scientific reports

OPEN

Fuzzy optimization of municipal solid waste collection routing under uncertain emissions

Yuxiao Zhang[1], Yuhan Wei[2], Bokai Zhang[1], Yichen Wu[1] & Shuai Pan[3]✉

The uncertainty in municipal solid waste (MSW) emissions poses significant challenges to collection and transportation operations, causing vehicles to be under-loaded or overloaded; in some cases, waste may not be cleared in a timely manner, thereby affecting residents' quality of life. To study the impact of uncertain waste emissions on MSW operations, this paper investigates the MSW vehicle routing problem from a fuzzy programming perspective. Firstly, based on fuzzy credibility theory, trapezoidal fuzzy numbers are introduced to represent the waste emissions at collection points, and a multi-depot MSW routing optimization model is formulated to minimize operational cost while incorporating the decision maker's subjective preference constraints. Then, an improved adaptive large neighborhood search algorithm (ALNS-TS) is developed by combining 12 neighborhood criteria with a tabu search (TS) mechanism to enhance global search capability. Subsequently, case studies compare routing schemes under deterministic and uncertain emissions, evaluate multiple intelligent optimization algorithms in terms of solution quality and computational efficiency, and conduct a sensitivity analysis with respect to the subjective preference values. Finally, specific and effective managerial recommendations are provided to support practical decision-making in MSW collection and transportation operations. This study effectively addresses the challenges posed by uncertain waste emissions and offers value for MSW managers.

Keywords Municipal solid waste, Vehicle routing optimization, Fuzzy programming, Uncertain emissions

Municipal solid waste (MSW) refers to various types of waste generated from the daily activities of urban residents. Its main sources include households, shopping malls, the catering industry, and public places, and it is characterized by large quantities and wide distribution[1,2]. As urbanization progresses, the amount of MSW continues to increase, leading to greater challenges in the MSW collection and transportation process[3]. In 2023, over 2 billion tons of MSW were generated globally, and by 2050, it is expected to reach 3.8 billion tons[4]. Therefore, the efficient MSW collection and transportation process is crucial for residents' quality of life, environmental protection, and sustainable urban development.

However, due to factors such as public events, holidays, emergencies, and weather conditions, waste emissions are often characterized by significant uncertainty. This uncertainty brings challenges to the MSW collection and transportation process, which can result in collection vehicles being either under-loaded or overloaded; in some situations, waste may not be cleared in a timely manner, thereby affecting residents' quality of life. These challenges are particularly evident in China, where the MSW collection and transportation process lags the waste treatment process by about 10 years[5,6]. Furthermore, the China Association of Circular Economy has pointed out that the cost of the MSW collection and transportation process accounts for 60% to 70% of the total waste management expenditure[6]. For instance, the total cost for processing one ton of waste is 400 RMB, of which 300 RMB is attributed to the MSW collection and transportation process in Shanghai[6]. Therefore, studying the MSW vehicle routing optimization from a fuzzy programming perspective is essential for enhancing waste management efficiency, reducing operational cost, and improving residents' quality of life in urban areas.

Although existing research has made many efforts in the MSW vehicle routing optimization problem, it typically sets waste emissions as constant values, thereby overlooking the impact of uncertain waste emissions on the collection and transportation process[7–10]. This neglect may lead to improper route plans, thereby reducing the management quality of the MSW collection and transportation process. Specifically, the remaining load capacity of collection vehicles may not be sufficient to satisfy the waste emissions at the next collection point, leading to

[1]School of Economics and Management, Beijing Jiaotong University, Beijing 100044, People's Republic of China. [2]School of International Economics and Trade, Lanzhou University of Finance and Economics, Lanzhou 730101, People's Republic of China. [3]School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, People's Republic of China. ✉email: halo0710@bjtu.edu.cn

the failure of the collection and transportation operation. This not only increases the additional transportation distance and operational cost of the MSW collection and transportation process, but more importantly, it is highly likely to result in the failure to clean up waste at the collection points in a timely manner, affecting the quality of life of residents. Recently, some studies have characterized the uncertain waste emissions using methods such as stochastic programming and fuzzy programming[11–13]. For example, stochastic programming methods fit historical data to a probability distribution, converting uncertain waste emissions into deterministic values, but this requires a large amount of historical data, which limits its practical applicability[14–16]. As for fuzzy programming methods, they mainly include triangular fuzzy numbers and trapezoidal fuzzy numbers[17,18]. Among them, the membership function curve of triangular fuzzy numbers is triangular, which can only represent the most likely value with a single point[19–21]. This makes it less flexible, with weaker adaptability, and unable to accurately reflect the changes in uncertainty in real-world problems. In contrast, trapezoidal fuzzy numbers effectively address the limitations of triangular fuzzy numbers[22]. However, surprisingly, few studies have used trapezoidal fuzzy numbers to characterize the uncertain waste emissions. Therefore, the impact of uncertain waste emissions on the MSW vehicle routing optimization problem remains underexplored. Further research is urgently needed to address the gap.

Moreover, the MSW vehicle routing optimization problem has NP-hard properties, with complex constraints, and uncertain waste emissions further increase the problem's complexity, expanding the solution space and raising the difficulty of finding an optimal solution. Therefore, exact algorithms struggle to find high-quality solutions within a reasonable time, while traditional heuristic algorithms, due to the lack of dynamic adjustment mechanisms, find it difficult to balance exploration and exploitation of the solution space, often leading to getting stuck in local optima when solving complex optimization problems[23]. Notably, ALNS is a powerful heuristic algorithm that, by combining various neighborhood criteria with adaptive mechanisms, can flexibly and efficiently handle optimization problems with high complexity and large solution spaces[24]. As a result, it is widely applied to solve complex combinatorial optimization problems[25]. However, ALNS searches based on the neighborhood of the current solution. If the neighborhood is limited or lacks a mechanism to escape, it may remain near a local optimum and fail to find the global optimum, making it prone to getting stuck in a local optimum[26,27]. Therefore, improving ALNS to effectively solve the problem remains a challenge.

Compared with previous studies, this research offers three main advantages. First, rather than assuming deterministic emissions or relying on data-intensive probabilistic fitting, we model uncertain MSW emissions using trapezoidal fuzzy numbers and incorporate the decision maker's subjective preference, enabling an explicit trade-off between operational cost and service reliability while capturing "uncertain yet relatively stable" emission patterns under limited data. Second, to solve the resulting NP-hard problem, we develop a tailored ALNS-TS algorithm with 12 neighborhood criteria and a tabu mechanism, which enhances global exploration, robustness, and efficiency under complex constraints and uncertainty. Third, extensive computational experiments compare uncertain vs. deterministic routing, benchmark against alternative heuristics, and conduct sensitivity analysis on preference levels, thereby validating the proposed model and algorithm and yielding actionable managerial recommendations for MSW collection and transportation operations.

The main innovations and contributions of this study are directly aligned with the gaps identified in the existing literature.

(1) Introduction of trapezoidal fuzzy numbers to characterize waste emissions. Given the fluctuations in waste emissions at collection points due to various real-life factors, the introduction of trapezoidal fuzzy numbers provides a more accurate representation of waste emissions, better capturing the uncertainty and variability in the real-world problem.
(2) ALNS-TS — an efficient solving algorithm for the problem. This paper proposes an improved ALNS that includes 12 neighborhood criteria and incorporates a tabu search mechanism for further optimization. The method effectively prevents the emissions of duplicate solutions through TS, enhancing the diversity of the solution space and improving the global search capability.
(3) Providing theoretical support and solutions for MSW management fields. By accurately reflecting waste emissions, rather than simply treating them as constants, this study provides a robust and practical decision-support for MSW managers. In particular, it offers specific and effective managerial recommendations to support decision-making in MSW collection and transportation operations, while also contributing to the literature on MSW collection and transportation processes.

Literature review
Waste vehicle routing optimization problem
The waste vehicle routing optimization problem has attracted widespread attention from scholars over the past few decades. Hou et al. [7] studied the e-waste recycling vehicle routing problem, considering factors such as vehicle maximum load and recycling station closing time, and developed an optimization model to minimize transportation cost for recycling order routes. Li et al. [8] addressed the vehicle routing problem for urban solid waste collection and transportation under carbon emission conditions, developing a multi-objective mathematical model to minimize operational cost and differences in employee workload. Wang et al. [9], to improve construction waste transportation efficiency and reduce carbon emissions, proposed a dynamic time-dependent green vehicle routing problem for decoration waste collection, aiming to minimize fuel cost. Hu et al. [10] explored the vehicle routing optimization problem for household medical waste logistics, considering the leakage risks of medical waste, and developed a model to minimize transportation cost and environmental pollution. However, despite the significant contributions of these studies to the waste vehicle routing optimization problem, they overlook the fact that, under real-world conditions, waste emissions are influenced by multiple factors, such as

public events, holidays, emergencies, and weather conditions, leading to uncertain emissions. Simply setting waste emissions as constant values limits the applicability of these models to complex real-world problems.

Fortunately, Vu et al. [11] adopted an artificial neural network prediction model to forecast the waste emissions at collection points, aiming to find the shortest waste collection route. Qin et al. [12] assumed that the uncertain demand follows a normal distribution and established a vehicle routing optimization model aimed at minimizing operational cost. Zhang et al. [13] fitted the distribution characteristics of historical data samples to a Gaussian distribution function and established a distributed robust vehicle routing model applicable under uncertain conditions. Oteng et al. [14] used a Weibull distribution model to predict photovoltaic waste in South Australia over the next 30 years, and developed a related waste collection vehicle routing optimization model aimed at minimizing pollutant generation. Similarly, Higuchi and Isobe[15], Wang et al. [16], also used probability distribution functions to predict uncertainty. However, the use of stochastic programming methods to fit probability distributions or the application of neural networks typically requires a large amount of historical data, which clearly limits the widespread application of these methods in practice. On the other hand, Yang et al. [17] addressed the vehicle routing problem for waste collection with uncertain demand by proposing triangular fuzzy numbers to represent the recycling demand and establishing a vehicle routing optimization model aimed at minimizing operational cost. Avila-Torres and Arratia-Martinez[18] addressed the priority recycling route problem under uncertain conditions by using triangular fuzzy numbers to describe uncertain demand and developed a fuzzy mixed-integer linear programming model. Likewise, Bahri et al. [19], Sharma et al. [20], and Mahmoodirad et al. [21] also used triangular fuzzy numbers to represent uncertain demand. However, triangular fuzzy numbers, due to their triangular membership function and the use of a single point to represent the most likely value, lack flexibility in representing uncertainty, have poor adaptability, and fail to accurately reflect the dynamic changes in fuzziness in real-world problems[22]. Here, to facilitate a clear comparison, Table 1 summarizes how emissions/demands are represented in the related literature. Therefore, how to effectively study the impact of uncertain waste emissions on the MSW vehicle routing optimization problem remains an urgent research gap that needs to be addressed.

Solution method

With the continuous development of heuristic methods, research on heuristic algorithms in vehicle routing problems has been increasing. For example, common algorithms include genetic algorithm (GA), ant colony optimization (ACO), particle swarm optimization (PSO), and simulated annealing (SA). Specifically, Ouertani et al. [28] solved the multi-compartment vehicle routing problem for health-care waste transportation using an improved GA. Roy et al. [29] used an improved ACO to address the vehicle routing problem for collecting Internet-of-Things-based smart waste bins. Likewise, Peña et al. [30] employed an ACO to solve a sustainable two-stage waste collection routing problem. Salawudeen et al. [31] adopted an improved PSO to optimize waste collection routes for the Ogun State Waste Management Agency. Furthermore, Yu et al. [32] utilized an improved SA to solve the multi-depot waste collection vehicle routing problem with time windows and self-delivery options. These algorithms have been widely applied in the waste management field and have demonstrated strong performance. However, the MSW vehicle routing optimization problem, due to complex constraints and uncertain waste emissions, increases the problem's complexity, expands the solution space, and raises the difficulty of finding an optimal solution. Therefore, traditional heuristic algorithms have difficulty balancing exploration and exploitation of the solution space, often leading to getting stuck in local optima or even failing to find a solution. Notably, ALNS performs local optimization of solutions in multiple neighborhoods through iterative processes, using an adaptive mechanism to select and adjust the neighborhood structure[24]. By dynamically adjusting the search strategy based on historical search experience, ALNS improves the quality of the solutions[24]. For example, Chen et al. [33] successfully used ALNS to solve the multi-compartment vehicle routing problem in cold chain distribution. Wang et al. [25] applied ALNS to address the dynamic vehicle routing problem with time windows in multiple depots. Likewise, Liu et al. [34], Voigt et al. [35], as well as Bustos-Coral and Costa[36], also applied ALNS to solve various vehicle routing problems.

However, recently, Akpunar and Akpinar[26] pointed out that when solving complex combinatorial optimization problems, if the neighborhood is limited or lacks a mechanism to escape, ALNS may remain near a local optimum and fail to find the global optimum, making it prone to getting stuck in a local optimum.

Category	References	Emissions/demand representation	Typical data requirement	Main limitation
Deterministic	Hou et al. [7]; Li et al. [8]; Wang et al. [9]; Hu et al. [10]	Emissions/demand treated as known constant values	Low	Ignores variability caused by events/holidays/weather, limiting real-world applicability
Stochastic programming	Vu et al. [11]; Qin et al. [12]; Zhang et al. [13]; Oteng et al. [14]; Higuchi et al. [15]; Wang et al. [16]	Fit probability distributions	High (distribution fitting)	Requires sufficient high-quality historical data; transferability may be limited
Fuzzy programming (triangular)	Yang et al. [17]; Avila-Torres et al. [18]; Bahri et al. [19]; Sharma et al. [20]; Mahmoodirad et al.[21]	Use triangular fuzzy numbers to model uncertainty	Medium	Single "most likely" point and rigid triangular membership; limited flexibility to capture dynamic fuzziness
This study	–	Trapezoidal fuzzy numbers + credibility-based constraints	Medium	Better flexibility via an interval of most probable values

Table 1. Comparison of emission/demand representation methods in the related literature.

Similarly, Voigt[27] also proposed the same viewpoint. Therefore, how to improve ALNS to effectively solve the MSW vehicle routing optimization problem and avoid getting stuck in local optima remains a challenge.

Model formulation
Problem description
This study investigates the MSW vehicle routing optimization problem from a fuzzy programming perspective, with the collection and transportation network shown in Fig. 1. In the urban area, there are multiple waste transfer stations, each responsible for waste collection at collection points within its designated area. During this process, the remaining load capacity of the collection vehicles gradually decreases, and the vehicles also face the challenge of uncertain waste emissions at subsequent collection points. If the collection vehicle arrives at the next waste collection point and finds that the remaining load capacity is insufficient to handle the actual waste emissions, it indicates a failure in the collection process. The vehicle will then return directly to the waste transfer station, while the collection point will await another vehicle to complete the collection, continuing until all collection points within the designated area have been serviced. In addition, to minimize the impact of waste collection and transportation operations on residents' daily lives, the working hours of the collection vehicles are strictly limited to 4 a.m. to 6 a.m. each day. The optimization objective is to minimize the operational cost of waste collection vehicles in the urban area. To facilitate modeling and solution, the following assumptions are made.

(1) The number of collection vehicles at the waste transfer station is unlimited.
(2) The collection time at waste collection points is linearly related to the waste emissions.
(3) The speed of the collection vehicles is stable.

Notations
The parameters and variables used in this paper are explained in Table 2.

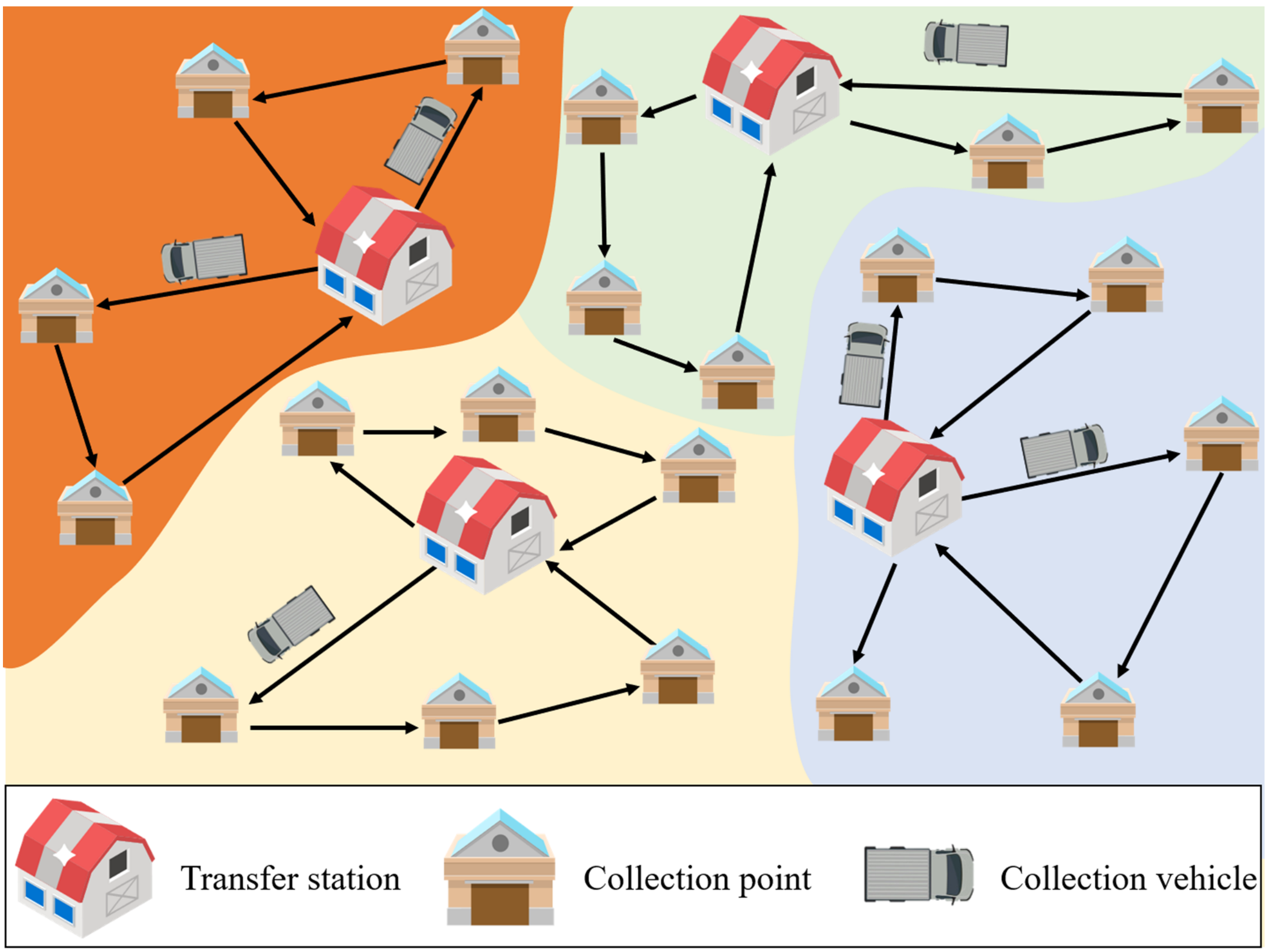

Fig. 1. MSW collection and transportation network.

Notations	Description
Sets	
W	The set of waste transfer stations, $w \in W$
N	The set of collection points, $i \in N$
K	The set of collection vehicles, $k \in K$
Parameters	
E_k^w	The rated load capacity of the collection vehicle *k* dispatched by waste transfer station *w*, in kg, $w \in W, k \in K$
u_k^w	The transportation cost per kilometer for collection vehicle *k* dispatched from transfer station *w*, in RMB/km, $w \in W, k \in K$
h_k^w	The startup cost of the collection vehicle *k* dispatched by waste transfer station *w*, in RMB, $w \in W, k \in K$
$\widetilde{e}_i^w$	The waste emission at collection point *i* within the jurisdiction of transfer station *w*, in kg, $w \in W, i \in N$
$d_{i,j}^w$	Distance from collection point *i* to *j* within the jurisdiction of transfer station *w*, in km, $w \in W, i, j \in N$
$d_{0,i}^w$	The distance from transfer station *w* to collection point *i*, in km, $w \in W, i \in N$
$d_{i,0}^w$	The distance from collection point *i* to transfer station *w*, in km, $w \in W, i \in N$
t_i^w	The waste collection time at collection point *i*, in min, $w \in W, i \in N$
$q^{w,k}$	The cleaning capacity of collection vehicle *k* dispatched by transfer station *w*, in kg/min, $w \in W, k \in K$
v_k^w	The driving speed of collection vehicle *k* dispatched by transfer station *w*, in kg/min, $w \in W, k \in K$
$s_{k,i}^w$	The remaining load capacity of collection vehicle *k* when it arrives at collection point *i*, in kg, $w \in W, i \in N, k \in K$
$T_{\max}$	The maximum collection time at the collection point, i.e., 120 min
$t_{i,j}^w$	The vehicle driving time from collection point *i* to collection point *j* within the jurisdiction of transfer station *w*, $w \in W, i, j \in N$
Decision variables	
$x_{i,j}^{w,k}$	1 if collection vehicle *k* dispatched by transfer station *w* travels from collection point *i* to collection point *j* and 0 otherwise
$y_i^{w,k}$	1 if collection vehicle *k* dispatched by transfer station *w* completes the collection operations at collection point *i* and 0 otherwise
z_k^w	1 if collection vehicle *k* dispatched by transfer station *w* for waste collection operations and 0 otherwise

Table 2. Summary of notations.

Uncertain waste emissions

Fuzzy chance-constrained programming approach is an uncertain mathematical programming based on possibility theory and fuzzy set theory[37]. The theory states that the decision made ensures the possibility of satisfying the fuzzy constraint is no less than the given uncertain waste emissions preference value. This fuzzy chance constraint can be transformed into a deterministic form, making the fuzziness clear.

As for the MSW vehicle routing optimization problem, before the collection vehicle reaches the collection point, the amount of waste generated cannot be determined. Therefore, this paper introduces fuzzy credibility theory and decision makers' subjective preference values, uses trapezoidal fuzzy numbers to characterize the uncertain waste emissions, preprocesses the problem, and constructs a mathematical model. Specifically, let U be a universe of discourse consisting of objects, and $\widetilde{A}$ be a fuzzy set defined on the universe U, namely, (1).

$$\mu_{\widetilde{A}}(x) : U \to (0, 1),\ \ x \in U \tag{1}$$

where $\mu_{\widetilde{A}}$ is the membership function, which reflects the degree to which an element x in the universe U belongs to the fuzzy set. Then, let $\widetilde{e}$ be a fuzzy number on the real number domain R, and define a membership function for $\mu_{\widetilde{e}}(x) : \mathrm{R} \to (0,1),\ x \in \mathrm{R}$. Thus, $\mu_{\widetilde{e}}(x)$ is defined as (2).

$$\mu_{\widetilde{e}}(x) = \begin{cases} \dfrac{x-a}{b-a},\ a \le x < b \\ 1,\ b \le x \le c \\ \dfrac{d-x}{d-c},\ c < x \le d \\ 0,\ \text{others} \end{cases} \tag{2}$$

where $\widetilde{e}$ is a trapezoidal fuzzy number, $\widetilde{e} = (a, b, c, d),\ -\infty < a \le b \le c \le d < \infty$, and $b \le x \le c$ is the relative most probable interval. When $a = b = c = d$, $\widetilde{e}$ loses its uncertainty and becomes a definite value.

However, when $b = c$, $\widetilde{e}$ is a triangular fuzzy number. Specifically, when $\widetilde{e}$ is a triangular fuzzy number, $\mu_{\widetilde{e}}(x)$ is defined as (3). Furthermore, the triangular fuzzy number and the trapezoidal fuzzy number are illustrated in Fig. 2.

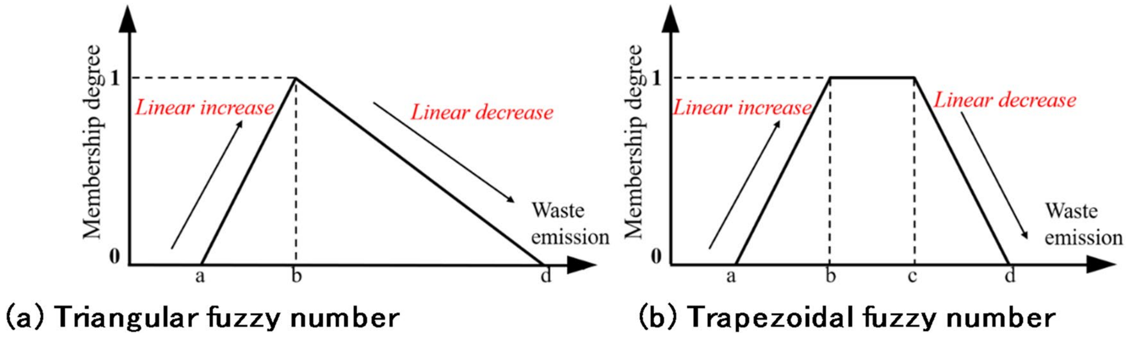

Fig. 2. Fuzzy number functions.

$$\mu_{\widetilde{e}}(x) = \begin{cases} \frac{x-a}{b-a}, \ a \le x < b \\ \frac{d-x}{d-b}, \ b \le x \le d \\ 0, \ \text{others} \end{cases} \tag{3}$$

Obviously, according to Eqs. (2)–(3) and Fig. 2, compared with the triangular fuzzy number, the trapezoidal fuzzy number provides a more refined representation of "uncertain yet relatively stable" information. A triangular fuzzy number has a single peak, implicitly assuming a unique most plausible value; this assumption can be overly restrictive when the demand is equally likely within a certain range. By contrast, a trapezoidal fuzzy number introduces a plateau (i.e., the relative most probable interval ([b, c])), as shown in Fig. 2(b), allowing multiple values to share the same maximum membership degree, which better matches the reality that MSW generation fluctuates within an interval due to public events, holidays, emergencies, and weather conditions. Hence, trapezoidal fuzzy numbers often yield more robust and interpretable uncertainty descriptions.

As for the MSW vehicle routing optimization problem from a fuzzy programming perspective, the collection vehicle k departs from transfer station w, having completed the collection operations for the first l collection points. The remaining loading capacity of vehicle k is $s_{k,l}^{w}$. Let the waste emissions amount at the collection point $l+1$ be a trapezoidal fuzzy number, denoted as $\widetilde{e}_{l+1}^{w}$. Then, there exists $\widetilde{e}_{l+1}^{w} = (e_{l+1,1}^{w}, e_{l+1,2}^{w}, e_{l+1,3}^{w}, e_{l+1,4}^{w})$. Here, $e_{l+1,1}^{w}$ is the fuzzy lower bound of the waste emissions at the collection point $l+1$, $e_{l+1,2}^{w}$ is the fuzzy upper bound on the left, $e_{l+1,3}^{w}$ is the fuzzy upper bound on the right, and $e_{l+1,4}^{w}$ is the fuzzy lower bound on the right.

According to fuzzy credibility theory, the waste emissions amount $\widetilde{e}_{l+1}^{w}$ at the next collection point $l+1$ is less than or equal to the remaining loading capacity $s_{k,l}^{w}$ of the vehicle, subject to the fuzzy chance constraint as shown in (4).

$$Cr\left\{\widetilde{e}_{l+1}^{w} \le s_{k,l}^{w}\right\} \ge \alpha \ \forall w \in W, l \in N, k \in K \tag{4}$$

Equation (4), Cr represents the credibility of the fuzzy event. The larger the value of Cr, the higher the credibility for collection vehicle k to travel from collection point l to collection point $l+1$. When $Cr=1$, it means that collection vehicle k is performing the collection operations from collection point l to collection point $l+1$. Additionally, α $(\alpha \in [0,1])$ represents the decision maker's confidence in the decision-making process, reflecting the decision maker's preference for the uncertainty in the collection operations. When $Cr>\alpha$, it indicates that collection vehicle k proceeds to collection point $l+1$; otherwise, it means that collection vehicle k returns to the transfer station w, and the collection operation at point $l+1$ is completed by another vehicle. This process is repeated until all the collection operations are finished.

In fuzzy chance-constrained programming, for a given value v and a trapezoidal fuzzy number $\widetilde{f} = (f_1, f_2, f_3, f_4)$, where $f_1 < f_2 < f_3 < f_4$, $Cr\{\}$ is defined as shown in (5) according to Zarandi et al. [38].

$$Cr\{f \le v\} = \begin{cases} 1, \ f_4 \le v \\ \frac{f_4 - 2f_3 + v}{2(f_4 - f_3)}, \ f_3 \le v \le f_4 \\ 0.5, \ f_2 \le v \le f_3 \\ \frac{v - f_1}{2(f_2 - f_1)}, \ f_1 \le v \le f_2 \\ 0, \ \text{otherwise} \end{cases} \tag{5}$$

By replacing v with $s_{k,l}^{w}$, and $\widetilde{f} = (f_1, f_2, f_3, f_4)$ with $\widetilde{e}_{l+1}^{w} = (e_{l+1,1}^{w}, e_{l+1,2}^{w}, e_{l+1,3}^{w}, e_{l+1,4}^{w})$, we obtain (6), which is equivalent to the fuzzy chance constraint in (4) and (5).

$$Cr\left\{\widetilde{e}_{l+1}^{w} \le s_{k,l}^{w}\right\} = \begin{cases} 1, \ e_{l+1,4}^{w} \le s_{k,l}^{w} \\ \dfrac{e_{l+1,4}^{w} - 2e_{l+1,3}^{w} + s_{k,l}^{w}}{2\left(e_{l+1,4}^{w} - e_{l+1,3}^{w}\right)}, \ e_{l+1,3}^{w} \le s_{k,l}^{w} \le e_{l+1,4}^{w} \\ 0.5, \ e_{l+1,2}^{w} \le s_{k,l}^{w} \le e_{l+1,3}^{w} \\ \dfrac{s_{k,l}^{w} - e_{l+1,1}^{w}}{2\left(e_{l+1,2}^{w} - e_{l+1,1}^{w}\right)}, \ e_{l+1,1}^{w} \le s_{k,l}^{w} \le e_{l+1,2}^{w} \\ 0, \text{otherwise} \end{cases} \ge \alpha \tag{6}$$

Based on (6), the waste emissions amount $\widetilde{e}_{l+1}^{w}$ at collection point $l+1$ can be clarified. When $\alpha \in [0, 0.5]$, $Cr\left\{\widetilde{e}_{l+1}^{w} \le s_{k,l}^{w}\right\} \ge \alpha$, i.e., $s_{k,l}^{w} - e_{l+1,1}^{w} \ge 2\alpha(e_{l+1,2}^{w} - e_{l+1,1}^{w})$, then $\widetilde{e}_{l+1}^{w}$ can be transformed into (7).

$$\widetilde{e}_{l+1}^{w} = 2\alpha e_{l+1,2}^{w} + (1-2\alpha)e_{l+1,1}^{w} \tag{7}$$

Similarly, when $\alpha \in [0.5, 1]$, $Cr\left\{\widetilde{e}_{l+1}^{w} \le s_{k,l}^{w}\right\} \ge \alpha$, i.e., $e_{l+1,4}^{w} + s_{k,l}^{w} - 2e_{l+1,3}^{w} \ge 2\alpha(e_{l+1,4}^{w} - e_{l+1,3}^{w})$, then $\widetilde{e}_{l+1}^{w}$ can be transformed into (8).

$$\widetilde{e}_{l+1}^{w} = (2-2\alpha)e_{l+1,3}^{w} + (2\alpha - 1)e_{l+1,4}^{w} \tag{8}$$

Objective functions

To improve the management quality of the waste collection and transportation process, this paper takes the minimum operational cost of collection vehicles as the objective function. Based on fuzzy credibility theory, it establishes the MSW vehicle routing optimization mathematical model from a fuzzy programming perspective, as shown in (9) to (11).

$$\min f = f_1 + f_2 \tag{9}$$

$$\begin{aligned} f_1 = &\sum_{w\in W}\sum_{k\in K}\sum_{i\in N}\sum_{j\in N} d_{i,j}^{w} \cdot x_{i,j}^{w,k} \cdot z_k^{w} \cdot u_k^{w} + \sum_{w\in W}\sum_{k\in K}\sum_{i\in N} d_{0,i}^{w} \cdot x_{0,i}^{w,k} \cdot z_k^{w} \cdot u_k^{w} \\ &+ \sum_{w\in W}\sum_{k\in K}\sum_{i\in N} d_{i,0}^{w} \cdot (1 - y_i^{w,k}) \cdot z_k^{w} \cdot u_k^{w} \end{aligned} \tag{10}$$

$$f_2 = \sum_{w\in W}\sum_{k\in K} z_k^{w} \cdot h_k^{w} \tag{11}$$

Equation (9) consists of two parts. The first part is (10), which represents the transportation cost of collection vehicles. The second part is (11), which represents the startup cost of the collection vehicles. Furthermore, (10) consists of three parts. The first part represents the transportation cost between collection points, the second part represents the transportation cost from the transfer station to the collection points, and the third part represents the transportation cost incurred when the vehicle fails to collect due to insufficient remaining loading capacity and must return to the transfer station.

Related constraints

$$\sum_{w\in W}\sum_{k\in K} y_i^{w,k} = 1 \ ,\forall i \in N \tag{12}$$

$$\sum_{w\in W}\sum_{k\in K}\sum_{i\in N} x_{i,j}^{w,k} \ge 1 \ ,\forall j \in N \tag{13}$$

$$\widetilde{T}^{w,k} = \sum_{j\in N}\sum_{i\in N} t_{i,j}^{w,k} + \sum_{i\in N} \widetilde{t}_i^{w,k} = \widetilde{e}_i^{w} / q^{w,k} + \left[\sum_{i\in N}\sum_{j\in N} d_{i,j}^{w} \cdot x_{i,j}^{w,k} + \sum_{i\in N} d_{0,i}^{w} \cdot x_{0,i}^{w,k}\right] / v_k^{w} \tag{14}$$

$$\widetilde{T}^{w,k} \le T_{\max} \ \forall w \in W, \ k \in K \tag{15}$$

$$\sum_{j\in N\cup\{0\}} x_{j,i}^{w,k} - \sum_{j\in N\cup\{0\}} x_{i,j}^{w,k} = \begin{cases} 1 \text{ if } i = 0 \\ 0 \text{ if } i \in N \quad \forall w \in W, \ k \in K \\ -1 \text{ if } i = 0 \end{cases} \tag{16}$$

$$s_{k,i}^{w} = E_k^{w} - \sum_{j\in N} \widetilde{e}_j^{w} \cdot y_j^{w,k} \ ,\forall w \in W, k \in K, i \in N \tag{17}$$

$$\sum_{i\in N} \widetilde{e}_{i+1}^{w} \cdot y_i^{w,k} \le E_k^{w} \cdot z_w^{k} \ ,\forall w \in W, k \in K \tag{18}$$

$$Cr\left\{\ \widetilde{e}_{i+1}^{w}-s_{k,i}^{w}\le 0\right\}\ge \alpha\ ,\forall w\in W,k\in K,i\in N \tag{19}$$

$$y_{i}^{w,k}=\begin{cases}1\ \text{if}\ s_{k,i}^{w}\ge \widetilde{e}_{i+1}^{w},x_{i,j}^{w,k}=1\\ 0\ \text{if}\ s_{k,i}^{w}< \widetilde{e}_{i+1}^{w},x_{i,j}^{w,k}=0\end{cases},\ \forall w\in W,k\in K,i,j\in N \tag{20}$$

$$x_{i,j}^{w,k}\in(0,1)\ ,\forall w\in W,k\in K,i,j\in N \tag{21}$$

$$z_{k}^{w}\in(0,1)\ ,\forall w\in W,k\in K \tag{22}$$

Equation (12) is the constraint on the number of collections at each collection point, meaning that each collection point can only be served once. Equation (13) allows multiple collection vehicles to go to the same collection point. Equation (14) to (15) are the collection time constraints, which prevent the collection operations from affecting the daily lives of residents. Equation (16) represents the node flow balance constraint. Equation (17) is the constraint on the remaining loading capacity of the collection vehicle. Equation (18) is the constraint on not exceeding the vehicle's rated load capacity. Equation (19) ensures that the credibility of the waste emissions amount at the collection point being less than the vehicle's remaining loading capacity is greater than the decision maker's subjective preference value. Equation (20) is the decision variable for whether the vehicle completes the collection operation at the collection point.

Solution methodology

The MSW vehicle routing optimization problem from a fuzzy programming perspective is an NP-Hard problem, and the difficulty of solving it increases exponentially with the problem size. ALNS can adaptively select a neighborhood combination from a set of neighborhood criteria by dynamically adjusting the weight coefficient, generating the neighborhood structure of solutions[24,25]. However, ALNS may get stuck in a local optimum when facing optimization problems with high complexity and large solution spaces[26,27].

Notably, Gmira et al., and Cai et al. have pointed out that TS is an extension of local neighborhood search and is widely used in the field of optimization problems[39,40]. The principle of TS is to use a short-term memory of the tabu list to prevent revisiting previously visited positions[39]. Although the introduction of the tabu list may temporarily degrade the solution quality, it increases the diversity of the solution space, which helps escape from local optima to some extent, thus providing certain advantages in practical applications. Therefore, this paper proposes a hybrid heuristic algorithm named ALNS-TS. By improving search efficiency and increasing search diversity, ALNS-TS helps ALNS escape local optima and more effectively explore the global optimum. Figure 3 shows the algorithm flowchart of ALNS-TS.

Chromosome encoding

The solution to the problem adopts a direct arrangement encoding method. In this approach, the solution consists of routes, with each route being represented by an array storing the collection route of vehicle *k*. The first position represents the transfer station number; the second position represents the vehicle number; the third position represents the collection point number; and so on, and the last position represents the transfer station.

Initial feasible solution

Considering that the number of collection vehicles dispatched by the transfer station is a variable, under the constraints of vehicle collection time and rated load capacity, paths can be merged to reduce the collection mileage according to the triangular inequality theorem, as shown in (23). Therefore, in this study, the Clarke-Wright Savings algorithm is used to construct the initial feasible solution[7].

$$D(i,j)=d(w,i)+d(w,j)-d(i,j) \tag{23}$$

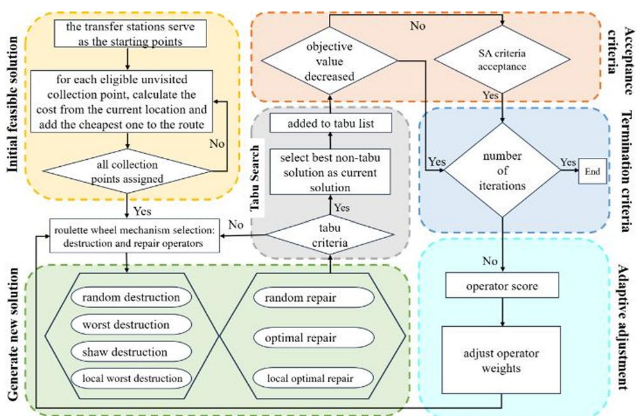

Fig. 3. The algorithm flow of ALNS-TS.

In (23), $d(w, j)$ is the distance from the transfer station to collection point j, and $d(i, j)$ is the distance from collection point i to collection point j.

Neighborhood criteria

The neighborhood criteria refer to the pairing combination of the destruction operator and the repair operator, used to optimize the initial feasible solution[24–27]. In other words, based on the initial feasible solution, a certain destruction operator is selected to remove some collection points from the route, and then a certain repair operator is used to insert collection points, resulting in a new solution. This study employs four destruction operators, three repair operators, and a total of 12 neighborhood criteria to explore new solutions.

Worst destruction operator
The worst destruction operator calculates the difference in the objective function before and after the destruction of each collection point[24,25]. In other words, the greater the difference, the more significant the impact of inserting that collection point on the objective function, and thus it should be prioritized for destruction, as shown in (24).

$$\mathrm{Destroy}_{\mathrm{worst}} = \{ i \,|\Delta f(i) = \max(\Delta f(i)) \} \tag{24}$$

Random destruction operator
The random destruction operator removes several collection points or route segments from the current solution by randomly selecting them, generating a new solution[26,27]. The goal is to explore a broader solution space by introducing randomness.

Local worst destruction operator
The local worst destruction operator removes the worst collection points within the neighborhood of the current solution, adjusting the local range of the solution to explore the solution space more thoroughly[26].

Shaw destruction operator
The shaw destruction operator randomly destroys several collection points in the current solution and calculates the correlation between these collection points and other nodes[24,25].

Optimal repair operator
The optimal repair operator inserts the destroyed collection points into the positions that bring the maximum improvement[25]. By evaluating all possible insertion positions, it selects the position that minimizes operational cost, as shown in (25).

$$\mathrm{Repair}_{\mathrm{best}} = \{ i \,|\Delta f(i) = \min(\Delta f(i)) \} \tag{25}$$

Random repair operator
The random repair operator randomly inserts the destroyed collection points into different positions within the current solution, increasing the diversity of the solution[24].

Local optimal repair operator
The local optimal repair operator selects the best insertion position within the local neighborhood of the solution to minimize the change in the objective function[24,26]. It is suitable for local search and helps refine the quality of the solution.

It is important to note that the execution process of the destruction-repair operators must satisfy the constraints of collection time and vehicle rated load capacity, to ensure that the newly generated solutions meet the model's requirements.

Neighborhood combination selection strategy and weight coefficient update

The neighborhood combination selection strategy determines how to select destruction and repair operators during the search process, directly affecting the solution quality and search efficiency[25]. A roulette wheel mechanism is used to select the type of destruction and repair operators. Let $\rho^{-}=\{\rho^{-}|1, 2, \cdots, b\}$ represent the set of destruction operators and $\rho^{+}=\{\rho^{+}|1, 2, \cdots, a\}$ represent the set of repair operators, with $\rho^{-}(b)$ and $\rho^{+}(a)$ indicating the weight coefficients of the destruction and repair operators, respectively. The probability calculation is shown in (26). After each iteration, the weight coefficients are dynamically adjusted based on the operator performance, as shown in (27).

$$\begin{cases} p(b) = \rho^{-}(b) / \sum_{j=1}^{b} \rho^{-}(b) \\ p(a) = \rho^{+}(a) / \sum_{j=1}^{a} \rho^{+}(a) \end{cases} \tag{26}$$

$$\omega_i' = (1-\delta)\omega_i + \delta \frac{s_i}{\theta_i} \tag{27}$$

where w_i is the weight of operator i, δ is the weight forgetting coefficient, s_i is the accumulated score of operator i in the current cycle, and θ_i is the accumulated usage count of operator i in the current cycle.

TS mechanism

The tabu object is the ordered sequence L of collection operations, and the length of the tabu list is H. After each iteration, a new solution L that satisfies the acceptance criteria is stored in the tabu list. After a certain period of H, this solution will be removed from L. When a new solution L_{new} is obtained, it is checked whether L_{new} already exists in L. If L_{new} has been accepted and is in L, the algorithm proceeds to the next iteration. Otherwise, if L_{new} is not accepted and is not in L, the subsequent operations will be performed.

Simulated annealing criteria

During the algorithm's iterative optimization process, if the new solution is better than the current solution, the new solution replaces the current one. If the new solution results in greater operational cost than the current solution, the simulated annealing criterion is used to decide whether to accept the new solution, as shown in (28). Considering the high complexity of the problem, this study employs a logarithmic annealing mechanism to ensure that the algorithm can sufficiently explore the solution space and avoid prematurely converging to a local optimum, as shown in (29).

$$p = e^{\left(\frac{100}{T}\left(\frac{f_n - f_c}{f_c}\right)\right)} \tag{28}$$

$$T_n = \frac{T_0}{1 + \eta \cdot \ln(1 + n)} \tag{29}$$

Here, T is the temperature parameter, T_0 is the initial temperature, and η is the temperature decay coefficient.

Computational study

Considering that there are currently no standard test cases for uncertain waste emissions, this paper employs the Solomon test library sample C205 to validate the effectiveness of the proposed model and algorithm. Since the uncertain emission of the sample point with ID 0 in the C205 sample library is 0, it is not included in the test case validation. Next, the K-means clustering algorithm is used to divide all data into four groups based on the Euclidean distance between sample points. In each group, a sample point is randomly selected as the waste transfer station, and the remaining sample points serve as waste collection points. Finally, the arrangement of collection points within the jurisdiction of different transfer stations is shown in Fig. 4.

The waste emissions $\widetilde{e}_i^w$ at each collection point are multiplied by 30. The waste collection point service time from is 4 a.m. to 6 a.m. Regarding the parameter settings, an orthogonal experiment $\mathrm{L}_9(3^9)$ was designed to obtain the optimal parameter combination. Specifically, the forgetting coefficient (δ) is set to 0.15, the length of the tabu list (H) is set to 10, the temperature decay coefficient (η) is set to 0.95, the initial temperature (T_0) is set to 800, the decision maker's subjective preference value (α) is set to 0.75, the number of iterations is set to 1,000, and the destruction rate is set to 0.4. The remaining parameter settings are shown in Table 3. The algorithm code is based on Python 3.8, running on a Windows 10 system with an Intel® Core™ i5-5200 CPU.

Comparison of routes for deterministic and uncertain waste emissions

To validate the effectiveness of the algorithm and model, the vehicle routing problems for deterministic and uncertain waste emissions are solved separately. First, calculations are performed under deterministic waste emissions. The case study was run 30 times, with the minimum operating cost and corresponding route plans presented in Table 4, and the collection process depicted in Fig. 5. Next, calculations are performed under uncertain waste emissions. The uncertain waste emissions at the collection points i are represented by the trapezoidal fuzzy number $\widetilde{e}_i^w = (30 \cdot e_i^w - 150,\ 30 \cdot e_i^w - 70,\ 30 \cdot e_i^w + 70,\ 30 \cdot e_i^w + 150)$ (where e_i^w is the demand from the original C205 sample library). Similarly, the case study is run 30 times, with the minimum operating cost and corresponding route plans presented in Table 5, and the collection process depicted in Fig. 6. The algorithm iterations under both emission scenarios are shown in Fig. 7.

Based on Tables 4 and 5; Figs. 5, 6 and 7, the operating cost under deterministic emissions is 252.7 RMB lower than that under uncertain emissions. Specifically, the minimum operating cost under deterministic emissions is 4,114.5 RMB with the corresponding collection and transportation mileage of 925.3 km, while under uncertain emissions, the minimum operating cost is 4,367.2 RMB with the corresponding mileage of 977.5 km. This is because under uncertain emission conditions, the waste emissions at collection points are represented as trapezoidal fuzzy numbers with inherent fluctuations. Consequently, when the collection vehicle arrives at the next collection point, it may find that the waste emissions exceed the vehicle's remaining effective load, prompting a return to the transfer station. This leads to additional mileage and subsequently increases operating cost.

Furthermore, based on Tables 4 and 5; Figs. 5, 6 and 7, the route plans under uncertain emissions require 2 more vehicles than the deterministic emissions plans, with an additional 52.2 km in mileage. The reasons are as follows: to ensure that all collection points are serviced within the prescribed time, additional vehicles are required. However, the extra vehicles inevitably lead to underutilized loading capacity, resulting in wasted transportation resources and increased operating cost. Consequently, the collection and transportation plans under uncertain emissions not only require extra vehicles but also increase both mileage and operating cost.

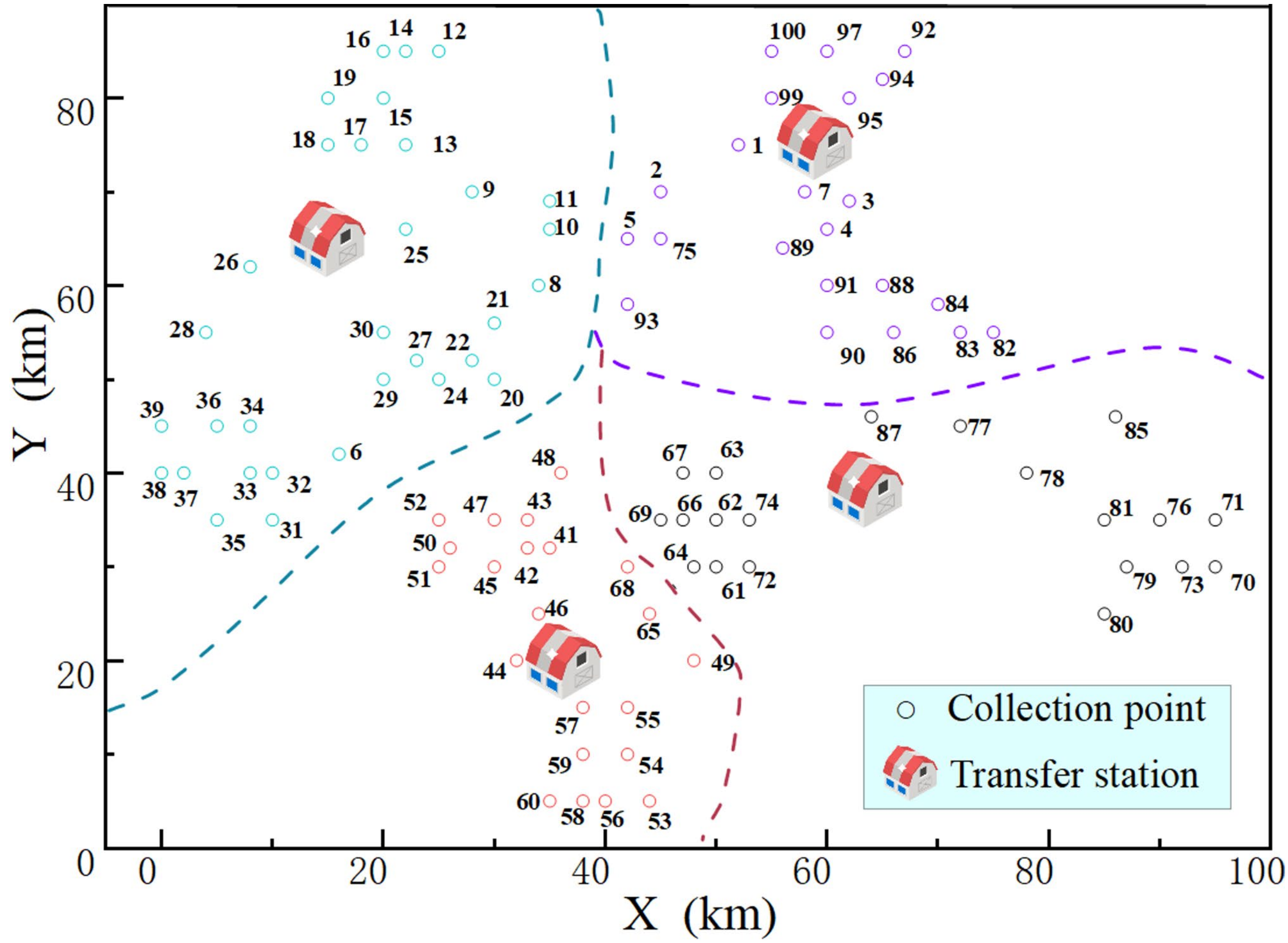

Fig. 4. The distribution of collection points within the jurisdiction of different transfer stations.

Transfer station	Location	Vehicle rated load capacity (kg)	Driving speed (km h^{-1})	Clearing capability (kg min^{-1})	Transportation cost (RMB km^{-1})	Startup cost (RMB)
w_1	(14, 66)	4000	35	100	4.2	50
w_2	(58, 75)	3200	43	80	3.5	30
w_3	(36, 18)	3500	40	65	3.9	30
w_4	(62, 40)	3200	45	80	3.0	50

Table 3. Summary of parameters.

Sensitivity analysis of decision maker's confidence

In the model reliability constraints, the decision maker can set the subjective preference value α (i.e., Constraint (18)). Therefore, we perform a sensitivity analysis on α to investigate its impact on operating cost. With all other parameters remaining unchanged, the decision maker's subjective preference value α is incrementally increased from 0.15 to 0.95 in steps of 0.1. The operating cost corresponding to different α values is shown in Fig. 8.

According to Fig. 8, as the decision maker's subjective preference value α increases, the operating cost gradually rises. Specifically, as α increases from 0.15 to 0.95, the operating cost climbs from 4,139.2 RMB to nearly 4,532.1 RMB. This is because, in the decision-making process, the subjective preference value α reflects the degree of acceptance for uncertainty and risk. A higher α indicates that the decision maker is more confident in achieving the collection and transportation tasks within the prescribed service time, which in turn requires dispatching more collection vehicles from the transfer station, thereby increasing the operating cost. Hence, there is a positive correlation between α and operating cost: the greater the confidence (i.e., the higher the α value), the less risk is considered during decision making, which ultimately leads to higher operating cost.

Based on Fig. 8, the optimal subjective preference value α is 0.75. Although the operating cost increases with the subjective preference value, the cost increment is relatively small at $\alpha = 0.75$, and, compared to higher values such as 0.85, the operating cost remains lower. This setting allows decision makers to maintain high confidence

Transfer station	Vehicles	Route plans	Vehicles	Route plans
w_1	k_1^1	w_1-29-6-32-31-35-33-w_1	k_1^4	w_1-36-34-37-38-39-28-26-w_1
	k_1^2	w_1-13-12-14-16-19-18-w_1	k_1^5	w_1-8-21-22-20-24-27-30-w_1
	k_1^3	w_1-15-17-9-11-10-25-w_1		
w_2	k_2^1	w_2-99-100-97-92-94-w_2	k_2^3	w_2-1-89-91-90-86-84-83-82-w_2
	k_2^2	w_2-2-5-93-75-w_2	k_2^4	w_2-7-4-88-3-95-w_2
w_3	k_3^1	w_3-60-58-56-53-59-w_3	k_3^3	w_3-49-65-68-46-w_3
	k_3^2	w_3-57-54-55-w_3	k_3^4	w_3-44-45-50-51-52-47-43-48-42-41-w_3
w_4	k_4^1	w_4-78-81-85-87-w_4	k_4^3	w_4-63-66-69-67-w_4
	k_4^2	w_4-74-62-64-61-72-w_4	k_4^4	w_4-80-79-73-70-71-76-77-w_4
Operational cost	4,114.5 RMB			

Table 4. Minimum route plans for deterministic waste emissions.

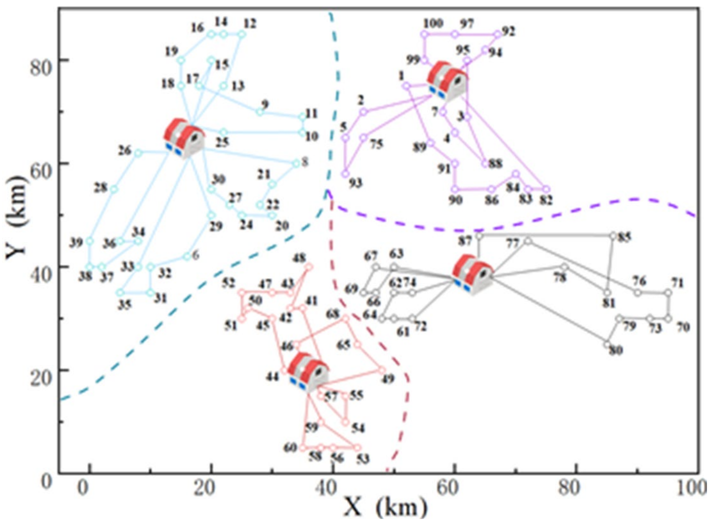

Fig. 5. The collection and transportation process for deterministic waste emissions.

Transfer station	Vehicles	Route plans	Vehicles	Route plans
w_1	k_1^1	w_1-31-35-32-34-37-38-w_1	k_1^4	w_1-29-6-33-39-36-28-26-w_1
	k_1^2	w_1-17-14-12-16-19-18-w_1	k_1^5	w_1-11-10-8-21-20-22-24-27-30-w_1
	k_1^3	w_1-25-9-13-15-w_1		
w_2	k_2^1	w_2-3-88-4-7-w_2	k_2^4	w_2-1-99-100-97-92-94-w_2
	k_2^2	w_2-75-93-5-2-w_2	k_2^5	w_2-89-91-90-86-83-82-84-w_2
	k_2^3	w_2-95-w_2		
w_3	k_3^1	w_3-59-53-56-58-60-w_3	k_3^4	w_3-45-51-50-52-47-43-42-46-w_3
	k_3^2	w_3-57-w_3	k_3^5	w_3-41-48-68-65-49-55-54-w_3
	k_3^3	w_3-44-w_3		
w_4	k_4^1	w_4-74-62-69-64-w_4	k_4^3	w_4-87-76-71-70-73-80-w_4
	k_4^2	w_4-77-85-79-81-78-w_4	k_4^4	w_4-63-67-66-61-72-w_4
Operational cost	4,367.2 RMB			

Table 5. Minimum route plans for uncertain waste emissions.

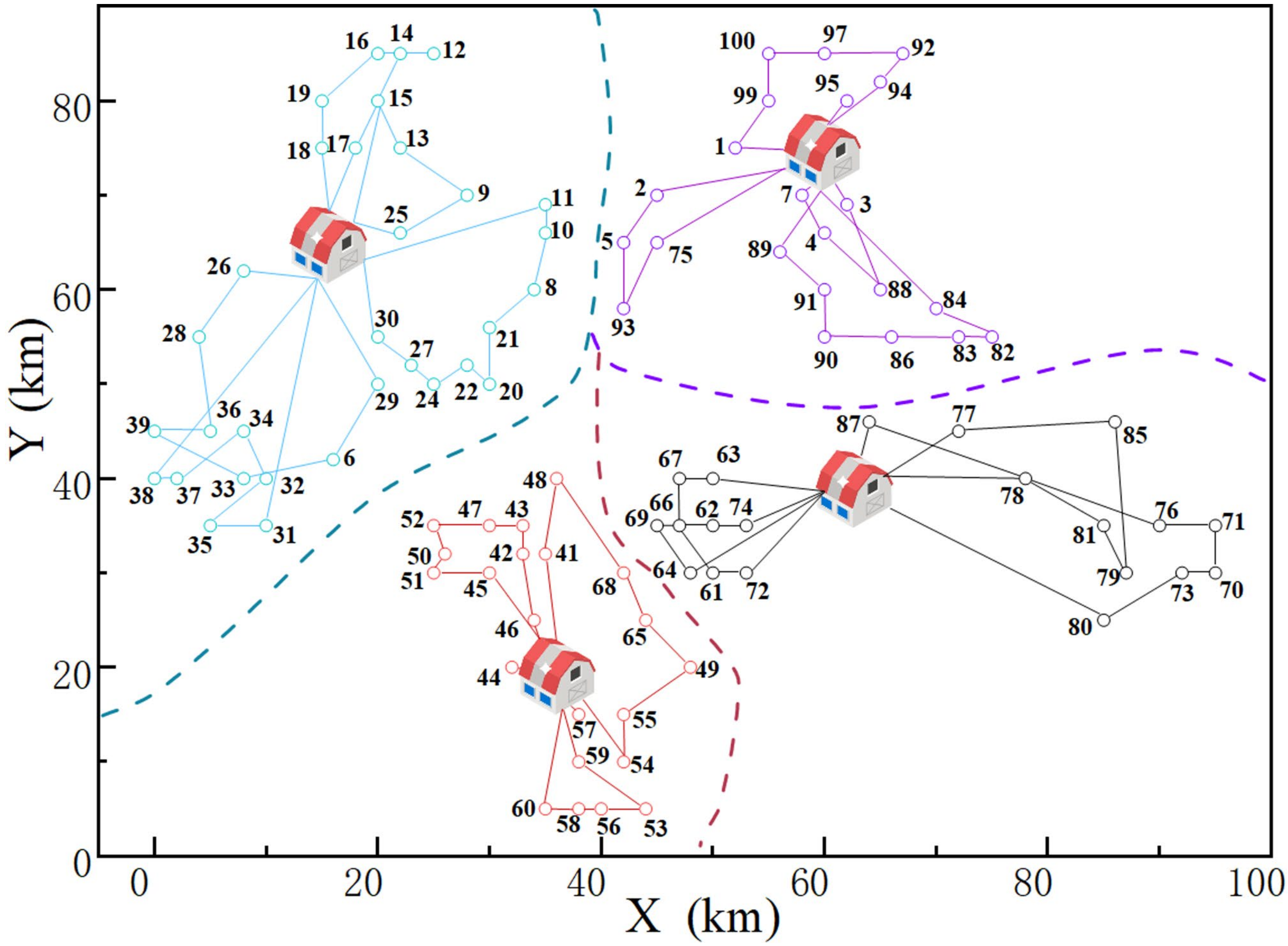

Fig. 6. The collection and transportation process for uncertain waste emissions.

while remaining sensitive to uncertainties. Therefore, in actual collection and transportation operations, the optimal subjective preference value α can be set to 0.75.

Comparative extended cases on deterministic and uncertain waste emissions

In this section, similar cases are carried out on the Solomon test library samples R101, RC208, and C205, to further verify that uncertainty poses challenges to the MSW collection and transportation process. Here, for R101 and RC208, some collection points have excessively small demand values. If trapezoidal fuzzy numbers are applied, it may result in negative demand at certain collection points, which is obviously illogical. For example, the emission of point 17 in R101 is 2, and the emission of point 62 in RC208 is 3. If the trapezoidal fuzzy numbers described in Sect. 5.1 are adopted, the minimum trapezoidal fuzzy emission of point 17 in R101 would be – 90, and that of point 62 in RC208 would be – 60. Therefore, the emissions of these points in R101 and RC208 can be equivalently replaced with those of the corresponding points in C205. For example, the emission of point 17 in R101 is changed from 2 to 20.

Furthermore, for the three datasets R101, RC208, and C205, eight groups of comparative cases were designed under deterministic and uncertain emission quantities, denoted as Group 1, Group 2, …, Group 8. Specifically, the trapezoidal fuzzy emissions in these 8 groups are denoted as ($15{\cdot}e_i^w$ – 50, $15{\cdot}e_i^w$ – 20, $15{\cdot}e_i^w$ + 20, $15{\cdot}e_i^w$ + 50), ($20{\cdot}e_i^w$ – 100, $20{\cdot}e_i^w$ – 50, $20{\cdot}e_i^w$ + 50, $20{\cdot}e_i^w$ + 100), ($20{\cdot}e_i^w$ – 150, $20{\cdot}e_i^w$ – 70, $20{\cdot}e_i^w$ + 70, $20{\cdot}e_i^w$ + 150), ($25{\cdot}e_i^w$ – 100, $25{\cdot}e_i^w$ – 50, $25{\cdot}e_i^w$ + 50, $25{\cdot}e_i^w$ + 100), ($25{\cdot}e_i^w$ – 150, $25{\cdot}e_i^w$ – 70, $25{\cdot}e_i^w$ + 70, $25{\cdot}e_i^w$ + 150), ($30{\cdot}e_i^w$ – 100, $30{\cdot}e_i^w$ – 50, $30{\cdot}e_i^w$ + 50, $30{\cdot}e_i^w$ + 100), ($30{\cdot}e_i^w$ – 150, $30{\cdot}e_i^w$ – 70, $30{\cdot}e_i^w$ + 70, $30{\cdot}e_i^w$ + 150), ($35{\cdot}e_i^w$ – 100, $35{\cdot}e_i^w$ – 50, $35{\cdot}e_i^w$ + 50, $35{\cdot}e_i^w$ + 100), respectively. Correspondingly, the deterministic emissions in these 8 groups are enlarged 15 -fold, 20 -fold, 20 -fold, 25 -fold, 25 -fold, 30 -fold, 30 -fold, and 35 -fold, respectively. The remaining parameter settings remain unchanged. Each test is independently executed 30 times, and the average value is taken to reduce random errors. Finally, the operational cost of the 3 datasets is compared across these eight groups of comparative cases, and the specific differences (i.e., the operational cost under uncertain emissions minus that under deterministic emissions) are shown in Fig. 9. Moreover, the computational time of the 3 datasets is compared across these eight groups of comparative cases, and the differences (i.e., the computational time under uncertain emissions minus that under deterministic emissions) are shown in Fig. 10.

As shown in Fig. 9, regardless of the dataset type, the operational cost under deterministic emissions is generally lower than that under uncertain emissions. For example, in the R101 dataset, the minimum difference

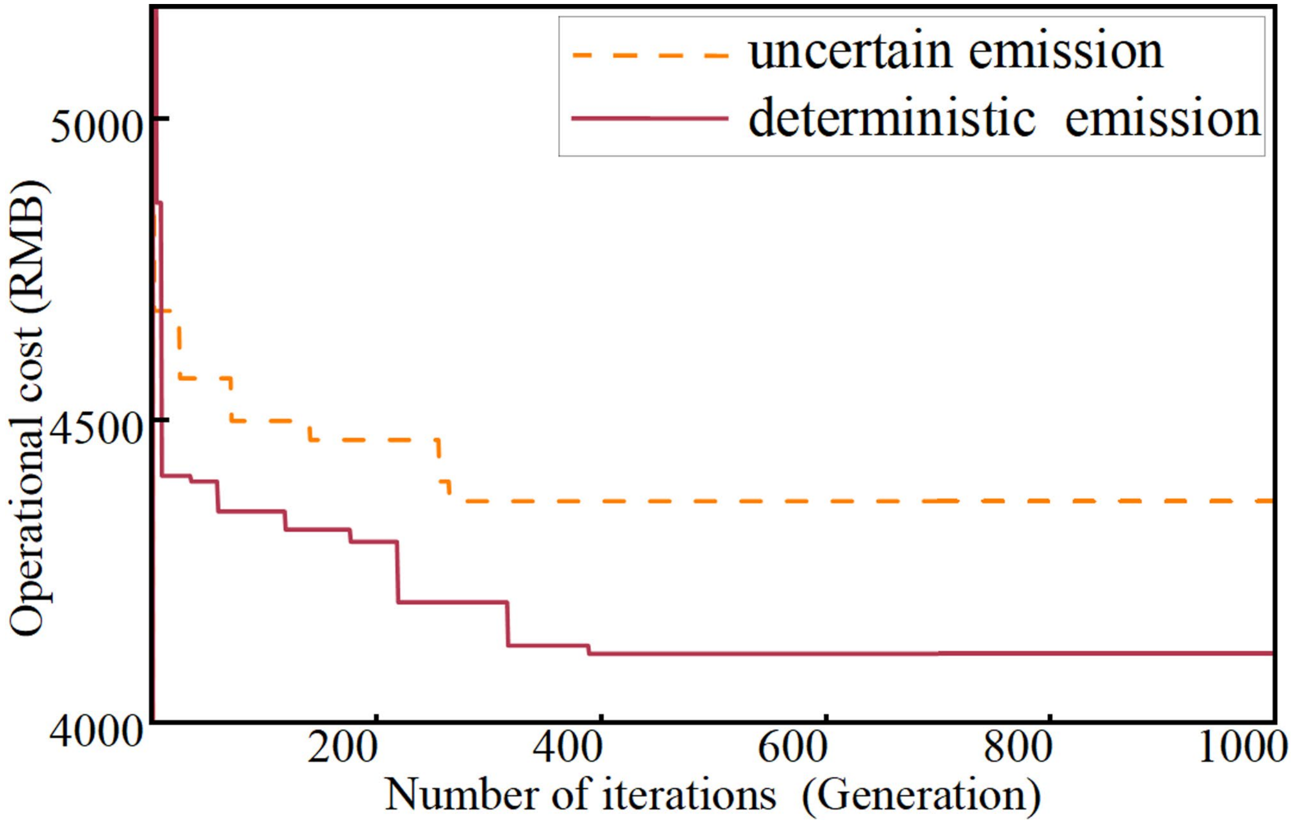

Fig. 7. Algorithm convergence iterations under two types of waste emissions.

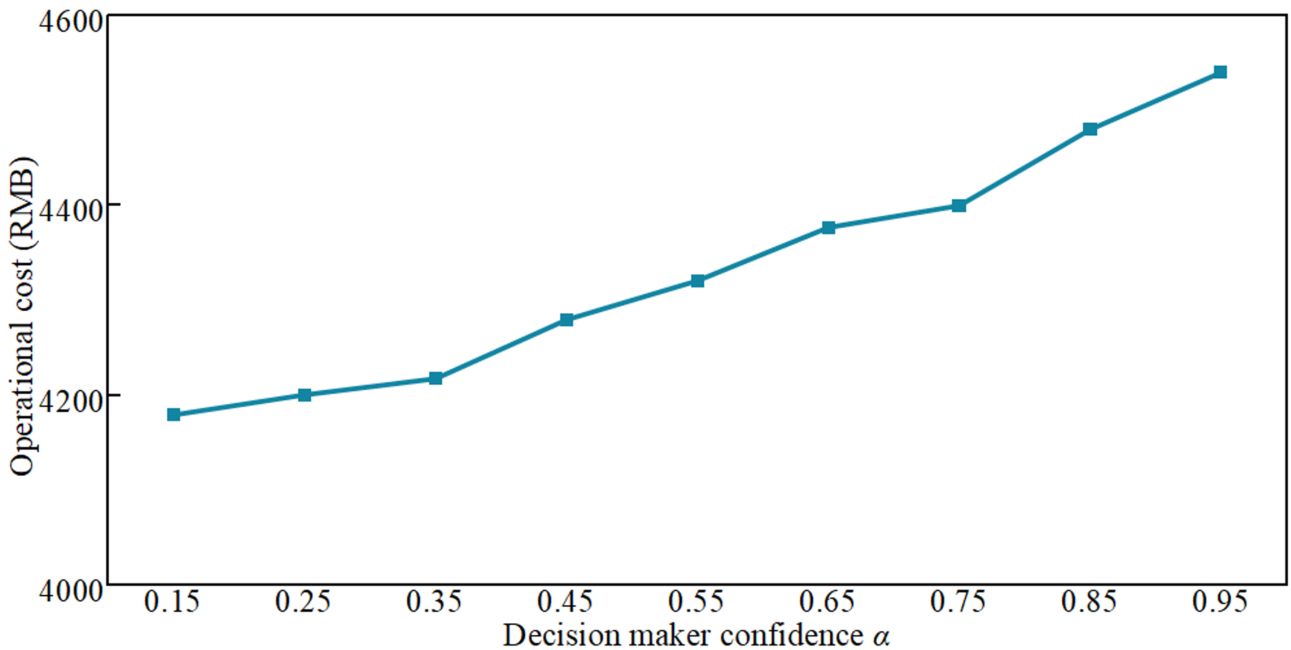

Fig. 8. Sensitivity analysis of the decision maker subjective preference values.

between the two is 80.2 RMB in Group 1, and the maximum difference is 201.5 RMB in Group 8. Similarly, a similar variation trend also occurs in the RC208 and C205 datasets. This is because, under uncertain emission conditions, the waste emissions at collection points fluctuate greatly. When the collection vehicle arrives at the next collection point, the waste emission may exceed the remaining effective load of the vehicle, which leads to

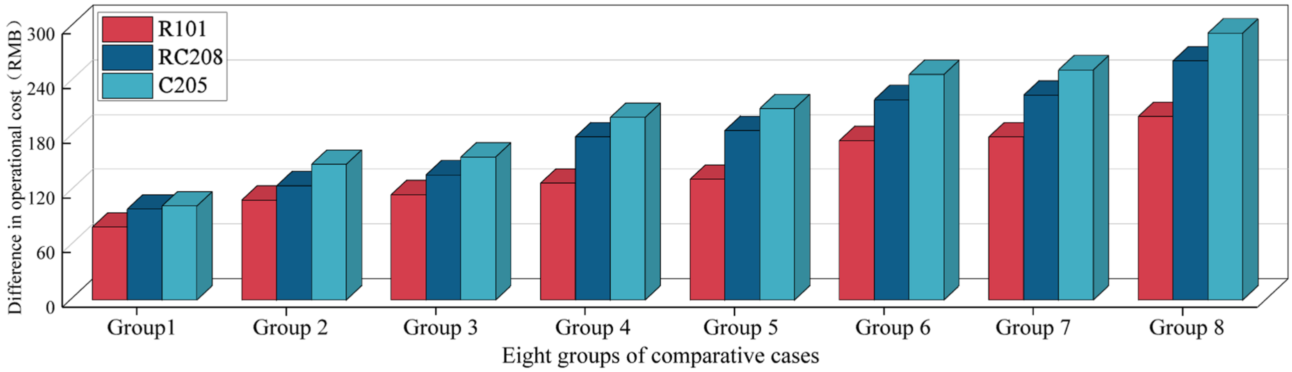

Fig. 9. Differences in operational cost of the three datasets across different comparative cases.

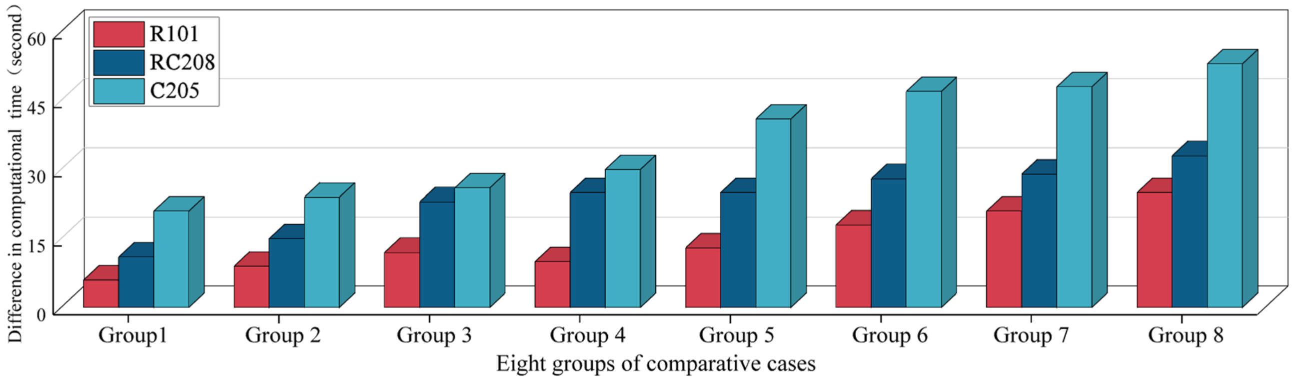

Fig. 10. Differences in computational time of the three datasets across different comparative cases.

additional transportation distance and thereby increases the operational cost. On the other hand, to ensure that the collection points are effectively served within the prescribed time, additional vehicles need to be dispatched to complete the collection and transportation tasks, which also increases the operational cost. Therefore, regardless of the dataset, the operational cost under uncertain emissions is higher than that under deterministic emissions.

Furthermore, as shown in Fig. 10, regardless of the dataset type, the computational time under uncertain emissions is consistently higher than that under deterministic emissions. For instance, in the R101 dataset, the minimum difference occurs in Group 1 (6.2 s), whereas the maximum difference is observed in Group 8 (25.3 s). A similar trend can also be found for the RC208 and C205 datasets. This is mainly because incorporating uncertain emissions introduces additional computational burdens: each candidate solution must be evaluated not only by the objective function but also by the credibility-based chance constraints (with the decision-maker preference level), which requires repeated credibility/feasibility checks during route construction and neighborhood moves. Moreover, the uncertainty-aware setting may trigger more frequent repairs (e.g., returning to the transfer station and reallocating service when the feasibility condition is not satisfied), effectively enlarging the search space and increasing the cost of solution evaluation, thereby leading to longer overall runtimes. However, it should be noted that the additional computational time remains within an acceptable range. For example, in Group 8 of the C205 dataset, the computational time under uncertain emissions is 142.5 s, compared with 89.2 s under deterministic emissions. Although the difference is 53.3 s, the overall runtime for the uncertain-emission case is still acceptable.

Algorithm performance comparison

To compare the solution performance of different algorithms, ALNS-TS, ALNS, GA, and ACO are applied to solve the eight uncertain-emission cases of the benchmark dataset C205. Among these methods, the parameter settings of ALNS are consistent with those. The GA parameters are determined via an orthogonal experimental design $L_9(3^4)$: the population size is set to 200, the crossover probability is 0.7, the mutation probability is 0.1, and the elitism rate is 0.1. Similarly, the ACO parameters are also selected based on the orthogonal experiments $L_9(3^4)$: the number of ants is 100, the pheromone importance coefficient is 0.9, the pheromone evaporation rate is 0.1, and the pheromone deposit constant is 10. In addition, the maximum number of iterations is set to 1,000 for all algorithms. The operational cost and computational time are recorded, as shown in Fig. 11.

As shown in Fig. 11(a), the tabu search mechanism effectively prevents ALNS from being trapped in local optima. Specifically, ALNS-TS reduces the operating cost by at least 157.5 RMB in Group 1 and by up to 338.5 RMB in Group 8 compared with ALNS. This improvement can be attributed to the TS mechanism, which records

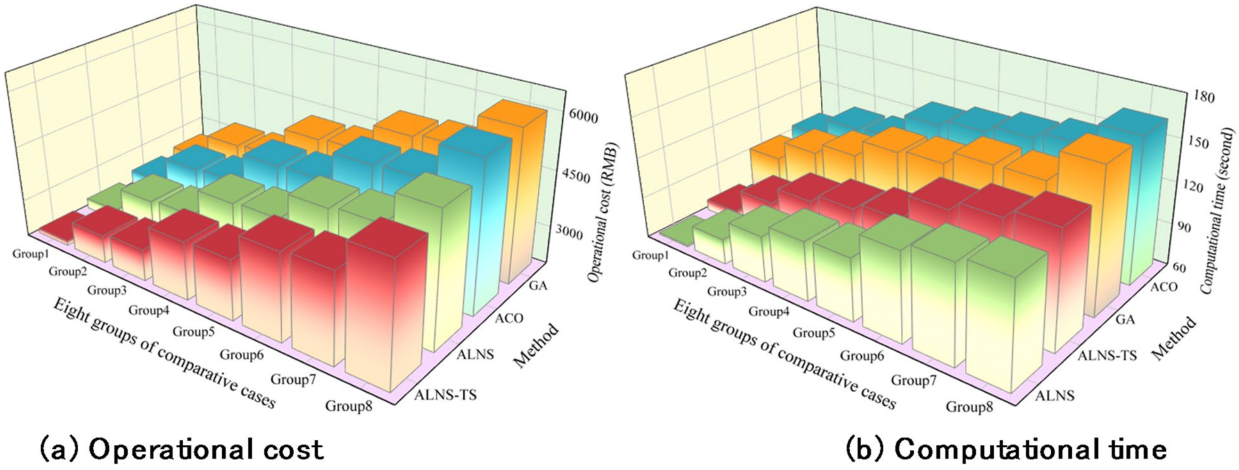

Fig. 11. Comparison of different methods.

previously explored routes and maintains a tabu list, thereby discouraging revisiting recently visited solutions and strengthening the global search capability of ALNS. In addition, TS helps the search escape local optima by promoting solution diversity and deeper exploration, enabling ALNS-TS to continue improving in the later stages and ultimately converge to a lower operating cost, thus exhibiting better solution quality and convergence behavior than ALNS. Although Fig. 11(b) indicates that incorporating TS slightly increases the computational time of ALNS-TS, the runtime remains within an acceptable range. According to our statistics, across all cases, the average computational time of ALNS-TS is only 7.2% higher than that of ALNS. Therefore, integrating the TS mechanism significantly enhances the overall performance of ALNS.

Furthermore, as shown in Fig. 11, ALNS-TS achieves the best overall solution performance, followed by ALNS and ACO, whereas GA performs the worst. Specifically, across all cases, ALNS-TS reduces the operating cost by an average of 13.5%, 6.2%, and 7.9% compared with GA, ALNS alone, and ACO, respectively. Although ALNS-TS incurs a slightly longer computational time than ALNS, it still reduces the average runtime by 15.6% and 14.1% relative to ACO and GA, respectively. This is because ALNS-TS combines the global search ability of ALNS with the local optimization capability of the tabu search mechanism. It dynamically adjusts 12 neighborhood criteria and uses tabu search to avoid redundant explorations, ultimately achieving lower operating cost and faster convergence. In contrast, ACO relies solely on pheromone updates, making it prone to local optima and slower convergence, while GA, based on random crossover and mutation, offers global search ability but suffers from lower convergence precision and poorer solution quality. Therefore, ALNS-TS demonstrates the best performance for solving this problem.

Insights into managing MSW collection routing

In real-world MSW collection operations, it is essential to account for uncertain emissions, because the actual waste generated at collection points is not constant and can vary substantially due to public events, holidays, emergencies, and weather conditions. Ignoring such uncertainty may lead to infeasible routes (e.g., insufficient remaining vehicle capacity upon arrival), unplanned returns to transfer stations, and last-minute vehicle dispatching, thereby increasing operational disruptions and overall cost. Based on this practical context, the following insights are provided.

(1) Trapezoidal fuzzy numbers more realistically and robustly represent MSW emission uncertainty than triangular ones. In practice, MSW emissions at collection points are often “uncertain yet relatively stable”, i.e., they fluctuate within an interval. Using trapezoidal fuzzy numbers allows managers to specify a relative most probable interval [b, c] rather than a single most likely point, which provides a more realistic uncertainty description and helps reduce the risk of infeasible collection (e.g., arriving with insufficient remaining capacity).

(2) How to choose the preference level α (service reliability vs. operational cost). The preference level α in the credibility-based chance constraints can be interpreted as a managerial “service reliability requirement”. A larger α leads to more conservative routing decisions, typically increasing operational cost but reducing the probability of service failure and the need for corrective actions. Therefore, managers can tune α according to policy requirements and local service standards: higher α is recommended for high-risk periods (e.g., holidays or public events), while a moderate α may be sufficient during normal periods to balance reliability and cost.

(3) Operational decision support for scheduling and contingency management. The proposed ALNS-TS provides effective routing plans within acceptable computational time, supporting day-to-day planning. In particular, it can be used for rapid scenario evaluation to generate contingency plans before special events or forecasted adverse weather, improving preparedness and service continuity.

Conclusion

Existing research often treats waste emissions as deterministic values, ignoring the impact of uncertain emissions on the MSW collection and transportation process. This may result in improper collection and transportation route plans, causing waste to not be cleared in a timely manner and thereby affecting residents' quality of life. Therefore, studying the MSW vehicle routing optimization from a fuzzy programming perspective can better reflect real-world issues and is essential for enhancing waste management efficiency.

To investigate the impact of uncertain waste emissions on route plans, this paper introduces trapezoidal fuzzy numbers to characterize waste emissions and proposes a multi-depot MSW vehicle routing optimization model with the objective of minimizing collection cost while incorporating the decision maker's subjective preference constraints. Then, we propose an ALNS-TS algorithm that optimizes ALNS through a tabu search mechanism to prevent it from getting trapped in local optima. Subsequently, case studies are designed to compare waste collection and transportation plans under deterministic and uncertain emissions, to compare the results of different algorithms, and to perform a sensitivity analysis on the subjective preference value. Finally, specific and effective managerial recommendations are provided to support practical decision-making in MSW collection and transportation operations.

This paper provides a robust and practical solution for MSW managers, while also contributing to the literature on MSW collection and transportation routes. However, this study's limitation is that it does not consider inter-station coordination (e.g., load balancing, cross-station vehicle sharing, or dynamic reassignment). Incorporating such collaborative mechanisms may further improve system-level efficiency and service reliability, which will be explored in future work.

Data availability

The datasets involved in this study are publicly available. The specific URLs are as follows: https://github.com/CervEdin/solomon-vrptw-benchmarks/blob/main/c/2/c205.jsonhttps://github.com/CervEdin/solomon-vrptw-benchmarks/blob/main/r/1/r101.jsonhttps://github.com/CervEdin/solomon-vrptw-benchmarks/blob/main/rc/2/rc208.json.

Received: 23 September 2025; Accepted: 3 January 2026
Published online: 08 January 2026

References

1. Munir, M. T., Li, B., Naqvi, M. & Nizami, A. S. Green loops and clean skies: optimizing municipal solid waste management using data science for a circular economy. *Environ. Res.* **243**, 117786 (2024).
2. Priyadarshi, M., Maratha, M., Anish, M. & Kumar, V. Dynamic routing for efficient waste collection in resource constrained societies. *Sci. Rep.* **13**, 2365 (2023).
3. Zhao, T. et al. Municipal solid waste (MSW) under the population shrinking and aging: Spatio-temporal patterns, driving forces, and the impact of smart City development. *J. Clean. Prod.* **434**, 140124 (2024).
4. Masterson, V. Global urban waste exceeds 2 billion tons annually, enough to cover twice the Earth-Moon distance. (2024). https://cn.weforum.org/stories/2024/06/https-www-weforum-org-agenda-2024-04-circular-economy-waste-management-unep-cn
5. China Association of Circular Economy. The past five years of MSW collection & transport: a tough road. (2015). www.chinacace.org/tech/view?id=4919
6. National Development and Reform Commission. The 14th five-year plan for municipal domestic-waste sorting & treatment facilities development. (2021). www.ndrc.gov.cn/xwdt/tzgg/202105/P020210513624071907544.pdf
7. Hou, Y., Shen, Y., Han, H. & Wang, J. Multi-task differential evolution algorithm with dynamic resource allocation: A study on e-waste recycling vehicle routing problem. *Swarm Evol. Comput.* **92**, 101806 (2025).
8. Li, W. et al. Multi-objective optimization of municipal solid waste collection based on adaptive large neighborhood search. *Electronics* **14**, 103 (2024).
9. Wang, W. et al. A two-phase algorithm for the dynamic time-dependent green vehicle routing problem in decoration waste collection. *Expert Syst. Appl.* **262**, 125570 (2025).
10. Hu, J., Zhang, Y., Liu, Y., Hou, J. & Zhang, A. Optimization of household medical waste recycling logistics routes: considering contamination risks. *PloS One*. **19**, 311582 (2024).
11. Vu, H. L., Bolingbroke, D., Ng, K. T. W. & Fallah, B. Assessment of waste characteristics and their impact on GIS vehicle collection route optimization using ANN waste forecasts. *Waste Manage.* **88**, 118–130 (2019).
12. Qin, J., Ye, Y., Cheng, B., Zhao, X. & Ni, L. The emergency vehicle routing problem with uncertain demand under sustainability environments. *Sustainability-Basel* **9**, 288 (2017).
13. Zhang, J., Sun, Y., Feng, Q., Zhao, Y. & Wang, Z. Data-driven robust optimization of the vehicle routing problem with uncertain customers. *Complexity*. 9064669 (2022). (2022).
14. Oteng, D., Zuo, J. & Sharifi, E. Environmental emissions influencing solar photovoltaic waste management in australia: an optimized system network of waste collection facilities. *J. Environ. Manage.* **314**, 115007 (2022).
15. Higuchi, C. & Isobe, A. Reduction scenarios of plastic waste emission guided by the probability distribution model to avoid additional ocean plastic pollution by 2050s. *Mar. Pollut Bull.* **207**, 116791 (2024).
16. Wang, C., Ni, Y. & Yang, X. The production routing problem under uncertain environment. *IEEE Access.* **9**, 15375–15387 (2021).
17. Yang, T., Wang, W. & Wu, Q. Fuzzy demand vehicle routing problem with soft time windows. *Sustainability* **14**, 5658 (2022).
18. Avila-Torres, P. A. & Arratia-Martinez, N. M. Fuzzy inventory-routing problem with priority customers. *Soft Comput.* **28**, 7947–7961 (2024).
19. Bahri, O. & Talbi, E. G. Ben Amor, N. A generic fuzzy approach for multi-objective optimization under uncertainty. *Swarm Evol. Comput.* **40**, 166–183 (2018).
20. Sharma, M. K., Chaudhary, S., Kumar, S., Malik, A. K. & Saha, A. K. A three-dimensional probabilistic fermatean neutrosophic hesitant green transportation system for the sustainable management of biomedical waste. *Eng. Appl. Artif. Intel.* **133**, 108383 (2024).
21. Mahmoodirad, A., Pamucar, D. & Niroomand, S. An optimization scheme for the fuzzy cost-based assembly line balancing problem for the case of nuzzle production line in petroleum industries. *Facta Univ. Ser. Mech. Eng* (2025).
22. Mirzaei, N., Mahmoodirad, A. & Niroomand, S. An uncertain multi-objective assembly line balancing problem: A credibility-based fuzzy modeling approach. *Int. J. Fuzzy Syst.* **21**, 2392–2404 (2019).

23. Thakur, G., Pal, A., Mittal, N., Yajid, M. S. A. & Gared, F. A significant exploration on meta-heuristic based approaches for optimization in the waste management route problems. *Sci. Rep.* **14**, 14853 (2024).
24. Ropke, S. & Pisinger, D. An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. *Transp. Sci.* **40**, 455–472 (2006).
25. Wang, S., Sun, W. & Huang, M. An adaptive large neighborhood search for the multi-depot dynamic vehicle routing problem with time windows. *Comput. Ind. Eng.* **191**, 110122 (2024).
26. Satir Akpunar, Ö. & Akpinar, Ş. A hybrid adaptive large neighborhood search algorithm for the capacitated location routing problem. *Expert Syst. Appl.* **168**, 114304 (2021).
27. Voigt, S. A review and ranking of operators in adaptive large neighborhood search for vehicle routing problems. *Eur. J. Oper. Res.* **322**, 357–375 (2025).
28. Ouertani, N., Nouaouri, I., Ben-Romdhane, H., Allaoui, H. & Krichen, S. A new adaptive genetic algorithm embedded in a two-phase heuristic to solve the multi-compartment vehicle routing problem: A real case study in healthcare waste transportation. *J. Comput. Sci.* **72**, 102104 (2023).
29. Roy, A., Manna, A., Kim, B. & Moon, I. IoT-based smart Bin allocation and vehicle routing model in solid waste management: a case study in South Korea. *Comput. Ind. Eng.* **171**, 108457 (2022).
30. Peña, D. A., Montoya-Torres, J. R. & Amodeo, L. A comprehensive methodology for Understanding waste picker behavior and its influence on waste collection in a two-echelon sustainable waste collection and routing problem. *Socio-Econ Plan. Sci.* **102**, 102288 (2025).
31. Salawudeen, A. T., Akut, K., Momoh, M., Ibrahim, A. & Yusuf, K. A. Novel solid waste instance creation: optimized capacitated vehicle routing solution and comparison of limited and unlimited waste collection in developing cities. *Syst. Soft Comput.* **6**, 200099 (2024).
32. Yu, V. F. et al. Using simulated annealing to solve the multi-depot waste collection vehicle routing problem with time window and self-delivery option. *Mathematics-Basel* **12**, 501 (2024).
33. Chen, L., Liu, Y. & Langevin, A. A multi-compartment vehicle routing problem in cold-chain distribution. *Comput. Oper. Res.* **111**, 58–66 (2019).
34. Liu, S., Sun, J., Duan, X. & Liu, G. Parallel adaptive large neighborhood search based on spark to solve VRPTW. *Sci. Rep.* **14**, 23809 (2024).
35. Voigt, S., Frank, M., Fontaine, P. & Kuhn, H. Hybrid adaptive large neighborhood search for vehicle routing problems with depot location decisions. *Comput. Oper. Res.* **146**, 105856 (2022).
36. Bustos-Coral, D. & Costa, A. M. Adaptive large neighborhood search for drayage routing problems involving longer combination vehicles. *Comput. Oper. Res.* **173**, 106826 (2025).
37. Liu, B. Fuzzy random chance-constrained programming. *IEEE Trans. Fuzzy Syst.* **9**, 713–720 (2001).
38. Zarandi, M. H. F., Hemmati, A. & Davari, S. The multi-depot capacitated location-routing problem with fuzzy travel times. *Expert Syst. Appl.* **38**, 10075–10084 (2011).
39. Gmira, M., Gendreau, M., Lodi, A. & Potvin, J. Y. Tabu search for the time-dependent vehicle routing problem with time windows on a road network. *Eur. J. Oper. Res.* **288**, 129–140 (2021).
40. Cai, L., Wang, X., Luo, Z. & Liang, Y. A hybrid adaptive large neighborhood search and Tabu search algorithm for the electric vehicle relocation problem. *Comput. Ind. Eng.* **167**, 108005 (2022).

Acknowledgements
This research described in the paper was supported by National Natural Science Foundation of China (No. 62203468), Science and Technology Development Program of China Railway Lanzhou Group Co., Ltd. (No. LZJKY2022060-2).

Author contributions
Y.Z.: Writing—original draft preparation, writing—review and editing, methodology, software; Y.W.: Writing—review and editing, methodology, conceptualization, visualization, software; B.Z.: Writing—original draft preparation, writing—review and editing; Y.W.: Software, supervision, validation, data curation; S.P.: Validation, resources, funding acquisition.

Funding
National Natural Science Foundation of China (Grant No. 62203468), Science and Technology Development Program of China Railway Lanzhou Group Co., Ltd. (Grant No. LZJKY2022060-2).

Declarations

Competing interests
The authors declare no competing interests.

Additional information
Correspondence and requests for materials should be addressed to S.P.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by-nc-nd/4.0/.

© The Author(s) 2026