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Optimization model for designing disruption-oriented network of laboratory services and managing procurement of health items under uncertainty: A real-world case study

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Abstract

In today's turbulent world, unpredictable events with various effects on human health have highlighted the importance of an agile and integrated network to provide health services. Providing health services to applicants is realized when procurement of the required health items is effectively and efficiently managed. In the present research, a practical approach is taken to design an integrated network to provide laboratory services and manage the procurement of related items under uncertainty. For this purpose, a multi-product and multi-period optimization model is presented to minimize the expected costs. Also, a scenario-based robust optimization approach is adopted for uncertainty programming. Moreover, a real-world case study in Iran is employed to ensure the effectiveness and efficiency of the presented model. Integrating the network of providing laboratory services and managing the procurement of related consumable items, employing geological software such as Arc GIS to locate potential facilities in laboratory service network, and simultaneously dealing with disruptions and operational risks in healthcare networks are the distinctive research contributions. The obtained results indicate the advantages of designing an integrated network to provide laboratory services and manage the procurement of relevant items to save costs and improve the quality of providing service to applicants. In general, it could be observed that a lack of planning to deal with disruptive incidents could cause severe damage to the performance of the studied integrated network.
Keywords: Procurement of laboratory items, health service network, scenario-based robust optimization, operational risk, disruptive incident

1- Introduction

Today, countries are exposed to various threats, such as pandemics, wars, etc., which always threaten human health. This issue highlights the necessity of health service networks and the use of their facilities to provide relief and emergency services to applicants (Desi-Nezhad et al., 2022). Procuring health items, such as medicine, equipment, etc., at the appointed time with the desired quality plays an essential role in providing health services, which shows the importance of procurement management in health service networks and the necessity of planning the two mentioned fields in an integrated manner (PG Petroianu et al., 2021).

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Therefore, proper health services could be provided to applicants in health systems only if integrated decisions could be made in designing health service networks and managing the procurement of health items. This will cause better coordination and communication between different facilities and providers of health services and consumables. Also, it leads to reduced costs and waste by optimizing the procurement, distribution, and utilization of consumables. This causes increased access and availability of health services and consumables for the applicants, especially in remote and underserved areas. Finally, it leads to enhanced network resilience and reliability in disruptive events or emergencies and improved monitoring and evaluation of the network performance and health service quality indicators (Desi-Nezhad et al., 2022).

Decisions are constantly made based on ambiguous conditions under various disruption risks and uncertainty (Nili et al., 2021b; Sadrabadi et al., 2023). Disruptions are unpredictable destructive events with low occurrence probability and have both natural and human origins, which could cause irreparable damage to a system if they occur (Sadrabadi, Ghousi, et al., 2021). However, operational risks caused by usual uncertainties could be predicted and controlled in the activity space of different systems. These risks occur normally and cause partial loss to the performance of a system (Nili et al., 2021a; Sadrabadi, Jafari-Nodoushan, et al., 2021). Managing health item procurement and providing health services occurs in an environment where there is always the possibility of disruptive incidents and operational risks that could have irreparable effects on the performance of health systems. Thus, adopting a suitable approach for risk management in integrated systems is of particular importance for providing health services and managing the procurement of relevant items (Christopher & Peck, 2004; Dehghani Sadrabadi et al., 2019; Fahimnia & Jabbarzadeh, 2016; Fiksel, 2006; Pettit et al., 2010)

This research presents a single-objective optimization model to integrate the network of providing laboratory services and managing the procurement of health items under uncertainty and disruptive incidents. A series of decisions related to supplier selection, supply chain network design, and managing service networks are made to minimize the system's expected cost. A scenario-based robust optimization approach is used to plan uncertainty. Moreover, the impact of disruptions is partially applied to the capacity of facilities. Integrating the network of providing laboratory services and supply chains related to the procurement of laboratory consumables is among the strengths of the present research.

The main contributions of the present study are as follows: Herein, managing health services and health items procurement together to improve the quality of service for the applicants has been considered, especially for laboratory services. Arc GIS software is employed to find potential locations based on geological criteria for establishing new facilities in the laboratory service networks. The present research addresses managing multiple disruptions and operational risks affecting the performance of integrated laboratory service network by adopting an efficient approach. Two types of coverage radius are considered for locating facilities in the under-study integrated network that can make the laboratory service providing more consistent and quicker for the applicants.

The research questions are as follows: What is the optimal network configuration for providing laboratory services and supplying the required consumables? What are the optimal locations for establishing facilities in the under-study healthcare network? How can disruptions and operational risks affect the desired network performance and how can these negative effects be reduced? What is the optimal inventory of laboratory consumables held by the desired network's facilities? What is the amount of defective laboratory consumables purchased from suppliers?

The rest of the paper is organized as follows: The second section reviews the papers to determine shortcomings and extract research contributions. The third section conceptualizes the problem and presents a mathematical formulation by defining the problem. The fourth section presents the scenario-based robust optimization approach for uncertainty planning. The fifth section presents the results and analyses resulting from solving the optimization model.

2- Literature review

This section reviews studies on supply chain network design to manage the procurement of health items and design the health service network. In this way, shortcomings of the previous research could be identified to adopt a set of contributions in the present research. Supply chains consist of components to supply the items required by a system providing services or manufacturing products. Item procurement in any system could be managed only through an effective and efficient supply chain, which aims to provide high-quality items at the right time. In health service delivery systems, the optimal design of the supply chain network of the required items is of great importance because this is directly associated with the health of patients and service applicants.

Ensafian and Yaghoubi (2017) configured a supply chain network for the processing and distributing of blood platelets under perishability conditions. The objective functions included minimizing the total network design costs and maximizing the freshness of delivered blood products. They used the robust optimization approach for planning uncertainty in supply chain management. Hamdan and Diabat (2020) presented a mathematical model based on humanitarian procurement to design the distribution network of blood products. Their objective functions included minimizing the service time and the cost of dispatching blood to hospitals during a disaster. The stochastic robust optimization approach was used to control the ambiguity in estimating the input parameters. Alizadeh et al. (2021) designed a supply chain network to supply and distribute influenza vaccines during the COVID-19 pandemic, considering dynamic demand. The objectives considered by them included minimizing the total cost, maximizing demand allocation based on customer prioritization, and minimizing the maximum lost sales demand. Modeling was based on the deterministic approach. Kamran et al. (2022) presented a simulation-based mathematical model for designing a vaccine supply chain network during the COVID-19 pandemic. The goals were minimizing the expected system costs, maximizing the utility of vaccine applicants, and maximizing social justice in vaccine distribution. The stochastic programming approach was employed in the presented model to deal with uncertainty. Dastgoshade et al. (2022) presented an optimization model for vaccine distribution network design considering social justice concepts. The objective functions included maximizing the amount of vaccine allocated to two groups of qualified applicants simultaneously. Attempts were made to deal with operational risks affecting vaccine distribution in the incidence of the COVID-19 pandemic using stochastic programming methods. Valizadeh et al. (2023) presented an optimization approach to developing an agile network for vaccine supply and distribution during the outbreak of the COVID-19 pandemic. This research aimed to simultaneously minimize the following three objective functions: Risk of not observing justice in vaccine distribution, risk of death of applicants due to vaccine unavailability, and expected costs of procurement management. This research dealt with uncertainty using the stochastic robust optimization approach.

Today, health service networks are considered the most important urban facilities due to the increasing importance of healthcare and its role in public health (Alinaghian et al., 2021). The growing population and rising treatment costs have made it difficult to achieve the goals of health service networks (Lian, 2003). Therefore, designing an efficient and effective health service network is of great importance for providing cheaper, faster, and real-time services to different groups of society (Attari et al., 2022; Mousazadeh et al., 2018; Syam & Côté, 2010). In the following, some of the papers carried out on health service delivery network design are reviewed. Haeri et al. (2021) presented an efficient approach for designing a health service network to optimize the total costs of network design simultaneously, the social effects of sustainable development, and the facility's efficiency. The uncertainty of the parameters was dealt with by taking into account the possibility measure, applying flexible programming, and adopting a robust optimization approach. Zarrinpoor et al. (2017) proposed a model for designing a health service network in which the facilities are exposed to disruptions and the quality of services is guaranteed. The purpose of the proposed two-stage model was to minimize the total network costs. They used the stochastic robust optimization approach to deal with uncertainty. Mousazadeh et al. (2018) proposed a hybrid approach for designing health service networks to improve accessibility, develop social sustainability requirements, and establish justice in service delivery. They used stochastic and possibilistic programming approaches to deal with the uncertainty. Yin and Büyüktahtakın (2021) provided a mathematical model for procuring and distributing health items and equipment to deal with pandemic diseases. In this research, decisions were made to minimize network design costs. Multi-stage stochastic programming method was used to control and manage operational risks. Bertsimas et al. (2022) presented an optimization model to design a vaccine distribution network in which decisions were made to minimize the number of dead patients and the total distance traveled to procure the vaccine. Uncertainty management was done for estimating the problem input parameters using a robust optimization method. Attari et al. (2022) presented a mathematical model to achieve an optimal configuration for the health service delivery network in the incidence of disruptive incidents affecting the facilities. Decisions were made to minimize network design costs. Uncertainty in parameter estimation was managed using the robust stochastic optimization method. Desi-Nezhad et al. (2022) proposed a two-stage stochastic programming model to design a disaster relief network that transports injured people from affected areas to hospitals under uncertainty and disruption, while considering economic, social and environmental sustainability. They aimed to determine the optimal locations of transfer points and the flows between network nodes. The paper applies the model to a case study in Tehran, Iran and analyzes the results.

Reviewing the literature revealed a set of shortcomings as follows: First, simultaneous and integrated management of providing health services and procuring health items for improving the quality of providing services to applicants has received less attention. It should be noted that this point has never been addressed in providing laboratory services. Second, using technical tools considered in geological studies such as Arc GIS software to locate the potential points for constructing facilities and providing services in health networks needs more attention. Third, in health service delivery network design and item procurement management, it is important to pay attention to disruptive incidents and investigate their effects on the desired network performance. Fourth, to integrate the health service delivery network and health item procurement management simultaneously, adopting an effective and efficient approach to manage uncertainty in parameter estimation could be interesting. Fifth, applying a coverage radius for providing facilities in the health system could improve uniformity and increase speed in providing services to applicants.

This research presents an optimization model to integrate the network of providing laboratory services and managing item procurement in the incidence of multiple disruptive incidents and uncertainty. Decisions are made to minimize network design costs. In this research, the total number of candidate spots for constructing facilities in the integrated network is examined using the specialized geological software of Arc GIS and considering a set of geographical and technical criteria. The constraint of maximum coverage radius for facilities is applied to consider justice in providing services, minimize service time, increase service speed and quality of service, provide health items, and establish uniformity of services and items between different facilities. This research considers the effect of multiple disruptions on facility capacity using a two-stage stochastic programming approach. Moreover, uncertainty in estimating model input parameters is managed by adopting a scenario-based robust optimization approach. Decisions that the model could make include selecting suppliers, determining the flow volume of services and items between facilities, the amount of inventory in different facilities, and other decisions related to the design of the health service network and procurement management.

3- Problem definition and modeling

This research investigates the problem of designing an integrated network of medical laboratory services and a supply chain of consumable items. The studied 5-level network comprises sampling centers, laboratory centers, hybrid distribution-collection centers, and suppliers. This network is responsible for providing services to the applicant area, supplying laboratory consumables, and collecting and returning defective items to suppliers simultaneously. Forward and reverse flows in the under-study network cause the structure to include a hybrid forward-reverse flow. There are two different types of flow in this network: The first type of flow includes the blood samples collected from the applicants, which are sent from blood sampling centers to laboratory centers daily to be tested. The second type of flow includes forward and reverse flows. In the forward flow, consumable items required by the service network are provided by making a contract with the selected suppliers and stored in hybrid distribution collection centers. Consumable items required by the network are divided into two separate types: The first type includes all kinds of laboratory kits that are used in laboratory centers to test blood samples. The second type of consumables includes all kinds of laboratory tubes and other essential sampling items that are sent from laboratory centers to sampling centers to be used in the blood sampling process. In the reverse direction of the second type of flow, the first type of defective consumables identified in the laboratory centers are collected, stored, and returned to suppliers through hybrid distribution collection centers. However, returning the second type of consumables is not cost-effective due to the very small percentage of defective items. Services are provided to sampling and laboratory centers based on the maximum coverage level of facilities. Fig 1 indicates the configuration of the under-study integrated network.

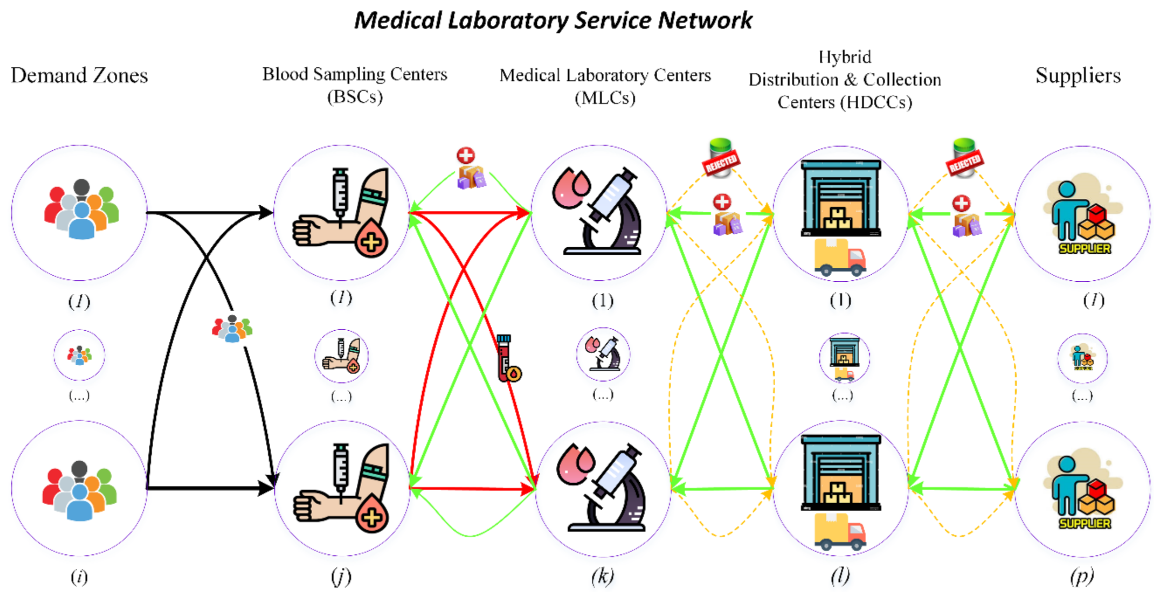


Fig 1. Configuration of the under-study integrated laboratory service-supply chain network

Managing procurement of laboratory items as well as planning to provide laboratory services to meet the applicants' needs is always faced with various disruptive incidents and uncertainty caused by operational risks. Therefore, the integrated network design for providing laboratory services and procuring relevant items requires an effective and efficient approach to managing the aforementioned risks. The purpose of solving the model presented in this research is to make decisions about selecting suppliers, determining optimal locations for establishing some facilities, specifying the optimal flow volume between different network levels, determining the inventory held in some facilities, and other decisions related to designing the under-study network. In the following, some assumptions are briefly presented to make the performance of the proposed model closer to real-world problems:

- In the present model, there is no possibility of a lack of procuring laboratory items and providing laboratory services. Thus, demand fulfillment is necessary.
- Due to rapid perishability, it is not possible to keep blood inventory in laboratories and sampling centers. Accordingly, blood samples are sent to be tested daily.
- The condition of applying the coverage radius to operate various facilities is considered.
- It is not possible to spread the effect of disruptions among different facilities. Thus, we are faced with isolated disruptions in the studied network.
- The under-study network is exposed to multiple disruptions, which partially impact the facility's capacity.
- The route of transporting defective consumables from laboratory centers to suppliers is selected from among the forward paths of the second type of flow, which is used to transfer the purchased consumables to laboratory centers.

- The route of transporting consumables from laboratory centers to sampling centers is selected from among the forward paths of the first type of flow used to transport blood samples to laboratory centers.

4- Mathematical modeling

4-1- Notations

The set of indices, parameters, and decision variables required for modeling the present problem are presented as follows:

4-1-1- Indices and sets

c	A set of demand points for receiving laboratory services	$c \in C$
d	A set of candidate points for constructing blood sampling centers	$d \in D$
e	A set of candidate points for constructing laboratories	$e \in E$
f	A set of candidate points for constructing distributors	$f \in F$
g	A set of potential suppliers of laboratory commodities	$g \in G$
p	A set of laboratory commodities	$p \in \{P \cup P' \mid P \neq P'\}$
t	A set of periods	$t \in T$

4-1-2- Parameters

Cu_c^t	Demand for receiving laboratory services in region c at time t.
ECB_d^t	Fixed cost of establishing sampling center d at time t.
ECL_e^t	Fixed cost of establishing laboratory e at time t.
ECD_f^t	Fixed cost of establishing distributor f at time t.
CCS_g^t	Fixed cost of signing a contract with supplier g to provide laboratory commodities at time t.
CUP_{gp}	Unit cost of remaining unused capacity of laboratory product type p in supplier g.
SCB_{de}^t	Unit cost of transporting blood from sampling center d to laboratory e at time t.
SCS_{gfp}^t	Unit cost of transporting laboratory commodities type p between supplier g and distributor f at time t.
SCD_{fep}^t	Unit cost of transporting laboratory commodities type p between distributor f and laboratory e at time t.
SCL_{edp}^t	Unit cost of transporting laboratory commodities type $p \in P'$ from laboratory e to sampling center d at time t.
OCS_{gp}	Fixed cost of ordering laboratory commodities type p from supplier g.
OCD_p	Fixed cost of ordering laboratory commodities type p from distributors.

HCD_{fp}	Unit cost of holding laboratory commodity type p in distributor f .
$HCRD_{fd}$	Unit cost of holding defective laboratory commodity type $p \in P$ in distributor f .
HCL_{ep}	Unit cost of holding laboratory commodity type p in laboratory e .
$HCRL_{ep}$	Unit cost of holding defective laboratory commodity type p in laboratory e.
HCB_{dp}	Unit cost of holding laboratory commodity type $p \in P'$ in sampling center d .
$SCapP_{gp}$	Maximum capacity of supplying laboratory commodity type p in supplier g .
RS_{gp}	Percentage of disrupted capacity of supplying laboratory product type p in supplier g .
$DCapP_{fp}$	Maximum capacity of storing laboratory commodity type p in distributor f.
$LCapP_{ep}$	Maximum capacity of storing laboratory commodity type p in laboratory e .
$BCapP_{dp}$	Maximum capacity of storing laboratory commodity type p in sampling center d .
$LCapO_e$	Maximum capacity of testing blood samples in laboratory e .
RL_e	Percentage of disrupted capacity of testing blood samples in laboratory e .
IRP_p	Amount of income per unit of defective laboratory commodity type p to suppliers.
Dis_{cd}	Distance between demand point c and sampling center d .
$D'is_{de}$	Distance between sampling center d and laboratory e .
BR	Maximum coverage radius of sampling centers.
LR	Maximum coverage radius of laboratories.
β_p	Consumption coefficient of laboratory commodity type p .
γ_p	Percentage of defective purchased laboratory commodities type p .
ω	Percentage of storage capacity considered for keeping defective laboratory commodity in laboratories and collection centers.
BM	Sufficiently large positive number.

4-1-3- Decision variables

- **Binary decision variables**

OD_d	The value is 1 if the sampling center is established at candidate point d; otherwise, it is equal to 0.
OE_e	The value is 1 if the laboratory is established at candidate point e; otherwise, it is equal to 0.
OF_f	The value is 1 if the distributor is established at candidate point f; otherwise, it is equal to 0.
SG_g	The value is 1 if the contract of supplying commodities is concluded with supplier g; otherwise, it is equal to 0.

CD_{cd}^{t}	The value is 1 if customers in region c go to sampling center d at time t; otherwise, it is equal to 0.
DE_{de}^{t}	The value is 1 if sampling center d is assigned to laboratory e at time t; otherwise, it is equal to 0.
GF_{gfp}^{t}	The value is 1 if the order of laboratory commodities type p is sent by supplier g to distributor f at time t; otherwise, it is equal to 0.
FE_{fep}^{t}	The value is 1 if the order of laboratory commodities type p is sent by distributor f to laboratory e at time t; otherwise, it is equal to 0.

- **Positive decision variables**

A_{cd}^{t}	Number of laboratory service applicants go from region c to sampling center d at time t for blood sampling
B_{de}^{t}	Number of blood samples transported from sampling center d to laboratory e at time t
H_{gfp}^{t}	Number of laboratory commodity type p sent from supplier g to distributor f at time t
K_{fep}^{t}	Number of laboratory commodity type p sent from distributor f to laboratory e at time t
$B_{edp}^{\prime t}$	Number of laboratory commodity type p sent from laboratory e to sampling center d at time t
$K_{efp}^{\prime t}$	Number of defective laboratory commodity type p returned from laboratory e to distributor f at time t
$H_{fgp}^{\prime t}$	Number of defective laboratory commodity type p returned from distributor f to supplier g at time t
SF_{fp}^{t}	Amount of inventory of laboratory commodity type p in distributor f at time t
SRF_{fp}^{t}	Amount of inventory of defective laboratory commodity type p in distributor f at time t
SE_{ep}^{t}	Amount of inventory of laboratory commodity type p in laboratory e at time t
SRE_{ep}^{t}	Amount of inventory of defective laboratory commodity type p in laboratory e at time t
SD_{dp}^{t}	Amount of inventory of laboratory commodity type p in sampling center d at time t

4-2- Equations

According to the aforementioned notations, a deterministic mathematical model is presented to formulate the under-study problem and design a medical laboratory service network and supply chain of laboratory consumables in an integrated manner.

$$
\begin{aligned}
MinZ = & \sum_{d\in D}\sum_{t\in T} ECB_d^t\, OD_d + \sum_{e\in E}\sum_{t\in T} ECL_e^t\, OE_e + \sum_{f\in F}\sum_{t\in T} ECD_f^t\, OF_f + \sum_{g\in G}\sum_{t\in T} CCS_g^t\, SG_g \\
& + \sum_{d\in D}\sum_{e\in E}\sum_{t\in T} SCB_{de}^t\, B_{de}^t + \sum_{g\in G}\sum_{f\in F}\sum_{p\in\{P\cup P'\}}\sum_{t\in T} SCS_{gfp}^t H_{gfp} + \sum_{f\in F}\sum_{e\in E}\sum_{p\in\{P\cup P'\}}\sum_{t\in T} SCD_{fep}^t\, K_{fep}^t \\
& + \sum_{e\in E}\sum_{d\in D}\sum_{p\in P'}\sum_{t\in T} SCL_{edp}^t B'^t_{edp} + \sum_{e\in E}\sum_{f\in F}\sum_{p\in P}\sum_{t\in T} SCD_{fep}^t K'^t_{efp} + \sum_{f\in F}\sum_{g\in G}\sum_{p\in P}\sum_{t\in T} SCS_{gfp}^t\, H'^t_{fgp} \\
& + \sum_{g\in G}\sum_{f\in F}\sum_{p\in\{P\cup P'\}}\sum_{t\in T} OCS_{gp}\, GF_{gfp}^t + \sum_{f\in F}\sum_{e\in E}\sum_{p\in\{P\cup P'\}}\sum_{t\in T} OCD_p\, FE_{fep}^t \\
& + \sum_{f\in F}\sum_{p\in\{P\cup P'\}}\sum_{t\in T} HCD_{fp}\, SF_{fp}^t + \sum_{e\in E}\sum_{p\in\{P\cup P'\}}\sum_{t\in T} HCL_{ep}\, SE_{ep}^t + \sum_{d\in D}\sum_{p\in P'}\sum_{t\in T} HCB_{dp}\, SD_{dp}^t \\
& + \sum_{e\in E}\sum_{p\in P}\sum_{t\in T} HCRL_{ep}\, SRE_{ep}^t + \sum_{f\in F}\sum_{p\in P}\sum_{t\in T} HCRD_{fp}\, SRE_{fp} \\
& + \sum_{g\in G}\sum_{p\in\{P\cup P'\}}\sum_{t\in T} CUP_{gp}\left(SCapP_{gp} SG_g \left(1-RS_{gp}\right) - \sum_{f\in F} H_{gfp}^t \right) - \sum_{g\in G}\sum_{f\in F}\sum_{p\in P}\sum_{t\in T} IRP_p\, H'^t_{fgp}
\end{aligned} \tag{1}
$$

$$\sum_d A_{cd}^t = Cu_c^t \qquad \forall c\in C, t\in T \tag{2}$$

$$\sum_f H_{gfp}^t \le SCapP_{gp}\, SG_g\left(1-RS_{gp}\right) \qquad \forall g\in G,\ p\in\{P\cup P'\},\ t\in T \tag{3}$$

$$\sum_d B_{de}^t \le LCapO_e\, OE_e\left(1-RL_e\right) \qquad \forall e\in E,\ t\in T \tag{4}$$

$$SF_{fp}^t \le \left(1-\theta\right) DCapP_{fp}\, OF_f \qquad \forall f\in F,\ p\in\{P\cup P'\},\ t\in T \tag{5}$$

$$SE_{ep}^t \le \left(1-\theta\right) LCapP_{ep}\, OE_e \qquad \forall e\in E,\ p\in\{P\cup P'\},\ t\in T \tag{6}$$

$$SD_{dp}^t \le BCapP_{dp}\, OD_d \qquad \forall d\in D,\ p\in P',\ t\in T \tag{7}$$

$$SRE_{ep}^t \le \theta\, LCapP_{ep}\, OE_e \qquad \forall e\in E,\ p\in P,\ t\in T \tag{8}$$

$$SRF_{fp}^t \le \theta\, DCapP_{fp}\, OF_f \qquad \forall f\in F,\ p\in P,\ t\in T \tag{9}$$

$$\sum_{e} B_{de}^{t} = \sum_{c} A_{cd}^{t} \qquad \forall\, d \in D,\, t \in T \tag{10}$$

$$SF_{fp}^{t-1} + \sum_{g} H_{gfp}^{t} - \sum_{e} K_{fep}^{t} = SF_{fp}^{t} \qquad \forall\, f \in F,\ p \in \{P \cup P'\},\, t \in T \tag{11}$$

$$SE_{ep}^{t-1} + \sum_{f} K_{fep}^{t} - \left(\left(\beta_p \sum_{d} B_{de}^{t} \right) / \left(1-\gamma_p\right) \right) = SE_{ep}^{t} \qquad \forall\, e \in E,\ p \in P,\, t \in T \tag{12}$$

$$SE_{ep}^{t-1} + \sum_{f} K_{fep}^{t} - \sum_{d} B_{edp}^{\prime t} = SE_{ep}^{t} \qquad \forall\, e \in E,\ p \in P',\, t \in T \tag{13}$$

$$SD_{dp}^{t-1} + \sum_{e} B_{edp}^{\prime t} - \beta_p \sum_{c} A_{cd}^{t} = SD_{dp}^{t} \qquad \forall\, d \in D,\ p \in P',\, t \in T \tag{14}$$

$$SRE_{ep}^{t-1} + \left(\beta_p \sum_{d} B_{de}^{t} \right) \gamma_p - \sum_{f} K_{efp}^{\prime t} = SRE_{ep}^{t} \qquad \forall\, e \in E,\ p \in P,\, t \in T \tag{15}$$

$$SRF_{fp}^{t-1} + \sum_{e} K_{efp}^{\prime t} - \sum_{g} H_{fgp}^{\prime t} = SRF_{fp}^{t} \qquad \forall\, f \in F,\ p \in P,\, t \in T \tag{16}$$

$$\sum_{e} DE_{de}^{t} \le 1 \qquad \forall d \in D, t \in T \tag{17}$$

$$A_{cd}^{t} \le BM.CD_{cd}^{t} \qquad \forall\, c \in C,\, d \in D,\, t \in T \tag{18}$$

$$B_{de}^{t} \le BM.DE_{de}^{t} \qquad \forall\, d \in D,\, e \in E,\, t \in T \tag{19}$$

$$H_{gfp}^{t} \le BM.GF_{gfp}^{t} \qquad \forall\, g \in G,\ f \in F,\ p \in \{P \cup P'\},\, t \in T \tag{20}$$

$$K_{fep}^{t} \le BM.FE_{fep}^{t} \qquad \forall\, f \in F,\, e \in E,\ p \in \{P \cup P'\},\, t \in T \tag{21}$$

$$B_{edp}^{\prime t} \le BM.DE_{de}^{t} \qquad \forall\, d \in D,\, e \in E,\ p \in P',\, t \in T \tag{22}$$

$$K_{efp}^{\prime t} \le BM.FE_{fep}^{t} \qquad \forall\, e \in E,\ f \in F,\, p \in P,\, t \in T \tag{23}$$

$$H_{fgp}^{\prime t} \le BM.GF_{gfp}^{t} \qquad \forall\, f \in F,\, g \in G,\ p \in P,\, t \in T \tag{24}$$

$$CD_{cd}^{t}\,.Dis_{cd} \leq BR.OD_{d} \qquad \forall c \in C,\ d \in D,\ t \in T \tag{25}$$

$$DE_{de}^{t}\,.D'is_{de} \leq LR.OE_{e} \qquad \forall d \in D,\ e \in E,\ t \in T \tag{26}$$

$$DE_{de}^{t} \leq OD_{d} \qquad \forall d \in D,\ e \in E,\ t \in T \tag{27}$$

$$FE_{fep}^{t} \leq OE_{e} \qquad \forall f \in F,\ e \in E,\ p \in \{P \cup P'\},\ t \in T \tag{28}$$

$$FE_{fep}^{t} \leq OF_{f} \qquad \forall f \in F,\ e \in E,\ p \in \{P \cup P'\},\ t \in T \tag{29}$$

$$GF_{gfp}^{t} \leq OF_{f} \qquad \forall g \in G,\ f \in F,\ p \in \{P \cup P'\},\ t \in T \tag{30}$$

$$GF_{gfp}^{t} \leq SG_{g} \qquad \forall g \in G,\ f \in F,\ p \in \{P \cup P'\},\ t \in T \tag{31}$$

$$A_{cd}^{t}, B_{de}^{t}, H_{gfp}^{t}, K_{fep}^{t}, SF_{fp}^{t}, SE_{ep}^{t} \geq 0 \qquad \begin{array}{l} \forall c \in C,\ d \in D,\ e \in E,\ f \in F, \\ g \in G,\ p \in \{P \cup P'\},\ t \in T \end{array} \tag{32}$$

$$SD_{dp}^{t}, B_{edp}^{\prime t} \geq 0 \qquad \forall d \in D,\ e \in E,\ p \in P',\ t \in T \tag{33}$$

$$K_{efp}^{\prime t}, H_{fgp}^{\prime t}, SRE_{ep}^{t}, SRF_{fp}^{t} \geq 0 \qquad \forall e \in E,\ f \in F,\ g \in G,\ p \in P,\ t \in T \tag{34}$$

$$OD_{d}, OE_{e}, OF_{f}, SG_{g}, CD_{cd}^{t}, DE_{de}^{t}, GF_{gfp}^{t}, FE_{fep}^{t} \in \{0.1\} \qquad \begin{array}{l} \forall d \in D,\ e \in E,\ f \in F,\ g \in G, \\ p \in \{P \cup P'\},\ t \in T \end{array} \tag{35}$$

The objective function (1) minimizes the total expected cost of the medical laboratory service network and supply chain of laboratory consumables, which consists of fixed costs (costs of establishing facilities and contracting with suppliers) and variable costs (transportation, ordering, holding, and penalty of remaining unused capacity of suppliers and variable income resulting from returning defective laboratory consumables to suppliers). Equation (2) shows the satisfaction of customers' demand for laboratory services in different regions. Equations (3) and (4) indicate constraints of a maximum capacity of supplying laboratory consumables considering the condition of contracting with suppliers and the maximum operating capacity of laboratory centers in testing blood samples considering establishment conditions, respectively. Equations (5)-(9) guarantee the maximum capacity of storing healthy and defective consumables at distribution and collection centers, laboratory centers, and blood sampling centers, considering the condition of establishing facilities. Equation (10) shows the constraint of flow balance at blood sampling centers. Equations (11)-(14) express the inventory balance of laboratory consumables at distribution centers, laboratories, and sampling centers. Considering the collection and return of the first type of defective consumables, Equations (15) and (16) ensure the inventory balance of returned consumables at laboratories and collection centers. Equation (17) indicates the constraint of the indivisibility of blood samples sent from sampling centers to laboratories. Equations (18)-(24) guarantee that flow is established between facilities at different levels if they are assigned to each other. Equations (25) and (26) express constraints of service coverage radius of sampling centers and laboratories to the areas requesting services and blood sampling centers, respectively. Equations (27)-(31) indicate logical relationships between allocating facilities to each other and establishing facilities. Equations (32)-(35) represent logical constraints related to positive and binary variables.

5- Coping with uncertainty in estimating problem parameters

In mathematical optimization problems, estimating parameters used in modeling is always associated with uncertainty, which will vary based on the level of access to historical data. Researchers have proposed several methods to control errors while estimating parameters in mathematical programming problems. Robust optimization and stochastic programming approaches are widely used in this field. In mathematical optimization problems, the availability of sufficient and reliable data provides the possibility of estimating appropriate statistical distribution for random parameters and using a stochastic programming approach, in which ambiguity in parameter estimation is resolved by defining a set of unique scenarios with specific probabilities (Sadrabadi, Jafari-Nodoushan, et al., 2021). In conditions where there is an insufficient amount of data as a range of numbers, the data have random fluctuations. Thus, uncertainty in parameter estimation could be dealt with using a robust optimization approach (Dehghani Sadrabadi et al., 2019). It should be noted that the aforementioned approach could be considered in combination with robust optimization to increase the ability of the stochastic programming method to deal with uncertainty.

In the present research, disruptions are defined as independent scenarios with a certain occurrence probability, so uncertainty in estimating the percentage of disrupted capacity of supplying consumables by the supplier (RS_{gps}), percentage of disrupted capacity of testing blood samples in the laboratory (RL_{es}) and the number of applicants demanding for laboratory services (Cu^{t}_{cs}) could be managed due to the availability of sufficient data and probability of estimating statistical distribution by integrating stochastic programming and robust optimization. Strategic decision variables (except allocating facilities to each other) independent of the scenario (first stage) and other decision variables dependent on the scenario (second stage) are considered to develop a two-stage stochastic programming model.

In the literature, various approaches have combined stochastic programming and robust optimization, one of the most well-known of which is the stochastic robust optimization approach presented by Mulvey et al. (1995). In this method, attempts are made to establish a trade-off between feasibility robustness and optimality robustness by taking into account the standard deviation of the objective function values under each scenario from the nominal value of that scenario as well as the violation or infeasibility of non-deterministic constraints. Aghezzaf et al. (2010) developed a stochastic robust optimization approach based on the method presented by Mulvey et al. (1995), in which attempts are made to control optimality robustness along with the expected value of the objective function considering the maximum deviation of the objective function values under each scenario from the nominal value of that scenario (maximum regret). In the following, explanations are provided regarding implementing the method presented by Aghezzaf et al. (2010) on the two-stage stochastic model.

Each possible scenario is considered using an index $s \in S$ with the occurrence probability of π_s . z^*_S represents the nominal optimal value of the objective function under possible scenario $s \in S$. In conditions where the nature of the objective function of the two-stage model is of minimizing type, applying Aghezzaf's robust optimization method to the two-stage stochastic model leads to the development of the objective function of the robust problem as equation (36). It should be noted that complying with the technical constraint of the problem is still mandatory.

$$Min \quad \eta \sum_{s \in S} \pi_s z_s + (1-\eta) \underset{s \in S}{Max}\left(z_s - z_s^*\right) \tag{36}$$

In equation (36), $\eta \in [0,1]$ is the risk preference level, which represents the decision maker's tendency against risk. This equation consists of two components of expected value $\sum_{s \in S} \pi_s z_s$ and maximum regret $Max_{s \in S}\left(z_s - z_s^*\right)$. Balance could be established between the two mentioned components by changing parameter η. It should be noted that considering low values for parameter η leads to low variability and high stability of model results. The linearization process is performed due to the nonlinear nature of maximum regret $Max_{s \in S}\left(z_s - z_s^*\right)$ considering an unconstrained variable (denoted by y) and using equations (37) and (38).

$$z_s - z_s^* \le y \tag{37}$$

$$y : free \tag{38}$$

6- Real-world case study

Medical laboratory services are among the most important parts of paraclinical services, which could reveal abnormalities and diseases hidden in the patient's body to the physician. Diagnosis, treatment, and prescription of drugs by physicians are based on laboratory reports. Therefore, the quality of laboratory services will play an important role in public health, so its poor performance could impose high financial costs on patients and insurers and disrupt the treatment process. For this reason, using novel technology, advanced equipment, and experienced and efficient laboratory personnel is very important.

Due to currency fluctuations and the high cost of access to laboratory technologies and equipment in Iran, establishing well-equipped and high-quality laboratory centers involves a high cost. Moreover, it could be observed that these centers have high service costs due to not using all the operating capacity originating from the access of limited society groups to these services as well as inefficiency in providing laboratory consumables on a small scale. Therefore, they could not adhere to the tariffs specified by the Ministry of Health and Medical Education due to the heavy investment made, and poor society groups will be deprived of access to quality services. Developing an integrated network of laboratory services and supplying laboratory consumables are among the effective solutions to solve this problem. In this network, all the operating capacity of the laboratory could be used by concentrating laboratory equipment and technologies and establishing sampling centers, in addition to providing access to quality services to all groups of society. Due to the high volume of laboratory consumables required to provide services to clients, integration in the service network increases by creating the supply chain of consumables, and the cost of supplying consumables decreases and, finally, the cost of services decreases, and quality services will be available to everyone with approved tariffs.

In the present research, a case study was investigated in Tehran-Iran to evaluate the performance of mathematical formulation in the real world, considering the relevant data. Programming and management of the studied network are based on the time horizon of 36 months during 12 time periods. The studied network aims to provide laboratory items and services in Tehran to achieve fast and high-quality services. The products required for sampling and diagnostic kits used in laboratory centers are the items that require logistics planning to supply from reliable sources. In this research, Arc GIS is used to determine the candidate location for establishing facilities and a set of 12 optimal clusters related to service demand points. It should be noted that demand point clusters are determined considering two different types of coverage radius to ensure justice in providing services to applicants, provide uniform services by different centers, respect the social status of applicants, minimize their waiting time for receiving services, and improve the quality of services.

7- Results

In this section, a set of numerical outputs resulting from solving the developed mathematical model is visualized, presented, and analyzed. It should be noted that the model is coded using GAMS optimization software. An ASUS laptop with a *Core I9* processor and 16 *GB DDR5* temporary memory is used to run and solve the presented model.

7-1- Numerical outputs

In this section, optimal strategic decisions resulting from solving the mathematical model are presented, and the performance of the studied network is examined under various disruptions. Moreover, the achievements of managing disruptive incidents, various components of costs of the developed system, and the effect of adopting a robust optimization approach on managing uncertainty in the present problem are addressed.

7-1-1- Optimal points determined for establishing new facilities

In the studied network, strategic decisions include determining selected suppliers of laboratory consumables and choosing optimal locations for establishing laboratories, blood sampling facilities, and distribution and collection centers. Fig 2 illustrates a schematic of strategic decisions taken about selecting optimal points for establishing new facilities.

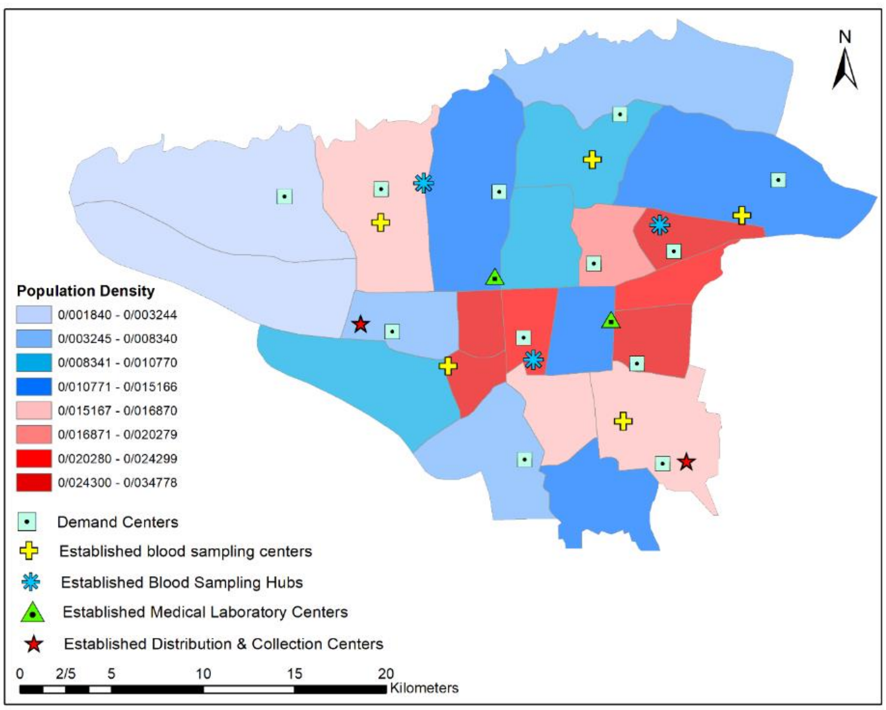


Fig 2. Facilities selected for construction in the network of laboratory services

7-1-2- Examining changes in network design cost due to the occurrence of disruptive incidents at different levels

Fig 3 indicates changes in the total cost due to disruptive incidents at different levels of the studied network.

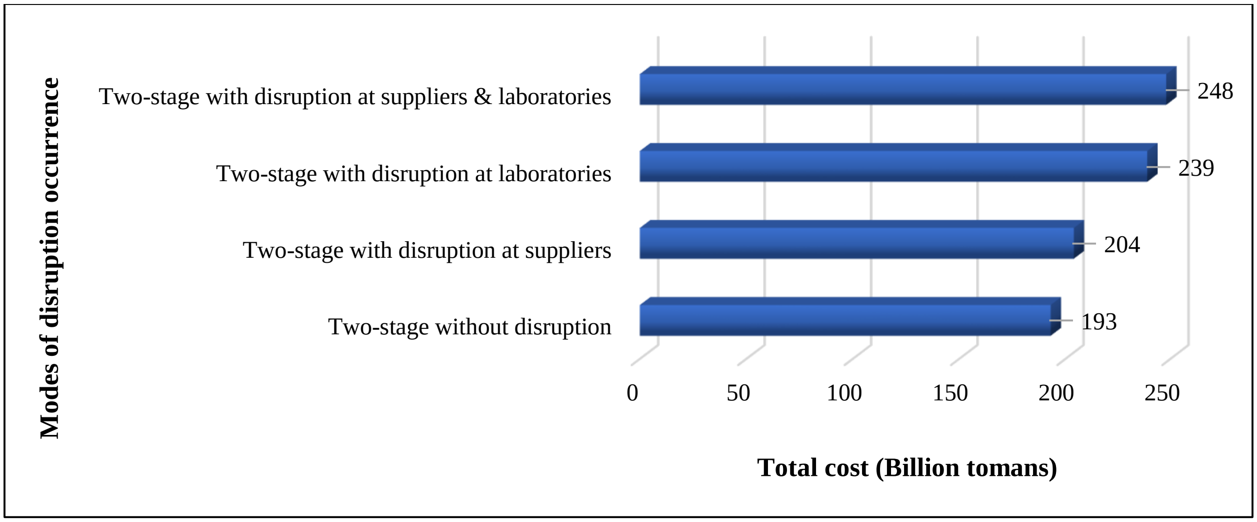


Fig 3. Cost performance of the studied network in case of disruption occurrence in different facilities

As observed, the simultaneous disruption of laboratories and suppliers has the greatest impact on network performance, subsequently increasing the total cost. Disruption of laboratories and suppliers are independently ranked second and third in terms of the impact of disruptions on network design costs. The observed behavior is since disruptions have mutual effects on each other in the situation of disruption occurrence in different facilities, which intensifies the collective effects of disruptive incidents on the performance of the studied network.

7-1-3- Effect of adopting scenario-based robust optimization approach on uncertainty planning

Fig 4 shows the effects of adopting the scenario-based robust optimization approach regarding cost to plan uncertainty under different modes of disruptions occurrence.

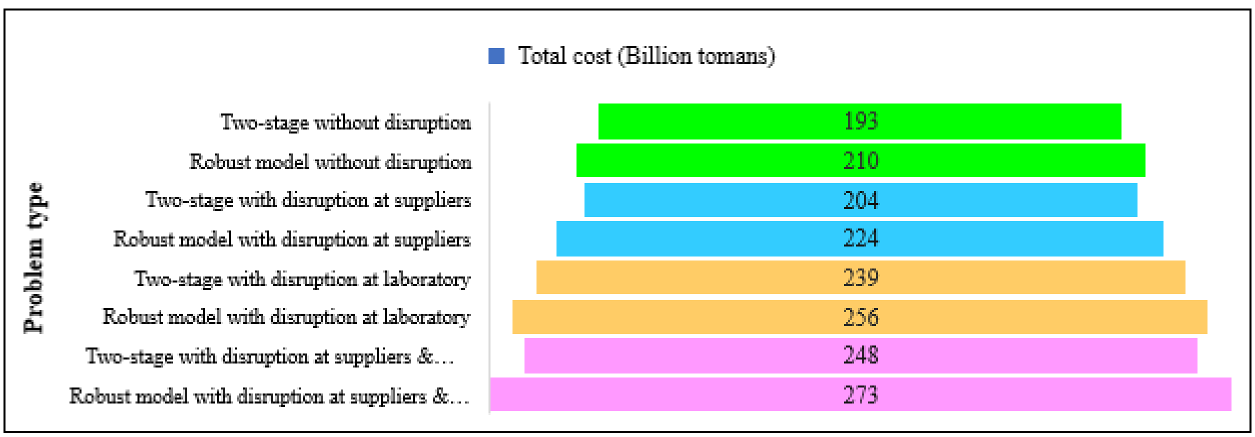
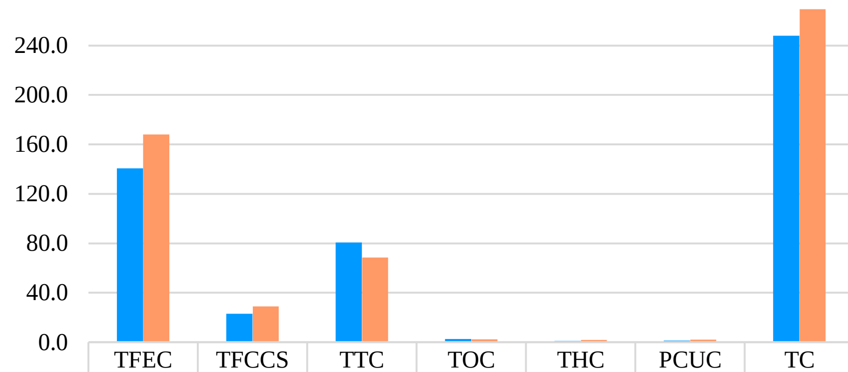


Fig 4. Effect of adopting scenario-based robust optimization approach on the total cost of the network under different modes of disruption occurrence

As indicated in the diagram, disruptive incidents in several facilities simultaneously have a more significant effect than the disruption of each stand-alone facility in terms of cost. Applying the scenario-based optimization approach to plan uncertainty caused by operational risks increases total costs under different modes of disruption occurrence. This behavior is logical because managing operational risks in the studied network requires spending more money.

7-1-4- Examining effects of adopting the scenario-based robust optimization approach compared to the two-stage stochastic model in terms of costs

Fig 5 compares components of the total cost of network design in the scenario-based robust optimization model compared to the two-stage stochastic model in the situation of disruptive incidents.



	TFEC	TFCCS	TTC	TOC	THC	PCUC	TC
Two-stage with Disruption at Supplier and laboratory	140.6	23.0	80.5	2.5	1.0	1.4	248
Robust model with Disruption at Supplier and laboratory	168.0	29.0	68.4	2.2	1.7	2.1	269.3

Two-stage with Disruption at Supplier and laboratory   Robust model with Disruption at Supplier and laboratory

Fig 5. Network design cost components' in the scenario-based robust model compared to the two-stage stochastic model

Applying the scenario-based robust optimization approach to the two-stage stochastic model increases the total cost of network design, fixed cost of establishing facilities, cost of signing a contract with suppliers, cost of maintaining the inventory, and penalty due to the remaining unused capacity of the facility, which is represented by TC, TEEC, TFCCS, THC, and PCUC, respectively. Moreover, applying the scenario-based robust optimization approach significantly reduces the costs of order registration and transporting items, which TOC and TTC represent. The observed behavior is generally quite logical because managing operational risks by adopting the scenario-based robust optimization approach reduces the flow between facilities and order volume. Furthermore, the increased capacity of the studied network against sudden fluctuations in the business environment leads to establishing more facilities, signing contracts with more suppliers, and increasing the inventory of laboratory items to improve providing services to applicants.

7-2- Examining effects of exogenous parameters by sensitivity analysis

Verification of a mathematical model ensures its correct performance in the real world. Sensitivity analysis is among the common approaches for verifying mathematical models and examining the effect of changes in exogenous parameters (i.e., uncontrollable by the studied system) on changes in objective functions of the mathematical model. In the present research, the sensitivity analysis of two parameters, i.e., number of applicants for laboratory services in different regions (represented by Cu_{cs}^{t}) and percentage of the reduced capacity of suppliers of laboratory consumables (represented by RS_{gps}), on the total cost of the network design is discussed as follows:

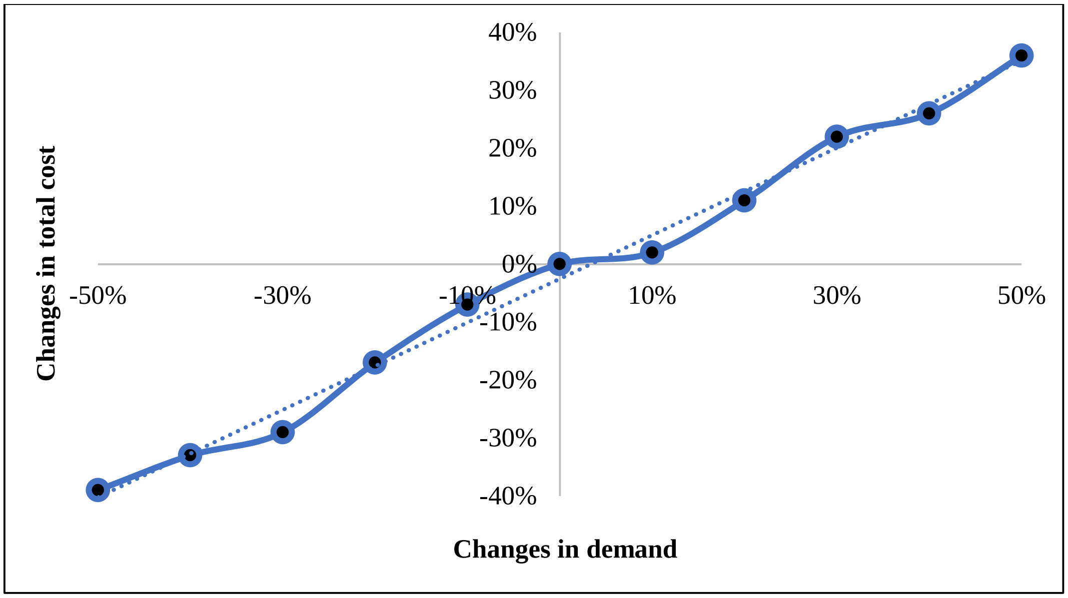


Fig 6. Sensitivity analysis of demand of applicants for laboratory services in different regions

Fig 6 examines the effect of changes in the number of applicants for laboratory services in different regions on the total cost of the studied network design. A general observation indicates that increasing the mentioned parameter could increase the total cost with a relatively high slope, and decreasing this parameter could reduce the total cost. The occurrence of this behavior is completely logical because the increased number of applicants for laboratory services in different regions increases the number of people who apply for services, the necessity of establishing more facilities, transfers between different facilities, the number of orders, and the necessity of maintaining a larger volume of inventory.

Fig 7 shows the effect of changes in the percentage of the reduced capacity of suppliers of laboratory consumables on changes in the total cost of the studied network design.

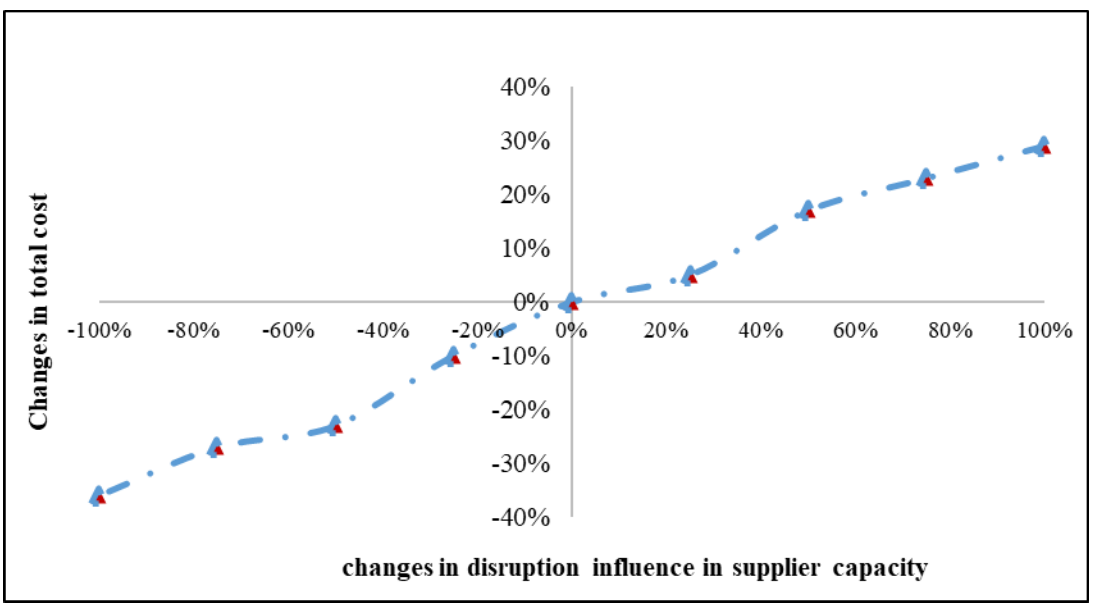


Fig 7. Sensitivity analysis of the percentage of the reduced capacity of suppliers of laboratory consumables

As indicated in the figure, increasing the mentioned parameter increases the total cost with a relatively high slope, and decreasing this parameter reduces the total cost. The reason for this behavior is that reducing the capacity of suppliers of laboratory consumables increases the need to sign contracts with more suppliers and the number of orders, which increases the total cost.

8- Concluding remarks

Today, the role of health service delivery networks in providing quality and reliable services for applicants is of particular importance. Providing optimal health services by networks is achieved when the required items, equipment, and facilities are procured efficiently. Hence, designing an integrated network to provide health services and manage the procurement of items required to advance the network is very important. Due to the numerous outbreaks of pandemic diseases such as COVID-19, the importance of providing laboratory services and relevant items has recently been highlighted to diagnose diseases and refer patients to medical centers quickly. This point was also addressed in the present research.

In this research, a single-objective and multi-period mathematical model was presented to integrate the network of providing laboratory services and managing the procurement of consumables in the event of disruptive incidents and operational risks. The strategic and tactical decisions discussed in the model included common measures of network design, i.e., choosing the supplier, determining the flow volume between facilities, specifying the inventory maintained by some facilities, and other relevant decisions, to minimize the system's total cost. The scenario-based robust optimization approach was employed to deal with uncertainty and ambiguity in estimating the input parameters of the mathematical model.

Although this research provided significant contributions, this includes some shortcomings that, if covered, could greatly contribute to the richness of the research literature. Considering other important objective functions in network design for providing laboratory services, such as paying attention to justice in the distribution of laboratory items, meeting the environmental and social requirements related to sustainable development, and achieving the minimum total waiting time for providing services, etc. could greatly improve achievements of the presented model. Adopting preventive and reactive resiliency measures for dealing with negative effects caused by disruptive incidents and improving the process of providing health services applicants should be considered. Applying deep learning approaches to predict the number of applicants for laboratory services and determine the partial effect of disruptions on the capacity of facilities could greatly contribute to making the studied network intelligent. Also, adopting a data-driven robust optimization approach for managing uncertainty caused by ambiguous parameters is of great importance.

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