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Modeling Critical Resource Allocation and Sharing under Pandemic Situation

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Abstract *–During pandemics and epidemics, healthcare systems may respond quickly to massive increases in demand by establishing surge capacity in facilities. However, adding new resources may not be the most effective approach. Given the inherent uncertainty of demand during pandemics, this paper develops a stochastic optimization model designed to improve the allocation and sharing of critical resources. The objective is to enhance the responsiveness of healthcare systems to substantial surges in demand during pandemics. The model integrates warehouse selections for vendor-managed inventory (VMI), inventory policies, and delivery decisions to investigate a healthcare supply network configuration problem. This problem considers multiple sourcing, various products, multiple periods, and lateral transshipment. Numerical experiments are conducted to verify the advantage of the proposed stochastic model, which, despite its higher overall cost, demonstrates its superiority over the deterministic approach. The results further indicate that resource sharing can significantly improve the resilience of healthcare systems and enhance patients' access to care during pandemics.*

Keywords– Epidemics/pandemics, Healthcare supply chain, Resource sharing, Stochastic programming, vendor-managed inventory.

I. INTRODUCTION

A pandemic is the global spread of an infectious disease that affects a significant portion of the world's population. Throughout human history, we have experienced several catastrophic pandemics, with the Black Death and the 1918-1919 flu pandemic being the most devastating. The Black Death, which ravaged Europe, Africa, and Asia from 1346 to 1353 and is believed to have been caused by the plague, is estimated to have killed 75 to 200 million people. Similarly, the 1918-1919 influenza pandemic, often referred to as the "Spanish flu," also caused the deaths of approximately 20 to 40 million people (MPHonLine, 2020).

The most recent significant global outbreak is Coronavirus Disease 2019 (COVID-19), officially declared a pandemic by the World Health Organization on March 11, 2020. Since its emergence in China, this pandemic has infected over 670 million individuals worldwide and has tragically resulted in more than 6.5 million deaths (Johns Hopkins Coronavirus Resource Center, 2020). The main challenge posed by the COVID-19 outbreak has been a significant increase in demand for vital medical resources, including personal protective equipment (PPE), medicines, and ventilators (Barrett et al., 2020; Li et al., 2020; Paul & Chowdhury, 2021; Remko, 2020). This surge led to a global shortage of healthcare resources (Chamola et al., 2020; Grimm, 2021; Litton et al., 2021; Sen-Crowe et al., 2021; Winkelmann et al., 2022). Therefore, suppliers face a great challenge in efficiently delivering these resources to demand sites.

Inspired by this insight, this paper aims to design an efficient healthcare supply chain network. To minimize transportation costs and improve the level of service, the supplier selects specific locations for the construction of

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warehouses for storing critical resources. These selected warehouses are then strategically allocated to surrounding demand locations, with the supplier retaining control over the management of the products stored within them. This approach involves implementing a vendor-managed inventory (VMI) strategy. Delivery of products to demand locations is facilitated through direct shipment services. The complexity of the task lies in simultaneously determining VMI storage locations within the healthcare system, assigning demand locations, creating inventory policies, and developing a resource distribution plan. The overarching goal is to minimize costs while effectively meeting demand requirements.

Within a network of facilities, like medical centers, one effective strategy for enhancing performance is transshipment. Lateral transshipment involves the transfer of stocks between locations within the same tier of an inventory system. Essentially, this method involves redistributing inventory across the network to bring about balance. In essence, transshipment can be an effective means to align the existing disparity between the current or future demand and the inventory of products among demand sites. Furthermore, transshipment enhances demand sites' ability to address shortages more efficiently by utilizing nearby sites' stocks. Thus, in our problem, we consider mutual regions that can share a portion of their in-hand inventory with nearby demand sites in emergencies.

The problem involves integrating strategic, tactical, and operational decisions within the healthcare network. At the strategic level, the decision involves determining the optimal quantity and location for warehouses, as well as assigning demand sites to these warehouses. Poor decisions in warehouse locations can lead to service deficiencies and increased overall expenses. Furthermore, the allocation of each demand site directly impacts shipping costs.

Once established, the VMI warehouse plays a central role in stocking and delivering products to assigned locations. Therefore, the tactical challenge is to determine the appropriate inventory level while complying with the VMI policy. Excessive inventory increases storage costs and can exceed warehouse capacity, while insufficient inventory can lead to product shortages. The ideal inventory level is affected by various factors, including storage locations, requirements of the locations served, storage costs, delivery costs, and storage capacity. This tactical decision issue is intertwined with the strategic challenge, necessitating the supplier to consider VMI warehouse location and inventory decision simultaneously. The operational one involves the periodic distribution of critical resources to demand sites.

To model this context, considering inherent demand uncertainty during a pandemic, a two-stage healthcare supply chain network model is adopted.

The main contributions of this paper are summarized as follows: First, a resilient healthcare supply chain in the response phase of a pandemic is introduced. Second, a decision framework is proposed for optimizing facility location decisions in conjunction with VMI strategy, warehouse size, inventory management, lateral transshipment, and resource distribution plans within the healthcare supply chain network. This paper also considers some features including managing multiple products as well as addressing wastage and shortage. Third, a two-stage stochastic programming approach is applied to adapt to the uncertain demand inherent in pandemic scenarios.

The remainder of this paper is structured as follows. Section 2 provides a review of related literature on healthcare supply chain network design in the epidemic/pandemic context. In Section 3, a modeling framework is described, and the mathematical formulation of the two-stage stochastic programming model is presented. In Section 4, numerical experiments are conducted. Finally, in section 5, we concluded the paper concludes.

II. LITERATURE REVIEW

Optimal distribution of resources is of paramount importance in various sectors, particularly in disease control and disaster relief, where resources are often limited (Cao & Huang, 2012; Gupta et al., 2016; Khadem et al., 2021; Mohammadi et al., 2021). The urgency of this matter has been highlighted during the COVID-19 pandemic when critical resources such as personal protective equipment (PPE), testing kits, hospital beds, ventilators, and vaccines require strategic allocation at all levels (Emanuel et al., 2020). To address the need for optimized ventilator allocation, Bertsimas et al. (2021) developed a deterministic optimization model. Their approach facilitates the sharing of ventilators between hospitals in different US states. Lampariello & Sagratella (2021) addressed a single-period allocation problem for COVID-19 test kits to optimize utility functions related to disease detection capabilities in various geographical areas. Santini (2021) examined the effective distribution of swabs and reagents to laboratories to maximize the volume of COVID-19 tests performed. This challenge was addressed by creating a deterministic integer programming model that involves sharing swabs and reagents between different laboratories over an extended planning horizon. By focusing attention on the distribution of personal protective equipment, particularly surgical and respiratory masks, in health centers struggling with extremely low supplies, Dönmez et al. (2022) developed a multi-period, multi-objective, non-linear resource allocation model. Their goal was to reduce the deprivation costs associated with shortages while minimizing infections among patients and healthcare workers.

In dealing with uncertain demand, Mehrotra et al. (2020) used stochastic programming methods and generated various scenarios to represent unpredictable patient numbers resulting from the uncertain spread of the disease. The objective was to redistribute and share medical resources between different hospitals. Yin et al. (2023) extended the approach to a multi-stage stochastic programming model that incorporated evolving transmission dynamics and took into account risk-averse considerations. It is important to note that these studies focused on resource allocation and redistribution among established facilities in specific regions and ignored the decision-making process regarding facility locations and associated capacities. Liu et al. (2023) addressed the problem of locating testing facilities to meet the fluctuating demand for test kits during pandemics. The introduced optimization framework was divided into two phases: the first phase involved pre-positioning strategies to meet predetermined fill rate requirements, and the second phase involved dynamically adapting capacity to changing demand. Meanwhile, Li et al. (2023) examined a mask production planning issue associated with uncertain demand during the COVID-19 pandemic. This problem involved assembly line balancing and capacitive lot sizing, which were addressed through a two-stage stochastic model from a risk-averse perspective. Fattahi et al. (2023) studied resource planning strategies to enhance healthcare system responses during epidemics and pandemics. They aimed to optimize access to patient care without extensive capacity expansion within pandemic time constraints by targeting different patient types and resources. The research employed a multi-stage stochastic program and an agent-based stochastic model to simulate uncertain parameters, providing a data-driven rolling horizon procedure for real-time decision-making. Vahdani et al. (2023) considered two consumable and reusable products to address the problem of multi-period production-inventory-sharing to reduce medical product shortages. They suggested a customized compartmental susceptible-exposed-infectious-hospitalized-recovered-susceptible (SEIHRS) epidemiological model with a control policy, which included an element considering the impact of people's behavioral responses to their awareness of appropriate precautions. The model was solved by an accelerated Benders decomposition-based algorithm with customized valid inequalities. Ultimately, the COVID-19 pandemic in France was taken into consideration as a realistic case study to assess the decomposition method's computational ability. In the aftermath of the COVID-19 pandemic, Alizadeh et al. (2024) presented a scenario-based two-stage stochastic programming model for designing a green closed-loop supply chain network. The uncertainty of greenhouse gas emissions was addressed in various possible scenarios. Using an accelerated Benders decomposition algorithm, the researchers solved the mathematical model across multiple dimensions and then analyzed and evaluated the results in different scenarios. Kiss & Elhedhli (2024) explored a resource pooling problem and proposed a strategy to increase capacity by acquiring distribution and warehousing capacity from private transport companies in exchange for compensation. They presented a model for capacity procurement and PPE distribution planning assuming sufficient supply to efficiently secure storage and distribution capacity from external sources and meet demand. For scenarios of inadequate supply, they developed a priority-based model that took the severity of the pandemic into account. To address the uncertain demand, they used a two-stage stochastic programming approach with recourse and solved the problem using Benders decomposition and sample average approximation techniques.

Adopting a robust optimization approach, Manupati et al. (2021) focused on establishing convalescent plasma bank facilities dedicated to the treatment of COVID-19. The main objective was to identify the most effective locations for plasma banks and strategically allocate plasma collection facilities to ensure optimized plasma flow while minimizing losses due to plasma perishability. To achieve this, they developed a robust mixed-integer linear programming (MILP) model that optimized both the total supply chain costs and the transportation time of plasma while taking storage costs into account to reduce waste. Baloch et al. (2022) shifted their focus to optimizing underutilized distribution networks to improve government delivery networks for critical healthcare resources. The research addressed dynamic distribution planning, including repurposing storage facilities, demand distribution, and timely distribution of PPE across jurisdictions. The goal was to maximize demand fulfillment while optimizing economic value for participating networks. To deal with supply uncertainty, they used a robust framework that provided a mixed-integer programming formulation for the adversarial problem. Shang et al. (2022) addressed a supply network configuration issue influenced by a real-world scenario in the healthcare supply sector. Their research incorporated optimization of warehouse location, inventory, and delivery routing, with a focus on vendor-managed inventory. Basciftci et al. (2023) presented a moment-based distributionally robust optimization approach to address uncertainty in disease transmission while identifying optimal locations for distribution centers as well as their capacities, shipping volumes, and inventory levels. Their study included numerical experiments that analyzed the distribution of COVID-19 vaccines in the United States and testing kits in Michigan under various possible scenarios.

This study relates to the field of facility location under uncertain conditions. When there is knowledge or accurate estimation of the distribution of uncertain parameters, facility location problems are often presented as stochastic programs, aiming to optimize expected total costs in a risk-neutral context (Dönmez et al., 2021; Govindan et al., 2017; Kundu et al., 2022). However, in certain situations, like the one examined in this study, it is necessary to incorporate operational decisions into this strategic-level issue. This research expands upon this area by addressing decisions related to facility location and capacity, taking into account factors like inventory, shipments, and unmet demand, all within a two-stage stochastic programming framework. While prior studies have addressed uncertain demand in facility planning, a comprehensive decision framework for optimizing facility location decisions in conjunction with VMI strategy, multi-period capacity allocation, inventory management, lateral transshipment, and resource distribution plans within a healthcare supply chain network that handles multiple product types has not been considered. Thus, this paper contributes to the facility location literature by addressing this complex setting through a two-stage stochastic optimization approach. Table I presents a summary of the reviewed related references to give a clear overview of the innovations presented in this paper.

Table I. Classification of the relevant papers.

References	Modeling method	VMI	Product	Decisions			
				L	I	D	T
Mehrotra et al. (2020)	Two-stage SP		Single		✓	✓	✓
Bertsimas et al. (2021)	Deterministic		Single		✓	✓	✓
Lampariello and Sagratella (2021)	Deterministic		Single			✓	
Manupati et al. (2021)	RO		Single	✓	✓	✓	
Santini (2021)	Deterministic		Single		✓	✓	
Baloch et al. (2022)	RO		Single		✓	✓	
Dönmez et al. (2022)	Deterministic		Single		✓	✓	
Shang et al. (2022)	RO	✓	Multi	✓		✓	
Basciftci et al. (2023)	RO		Single	✓	✓	✓	
Fattahi et al. (2023)	Multi-stage SP		-		✓		✓
Vahdani et al. (2023)	SEIHRS model		Multi		✓	✓	✓
Liu et al. (2023)	Two-stage SP		Single	✓	✓	✓	
Yin et al. (2023)	Multi-stage SP		Single	-	-	-	-
Li et al. (2023)	Two-stage SP		Single	✓	✓		
Alizadeh et al. (2024)	Two-stage SP		Multi		✓	✓	
Kiss and Elhedhli (2024)	Two-stage SP		Single	✓		✓	
This paper	***Two-stage SP***	✓	***Multi***	✓	✓	✓	✓

L: Location; I: Inventory; D: Distribution; T: Transshipment.

III. PROBLEM DEFINITION AND MODEL FORMULATION

A. Problem description

In a pandemic response phase, a two-echelon healthcare supply chain is considered, comprising VMI warehouses and medical centers. The supplier provides a variety of medical products for open VMI warehouses. Medical centers are assigned to specific open VMI warehouses, and emergency demands are fulfilled by their respective assigned warehouse. To address critical resource shortages during a pandemic, this paper also incorporates lateral transshipment, allowing demand sites to share emergency supplies from their inventories with other demand sites in the network. The planning horizon spans multiple periods. When an order is received, products are shipped directly to the demand sites. It is important to note that this is a multi-sourcing supply chain, meaning that a demand site can receive emergency supplies from one or more VMI warehouses within its coverage radius.

Decisions are made in two stages. The first stage focuses on selecting VMI warehouse locations, determining their size, assigning each medical center to a VMI warehouse, and establishing order quantities. In the second stage, with the revelation of pandemic information, the decision-maker devises the daily distribution plan of critical resources to medical centers. In addition, the transshipment flow between medical centers is made to optimize the matching of resource supply and demand throughout the healthcare supply chain network. The objective is to minimize the total cost, encompassing both the first and second stages of the healthcare supply chain network within a specified planning horizon.

B. Problem assumption and notation

The modeling is based on the following assumptions:

- A maximum service distance (β) is set to ensure that all demand sites have an equal chance of receiving prompt service. Responsive service regions are denoted by the variable ϕ_i.
- Facilities are selected with appropriate initial capacity in the first period and are not destroyed later.
- The supplier has enough capacity to manufacture the products.
- The demand for products in each period is stochastic.
- The shortage of products in demand sites is permissible, which is reflected by unsatisfied demand.
- Demand sites with excess inventory may transfer the additional portion to demand sites with additional needs.
- Multi-sourcing is allowed; the demand site can receive products from one or more VMI warehouses within its coverage radius.

The sets, the parameters, and the decision variables used in the model are given below.

Table II. Sets and indices for the healthcare supply chain network problem.

Notation	Definition
I	The set of demand sites, indexed by $i, h \in I := \{1,2,\dots,I\}$.
J	The set of candidate VMI warehouses sites, indexed by $j \in J := \{1,2,\dots,J\}$.
K	The set of VMI warehouses sizes, indexed by $k \in K := \{1,2,\dots,K\}$.
M	The set of critical medical product types, indexed by $m \in M := \{1,2,\dots,M\}$.
T	The set of time periods, indexed by $t \in T := \{1,2,\dots,T\}$.
S	The set of scenarios, indexed by $s \in S := \{1,2,\dots,S\}$.

Table III. Input parameters for the healthcare supply chain network problem.

Notation	Definition
F_k	The fixed cost to open a VMI warehouse with capacity level k.
C_m	Unit ordering cost for a resource of type m.
Cap_k	The storage capacity of a VMI warehouse in size k.
d_{ji}	The transportation distance between demand site i and VMI warehouse j.
β	A maximum acceptable service distance, is defined as the maximum transportation distance that a VMI warehouse can serve a demand site.
ϕ_i	The set of potential VMI warehouse j capable of covering demand site i, i.e., $\phi_i = \{j \in J \| d_{ji} \le \beta\}$.
TC_{jim}	Unit transportation cost of the resource m from VMI warehouse j to demand site i.
TC_{ihm}	Unit transshipment cost of the resource m from demand site i to demand site h.
I_{im}^0	The initial inventory of resource m at demand site i.
P^s	Likelihood of occurrence of scenario s.
ξ_{imt}^s	The quantity of demand for resource m at demand site i under scenario s.
π	The unit deprivation cost of the resource.
h	The unit holding cost of the resource.

Table IV. Decision variables for the healthcare supply chain network problem.

Notation	Definition
The first stage	
$y_{jk} \in \{0,1\}$	1 if a VMI warehouse with capacity level k is opened; 0 otherwise.
q_{jmt}	The delivery quantity of resource m for VMI warehouse j during period t.
The second stage	
z_{jimt}^s	The quantity of resource m transported from VMI warehouse j to demand site i in period t under scenario s.
x_{ihmt}^s	The transshipment amount of resource m from demand site i to demand site h in period t under scenario s.
B_{imt}^s	The shortage amount of resource m at demand site i in period t under scenario s.
I_{mit}^s	The on-hand inventory of resource m at demand site i in period t under scenario s.

C. Two-stage stochastic programming model

Let $\boldsymbol{\xi}$ be the vector of uncertain demand and P denotes its probability distribution. We consider a finite set S of realizations of the random vector $\boldsymbol{\xi}$. More specifically, for each scenario $s \in S$, we denote the demand realization of resource m at demand site i in period t as ξ_{imt}^s for all $m \in M$, $i \in I$, and $t \in T$. Therefore, $\boldsymbol{\xi} = [\xi_{imt}^s, s \in S, i \in I, m \in M, t \in T]^{\mathrm{T}}$. Note that this paper uses bold letters to represent vectors and matrices.

Using the notations, the following two-stage SP model is formulated:

$$\min_{y,q}\left\{\sum_{j\in J}\sum_{k\in K} F_k y_{jk} + \sum_{m\in M}\sum_{j\in J}\sum_{t\in T} C_m\, q_{jmt} + E[Q(y,q,\xi^s)]\right\} \tag{1}$$

S.t:

$$\sum_{k\in K} y_{jk} \leq 1 \quad \forall j \in J \tag{2}$$

$$\sum_{j\in \phi_i} \sum_{k\in K} y_{jk} \geq 1 \quad \forall i \in I \tag{3}$$

$$\sum_{m\in M} q_{jmt} \leq \sum_{k\in K} Cap_k \, y_{jk} \quad \forall j \in J, \forall t \in T \tag{4}$$

$$q_{jmt} \geq 0 \qquad \forall j \in J; m \in M; t \in T \tag{5}$$

$$y_{jk} \in \{0,1\}, \quad \forall j \in J; k \in K \tag{6}$$

Where

$Q(y, q, \xi^s) =$

$$\min_{z,x,I,B} \sum_{s\in S} P^s \left\{ \sum_{j\in J} \sum_{i\in I} \sum_{m\in M} \sum_{t\in T} TC_{jim} \, z_{jimt}^s + \sum_{i\in I} \sum_{h\in I\setminus\{i\}} \sum_{m\in M} \sum_{t\in T} TC_{ihm} \, x_{ihmt}^s + \sum_{i\in I} \sum_{m\in M} \sum_{t\in T} \pi B_{imt}^s + \sum_{i\in I} \sum_{m\in M} \sum_{t\in T} h \, I_{imt}^s \right\} \tag{7}$$

$$q_{jmt} \geq \sum_{i\in I} z_{jimt}^s \quad \forall j \in J, \forall m \in M, \forall t \in T, \forall s \in S \tag{8}$$

$$I_{im}^0 + \sum_{j\in \phi_i} z_{jimt}^s + \sum_{h\in I\setminus\{i\}} x_{himt}^s + B_{imt}^s - I_{imt}^s - \sum_{h\in I\setminus\{i\}} x_{ihmt}^s = \xi_{imt}^s \quad \forall i \in I, \forall m \in M, \forall t \in T, \forall s \in S \tag{9}$$

$$x_{ihmt}^s, z_{jimt}^s, B_{imt}^s, I_{imt}^s \geq 0 \qquad \forall m \in M; j \in J; i, h \in I \& i \neq h; t \in T; s \in S \tag{10}$$

Here, E is the expected value operator. Given the first-stage decisions $(\mathbf{y}, \mathbf{q})$ and the random input data vector ξ^s, $Q(y, q, \xi^s)$ represents the random optimal value of the second stage objective value. In the first stage, the "here-and-now" decisions $(\mathbf{y}, \mathbf{q})$ are made before the stochastic parameters $\tilde{\xi}$ are realized. As captured in Equation (1), the objective function is to minimize the total cost, including the VMI warehouse opening cost and the ordering cost. Constraint (2) guarantee that at most one type of VMI warehouse can be built at each candidate location site. Constraint (3) ensure that each demand site can be served by at least one VMI warehouse within the coverage radius. Constraint (4) serve a dual purpose: restricting the resource delivered to VMI warehouse j from exceeding its storage capacity, and mandating that resource ordering occurs only if a candidate site is selected as a VMI warehouse.

In the second stage, once the stochastic parameters $\tilde{\xi}$ are realized, the "wait-and-see" decisions $(\mathbf{x}, \mathbf{z}, \mathbf{B}, \mathbf{I})$ are made. In the formulation model, these scenario-specific decisions are represented by the superscript $s \in S$. Constraint (7) aims to minimize the total transportation cost from the VMI warehouses to the demand sites, along with the transshipment cost between demand sites, penalty costs for unsatisfied demand, and holding costs. Constraint (8) establishes links between the first-stage variables and the second-stage recourse decisions, ensuring that the total resource transportation volume for each scenario remains below the total inventory in the opened VMI warehouse. Constraint (9) represents flow-balance constraints to reflect the changes in inventory and shortage levels, based on the quantity of resources received and the demand level at each site i, for each period t in each scenario s. Finally, Constraints (5), (6) and (10) define the domain of first-stage and second-stage decision variables, respectively.

IV. NUMERICAL EXPERIMENTS

To demonstrate the performance of the proposed model, we conduct numerical experiments using a small-sized example. These experiments are carried out by the GAMS 24.1.2 software on a personal computer (Lenovo with Intel(R) Core (TM) i5-9300H 2.40 GHz CPU and 16.0 GB RAM), running on the Microsoft Windows 10 operating system.

The network comprises 11 demand sites and 16 candidate VMI warehouses, as depicted in Fig. (1). In the next step, the sensitivity of the deterministic model is analyzed and the experiments are conducted on the two-stage stochastic model within the framework of a pandemic environment.

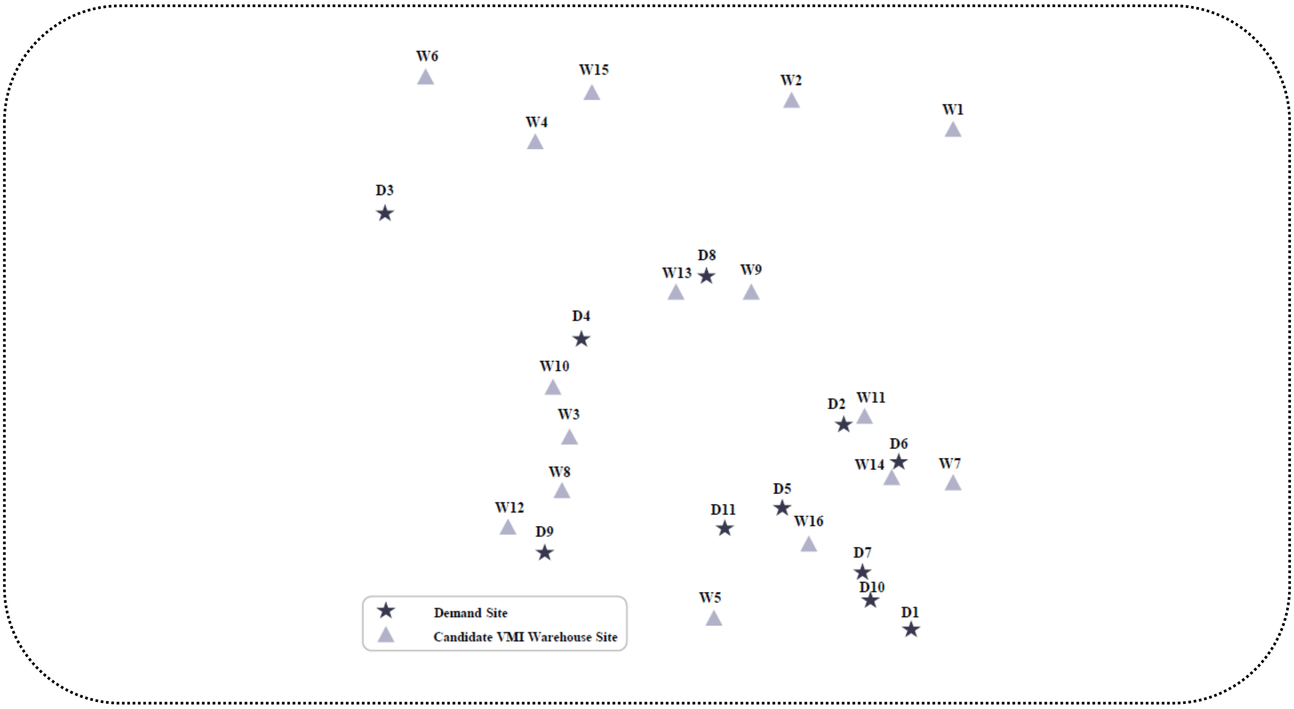


Fig. 1. An illustration of a small-sized example network.

A. Model analysis

To conduct the experiments, the basic input data have been provided as follows. The distances between the VMI warehouses and demand sites (d_{ji}) have been detailed in Table V, and the distances between demand sites (d_{ih}) can be found in Table VI, respectively. We specify the maximum acceptable service distance (β) to 512 kilometers. Three levels of VMI warehouse have been utilized, i.e., $|K| = 3$. Table VII presents the fixed costs (F_k) and storage capacities (Cap_k) associated with each warehouse category. Three types of medical products have been considered, i.e., $|M| = 3$. Table VIII displays the unit ordering cost (C_m) and unit transportation cost (TC_{jim}) for each medical product from the VMI warehouse to the demand site. To account for uncertain demands (ξ^s_{imt}), three scenarios have been considered, i.e., $|S| = 3$ for the discrete probability distribution, as listed in Table IX. The unit holding cost (h) and the unit deprivation cost (π)have been assumed to be 25 and 100, respectively.

Table V. Distance of VMI warehouses and demand sites.

	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13	W14	W15	W16
D1	861	928	647	1,042	326	1,232	260	615	639	713	378	680	696	268	1,061	222
D2	534	559	445	702	400	901	201	473	274	474	34	576	357	116	702	213
D3	930	682	482	271	872	246	1,025	555	607	404	847	572	484	933	398	889
D4	697	526	168	350	526	515	646	267	286	98	473	349	165	552	426	509
D5	705	698	368	752	224	939	275	361	378	425	207	450	411	183	782	74
D6	576	642	534	810	407	1,010	93	549	379	572	99	646	467	26	807	200
D7	773	816	532	917	261	1,107	208	510	518	594	271	585	572	172	937	101
D8	466	325	356	370	590	572	528	442	71	318	344	544	67	450	371	486
D9	978	867	204	708	290	838	666	106	559	281	564	78	489	573	796	427
D10	817	863	561	958	259	1,148	239	531	563	626	316	601	614	215	981	136
D11	777	740	301	739	157	916	372	276	412	370	296	358	415	281	784	137

Table VI. Distances between demand sites.

Demand Site	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11
D1	0	371	1,111	732	295	290	125	690	606	87	346
D2	371	0	825	449	176	109	257	334	530	304	263
D3	1,111	825	0	383	818	933	989	536	635	1,024	773
D4	732	449	383	0	437	554	608	232	372	645	403
D5	295	176	818	437	0	203	171	416	391	208	98
D6	290	109	933	554	203	0	198	441	591	240	301
D7	125	257	989	608	171	198	0	567	516	46	235
D8	690	334	536	232	416	441	567	0	543	611	435
D9	606	530	635	372	391	591	516	543	0	529	294
D10	87	304	1,024	645	208	240	46	611	529	0	260
D11	346	263	773	403	98	301	235	435	294	260	0

Table VII. Categories, fixed costs, and storage capacity of VMI warehouses.

Size Category (k)	$F_k(10^5)$	$Cap_k(10^3 units)$
1	5	70
2	7	100
3	10	140

Table VIII. Unit transportation cost and ordering cost of medical products.

Medical Product Types (m)	C_m	TC_{jim}
1	2	0.8
2	4	0.5
3	1	0.3

Table IX. Scenarios of uncertain demand.

Demand Site	Scenario 1 ($p = 0.3$)			Scenario 2 ($p = 0.6$)			Scenario 3 ($p = 0.1$)		
	$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 2$	$m = 3$
D1	500	1,500	1,700	4,500	25,000	20,000	30,000	40,000	45,000
D2	1,300	1,500	2,100	9,000	12,000	20,000	30,000	65,000	50,000
D3	1,300	3,000	1,700	4,500	12,000	15,000	30,000	65,000	45,000
D4	1,300	3,000	2,100	9,000	25,000	15,000	20,000	65,000	50,000
D5	1,300	1,500	2,100	9,000	25,000	15,000	20,000	40,000	45,000
D6	1,300	3,000	2,100	4,500	25,000	20,000	30,000	40,000	50,000
D7	500	3,000	2,100	4,500	12,000	15,000	20,000	40,000	45,000
D8	1,300	1,500	1,700	9,000	25,000	20,000	30,000	65,000	50,000
D9	1,300	3,000	1,700	9,000	25,000	20,000	30,000	40,000	45,000
D10	1,300	1,500	2,100	9,000	25,000	20,000	20,000	40,000	45,000
D11	500	1,500	2,100	4,500	25,000	15,000	20,000	65,000	50,000

The optimal solution for the SP model involves selecting eight VMI warehouses for the active storage of medical supplies in response to disease outbreaks. The Mixed Integer Programming (MIP) model utilizes the SP second-stage solution to determine the quantities of medical products for direct shipment and transshipment in each pandemic scenario across all time periods. The detailed results can be found in Fig. (2) and Table X.

The primary considerations in warehouse selection include operating cost, capacity, and proximity to demand sites. In this particular case, the chosen VMI warehouses are W5, W6, W10, W11, W12, W13, W14, and W16. Despite VMI warehouses 11, 14, and 16 having the highest operating costs, they are significantly closer to a large proportion of demand sites, allowing them to cover 82%, 73%, and 91% of demand sites, respectively. Conversely, Warehouse 6 exhibits the lowest coverage rate, namely 9%. However, its strategic proximity to demand site 3 makes it the most cost-effective option for serving that particular site.

The selected VMI warehouses prioritize serving the nearest demand site, provided their resource supplies are adequate. On average, across various scenarios, seven out of eleven demand sites (64%) are served by a single warehouse. In cases where a warehouse faces a resource shortage for serving the closest demand sites, the second closest one is assigned to fulfill their needs.

As an alternative way to summarize the detailed results, Table XI and Table XII provide the quantities of medical products directly shipped and transshipped for each scenario. To simplify our analysis, the transshipment cost can be disregarded in the second stage, and this assumption is justified for several reasons. Firstly, the cost associated with shortages is typically higher than reallocating costs, mainly due to the paramount importance of preserving human lives. Thus, in situations where there is a shortage of resources at certain demand sites while others have excess supplies, transshipment is almost certain to occur to mitigate the shortages. Consequently, this assumption is both practical and realistic.

Furthermore, when compared to the long-term ordering costs in the first stage, the influence of transshipment costs on immediate decisions, such as order quantities, can be considered negligible. Therefore, this relatively mild assumption does not compromise the overall modeling accuracy.

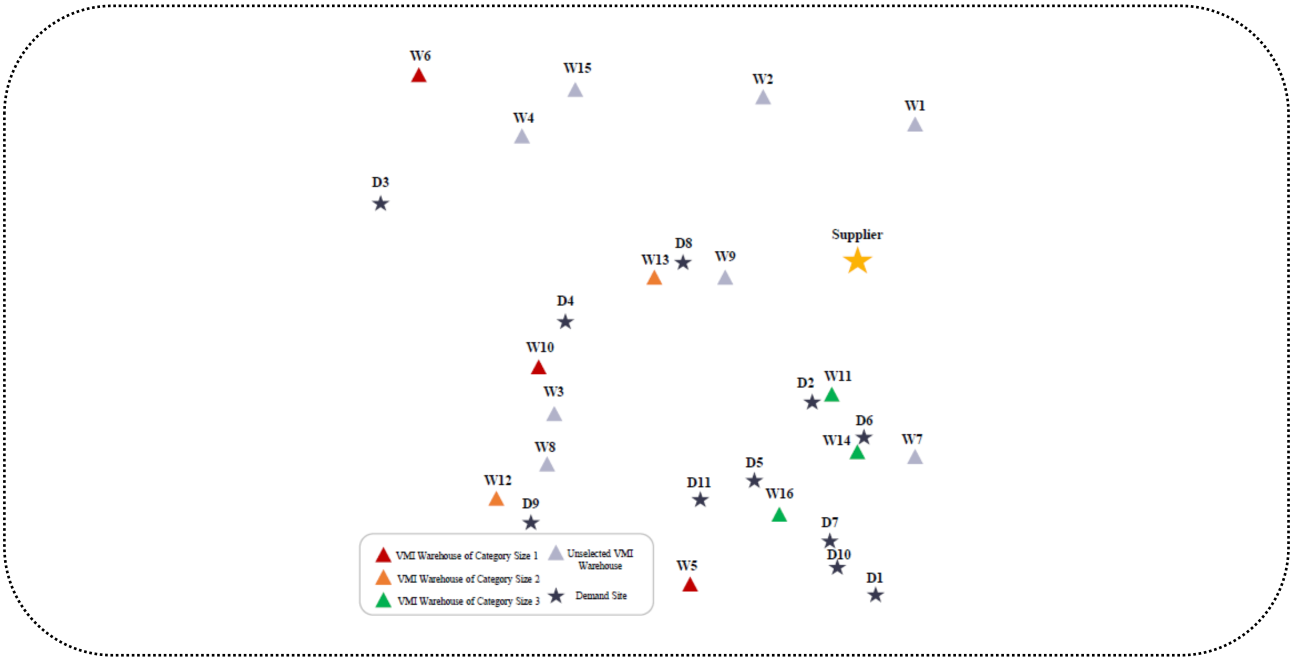


Fig. 2. Results of VMI warehouses location and capacity limitation.

Table X. Facility location, demand sites allocation, and order quantity in the first week.

VMI Warehouse	Capacity Level (k)	Demand Site	Order Quantity (q_{jm1})		
			$m = 1$	$m = 2$	$m = 3$
W1					
W2					
W3					
W4					
W5	Level 1	{11}		24,807	45,193
W6	Level 1	{3}			47,260
W7					
W8					
W9					
W10	Level 1	{4}	8,850	24,779	36,371
W11	Level 3	{2}	31,458	56,027	52,515
W12	Level 2	{9}	10,793	41,956	47,252
W13	Level 2	{4, 8}	9,351	29,620	61,030
W14	Level 3	{1, 6, 7}	31,440	41,992	66,568
W15					
W16	Level 3	{1, 5, 7, 10, 11}	9,316	64,843	65,841

Table XI. Quantity of direct shipment from VMI warehouses to demand sites under each scenario in the first week.

Warehouse	Demand Site	Scenario 1 ($p = 0.3$)			Scenario 2 ($p = 0.6$)			Scenario 3 ($p = 0.1$)		
		$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 2$	$m = 3$
W5	D11					24,807	14,574		24,807	45,193
W6	D3			1,498			14,169			47,260
W10	D4	1,171	2,923	1,986	8,850	24,779	14,552	8,850	24,779	36,371
W11	D2	1,247	1,459	2,094	9,353	12,512	20,936	31,458	56,027	52,515
W12	D9	1,232	3,008	1,673	9,337	26,166	20,936	10,793	41,956	47,252
W13	D4									8,511
	D8	1,245	1,467	1,677	9,351	26,204	20,940	9,351	29,620	52,519
W14	D1						870			
	D6	1,229	3,044	2,093	4,598	26,202	20,935	31,440	41,992	52,514
	D7									14,055
W16	D1			949						
	D5	1,211	1,434	2,099	9,316	26,171	15,678	9,316	41,960	47,257
	D7	385	3,029	2,086	12,503	15,665			22,883	18,584
	D10		1,433	2,089		26,169	20,932			
	D11		1,289	2,009						

B. Sensitivity analysis

In this section, a sensitivity analysis is conducted to explore the impact of specific parameters on the configuration of the supply network in the proposed model. Initially, this paper focuses on understanding how key parameters affect decisions related to demand site allocation, inventory management, and distribution planning. These parameters encompass the shortage cost, transportation cost through direct shipping, and the transshipment cost. As a result, how variations in parameters π, TC_{jim}, and TC_{ihm} impact both the total cost and the overall network structure will be evaluated. Figs. (3) and (4) visually depict the impact of parameters TC and π on the overall cost and the number of warehouses, respectively.

Examination of these data reveals that the overall system cost rises as transportation costs (TC_{jim}) and unit shortage costs (π) increase. Specifically, the total cost exhibits a rapid upswing with the escalation of TC_{jim} when $TC_{jim} \leq 0.9$. However, as TC_{jim} continues to increase, the total cost experiences a slower rate of ascent.

Additionally, the quantity of warehouses grows proportionally with the increase in unit shortage costs but diminishes in response to higher unit delivery costs. As π rises, the upward trajectory in the number of Vendor-Managed Inventory (VMI) warehouses corresponds to that of the total cost. Conversely, with the augmentation of TC, the reduction in the number of VMI warehouses is not substantial, as this decrease is also affected by the shortage cost.

Proceeding, we will delve further into the analysis of the supply network structure. As the unit shortage cost rises, distinct variations in the supply network structure become apparent, as depicted in Fig. (5). The network structures for different values of π are illustrated in Figs. (5a) through (5d) corresponding to $\pi = 112.5$ & $h = 100$, $\pi = 125$ & $h = 100$, $\pi = 137.5$ & $h = 100$, and $\pi = 150$ & $h = 100$, respectively. Fig. (5a) features eight VMI warehouses, while Fig. (5b) showcases a network with nine VMI warehouses. Similarly, both Fig. (5c) and Fig. (5d) exhibit configurations with 9 VMI warehouses each. These variations underscore the impact of the shortage cost on the evolving structure of the supply network. Upon comparing Figs. (5a) and (5c), it becomes evident that candidate sites 5 and 7 are strategically chosen to establish VMI warehouses of category size 2. This strategic placement is aimed at meeting demand requirements and mitigating shortage costs effectively.

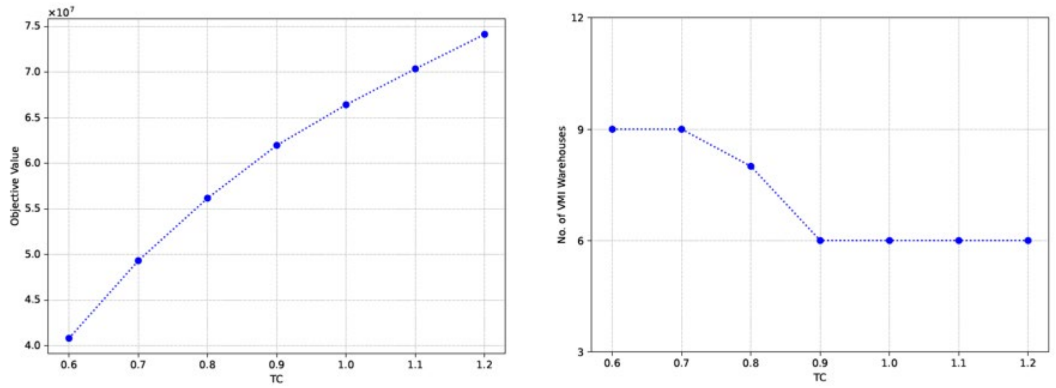


Fig. 3. Effect of the delivery cost.

Table XII. Quantity of transshipment between mutual sites under each scenario in the first week.

Demand Site	Demand Site	Scenario 1 ($p = 0.3$)			Scenario 2 ($p = 0.6$)			Scenario 3 ($p = 0.1$)		
		$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 2$	$m = 3$
D2	D1		73	105		626	1,047	1,573		2,626
	D10	62			468					
D3	D4									2,363
D4	D3	59	146	99	442	1,239	728			
D5	D1		72	105		1,309	784			
	D7								2,098	
	D10	61			466					2,363
D6	D1		152	105		1,310	1,047	1,572		
	D10	61			230					2,626
	D11							2,100		
D7	D1		151	104		625	783			
	D11	19								
D8	D4	62	73	84	468	1,310	1,047			2,626
D9	D4								2,098	
	D11	62	150	84	467	1,308	1,047			2,363
D10	D1		72	104		1,308	1,047			
D11	D1		64	100		1,240	729			

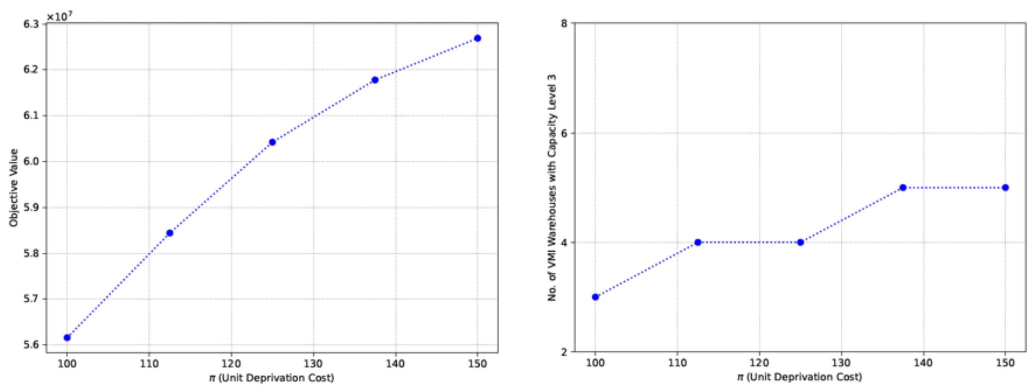
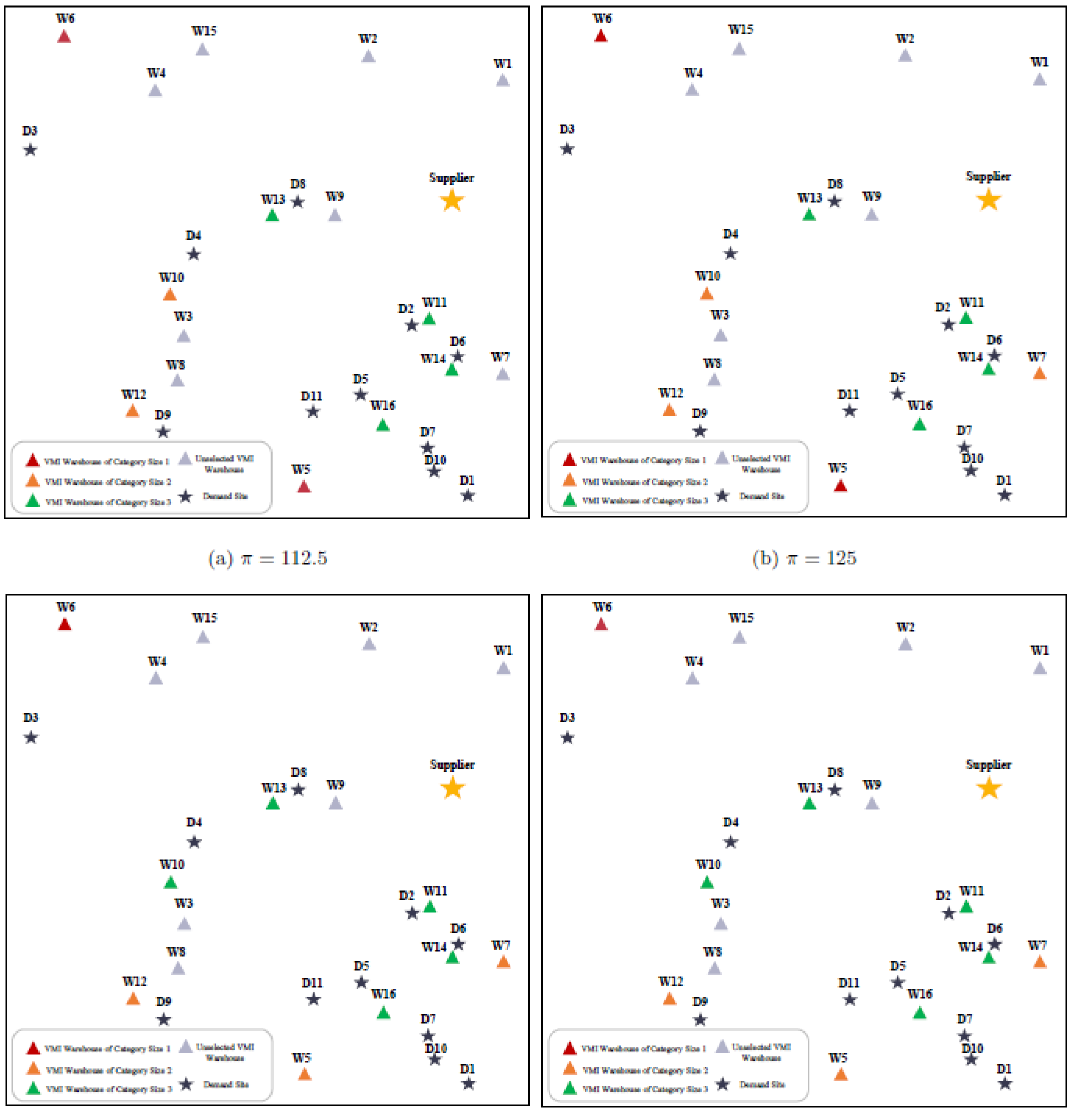


Fig. 4. Effect of the unit deprivation cost

Overall, these parameters significantly impact the system cost, with the network structure showing heightened sensitivity to both the shortage and transportation cost through direct shipping. This increased sensitivity is logical, considering the direct influence of these costs on the network structure. On the flip side, the inventory holding cost and the delivery cost through transshipment exert an indirect impact on the network structure by shaping inventory management.

Further, the significance of stochastic programming compared with the deterministic model are highlighted. Fig. (6) illustrates how variations in demand affect the overall cost for both the deterministic and stochastic programming models. Due to the stochastic programming model's consideration of the probability distribution of uncertain parameters, it is evident that the optimal objective values of the stochastic programming model are consistently greater than those of the deterministic model. However, by using a stochastic programming approach the robustness of decisions can be increased.



(a) $\pi = 112.5$ (b) $\pi = 125$

(c) $\pi = 137.5$ (d) $\pi = 150$

Fig. 5. Effect of the unit shortage cost on warehouses structure.

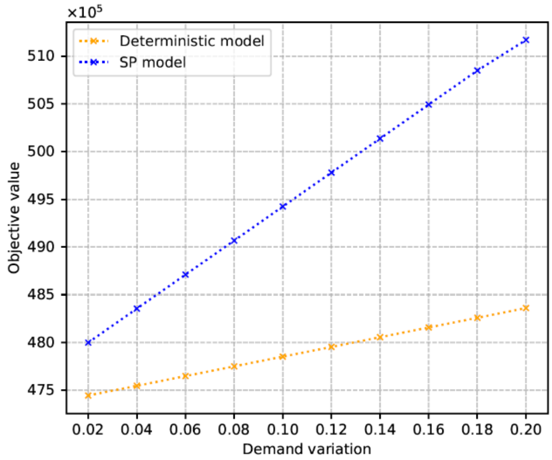


Fig. 6. Model comparisons based on demand variations.

V. CONCLUSION

This paper studied a healthcare supply chain network design problem in a stochastic and pandemic environment. The problem integrated VMI warehouse selection, inventory management, and delivery decisions. It also incorporated features such as multi-products, multi-periods, and demand uncertainty. In response to resource shortages during a pandemic, the resilient resource sharing strategy was introduced to enable demand sites to share emergency supplies from their inventories with other sites in the network.

To address demand uncertainty, a stochastic programming model was proposed. In the first stage, optimal decisions were made for the location of the VMI warehouses as well as their size and order quantities. In this stage, ordered products were transported directly from the selected open VMI warehouses to demand sites via package carriers or third-party logistics services. The second stage involved making recourse decisions on transportation plans for each scenario. In this stage, by considering reallocating products among demand sites, the responsiveness of the healthcare system was improved to substantial surges in demand during epidemics and pandemics. Additionally, a sensitivity analysis of the integrated model was conducted, demonstrating the advantages of the proposed stochastic optimization model. Although the stochastic approach had higher total costs compared to the deterministic model, it made more robust decisions. Numerical experiments on a small-sized example further illustrated the model's effectiveness. In this regard, it was found that the proposed resource sharing strategy could reduce the required overall capacity by improving the allocation and distribution of products.

While this paper focused on healthcare operations management during pandemics, the models and insights developed can also be applied to other service industries facing substantial increases in demand. One limitation of this research lies in the potential scalability issues as the supply network expands or the number of products, periods, and demand sites increases, making the problem size challenging for off-the-shelf solvers. Therefore, a relevant future endeavor would involve developing an efficient algorithm specifically tailored for solving large-scale instances.

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