A bi-objective robust optimization approach for the management of infectious wastes with demand uncertainty during a pandemic

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ABSTRACT

The current global COVID-19 pandemic attracts public attention to the management of waste generated by health-care activities. Due to the hazardous nature, infectious waste requires the design of a multi-tiered system to provide cost-efficient and eco-friendly services of waste collection, transportation, treatment, and final disposal. However, the impact of uncertainties has not been well studied in the existing literature. Considering the presence of random waste generation during a pandemic, we aim to answer the following questions: 1) where to locate temporary transfer stations and temporary treatment centers; 2) how to plan collection tours among the small generation nodes and temporary transfer stations; 3) how to plan the direct transportation from large generation nodes to treatment centers; 4) how to transport waste from temporary transfer stations to treatment centers, and 5) how to transport wastes from treatment centers to disposal facilities. The relevant cost and associated risk are respectively formulated and assessed using a scenario-based bi-objective robust approach. The complexity of the resulting mathematical model motivated the adaption and comparison of three multi-objective optimization approaches, including the goal programming method, a lexicographic weighted Tchebycheff approach, and an augmented ϵ-constraint solution technique. A case study based on the real situation in Wuhan, China, during the COVID-19 outbreak is conducted to demonstrate the workability of the proposed model and provide managerial insights for infectious waste management. The computational results show that our proposed model can more than double the demand fulfillment rate at an approximately 40% lower cost when facing a distinctively high increment in the amount of infectious waste.

1. Introduction

With the progress of the current global COVID-19 pandemic, proper management of waste generated by health-care activities has drawn much attention lately. In general, health-care waste contains both potential infectious waste and general non-infectious materials (WHO, 2005). To be specific, infectious waste includes sharps (syringes or needles, blades) and non-sharp materials that have been in contact with human blood, isolation wastes from highly infectious patients, and other contaminated materials infected with human pathogens. Generated in almost all federal facilities, such as hospitals, laboratories, nursing homes, and research centers, this type of wastes is known or tested to have one or more dangerous traits, namely reactivity and toxicity. Even though infectious waste only consists of less than 18% of the total health-care waste in primary health centers (WHO, 2005), on many occasions when no categorization of waste takes place, the entire mixed volume of health-care waste needs to be considered infectious.

Particularly when the COVID-19 pandemic hit, the existing waste management system has been facing an unprecedented challenge. First, the massive incremental rate of infectious waste volume has been generated from infected patients. As the pandemic spreads all over the world and turns to a rather long term, the pressure has become even heavier. What has made the situation even worse is a new group of waste consisting of single-use plastic items and personal protective equipment (PPEs) (Haque et al., 2021), which is certainly infectious and can threaten the public and environment. Furthermore, the limited capacity of the medical system has pushed patients with minor symptoms to recover at community clinics or even at home, which led to substantial waste sources with rather small generation volumes. The harmful nature of these substances and unique properties during an unexpected pandemic necessitates a cost-efficient and eco-friendly logistics system that can be easily implemented and managed.

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Combining the facility location and vehicle-routing decisions, the first hazardous waste management model was presented by Zografos and Samara (1989). Then, this type of problem has been broadly examined for hazardous wastes. Similar to other hazardous wastes, the management of infectious waste includes collection, transportation, treatment, and disposal. A detailed review and comparison of those works are provided in Section 2. Despite all existing efforts, there still lacks a comprehensive decision structure for location, routing, and vehicle managing in hazardous waste management. Especially when an unanticipated outbreak of an infectious disease occurs, such as the ongoing COVID-19 pandemic, developing and maintaining a robust yet flexible management system for the sudden increase in the amount of infectious waste (i.e., demand) is extremely important to public health. To achieve this purpose, the impact of uncertainties, especially the uncertain waste generation amount during a pandemic, needs to be integrated into the decision making process.

In most cases, a pandemic is unpredictable, and the severity level of the outbreak is hard to estimate. Under such a highly uncertain circumstance, how fast the system can adapt to the progress of the situation is of vital importance. To ensure the effective and efficient management of infectious waste, we herein propose the idea of using temporary facilities, which can be quickly converted from regular waste facilities at a relatively low cost. To be specific, we define the robust infectious waste location-routing problem as a joint decision simultaneously optimizing temporary facility location, tour planning, route design, and vehicle acquisition decisions, so to minimize the associated total cost and risk in the presence of uncertain waste generation. This work aims to assist the decision-maker in answering the following questions.

● Where to locate temporary transfer stations?
● Where to locate temporary treatment facilities?
● How to organize the tours for collecting infectious wastes among the small generation nodes and temporary transfer stations?
● How many vehicles are required for the infectious waste collection?
● How to route infectious waste shipments from temporary stations to treatment facilities?
● How to route infectious waste shipments from treatment facilities to disposal facilities?

The contribution of this paper is fourfold. *First*, focusing on infectious waste management especially during a pandemic situation based on the existing medical waste system, we design a multi-tiered framework to provide cost-efficient and eco-friendly services of the waste collection, transportation, treatment, and final disposal. A systematic strategy is proposed to transfer the existing facilities for regular wastes to temporary ones that are capable of processing infectious wastes during a pandemic. The bi-objective mathematical model jointly considered temporary facility locations, collection tours, direct routes, and the number of vehicles in addition to the regular location-routing problem setting. *Second*, we present the vehicle-routing issue in the proposed model by adopting a two-community flow formulation. To be specific, the system uncertainties on waste generation are addressed by using a robust optimization approach, where the decisions are made based on different scenarios with various levels of uncertainties. *Third*, three solution procedures, adapted from the weighted goal programming method, lexicographic weighted Tchebycheff approach, and augmented ϵ-constraint solution technique, are developed to solve the proposed robust bi-objective problem. The performances of these procedures are compared through a set of hypothetical cases with different scales. *Four*, we apply the model and solution approaches to the real-world COVID-19 outbreak situation of Wuhan in China. The results show that, by employing temporary facilities, the infectious management system can respond to sudden demand increase more effectively and efficiently with a much higher demand fulfillment rate at a lower cost. A series of sensitivity analyses are conducted for managerial insights that can be

applied to similar situations, especially during an unforeseen pandemic.

Fig. 1 illustrates the research framework of the present work. After an overview of the relevant literature with detailed comparisons in Section 2, the problem statement is provided in Section 3. For the major component of this research, Section 4 constructs a novel bi-objective robust model, where the two-community flow formulation is customized to formulate the vehicle-routing problem under various uncertainty scenarios. To identify competitive efficient solutions for the proposed model, Section 5 provides three multi-objective algorithms modified from various techniques, which are then tested and compared through a set of hypothetical instances. A realistic case study of Wuhan is reported in Section 6, where a series of analyses are conducted for practical insights (Section 7). Finally, Section 8 provides the concluding remarks and future research directions.

2. Literature review

This section reviews the four most relevant streams of research, namely the hazmat risk assessment, hazardous waste management, medical waste management, and robust optimization in hazmat transportation.

2.1. Hazmat risk assessment

The risk assessment is generally quantified as the product of the probability of risk factor and the severity of harm to exposed receptors owing to the potential spill accidents happening on the route (Alp, 1995). The traditional risk is widely used in early studies (Erkut and Verter, 1998; Erkut and Ingolfsson, 2005; Erkut et al., 2007). Later, several improved models, such as perceived risk Abkowitz and Cheng (1988), mean-variance model (Erkut and Ingolfsson, 2000), disutility (Erkut and Ingolfsson, 2000), conditional risk (NHTSA, 2015), were developed to address the risk assessment in hazmat transportation. Saccomanno and Haastrup (2003) only used the accident probability to estimate risks and simplified the traditional model. The societal risk is calculated as the sum of residents exposed to hazmat transportation, which was formulated as the model of "population exposure" in ReVelle et al. (1991). Time-based risk measures have also been applied to hazmat transportation, examples include Zhao and Ke (2019) in emergency logistics, and Esfandeh et al. (2016) and Ke et al. (2020) in toll policy setting.

In the hazardous waste literature, the majority concentrated on the societal impact, which can be evaluated by the population exposure, such as Alumur and Kara (2007); Zhao and Zhao (2010). Some also considered the amount of waste and the incident rate (Nema and Gupta, 1999, 2003), which may influence the actual population exposed to possible incidents. Few exceptions include Zografos and Samara (1989), which used edge weights to represent the risks associated with the network links; Zhao and Verter (2015), which presented an environmental risk assessment (ERA) emphasizing the airborne ingredients of used oil released into the environment upon incident; and Zhao and Ke (2017), which presented an ERA combining formulation of the TNT equivalence and environmental models. More details about risk approaches in this group of literature can be found in Table 1.

2.2. Hazardous waste management

Table 1 provides the taxonomy of relevant literature on the management of hazardous wastes, which contains the model condition (waste types and facilities), decisions (location, routing, tour, and vehicle), risk assessment, and uncertainty consideration.

From the aspect of model condition and decisions, several early studies (Zografos and Samara, 1989; ReVelle et al., 1991; Stowers and Palekar, 1993; Cappanera et al., 2004) only addressed one type of hazmat and a single facility. Although the examinations were later extended to multiple facilities that involved in managing hazardous
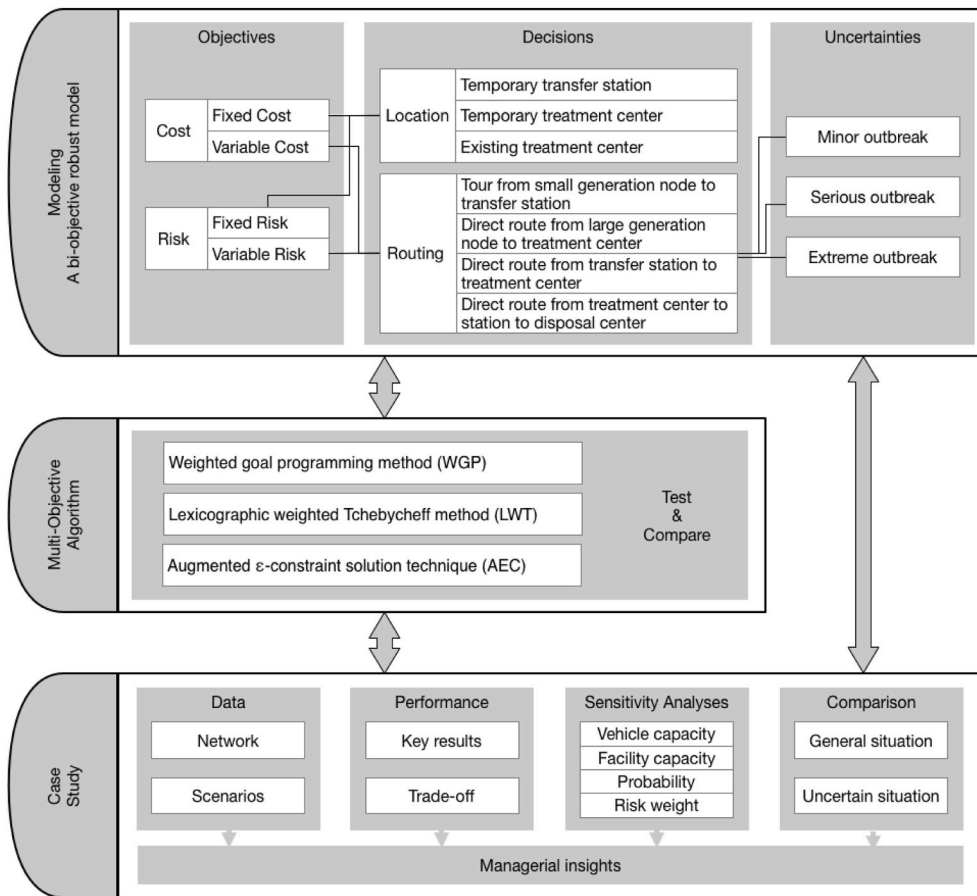
Fig. 1. Research framework.

wastes, most of these works (Jacobs and Warmerdam, 1994; Current and Ratick, 1995; Wyman and Kuby, 1995; Alidi, 1996; Giannikos, 1998) only concerned the location and routing (direct trips, which travel from one location to another in one direction) decisions. Zhao and Verter (2015) and Zhao and Zhu (2016) integrated the tour design (i.e., the vehicle can start and end at the same facility) and vehicle planning into consideration. More recently, Zhao and Ke (2017) first incorporated the inventory into the decision making process, especially the risk assessment, of hazardous waste management. They constructed a multi-depot vehicle-routing model to minimize the environmental risk associated with facility location, inventory level, and transportation routes.

Another group of research (such as List et al. (1991); Alidi (1992); Nema and Gupta (1999), to name a few) took into account multiple types of hazmat and several facilities. But nearly all of the decisions were again limited in location and routing, except for Zhao et al. (2016); Rabbani et al. (2018, 2019). Focusing on the network design for a regional hazardous waste system, Zhao et al. (2016) established a multi-objective optimization model to identify the location of various facilities and optimal transportation routes among those facilities. Addressing different types of hazmat and compatibility issues, Rabbani et al. (2018) proposed a location-routing problem to simultaneously minimize the total cost, total transportation risk, and site risk. That model was then solved by a multi-objective evolutionary algorithm. The remaining two papers are reviewed later in the hazardous-waste literature with uncertainty considerations.

Note that most of the aforementioned research investigated the problem of managing hazardous wastes under a deterministic environment, while overlooked the dynamic and uncertain nature of real-world practices. So far only three studies have contributed to the hazardous waste literature by incorporating uncertainties into their decision

makings. Zhang and Zhao (2011) used triangular fuzzy numbers to describe the uncertain waste generation amount, and then proposed a multi-objective mixed-integer model to examine the facility location, technology adoption, and vehicle routing problem. Rabbani et al. (2019) targeted the integrated decisions of location, routing, and inventory with uncertainties in generated wastes and population at risk. A multi-objective stochastic mixed-integer nonlinear programming model was developed and solved by a sim-heuristic approach that combined the Monte Carlo simulation and non-dominated sorting genetic algorithm.

2.3. Medical waste management

As a special type of hazardous waste, medical waste has not yet been properly examined from the location and routing perspective. Only limited papers have looked into applying analytical models or quantitative technologies (Kargar et al., 2020). Below we provide a survey of the most relevant publications in this research stream.

Shih and Lin (2003) studied the routing and scheduling problems in an infectious waste collection system. They incorporated the dynamic and integer programming models to minimize cost and risk simultaneously along with balancing carrying loads. Shi et al. (2009) presented a mixed-integer linear programming (MILP) model to minimize the cost in reverse logistics networks for medical wastes. Almeida (2010) examined hazardous medical waste management in Portugal and proposed a MILP approach that optimizes the location and allocation costs. Nolz et al. (2014) formulated the logistics system for infectious medical wastes as a collector-managed inventory routing problem, which employed the radio frequency identification technology to improve the planning process. Budak and Ustundag (2017) designed a multi-period

Table 1
Taxonomy of literature on hazardous waste management.

Author (year)	Condition			Decision				UncertainRiskAssessment	WasteGeneration
	FacilityType	TemporaryFacility	WasteType	Location	Route	Tour	Vehicle		
Zografos and Samara (1989)	Single	No	General	Yes	Yes	No	No	Edage weight	No
ReVelle et al. (1991)	Single	No	General	Yes	Yes	No	No	Pop[a]	No
Stowers and Palekar (1993)	Single	No	General	Yes	Yes	No	No	Pop	No
Jacobs and Warmerdam (1994)	Multiple	No	General	Yes	Yes	No	No	Pop × Amount × Inc[b]	No
Current and Ratick (1995)	Multiple	No	General	Yes	Yes	No	No	Pop	No
Wyman and Kuby (1995)	Multiple	No	General	Yes	Yes	No	No	Pop	No
Alidi (1996)	Multiple	No	General	Yes	Yes	No	No	N/A	No
Giannikos (1998)	Multiple	No	General	Yes	Yes	No	No	Pop	No
Cappanera et al. (2004)	Single	No	General	Yes	Yes	No	No	N/A	No
List et al. (1991)	Multiple	No	General	Yes	Yes	No	No	Impact area	No
Alidi (1992)	Multiple	No	General	Yes	Yes	No	No	N/A	No
Nema and Gupta (1999)	Multiple	No	General	Yes	Yes	No	No	Pop × Amount × Inc	No
Nema and Gupta (2003)	Multiple	No	General	Yes	Yes	No	No	Pop × Amount × Inc	No
Alumur and Kara (2007)	Multiple	No	General	Yes	Yes	No	No	Pop × Amount	No
Zhao and Zhao (2010)	Multiple	No	General	Yes	Yes	No	No	Pop × Amount	No
Shuai and Zhao (2011)	Multiple	No	General	Yes	Yes	No	No	Pop × Amount	No
Zhang and Zhao (2011)	Single	No	General	Yes	Yes	No	No	Pop × Amount	Yes
Samanlioglu (2013)	Multiple	No	General	Yes	Yes	No	No	Pop × Amount	No
Zhao and Verter (2015)	Multiple	No	Special (used oil)	Yes	Yes	Yes	Yes	Pollution volume	No
Ghezavati and Morakabatchian (2015)	Multiple	No	General	Yes	Yes	No	No	Pop	No
Zhao and Zhu (2016)	Multiple	No	Special (explosive)	Yes	Yes	Yes	Yes	Pop	No
Zhao et al. (2016)	Multiple	No	General	Yes	Yes	Yes	No	Pop	No
Zhao and Ke (2017)	Multiple	No	Special (explosive)	Yes	Yes	Yes	Yes	Impact volume	No
Rabbani et al. (2018)	Multiple	No	General	Yes	Yes	Yes	No	Pop	No
Rabbani et al. (2019)	Multiple	No	General	Yes	Yes	Yes	No	Pop	Yes
The present study	Multiple	Yes	Special (Infectious)	Yes	Yes	Yes	Yes	Pop	Yes

[a] Population exposure.
[b] Incident rate.

and multi-type reverse logistics network for medical wastes to improve the effectiveness of the situation in Turkey. Sensitivity analyses were performed to reveal the facility strategies in terms of incremental changes in the amount of waste. Focusing on the medical waste collection in Northern Jordan, Alshraideh (2017) constructed a route scheduling model to minimize the travel distance considering the truck capacity, the weekly number of visits, the timing between visits, and the service level. Mantzaras and Voudrias (2017) integratively optimized the locations and capacities of treatment facilities and transfer stations, number of vehicles, and vehicle routings, such that the total cost of the logistics system for infectious medical waste is minimized. Gergin et al. (2019) worked on the continuous multiple facility location problem in health-care waste management. An Artificial-Bee-Colony-based clustering algorithm is developed and tested for realistic situations. Embedding the decision of pharmacological waste collection into a medical goods distribution problem, Osaba et al. (2019) modeled a multi-attribute vehicle routing problem with pickups and deliveries. Yao et al. (2020) developed a risk mitigation-oriented bi-level equilibrium optimization model for a soft-path solution in locating medical waste disposal centers. Kargar et al. (2020) designed a multi-item and multi-period model for a medical waste reverse supply chain, where both sustainability and environmental criteria are considered. Tirkolaee et al. (2021) investigated the location-routing problem for medical waste under the pandemic setting. They utilized a fuzzy chance-constrained approach to deal with the demand uncertainty and time windows.

2.4. Robust optimization in hazmat transportation

The location and routing problem in hazmat transportation has been studied for a long time as evidenced by the extensive literature. To address uncertainties in hazmat transportation, three main alternative techniques have been applied: fuzzy logic (Ghatee et al., 2009; Du et al., 2017; Ke et al., 2020), stochastic programming (Opasanon and Miller-Hooks, 2006; Gülpinar et al., 2013; Ardjmand et al., 2016; Rabbani et al., 2019), and robust optimization. Although fuzzy approaches can be used to describe vague and imprecise information, especially linguistic variables, stochastic and robust models are considered superior in the sense that they follow a mechanism to adapt to uncertainties. Stochastic programming is applicable when the input parameters are probabilistic but following a known probability distribution with known estimators. The major issue with stochastic programming is the difficulty of obtaining the probability distribution functions of the underlying stochastic parameters, which has become a huge disadvantage for those who plan to utilize this approach. In the case of robust optimization, the approach is to obtain an optimal solution that is robust and feasible for a set of uncertain data. In the following, we review the studies in the hazmat transportation literature that explicitly deal with uncertainty by applying robust optimization.

Xin et al. (2013) proposed a hazmat transportation network design problem with uncertain edge risk. A robust heuristic approach through a simple heuristic was developed and tested on a network in China. They proved that the robust interval risk scenario network performs better than the deterministic scenario network. Kwon et al. (2013) studied a robust shortest path problem where the cost is computed by multiplying two uncertain factors. A path enumeration approach based on a K-shortest path finding algorithm was applied to hazmat transportation for illustration purposes. A robust facility location problem for hazmat transportation considering routing decisions of hazmat carriers was investigated by Berglund and Kwon (2014). In an elaborated discussion, they reiterated that the stochastic model is less effective for hazmat location and routing problems and acknowledged that the robust approach is more appropriate. Risk uncertainty on network links was also considered by Sun et al. (2015). Under the assumption that the

availability of links is influenced by the ban on a few of them by government regulations for hazmat transportation, they considered the worst-case risk-measures with an uncertain budget for flexible decision making. Chiou (2017) integrated the signal-setting policy to hazmat network design through a min-max bi-level robust programming model. Risk-averse signal settings were determined under budget-of-uncertainty demand when taking into consideration the travel delay caused by regular traffic. Ma et al. (2018) developed a multi-objective robust optimization model on the basis of the Bertsimas-Sim robust optimization theory. They used a fuzzy C-means clustering particle swarm optimization algorithm to cluster the demand points, and then an adaptive archives grid to compute the robust route of transportation. More recently, robust optimization has also been applied to gauging the disruptions in a hazmat transportation network. Ke (2020) applied a scenario-based robust optimization approach to efficiently managing random disruptions existing in rail-truck intermodal hazmat transportation systems.

2.5. Literature gaps and contributions to knowledge

As indicated in Table 1, only two papers in hazardous waste management have examined the uncertain generation amounts, and none of those are designed for medical waste. Given the infectious nature, this type of waste requires a specially structured logistics system, specifically when the decisions need to be made promptly to adapt to a pandemic situation. To bridge this gap, we herein adopt the robust optimization approach to construct a flexible yet robust network for waste management to hedge against uncertainties in the sudden and massive increase of generated infectious waste.

In medical waste management, only one recent paper by Tirkolaee et al. (2021) has concentrated on the situation under pandemic. Our research differs from their work in the following two aspects. First, our 4-tiered logistics network is more complicated yet realistic. Rather than building up a new network, we focus on how to fully occupy the existing network by converting regular facilities to those compatible with infectious wastes. This strategy is particularly suitable for reacting to the sudden outbreak of disease, not only because of the low cost, but also the prompt implementation in practice. Second, whereas we do not address the time-window issue, we model the demand uncertainty via a set of scenarios, which can better reflect the real circumstances under various probabilities, compared to the fuzzy constraint used in their work. The additional penalty term based on objective variations in our model further ensures the stability of the entire system.

To the best of our knowledge, this is the first attempt in the literature to apply the robust optimization approach to the management of infectious waste under the situation of a pandemic. By considering various scenarios, from a minor outbreak to a major epidemic, our proposed model is able to swiftly enhance the system preparedness and efficiently plan the waste collection and treatment processes.

3. Problem statement

Let $N(V, E)$ be a road network with vertex set V and edge set E. We herein pay close attention to the infectious waste management during an ongoing pandemic, and propose a novel robust bi-objective model for the infectious waste location-routing problem that can be implemented to the situation when a quick system transformation is required after perceiving an outbreak, or when the system preparedness needs to be improved during regular operations.

In more detail, we conceive infectious waste management as a four-tiered framework based on the existing hazardous waste management system. As illustrated in Fig. 2, laboratories and clinics are considered as small generation nodes in the first tier, while major hospitals or other medical facilities are classified as large generation nodes placed in the second tier. Due to the outbreak of infectious disease, additional temporary transfer stations are also required to be developed at the second
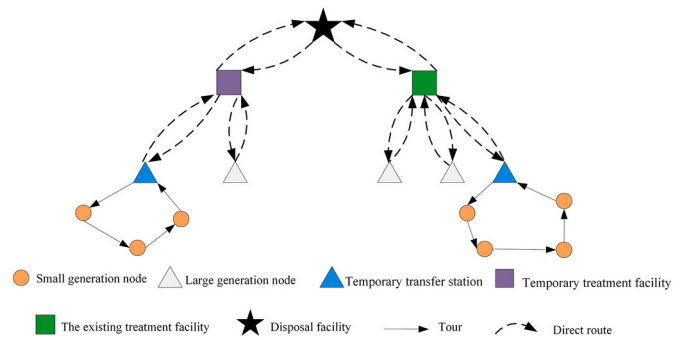

Fig. 2. A sample network for the infectious waste management.

tier for waste collection and transit. With these additional stations, vehicles perform tours starting from the station, traveling through multiple small generation nodes to collect the available infectious waste, and finally return to the same station. Furthermore, treatment (both temporary and existing) and disposal facilities are respectively positioned in the rest two tiers. The wastes collected at temporary transfer stations and large generation nodes are often directly routed to the treatment facilities by larger vehicles. Also, the waste residue is directly transported from treatment facilities to disposal facilities.

As depicted in Fig. 2, two types of trips need to be designed in this work. Direct routes are those directly connecting two vertices (between the large generation node and treatment facility, or between the treatment facility and disposal center). On the other hand, starting and ending at the same opened temporary transfer station, tours are used to collect wastes from small generation nodes. Multiple vehicles may be needed because of the limited vehicle capacity.

To construct this capacitated vehicle routing problem, we introduce the two-commodity flow formulation provided by Baldacci et al. (2004), which effectively eliminates sub-tours by employing copies of the original hubs. According to the formulation structure, we redefine a tour as a vehicle route that starts from the opened temporary transfer station to its copy through at least one small generation node.

Moreover, two types of flows are considered in this formulation: the first type, indicating the load on the vehicle, is from the opened temporary transfer station via generation nodes to its copy, while the other one, from the copy back to the opened temporary transfer station, shows the empty space on the same vehicle. In addition to the basic flow rules, we define the vehicle routes as (1) each route starts at an opened temporary transfer station, and ends at its copy; (2) each vehicle visits at least one small generation node; (3) each small generation node is visited exactly once by only one vehicle; and (4) the total amount of infectious waste shipped by each vehicle cannot exceed the vehicle capacity. As to the located temporary transfer station, the total amount of collected infectious waste cannot exceed the station capacity.

4. Model development

In this section, we first introduce the assumptions and notation, and then present the mathematical model under the consideration of random waste generation amounts in different scenarios.

4.1. Assumptions and notation

Our robust model is formulated in view of the random waste amount generated at each generation node, i.e., the amount of waste stored and proceeded at each facility is stochastic. A central decision-maker is assumed herein to locate multiple temporary facilities and arrange vehicle routes visiting all the infectious waste generation and management sites. This assumption is consistent with most real-world infectious waste management situations where the governments perform as the decision-maker.

Two objectives of minimizing the total cost and risk are considered based on a set of uncertain scenarios. The cost objective includes the expenditure on temporary facility location, infectious waste operation, transportation, and the corresponding vehicle service, while the risk is evaluated as the potential impacts on the surrounding population en-route and at the site.

To specify the study scope and to facilitate the model formulation, we postulate the following assumptions.

1. Facilities meet the security requirements of storing and handling infectious waste.

2. Vehicles meet the security requirements of shipping infectious waste.
3. The amount of waste generated at each node varies in different scenarios with corresponding probabilities.
4. All generated infectious waste should be processed in the waste management system.
5. The worst case is considered in assessing the risk by modeling the total amount on the truck or at the facility as the potential risk source.

The following sets, parameters, and decision variables are used in our mathematical model.

Sets	
$N(V, E)$	a road network with vertex set V and edge set E, where $V = L \cup G \cup T \cup (\bar{T}) \cup C \cup C' \cup D$.
L (1, 2, …, l)	large infectious waste generation nodes, including the cabin hospitals and major hospitals.
G (1, 2, …, g)	small infectious waste generation nodes, including the laboratory and clinics.
T (1, 2, …, t)	candidates for temporary transfer stations.
$\bar{T}(1, 2, …, \bar{t})$	copies of candidates for temporary transfer stations.
C (1, 2, …, c)	candidates for treatment centers.
C'(1, 2, …, c')	existing treatment centers.
D (1, 2, …, d)	disposal centers, which are already located in the network.
S (1, 2, …, s)	uncertain scenarios.
Parameters	
ρ_s	the probability of scenario $s \in S$, where

$$\sum_{s \in S} \rho_s = 1. \tag{1}$$

g_{is}	amount of infectious waste generated at node $i \in L \cup G$ at scenario $s \in S$.
$FC_i^{station}$	fixed cost of locating temporary transfer station $i \in T$.
FC_i^{treat}	fixed cost of locating treatment center $i \in C$.
AC_i^{treat}	fixed cost of activating existing treatment center $i \in C'$.
$CAP_i^{station}$	capacity of temporary transfer station $i \in T$.
CAP_i^{treat}	capacity of treatment center $i \in C \cup C'$.
$VC_i^{station}$	variable cost of operating one unit of waste at temporary transfer station $i \in T$.
VC_i^{treat}	variable cost of processing one unit of waste at treatment center $i \in C \cup C'$.
TC^{tour}	vehicle cost of transporting waste per kilometer in the tour.
$TC^{treat-tran}$	vehicle cost of transporting waste per km to the treatment center vis a direct route.
$TC^{dispo-tran}$	vehicle cost of transporting waste per km from the treatment center to the disposal center via a direct route.
$VCAP^{tour}$	vehicle capacity for collection tours among small generation nodes.
$VCAP^{treat-tran}$	vehicle capacity for the direct route to the treatment center.
$VCAP^{dispo-tran}$	vehicle capacity for the direct route from the treatment center to the disposal center.
VFC	fixed cost of a vehicle required for a tour.
DIS_{ij}	length of edge $(i, j) \in E$.
α	percentage of the infectious waste residue after treatment.
POP_{ij}^{edge}	population exposed on edge $(i, j) \in E$.
POP_i^{node}	population exposed on node $i \in V$.
Design variables	
τ_i	1, if temporary transfer station is located at node $i \in T$; 0, otherwise.
γ_i	1, if treatment center is located at node $i \in C$; 0, otherwise.
γ_i'	1, if existing treatment center is activated at node $i \in C'$; 0, otherwise.
Control variables	
w_{ijms}	1 if edge $(i, j) \in E$ appears in the vehicle route ending at copy station $m \in \bar{T}$ in scenario $s \in S$; 0, otherwise.
o_{ims}	1 if the waste produced at small generation node $i \in G$ is collected at temporary station $m \in \bar{T}$ in scenario $s \in S$; 0, otherwise.
x_{ijms}	amount of waste shipped by the vehicle on edge $(i, j) \in E$ in a route ending at copy station $m \in \bar{T}$ in scenario $s \in S$.
x_{jims}	amount of empty space in the vehicle on edge $(i, j) \in E$ in a route ending at copy station $m \in \bar{T}$ in scenario $s \in S$.
y_{ijs}	times of transporting infectious waste to the treatment centers on edge $(i, j) \in E$ in scenario $s \in S$.
z_{ijs}	times of transporting infectious waste residue to the disposal centers on edge $(i, j) \in E$ in scenario $s \in S$.
ν_{ijs}	amount of infectious waste transported to treatment centers on edge $(i, j) \in E$ in scenario $s \in S$.
η_{ijs}	amount of infectious waste transported to disposal centers on edge $(i, j) \in E$ in scenario $s \in S$.
p_{is}	amount of infectious waste collected at temporary transfer station $i \in T$ in scenario $s \in S$, where

$$p_{is} = p_{ms} = \sum_{j \in G} x_{jims}, \quad \forall m \in \bar{T}, m - i = |T|, s \in S. \tag{2}$$

(continued)

q_{is}	amount of infectious waste processed at treatment center $i \in C \cup C'$ in scenario $s \in S$, where
	$$q_{is} = \sum_{j \in L \cup T} \nu_{jis}, \quad \forall i \in C \cup C', s \in S. \tag{3}$$
K_s	number of vehicles needed in the infectious waste collection in scenario $s \in S$.

4.2. Objectives

The total cost of the infectious waste location-routing plan includes the fixed cost of facility location, the variable cost of processing at facilities, the transportation cost, and the cost of vehicle acquisitions. When the waste generation is random, the amount of waste at each facility, vehicle routes, and the number of vehicles needed are stochastic, which leads to variations in the cost and risk. To account for this variability, we formulate the cost and risk objective individually with three components: the fixed design component, the expected component, and the penalty component based on variations over different uncertain scenarios.

Let NC and NR be the fixed components for the cost and risk, respectively. These two values are computed based on the design variables, which are not variable in regards to the uncertain demand. We can compute NC and NR as follows:

$$NC = \sum_{i \in T} \tau_i FC_i^{station} + \sum_{i \in C} \gamma_i VC_i^{treat} + \sum_{i \in C'} \gamma_i' AC_i^{treat}, \tag{4}$$

$$NR = \sum_{i \in T} \tau_i POP_i^{node} + \sum_{i \in C} \gamma_i POP_i^{node} + \sum_{i \in C'} \gamma_i' POP_i^{node}. \tag{5}$$

Eq. (4) includes the fixed cost of locating temporary facilities (transfer stations and treatment centers), and activating the existing facilities (treatment centers). Eq. (5) indicates the fixed risk, which contains the exposed population at opened facilities.

For each scenario $s \in S$, we denote the cost and risk as SC_s and SR_s, which can be expressed as

$$SC_s = \begin{bmatrix} K_s VFC + \sum_{i \in T} p_{is} VC_i^{station} \\ + \sum_{i \in C \cup C'} q_{is} VC_i^{treat} \\ + \sum_{i,j \in G \cup T \cup \overline{T}} \sum_{m \in \overline{T}} \frac{w_{ijms} DIS_{ij} TC^{tour}}{2} \\ + \sum_{i \in L \cup T} \sum_{j \in C \cup C'} y_{ijs} DIS_{ij} TC^{treat-tran} \\ + \sum_{i \in C \cup C'} \sum_{j \in D} z_{ijs} DIS_{ij} TC^{dispo-tran} \end{bmatrix} \tag{6}$$

,

$$SR_s = \begin{bmatrix} \sum_{i,j \in G \cup T \cup \overline{T}} \sum_{m \in \overline{T}} \frac{w_{ijms} POP_{ij}^{edge}}{2} \\ + \sum_{i \in L \cup T} \sum_{j \in C \cup C'} y_{ijs} POP_{ij}^{edge} \\ + \sum_{i \in C \cup C'} \sum_{j \in D} z_{ijs} POP_{ij}^{edge} \end{bmatrix} \tag{7}$$

Eq. (6) gives the variable cost based on the uncertain waste generation amount, which includes the cost of vehicle acquisition, the variable cost in the transit station, the variable cost in the treatment center, the

transportation cost in the tour, the transportation cost to the treatment centers, and the transportation cost to the disposal centers. Eq. (7) is the variable risk, containing the risk of transportation in the tour, the risk of transportation en route to the treatment centers, and the risk of transportation en route to the disposal centers.

Then denote the expected cost and risk respectively by Δ^{COST} and Δ^{RISK}, which can be calculated as:

$$\Delta^{COST} = \sum_{s \in S} \rho_s SC_s, \tag{8}$$

$$\Delta^{RISK} = \sum_{s \in S} \rho_s SR_s. \tag{9}$$

Eq. (8) presents the expected cost over all scenarios on vehicle acquisitions, operations at facilities (including temporary transfer stations, temporary and existing treatment centers), and transportation. Eq. (9) computes the exposed population resulting from the infectious waste transportation, which is then summed over all uncertain scenarios for the expected risk.

For the corresponding variabilities in cost and risk, expressed by φ^{COST} and φ^{RISK}, we have:

$$\varphi^{COST} = \sum_{s \in S} \rho_s \left| SC_s - \Delta^{COST} \right|, \tag{10}$$

$$\varphi^{RISK} = \sum_{s \in S} \rho_s \left| SR_s - \Delta^{RISK} \right| \tag{11}$$

Eqs. (10) and (11) tracks how the cost and risk vary across scenarios vis-à-vis expected cost and risk determined in Eqs. (8) and (9), respectively.

Combining the above components, we can now write our two objectives as:

$$\min COST = NC + \Delta^{COST} + \omega \varphi^{COST}, \tag{12}$$

$$\min RISK = NR + \Delta^{RISK} + \varpi \varphi^{RISK}, \tag{13}$$

where parameters ω and ϖ are the weights used to evaluate the importance of the cost and risk variation, respectively.

Note that these two objectives are nonlinear due to the absolute terms φ^{COST} and φ^{RISK}. Applying the linearization approach proposed by (Yu and Li, 2000), we introduce two auxiliary variables θ_s and δ_s respectively for the cost and the risk objectives. Then Objectives (12) and (13) can be rewritten as:

$$\min COST = NC + \Delta^{COST} + \omega \sum_{s \in S} \rho_s \left[SC_s - \Delta^{COST} + 2\theta_s \right], \tag{14}$$

$$\min RISK = NR + \Delta^{RISK} + \varpi \sum_{s \in S} \rho_s \left[SR_s - \Delta^{RISK} + 2\delta_s \right] \tag{15}$$

s.t.
$$SC_s - \Delta^{COST} + \theta_s \geq 0, \quad \forall s \in S \tag{16}$$

$$SR_s - \Delta^{RISK} + \delta_s \geq 0, \quad \forall s \in S \tag{17}$$

4.3. Mathematical model

Next, we present the entire mathematical model IWM(A) as follows.

min $COST$
min $RISK$

Subject to (1)–(9), (16)–(17), and

$$\sum_{\substack{j\in G\cup T\cup \overline{T}\\ j\neq i}} \left(x_{ijms} - x_{jims}\right) = 2g_{is}o_{ims}, \quad \forall i\in G, \forall m\in \overline{T}, \forall s\in S; \tag{18}$$

$$\sum_{i\in G}\sum_{m\in T} x_{mims} = K_s VCAP^{tour} - \sum_{i\in G} g_{is}, \quad \forall s\in S; \tag{19}$$

$$\sum_{i\in G} x_{imms} = \sum_{i\in G} g_{is}o_{ims}, \quad \forall m\in \overline{T}, \forall s\in S; \tag{20}$$

$$\sum_{i\in G}\sum_{j\in T}\sum_{m\in T} x_{ijms} \leq K_s VCAP^{tour}, \quad \forall s\in S; \tag{21}$$

$$x_{ijms} + x_{jims} = VCAP^{tour} w_{ijms}, \quad \forall i,j\in G\cup T\cup \overline{T}, i\neq j, \forall m\in \overline{T}, \forall s\in S; \tag{22}$$

$$\sum_{\substack{i\in G\cup T\cup \overline{T}\\ j\prec i}} w_{ijms} + \sum_{\substack{i\in G\cup T\cup \overline{T}\\ j\succ i}} w_{ijms} = 2o_{jms}, \quad \forall j\in G, \forall m\in \overline{T}, \forall s\in S; \tag{23}$$

$$\sum_{\substack{j\in G\cup T\cup \overline{T}\\ j\neq m}} \left(w_{ijms} + w_{jims}\right) = 0, \quad \forall i\in C, \forall m\in \overline{T}, m-i=|T|, \forall s\in S; \tag{24}$$

$$\sum_{\substack{j\in G\cup T\cup \overline{T}\\ j\neq m}} \left(w_{ijms} + w_{jims}\right) = 0, \quad \forall i,m\in \overline{T}, i\neq m, \forall s\in S; \tag{25}$$

$$\sum_{m\in T} o_{ims} = 1, \quad \forall i\in G, \forall s\in S; \tag{26}$$

$$w_{ijms} \leq \tau_i, \quad \forall i\in T, \forall j\in G\cup T\cup \overline{T}, \forall m\in \overline{T}, m-i=|T|, \forall s\in S; \tag{27}$$

$$p_{is} \leq CAP^{station}\tau_i, \quad \forall i\in T, \forall s\in S; \tag{28}$$

$$q_{is} \leq CAP^{treat}\left(\gamma_i + \gamma_i'\right), \quad \forall i\in C\cup C', \forall s\in S \tag{29}$$

$$g_{is} = \sum_{j\in C\cup C'} \nu_{ijs}, \quad \forall i\in L, \forall s\in S; \tag{30}$$

$$\sum_{j\in C\cup C'} \nu_{ijs} = p_{is}, \quad \forall i\in T, \forall s\in S; \tag{31}$$

$$\sum_{j\in D} \eta_{ijs} = \alpha q_{is}, \quad \forall i\in C\cup C', \forall s\in S; \tag{32}$$

$$\frac{\nu_{ijs}}{VCAP^{treat-tran}} \leq y_{ijs}, \quad \forall i\in L\cup T, \forall j\in C\cup C', \forall s\in S; \tag{33}$$

$$\frac{\eta_{ijs}}{VCAP^{dispo-tran}} \leq z_{ijs}, \quad \forall i\in C\cup C', \forall j\in D, \forall s\in S; \tag{34}$$

$$\sum_{i\in L\cup T} \nu_{ijs} \leq M\left(\gamma_i + \gamma_i'\right), \quad \forall j\in C\cup C', \forall s\in S; \tag{35}$$

$$\tau_i \text{ binary}, \quad \forall i\in T; \tag{36}$$

$$\gamma_i \text{ binary}, \quad \forall i\in C; \tag{37}$$

$$\gamma_i' \text{ binary}, \quad \forall i\in C'; \tag{38}$$

$$w_{ijms}, w_{jims} \text{ binary}, \quad \forall (i,j)\in E, \forall m\in \overline{T}, \forall s\in S; \tag{39}$$

$$o_{ims} \text{ binary}, \quad \forall i\in G, \forall m\in \overline{T}, \forall s\in S \tag{40}$$

$$x_{ijms}, x_{jims} \geq 0, \quad \forall (i,j)\in E, \forall m\in \overline{T}, \forall s\in S; \tag{41}$$

$$\nu_{ijs} \geq 0, \quad \forall i\in T, \forall j\in C\cup C', \forall s\in S; \tag{42}$$

$$\eta_{ijs} \geq 0, \quad \forall i\in C\cup C', \forall j\in D, \forall s\in S; \tag{43}$$

$$p_{is} \geq 0, \quad \forall i\in T, \forall s\in S; \tag{44}$$

$$q_{is} \geq 0, \quad \forall i\in C\cup C', \forall s\in S; \tag{45}$$

$$y_{ijs} \geq 0, \text{integer}, \quad \forall i\in T, \forall j\in C\cup C', \forall s\in S; \tag{46}$$

$$z_{ijs} \geq 0, \text{integer}, \quad \forall i\in C\cup C', \forall j\in D, \forall s\in S; \tag{47}$$

$$K_s \geq 0, \text{integer}, \quad \forall s\in S; \tag{48}$$

$$\theta_s, \delta_s \geq 0, \quad \forall s\in S. \tag{49}$$

Constraints (18) to (21) define consistent flows from temporary transfer stations to the copy temporary transfer stations, where Constraint set (18) states that, in each scenario, the total net flow at each small generation node is double that of the waste amount generated at this node, which is shipped to the copy of a temporary transfer station. Constraint set (19) ensures that the total outflow of a copy transfer station is equal to the residual capacity of vehicles in each scenario. Constraint set (20) means that the total inflow of a copy temporary transfer station in each scenario is equal to the total generation amount of allocated wastes from all small generation nodes assigned to this station. Constraint set (21) makes sure that the total inflow of copy temporary transfer stations should satisfy the total vehicle capacity constraint at each scenario. Constraint set (22) guarantees that both x_{jiml} and x_{ijml} take feasible values. Constraint set (23) shows that each small generation node connects two edges. Constraint sets (24) and (25) indicate that each vehicle should start at a temporary transfer station and end at the corresponding copy. Constraint (26) shows that the wastes produced at each small generation node are finally transported to only the copy of one temporary transfer station in each scenario. Meanwhile, Constraint set (27) ensures that a vehicle only starts from an opened temporary transfer station in each scenario. The capacity constraints are given by Constraint sets (28) and (29). Constraint sets (30) to (32) are the waste flow equations in each scenario. Constraint sets (33) and (35) provide logic constraints of decision variables. The variable domains are given by Constraints (36) to (49).

5. Solution procedure

This infectious waste location-routing problem, IWM(A), is constructed as a bi-objective robust mixed-integer linear optimization model including both binary and continuous decision variables. We measure the cost in monetary value, and quantify the risk as the total exposed population. Suppose e is the number of edges, l is the number of large generation nodes, g is the number of small generation nodes, t is the number of temporary transfer station candidates, c and c' are respectively the number of temporary treatment center candidates and existing treatment centers, d is the number of disposal centers, and s is the number of scenarios. There are a total of $2e^2s + gts + t + c + c'$ binary decision variables, $(cds + c'ds + cst + c'st + s)$ integer decision variables, and $(2ets^2 + cds + c'ds + cts + c'ts + ts + cs + c's + 2s)$ continuous decision variables in our proposed model, which subjects to $(2gt^3s + 5gt^2s + 4t^3s + g^2ts + cdes + stc' + 4tcs + 2c'de + 2gts + lsc + lsc' + ets - t^2s + 5cs + 4c's + 3ts + 2es + gs + ls + t + c + c' + 7s + 7)$ constraints. The model complexity causes difficulty in finding optimal solutions by a commercial solver. As a consequence, in this section, we present three solution procedures, adapted from the weighted goal programming method, lexicographic weighted Tchebycheff approach, and augmented ϵ-constraint solution technique.

5.1. Weighted goal programming method (WGP)

Introduced by Charnes et al. (1955), goal programming is a useful

technique in balancing several decision goals via minimizing the deviation of goals. As an alternative to goal programming, WGP effectively manages the deviation between the target value and the realized solu-

5.2. Lexicographic weighted Tchebycheff method (LWT)

Bowman (1976) first proposed the weighted Tchebycheff technique

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Algorithm 5.1 Weighted goal programming method (WGP)

Step 1 Input data.

Step 2 Solve the corresponding single objective problem h_n for optimal solution h_n^*.

Step 3 Compute ξ_n by Eq. (51).

Step 4 Varying the value of λ_n, formulation and solve the single-objective model IWM(B-1).

Step 5 Output the optimal solution.

---

tion by adjusting the weights of different sub-goals. This method has the advantages of directness and flexibility when dealing with different decision preferences, as a result, the optimal solution can be obtained within a reasonable CPU time. The technique has been widely employed as an efficient conversion approach for solving the multi-objective problem in hazardous waste management (Zografos and Samara, 1989; Giannikos, 1998; Zhao and Zhao, 2010), along with other areas (Leung and Lai, 2002; Chang and Lee, 2010; Kanoun et al., 2010). Alumur and Kara (2007) applied the linear weighting method to simplify their multi-objective model. They obtained various efficient solutions according to different weights of sub-objectives.

Unlike the solution procedure designed by previous works in the literature, we notice the importance of the weight of each sub-objective, and hence verify it to derive different plans for our location-routing problem. We revise WGP by Tamiz et al. (1998) and rewrite IWM(A) as:

$$\textbf{IWM(B-1)} \qquad \min \quad \sum_n \lambda_n \xi_n \beta_n$$
$$\text{s.t.} \qquad (1)-(9),(16)-(17),(18)-(49) \text{ and} \qquad (50)$$
$$h_n - \beta_n = h_n^*$$
$$n = 1,2$$

Parameter λ_n is the positive weights respectively given to deviations, where $\sum_n \lambda_n = 1$. β_n denotes the non-negative deviation for sub-objective n, which is presented by h_n, and h_n^* is the target value of the sub-objective. We also define ξ_n as the normalization factor of each sub-objective with the adopting of percentage normalization technique, where

$$\xi_n = 100/h_n^*. \qquad (51)$$

The objective in IWM(B-1) is the achievement function of a minimization problem. The two additional equations are the deviation constraints in a WGP model, which means that the non-negative deviation for each sub-objective is computed from the corresponding target value. Given the target value and normalization factor, IWM(B-1) can be easily solved. Algorithm 5.1 lists the major steps of this approach.

to minimize the weighted Tchebycheff distance between feasible points and ideal points in the target space, and hence to generate a non-dominated solution set by adjusting the target weights parametrically. Later, to avoid weak non-dominant solutions, the Lexicographic weighted Tchebycheff was developed by Shin et al. (2011) based on the original method. Comparing to the general linear weighted sum method, this improved approach has better performance in identifying different and uniform non-dominant solutions. Although the corresponding computational complexity needs to be increased, the Lexicographic weighted Tchebycheff can effectively avoid the disadvantage of returning weak non-dominant solutions. Applications of this approach can be found in Jorgen and Wiecek (1999) and Klamroth and Jorgen (2007).

To solve our model, we customize the LWT method presented by Samanlioglu (2013) and transform IWM(A) as follow.

$$\textbf{IWM(B-2)} \qquad lex\min\left\{\phi, e^T\left[\sum_n \xi_n'\left(h_n - h_n'\right)\right]\right\}$$
$$\text{s.t.} \qquad (1)-(9),(16)-(17),(18)-(49) \text{ and}$$
$$\phi \geq \lambda_n(h_n - h_n') \qquad (52)$$
$$h_n' = h_n^* - 0.1$$
$$n = 1,2.$$

In IWM(B-2), e^T is the transpose of the sum vector (i.e., $e^T = [1,1]$), λ_n is the positive weights for deviations, where $\sum_n \lambda_n = 1$, ξ_n' is the normalization factor value for sub-objective n, which can be obtained with the optimal value of each sub-objective problem h_n^* as

$$\xi_n' = \frac{h_n - h_n^*}{h_n}. \qquad (53)$$

The detailed steps of this method are given in Algorithm 5.2.

Algorithm 5.2 Lexicographic weighted Tchebycheff method (LWT)

Step 1 Input data.

Step 2 Solve the corresponding single objective problem h_n for optimal solution h_n^*.

Step 3 Compute ξ_n' by Eq. (53).

Step 4 Varying the value of λ_n, formulation and solve the single-objective model IWM(B-2).

Step 5 Output the optimal solution.

Table 2
Numerical tests based on random instances.

	Instance	WGP		LWT		AEC	
		Gap (%)	CPU (s)	Gap (%)	CPU (s)	Gap (%)	CPU (s)
#1	15-(4,2)-(2,2,2,2)	1.01	638	0.52	546	0.03	475
#2	30-(10,5)-(4,4,2,2)	3.91	1276	1.92	1016	0.05	877
#3	50-(20,10)-(8,8,2,2)	71.88	3567	62.94	3482	1.01	3444
#4	80-(30,20)-(16,16,4,4)	99.16	7200	86.39	6936	16.19	6774

5.3. Augmented ε-constraint solution technique (AEC)

Considered as a powerful and efficient technique in comparison with the weighted sums approach, the ε-constraint solution technique was designed to deal with optimization problems with multiple objectives by solving a series of single-objective subproblems, where other objectives are transformed into constraints (Chankong and Haimes, 2008; Bérubé

et al., 2009). Extended from the standard version, the augmented ε-constraint approach developed by Mavrotas (2009) can effectively accelerate the optimization process by removing redundant solutions, and hence is applied to solve our model. Accordingly, IWM(A) can be rewritten as:

$$
\begin{aligned}
\textbf{IWM(B-3)} \quad & \min h_1 - eps \times \mu_2 / r \\
\text{s.t.} \quad & (1)-(9),(16)-(17),(18)-(49) \text{ and} \\
& h_2 + \mu_2 = \epsilon \\
& \mu_2 \geq 0
\end{aligned}
\tag{54}
$$

Here, the cost objective function is set as h_1 to be minimized in the objective, and the risk objective function h_2 is incorporated as a constraint with an enforcing upper bound ϵ and a corresponding surplus variable μ_2. In model IWM(B-3), *eps* is an adequately small number within interval $[10^{-6}, 10^{-3}]$. To avoid any scaling issue, *r* is in the range of the risk objective function from its maximum to minimum. By dividing *r* into *k* equal intervals, the value of ϵ is adjusted for corresponding Pareto solutions. Please see Algorithm 5.3 for the detailed procedure.

Algorithm 5.3 Augmented ε-constraint solution technique (AEC)

Step 1 Input data.

Step 2 Solve h_1 and h_2 individually for optimal solutions h_2^{max} and h_2^{min}.

Step 3 Set $r = h_2^{max} - h_2^{min}$, which is then divided into k equal intervals.

Step 4 Let $\kappa = 1$.

Step 5 Compute $\varepsilon = h_2^{max} - \kappa r / k$, then formulate and solve IWM(B-3).

Step 6 If $\kappa = k - 1$, go to Step 7; otherwise, $\kappa = \kappa + 1$ and go to Step 5.
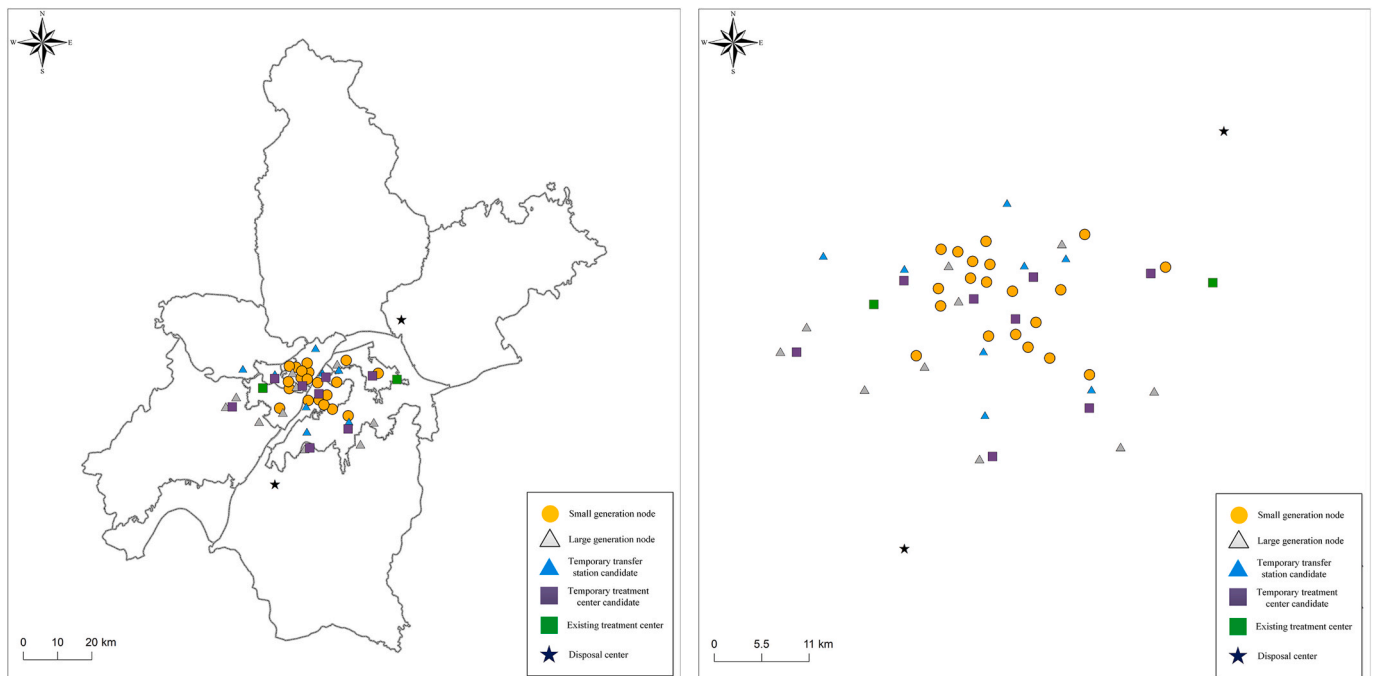
Step 7 Output the optimal solution.

Fig. 3. The medical waste management network in Wuhan, China.

Table 3
Data for generation nodes.

Node		Name	Amount of waste generation (kg/day)		
			Scenario 1	Scenario 2	Scenario 3
Small generation node	1	Wuhan Red Cross Hospital	2.30	164.00	934.80
	2	The Sixth Hospital of Wuhan	2.18	156.00	889.20
	3	The Third Hospital of Wuhan	2.09	149.50	852.15
	4	Wuhan Hankou Hospital	1.97	141.00	803.70
	5	Wuhan Children's Hospital	1.80	128.50	732.45
	6	Hubei Six Seven Two Integrated Traditional Chinese and Western Medicine Orthopaedics Hospital	1.75	125.00	712.50
	7	Hubei Hospital of traditional Chinese Medicine (Guanggu branch)	1.74	124.50	709.65
	8	The Seventh Hospital of Wuhan	1.57	112.00	638.40
	9	General Hospital of the Central People's Liberation Army	1.57	112.00	638.40
	10	Zhongnan Hospital of Wuhan University	1.56	111.50	635.55
	11	Huarun Wisco General Hospital	1.53	109.50	624.15
	12	Wuhan Youfu Hospital	1.46	104.50	595.65
	13	The Third People's Hospital of Hubei Province	1.30	93.00	530.10
	14	General Hospital of The Yangtze River Shipping	1.26	90.00	513.00
	15	The second Hospital of WISCO	1.08	77.00	438.90
	16	The Eighth Hospital of Wuhan	0.97	69.50	396.15
	17	Wuhan Zijing Hospital	0.97	69.00	393.30
	18	Wuhan Traditional Chinese Medicine Hospital (Hanyang branch)	2.35	168.00	957.60
	19	Liyuan hospital	0.83	59.50	339.15
	20	Wuhan Lung Branch Hospital	0.78	56.00	319.20
Large generation node	21	Wuhan Leishenshan Hospital	7.29	521.00	2969.70
	22	Taikang Tongji (Wuhan) Hospital	7.19	513.50	2926.95
	23	Wuhan NO.1 Hospital	7.14	510.00	2907.00
	24	Wuhan Huoshenshan Hospital	6.75	482.00	2747.40
	25	Tongji Hospital (Sino-French Eco-City Branch)	6.56	468.50	2670.45
	26	Wuhan Union Cancer Hospital	5.70	407.00	2319.90
	27	Tongji Hospital (Guanggu branch)	5.26	376.00	2143.20
	28	Whan Union Hospital West Campus	5.00	357.00	2034.90
	29	The Ninth Hospital of Wuhan	4.84	345.50	1969.35
	30	Renmin Hospital of Wuhan University (Eastern Hospital)	4.68	334.50	1906.65

5.4. Numerical tests

The three solution approaches discussed in the previous section are proved to be feasible in solving bi-objective models. This section evaluates the scalability of these algorithms through a series of random problem instances in various sizes. All computations are performed on a computer equipped with a 2.2 GHz Intel processor and 2 GB RAM by using IBM ILOG CPLEX 12.10 with active standard CPLEX cuts.

Table 2 gives the computational results in terms of computational gaps and CPU times (in second). We label the instances as "$|V| - (|G|, |L|) - (|T|, |C|, |C'|, |D|)$", where $|V|$, $|G|$, $|L|$, $|T|$, $|C|$, $|C'|$, and $|D|$ respectively indicate the numbers of network nodes, small generation nodes, large generation nodes, temporary transfer stations, temporary treatment centers, existing treatment centers, and disposal centers. The maximum computation time for the Instance sets #3 and #4 are specified to be 3600 and 7200 s, respectively. Each set of instances are solved 50 times, and the numbers presented in the table are the corresponding average of each iteration over the 50 tests.

It is evident that larger networks require more computational times, and lead to much larger gaps. But comparing the three techniques over the four instances, the AEC approach clearly outperforms the other two; and the superiority enhances as the size of the instance increases. To be specific, for a small network (instance #1 with 15 nodes), the improvements from WGP and LWT to AEC are approximately 97% and 93% in gaps, and 26% and 13% in times, respectively. When the network is large enough (instance #4 with 80 nodes), both WGP and LWT cannot provide a satisfactory solution within the computational time limit (with extremely wide gaps of 99.16% and 86.39%), while AEC can achieve a reasonable average gap of 16.19% (respectively 83% and 81% less than those of WGP and LWT) in the least amount of time. Therefore, we confirm that AEC is explicitly advantageous in the three algorithms, and thus is applied to conduct our case study in the next section.

6. Case study: The Wuhan network

This case study is conducted based on the real situation in Wuhan during the outbreak of COVID-19 in early 2020. Before the outbreak, the city has over 100 hospitals or clinics of various sizes distributed in 13 regions. We herein consider 30 hospitals and clinics as infectious waste generation nodes according to the data provided by the official authority for Hubei medical waste management (Wuhan Municipal Health Commission, 2020). The nodes with less than 500 sickbeds are considered as small infectious waste generation nodes, while others are classified as large generation nodes. This network is illustrated in Fig. 3.

6.1. Relevant data

To thoroughly address different phases during the progress of a pandemic, we study three scenarios in this case study. The first scenario represents the phase when only a minor sign of outbreak is shown, and a potential pandemic threat is considered; the second scenario reflects the situation during a serious outbreak or even a pandemic; and the last one is the worst-case scenario where an extreme circumstance is assumed with a significantly high number of patients. Under this setting, we apply the statistical data collected from Wuhan during COVID-19 to estimate the waste amount for each generation node. To be specific, we use the maximum capacity of each generation node as the number of used sickbeds for the worst-case scenario (Scenario 3), and therefore this number for each small generation node is randomly set within the range [50, 450], while in each large generation node, the corresponding number is assumed from 650 to 1250. In Scenarios 1 and 2, the occupancy rates of sickbeds for those nodes are assumed to be random within ranges of [0, 1%] and [15%, 20%], respectively. Each COVID-19 patient is estimated to produce approximately 2.2–2.8 kg of infectious waste in one day (Institute for Global Environmental Strategies, 2020), and hence

Table 4
Data for facilities.

Node			Name	Fixed cost($\times 10^3$ $)	Unit variable cost ($/ton)	Exposed pop.($\times 10^3$)
Temporary transfer station		31	Ziyang Garbage Transfer Station	650	1950	37.46
		32	Hanjiadun Garbage Transfer Station	600	1950	33.97
		33	Zhangjiawan Garbage Transfer Station	500	1950	3.68
		34	Baibuting Garbage Transfer Station	550	1950	9.34
		35	Changqing Street Urban Management Sanitation Station Garbage Transfer Station	450	1950	3.66
		36	Yangyuan Domestic Waste Transfer Station	630	1950	40.95
		37	Jianshe One Road Garbage Transfer Station	540	1950	24.05
		38	Halecheng Garbage Transfer Station	500	1950	13.83
Temporary treatment center		39	Wuhan NO.1 Hospital	5200	2600	37.46
		40	Wuhan Leishenshan Hospital	4800	2600	33.97
		41	Wuhan Huoshenshan Hospital	5500	2600	3.68
		42	Yangyuan Domestic Waste Transfer Station	5000	2600	9.34
		43	Hongshan Gymnasium	4600	2600	3.66
		44	Hubei Institute of Engineering Technology	4900	2600	40.95
		45	Optical Valley Exhibition Center of East Lake High-tech Zone	5300	2600	24.05
		46	Hanjiadun Garbage Transfer Station	5900	2600	13.83
Existing treatment center		47	Wuhan Hanshi Medical Waste Incineration and Disposal Center	390	1560	5.18
		48	Wuhan North Lake Yunfeng Environmental Protection Technology Company	390	1560	1.675
Disposal center		49	Changshankou Sanitary Landfills	–	–	442
		50	Chenjiachong Sanitary Landfills	–	–	1527

the value is randomly generated within this interval. Multiplying the total number of the used sickbeds and the average daily generation for the patient occupying those sickbeds, we obtain the total amount of infectious wastes. The resulting generation amounts of 20 small generation nodes and 10 large generation nodes are listed in Table 3, where the probabilities of the three scenarios are set as 0.25, 0.5, and 0.25.

The current system contains 8 general waste collection stations, each with a daily capacity of 3 tons. These stations are considered as the candidates for temporary transfer stations (Table 4). The data for the 8 temporary treatment centers candidates and 2 existing treatment centers are also presented in Table 4. The capacity of the temporary facilities is 3 tons/day, and 10 tons/day for the existing ones. The Changshankou and Chenjiachong sanitary landfills, each with a capacity of 10 tons/day, are considered as the two disposal centers in this work. The potential exposed populations at these two centers are 442 and 1,527, respectively. Also note that we collect the number of residents within the radius of 800 m from the operated facility as the potentially exposed population (Alumur and Kara, 2007); and the fixed and variable costs for each facility are based on the work of (Yu et al., 2020).

The exposed population on each edge, in this work, is calculated as half of the sum of the population located at the original and destination nodes of this edge. All population data are obtained from the GIS database. Three types of vehicles are considered in this case, which make tours, direct routes to treatment centers, and direct routes to disposal centers, respectively. The unit transportation cost of waste collection is $ 200/km. Each vehicle served in this phase costs 160 thousand dollars, with a capacity of 1.5 tons. The unit cost of transporting waste to the treatment centers is $ 100/km, and the related vehicle's capacity is 3 tons. The unit cost for routing waste to the final disposal centers is $ 50/km, and the vehicle's maximum load is 0.5 tons.

6.2. Computational results

We compute the single sub-objective results individually in the first step in this realistic case. Each single-objective problem involves 31,602

Table 5
Results of optimizing each objective individually.

Subobjective	Cost ($\times 10^6$ $)	Risk ($\times 10^3$ people)	Gap (%)	CPU time (s)
Min cost	33.91	1601.80	0.01	1767
Min risk	35.62	1297.00	0.97	1800

binary decision variables, 603 integer decision variables, 31,776 continuous decision variables, and 71,937 constraints. It can be noted in Table 5 that the obtained optimal solutions can achieve the gap of 1.00% within 1800s. Comparing to the "min cost" solution, The "min risk" solution reduces the risk by 19% with only 5% increase in cost.

We next solve the case with the augmented ϵ-constrained approach, which is illustrated to be the most effective and efficient in the last section. Fig. 4 depicts the trade-off curve based on 15 iterations and highlights the three salient solutions with round nodes ("min risk", "min cost", and "intermediate" solutions). From the risk perspective, several rather big gaps can be observed, all are close to the three salient solutions. Starting from the "min cost" solution, with a less than 0.9% extra cost, the risk can be reduced by nearly 2.8%. For the two intervals near the "min risk" solution, an approximately 1% average increase of cost can lead to an average of 1.6% cut in risk. The largest risk gap exists between the "intermediate" solution (obtain from iteration 7) and that from iteration 6, where the 4.4% risk change only requires about 0,.27% additional cost.

In more detail, Table 6 lists the details of the "intermediate" solution, which can be obtained at 3582s with a gap of 0.30%. For this specific solution, the total cost and risk are respectively 34.52×10^6 dollars and 1453.00×10^3 people. To be specific, at the network design level, five temporary transfer stations, six temporary treatment centers, and two existing treatment centers are set up. However, due to the difference in the waste amount, not all these facilities are occupied. For the first two scenarios, only one station, station 37, is used, while 2 vehicles, each
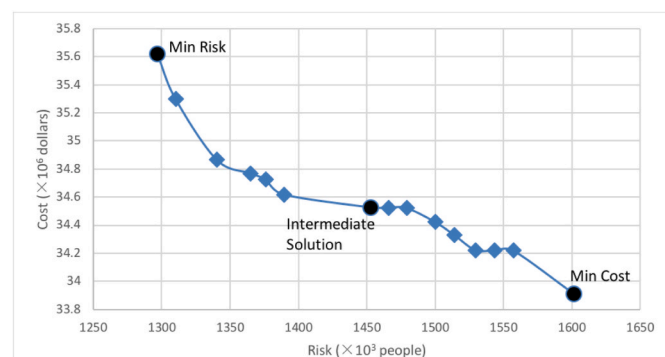

Fig. 4. Trade-off curve.

Table 6

Recommended location-routing plan (the intermediate solution).

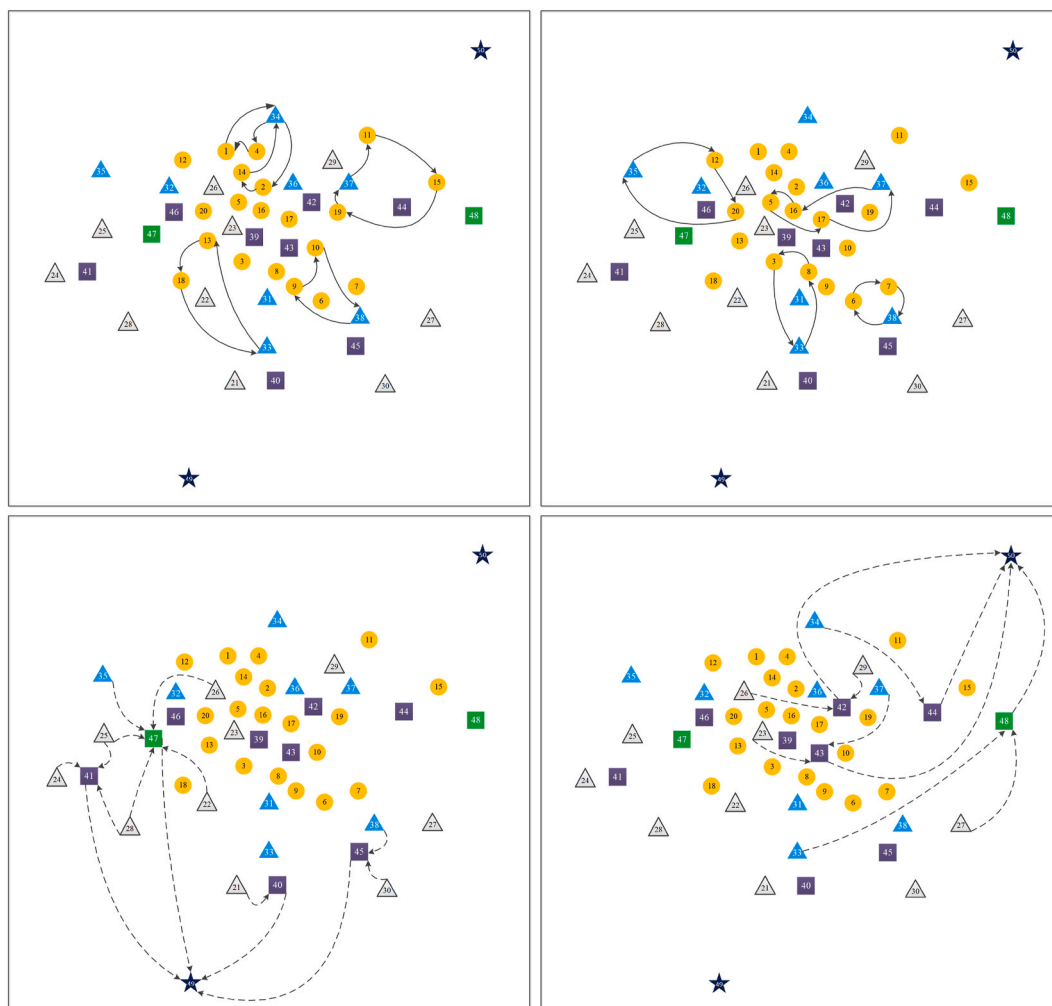|		Scenario 1	Scenario 2	Scenario 3
Transfer station		33,34,35,37,38	33,34,35,37,38	33,34,35,37,38
Treatmentcenter	Temporary	40,41,42,43,44,45	40,41,42,43,44,45	40,41,42,43,44,45
	Existing	47,48	47,48	47,48
Number of vehicles		1	2	9
Tour		37-19-17-16-2-5-14-4-1-12-20-13-18-3-8-10-9-6-7-15-11-37.	37-11-15-7-6-9-8-10-19-37; 37-17-3-18-13-20-16-2-5-14-1-12-4-37.	33-8-3-33; 33-13-18-33; 34-4-1-34; 34-2-14-34; 35-12-20-35; 37-11-15-17-37; 37-16-5-19-37; 38-9-10-38; 38-6-7-38.
Route	Station-Treatment	37-42.	37-42; 37-48.	33-48; 34-44; 35-47; 37-43; 38-45.
	Largegeneration-Treatment	21-40; 22-41; 23-42; 24-41; 25-41; 26-42; 27-45; 28-41; 29-42; 30-45.	21-40; 22-40; 23-47; 24-47; 25-47; 26-47; 27-42; 28-47; 29-42; 30-40.	21-40; 22-47; 23-43; 24-41; 25-41; 25-47; 26-42; 26-47; 27-48; 28-41; 28-47; 29-42; 30-45.
	Treatment-Disposal	40-49; 41-49; 43-50; 45-49.	40-49; 47-49; 42-50.	40-49; 41-49; 42-50; 43-50; 44-50; 45-49; 47-49; 48-50.

Fig. 5. Recommended optimal plan.

perform one tour, are needed for Scenario 2, rather than only 1 for Scenario 1. As the extreme case, Scenario 3 requires 9 vehicles/tours, and all facilities are employed. The immense amount of demand in this scenario also lead to multiple tours for one transfer station and multiple direct routes between large generation nodes and treatment centers. The detailed routes and tours are depicted in Fig. 5.

6.3. Comparisons of the current system with recommended plan under the pandemic and normal situations

As discussed previously, one of the main contributions of the present work is to upgrade the existing network by using temporary facilities, which can be transferred from regular facilities. To show the strength of this strategy, we conduct two comparisons of the current system

Table 7

Comparisons of the current system with recommended plan under the pandemic and normal situations.

Pandemic situation	Current system	Recommended plan	Change(%)
Transportation risk ($\times 10^3$ people)	463.02	434.53	−6.15
Transportation cost ($\times 10^6$ dollars)	4.83	2.86	−40.79
Number of vehicles	20	9	−55.00
Average usage of facility capacity (%)	304.17	40.15	−86.80
Demand fulfillment (%)	32.88	100	+204.14
Normal situation	Current system	Recommended plan	Change(%)
Transportation risk ($\times 10^3$ people)	55.56	58.15	+4.67
Transportation cost ($\times 10^6$ dollars)	0.58	0.43	−25.86
Number of vehicles	20	1	−95
Average usage of facility capacity (%)	36.72	8.71	−76.28
Demand fulfillment (%)	100	100	–

(without temporary facilities) and our recommended plan (with temporary facilities) respectively under the pandemic and normal situations. The comparison based on various criteria is summarized in Table 7.

For the pandemic situation, we consider all three scenarios, and the results are based on the mean values over all scenarios. It can be easily seen that the recommended plan greatly improves the performance of the waste management network. In the current system, each vehicle is assigned to make a direct route from the treatment center to a certain hospital, and thus we only optimize the tour plan for the waste collection among small generation nodes. Supposing each small generation node is served by one vehicle, there require at least 20 vehicles in line with the current operation. However, in the recommended solution, the number of required vehicles decreases to 9, a reduction of 55%. The transportation risk and cost can be accordingly reduced by 6.15% and 40.79%, respectively, due to the reduction in the number of vehicle routes. Moreover, as the outbreak of COVID-19 becoming more severe, the requirements for infectious waste collection and treatment increase sharply. Based on this case, the existing treatment centers are unable to operate all the generated wastes, especially in Scenario 3. This resulted in a facility capacity usage of 304.17%, and only 32.88% of the waste can be processed. On the other hand, by locating 5 temporary transfer

stations and 6 temporary treatment centers, the overload situation can be eliminated: the capacity usage is lowered by 86.80% to only 40.15%, and all demand can be satisfied (a 100% satisfaction rate). The benefit of this reduction in the facility capacity usage is not only to fulfill all required waste treatment in all assumed scenarios; more importantly, the active redundancy given by free facility capacities can enhance the
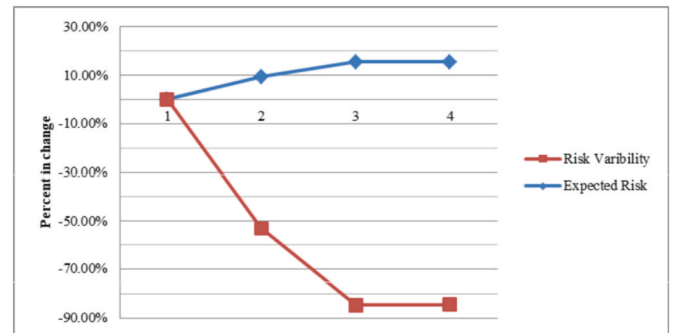

Fig. 6. Variation in the variability weight for the risk objective (ϖ).

Table 8

Variation in the vehicle capacity for waste collection.

Vehicle capacity	Cost ($\times 10^6$ \$)	Transfer station	Temporary treatment center	Existing treatment center	Number of vehicles[a]	Transportation cost[a] ($\times 10^6$ \$)
1.0	34.43	33,34,35,37,38	39,40,42,43,44,45	47,48	(1, 3, 16)	(0.13, 0.37, 1.91)
1.5	33.90	33,34,35,37,38	41,42,43,44,45,46	47,48	(1, 2, 9)	(0.13, 0.26, 1.12)
2.0	33.84	33,34,35,37,39	39,40,42,43,44,45	47,48	(1, 2, 8)	(0.13, 0.26, 1.03)

[a] (Scenario 1, Scenario 2, Scenario 3).

Table 9

Variation in the facility capacity.

Facility capacity	Cost($\times 10^6$ \$)	Transfer station	Temporary treatment center	Existing treatment center	Number of vehicles[a]	Transportation cost[a]($\times 10^6$ \$)
2.5	40.08	33,34,35,37,38	39,40,41,42,43,44,45	47,48	(1, 2, 10)	(0.13, 0.26, 1.24)
3.0	33.90	33,34,35,37,38	41,42,43,44,45,46	47,48	(1, 2, 9)	(0.13, 0.26, 1.12)
3.5	33.78	33,34,35,37,39	39,40,42,43,44,45	47,48	(1, 2, 11)	(0.13, 0.26, 1.37)

[a] (Scenario 1, Scenario 2, Scenario 3).

Table 10

Variation in the probability of scenario.

Probability[a] ρ_s	Cost ($\times 10^6$ \$)	Transfer station	Temporary treatment center	Existing treatment center	Number of vehicles[a]	Transportation cost[a] ($\times 10^6$ \$)
(0.5, 0.25, 0.25)	34.04	33,34,35,37,38	39,40,42,43,44,45	47,48	(1, 2, 11)	(0.13, 0.26, 1.37)
(0.25, 0.5, 0.25)	33.90	33,34,35,37,38	41,42,43,44,45,46	47,48	(1, 2, 9)	(0.13, 0.26, 1.12)
(0.25, 0.25, 0.5)	34.24	33,34,35,37,39	39,40,42,43,44,45	47,48	(4, 5, 9)	(0.51, 0.67, 1.12)

[a] (Scenario 1, Scenario 2, Scenario 3).

system reliability and prevent performance decline when facing even worse situations.

The next comparison is to show that our proposed optimization can also apply to the normal situation. We take 0.3 kg as the amount of infectious waste generated by each patient when there is no outbreak. As can be noticed, despite the minor increment of 4.67% in the transportation risk, our recommended solution can decrease the transportation cost by almost 26%, and drop the number of required vehicles from 20 to 1. All demand can be fulfilled in both plans, but the facility usage of the recommended plan is more than 76% lower than the current system. The extra capacity can be used to react to any unpredictable demand increase, which gives the system additional flexibility.

6.4. Sensitivity analyses

In this section, we further analyze the impacts of variations in several parameters on the main results. All calculations are conducted based on the Wuhan case with cost minimization unless stated otherwise.

6.5. Variation in the vehicle capacity for waste collection

The vehicle capacity is varied from the current 1.5 tons to 1.0 and 2.0 tones, and the results are compared in Table 8. It is intuitive that the vehicle capacity directly affects the amount of waste that can be collected in one tour. Hence, the number of vehicles required in the tour decreases, and the corresponding transportation cost and total cost also reduce, as the capacity increases. On the other hand, when the capacity decreases, the number of vehicles and the resulting costs are both higher.

6.6. Variation in the facility capacity

The facility capacity, for both the treatment center and transfer station, has effects on the decisions related to the operations at those facilities. We change the value of facility capacity up and down by 0.5 tones and compare the corresponding results (Table 9). Note that the change of facility capacity influences both facility and transportation costs. In particular, as the capacity of the treatment center decreases, the amount of waste that can be proceeded in the center is lower, and hence additional treatment centers are needed to be established. Furthermore, an opened transfer station requires at least one vehicle. So the number of vehicles increases as more stations are located, which in turn results in higher costs.

6.7. Variation in the probabilities of scenarios

Our original calculation sets the three probabilities as 0.25, 0.5, and 0.25. For a general problem, these values can be derived from historical data. However, the present focus of our work is on an unexpected pandemic, which may not be seen from any human history. Therefore, it becomes almost impossible to accurately estimate the probabilities for various scenarios. To obtain a comprehensive understanding of the impacts, we vary the value of probabilities in different values and show the comparison in Table 10. When the probability of an extensive outbreak is lower (i.e., $\rho = (0.5, 025, 0.25)$), the overall cost is more than the base case since enough facilities must be set up for the extreme scenario, and most facilities are only used in the extreme scenario. In the meantime, the cost in the case with a high probability of the extreme scenario (i.e., $\rho = (0.25, 025, 0.5)$) is even higher due to the massive amount of waste. Note that in this case the numbers of vehicles for Scenarios 1 and 2 also increase. The reason is twofold. On one hand, the model objective optimizes the expected value while keeping the variability among scenarios minimum. On the other hand, the huge difference in the waste amounts and more focus on the worst-case scenario induce the model to give a rather stable location-routing plan, which leads to higher vehicle numbers in all scenarios.

6.8. Variation in the variability weight for the risk objective

In our optimization model, the penalty term plays a key role in maintaining robustness across different scenarios. This analysis specifically examines the benefit of considering risk variability in the risk objective. In our original calculation, we set the value of ϖ as 1, which is now increased incrementally to 4 to show the impact. The percentage changes of the expected risk and risk variability are computed according to the base case, and the resulting trend is depicted in Fig. 6. Note that we herein use the non-dominated "min risk" solution for a better illustration. It can be observed that the variability of risk can be significantly reduced by raising the value of ϖ, without too much influence on the expected cost. In fact, when $\varpi = 4$ (and any values beyond 4), the risk variability drops to almost zero, while the expected value is only up by roughly 15%. The significance of this result lies in easing the potential threat to public health even in a high-demand scenario, which then keeps the risk within a tolerable range under different conditions.

7. Managerial insights

The currently ongoing COVID-19 pandemic has been posing devastating impacts on every level of society and across all economic sectors. For solid waste management, municipalities are facing the challenge of continuing essential services of waste collection and management while at the same time accounting for growing streams of potentially infectious waste, as well as protecting the lives of essential workers. To overcome such pressure, it is vital to prepare the medical-waste management system with a certain degree of redundancy for pandemics, which, however, may lead to a significantly high cost. This large amount of expenditure may not be affordable, especially to developing countries.

One of the primary messages from the United Nations Environment Programme is to use existing waste management systems to their fullest, whenever possible. Responsively, our proposed strategy of using regular amenities as temporary infectious-waste-compatible facilities can fulfill the emergency demand at a much lower cost. Another aspect of redundancy is reflected by the capacities, including both vehicles and facilities. To mitigate the relevant cost that may be resulted from maintaining extra capacities, implementing collection tours among small generation nodes (rather than using direct tours) can practically decrease the number of required vehicles and hence the expenses. Therefore, the present work provides a practical approach for the government and health-care managers to design and construct waste management systems that can defend against the sudden increase of infectious waste during unforeseen pandemics.

In addition to the overall system preparedness, our recommended solutions given by different scenarios from a minor outbreak to a major epidemic can facilitate a practical sequence of responsive plans (including the number of vehicles, the number and locations of occupied facilities, as well as tour and route arrangements) at various phases of a pandemic. The implementation of a pre-defined weight for risk variability further ensures the system robustness under various uncertain situations.

8. Conclusion

Acting as a wake-up call, the COVID-19 pandemic necessitates a comprehensive management system for health-care waste especially under unprecedented uncertainties in the amount of waste. To fill a missing link in the hazardous waste management literature, we propose a bi-objective robust optimization model for the location-routing problem of infectious wastes with demand uncertainty. More particularly, the uncertainty is considered in various scenarios, which induce a set of control decisions for each scenario along with design decisions across all scenarios. The numbers and locations of temporary facilities, such as the transfer station and treatment center, are determined with consideration

of possible high-demand situations that may be caused by a future pandemic. Given the locations, small and large generation nodes are assigned respectively to temporary transfer stations and treatment centers. Corresponding collection tours and direct routes are also planned. Given the complexity of our model, we adapted three solution procedures from the literature, namely the weighted goal programming method, the lexicographic weighted Tchebycheff approach, and the augmented ϵ-constraint solution technique, which are then implemented and tested based on the solution quality and computational time. The numerical tests indicate that the augmented ϵ-constraint approach can provide the best solution within the shortest time. For practical demonstration, we applied the proposed model and solution procedure to a real-world case study based on the situation of the COVID-19 outbreak in Wuhan, China, from which managerial insights are derived to benefit the government and other stakeholders.

For future research, we would like to explore the impacts of time-relevant issues, such as time window, time-varying cost/risk, to name a few. The evaluation of infectious risks associated with waste collection and treatment also needs to be revisited with consideration of decision-maker's perception or attitude. Moreover, hazardous waste management is usually concerned by multiple parties, including the government, manager, and residents, and different parties may have different preferences and objectives. It would be interesting to examine the interactions among those parties, as well as the corresponding impacts on the management decisions. Another possible future direction is to incorporate the effects of carbon emissions on total cost and risk during the management of hazardous waste, especially when the transshipment phase is added to the existing system.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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