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RESEARCH ARTICLE

Routing Optimization for Healthcare Waste Collection With Temporary Storing Risks and Sequential Uncertain Service Requests

MENG ZHANG[1], **WEI CUI**[2,3], **QI JIANG**[2,3], **AND NENGMIN WANG**[2,3]
[1]School of Economics and Management, Xi'an Technological University, Xi'an, Shaanxi 710021, China
[2]School of Management, Xi'an Jiaotong University, Xi'an, Shaanxi 710049, China
[3]ERC for Process Mining of Manufacturing Services in Shaanxi Province, Xi'an, Shaanxi 710049, China

Corresponding author: Nengmin Wang (wangnm@mail.xjtu.edu.cn)

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ABSTRACT The effective disposal of healthcare waste is a highly concerned issue. Healthcare waste collection poses transport risks and temporary storing risks, and the deliberation undertaken by decision-makers concerning waste collection entails potential scenario wherein some hospitals have not yet submitted their service requests and may submit their requests during the healthcare waste collection procedure. A routing optimisation problem for healthcare waste collection with temporary storing risks and sequential uncertain service requests is introduced. A two-stage decision-making is proposed and mathematical models corresponding to each stage are developed. Different solution algorithms are developed for different stages or different scales of instances, including the improved ε-constraint method and Non-dominated Sorting Genetic Algorithm-II for the solution procedure in Stage 1, and the Compare-choose-move algorithm for the solution procedure in Stage 2. Finally, the models and algorithms are tested by numerical instances and several suggestions for healthcare waste collection have been proposed based on sensitivity analysis.

INDEX TERMS Healthcare waste collection, routing optimization, sequential uncertain service request, temporary storing risk.

I. INTRODUCTION

Healthcarewaste is a type of waste with highly risk, such as items contaminated with patient blood, bodily fluids, excreta, etc. Containing infectious substances, healthcare waste poses a significant risk in the transmission of diseases. Consequently, the effective disposal of healthcare waste while preventing secondary pollution has emerged as a prominent concern for governments and the public [1]. There has been a rapid surge in the volume of healthcare waste after the outbreak of the COVID-19 epidemic [2]. Timely collection of healthcare waste has gained paramount importance and attention. For example, in China, healthcare waste was normally stored in the healthcare institutes and collected at a frequency of every two days before 2020. But now, it is required that healthcare waste generated every day must be collected in the day so as to reduce the storing risk of hospitals, namely Production Every Day and Clearance Every Day mode.

The process of healthcare waste collection follows a sequential pattern encompassing the steps of "temporary storage in hospitals → retrieval by the collection vehicle → transportation to the treatment center". After the COVID-19 epidemic, many hospitals across China have been equipped with sensors in their healthcare waste temporary storage places. These sensors are programmed to trigger service requests to healthcare waste treatment center upon the attainment of the certain waste accumulation thresholds. Therefore, in situations similar to Production Every Day and Clearance

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Every Day mode in China, the strategic deliberation undertaken by decision-makers concerning waste collection entails potential scenario wherein some hospitals have not yet submitted their service requests which may be submitted during the collection procedure.

The route of collection vehicles is the key to safe and efficient healthcare waste collection, mainly for three reasons. First, the collection vehicles loaded with healthcare waste may encounter accidents, such as collisions, rollovers, etc., which can easily lead to the spread of diseases or environmental pollution [3]. It is necessary to control the transport risks of collection vehicles. Then, temporary storing healthcare waste in hospitals may also cause infectious risk [4]. Thus, it is also necessary to reduce the temporary storing risk within hospitals as much as possible by reasonable route planning. In addition, the Production Every Day and Clearance Every Day mode, within which a part of the requests for healthcare waste collection have uncertainty, pose a challenge for the decisions.

The outbreak of infectious diseases, exemplified by the COVID-19 epidemic, has also raised scholars' attention pertaining to healthcare waste collection. The relevant research mainly focuses on the collection of industrial hazardous waste and healthcare waste. These works do not yet effectively address the above challenges. On one hand, research related to industrial hazardous waste collection fails to adequately capture the distinct features of healthcare waste collection well, particularly the imperative to mitigate risks brought by healthcare waste. On the other hand, research related to healthcare waste collection is mainly based on premise that all hospitals have proposed their requests and the decision-makers conduct overall planning, neglecting the probable situation that some hospitals have not yet submitted their service requests. In addition, research that considers the minimizations of both transport risk and temporary storing risk is rare, which also leads to a gap.

This paper introduces a routing optimisation problem for healthcare waste collection with temporary storing risks and sequential uncertain service requests. The goal of this problem is to determine the routes for healthcare waste collection, with the aims of minimizing the total transport risk and the maximum temporary storing risk of each hospital simultaneously. A part of the hospitals has already submitted service requests and their quantities of healthcare waste are known. However, other hospitals have not submitted their service requests. Whether they will submit service requests, alongside their quantities of healthcare waste, are completely uncertain and cannot be predicted in advance. The submission of service requests from these hospitals is with the characteristics of sequential uncertainty. Only when a service request is submitted can the decision-makers know the quantity of healthcare waste.

This paper makes primary contributions in several aspects. First, considering the actual situation where some hospitals may submit real-time service requests during the healthcare waste collection, we propose a two-stage decision-making. The initial collection plan for the hospitals that have submitted service requests before starting collection is determined in Stage 1, and the sequential uncertain service requests that the hospitals submitted during the collection procedure are addressed dynamically in Stage 2. Second, both the transport risk and temporary storing risk are considered in this research, and comparative analysis to the proposed models and algorithms has shown that they can effectively reduce the risks of healthcare waste collection. Third, the variations of risk related parameters, number and capacity of vehicles are analyzed, and several suggestions for healthcare waste collection have been proposed.

This paper is structured in the following manner. Section II offers an extensive review of related researches. Section III is the problem formulation. Section IV is the two-stage decision-making and mathematical models. Solution algorithms are developed in Section V. Numerical results are presented in Section VI. In the end, Section VII provides conclusion.

II. LITERATURE REVIEW

Since healthcare waste collection is a risky process and revolves primarily around routing decisions, previous research in this field includes two categories: routing for hazardous waste collection and routing for healthcare waste collection. Hereafter, two streams of research will be sorted out separately.

A. ROUTING FOR HAZARDOUS WASTE COLLECTION

Routing for hazardous waste collection predominantly concentrates on industrial hazardous waste, encompassing materials such as flammable and explosive waste, corrosive waste, and radioactive nuclear waste, etc. In these researches, the primary objective is to determine the transport routes, minimizing the total risk and cost simultaneously. While akin to research about hazardous materials transportation, e.g., [5], [6], and [7], routes of vehicles in these researches are based on reverse logistics. Although attention to routing for hazardous materials transportation began around 2010, a notable surge in research concerning hazardous waste collection has been observed since 2015. Research concerning routing for hazardous waste collection can be categorized into two primary domains. The first category mainly considers vehicle routing, and the second category combines routing with location or other decision-making aspects.

For the first category, Zhao and Zhu formulated a bi-objective routing model for hazardous waste management, focusing on minimizing the total risk and total cost. A modified Tchebycheff method is adopted to tackle the problem [8]. Yu et al. developed a bi-objective mixed integer program (MIP) model to achieve the objectives of minimizing the population exposed to hazardous waste and maintaining a high efficiency in the collection process at the same time. An approximation goal programming algorithm is employed to address the problem [9]. Saeidi-Mobarakeh et al. formulated a bi-level model with the strategic reverse network design. The fluctuation of hazardous waste generation rate in different scenarios is considered as uncertainty and a three-part solution approach is employed accordingly [10]. Wang et al. considered three objectives when addressing the vehicle routing for paint waste management, that is, to minimize transportation costs, to minimize transport or sites risks, and to maximize the convenience for the waste collection [11].

For the second category, Zhao and Ke introduced the consideration of inventory risk within a location-routing (LR) model, seeking to reduce the system's overall cost and environmental risks [12]. Rabbani et al. presented a multi-objective LR model for industrial waste, minimizing the total cost, total transport risk, and the site risk concurrently. To address the problem, two kinds of algorithms are implemented [13]. Rabbani et al. incorporated LR and inventory control into a multi-objective model for industrial waste collection, aiming to minimize both the overall cost and total environmental risk. An approach which integrates Monte Carlo simulation is developed [14]. Zhao and Huang presented a bi-objective MIP for regional hazardous waste management minimizing the overall cost and risk associated with the locating and transporting processes [15]. Rabbani et al. proposed a multi-objective LR model achieving workload balance. Three algorithms are employed to tackle the problem efficiently [16].

From the above analysis, it is evident that although routing for hazardous waste collection has already considered the risk, these researches are mainly centered on the collection for industrial waste. In addition to risks, there are still differences between healthcare waste and industrial waste. These differences have given birth to routing for healthcare waste collection.

B. ROUTING FOR HEALTHCARE WASTE COLLECTION

Healthcare waste falls under the category of hazardous waste in precise terms. However, routing for healthcare waste collection necessitates a keen understanding of the characteristics of healthcare waste. These characteristics includes service requests originating from healthcare institutions, transportation of collected waste to healthcare waste treatment centers, and the network which is mainly based on a city, etc. After the outbreak of the COVID-19 epidemic, there has been a substantial proliferation in relevant research in this field. Considering the uncertainty in various parameters, these researches can be classified into the following two distinct categories.

1) ROUTING FOR HEALTHCARE WASTE COLLECTION WITHOUT UNCERTAINTY

Routing for healthcare waste collection without uncertainty can be understood as routing for hazardous waste collection considering the particularity brought by the characteristics of healthcare waste. Gao et al. explored the periodic vehicle routing of healthcare waste recycling, taking into account different collection strategies and time windows, aiming to minimize the total travelling distance. Particle Swarm Optimization approach is adopted as the computational method [17]. Zhang et al. presented a two-stage multi-cycle routing of healthcare waste recycling to minimize the total cost. To address this problem, the Clarke-Wright algorithm and the variable neighbor search algorithm are used respectively [18].

The above research primarily focusses on single-objective problem, but there is an increasing body of literature dedicated to multi-objective problem. For example, Taslimi et al. introduced a model to minimize the occupational risk at the healthcare centers and transportation risk of healthcare waste. The inventory dynamics is considered and a heuristic algorithm is employed [4]. Nikzamir et al. presented a model for two kinds of healthcare wastes, aiming to minimize the network costs and mitigate the risk of being exposed to pollution. A benders decomposition algorithm is utilized to obtain the optimal solutions [19]. Eren and Tuzkaya focused on minimizing transportation distance and maximizing the safety of vehicles. AHP method is used to obtain security scores and a traveling salesman problem with the goal of maximum safety is analyzed [20]. Ghannadpour et al. addressed a routing problem specific to small medical centers incorporating the objectives for sustainable development. A self-adaptive algorithm is employed to obtain the social objective of minimizing the collecting time, environmental objective of minimizing the environmental hazards, and the economic objective of minimizing the costs [21]. Erdem explored the vehicle routing problem of electric healthcare waste collection. To address the problem, two heuristic algorithms are applied to deal with the problem [22].

2) ROUTING FOR HEALTHCARE WASTE COLLECTION WITH UNCERTAINTY

The researches summarized above have not taken into account of the influence of uncertainty factors. However, there exist several researches that specifically focus on uncertainty, with fuzzy theory being a commonly employed approach. For example, Yao et al. conducted an investigation into a location-allocation of healthcare waste from the perspectives of hospitals and governments. The uncertainty in facility location represented as the values of demands and transportation cost is delt with fuzzy random variables [23]. Govindan et al. developed a multi-product, multi-period MIP model for healthcare waste collection. A fuzzy methodology is used to address the uncertain aspiration levels of variables [24]. Tirkolaee et al. introduced a multi-trip LR problem for healthcare waste. The uncertainty of the demand parameter is considered as an independent triangular fuzzy number and a chance-constrained approach is used as the solution method [25].

In addition to the utilization of the fuzzy theory to address uncertainty, other types of uncertainties have also been considered. Nikzamir and Baradaran focused on minimizing both total costs and contamination emission for healthcare waste LR. The stochastic nature of the emission depends on the transporting times is considered as a normal random variable and a meta-heuristic approach is employed [26]. Govindan et al. formulated a circular economy transition model. The uncertainty brought by the amount of waste generated by hospitals is solved by using a scenario-based approach [27].

Based on the above analysis, it is evident that these researches mainly address uncertainty through methods such as fuzzy numbers and expected values. However, in the context of such as Production Every Day and Clearance Every Day mode, accurately estimating the sequential uncertain service requests poses considerable challenges. How to minimize the total transport risk and maximum temporary storing risk in healthcare waste collection simultaneously is also an unexplored issue.

We investigate the routing optimisation problem for healthcare waste collection with temporary storing risks and sequential uncertain service requests introduced in this paper. Unlike previous studies, hospitals that have submitted service requests before starting collection and will submit their service requests during the collection procedure are considered. The minimizations of total transport risk and the maximum temporary storing risk are also considered simultaneously. To the best of our knowledge, there is no existing research related to healthcare waste collection that has addressed this problem. The problem formulation will be provided firstly in the next section.

III. PROBLEM FORMULATION

$G(V, E)$ is an abstract network which originates from real roads, where $V = \{v_0\} \cup V' \cup V''$ is the set of vertexes; $E = \{e(v_i, v_j)|v_i, v_j \in V\}$ is the set of edges in network $G(V, E)$. v_0 represents the healthcare waste treatment center; $V' \cup V''$ represents the set of hospitals. For the hospitals in $V' = \{v_1, v_2, \cdots, v_n\}$, they have already submitted service requests and their quantities of healthcare waste are known. For the hospitals in $V'' = \{v_{n+1}, v_{n+2}, \cdots, v_{n+m}\}$, they have not submitted their service requests. Whether they will submit service requests and their quantities of healthcare waste are completely uncertain. Healthcare waste poses risks during transportation. Additionally, hospitals encounter temporary storing risks while awaiting the collection. The goal of this problem is to determine the routes for healthcare waste collection, with the aims of minimizing the total transport risk and the maximum temporary storing risk simultaneously.

A. ASSUMPTIONS

1) The risks are related to the quantity of healthcare waste.
2) After the collection for hospitals in V' starts, each hospital $v_i \in V''$ may submit service requests that are unpredictable in advance. Only when a service request from $v_i \in V''$ is submitted can the decision-makers know the quantity of healthcare waste.
3) The submission of service requests is with the characteristic of sequential uncertainty. According to the order in which service requests are submitted, hospitals are recorded as $v_{n+1}, v_{n+2}, \cdots, v_{n+m}$.

B. NOTATION

For the convenience of the following discussion, we provide parameters used in the mathematical model here, as shown in Table 1.

TABLE 1. Meanings of parameters.

Parameter	Meaning
l_{ij}	Length of $e(v_i, v_j)$.
vol_{ij}	Travelling velocity of vehicles on $e(v_i, v_j)$.
q_i	Quantity of healthcare waste to be collected in v_i.
Q	Capacity of vehicles.
K	Number of vehicles can be used for the collection.
P_{ij}	Accident rate of $e(v_i, v_j)$.
p_{ij}	Conditional probability for a diffusion given the accident on $e(v_i, v_j)$.
d_{ij}	Diffusion time on $e(v_i, v_j)$.
w_{ij}	Wind speed on $e(v_i, v_j)$.
ρ_{ij}	Density of population on $e(v_i, v_j)$.
t_i^S	Time point when hospital v_i submits service request.
θ_i	Infection coefficient of temporary storing healthcare waste in hospital v_i.

The decision variables used include 0-1 variable x_{ij}^k that equals to 1 if vehicle k passes $e(v_i, v_j)$, 0-1 variable y_i^k that equals to 1 if vehicle k serves hospital v_i, non-negative variable u_i^k that represents the load of vehicle k when leaving v_i, and non-negative variable t_i^k that represents the time when vehicle k serves hospital v_i.

C. RISK MEASUREMENT

The risks of healthcare waste collection encompass two different sources, i.e., the transport risk and the temporary storing risk. Transport risk refers to the risk when healthcare waste is transported by the collection vehicles. Temporary storing risk refers to the risk when healthcare waste is temporarily stored in hospitals before the arrival of collection vehicles. In this research, we consider minimizing the total transport risk and the maximum temporary storing risk.

For the transport risk, we define the transport risk as the expected consequence, similar to the approach of [6]. Considering that infectious substances may diffuse in the air after an accident, we incorporate the Gaussian plume model into the measurement of risk. Fig. 1 depicts a schematic diagram illustrating the Gaussian plum and the area of population

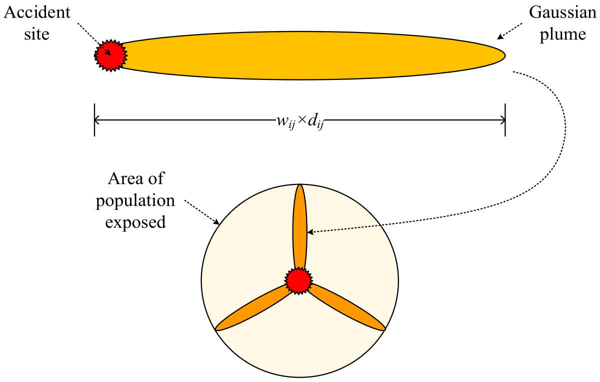


FIGURE 1. Schematic diagram of the diffusion.

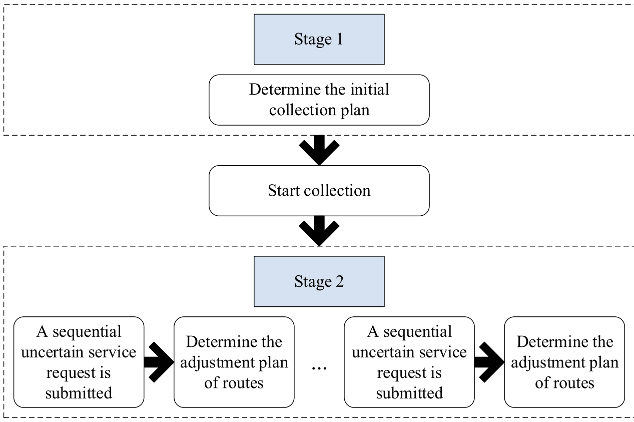


FIGURE 2. Two-stage decision-making process of the proposed problem.

exposed by transporting healthcare waste. Then, the following definitions are provided.

Definition 1: The area of population exposed if an accident occurs on $e(v_i, v_j)$ is $\pi w_{ij}^2 d_{ij}^2$.

Definition 2: The risk of transporting healthcare waste on $e(v_i, v_j)$ is $P_{ij} p_{ij} \rho_{ij} \pi w_{ij}^2 d_{ij}^2 u_i^k x_{ij}^k$.

For the temporary storing risk, similar to the approach of [4], the following definition is provided.

Definition 3: The temporary storing risk in hospital v_i is $\theta_i q_i (\sum_{k=1}^{K} t_i^k - t_i^S)$.

Finally, the total transport risk should be $\sum_{i\in V}\sum_{j\in V}\sum_{k=1}^{K} TR_{ij}^k = \sum_{i\in V}\sum_{j\in V}\sum_{k=1}^{K} P_{ij} p_{ij} \rho_{ij} \pi w_{ij}^2 d_{ij}^2 u_i^k x_{ij}^k$. The maximum temporary storing risk of each hospital should be $\max_i SR_i = \max_i \theta_i q_i (\sum_{k=1}^{K} t_i^k - t_i^S)$.

IV. TWO-STAGE DECISION-MAKING AND MATHEMATICAL MODELS

A. TWO-STAGE DECISION-MAKING

The proposed problem in the above section leads to a two-stage decision-making. Normally, the initial collection plan is arranged in advance. When the collection begins, the uncertain service requests will be submitted sequentially. The two-stage decision-making process is presented as Fig. 2. In Stage 1, the decision-makers need to determine the initial collection plan for the hospitals that have submitted service requests before the collection starts. In Stage 2, the decision-makers need to address the sequential uncertain service requests that the hospitals submitted during the collection procedure.

B. MATHEMATICAL MODELS

According to the service requests submitted by hospitals in V', the mathematical model to determine the initial collection plan in Stage 1 is developed as follows.

Model M**:**

$$\min f_1 = \min \sum_{i\in V}\sum_{j\in V}\sum_{k=1}^{K} TR_{ij}^k \tag{1}$$

$$\min f_2 = \min \max_i SR_i \tag{2}$$

$$s.t. \sum_{h\in V\backslash V''} x_{hi}^k = \sum_{j\in V\backslash V''} x_{ij}^k \quad (i \in V\backslash V''; k=1,2,\cdots,K) \tag{3}$$

$$\sum_{h\in V\backslash V''} x_{hi}^k = y_i^k \quad (i\in V'; k=1,2,\cdots,K) \tag{4}$$

$$\sum_{k=1}^{K} y_i^k = 1 \quad (i \in V') \tag{5}$$

$$\sum_{i\in V'} q_i y_i^k \le Q \quad (k=1,2,\cdots,K) \tag{6}$$

$$u_0^k = 0 \quad (k=1,2,\cdots,K) \tag{7}$$

$$u_i^k + q_j - u_j^k \le (1 - x_{ij}^k)M \quad (i\in V\backslash V''; j \in V'; k=1,2,\cdots,K) \tag{8}$$

$$t_0^k = 0 \quad (k=1,2,\cdots,K) \tag{9}$$

$$t_i^k + \frac{l_{ij}}{vol_{ij}} - t_j^k \le (1 - x_{ij}^k)M \quad (i\in V\backslash V''; j \in V'; k=1,2,\cdots,K) \tag{10}$$

$$TR_{ij}^k = P_{ij} p_{ij} \rho_{ij} \pi w_{ij}^2 d_{ij}^2 u_i^k x_{ij}^k \quad (i,j \in V\backslash V''; k=1,2,\cdots,K) \tag{11}$$

$$SR_i = \theta_i q_i (\sum_{k=1}^{K} t_i^k - t_i^S)(i \in V') \tag{12}$$

$$t_i^S = 0 \quad (i\in V') \tag{13}$$

$$\sum_{i\in W}\sum_{j\in W} x_{ij}^k \le |W| - 1 \quad (W \subseteq V'; k=1,2,\cdots,K) \tag{14}$$

$$u_i^k, t_i^k \ge 0 \quad (i \in V\backslash V''; k=1,2,\cdots,K) \tag{15}$$

$$x_{ij}^k, y_i^k \in \{0,1\} \quad (i,j \in V\backslash V''; k=1,2,\cdots,K) \tag{16}$$

Objective (1) minimizes the maximum transport risk. Objective (2) minimizes the maximum temporary storing risk. Constraint (3) imposes the stipulation that each vehicle cannot stay at each hospital without leaving and finally returns to the treatment center. Constraint (4) guarantees that a vehicle must visit a hospital in order to serve it. Constraint (5) guarantees that each hospital can only be served by one vehicle. Constraint (6) guarantees that the capacity of vehicles will not be exceeded. Constraints (7)-(8) represent the real-time loads of vehicles. Constraints (9)-(10) represent the relationships between time points. Constraints (11)-(13) are the expressions of risks. Constraint (14) forbids subtours. Constraints (15)-(16) show the ranges of decision variables.

For Stage 2, the service requests from $v_i \in V''$ are unable to be predicted in advance. We have conducted several interviews with healthcare waste collection companies in some major cities in China. It turns out that decision makers tend to reduce significant adjustments to the initial plan since the process is extreme complex and brings a lot of unnecessary trouble. For each uncertain service request that submitted during the collection procedure, it is preferable to adjust the route of one vehicle in the initial plan or arrange an additional vehicle.

Therefore, when an uncertain service request is submitted in Stage 2, we choose a vehicle from the initial routing plan or an additional vehicle, and insert the requested hospital into the route of this vehicle, as shown in Fig. 3. It is worth noting that all vehicles from the initial routing plan have already dispatched, thus their current position is not v_0.

Besides, due to the inevitable increase in transport risk caused by adjusting the routes, the optimization of Stage 2 aims to minimize total transport risk and ensure that it does not result in maximum temporary storing risk exceeding the result of Stage 1. Then, the hospital currently submitting service request is recorded as v_λ. The current position of each vehicle is recorded as v_0^k. Each unfinished part of route of each vehicle in the initial plan is recorded as $V_C^k = \{v_0^k, \cdots, v_0\}$. 0-1 variable $N_\lambda^k(v_i)$ is used that equals to 1 if v_λ is inserted after v_i in the route of vehicle k. $f_1^k(v_i)$ and $f_2^k(v_i)$ are used to represent the values of objective functions if v_λ is inserted after v_i in the route of vehicle k. The mathematical model in Stage 2 is shown as follows.

Model M':

$$\min f_3 = \min \sum_{i \in V_C^k} \sum_{k=1}^{K} f_1^k(v_i) N_\lambda^k(v_i) \tag{17}$$

$$s.t. \sum_{i \in V} \sum_{k=1}^{K} N_\lambda^k(v_i) = 1 \tag{18}$$

$$q_\lambda \sum_{i \in V} N_\lambda^k(v_i) + \sum_{j \in V'} q_j y_j^k \leq Q(k = 1, 2, \cdots, K) \tag{19}$$

$$\sum_{i \in V} f_2^k(v_i) N_\lambda^k(v_i) \leq f_2^* \quad (k = 1, 2, \cdots, K) \tag{20}$$

$$N_\lambda^k(v_i) \in \{0, 1\} \quad (i \in V; k = 1, 2, \cdots, K) \tag{21}$$

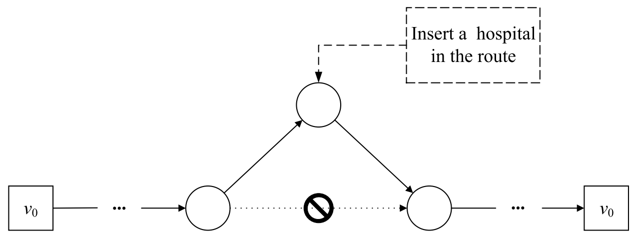


FIGURE 3. Schematic diagram of the adjustment of the route.

Objective (17) minimizes the total transport risk. Constraint (18) imposes the stipulation that v_λ can only be assigned to one vehicle. Constraint (19) guarantees that the capacity of vehicles will not be exceeded. Constraint (20) guarantees that the maximum temporary storing risk will not exceed f_2^*, where f_2^* is the maximum temporary storing risk of Stage 1. Constraint (21) shows the range of the decision variable.

V. SOLUTION ALGORITHMS

Given that the proposed problem involves a two-stage decision-making, different solution algorithms are designed in each stage, as shown in Fig. 4. In Stage 1, a bi-objective programming Model M needs to be solved. We develop an improved ε-constraint method to generate the entire Pareto front for small-scale instances, and Non-dominated Sorting Genetic Algorithm-II (NSGA-II) for large-scale instances. In Stage 2, a Compare-choose-move Algorithm is developed to deal with sequential uncertain service requests.

A. SOLUTION ALGORITHMS FOR STAGE 1

The ε-constraint method is an effective algorithm for exactly solving multi-objective programming. For a bi-objective programming model, the ε-constraint method can transform one objective into a constraint by ε, thereby obtaining a single objective model. By solving the single objective model multiple times under different values of ε, the Pareto front can be obtained [28]. Then, by further combining the ε-constraint method with an exact algorithm, all Pareto optimal solutions can be generated.

To generate the entire Pareto front of Model M, a few steps are necessary. Firstly, Model M requires linearization processing owing to its nonlinear characteristics. Secondly, some improvements to the ε-constraint method are added to accelerate the solution procedure.

1) LINEARIZATION PROCESSING

The nonlinearity of Model M is primarily attributed to Constraint (11) as it contains $u_i^k x_{ij}^k$. Thus, Constraint (11) will be substituted with a set of linear efficient inequalities. Since x_{ij}^k is a 0-1 variable, based on the numerical relationship between x_{ij}^k and u_i^k, we have the following proposition.

Proposition 1: $X_{ij}^k = u_i^k x_{ij}^k$ is equivalent to $X_{ij}^k \leq x_{ij}^k M$, $X_{ij}^k \leq u_i^k$, $X_{ij}^k \geq u_i^k - (1 - x_{ij}^k)M$, and $X_{ij}^k \geq 0$.

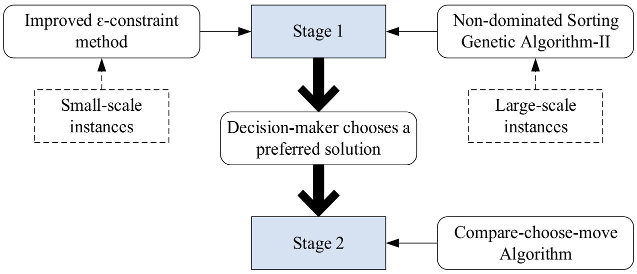


FIGURE 4. **Solution algorithms for different stages.**

Proof: Please see Appendix A.

Therefore, by integrating Proposition 1, we can replace Constraint (11) with a set of linear constraints, and have the following bi-objective linear programming model.

Model M^L:

$$\min f_1 = \min \sum_{i\in V}\sum_{j\in V}\sum_{k=1}^{K} TR_{ij}^k \tag{22}$$

$$\min f_2 = \min \max_i SR_i \tag{23}$$

s.t. Constraints(3) – (10) and (12) – (16).

$$TR_{ij}^k = P_{ij}p_{ij}\rho_{ij}\pi w_{ij}^2 d_{ij}^2 X_{ij}^k \quad (i,j\in V\backslash V''; k=1,2,\cdots,K) \tag{24}$$

$$X_{ij}^k \le x_{ij}^k M \quad (i,j\in V\backslash V''; k=1,2,\cdots,K) \tag{25}$$

$$X_{ij}^k \le u_i^k \quad (i,j\in V\backslash V''; k=1,2,\cdots,K) \tag{26}$$

$$X_{ij}^k \ge u_i^k - (1-x_{ij}^k)M \quad (i,j\in V\backslash V''; k=1,2,\cdots,K) \tag{27}$$

$$X_{ij}^k \ge 0 \quad (i,j\in V\backslash V''; k=1,2,\cdots,K) \tag{28}$$

2) FAST METHODS OF COMPUTING THE BOUNDS OF ε

The initial step in implementing the ε-constraint method is to transform Model M^L into a single objective Model M_0 with ε-constraint. Then, the lower and upper bounds of ε need to be computed before solving Model M_0 several times with different values of ε. Model M_0 is presented below. Generally speaking, the bounds of ε are generated by solving the following Model M_1 and Model M_2.

Model M_0:

$$\min f_1 = \min \sum_{i\in V}\sum_{j\in V}\sum_{k=1}^{K} TR_{ij}^k \tag{29}$$

s.t. Constraints (3) – (10) and (12) – (16), and (24) – (28).

$$\varepsilon \ge \max_i SR_i \tag{30}$$

Model M_1:

$$\min f_1 = \min \sum_{i\in V}\sum_{j\in V}\sum_{k=1}^{K} TR_{ij}^k$$

s.t. Constraints (3) – (10) and (12) – (16), and (24) – (28). (31)

Model M_2:

$$\min f_2 = \min \max_i SR_i$$

s.t. Constraints (3) – (10) and (12) – (16), and (24) – (28). (32)

Both Model M_1 and Model M_2 are NP-hard mixed integer programming models. The solution procedure for these models necessitates considerable computing times. This prompts us to propose an improved ε-constraint method, which notably circumvents the necessity of solving Model M_1 and Model M_2 in order to acquire the bounds of ε.

The lower bound of ε corresponds to the optimal solution of Model M_2. By analyzing $\max_i SR_i$, we derive the following property.

Property 1: The lower bound of $\max_i SR_i$ is $\max_i \theta_i q_i T^{SP}(v_0, v_i)$, where $T^{SP}(v_0, v_i)$ represents the travel time of the shortest path from v_0 to v_i.

Proof: Please see Appendix B.

Property 1 elucidates that $\max_i \theta_i q_i T^{SP}(v_0, v_i)$ is the lower bound of $\max_i SR_i$, and it is the lower bound f_2^L of f_2. Then, $f_2^L = \max_i \theta_i q_i T^{SP}(v_0, v_i)$. To compute $\max_i \theta_i q_i T^{SP}(v_0, v_i)$, the application of Dijkstra's algorithm is requisite, with a result computational time-complexity of $O(n^2)$. This approach is also a polynomial-time fast method. Though f_2^L is not a strict bound, it is also applicable.

For the upper bound f_2^U, we set $f_2^U = M$, where M is a large positive number. During the procedure of ε-constraint method, it may generate one dominated solution, and this solution will finally be deleted.

3) ENTIRE SOLUTION PROCEDURE

Based on the fundamental of the ε-constraint method, by integrating the above linearization processing and fast methods to compute the bounds of ε, the entire solution procedure of the improved ε-constraint method is proposed as follows, where ζ is a small enough positive number.

Step 1: Use linearization processing to obtain Model M^L.

Step 2: Transform Model M^L and obtain Model M_0.

Step 3: Use Dijkstra's algorithm to obtain f_2^L.

Step 4: Set $\varepsilon = f_2^U = M$, $F = \emptyset$.

Step 5: Solve Model M_0 and obtain the solution $(f_1(X), f_2(X))$. Merge $(f_1(X), f_2(X))$ into F. Set $\varepsilon = \varepsilon - \zeta$. If $\varepsilon \ge f_2^L$, turn to Step 5. Else, turn to Step 6.

Step 6: Delete dominated solutions from F. Output Pareto front F.

The above improved ε-constraint method is suitable for solving small-scale instances. Although its efficiency has been improved compared to the ε-constraint method without improvements. However, it is still necessary to solve Model M_0 multiple times throughout the entire solution procedure. Since Model M_0 is a NP-hard mixed integer programming model, the computational burden caused by this prompts us to lean towards using NSGA-II for dealing with large-scale instances. According to [29], the NSGA-II for solving Model M_0 is developed. Here, we will not introduce the entire procedure redundantly, and the specific parameter values for applying NSGA-II will be reported in Section VI.

B. COMPARE-CHOOSE-MOVE ALGORITHM FOR STAGE 2

In Stage 2, the decision-makers are confronted with the challenge of handling sequential uncertain service requests that cannot be predicted in advance. All relevant information is not available until a service request has been submitted. We design a Compare-choose-move (CCM) algorithm for addressing this issue.

1) EXECUTION PROCESS OF CCM ALGORITHM

The execution process of CCM algorithm is elucidated as follows. Assuming v_λ is inserted after v_i^k in the route of vehicle k, compute the values of objective functions $f_1^k(v_i)$ and $f_2^k(v_i)$. Check each insert point and find the one corresponding to $\min_i f_1^k(v_i)$ and $f_2^k(v_i) \leq f_2^*$. Record the values of objective functions as f_1^k and f_2^k.

Finally, compute and compare each f_1^k and f_2^k for different routes of vehicles. Until the insert point corresponding to $\min_k f_1^k$ and $f_2^k \leq f_2^*$ is found. Insert v_λ into this point and update the routes of vehicles. Whenever a new service request is submitted, record the corresponding hospital as v_λ, and repeat the above process. The schematic diagram of the CCM algorithm is shown in Fig. 5.

2) DETAILED STEPS OF CCM ALGORITHM

The detailed steps of CCM are proposed as follows. v_i^k represents the i^{th} vertex on the route of vehicle k. $TR^k[v_i, v_j, LOAD]$ represents the transport risk from v_i to v_j, where $LOAD$ is the load of the vehicle. $u(v_i)$ represents the current load of the vehicle leaving v_i. $SR^k[TIME, q_i]$ represents the temporary storing risk of v_i, where $TIME$ is the time it takes for v_i to receive the service. $t(v_i)$ represents the current time when the vehicle arrives at v_i. $T(v_i, v_j)$ represents the travel time from v_i to v_j.

Step 1: Set $\lambda = n+1, i = 0, k = 1$.

Step 2: Compute $TR_I^k = TR^k[v_i^k, v_\lambda, u(v_i^k)]$, $TR_{II}^k = TR^k[v_\lambda, v_{i+1}^k, u(v_i^k) + q_\lambda]$, and $TR_{III}^k = \sum_{h \geq i+1} TR^k[v_h^k, v_{h+1}^k, q_\lambda]$. Record $f_1^k(v_i^k) = f_1^* + TR_I^k + TR_{II}^k + TR_{III}^k$.

Step 3: Compute $SR_I^k = SR^k[t(v_i^k) + T(v_i^k, v_\lambda) - t_\lambda^S, q_\lambda]$, $SR_{II}^k = SR^k[t(v_i^k) + T(v_i^k, v_\lambda) + T(v_\lambda, v_{i+1}^k), q(v_{i+1}^k)]$, and $SR_{III}^k = \max_{h > i+1} SR^k[t(v_h^k) + T(v_i^k, v_\lambda) + T(v_\lambda, v_{i+1}^k), q(v_h^k)]$. Record $f_2^k(v_i^k) = \max\{f_2^*, SR_I^k, SR_{II}^k, SR_{III}^k\}$.

Step 4: If $f_2^k(v_i^k) \leq f_2^*$ and $f_1^k(v_i^k) < f_1^k$, set $f_1^k = f_1^k(v_i^k)$ and $f_2^k = f_2^k(v_i^k)$. If $v_{i+1}^k \neq v_0$, set $i = i+1$, turn to Step 2. Else, turn to Step 5.

Step 5: If $f_1^k < f_1'$, set $f' = f_1^k$. If $k < K$, set $k = k+1$ and $i = 0$, turn to Step 2. Else, turn to Step 6.

Step 6: Set $N_\lambda^k(v_i) = 1$ corresponds to f'. Output $N_\lambda^k(v_i)$. If $\lambda < n+m$, set $\lambda = \lambda + 1$, $i = 0$, and $k = 1$, turn to Step 2.

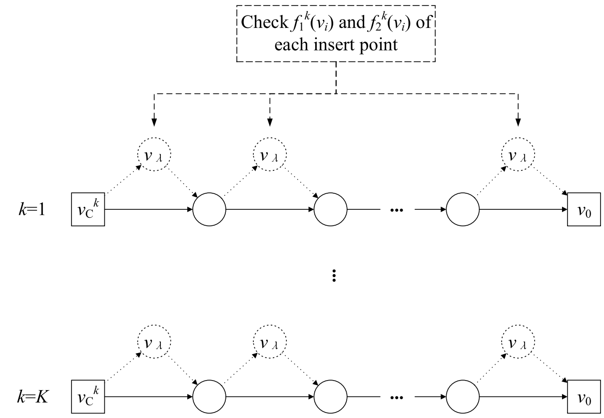


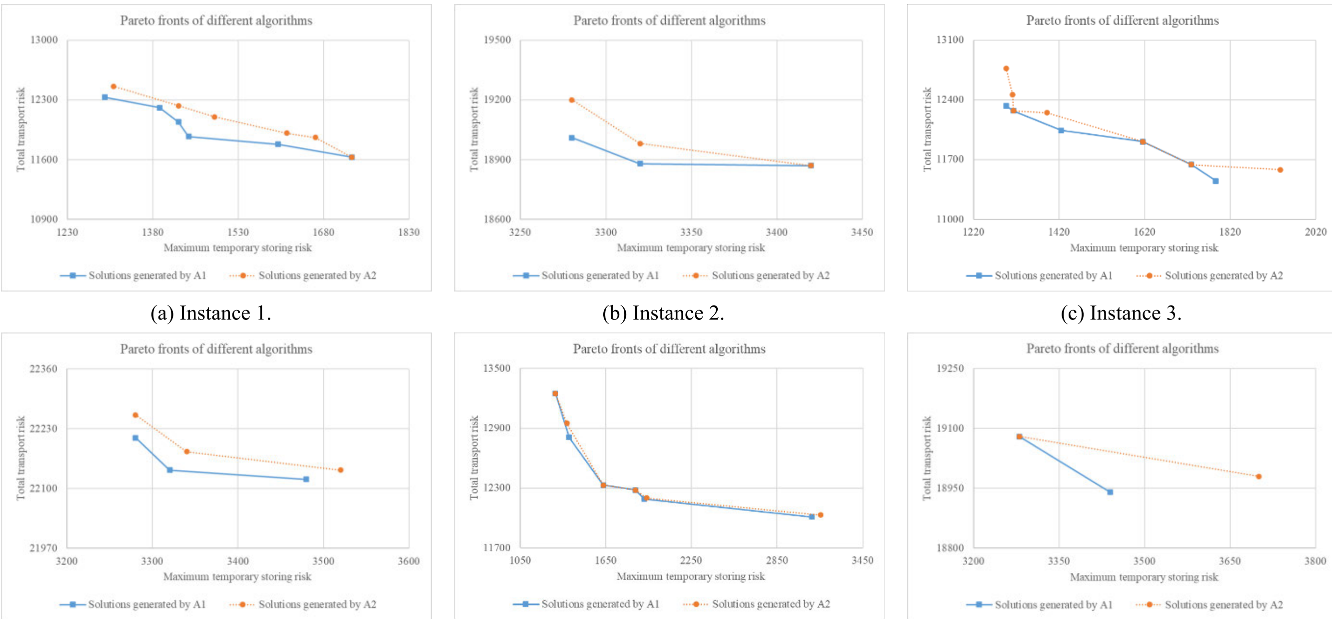
FIGURE 5. Schematic diagram of the CCM algorithm.

The computational time-complexity of Step 2 amounts to $O(n)$. The computational time-complexity of Step 3 amounts to $O(n)$. Given that the cyclic count of Step 2 to Step 4 is n, the computational time-complexity is $O(n^2)$. Furthermore, the cyclic count of Step 2 to Step 5 is n, the computational time-complexity is $O(n^3)$. Finally, the cyclic count of Step 2 to Step 6 is m, the computational time-complexity is $O(mn^3)$. Consequently, we can derive the following theorem.

Theorem 1: The computational time-complexity of CCM algorithm is $O(mn^3)$. CCM algorithm is a polynomial-time algorithm.

VI. NUMERICAL RESULTS

In this section, we test the proposed model and algorithms through numerical instances. A total of 12 instances are generated, stemmed from Solomon's instances, as shown in Table 2. Instances 1-6 are small-scale and can be exactly solved, while Instances 7-12 are relevant large-scale. The positions of vertexes in the networks of Solomon's instances are retained for our instances, but a part of vertexes is set to V' and the other part to V''. The values of each q_i are aligned with those presented in Solomon's instances, and the value of Q is set to 100. Furthermore, we adopted various parameters from the context of Xi'an, a large city in western China. Specifically, $w_{ij} = 1.8$m/s is set according to the average wind speed in Xi'an city. $d_{ij} = 30$minand $P_{ij}p_{ij} = 0.081\%$ are configured based on the Statistical Yearbook published by the local government, and each θ are randomly generated between [0.5, 1.5]. What is more special is the times when hospitals $v_i \in V''$ submit service requests. We randomly generate a set of service requests for hospitals $v_i \in V''$, which remain unknown during the decision-making process and are submitted sequentially. All used solution algorithms are programed by Microsoft Visual Studio 2017 and CPLEX Ver. 12.6. For applying NSGA-II, the population size is set to $N = 500$, the number of iterations is set to $gen_{\max} = 1000$, and the probabilities of cross and mutation are set to



(a) Instance 1. (b) Instance 2. (c) Instance 3.
(d) Instance 4. (e) Instance 5. (f) Instance 6.

FIGURE 6. Generated solutions of different algorithms.

$P_C = 0.8$ and $P_M = 0.05$, respectively. For each instance, each program will run 10 times and take the average value.

A. TESTING AND ANALYSIS OF SOLUTION ALGORITHMS

The efficacy of the proposed solution algorithms is tested. For the convenience of representation, "A1" is designated for the approach integrating the improved ε-constraint method in Stage 1 and the CCM algorithm in Stage 2. Similarly, "A0" signifies the method employing the ε-constraint method without improvements in Stage 1 and the CCM algorithm in Stage 2. Lastly, "A2" denotes the method implementing the NSGA-II in Stage 1 and the CCM algorithm in Stage 2. Applying A1, A0, and A2 on Instances 1-12 yields distinct computing times, as shown in Table 3.

It can be seen that the computing times of A1 are significantly shorter than those of A0. Specifically, the average computing time of A1 is only 68.61% of the computing time of A0. This indicates that the improvements of the ε-constraint method has indeed accelerated the solution procedure. Moreover, as we can also see from Table 3, the computing times of A2 are shorter than those of A1, and both A1 and A0 cannot solve Instances 7-12 within reasonable times. But A2 cannot provide exact solutions, as can be seen from the Pareto fronts shown in Fig. 6.

Table 4 shows several indicators for different algorithms, including the number of generated solutions, coincident points on the Pareto front, and maximum difference between the solutions generated by A2 and A1. The average maximum difference on f_1 and f_2 are 0.60% and 1.35%, demonstrating that the performance of A2 is not bad. Therefore, the solution framework shown in Fig. 4 and the proposed solution

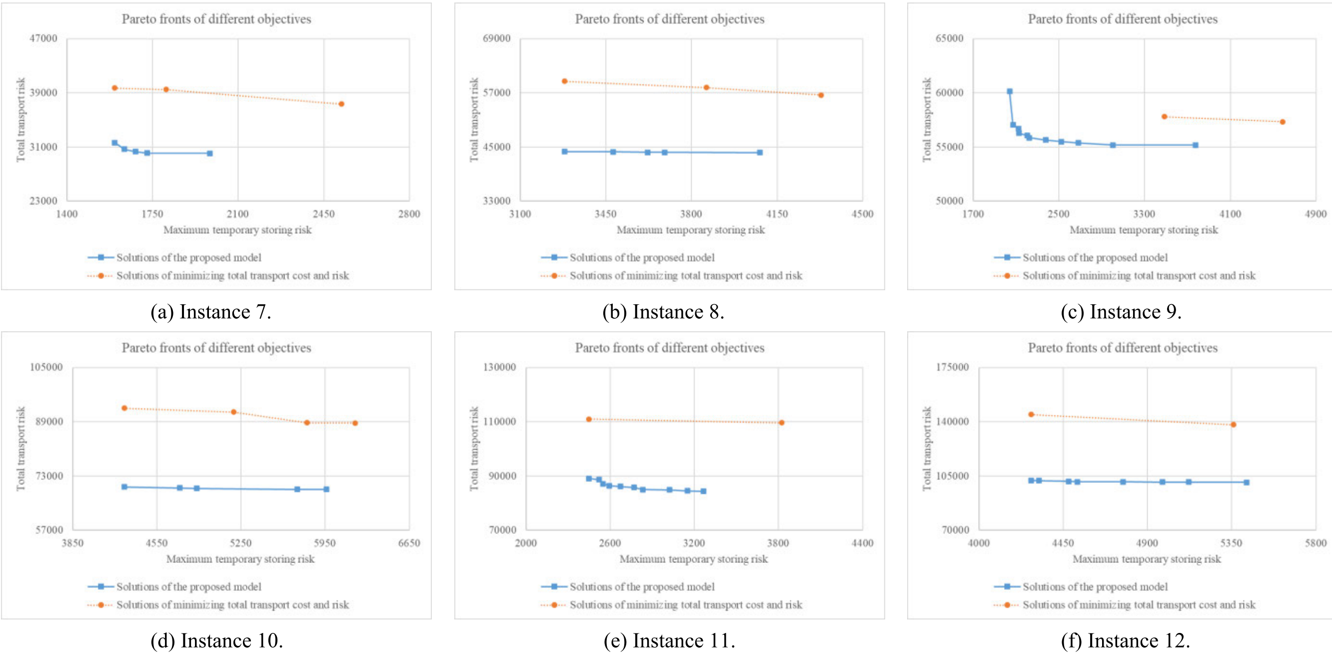
TABLE 2. Sources of instances.

No.	Source	$\lvert V' \rvert$	$\lvert V'' \rvert$
1	$v_0 - v_{17}$ of R101	12	5
2	$v_0 - v_{17}$ of RC101	12	5
3	$v_0 - v_{17}$ of R102	12	5
4	$v_0 - v_{17}$ of RC102	12	5
5	$v_0 - v_{17}$ of R103	12	5
6	$v_0 - v_{17}$ of RC103	12	5
7	$v_0 - v_{40}$ of R101	30	10
8	$v_0 - v_{40}$ of RC101	30	10
9	$v_0 - v_{65}$ of R102	50	15
10	$v_0 - v_{65}$ of RC102	50	15
11	R103	80	20
12	RC103	80	20

algorithms can solve both small-scale and large-scale instances effectively.

B. COMPARATIVE ANALYSIS WITH OTHER MODEL

In order to verify the effectiveness of the proposed model, we compared and analyzed our model in Section IV with another model. We have chosen a traditional model for hazardous waste collection, where the two objectives of the model are the minimization of total transport cost and risk respectively. The expression of total transport cost is



(a) Instance 7. (b) Instance 8. (c) Instance 9.

(d) Instance 10. (e) Instance 11. (f) Instance 12.

FIGURE 7. Generated solutions of different objectives.

TABLE 3. Computing times of different algorithms.

No.	Computing times (second)			Ratio between computing times	
	A0	A1	A2	A1 / A0	A2 / A1
1	161	130	96	80.75%	73.85%
2	155	115	106	74.19%	92.17%
3	224	158	92	70.54%	58.23%
4	303	173	96	57.10%	55.49%
5	212	137	96	64.62%	70.07%
6	211	136	95	64.45%	69.85%
7	-	-	151	-	-
8	-	-	154	-	-
9	-	-	284	-	-
10	-	-	286	-	-
11	-	-	442	-	-
12	-	-	432	-	-
			Average ratio	68.61%	69.94%

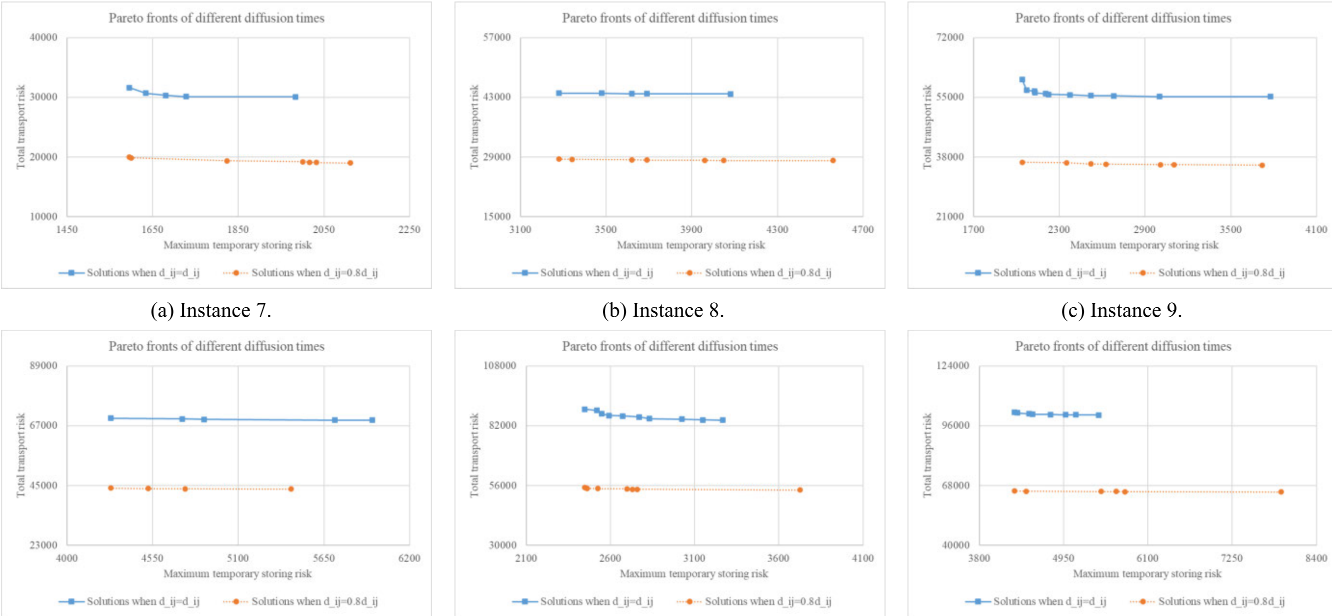
TABLE 4. Indicators for the results of different algorithms.

No.	Number of generated solutions		Coincident points on the Pareto front	Maximum difference between the solutions generated by A2 and A1	
	A1	A2		f_1	f_2
1	6	6	1	0.76%	1.55%
2	3	3	1	1.51%	0.00%
3	6	7	3	0.85%	1.56%
4	3	3	0	0.14%	0.58%
5	6	6	3	0.21%	0.65%
6	2	2	1	0.11%	3.78%
7	-	5	-	-	-
8	-	5	-	-	-
9	-	11	-	-	-
10	-	5	-	-	-
11	-	10	-	-	-
12	-	8	-	-	-
			Average difference	0.60%	1.35%

$\sum_{i \in V} \sum_{j \in V} \sum_{k=1}^{K} l_{ij} x_{ij}^k$. After replacing $\max_i SR_i$ in the proposed model in Section IV with $\sum_{i \in V} \sum_{j \in V} \sum_{k=1}^{K} l_{ij} x_{ij}^k$, we have also prepared NSGA-II and CCM algorithm for generating the solutions. All algorithms that involve temporary storing risks have been replaced with transport costs.

The results of our proposed model and the model that minimizes total transport cost and risk are shown in Fig. 7. Although the objectives of the two models are different, we still show the values of total transport risk and maximum temporary storing risk corresponding to each solution in Fig. 7. It can be seen that there is a significant difference in the corresponding values of total transport risk and maximum temporary storing risk between the two sets of results.

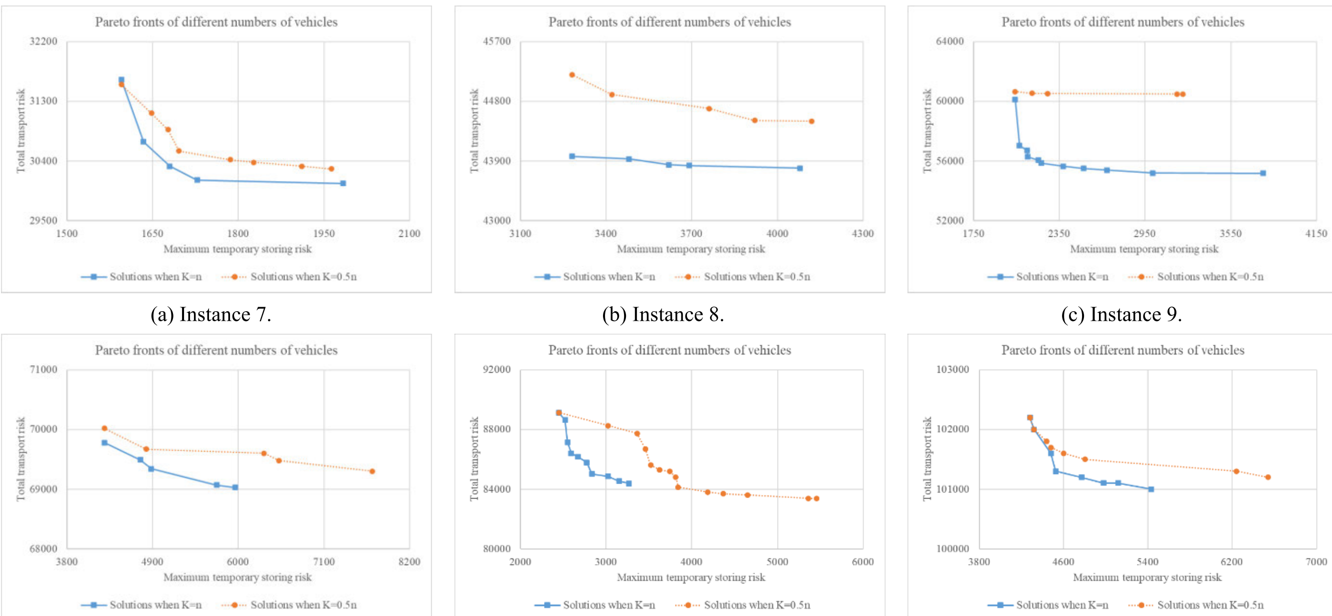
For a comprehensive comparison, we calculated the average values of total transport risk and maximum temporary storing risk of different series of results for each instance, as shown in Table 5. It is evident that the average total transport risk and average maximum temporary storing risk of the solutions of the proposed model are both lower. The average ratios of two kinds of risks are 79.74% and 87.63% respectively. This indicates that through our proposed model, total transport risk and maximum temporary storing risk can be effectively reduced.



(a) Instance 7. (b) Instance 8. (c) Instance 9.

(d) Instance 10. (e) Instance 11. (f) Instance 12.

FIGURE 8. **Generated solutions of different diffusion times.**



(a) Instance 7. (b) Instance 8. (c) Instance 9.

(d) Instance 10. (e) Instance 11. (f) Instance 12.

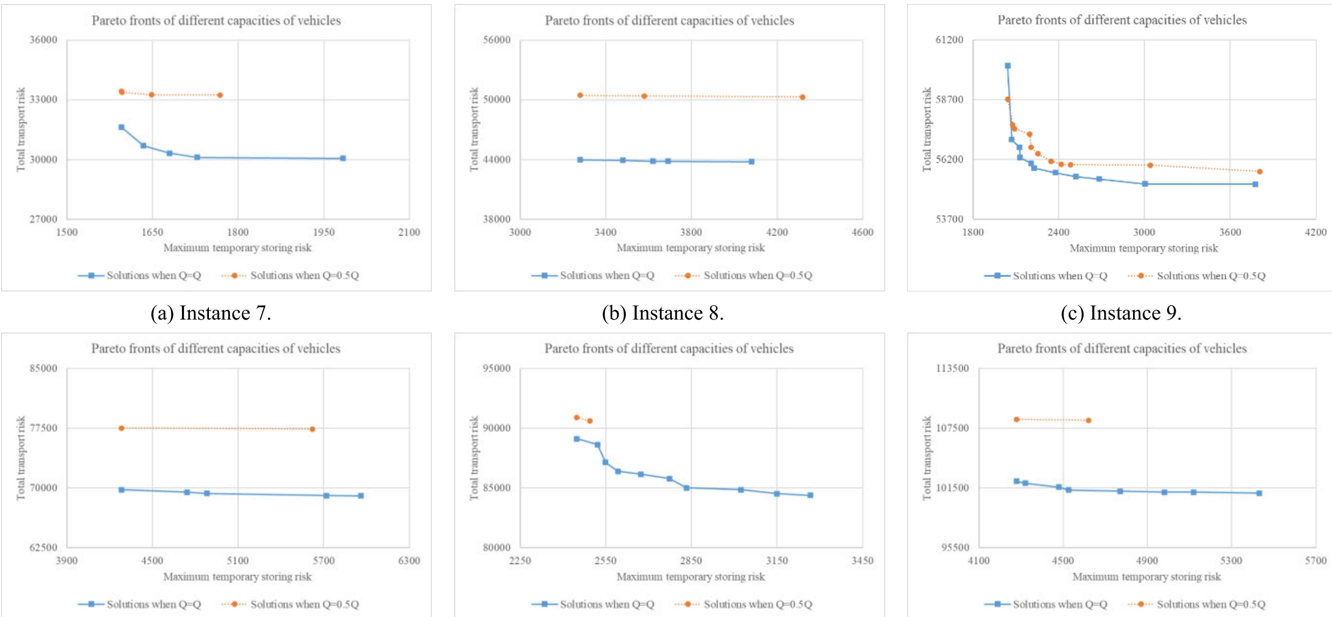
FIGURE 9. **Generated solutions of different numbers of vehicles.**

C. SENSITIVITY ANALYSIS

1) ANALYSIS OF DIFFERENT RISK RELATED PARAMETERS

The local government can reduce the risks of healthcare waste collection with a commonly employed approach which is to reduce diffusion times. By investing resources and improving management skills, rescue teams can expedite their arrival at the accident sites, thereby reducing diffusion time and risks. We reduce the diffusion times by 20% and compute the results, as shown in Fig. 8.

It can be seen from Fig. 8 that transport risks can be significantly reduced by reducing diffusion times. At the same time, there are instances wherein the concurrent mitigation of maximum temporary storing risk is achieved. The risk reduction requires allocation of limited resources, and the



(a) Instance 7. (b) Instance 8. (c) Instance 9.

(d) Instance 10. (e) Instance 11. (f) Instance 12.

FIGURE 10. Generated solutions of different capacities of vehicles.

TABLE 5. Average objective values of different results.

No.	Average total transport risk		Average maximum temporary storing risk	
	Solutions of the proposed model	Solutions of minimizing total transport cost and risk	Solutions of the proposed model	Solutions of minimizing total transport cost and risk
7	30562	38843	1724	1975
8	43872	58087	3630	3823
9	56267	57570	2468	4037
10	69342	90540	5116	5368
11	86209	110300	2783	3135
12	101438	141400	4738	4820
	Average ratio	79.75%	Average ratio	87.63%

efficacy associated to the reduction of diffusion times is a good choice.

2) ANALYSIS OF DIFFERENT NUMBERS OF VEHICLES

Healthcare waste collection, especially during outbreaks of infectious diseases, often encounters constraints in terms of vehicle availability. Thus, we evaluate varied numbers of vehicles and attempt to explore the impact of varying vehicle numbers on the results. We have computed the results of halving the number of vehicles, as shown in Fig. 9.

The Pareto fronts in Fig. 9 denote that when the numbers of vehicles decrease, there is a pronounced escalation in both the transport risk and temporary storing risk. This phenomenon indicates that the numbers of vehicles have a significant impact on risks. It is very necessary to ensure an adequate number of vehicles or at least to prepare as many vehicles as possible when conducting healthcare waste collection.

3) ANALYSIS OF DIFFERENT CAPACITIES OF VEHICLES

In reality, there may be more than one type of vehicles available for healthcare waste collection. Thus, we evaluate varied capacities of vehicles and present the results, as depicted in Fig. 10. It is anticipated that an increase in the capacities of vehicles should bring about a reduction in associated risks. Because larger-capacity vehicles can bring more feasible routes, thereby facilitating the computation of a more optimal solution.

However, a nuanced analysis of the obtained results in Fig. 10 reveals that a correlation between increased capacities of vehicles and risk reduction does not hold universally. It is likely that the routes capable of serving more hospitals with a larger capacity of vehicles will lead to higher temporary storing risk. Hospitals situated at the extremities of these routes inevitably encounter prolonged waiting periods, so these routes are less effective under the influence of mitigating temporary storing risk. Furthermore, a comprehensive deliberation of healthcare waste collection necessitates the inclusion of economic factors, as the deployment of distinct vehicular configurations aligns with divergent cost structure. Therefore, it is incumbent upon decision-makers to diligently populate the model with the requisite parameters for all optional vehicles, compute the results and ultimately select the most appropriate vehicle type.

VII. CONCLUSION

Healthcare waste is a type of waste with highly infectious risk, and the effective disposal of healthcare waste is a highly concerned issue. Healthcare waste collection poses transport risk and temporary storing risk, and the strategic deliberation undertaken by decision-makers concerning waste collection entails potential scenario wherein some hospitals have not yet submitted their service requests which may be submitted during the collection procedure. The route of collection vehicles is the key to safe and efficient healthcare waste collection. A routing optimisation problem for healthcare waste collection with temporary storing risks and sequential uncertain service requests is introduced. The goal of this problem is to determine the routes for healthcare waste collection, with the aims of minimizing the total transport risk and the maximum temporary storing risk of each hospital simultaneously.

A two-stage decision-making for the problem is proposed. The decision-makers determine the initial collection plan for the hospitals that have submitted service requests before starting collection in Stage 1, and address the sequential uncertain service requests that the hospitals submitted during the collection procedure in Stage 2. The mathematical models for both stages are developed. Different solution algorithms are proposed. In Stage 1, an improved ε-constraint method to generate the entire Pareto front for small-scale instances, and NSGA-II for large-scale instances are proposed. In Stage 2, a Compare-choose-move Algorithm is developed to deal with sequential uncertain service requests and generate the route of the additional vehicles.

The results of testing the solution algorithms with a series of instances show that the proposed solution algorithms can solve both small-scale and large-scale instances effectively. And a comparison between the proposed model and another model is conducted. Through the analysis of risk related parameters, we find that the local government should reduce diffusion times so as to improve the healthcare waste collection risk management efficiently. Through the analysis of different numbers of vehicles, we find that it is very necessary to ensure an adequate number of vehicles or at least to prepare as many vehicles as possible. Through the analysis of different capacities of vehicles, we find that a correlation between augmented capacities of vehicles and risk reduction is not universally applicable and choosing appropriate vehicle type is necessary.

Future research can expand the work in this paper from two aspects. First, developing more realistic risk measurements and combining them with sequential uncertain service requests in healthcare waste collection can be considered in the future. Second, the healthcare waste collection procedures in some cities include transit stations. Researches with the consideration of transit stations is one of the future directions.

APPENDIX A
PROOF OF PROPOSITION 1

If $x_{ij}^k = 0$, then we have $X_{ij}^k \leq x_{ij}^k M \Rightarrow X_{ij}^k \leq 0$, and $X_{ij}^k \geq 0$. The value of X_{ij}^k in this case can only be equal to 0.

If $x_{ij}^k = 1$, then we have $X_{ij}^k \leq u_i^k$, and $X_{ij}^k \geq u_i^k - (1 - x_{ij}^k)M \Rightarrow X_{ij}^k \geq u_i^k$. The value of X_{ij}^k in this case can only be equal to u_i^k.

To sum up, this set of linear inequalities can replace $X_{ij}^k = u_i^k x_{ij}^k$ in all cases.

APPENDIX B
PROOF OF PROPERTY 1

SR_i is the temporary storing risk of hospital v_i, and $SR_i = \theta_i q_i (\sum_{k=1}^{K} t_i^k - t_i^S) = \theta_i q_i \sum_{k=1}^{K} t_i^k$. Obviously, when a vehicle starts from v_0 and chooses the shortest path directly to reach v_i, hospital v_i has the shortest waiting time for the service.

Then, the lower bound of $\max_i SR_i$ should be $\max_i \theta_i q_i T^{SP}(v_0, v_i)$, where $T^{SP}(v_0, v_i)$ represents the travel time along the shortest path from v_0 to v_i.

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MENG ZHANG received the B.S. degree in engineering management from the Jiangsu University of Science and Technology, in 2011, the M.S. degree in logistics engineering from Xi'an Technological University, in 2014, and the Ph.D. degree in management science and engineering from Xi'an Jiaotong University, in 2019.

From 2019 to 2022, he was a Lecturer and a Postdoctoral Fellow with Xi'an Jiaotong University. He is currently an Associate Professor with the School of Economics and Management, Xi'an Technological University. He has authored two books and more than 20 articles in peer-reviewed academic journals, including IEEE Transactions on Intelligent Transportation Systems, *Transportation Research Part E: Logistics and Transportation Review*, IEEE Transactions on Engineering Management. His research interests include hazardous materials transportation and logistics system optimization.

WEI CUI received the B.S. degree in measurement and control technology and instruments from Xidian University, in 2004, and the M.S. degree in signal and information processing from the Xi'an Institute of Optics and Precision Mechanics of CAS, in 2007. He is currently pursuing the Ph.D. degree with the School of Management, Xi'an Jiaotong University.

He has authored two articles in peer-reviewed academic journals. His research interests include healthcare waste collection and multi-objective optimization.

QI JIANG received the B.S. degree in English and the M.S. degree in English language and literature from Hunan Normal University, in 2010 and 2013, respectively. She is currently pursuing the Ph.D. degree with the School of Management, Xi'an Jiaotong University.

From 2013 to 2019, she was a Lecturer with the Hunan Institute of Technology. She has authored a book and more than five articles in peer-reviewed academic journals, including *Expert Systems with Applications* and *International Journal of Information Management*. Her research interests include risk management and supply chain operations.

NENGMIN WANG received the B.S. degree in investment economy and the M.S. degree in management science and engineering from the Central South University of Technology, in 1997 and 2000, respectively, and the Ph.D. degree in management science and engineering from Xi'an Jiaotong University, in 2003.

He is currently a Professor with the School of Management, Xi'an Jiaotong University. He has authored five books and more than 70 articles in peer-reviewed academic journals, including IEEE Transactions on Intelligent Transportation Systems, *European Journal of Operational Research*, and *International Journal of Production Research*. His research interests include sustainable operation management and supply chain management.