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ORIGINAL RESEARCH

A data-driven optimization model to response to COVID-19 pandemic: a case study

Amin Eshkiti[1] · Fatemeh Sabouhi[1] · Ali Bozorgi-Amiri[1]

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Abstract

COVID-19 is a highly prevalent disease that has led to numerous predicaments for healthcare systems worldwide. Owing to the significant influx of patients and limited resources of health services, there have been several limitations associated with patients' hospitalization. These limitations can cause an increment in the COVID-19-related mortality due to the lack of appropriate medical services. They can also elevate the risk of infection in the rest of the population. The present study aims to investigate a two-phase approach to designing a supply chain network for hospitalizing patients in the existing and temporary hospitals, efficiently distributing medications and medical items needed by patients, and managing the waste created in hospitals. Since the number of future patients is uncertain, in the first phase, trained Artificial Neural Networks with historical data forecast the number of patients in future periods and generate scenarios. Through the use of the K-Means method, these scenarios are reduced. In the second phase, a multi-objective, multi-period, data-driven two-stage stochastic programming is developed using the acquired scenarios in the previous phase concerning the uncertainty and disruption in facilities. The objectives of the proposed model include maximizing the minimum allocation-to-demand ratio, minimizing the total risk of disease spread, and minimizing the total transportation time. Furthermore, a real case study is investigated in Tehran, the capital of Iran. The results showed that the areas with the highest population density and no facilities near them have been selected for the location of temporary facilities. Among temporary facilities, temporary hospitals can allocate up to 2.6% of the total demand, which puts pressure on the existing hospitals to be removed. Furthermore, the results indicated that the allocation-to-demand ratio can remain at an ideal level when disruptions occur by considering temporary facilities. Our analyses focus on: (1) Examining demand forecasting error and generated scenarios in the first phase, (2) exploring the impact of demand parameters on the allocation-to-demand ratio, total time and total risk, (3) investigating the strategy of utilizing temporary hospitals to address sudden changes in demand, (4) evaluating the effect of disruption to facilities on the supply chain network.

✉ Ali Bozorgi-Amiri
alibozorgi@ut.ac.ir

Amin Eshkiti
amin.eshkiti@ut.ac.ir

Fatemeh Sabouhi
fatemehsabouhi@ut.ac.ir

[1] School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran

Keywords Data-driven two-stage stochastic programming · COVID-19 pandemic · Artificial neural network · Waste management · Distribution of medications

1 Introduction

The World Health Organization (WHO) reports that the pandemic of COVID-19 has affected over 200 countries across the globe, with over 219 million people infected and 4.5 million people dead (WHO, 2021). The particularly high number of patients in this unprecedented experience necessitates proper resource management and an effective supply chain network (SCN) (Sharma et al., 2020; Eshkiti, Bozorgi-Amiri, and Sabouhi 2022). The leading implications triggered by this pandemic are the lack of hospital beds, insufficient medical supplies required for patients and the healthcare system, and waste management in hospitals, which has caused global complications (Rowan & Laffey, 2020; Sun et al., 2021). As a result, quick responses and solutions are vital to respond to these challenges.

As COVID-19 cases continue to rise, one of the major worries is the inadequacy of the medical infrastructure to fulfill patients' needs, particularly in the case of hospital beds and ICU beds; the lack of these facilities can lead to a dramatically high mortality rate associated with the disease (Choi, 2021; Volpato et al., 2020). This issue is considered a crisis even in some developed countries with competent healthcare systems (Gatto et al., 2020; Patel et al., 2020). Additionally, COVID-19 patients in hospitals have occupied hospital beds, reducing the capacity of hospitals, as a result of which patients suffering from other diseases cannot be hospitalized. The lack of empty hospital beds also exposes non-COVID-19 patients to the infection because they are more vulnerable to the virus. Moreover, as the number of patients increases, the health workers, who have the most contact with COVID-19 patients, are more likely to become infected with the virus. The absence of health workers due to being sick decreases the service capacity of many sectors, such as hospitals.

Prior to the COVID-19 epidemic, medicine shortages were a severe concern. However, the increased demand for certain medications and government restrictions implemented in some cases as a result of the pandemic aggravated the problem. Due to the pandemic, an increase in demand for medications and medical equipment is inevitable. Hence, paying extra attention to the supply of medical equipment and the medications needed by patients is of particular necessity (Goodarzian et al., 2021a, b; Shuman et al., 2020).

Along with the aforementioned factors, another issue that is equally crucial is the proper handling of infectious medical waste (IMW) within hospital. During the COVID-19 outbreak, various types of medical and hazardous waste were generated, such as infected protective equipment like masks and gloves (Sharma et al., 2020). Handling IMW is a critical part of managing a infectious disease as inappropriate collection and mismanagement of these wastes can exacerbate the spread of the infection and put patients and the healthcare system under a great deal of pressure (Kargar et al., 2020a). Earlier studies have demonstrated that one of the primary ways hospital staff are infected with diseases is the unwanted contact with infectious waste at the point of generation of the IMW. A hospital in a developed country, such as the US or the UK, has a legal duty to prevent infections caused by improper handling of IMW (WHO, 2014). As a result, the disposal and safe processing of IMW is a critical component of an efficient emergency response. Adequate healthcare waste management encompasses suitable procedures for collecting, segregating, storing, transporting, treating, and disposing of waste. For this reason, given the high risks of IMW, which can infect people and impair other actions for controlling the pandemic to, governments declare IMW management as necessary and of high priority (UNEP, 2020). Thus, considering an integrated approach to allocating patients to hospitals, supplying their medicinal items, and managing hospital waste is of particular importance (Goodarzian et al., 2021a).

The main challenges faced in the management of this pandemic are the uncertainty over the number of patients and disruptions in the capacity of facilities due to this uncertainty which is believed to be a burden regarding patients' hospitalization, medical items distribution, and waste management (Koffman et al., 2020).

Disruption in the capacity of facilities could have various justifications, including the followings:

- Owing to the consequences of the COVID-19 pandemic concerning the SC of personal protective equipment (PPE) and surges in the number of patients requiring hospitalization, many healthcare professionals are dying in hospitals, and physicians have become infected with this virus because of the lack of PPE, causing hospitals to have reduced their capacity (Yoshida et al., 2020).
- As a result of the infection of people working in waste treatment and disposal facilities resulting from close contact with waste infected with the COVID-19 virus, as well as a significant rise in the volume of generated waste (such as PPEs and masks, for example, which are disposable), waste management facilities have faced a reduction in capacity (Teymourian et al., 2021).
- The disruption in PPE supply exacerbated by the healthcare crisis caused by a demand shock, the government's failure to manage and distribute domestic supplies, and significant interruptions to PPE's worldwide SC (Cohen & Rodgers, 2020).

Numerous approaches exist to manage the uncertainty in an optimization problem (Sadrabadi et al. 2023). The method of stochastic programming has been frequently employed to tackle an optimization problem with uncertainty. When coping with uncertainty via the stochastic method a set of scenarios must be created to resemble the uncertain parameters. These created scenarios ought to correspond to possible occurrences of the uncertain parameters and their dependent probabilities (Desi−Nezhad, Sabouhi, and Sadrabadi 2022). Machine Learning (ML) is one of the most widely utilized approaches to forecasting time series and has been proposed as an alternative statistical time series forecasting method. ML forecasting is one of the most effective approaches to capturing patterns in the sequence data, forecasting time series analysis, and obtaining scenarios for planning (Makridakis et al., 2018).

To respond to the pandemic of COVID-19, temporary facilities (for example temporary hospitals), the distribution of relief items and medicines, and waste management must be consideration. Thus, in this paper, a hybrid approach was proposed. In the first phase, by training number of Artificial Neural Networks (ANN), the number of patients in future periods and disruption scenarios were forecasted. Subsequently, using the K-Means method, these obtained scenarios were reduced. In the second phase, a data-driven two-stage stochastic model was proposed. In this model, given the fact that several hospitals in many countries mostly function based on their maximum patient's capacity, locating temporary hospitals to allocate patients were also considered. Furthermore, the proposed mathematical model considers the distribution of the required medications to hospitals by locating distribution centers. Due to the significant amount of IMW produced in hospitals and their high risk of disease transmission, waste management was also considered in the model by taking into account the existing waste disposal centers and setting up temporary disposal centers along with temporary transfer centers.

The following sections of the article are organized as such: In Sect. 2, an overview of the literature on the subject is presented. The two-phase approach to supply chain network design (SCND) is presented in Sect. 3. Sect. 4 presents the computational results of the case study. Sect. 5 discusses the findings and managerial insights. Finally, Sect. 6 concludes the paper.

2 Literature review

Within this section of the article, the papers conducted in the four following areas are reviewed: models for forecasting the number of COVID-19 patients, data-driven optimization and scenario generation and reduction in SCND, supply chain networks for resource allocation and distribution during COVID-19 outbreak, and medical waste management during COVID-19 outbreak. Afterward, research gaps are presented.

2.1 Models for forecasting the number of COVID-19 patients

Due to the significant number of individuals affected by COVID-19 and the elevated rate of fatalities, one of the utmost important tasks is to make highly accurate forecasts regarding the number of patients. An accurate prediction can contribute to revealing the surge in demands; as a result, governments will be able to take preventive actions more efficiently (Abbasimehr & Paki, 2021). ML models and ANN have been widely used to forecast the number of confirmed COVID-19 patients and have shown good performance in this regard. (Kırbaş et al., 2020), employing Nonlinear Autoregression Neural Network (NARNN) model, Auto-Regressive Integrated Moving Average (ARIMA) approach, and Long-Short Term Memory (LSTM) model, predicted the number of confirmed COVID-19 cases in various countries. They found that the LSTM model has the greatest performance among the other approaches. Considering Polynomial Regression and hyperparameter optimization while using the Gaussian process regression, (Dhamodharavadhani & Rathipriya, 2021) estimated the mortality rate of COVID-19 in India. (Wang et al., 2020) trained an LSTM model on the data of daily confirmed cases by Johns Hopkins University to forecast 150 consecutive days in Russia, Peru, and Iran. Other researchers have published similar articles in this regard, such as (Abbasimehr & Paki, 2021; Arora et al., 2020; Melin et al., 2020; Shahid et al., 2020). In addition to using ML methods for forecasting the cases of COVID-19, other models, such as SEIR, have been utilized to estimate the epidemiological parameters of COVID-19, and the obtained predicted parameters are utilized to forecast future cases (Godio et al., 2020; Gopal et al., 2021; Kumar et al., 2021; Malik et al., 2021; Zhan et al., 2021).

2.2 Data-driven optimization, scenario generation and reduction in supply chain network design

Primary efforts in data-driven supply chains focus on Robust optimization and ML techniques for identifying the uncertainty sets. Using Support vector clustering for obtaining the uncertainty set for uncertain parameters, a data-driven model that systemically designs and optimizes the supply chain of biodiesel production from the wastewater sludge by (Mohseni & Pishvaee, 2020). In a similar approach, (K. M. Gumte et al., 2021a, 2021b) used a neuro-fuzzy clustering mechanism for clustering the uncertain space to identify the optimal uncertainty regions. After clustering, by calculating the local density of points, creating the boundary of the acquired cluster, generating a hypercube with the use of the minimum and maximum boundaries of each dimension of the cluster, and employing the Sobol sampling approach, they calculated the new uncertain dataset used for the worst- and best-case scenarios in their proposed Robust optimization. Similarly, (K. Gumte et al., 2021a, 2021b) used neuro-fuzzy C-means clustering for obtaining the uncertainty sets.

In the problems of SCND considering uncertainty, the stochastic programming approach has been frequently employed to tackle an optimization problem under uncertainty. Stochastic parameters are usually represented by discrete scenarios with known probabilities. Research studies have allocated significant efforts to creating effective scenarios in stochastic programming. (Govindan & Fattahi, 2017) used the Latin Hypercube Sampling method for scenario generation and the backward scenario reduction method for decreasing the scenarios' number. In order to make decisions about expanding a food company, according to the available historical data and considering market intelligence, business sense, and the intuition of the management, (Aras & Bilge, 2018) considered different scenarios for demand. In another study, through Cholesky's factorization method for generating the scenarios and by decreasing the number of generated scenarios with the K-Means algorithm, (Khatami et al., 2015) proposed a closed-loop SCND with uncertainty in return and demand. In this regard, (Snoeck et al., 2019), using the Monte Carlo method, generated scenarios for parameters of selling price, demand, transportation costs, and feedstock price to assess the value of investments in mitigation and the costs of disruptions in the chemical supply chain. Similarly, (Gholami-Zanjani et al., 2021) utilized the Monte Carlo method for generating the demand scenarios for a resilient food SCND. Afterwards, they used Fuzzy Bezdek Clustering method for reducing the number of generated scenarios. In a similar context, to generate scenarios related to operating costs and environmental impacts parameters, (Feitó-Cespón et al., 2021) used a Fuzzy Inference System methodology. Subsequently, using the obtained scenarios, they proposed a reverse SCND in the context of the plastic recycling process.

2.3 Supply chain networks for resource allocation and distribution during COVID-19 outbreak

Because of the severe damage wrought by COVID-19, the demand for resources has risen dramatically, and the need to optimize resource allocation and distribution of relief items and medicines has become increasingly important (Jordan et al., 2021; Yaqoubi et al., 2022). Because transfusing plasma from severe COVID-19 cases can reduce the effects of the disease on new patients, (Shirazi et al., 2021) developed a bi-objective stochastic optimization-simulation model for the plasma supply chain during the COVID-19 pandemic. By simulating the quantity of plasma demand, they developed a supply chain to find the location of blood collection centers, locate temporary plasma processing centers, allocate them beside the existing process centers to collection centers, and allocate facilities to the hospitals. Other respiratory diseases, such as the flu, could put extra pressure on the health services during the COVID-19 pandemic. In this regard, (Rastegar et al., 2021) attempted to optimize the allocation of influenza vaccines by locating distribution centers and considering allocating demands to the hospitals. (Sarkar et al., 2021) developed a data-driven optimization model for the allocation of patients to the hospitals by developing a compartmental model to delineate the spread of the COVID-19 virus and applying Pareto analysis to categorize the cities that have been affected the most by the COVID-19 pandemic.

(Goodarzian et al., 2021b) developed a sustainable medical SCN considering the production of COVID-19-related medicines, the distribution centers' location and distribution of medications, facility allocation, and inventory control. They also used a simulation-based approach to determine the number of medicines required for COVID-19 patients. Finally, they used three meta-heuristics: Firefly algorithm hybrid with Variable Neighborhood Search, Ant Colony Optimization, and Fish Swarm Algorithm in a case study. Concerning the resource sharing for critical medical resources, (Mehrotra et al., 2020) developed a stochastic model for allocating ventilators to demand regions and then used the model to solve a case study of different states in the United States. (Gilani & Sahebi, 2022) proposed a vaccine distribution supply chain model by considering economic, social, and environmental dimensions. This model considers domestic or foreign vaccine production, vaccine distribution centers, different modes of transportation, types of vaccines, and the amount of vaccine sent to medical centers. Similarly, (Shiri & Ahmadizar, 2022) proposed a vaccine SCN for the COVID-19 pandemic. In this study, they first generated the demand scenarios using the Monte Carlo method; then, to distribute vaccines, by locating distribution centers, healthcare infrastructures are allocated to these hubs by considering minimization of the total cost as the objective function.

2.4 Medical waste management during COVID-19 outbreak

Another important aspect of planning the COVID-19 pandemic response is the management of IMW (Peng et al., 2020). Owing to the great number of people who are infected with the virus, the IMW generated in hospitals has faced dramatic growth. Therefore, the waste management is believed to be a vital part of managing the COVID-19 pandemic. (Tirkolaee et al., 2021) developed a location-routing mathematical model considering sustainability and time windows for management of medical waste during the COVID-19 pandemic. This model aims to minimize three objectives: total violation from time windows, total traveling time, and set up of disposal centers-associated infection risk. In another study, (Kargar et al., 2020b) presented a reverse logistics network design for waste management amid the COVID-19 pandemic. The IMW generated is handled with the landfills and existing and temporary treatment centers. This model tries to minimize three objectives: the total costs, the associated infection risk from transportation and processing of IMW in treatment centers, and uncollected wastes. Similarly, (H. Yu et al., 2020b) proposed a reverse logistics model for waste management during an epidemic outbreak. In this study, hospitals and healthcare centers are considered as the source of generating IMW. For managing these wastes, they have considered temporary waste transit centers, existing and temporary waste treatment centers, and waste disposal centers. They aim to minimize the infection risk of uncollected wastes, the infection risk of transportation and treatment of the wastes, and the total costs. Table 1 depicts the specific features of the reviewed studies.

2.5 Research gaps

As stated by the review of literature, it can be primarily seen that no studies included an integrated SCND to respond to the pandemic of COVID-19 in terms of patient allocation to the existing and temporary hospitals, medication distribution, waste management, infection risk of constructing temporary facilities and waste management, and disruption in the capacity of facilities altogether. Secondly, there is a lack of data-driven modeling to make use of available data from COVID-19 disease; this is particularly important since many of the components associated with the pandemic of COVID-19, including the number of patients in future periods, are unknown, can be accurately addressed using certain methods (ML and

Table 1 The classification of reviewed papers

References	Decision-Level				Objectives			Number of objectives		Condition	
	Location	Allocation	Inventory	Distribution	Maximizing Coverage	Minimizing Risk	Minimizing Time	Single	Multi	Deterministic	Uncertain
Yu et al., (2020a, b)	✓	✓	–	–	–	✓	–	–	✓	✓	–
Kargar et al. (2020b)	✓	✓	–	–	–	✓	–	–	✓	✓	–
Mehrotra et al. (2020)	–	✓	✓	–	✓	–	–	✓	–	–	✓
Tirkolaee et al. (2021)	✓	✓	–	–	–	✓	✓	–	✓	–	✓
Goodarzian et al., (2021a, b)	✓	✓	✓	✓	✓	–	–	–	✓	–	✓
Sarkar et al. (2021)	–	✓	–	–	–	–	–	✓	–	✓	–
Rastegar et al. (2021)	✓	✓	✓	✓	✓	–	–	✓	–	✓	–
Shirazi et al. (2021)	✓	✓	✓	✓	–	–	✓	–	✓	–	✓
Gilani and Sahebi (2022)	✓	✓	✓	✓	–	–	–	–	✓	–	✓
Shiri and Ahmadizar (2022)	✓	✓	✓	✓	–	–	–	–	✓	–	✓
Current research	✓	✓	✓	✓	✓	✓	✓	–	✓	–	✓

References	Commodity		Constraints				Disruption		Patient allocation to hospitals	Distribution of medications	Waste Management	Data-driven
	Single	Multi	Capacity	Minimum coverage threshold	Inventory	Budget	Partial	Complete				
Yu et al., (2020a, b)	✓	–	✓	–	–	–	–	–	–	–	✓	–
Kargar et al. (2020b)	✓	–	✓	–	–	–	–	–	–	–	✓	–
Mehrotra et al. (2020)	✓	–	–	–	✓	–	–	–	–	✓	–	–

Table 1 (continued)

References	Commodity		Constraints				Disruption		Patient allocation to hospitals	Distribution of medications	Waste Management	Data-driven
	Single	Multi	Capacity	Minimum coverage threshold	Inventory	Budget	Partial	Complete				
Tirkolaee et al. (2021)	✓	–	✓	–	–	✓	–	–	–	–	✓	–
Goodarzian et al., (2021a, b)	–	✓	✓	–	✓	–	–	–	–	✓	–	–
Sarkar et al. (2021)	–	–	✓	–	–	–	–	–	✓	–	–	✓
Rastegar et al. (2021)	✓	–	✓	✓	–	✓	–	–	–	✓	–	–
Shirazi et al. (2021)	–	✓	✓	–	–	–	–	–	–	✓	–	–
Gilani and Sahebi (2022)	–	✓	✓	✓	✓	–	–	–	–	✓	–	✓
Shiri and Ahmadizar (2022)	–	✓	✓	–	✓	–	–	–	–	✓	–	✓
Current research	–	✓	✓	✓	✓	✓	✓	–	✓	✓	✓	✓

ANN). Many countries around the world provide daily updates on the number of people infected and deaths by COVID-19 amid the ongoing pandemic. Through time, and due to the persistence of this epidemic, it could be seen that there is a lot of time series data available. The use of historical data and tools like ML or time series analysis can contribute to accurate forecasting of the number of infected people in future periods. One of the vital problems of supply chains (commercial and humanitarian) throughout the COVID-19 pandemic is the uncertainty in demand (Raj et al., 2022). When uncertainty is present in decision-making, it can lead to certain problems, such as medical resource distribution, reducing or limiting the ability to provide care to patients, providing temporary healthcare solutions, and many other problems. Data-driven SCNDs, such as the proposed two-phase approach in this study, can positively impact the financial performance, responsiveness, and resource management of the supply chains (W. Yu et al., 2018). Thirdly, a few papers have considered the disruption in the capacity of facilities, such as hospitals, distribution centers, as well as waste transfer and disposal centers simultaneously. Finally, investigation of the specific features of COVID-19 disease, such as the probability of different demand scenarios, prioritizing the allocation of severe patients to the existing and more advanced facilities and non-severe patients to temporary ones with a lower service level, and the specific medicine requirements for each group of patients has not been comprehensively carried out in the literature.

In this study, a two-phase approach is presented by mathematical modeling the specific characteristics of the COVID-19 pandemic. As part of the first phase, using the ANN, the number of patients in the future periods was forecasted, and scenarios were generated. Afterward, using the K-Means method, the obtained scenarios were reduced. Ultimately, in the second phase, a data-driven two-stage stochastic programming (TSSP) model was proposed using the obtained scenarios in the first phase, which has three objectives, namely maximizing the minimum allocation of COVID-19 patients to hospitals, minimizing the total transportation time, and minimizing the total infection risk associated with the temporary facility installation and transportation of medical supplies and IMW. In the proposed model, the following factors were considered: locating temporary facilities (temporary hospitals and temporary waste transfer and disposal centers), disruption in the capacity of facilities, medication distribution by locating distribution centers, and waste management.

3 A two-phase approach for supply chain network design

Amidst the COVID-19 pandemic, one of the biggest challenges is the lack of adequate hospital beds for patients. Given the fact that the lack of medical care for patients can raise the chance of an increase in the severity of their disease, locating temporary hospitals is essential. However, COVID-19 disease is more severe in some and milder in others. Therefore, patients' hospitalization should be prioritized, and people with more severe conditions should be prioritized. In addition, they should be allocated to the existing hospitals (which are more equipped than temporary ones). For this purpose, a multi-objective, three-echelon, multi-product, multi-period, data-driven mixed-integer two-stage stochastic linear programming model is proposed. As shown in Fig. 1, COVID-19 patients with any level of severity of the disease are initially allocated to the existing hospitals. Thereafter, if there is no more bed capacity in the existing hospitals, with locating temporary hospitals, patients with lower disease severity are assigned to these established temporary hospitals. Depending on the patients' need for medications, the required medications from distribution centers are then provided to the hospitals by locating distribution centers. Subsequently, considering the IMW

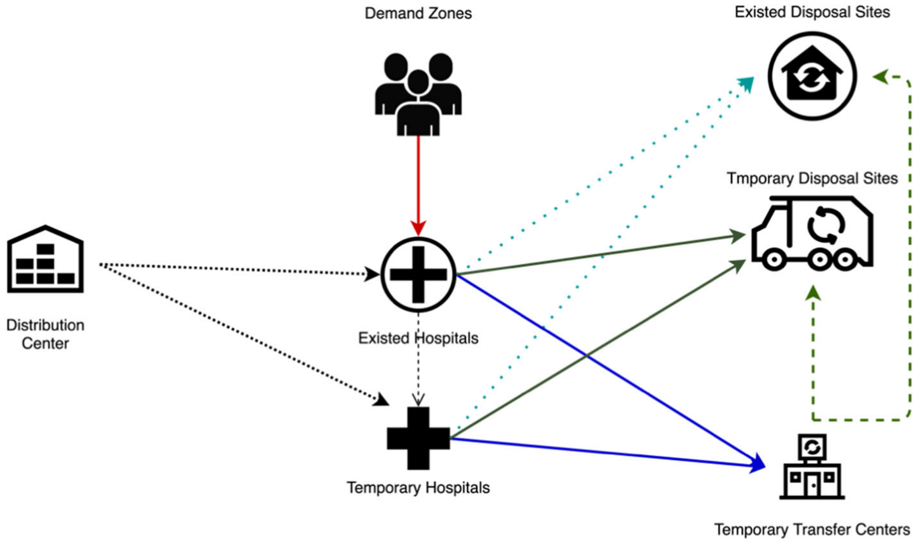

Fig. 1 The proposed SCN

produced in hospitals, infectious wastes are handled in two ways. The first strategy involves transferring waste directly to the existing disposal facilities for waste. Afterward, with the completion of the processing capacity of the existing waste disposal centers, if necessary, temporary waste disposal centers are set up. In the second strategy, by establishing temporary waste transfer centers, the wastes are first transferred to these centers and then sent to the existing and temporary waste disposal centers. Among all the above-mentioned challenges, the most pivotal part of supply chain management to respond to this pandemic is knowing the number of patients for the planning horizon. Therefore, forecasting the number of patients for future periods is known to be one of the main components of effective disease management; this is because of the growing number of infected cases, as a result of which, more medical staff and health workers could become infected, causing disruptions and underperformance in distribution centers, hospitals, and waste management centers due to their absence.

This problem necessitates making efficient decisions about the following:

- The location of the distribution centers
- The location of the temporary hospitals
- The quantity of medications transported from distribution centers to medical facilities
- The number of patients allocated to hospitals
- The location of temporary disposal and transfer centers
- The amount of uncollected IMW in hospitals
- The quantity of waste transferred from hospitals to the waste disposal or transfer centers

This research is divided into two phases in this regard. In the first phase, several recurrent neural networks with LSTM architecture were trained on the historical data to forecast the number of patients in future periods and generate demand scenarios. The latest daily data of COVID-19 allows accurate forecasts using state-of-the-art tools, such as ML and deep learning (DL). Additionally, the daily data of the number of infected people available is suitable for ML owing to the long time since the pandemic started. On the other hand, time series data that cover a broad period capture more trends and seasonality embedded in them,

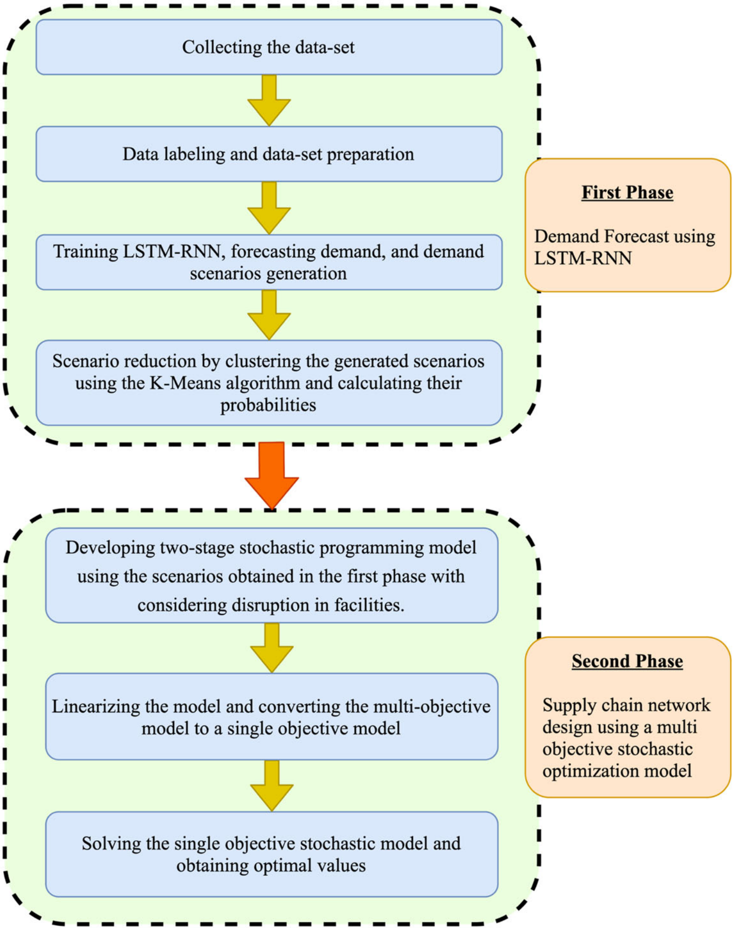

Fig. 2 The steps of the proposed approach

making the forecasts more accurate. Via the K-Means clustering method (Jain et al., 1999), the created scenarios were then clustered, and the final scenarios were obtained. During the second phase, a TSSP mathematical model was developed using the demand scenarios obtained in the first phase. Subsequently, following the conversion of the suggested model into a linear form, the multi-objective model was turned into a single-objective model employing augmented ε-constraint method (AUGMECON2).

Figure 2 depicts the steps of the two-phase approach. In the following sections, we elaborate on each phase.

3.1 Phase one: forecasting the demand using LSTM-RNN

DL methods, especially RNNs, are suitable for processing sequences like time-series and have been widely utilized in this area. However, the major drawback of recurrent neural

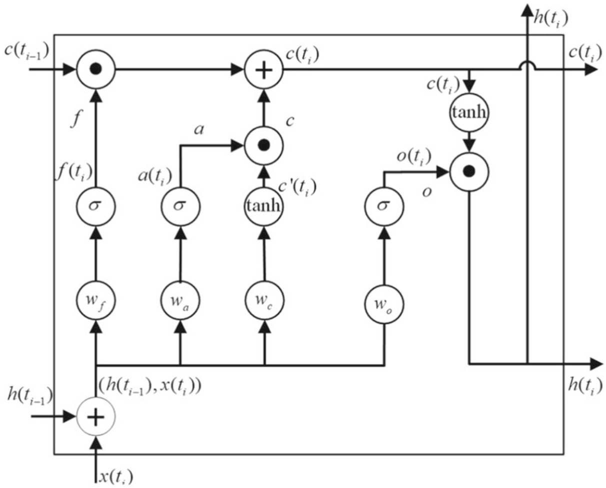

Fig. 3 Architecture of LSTM (Greff et al., 2017)

networks is the issue of vanishing or exploding gradients, which makes training challenging (Abbasimehr & Paki, 2021). As an extension of RNN, LSTM excels in forecasting time series data owing to its capability of maintaining long-term temporal dependencies (allowing it to store information for extended periods) (Greff et al., 2017). LSTM-RNNs are more accurate than traditional ANNs for time series data because they can capture long-term dependencies. This makes them ideal for predicting future trends and forecasting time series. It handles the vanishing gradient problem because of which learning is terminated in neural networks. Additionally, LSTM-RNNs are becoming increasingly popular for their ability to resist noise interference and their capacity to handle higher levels of complexity than traditional RNNs.

Every LSTM block comprises of a cell state, a forget gate, an input gate, and an output gate. The structure of an LSTM block is illustrated in Fig. 3. In LSTM, $x(t_i)$ is the input value, $h(t_i)$ and $h(t_{i-1})$ are the output values at the time points t_i and t_{i-1}, respectively, and $c(t_i)$ and $c(t_{i-1})$ represent the cell states at the time points t_i and t_{i-1}, respectively. The functioning of each LSTM block is as follows:

- The forget gate $f(t_i)$ computes and preserves the information in $c(t_{i-1})$ using $x(t_i)$ and $h(t_{i-1})$ along with sigmoid activation.
- Using the $x(t_i)$ and $h(t_{i-1})$, the input gate $a(t_i)$ computes the value of $c(t_i)$.
- By applying tanh and sigmoid on $c(t_i)$, the output gate $o(t_i)$ implements regulation.

The mathematical expression for the forward learning process of an LSTM block is as follows:

$$a(t_i) = \sigma(w_a x(t_i) + w_{ha} h(t_{i-1}) + b_a) \tag{1}$$

$$f(t_i) = \sigma(w_f x(t_i) + w_{hf} h(t_{i-1}) + b_f) \tag{2}$$

$$c(t_i) = f_t \times c(t_{i-1}) + a_t \times tanh(w_x x(t_i) + w_{hc}(h(t_{i-1}) + b_c)) \tag{3}$$

$$o(t_i) = \sigma(w_o x(t_i) + w_{ho} h(t_{i-1}) + b_o) \tag{4}$$

$$h(t_i) = o(t_i) \times tanh(c(t_i)) \tag{5}$$

Here, the activation functions are sigmoid (σ) and tanh, and the symbol $\times$ denotes pointwise multiplication, $\{b_c, b_f, b_a, , b_o\}$ denote the biases of the cell state, forget gate, input gate, and output gate, respectively, $\{w_c, w_f, w_a, w_o\}$ are the weights matrix of cell state, forget gate, input gate, and output gate, respectively, $\{w_{ha}, w_{hf}, w_{hc}, w_{ho}\}$ are the recurrent weights, and finally, $\{a(t_i), f(t_i), c(t_i), o(t_i)\}$ show the output results of the gates. The learning steps of an LSTM are as below:

1. Computing the output using Eqs. (1) to (5) (forward learning).
2. Calculating the error between the output and input data labels.
3. Backpropagation and updating each gate's weight using an optimization algorithm.

At the end of the process, the optimal weights and biases are determined by repeating the aforementioned steps for a given number of iterations.

The architecture used for the proposed neural networks is shown in Fig. 4, consisting of LSTM neurons with Rectified Linear Unit (ReLU) activation function for the first layer, which gets the data as input. In the next layer, fully connected Dense neurons with ReLU activation function are utilized. Regularization, particularly the appropriate use of the drop-out layer, is critical to the performance, given the intricacy of the proposed models. Studies have shown that with this type of artificial neural network architecture and through the use of this network for forecasting time series, drop-out layers with a rate of 0.5 are of great importance to prevent overfitting and enhance the generalization of the resulted model (Lipton et al., 2016). Therefore, a drop-out layer with a rate of 0.5 is applied. Eventually, fully connected Dense neurons with ReLU activation are used in the final layer for providing the output.

According to Fig. 4, the inputs with the size of 5×1 (the number of periods specified) are entered into 100 LSTM blocks. Moreover, in the final layer, there are five fully connected Dense neurons giving an output with the size of 5×1 (as much as the number of periods desired for forecasting). It should be noted that this architecture is based on the actions taken

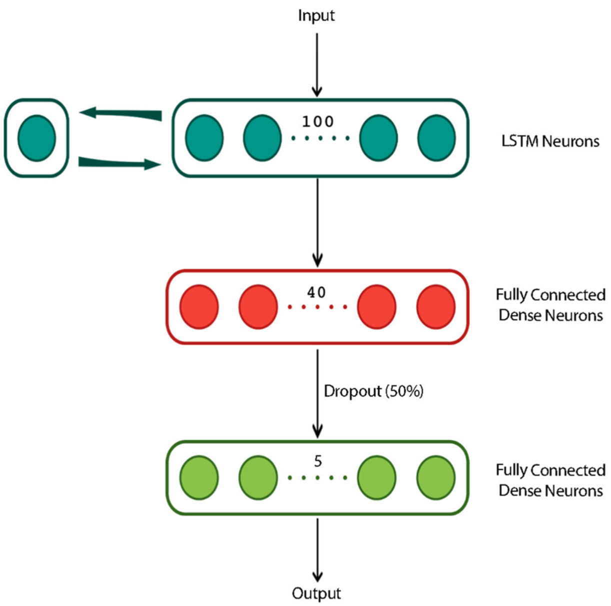

Fig. 4 The proposed ANN architecture

during data preparation. Therefore, the input and output data sizes depend on how the data and the desired outcomes from running this network are labeled in this research, since the data are considered to be five time periods as input and the subsequent five time periods as labels, the proposed network will finally forecast the demand for five periods.

3.1.1 Data preparation

Three fundamental data preparation tasks used to prepare data for forecasting are data cleaning, normalization, and data labeling. Given a time series of length N $\{x(t_i), i = 1, 2, \ldots, N\}$, the preprocessing steps are as follows:

- **Data cleaning**
  In the case of noisy and missing values in the given time series, the noisy values need to be smoothed out, and the missing values must be replaced using a suitable methodology.
- **Data normalization**
  The given $x(t_i)$ time series is normalized as follow, and the result represented as $\{x_n(t_i), i = 1, 2, \ldots, N\}$:

$$x_n(t_i) = \frac{x(t_i) - \min(x)}{\max(x) - \min(x)} \tag{6}$$

  where $\max(x)$ and $\min(x)$ respectively are the maximum and the minimum values of x.
- **Data labeling**
  For its input, the proposed ANN model requires examples in the input–output format. As a result, each example must be a pair of an input object and the desired output value (label). For obtaining the mentioned format from the given normalized time series $x_n(t_i)$, we should divide the $x_n(t_i)$ into examples with the desired length of K. For this purpose, by considering L as the total length of $x_n(t_i)$, input–output pairs (I_i) are as follows:

$$I_1 = \begin{cases} input : \{x_n(t_1), x_n(t_2), \ldots, x_n(t_K)\} \\ output : \{x_n(t_{K+1}), x_n(t_{K+2}), \ldots, x_n(t_{2K})\} \end{cases} \tag{7}$$

$$I_2 = \begin{cases} input : \{x_n(t_2), x_n(t_3), \ldots, x_n(t_{K+1})\} \\ output : \{x_n(t_{K+2}), x_n(t_{K+3}), \ldots, x_n(t_{2K+1})\} \end{cases} \tag{8}$$

$$I_{L-2K+1} = \begin{cases} input : \{x_n(t_{L-2K+1}), x_n(t_{L-K}), \ldots, x_n(t_{L-K})\} \\ output : \{x_n(t_{L-K+1}), x_n(t_{L-K+2}), \ldots, x_n(t_L)\} \end{cases} \tag{9}$$

This procedure gives the total number of $L-2K+1$ instances for the input of the proposed ANN. An example of the mentioned procedure for a simple time series with a length of 10 and considering $K = 4$ is presented in Fig. 5 which makes. $L - 2K + 1 = 10 - 2 \times (4) + 1 = 3$ labeled instances.

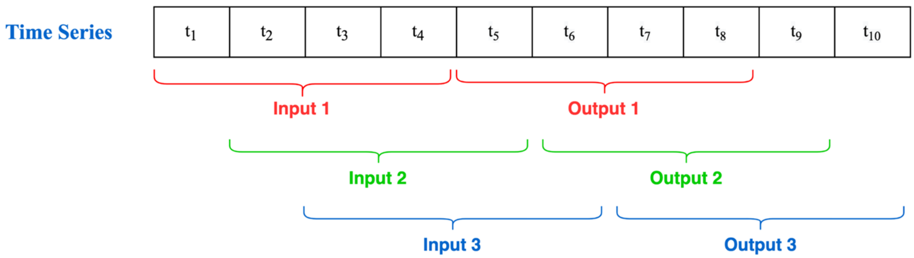

Fig. 5 A simple example of the procedure of data labeling

3.1.2 K-Means clustering method

There are many methods and algorithms for clustering data. The clustering algorithm of K-Means is amongst the most prevalent and frequently used algorithms (Sabouhi et al., 2021). This methos attempts to divide n observations into k clusters. (James et al., 1967). Let t_m be the vector of mth observation (forecasted time series) where each observation has e elements. Now, the subsequent actions have been finished:

- **Step 1** Randomly choose k data points as the initial Centroids (cluster centers) and call them c_k.
- **Step 2** Find the distance between each observation (t_m) and the selected k centroids as follows:

$$d_k^m = \sqrt{\sum_{e=1}^{e} \left(t_m^e - c_k^e\right)^2} \quad \begin{array}{l} \forall m \in 1, 2, ..., n \\ \forall k \in 1, 2, ..., k \end{array} \tag{10}$$

  where t_m^e is the eth element of vector t_m and c_k^e is the eth element of vector c_k. d_k^m will be the distance between observation m and centroid k.
- **Step 3** Now, based on the distance discovered, assign each data point to the nearest centroid. If observation t_m is assigned to c_k centroid, set $m_{mk} = 1$, 0 otherwise.
- **Step 4** Take the average of the observations in each cluster group to update the centroid position as follows:

$$c_k = \frac{\sum_{m=1}^{n} m_{mk} t_i}{\sum_{m=1}^{n} m_{mk}} \quad \forall k \in 1, 2, ..., k \tag{11}$$

- **Step 5** Repeat Steps 2 to 4 until our centroids remain steady.
  For selecting the ideal value for clusters' number (k), the Elbow method was used (Bholowalia & Kumar, 2014). In this approach, we adjust the clusters' number (k) from 1 to a chosen number. Afterward, for each value of k, we calculate the total distance between the observations and the centroids. Finally, when we plot the obtained values with the k value, the resulting plot exhibits an Elbow shape. The sum of the distances remains almost the same from the elbow point, Hence, the k value that corresponds to this point represents the optimal number of clusters or the optimal k value.

3.2 Developing two-stage stochastic data-driven programming

The second phase of the proposed two-phase approach develops a multi-objective stochastic optimization model for locating distribution centers, temporary hospitals, temporary waste disposal centers, and temporary waste transfer centers. Furthermore, considering disruption in the capacity of the mentioned facilities, the proposed model considers patients' allocation to hospitals, distribution of drugs to hospitals, and waste management. The created model has three objectives: (1) maximizing the minimum patients' allocation to hospitals within all regions, (2) minimizing the sum of transportation times, and (3) minimizing the total risk of disease outbreak by establishing temporary facilities, waste transportation, and uncollected waste in hospitals.

In TSSP, the model makes two sets of decisions: first-stage decisions and second-stage decisions (Birge & Louveaux, 2011). The decisions of first-stage are made prior to comprehending the scenarios obtained from the first phase, including setting up distribution centers, locating temporary hospitals, and locating temporary waste disposal and transfer centers (Sabouhi & Jabalameli, 2019). The decisions in the second stage are related to the scenarios obtained from the first phase; considering the impact of these scenarios on disruption of the capacity of facilities and the demand, these decisions include the allocation of patients to hospitals, the medications' number transferred to hospitals from distribution centers, the amount of medications inventory at hospitals, the amount of waste transferred from hospitals to waste disposal and transfer centers, as well as the quantity of uncollected waste in hospitals. Followed by the mathematical model, the next section outlines the sets, parameters, and decision variables.

3.2.1 Mathematical model

Sets and indices

Set of regions,$m \in M$	M
Set of existing hospitals,$h \in P$	P
Set of potential locations for temporary hospitals,$h' \in S$	S
Set of all hospitals, $H = P \cup S$,$h \in H$	H
Set of existing waste disposal centers,$q \in U$	U
Set of potential locations for temporary waste disposal centers,$q \in R$	R
Set of all waste disposal centers, $Q = U \cup R$,$q \in Q$	Q
Set of potential locations for temporary transfer centers $l \in L$	L
Set of different disease severity in patients,$i \in I$	I
Set of potential locations for distribution centers,$k \in K$	K
Set of time periods,$t \in T$	T
Set of medications,$d \in D$	D
Set of demand scenarios,$v \in V$	V

Parameters

de_{imt}^{v}	Forecasted patients' number (demand) with disease severity of $i \in I$ in region $m \in M$ in time period $t \in T$ under scenario $v \in V$
st_k	Set-up cost of distribution center $k \in K$
pr_d	Medication's purchase price per unit $d \in D$
tr_{kh}	Per-unit transportation time of the medication $d \in D$ from distribution center $k \in K$ to hospital $h \in H$
hl_h	Per-unit holding cost of medication in warehouse of hospital $h \in H$ for each time-period
θ_i	The lowest fraction of group $i \in I$ that must be included (coverage rate)
β_{ktd}	The maximum capacity of distribution center $k \in K$ for supplying medication $d \in D$ in time-period $t \in T$

cp_h	Capacity of patients in hospital $h \in H$
cw_h	Warehouse capacity of hospital $h \in H$ for medication storage
$ch_{h'}$	Set-up cost of temporary hospital $h' \in S$
cq_q	Set-up cost of temporary disposal center $q \in R$
cl_l	Set-up cost of temporary transfer center $l \in L$
th_{mh}	Travel time between region m and existed hospital $h \in P$
$ts_{hh'}$	Travel time between existed hospital $h \in P$ and temporary hospital $h' \in S$
tl_{hl}	Travel time between hospital $h \in H$ and transfer center $l \in L$
tc_{lq}	Travel time between transfer center $l \in L$ and disposal center $q \in Q$
tq_{hq}	Travel time between hospital $h \in H$ and disposal center $q \in Q$
φ	Conversion factor of time travel to cost
dn_{id}	1 if group type $i \in I$ need medication type $d \in D$, 0 otherwise
hp_{iht}	1 if patient from group type $i \in I$ can be served by hospital $h \in H$ at time period $t \in T$, 0 otherwise
$ph_{h'}$	Population exposure around temporary hospital $h' \in S$
pa_q	Population exposure around temporary disposal center $q \in R$
el_l	Population exposure around temporary transfer center $l \in L$
rq_{hq}	Population exposure around transportation route of waste from hospital $h \in H$ to disposal center $q \in Q$
rl_{hl}	Population exposure around transportation route of waste from hospital $h \in H$ to transfer center $l \in L$
rc_{lq}	Population exposure around transportation route of waste from transfer center $l \in L$ to disposal center $q \in Q$
ar_h	Probability of accidental risk at hospital $h \in H$
ri	Reproduction number of the disease
wr	Waste generation rate per person
pq_{qt}	Unit processing cost in disposal center $q \in Q$ at period $t \in T$
pl_{lt}	Unit processing cost in transfer center $l \in L$ at period $t \in T$
sq_q	Capacity of disposal center $q \in Q$
sl_l	Capacity of transfer center $l \in L$
BG_1	Budget available for set-up costs of temporary hospitals and distribution centers, and transportation of patients and medications
BG_2	Budget available for set-up costs of temporary waste disposal and transfer centers, and waste transportations, and waste processing costs
π_v	Probability of occurrence of scenario $v \in V$
dh_{hv}	Percentage of capacity disruption in hospital $h \in H$ under scenario $v \in V$
ds_{lv}	Percentage of capacity disruption in transfer center $l \in L$ under scenario $v \in V$
dt_{qv}	Percentage of capacity disruption in disposal center $q \in Q$ under scenario $v \in V$
dk_{kv}	Percentage of capacity disruption in distribution center $k \in K$ scenario $v \in V$

Decision variables

ω_k	1 if distribution center k is set up, 0 otherwise
W^v_{htd}	Number of medications $d \in D$ stored in hospital $h \in H$ warehouse in time-period $t \in T$ under scenario $v \in V$
X^v_{khtd}	Number of medications $d \in D$ transported from distribution center $k \in K$ to hospital $h \in H$ in time-period $t \in T$ under scenario $v \in V$
$EH_{h't}$	1 if temporary hospital $h' \in S$ is set up in period $t \in T$, 0 otherwise
Z^v_{imht}	Number of patients with disease severity of $i \in I$ at region $m \in M$ that are assigned to existed hospital $h \in P$ in period $t \in T$ under scenario $v \in V$
$Y^v_{ihh't}$	Number of patients with disease severity of $i \in I$ at existed hospital $h \in P$ that are assigned to temporary hospital $h' \in S$ in time period $t \in T$ under scenario $v \in V$
O_{qt}	1 if temporary disposal center $q \in R$ is set up in time period $t \in T$, 0 otherwise
E_{lt}	1 if temporary transfer center $l \in L$ is set up in time period $t \in T$, 0 otherwise
ML^v_{hlt}	Waste amount transported from hospital $h \in H$ to temporary transfer center $l \in L$ in time period $t \in T$ under scenario $v \in V$
MQ^v_{hqt}	Waste amount transported from hospital $h \in H$ to disposal center $q \in Q$ in time period $t \in T$ under scenario $v \in V$
MC^v_{lqt}	Waste amount transported from transfer center $l \in L$ to disposal center $q \in Q$ in time period $t \in T$ under scenario $v \in V$
UC^v_{ht}	Amount of uncollected of waste at hospital $h \in H$ in time period $t \in T$ under scenario $v \in V$

Objective functions

$$Max\ Z_1 = \underset{i,m,t}{Min}\left\{\sum_{v\in V}\pi_v\left(\frac{\sum_{h\in P} Z^v_{imht}}{de^v_{imt}}\right)\right\} \tag{12}$$

$$Min\ Z_2 = \sum_v \pi_v \left[\begin{array}{l}\sum_{h\in H}\sum_{k\in K}\sum_{t\in T}\sum_{d\in D} X^v_{khtd}\times tr_{kh} + \sum_{h\in P}\sum_{i\in I}\sum_{t\in T}\sum_{m\in M} Z^v_{imht}\times th_{mh}+\\ \sum_{h\in P}\sum_{h'\in S}\sum_{t\in T}\sum_{i\in I} Y^v_{ihh't}\times ts_{hh'} + \sum_{t\in T}\sum_{q\in Q}\sum_{h\in H} MQ^v_{hqt}\times tq_{hq} +\\ \sum_{t\in T}\sum_{h\in H}\sum_{l\in L} ML^v_{hlt}\times tl_{hl}+\sum_{l\in L}\sum_{q\in Q}\sum_{t\in T} MC^v_{lqt}\times tc_{lq}\end{array}\right] \tag{13}$$

$$Min\ Z_3 = \sum_{t\in T}\sum_{q\in R} O_{qt} \times pa_q + \sum_{l\in L}\sum_{t\in T} E_{lt} \times el_l + \sum_{h'\in S}\sum_{t\in t} \mathrm{EH}_{h't} \times ph_{h'} + \sum_{v}\pi_v \left[\begin{array}{l} \sum_{h\in H}\sum_{t\in T} ar_h \times UC^v_{ht} \times ri + \sum_{t\in T}\sum_{h\in H}\sum_{q\in Q} MQ^v_{hqt} \times rq_{hq} + \\ \sum_{h\in H}\sum_{l\in L}\sum_{t\in T} ML^v_{hlt} \times rl_{hl} + \sum_{t\in T}\sum_{l\in L}\sum_{q\in Q} MC^v_{lqt} \times rc_{lq} \end{array}\right] \tag{14}$$

The first objective function, Eq. (12), allocates patients by maximizing the minimum allocation-to-demand ratio per group in each region and each period. Furthermore, Eq. (13) expresses the second objective function and attempts to minimize the sum of transportation times, including the patients' transportation to hospitals, transportation time of medications to hospitals, and waste transportation time to transfer and disposal centers. Finally, The third objective function, given by Eq. (14) seeks to minimize the total risk of disease outbreaks by considering population exposure to establishing temporary facilities and waste transportation and the risk of disease outbreaks caused by uncollected waste in hospitals.

Constraints

$$\sum_{h\in P} Z^v_{imht} \geq \theta_i \times de^v_{imt} \quad \begin{array}{l}\forall i \in I, m \in M,\\ \forall t \in T, v \in V\end{array} \tag{15}$$

$$\sum_{m\in M} Z^v_{imht} \leq \sum_{m\in M} de^v_{imt} \quad \begin{array}{l}\forall h \in P, i \in I,\\ \forall v \in V, t \in T\end{array} \tag{16}$$

$$\sum_{h\in P} Z^v_{imht} \leq de^v_{imt} \quad \begin{array}{l}\forall i \in I, m \in M,\\ \forall t \in T, v \in V\end{array} \tag{17}$$

Constraints (15) to (17) make the lower and upper bound for the variable of patient allocation to hospitals (Z^v_{imht}). Constraint (15) guarantees that patients with different levels of severity must be allocated to the hospitals at least at the coverage rate, which ensures that the number of patients allocated to hospitals cannot be less than a threshold. Constraint (16) ensures that the total allocation of patients in all regions per severity group must be less than or equal to the total number of patients in all regions, which guarantees that the patients' allocation to hospitals cannot exceed the total demand. Similarly, constraint (17) also ensures that the allocation of patients from regions to hospitals must be less than or equal to the number of patients in each region.

$$\sum_{h'\in S} Y^v_{ihh't} \leq \sum_{m\in M} Z^v_{imht} \quad \begin{array}{l}\forall h \in P, i \in I,\\ \forall t \in T, v \in V\end{array} \tag{18}$$

Based on the Constraint (18), the allocation of patients from the existing hospitals to temporary hospitals should not exceed the number of them in the existing hospital.

$$EH_{h't} \leq \frac{\sum_{i\in I}\sum_{m\in M} Z^v_{imht} - \sum_{i\in I} Y^v_{ihh't}}{(1-dh_{hv})cp_h} \quad \begin{array}{l}\forall h \in P, h' \in S,\\ \forall t \in T, v \in V\end{array} \tag{19}$$

Constraint (19) ensures that a temporary hospital is set up and used if only the existing hospitals' capacity is completed (considering the capacity reduction due to disruption in the existing hospitals).

$$\sum_{h\in P}\sum_{i\in I} Y^{v}_{ihh't} \le (1-dh_{h'v}) \times EH_{h't} \times cp_{h'} \ \forall h' \in S, t \in T, v \in V \tag{20}$$

$$\sum_{m\in M}\sum_{i\in I} Z^{v}_{imht} - \sum_{h'\in S}\sum_{i\in I} Y^{v}_{ihh't} \le (1-dh_{hv}) \times cp_{h} \ \forall h \in P, v \in V, t \in T \tag{21}$$

$$\sum_{h\in H} X^{v}_{khtd} \le (1-dk_{kv}) \times \beta_{ktd} \times \omega_{k} \ \begin{array}{l}\forall k \in K, d \in D,\\ \forall t \in T, v \in V\end{array} \tag{22}$$

Constraints (20), (21) and (22) respectively define the available capacity in the existing hospitals, temporary hospitals, and distribution centers considering the disruption in their capacity.

$$\sum_{k\in K} X^{v}_{khtd} \ge \sum_{h'\in S}\sum_{m\in M}\left(Z^{v}_{imht} - Y^{v}_{ihh't}\right) \times dn_{id} - W^{v}_{h,t-1,d} \ \begin{array}{l}\forall i \in I, h \in P,\\ \forall d \in D, v \in V,\\ \forall t \in T\end{array} \tag{23}$$

$$\sum_{k\in K} X^{v}_{kh'td} \ge \sum_{h\in P} Y^{v}_{ihh't} \times dn_{id} - W^{v}_{h',t-1,d} \ \begin{array}{l}\forall i \in I, h' \in S,\\ \forall d \in D, t \in T,\\ \forall v \in V\end{array} \tag{24}$$

$$\sum_{k\in K}\sum_{d\in D} X^{v}_{kh'td} \le cw_{h'} \times EH_{h't} \ \forall h' \in S, v \in V, t \in T \tag{25}$$

$$\sum_{k\in K}\sum_{d\in D} X^{v}_{khtd} \le cw_{h} \ \forall h \in P, v \in V, t \in T \tag{26}$$

Constraints (23) and (24) indicate that the allocation of medications from distribution centers to hospitals should be greater than or equal to the number of medications patients need, considering the amount of medication stock in the hospitals' warehouse. Constraints (25) and (26) guarantee that the number of medications sent to hospitals does not exceed their storage capacity.

$$\begin{aligned} W^{v}_{htd} =& W^{v}_{h,t-1,d} + \sum_{k\in K} X^{v}_{khtd} \\ &- \left(\sum_{i\in I}\sum_{m\in M} Z^{v}_{imht} \times dn_{id} - \sum_{i\in I}\sum_{h'\in S} Y^{v}_{ihh't} \times dn_{id}\right) \end{aligned} \ \begin{array}{l}\forall h \in P, d \in D,\\ \forall t \in T, v \in V\end{array} \tag{27}$$

$$W^{v}_{h'td} = W^{v}_{h',t-1,d} + \sum_{k\in K} X^{v}_{kh'td} - \sum_{i\in I}\sum_{h\in P} Y^{v}_{ihh't} \times dn_{id} \ \begin{array}{l}\forall h' \in S, d \in D,\\ \forall t \in T, v \in V\end{array} \tag{28}$$

$$\sum_{d\in D} W^{v}_{htd} \le cw_{h} \ \forall h \in H, t \in T, v \in V \tag{29}$$

Constraints (27) and (28) calculate the medication inventory at hospitals at the end of each period. Additionally, Constraint (29) ensures that at the end of each period, the hospitals' stock level does not exceed the storage capacity of that hospital.

$$\sum_{m\in M} Z^{v}_{imht} - \sum_{h'\in S} Y^{v}_{ihh't} \le hp_{iht} \times (1-dh_{hv}) \times cp_{h} \ \begin{array}{l}\forall h \in P, t \in T,\\ \forall i \in I, v \in V\end{array} \tag{30}$$

$$\sum_{h\in P} Y^{v}_{ihh't} \le hp_{ih't} \times (1-dh_{h'v}) \times cp_{h'} \ \begin{array}{l}\forall h' \in S, v \in V,\\ \forall t \in T, i \in I\end{array} \tag{31}$$

Given the fact that some hospitals cannot serve a group of patients in some periods (such as temporary hospitals that cannot serve patients with high disease severity in any period), Constraints (30) and (31) ensure that patients with a specific severity group can only be hospitalized provided that the hospital can accept patients with that level of severity.

$$\left(\begin{array}{l}\sum_{k\in K} st_k \times \omega_k + \sum_{h\in H}\sum_{k\in K}\sum_{t\in T}\sum_{d\in D} pr_d \times X^v_{khtd} + \\ \sum_{h\in H}\sum_{k\in K}\sum_{t\in T}\sum_{d\in D} tr_{kh} \times X^v_{khtd} \times \varphi + \sum_{h\in H}\sum_{t\in T}\sum_{d\in D} hl_h \times W^v_{htd} + \\ \sum_{h'\in S}\sum_{t\in T} ch_{h'} \times EH_{h't} + \sum_{h\in P}\sum_{t\in T}\sum_{i\in I}\sum_{m\in M} th_{mh} \times Z^v_{imht} \times \varphi + \\ \sum_{h'\in S}\sum_{h\in H}\sum_{t\in T}\sum_{i\in I} ts_{hh'} \times Y^v_{ihh't} \times \varphi \end{array}\right) \le BG_1 \ \forall v \in V \tag{32}$$

$$\left(\begin{array}{l}\sum_{t\in T}\sum_{q\in Q}\sum_{h\in H} MQ^v_{hqt} \times tq_{hq} \times \varphi + \sum_{t\in T}\sum_{h\in H}\sum_{l\in L} ML^v_{hlt} \times tl_{hl} \times \varphi + \\ \sum_{t\in T}\sum_{l\in L}\sum_{q\in Q} MC^v_{lqt} \times tc_{lq} \times \varphi + \sum_{h\in H}\sum_{q\in Q}\sum_{t\in T} MQ^v_{hqt} \times pq_{qt} + \\ \sum_{l\in L}\sum_{t\in T}\sum_{q\in Q} MC^v_{lqt} \times pq_{qt} + \sum_{l\in L}\sum_{h\in H}\sum_{t\in T} ML^v_{hlt} \times pl_{lt} + \\ \sum_{t\in T}\sum_{q\in R} O_{qt} \times cq_q + \sum_{t\in T}\sum_{l\in L} E_{lt} \times cl_l \end{array}\right) \le BG_2 \ \forall v \in V \tag{33}$$

Constraints (32) and (33) determine the maximum budget. Constraint (32) includes the total cost of constructing temporary hospitals and distribution centers, transporting patients to hospitals, sending medications to hospitals, and the inventory costs in hospitals. Moreover, Constraint (33) comprises the total temporary disposal and transfer centers setup costs, waste transportation costs, and waste processing costs in the disposal and transfer centers.

$$\sum_{q\in Q} MQ^v_{hqt} + \sum_{l\in L} ML^v_{hlt} \le wr \times \left(\sum_{i\in I}\sum_{m\in M} Z^v_{imht} - \sum_{i\in I}\sum_{h'\in S} Y^v_{ihh't}\right) \quad \begin{array}{l}\forall h \in P, t \in T,\\ \forall v \in V\end{array} \tag{34}$$

$$\sum_{q\in Q} MQ^v_{h'qt} + \sum_{l\in L} ML^v_{h'lt} \le wr \times \sum_{i\in I}\sum_{h\in P} Y^v_{ihh't} \ \forall h' \in S, t \in T, v \in V \tag{35}$$

Constraints (34) and (35), by calculating the amount of waste generated in each hospital, ensure that the total amount of waste sent from a hospital to waste transfer and disposal centers should not exceed the amount of waste in that hospital.

$$\begin{aligned} UC^v_{ht} = UC^v_{h,t-1} + wr \times \left(\sum_{m\in M}\sum_{i\in I} Z^v_{imht} - \sum_{i\in I}\sum_{h'\in S} Y^v_{ihh't}\right) \\ - \left(\sum_{q\in Q} MQ^v_{hqt} + \sum_{l\in L} ML^v_{hlt}\right) \end{aligned} \quad \begin{array}{l}\forall h \in P, t \in T,\\ \forall v \in V\end{array} \tag{36}$$

$$UC^v_{h't} = UC^v_{h',t-1} + wr \times \sum_{i\in I}\sum_{h\in P} Y^v_{ihh't} - \left(\sum_{q\in Q} MQ^v_{h'qt} + \sum_{l\in L} ML^v_{h'lt}\right) \quad \begin{array}{l}\forall h' \in S, t \in T,\\ \forall v \in V\end{array} \tag{37}$$

Constraints (36) and (37) calculate the amount of uncollected waste in each hospital.

$$\sum_{h\in H} ML_{hlt}^{v} \leq (1-ds_{lv}) \times sl_l \times E_{lt} \quad \begin{array}{l}\forall l \in L, t \in T,\\ \forall v \in V\end{array} \tag{38}$$

$$\sum_{h\in H} MQ_{hqt}^{v} + \sum_{l\in L} MC_{lqt}^{v} \leq (1-dt_{qv}) \times sq_q \times O_{qt} \quad \begin{array}{l}\forall t \in T, q \in R,\\ \forall v \in V\end{array} \tag{39}$$

$$\sum_{h\in H} MQ_{hqt}^{v} + \sum_{l\in L} MC_{lqt}^{v} \leq (1-dt_{qv}) \times sq_q \quad \begin{array}{l}\forall q \in U, \forall t \in T,\\ \forall v \in V\end{array} \tag{40}$$

$$\sum_{q\in Q} MC_{lqt}^{v} = \sum_{h\in H} ML_{hlt}^{v} \quad \begin{array}{l}\forall t \in T, v \in V,\\ \forall l \in L\end{array} \tag{41}$$

Constraints (38), (39), and (40) are respectively the capacity constraints of temporary transfer centers, temporary disposal centers, and the existing disposal centers. Constraint (41) is the flow balance constraint of the temporary transfer centers.

$$\omega_k, EH_{h't}, O_{qt}, E_{lt} \in \{0,1\} \; \forall k \in K, h' \in S, t \in T, q \in R, l \in L \tag{42}$$

$$W_{htd}^{v}, X_{khtd}^{v}, ML_{hlt}^{v}, MQ_{hqt}^{v}, MC_{lqt}^{v}, UC_{ht}^{v} \geq 0 \quad \begin{array}{l}\forall h \in H, t \in T,\\ \forall d \in D, v \in V,\\ \forall k \in K, l \in L,\\ \forall q \in Q\end{array} \tag{43}$$

$$Z_{imht}^{v}, Y_{ihh't}^{v} \geq 0 \; \forall m \in M, i \in I, h \in P, h' \in S, t \in T, v \in V \tag{44}$$

The constraints (42) to (44) show the properties of the decision variables.

3.2.2 Linearization

Due to the nonlinearity of the objective function (12), we deal with its linearization method in this section. The new free variable μ will be replaced with $Min\left\{\sum_{v\in V} \pi_v \times \frac{\sum_{h\in P} Z_{imht}^{v}}{de_{imt}^{v}}\right\}$ in the objective function (12). Therefore, the following statement is correct:

$$\mu = Min\left\{\sum_{v\in V} \pi_v \times \frac{\sum_{h\in P} Z_{imht}^{v}}{de_{imt}^{v}}\right\} \forall i \in I, t \in T, m \in M \tag{45}$$

Therefore, considering $\mu \leq \sum_{v\in V} \pi_v \times \frac{\sum_{h\in P} Z_{imht}^{v}}{de_{imt}^{v}}$ and also μ seeks to maximize in the first objective function, then it always takes the lowest value of $\sum_{v\in V} \pi_v \times \frac{\sum_{h\in P} Z_{imht}^{v}}{de_{imt}^{v}}$(Asghari et al., 2022; Rastegar et al., 2021). According to Eq. (45), the linear model presented will be as follows:

$$Max Z_1 = \mu \tag{46}$$

Objective function (13) and (14)

$$s.t.$$

$$\mu \leq \sum_{v\in V} \pi_v \times \frac{\sum_{h\in P} Z_{imht}^{v}}{de_{imt}^{v}} \; \forall i \in I, t \in T, m \in M \tag{47}$$

Constraints (15) to (44)

3.2.3 Multi-objective solution technique

One of the frequently employed methods for multi-objective programming is ε-constraint. This study employs an refined form of the augmented ε-constraint method, called AUGMECON2, was utilized to find the exact Pareto set of the multi-objective problem (Mavrotas & Florios, 2013). The ε-constraint method involves optimizing one objective function and converting the others into constraints, setting an upper bound limit for each. By altering the boundaries and solving the single-objective model, efficient solutions can be obtained. In the following, the AUGMECON2 method is explained:

$$\max\left(f_1(x) + \varepsilon \times \left(\frac{L_2}{d_2} + \frac{L_3}{d_3} \times 10^{-1} + ... + \frac{L_p}{d_p} \times 10^{-(p-2)}\right)\right) \tag{48}$$

$$s.t.$$

$$f_2(x) - L_2 = e_2 \tag{49}$$

$$\vdots$$

$$f_p(x) - L_p = e_p \tag{50}$$

$$x \in S,\ \mathrm{L}_i \in R^+ \tag{51}$$

In Eqs. (48) to (51), $e_1, e_2, \ldots, e_p$ are the right-hand side parameters acquired from each specific iteration of the grid points of the $f_2(x), f_3(x), \ldots, f_p(x)$ objective functions. Parameters $d_2, d_3, \ldots, d_p$ are the difference between the best and worst values of the respective objective functions and the variables $L_2, L_3, \ldots, L_p$ are the surplus variables of the corresponding constraints. In addition, $\varepsilon \in [10^{-6}, 10^{-3}]$ and S is the feasible region. Figure 6 illustrates the steps of this method.

Accordingly, the proposed mathematical model using the AUGMECON2 method will be as follows:

$$Max\left(\mu + \varepsilon \times \left((\frac{L_2}{d_2}) + (\frac{L_3}{d_3} \times 10^{-1})\right)\right) \tag{52}$$

$$s.t.$$

$$\sum_{v} \pi_v \left[\begin{array}{l} \sum_{h\in H}\sum_{t\in T}\sum_{k\in K}\sum_{d\in D} X^v_{khtd} \times tr_{kh} + \sum_{t\in T}\sum_{i\in I}\sum_{h\in P}\sum_{m\in M} Z^v_{imht} \times th_{mh} + \\ \sum_{h\in P}\sum_{h'\in S}\sum_{t\in T}\sum_{i\in I} Y^v_{ihh't} \times ts_{hh'} + \sum_{q\in Q}\sum_{h\in H}\sum_{t\in T} MQ^v_{hqt} \times tq_{hq} + \\ \sum_{h\in H}\sum_{l\in L}\sum_{t\in T} ML^v_{hlt} \times tl_{hl} + \sum_{l\in L}\sum_{t\in T}\sum_{q\in Q} MC^v_{lqt} \times tc_{lq} \end{array}\right] - L_2 = e_2 \tag{53}$$

Step1: We solve the model several times by considering only one of the objectives to determine each objective function's best (F_p^{best}) and worst values (F_p^{nadir}) and then we calculate:

$$r_p = F_p^{best} - F_p^{nadir}$$

Step2: Choose a main objective function and transform the remaining objective functions into constraints.

Step3: Lets consider variable $i = 1$ as a counter and select a predetermined number k for number of the iterations.

Step4: e_p for each iteration can calculate as follows:

$$e_p = F_p^{nadir} + i \times \frac{d_p}{k}$$

Step5: Solve the model and $i = i + 1$

Step6: If $i < k$ then then go to the Step4, otherwise end the algorithm.

Fig. 6 Steps of the AUGMECON2 method

$$\left\{ \begin{array}{l} \sum_{t \in T} \sum_{q \in R} O_{qt} \times pa_q + \sum_{t \in T} \sum_{l \in L} E_{lt} \times el_l + \sum_{h' \in S} \sum_{t \in t} \mathrm{EH}_{h't} \times ph_{h'} + \\ \sum_{v} \pi_v \left[\begin{array}{l} \sum_{h \in H} \sum_{t \in T} ar_h \times UC_{ht}^{v} \times ri + \sum_{h \in H} \sum_{t \in T} \sum_{q \in Q} MQ_{hqt}^{v} \times rq_{hq} + \\ \sum_{h \in H} \sum_{l \in L} \sum_{t \in T} ML_{hlt}^{v} \times rl_{hl} + \sum_{q \in Q} \sum_{t \in T} \sum_{l \in L} MC_{lqt}^{v} \times rc_{lq} \end{array} \right] \end{array} \right\} - L_3 = e_3 \tag{54}$$

Constraints (15) to (44) and Constraint (47).

4 Computational results

In this section, in addition to explaining the case study, we present the results obtained from two phases of the suggested method in Sect. 3. To realize this, we first present the results obtained from the demand forecast by the proposed ANNs (first phase). Then, in the second phase, we will solve the proposed mathematical model using the results obtained from the first phase.

4.1 Case study

Tehran is the capital of Iran, which has one of the highest mortality rates for COVID-19 patients in Iran. The increase in the number of patients has led to the shortage of hospital beds for patients. Tehran has 22 districts. After the surveys, 15 hospitals in this city were found to be currently considered for the hospitalization of COVID-19 patients. The information about these hospitals was obtained from the Ministry of Health and Medical Education (MOHME). The location and bed capacity of these hospitals are shown in Table 6 of Appendix 1.

Moreover, to find the distances between the districts of Tehran, the center of each district was selected, which is shown in the Table 7 of Appendix 1. Furthermore, 10 waste disposal centers dedicated to waste management of the COVID-19 were identified in Tehran, whose locations are presented in Table 8 of Appendix 1. Finally, this research identified and considered six candidate locations for temporary hospitals, four candidate locations for temporary waste disposal centers, four potential locations for temporary waste transfer centers, and seven candidate locations for distribution centers. Figure 7 exhibits all the locations in this case study.

In the following, the Neshan map API has been used under the average traffic conditions of Tehran city to obtain the time interval between network points. Furthermore, for the set of medications in this case study, two medications, Naproxen and Famotidine, the most prescribed by physicians in Iran for COVID-19 patients, have been considered. The risk of a facility (population exposure around facilities) was calculated using (Zhao et al., 2016):

$$Risk = \pi r^2 \left(km^2\right) \times \text{Populationdensity}(\text{People/km}^2) \tag{55}$$

where the impacted radius (r) is set to 1 km for transfer centers, 3 km for disposal centers, and 4 km for hospitals. Similarly, the risk of disease spread associated with transportation routes was calculated as the population's exposure within a 500 m range along the transportation route. The risk of probable accidents at the hospitals (ar_h) was also considered to be 0.0007

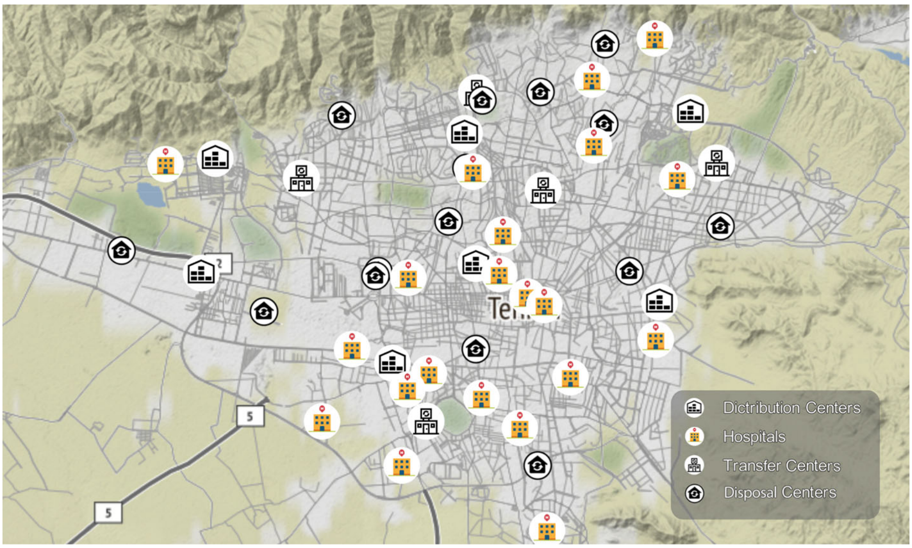

Fig. 7 Location of hospitals, distribution centers, and waste disposal and transfer centers on the map

Table 2 Parameter values of this case study ($: Dollars, $/S: Dollar/seconds, M^3: Cubic meters)

Parameters	Values
Per-dose purchasing cost of medications (pr_d)	$pr_1 = 0.16(\$)$ $pr_2 = 0.2\ (\$)$
Coverage rate for each severity group of patients (θ_i)	$\theta_1 = 0.7$ $\theta_2 = 0.5$
Budgets (BG_1, BG_2)	$BG_1 = 3,600,000(\$)$ $BG_2 = 1,000,000\ (\$)$
Conversion factor of time travel to cost (φ)	$\varphi = 0.00005(\$/S)$
Waste generation rate per person (wr)	$wr = 2.3(M^3)$

(Yu et al., 2020a). Finally, based on several studies, different values have been reported for the reproduction number of COVID-19 (ri), and herein, we used the value of 2.5; the majority of studies have reported a number close to it (Achaiah et al., 2020). The values of other important parameters of this case study are shown in Table 2.

4.1.1 Phase one results—demand forecasting using LSTM-RNN

Management of the patients' allocation to hospitals necessitates proper and accurate forecasting concerning the number of patients. For this purpose, ANNs were trained using the historical data obtained from MOHME. The data timespan used for training is from 19 February 2020 to 26 October 2021. These data include the number of patients admitted to hospitals, classified into two groups: patients with mild and severe disease conditions. Accordingly, for each group of severity levels, 100 ANNs were trained to forecast the number of patients of that group in future periods. Given the fact that the duration of hospitalization of patients in the hospital is approximately 14 days for COVID-19 (Vekaria et al., 2021), each period in this study consists of a total of 14 days. We considered $k = 5$, which divides the data into labeled instances with a length of 5 according to Eq. (9). Primarily, the data concerning the daily number of patients were cleaned and normalized. Subsequently, the data of each of the 14 consecutive days were added together to form the suggested time period in this study. According to the start and end time of the collected data, a total of 615 days of data was available. As a result, the input to the model was five consecutive periods, with the label being five consecutive periods following the previous five.

To measure the effectiveness of the proposed ANNs for demand forecasting, four measures, namely Root-mean-square deviation (RMSE), Mean squared error (MSE), Mean absolute error (MAE), and Mean absolute percentage error (MAPE), were employed. The following equations give the definitions of RMSE, MSE, MAE, and MAPE:

$$RMSE = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(U_i - R_i)^2} \tag{56}$$

$$MSE = \frac{1}{M}\sum_{i=1}^{M}(U_i - R_i)^2 \tag{57}$$

$$MAE = \frac{1}{M}\sum_{i=1}^{M}|U_i - R_i| \tag{58}$$

$$MAPE = \frac{1}{M}\sum_{i=1}^{M}\left|\frac{U_i - R_i}{U_i}\right| \tag{59}$$

where U_i is the actual value at time point i and R_i is the predicted value of the time point i. The performance of the ANNs is shown in Fig. 19 of Appendix 2 for predicting severe cases and Fig. 20 of Appendix 2 for predicting less severe cases.

After training ANNs on the data of severe and less severe patients, 100 ANNs were prepared for each group. Subsequently, the number of patients in each group for future periods was forecasted using these trained machines. The forecasting results show that areas with a higher population density will have more infected people in future periods. The obtained results indicate that according to the positive correlation between the population density of the districts and the number of people infected, the regions whose number of infected people is forecasted to be the highest in Fig. 8 are the those having a high population density in Tehran city (Bhadra et al., 2021).

Ultimately, via the K-Means clustering method, all the forecasts for each group of patients' severity were clustered into three clusters, giving the final three demand scenarios. To obtain the number of clusters, we used the Elbow method. As seen in Fig. 9, the optimal value of k (Number of clusters) is 3.

All the clustered scenarios for the number of severe and less severe patients in future periods are represented in Figs. 21, 22, 23, 24 of Appendix 3. Finally, as the representative of each cluster, the center of each cluster was selected as the demand forecast used in the mathematical model. The numerical results of the forecasts are given in Table 9 of Appendix

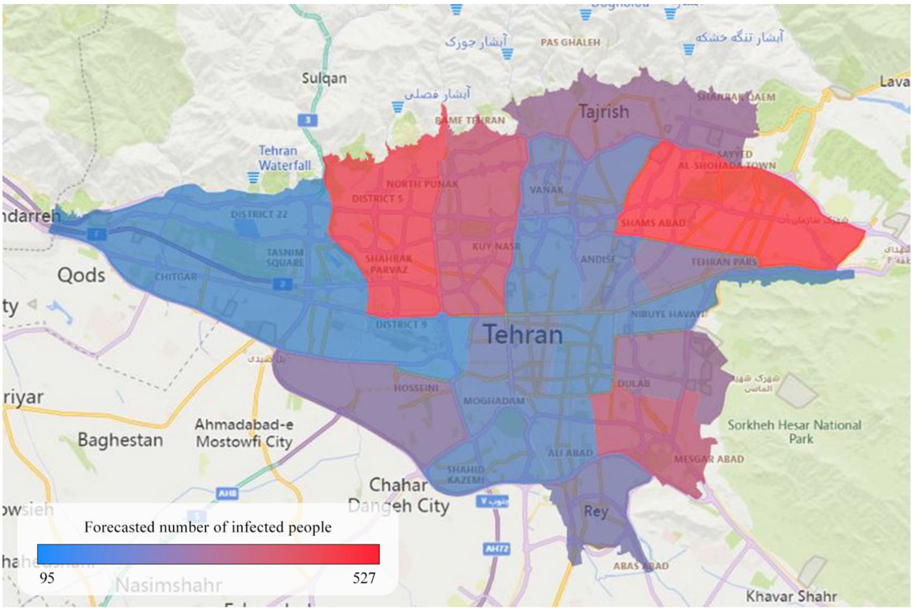

Fig. 8 Forecasted number of demands per district

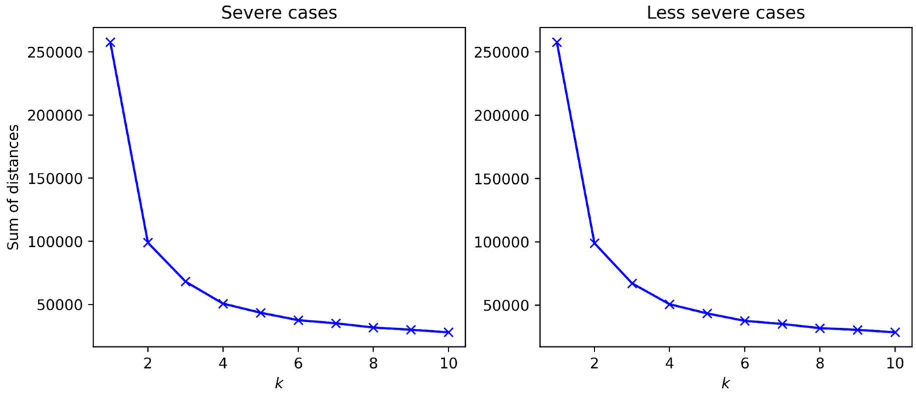

Fig. 9 The Elbow method's result

Table 3 Probability of scenarios' occurrence

Scenario	Probability of occurrence of scenario (π_v)
1	0.295
2	0.435
3	0.27

3. It should be noted that as a result of insufficient disclosure of the number of patients in each district separately by MOHME, the forecasted number of patients for each district was obtained using the population density of each district. Eventually, the probability of occurrence of each scenario (cluster) was calculated according to the number of members in each cluster divided by the total number of forecasts made, which is presented in Table 3.

4.1.2 Phase two results—solving the two-stage stochastic programming mathematical model

The solution time of the ε-constraint method for solving the proposed model with the GUROBI solver of GAMS software was 2 min and 23 s; the objective values are reported in Table 4. Additionally, Fig. 10 shows the values of objective functions.

The Pareto frontier of solving the presented case study using the proposed model is plotted in Fig. 11.

Table 5 depicts the located distribution centers, temporary hospitals, temporary disposal centers, and temporary transfer centers for each Pareto solution. As can be seen, since the first objective function was chosen as the primary objective function, and the other objective functions were transferred to the constraints, with the minimum allocation-to-demand ratio reduction, fewer temporary hospitals were established. Moreover, in the first few of Pareto's solutions, the waste management budget was not fully utilized, leaving room for locating temporary transfer centers. Since these temporary transfer centers were not used, their selection was solely in view of sufficient funding. The locations chosen for temporary waste disposal centers are generally locations 12 and 15. These choices were made due to the lower capacity of the existing waste disposal centers near these temporary facilities. Figure 12 demonstrates the located temporary hospitals along with temporary disposal and transfer centers.

Table 4 Corresponding values of objective functions of the Pareto solutions

Number of Pareto solution	Optimal solutions of objective functions		
	Z_1(Min allocation-to-demand ratio)	Z_2 (S)	Z_3(People)
1	0.899615385	59,196,413.25	77,671.43315
2	0.8956	54,719,609.21	70,064.46742
3	0.897359551	50,846,963.03	62,444.00923
4	0.883787879	43,501,600.45	54,675.46417
5	0.848390092	41,926,103.41	47,150.76925
6	0.776042355	37,723,515.34	38,890.39003
7	0.745545294	33,418,218.05	32,054.22867
8	0.675088415	29,061,031.8	24,414.50981
9	0.515546104	24,703,845.56	16,705.75834

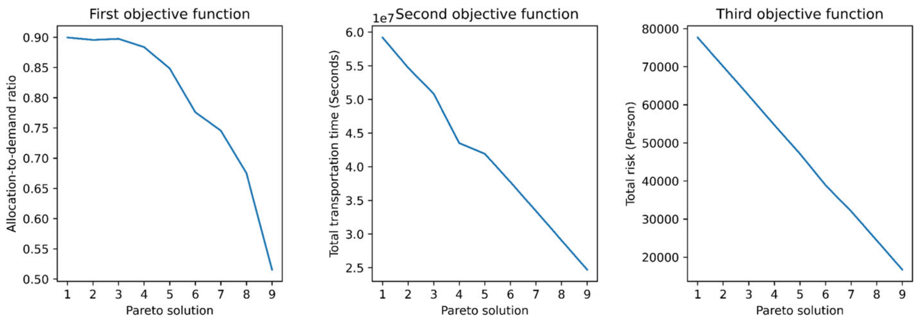

Fig. 10 Values of objective functions

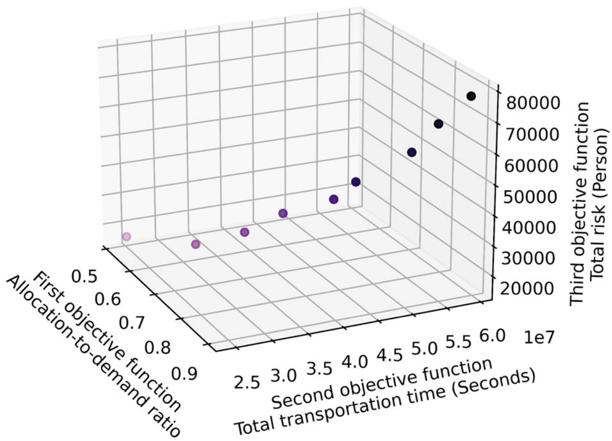

Fig. 11 Pareto frontier of solving the case study

Table 5 Location of facilities in each Pareto solution

	Time period	Distribution centers							Temporary hospitals						Temporary disposal centers				Temporary transfer centers				
		1	2	3	4	5	6	7	1	2	3	4	5	6	1	2	3	4	1	2	3	4	5
Pareto solu-tion 1	1	✓	–	–	–	–	–	–	–	–	✓	–	–	–	✓	✓	–	✓	✓	–	–	–	–
	2	✓	–	–	–	–	–	–	–	–	✓	–	–	–	✓	✓	✓	–	–	–	–	–	–
	3	✓	–	–	–	–	–	–	–	–	✓	–	–	–	–	–	✓	–	–	–	–	–	–
	4	✓	–	–	–	–	–	–	✓	–	–	–	–	✓	–	–	–	–	–	–	✓	–	–
	5	✓	–	–	–	–	–	–	✓	–	✓	–	–	–	–	–	–	–	–	–	–	–	–
Pareto solu-tion 2	1	–	✓	✓	✓	–	–	–	–	–	–	✓	–	–	✓	✓	–	✓	✓	–	–	–	–
	2	–	✓	✓	✓	–	–	–	–	–	✓	–	–	–	–	✓	–	–	–	–	–	–	–
	3	–	✓	✓	✓	–	–	–	–	–	–	✓	–	–	✓	–	–	–	–	–	–	–	–
	4	–	✓	✓	✓	–	–	–	–	–	✓	–	–	–	✓	–	–	–	–	–	–	✓	–
	5	–	✓	✓	✓	–	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–	–	–
Pareto solu-tion 3	1	–	–	–	✓	✓	–	–	–	–	✓	–	–	–	✓	✓	–	✓	–	–	–	–	–
	2	-	–	–	✓	✓	–	–	–	–	✓	✓	–	–	✓	–	–	✓	–	–	–	–	–
	3	–	–	–	✓	✓	–	–	–	–	✓	–	–	–	✓	–	–	✓	–	–	–	–	–
	4	–	–	–	✓	✓	–	–	–	–	✓	–	–	–	✓	–	–	–	–	–	–	–	–
	5	–	–	–	✓	✓	–	–	–	–	✓	–	–	–	–	–	–	–	–	✓	–	–	–
Pareto solu-tion 4	1	✓	✓	✓	✓	✓	–	✓	–	–	–	–	–	–	✓	✓	–	✓	–	–	–	–	–
	2	✓	✓	✓	✓	✓	–	✓	–	–	✓	–	–	–	✓	–	–	✓	–	–	–	–	–
	3	✓	✓	✓	✓	✓	–	✓	–	–	–	–	–	–	✓	✓	–	–	–	–	–	–	–
	4	✓	✓	✓	✓	✓	–	✓	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–
	5	✓	✓	✓	✓	✓	–	✓	–	–	✓	–	–	–	–	–	–	–	–	–	–	–	–

Table 5 (continued)

	Time period	Distribution centers							Temporary hospitals						Temporary disposal centers				Temporary transfer centers				
		1	2	3	4	5	6	7	1	2	3	4	5	6	1	2	3	4	1	2	3	4	5
Pareto solu-tion 5	1	✓	✓	✓	✓	✓	✓	✓	–	–	✓	–	–	–	✓	✓	–	✓	–	–	–	–	–
	2	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	✓	–	✓	–	–	–	–	–
	3	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–
	4	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–
	5	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–
Pareto solu-tion 6	1	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	✓	–	✓	–	–	–	–	–
	2	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	✓	–	✓	–	–	–	–	–
	3	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–
	4	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–
	5	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Pareto solu-tion 7	1	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	✓	–	✓	–	–	–	–	–
	2	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	✓	–	✓	–	–	–	–	–
	3	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	–	–	✓	–	–	–	–	–
	4	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–
	5	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Pareto solu-tion 8	1	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	✓	–	✓	–	–	–	–	–
	2	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	✓	–	✓	–	–	–	–	–
	3	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	–	–	✓	–	–	–	–	–
	4	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–

Table 5 (continued)

	Time period	Distribution centers							Temporary hospitals						Temporary disposal centers				Temporary transfer centers				
		1	2	3	4	5	6	7	1	2	3	4	5	6	1	2	3	4	1	2	3	4	5
	5	✓	✓	✓	✓	✓	✓	✓	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Pareto solution 9	1	✓	✓	✓	✓	✓	–	✓	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	2	✓	✓	✓	✓	✓	–	✓	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	3	✓	✓	✓	✓	✓	–	✓	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	4	✓	✓	✓	✓	✓	–	✓	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	5	✓	✓	✓	✓	✓	–	✓	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–

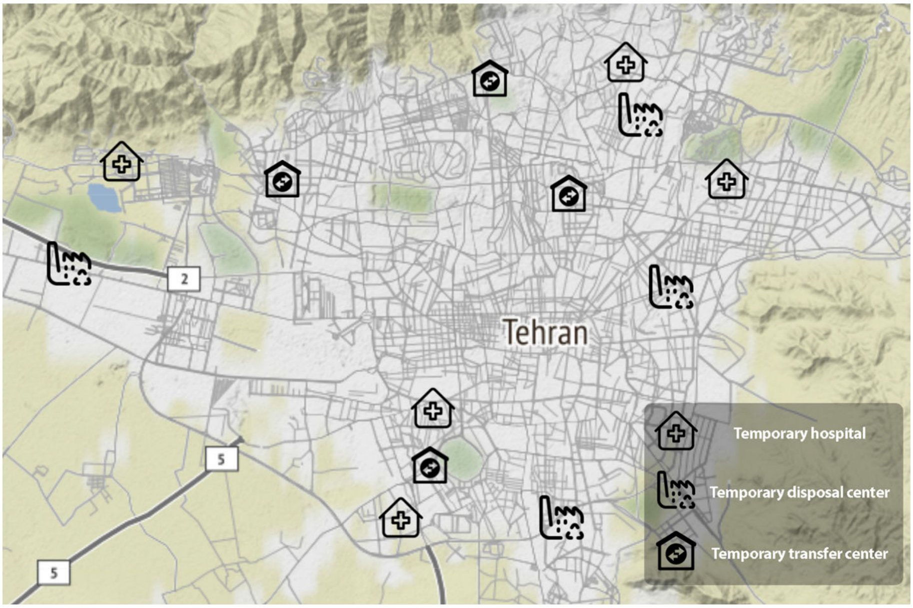

Fig. 12 Located temporary facilities

According to Fig. 12, temporary hospitals were located where there are either fewer existing hospitals available or locations where there are no existing hospitals. Similarly, temporary disposal centers were established in the areas with no existing waste disposal centers in their vicinity. Also, according to the results of the forecasts, shown in Fig. 8 and Table 9 of Appendix 3, it can be concluded that another main reason behind choosing these areas as the location of temporary facilities is the high number of forecasted patients in them; for example, the fourth district of Tehran city has the highest number of patients according to the data obtained from MOHME and the forecasts made; as a result, a temporary hospital has been located in this area, as well as temporary disposal centers near this area. It should be noted that population density alone is not the reason for locating temporary facilities, and some other aspects, such as the insufficient capacity of hospitals in some areas (such as areas 18, 19, and 22), should also be taken into consideration.

Figure 13 shows the percentage of the demand allocated to each hospital in the chosen Pareto solutions for each scenario. As seen, the percentage of the patients allocated to the existing and temporary hospitals and the percentage of those not allocated to hospitals vary in each Pareto solution and each scenario. With the decrease in the minimum allocation-to-demand ratio, the allocation of patients to temporary hospitals declines and eventually reaches zero. The number of patients not allocated to hospitals, on the other hand, increases. For note, the proposed mathematical model locates temporary hospitals and allocates patients to them only when filling the capacity of existing hospitals. For this reason, the allocation priority always goes to existing hospitals, which is indicated through the low percentage of allocated patients to temporary hospitals.

In Pareto solution #1, the uncovered demand obviously peaked at scenario #1 and reached the lowest in scenario #3. According to Table 9 of Appendix 3, the demand forecasts of scenario #1 were higher than those of scenarios #2 and #3 on average; the demand forecasts of scenario 3 were also lower on average than those of the other two scenarios, which apparent

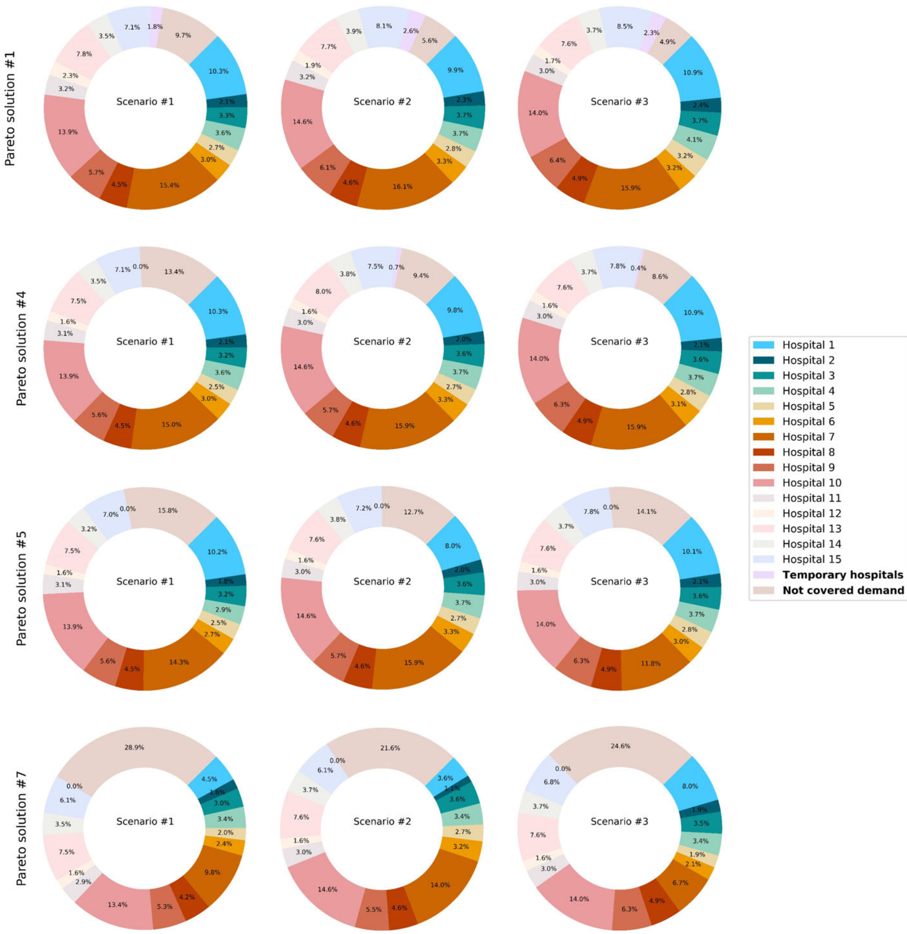

Fig. 13 Percentage of patients' allocation to each hospital in Pareto solutions for each scenario

from the percentage of demand that remains uncovered in each scenario. As both total time and total risk decreased, the minimum allocation-to-demand ratio was reduced until the threshold for covering each group of patients' severity was obtained. For this reason, following Pareto solution #4, temporary hospitals were not considered, and allocation to temporary hospitals reached zero.

Figure 14 represents the total amount of uncollected waste. The amount of waste not collected decreased with the reduction in the total risk. In addition, the establishment of waste disposal centers reduced the total risk, which resulted in a reduction in uncollected waste.

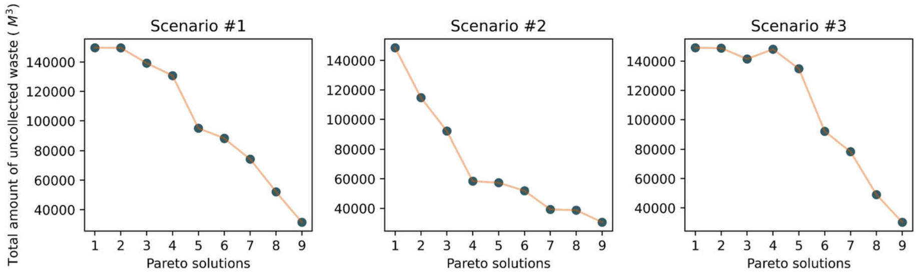

Fig. 14 Total amount of the uncollected waste in each scenario

4.2 Sensitivity analyses

Various sensitivity analyses on certain key parameters were undertaken and presented in this section to assess the performance of the proposed mathematical model. To this end, primarily, the adjustments to the results made by decreasing and increasing the forecasted demand were examined. As seen in Fig. 15, when the demand declines, the minimum allocation-to-demand ratio increases; for example, if we lowered the demand by 20% of its actual value, the model maintained a higher allocation-to-demand ratio overall. Furthermore, in cases where we increased the demand, the minimum allocation of patients to hospitals generally decreased.

The sensitivity analysis of the demand parameter on the second and third objective functions is shown in Fig. 16. As can be seen, the overall risk of the disease outbreak is reduced

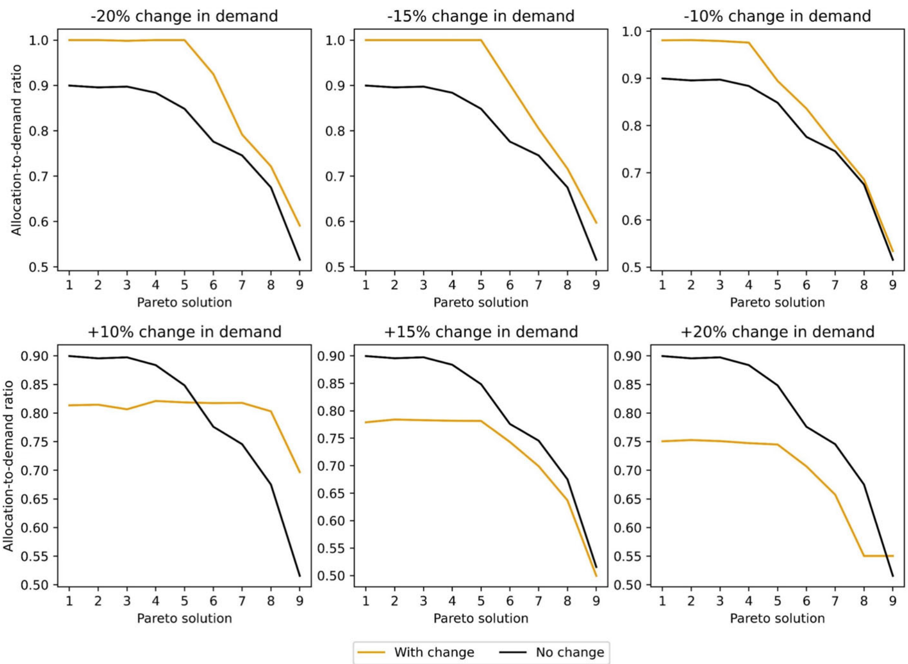

Fig. 15 The sensitivity analysis of demand parameter on the first objective function

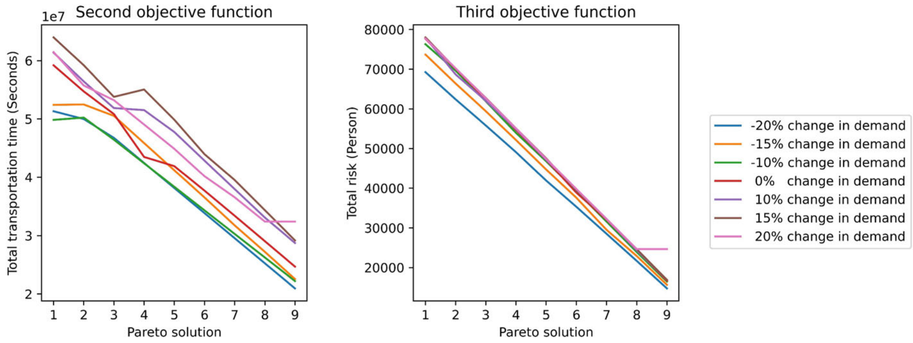

Fig. 16 The sensitivity analysis of demand parameter on the second and third objective functions

with a decrease in demand, which is due to less transportation and lower levels of uncollected waste in hospitals. Furthermore, with a reduction in the demand, the total time also decreases. The main reasons behind this behavior include the lower transport of patients between hospitals and the lower level of medication distribution.

Disruptions in the capacity of the proposed network facilities are one of the main parameters that can impact all the objective functions. Therefore, the proposed model was solved by considering different combinations of disruptions in order to identify the most effective ones. Initially, the model was solved without considering any disruptions. Afterward, the effects of each disruption were examined separately, and in the end, the model was solved by considering all the disruptions simultaneously. The results of this proposed process are shown in Fig. 17.

According to the results obtained from Fig. 17, the simultaneous influence of all disruptions leads to the lowest allocation-to-demand ratio and causes high total time and total risk. Moreover, since no disruptions lead to the highest allocation-to-demand ratio, the total time and total risk are minimized. It can also be concluded that hospital disruption significantly impacts the allocation-to-demand ratio. Correspondingly, disruption of distribution centers, waste disposal centers, and waste transfer centers has a considerable impact on the total time and total risk. This impact stems from less efficient medication distribution and waste management. Thus, hospital disruption could be an important parameter of the proposed model.

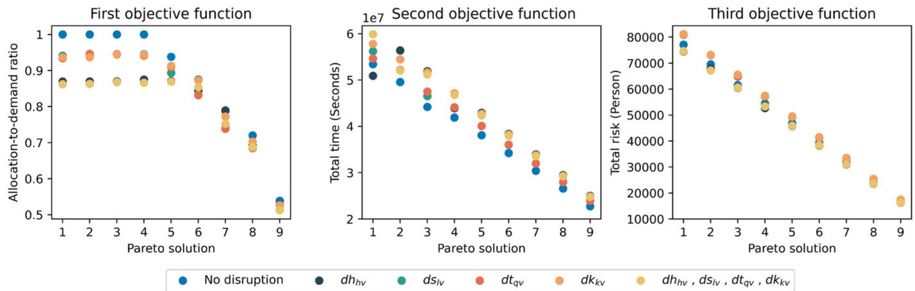

Fig. 17 Values of objective functions by considering different combinations of disruption parameters

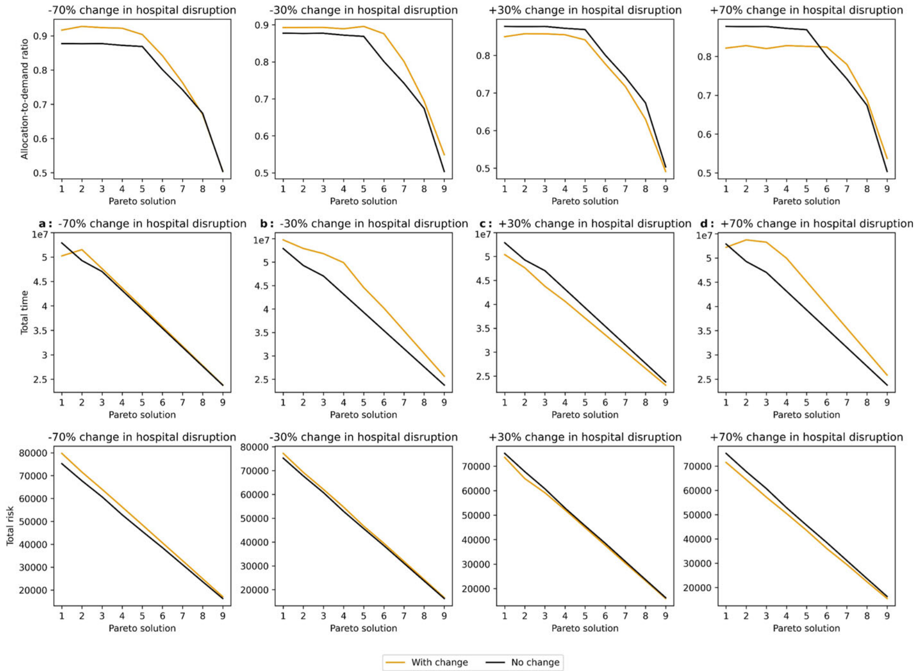

Fig. 18 Sensitivity analysis of hospitals disruption

Figure 18 illustrates the sensitivity analysis of hospital disruption on objective functions. Based on this figure, with greater disruption of hospitals, the minimum allocation-to-demand ratio increased. Correspondingly, the minimum allocation-to-demand ratio decreased with less disruption, which was predictable. Nonetheless, by changing the disruption parameter, different behaviors of the second objective function were observed. The total time slightly increased with a sharp decrease in the disruption parameter (Section a). This increase is due to the rise in hospitals' capacity, which increases the allocation of patients to hospitals. On the other hand, due to the decrease in transportation time owing to greater access to closer hospitals, the total time increase still remains slight. With a minor decrease in hospital disruption (Section b), the capacity of hospitals slightly increased, which augmented the allocation of patients to hospitals. However, this rise in the capacity of hospitals was not effective enough for a more optimal patient allocation (allocation to closer hospitals). Hence, the total time saw a more significant increase. With a slight increase in hospital disruption, patients' allocation decreased, which reduced the total time (Section c). Nevertheless, with further growth in this disruption, the second objective function showed a different behavior. With a significant increase in disruption parameter, since the capacity of hospitals is much more impaired, and due to the lower optimized allocations (allocation of patients to distant hospitals due to the lack of capacity in nearby hospitals), the total time considerably increased (Section d). The lowest sensitivity to hospital disruption belonged to the third objective function. By allocating patients to other hospitals in a situation where the hospital disruption did not change, the transportation-related risks changed; they were smaller in comparison with the risk of establishing temporary facilities. They, therefore, made minor changes in the overall risk.

5 Discussion

This section presents the main findings and outputs of our study. In the first phase of our two-phase approach, the number of patients in future periods was forecasted using historical data utilizing various neural networks with LSTM-RNN architecture to cope the uncertainty in demand. After generating scenarios and reducing them using the K-Means algorithm, the output obtained from the first phase was three scenarios for each group of severe and less severe patients. Using the forecasted scenarios and developing the mathematical model by monitoring the response to COVID-19 in most parts of the world, particularly the countries with the highest number of COVID-19 cases, using expert opinions, and reviewing the literature review, the output of the second phase showed that temporary hospitals could reduce the dramatically high pressure on the existing hospitals. It is feasible to transport less severe patients to temporary hospitals and vacate equipped beds in the existing ones to treat patients with severe conditions. This is particularly important since a high percentage of COVID-19 patients can recover by standard care (Baud et al., 2020).

A higher and better demand coverage leads to the following problems: the supply of medications and waste management. Solving the proposed mathematical model, the necessity to set up distribution centers is undeniable. This issue is important since by using of temporary hospitals, a higher percentage of patients can be hospitalized, increasing the demand for medications. On the other hand, due to the increased patient coverage, the amount of waste generated in hospitals also rises. Therefore, locating distribution and temporary transfer and disposal centers is highly important. For example, the sensitivity analysis showed that disruption in distribution centers could reduce demand coverage and significantly increase risk and time in the system.

One of the issues that has been less addressed in the literature is the consideration of an objective function to minimize the network's total transportation time. Taking transportation time of patients and medications distribution and waste management into account is highly impressive due to the high risk of disease spread and, consequently, the increase in the number of patients. Managerial insights could be summarized as follows:

- Data-driven decision-making and using tools such as ANN to forecast demand can help decision-makers overcome uncertainties more efficiently and improve the quality of answers. Also, a more accurate forecast of the demand makes planning the resources better and more equitable.
- By assigning an appropriate budget to set up temporary hospitals, the coverage of patients can be maintained at a high level.
- Temporary waste management facilities such as temporary transfer and disposal centers can help achieve improved waste management by reducing the amount of waste that is not collected in hospitals.
- Facilities disruption can reduce patient coverage and increase transportation time and the risk of disease outbreak. However, considering different demand and disruption scenarios can reduce the destructive effects of disruption.
- Due to the tremendous increase in demand for medication needed by COVID-19 patients and PPE, the location of distribution centers is very important. The lack of these items can lead to an increase in the probability of death of patients and the probability of medical staff infection and could disrupt the healthcare services.

6 Conclusion

COVID-19 has caused disease and a high rate of disease-related death worldwide. Following the widespread vaccination in most countries, it seemed as though the international community could effectively deal with the outbreak of this disease. Meanwhile, various virus mutations have repeatedly shown up (as of this writing, the Delta and Omicron mutations), indicating that we have a long way to go (Karim & Karim, 2021). One of the main concerns with the widespread prevalence of this disease is the lack of adequate capacity in hospitals to provide medical care to the affected people. Capacity completion of hospitals increases the risk of mortality and, on the other hand, puts inordinate pressure on the medical staff.

Additionally, due to the high number of COVID-19 patients, other significant problems, such as the supply of required medications and the management of waste generated by hospitals, have become pivotal and require planning. Nevertheless, a missing link is the uncertainty regarding the number of patients in future periods. Accordingly, this paper proposed a two-phase approach for the SCND to respond to the COVID-19 pandemic. This approach could contribute to the following decisions:

- Forecasting the number of patients in future time periods.
- Allocation of patients to hospitals.
- Locating temporary hospitals if the existing hospitals are under the condition of full capacity.
- Distribution of required medications by locating distribution centers.
- Waste management with locating temporary facilities for waste transfer and disposal.

Given the fact that each neural network fits the data differently and delivers a distinct forecast, the K-Means method was employed to obtain the demand scenarios. It is noteworthy that methodologies like ML can make the decision process swifter and more accurate. In the second phase, using the results obtained from the first stage, the mixed integer linear TSSP model was proposed to optimally allocate patients to hospitals, establish temporary hospitals, distribute required medications, and manage wastes. The proposed model also considered different types of patient groups based on the level of disease severity, a minimum threshold for covering these groups, and disruption of facilities. The objectives of the proposed model include maximizing the minimum allocation-to-demand ratio, minimizing the total transportation time, and minimizing the risk of the disease spread.

Despite the utility of the proposed two-phase approach, our investigation is not without limitations. It is important to acknowledge that our approach may not have addressed all potential challenges, such as issues related to vehicle routing, supplier selection for medications, supply of raw materials and products during an epidemic outbreak, or considering sustainability aspects in mathematical modeling. Therefore, to address the limitations of the presented approach, we suggest the following future research directions:

- Applying the two-phase approach outlined in this research to respond to another epidemic disease, such as the monkeypox outbreak.
- Employing robust optimization methods to address uncertainty in modeling
- Considering the global supply chain for the supply of raw materials and products during epidemic conditions
- Incorporate the supplier selection and order allocation problems in the proposed model
- Including vehicles routing and scheduling decisions in the modeling
- Considering sustainability aspects in the mathematical modeling.

Owing to the adaptability of the proposed method, the findings of this study can be used to manage similar situations, such as the case of another infectious disease. Also, despite considering the specific features of the COVID-19 disease in the presented modeling, the presented framework can be used in other areas, such as forecasting other goods or services demand (first phase) and supply chains with commercial approaches (second phase). Furthermore, it seems vital to investigate the COVID-19 vaccine supply chain similar to this article.

Data availability The data set analyzed during the current study is not available to the public due to non-public classification by the Ministry of Health and Medical Education of Iran. This ministry will review the request for access to this data (Website: https://ird.behdasht.gov.ir/).

Declarations

Competing interests The authors do not have any competing interests that are pertinent to the content of this article.

Appendix 1

See Tables 6, 7, 8.

Table 6 Hospitals accepting COVID-19 patients in Tehran

Hospitals	Bed capacity	Latitude	Longitude
Firoozabadi-Rey hospital	520	35.5943945	51.4343476
Kashani hospital	104	35.6402461	51.4191037
Yaft-Abad hospital	177	35.6435813	51.3091893
Ziaeian educational and medical center	187	35.6575695	51.3568917
Shariat Razavi hospital	134	35.6757574	51.3263193
Shohadaye Gomnam hospital	163	35.6631518	51.4475564
Besat Nahaja hospital	780	35.6799936	51.4946576
Torfe hospital	234	35.6956125	51.4326459
Amir Alam hospital	299	35.6996335	51.4235131
Firouzgar hospital	728	35.7096129	51.408034
Imam Khomeini hospital complex	156	35.6541212	51.3979503
Hajar hospital	86	35.7274134	51.4100699
Baqiyatallah hospital	390	35.7559829	51.3929919
Labbafi Nezhad hospital	185	35.7675141	51.4604647
Masih Daneshvari hospital	377	35.8156572	51.4942882

Table 7 Location of districts' center

Districts	Latitude	Longitude	Districts	Latitude	Longitude
District 1	35.8029384	51.46834	District 12	35.6801535	51.4264295
District 2	35.7555075	51.362355	District 13	35.717432	51.5351318
District 3	35.7671105	51.4312525	District 14	35.669389	51.4667743
District 4	35.7469847	51.5348134	District 15	35.6332757	51.4854205
District 5	35.7712488	51.3042435	District 16	35.642582	51.4042669
District 6	35.7264867	51.4024725	District 17	35.6537044	51.3685725
District 7	35.7222006	51.446178	District 18	35.6500037	51.3120996
District 8	35.7271855	51.5028226	District 19	35.6346276	51.3664915
District 9	35.6865153	51.3148395	District 20	35.590875	51.4408457
District 10	35.6838383	51.3668275	District 21	35.7113528	51.2151755
District 11	35.6800609	51.39545	District 22	35.7478881	51.19041

Table 8 Location of disposal centers

Disposal center	Latitude	Longitude
1	35.7877078	51.3985997
2	35.8133257	51.4665776
3	35.8167608	51.4989468
4	35.7811179	51.320419
5	35.7916067	51.430872
6	35.7332047	51.379835
7	35.7353326	51.3738804
8	35.6759258	51.3946918
9	35.7311486	51.5304127
10	35.6930459	51.2772299

Appendix 2

See Figs. 19, 20.

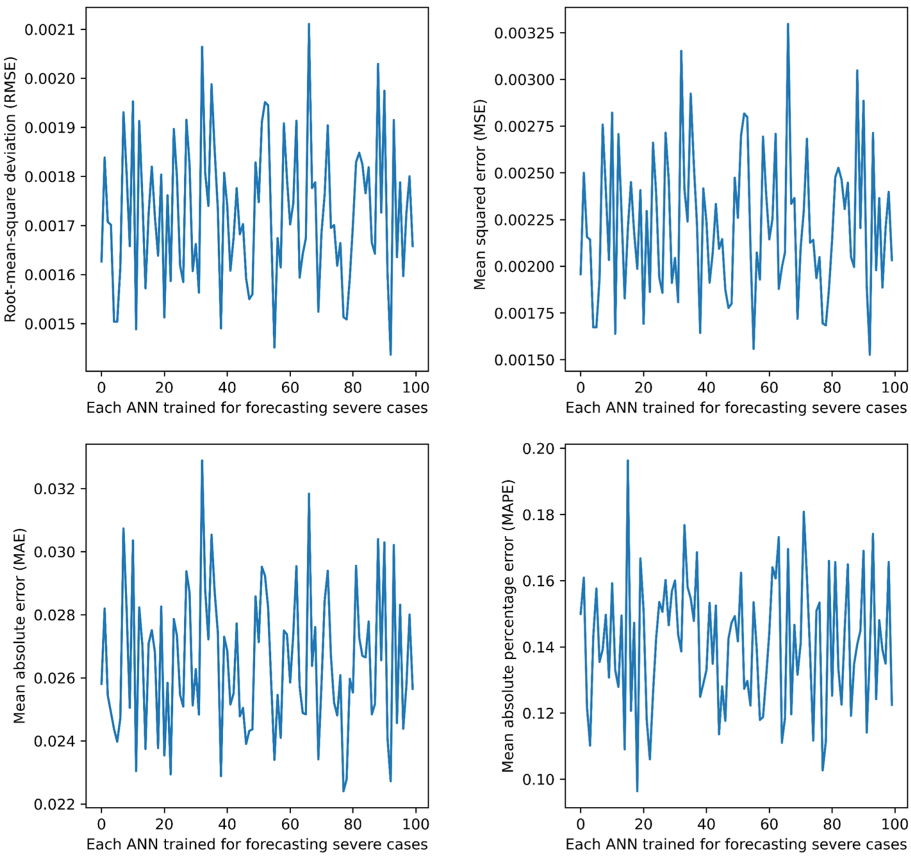

Fig. 19 Performance of the proposed ANNs for predicting severe cases

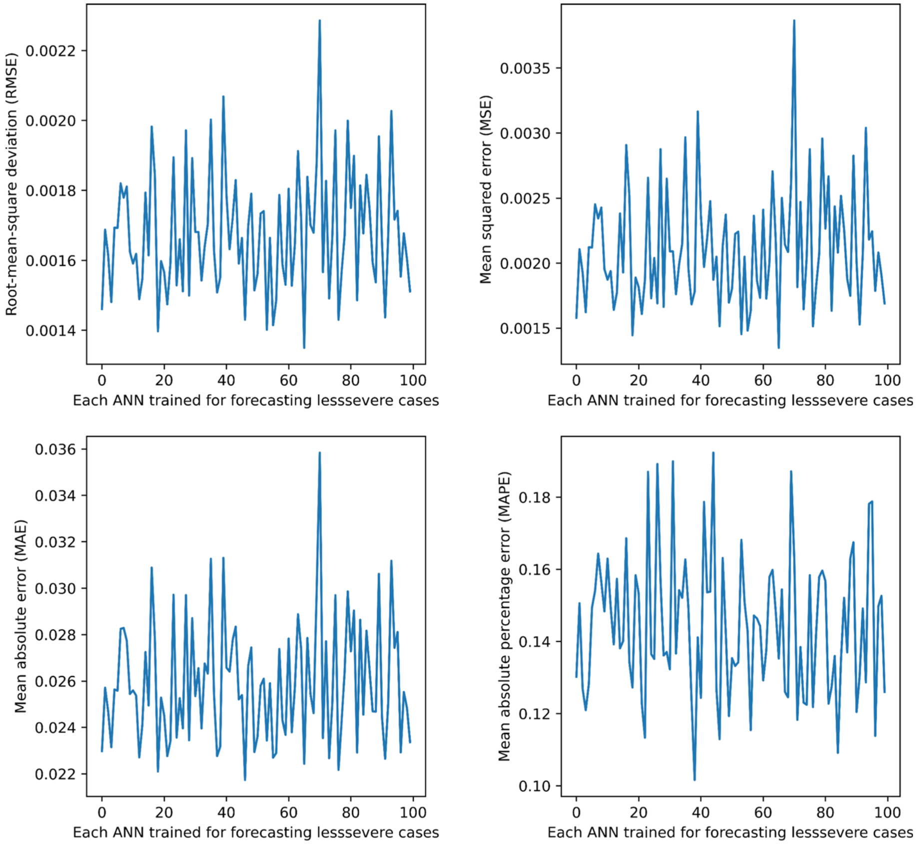

Fig. 20 Performance of the proposed ANNs for predicting less severe cases

Appendix 3

See Table 9 and Figs. 21, 22, 23, 24).

Table 9 Demand forecasting results

	Districts	Severe					Less severe				
		t = 1	t = 2	t = 3	t = 4	t = 5	t = 1	t = 2	t = 3	t = 4	t = 5
Scenario 1	1	109	109	108	109	109	178	178	178	178	178
	2	151	151	150	151	151	248	247	248	248	248
	3	71	71	71	71	71	117	117	117	117	117
	4	199	199	198	200	199	327	326	327	327	327

Table 9 (continued)

	Districts	Severe					Less severe				
		t = 1	t = 2	t = 3	t = 4	t = 5	t = 1	t = 2	t = 3	t = 4	t = 5
	5	186	186	185	186	186	305	305	305	305	305
	6	55	55	54	55	55	90	89	90	90	90
	7	67	67	66	67	67	110	109	110	110	110
	8	93	93	93	93	93	153	152	153	153	153
	9	38	38	38	38	38	62	62	62	62	62
	10	71	71	71	71	71	116	116	116	116	116
	11	67	67	66	67	67	110	109	110	110	110
	12	52	52	51	52	52	85	84	85	85	85
	13	53	53	53	53	53	87	87	87	87	87
	14	107	107	106	107	107	175	174	175	175	175
	15	142	142	141	142	142	233	233	233	233	233
	16	56	56	56	57	56	93	92	93	93	93
	17	61	61	60	61	61	100	99	100	99	100
	18	91	91	90	91	91	149	149	149	149	149
	19	55	55	55	55	55	91	91	91	91	91
	20	80	80	79	80	80	131	131	131	131	131
	21	41	41	41	41	41	67	67	67	67	67
	22	40	40	40	40	40	66	65	66	66	66
Scenario 2	1	106	106	106	106	106	174	173	174	174	173
	2	147	148	148	148	148	242	241	243	242	241
	3	70	70	70	70	70	114	114	115	114	114
	4	194	195	195	195	195	318	318	320	319	318
	5	181	182	182	182	182	297	297	299	298	297
	6	53	53	53	53	53	87	87	88	87	87
	7	65	65	65	65	65	107	107	107	107	106
	8	91	91	91	91	91	149	149	149	149	148
	9	37	37	37	37	37	61	61	61	61	60
	10	69	69	69	69	69	113	113	114	114	113
	11	65	65	65	65	65	107	107	107	107	106
	12	50	50	50	50	50	82	82	83	83	82
	13	52	52	52	52	52	85	85	85	85	85
	14	104	104	104	104	104	170	170	171	171	170
	15	139	139	139	139	139	227	227	228	228	227
	16	55	55	55	55	55	90	90	91	90	90
	17	59	59	59	59	59	97	97	97	97	97
	18	89	89	89	89	89	145	145	146	146	145
	19	54	54	54	54	54	88	88	89	89	88
	20	78	78	78	78	78	127	127	128	128	127

Table 9 (continued)

	Districts	Severe					Less severe				
		t = 1	t = 2	t = 3	t = 4	t = 5	t = 1	t = 2	t = 3	t = 4	t = 5
	21	40	40	40	40	40	65	65	66	66	65
	22	39	39	39	39	39	64	64	64	64	64
Scenario 3	1	104	104	104	104	104	168	170	169	169	170
	2	144	145	145	145	145	233	237	235	235	236
	3	68	68	68	68	68	110	112	111	111	112
	4	190	191	191	191	191	307	312	310	310	311
	5	177	178	178	178	178	287	291	290	289	291
	6	52	52	52	52	52	84	85	85	85	85
	7	64	64	64	64	64	103	105	104	104	104
	8	89	89	89	89	89	144	146	145	145	145
	9	36	36	36	36	36	59	59	59	59	59
	10	68	68	68	68	68	109	111	111	110	111
	11	64	64	64	64	64	103	105	104	104	104
	12	49	49	49	49	49	80	81	80	80	81
	13	51	51	51	51	51	82	83	83	83	83
	14	102	102	102	102	102	164	167	166	166	167
	15	136	136	136	136	136	219	223	221	221	222
	16	54	54	54	54	54	87	88	88	88	88
	17	58	58	58	58	58	94	95	94	94	95
	18	87	87	87	87	87	140	142	142	141	142
	19	53	53	53	53	53	85	87	86	86	87
	20	76	76	77	76	76	123	125	124	124	125
	21	39	39	39	39	39	63	64	64	64	64
	22	38	38	38	38	38	62	63	62	62	62

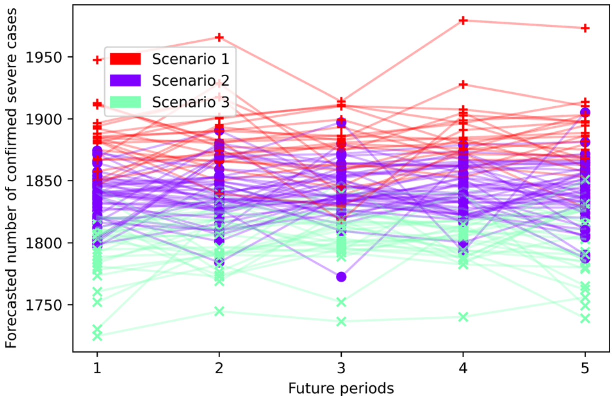

Fig. 21 All the clustered scenarios of the number of severe patients

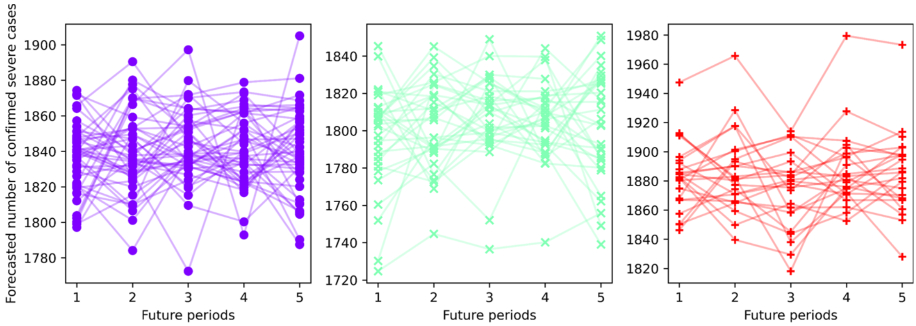

Fig. 22 Each cluster of the scenarios for the number of severe patients

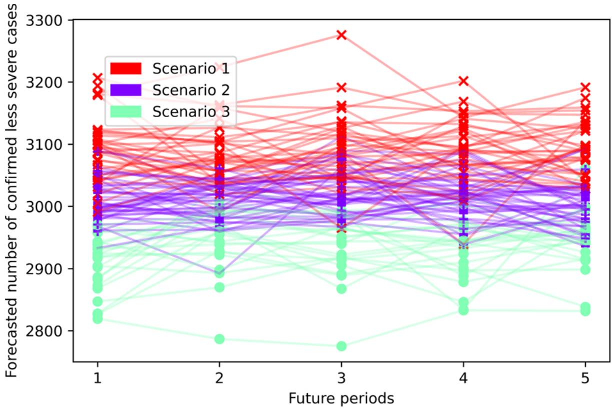

Fig. 23 All the clustered scenarios of the number of less severe patients

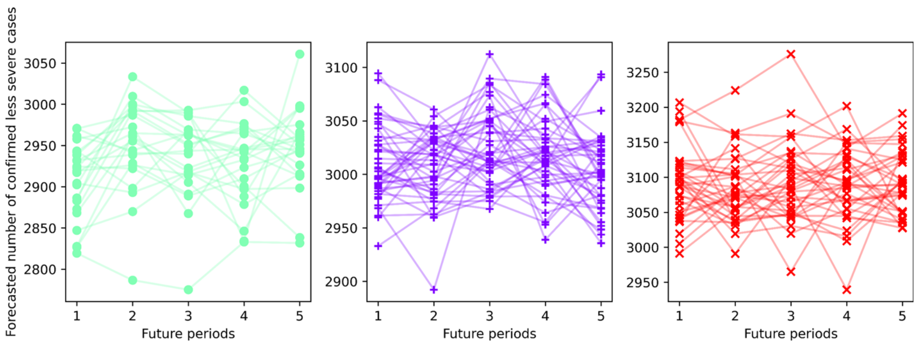

Fig. 24 Each cluster of scenarios for the number of less severe patients

References

Abbasimehr, H., & Paki, R. (2021). Prediction of COVID-19 confirmed cases combining deep learning methods and Bayesian optimization. *Chaos, Solitons and Fractals,*. https://doi.org/10.1016/j.chaos.2020.110511

Achaiah, N. C., Subbarajasetty, S. B., & Shetty, R. M. (2020). R0 and re of covid-19: Can we predict when the pandemic outbreak will be contained? *Indian Journal of Critical Care Medicine, 24*(11), 1125–1127. https://doi.org/10.5005/jp-journals-10071-23649

Aras, N., & Bilge, Ü. (2018). Robust supply chain network design with multi-products for a company in the food sector. *Applied Mathematical Modelling, 60*, 526–539. https://doi.org/10.1016/j.apm.2018.03.034

Arora, P., Kumar, H., & Panigrahi, B. K. (2020). Prediction and analysis of COVID-19 positive cases using deep learning models: A descriptive case study of India. *Chaos, Solitons and Fractals*. https://doi.org/10.1016/j.chaos.2020.110017

Asghari, M., Fathollahi-Fard, A. M., Mirzapour Al-E-Hashem, S. M. J., & Dulebenets, M. A. (2022). Transformation and linearization techniques in optimization: A state-of-the-art survey. *Mathematics*. https://doi.org/10.3390/MATH10020283

Baud, D., Qi, X., Nielsen-Saines, K., Musso, D., Pomar, L., & Favre, G. (2020). Real estimates of mortality following COVID-19 infection. *The Lancet Infectious Diseases, 20*(7), 773. https://doi.org/10.1016/S1473-3099(20)30195-X

Bhadra, A., Mukherjee, A., & Sarkar, K. (2021). Impact of population density on Covid-19 infected and mortality rate in India. *Modeling Earth Systems and Environment, 7*(1), 623–629. https://doi.org/10.1007/s40808-020-00984-7

Bholowalia, P., & Kumar, A. (2014). EBK-means: A clustering technique based on elbow method and K-means in WSN. *International Journal of Computer Applications, 105*(9), 975–8887. https://doi.org/10.5120/18405-9674

Birge, J. R., & Louveaux, F. (2011). Introduction to Stochastic Programming. *Springer Series in Operations Research and Financial Engineering*. New York: Springer. https://doi.org/10.1057/palgrave.jors.2600031

Choi, T. M. (2021). Fighting against COVID-19: What operations research can help and the sense-and-respond framework. *Annals of Operations Research*. https://doi.org/10.1007/s10479-021-03973-w

Cohen, J., & van der Rodgers-Meulen, Y. (2020). Contributing factors to personal protective equipment shortages during the COVID-19 pandemic. *Preventive Medicine, 141*, 106263. https://doi.org/10.1016/j.ypmed.2020.106263

Desi-Nezhad, Z., Fatemeh, S., & Mohammad Hossein, D.S. (2022). An Optimization Approach for Disaster Relief Network Design under Uncertainty and Disruption with Sustainability Considerations. *RAIRO-Operations Research, 56*(2),751–68. https://doi.org/10.1051/ro/2022021

Dhamodharavadhani, S., & Rathipriya, R. (2021). Novel COVID-19 mortality rate prediction (MRP) model for India using regression model with optimized hyperparameter. *Journal of Cases on Information Technology*. https://doi.org/10.4018/JCIT.20211001.oa1

Eshkiti, A., Bozorgi-Amiri, A., & Sabouhi, F. (2022). A bi-objective mathematical model to respond to COVID-19 pandemic. *Journal of Industrial and Systems Engineering, 14*(3), 221–236.

Feitó-Cespón, M., Costa, Y., Pishvaee, M. S., & Cespón-Castro, R. (2021). A fuzzy inference based scenario building in two-stage optimization framework for sustainable recycling supply chain redesign. *Expert Systems with Applications*. https://doi.org/10.1016/j.eswa.2020.113906

Gatto, M., Bertuzzo, E., Mari, L., Miccoli, S., Carraro, L., Casagrandi, R., & Rinaldo, A. (2020). Spread and dynamics of the COVID-19 epidemic in Italy: Effects of emergency containment measures. *Proceedings of the National Academy of Sciences of the United States of America, 117*(19), 10484–10491. https://doi.org/10.1073/pnas.2004978117

Gholami-Zanjani, S. M., Klibi, W., Jabalameli, M. S., & Pishvaee, M. S. (2021). The design of resilient food supply chain networks prone to epidemic disruptions. *International Journal of Production Economics, 233*, 108001. https://doi.org/10.1016/j.ijpe.2020.108001

Gilani, H., & Sahebi, H. (2022). A data-driven robust optimization model by cutting hyperplanes on vaccine access uncertainty in COVID-19 vaccine supply chain. *Omega (United Kingdom), 110*, 102637. https://doi.org/10.1016/j.omega.2022.102637

Godio, A., Pace, F., & Vergnano, A. (2020). Seir modeling of the italian epidemic of sars-cov-2 using computational swarm intelligence. *International Journal of Environmental Research and Public Health, 17*(10), 3535. https://doi.org/10.3390/ijerph17103535

Goodarzian, F., Ghasemi, P., Gunasekaren, A., Taleizadeh, A. A., & Abraham, A. (2021a). A sustainable-resilience healthcare network for handling COVID-19 pandemic. *Annals of Operations Research*. https://doi.org/10.1007/s10479-021-04238-2

Goodarzian, F., Taleizadeh, A. A., Ghasemi, P., & Abraham, A. (2021). An integrated sustainable medical supply chain network during COVID-19. *Engineering Applications of Artificial Intelligence, 100*(January), 104188. https://doi.org/10.1016/j.engappai.2021.104188

Gopal, K., Lee, L. S., & Seow, H. V. (2021). Parameter estimation of compartmental epidemiological model using harmony search algorithm and its variants. *Applied Sciences (switzerland), 11*(3), 1–25. https://doi.org/10.3390/app11031138

Govindan, K., & Fattahi, M. (2017). Investigating risk and robustness measures for supply chain network design under demand uncertainty: A case study of glass supply chain. *International Journal of Production Economics, 183*, 680–699. https://doi.org/10.1016/j.ijpe.2015.09.033

Greff, K., Srivastava, R. K., Koutnik, J., Steunebrink, B. R., & Schmidhuber, J. (2017). LSTM: A search space odyssey. *IEEE Transactions on Neural Networks and Learning Systems, 28*(10), 2222–2232. https://doi.org/10.1109/TNNLS.2016.2582924

Gumte, K. M., Devi Pantula, P., Miriyala, S. S., & Mitra, K. (2021). Data driven robust optimization for handling uncertainty in supply chain planning models. *Chemical Engineering Science, 246*, 116889. https://doi.org/10.1016/j.ces.2021.116889

Gumte, K., Pantula, P. D., Miriyala, S. S., & Mitra, K. (2021). Achieving wealth from bio-waste in a nationwide supply chain setup under uncertain environment through data driven robust optimization approach. *Journal of Cleaner Production, 291*, 125702. https://doi.org/10.1016/j.jclepro.2020.125702

Jain, A. K., Murty, M. N., & Flynn, P. J. (1999). Data clustering: A review. *ACM Computing Surveys, 31*(3), 264–323. https://doi.org/10.1145/331499.331504

James, M., et al. (1967). Some methods for classification and analysis of multivariate observations. *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, 1*(14), 281–297.

Jordan, E., Shin, D. E., Leekha, S., & Azarm, S. (2021). Optimization in the context of COVID-19 prediction and control: A literature review. *IEEE Access, 9*, 130072–130093. https://doi.org/10.1109/ACCESS.2021.3113812

Kargar, S., Pourmehdi, M., & Paydar, M. M. (2020). Reverse logistics network design for medical waste management in the epidemic outbreak of the novel coronavirus (COVID-19). *Science of the Total Environment, 746*, 141183. https://doi.org/10.1016/j.scitotenv.2020.141183

Kargar, S., Pourmehdi, M., & Paydar, M. M. (2020). Reverse logistics network design for medical waste management in the epidemic outbreak of the novel coronavirus (COVID-19). *Science of the Total Environment*. https://doi.org/10.1016/j.scitotenv.2020.141183

Karim, S. S. A., & Karim, Q. A. (2021). Omicron SARS-CoV-2 variant: A new chapter in the COVID-19 pandemic. *The Lancet, 398*(10317), 2126–2128. https://doi.org/10.1016/s0140-6736(21)02758-6

Khatami, M., Mahootchi, M., & Farahani, R. Z. (2015). Benders' decomposition for concurrent redesign of forward and closed-loop supply chain network with demand and return uncertainties. *Transportation Research Part e: Logistics and Transportation Review, 79*, 1–21. https://doi.org/10.1016/j.tre.2015.03.003

Kırbaş, İ, Sözen, A., Tuncer, A. D., & Kazancıoğlu, F. Ş. (2020). Comparative analysis and forecasting of COVID-19 cases in various European countries with ARIMA, NARNN and LSTM approaches. *Chaos, Solitons and Fractals, 138*(January), 110015. https://doi.org/10.1016/j.chaos.2020.110015

Koffman, J., Gross, J., Etkind, S. N., & Selman, L. (2020). Uncertainty and COVID-19: How are we to respond? *Journal of the Royal Society of Medicine, 113*(6), 211–216. https://doi.org/10.1177/0141076820930665

Kumar, A., Choi, T. M., Wamba, S. F., Gupta, S., & Tan, K. H. (2021). Infection vulnerability stratification risk modelling of COVID-19 data: A deterministic SEIR epidemic model analysis. *Annals of Operations Research*. https://doi.org/10.1007/s10479-021-04091-3

Lipton, Z. C., Kale, D. C., Elkan, C., & Wetzel, R. (2016). Learning to diagnose with LSTM recurrent neural networks. In 4th International conference on learning representations, ICLR 2016 - Conference Track Proceedings, 1–18.

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and Machine Learning forecasting methods: Concerns and ways forward. *Plos One, 13*(3), e0194889. https://doi.org/10.1371/journal.pone.0194889

Malik, A., Kumar, N., & Alam, K. (2021). Estimation of parameter of fractional order COVID-19 SIQR epidemic model. *Materials Today: Proceedings*. https://doi.org/10.1016/j.matpr.2020.12.918

Mavrotas, G., & Florios, K. (2013). An improved version of the augmented s-constraint method (AUGMECON2) for finding the exact pareto set in multi-objective integer programming problems. *Applied Mathematics and Computation, 219*(18), 9652–9669. https://doi.org/10.1016/j.amc.2013.03.002

Mehrotra, S., Rahimian, H., Barah, M., Luo, F., & Schantz, K. (2020). A model of supply-chain decisions for resource sharing with an application to ventilator allocation to combat COVID-19. *Naval Research Logistics, 67*(5), 303–320. https://doi.org/10.1002/nav.21905

Melin, P., Monica, J. C., Sanchez, D., & Castillo, O. (2020). Multiple ensemble neural network models with fuzzy response aggregation for predicting covid-19 time series: The case of mexico. *Healthcare (switzerland), 8*(2), 181. https://doi.org/10.3390/healthcare8020181

Mohseni, S., & Pishvaee, M. S. (2020). Data-driven robust optimization for wastewater sludge-to-biodiesel supply chain design. *Computers & Industrial Engineering, 139*, 105944. https://doi.org/10.1016/j.cie.2019.07.001

Patel, P. D., Cobb, J., Wright, D., Turer, R. W., Jordan, T., Humphrey, A., Kepner, A. L., Smith, G., & Rosenbloom, S. T. (2020). Rapid development of telehealth capabilities within pediatric patient portal infrastructure for COVID-19 care: Barriers, solutions, results. *Journal of the American Medical Informatics Association, 27*(7), 1116–1120. https://doi.org/10.1093/jamia/ocaa065

Peng, J., Wu, X., Wang, R., Li, C., Zhang, Q., & Wei, D. (2020). Medical waste management practice during the 2019–2020 novel coronavirus pandemic: Experience in a general hospital. *American Journal of Infection Control, 48*(8), 918–921. https://doi.org/10.1016/j.ajic.2020.05.035

Raj, A., Mukherjee, A. A., de Sousa Jabbour, A. B. L., & Srivastava, S. K. (2022). Supply chain management during and post-COVID-19 pandemic: Mitigation strategies and practical lessons learned. *Journal of Business Research, 142*, 1125–1139. https://doi.org/10.1016/j.jbusres.2022.01.037

Rastegar, M., Tavana, M., Meraj, A., & Mina, H. (2021). An inventory-location optimization model for equitable influenza vaccine distribution in developing countries during the COVID-19 pandemic. *Vaccine, 39*(3), 495–504. https://doi.org/10.1016/j.vaccine.2020.12.022

Rowan, N. J., & Laffey, J. G. (2020). Challenges and solutions for addressing critical shortage of supply chain for personal and protective equipment (PPE) arising from Coronavirus disease (COVID19) pandemic – Case study from the Republic of Ireland. *Science of The Total Environment, 725*, 138532. https://doi.org/10.1016/j.scitotenv.2020.138532

Sabouhi, F., & Jabalameli, M. S. (2019). A stochastic bi-objective multi-product programming model to supply chain network design under disruption risks. *Journal of Industrial and Systems Engineering, 12*(3), 196–209.

Sabouhi, F., Jabalameli, M. S., & Jabbarzadeh, A. (2021). An optimization approach for sustainable and resilient supply chain design with regional considerations. *Computers and Industrial Engineering*. https://doi.org/10.1016/j.cie.2021.107510

Sadrabadi, M. H. D., Sabouhi, F., Bozorgi-Amiri, A., & Sheikhalishahi, M. (2023). A robust-stochastic data envelopment analysis model for supplier performance evaluation of the telecommunication industry under uncertainty. *RAIRO-Operations Research, 57*(1), 263–290. https://doi.org/10.1051/ro/2022021

Sarkar, S., Pramanik, A., Maiti, J., & Reniers, G. (2021). COVID-19 outbreak: A data-driven optimization model for allocation of patients. *Computers and Industrial Engineering, 161*, 107675. https://doi.org/10.1016/j.cie.2021.107675

Shahid, F., Zameer, A., & Muneeb, M. (2020). Predictions for COVID-19 with deep learning models of LSTM, GRU and Bi-LSTM. *Chaos, Solitons and Fractals, 140*(January), 110212. https://doi.org/10.1016/j.chaos.2020.110212

Sharma, H. B., Vanapalli, K. R., Cheela, V. S., Ranjan, V. P., Jaglan, A. K., Dubey, B., Goel, S., & Bhattacharya, J. (2020). Challenges, opportunities, and innovations for effective solid waste management during and post COVID-19 pandemic. *Resources, Conservation and Recycling, 162*(May), 105052. https://doi.org/10.1016/j.resconrec.2020.105052

Shirazi, H., Kia, R., & Ghasemi, P. (2021). A stochastic bi-objective simulation–optimization model for plasma supply chain in case of COVID-19 outbreak. *Applied Soft Computing, 112*(January), 107725. https://doi.org/10.1016/j.asoc.2021.107725

Shiri, M., & Ahmadizar, F. (2022). An equitable and accessible vaccine supply chain network in the epidemic outbreak of COVID-19 under uncertainty. *Journal of Ambient Intelligence and Humanized Computing*. https://doi.org/10.1007/s12652-022-03865-2

Shuman, A. G., Fox, E. R., & Unguru, Y. (2020). COVID-19 and drug shortages: A call to action. *Journal of Managed Care and Specialty Pharmacy, 26*(8), 945–947. https://doi.org/10.18553/jmcp.2020.26.8.945

Snoeck, A., Udenio, M., & Fransoo, J. C. (2019). A stochastic program to evaluate disruption mitigation investments in the supply chain. *European Journal of Operational Research, 274*(2), 516–530. https://doi.org/10.1016/j.ejor.2018.10.005

Sun, S., Xie, Z., Yu, K., Jiang, B., Zheng, S., & Pan, X. (2021). COVID-19 and healthcare system in China: Challenges and progression for a sustainable future. *Globalization and Health, 17*(1), 1–8. https://doi.org/10.1186/s12992-021-00665-9

Teymourian, T., Teymoorian, T., Kowsari, E., & Ramakrishna, S. (2021). Challenges, strategies, and recommendations for the huge surge in plastic and medical waste during the Global COVID-19 pandemic with circular economy approach. *Materials Circular Economy, 3*(1), 1–14. https://doi.org/10.1007/s42824-021-00020-8

Tirkolaee, E. B., Abbasian, P., & Weber, G.-W. (2021). Sustainable fuzzy multi-trip location-routing problem for medical waste management during the COVID-19 outbreak. *Science of The Total Environment, 756*, 143607. https://doi.org/10.1016/j.scitotenv.2020.143607

UNEP. (2020). Waste management an essential public service in the fight to beat COVID-19. United Nation Environment Programme, 1–10.

Vekaria, B., Overton, C., Wiśniowski, A., Ahmad, S., Aparicio-Castro, A., Curran-Sebastian, J., Eddleston, J., Hanley, N. A., House, T., Kim, J., Olsen, W., Pampaka, M., Pellis, L., Ruiz, D. P., Schofield, J., Shryane, N., & Elliot, M. J. (2021). Hospital length of stay for COVID-19 patients: Data-driven methods for forward planning. *BMC Infectious Diseases, 21*(1), 1–15. https://doi.org/10.1186/s12879-021-06371-6

Volpato, S., Landi, F., & Incalzi, R. A. (2020). A Frail Health Care System for an Old Population: Lesson form the COVID-19 Outbreak in Italy. *Journals of Gerontology - Series A Biological Sciences and Medical Sciences, 75*(9), e126–e127. https://doi.org/10.1093/gerona/glaa087

Wang, P., Zheng, X., Ai, G., Liu, D., & Zhu, B. (2020). Time series prediction for the epidemic trends of COVID-19 using the improved LSTM deep learning method: Case studies in Russia, Peru and Iran. *Chaos, Solitons and Fractals, 140*(January), 110214. https://doi.org/10.1016/j.chaos.2020.110214

WHO. (2014). Safe management of wastes from health-care activities. www.who.int

WHO. (2021). COVID-19 weekly epidemiological update, 6 April 2021.

Yaqoubi, A., Sabouhi, F., Bozorgi-Amiri, A., & Amalnick, M. S. (2022). A light robust optimization model for a hierarchical healthcare network. *Kybernetes*. https://doi.org/10.1108/K-02-2022-0276

Yoshida, I., Tanimoto, T., Schiever, N., Patelli, F., & Kami, M. (2020). Characteristics of doctors' fatality due to COVID-19 in Western Europe and Asia-Pacific countries. *QJM, 113*(10), 713–714. https://doi.org/10.1093/QJMED/HCAA159

Yu, H., Sun, X., Solvang, W. D., & Zhao, X. (2020). Reverse logistics network design for effective management of medical waste in epidemic outbreaks: Insights from the coronavirus disease 2019 (COVID-19) outbreak in Wuhan (China). *International Journal of Environmental Research and Public Health, 17*(5), 1770. https://doi.org/10.3390/ijerph17051770

Yu, H., Sun, X., Solvang, W. D., & Zhao, X. (2020b). Reverse logistics network design for effective management of medical waste in epidemic outbreaks: Insights from the coronavirus disease 2019 (COVID-19) outbreak in Wuhan (China). *International Journal of Environmental Research and Public Health, 17*(5), 1770. https://doi.org/10.3390/ijerph17051770

Yu, W., Chavez, R., Jacobs, M. A., & Feng, M. (2018). Data-driven supply chain capabilities and performance: A resource-based view. *Transportation Research Part e: Logistics and Transportation Review, 114*, 371–385. https://doi.org/10.1016/j.tre.2017.04.002

Zhan, C., Zheng, Y., Lai, Z., Hao, T., & Li, B. (2021). Identifying epidemic spreading dynamics of COVID-19 by pseudocoevolutionary simulated annealing optimizers. *Neural Computing and Applications, 33*(10), 4915–4928. https://doi.org/10.1007/s00521-020-05285-9

Zhao, J., Huang, L., Lee, D. H., & Peng, Q. (2016). Improved approaches to the network design problem in regional hazardous waste management systems. *Transportation Research Part e: Logistics and Transportation Review, 88*, 52–75. https://doi.org/10.1016/J.TRE.2016.02.002