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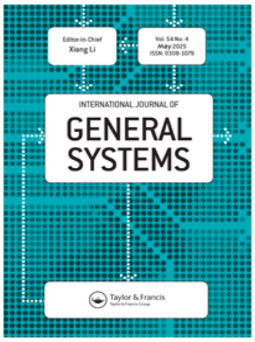

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Managing lead times and backlogging in a resilient distribution network under demand uncertainty

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ABSTRACT

In this work, we propose a novel multi-period location-inventory problem that assumes demand uncertainty, periodic review, backlogging, and lead times. The problem stems from the need to strategically manage distribution centers (DCs) to enhance the resilience of the supply chain, while providing a high service level to customers. A trade-off is sought between distribution resilience and stock-out risks on the one hand, and financial resources on the other hand. A progressive phase-in of the DCs is considered. The problem is cast as a two-stage decision-making process under uncertainty. A mixed-integer linear programming model is formulated. Two resilience indicators are adopted to access the results of a series of computational tests. Based on the experiments, it was found that the financial resources required to establish DCs throughout the planning horizon directly affect the long-term resilience of the supply chain. Nevertheless, the model proposed in this study can ensure that the supply chain resilience remains at a satisfactory level within the given financial resources.

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Supply chain resilience; location-inventory; multi-period facility location; backlogging; demand uncertainty

1. Introduction

With the fast development of mobile internet and e-commerce, a large number of entrants has emerged in the market. The intense competition has increasingly pushed enterprises to focus on strategic management aiming at enhancing supply chain resilience. This trend has led the entrants, characterized by their pursuit of excellence in niche markets and customer-centric approaches, to increasingly opt for establishing their own distribution centers (DCs), thereby building their own distribution networks (Bak et al. 2020; Yavas and Ozkan-Ozen 2020). Specifically, this strategic decision is driven by the desire of the entrants to maintain high standards of distribution resilience, exercise direct control over distribution processes, and align logistics operations more precisely with customer expectations. A growing number of entrants are adopting this strategy. Examples include SHEIN, Everyday Chain, Banu Hotpot, and Baman Rice Noodles, all of which have seen steady growth in recent years (Y. Chen 2023).

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The common characteristic of the entrants mentioned above is that they are small and medium-sized enterprises in the early stages of entry. This study specifically focuses on this type of enterprise, which has several distinguishing characteristics compared to the established large firms in the market. First, they typically do not need to go through cumbersome and time-consuming processes when making decisions. This results in shorter decision-making cycles and a stronger ability to respond to external changes. Second, inventory decisions are crucial for them and can easily become a critical weakness if not properly handled. Due to relatively insufficient funds, entrants cannot stockpile large quantities of inventory. Finally, in a highly competitive market, they often cannot occupy a dominant position.

Inevitably, the first obstacle these entrants encounter in the process of development and growth is limited financial resources. Managers could rely on a comprehensive plan to fully address various potential future challenges. However, this would require a substantial one-time investment calling for large financial resources. Often, this represents a heavy burden. By modifying the perspective, an entrant can change its approach to continuously adjusting its decisions in response to external changes and gradually invest a certain amount of financial resources to support it. Often, due to limited financial resource management and utilization, the latter is more realistic and presents a highly feasible strategic path. It requires entrants to adopt a multi-stage approach for developing and expanding their storage and distribution networks. This calls for strategic planning and allocating financial resources over multiple time periods (Prajogo, Mena, and Nair 2017). Such approach is crucial for the entrants, allowing them to gradually build service capabilities in line with evolving external demand and market dynamics (Brandenburg 2018). Furthermore, apart from the limited financial resources, entrants face other long-standing service-related challenges, which include demand uncertainty, lead times, and backlogging (DuHadway et al. 2020; Kraude et al. 2018; Pavlov et al. 2017). The above mentioned uncertainty, complicates the management of lead times and increases the risk of stock-outs if not properly handled (Aldrighetti et al. 2021). Accordingly, entrants should employ strategic and adaptive approaches when planning and managing their storage and distribution networks, seeking a trade-off between high-quality service and financial commitments. To the best of our knowledge, no previous model has addressed the multi-period location problem for such companies while simultaneously considering demand uncertainty, periodic review, backlogging, and lead times.

More specifically, entrants may need to find an equilibrium calling for gradually building their own DCs while operating under limited financial resources. This involves careful planning ensuring an efficient and effective DC network that can support a growing business without compromising service quality and financial stability. This trade-off is the primary focus of this paper. Particularly, we seek to analyze how entrants can strategically determine the optimal locations and timings for establishing DCs within the existing financial resources. The study also rigorously looks into the resilience of distribution services, including the determination of logistics links and the quantification of goods flow from the upper level of the supply chain (factories) to DCs, and then to the lower level elements in the chain (retailers). A pivotal aspect of this analysis involves a detailed examination of lead time from manufacturing facilities to DCs. Concurrently, the research delves into the implications of uncertainty demand at retail stores, necessitating a nuanced approach to managing stock-outs in a multi-period planning context.

A two-stage stochastic optimization model is proposed to account for the underlying demand uncertainty. In the first stage, a strategic decision is made regarding the location and timing of establishing DCs over multiple time periods. Additionally, within each period, the logistics connections between manufacturing factories and the established DCs are determined, as well as the connections between the established DCs and retail stores.

In the second stage, i.e. after uncertain demand is disclosed, we determine the amounts to be shipped from manufacturing factories to DCs and from the DCs to retailers. Moreover, the model is extended to account for lead times of the batches the DCs order to the manufacturing facilities. Finally, by integrating the characteristics of the demand distribution from retail stores, we consider a finite set of scenarios that allows finding a compact mixed-integer linear programming formulation for the deterministic equivalent problem. The resulting model can be handled by a general-purpose optimization solver. This is of utmost relevance for practitioners who often do not master sophisticated optimization skills allowing them to devise and implement specially tailored algorithms for complex problems.

It is worth noting that the goal of the investigated problem is to minimize the costs associated with using and operating distribution centers for entrants in the market, including maximizing the revenue from goods distribution. In other words, this study provides a practical distribution center operation management method for entrants, aiming to minimize their cost expenditures and enhance the efficiency of capital utilization.

An experimental study is conducted using randomly generated data. We analyze the scalability of the proposed model. Subsequently, we introduce two resilience evaluation indicators specifically designed to measure the ratio of established DCs and the proportion of goods delivered on time to retail stores. Finally, we report on the results of multiple experiments to test the impact of financial resources available on the supply chain resilience. In particular, we provide several useful managerial insights for entrants when managing their distribution centers.

The main contributions of this study are summarized as follows:

(1) Taking into consideration the real-life occurrence of stock-outs, we address a stochastic multi-period location-allocation-inventory problem under periodic review, by developing a two-stage stochastic programming model under demand uncertainty.
(2) We propose a targeted model extension to incorporate lead times and transform the extended model into a mixed-integer linear programming model, enabling its solvability by general-purpose solvers.
(3) We introduce two indicators to measure the ratio of established DCs and the proportion of goods timely delivered to the retail stores. Furthermore, we analyze the impact of the financial resources available as well as lead time in the supply chain resilience.

The remainder of this paper is organized as follows: Section 2 presents an overview of the literature related to the problem under investigation. Section 3 focuses on the detailed problem description and mathematical modeling aspects. In Section 4, the targeted model extension approach to incorporate lead times is proposed as well as the solution framework. Section 5 reports the results of the numerical experiments performed to assess the relevance of the methodological contributions. The paper concludes with an overview of the work done and some hints for further research.

2. Literature review

This work stems from the need to decide where and when to establish a set of distribution centers to better support the operations of a market entrant that wants to distribute its goods, while ensuring a proper management of its financial resources. Thus, the type of research to be conducted primarily falls within the field of supply chain management. Additionally, since the decision-making process relies on a finite planning horizon divided into several time periods, it also encompasses the area of multi-period facility location, which is an important and well-established topic within location science (Nickel and Saldanha-da Gama 2019). In this section, we provide an overview of the literature related to those themes.

2.1. Facility location in supply chain management

Facility location plays a major role in strategic supply chain planning (Melo, Nickel, and Saldanha-da-Gama 2009). It is related to selecting locations for facilities such as factories, warehouses, and DCs, to support different logistics operations. Typically, one seeks to minimize costs while maximizing efficiency or service levels (Dunke et al. 2018; Melo, Nickel, and Saldanha-da-Gama 2009; Saldanha-da-Gama 2022).

Given the nature of facility location problems, they plays a significant role in many areas, such as (commercial) distribution logistics and transportation. This exerts a profound influence on fields like last-mile delivery, freight transportation, and cold supply chain design, to mention a few. Below, we review the research in these and related domains.

In the field of commercial logistics, Irawan et al. (2023) investigate a logistics problem in the context of offshore wind turbine maintenance. The authors introduce a two-stage stochastic programming model to optimize the service operation vessel locations and safe transfer boat routes, minimizing total maintenance costs. Uncertainty regards weather conditions and travel time. Chen et al. (2023) focuses on optimizing the location of DCs by introducing a joint demand distribution function based on time and space. A bi-objective optimization model is derived seeking to minimize total costs and maximize customer time satisfaction. Chang, Chiang, and Chang (2024) present a two-stage stochastic programming model for a location-routing problem with the goal of minimizing the total expected cost. Specifically, in the first stage, the locations of distribution centers and the fleet size are determined. In the second stage, routes to fulfill demands are determined adapting to how uncertainty reveals. Nawazish, Padhi, and Cheng (2022) investigate a multicriteria facility location model based on efficiency, effectiveness, and equity. Jabbarzadeh, Fahimnia, and Rastegar (2017) focus on designing and implementing sustainable, efficient electricity supply chains. They develop a multistage robust optimization model aiming to maximize profit, minimize greenhouse gas emissions, and enhance network resilience.

In the field of freight transportation, Musolino et al. (2019) present a methodology with two integrated levels to evaluate candidate DC locations in cities to improve the sustainability of urban freight transport: an outer level that defines feasible DC locations and evaluates locations based on sustainability indicators; and an inner level that, for each DC location, simulates carrier routing behavior in delivering goods to retailers under variable restocking demand scenarios using a vehicle routing model. Guo and Matsuda (2023) investigate the selection of DCs with two main objectives: defining the significance of criteria influencing DC selection using the analytic hierarchy process and ranking pre-existing private DCs while assessing their location tendencies. Wan, Chen, and Dong (2021) present a bi-objective DC location model capturing uncertainty using fuzzy numbers to balance urgency and cost by optimizing the placement of DCs for collecting and dispatching relief materials. Pham, Nguyen, and Bui (2022) propose a mixed-integer linear programming model for a multi-trip and multi-depot (multiple DCs) vehicle routing problem for dairy product delivery. The authors develop an adaptive large neighborhood search algorithm seeking to minimize the unserved demand, the number of vehicles, and the total distance traveled.

In the context of cold chain transportation, Zhang et al. (2021) introduce a bi-level programming model to optimize the location and scale of competitive cold chain DCs, with the upper level minimizing total system costs and the lower level representing customer choice behavior. Focusing on both route optimization and DC location selection, Wang et al. (2024) develop a cold chain logistics DC location model to minimize carbon emissions and costs, incorporating factors in terms of cargo types, transportation, cargo damage, refrigeration costs, and penalties. Taouktsis and Zikopoulos (2024) present an approach that seeks to better support decision-making by developing a tool that aids in the rapid selection of optimal DC locations, addressing a facility location-routing problem to identify suitable nodes in volatile and complex scenarios.

The application of facility location in supply chain management is currently vast. It spans different contexts as those above described. Nevertheless, there remains a noticeable gap in research specifically targeting supply chain management for new market entrants, especially concerning the location selection and establishment timing of DCs looking ahead to inventory management.

2.2. Multi-period facility location under uncertainty

Multi-period facility location is a complex topic in operations research and supply chain management. It deals with selecting locations for installing facilities over a planning horizon divided into multiple time periods. This setting is particularly relevant in industries where demand, costs, and other factors change over time, especially when addressing uncertain facility location problems. These changes necessitate a reevaluation of facility locations and possibly other related factors.

As is commonly recognized, research on facility location encompasses a variety of problem types, including fixed-charge facility location, hub location, covering location, etc. The research on these problems is gradually expanding to consider multi-period settings (Nickel and Saldanha-da Gama 2019).

More recently, Bakker and Nickel (2024) analyze multi-period capacitated facility location problems, weighing the flexibility of adapting decisions over time against the complexity of the resulting models and need for satisfying the capacity constraints. Sauvey, Melo, and Correia (2020) consider a multi-period facility location problem by optimally selecting facility locations and their capacities and allocating customer demand over time. The authors distinguish between those customers who require on-time delivery and those who accept delayed deliveries up to a certain threshold. The goal is to minimize the total fixed and variable costs. Zhang et al. (2023) propose a multi-period optimization model for planning the location of public electric vehicle charging stations and their capacities in urban centers. Predicted spatiotemporal distributions of charging demands are adopted. The goal is to minimize total costs across all periods while ensuring that all the predicted demand is satisfied. Štádlerová, Schütz, and Tomasgard (2023) address a problem that consists of identifying optimal locations for hydrogen production facilities and their expansion over time in the context of maritime transportation. The goal is to minimize total cost, which include both long-term investment and short-term variable production costs. In the context of hub covering location problems, Khaleghi and Eydi (2023) investigate a bi-objective nonlinear model for designing a multi-period, continuous-time hub network, aiming to minimize costs and maximize responsiveness by reducing travel times, while determining optimal timing for hub locations, allocations, capacity expansions, and vehicle routing. Seeking to optimize the distribution of humanitarian aid to refugee camps, Monemi et al. (2021) develop a mixed-integer linear programming model for the multi-period hub location problem with serial demands in war-affected areas. Focusing on assigning doctors to health centers within a district over a planning horizon with discrete periods, Vatsa and Jayaswal (2021) study a robust capacitated multi-period maximal covering location problem, while considering constraints related to demand coverage, facility capacity, and server availability across various scenarios.

Analyzing the literature on multi-period facility location one concludes that not only does it span various types of facilities and contexts but also it emphasizes integration with operations and supply chain management. Some aspects of relevance include the existence of multiple layers of facilities and routing decisions.

Mohamed et al. (2023) tackle a two-echelon stochastic multi-period capacitated location-routing problem in distribution network design, aiming to determine the optimal number and location of DCs, along with capacity allocation between the two distribution echelons to meet future demand. Wang et al. (2023) focus on a two-echelon multi-depot multi-period location-routing problem with pickup and delivery. The authors formulate the problem using a bi-objective mathematical model to minimize total operational costs and the number of vehicles required. An algorithm is proposed that is based on the combination of particle swarm optimization with k-means clustering. Gafti et al. (2023) introduce a mixed-integer linear programming model for a multi-period location-routing problem. The problem seeks to make an optimal usage of a municipal solid waste system to feed a bioenergy supply chain. The total cost is to be minimized. It includes waste collection, transportation, biofuel allocation from conversion centers to consumption points, and the establishment of new consumption points as to be minimized. Aloullal, Saldanha-da Gama, and Todosijević (2023) present a mixed-integer linear programming model for a multi-period hub location-routing problem, assuming that each hub has one uncapacitated vehicle operating a single route for simultaneous pickup and delivery. An approximate algorithm based on a so-called fix-and-relax scheme is devised.

Luo, Wan, and Wang (2022) introduce a multi-period location–allocation model for dynamically managing the deployment of emergency hospitals, allocation of medical supplies, and patient management during epidemics, considering the dynamic arrival of supplies, patient transfer fairness, and state transitions across different periods. Yang et al. (2023) introduce a distributionally robust optimization model for a multi-period

Table 1. Table of literature review.

Publication	Uncertainty	Lead Time	Multi-period	Objective	Method
Bakker and Nickel (2024)	×	×	✓	Maximize profits	Exact solution
Sauvey, Melo, and Correia (2020)	×	×	✓	Minimize cost	Heuristic
J. Zhang et al. (2023)	✓	×	✓	Minimize cost	Heuristic
Štádlerová, Schütz, and Tomasgard (2023)	×	×	✓	Minimize cost	Exact solution
Khaleghi and Eydi (2023)	×	×	✓	Minimize cost & travel time	Heuristic
Monemi et al. (2021)	×	×	✓	Minimize cost	Exact solution
Vatsa and Jayaswal (2021)	✓	×	✓	Maximize total demand	Exact solution
Mohamed et al. (2023)	✓	×	✓	Minimize cost	Exact solution
Y. Wang et al. (2023)	×	×	✓	Minimize cost	Heuristic
Gafti et al. (2023)	×	×	✓	Minimize cost	Exact solution
Aloullal, Saldanha-da Gama, and Todosijević (2023)	×	×	✓	Minimize cost	Heuristic
Luo, Wan, and Wang (2022)	×	×	✓	Minimize cost	Exact solution
Yang et al. (2023)	✓	×	✓	Minimize cost	Exact solution
This paper	✓	✓	✓	Minimize cost	Exact solution

location-allocation problem, seeking to allocate multiple resources and capacity levels under uncertain emergency demand and considering resource fulfillment time. A mixed-integer linear program is proposed to minimize operating costs, efficiency, and equity.

From the above literature review, we conclude that multi-period facility location problem has received widespread attention from scholars and also that it has been intertwined with various other decisions of relevance in logistics and supply chain management. However, research specifically focused on multi-period problems gathering location, allocation, and lead time, specifically tailored to plan for the supply chains of new market entrants when a careful planning of DCs is at stake, has not yet been studied (see Table 1). In the following sections, we conduct a detailed study focusing on this gap.

3. Problem description and model formulation

3.1. Problem description

We seek to design a multi-echelon distribution system (see Figure 1). The related facilities include factories (at the upper level) and DCs (intermediate level). A set of retailers (lower level) is to be supplied. Location decisions are to be made for the DCs. A set of potential locations is given. A planning horizon is assumed, which is divided into a finite set of periods. To simplify, we assume that no DC is operating at the beginning of the planning horizon. However, that this assumption can be easily relaxed. The factories are assumed to have an unlimited production capacity (or at least, large enough to not cause any limitation in the context of our system) and a single commodity is assumed.

Over the planning horizon, the DC network can be expanded, although a maximum number of new DCs can be established in each period (e.g. due to budget or technical constraints). Given that for entrants with limited funds, obtaining the right to use distribution centers through leasing is a more feasible light asset operation model, we do not consider the construction time of distribution centers. Additionally, the possibility of facility closure

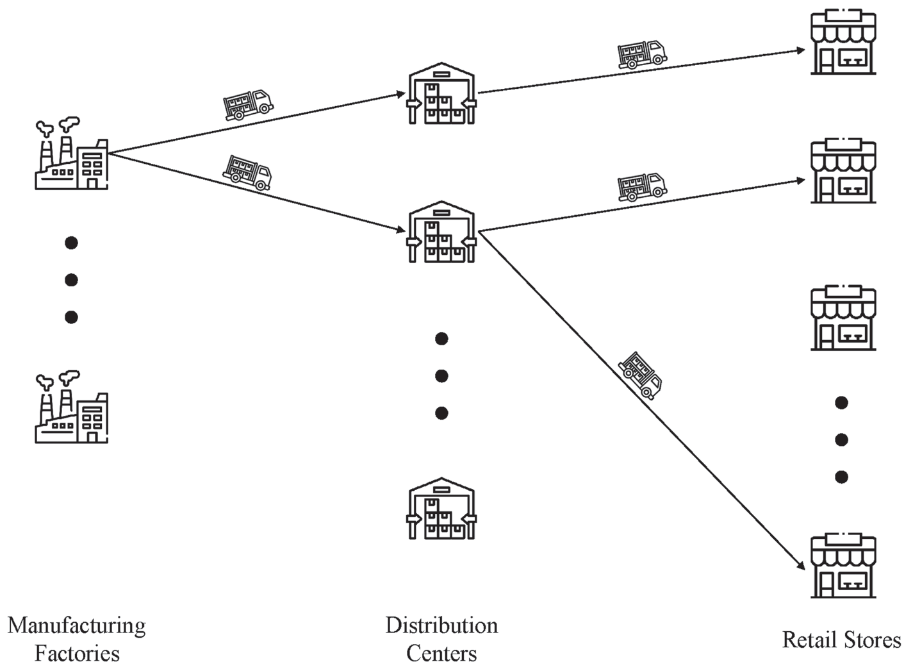


Figure 1. The diagram illustrating the transportation of commodities from the manufacturing factories to retail stores within a certain time period.

is not considered. In other words, once a facility at a particular location is selected to be opened in some period, it will remain open until the end of the planning horizon.

In each period of the planning horizon, the commodity flows from the factories to the DCs and from these to the retailers. Single sourcing is assumed, i.e. a DC is supplied from a single factory, and a retailer is supplied from a single DC. Note, however, that the assignment can change over time. We assume that the transportation capacity from the factories to the DCs is unlimited, and also that the DCs can maintain an unlimited inventory from one time period to the following one.

The above assumptions are of practical relevance in many settings and thus can be found in much related literature (see Nickel and Saldanha-da Gama 2019 and the references therein). In these references, the authors provide a detailed related discussion, and interested readers can delve deeper to find that the above assumptions are commonly shared by researchers.

However, to better reflect potential real-world operations, we assume that backlogging and lead time are allowed. This means that during stock-outs, retailers may experience temporary shortages, but the missing quantities will be fulfilled at a later period. Additionally, orders require a certain lead time. To make the model easier to understand, we first address the case without lead time, and then, in Subsection 3.3, we introduce it.

The financial dynamics of such a system are driven by a variety of costs and revenues. They include the cost of installing (e.g. renting) DCs, as well as the associated costs of allocating retail stores to these DCs, which encompass transportation expenses. Moreover, an order issued by a DC to be supplied by its allocated factory incurs fixed costs, as well as variable costs (dependent on the batch size). We also consider holding costs at the DCs.

In terms of revenues, each unit being transported from the DC to a retailed generates an income, which may vary depending on whether the delivery is timely or comes with a delay.

It is noteworthy that a significant unknown quantity in our problem is the demand level per period at the retailers. Given the nature of such short-term uncertainty we assume it to be fairly well represented by a random variable with a given cumulative distribution function (Correia and Saldanha-da Gama 2019). We assume demands across retailers to be independent.

The primary objective of the problem is overall cost minimization while ensuring demand satisfaction. The decisions in this context are time-dependent and concern three aspects: location, allocation, and inventory. They include (i) when and where to install DCs, (ii) how to allocate the operational DCs to the factories, (iii) how to assign retail stores to the operational DCs, (iv) when to replenish the DCs, (v) the supply quantities that DCs should receive, (vi) the inventory levels that DCs should retain for the next period, (vii) the inventory quantities that retail stores should receive on time, and (viii) the backlogged quantities.

3.2. Model formulation

The location-allocation-inventory problem under demand uncertainty outlined in the previous section can be formulated mathematically as a two-stage stochastic optimization problem. In the first stage, the focus is put on location and allocation decisions – where and when to install DCs, and how to allocate them to the factories and the retailed to them. In the second stage, adaptive inventory management decisions are made – managing stock levels, order quantities, and distribution strategies to retailers. As the name indicates, these decisions adapt to how demand is revealed. It is worth noting that we place allocation decisions in the first stage because, given the uncertainty considered in this study, it cannot be guaranteed that the service level will be met 100% in each period. Therefore, the allocation decisions represent a more strategic or tactical decision made beforehand to ensure that some facilities are established to meet potential demand.

To formulate the problem we introduce the relevant notation to be used hereafter.

Sets:

- K, set of factories.
- I, set of candidate distribution centers (DCs).
- J, set of retail stores.
- T, set of time periods.
- T_t, subset of time periods that includes all periods from period 1 to t, i.e., $T_t = \{1, 2, \ldots, t\}$.

Parameters:

- F_{it}, fixed cost for installing a DC at $i \in I$ in period $t \in T$, plus any other related costs, e.g. operation) from period t until the end of the planning horizon.
- C^1_{ikt}, cost for having DC $i \in I$ allocated to factory $k \in K$ in period $t \in T$.
- C^2_{ijt}, cost for having DC $i \in I$ allocated to retailer $j \in J$ in period $t \in T$.
- n_t, maximum number of DCs that can be installed in period $t \in T$.

g_{ikt}, fixed cost incurred by DC $i \in I$ for placing an order at factory $k \in K$ at (the beginning of) period $t \in T$.
a_{ikt}, unit cost incurred by DC $i \in I$ when placing an order at factory $k \in K$ at (the beginning of) period $t \in T$.
h_{it}, unit holding cost at DC $i \in I$ for the amount left in stock at (the end of) period $t \in T$.
p_{ijts}, unit revenue for the items sent to retailer $j \in J$ from DC $i \in I$ in period $t \in T$ to satisfy the demand from period $s \in T_t$.

First-Stage Decision Variables:

$$y_{it} = \begin{cases} 1, & \text{if DC } i \in I \text{ is operating in period } t \in T, \\ 0, & \text{otherwise.} \end{cases}$$

$$w_{ikt} = \begin{cases} 1, & \text{if DC } i \in I \text{ is supplied from factory } k \in K \text{ in period } t \in T, \\ 0, & \text{otherwise.} \end{cases}$$

$$x_{ijt} = \begin{cases} 1, & \text{if DC } i \in I \text{ supplies retail store } j \in J \text{ in period } t \in T, \\ 0, & \text{otherwise.} \end{cases}$$

The problem we are investigating can be formulated as follows:

$$\text{minimize} \quad \sum_{t\in T}\sum_{i\in I} F_{it}(y_{it} - y_{i,t-1}) + \sum_{t\in T}\sum_{i\in I}\sum_{k\in K} C^1_{ikt} w_{ikt} + \sum_{t\in T}\sum_{i\in I}\sum_{j\in J} C^2_{ijt} x_{ijt} + \mathcal{Q}(\boldsymbol{w}, \boldsymbol{x}, \boldsymbol{y}), \tag{1}$$

$$\text{subject to} \quad \sum_{i\in I} (y_{it} - y_{i,t-1}) \le n_t, \quad \forall t \in T, \tag{2}$$

$$y_{it} \ge y_{i,t-1}, \quad \forall i \in I,\ t \in T, \tag{3}$$

$$\sum_{i\in I} x_{ijt} = 1, \quad \forall j \in J, t \in T, \tag{4}$$

$$x_{ijt} \le y_{it}, \quad \forall i \in I,\ j \in J,\ t \in T, \tag{5}$$

$$\sum_{k\in K} w_{ikt} = y_{it}, \quad \forall i \in I,\ t \in T, \tag{6}$$

$$x_{ijt} \in \{0, 1\}, \quad \forall i \in I,\ j \in J,\ t \in T, \tag{7}$$

$$w_{ikt} \in \{0, 1\}, \quad \forall i \in I,\ k \in K,\ t \in T, \tag{8}$$

$$y_{it} \in \{0, 1\}, \quad \forall i \in I, t \in T. \tag{9}$$

Since no DC is initially operational, we set $y_{i0} = 0, \forall i \in I$. Nevertheless, these values can change according to other initial settings, namely if we are planning for a system that is currently operational, *i.e.*, a rolling horizon planning can be easily considered.

In the above model, inequalities (2) ensure that the maximum number of DCs that can be installed at each period is not surpassed, while inequalities (3) guarantee that a DC will be working all the subsequent periods from the moment it is installed. Equalities (4) and inequalities (5) ensure that in each period each retailer is supplied from a single and operational DC. Equalities (6) ensure the single allocation of operational DCs to factories in each period. Constraints (7)–(9) define the domain of the decision variables.

The first term of the objective function (1) represents the total cost of opening and operating DCs. The second term is the total cost of allocating the DCs to the factories. The third term is the total allocation cost of retailers to DCs. The fourth term represents the financial consequence in the future for making the decision conveyed by the first-stage variables. If we assume a neutral attitude of the decision-maker towards risk, that consequence can be represented by the expected total inventory costs given a first-stage decision.

Let $\boldsymbol{\xi} = [\boldsymbol{\xi}_{jt}]_{(j \in J, t \in T)}$ be the random process describing the demand throughout the planning horizon. For each $j \in J$, $t \in T$, $\boldsymbol{\xi}_{jt}$ is a random variable representing the demand of retailer j in period t. Therefore we define $\mathcal{Q}(\boldsymbol{w}, \boldsymbol{x}, \boldsymbol{y}) = \mathbb{E}_{\boldsymbol{\xi}}[Q(\boldsymbol{w}, \boldsymbol{x}, \boldsymbol{y}; \boldsymbol{\xi})]$, with $Q(\boldsymbol{w}, \boldsymbol{x}, \boldsymbol{y}; \boldsymbol{\xi})$ standing for the second-stage objective function value under scenario $\boldsymbol{\xi}$.

As we mentioned above, the second-stage decisions are adaptive i.e. they adjust to the actual demand observed.

Second-stage decision variables:

$r_{ikt}(\boldsymbol{\xi}) = \begin{cases} 1, & \text{if D} + i \in I \text{ places an order at factory } k \in K \text{ at the beginning of period} \\ t \in T, & 0, \text{otherwise.} \end{cases}$

$q_{ikt}(\boldsymbol{\xi})$, the quantity that DC $i \in I$ receives from factory $k \in K$ at the beginning of period $t \in T$.

$u_{it}(\boldsymbol{\xi})$, the quantity that remains in DC $i \in I$ at the end of period $t \in T$.

$v_{ijts}(\boldsymbol{\xi})$, the quantity that DC $i \in I$ sends to retail store $j \in J$ in period $t \in T$ to satisfy their demand at period $s \in T_t$.

For each observation $\hat{\boldsymbol{\xi}}$ of $\boldsymbol{\xi}$ we can now specify the second-stage optimization problem.

$$Q(\boldsymbol{w}, \boldsymbol{x}, \boldsymbol{y}; \hat{\boldsymbol{\xi}}) = \min \quad \sum_{t \in T} \sum_{k \in K} \sum_{i \in I} \left(g_{ikt}\, r_{ikt}(\hat{\boldsymbol{\xi}}) + a_{ikt}\, q_{ikt}(\hat{\boldsymbol{\xi}}) \right) + \sum_{t \in T} \sum_{i \in I} h_{it} u_{it}(\hat{\boldsymbol{\xi}}) - \sum_{t \in T} \sum_{s \in T_t} \sum_{j \in J} \sum_{i \in I} p_{ijts} v_{ijts}(\hat{\boldsymbol{\xi}}), \tag{10}$$

$$\text{s.t.} \quad \sum_{k \in K} q_{ikt}(\hat{\boldsymbol{\xi}}) + u_{i,t-1}(\hat{\boldsymbol{\xi}}) = u_{it}(\hat{\boldsymbol{\xi}}) + \sum_{j \in J} \sum_{s \in T_t} v_{ijts}(\hat{\boldsymbol{\xi}}), \quad \forall i \in I,\ t \in T, \tag{11}$$

$$q_{ikt}(\hat{\boldsymbol{\xi}}) \leq M\, r_{ikt}(\hat{\boldsymbol{\xi}}), \quad \forall i \in I,\ k \in K,\ t \in T, \tag{12}$$

$$r_{ikt}(\hat{\boldsymbol{\xi}}) \leq w_{ikt}, \quad \forall i \in I,\ k \in K\ t \in T, \tag{13}$$

$$u_{it}(\hat{\boldsymbol{\xi}}) \leq M\, y_{it}, \quad \forall i \in I,\ t \in T, \tag{14}$$

$$v_{ijtt}(\hat{\boldsymbol{\xi}}) + \sum_{s \in T \setminus T_t} v_{ijst}(\hat{\boldsymbol{\xi}}) \leq M\, x_{ijt}, \quad \forall i \in I, j \in J, t \in T, \tag{15}$$

$$\sum_{i\in I}\left(v_{ijtt}(\hat{\boldsymbol{\xi}}) + \sum_{s\in T\setminus T_t} v_{ijst}(\hat{\boldsymbol{\xi}})\right) = \hat{\xi}_{jt},$$

$$\forall j \in J, t \in T, \tag{16}$$

$$r_{ikt}(\hat{\boldsymbol{\xi}}) \in \{0,1\}, \quad \forall i \in I, k \in K, t \in T, \tag{17}$$

$$q_{ikt}(\hat{\boldsymbol{\xi}}) \geq 0, \quad \forall i \in I,\ k \in K, t \in T, \tag{18}$$

$$u_{it}(\hat{\boldsymbol{\xi}}) \geq 0, \quad \forall i \in I, t \in T, \tag{19}$$

$$v_{ijts}(\hat{\boldsymbol{\xi}}) \geq 0, \quad \forall i \in I, j \in J, t \in T, s \in T_t. \tag{20}$$

Since no DC is initially operating, we set $u_{i0}(\hat{\boldsymbol{\xi}}) = 0, \forall i \in I$. Nevertheless, as discussed for the first-stage problem, a different *status quo* can be easily accommodated.

In the second-stage model, the first term of the objective function (10) represents the total cost of batch orders, encompassing both fixed and variable costs. The total holding cost paid at the DCs is represented by the second term in the objective function. The last term reflects the total revenue generated from supplying the retailers.

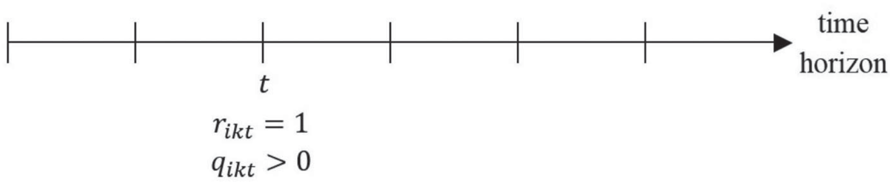
Equalities (11) are the inventory-balance constraints. Inequalities (12) guarantee that, for each period, a DC can be replenished from a manufacturing factory only if an order was placed in that same period. M is a large enough number. Inequalities (13) ensure that a DC can only place an order to a factory if it is allocated to it in the same period. Inequalities (14) state that, for each period, a DC can only hold inventory if it is operational. Inequalities (15) guarantee that a DC can only supply a retailer in some period if the latter is allocated to the former in that period. Equalities (16) ensure that all demand is supplied over the planning horizon. Constraints (17)–(20) define the domain of the decision variables.

3.3. Handling lead times

The two-stage stochastic programming model just proposed considers stock-outs and the related backlogging but does not consider lead time from manufacturing factories to DCs. When lead time becomes non-negligible, adjustments are needed in the second-stage model. Particularly, modifications are required in some decision variables, thus resulting in a targeted model extension approach as follows.

Let ρ_t be the number of base units in which a period is divided (e.g. days when a period is a week; weeks when a period is a month, etc). Denote by l_{ikt} the lead time (in base time units) associated with factory $k \in K$ when getting an order from DC $i \in I$ in (the beginning of) period $t \in T$. Accordingly, $\Delta_{ikt} = \lfloor \frac{l_{ikt}}{\rho_t} \rfloor$ is the number of periods it takes an order placed at the beginning of period t to arrive to DC $i \in I$ from manufacturing factory $k \in K$ (see Figure 2). Thus, $T_{ik} = \{t + \Delta_{ikt} \in T : t \in T\}$ is the period at which DC $i \in I$ receives the order.

Although there is no need to consider additional decision variables, those associated with the factories need modification. In the case of variables $r_{ikt}(\xi)$, they retain the same meaning, but now $t \in T_{ik}$ instead of $t \in T$. In addition, the variables $q_{ikt}(\boldsymbol{\xi})$ are now defined as follows:



(a) Case when there are no lead times between supplier k and DC i.

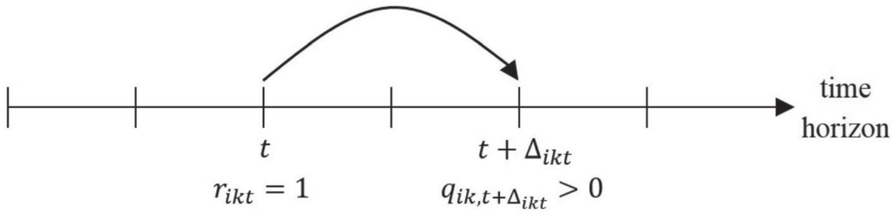


Figure 2. Comparison between the moment an order is placed (beginning of period t) and the time of replenishment without lead times (a), and with lead times (b).

$q_{ikt}(\boldsymbol{\xi})$, the quantity DC $i \in I$ receives from manufacturing factory $k \in K$ during period $t \in T_{ik}$ from an order placed in the beginning of period $t - \Delta_{ikt}$ under demand scenario $\boldsymbol{\xi}$.

To simplify notation, we now consider $q_{ikt}(\boldsymbol{\xi}) = 0, \forall i \in I, k \in K, t \in T \backslash T_{ik}$. This way, $q_{ikt}(\boldsymbol{\xi})$ is defined for all the periods of the planning horizon.

Regarding the first-stage problem, no change is needed. Regarding the second-stage one, given that neither the objective function nor the constraints suffer major alterations, their meaning remains the same. Nevertheless, the formulation needs changing as follows ($\hat{\boldsymbol{\xi}}$ keeps denoting an observation of $\boldsymbol{\xi}$):

$$Q(\boldsymbol{w}, \boldsymbol{x}, \boldsymbol{y}; \hat{\boldsymbol{\xi}}) = \min \quad \sum_{t \in T_{ik}} \sum_{k \in K} \sum_{i \in I} \left(g_{ik,t-\Delta_{ikt}}\, r_{ik,t-\Delta_{ikt}}(\hat{\boldsymbol{\xi}}) + a_{ik,t-\Delta_{ikt}}\, q_{ikt}(\hat{\boldsymbol{\xi}}) \right) + \sum_{t \in T} \sum_{i \in I} h_{it} u_{it}(\hat{\boldsymbol{\xi}}) - \sum_{t \in T} \sum_{s \in T_t} \sum_{j \in J} \sum_{i \in I} p_{ijts} v_{ijts}(\hat{\boldsymbol{\xi}}), \tag{21}$$

$$\text{s.t.} \quad \sum_{k \in K} q_{ikt}(\hat{\boldsymbol{\xi}}) + u_{i,t-1}(\hat{\boldsymbol{\xi}}) = u_{it}(\hat{\boldsymbol{\xi}}) + \sum_{j \in J} \sum_{s \in T_t} v_{ijts}(\hat{\boldsymbol{\xi}}), \quad \forall i \in I,\ t \in T, \tag{22}$$

$$q_{ikt}(\hat{\boldsymbol{\xi}}) \leq M\, r_{ik,t-\Delta_{ikt}}(\hat{\boldsymbol{\xi}}), \quad \forall i \in I,\ k \in K,\ t \in T_{ik} \tag{23}$$

$$r_{ik,t-\Delta_{ikt}}(\hat{\boldsymbol{\xi}}) \leq w_{ik,t-\Delta_{ikt}}, \quad \forall i \in I,\ k \in K,\ t \in t_{ik} \tag{24}$$

$$u_{it}(\hat{\boldsymbol{\xi}}) \leq M\, y_{it}, \quad \forall i \in I,\ t \in T \tag{25}$$

$$v_{ijtt}(\hat{\boldsymbol{\xi}}) + \sum_{s \in T \backslash T_t} v_{ijst}(\hat{\boldsymbol{\xi}}) \leq M\, x_{ijt}, \quad \forall i \in I, j \in J, t \in T \tag{26}$$

$$\sum_{i\in I}\left(v_{ijtt}(\hat{\boldsymbol{\xi}}) + \sum_{s\in T\setminus T_t} v_{ijst}(\hat{\boldsymbol{\xi}})\right) = \hat{\xi}_{jt},$$

$$\forall j \in J, t \in T \tag{27}$$

$$r_{ikt}(\hat{\boldsymbol{\xi}}) \in \{0,1\}, \quad \forall i \in I, k \in K, t - \Delta_{ikt} \in T_{ik}, \tag{28}$$

$$q_{ikt}(\hat{\boldsymbol{\xi}}) \geq 0, \quad \forall i \in I,\ k \in K, t \in T_{ik} \tag{29}$$

$$u_{it}(\hat{\boldsymbol{\xi}}) \geq 0, \quad \forall i \in I, t \in T \tag{30}$$

$$v_{ijts}(\hat{\boldsymbol{\xi}}) \geq 0, \quad \forall i \in I, j \in J, t \in T, s \in T_t. \tag{31}$$

4. Compact reformulations

Abstracting a problem into a model is one thing, but reality is another. In practice, it is unrealistic to think that we accurately know the future demands of retail stores in actual operational processes. However, in the era of big data and artificial intelligence, it is reasonable to assume that we can define a set of potential demand scenarios and estimate their likelihood of occurrence using powerful forecasting methods. This forms the primary foundation for the approach we use to solve the problem under investigation. Therefore, we did not adopt robust optimization methods to handle the uncertainty in this study. In other words, we consider a representative sample of the underlying stochastic process.

In the two-stage stochastic mixed-integer linear models introduced previously, $\boldsymbol{\xi}$ is a $|J| \times |T|$ random matrix. Recall that each entry $\boldsymbol{\xi}_{jt}$ is a random variable representing the demand of retailer $j \in J$ in period $t \in T$. Let Ω be the finite set of demand scenarios elicited as representing the support of the random matrix. For each scenario $\omega \in \Omega$, there is a matrix $\boldsymbol{\xi}^{\omega}$, where each entry ξ^{ω}_{jt} is the demand of retailer $j \in J$ at period $t \in T$ under that scenario. Let parameter π^{ω} denote the probability that demand scenario $\omega \in \Omega$ occurs, where $\pi^{\omega} > 0, \forall \omega \in \Omega$, and $\sum_{\omega\in\Omega} \pi^{\omega} = 1$.

Due to these considerations, the two-stage stochastic models above introduced can be reformulated as compact mixed-integer linear programming models – the so-called extensive forms of the corresponding deterministic equivalents. Notice that only the second-stage decision variables and the constraints involving the random matrix $\boldsymbol{\xi}$ require changing.

We start by ignoring lead times. Consider the following redefinition of the second-stage variables:

$$r^{\omega}_{ikt} = \begin{cases} 1, & \text{if DC } i \in I \text{ places an order at factory } k \in K \text{ in the beginning of period} \\ & t \in T \text{ under demand scenario } \omega \in \Omega, \\ 0, & \text{otherwise} \end{cases}$$

q^{ω}_{ikt}, quantity DC $i \in I$ receives from manufacturing factory $k \in K$ in the beginning of period $t \in T$ under demand scenario $\omega \in \Omega$.

u^{ω}_{it}, quantity that remains in DC $i \in I$ at the end of period $t \in T$ under demand scenario $\omega \in \Omega$.

v^{ω}_{ijts}, quantity DC $i \in I$ sends to retailer $j \in J$ in period $t \in T$ to satisfy their demand from period $s \in T_t$ under demand scenario $\omega \in \Omega$.

Recall that in this problem no DC is operating initially. Thus, we directly set $y_{i0} = 0, \forall i \in I$, and $u^{\omega}_{i0}(\boldsymbol{\xi}) = 0, \forall i \in I, \omega \in \Omega$.

We can reformulate the objective function (1) as follows:

$$\begin{aligned}\varphi(\boldsymbol{w}, \boldsymbol{x}, \boldsymbol{y}) = &\sum_{t\in T}\sum_{i\in I} F_{it}(y_{it} - y_{i,t-1}) + \sum_{t\in T}\sum_{i\in I}\sum_{k\in K} C^1_{ikt} w_{ikt} \\ &+ \sum_{t\in T}\sum_{i\in I}\sum_{j\in J} C^2_{ijt} x_{ijt} + \sum_{\omega\in\Omega}\pi^{\omega}\Bigg(\sum_{t\in T}\sum_{i\in I}\sum_{k\in K}(g_{ikt} r^{\omega}_{ikt} + a_{ikt} q^{\omega}_{ikt}) \\ &+ \sum_{t\in T}\sum_{i\in I} h_{it} u^{\omega}_{it} - \sum_{t\in T}\sum_{s\in T_t}\sum_{i\in I}\sum_{j\in J} p_{ijts} v^{\omega}_{ijts}\Bigg). \end{aligned} \tag{32}$$

The full problem can now be reformulated as follows:

$$\text{minimize} \quad \varphi(\boldsymbol{w}, \boldsymbol{x}, \boldsymbol{y}), \tag{B2}$$

$$\text{subject to} \quad \sum_{i\in I}(y_{it} - y_{i,t-1}) \le n_t, \quad \forall t \in T, \tag{2}$$

$$y_{it} \ge y_{i,t-1}, \quad \forall i \in I, t \in T, \tag{3}$$

$$\sum_{i\in I} x_{ijt} = 1, \quad \forall j \in J, t \in T, \tag{4}$$

$$x_{ijt} \le y_{it}, \quad \forall i \in I, j \in J, t \in T, \tag{5}$$

$$\sum_{k\in K} w_{ikt} = y_{it}, \quad \forall i \in I, t \in T, \tag{6}$$

$$\sum_{k\in K} q^{\omega}_{ikt} + u^{\omega}_{i,t-1} = u^{\omega}_{it} + \sum_{j\in J}\sum_{s\in T_t} v^{\omega}_{ijts}, \ \forall i \in I, \ t \in T, \ \omega \in \Omega, \tag{39}$$

$$q^{\omega}_{ikt} \le M\, r^{\omega}_{ikt}, \quad \forall i \in I, \ k \in K, \ t \in T, \ \omega \in \Omega, \tag{40}$$

$$r^{\omega}_{ikt} \le w_{ikt}, \quad \forall i \in I, \ k \in K, \ t \in T, \ \omega \in \Omega \tag{41}$$

$$u^{\omega}_{it}, \le M\, y_{it}, \quad \forall i \in I, \ t \in T, \ \omega \in \Omega, \tag{42}$$

$$v^{\omega}_{ijtt} + \sum_{s\in T\setminus T_t} v^{\omega}_{ijst} \le M\, x_{ijt}, \quad \forall i \in I, j \in J, t \in T, \ \omega \in \Omega, \tag{43}$$

$$\sum_{i\in I}\left(v^{\omega}_{ijtt} + \sum_{s\in T\setminus T_t} v^{\omega}_{ijst}\right) = \xi^{\omega}_{jt}, \quad \forall j \in J, t \in T, \ \omega \in \Omega, \tag{44}$$

$$r^{\omega}_{ikt} \in \{0, 1\}, \quad \forall i \in I, k \in K, t \in T, \ \omega \in \Omega, \tag{45}$$

$$q^{\omega}_{ikt} \ge 0, \quad \forall i \in I, \ k \in K, t \in T, \ \omega \in \Omega, \tag{46}$$

$$u^{\omega}_{it} \ge 0, \quad \forall i \in I, t \in T, \ \omega \in \Omega, \tag{47}$$

$$v^{\omega}_{ijts} \ge 0, \quad \forall i \in I, j \in J, t \in T, s \in T_t, \ \omega \in \Omega, \tag{48}$$

$$w_{ikt} \in \{0, 1\}, \quad \forall i \in I, k \in K, t \in T, \tag{7}$$

$$x_{ijt} \in \{0, 1\}, \quad \forall i \in I, j \in J, t \in T, \tag{8}$$

$$y_{it} \in \{0,1\}, \quad \forall i \in I, t \in T. \tag{9}$$

Several constraints in the above extensive formulation remain unchanged, with the meaning described in Section 3.

In practice it may be necessary to impose a limit, say N, on the number of DCs that can be setup. This case can be easily embedded in the previous modeling frameworks by considering the following additional constraints:

$$\sum_{i \in I} y_{i|T|} \leq N. \tag{52}$$

This constraint, if needed, should be added as it is to the first-stage models discussed in Section 3.2 and to the mixed-integer linear programming model proposed in this section.

5. Computational results

In this section, we report on a series of computational experiments performed to assess the modeling framework introduced in this paper. We begin by assessing the relevance and feasibility of the proposed model. Subsequently, we conduct a sensitivity analysis on the key parameters, focusing on examining how varying levels of financial resources and lead time affect the supply chain resilience of entrants. In the computational process, a set of instances is first generated. Detailed data generation procedures are provided in the Appendix. For the instances derived from real-world data, the location data is exactly the same as in the actual scenario, and the demand data follows the generation rules specified in the Appendix.

All the experiments were performed in a computer equipped with a 12th Gen Intel(R) Core(TM) i5-12500 3.00 GHz Processor, 8.00 GB RAM, and running Windows 10 Enterprise version 22H2. The optimization models were solved using the MILP algorithms available on the IBM ILOG CPLEX Optimization Studio, version 22.1.0. Unless stated otherwise, the default parameter configuration of the solver is adopted.

5.1. Scalability assessment

The need for designing resilient supply chains has been widely recognized and worked out over the past decades. This has led to the development of so-called resilience evaluation indicators. Following Asheim et al. (2020) and Carvalho et al. (2022) we consider the following:

(1) Percentage of the retailers' demand delivered on time (DDOT (%)) under each demand scenario.
(2) Percentage ratio between the number of open DCs and the number of candidate locations available (DCs ratio (%)).

We point out that 100 instances were generated with up to 10 factories, 50 retailers, and 250 demand scenarios. The first results are presented in Table 2. In this table, the first column specifies the tested instance (See the Appendix for the related details). The second column presents the computing time in seconds. The third and fourth columns present the above indicators: DCs ratio (%) and DDOT (%). For each base instance, we considered both Uniform and Gaussian (Normal) demand distributions, and for each distribution, we tested three different random scenarios. These details are included in the Appendix. We note that all the instances solved to proven optimality returned negative optimal objective function values, which indicates a profit.

The information presented in Table 2 reveals that the instances can be quickly solved by the commercial solver as long as there is available memory. Specifically, the instance that took the longest time (instance 12U, with 2,033,400 decision variables and 2 425,812 constraints) was solved in less than ten minutes. On the other hand, considering instances 11U and 11N, we observe that only one was solvable and yet they comprise the same number of decision variables (1,545,500) and constraints (1,864,812). The only difference in the parameters of these two instances lies in the values for the retailers' demands.

In the scatter plots presented in Figures 3 and 4, we can observe that the majority of the instances that were solved took less than a minute and a half, comprising less than 500,000 decision variables and less than 1,000,000 constraints. It is not surprising that large-scale instances tend to take longer to be solved, but this is not a rule. For example, instance 6N required 328 seconds to be solved, but instance 6U, which has the same number of decision variables and constraints, was solved in less than 37 seconds. This difference may be due to the specificity of the values of the parameters, although such a phenomenon is not frequently observed.

The values for DDOT (%) for each demand scenario from Table 2 are high. This is in some sense positive because it means that in most cases, demand is supplied on time – a feature of practical relevance. Overall, the lowest percentage observed was 83.25% for the fourth demand scenario in instance 24N and the highest was 99.47% for the first demand scenario in instance 7N.

Regarding the values for the DCs ratio (%), from Table 2, we can see that for the majority of the instances, the results dictate that at least half of the potential locations for DCs should be opened. 50 out of the 91 solved instances showed a DC ratio (%) of at least 75%. Moreover, for 30 instances that value is 100%. These results may be highly affected by the values for the fixed cost of locating a DC particularly when compared to the total revenues. This makes us wonder about the impact of financial resources bolstered by Fintech on the resilience of the supply chain.

5.2. Sensitivity analysis under different parameters

In this subsection, we conducted sensitivity analyses on both financial resources and lead time, as these two factors represent key challenges faced by small entrant firms and are also central innovations of this study. After completing the experiments, we provide detailed analysis of the results.

5.2.1. The impact of the financial resources

First, we report on additional results obtained by re-doing the tests above described to understand the impact of the financial resources for installing DCs on the supply chain resilience. We simply multiply the original values of F_{it} by 100. The results from the new experiments are presented in Table 3 and analyzed afterwards.

Table 2. Computing time and resilience evaluation indicators.

Instance	Computing time (sec.)	DCs ratio (%)	DDOT (%)
1U	0.312	70	94.78, 95.57
1N	0.282	70	95.93, 94.70
2U	0.766	60	93.32, 95.18, 95.71, 94.59, 95.47
2N	0.640	60	92.81, 95.97, 95.00, 94.58, 95.26
3U	0.688	60	89.24, 88.74
3N	0.797	60	95.76, 94.61
4U	1.781	100	94.06, 93.76, 93.98
4N	1.813	100	93.97, 93.57, 94.19
5U	13.594	100	90.03, 89.56, 90.73
5N	10.656	100	89.74, 89.55, 90.55
6U	36.328	100	94.81, 94.37, 94.32
6N	328.000	100	94.62, 92.97, 94.87
7U	2.828	40	98.47, 97.49, 98.62
7N	1.687	44	99.47, 98.78, 99.40
8U	5.594	76	91.47, 91.93, 91.50, 91.05, 91.84
8N	5.204	72	91.79, 91.66, 92.26, 92.61, 91.74
9U	35.125	96	94.08, 94.01
9N	36.906	96	94.03, 93.55
10U	15.094	44	93.72, 94.16, 94.27
10N	10.813	44	95.33, 95.46, 95.38
11U	–	*	–
11N	295.047	100	94.93, 94.81, 95.05
12U	571.828	50	94.54, 94.31, 94.14, 93.93, 94.64
12N	508.937	50	94.95, 94.74, 94.77, 94.56, 94.83
13U	41.515	60	88.82, 89.54, 88.07, 88.49, 88.90
13N	41.719	60	88.54, 88.47, 87.22, 88.58, 88.87
14U	0.406	50	83.52, 84.74
14N	0.437	50	83.64, 84.62
15U	3.812	100	92.01, 92.42
15N	3.578	100	92.82, 92.41
16U	10.672	100	93.07, 92.82, 92.64, 92.51, 91.88
16N	10.562	100	93.17, 92.24, 92.34, 92.43, 92.03
17U	4.516	90	96.31, 96.26
17N	2.906	90	96.75, 96.61
18U	3.672	90	96.15, 95.92, 96.36
18N	7.406	90	96.08, 96.01, 96.87
19U	6.360	90	93.69, 94.02, 93.74, 93.71, 93.66
19N	7.672	80	91.33, 91.84, 91.60, 91.97, 91.58
20U	18.516	100	90.14, 90.46, 90.83
20N	21.078	100	90.11, 90.46, 90.78
21U	6.860	100	94.15, 94.69, 94.17
21N	7.312	100	94.73, 93.69, 93.98
22U	1.203	52	96.47, 96.84
22N	1.547	52	96.44, 96.85
23U	2.437	100	95.86, 95.14
23N	2.047	100	95.23, 94.85
24U	23.328	92	84.99, 84.15, 83.73, 83.39, 84.51
24N	25.516	92	85.28, 84.74, 84.21, 83.25, 83.70
25U	7.719	40	94.75, 95.03
25N	7.032	40	94.61, 94.96
26U	10.844	40	94.73, 94.57, 94.30
26N	11.000	40	94.79, 94.56, 94.47
27U	64.375	100	94.32, 94.58, 94.46, 95.10, 94.37
27N	54.484	100	87.76, 87.35, 87.48, 87.75, 87.28
28U	1.032	34	97.84, 96.95
28N	0.813	34	97.32, 97.05
29U	3.719	34	97.76, 96.56, 96.86, 97.91, 97.78
29N	3.844	34	97.29, 96.56, 96.83, 97.18, 97.13
30U	12.891	52	94.84, 94.01, 94.08
30N	13.844	52	95.70, 95.32, 95.12

(*continued*).

Table 2. Continued.

Instance	Computing time (sec.)	DCs ratio (%)	DDOT (%)
31U	–	*	–
31N	–	*	–
32U	–	*	–
32N	–	*	–
33U	0.515	30	97.53, 99.05
33N	0.453	30	98.00, 98.73
34U	2.781	90	97.43, 96.60, 96.29, 96.33, 96.15
34N	2.765	90	97.12, 96.24, 96.53, 96.24, 95.96
35U	9.360	100	93.38, 92.84, 92.36, 92.21, 91.58
35N	9.500	100	92.74, 92.34, 92.62, 92.11, 91.84
36U	2.016	100	95.86, 95.51, 96.13, 96.48, 95.71
36N	3.187	90	97.44, 97.69, 97.86, 97.80, 97.94
37U	5.890	100	95.15, 94.99, 95.11, 95.15, 94.91
37N	6.093	100	95.00, 95.39, 95.27, 95.70, 95.19
38U	4.812	84	98.15, 98.60, 98.69, 98.28, 98.24
38N	3.797	84	97.86, 97.93, 97.68, 98.14, 98.18
39U	17.797	100	97.30, 97.76, 97.85
39N	20.734	100	97.81, 97.81, 97.85
40U	2.969	92	96.65, 97.21
40N	3.079	92	97.07, 96.79
41U	19.187	100	95.94, 95.37
41N	15.281	100	95.89, 95.98
42U	26.125	88	95.90, 96.16, 95.81, 96.37, 95.75
42N	19.438	92	95.31, 95.51, 95.37, 95.88, 96.11
43U	1.485	42	97.12, 96.70
43N	1.312	42	96.64, 94.91
44U	2.000	40	95.70, 97.39, 95.60
44N	2.094	44	96.25, 97.86, 96.18
45U	7.797	58	97.66, 98.39, 97.19, 97.77, 96.93
45N	5.703	56	98.01, 97.04, 97.72, 97.06, 96.95
46U	4.609	46	97.36, 97.26
46N	4.516	44	86.56, 85.26
47U	17.922	70	96.98, 97.56
47N	16.125	68	95.55, 96.08
48U	246.422	100	84.24, 85.17, 85.40, 85.09, 85.18
48N	227.797	100	84.16, 84.76, 84.97, 84.83, 84.68
49U	–	*	–
49N	–	*	–
50U	–	*	–
50N	–	*	–

* Out-of-memory.

When comparing Tables 2 and 3, the differences are noticeable. First, it was possible to solve instances 11U, 31U, and 31N (before, the machine ran out of memory when tackling these instances). Second, instances seem to take longer to be solved and to have lower values for both DCs ratio (%) and DDOT (%) for each demand scenario. Out of the 91 instances that were solved in both situations, in the second run of tests, 73 required a higher computing time. In 77 instances, the difference between the computing times is under one minute, while in only six instances, the difference is greater than five minutes.

Observing Figures 5 and 6 we realize that a large majority of instances were solved in less than five minutes and had at most 500,000 decision variables and 1,000,000 constraints.

In Figure 7, we observe that in both experimental settings (original setup costs and those multiplied by 100), most of the instances were solved in less than a minute, but only in the second set of tests, can we find instances taking longer than ten minutes to be solved. Instances 48N, 31U, and 31N were the ones that took the longest to solve, requiring between

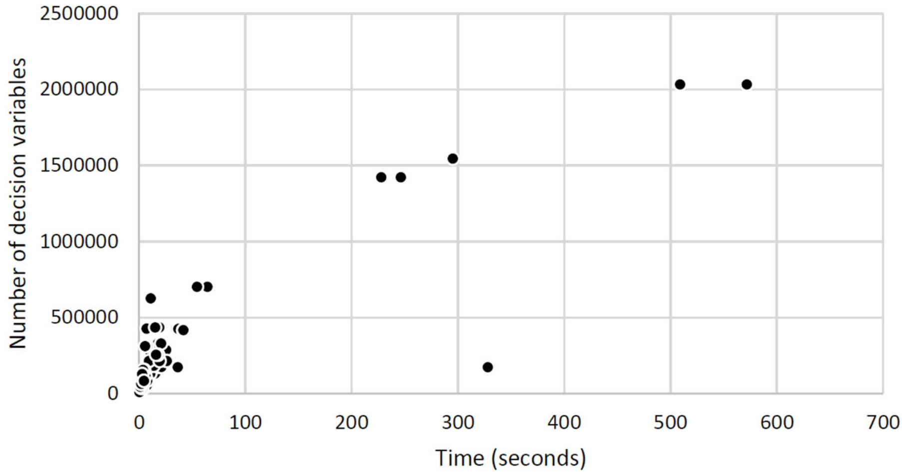


Figure 3. Computing time required to solve an instance versus the number of decision variables.

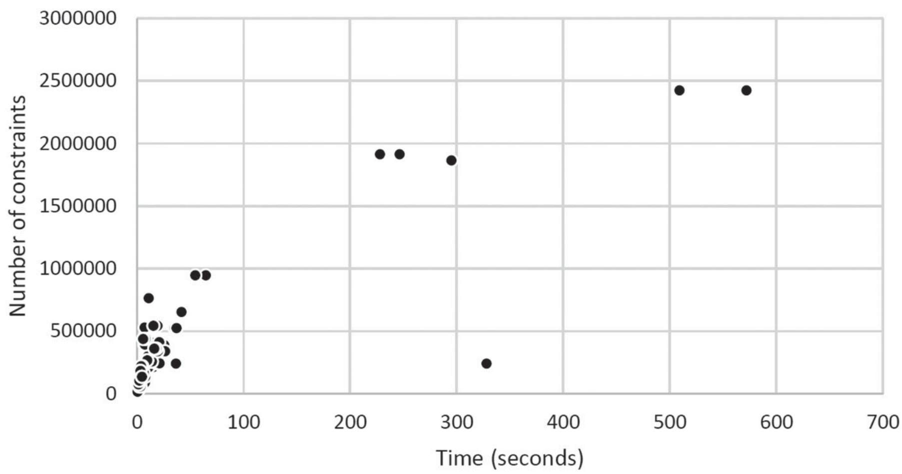


Figure 4. Computing time required to solve an instance versus the number of constraints.

34 and 42 minutes, while instances 1U and 1N were the ones that took the least time to be solved (less than 0.2 seconds).

Regarding the DCs ratio (%) registered for the new experiments, as hypothesized previously, they are lower than those registered in Table 2. In the first group of tests, the majority of instances (52.75%) had DC ratios (%) in the interval (80, 100], while (0, 20] is the interval where we observe the majority of instances from the new group of tests (67.02%). This is a significant difference, indicating that financial resources primarily affect the number of distribution centers constructed in the supply chain. Figure 8 details the variations between these groups.

Given that the DCs ratio (%) registered for the new tests is lower than the original tests, it is expected to see some decrease in the values for DDOT (%) for each demand scenario. Even though this is what occurs, they remain generally high. Only 14 out of the 94 solved

Table 3. Computing time and resilience evaluation indicators – increased fixed costs.

Instance	Computing time (sec.)	DCs ratio (%)	DDOT (%)
1U	0.172	10	87.14, 85.54
1N	0.172	10	87.97, 87.22
2U	0.360	10	85.25, 86.86, 87.76, 86.68, 85.45
2N	0.407	10	86.46, 86.67, 86.17, 85.13, 86.35
3U	0.594	20	87.45, 86.89
3N	0.609	20	87.00, 86.21
4U	5.375	100	47.95, 49.29, 50.92
4N	6.906	20	88.07, 87.02, 87.64
5U	14.110	40	87.34, 85.79, 85.98
5N	11.297	40	86.77, 86.53, 86.20
6U	42.125	100	44.72, 44.08, 44.28
6N	35.813	100	44.70, 44.10, 44.77
7U	1.921	4	88.16, 90.36, 89.58
7N	1.579	4	88.97, 88.29, 87.62
8U	9.906	8	79.29, 77.71, 78.02, 78.42, 78.23
8N	10.359	8	80.00, 78.56, 79.06, 79.22, 79.24
9U	42.531	24	86.16, 86.74
9N	41.704	24	86.75, 87.59
10U	15.328	44	91.95, 92.13, 90.83
10N	13.875	44	91.18, 92.55, 91.50
11U	489.094	100	74.67, 74.83, 75.00
11N	633.687	100	74.58, 74.57, 75.23
12U	1824.406	20	92.69, 93.04, 93.01, 92.55, 92.79
12N	1487.828	20	92.36, 92.26, 92.30, 92.04, 92.42
13U	118.422	10	91.41, 91.36, 90.63, 92.02, 90.83
13N	171.484	10	91.39, 91.64, 90.82, 91.29, 91.21
14U	0.328	10	70.49, 71.39
14N	0.329	10	69.02, 70.68
15U	2.875	20	81.66, 81.63
15N	3.062	20	81.57, 81.77
16U	16.015	20	82.40, 84.07, 81.70, 81.85, 81.84
16N	14.579	20	81.74, 82.63, 81.00, 81.86, 80.80
17U	3.813	30	89.36, 89.00
17N	3.656	30	87.80, 89.22
18U	4.968	30	74.12, 73.11, 72.65
18N	5.719	30	89.19, 89.80, 89.23
19U	7.875	30	52.02, 53.33, 51.65, 51.33, 52.97
19N	12.766	30	88.37, 89.28, 89.32, 89.15, 88.57
20U	21.625	50	68.83, 68.17, 69.01
20N	26.484	50	84.98, 85.61, 85.29
21U	25.297	16	89.24, 89.61, 88.26
21N	25.750	16	88.34, 88.90, 87.75
22U	2.312	8	94.28, 93.10
22N	1.906	8	95.19, 94.66
23U	6.141	16	84.70, 83.49
23N	8.422	16	86.65, 87.72
24U	38.844	12	88.62, 87.45, 88.33, 88.65, 87.91
24N	49.719	12	88.26, 87.34, 88.43, 88.77, 88.35
25U	7.860	20	92.11, 91.08
25N	8.688	20	91.33, 91.25
26U	13.109	20	91.45, 91.64, 91.44
26N	11.000	40	94.79, 94.56, 94.47
27U	64.375	100	94.32, 94.58, 94.46, 95.10, 94.37
27N	54.484	100	87.76, 87.35, 87.48, 87.75, 87.28
28U	1.032	34	97.84, 96.95
28N	0.813	34	97.32, 97.05
29U	3.719	34	97.76, 96.56, 96.86, 97.91, 97.78
29N	3.844	34	97.29, 96.56, 96.83, 97.18, 97.13
30U	12.891	52	94.84, 94.01, 94.08
30N	13.844	52	95.70, 95.32, 95.12

(*continued*).

Table 3. Continued.

Instance	Computing time (sec.)	DCs ratio (%)	DDOT (%)
31U	–	*	–
31N	–	*	–
32U	–	*	–
32N	–	*	–
33U	0.515	30	97.53, 99.05
33N	0.453	30	98.00, 98.73
34U	2.781	90	97.43, 96.60, 96.29, 96.33, 96.15
34N	2.765	90	97.12, 96.24, 96.53, 96.24, 95.96
35U	9.360	100	93.38, 92.84, 92.36, 92.21, 91.58
35N	9.500	100	92.74, 92.34, 92.62, 92.11, 91.84
36U	2.016	100	95.86, 95.51, 96.13, 96.48, 95.71
36N	3.187	90	97.44, 97.69, 97.86, 97.80, 97.94
37U	5.890	100	95.15, 94.99, 95.11, 95.15, 94.91
37N	6.093	100	95.00, 95.39, 95.27, 95.70, 95.19
38U	4.812	84	98.15, 98.60, 98.69, 98.28, 98.24
38N	3.797	84	97.86, 97.93, 97.68, 98.14, 98.18
39U	17.797	100	97.30, 97.76, 97.85
39N	20.734	100	97.81, 97.81, 97.85
40U	2.969	92	96.65, 97.21
40N	3.079	92	97.07, 96.79
41U	19.187	100	95.94, 95.37
41N	15.281	100	95.89, 95.98
42U	26.125	88	95.90, 96.16, 95.81, 96.37, 95.75
42N	19.438	92	95.31, 95.51, 95.37, 95.88, 96.11
43U	1.485	42	97.12, 96.70
43N	1.312	42	96.64, 94.91
44U	2.000	40	95.70, 97.39, 95.60
44N	2.094	44	96.25, 97.86, 96.18
45U	7.797	58	97.66, 98.39, 97.19, 97.77, 96.93
45N	5.703	56	98.01, 97.04, 97.72, 97.06, 96.95
46U	4.609	46	97.36, 97.26
46N	4.516	44	86.56, 85.26
47U	17.922	70	96.98, 97.56
47N	16.125	68	95.55, 96.08
48U	246.422	100	84.24, 85.17, 85.40, 85.09, 85.18
48N	227.797	100	84.16, 84.76, 84.97, 84.83, 84.68
49U	–	*	–
49N	–	*	–
50U	–	*	–
50N	–	*	–

* Out-of-memory.

instances have scenarios with DDOT (%) lower than 75%, and three of them have scenarios with DDOT (%) lower than 50%. The lowest percentage registered is 44.08% from the second scenario in instance 6U and 98.66% from the third scenario in instance 29U is the highest one. In Table 2, 85.7% of the instances have the worst scenario with a DDOT (%) higher than 90%. In the results from the new tests (Table 3), that percentage decreases to 41.5%. This also demonstrates that changes in financial resources significantly impact the resilience of the supply chain, resulting in the inability to meet the demands of most customers in a timely manner. Nonetheless, in 81.9% of the instances, from the new tests, the worst scenario had a DDOT (%) higher than 80%, indicating that our proposed model can ensure the resilience of the supply chain is maintained at a satisfactorily level even in the most adverse conditions.

In the majority of the instances, the DDOT (%) from Table 3 decreased for all scenarios, when compared to those from Table 2. However, instances 13U, 13N, 24U, 24N, 46N, and

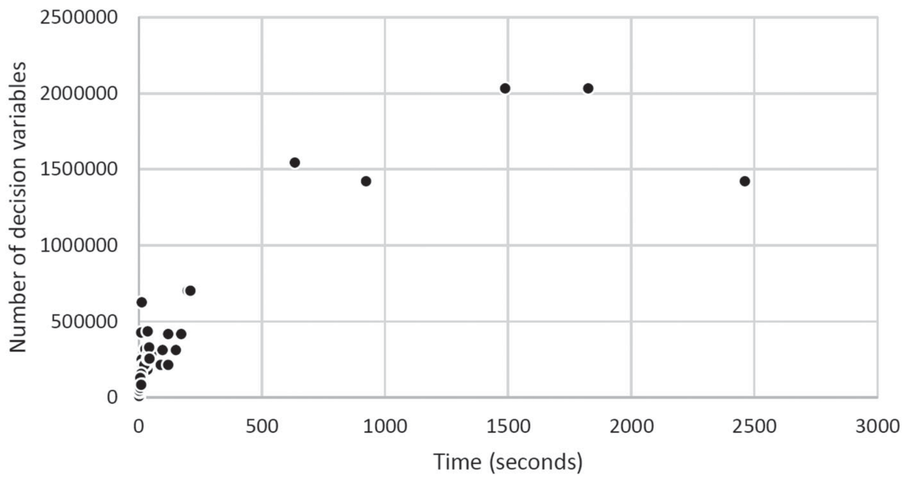


Figure 5. Computing time required to solve an instance versus the number of decision variables.

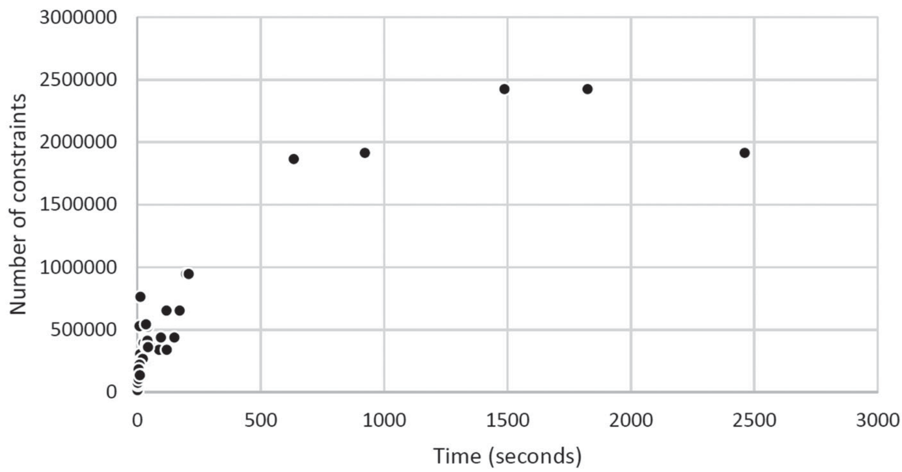


Figure 6. Computing time required to solve an instance versus the number of constraints.

48N showed an increase for all scenarios, while only some scenarios from instances 28N, 29U, and 29N showed an increase (and the remaining scenarios a decrease). In Figure 9, it is possible to observe the differences between the DDOT (%) from all scenarios given the magnitude of the setup costs. The majority of demand scenarios from the first group of tests had a DDOT (%) of at least 90%, while the majority from the second group resulted in values between 85% and 95%. This experimental phenomenon corroborates the conclusions we drew earlier.

In short, the mixed-integer linear programming model proposed in Section 4 works well as it was expected. It was also seen that the values for F_{it} affect decisively the percentage of DCs ratio (%), and the percentages from each demand scenario's DDOT (%) as well. Results from multiple experiments indicate that the financial resources of establishing DCs, such as land usage fees, directly impact the rate at which enterprises set up DCs and also

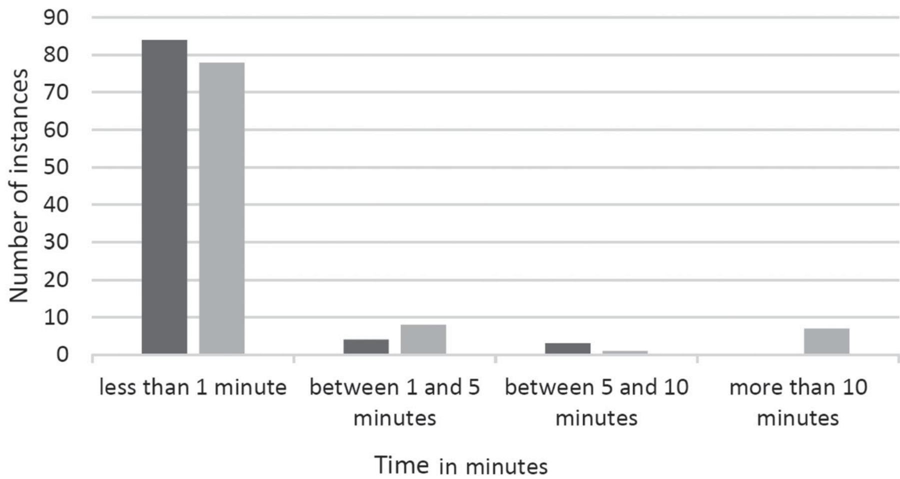


Figure 7. Computing time required to solve the instances according to the magnitude of the setup costs.

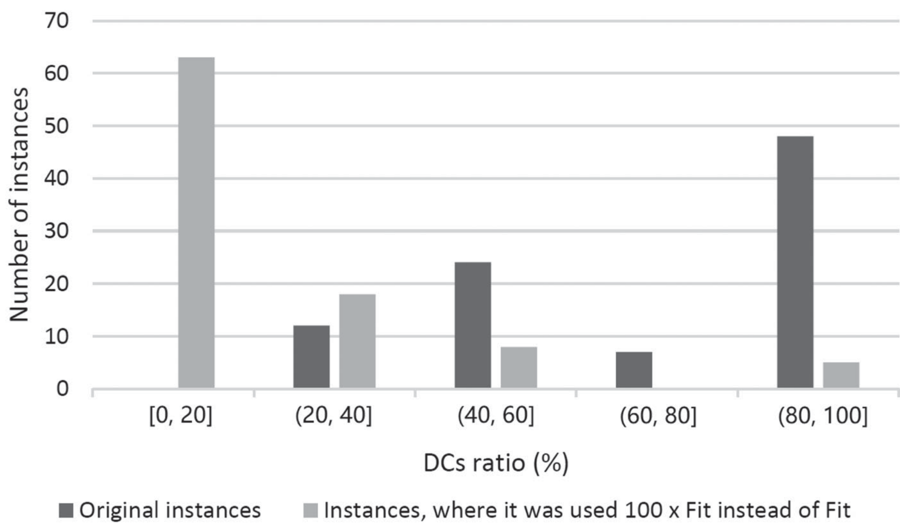


Figure 8. DCs ratios (%) according to the magnitude of the setup costs.

significantly affect the on-time delivery rates for goods by entrants, which in turn means a substantial impact on the supply chain resilience. The experimental results align well with common logic, as investing too much capital in the fixed costs of facilities will inevitably lead to a reduction in other operational investments for the enterprise, thereby positively affecting its operational resilience and service level.

5.2.2. *The impact of the lead time*

An important contribution of our work is the inclusion of the lead time in the supply chain network design problem we are investigating. This naturally raises curiosity about the impact of lead time on the decisions and corresponding operational outcomes.

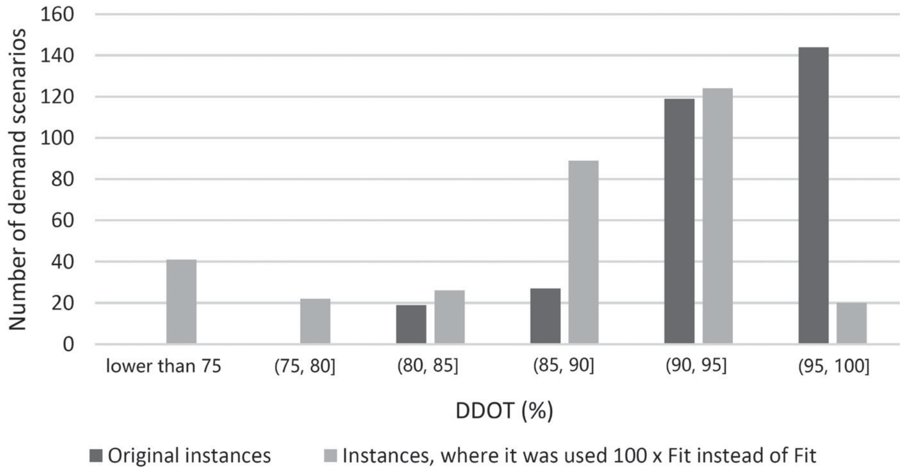


Figure 9. Bar graph of the DDOT (%) by the instances' typology.

To investigate this aspect, in this section, we report on a series of experiments based on the real-world challenges faced by a restaurant chain in Beijing. In particular we focus on the impact of changes in lead time. The studied enterprise has 10 retail stores, 8 potential warehouses, and 4 production factories, with the locations of these facilities shown in Figure 10. The uncertain demand generated by retail stores has three scenarios, corresponding to the average demand during peak, off-peak, and low-peak periods. In the experiments whose results we report next, we worked with different numbers of periods in the planning horizon, namely 10, 15, 20, and 25. Based on this, we worked with values for the lead time ranging from 0 to 5 and calculate the impact of changes in that parameter on the enterprise's decisions and corresponding resilience indicators for different total decision-making periods. The relevance of considering different lengths for the planning horizon and different lead times is also related to the fact that different commodities are at stake in the case we are considering, each calling for a different setting.

It is worth noting that due to the sensitivity of sales demand data for the enterprise, we cannot use the actual data from the aforementioned restaurant company in a widely accessible research paper. Thus, we decided to proceed in this paper by using the data generation method introduced at the beginning of this section to generate the other data parameters for this experiment. Based on this dataset, we can further conduct experiments and sensitivity analysis by using the methods proposed in the above two sections.

Figure 11 depicts the results. The horizontal axis represents the lead time, and the vertical axis represents the corresponding DDOT (%) values. In addition, the green line with stars represents the changes in the enterprise's DDOT (%) value as lead time changes when the total number of decision periods is 10. The black line with circles represents the changes in the enterprise's DDOT (%) value as lead time changes when the total number of decision periods is 15. The red line with diamonds and the blue line with squares represent the scenarios when the total number of decision periods is 20 and 25, respectively. From the trends of the four lines, we can draw the following conclusions:

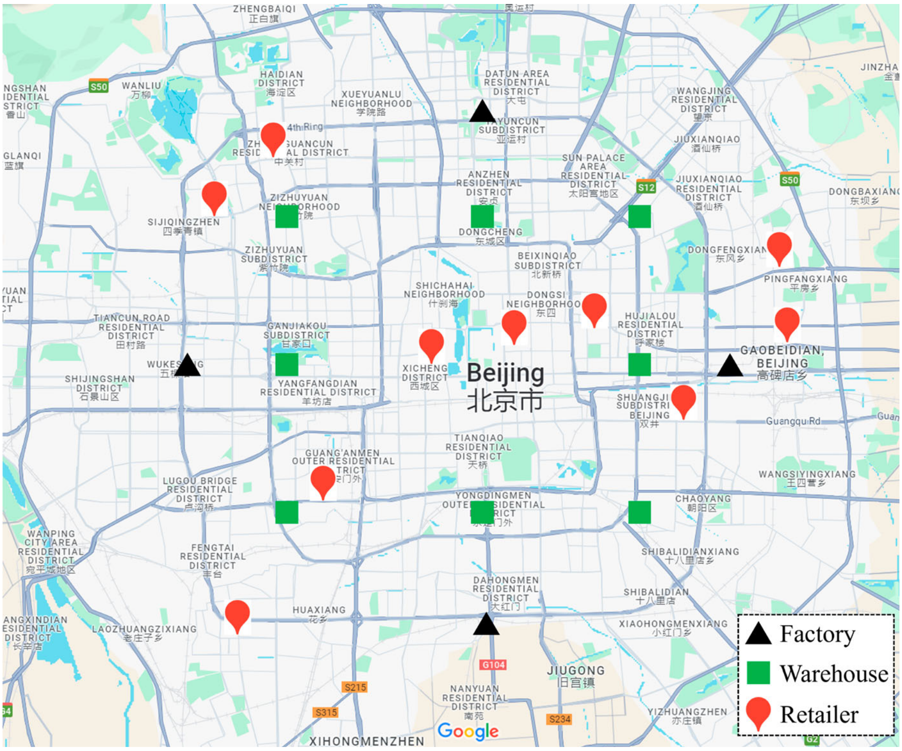


Figure 10. The setting underlying a Beijing catering enterprise.

- The impact of lead time on the studied enterprise is significant with a longer lead time resulting in a lower DDOT (%) irrespective of the length of the planning horizon.
- An increased length in the planning horizon results in an improved DDOT (%) within a certain range. This effect is more pronounced when the lead times are higher. This can be explained by a higher flexibility in the decision-making process provided by a longer planning horizon.
- Finally, there seems to be a plateau for the length of the planning horizon above which it is no longer possible to improve the DDOT (%). In fact, by moving from 20 to 25 periods we do not observe a further increase in the DDOT (%).

6. Conclusions

In this paper, a two-stage stochastic multi-period location-allocation-inventory problem was investigated that can simultaneously tackle stock-outs and lead times. Periodic review was assumed. In the first stage, location and allocation decisions are made. After uncertainty is revealed, adaptive decisions are considered including those related to inventory management. The modeling framework proposed allows an entrant in the market to strategically plan DC locations and manage logistics operations over time under demand uncertainty. An extended model was also proposed to accommodate lead times. Besides,

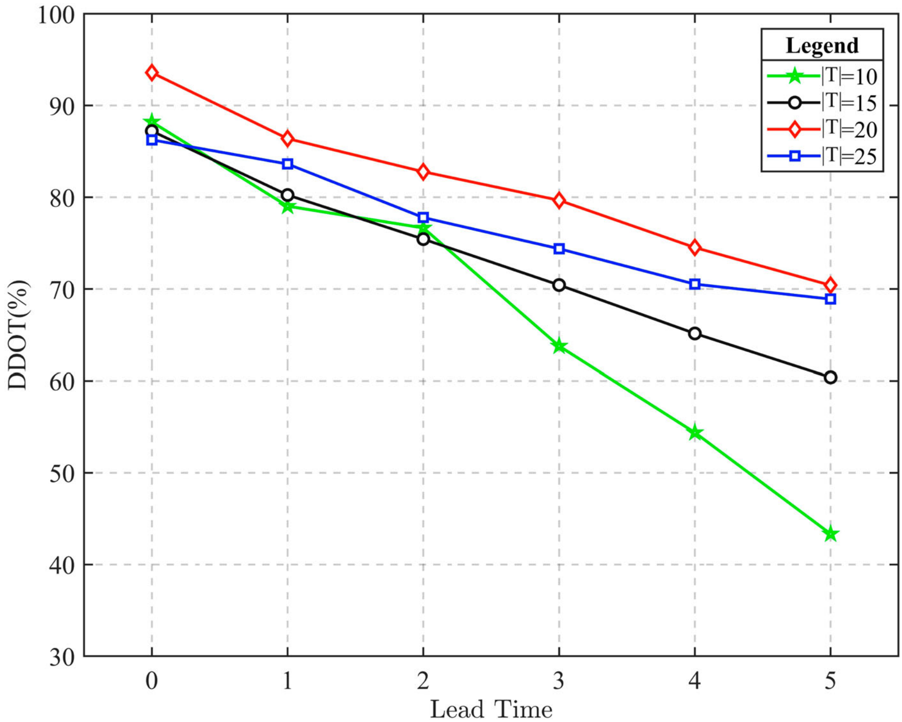


Figure 11. The changes in DDOT(%) under different lead times.

a compact mixed-integer linear programming model was proposed assuming uncertainty reasonably well captured by a finite set of scenarios.

A series of computational tests were conducted, including sensitivity analyses on financial resources and lead time, using both a set of randomly generated instances and instances based on the actual operating environment of an enterprise. Based on the analysis of the experimental results, several management insights for entrants were proposed.

First, entrant firms highlighted in this study should give priority to the strategic allocation of financial resources, particularly when selecting and establishing distribution centers (DCs). Since financial resources have a considerable influence on the decision-making process related to the location and establishment of DCs, prudent management during this early stage can improve the firm's ability to scale its supply capacity more effectively.

Second, lead time plays a vital role in meeting customer demand on time. Firms should make every effort to reduce lead times where possible, as extended lead times can detrimentally affect both customer satisfaction and the firm's operational efficiency. In cases where further reductions in lead time are not viable, the model presented in this study suggests that extending the planning horizon can help boost operational resilience. By planning further ahead, firms can better handle supply and demand uncertainty, thereby improving their overall performance.

However, while extending the planning horizon can contribute to improved performance and resilience, firms should be aware of the law of diminishing returns. Continuously increasing the planning horizon will not indefinitely enhance key performance indicators, and eventually, the costs associated with longer planning cycles may outweigh the benefits. Therefore, firms should carefully assess the balance between extending the planning horizon and other strategic priorities to prevent overburdening their operations and resources. If lead time continues to pose a significant challenge, firms may need to re-evaluate their strategies for lead time reduction. As the firm evolves and market dynamics change, new opportunities for reducing lead time may arise, such as adopting advanced technologies, improving supplier collaborations, or optimizing logistics operations.

The work done opens research avenues that are worth exploring. For example, in each demand scenario, understanding the average time elapsed from the moment a retailer issues an order until it is fulfilled would be valuable for those orders leading to backlog. Another interesting aspect is to analyze the impact of changes in stochastic demand distribution on the resilience indicators.

Additionally, expanding the focus from a single product supply to multiple products could provide further depth to the study. Designing heuristic solution methods for large-scale problems encountered in the real-world is also of great significance. Although two resilience indicators are proposed in this study, expanding the evaluation to include additional metrics such as supply chain flexibility, response speed, and cost-effectiveness would provide a more comprehensive assessment of supply chain resilience.

Finally, the approach proposed in this study can be extended to other areas of operations management, such as hazardous material transportation (Fan et al. 2019; Geng et al. 2024), emergency rescue management (Hong et al. 2023; Zhang et al. 2022), electric charging stations (Wu and Jia 2022; Zhang, Li, and Saldanha-da Gama 2024). By incorporating the unique characteristics of these issues, it is possible to analyze other features of interest to managers.

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Disclosure statement

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Appendix. Data generation

Recall the mixed-integer linear programming problem presented in Section 4. Ten sets of parameters are used out of which eight were already part of the two-stage stochastic linear programming model presented in Section 3. These original parameters are $n_t, F_{it}, h_{it}, C^1_{ikt}, g_{ikt}, a_{ikt}, C^2_{ijt}$ and p_{ijts}, $t \in T, i \in I, k \in K, j \in J, s \in T_t$. The other two are π^ω and ξ^ω_{jt}, where $\omega \in \Omega, j \in J$ and $t \in T$.

In all instances, a uniform distribution across the scenario set is assumed:

$$\pi^\omega = \frac{1}{|\Omega|}, \quad \forall\, \omega \in \Omega.$$

For the remainder parameters, the data generation is based on pseudo-random numbers from a discrete Uniform distribution in $\{a, \dots, b\}$, $a < b$. For each parameter, the values adopted for a and b are presented in Table A1 – *initalMin* and *initalMax*, respectively. By considering discrete Uniform distributions, it is ensured that the obtained values are integers.

The generation of the values $n_t, t \in T$, is accomplished according to Algorithm A1. For each time period, a pseudo-random number is generated (according to the values stated in Table A1). For the first period, if the generated number is zero, then one DC can be opened at that period.

The data generation procedure for parameters F_{it}, h_{it}, C^1_{ikt}, g_{ikt}, a_{ikt}, and C^2_{ijt} is given by Algorithm A2. Although similar, it is not equal to the previous procedure. First, notice that all parameters are indexed in $t \in T$. To simplify the explanation, let the remaining indices be known as the "situational indexes". For instance, the "situational indexes" of C^1_{ikt} are $i \in I$ and $k \in K$. Just like in the process of generating the values of n_t, for this group of parameters, their values will be pseudo-random numbers from a discrete Uniform distribution. However, it will not be the discrete Uniform

Table A1. Table for generating parameters.

Parameter	*initalMin*	*initalMax*
n_t	0	$\frac{\lvert I \rvert}{2}$
F_{it}	10,000	50,000
C^1_{ikt}	100	500
C^2_{ijt}	100	500
g_{ikt}	50	200
a_{ikt}	1	25
h_{it}	1	30
p_{ijts}	10	60
ξ^{ω}_{jt}	100	1000

distribution in $\{initalMin, \dots, initialMax\}$. Instead, to create extra diversity, for each group of situational indexes, the values of *initalMin* and *initialMax* will be replaced by *newMin* and *newMax*, which are obtained according to Algorithm A3. This algorithm is designed so that it is impossible that these new values are negative or that *newMax* is inferior to *newMin*. Its main goal is to introduce more variability into the data to be generated.

Algorithm A1: Data generator for n_t.

Input: *initalMin*, *initialMax*
Output: n_t
for *each* $t \in T$ **do**
  $n_t \leftarrow Uniform\{initalMin, initialMax\}$
  if $t = 1$ *and value* $= 0$ **then**
    $n_t \leftarrow 1$

Algorithm A2: Data generator for F_{it}, h_{it}, C^1_{ikt}, g_{ikt}, a_{ikt} and C^2_{ijt}.

Input: *initalMin*, *initialMax*
Output: F_{it}, h_{it}, C^1_{ikt}, g_{ikt}, a_{ikt} and C^2_{ijt}
for *each situational index* **do**
  $(newMin, newMax) \leftarrow NewLimits(initalMin, initialMax)$
  for *each* $t \in T$ **do**
    $value \leftarrow Uniform\{newMin, newMax\}$

Regarding the parameter p_{ijts}, the reasoning underlying Algorithm A2 is used, but with a twist. Recall that p_{ijts} refers to the unit revenue obtaining from supplying retailer $j \in J$ from DC $i \in I$ in period $t \in T$ to satisfy the retailer's demand of period $s \in T_t = \{1, \dots, t\}$). When $t = s$, the product is sold at the period it is requested. When $t \neq s$, the product is being sold with a delay of $t-s$ periods. For this reason, the values generated for this parameter obey the following rule: for each period that the delivery is delayed, the retail store may be given a non-specified discount. Algorithm A4 formalizes the procedure.

When it comes to the generation of retailers' demands two possibilities were considered: In the first, it is assumed that the demand follows a Uniform distribution, and therefore Algorithm A2 is

Algorithm A3: New limits generator.

Input: *oldMin*, *oldMax*
Output: *initalMin*, *initialMax*
Function `NewLimits`(*oldMin*, *oldMax*)**:**
    $u_0, u_1, u_2 \leftarrow Uniform\{0, 100\}$
    $v_1, v_2 \leftarrow Uniform\{\lfloor \frac{oldMin \times u_0}{100} \rfloor, \lceil \frac{oldMax \times u_0}{100} \rceil\}$
    $w \leftarrow 1$
    if $u_1 < 50$ *and* $v_1 < oldMin$ **then**
        $w \leftarrow -1$
    $newMin \leftarrow oldMin + w \times v_1$
    $w \leftarrow 1$
    if $u_2 < 50$ *and* $v_2 < oldMax - newMin$ **then**
        $w \leftarrow -1$
    $newMax \leftarrow oldMax + w \times v_2$
    return *newMin*, *newMax*

adopted. Note that in this case, $\omega \in \Omega$ is part of the "situational indexes". In the second possibility, a Gaussian distribution is assumed. The expected value chosen is the average of the values obtained after applying Algorithm A3; the standard deviation is the absolute value of the subtraction of the chosen expected value with the average of *initialMin* and *initialMax*. When generating the values, only those between the limits defined are accepted.

Algorithm A4: Data generator for p_{ijts}.

Input: *initalMin*, *initialMax*
Output: p_{ijts}
for *each* $i \in I$ *and* $j \in J$ **do**
    $(newMin, newMax) \leftarrow NewLimits(initalMin, initialMax)$
    for *each* $t \in T$ *and* $s \in T_t$ **do**
        if $t = s$ **then**
            $p_{ijts} \leftarrow Uniform\{newMin, newMax\}$
        else
            $p_{ijts} \leftarrow Uniform\{newMin, p_{ij,t-1,s}\}$

The algorithms presented in this section were implemented in C++ programming language using Eclipse IDE. As inputs, the user only needs to indicate the dimensions of the sets K, I, J, T, and Ω. Two different instances are generated, that differ on the costumers' demand data. In one case it is generated using the Uniform distribution and in the other using the Normal distribution, as described previously. Two files are generated. A txt file is created that allows a user to easily read the data. It contains both retail stores' demand cases. A dat file is also created that is prepared to be directly loaded by CPLEX.

The dimensions of sets K, I, J, T and Ω of the instances generated are listed in Table A2. The letters "U" and "N" next to the instances' number refer to the retail stores' demand generation process:

Algorithm A5: Data generator for ξ_{jt}^{ω} with normal demand.

```
Input: initalMin, initialMax
Output: ξ_jt^ω
for each i ∈ I and j ∈ J do
    (newMin, newMax) ← NewLimits(initialMin, initialMax)
    initialMean ← (initalMax + initalMin) / 2
    newMean ← (newMax + newMin) / 2
    diff ← |initialMean − newMean|
    for each t ∈ T do
        Repeat
        ξ_jt^ω ← Gaussian{newMin, newMax}
        Until newMin ≤ ξ_jt^ω ≤ newMax
```

Uniform and Gaussian (Normal) distributions, respectively. In this table, the number of decision variables and constraints are also indicated. It is expected that the set whose dimension has the largest impact on the number of decision variables and constraints is T (it is present in all of them). On the other hand, K is expected to have the least impact, since it is only present in three groups of decision variables and in about a quarter of the constraints' groups.

Table A3 shows, for each set, the number of instances being considered per set dimension for a type of retailers demand generation method.

To observe the relationship between the number of decision variables and the number of constraints, these values are depicted in a scatter plot presented in Figure A1. It appears that the latter increases linearly concerning the former, which is in line with our understanding.

Table A2. Instances' dimensions and characteristics.

Instance	$\|K\|$	$\|I\|$	$\|J\|$	$\|T\|$	$\|\Omega\|$	# Variables	# Constraints
1U, 1N	3	10	50	3	2	8040	13, 533
2U, 2N	3	10	50	3	5	17, 670	28, 833
3U, 3N	3	10	100	3	2	15, 540	25, 983
4U, 4N	3	10	100	6	3	70, 500	98, 466
5U, 5N	3	10	100	12	3	249, 000	304, 932
6U, 6N	3	10	250	6	3	174, 000	241, 566
7U, 7N	3	25	50	3	3	28, 125	45, 678
8U, 8N	3	25	50	6	5	144, 600	197, 706
9U, 9N	3	25	100	12	2	425, 400	524, 412
10U, 10N	3	25	250	3	3	133, 125	213, 078
11U, 11N	3	25	250	12	3	1, 545, 500	1, 864, 812
12U, 12N	3	50	100	12	5	2, 033, 400	2, 425, 812
13U, 13N	3	50	250	3	5	418, 350	654, 153
14U, 14N	5	10	50	3	2	8, 340	14, 073
15U, 15N	5	10	50	12	2	87, 360	110, 292
16U, 16N	5	10	50	12	5	208, 320	255, 372
17U, 17N	5	10	250	3	2	38, 340	63, 873
18U, 18N	5	10	250	3	3	53, 670	87, 813
19U, 19N	5	10	250	3	5	84, 330	135, 693
20U, 20N	5	10	250	6	3	174, 840	243, 126
21U, 21N	5	25	50	12	3	319, 200	393, 012
22U, 22N	5	25	100	3	2	39, 600	64, 953
23U, 23N	5	25	100	6	2	124, 200	174, 906
24U, 24N	5	25	100	6	5	286, 650	389, 556
25U, 25N	5	25	100	12	2	428, 400	529, 812
26U, 26N	5	25	100	12	3	626, 700	762, 912
27U, 27N	5	25	250	6	5	702, 900	946, 206
28U, 28N	5	50	50	3	2	41, 700	68, 553
29U, 29N	5	50	50	3	5	91, 650	146, 853
30U, 30N	5	50	50	6	3	184, 200	256, 806
31U, 31N	5	50	250	6	5	1, 405, 800	1, 883, 406
32U, 32N	5	50	250	12	5	5, 061, 600	6, 016, 812
33U, 33N	10	10	50	3	2	9, 090	15, 423
34U, 34N	10	10	50	6	5	62, 460	88, 986
35U, 35N	10	10	50	12	5	214, 920	267, 972
36U, 36N	10	10	100	3	5	36, 480	59, 643
37U, 37N	10	10	100	6	5	117, 960	164, 286
38U, 38N	10	25	50	6	5	156, 150	219, 756
39U, 39N	10	25	50	12	3	329, 700	412, 512
40U, 40N	10	25	100	6	2	127, 950	181, 656
41U, 41N	10	25	100	12	2	435, 900	543, 312
42U, 42N	10	25	250	3	5	214, 950	340, 353
43U, 43N	10	50	50	3	2	45, 450	75, 303
44U, 44N	10	50	50	3	3	63, 600	104, 403
45U, 45N	10	50	50	6	5	312, 300	437, 706
46U, 46N	10	50	100	3	2	82, 950	135, 753
47U, 47N	10	50	100	6	2	255, 900	361, 506
48U, 48N	10	50	250	6	5	1, 422, 300	1, 914, 906
49U, 49N	10	50	250	12	3	3, 119, 400	3, 772, 212
50U, 50N	10	50	250	12	5	5, 094, 600	6, 079, 812

Table A3. Table for generate parameters.

Set	K			I			J			T			Ω		
Dimension	3	5	10	10	25	50	50	100	250	3	6	12	2	3	5
Frequency	13	19	18	18	17	15	19	16	15	19	16	15	16	14	20

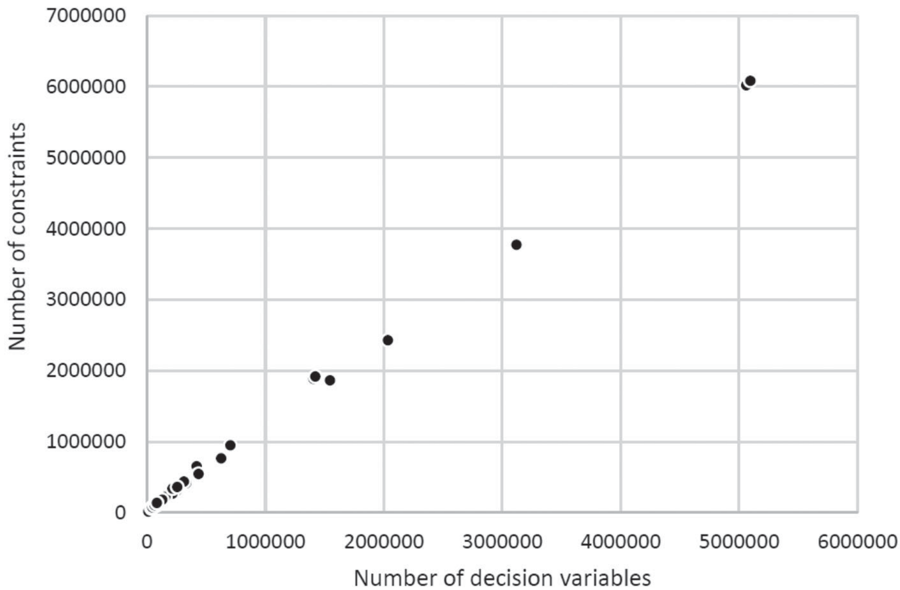

Figure A1. Scatter plot of the number of decision variables and number of the constraints.