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# Data-Driven Rolling Horizon Approach for Dynamic Design of Supply Chain Distribution Networks under Disruption and Demand Uncertainty

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## ABSTRACT

We address the dynamic design of supply chain networks in which the moments of demand distribution function are uncertain and facilities' availability is stochastic because of possible disruptions. To incorporate the existing stochasticity in our dynamic problem, we develop a multi-stage stochastic program to specify the optimal location, capacity, inventory, and allocation decisions. Further, a data-driven rolling horizon approach is developed to use observations of the random parameters in the stochastic optimization problem. In contrast to traditional stochastic programming approaches that are valid only for a limited number of scenarios, the rolling horizon approach makes the determined decisions by the stochastic program implementable in practice and evaluates them. The stochastic program is presented as a quadratic conic optimization, and to generate an efficient scenario tree, a forward scenario tree construction technique is employed. An extensive numerical study is carried out to investigate the applicability of the presented model and rolling horizon procedure, the efficiency of risk-measurement policies, and the performance of the scenario tree construction technique. Several key practical and managerial insights related to the dynamic supply chain network design under uncertainty are gained based on the computational results. [Submitted: April 15, 2019. Revised: April 20, 2020. Accepted: June 17, 2020.]

***Subject Areas: Conic optimization, Data-driven rolling horizon approach, Dynamic supply chain network design, Multi-stage stochastic programming, and Risk management.***

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\*Kannan Govindan and Mohammad Fattahi have equal contributions to this study.

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## INTRODUCTION

In supply chain (SC) management, a main planning problem is the SC design that includes long-term strategic decisions. These decisions should be practical for a long time under uncertain and complex business environments. Over time, when a SC has been influenced by strategic decisions, many parameters, such as demand, supply, and SC costs, have inherent uncertainty and it is impossible to have accurate forecasts for them. Further, disruption events such as earthquakes, economic crises, strikes, and terrorist attacks have significant impacts on a SC's functionality and affect the performance of the SC's components within an undefined time. As reported by the Business Continuity Institute (Alcantara, Riglietti, & Aguada, 2017), in 2017, one-third of 408 surveyed companies were faced with at least one disruption occurrence in their SC network, and one in every five disrupted SCs stated cumulative losses of at least 1,000,000 € due to disruption events. Several companies, such as IBM and Ford Motor Company, used quantitative models to achieve optimal planning and design decisions under uncertain parameters and disruption events (Simchi-Levi, Schmidt, & Wei, 2014; Lu, Ran, & Shen, 2015).

On the other hand, to capture the changing environment in which a SC will operate, the supply chain network design (SCND) problem with multiple periods, called dynamic SCND, has been more attractive (see, e.g., Alonso-Ayuso, Escudero, Garín, Ortuño, & Pérez, 2003; Nickel, Saldanha-da-Gama, & Ziegler, 2012; Krægpøth, Stentoft, & Jensen, 2017; Shen, Liang, Shen, & Teo, 2019). In the dynamic SCND, opportunities for future adjustments may be considered in the design and strategic decisions, which are applicable for dealing with unstable target markets, expanding the SC for new emerging markets, and handling budget limitations for the large investment on the network design. This study addresses the dynamic SCND under stochastic demand and disruption events, which is scarcely addressed in the literature based on the existing surveys (e.g., Govindan, Fattahi, & Keyvanshokoh, 2017). Such a problem setting can lead to a multi-stage stochastic programming model.

There is a wealth of works in the SCND under uncertainty (Govindan et al., 2017; Darbari et al., 2019) and multi-stage stochastic programs (MSSP) are employed by some studies (Nickel et al., 2012; Fattahi & Govindan, 2018; Fattahi, Govindan, & Keyvanshokoh, 2018). However, using multi-stage stochastic programming approach has two main drawbacks in the practice: (i) the obtained mathematical models from this approach are computationally expensive and, in the SCND phase, the existing data regarding stochastic parameters are not sufficient to approximate their true probability distribution, (ii) many decisions obtained from them are scenario dependent and they are not readily implementable in practice. Although robust optimization methods are presented to address the first drawback, they are criticized because of their over-conservative solutions in accordance with the worst-case scenario that neglects the probabilistic nature of stochastic parameters (Fattahi, Govindan, & Maihami, 2020). In addition to the mentioned drawbacks of the multi-stage stochastic programming, we lack answers to this key question in the practice: How can the dynamic design of a SC network be adjusted based on the realization of stochastic parameters, such as the target market's

changes and long-run demand rates, and the occurrence of disruption events over time to reduce SC loss performance and operational risks?

In this study, an MSSP is developed that optimizes strategic and tactical decisions, including location, capacity, inventory, and allocation decisions, simultaneously. Methodologically, this paper is the first to formulate the corresponding MSSP as a conic quadratic mixed-integer programming (CQMIP) model, which is solvable for large-sized instances in a reasonable time. The lack of historical information related to customers' demands in the design phase motivates us to consider the moment uncertainty related to demands' distribution function over multiple periods. This work constitutes the first consideration of this issue in the dynamic SCND literature to our knowledge. Furthermore, because of disruption events, facilities' availability is stochastic over the planning horizon. To efficiently capture the existing uncertainties in the MSSP, we generate stochastic parameters by using a simulation approach, and then the generated random samples are reduced and converted to a scenario tree by a forward scenario tree construction technique that is initially proposed by Heitsch and Römisch (2009). Finally, we obtain the risk-averse decisions by employing the conditional value at risk (CVaR) as the problem's objective function.

To address the second mentioned drawback of the multi-stage stochastic programming and the research question, we propose a data-driven rolling horizon procedure as an innovative way of using data that is realized as time progresses and of adjusting the decisions in practice for stochastic optimization problems. By this approach, we use observations of the stochastic parameters over time as direct inputs to the dynamic SCND problem. The data related to moments of demands' distribution function can be correlated over the time horizon, and by observing the data related to demands in one planning period, we can update our scenario tree in solving the MSSP for the next periods in a rolling horizon manner.

Generally, there are a number of strategies to mitigate the impacts of uncertainty in the SC design phase (see Tang, 2006; Tomlin, 2006; Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007; Yildiz, Yoon, Talluri, & Ho, 2016; Govindan et al., 2017; Azadegan, Mellat Parast, Lucianetti, Nishant, & Blackhurst, 2019). One of the well-known strategies to reduce the effects of stochastic demand is risk pooling (Eppen, 1979) that aggregates demands over various areas. On the other hand, the risk diversification can be employed under the disruption risks (Mak & Shen, 2012). By consideration of the demand uncertainty and disruption risk, our study optimizes the design decisions and makes a trade-off between these two opposing strategies. Furthermore, we adjust the allocation decisions as a contingency strategy after disruption events to return the SC to its original state.

The paper is organized as follows: the corresponding literature is briefly presented in section Literature Review. The problem description and formulation are presented in section Problem Description and Formulation. The explanation regarding the scenario tree construction technique is presented in section Scenario Tree Construction. The data-driven rolling horizon procedure is explained in section Data-Driven Rolling Horizon Approach. We present experimental results and sensitivity analyses in section Computational Study. Section Managerial Implications contains managerial implications. In section Conclusions, we conclude this study.

## LITERATURE REVIEW

In today's complex and uncertain business environment, it is crucial to integrate the strategic and design decisions with operational/tactical ones in the SC design phase to obtain an efficient SC system. In a facility location problem, Daskin, Coullard, and Shen (2002) assume retailers' demand follows a normal distribution function with known mean and variance. In this study, distribution centers follow a continuous  $(r, Q)$  policy to control their inventory, and a mixed-integer nonlinear programming (MINLP) model is presented. The modeling approach developed by Daskin et al. (2002) is taken into account in several studies such as Atamtürk, Berenguer, and Shen (2012), Qi, Shen, and Snyder (2010), Shen and Qi (2007), Shen, Coullard, and Daskin (2003), Snyder, Daskin, and Teo (2007), and Fattahi et al. (2020). These single-period studies fail to consider the possible adjustments in the strategic decisions of a SC over time. Further, by assuming the stationary of the demand distribution function, they cannot consider the violate environment in which the SC operates. To address these issues, we develop a dynamic SCND and, by using the stochastic programming approach, we capture the uncertainty of moments, including mean and variance, in the customers' demand distribution function through finite discrete scenarios.

By using the stochastic programming approach, various uncertainty types are investigated in the SCND problem (see Snyder, 2006; Govindan et al., 2017). Sheppard (1974) studied a facility location problem with a scenario approach, and scenario-based stochastic programming models have been gradually exploited that may be categorized into two-stage and multi-stage stochastic programs. Two-stage stochastic programming is popular for the SCND because of the two-stage nature of this problem. Indeed, long-term strategic decisions, as first-stage decisions, have to be made before the uncertainty observation, and operational/tactical decisions should be made as second-stage decisions. In this approach, it is supposed that in a single moment, the uncertain parameters become disclosed. However, in many applications, the uncertain parameters have been progressively observed over a multi-period planning horizon in more than one time, and the multi-stage stochastic programming would be a more suitable approach for such a setting. We employ a multi-stage decision-making framework, which optimizes the decisions at each stage as a function of the observed outcomes and uncertainties up to that stage. The MSSPs are used for the SCND in a limited number of studies (see, e.g., Nickel et al., 2012; Fattahi et al., 2018; Fattahi & Govindan, 2018). As mentioned before, in these studies, the optimal decisions from solving the MSSPs are not implementable in practice due to their dependency on considered scenarios. We address this issue for the first time by proposing a data-driven rolling horizon framework.

Recently, the SCND under disruption events has received significant attention in both practice and academia (see survey studies associated with this area, such as Klibi, Martel, & Guitouni, 2010; Snyder et al., 2016; Govindan et al., 2017). A large percentage of papers related to the SCND under disruptions consider a pre-specified probability disruption related to a facility and/or transportation link, and the developed models are called "reliable SCND" (e.g., Berman, Krass, & Menezes, 2007; Cui, Ouyang, & Shen, 2010; Qi et al., 2010). This approach is not

suitable for addressing time aspects of disruption events, and most of these studies are single period without consideration of facilities' return after disruptions. On the other hand, stochastic programming approaches are widely employed in this area in which the uncertainty from man-made or natural disruptions are considered by discrete scenarios (e.g., Peng, Snyder, Lim, & Liu, 2011; Klibi & Martel, 2012; Mak & Shen, 2012; Klibi & Martel, 2013; Fattahi, Govindan, & Keyvanshokoo, 2017). Although using the multi-stage stochastic programming is still scarce for dealing with disruption events over multiple periods, this technique can adjust design and allocation decisions based on the occurrence of disruptions as contingency strategies to recover a disrupted SC. In addition, weighted mean-risk objectives can be used to hedge against the disruption risks, and we also examine the risk-averse decisions by employing CVaR as the objective function of the MSSP.

### Literature Gaps

Based on Govindan et al. (2017), as the latest published survey paper in the area of SCND under uncertainty, most studies from recent years contribute to the literature by addressing new paradigms in SC management such as considering perishable products, sustainability aspects (Govindan, Rajeev, Padhi, & Pati, 2020; Govindan, Shankar & Kannan, 2020; Kannan, Mina, Nosrati-Abarghoee, & Khosrojerdi, 2020), and disruption risks. In accordance with our literature review, in spite of enormous advancements in the area of data analytics, we could not find any study to use the observed data, especially the realization of stochastic parameters, over time in dynamic design of SC networks. We deal with this issue by integrating the rolling horizon approach and multi-stage stochastic programming. As a consequence, a data-driven rolling horizon framework is proposed to: (i) make the decisions of the MSSP implementable in real practices, (ii) empirically evaluate the performance of the design decisions obtained by the MSSP, and (iii) use the observed stochastic parameters for future planning.

MSSPs for the SCND are scarcely developed, and addressing their computational tractability in solving large-sized real-world problems is a main challenge. Another significant aspect of using MSSPs is to construct an efficient scenario tree that properly captures the existing uncertainties. In this study, we formulate the MSSP as a computationally tractable CQMIP model and employ a forward scenario tree construction approach for our problem.

## PROBLEM DESCRIPTION AND FORMULATION

Here, a multi-period SCND problem is considered. In the SC network, distribution centers (DCs) send final products to geographically dispersed customer zones. Based on Javid and Azad (2010), the handling capacity is considered for DCs, which limits the total products that can be processed and forwarded from each DC to customer zones in each time period.

Two types of uncertainty are considered in this study. Customers' demand has a normal distribution and its moments, including mean and variance, are assumed to be stochastic and time-variable. The uncertainty of parameters related to demands' distribution function is introduced in a location-inventory model proposed

by Snyder et al. (2007) in which location decisions have to be determined before observing the stochastic parameters, and inventory decisions are determined after the uncertainty realization. As emphasized by Mak and Shen (2012), it is a favorable assumption that allows inventory decisions, as tactical decisions, to be made after observation of stochastic parameters. To capture time-variable parameters and the change of long-run demand rates, we consider multiple strategic time periods and propose a dynamic SCND problem (e.g., Aghezzaf, 2005; Mak & Shen, 2012).

We consider that each DC may be disrupted according to Mak and Shen (2012) and Snyder, Scaparra, Daskin, and Church (2006). When a disruption happens for a DC in a time period, it cannot provide any product to customers in the corresponding period. In our dynamic SCND, for the SC recovery, the disrupted DC will be activated again in the next period by paying the corresponding recovery cost. This assumption is practical because of the long time of strategic periods in the dynamic SCND.

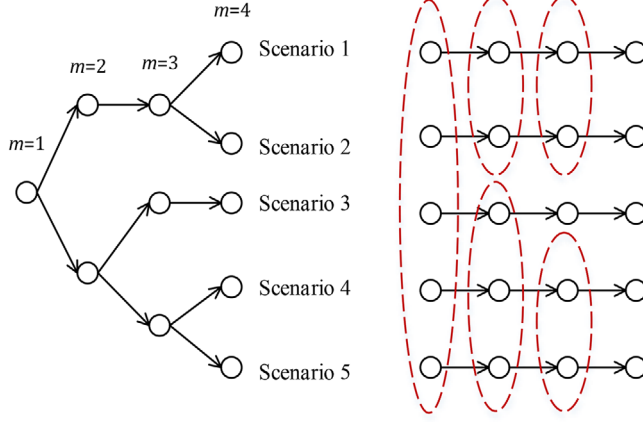
In the problem, (i) the capacity and location of DCs, (ii) the inventory policy in DCs, and (iii) allocation decisions have to be determined to minimize the expected total SC cost. The location and capacity decisions for DCs should be determined at each period before uncertainty realization. In this paper, to have a dynamic SC design (see, e.g., Melo, Nickel, & Da Gama, 2006; Hinojosa, Kalcsics, Nickel, Puerto, & Velten, 2008; Thanh, Bostel, & Péton, 2008), we can change the location and capacity of DCs over the planning horizon. The inventory policy of DCs and allocation decisions are considered scenario-dependent as tactical level decisions. Other key assumptions of our optimization model are:

- i. A set of potential locations is considered for the activation of DCs, and their locations should be determined in each period.
- ii. A set of capacity levels is taken into account for the activation of DCs, and a fixed location cost for opening a DC with a capacity level is considered.
- iii. An inventory policy  $(Q_i, r_i)$  is followed by each DC. In this policy, whenever the inventory level in DC  $i$  drops below or to a reorder level  $r_i$ , the DC places an order for  $Q_i$  units from a manufacturer/supplier.
- iv. In each period, each customer zone should be assigned to only one active DC. It is worth noting that we consider a virtual uncapacitated DC, indexed by  $i_0$ , and in the case of not serving a customer, the SC must allocate the customer to it.
- v. In each period, opening a new DC, closing an existing DC, and changing the capacity level of an existing DC are possible actions.

### **Multi-stage Stochastic Programming**

Generally, an MSSP with  $M$ -stage contains sequential stochastic parameters  $\xi_1, \xi_2, \dots, \xi_{M-1}$ , and the realization of them can be shown by a scenario tree, discretely. However, it is possible to consider the stochastic parameters in stage  $M$ ,  $\xi_M$ , that can typically affect the problem's objective function (Dupačová, 1995). In this paper, a scenario tree is taken into account as a set of scenarios that is denoted by  $S$  and the scenarios' number is presented by  $|S|$ . Further,  $\pi^1, \pi^2, \dots$ , and  $\pi^{|S|}$

**Figure 1:** A scenario tree example: the corresponding scenario fan is shown in the right-hand side, and nodes with the same realization of uncertainty are highlighted.



represent the corresponding probability of scenarios. Here, a realization related to stochastic parameters in scenario  $s \in S$  is denoted as  $(\xi_1^s, \xi_2^s, \dots, \xi_{M-1}^s)$ .

In MSSPs, the optimal decisions must be non-anticipative, meaning that at each stage, the decisions must not be made based on the observation of stochastic parameters in the next stages. In this study, to formulate an MSSP for the problem, a set of non-anticipativity constraints is explicitly modeled. In optimization problem (1), a general formulation is presented for the MSSPs with non-anticipativity constraints in which  $\mathbf{x}_m^s$  is the decisions vector in stage  $m$  and scenario  $s$ , and these decisions have to be determined before the uncertainty realization in each stage as here-and-now decisions.  $\chi_m^s$  is the feasible region for  $\mathbf{x}_m^s$ . As shown in optimization problem (1), in the first stage,  $\mathbf{x}_1^s = \mathbf{x}_1^{s'}$  for each pair of scenarios  $s$  and  $s' \in S$ . Further, for  $m > 1$  and  $s, s' \in S$  such that  $(\xi_1^s, \xi_2^s, \dots, \xi_{m-1}^s) = (\xi_1^{s'}, \xi_2^{s'}, \dots, \xi_{m-1}^{s'})$ , we have  $\mathbf{x}_m^s = \mathbf{x}_m^{s'}$ . Figure 1 illustrates an example scenario tree for stochastic parameters in three periods related to a four-stage stochastic program, and in Figure 1, the nodes of scenarios with the same realization of uncertainty in each stage are shown.

It should be mentioned that non-anticipativity constraints in our optimization model should be considered for strategic design decisions, including location and capacity decisions, at each stage as here-and-now decisions.

$$\text{Min} \sum_{s=1}^{|S|} \pi_s f(\mathbf{x}_1^s, \mathbf{x}_2^s, \dots, \mathbf{x}_M^s \mid \xi_1^s, \xi_2^s, \dots, \xi_{M-1}^s),$$

s.t:

$$\mathbf{x}_m^s \in \chi_m^s \quad m = 1, \dots, M, \forall s \in S, \quad (1)$$

$$\mathbf{x}_1^s = \mathbf{x}_1^{s'} \quad \forall s, s' \in S,$$

$$\mathbf{x}_m^s = \mathbf{x}_m^{s'} \quad m = 2, \dots, M, \forall s, s' \in S: (\xi_1^s, \xi_2^s, \dots, \xi_{m-1}^s) = (\xi_1^{s'}, \xi_2^{s'}, \dots, \xi_{m-1}^{s'}).$$



**Table 1:** The notations.**Sets**

$J$	Customer zones set ( $j \in J$ ),
$I$	Candidate DCs set ( $i \in I$ ),
$N$	Capacity levels set for the activation of DCs ( $n, n' \in N$ ). Capacity level 0 is considered in set $N$ meaning that the DC is not activated,
$S$	Scenarios set ( $s, s' \in S$ ),
$T$	Time periods set ( $t \in T$ ).

**Parameters**

$f_{i,n}$	The fixed cost for the activation of DC $i$ with capacity option $n$ at the first period. The selection of level $n = 0$ means that the DC is not activated,
$c_{i,n,n'}$	The fixed cost of increasing the capacity level of DC $i$ from $n$ to $n'$ . By this parameter, the cost of opening DCs in each period can also be defined, and if $n \geq n'$ , this parameter value would be zero,
$rc_{i,n}$	The cost of recovering DC $i$ with capacity option $n$ after disruption,
$o_{i,n}$	The fixed cost for the operation of DC $i$ with capacity option $n$ during one period,
$v_{i,j}$	The cost of transporting one unit product from DC $i$ to customer zone $j$ ,
$l$	The cost of lost sale regarding per unit of product,
$b_{i,n}$	The amount of handling capacity option $n$ for DC $i$ , over one period,
$h_i$	The cost of holding inventory for one unit product over each period at DC $i$ ,
$p_i$	The fixed cost of placing an order at DC $i$ ,
$Lt_i$	The lead time, as a fraction of one time period, of DC $i$ ,
$g_i$	The fixed cost related to per shipment from the supplier to DC $i$ ,
$a_i$	The transportation cost related to per unit of product from the supplier to DC $i$ ,
$\mu_{j,t}^s$	Mean of demand at customer $j$ in period $t$ and scenario $s$ ,
$\sigma_{j,t}^s$	Demand's standard deviation of customer $j$ in period $t$ and scenario $s$ ,
$\varphi_{i,t}^s$	$\varphi_{i,t}^s$ equals 1 if DC $i$ is disrupted in period $t$ and scenario $s$ and 0 otherwise,
$\alpha$	Desired service level for the satisfaction of customer orders,
$z_\alpha$	Standard normal deviation related to the service level $\alpha$ , i.e., $Z$ is the standard normal distribution function and $p(Z \leq z_\alpha) = \alpha$ ,
$\pi^s$	The probability of scenario $s$ .

**Variables**

$X_{i,n,t}^s$	1 if DC $i$ with capacity option $n$ is activated in period $t$ under scenario $s$ ,
$Y_{i,j,t}^s$	1 if customer $j$ is allocated to DC $i$ in period $t$ and scenario $s$ ,
$Q_{i,t}^s$	The order size at DC $i$ in period $t$ and scenario $s$ ,
$R_{i,t}^s$	The cost of opening/capacity increase of DC $i$ , in period $t$ and scenario $s$ .

**Problem Formulation**

The employed notations for making the mathematical model are reported in Table 1.

The objective function of the problem under each scenario contains the following costs:

- i. The fixed cost of activation and capacity increase of DCs over the planning horizon, given as  $\sum_{i \in I} \sum_{t \in T} R_{i,t}^s$ ,
- ii. The operating cost of DCs over the planning horizon, given as  $\sum_{i \in I} \sum_{n \in N} \sum_{t \in T} o_{i,n} X_{i,n,t}^s$ ,
- iii. The operational cost at each DC contains the holding cost of working inventory, the safety stock cost, the fixed cost of ordering products, and

the shipment cost from suppliers to the DC. Where  $Q_{i,t}^s$  represents the order size at DC  $i$  in period  $t$  and scenario  $s$ ,  $p_i \frac{\sum_{j \in J} \mu_{j,t}^s Y_{i,j,t}^s}{Q_{i,t}^s}$  is the fixed cost of ordering products, and  $h_i \frac{Q_{i,t}^s}{2}$  captures the holding cost associated with the working inventory in period  $t$ . Further, in period  $t$ , the safety stock cost is  $h_i z_\alpha \sqrt{L t_i \sum_{j \in J} (\sigma_{j,t}^s)^2 Y_{i,j,t}^s}$ . Since the shipment cost of an order of size  $R$  from the supplier to DC  $i$  is equal to the fixed shipment cost plus the variable cost as  $g_i + R a_i$ , we can obtain the total cost of shipment from the supplier to DC  $i$  as  $g_i \frac{\sum_{j \in J} \mu_{j,t}^s Y_{i,j,t}^s}{Q_{i,t}^s} + a_i \sum_{j \in J} \mu_{j,t}^s Y_{i,j,t}^s$ .

- iv. Under each scenario, the lost sale cost is equal to  $l \times \sum_{t \in T} \sum_{j \in J} \mu_{j,t}^s Y_{i_0,j,t}^s$ ,
- v. The transportation cost from DCs to customers, given as  $\sum_{i \in I} \sum_{j \in J} \sum_{t \in T} v_{i,j} \mu_{j,t}^s Y_{i,j,t}^s$ .

The MINLP model of the problem is as follows:

$$\text{Min: } \sum_{s \in S} \pi^s \left( \begin{aligned} & \sum_{i \in I} \sum_{t \in T} R_{i,t}^s + \sum_{i \in I} \sum_{n \in N} \sum_{t \in T} r c_{i,n} \phi_{i,t}^s X_{i,n,t}^s + \sum_{i \in I} \sum_{n \in N} \sum_{t \in T} o_{i,n} X_{i,n,t}^s \\ & + \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} v_{i,j} \mu_{j,t}^s Y_{i,j,t}^s + \sum_{i \in I} \sum_{t \in T} a_i \left( \sum_{j \in J} \mu_{j,t}^s Y_{i,j,t}^s \right) \\ & + l \sum_{t \in T} \sum_{j \in J} \mu_{j,t}^s Y_{i_0,j,t}^s + \sum_{i \in I} \sum_{t \in T} (p_i + g_i) \frac{\sum_{j \in J} \mu_{j,t}^s Y_{i,j,t}^s}{Q_{i,t}^s} \\ & + \sum_{i \in I} \sum_{t \in T} h_i \frac{Q_{i,t}^s}{2} + \sum_{i \in I} \sum_{t \in T} h_i z_\alpha \sqrt{L t_i \sum_{j \in J} (\sigma_{j,t}^s)^2 Y_{i,j,t}^s} \end{aligned} \right). \quad (2)$$

$$\sum_{n \in N} X_{i,n,t}^s = 1, \quad \forall i \in I, \forall t \in T, \forall s \in S, \quad (3)$$

$$\sum_{n \in N} f_{i,n} X_{i,n,t}^s \leq R_{i,t}^s, \quad \forall i \in I, \forall t = 1, \forall s \in S, \quad (4)$$

$$c_{i,n,n'} (X_{i,n',t}^s + X_{i,n,t-1}^s - 1) \leq R_{i,t}^s, \quad \forall i \in I, \forall t \in T \setminus \{1\}, \forall s \in S, \forall n, n' \in N \quad (5)$$

$$\sum_{i \in (I \cup \{i_0\})} Y_{i,j,t}^s = 1, \quad \forall j \in J, \forall t \in T, \forall s \in S, \quad (6)$$

$$\sum_{j \in J} \mu_{j,t}^s Y_{i,j,t}^s \leq (1 - \phi_{i,t}^s) \left( \sum_{n \in N} b_{i,n} X_{i,n,t}^s \right), \quad \forall i \in I, \forall t \in T, \forall s \in S, \quad (7)$$

$$X_{i,n,t}^s = X_{i,n,t}^{s'}, \quad \forall i \in I, \forall t = 1, \forall n \in N, \forall s, s' \in S, \quad (8)$$

$$\begin{aligned} X_{i,n,t}^s &= X_{i,n,t}^{s'}, \quad \forall i \in I, \forall t \in T, \forall n \in N, \forall s, s' \in S : (\xi_1^s, \xi_2^s, \dots, \xi_{t-1}^s) \\ &= (\xi_1^{s'}, \xi_2^{s'}, \dots, \xi_{t-1}^{s'}), \end{aligned} \quad (9)$$

$$\mathbf{X}, \mathbf{Y} \in \{0, 1\}, \quad (10)$$

$$\mathbf{Q}, \mathbf{R} \geq 0. \quad (11)$$

The objective of our problem, presented by mathematical expression (2), is to minimize the expected total SC cost over the planning horizon. In each period and scenario, constraints (3) determine the status of DCs. Based on these constraints, for each DC, only one capacity level must be chosen and assigning capacity level 0 to a DC means that the DC is not activated. In the first period, if capacity level  $n$  is assigned to DC  $i$ , constraints (4) impose variable  $R_{i,t}^s$  to be greater than  $f_{i,n}$  under each scenario. Therefore, as the problem's objective function minimizes the total cost of the SC,  $R_{i,t}^s$  becomes equal to  $f_{i,n}$ . Constraints (5), same as constraints (4), are to compute the cost of activation/capacity increase of each DC in each period and scenario. Constraints (6) guarantees that each customer should be assigned to only one DC. It should be noted that assigning a customer to DC  $i_0$  means that the corresponding customer is not served. Constraints (7) assure that the amount of products that can be handled by a DC during each period is less than or equal to the DC's handling capacity, if the DC is not disrupted. The non-anticipativity constraints are formulated as constraints (8) and (9). Based on constraints (10), the corresponding variables are binary, and finally constraints (11) enforce the corresponding variables to not take negative values. The decision variables' indices are eliminated for convenience in constraints (10) and (11).

### Conic Quadratic Mixed Integer Programming Formulation

We reformulate the optimization model as a CQMIP in this sub-section. The main advantage of this reformulation is that the obtained formulation is solvable by standard optimization software packages such as CPLEX.

Decision variable  $Q_{i,t}^s$  in MINLP model (2–11) only appears in objective function (2), which is convex in  $Q_{i,t}^s > 0$ . First, the optimal value of  $Q_{i,t}^s$  is achieved by the derivative of the objective function with respect to  $Q_{i,t}^s$ . Therefore, the optimal value for  $Q_{i,t}^s$  is as:  $Q_{i,t}^{s*} = \sqrt{2(p_i + g_i) \frac{\sum_{j \in J} \mu_{j,t}^s Y_{i,j,t}^s}{h_i}}$ .

As a consequence, the objective function is:

$$\text{Min: } \sum_{s \in S} \pi^s \left( \begin{aligned} & \sum_{i \in I} \sum_{t \in T} R_{i,t}^s + \sum_{i \in I} \sum_{n \in N} \sum_{t \in T} r c_{i,n} \varphi_{i,t}^s X_{i,n,t}^s + \sum_{i \in I} \sum_{n \in N} \sum_{t \in T} o_{i,n} X_{i,n,t}^s \\ & + \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} v_{i,j} \mu_{j,t}^s Y_{i,j,t}^s + \sum_{i \in I} \sum_{t \in T} a_i \left( \sum_{j \in J} \mu_{j,t}^s Y_{i,j,t}^s \right) \\ & l \sum_{t \in T} \sum_{j \in J} \mu_{j,t}^s Y_{i_0,j,t}^s + \sum_{i \in I} \sum_{t \in T} \sqrt{2(p_i + g_i) h_i} \sum_{j \in J} \mu_{j,t}^s Y_{i,j,t}^s \\ & + \sum_{i \in I} \sum_{t \in T} h_i z_\alpha \sqrt{L_i \sum_{j \in J} (\sigma_{j,t}^s)^2 Y_{i,j,t}^s} \end{aligned} \right). \quad (12)$$

In accordance with Atamtürk et al. (2012), auxiliary variables  $K_{i,t}^s$  and  $L_{i,t}^s$  are introduced to present the objective's nonlinear terms and based on the fact that  $(Y_{i,j,t}^s)^2 = Y_{i,j,t}^s$ , we present the CQMIP formulation as follows:

$$\text{Min: } \sum_{s \in S} \pi^s \left( \begin{array}{l} \sum_{i \in I} \sum_{t \in T} R_{i,t}^s + \sum_{i \in I} \sum_{n \in N} \sum_{t \in T} rc_{i,n} \varphi_{i,t}^s X_{i,n,t}^s + \sum_{i \in I} \sum_{n \in N} \sum_{t \in T} o_{i,n} X_{i,n,t}^s \\ + \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} v_{i,j} \mu_{j,t}^s Y_{i,j,t}^s + \sum_{i \in I} \sum_{t \in T} a_i \left( \sum_{j \in J} \mu_{j,t}^s Y_{i,j,t}^s \right) \\ + l \sum_{t \in T} \sum_{j \in J} \mu_{j,t}^s Y_{i_0,j,t}^s + \sum_{i \in I} \sum_{t \in T} \sqrt{2(p_i + g_i)} h_i K_{i,t}^s \\ + \sum_{i \in I} \sum_{t \in T} h_i z_{i\alpha} \sqrt{L_t} L_{i,t}^s \end{array} \right), \quad (13)$$

Subject to: (3)–(11).

$$\sum_{j \in J} \mu_{j,t}^s (Y_{i,j,t}^s)^2 \leq (K_{i,t}^s)^2 \quad \forall i \in I, \forall t \in T, \forall s \in S, \quad (14)$$

$$\sum_{j \in J} (\sigma_{j,t}^s)^2 (Y_{i,j,t}^s)^2 \leq (L_{i,t}^s)^2 \quad \forall i \in I, \forall t \in T, \forall s \in S, \quad (15)$$

$$K_{i,t}^s \geq 0 \quad \forall i \in I, \forall t \in T, \forall s \in S, \quad (16)$$

$$L_{i,t}^s \geq 0 \quad \forall i \in I, \forall t \in T, \forall s \in S. \quad (17)$$

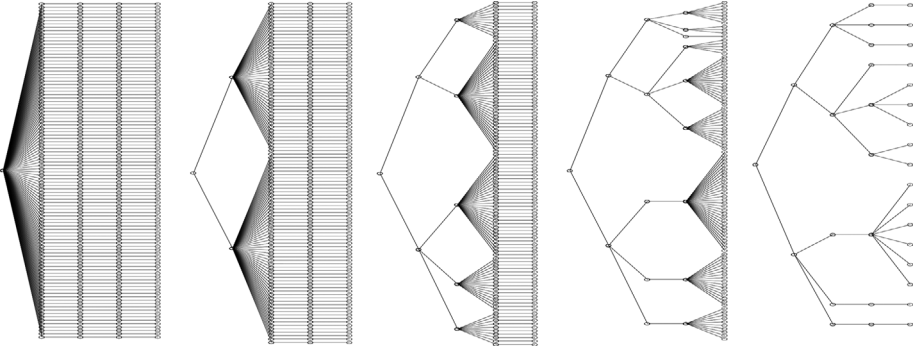
At the present formulation, in the CQMIP model, the constraints are either linear or conic quadratic, and the objective function is linear.

## SCENARIO TREE CONSTRUCTION

A key issue in MSSPs is to generate a scenario tree that efficiently captures the stochasticity of time-variable parameters. In this paper, at the first step, we generate the corresponding multivariate stochastic parameters, including mean and variance of customers' demand and parameter  $\varphi_{i,t}^s$  corresponding to the DCs' availability, as a scenario fan by using a sampling method (Helton & Davis, 2003). Then, in the second step, to obtain a scenario tree from this scenario fan, we apply the forward scenario tree generation approach.

A first order autoregressive (AR) model is considered for generating the demands' mean and SD that are given by the formula  $\mu_{j,t}^s = \alpha_j^{(\mu)} + \beta_j^{(\mu)} \times \mu_{j,t-1}^s + \varepsilon_{j,t,s}^{(\mu)}$  and  $\sigma_{j,t}^s = \alpha_j^{(\sigma)} + \beta_j^{(\sigma)} \times \sigma_{j,t-1}^s + \varepsilon_{j,t,s}^{(\sigma)}$ , respectively. For each customer,  $\varepsilon$  is the error term that has the normal distribution function with mean zero and a predetermined SD. For the scenario fan generation, these error terms should be simulated based on their time-independent and continuous distributions, discretely. By using parameter  $\beta$ , we can capture the long-run rate of mean and variance of the demand.

In this study, the disruption occurrence is modeled via Bernoulli random variable such as demonstrated in Peng et al. (2011), Mak and Shen (2012), and Fattahi

**Figure 2:** The scenario tree construction process.

et al. (2017). The disruption incidence in each period and at each DC does not influence on the disruption incidence's probability in other DCs and next periods. We consider Bernoulli distribution with parameter  $pr_{i,t}$  that represents the disruption occurrence probability in period  $t$  at DC  $i$ . As a consequence, parameter  $\varphi_{i,t}^s$  is defined as a binary indicator that is equal to 1, if in period  $t$  and scenario  $s$ , a disruption event happens at DC  $i$ .

A huge number of scenarios makes the MSSP computationally intractable, and it is crucial to reduce the scenarios' number efficiently. In our approach, the scenarios are first generated in the form of a scenario fan and a scenario tree construction approach, developed by Heitsch and Römisch (2009), is exploited to reduce the scenarios' number and achieve a scenario tree. This method is also used by Fattahi et al. (2017), Fattahi et al. (2018), and Fattahi and Govindan (2018). A brief explanation regarding the used scenario tree construction technique is provided in Appendix A. In this approach, we alter the scenario fan by bundling scenarios, which produces scenario trees with fewer scenarios in comparison with the initial scenario fans. The number of final scenarios in the corresponding approach depends on a constant parameter  $\zeta_p$ ,  $0 \leq \zeta_p \leq 1$ , which demonstrates a reduction scale in comparison with the initial scenario fan. If the value of  $\zeta_p$  increases, the final scenarios' number will decrease, relatively. Figure 2 shows the scenario tree construction process in which we obtain a scenario tree with 17 scenarios from a scenario fan with 100 scenarios.

## DATA-DRIVEN ROLLING HORIZON APPROACH

Here, we present a rolling horizon framework for decision-making in practice based on the developed MSSP. As the main advantage of this framework, it enables data-driven decisions by using the observed data over the past time horizon. In other words, by the realization of stochastic parameters in one period, we can adopt their time series for the next period(s) and update the scenario tree to capture any possible seasonality or trend in the data.

Furthermore, the presented framework resolves a critical limitation of traditional multi-stage stochastic programming decisions, which are valid only for

a limited number of scenarios and approximates the truth objective from implementing the obtained decisions from the MSSP in reality (Chand, Hsu, & Sethi, 2002).

Here, realized stochastic parameters are presented as a data set in the form of sample paths. Each sample path and the set of all paths are illustrated by  $\omega$  and  $\Omega$ , respectively. Further, the optimal implementable decisions related to period  $t$  are the given optimal here-and-now decisions at this period, which are achieved by solving the MSSP comprising  $t, t + 1, \dots, t + |T| - 1$  periods.

To evaluate implementable decisions in time period  $t$  and obtain the problem status at period  $t+1$ , the MSSP with  $t, t + 1, \dots, t + |T| - 1$  periods should be solved in which at period  $t$ , the here-and-now decisions are fixed based on their optimal value, and stochastic parameters are known according to path  $\omega$ . To achieve data-driven decisions, in the implementation phase, we will use an updated scenario tree with  $|T| - 1$  periods that is based on the observed stochastic parameters at period  $t$ .

At the first period, we solve the MSSP with  $|T|$  periods. Then, in implementation of the obtained decisions at  $t = 1$  by realized path  $\omega$ , variables  $X_{i,n,t=1}$  and  $R_{i,t=1}$  are fixed in the stochastic model, denoted by  $\bar{X}_{i,n,t=1}$  and  $\bar{R}_{i,t=1}$ , and the first period objective function is:

$$\left\{ \begin{array}{l} \sum_{i \in I} \bar{R}_{i,t=1} + \sum_{i \in I} \sum_{n \in N} rc_{i,n} \phi_{i,t=1}^{(\omega)} \bar{X}_{i,n,t=1} + \sum_{i \in I} \sum_{n \in N} o_{i,n} \bar{X}_{i,n,t=1} \\ + \sum_{i \in I} \sum_{j \in J} v_{i,j} \mu_{j,t=1}^{(\omega)} Y_{i,j,t=1}^{(\omega)} + \sum_{i \in I} a_i \left( \sum_{j \in J} \mu_{j,t=1}^{(\omega)} Y_{i,j,t=1}^{(\omega)} \right) \\ + l \sum_{j \in J} \mu_{j,t=1}^{(\omega)} Y_{i_0,j,t=1}^{(\omega)} + \sum_{i \in I} \sqrt{2(p_i + g_i)} h_i K_{i,t=1}^{(\omega)} + \sum_{i \in I} h_i z_\alpha \sqrt{L t_i} L_{i,t=1}^{(\omega)} \end{array} \right\}.$$

Then, in the next time period, we solve the MSSP corresponding to the new state of the problem after implementation of the optimal decisions in previous periods, called as "rolling horizon model." In our stochastic problem, the rolling horizon model for time  $t, t > 1$ , is similar to our MSSP after some adjustments.

Consider  $T_H$  and  $S_H$  are the set of periods and scenarios in the rolling horizon model, respectively. Then to obtain the rolling horizon model based on the presented MSSP, we change sets  $T$  and  $S$  by  $T_H$  and  $S_H$ , successively. In addition,  $X_{i,n}^*$  presents a binary indicator that equals 1 if DC  $i$  with capacity level  $n$  has been activated in the previous time period, and hence constraints (4) are removed in the rolling horizon model and constraints (5) are modified as follows:

$$c_{i,n,n'} (X_{i,n',t}^s + X_{i,n}^*) \leq R_{i,t}^s \quad \forall i \in I, \forall t \in T_H, \forall s \in S_H, \forall n, n' \in N. \quad (18)$$

As previously explained, in period  $t$ , to evaluate the problem's true objective value related to implementable decisions in this time period (obtained from solving rolling horizon model), the MSSP should be solved in which period  $t$  is the first period, the implementable decisions are fixed based on their optimal value in period  $t$ , stochastic parameters in the period  $t$  are known according to path  $\omega$ , and

**Figure 3:** The rolling horizon procedure.

<p><b>Step 1.</b> Consider sample path <math>\omega</math> related to the realized stochastic parameters over <math> T </math> periods; Start from the beginning period;</p> <p><b>Step 2.</b> By an MSSP with <math> T </math> periods:</p> <p style="padding-left: 20px;"><b>For</b> <math>t = 1</math> to <math>t =  T </math> <b>do</b></p> <p style="padding-left: 40px;">a) Generate a scenario tree with <math> T </math> periods based on the observation of stochastic parameters in the previous periods;</p> <p style="padding-left: 40px;">b) Solve the rolling horizon model that contains <math> T </math> periods by the generated tree and the current state of the problem;</p> <p style="padding-left: 40px;">c) Implement the achieved optimal decisions for period <math>t</math> based on path <math>\omega</math> to obtain the true objective function at period <math>t</math> and to determine the problem's state at the end of period <math>t</math>;</p> <p style="padding-left: 20px;"><b>End For</b></p> <p><b>Step 3.</b> Store the objective function value for sample path <math>\omega</math> and return to <b>Step 1</b> unless the number of simulation runs is sufficient;</p>
---

an updated scenario tree is employed. The corresponding objective function is as follows:

$$\left\{ \begin{aligned} & \sum_{i \in I} \bar{R}_{i,t} + \sum_{i \in I} \sum_{n \in N} rc_{i,n} \varphi_{i,t}^{(\omega)} \bar{X}_{i,n,t} + \sum_{i \in I} \sum_{n \in N} o_{i,n} \bar{X}_{i,n,t} + \sum_{i \in I} \sum_{j \in J} v_{i,j} \mu_{j,t}^{(\omega)} Y_{i,j,t}^{(\omega)} \\ & + \sum_{i \in I} a_i \left( \sum_{j \in J} \mu_{j,t}^{(\omega)} Y_{i,j,t}^{(\omega)} \right) + l \sum_{j \in J} \mu_{j,t}^{(\omega)} Y_{i_0,j,t}^{(\omega)} + \sum_{i \in I} \sqrt{2(p_i + g_i)} h_i K_{i,t}^{(\omega)} \\ & + \sum_{i \in I} h_i z_\alpha \sqrt{L_t} L_{i,t}^{(\omega)} \end{aligned} \right\}.$$

The above-mentioned process should be iterated until we obtain the problem's final state at the end of sample path  $\omega$  and approximate the true objective function of the problem related to path  $\omega$ . The rolling horizon approach is presented as a pseudo code in Figure 3. Further, Figure 4 shows how the proposed approach works for solving the MSSP in a rolling horizon manner for our problem with  $|T| = 4$ .

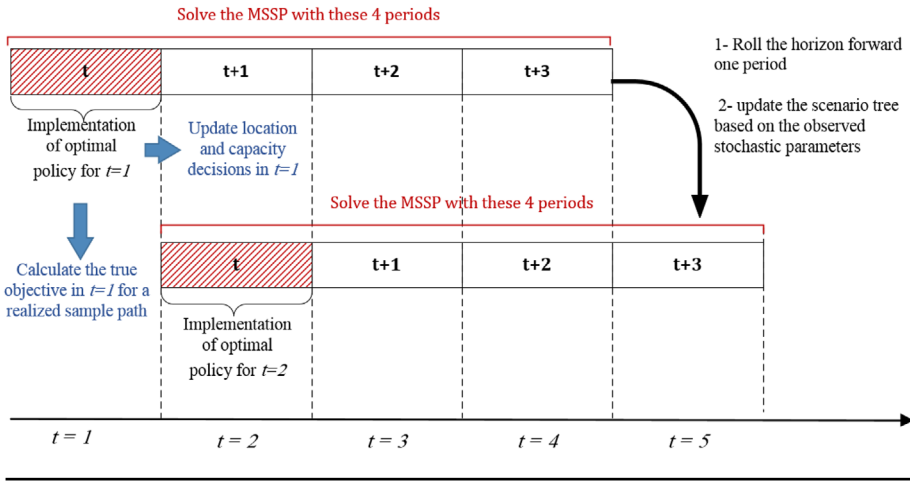
## COMPUTATIONAL STUDY

In this section, we use GAMS 24.1 by CPLEX solver to solve the MSSP, and for all implementations, a personal computer with Intel Core i7-640 M CPU (2.8 GHz), with 4.00 GB of RAM, is used.

### Assessment of the CQMIP Model Performance

Several instances are used to investigate the CQMIP model's applicability. The main parameters of the CQMIP model are based on Appendix B. It should be mentioned that in the problem instances, we consider four capacity levels in which the first capacity level is 0 and the length of each time period is equal to 6 months. Here,

**Figure 4:** The data-driven rolling horizon procedure.



100 scenarios in the form of a scenario fan are generated to capture the stochasticity of parameters, and next, we employ the forward scenario tree generation method in which the value of  $\zeta_p$  is set to 0.7 or 0.8. Table 2 illustrates the CPU time and optimal objective value from solving instances. The main characteristics of instances are also reported in Table 2.

As illustrated by Table 2, by focusing on the results obtained by the presented CQMIP model, we observe that most of our runs reach to the optimal solution fast, and we can solve the proposed model by the CPLEX solver. As a consequence, we can conclude that our approach performs well in the experimental results. Further, the number of scenarios is sensitive to  $\zeta_p$ , and as we increase the number of scenarios and the size of the model, the CPU time increases.

### The Importance of the Multi-stage Stochastic Program

In this section, the importance of the presented stochastic model is investigated by comparing the MSSP with the two-stage stochastic programming formulation of the optimization problem in terms of the value of the objective function. Therefore, the relative value of the multi-stage stochastic programming (RVMS) is computed for several problem instances as a well-known criterion (Huang & Ahmed, 2009). Let  $OF^{TS}$  and  $OF^{MS}$  be the optimal value related to the objective of the two-stage and multi-stage stochastic program, respectively. Then,  $OF^{TS} \geq OF^{MS}$  and the RVMS is defined as  $\frac{OF^{TS} - OF^{MS}}{OF^{TS}} \times 100\%$ .

In the two-stage stochastic programming model, we assume the capacity and location decisions have to be determined in all periods before uncertainty realization as the first stage decisions. It should be mentioned that in dynamic two-stage stochastic models, first stage decisions are made for multiple periods in many studies (e.g., Aghezzaf, 2005). To obtain the two-stage stochastic program, we relax non-anticipativity constraints from the stochastic model, and enforce decision



**Table 2:** The results from solving CQMIP model for instances.

Instance	( $ I ,  J ,  T $ )	$\zeta_p,  S $	Optimal objective value	CPU time (S)
1	(8,10,4)	0.7, 19	8.77E+05	8
2	(8,10,6)	0.7, 15	1.34E+06	9
3	(10,15, 4)	0.7, 18	1.20E+06	8
4	(10, 15, 6)	0.7, 16	1.90E+06	10
5	(15, 20, 4)	0.7, 14	1.46E+06	8
6	(15, 20, 6)	0.7, 17	2.25E+06	15
7	(20, 25, 4)	0.7, 16	1.60E+06	11
8	(20, 25, 6)	0.7, 15	2.57E+06	22
9	(25, 30, 4)	0.7, 18	2.11E+06	26
10	(25, 30, 6)	0.7, 16	3.02E+06	38
11	(30, 35, 4)	0.7, 18	2.36E+06	34
12	(30, 35, 6)	0.7, 16	3.41E+06	41
13	(40, 50, 4)	0.7, 17	3.16E+06	49
14	(40, 50, 6)	0.7, 19	4.61E+06	83
15	(50, 70, 4)	0.8, 10	4.14E+06	74
16	(60, 75, 4)	0.8, 9	4.47E+06	79
17	(70, 90, 4)	0.8, 11	5.21E+06	129
18	(80, 100, 4)	0.8, 9	5.98E+06	177
19	(90, 110, 4)	0.8, 12	6.33E+06	232
20	(100, 120, 4)	0.8, 10	6.87E+06	329
21	(120, 150, 4)	0.8, 8	7.70E+06	784
22	(130, 170, 4)	0.8, 12	9.12E+06	903
23	(140, 200, 4)	0.8, 9	1.05E+07	1018
24	(150, 220, 4)	0.8, 10	1.21E+07	1442
25	(160, 250, 4)	0.8, 11	1.30E+07	2241
26	(170, 280, 4)	0.8, 10	1.46E+07	2891
27	(180, 300, 4)	0.8, 8	1.56E+07	2919
28	(200, 400, 4)	0.8, 11	–	<i>Out of memory</i>

variables  $\mathbf{X}$ , location, and capacity decisions at each period, to have the identical values in all scenarios by adding the following constraints:

$$X_{i,n,t}^s = X_{i,n,t}^{s'}, \quad \forall i \in I, \forall t \in T, \forall n \in N, \forall s, s' \in S. \quad (19)$$

In Table 3, the RVMS values are calculated for 12 problem instances.

The reported values of RVMS criterion in Table 3 highlights the significance of using multi-stage stochastic programming in our problem setting. Based on the results, the average of the RVMS is 3.25%, and we can see that by increasing the periods' number in problem instances, the value of the RVMS increases, relatively.

### Application of the MSSP

The data related to instances 11 and 12 with  $|I| = 30$  potential locations for DCs,  $|J| = 35$  customers are generated based on Iran's geographical network. In these instances, the transportation costs are achieved by the available data from Iran's Road Maintenance and Transportation Organization and the mean value of

**Table 3:** Investigation of the RVMS.

Instance number	$OF^{TS}$	$OF^{MS}$	$OF^{TS}-OF^{MS}$	RVMS (%)
1	8.61E+05	8.77E+05	1.56E+04	1.81%
2	1.30E+06	1.34E+06	3.87E+04	2.97%
3	1.17E+06	1.20E+06	2.51E+04	2.14%
4	1.82E+06	1.90E+06	7.59E+04	4.16%
5	1.43E+06	1.46E+06	2.68E+04	1.87%
6	2.20E+06	2.25E+06	4.67E+04	2.12%
7	1.56E+06	1.60E+06	3.58E+04	2.29%
8	2.45E+06	2.57E+06	1.18E+05	4.83%
9	2.03E+06	2.11E+06	7.96E+04	3.92%
10	2.87E+06	3.02E+06	1.52E+05	5.29%
11	2.27E+06	2.36E+06	8.65E+04	3.74%
12	3.04E+06	3.41E+06	1.33E+05	3.93%

demands are generated based on the population of customer zones. We use instance 11 to analyze the optimal solution of the MSSP. The candidate locations of DCs and customer zones associated with the SC network in instances 11 and 12 are shown in Figure 5.

By solving the MSSP in the considered problem instance, the optimal objective value is 2.36E+06. Using the rolling horizon approach, we approximate the true expected of the SC cost from implementation of the MSSP's solution through the planning horizon, and here, 100 realizations related to the random parameters from the first period until the last one are simulated. The expected value of simulation responses is 2.45E+06. Therefore, the relative difference between the MSSP's optimal objective and the mean of rolling horizon responses is 3.8%. In Figure 6a, the frequency of simulation responses over planning horizon is illustrated and in Figure 6b, the cumulative of the rolling horizon responses' mean from the first period until the end of planning horizon is shown. Further, the minimum and maximum of SC costs from simulating different sample paths are shown in Figure 6b.

The impact of transportation and inventory costs: here, we consider two weight factors  $\lambda_T$  and  $\lambda_I$  for transportation and inventory costs, respectively. Next, for a set of scenarios in problem instance 11, 15, and 20, we solve the MSSP for different values for these factors. In Table 4, the average number of open DCs in each time period is reported for these various values of  $\lambda_T$  and  $\lambda_I$ .

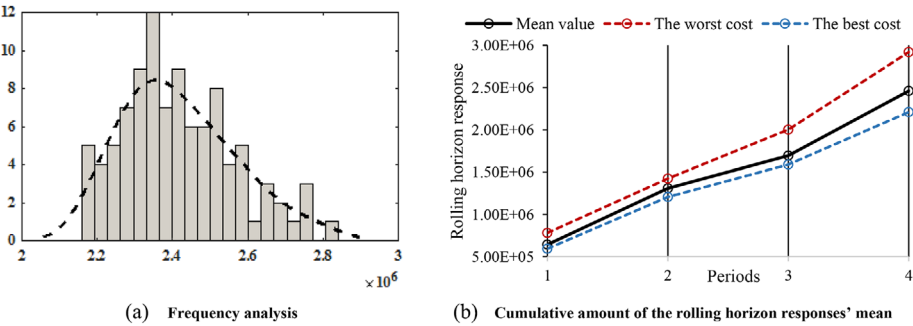
The reported results in Table 4 highlight an important issue. When the inventory cost in comparison with the transportation cost becomes larger, fewer DCs are averagely activated in the optimal decisions, and in our optimization problem, a risk pooling strategy is preferred.

The importance of periods' duration in dynamic SCND: By using the rolling horizon approach, we investigate how the considered duration of periods in our planning process affects the quality of the obtained optimal decisions from solving our MSSP in terms of the total SC cost. To do so, we assume that there is not any uncertainty regarding the disruption of DCs. Then, we examine problem

**Figure 5:** The considered network for problem instance 11. (a) Frequency analysis, (b) Cumulative amount of the rolling horizon responses' mean.



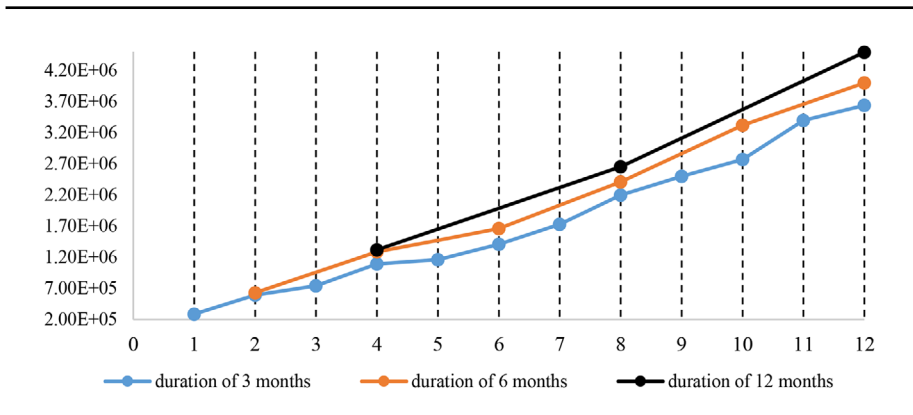
**Figure 6:** The rolling horizon response for problem instance 11.



**Table 4:** The sensitivity of optimal decisions to weight factors of transportation and inventory costs.

Instance number	Input parameters			Output
	$\lambda_T$	$\lambda_I$	# potential DCs	Average of open DCs in each period
Problem instance 11	1	1	30	23.6
	0.2	2	30	21.5
	2	0.2	30	26.9
Problem instance 15	1	1	50	39.9
	0.2	2	50	37.4
	2	0.2	50	44.5
Problem instance 20	1	1	100	88.7
	0.2	2	100	83.8
	2	0.2	100	91.2

**Figure 7:** The impact of duration of periods in the SC costs.



instance 11 for various lengths of time periods including 3, 6, and 12 months. When we change the periods’ duration, we will update the value of some problem’s parameters such as the mean and variance of demands, holding inventory costs, and lead time value. In Figure 7, the performance of obtained decisions from solving problem instance 11 with different durations of periods is illustrated over 3 years. Further, we have also done this analysis for instances 11, 15, and 20 over 2 years, and those results are reported in Table 5.

As shown by Figure 7 and Table 5, we observe that as the length of periods in our planning process decreases, the performance of the decisions get improved gradually. Such an improvement becomes more highlighted when we roll forward the optimal planning decisions for more periods (see Figure 7).

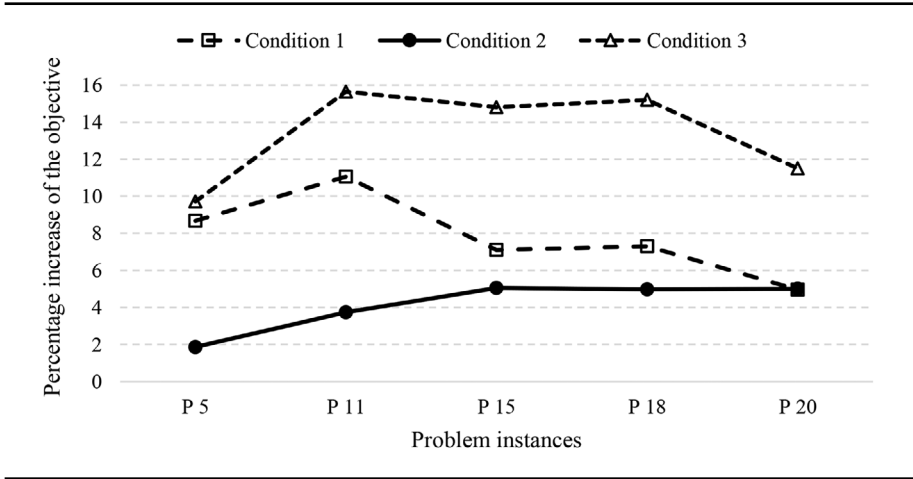
### Investigating the Disruptions’ Impact on the SC Cost

We consider if a disruption happens at a DC, the DC would not serve the customers over one time period. The modeling approach of disruptions in the context of

**Table 5:** The rolling horizon response for various durations of planning periods.

Instance number	Expected of rolling horizon responses over 2 years		
	Duration of 3 months	Duration of 6 months	Duration of 12 months
Problem instance 11	2.05E6	2.18E6	2.32E6
Problem instance 15	3.83E6	4.02E6	4.32E6
Problem instance 20	6.29E6	6.58E6	6.89E6

**Figure 8:** Analysing different conditions related to DCs’ disruptions.



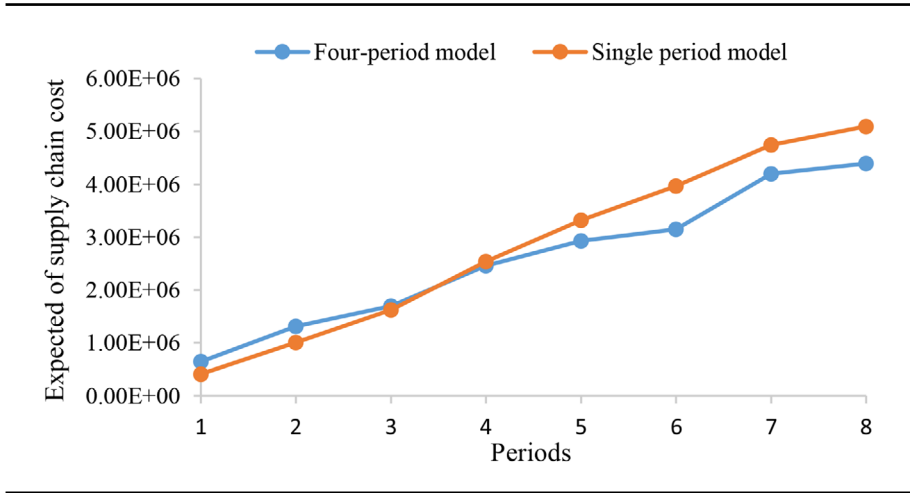
facility location and SCND has a significant impact on optimal location decisions. The multi-stage stochastic programming and the possibility of dynamic design can enhance the ability of a network to respond to customers after disruptions. Here, we solve several instances under three conditions related to the occurrence of disruptions that are defined as follows:

*Condition 1:* The disruption occurrence probability at DCs in the scenario tree construction approach is generated by uniform distribution function on the interval  $[0, 0.5]$ .

*Condition 2:* The two-stage stochastic programming formulation is used for the optimization problem (see section The Importance of the Multi-stage Stochastic Program). In other words, the design decisions for all periods must be determined before the uncertainty realization, and we cannot change the decisions based on the observation of stochastic parameters over planning periods.

*Condition 3:* In this condition we consider both conditions (1) and (2), and the two-stage stochastic program is used in which the disruption occurrence probability at DCs is generated by uniform distribution function on the interval  $[0, 0.5]$ .

We solve several instances, including instances 5, 11, 15, 18, 20, and 22, under these conditions, and Figure 8 illustrates the objective value’s percentage increase under these conditions for these instances.

**Figure 9:** The comparison between static and dynamic decisions.

By using the MSSP, it is possible to respond to the disruption events over the planning horizon based on the observed disruptions, and Figure 8 shows another significant feature of our MSSP. Furthermore, it is shown that the impact of disruptions on the SC cost is meaningful and dependent on the modelling approach.

### The Importance of Dynamic Design

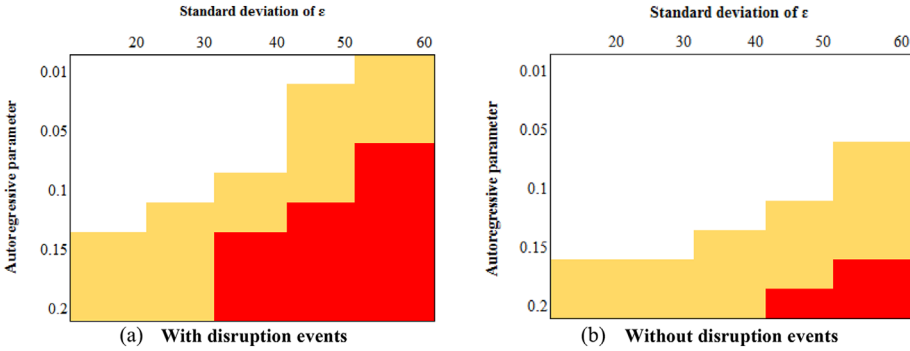
To investigate the significance of the dynamic design for our SCND problem, we develop single-period two-stage stochastic program to design/redesign the SC network at the beginning of each period. Then, by the rolling horizon approach, we compare the long-term impact of dynamic design with the static one. Figure 9 illustrates the obtained results from simulating the static and dynamic decisions in problem instance 11 and shows the importance of the dynamic design. Further, the dynamic design is compared with the static one in problem instances 8, 15, and 20, and its average relative superiority in the examined instances over 8 time periods is 12.9%.

### The Importance of Data-Driven Decisions

The proposed rolling horizon approach enables data-driven decisions by using the observed data over the past time horizon and, to do so, in the implementation phase, we use an updated scenario tree based on the realization of stochastic parameters. In our problem setting, the significance of data-driven decisions on the SC objective is mostly dependent on the observed demand over each strategic period. It is worth noting that in reality, the mean and variance of the realized demand in each strategic period should be calculated based on the demand observation in some considered tactical/operational time slots over each strategic period.

To examine the importance of data-driven decisions, we have considered various values for  $\beta_j^{(\mu)}$  (autoregressive parameter of the demand stochastic process) and the variance of the error term in its stochastic process. Then, in problem

**Figure 10:** The significance of data-driven decisions: the improvement related to the data-driven decisions, in the red part is more than 7%, in the orange part is between 2% and 7%, and in the white part is less than 2%. (a) With disruption events; (b) Without disruption events.



instance 11, we examine the MSSP’s optimal decisions by the rolling horizon decision-making framework with and without updating the scenario tree based on the demand observation. As a consequence, the superiority of data-driven decisions are obtained in various values of parameters related to the demand stochastic process (see Figure 10). In Figure 10a, the results are shown for the SCND under disruption events and in Figure 10b, we have not considered disruption events in the SC network.

By focusing on the results presented in Figure 10, we can conclude that by increasing the dependency of the mean demand to their value in previous periods (autoregressive parameter) and its variability, the improvement of data-driven decisions increases meaningfully. Further, the data-driven decisions’ significance increases under disruption events.

**Evaluation of the Scenario Tree Generation Method**

In-sample and out-of-sample stability analysis are performed to examine the efficiency of the scenario tree construction method. In-sample stability guarantees that if we employ various generated scenario trees from identical input parameters for solving the MSSP, the obtained optimal objective values are approximately the same. In Table 6, the optimal values of the objective from solving the MSSP with various scenario trees are illustrated for several instances. Further, in accordance with the minimum and maximum objective function’s values of a problem instance with consideration of various scenario trees, the error of in-sample stability is obtained as:

$$E_{In-Sample} = \frac{\text{Maximum of objective values} - \text{Minimum of objective values}}{\text{Mean of objective values}}.$$

Further, to examine the out-of-sample stability, we should use a simulation approach to approximate the problem’s true objective value based on the optimal

**Table 6:** In-sample stability analysis.

Problem instances	$\zeta = 0.7$			$\zeta = 0.8$		
	# of scenarios	Objective function value	In-sample stability error	# of scenarios	Objective function value	In-sample stability error
<b>5</b>	14	1.46E6	3.3%	9	1.49E6	4.6%
	17	1.49E6		8	1.56E6	
	18	1.51E6		10	1.55E6	
<b>8</b>	15	2.57E6	2.4%	12	2.57E6	3.6%
	17	2.51E6		11	2.48E6	
	16	2.54E6		11	2.54E6	
<b>11</b>	18	2.36E6	2.6%	8	2.32E6	3.8%
	16	2.42E6		11	2.41E6	
	16	2.37E6		9	2.40E6	
<b>15</b>	15	4.18E6	3.8%	10	4.14E6	4.3%
	20	4.26E6		8	4.10E6	
	18	2.19E6		10	4.28E6	

**Table 7:** The analysis of out-of-sample stability.

Problem instances	Objective function value	Rolling horizon expected response	Out-of-sample stability error
5	1.46E6	1.51E6	3.42%
8	2.57E6	2.61E6	1.56%
11	2.36E6	2.45E6	3.81%
15	4.14E6	4.32E6	4.35%

decisions. The out-of-sample stability assures that the true objective value is near the problem’s optimal objective. We use the rolling horizon approach to approximate the true objective value. If we denote the rolling horizon approach’s expected response and the MSSP’s objective value as  $ER^{RH}$  and  $OF^*$ , the error of out-of-sample stability can be obtained as  $\frac{|ER^{RH}-OF^*|}{OF^*} \times 100\%$ . In Table 7, the error of out-of-sample stability is reported for several instances.

Presented results in Tables 6 and 7 show that our scenario tree generation approach has a good stability performance.

**The Effect of Risk Consideration**

In this section, to obtain risk-averse decisions, we consider CVaR as the objective function of the problem. CVaR is a well-behaved risk measure and in a stochastic program, we can formulate it by linear programming techniques (Ahmed, 2006). If  $F_P(\cdot)$  denotes the cumulative distribution function of random variable  $P$ , Value at Risk at the confidence level  $\alpha, VaR_\alpha$ , is:

$$VaR_\alpha(P) = \inf \{ \eta \in \mathbf{R}: F_P(\eta) \geq \alpha \}.$$



$CVaR_\alpha$ , the conditional value at risk at the confidence level  $\alpha$ , is defined as:

$$CVaR_\alpha(P) = E((P | P \geq VaR_\alpha)).$$

$CVaR_\alpha$  is formulated by Rockafellar and Uryasev (2002) as:

$$CVaR_\alpha(P) = \inf_{z \in \mathbb{R}} \left\{ z + \frac{1}{1-\alpha} E[(P - z)^+] \right\}.$$

If we assume  $OF^s$  as the optimal value of the MSSP's objective function in scenario  $s$ , we can consider  $CVaR_\alpha$  as the objective function of the MSSP as:

$$\text{Min} : CVaR_\alpha = \eta + \frac{1}{1-\alpha} \left( \sum_{s \in \mathcal{S}} \pi_s d_s \right)$$

Subject to:

Constraints (3–11),

Constraints (14–17),

$$d^s \geq OF^s - \eta, \quad \forall s \in \mathcal{S},$$

$$d^s \geq 0, \quad \forall s \in \mathcal{S},$$

$$\eta \in \mathbb{R},$$

where the corresponding loss of scenarios  $s$  is denoted by  $d^s$ .

By solving the risk-averse model for problem instance 11, the optimal value of CVaR at confidence level 0.95 is 2.51E+06 and the expected SC cost is 2.47E+06. Further, to distinguish and evaluate better the optimal decisions from the expected value objective function and  $CVaR_{0.95}$  in the MSSP, we implement the decisions in a rolling horizon manner, and Figure 11 illustrates the cumulative mean response of the rolling horizon approach over eight periods.

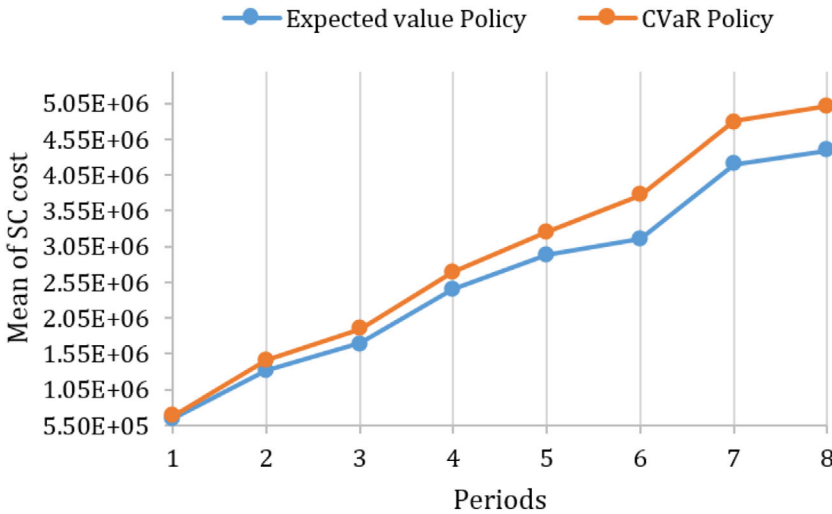
In Table 8, we report the mean, standard deviation (SD), and 75% quartile (QT) of rolling horizon responses from implementing the risk-averse and risk-neutral decisions over eight periods in some problem instances.

In Table 8, we can see that the implementation of the decisions from the MSSP with CVaR objective in comparison with the expected value objective leads to a SC cost distribution with higher mean and lower SD and 75% QT. Further, the average number of established DCs over the planning horizon relatively increases in the risk-averse policy.

## MANAGERIAL IMPLICATIONS

The presented data-driven rolling horizon approach introduces an innovative way of using data, which is revealed as time progresses and adjusts the decisions for MSSPs in practice. Furthermore, the trend and seasonality, which are often observed in stochastic parameters, can be captured over time by this approach. Although this decision-making framework is employed for the dynamic SCND in our study, other optimization problems with the multi-stage stochastic programming setting can also apply it.

**Figure 11:** The rolling horizon response from CVaR and mean objectives.



**Table 8:** The simulation responses' statistics of obtained decisions from the CVaR and expected value objective.

Problem instances	Statistics	CVaR <sub>0.95</sub> objective	Expected value objective
5	Mean	1.62E+06	1.51E+06
	Standard deviation	9.94E+04	2.98E+05
	75% QT	1.66E+06	1.69E+06
8	Mean	2.81E+06	2.61E+06
	Standard deviation	1.26E+05	3.42E+05
	75% QT	2.92E+06	2.98E+06
11	Mean	2.69E+06	2.45E+06
	Standard deviation	1.64E+05	4.02E+05
	75% QT	2.75E+06	2.86E+06
15	Mean	4.68E+06	4.32E+06
	Standard deviation	1.91E+05	4.94E+05
	75% QT	4.84E+06	5.01E+06

Generally, it is highlighted in the literature that operational risk management, induced by various uncertainty types, in the SC system depends on the knowledge and information-sharing. However, for the dynamic SCND, the research question of our study is addressed by the proposed data-driven decision making framework as an action plan for adjusting the SC network based on the realization of uncertain parameters, such as target market's changes and long-run demand rates, and the occurrence of disruption events over time. The corresponding action plan includes three main steps as follows:

- i. For decision-making in each strategic period, generate a scenario tree for the stochastic parameters and solve the corresponding MSSP,
- ii. Implement the decisions related to the current period and gather the data related to the realization of stochastic parameters until the next decision-making period,
- iii. Update the input parameters related to the scenario tree generation and MSSP based on the observed data and optimal decisions in previous periods, respectively.

Many corporations, such as Toyota, Honda, Intel, and BMW devote a substantial effort to hedge against SC operational risks by quantitative models (Simchi-Levi et al., 2014; Lu et al., 2015). By our approach, which can be easily adopted based on different SC networks, companies are able to use the right information in real-time and to take proactive actions as early as possible or at least before the customers suffer from the negative impacts of disruption events and inherent uncertainties.

In this study, we have found that the dynamic design of SC networks by using the multi-stage stochastic programming makes a SC flexible to change its decisions in response to various uncertain events that may happen in each time period. In our problem, the MSSP in comparison with the dynamic two-stage stochastic program and single period stochastic model improves the SC cost, meaningfully.

In modeling the disruption of SC facilities, we have assumed that a disrupted facility can be recovered in the next periods, in contrast to most of the previous studies. Furthermore, by increasing the probability of disruption events, it is shown that the MSSP is a more powerful optimization tool in comparison with the two-stage stochastic programming in hedging against disruption risks.

Based on our experimental results, in the case of high transportation cost in relation to the inventory cost and the existence of the disruption risk, the number of established DCs increases. On the other hand, the risk pooling strategy deals efficiently with increasing the inventory cost, and the number of active DCs decreases in such a situation. Furthermore, it is highlighted that the significance of data-driven decisions increases by the presence of disruption events and the increase of mean demand dependency to previous periods and variability.

We develop the MSSP with the CVaR objective for risk-averse decision makers, and we investigate the risk-neutral and risk-averse SC configuration based on the SC cost by using the rolling horizon simulation. Our experimental results show that the risk-averse decisions make the expected of SC cost worse, but the standard deviation and 75% QT associated with the SC cost distribution decrease about 60% and 5%, respectively. Therefore, in many practical situations, we can increase the robustness of the SC cost by employing the CVaR as the objective function.

## CONCLUSIONS

We deal with a new dynamic supply chain distribution network design problem in which the moments of customers' demands are uncertain and the availability of distribution centers is stochastic because of disruption events. Under a multi-

period setting, an MSSP with non-anticipativity constraints is developed to obtain the optimal design/redesign, capacity, allocation, and inventory decisions.

Methodologically, we first formulate our problem as an MINLP model, and then by using the special structure of the problem, reformulate it as a CQMIP model, which is solvable by the CPLEX as a commercial solver. The real-world applicability of the proposed MSSP is deeply investigated. A new data-driven decision-making approach is developed to implement the decisions made by the MSSP in reality. This approach enables decision makers to employ the data that is realized over time and to adjust the corresponding decisions in a rolling horizon framework.

In the computational results, we illustrate the validity of our model and its accuracy in practice. The significance of the dynamic design, data-driven decisions, and the length of planning periods in our decision-making process are also highlighted. Furthermore, by using the CVaR as the problem's objective function, the risk-averse decisions are obtained and analyzed.

To create a scenario tree that efficiently captures the existing uncertainty in our optimization problem, a simulation approach is used to generate a scenario fan. Next, we reduce the scenarios' number and convert them into a scenario tree by applying the forward scenario tree construction technique. The in-sample and out-of-sample stability analysis confirm the efficiency of this method.

There are also many opportunities to consider other operational or tactical planning level decisions in the problem. Furthermore, our optimization problem can be extended for decision-making under scarce data conditions by using the moment-based distributionally robust optimization approach in interesting future work.

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## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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