A sustainable medical waste management system design in the face of uncertainty and risk during COVID-19

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Abstract

COVID-19's developing trend has put the waste management systems of governments all over the world in jeopardy. The increasing rise of infectious medical waste has now become a serious problem. This paper presents a multi-period multi-objective model for designing a medical waste management system during the COVID-19 pandemic. The model aims to reduce total costs of infectious medical waste management while also reducing the environmental impact of treatment centers, disposal centers, and transportation. It also aims to maximize the suitability of treatment technology based on social considerations and reduce the risk associated with processing and transporting COVID-19 waste. Different strategic and operational decisions are taken into account that include the selection of treatment technologies, the location of treatment and disposal centers, the flow of generated medical waste between facilities, and the number of vehicles required for the medical waste transport. The model tackles the uncertainty associated with model parameters, and it uses a credibility-based possibilistic programming method to deal with uncertainties. The suggested model is solved using an interactive fuzzy programming method and the importance of social indicators for selecting treatment technology is determined using the fuzzy best–worst approach. The effectiveness of the model is demonstrated by a practical case study in Shiraz, Iran. The numerical results can help system designers to achieve the most suitable trade-off between the sustainability goals and the safety viewpoint.

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1 Introduction

The COVID-19 pandemic is currently posing a threat to all countries around the world. This disease has emerged as one of the most pressing public health concerns, with immediate implications for human health and the global economy. By June 14, 2022, the World Health Organization (WHO) recorded 533,816,957 confirmed cases and 6,309,633 deaths worldwide. Approximately 71% of all new and combined cases appear to be attributed to the European and Americas regions (WHO, 2022).

The rapid growth of medical waste production is one of the most significant new threats during the COVID-19 pandemic. Hospitals, clinics, diagnostic laboratories, research facilities, and other institutions can generate this type of waste. Residential areas may be considered another source of medical waste generation since certain infected people are quarantined in their homes. The expanded usage of personal protection devices like face masks and gloves, as well as plastic-based medical equipment such as diagnostic kits and hand sanitizer tubes, has changed the composition of medical waste dramatically (UNEP, 2020).

Because of its infectious nature, the medical waste produced during COVID-19 can be considered a hazardous material. The improper management of infectious medical waste could have negative environmental, economic, and social consequences. According to the International Finance Corporation (IFC, 2020), improper waste management may have a more severe effect than COVID-19, as it can raise the risk of disease transmission and result in 400,000 to 1 million deaths per year. Moreover, according to Kampf et al. (2020), the COVID-19 virus will live for around 9 days on steel, plastic, and glass surfaces. As a result, implementing an effective medical waste management system (MWMS) to handle COVID-19 contaminated waste should be deemed an immediate and critical public concern in order to reduce the secondary effects on human and environmental health (UNEP, 2020), particularly in countries where COVID-19 cases are prevalent.

MWMSs, particularly for infectious and hazardous waste, are among the most critical waste management schemes, requiring a variety of strategic and operational decisions with both short- and long-term implications. These decisions include collection of medical waste from its source areas, waste management technology selection, location of waste treatment and disposal centers, transportation, and collection vehicle selection. Furthermore, essential related issues such as disinfection, staff protection, and preparation must be considered (UNEP, 2020). Precisely, such practical decisions have a substantial uncertainty, which can put the planned system at risk. Due to the dynamic environment of the MWMS, the respective costs, induced medical waste, and the necessary budget fluctuate over the planning horizon. Medical waste generation rates became significantly more unpredictable after the COVID-19 pandemic. While it is clear that the pandemic raises the amount of medical waste caused, full data on COVID-19-related medical waste is difficult to obtain. Uncertain parameters can have a substantial impact on the overall performance of MWMSs, and ignoring them can put the designed system at risk. Such uncertainties must be considered when planning the system; otherwise, deterministic parameters will result in solutions that are neither optimal nor feasible.

Randomness and epistemic uncertainty are two types of uncertainty that can occur in the input data. Randomness is used when there is sufficient reliable historical data to characterize uncertain parameters using explicit probabilistic information. In other words, every frequency-based phenomenon can be described as random data for which discrete or continuous probability distributions are generated using historical data. The absence of knowledge about the precise values of model parameters causes epistemic uncertainty (Oberkampf et al., 2002). Indeed, insufficient information about the system is the fundamental source of epistemic uncertainty, with examples including little or no experimental data for a parameter, a range of possible parameter values provided by expert opinions, and a lack of comprehension of sophisticated processes (Oberkampf et al., 2002). There isn't enough data to adequately estimate probability distributions of unknown parameters because of the dynamic and imprecise nature of COVID-19 growth. Furthermore, because COVID-19 is not a frequency-based phenomenon, modeling uncertain parameters as random data is not a viable choice. In such cases, uncertainty will be captured by possibility distributions based on experts' subjective assessments, which are mostly based on their experiences and professional opinions (Zarrinpoor & Pishvaee, 2021).

In relation to the aforementioned issues, the research questions addressed in this paper are how to design an optimal MWMS in the face of uncertainty in real-world parameters in order to select the best treatment technology for handling COVID-19 infectious waste and provide a mathematical model to achieve all aspects of the sustainable development paradigm and hedge against the risk of COVID 19 spreading through waste transportation and processing at the same time, while taking many practical factors into account to define strategic and operational decisions. The location of treatment and disposal centers, the type of waste treatment technology used, the amount of handled and discarded waste, and the number of waste collection vehicles are all decisions that must be made. Facility capacity, interest rate, limited budget reflected in the allowed number of constructed facilities, multiple periods to account for the dynamic existence of constructed facilities, and maximum service distance restriction of undesirable facilities are all practical aspects that must be considered when designing an efficient MWMS. These questions have been attempted to be answered in this study by proposing a multi-objective, multi-period MWMS during COVID-19 while essential parameters are subject to the uncertainty. Economic, environmental, social, and risk considerations are all taken into account by the model. The overall costs of the MWMS design are minimized by the economic objective. The environmental objective minimizes the greenhouse gas (GHG) emissions from medical waste treatment and disposal, as well as waste transportation. The social objective maximizes the suitability of selecting treatment technologies, while the risk-oriented objective minimizes the risk of infectious medical waste collection and treatment. A credibility-fuzzy chance constrained programming approach (CFCCPA) is used to overcome epistemic uncertainty caused by a lack of information about the exact value of parameters during COVID-19. The weight of social factors for treatment technology selection is determined using a fuzzy best–worst method (FBWM). The developed model is solved using a fuzzy programming method. The effectiveness of the developed model is demonstrated by a practical case study.

The following is a breakdown of the paper's structure. The relevant literature is presented in Sect. 2. The definition and formulation of the model are explained in Sect. 3. The solution method is outlined in Sect. 4 and numerical experiments are discussed in Sect. 5. Section 6 concludes with findings and directions for future research.

2 Literature review

The related works for developing the COVID-19 MWMS with the aid of mathematical models are reviewed in this section. Kargar et al. (2020) proposed a reverse logistics model for medical waste, with objective functions of minimizing total costs, transportation risk, and overall uncollected waste volume. Tirkolaee et al. (2021) introduced a joint location and routing problem for collecting medical waste to minimize transportation time, time window violations, and disposal risk. Valizadeh et al. (2021a) proposed a bi-level model in which the overall expenses of infectious waste, as well as the hazards of viral transmission, are reduced. They also took into account the income earned by the energy produced and the waste that was recycled. Valizadeh et al. (2021b) proposes a leader–follower approach for hazardous infectious waste collection and government aid distribution to control COVID-19 and solved it by the Benders decomposition method combined with Karush–Kuhn–Tucker conditions. Eren and Tuzkaya (2021) presented a vehicle routing problem for collecting COVID-19-generated waste which can figure out the safest and quickest routes for vehicles. Tirkolaee and Aydin (2021) developed a mathematical model for transporting and collecting COVID-19 waste in order to reduce total costs and dangers. Zhao et al. (2021) provided a robust scenario-based model for managing COVID-19-related waste, in which both location and routing plans are taken into account in order to minimize total costs and risks. A real-world case study was undertaken in Wuhan to assess the model. Govindan et al. (2021) provided a mathematical model for medical waste management that aims to discover the best route for transportation vehicles to visit all COVID-19 medical waste production and collection centers while balancing overall expenses and pollution risk.

The works discussed in the context of MWMS are summarized in Table 1. According to the literature, none of the studies took into account treatment technology selection for infectious medical waste treatment. Although the maximum service limitation is one of the key characteristics of an undesirable facility location, none of the papers listed above include it in their modeling system. Only a few papers have considered the uncertainty associated with waste generation rate, including Tirkolaee et al. (2021), Valizadeh et al. (2021a), and Valizadeh et al. (2021b). Other sources of waste management system uncertainty, such as costs, risk, environmental impacts, and budget limitation, are ignored. None of the aforementioned studies proposed an integrated model for MWMSs that took into account simultaneously economic, environmental, social, and risk perspectives, as well as different practical aspects including capacity, maximum service restrictions, treatment technology selection, and multiple sources of uncertainty associated with parameters during the

Table 1 A summary of COVID-19 MWMS studies

References	Objective			Specific issues					Parameters		Source of uncertainty				
	Economic	Environmental	Social	Risk	Distance (Time)	Capacity	Service restriction	Technology selection	Uncertain	Deterministic	Waste generation	Costs	Environmental impact	Risk	Budget limitation
Kargar et al. (2020)	✓			✓		✓				✓					
Tirkolaee et al. (2021)	✓			✓		✓			✓		✓				
Valizadeh et al. (2021a)	✓			✓		✓			✓		✓				
Valizadeh et al. (2021b)	✓			✓		✓			✓		✓				
Eren and Tuzkaya (2021)				✓	✓					✓					
Tirkolaee and Aydin (2021)	✓			✓		✓				✓					
Zhao et al. (2021)	✓			✓		✓					✓				
Govindan et al. (2021)	✓			✓		✓				✓					
This study	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓	✓

COVID-19 outbreak. According to the existing gaps of the previous researches, the main contributions of this paper are:

- Development of a MWMS based on an innovative multi-period multi-objective mathematical model to mitigate the risk of COVID-19 spreading through medical waste treatment, disposal, and transportation.
- Considering economic, environmental, and social aspects of the sustainable development paradigm, simultaneously.
- Considering different strategic and operational decisions, which include installation of treatment and disposal centers, treatment technology selection, quantity of discarded and handled waste, and number of transportation vehicles.
- Considering social responsibility in treatment technology selection and using a FBWM to determine the importance weight of social factors.
- Taking into account the uncertainty of critical parameters such as costs, risk, environmental considerations, budget limitation, and waste generation rate and applying a CFCCPA to manage the uncertainty.
- Implementing an interactive fuzzy programming method to solve the proposed multi-objective model.
- Using real data of Fars province in solving the presented mathematical model.

3 Model description and formulation

This research aims to develop a management system design to handle infectious medical waste during COVID-19. The proposed network is depicted schematically in Fig. 1. The created infectious medical waste is collected from the generation points, as it can be seen. Residential areas, dedicated hospitals for the reception and care of COVID-19 patients, temporary hospitals, clinics for COVID-19 patients, COVID-19 diagnostic laboratories, and cemeteries are among the generation points. Since hospitals do not have enough capacity to accommodate all patients, some
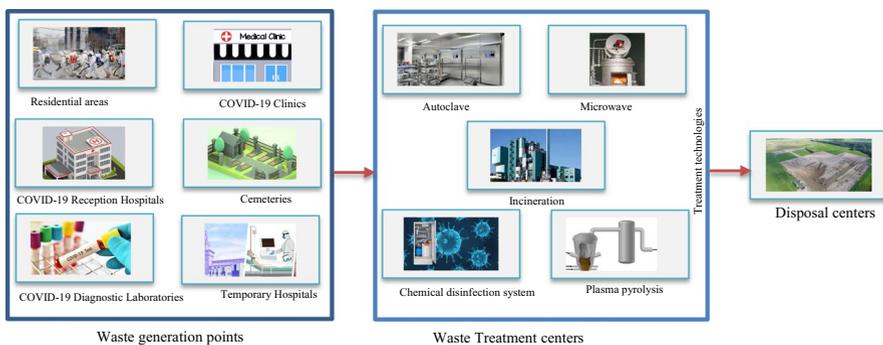

Fig. 1 The underlying structure of the proposed MWMS during COVID-19

temporary hospitals may be required. Since COVID-19 waste is contagious, it must be decontaminated before burial. To minimize the possibility of contamination, the collected medical waste is transported to treatment centers. As it can be seen, each treatment center can use a variety of treatment technologies, such as autoclave, microwave, incineration, chemical disinfection systems, and plasma pyrolysis. Various collection vehicles can carry hazardous waste from sources to treatment centers and processed waste from treatment to disposal centers.

The model takes into account a range of realistic aspects of undesirable facilities, including facility capacity limitations, service coverage limits, and the maximum number of facilities that can operate in a given area. The model simultaneously optimizes all sustainability pillars, including economic, environmental, and social considerations. The risk associated with processing and transporting COVID-19 waste is also taken into consideration in a separate objective to reflect the hazardous nature of the waste. For selecting treatment technologies, Global Reporting Initiative (GRI) guideline indicators (GRI, 2020) are considered to address the social impact of the planned network. The proposed model's decisions involve determining: (1) the location of treatment centers; (2) the location of disposal centers; (3) the type of waste treatment technology; (4) the quantity of handled waste; (5) the quantity of discarded waste; (6) the quantity of waste shipping between waste generation points and built facilities; and (5) the number of waste transportation vehicles. Because it is unclear how long COVID-19 will last, it is more practical to establish a planning horizon in which various strategic and operational decisions are made based on waste generation rates in each time period. If the planning horizon is not taken into account, decisions about facility location must be made from the start, and further facilities may not be added to the system. In this case, if large-capacity treatment or disposal centers are built at the outset, infectious medical waste may reduce dramatically in response to COVID-19 growth, and the system will incur greater expenses as a result of the additional capacity. Furthermore, if a treatment or disposal facility with a little capacity is built at the outset, infectious medical waste would likely increase rapidly, and the system will be unable to handle the need to deal with such a large amount of waste. Therefore, all of above-mentioned decisions are determined over multiple periods to account for the dynamic existence of the proposed structure in the presence of COVID-19. The notation and suggested mathematical model for managing COVID-19 infectious medical waste are described in the following subsections.

3.1 Notation

Below are descriptions of the indices, parameters, and decision variables. Symbols with a tilde are used to describe epistemic uncertainty in parameters.

Sets

I: Infectious medical waste generation points
J: Candidate locations for treatment centers

L: Candidate locations for disposal centers

V: Vehicle types

K: Treatment technologies

T: Periods

S: Social criteria

Parameters

$\widetilde{a}_{it}$: Amount of infectious medical waste produced at generation point i in period t

$\widetilde{ft}_{jkt}$: Fixed opening cost of treatment center j with technology k in period t

$\widetilde{fl}_{lt}$: Fixed opening cost of disposal center l in period t

$\widetilde{cc}_{it}$: Unit cost of collecting infectious medical waste from generation point i in period t

$\widetilde{tr}_{kt}$: Unit treatment cost with technology k in period t

$\widetilde{dc}_{lt}$: Unit disposing cost at disposal center l in period t

$\widetilde{tc}_{vt}$: Transportation cost of vehicle v per unit of infectious medical waste per kilometer in period t

$\widetilde{tn}_{vt}$: Transportation cost of vehicle v per unit of treated waste per kilometer in period t

d_{ij}: Distance between generation point i and treatment center j

d_{jl}: Distance between treatment center j and disposal center l

ca_{jk}: Capacity of treatment center j with technology k

cd_l: Capacity of disposal center l

cv_v: Capacity of vehicle v

$\widetilde{\beta}$: Maximum number of treatment centers that can be established

$\widetilde{\gamma}$: Maximum number of disposal centers that can be established

$\widetilde{\theta a}_j$: Number of people at risk for per unit of infectious medical waste processed at treatment center j

$\widetilde{\sigma c}_{ij}$: Number of people at risk during the transfer of per unit of infectious medical waste from generation point i to treatment center j

$\widetilde{\mu t}_{jk}$: Amount of GHG emissions for per unit of infectious medical waste processed at treatment center j with technology k

$\widetilde{\mu i}_l$: Amount of GHG emissions for per unit of treated waste processed at disposal center l

$\widetilde{\mu v}_v$: Amount of GHG emissions of vehicle v per kilometer

α_k: Percentage of mass reduction achieved with treatment technology k

τ_{ks}: Score of using treatment technology k for social criteria s

ς_s: Normalized weight of social criteria s

ζ: Maximum service distance restriction of a treatment center

ξ: Maximum service distance restriction of a disposal center

ir: Interest rate

M: A large number

Decision variables

y_{jkt}: 1 if location j is selected for the opening of a treatment center with technology k in period t, 0 otherwise

q_{lt}: 1 if location l is selected for the opening of a disposal center in period t, 0 otherwise

xa_{ijvt}: Quantity of waste transported from generation point i to treatment center j by vehicle v in period t

xc_{jlvt}: Quantity of waste transported from treatment center j to disposal center l by vehicle v in period t

wa_{jkt}: Quantity of treated waste at treatment center j with technology k in period t

wc_{lt}: Quantity of disposed waste at disposal center l in period t

oa_{vijt}: Number of vehicle v for transporting infectious medical waste from generation point i to treatment center j in period t

oc_{vjlt}: Number of vehicle v for transporting treated waste from treatment center j to disposal center l in period t

3.2 The economic objective

The economic objective minimizes the total cost of the MWMS. Fixed costs (FC), collection costs (CC), treatment costs (TRC), disposal costs (DC), and transportation costs (TC) are all included in this objective.

$$\min Z_1 = FC + CC + TRC + DC + TC \tag{1}$$

The fixed costs of establishing treatment and disposal centers are as follows:

$$FC = \sum_t (1 + ir)^{-(t-1)} \left[\sum_j \sum_k \widetilde{ft}_{jkt} \left(y_{jkt} - y_{jk,t-1} \right) + \sum_l \widetilde{fl}_{lt} \left(q_{lt} - q_{l,t-1} \right) \right] \tag{2}$$

The following is the costs of collecting infectious medical waste from generation points:

$$CC = \sum_i \sum_j \sum_v \sum_t (1 + ir)^{-(t-1)} \widetilde{cc}_{it} xa_{ijvt} \tag{3}$$

Equation (4) defines the treatment cost of built treatment centers:

$$TRC = \sum_j \sum_k \sum_t (1 + ir)^{-(t-1)} \widetilde{tr}_{kt} wa_{jkt} \tag{4}$$

In Eq. (5), the disposal cost is determined as follows:

$$DC = \sum_l \sum_t (1 + ir)^{-(t-1)} \widetilde{dc}_{lt} wc_{lt} \tag{5}$$

Equation ([6]) calculates the cost of transporting infectious medical waste between generation points and treatment centers, as well as the cost of transporting treated waste between treatment centers and disposal centers.

$$TC = \sum_t (1 + ir)^{-(t-1)} \left[\sum_i \sum_j \sum_v \widetilde{tc}_{vt} d_{ij} xa_{ijvt} + \sum_j \sum_l \sum_v \widetilde{tn}_{vt} d_{jl} xc_{jlvt} \right] \quad (6)$$

3.3 The environmental objective

The environmental objective minimizes the GHG emissions of the designed infectious MWMS. It considers the environmental impact of treatment centers (ETR), disposal centers (EED), and transportation (EET).

$$\min Z_2 = ETR + EED + EET \quad (7)$$

The environmental effect of treating infectious medical waste at treatment centers is described as follows:

$$ETR = \sum_j \sum_k \sum_t \widetilde{\mu t}_{jk} wa_{jkt} \quad (8)$$

The environmental effect of medical waste disposal centers is calculated as follows:

$$EED = \sum_l \sum_t \widetilde{\mu i}_l wc_{lt} \quad (9)$$

The following equation is used to measure the environmental effect of transporting infectious and treated medical wastes between various levels of the designed network:

$$EET = \sum_i \sum_j \sum_v \sum_t \widetilde{\mu v}_v d_{ij} oa_{vijt} + \sum_j \sum_l \sum_v \sum_t \widetilde{\mu v}_v d_{jl} oc_{vjlt} \quad (10)$$

3.4 The risk-oriented objective

The third objective function minimizes the risk of infectious medical waste treatment (RTR) and transportation (RT) for human health as follows:

$$\min Z_3 = RTR + RT \quad (11)$$

The following is how the risk of treating infectious medical waste is measured depending on the number of people in the vicinity of the treatment centers:

$$RTR = \sum_j \sum_k \sum_t \widetilde{\theta a}_j wa_{jkt} \tag{12}$$

The risk of transporting infectious medical waste is measured based on the number of people within a given distance between waste generation points and treatment centers as follows:

$$RT = \sum_i \sum_j \sum_v \sum_t \widetilde{\sigma c}_{ij} xa_{ijvt} \tag{13}$$

3.5 The social objective

The fourth objective maximizes the suitability of using the treatment technology based on the social considerations, as follows:

$$\max Z_4 = \sum_s \sum_k \sum_j \sum_t \varsigma_s \tau_{ks} \left(y_{jkt} - y_{jk,t-1} \right) \tag{14}$$

3.6 Constraints

$$\sum_i \sum_j \sum_v \sum_t xa_{ijvt} = \sum_i \sum_t \tilde{a}_{it} \tag{15}$$

$$\sum_k wa_{jkt} = \sum_i \sum_v xa_{ijvt}, \quad \forall j, t \tag{16}$$

$$wc_{lt} = \sum_j \sum_v xc_{jlvt}, \quad \forall l, t \tag{17}$$

$$\sum_l \sum_v xc_{jlvt} = \sum_k wa_{jkt} (1 - \alpha_k), \quad \forall j, t \tag{18}$$

$$\sum_k y_{jkt} \le 1, \quad \forall j, t \tag{19}$$

$$\sum_i \sum_v xa_{ijvt} \le \sum_k ca_{jk} y_{jkt}, \quad \forall j, t \tag{20}$$

$$\sum_j \sum_v xc_{jlvt} \le cd_l q_{lt}, \quad \forall l, t \tag{21}$$

$$\sum_j \sum_k \sum_t \left(y_{jkt} - y_{jk,t-1} \right) \le \tilde{\beta} \tag{22}$$

$$\sum_l \sum_t \left(q_{lt} - q_{l,t-1} \right) \le \tilde{\gamma} \tag{23}$$

$$xa_{ijvt} \le cv_v oa_{vijt}, \quad \forall i,j,v,t \tag{24}$$

$$xc_{jlvt} \le cv_v oc_{vjlt}, \quad \forall j,l,v,t \tag{25}$$

$$y_{jk,t-1} \le y_{jkt}, \quad \forall j,k,t \tag{26}$$

$$q_{l,t-1} \le q_{lt}, \quad \forall l,t \tag{27}$$

$$wa_{jkt} \le M y_{jkt}, \quad \forall j,k,t \tag{28}$$

$$wc_{lt} \le M q_{lt}, \quad \forall l,t \tag{29}$$

$$oa_{vijt} \le M \sum_k y_{jkt}, \quad \forall i,j,v,t \tag{30}$$

$$oc_{vjlt} \le M q_{lt}, \quad \forall j,l,v,t \tag{31}$$

$$oc_{vjlt} \le M \sum_k y_{jkt}, \quad \forall j,l,v,t \tag{32}$$

$$xa_{ijvt} = 0, \quad \forall i,v,t,j \in \left\{ J | d_{ij} > \zeta \right\} \tag{33}$$

$$xc_{jlvt} = 0, \quad \forall j,v,t,l \in \left\{ L | d_{jl} > \xi \right\} \tag{34}$$

$$y_{jkt}, q_{lt} \in \{0,1\}, \quad \forall j,k,l,t \tag{35}$$

$$xa_{ijvt}, xc_{jlvt}, wa_{jkt}, wc_{lt} \ge 0, \quad \forall i,j,v,l,k,t \tag{36}$$

$$oa_{vijt}, oc_{vjlt}, integer \quad \forall i,j,l,v,t \tag{37}$$

Constraint (15) ensures the flow balance of infectious medical waste. Constraint (16) balances the total treated waste with the collected waste. Constraint (17) maintains a balance between total discharged trash and waste moved from treatment to disposal locations. The amount of waste residue moved from treatment centers to

disposal centers is determined by constraint (18). Constraint (19) states that each treatment facility should only use one technology. The capacity of established centers is represented by constraints (20) and (21). Constraints (22) and (23) restrict the number of established treatment and disposal centers that can be located, respectively. The capacity constraints of transportation vehicles are expressed by constraints (24) and (25). Constraints (26) and (27) ensure that the established treatment centers would remain operational by the completion of the planning horizon. The infectious medical waste is only treated in a treatment center if the treatment center is built, according to constraint (28). Constraint (29) ensures that the handled waste will not be disposed of in an unopened disposal center. Constraints (30)–(32) state that if no treatment and disposal centers are established, no vehicles can be used. The maximum coverage radius restriction for located facilities is defined by constraints (33) and (34), respectively. Constraints (35)–(37) specify the binary, non-negative, and integer variables, respectively.

4 Solution method

The multi-objective possibilistic mixed integer linear programming model proposed is solved using a three-phase solution method. In the first phase, a CFCCPA is used to convert the original model into an equivalent crisp model. The significance weight of social factors in selecting the treatment technology is determined in the second phase using a FBWM. In the third phase, an interactive fuzzy programming technique is used to solve the proposed multi-objective model.

4.1 CFCCPA

The majority of model parameters are subject to substantial epistemic uncertainty. Possibility distributions are used to model uncertain parameters in mathematical programming. A possibilistic constraint can be transformed into a crisp constraint using a number of fuzzy measures such as possibility, necessity, and credibility. The possibility measure reflects the most optimistic level of the occurrence of an uncertain event involving possibilistic factors. Under the most pessimistic view, the necessity measure displays the corresponding lowest possible level. Meanwhile, the degree of certainty that an uncertain event will occur is represented by the credibility measure. Because the possibility and necessity measures represent the highly positive and negative potential levels of an event occurring, respectively, the credibility measure is more flexible than other fuzzy measurements in terms of avoiding extreme views. Furthermore, the credibility measure is a self-dual measure, despite the fact that the possibility measure lacks this attribute (Li & Liu, 2006). When a fuzzy event's credibility value reaches 1, the decision maker (DM) believes the fuzzy event will undoubtedly occur. A fuzzy event, on the other hand, can fail even if its possibility is 1, and it can hold even if its necessity is 0 (Pishvaee et al., 2012a).

To cope with uncertainty, a CFCCPA suggested by Li and Liu (2006) is used in this study. The DM can monitor the degree of trust in constraint fulfillment using

this approach, which is based on strong mathematical principles like the expected value of posibilistic numbers and the credibility measure. It also supports a variety of fuzzy numbers, including triangular and trapezoidal shapes (Pishvaee et al., 2014). The trapezoidal fuzzy distribution, which can be described by four sensitive points, is employed in this study to formulate uncertain parameters. It's worth noting that the triangular fuzzy distribution is a subset of the trapezoidal fuzzy distribution, with the identical second and third potential points (Pishvaee et al., 2012b). Although utilizing triangular fuzzy distributions with three sensitive points reduces the number of calculations, DMs can get a better approximation by constructing uncertain parameters as trapezoidal fuzzy distributions based on the available data and their expertise. The CFCCPA is briefly mentioned in the following parts.

Let $\widetilde{\tau}$ and r denote a fuzzy variable with membership function $\mu(x)$ and a real number, respectively. Liu and Liu (2002) described the credibility measure as follows:

$$Cr\{\tilde{\tau} \leq r\} = \frac{1}{2}\left(\underset{x \leq r}{Sup}\ \mu\ (x) + 1 - \underset{x > r}{Sup}\ \mu\ (x) \right) \tag{38}$$

By considering $Pos\{\tilde{\tau} \leq r\} = \underset{x \leq r}{Sup}\ \mu\ (x)$ and $Nec\{\tilde{\tau} \leq r\} = 1 - \underset{x > r}{Sup}\ \mu\ (x)$, the credibility measure is expressed as follows:

$$Cr\{\tilde{\tau} \leq r\} = \frac{1}{2}(Pos\{\tilde{\tau} \leq r\} + Nec\{\tilde{\tau} \leq r\}) \tag{39}$$

Using the above equations, the expected value of $\tilde{\tau}$ is calculated as follows:

$$E[\tilde{\tau}] = \int\limits_{0}^{\infty} Cr\{\tilde{\tau} \geq r\}dr - \int\limits_{-\infty}^{0} Cr\{\tilde{\tau} \leq r\}dr \tag{40}$$

If $\tilde{\tau}$ is a trapezoidal fuzzy number, its expected value can be written as:

$$E[\tilde{\tau}] = \frac{\tau^{(1)} + \tau^{(2)} + \tau^{(3)} + \tau^{(4)}}{4} \tag{41}$$

The following are the above-mentioned credibility measures of $\tilde{\tau}$:

$$Cr\{\tilde{\tau} \leq r\} = \begin{cases} 0 & r \in (-\infty, \tau^{(1)}] \\ \frac{r - \tau^{(1)}}{2(\tau^{(2)} - \tau^{(1)})} & r \in (\tau^{(1)}, \tau^{(2)}] \\ \frac{1}{2} & r \in (\tau^{(2)}, \tau^{(3)}] \\ \frac{r - 2\tau^{(3)} + \tau^{(4)}}{2(\tau^{(4)} - \tau^{(3)})} & r \in (\tau^{(3)}, \tau^{(4)}] \\ 1 & r \in (\tau^{(4)}, +\infty) \end{cases} \tag{42}$$

$$Cr\{\tilde{\tau} \geq r\} = \begin{cases} 1 & r \in \left(-\infty, \tau^{(1)}\right] \\ \frac{2\tau^{(2)} - \tau^{(1)} - r}{2\left(\tau^{(2)} - \tau^{(1)}\right)} & r \in \left(\tau^{(1)}, \tau^{(2)}\right] \\ \frac{1}{2} & r \in \left(\tau^{(2)}, \tau^{(3)}\right] \\ \frac{\tau^{(4)} - r}{2\left(\tau^{(4)} - \tau^{(3)}\right)} & r \in \left(\tau^{(3)}, \tau^{(4)}\right] \\ 0 & r \in \left(\tau^{(4)}, +\infty\right) \end{cases} \tag{43}$$

Equations (42) and (43) can be stated as follows when $\alpha > 0.5$ is taken into account:

$$Cr\{\tilde{\tau} \leq r\} \geq \alpha \Leftrightarrow r \geq (2 - 2\alpha)\tau^{(3)} + (2\alpha - 1)\tau^{(4)} \tag{44}$$

$$Cr\{\tilde{\tau} \geq r\} \geq \alpha \Leftrightarrow r \leq (2\alpha - 1)\tau^{(1)} + (2 - 2\alpha)\tau^{(2)} \tag{45}$$

The following equations for $\tau^{(2)} \leq r \leq \tau^{(3)}$ will be obtained using Eqs. (44) and (45):

$$Cr\{\tilde{\tau} \leq r\} = \frac{1}{2} \tag{46}$$

$$Cr\{\tilde{\tau} \geq r\} = \frac{1}{2} \tag{47}$$

In Eqs. (46) and (47), r and $\tilde{\tau}$ are indifferent or nearly equal (Pishvaee et al., 2014). The CFCCPA for the developed model is as follows:

$$\min Z_1$$

$$= \sum_t (1 + ir)^{-(t-1)} \left[\sum_j \sum_k E\left[\widetilde{ft}_{jkt}\right](y_{jkt} - y_{jk,t-1}) + \sum_l E\left[\widetilde{fl}_{lt}\right](q_{lt} - q_{l,t-1}) \right.$$

$$+ \sum_i \sum_j \sum_v E\left[\widetilde{cc}_{it}\right]xa_{ijvt} + \sum_j \sum_k E\left[\widetilde{tr}_{kt}\right]wa_{jkt} + \sum_l E\left[\widetilde{dc}_{lt}\right]wc_{lt}$$

$$\left. + \sum_i \sum_j \sum_v E\left[\widetilde{tc}_{vt}\right]d_{ij}xa_{ijvt} + \sum_j \sum_l \sum_v E\left[\widetilde{tn}_{vt}\right]d_{jl}xc_{jlvt} \right] \tag{48}$$

$$\min Z_2$$

$$= \sum_j \sum_k \sum_t E\left[\widetilde{\mu t}_{jk}\right]wa_{jkt} + \sum_l \sum_t E\left[\widetilde{\mu i}_l\right]wc_{lt}$$

$$+ \sum_i \sum_j \sum_v \sum_t E\left[\widetilde{\mu v}_v\right]d_{ij}oa_{vijt} + \sum_j \sum_l \sum_v \sum_t E\left[\widetilde{\mu v}_v\right]d_{jl}oc_{vjlt} \tag{49}$$

$$\min Z_3 = \sum_j \sum_k \sum_t E\left[\widetilde{\theta a}_j\right]wa_{jkt} + \sum_i \sum_j \sum_v \sum_t E\left[\widetilde{\sigma c}_{ij}\right]xa_{ijvt} \tag{50}$$

$$\max Z_4$$
$$s.t. \ (16) - (21), \ (24) - (37)$$

$$Cr\left\{ \sum_i \sum_j \sum_v \sum_t xa_{ijvt} \geq \sum_i \sum_t \tilde{a}_{it} \right\} = \frac{1}{2} \tag{51}$$

$$Cr\left\{ \sum_i \sum_j \sum_v \sum_t xa_{ijvt} \leq \sum_i \sum_t \tilde{a}_{it} \right\} = \frac{1}{2} \tag{52}$$

$$Cr\left\{ \sum_j \sum_k \sum_t \left(y_{jkt} - y_{jk,t-1} \right) \leq \tilde{\beta} \right\} \geq \alpha \tag{53}$$

$$Cr\left\{ \sum_l \sum_t \left(q_{lt} - q_{l,t-1} \right) \leq \tilde{\gamma} \right\} \geq \alpha \tag{54}$$

The expected values of trapezoidal fuzzy numbers are used to transform the above model into the corresponding crisp model as follows:

$$\min Z_1$$
$$= \sum_t (1 + ir)^{-(t-1)} \left[\sum_j \sum_k \left(\frac{ft_{jkt}^{(1)} + ft_{jkt}^{(2)} + ft_{jkt}^{(3)} + ft_{jkt}^{(4)}}{4} \right) (y_{jkt} - y_{jk,t-1}) \right.$$
$$+ \sum_l \left(\frac{fl_{lt}^{(1)} + fl_{lt}^{(2)} + fl_{lt}^{(3)} + fl_{lt}^{(4)}}{4} \right) (q_{lt} - q_{l,t-1}) + \sum_i \sum_j \sum_v \left(\frac{cc_{it}^{(1)} + cc_{it}^{(2)} + cc_{it}^{(3)} + cc_{it}^{(4)}}{4} \right) xa_{ijvt}$$
$$+ \sum_j \sum_k \left(\frac{tr_{kt}^{(1)} + tr_{kt}^{(2)} + tr_{kt}^{(3)} + tr_{kt}^{(4)}}{4} \right) wa_{jkt} + \sum_l \left(\frac{dc_{lt}^{(1)} + dc_{lt}^{(2)} + dc_{lt}^{(3)} + dc_{lt}^{(4)}}{4} \right) wc_{lt}$$
$$+ \sum_i \sum_j \sum_v \left(\frac{tc_{vt}^{(1)} + tc_{vt}^{(2)} + tc_{vt}^{(3)} + tc_{vt}^{(4)}}{4} \right) d_{ij} xa_{ijvt} + \sum_j \sum_l \sum_v \left(\frac{tn_{vt}^{(1)} + tn_{vt}^{(2)} + tn_{vt}^{(3)} + tn_{vt}^{(4)}}{4} \right) d_{jl} xc_{jlvt} \right] \tag{55}$$

$$\min Z_2$$
$$= \sum_j \sum_k \sum_t \left(\frac{\mu t_{jk}^{(1)} + \mu t_{jk}^{(2)} + \mu t_{jk}^{(3)} + \mu t_{jk}^{(4)}}{4} \right) wa_{jkt} + \sum_l \sum_t \left(\frac{\mu i_l^{(1)} + \mu i_l^{(2)} + \mu i_l^{(3)} + \mu i_l^{(4)}}{4} \right) wc_{lt}$$
$$+ \sum_i \sum_j \sum_v \sum_t \left(\frac{\mu v_v^{(1)} + \mu v_v^{(2)} + \mu v_v^{(3)} + \mu v_v^{(4)}}{4} \right) d_{ij} oa_{vijt}$$
$$+ \sum_j \sum_l \sum_v \sum_t \left(\frac{\mu v_v^{(1)} + \mu v_v^{(2)} + \mu v_v^{(3)} + \mu v_v^{(4)}}{4} \right) d_{jl} oc_{vjlt} \tag{56}$$

$$\min Z_3$$

$$
= \sum_j \sum_k \sum_t \left(\frac{\theta a_j^{(1)} + \theta a_j^{(2)} + \theta a_j^{(3)} + \theta a_j^{(4)}}{4} \right) w a_{jkt}
$$
$$
+ \sum_i \sum_j \sum_v \sum_t \left(\frac{\sigma c_{ij}^{(1)} + \sigma c_{ij}^{(2)} + \sigma c_{ij}^{(3)} + \sigma c_{ij}^{(4)}}{4} \right) x a_{ijvt}
\tag{57}
$$

$$\max Z_4$$
$$s.t.\ (16) - (21), (24) - (37)$$

$$
\sum_i \sum_j \sum_v \sum_t x a_{ijvt} \geq \sum_i \sum_t a_{it}^{(2)}
\tag{58}
$$

$$
\sum_i \sum_j \sum_v \sum_t x a_{ijvt} \leq \sum_i \sum_t a_{it}^{(3)}
\tag{59}
$$

$$
\sum_j \sum_k \sum_t \left(y_{jkt} - y_{jk,t-1} \right) \leq \left[(2\alpha - 1)\beta^{(1)} + (2 - 2\alpha)\beta^{(2)} \right]
\tag{60}
$$

$$
\sum_l \sum_t \left(q_{lt} - q_{lt-1} \right) \leq \left[(2\alpha - 1)\gamma^{(1)} + (2 - 2\alpha)\gamma^{(2)} \right]
\tag{61}
$$

4.2 FBWM

Rezaei (2015) introduced the best–worst method, which is one of the most recent weighting techniques. This method utilizes fewer pairwise comparisons, has a higher stability rate, and gives more realistic results than prior weighting methods such as the analytic hierarchy process (AHP) method. In the case of a decision problem with n parameters, the AHP procedure requires $\frac{n \times (n-1)}{2}$ pairwise comparisons, whereas the best–worst method requires $2n - 3$ comparisons (Rezaei, 2015). The FBWM suggested by Guo and Zhao (2017) is used in this sub-section to assess the weight of social factors for selecting treatment technologies depending on the DM's desires. This method includes all of the benefits of the best–worst method, plus it incorporates the uncertainty of objective things and the fuzziness of human thought, allowing DMs to develop more compatible results with real-world scenarios (Guo & Zhao, 2017). The following is a summary of this strategy:

Step 1: For the decision-making issue, a set of significant factors is specified.

Step 2: The best and worst factors are identified by the DM.

Step 3: The fuzzy priorities of the best factor over all other factors are defined based on the linguistic terms of DMs shown in Table 2. The following is the fuzzy best-to-others vector:

Table 2 Linguistic scales for importance (Guo & Zhao, 2017)

Linguistic scale	Triangular fuzzy scale
Equally important	$(1, 1, 1)$
Weakly important	$(2/3, 1, 3/2)$
Fairly important	$(3/2, 2, 5/2)$
Very important	$(5/2, 3, 7/2)$
Absolutely important	$(7/2, 4, 9/2)$

$$\tilde{A}_B = \left(\tilde{a}_{B1}, \tilde{a}_{B2}, \ldots, \tilde{a}_{Bn} \right) \tag{62}$$

where $\tilde{a}_{Bj}$ denotes the fuzzy priority for the best factor over factor j and n is the number of factors.

Step 4: The fuzzy others-to-worst vector is generated using the fuzzy priorities of all the factors over the worst factor, as follows:

$$\tilde{A}_W = \left(\tilde{a}_{1W}, \tilde{a}_{2W}, \ldots, \tilde{a}_{nW} \right) \tag{63}$$

Step 5: To determine the optimum fuzzy weight for the factor, use the following model:

$$min \tilde{\xi} \tag{64}$$

$$\left| \frac{\tilde{w}_B}{\tilde{w}_j} - \tilde{a}_{Bj} \right| \leq \tilde{\xi}, \quad \forall j, \tag{65}$$

$$\left| \frac{\tilde{w}_j}{\tilde{w}_W} - \tilde{a}_{jW} \right| \leq \tilde{\xi}, \quad \forall j, \tag{66}$$

$$\sum_j R(\tilde{w}_j) = 1, \tag{67}$$

$$l_j^w \leq m_j^w \leq u_j^w, \quad \forall j, \tag{68}$$

$$l_j^w \geq 0, \quad \forall j. \tag{69}$$

where $\tilde{\xi} = (l^\xi, m^\xi, u^\xi)$. By considering $\tilde{\xi}^* = (\theta^*, \theta^*, \theta^*)$ and $\theta^* \leq l^{\tilde{\xi}}$, the above model is specified as follows:

$$min \ \tilde{\xi}^* \tag{70}$$

$$s.t. \ (67) - (69)$$

$$\left| \frac{\left(l_B^w, m_B^w, u_B^w\right)}{\left(l_j^w, m_j^w, u_j^w\right)} - \left(l_{Bj}, m_{Bj}, u_{Bj}\right) \right| \leq (\theta^*, \theta^*, \theta^*), \quad \forall j, \tag{71}$$

$$\left| \frac{\left(l_j^w, m_j^w, u_j^w\right)}{\left(l_W^w, m_W^w, u_W^w\right)} - \left(l_{jW}, m_{jW}, u_{jW}\right) \right| \leq (\theta^*, \theta^*, \theta^*), \quad \forall j, \tag{72}$$

$R\left(\tilde{w}_j\right)$ is determined as follows:

$$R\left(\tilde{w}_j\right) = \frac{l_j^w + 4m_j^w + u_j^w}{6} \tag{73}$$

4.3 The interactive fuzzy programming approach

Various solution methods have been introduced for solving multi-objective optimization problems. This research employs the interactive fuzzy programming method proposed by Torabi and Hassini (2008) because of its ability to calculate the degree of fulfillment of each objective. Because of its short processing time, this method can produce optimal solutions with a lot of flexibility, depending on the DM's preferences. It is regarded as one of the most successful interactive fuzzy methods because it can produce diverse solutions by modifying different weights for objectives. Furthermore, it can help the DM compare the generated solutions and choose the one that provides the best trade-off between competing objectives (Torabi & Hassini, 2008). The following is a summary of this approach:

Step 1: For maximizing and minimizing objectives, the positive ideal solution (PIS) and the negative ideal solution (NIS) are calculated as follows:

$$Z_\ell^{\text{PIS}} = \text{Max } Z_\ell, \quad Z_\ell^{\text{NIS}} = \text{Min } Z_\ell, \tag{74}$$

$$Z_\ell^{\text{PIS}} = \text{Min } Z_\ell, \quad Z_\ell^{\text{NIS}} = \text{Max } Z_\ell, \tag{75}$$

Equations (74) and (75) are used for maximizing and minimizing objectives, respectively.

Step 2: The calculation of a linear membership function for maximizing and minimizing objectives is as follows:

$$\mu_\ell(Z_\ell) = \begin{cases} 1 & Z_\ell > Z_\ell^{\text{PIS}}, \\ \frac{Z_\ell - Z_\ell^{\text{NIS}}}{Z_\ell^{\text{PIS}} - Z_\ell^{\text{NIS}}} & Z_\ell^{\text{NIS}} \leq Z_\ell \leq Z_\ell^{\text{PIS}}, \\ 0 & Z_\ell < Z_\ell^{\text{NIS}}, \end{cases} \tag{76}$$

$$\mu_\ell(Z_\ell) = \begin{cases} 1 & Z_\ell < Z_\ell^{\text{PIS}}, \\ \frac{Z_\ell^{\text{NIS}} - Z_\ell}{Z_\ell^{\text{NIS}} - Z_\ell^{\text{PIS}}} & Z_\ell^{\text{PIS}} \le Z_\ell \le Z_\ell^{\text{NIS}}, \\ 0 & Z_\ell > Z_\ell^{\text{NIS}}, \end{cases} \tag{77}$$

Step 3: The following is how to convert a multi-objective model into a single-objective one:

$$\text{Max } \lambda(x) = \varphi\lambda_0 + (1 - \varphi) \sum_\ell w_\ell \mu_\ell(x) \tag{78}$$

s.t.
$$\lambda_0 \le \mu_\ell(x), \quad \ell = 1, 2, \ldots \tag{79}$$

$$x \in F(x), \tag{80}$$

$$\lambda_0, \ \varphi \in [0, 1]. \tag{81}$$

where $\lambda_0 = \min_\ell \{\mu_\ell(x)\}$. φ and w_ℓ represent the compensation coefficient and the weight of ℓ-th objective, respectively.

Step 4: The process ends when the DM is pleased with the result. Otherwise, to find a suitable solution, the model must be changed by changing the value of φ and w_ℓ.

5 A case study

In this section, the performance of the developed model and the importance of its solution procedure are illustrated using data from Shiraz, Iran. The model is coded with GAMS23.4 optimization software, and it is solved using CPLEX solver. In this section, the analyzed case is discussed first, followed by the significance weight of social factors calculated using the FBWM. Finally, the experimental results of solving the model using the interactive fuzzy programming and the sensitivity analysis of the critical parameters are presented. All the experiments are performed on a computer Intel® Core ™ i3-2120 processor with a 3.3 gigahertz CPU and 4 gigabytes of RAM.

5.1 Case description

Shiraz, the capital of Fars province, has 1,609,615 inhabitants, making it one of Iran's most populous cities and the first in the country's southern half. It spans an area of around 217 square kilometers in Iran. Shiraz has 39 functioning hospitals, according to the Shiraz City Annual Report (SCAR, 2019). Organ transplants, eye surgery, beauty and skin care, chemotherapy and radiation therapy for various cancers, slimming treatments, cardiovascular surgery, orthopedics, and infertility

treatment are only a handful of the services offered by its well-equipped hospitals. Shiraz is recognized as one of the Middle East's largest medical centers. It currently receives patients from all over Iran, especially from the country's southern provinces. It also accepts patients from the Persian Gulf countries. Given Shiraz's broad medical potential and diverse range of medical services, an effective MWMS for treating and disposing of hazardous waste created by the city is critical. Infectious medical waste has to be disinfected before being discarded. The quantity of infectious medical waste released during COVID-19 increased, making medical waste decontamination more difficult. Although some hospitals have medical waste treatment centers, the management system for treating infectious medical waste produced in small medical centers, clinics, labs, cemeteries, and residential areas must also be coordinated.

On February 19, 2020, the first reported cases of COVID-19 in Iran were registered in the province of Qom. As of June 17, 2022, there were 629,100 confirmed cases and 8,036 deaths in Fars province. During this time, 620,893 cases of COVID-19 infection were released from hospitals or community isolation centers. A total of 2,155,946 test samples were obtained from ill and symptomatic patients (SUMS, 2022).
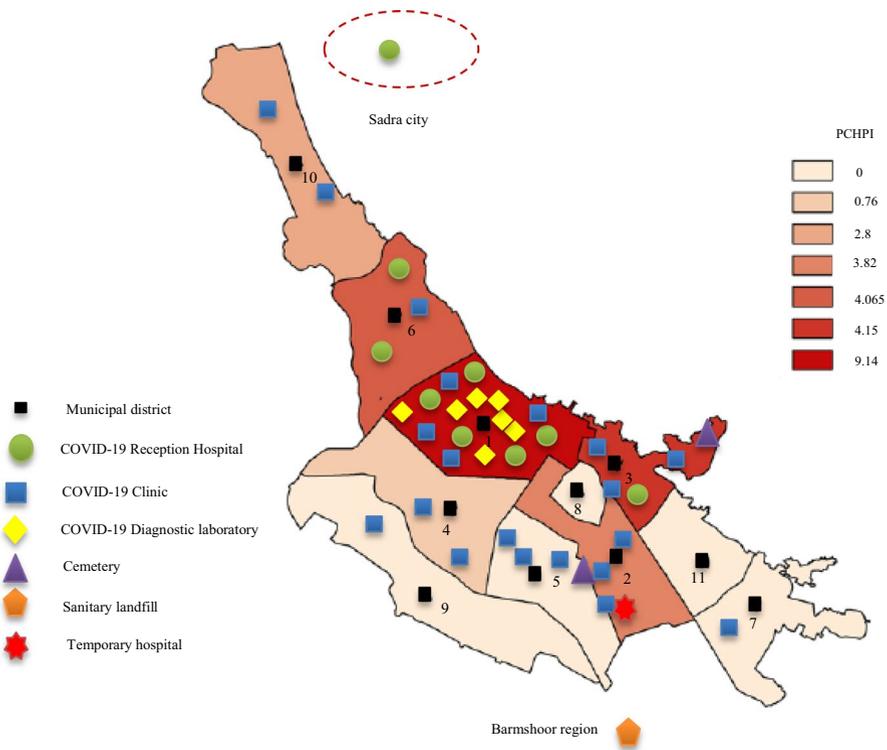

Fig. 2 A geographic map of Shiraz and COVID-19 waste generation points

Figure 2 depicts a Shiraz geographical map. PCHPI denotes per capita hospitals per 100,000 people in Fig. 2. Shiraz is divided into 11 municipal districts as can be seen. This map displays the current positions of treatment and disposal centers. There is one disposal center in the Barmshoor area, about 20 km west of Shiraz. However, its capacity is inadequate to accommodate such a large amount of COVID-19 contaminated medical waste. Furthermore, a centralized management system for treating infectious medical waste created by different sources is urgently needed.

COVID-19 reception hospitals, temporary hospitals, clinics serving COVID-19 patients, COVID-19 diagnostic laboratories, residential areas, and cemeteries are all considered waste generation points when evaluating the proposed model's results. In SCAR (2019), there are distinct maps for PCHPI, temporary hospitals, cemeteries, and clinics. The PCHPI geographical map is used in this study as the primary geographical map, and it displays the position of the generation points derived from their linked maps as precisely as possible. During the COVID-19 outbreak, a stadium in municipal district 2 has been designated as a temporary hospital with 100 beds for COVID-19 patients with mild to moderate symptoms. Only the major cemetery in municipal district 5 and one cemetery in municipal district 3 can dispose of COVID-19 deaths. Despite the fact that Shiraz city has a large number of clinics, Shiraz University of Medical Sciences only considers 20 of them for COVID-19 patients in all municipal districts except municipal districts 8 and 11. Eight hospitals in Shiraz and one in Sadra are accepting patients during this period. Sadra is a new city situated 15 km northwest of Shiraz. The number of hospitals, clinics, and labs treating COVID-19 patients rises as the number of reported cases grows. The quantity of medical waste produced by each hospital bed and the number of hospital beds occupied by COVID-19 patients for each time period are used to measure the medical waste generation rate for COVID-19 reception hospitals. It is worthy to note that 15–20% of patients will experience a serious type of the disease that will necessitate hospitalization. Intensive care is needed for around 25–33% of patients in hospitals. The infectious medical waste production for clinics is calculated using the number of patients who attend clinics and the quantity of medical waste generated by these patients over time. The number of diagnostic tests conducted each day and the amount of waste produced for each test are used to measure the waste generation rate for COVID-19 diagnostic laboratories. The number of patients in home quarantine and the amount of waste created by this community are used to calculate the generated infectious waste in residential areas. The amount of medical waste created in cemeteries is measured using the number of deaths during each time and the amount of waste generated for burial. A 12-month planning horizon is used, with each time period equivalent to one month.

5.2 Treatment technology selection results

The assessment of treatment technologies can be influenced by a variety of factors. The assessment is focused on social criteria because economic, environmental, and technical factors are expressed in the mathematical modeling in terms of costs, environmental impacts, capacities, and mass reduction. This
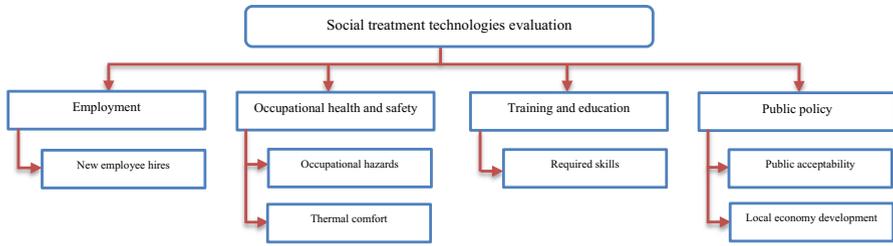
Fig. 3 Assessment factors for treatment technology selection

study employs GRI guideline metrics (GRI, 2020) to measure social responsibility in treatment technology selection. Accordingly, various social factors are evaluated, and the most important ones are chosen by an expert panel. Figure 3 depicts the final criteria as well as sub-criteria.

The weight of each social factor is determined using the FBWM. According to a group of experts, occupational hazards and new employee hires are the best and worst factors, respectively. Note that the factor of new employee hires is chosen as the worst criteria because treatment centers for COVID-19 tainted wastes are among the undesirable facilities and waste treatment must be performed with limited personnel intervention. According to experts' opinions, one of the most common ways for workers and patrons to become infected is by unintentional interaction with discarded infectious products at the point of generation. The optimum weight achieved by the FBWM for social factors is shown in Table 3.

Although a variety of thermal, physical, and chemical treatment methods can be used to process infectious medical waste, thermal disinfection is thought to be

Table 3 The optimum weighs for social factors

Symbol	Factors	Fuzzy weight	Crisp weight
c_1	New employee hires	(0.062, 0.066, 0.068)	0.066
c_2	Occupational hazards	(0.287, 0.315, 0.321)	0.312
c_3	Thermal comfort	(0.112, 0.152, 0.179)	0.149
c_4	Required skills	(0.112, 0.152, 0.179)	0.149
c_5	Public acceptability	(0.117, 0.144, 0.168)	0.143
c_6	Local economy development	(0.134, 0.184, 0.214)	0.181

Table 4 The score of each treatment technology based on each social factor

Technologies	Social factors					
	c_1	c_2	c_3	c_4	c_5	c_6
k_1	0.143	0.412	0.264	0.340	0.316	0.090
k_2	0.143	0.189	0.184	0.281	0.242	0.118
k_3	0.249	0.076	0.073	0.110	0.078	0.350
k_4	0.241	0.182	0.355	0.179	0.242	0.142
k_5	0.224	0.141	0.124	0.090	0.122	0.300

the most efficient method for sterilizing infected products, including the COVID-19 virus (Kampf et al., 2020). Experts have chosen autoclave (k_1), microwave (k_2), incineration (k_3), chemical disinfection system (k_4), and plasma pyrolysis (k_5) as five treatment technologies. The FBWM is used to calculate the score of each treatment technology for selected social factors. Expert views are used to decide the best and worst technologies for each social factor, and optimal weights are calculated. Table 4 represents the score of each treatment technology based on each social factor.

5.3 Experimental results

This sub-section presents the experimental results of the developed model. Figure 4 depicts the optimal network design of the model. This figure shows the network configuration from the economic, environmental, social, and safety perspectives. According to the experts' opinions, the weights for economic, environmental, social, and risk objectives are 0.3, 0.3, 0.2, and 0.2, respectively. It can be seen that the optimal network design differs depending on the viewpoint. When the economic-oriented model is considered, five treatment centers with incineration technology are built, as shown in Fig. 4a. It should be noted that incineration technology would result in a substantial mass reduction, and since only a small amount of residual is transported to disposal centers, the burden on them will be relieved. Five treatment centers with plasma pyrolysis technology and one new disposal center will be built under the environmental-oriented model. The environmental objective is significantly influenced by the transportation of treated waste between treatment and disposal centers. If plasma pyrolysis technology is used in treatment centers, only certain residues are transferred to disposal centers. If autoclave or microwave technologies are used, all decontaminated infectious medical waste must be transferred to disposal centers, which may result in a significant amount of emissions. Three treatment centers using plasma pyrolysis technology and one treatment center with incineration technology are being developed under the risk-oriented model. This model selects fewer locations with larger capacity for opening treatment centers in order to reduce the number of individuals who are subjected to infectious medical waste processing. When considering the social perspective, four treatment centers using plasma pyrolysis technology and one treatment center using autoclave technology are built. It should be noted that these two technologies have gained more weight in most of the considered criteria from a social standpoint. Four treatment centers with plasma pyrolysis technology and one with autoclave technology have been built using the proposed integrated model. Table 5 displays the comprehensive results for the optimal network designs. As can be observed, the optimal time period for developing the facilities is also reported in this table. During COVID-19, several hospitals or temporary hospitals are established in a short period of time, and medical waste management is also a critical need, with treatment and disposal centers built as quickly as possible to handle huge amounts of infectious medical waste. As a result, system designers must construct the treatment and disposal centers during the reported optimal periods; otherwise, a non-optimal MWMS design will be obtained, increasing the risk of COVID-19 spread, expenses, and negative environmental effects while drastically decreasing the system's social
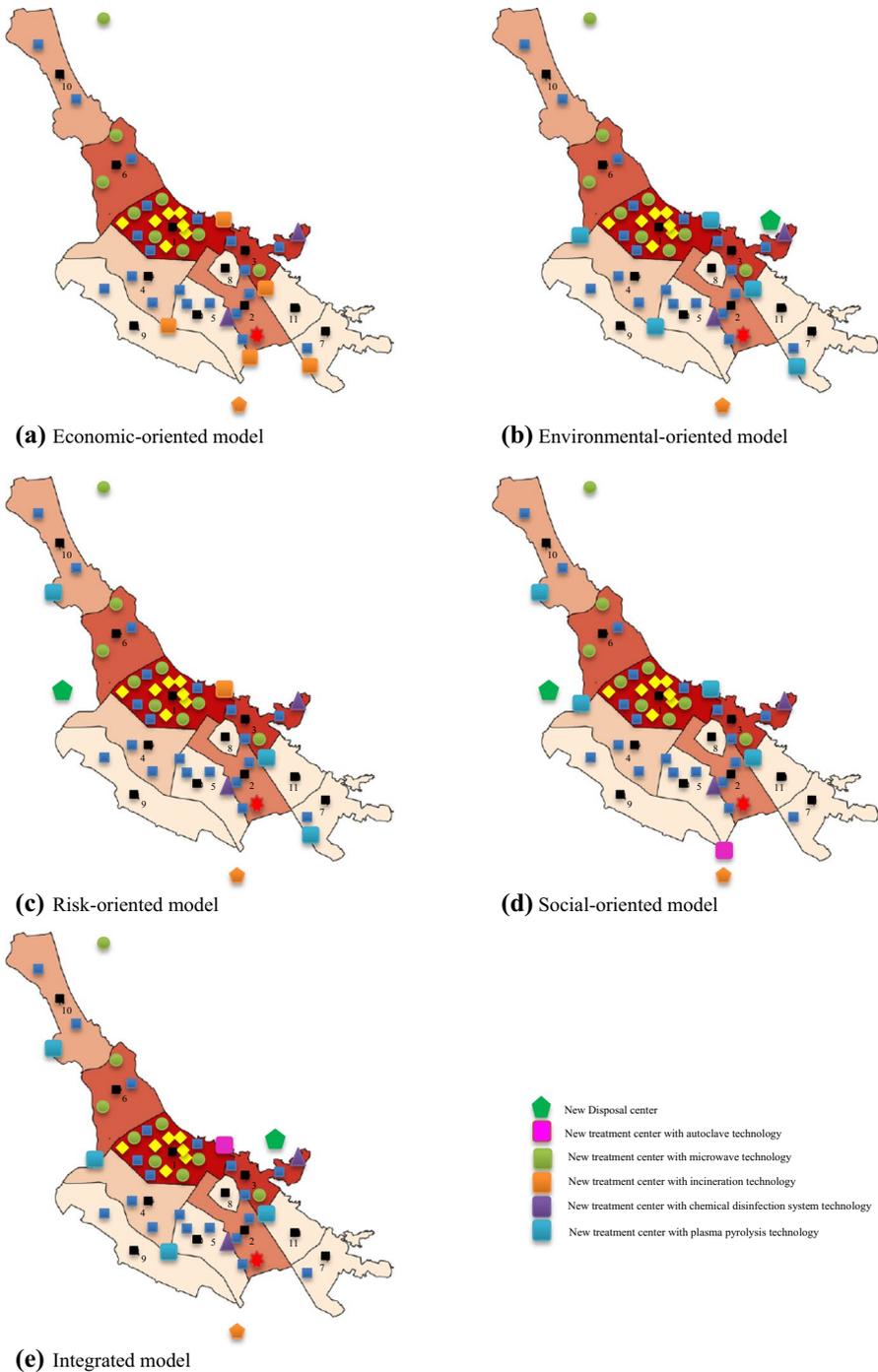
(a) Economic-oriented model

(b) Environmental-oriented model

(c) Risk-oriented model

(d) Social-oriented model

(e) Integrated model

Fig. 4 The optimal network design under different perspectives

Table 5 The detailed solutions under different perspectives

Model	Solution	Value
Economic-oriented	Z_1	1.61179E+10
	Z_2	1.265120E+8
	Z_3	1.55891E+12
	Z_4	0.710
	Constructed disposal centers $\left(q_{lt}\right)$	–
	Constructed treatment centers $\left(y_{jkt}\right)$	$y_{3,3,2}, y_{5,3,1}, y_{7,3,1}, y_{9,3,6}, y_{11,3,1}$
	Selected technologies	k_3
	CPU time (s)	7
Environmental-oriented	Z_1	2.15661E+10
	Z_2	1.708947E+7
	Z_3	1.90716E+12
	Z_4	0.812
	Constructed disposal centers $\left(q_{lt}\right)$	$q_{4,1}$
	Constructed treatment centers $\left(y_{jkt}\right)$	$y_{3,5,1}, y_{4,5,1}, y_{7,5,1}, y_{9,5,1}, y_{11,5,1}$
	Selected technologies	k_5
	CPU time (s)	13
Risk-oriented	Z_1	1.87590E+10
	Z_2	9.905430E+7
	Z_3	1.36565E+12
	Z_4	0.629
	Constructed disposal centers $\left(q_{lt}\right)$	$q_{2,1}$
	Constructed treatment centers $\left(y_{jkt}\right)$	$y_{3,3,2}, y_{7,5,1}, y_{10,5,1}, y_{11,5,1}$
	Selected technologies	k_3, k_5
	CPU time (s)	6
Social-oriented	Z_1	4.40163E+10
	Z_2	8.923562E+7
	Z_3	2.84344E+12
	Z_4	0.939
	Constructed disposal centers $\left(q_{lt}\right)$	$q_{2,1}$
	Constructed treatment centers $\left(y_{jkt}\right)$	$y_{3,5,1}, y_{4,5,4}, y_{5,1,1}, y_{10,5,1}, y_{11,5,1}$
	Selected technologies	k_1, k_5
	CPU time (s)	65
Integrated	Z_1	2.01338E+10
	Z_2	1.997169E+7
	Z_3	1.56542E+12
	Z_4	0.939
	Constructed disposal centers $\left(q_{lt}\right)$	$q_{4,1}$
	Constructed treatment centers $\left(y_{jkt}\right)$	$y_{3,1,1}, y_{4,5,8}, y_{9,5,1}, y_{10,5,2}, y_{11,5,1}$
	Selected technologies	k_1, k_5
	CPU time (s)	102
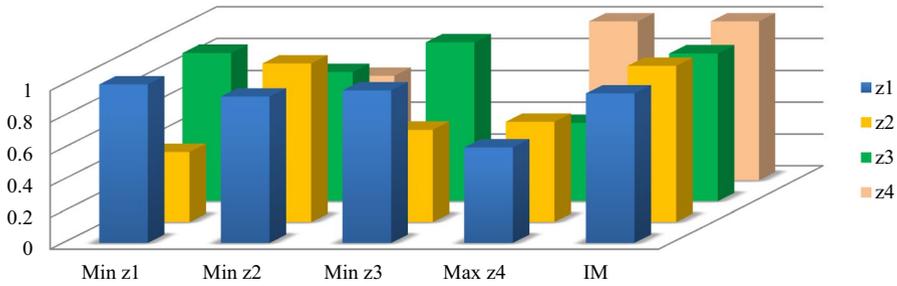
Fig. 5 The satisfaction degree of objective functions under different perspectives

(a) Cost components

(b) Environmental components
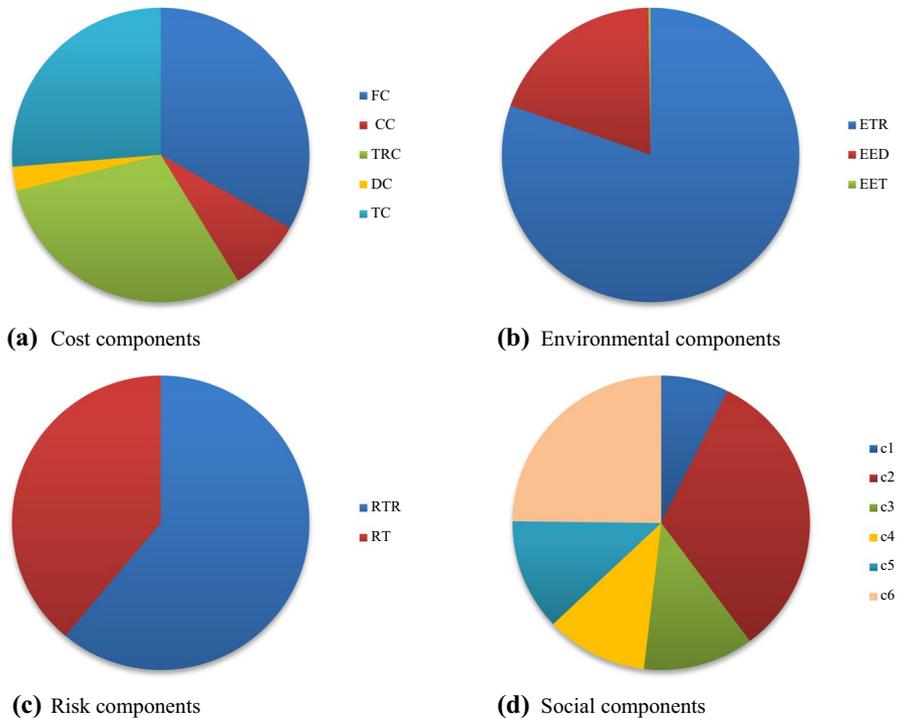
(c) Risk components

(d) Social components

Fig. 6 The detailed components of objective functions

responsibility. Figure 5 depicts the level of satisfaction with each objective from each perspective. In this figure, IM stands for the proposed integrated model. It is clear that a solution achieved by considering only one viewpoint could not work well in other situations. Since all objectives are satisfied to a fair degree in the IM solution, it can be inferred that the developed model produces solutions that are effective in all dimensions, simultaneously.

Figure 6 depicts the component analysis of objective functions obtained by the proposed integrated model. As it can be seen, the fixed installation cost makes up

the largest portion of the overall cost, accounting for 33% of the total. The treatment and transportation costs accounted for 30% and 26% of overall costs, respectively. Among the cost elements, disposing cost has the smallest share. According to Fig. 6b, treating, transportation, and disposing practices contribute 80.5%, 0.23%, and 19.27% to the environmental objective, respectively. The risk objective is dominated by treatment activities. Occupational hazards play an important role in achieving the social objective. Moreover, thermal comfort, required skills, local economy development and the public acceptability account for approximately 60% of the social objective.

As previously stated, by altering different weights for objectives based on the DMs' perspectives, the interactive fuzzy programming approach can yield a variety of solutions. As a result, Table 6 displays a variety of optimal solutions based on distinct objective importance weights. According to this table, the more the importance of an objective function, the higher the ideal value of that objective. The interactive fuzzy programming method enables the system designer to achieve the highest practical trade-off between various sustainability viewpoints and risk standpoint based on the relative importance of each objective. Another finding indicates that plasma technology is the best technology for treating COVID-19 infectious medical waste because it is chosen in all of the acquired solutions. The maximum CPU time for solving 10 instances is 2350 s, and the average CPU time is 1208 s. It can be inferred that the interactive fuzzy programming method can produce optimal results in a respectable amount of time.

5.4 Sensitivity analysis

This subsection illustrates the effects of key parameters on the designed system's objectives and strategic decisions, including the effects of generated waste, the outbreak period, and confidence levels.

5.4.1 The impact of generated waste

Figure 7 shows how different values of generated waste affect objective functions. Treatment facilities with more capacity will be needed to cope with the increased waste, and the fixed installation costs will increase. Moreover, the costs of transportation, collection, and treatment rise dramatically. Figure 7b, c show that the environmental and risk objectives grow up as $\tilde{a}_{it}$ increases. Excessive treatment and transportation activities for processing additional produced waste are primarily responsible for these rising trends. Overall, the results show that a small increase in produced waste would result in substantial increases in economic, environmental, and risk objectives, as well as a decrease in the social objective. The reduction in the social objective is largely due to an increase in occupational hazards associated with increased waste treatment. The effect of medical waste generation on the number and location of facilities is shown in Table 7. More treatment centers using plasma pyrolysis technology are established when the value of $\tilde{a}_{it}$ is higher. While, at a lower value of $\tilde{a}_{it}$, more treatment centers with autoclave technology are installed.

Table 6 Computational results under different significant weights of objectives

| No	Weights				Objectives				Selected technologies	CPU time (s)
	w_1	w_2	w_3	w_4	z_1	z_2	z_3	z_4		
1	0.8	0.1	0.05	0.05	1.810763E+10	2.113078E+7	1.61230E+12	0.812	k_5	2240
2	0.7	0.1	0.1	0.1	1.83121E+10	2.093344E+7	1.60981E+12	0.812	k_5	797
3	0.6	0.2	0.1	0.1	1.88727E+10	2.069210E+7	1.59981E+12	0.862	k_4, k_5	2350
4	0.5	0.2	0.2	0.1	1.95121E+10	2.039152E+7	1.57187E+12	0.862	k_4, k_5	1126
5	0.4	0.3	0.2	0.1	1.97563E+10	2.019760E+7	1.57119E+12	0.862	k_4, k_5	849
6	0.3	0.3	0.2	0.2	2.01338E+10	1.997169E+7	1.56542E+12	0.939	k_1, k_5	102
7	0.2	0.4	0.2	0.2	2.20356E+10	1.933787E+7	1.57000E+12	0.939	k_1, k_5	471
8	0.1	0.4	0.3	0.2	2.55363E+10	1.924005E+7	1.54177E+12	0.939	k_1, k_5	804
9	0.1	0.3	0.5	0.1	2.55845E+10	1.987818E+7	1.49875E+12	0.939	k_1, k_5	1533
10	0.1	0.5	0.1	0.3	2.51989E+10	1.907280E+7	1.60659E+12	0.939	k_1, k_5	1808
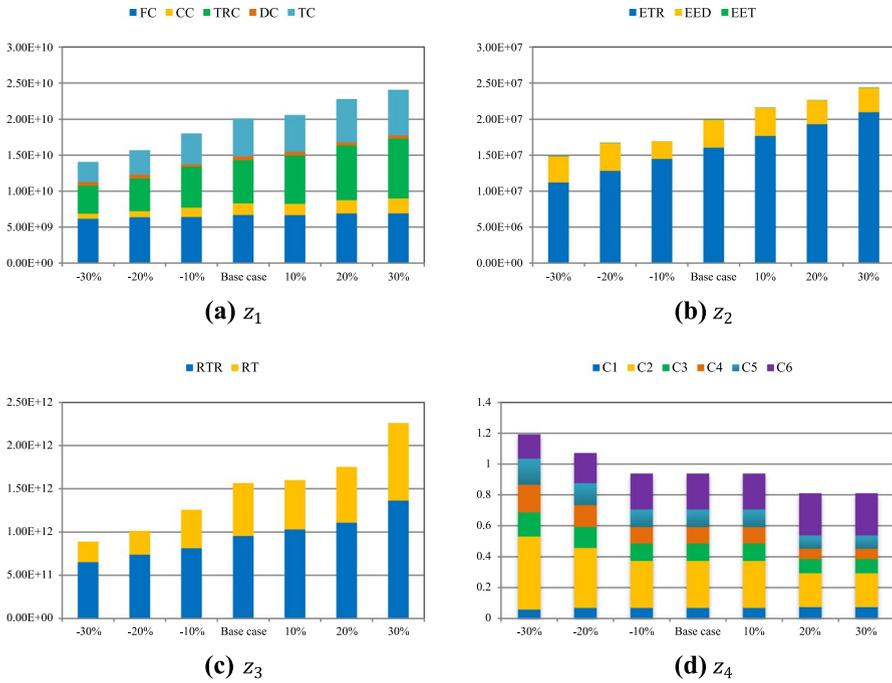
Fig. 7 The impact of $\widetilde{a}_{it}$ on objectives

Table 7 The impact of $\widetilde{a}_{it}$ on the number of facilities and their locations

% Change	Disposal centers		Treatment centers			
			Autoclave		Plasma pyrolysis	
	Number	Location	Number	Location	Number	Location
+30%	1	4	–	–	5	3, 4, 7, 9, 11
+20%	1	2	–	–	5	3, 7, 9, 10, 11
+10%	1	4	1	7	4	3, 5, 10, 11
Base case	1	4	1	3	4	4, 9, 10, 11
−10%	1	4	1	3	4	4, 7, 10, 11
−20%	1	2	2	5, 7	3	3, 4, 11
−30%	1	4	3	4, 10, 11	2	3, 7

5.4.2 The impact of the outbreak period

The effect of the outbreak period on objective functions is depicted in Fig. 8. Table 8 lists the locations of the facilities. The economic, environmental, and risk objectives all increase as the outbreak period lengthens. More treatment centers with plasma pyrolysis and incineration technologies are built as the outbreak period lengthens. However, since the maximum number of located facilities is considered, the fixed installation cost is not adjusted significantly, and the system would experience
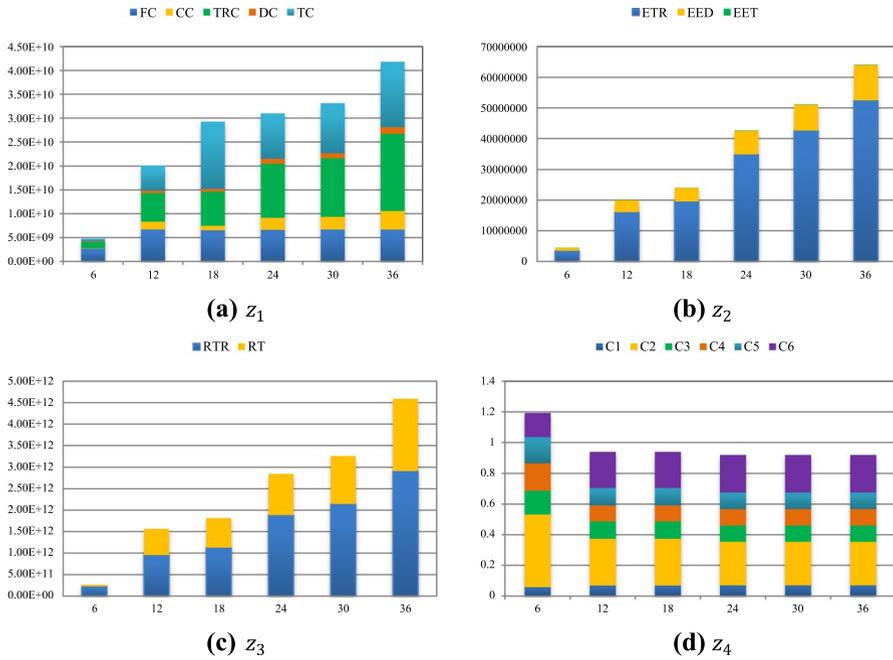
Fig. 8 The impact of the outbreak period on objectives

Table 8 The impact of the outbreak period on the number of facilities and their locations

$|T|$	Disposal centers		Treatment centers					
			Autoclave		Plasma pyrolysis		Incineration	
	Number	Location	Number	Location	Number	Location	Number	Location
6	–	–	3	5, 7, 11	2	3, 4	–	–
12	1	4	1	3	4	4, 9, 10, 11	–	–
18	1	4	1	4	4	3, 7, 9, 11	–	–
24	1	3	1	7	3	3, 10, 11	1	4
30	1	2	1	9	3	3, 7, 11	1	4
36	1	4	1	9	3	3, 7, 10	1	4

significantly higher costs due to the substantial rise in operational costs. For example, when $|T| = 36$, the total cost is 2.08 times higher than when $|T| = 12$. Moreover, the environmental and risk objectives for $|T| = 36$ are 3.21 and 2.92 times higher than for $|T| = 12$, respectively. The type of treatment technology chosen and the number of facilities have a big impact on the social objective. When $|T| = 6$, the social objective has the highest importance because the autoclave technology is chosen for three treatment centers. When $|T| = 12$ and 18, the social objective becomes steady since one treatment centers with autoclave technology and four ones with plasma pyrolysis technology have been installed. Since one treatment center

with the incineration technology is established when $|T| = 24$, 30, and 36, the least social objective function is obtained. Overall, it can be concluded that the outbreak period has a major effect on all of the objectives, as well as strategic decisions on the number and location of treatment and disposal centers and treatment technology selection.

5.4.3 The impact of the confidence level

Figure 9 depicts how the confidence level affects the objectives. The right-hand side of budget limits, which is reflected in the authorized number of opened facilities, is reduced when confidence levels are raised. In this situation, fewer facilities may be built, and the generated waste must be transported to facilities that are considerably farther away, resulting in higher travel expenses and total expenditures. The environmental and risk objectives are broadened as a result of sending waste to more distant facilities. A reduced level of social responsibility and fewer job prospects result from the need to build fewer facilities, which also lowers the social objective. Table 9 demonstrates how strategic decisions change as the confidence level rises. As can be observed, no disposal centers are built at the lower confidence levels, leaving Shiraz City's sole disposal center in the Barmshoor region, depicted in geographical map of Shiraz in Fig. 2, to deal with the waste produced. The budget is allocated to building more treatment centers at lower confidence levels. However, higher confidence levels result in the construction of one disposal center in the
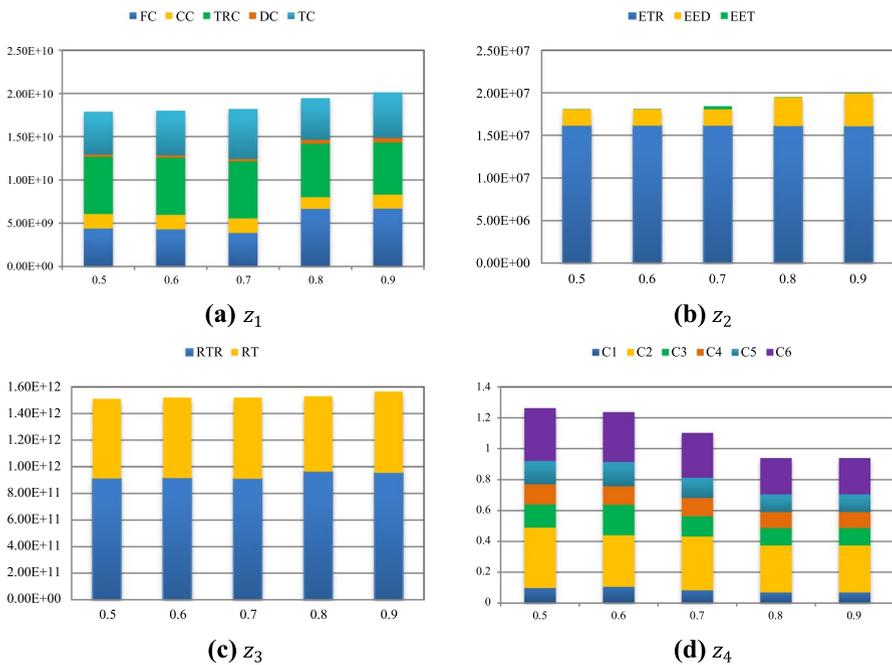

Fig. 9 The impact of the confidence level on objectives

Table 9 The impact of the confidence level on the number of facilities and their locations

α	Disposal centers		Treatment centers					
			Autoclave		Plasma pyrolysis		Chemical disinfection system	
	Number	Location	Number	Location	Number	Location	Number	Location
0.5	–	–	1	10	6	3, 4, 5, 7, 9, 11	–	–
0.6	–	–	–	–	4	3, 5, 7, 11	2	4, 10
0.7	–	–	1	4	5	3, 5, 7, 9, 11	–	–
0.8	1	4	1	4	4	3, 9, 10, 11	–	–
0.9	1	4	1	3	4	4, 9, 10, 11	–	–

network and a reduction in the number of treatment facilities. Because the value for the confidence levels of constraints is set based on expert opinions, these findings can help system designers choose an appropriate value. It may be concluded that the system will incur significantly higher expenses in order to produce more trustworthy findings with higher confidence levels. However, the risk of not being able to meet constraints lowers, resulting in a more resilient and immune response to uncertainty.

6 Conclusions

This paper addresses a waste management system for COVID-19-related infectious medical waste. The developed model investigates a variety of real-world decisions, such as treatment technology selection, treatment and disposal centers location, waste movement between generation points and built facilities, and transportation vehicle numbers. The model considers various practical aspects such as facility capacity, budget constraints reflected in the maximum number of constructed facilities, maximum service restrictions for undesirable waste treatment and disposal centers, and vehicle capacity. The economic, environmental, social, and risk views of policymakers are considered by objective functions. The proposed model accounts for the uncertainty in key parameters and a CFC-CPA is used to eliminate it. The suggested multi-objective model is solved by an interactive fuzzy programming method. The applicability of the developed model is demonstrated by a practical case study. The computational experiments show that (1) when sustainability and risk objectives are simultaneously approached, more cost is needed to improve the environmental effect, social suitability, and risk associated with treating infectious medical waste; (2) the interactive fuzzy programming approach will assist policymakers in determining the best trade-off between overall cost, environmental effect, risk, and social dimensions, where all objective functions are satisfied to a fair degree; (3) the fixed installation cost, the environmental impacts of treatment activities, the risk of waste treatment, and occupational hazards have the greatest impact on the economic, environmental, risk, and social objectives, respectively; (4) a slight increase in the amount of waste generated would result in substantial increases in economic, environmental,

and risk objectives, as well as a decrease in the social objective. As a result, policymakers should concentrate their attention on estimating the total amount of infectious medical waste produced by considering all of the generation points. Otherwise, a new network deployment with different treatment technologies would be achieved, resulting in a significant increase or decrease in the concerned objectives, and (5) since it is unclear how long this epidemic will last or whether it will be contained, the outbreak period must be considered in the modeling framework and its effect on the objectives and strategic decisions must be investigated. Otherwise, the system cost, environmental effects, risk, and social perspectives would be significantly underestimated or overestimated.

Future research will focus on developing various sustainability evaluation frameworks, like the social life cycle assessment method, to recognize the designed system's social sustainability pillar. In light of COVID-19's dynamic nature, it may be interesting to consider the capacity of treatment and disposal centers as an endogenous component that can be defined in the planning horizon. Because it is unknown how long COVID-19 will persist, it's fascinating to try to predict its development and spread, as well as the amount of COVID-19 infectious medical waste that will be generated. Accordingly, the predicted waste generation rate can be incorporated into the suggested mathematical model to create more trustworthy MWMS configurations. Different forecasting approaches, such as the autoregressive integrated moving average and machine learning regression methods, can be used in this situation. It could be interesting to look into the collection vehicle routing of infectious medical waste, in which incompatible hazardous medical waste types are not allowed to be transported together to avoid chemical interactions. In this case, it is necessary to schedule a diverse fleet of collection vehicles in order to collect waste in various vehicles that are compatible with their loads. Adopting other possibilistic programming approaches, such as the *Me* measure-based possibilistic chance constrained programming approach, may be an interesting problem for future research in light of the lack of data for the generated waste. The implementation of efficient heuristic and metaheuristic algorithms for solving large-scale instances of the proposed model may be another promising area of future research.

Declarations

Conflict of interest The author declares that she has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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