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A Mathematical Modeling approach for Supply Chain Management under Disruption and Operational Uncertainty

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Abstract

In this work, we proposed a two-stage stochastic programming model for a four-echelon supply chain problem considering possible disruptions at the nodes (supplier and facilities) as well as the connecting transportation modes and operational uncertainties in form of uncertain demands. The first stage decisions are supplier choice, capacity levels for manufacturing sites and warehouses, inventory levels, transportation modes selection, and shipment decisions for the certain periods, and the second stage anticipates the cost of meeting future demands subject to the first stage decision. Comparing the solution obtained for the two-stage stochastic model with a multi-period deterministic model shows that the stochastic model makes a better first stage decision to hedge against the future demand. This study demonstrates the managerial viability of the proposed model in decision making for supply chain network in which both disruption and operational uncertainties are accounted for.

1. Introduction and Literature Review

Recent events worldwide have caused fundamental changes in consumer behavior and supply chain entity dynamics. These changes on the other hand have knocked supply chain network off balance causing disruptions. Disruptions in supply processes pose significant threats to business operations[1] and can lead to increased operational cost, loss of profits, and damage the company's reputation[2]. Hedging against disruption is a call for concern in the supply chain community and

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there is evident that superior contingency planning can significantly mitigate the effects of disruptions. Developing a model that considers robust alternatives for supply chain is germane.

The nature of the global market has been forcing enterprises to expand their supply chain network consequently making the structure more complex and more susceptible to threats in the form of risks and uncertainties[3–5]. These risks are categorized into two: operational or disruptive[6]. The operational risks are due to uncertain parameters between the supply chain entities. Works in the literature have addressed mainly operational uncertainties[7–10]. Such uncertainties are due to supply-demand coordination events and may result from inadequate coordination between supply chain entities, thus leading to imperfect information and failed processes. Disruption uncertainties on the other hand results from man-made/natural disaster, pandemics, etc. Generally speaking, the supply chain disruptions are caused by events that are neither planned nor anticipated. These events are external to the supply chain network and deforms the existing supply chain topology[11,12]. We argue that in order to ensure that the supply chain achieves a balance between the total operating cost and service level, a supply chain network should be designed and operated with buffers to hedge against disruptions. This way the supply chain network can adapt to evolving supply/demand at the operational level and manage uncertainty effectively. Some strategies to incorporate buffers into supply chain includes (i) making the supply chain more flexible by expanding capacities and increasing sourcing options (alternative suppliers and backup suppliers); (ii) enhancing collaborations between supply chain entities by sharing information to improve forecasts and using clients' locations to store extra inventory; and (iii) improving the network's agility by introducing product commonality and holding reserve inventory. These not only help to keep supply chain functional during a disruption, but it also helps to prevent future delays.

Works of literature have pointed out the vulnerability of today's supply chains to disruptions and the need for a systematic analysis of supply chain vulnerability, security, and resiliency[1,6,13]. Furthermore, strategies to manage disruptions can be categorized into three main groups: mitigation strategies, recovery strategies and the passive acceptance approach[14]. The mitigation strategies are proactive measures and act in advance, irrespective of whether disruptions actually occur examples of such strategy include increasing amount of safety stock, multiple sourcing, capacity expansion and multimodal transportation options, while recovery strategies generally take actions after the occurrence of a disruption some of these strategies are alternative sourcing, rerouting of products, alternative inventory locations, outsourcing productions, and cooperation among supply chain entities. The third group accepts the risk of disruptions without any action. Such strategy may be appropriate when the mitigation or recovery cost outweighs their potential advantages.

Broadly speaking, the review of supply chain disruption frameworks can be grouped under simulation approaches and mathematical programming approaches[11,15]. The simulation approach has been used to study how different supply chain entities interact, and it provides dynamic details and behaviors of a network over time. The decisions are made from logical rules of each supply chain entity. There are notable studies on simulation of supply chain network under disruptions[16–22], these studies have given insights into best ways to manage disruptions and the potential benefits of such actions. Conversely, mathematical programming follows an analytical approach to make decisions using various optimization tools. This review focuses on the mathematical frameworks for supply chain models under disruption. Three dimensions are considered for the discussion of the mathematical frameworks: the first is the disruption management strategies which includes mitigation, recovery, or passive acceptance[23,24]. The

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second dimension is the nature of the model's formulation which corresponds to a Mixed Integer Programming (MIP) that could be linear or non-linear. The final dimension of the formulation is how the disruption is incorporated into the model. This could be deterministic or stochastic. In the deterministic formulation the disrupted entities are not considered while solving the optimization problem while the stochastic formulation treats the entities as random variables [25,26]. For an excellent review of literature Snyder et al [25] gave a summary for models used in the study of supply chain disruptions.

In a mathematical model, the supply chain network is viewed as a set of interconnected nodes or supply chain entities that are connected by directed arcs or the logistic chains. Disruptions can either happen to the arcs or the nodes. It is worth noting the works of Sawik[27–31], who developed an integrated approach for portfolio optimization under disruption. The stochastic programming model was used to integrate supplier selection, demand allocation, and customer order scheduling in a multi-echelon supply chain. The model was further improved by jointly optimizing supplier, production, and distribution. Namdar et al.[32] solved a stochastic MILP and considered sourcing options, collaborations, and visibility as strategies. Results indicates that the information sharing in this case buyers' warning capabilities plays a vital role in enhancing supply chain resilience. A bi-objective stochastic MILP was considered in Yoon et al.[33], the mitigation strategies considered was supplier selection. Moreover, the authors suggested that a combination of upstream and downstream risk mitigation strategies should be considered with supplier selections rather than considering these decisions independently. Using a bi-objective two-stage stochastic programming model, Torabi et al [34] developed a MILP model to address supplier selection and order allocation problem. To enhance the resilience level, the model applies several proactive strategies, suppliers' business continuity plans, fortification of suppliers, and contracting with backup suppliers. Jahani et al.[35] used a two-stage MIP model to study the impact of capacity/inventory disruption on a supplier's cost when the supplier has different service agreements with customers. The model can assist suppliers in determining their capacity level and location, allocating capacity to customers, and negotiating service level terms. Lim et al [36] considered a facility location problem in the presence of random disruption, they investigated the impact of misestimating the disruption probability and misestimating the correlation degree. Results indicate that the impact of disruption is much significant. Gholami-Zanjani et al.[37] applied stochastic programming/robust optimization to study the resilient supply chain design and inventory decisions, considering food product-specific characteristics and potential disruptions. The model allows the analysis of three resilient strategies to hedge against ripple effects for food supply chain network. Rezapour[38] proposed a supply chain network design problem under competition and disruption. The model is designed to find the most profitable network and risk mitigation policies. Sadeghi et al.[39] developed a multi-objective model for designing a supply chain network, considering resilience and sustainability, and used a robust scenario-based stochastic programming approach for potential disruption scenarios. This approach allows the average performance of the supply chain in each objective to improve. Azad et al[40] studied the design of a supply chain network in the presence of random disruption in capacity of distribution center and transportation modes. Conditional value at risk approach was used to control the risk of the decisions made in the presence of disruptions. The central theme of the mathematical programming approaches and simulations methods used in the literature has been to address the disruptions in a proactive or reactive manner. It is interesting to note that both strategies have its pros and cons. Interested readers are directed to the review articles by Kamalahmadi and Parast [41,42], Shekarian[12], Ivanov et al[11,13], and Snyder et al[25].

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Within Process Systems Engineering (PSE), disruption has been addressed by enhancing manufacturing site and distribution centers' robustness which improves the supply chain network's overall resiliency. To account for potential disruptions, Terrazas-Moreno et al.[43] developed a model that considers process capacity, parallel units, and intermediate storage as buffers for disruption. The objective is to balance capital investment with process robustness in the presence of uncertainty. Moreover, the expected stochastic flexibility was used to measure the process robustness. Using a similar robustness metric, Zhao et al.[44] utilized a bi-objective two-stage adaptive robust fractional programming model with decision-dependent uncertainty set to determine the optimal design and operating level parameters. Garcia-Herreros et al.[45] developed a framework for multicommodity supply chains with a focus on disruptions at the distribution centers. The model optimizes the distribution strategy in disruption situations to find design solutions that optimize investment and predicted distribution costs over a fixed time horizon. A MIP framework was developed by Ye et al.[46] where the goal is to optimize availability in serial systems when single units have fixed probabilities of being available. This was extended to include a stochastic failure process by modeling failures and repairs as a continuous time Markov chain[47]. Using a multi-objective two staged adaptive robust mixed integer fractional programming, Gong and You[48] optimized resiliency and cost of a network optimizing the network topology and design capacities in the first stage and optimal operation level in the second stage.

Despite the useful insights on ways supply chain can adapt to disruption situations, there are some shortcomings some of them are that most papers consider single source of disruptions, and the papers that considers multiple source of disruption focuses on nodes (supplier, facility or demands), address operational uncertainties, and include recovery costs in the model. Decisions are made with information about future disruptions and uncertain information about the operational parameter. To this end, we develop a multi-product supply chain disruption model with uncertain demand. We improved the model developed by Badejo and Ierapetritou[49] to tackle but operational and disruptive uncertainties simultaneously. . In particular, the model would incorporate the following: hedging against disruptions with alternative sourcing options; increased capacity utilization, outsourcing of products and multi-modal transportation options; adopting inventory policies that models the safety stock as well as alternative warehouse options; addressing the operational uncertainties using the two-stage formulations, and adopting a cost structure that ensures economy of scale.

To determine the efficacy of the stochastic model, a deterministic model is solved using the expected operational parameters. The results as well as the decisions are compared. The rest of the paper is organized as follows. Section 2 discusses the problem statement and the model development. The case study in section 3 demonstrates the performance of the model and solution framework. Section 4 discusses the results and section 5 concludes the paper.

2. Problem statement and theoretical framework

2.1. Problem Statement

The problem considers a multi-products customer-driven supply chain network which produces variety of products ($p \in P$) to meet the need of customer zones ($c \in C$). A comprehensive notation can be found in the appendix. Each product is typically composed of different raw materials ($r \in R$). And these materials are sourced from different suppliers ($s \in S$) with different capacities. As shown in Figure 1, the supply chain network consists of four echelons and can be represented by a directed graph with four sets of nodes: the supplier nodes ($s \in S$), the manufacturing facilities ($f \in F$), the warehouses ($w \in W$) and the customer zones ($c \in$

C) . The arcs represent the connecting links between nodes and embedded in each arc are ($m \in M$) modes of transportation. The reliability of each transportation nodes differs and affects the cost of using the transportation mode. The topology of the supply chain is such that during disruption, there are strategies to ensure robust delivery for its entities (nodes and arcs).

Following a discrete time paradigm, the horizon considered is discretized into T planning periods denoted by $t \in \{1, \ldots, |T|\}$. The supplier sets contain a set of main supplier that can supplier raw material r $s \in S_{a}^{r} \subset S$ and backup suppliers $s \in S_{b}^{r} \subset S$. It should be noted that within the sets of main suppliers there are alternative suppliers for raw material r. And there are backup suppliers for all raw materials as well. Such a strategy ensures that raw materials are delivered, irrespective of the disruption. Also, the main suppliers are preferred for two main reasons, the cost of supply α_s is lower and the quality of raw material γ_{rs} is better. Thus, the backups are only used when main suppliers are disrupted. At the manufacturing facility nodes, each manufacturing facility operates at a fixed cost of α_f^{FC}, and a unit production cost of α_f^{v}. The former can be attributed to utilities, labor, and other operational costs. Additionally, each facility has a potential for expansion where extra capacity $u \in U$ with capacity C_f^u is added to the main production line. This comes at a cost of α_f^u. Products that cannot be met are outsourced so as to reduce the backorder. At the warehouse nodes, there are two sets of warehouses: the main warehouses $w \in W_a \subset W$ owned by the enterprise and the backup warehouses $w \in W_b \subset W$ located at the customer locations. Similar expansion approach applied at the manufacturing nodes is available at the main warehouses as well. Thus, using extra units comes at an extra cost of α_w^u. Furthermore, the unit cost of storing inventory in the warehouse is α_w^{Inv}, This cost is higher for the backup warehouses. Within the supply chain network, products and raw materials are

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transported between adjacent nodes through the multi-modal arcs with m available transportation modes. Each arcs modes incurs a cost α_{ij}^{m} where $(i,j) \in \{(s,f),(f,w),(w,c)\}$.

The set of time periods is divided into two subsets: one that is certain and the uncertain time period. At the beginning of the certain period, customer demands for products d_{pct}. The demands for the uncertain periods are forecasted from a distribution $\hat{d}_{pct}(\theta) \sim N(\mu_p, \sigma_p)$. During each time periods, raw materials are ordered from suppliers to production facilities and manufactured products sent to the warehouse. At the warehouse there are decisions on quantities of products to ship to customers as well as the quantity to keep as inventory based on the adopted inventory policy. At the end of the certain products, products are delivered to the customers from the warehouses or by outsourcing. The unsatisfied demands are considered to be lost sales and a backorder penalty cost α_{p}^{pen} is incurred. It should be noted that other parameters in the supply chain such as material costs, quality of raw materials and transportation costs can also be uncertain, but we have assumed that they have low variability thus, the expected values for these parameters will suffice. For the case of other parameters, we sample from a uniform distribution $\wp \sim U(lb, ub)$, and the expected values calculated. This expected value is used. Which is precisely the midpoint of the intervals.

The nodes and arcs of the supply chain network are susceptible to disruptions and each entity reacts to disruption in unique ways. At the supplier nodes, when the main suppliers for a particular material are disrupted or unable to meet the demands for raw materials, the backup suppliers are used. Each non-disrupted manufacturing facility can expand its capacity in order to manage the disruptions at the manufacturing facility nodes. Also, there are options to outsource products to keep the customer service level high. The warehouses that are undisrupted controls

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the disruption at the warehouse nodes by adopting similar capacity expansion technique. Alternatively, inventory can be stored in the warehouses at the customer's location. Due to the multi-mode operation of the arcs connecting the adjacent nodes, disruptions in the arcs are managed by redistributing materials and transporting through the undisrupted arcs. The re-distribution is done to satisfy the objective.

It should be highlighted that the problem under consideration here takes the supply chain architecture as fixed by a higher-level (strategic level), and this design incorporates buffers to hedge against disruptions. The primary goal of the problems is to solve a tactical supply chain problem under uncertainty while also considering disruptions. This invariably requires balancing resource supply, production levels, and storage levels to uncertain product demand in an optimal way, while taking capacity utilization, resource availability, and disruption forecasts into account. The main decisions are raw material quantities from suppliers, production levels at manufacturing sites, capacity utilizations at the warehouses and manufacturing sites and transportation modes and quantities for each link in the supply chain network. The overall goal is to minimize the total cost and maintain a high service level. Thus, we want to utilize nodes at minimum cost in the network structure and find the flow path that transfers commodities at the lowest cost.

2.2. Model Development

In this section, we introduce the mathematical model for the supply chain under demand uncertainty and the disruption. We have adopted a two-stage stochastic modeling paradigm to hedge against the operational uncertianty and integrated an approach to help hedge against the supply chain disruption. In what follows, we describe the modeling assumptions , followed by the detailed formulation

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Modeling assumptions

Disruption is any event that affects the supply chain topology. In order to capture the nature of disruptions, as well as operational uncertainties, we have made some modeling assumptions as follows:

1. Operational parameters are assumed to follow a known distributions, the demand uncertainty follows a normal distribution, to account for disruption, it assumed that the variance of the distribution is high. For other parameters, a uniform distribution is sampled, and their expected values is used.
2. All supply chain entities can exist in two states: normal state and disrupted state. The entity is fully functional in the normal state, while the entities cannot function in the disrupted state.
3. Disruption can occur to all nodes (suppliers, facilities, and warehouses) and arcs (transportation routes between nodes), and in each disruption case, a subset of nodes and/or arcs are disrupted; once this happens, total capacity is lost.
4. Disruption of each node occurs independently; the interval is determined by the geometric distribution, which is the discrete counterpart of the exponential distribution.
5. In the event of disruptions, available measures provide alternatives, which come at extra costs to operations. These are discussed below:
    a. When a manufacturing facility node is disrupted, products manufacturing can be outsourced, and recovery is amortized till the facility gets back to normal operation
    b. When transport arcs are disrupted, the transportation is redistributed, but the recovery fee is still present till the arc comes back to normal operation.
    c. When the warehouse nodes are disrupted, products are stored in the customer location for a specified cost.

d. When supplier nodes are disrupted, alternate suppliers and backup suppliers are used to hedge against raw material demands.

6. A recovering facility cannot be disrupted until after full recovery. It should be noted that resources can be utilized to speed up the recovery process thus reducing the time for recovery. For simplicity, this tradeoff between recovery time and recovery cost is not considered in the model

To elaborate on assumption 5, there is a limit on the quantity of products that can be obtained through outsourcing; this helps to ensure that the model is as accurate as possible. Therefore, a sale is considered be lost whenever there is an inability to fulfill a demand from the manufacturing site or through outsourcing. In a similar fashion, at the supplier end, as stated in assumption 5d, alternative suppliers that supply the same raw material as the main suppliers can be disrupted. The backup suppliers provide other types of raw material. Therefore, if the main supplier and alternative supplier are unable to meet the demands of the manufacturing sites (either because of a disruption or because of restricted capacity), the backup suppliers are used, and more material will be required in this case to manufacture similar products at the manufacturing site.

To quantify the time the disruption happens, we assumed that the amount of time before disruption happens is random, and the interval duration between disruptions follows a geometric distribution[25]. It should be noted that the choice of geometric distribution is because we have used a discrete-time model. The geometric distribution is a discrete probability distribution that represents the probability of the number of successive failures before success is obtained in Bernoulli trial[50,51]. The underlying assumption in using this distribution is that the average time between events is known, but the events' disruptions themselves are spaced at random. It is

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possible to have back-to-back disruptions, but we can also go weeks between disruptions due to randomness. Thus, we assume that the waiting time until the disruption is geometrically distributed with a parameter (the average rate of occurrence), and the waiting times between each disruption are independent and geometrically distributed. The discretization of the time horizon considered is done according to time interval for possible disruption event. At each period, Bernoulli trial is performed, and if the trial leads to a success, then we have a disruption, otherwise there is no disruption. It should be noted that this procedure is done independently for all supply chain entities (nodes and arcs).

Model Formulation

The overall objective of the problem is to make feasible decisions on raw material and products flow through arcs and nodes to satisfy the customer demands in an optimal fashion. The optimality in this case is defined as the decisions that minimizes the entire supply chain cost such decisions has to be feasible,i.e. satisfy the constraints at each supply chain node. In what follows we discuss the mathematical formulation of the objective function as well as the constraints.

Objective Function:

Following a two-stage approach, the goal is to minimize the expected costs. This cost consists of the summations of all costs incurred, which are cost of raw materials, production of products, materials flow across all nodes, storage and the penalties incurred for unment demands. Quantitatively, this is shown in equation (1a). The breakdown of each costs in equation (1a) is shown in equation (1b)- (1h).

$$\min ExpectedCost$$

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$$ExpectedCost = \mathbb{E}\begin{bmatrix} Supply\ Cost\ (\theta) + Warehousing\ Cost(\theta) + \\ Operating\ Cost(\theta) + Outsourcing\ Cost\ (\theta) + \\ BackorderCost(\theta) \end{bmatrix}$$

$$SupplyCost\ (\theta) = \sum_{s}^{S}\sum_{t}^{T}\left(supCost_{s,t}(\theta) + \ sTCost_{s,t}\ (\theta)\right)$$

$$WarehousingCost(\theta) = \sum_{w}^{W}\sum_{t}^{T}\left(whCost_{w,t}(\theta) + \ wTCost_{w,t}(\theta)\right)$$

$$OperatingCost(\theta) = \sum_{f}^{F}\sum_{t}^{T}\left(fTCost_{f,t}(\theta) + \ fTCost_{f,t}(\theta)\right) \tag{1a}$$

$$OutsouringCost\ (\theta) = \ \sum_{t}^{T} outCost_{t}\ (\theta)$$

$$Backorder\ Cost(\theta) = \sum_{p}^{P}\sum_{c}^{C}\sum_{t}^{T}\left(B_{pct}(\theta) \times \alpha_{p}^{pen}\right)$$

$$supCost_{s,t}(\theta) = \sum_{r}^{R}\sum_{f}^{F}\sum_{m}^{M}\left(Q_{rsfmt}(\theta) \times \alpha_{rs}\right)\ \forall s \in S\ , t \in T \tag{1b}$$

$$sTCost_{s,t}(\theta) = \sum_{r}^{R}\sum_{f}^{F}\sum_{m}^{M} Q_{rsfmt}(\theta) \times \alpha_{m}^{sf} \qquad \forall s \in S; t \in T \tag{1c}$$

$$whCost_{w,t}(\theta) = \left(\sum_{p}^{P} I_{pwt}\ (\theta) \times \ \alpha_{w}^{inv}\right) + \ \left(\sum_{u} y_{w,t}^{u} \times \alpha_{w}^{u}\right)\ + \left(\ \alpha_{w|\ w\in W^{d}}^{rec}\right)\ \forall\ w \in W\ ; t \in T \tag{1d}$$

$$wTCost_{w,t}(\theta) = \sum_{p}^{P}\sum_{c}^{C}\sum_{m}^{M} Q_{pwcmt}(\theta) \times \alpha_{m}^{wc} \qquad \forall\ w \in W; t \in T \tag{1e}$$

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$$facCost_{f,t}(\theta) = \left(\sum_{w}^{W}\sum_{m}^{M} Q_{pfwmt}(\theta) \times \alpha_{f}^{op}\right) + \left(\sum_{u}^{U} y_{ft}^{u} \times \alpha_{f}^{u}\right) + \left(\alpha_{f|\, f\in F^{d}}^{rec}\right) \quad (1f)$$

$$fTCost_{f,t}(\theta) = \sum_{p}^{P}\sum_{w}^{W}\sum_{m}^{M} Q_{pfwmt}(\theta) \times \alpha_{m}^{fw} \quad \forall\ f \in F; t \in T \quad (1g)$$

$$outCost_{t}(\theta) = \sum_{p}^{P}\sum_{c}^{C} Q_{pct}(\theta) \times \alpha_{o} \quad \forall\ t \quad (1h)$$

The cost of raw materials supplied is captured by equation (1b) where $Q_{rsfmt}(\theta)$ represents the quantity of raw materials r from supplier s to manufacturing facility f transported by mode m, at time period t . similarly, equation (1c) shows the cost of transportation from supplier to manufacturing facility. Equations (1d) and (1e) represent the cost incurred at the warehouse nodes and transportation costs for shipping to the customers respectively. $I_{pwt}(\theta)$ is the inventory amount of product p stored in the warehouse w at the end of time period p, $y_{w,t}^{u}$ is a binary variable that is 1 when the unit u is used in warehouse w at time period t. The last term in equation (1d) is the cost of recovery. At the manufacturing facilities, $Q_{pfwmt}(\theta)$ is the quantity of products p from facility f to warehouse w using mode m at time period t. Equation(1f) shows the cost of production and recovery cost incurred by disrupted facilities. In a similar fashion as the warehouse the y_{ft}^{u} is a binary variable that is 1 when unit u is used in the facility f at time period t. Finally, the (1h) is used to calculate the cost of outsourcing productions and $Q_{pct}(\theta)$ is the quantity of outsourced products p delivered to customers c at the end of the time period t.

The problems solved in this work consider tactical decisions. These decisions are made within the constraints of the strategic supply chain decisions, which govern the supply chain's topology and facility design choices. This is the level where we can make decisions balancing cost and resiliency to disruption[43,44].We have focused on the aforementioned goals of this work is to show the interplay between operational uncertainty and disruption uncertainty as well as compare the performance of the deterministic model with the risk neutral stochastic model. The limitation of this work is that we have taken a risk neutral approach by using the expected cost objective.

Constraints

Flow Balances: The flow balance ensures continuity between the nodes through arcs. This balances are written for all nodes and are described by equations $(2a), (2b)$, and $(2c)$. The uncertainty in the demand for products p from customer locations c propagates to the continuity balance at the customer side as shown in equation (2a). The inventory of balance at the warehouse is shown in equation (2b). The balance ensures that the inventory at the beginning of the time period and at the end of the time is balanced by the quantity of products coming to the warehouse and that leaving the warehouse at the end of the time period. At the manufacturing sites, the quantity of products manufactured depends on the materials supplied from the suppliers and the corresponding yield of the raw materials. This is shown by equation (2c).

$$d_{pct}(\theta) - \sum_{w}^{W}\sum_{m}^{M} Q_{pwcmt}(\theta) + \quad Q_{pct}(\theta) = \mathcal{B}_{pct}(\theta) \quad \forall p \in P, c \in C, t \in T \tag{2a}$$

$$I_{pwt}(\theta) = I_{pwt-1}(\theta) + \sum_{f}^{F}\sum_{m}^{M} Q_{pfwmt}(\theta) - \sum_{c}^{C}\sum_{m}^{M} Q_{pwcmt}(\theta) \quad \forall p \in P, w \in W, t \in T \tag{2b}$$

$$\sum_{w}^{W}\sum_{m}^{M} Q_{pfwmt}(\theta) \ = \ \sum_{s}^{S}\sum_{m}^{M} Q_{rsfmt}(\theta) * \ \gamma_{rp} \quad \forall\, f \in F\,,\, r \in r,\, p \in P\,, t \in T \qquad (2c)$$

Warehouse Disruptions: For the warehouses, there are main warehouses and retailer location sites that are used as backup warehouses. Only the main warehouse can be disrupted and expanded. The capacity of the undisrupted warehouses W_a^n can be increased. Equations $(3a)$ ensure the selection and feasible expansion of undisrupted warehouses by fixing the disrupted warehouses capacity W_a^d to zero and ensuring that there is no expansion for the conventional model. y_{wt}^u is a binary variable which determines if expansion unit u is used in warehouse w at time period t Following that, equations $(3b)$ imply fixed capacity of the undisrupted warehouses which is to be used before considering the backup warehouse $W_{\mathcal{b}}$ located at the retailer locations. Equations $(3c) - (3d)$ ensure that the inventory is within the utilized capacity range, while equation $(3e)$ enforces that materials stored at a customer location should service only that customer where $I_{pwt}(\theta)$ is the inventory of product p in warehouse w at time period t; $Q_{pwcmt}(\theta)$ is the quantity of product from warehouse w to customer c using transportation mode m at time period t. The safety stock for the warehouses that are non-disrupted is modeled by equations $(3f)$ and $(3g)$. According to equation $(3f)$ the minimum inventory which is reviewed every period must be proportional to the standard deviation of the products and the replenishment lead time. This equation is valid for the case where demand for products is assumed independent and identically distributed[52] where z is the cumulative normal distribution

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coefficient for a given service level required. In this paper we have assumed a value of 1.65 and this means we keep a safety stock to obtain a service level of 95%.

$$y_{w,t}^{u} - y_{w,t}^{u'} \geq 0 \qquad \forall\ u < u'\,; w \in\ W\,;\ t \in T \tag{3a}$$

$$y_{w,t}^{u=1} = \begin{cases} 1, & \forall\, w \in W_a^n; t \in T \\ 0, & \forall w \in W_a^d; t \in T\,; t < t_R \end{cases}$$

$$y_{w,t}^{u=1} - y_{w',t} \geq 0 \qquad \forall\, w \in W_a^n;\quad w' \in W_{\mathcal{b}};\ \ t \in \mathbb{T} \tag{3b}$$

$$\sum_{p}^{P} I_{pwt}\,(\theta) \leq \sum_{u}^{U} y_{w,t}^{u} \times Cap_{w^u} \qquad \forall w \in W_a^n\ \ ;\ t \in T \tag{3c}$$

$$\sum_{p}^{P} I_{pwt}(\theta) \leq y_{w,t} \times Cap_w \qquad \forall\, w \in W_{\mathcal{b}}\ \ ;\ t \in T \tag{3d}$$

$$\sum_{m}^{M} Q_{pwcmt}(\theta) := 0 \quad \forall\, w = c;\ \ w \in W_{\mathcal{b}};\ t \in \mathbb{T} \tag{3e}$$

$$I_{pwt}^{ss} = z\sqrt{L \times \sigma_p} \tag{3f}$$

$$I_{pwt}(\theta) \geq\ \ I_{pwt}^{ss} \quad \forall w \in W_a^n\ \forall p \in P \tag{3g}$$

Facility Disruption: At the facility nodes, equation $(4a)$ restricts operations to only non-disrupted facilities $y_{f,t}^{u}$ is a binary variable which determines if unit u in facility f is in use, F^n, and ensures that facilities that are non-disrupted operate in full mode before expansion consideration. Thus, equation $(4a)$ enforces feasible integer selection. In equation $(4b)$, Q_{pfwmt} is the quantity of product from facility f to warehouse w using transportation mode m at time period t , and Cap_{f^u} expresses the total capacity of unit u in facility f; the equation enforce that the amount produced does not exceed the design capacities and equation $(4c)$ sets restrictions on the amount of products that can be outsourced, in the equation C^0 shows the maximum amount that can be outsourced, and Q_{pct} is the quantity of outsourced products transported to customer at the time periods.

$$y_{f,t}^{u} - y_{f,t}^{u'} \geq 0 \qquad \forall\ u < u'\ ; f \in\ F\ ;\ t \in T \tag{4a}$$

$$y_{f,t}^{u=1} = \begin{cases} 1, & \forall\ f \in F^{n};\ t \in T \\ 0, & \forall\ f \in F^{d};\ t \in T\ , t < t_{R} \end{cases}$$

$$\sum_{p}^{P}\sum_{w}^{W}\sum_{m}^{M} Q_{pfwmt}(\theta) \leq \sum_{u}^{U} y_{f,t}^{u} \times Cap_{f^{u}} \qquad \forall\ f \in\ F\ ;\ t \in T \tag{4b}$$

$$\sum_{p} Q_{pct}(\theta) \leq C^{o} \qquad \forall c \in c,\ t \in T \tag{4c}$$

Supplier Disruption: At the supplier nodes, the main suppliers that are undisrupted, $S_{a,t}^{n}$, are selected before considering backup suppliers, equation (5a) ensures these selections. Once the selections of suppliers are done, equation $(5b)$ limits the capacity of these suppliers.

$$y_{s,t} - y_{s',t} \geq 0 \quad \forall\ s \in\ S_{a,t}^{n}\ ;\ \ s' \in S_{b}, t \in T \tag{5a}$$

$$y_{s,t} = \begin{cases} 1, & \forall\ s \in\ S_{a,t}^{n} \\ 0, & \forall\ s \in\ S_{a,t}^{d} \end{cases}$$

$$\sum_{f}^{F}\sum_{m}^{M} Q_{rsfmt}\,(\theta) \leq y_{st} \times Cap_{s} \qquad \forall s \in S, r \in R, t \in T \tag{5b}$$

Transportation Capacity: the transportation links are multimodal, and each mode can be disrupted; whenever this happens, flow is redistributed between the available arc modes. Each of the transportation modes is limited by capacity $tCap_{m}^{ij}$ as shown in equations $(4a) - (4c)$ for all the links.

$$\sum_{r}^{R} Q_{rsfmt}(\theta) \leq y_{m,t}^{sf} \times tCap_{m}^{sf} \quad \forall s \in S; f \in F; m \in M; t \in T \tag{6a}$$

$$\sum_{p}^{P} Q_{pfwmt}(\theta) \leq y_{m,t}^{fw} \times tCap_{m}^{fw} \quad \forall f \in F; w \in W; m \in M; t \in T \tag{6b}$$

$$\sum_{p}^{P} Q_{pwcmt}(\theta) \leq y_{m,t}^{wc} \times tCap_{m}^{wc} \quad \forall w \in W; c \in C; m \in M; t \in T \tag{6c}$$

The model described above is referred to as the proposed model. The solutions obtained from the proposed model are compared with that of the nominal model. In the nominal model, there are no mitigation strategies, i.e., no outsourcing, no expansion possibility in the facilities (manufacturing facilities and warehouses), and no option for inventory storage at the customer locations.

After every optimization step, three metrics are used to quantify the efficiency of the solution, as shown in equations $(7a) - (7c)$.

$$unitCost_t(\theta) = \frac{totalCost_t(\theta)}{\left(\sum_p^P \sum_c^C \left(\sum_w^W \sum_m^M Q_{pwcmt}(\theta) + Q_{pct}(\theta)\right)\right)} \tag{7a}$$

$$serviceLevel_t(\theta) = \frac{\left(\sum_p^P \sum_c^C \left(\sum_w^W \sum_m^M Q_{pwcmt}(\theta) + Q_{pct}(\theta)\right)\right)}{\sum_c \sum_p d_{pct}(\theta)} \tag{7b}$$

$$SCEfficiency_t(\theta) = \frac{\left(\sum_p^P \sum_c^C \left(\sum_w^W \sum_m^M Q_{pwcmt}(\theta)\right)\right)}{\sum_c \sum_p d_{pct}(\theta)} \tag{7c}$$

Equation $(7a)$ represents the cost of supplying one unit of product to the customer, which determines the profit an enterprise makes if the selling price is fixed or determines the main price to deliver to customers if there is a limit on profit margin. Thus, lower unit cost indicates that the supply chain achieves service level at a low cost, and the higher unit cost indicates that the supply chain achieves service level at a higher cost; the latter happens when most demands are outsourced; disruption also increases unit costs. Equation $(7b)$ quantifies the service level, which is the fraction of the demand that the supply chain meets. Finally, equation $(7c)$ shows the supply chain efficiency, which reflects the demand the supply chain meets without outsourcing. In what follows we discuss the assumptions for the disruptions.

2.3 Solution Procedure:

Two-Stage Stochastic Model

The developed model in section 2.2 involves both integer variables and continuous variables as well as operational parameters that are uncertain. Considering the length of the time periods, the available information about the uncertainty in the future period and the availability of disruption considerations. A two-stage stochastic optimization is chosen to solve the problem. This can be expressed as shown in equation (8).

$$\min_{x,y^{sc}} \left\{ \begin{array}{c} \boldsymbol{c}^T x_1 \ + \mathbb{E}[\boldsymbol{f}^T x_2^{sc}] \\ subject\ to: \\ x_1 \in \mathcal{X}_1\ ;\ x_2{}^{sc} \in \mathcal{X}_2 \end{array} \right\} \tag{8}$$

where the variables $x_1$and x_2 represent the first and the second stage decisions, respectively, and $\mathcal{X}_1$ and $\mathcal{X}_2$ captures their feasible space. These are defined by equations (2) to (6). It should be noted that the decisions include both binary decisions and continuous decisions. The flow of the solution procedure is such that the disruption profile and the certain demands for the certain period are first realized, for the uncertain period the demands are forecasted, and disruption

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profiles are also predicted. This information is used to solve the two-stage stochastic model. Based on the structure of information, the integer decisions determine the arrangement of nodes, and the continuous variables are constrained by this arrangement. The decisions in the first stage include the integer decisions on the configuration of the facilities for all periods, the amount of products flowing across the adjacent nodes at the certain period, and the inventory stored at the end of the certain period. The second stage decisions, which are adjusted with respect to the uncertainty realized thus far, includes the products flowing across adjacent nodes for all possible scenarios of the uncertain period, and inventory policies to be adopted for all scenarios These second stage decisions determine the recourse cost, which is the second term in equation (8). Stochastic programming (SP) is a direct extension of deterministic mathematical programming. It considers the temporal relationships between decisions and observations of uncertainty early on by introducing the idea of recourse to ensure feasibility[53,54]. The two-stage models enable the decision-maker to adapt decisions at a later stage to the already observed realization of the uncertain data[53]. In robust optimization, the parameter uncertainties are reduced to a few uncertainties set by perturbing individual parameters away from some nominal problem instance[55]. The method optimizes the worst case, by guaranteeing outcomes under any possible realization. This approach ignores temporal context, and often times the decisions are conservative[56]. One reason the stochastic approach is selected is because we want to understand the interplay between the spatiotemporal decisions, operational uncertainty, and disruptions. In Markov decision process (MDP), decisions (or actions) are made sequentially based on how the system evolves over time, the evolution is characterized as a stochastic process[51]. The MDP procedure adapts a discrete time Markov chain into an optimization framework and makes optimal decisions which involves moving from one state to the other. This requires that the transition probability between states be determined[57]. For a large supply chain problem, characterizing the transition probability between states is non-trivial.

Rolling Horizon strategy

The purpose of the rolling horizon simulation is to examine the outcomes of implementing solution over a planning period. The solution to each time period captures only the spatial decisions of the supply chain; the effect of these decisions is further examined across the planning horizon using by the rolling horizon strategy, thus, accessing the spatial and temporal decisions of the supply chain. This strategy is applied to both the stochastic model and the deterministic model.

As shown in Figure 2, at the beginning of a planning period, the demand for the period and the disruption forecasts are available. The demand for the rest of the prediction horizon is uncertain and available in form of random variable. The prediction horizon is all time period considered in the problem. The model is solved considering all the prediction horizon, and the decisions for the current planning periods are implemented. The current state of the supply chain is passed to the next time period. This state includes the predetermined decisions from implementing the policies in the previous time period and act as the initial conditions. At the beginning of the next time period, the demands for that period and disruption forecasts are realized, while the demands for the following time periods in the prediction horizon are random variables. This process is repeated until the end of the time horizon under consideration. The difference between the implementation of the rolling horizon in this paper and others is the simultaneous consideration of the disruption events and the demand uncertainty. At each time period, there is a realized demand and also realized disruptions. This disruption affects the state of the supply chain thus a new configuration must be adopted.

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It should be noted that there is a similarity between the solution approach used here and the Model Predictive Control (MPC) philosophy. The key notion in MPC is to use a process model which can be mechanistic or empirical based to optimize the process inputs over forecasts of a process behavior made over a finite time horizon with a goal to make decisions that are feasible and robust[58,59]. In this work the model represents the supply chain and optimization is done across time periods over the supply chain components (nodes and arcs). While the optimized variables in MPC are the process inputs required to keep the system in safe operating range, the optimized variables in the case of the supply chain model are the spatial decisions (quantity of flows across arcs, the production and storage at transshipment nodes) to ensure that temporal demands are satisfied. This representation of the supply chain problem, requires a new modeling framework which is outside the scope of this work[60,61].

3. Case Study

In this section, we discuss a case study to explore the behavior of the proposed model in terms of the way decisions are made. For the case study, the deterministic model, and the two-stage stochastic model are solved under similar conditions and the results are compared. The behavior of a model implies the decisions made to keep efficiency and service level of supply chain high at optimal cost, as well as the computational efficiency.

The case study Figure 3, shown in is a generic four-echelon supply chain where three products are manufactured using two raw materials. There are six suppliers are available for the raw materials, four actual suppliers and two backup suppliers. Furthermore, the enterprise operates

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four manufacturing facilities, two warehouses, and supplies products to five customer zones. In addition to the available warehouses, products can be stored in the customer locations as well, in this case products are sent from the manufacturing facilities directly to the customer locations to be stored. This brings the total number of warehouses to seven. For the actual warehouses, when undisrupted, the enterprise runs inventory policies to keep a safety stock. The flows between the supply chain entities are managed by multi-modal arc.

The problem considers one month for every period thus the demand for a month is known apriori and make a forecast of the next four time periods to hedge against the future uncertainty. At the beginning of every time period, the demand for products is realized and there is an available forecast for future product demands. The goal is to make optimal tactical decisions amidst the disruption to minimize the total cost of operation for the certain period in the supply chain network, as well as hedge against the operational uncertainty for subsequent periods. The decisions made are the quantity of flow of each materials between adjacent nodes, production amount at each manufacturing site -which is a direct indicator of the use of the expansion, the inventory amount, quantity of products delivered to the customer from the supply chain network itself, the outsourced demands and the unmet demands. In the next section, we discuss the results obtained.

4. Results and Discussions

In this section, we discuss the results obtained from the case study. All computations were done on a PC with intel® core™ i7 -10510U, 2.30GHz, and 16GB of RAM. To investigate how the proposed model responds to disruption and operational uncertainty, we compare the results obtained from the two-stage model with the deterministic model. Twenty demand scenarios were sampled for each product for the uncertain periods and five time periods considered with only

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the first time period being certain. For the deterministic model, the expected values of the scenarios were used, and the stochastic model makes use of all scenarios. Both models were formulated and solved in GAMS/CPLEX (v 38.2.1). The deterministic model contains 6851 constraints, 8809 continuous, and 2262 binary variables, while the two-stage model 63781 constraints, 67139 continuous variables and 2262 discrete variables. The deterministic model obtained solutions to the model in 25 seconds and the two-stage model solves in 260 seconds. Table *1* shows the detailed breakdown of the metrics for both models. The total cost is the cost obtained from the optimization problem, while the implemented cost is the cost that is actually incurred in a certain period. The service level and supply chain efficiency indicate the fraction of demand satisfied and the fraction of demand that the supply chain satisfied without outsourcing. The cost per period shows the average cost for manufacturing all products. As noticed from *Table 1*, the total cost and implemented costs were higher for the stochastic model and so is the service level and supply chain efficiency. The costs incurred are a consequence of two major factors: the integer decisions for the selections within the available nodes (manufacturing sites and warehouses) and arcs (transportation modes); and the decisions on the degree to which the selected nodes and arcs are used. Figure *4* and Figure *5* show the disrupted and non-disrupted facilities as well as the selected ones for the manufacturing sites and the warehouses, respectively. Table *2* shows the breakdown of the implemented cost as well as the difference in the results obtained.

The facility selections shown in Figure *4* and Figure *5*, indicate that the stochastic solution selects higher capacity utilization for facilities both for manufacturing sites and warehouses. The decision for this selection is to minimize both costs of operating the nodes at the certain time period as well as minimizing the recourse cost for the unrealized demand scenarios. For the deterministic model, the results only select facilities to hedge against the certain demands and the average of all the possible scenarios. The consequence of this selection is increased fixed cost of each node as well as operating cost at the nodes while the advantage is reflected in the higher values for the service level and the supply chain efficiency. Table *2* shows that the stochastic solution suggests higher costs for all other cost components except the backorder cost and the outsourcing costs. It is worth noting that the higher level of inventory suggested by the stochastic model is a way to hedge against future demands based on the forecast. The two-stage stochastic model selects more warehouses when compared with the deterministic solution, consequently, incurs higher cost for inventory. Each model selects inventory policy so as to hedge against the variability in the future demands. In the stochastic model, there are twenty possible demand scenarios while the deterministic model has just one scenario which is the average of all the twenty scenarios available to the stochastic model. Thus, the higher inventory selected is a more robust approach because for all possible future scenarios and would play a bigger part in implemented cost in the future.

The inventory level plays a major role in meeting the product demands for future time periods by reducing production level for future time periods, augmenting the amount of products that is manufactured and/or reducing the quantity of products that is outsourced. Ultimately, this ensures a total cost reduction and delivery time in future time periods when the uncertain demands are realized. In the two-stage model the inventory is a key variable in balancing the recourse cost and the first stage cost. To show the advantage of the inventory policy adopted by the stochastic model, the rolling horizon procedure is used to show the dynamics of how both models makes spatial-temporal decisions. Figure 6 shows the metrics used to compare the deterministic and stochastic solution across all time periods, while Figure 7 shows the contributions of the implemented cost. As seen in the Figure 6 the stochastic model obtains a higher service level, supply chain efficiency and a lower unit cost of production for most of the time periods. However, the total cost for all time period is always greater than that of the deterministic model. These results are similar to that of Figure *4*. In Figure 7, the variation across the time periods reflects the variability in the demands, while the stack areas in the single periods shows the response to demands and disruption for that time period. Thus, high disruption level will cause demands to explore other alternatives thus increasing the overall supply chain cost.

According to Figure 7, within each time period, comparing individual cost components with the deterministic model shows that the cost incurred to achieve high production level is greater for the stochastic model, and the backorder cost is greater for the deterministic model. The results obtained for the stochastic model balances the total cost with the recourse cost for all scenarios considered. Thus, solution takes into consideration the demand volatility of the uncertain time periods, which in turn increases the activity levels at the nodes for the certain time periods. The advantage of this increased activity level is reflected in the service levels and the supply chain efficiency. It is also worth mentioning that the inventory amount in each period is greater for the stochastic models. These helps to hedge against the uncertainty in the demands for the future time periods.

5. Conclusions

In this article, a model for resilient supply chain network is formulated to deal with disruptions and operational uncertainty. Disruptions are taken as breakdown of supply chain network entities (nodes or arcs) and demand uncertainty is considered at the operational level. The main objective is to minimize the total cost of operating the supply chain and the decisions made are the flows

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between the nodes through arcs such that the demands are met. Further metrics used to characterize the quality of solution obtained are the service level, supply chain efficiency and the cost per unit product.

A deterministic multi-period model and a two-stage stochastic model compared in terms of the decisions made by each of them. The stochastic model outperforms the deterministic model on the basis of the service level achieved in the certain time period and the decisions to hedge against future uncertainty. We further used the rolling horizon framework to study the spatial temporal decisions made by these models and the results indicates that the stochastic model is better.

Although the stochastic model shows a better performance in future, we propose to incorporate risks measures into the stochastic model to ensure risk averse decisions. Multiple risk measures such as upside potential, downside-risks or managing variability will be explored to see what gives the best solutions[62–64]. The proposed model can be characterized as a mixed integer recourse model because it has both continuous and integer variables in the first and second stage. The time complexity of large-scale problems can be reduced by using decomposition strategies that exploit the structure of the model. Algorithms such as logic-based Benders decomposition[65], specialized branch and bound techniques[66], and the dual decomposition strategy[67] are applicable in this case. We direct interested readers to Torres et al.[68] and Kücükyavuz and Sen[26], for further information on these algorithms. Furthermore, we have assumed once an entity is disrupted, the full capacity is lost, this assumption can also be relaxed in future and the degree of disruption can be determined. Also, although the proposed model shows a superior performance in the operational phase, at the strategic level, the initial investment cost for the proposed structure is greater than the traditional supply chain networks because of the extra investment cost required for the expansion's spaces. For this, we argue that the potential benefit of such investment outweighs the high cost. Further work can be done for supply chain design will substantiate using the economic model (ROI model) of breakthrough period.

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Authors and Contributions

Oluwadare Badejo : Conceptualization; methodology; resources; writing - original draft.

Marianthi Ierapetritou: Conceptualization; supervision; writing-review & editing.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request

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Table 1: Metrics to compare the deterministic and stochastic solution

Metrics	***Deterministic***	***Stochastic***
Total Cost	200498	235659
Implemented Cost	34696.1	31215.4
Service Level	0.800844	0.987366
Cost Per Period	65.5602	47.8408
SC Efficiency	0.710049	0.896572
Time (sec)	25	260

Table 2: Breakdown of Implemented cost for the deterministic and two-stage stochastic model

	Implemented Cost		
	Deterministic	***Stochastic***	***Difference***
Supplier Cost	1763.49	2664.03	900.54
Facility	10989.7	16287.3	5297.6
Outsourcing	3222.08	3222.08	0
Inventory	228.437	1044.47	816.033
Transportation	4612.3	7079.21	2466.91
Backorder cost	13880.1	918.37	-12961.73

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Images

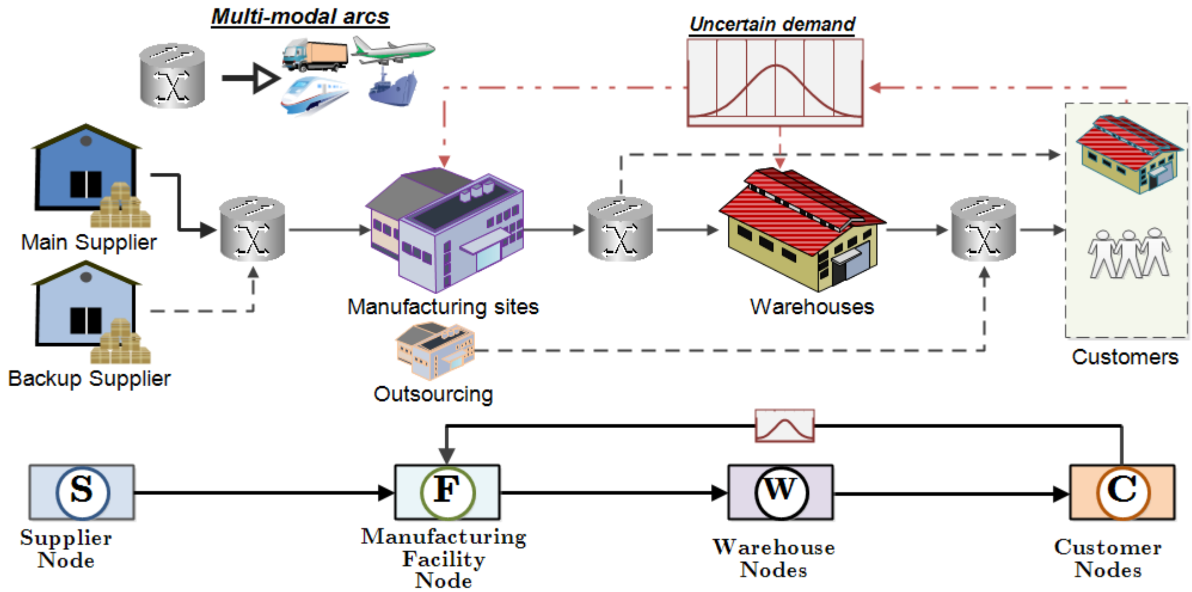

Figure 1: Four Echelon Supply Chain Network with Demands Fluctuations

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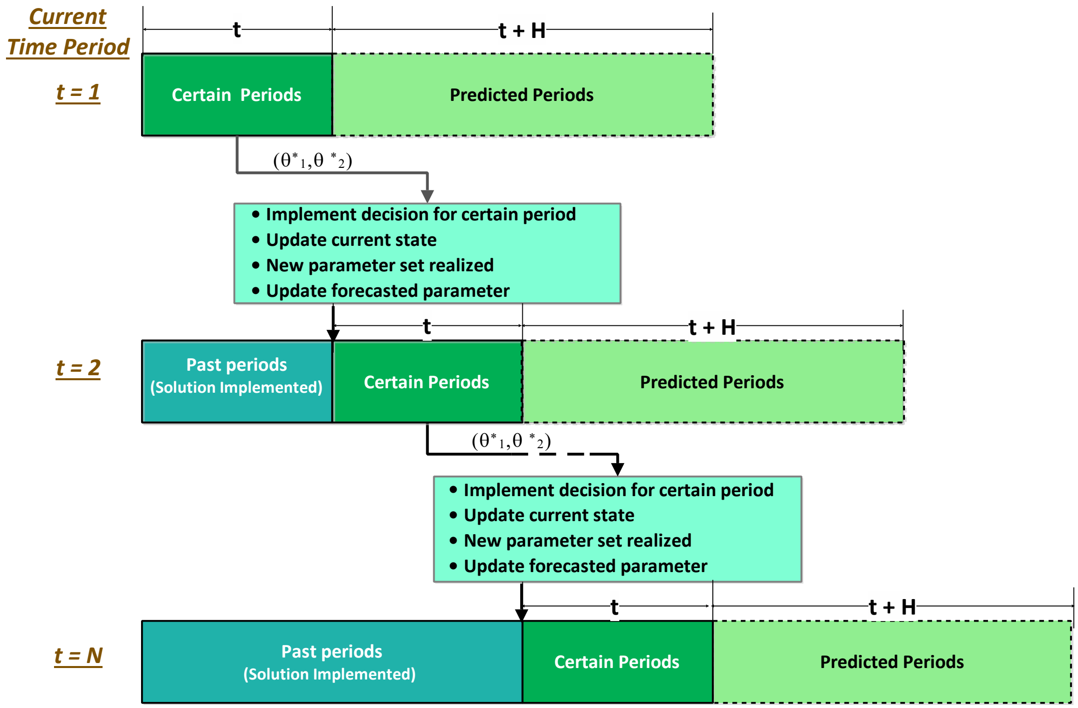

Figure 2: Rolling Horizon Strategy

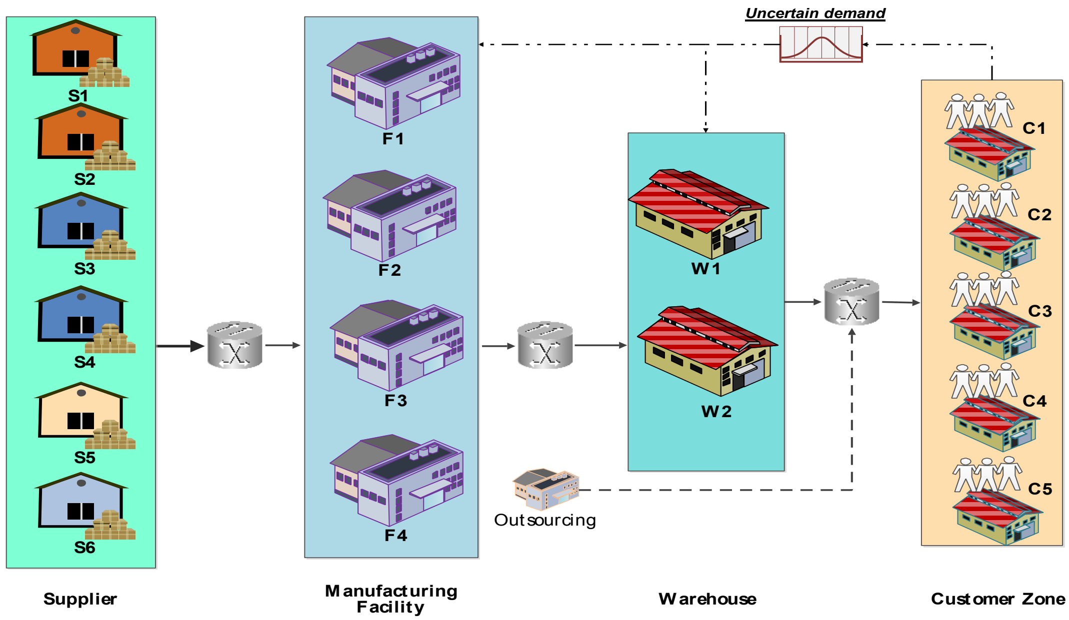

Figure 3: Supply Chain Topology for Case study

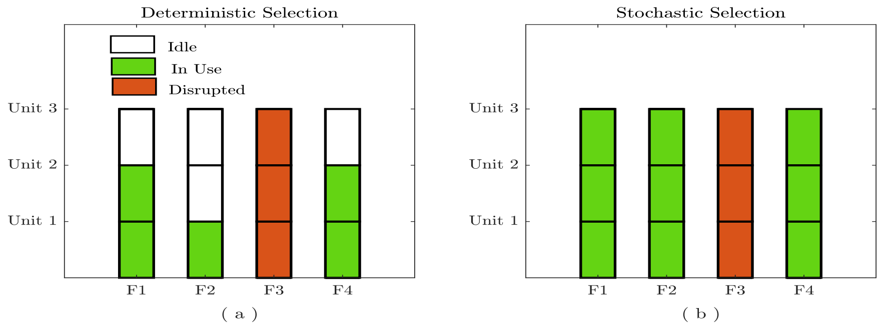

Figure 4: Manufacturing Site Selections for (a) Deterministic model; and (b) Stochastic two-stage model

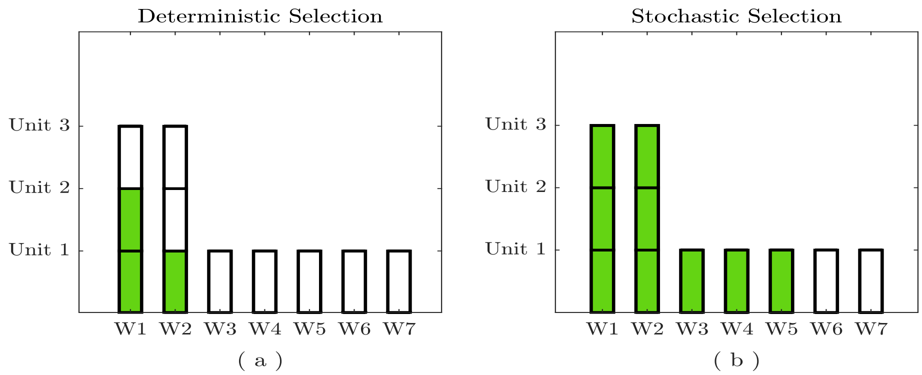

Figure 5: Warehouse Selections for (a) Deterministic model; and (b) Stochastic two-stage model

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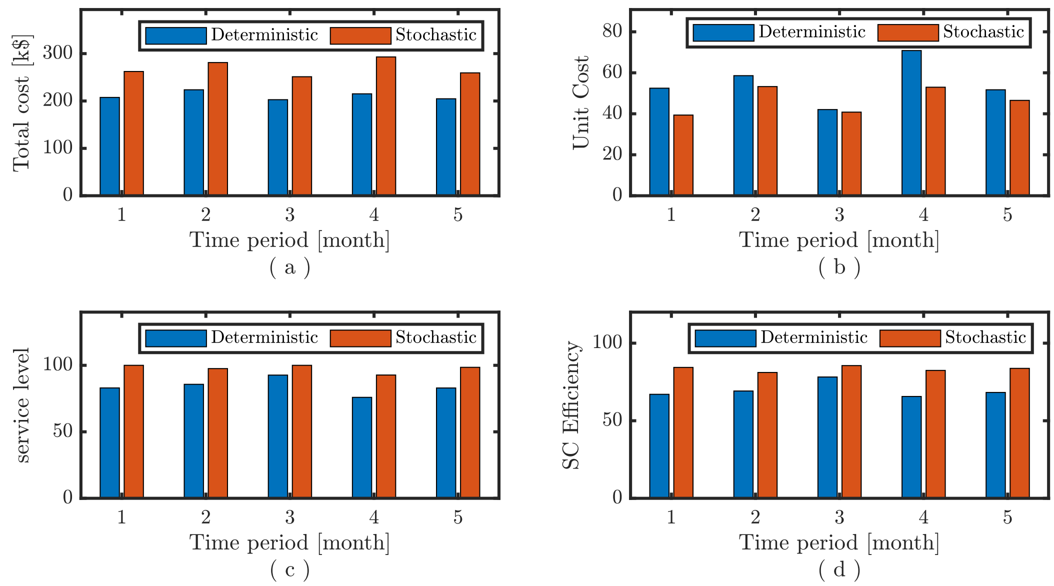

Figure 6:Solution for rolling horizon (a) Total Cost; (b) Unit Cost; (c) Service level; (d) Supply Chain efficiency

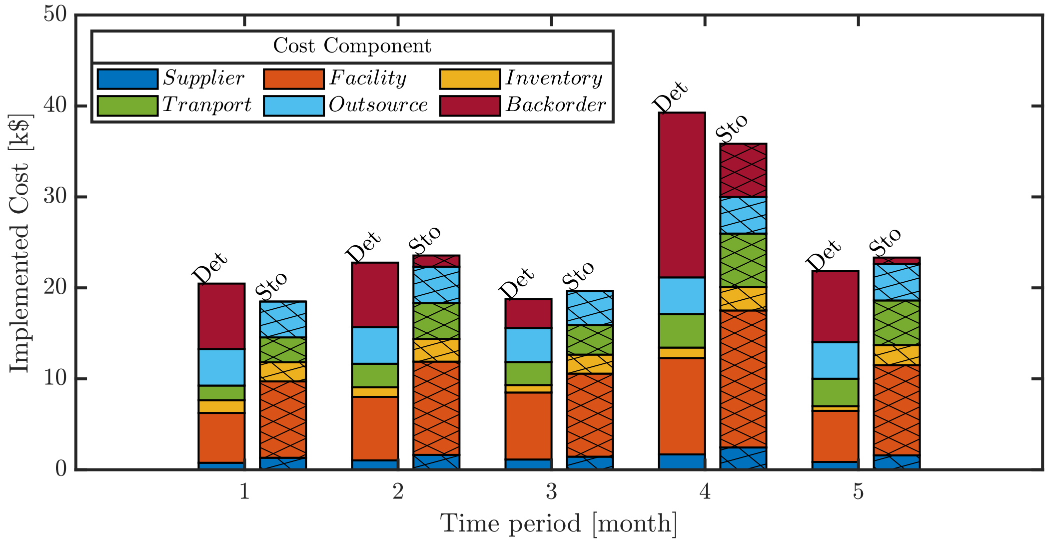

Figure 7:Implemented cost for the rolling horizon. The text on each bar (det = deterministic mode, and sto = stochastic model)