials are assumed to be abundant at all production sites with no shortages. Pre and post processing of produced units is incorporated into the aggregate cycle time, which helps maintaining some degree of simplicity without compromising the quality of the solution.

2.2. Simulation model

The simulation model, as shown in Fig. 2. below, consists of three main *agent types*; which are *containers* where the populations of agents reside, have their parameters values and functions stored and shared between them. Environment is the encompassing agent where all other agent populations live, demand points and production facilities are the other two agents populations. The simulation model runs once the optimization model has produced a production network structure, it imports the parameters values from the shared database (where the optimization model has exported its solution).

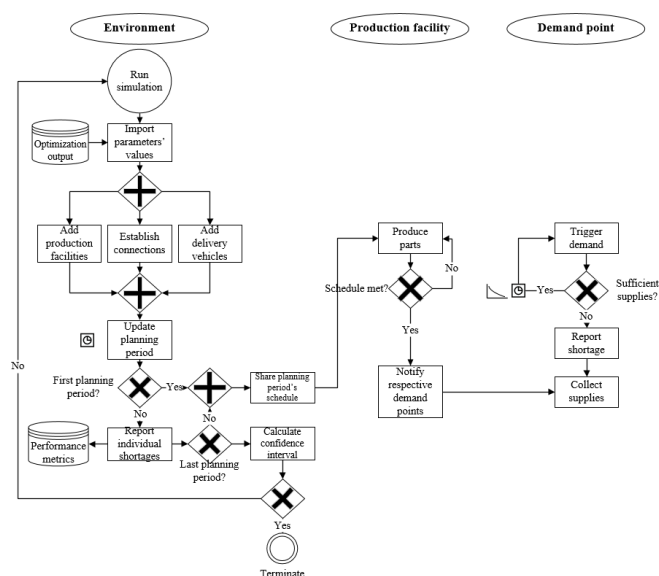


Fig. 2. Simulation model

Determined by the imported parameters values, the simulation model then adds the production facilities, establishes interconnections between these facilities (i.e. allocates demand nodes to production facilities) and adds delivery vehicles at the demand nodes, simultaneously. Then the planning period is updated; which is a recurrent event that is scheduled at the end of each planning period, and keeps recurring until the simulated time is finished. To elaborate more, if a simulation model is to simulate a week's worth of a system's operations divided into 7 days, then at the end of each day the planning period is updated, until day 7 is reached. Then, if the current planning period is any, but the last, the production

schedule (which was determined by the optimization model) is shared with all production facilities. If the planning period is not the first, then the model stores each individual demand point's shortages data that were obtained from the previous planning period. Then if the planning period is not the last one, the production facilities start producing according to the production schedule. After the production of each individual unit, the production schedule is checked inside the production facility agent, if the schedule is met then the production (for the current planning period) ends and the respective demand points are contacted to collect their supplies. Inside the demand points agents, a stochastically triggered event continuously generates demand several times in each planning period; if there were not sufficient supplies to meet the demand, then this shortages is reported and the supplies are ordered.

This process continues until the last planning period is reached; in which the confidence interval (CI), which can be found in [12], for a performance metric (could be cost or service level, depending on the model's objective). It is necessary to point out here that once the desired confidence interval (which is often set at 95%) is achieved, a few more replications are recommended since the confidence interval could fall back below the desired value [12].

If the desired confidence interval is reached, then the model terminates, otherwise the model performs another replication to add its corresponding values to the cumulative mean of the preceding values until the desired confidence interval is met. Upon the termination of the simulation model the means of the individual shortages is calculated and passed back to the optimization model as constraints to devise a new network topology and production plans to meet the observed performance.

3. Computational experiments

3.1. Case study

To demonstrate the applicability of the framework, a case study that aims to design a production network for the production of PPE specifically face shields, using AM is presented in this section.

During the 2019-2020 coronavirus COVID-19 outbreak, shortages in PPE posed serious danger to frontline healthcare workers [15]. Some countries, such as Italy, experienced a higher rate of mortality among frontline healthcare workers, partly due to the lack of adequate PPE [16]. In this study, the framework is applied to design a production network for the South East England region; England's most populous region. Data from the UK Government's open data dedicated coronavirus website (<https://coronavirus.data.gov.uk/>) regarding the region's constituent counties daily new cases were used as inputs to the framework's models. The region's 29 hospitals (with emergency departments and over 200 beds) were modelled as demand nodes and potential production sites. The data covered daily new cases in each county from 1 March 2020 till 30 April 2020 aggregated into weekly planning periods. Demand is assumed to be stochastic and follows the truncated normal distribution. The truncated normal

distribution was used to eliminate any negative values representing demand, which could very likely appear in models addressing highly uncertain parameters (i.e. high standard deviation) by imposing a non-negative lower bound. Table 1 below summarizes the values of the parameters used in this study. Mean demand in each hospital during each planning period is proportional to a percentage (here assumed 10%) of the number of weekly new cases reported in each county with regards to each hospital's proportional capacity (measured by number of beds) with the total county's capacity (i.e. total number of hospital beds in a county).

Table 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 results and discussion

When the framework was implemented with the parameters values presented above, the production network depicted in Fig. 3. was generated by the optimization model. Once the network presented in Fig. 3. was generated, its performance under uncertainty was evaluated by the simulation model.

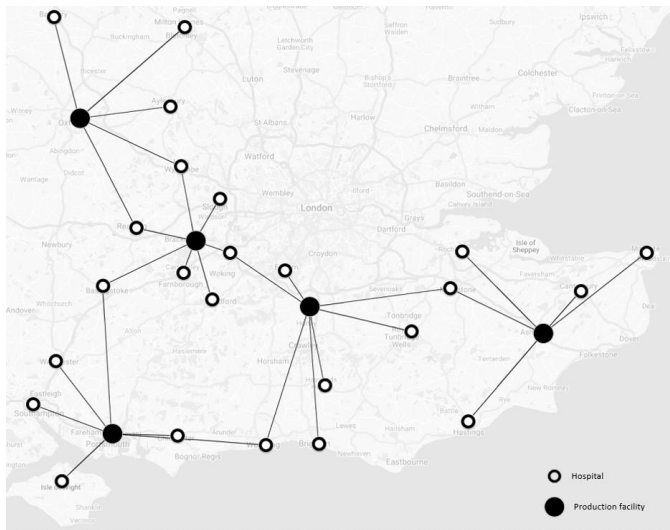


Fig. 3. Network structure from the first iteration

The optimization model was coded in Python and implemented in Gurobi 8.1.1 using branch and cut algorithm [17] and the simulation model was coded in Java and implemented in AnyLogic 7.3.2. The performance measure that the simulation model is designed to observe is the number of PPE shortages experienced by each hospital. It is assumed that PPE replenishments occur on a weekly basis where each hospital is supplied with a projected week's worth of equipment. Since the uncertainty of demand at hospitals is, as is expected in the context of this research, high (with standard deviation being

half of the original value), a significant number of simulation replications was required to produce a sufficiently reliable insightful output. When the confidence interval method [12] was used and a desired value of 95% (which indicates that there is a 95% chance that the *true mean* falls within the confidence interval) was selected, it took 180 replications to achieve the 95% value.

This number however increased once the solution was improved upon (i.e. more optimization simulation iterations were performed) because the performance measure (shortages) gradually decreased while uncertainty remained fixed. In other words the same degree of fluctuation remained but inside tighter bounds. Therefore, to ensure that the set confidence interval is met, and that it remains sufficiently narrow, a total of 1000 simulation replications were performed for each optimization-generated production network.

The production network generated by the optimization model should ideally be optimal in a highly certain environment, which is not the case in most real life scenarios. Therefore, when the simulation model was run, incorporating uncertainty in the form of key stochastic parameters, a number of improvements to the system's performance were identified. Fig. 4. depicts the improvements attained through employing the framework. Fig. 4. shows that the first solution had a mean of around 18 shortages experienced by all the 29 hospitals during all planning periods. This result could be acceptable in some cases, but in crisis situations it is likely that this number is desired to be much lower than that. Therefore when the simulation model was utilized, it evaluated the system's performance, observed where most shortages occurred and passed back a number of *recommendations* to the optimization model to guide its search for a new optimal solution given the new requirements. These requirements include supplying more PPE to hospitals that experienced shortages at the specific planning period that such shortages occurred, and if any, supply less to hospitals that experienced surpluses.

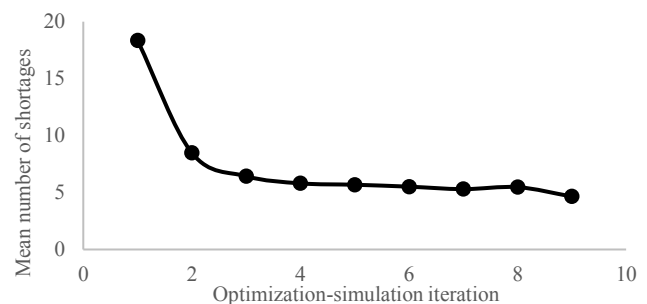


Fig. 4. Optimization-simulation outcome

After the simulation model's recommendations were passed back to the optimization model, and the optimization model generated a slightly different network structure and production and distribution plans to meet new requirements, multiple simulation replications again took place to evaluate the system's performance. The second iteration's performance showed an improvement of around 55% with respect to the number of shortages. This performance was achieved with the same resources being dedicated to the system (i.e. number of AM machines).

After the second iteration, the locations of the AM machines remained fixed; while some changes in supply allocations

slightly differed from one iteration to another. These slight differences, however, resulted in a slight increase in the total distance travelled. This slight increase is attributed to the objective function of the optimization model, being a minimization of the supply weighted distance travelled (i.e. allocated facilities nearer to where demand is higher). If this property is not desirable, then model (1) – (9) could easily be transformed to a minimax problem where the objective function minimizes the maximum distance between any hospital and production facility, regardless of the flow between them.

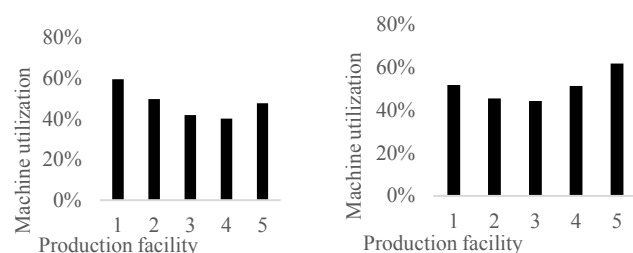


Fig. 5. Machines utilization in first (left) and last (right) iterations

The utilization of the AM machines was also observed during all simulation and is depicted in Fig. 5. above. The figure shows that the utilization of the AM machines remained relatively low, with an increase in the mean of machines utilization by 3% present between the first and the last iteration. Interestingly, however, the work load significantly shifted between locations in order to meet the new requirements passed as feedback from the simulation to the optimization model.

Finally, it is worth investigating the impact of the centralization of operations on the system's performance. Centralization may be desired due to the need for less operators to handle the processes of AM production, which can contribute greatly to cost reduction [18]. To assess the impact of centralization, a scenario where all five available AM machines were placed in one central location determined by the optimization model. This alteration of the structure had little impact on the AM machines' utilization and the number of shortages, but resulted in considerable increase in total distances travelled, as presented in Fig. 6 below.

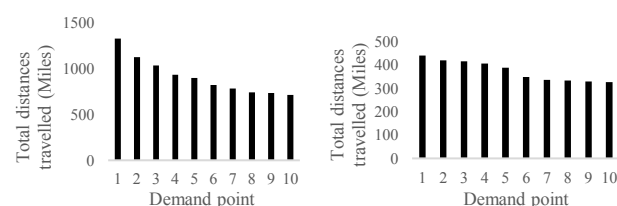


Fig. 6. Total distances travelled by the 10 highest demand points

4. Conclusion

This paper presented a model-based decision-making framework for the design of production and distribution networks for crises response. The framework accounts for uncertainty through several replications of stochastic modeling for each proposed network structure; passing back recommendations for areas of improvement so a new network incorporating these recommendations is generated, in an iterative process. The applicability of the framework was demonstrated on a case study for the production of PPE (face

shields) for frontline healthcare workers in South East England during the 2019-2020 coronavirus COVID-19 pandemic outbreak. The results indicated that although results generated by mathematical programs exhibited good performance (subjectively), the incorporation of real-life dynamics into the problem through simulation modeling, along with the exchange between these two models resulted in considerable improvements to the system's behaviour.

The framework could be extended in different ways. Firstly its constituent models formulations could be replaced with different formulations that could better suit a different purpose. Secondly the framework presented in this paper deals with a single product type; this assumption could be relaxed by replacing the single type with a vector of product types. Finally, the framework could be used in inter-disciplinary research where models from different fields, such as economics or epidemiology, could be incorporated for instance to provide projections for highly stochastic parameters.

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