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A Bi-Objective Model for the Location and Optimization Configuration of Kitchen Waste Transfer Stations

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Abstract: Since the implementation of China's mandatory waste sorting policy, the recycling of kitchen waste has become one of the core tasks of waste classification. The problem of designing the locations and the optimization configuration strategy for kitchen waste transfer stations faces great challenges in reconstructing the municipal solid waste collection and transportation system. This paper establishes an integer programming model for the bi-objectives of the location and optimal configuration for a kitchen waste transfer station, with the goal of minimizing the total cost and overall negative environmental impact. An improved non-dominated sorting genetic algorithm with an elite strategy (NSGA-II) is used to solve the problem, resulting in a Pareto-optimal solution set that includes several non-dominated solutions, thereby providing diversified choices for decision-makers. Finally, a pilot case involving cooperative enterprises is used as an example in this study, and the results demonstrate the effectiveness of the model and algorithm, as well as their feasibility in practice.

Keywords: kitchen waste; location of transfer station; resource configuration optimization; bi-objective optimization; improved NSGA-II

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1. Introduction

In China, a country with a huge population, the generation of kitchen waste (KW) has increased year by year, along with the rapid growth in the average income of its residents. More than 100 million tons of KW are generated each year [1,2]. The disposal of a large amount of KW places a heavy financial burden on government departments [3]. To enhance the efficiency of KW disposal, save costs, and reduce environmental pollution, the government has commissioned third-party enterprises to transport and dispose of KW within its jurisdiction through the issuance of franchises [4–6]. KW is generally transported to remote suburbs for centralized treatment [7]. According to statistics, the cost of waste collection and transportation (CT) accounts for 60–80% of the total waste disposal cost [8]. In practice, waste CT in larger cities generally adopts the form of transit transportation [9].

KW will first be transported by small vehicles from collection points to transfer stations (TSs) for temporary storage in bins and then centrally transferred to the final disposal site by large tankers [10]. Considering the clustering of TSs to form a scale effect in transportation, relevant studies have shown that the reasonable construction of waste TSs can greatly reduce the cost of waste CT and improve the efficiency of these processes. Therefore, the optimization of the location of KW transfer stations is of great significance [11,12].

Through the research, several challenges have been identified in the study of the locations of KW transfer. First, KW transfer stations are a typical type of semi-obnoxious facility [13,14]. KW is perishable and malodorous, and the odors generated from its storage and leachate, as well as the noise from the operation of the TSs, can have a significant impact on the environment and cause complaints from surrounding residents. If a TS is located too far from the point of KW generation, this will increase the cost of CT for enterprises and diminish the economic value of constructing the TSs. Secondly, the scarcity of urban land resources makes it difficult to provide sites for the construction of waste TSs [15,16]. Especially in the context of the waste sorting policy, it is necessary to reconstruct the municipal solid waste (MSW) sorting and collection system. This will require a significant number of new or reconstructed classified waste TSs. Thirdly, the construction cost of KW transfer stations is high [17]. To minimize the adverse impact on the surrounding environment and improve the operation efficiency of the TSs, a significant investment in intelligent equipment is often required [18,19]. This includes intelligent tanks, deodorization equipment, sewage treatment equipment, and various types of environmental monitoring equipment, which will add to the upfront investment costs of enterprises.

The location problem of waste TSs has always been a subject of extensive concern in the research community. In the past, the research has mainly focused on the location problem for mixed waste TSs [20]. With the continuous recognition of MSW classification in practice, study of the site selection for classified MSW TSs has gradually attracted the attention of scholars. For example, Rathore and Sarmah [11] proposed a site planning method that considered both classified and unclassified waste TSs, demonstrating that classified waste TSs can benefit solid waste management while addressing high collection costs and landfill issues. Mantzaras and Voudrias [21] studied the location problem of medical waste treatment facilities. Different types of MSW have different characteristics and features, but there are still shortcomings in terms of the location problem for classified waste TSs. Waste TSs are a typical type of NIMBY facility. The site selection for such facilities not only needs to consider the goal of minimizing costs but also often needs to consider the impact on the environment and society. Eiselt et al. [22] established a mixed-integer optimization model considering both cost and environmental negative effects in the site selection of MSW transfer stations and treatment plants. Yu and Solvang [23] comprehensively considered the balance between the operating costs, greenhouse gas emissions, and social equity and used the weighted sum method to generate the optimal solution to this multi-objective optimization problem. The uncertainty of MSW generation is an important consideration for the layout and planning of waste CT networks. Kůdela et al. [24] considered the uncertainty of waste generation and proposed a multi-objective, two-stage, mixed-integer stochastic programming location problem model, which was tested through a case study in the Czech Republic. Habibi et al. [25] established a multi-objective robust optimization model for MSW management systems to address the impact of uncertain waste generation by setting redundancy levels. Jia et al. [12] studied the problem of adjusting the TSs, constructed a location problem model based on mixed-integer linear programming, and verified the applicability of the model using Beijing as an example. Hashemi [26] studied a fuzzy multi-objective optimization model for the design of a sustainable reverse logistics network for MSW collection, considering emission reductions. Fuzzy theory and robust optimization methods provide excellent references for location problems in uncertain environments. In terms of the solving algorithms, the main approaches are either exact solving methods or heuristic methods. Rossit et al. [27] studied an exact method for locating multi-target MSW collection points in real scenarios, combining it with mathematical programming methods for processing. Farrokhi Asl et al. [28] and Rabbani et al. [29] evaluated the performance of a non-dominated sorting genetic algorithm (NSGA-II) and multi-objective particle swarm optimization in solving large-scale, dual-objective garbage collection site routing problems. Some improved heuristic methods have also been applied in the optimization of waste CT systems [30]. Due to the limitations of exact solving algorithms when there are many collection points, heuristic algorithms are often used due to their better applicability.

In summary, in the research on the locations for waste TSs, scholars have primarily considered factors such as the waste characteristics and collection methods, multi-objective optimization, the uncertainty of the waste generation volumes, and the design of the algorithms. However, through a limited literature search, we found almost no studies specifically addressing the location for KW transfer stations. Our investigations also revealed that in the existing KW collection and transportation systems, the lack of scientifically guided methods for selecting the locations for KW transfer stations has led to irrational construction planning. This has resulted in wasted funds and adverse impacts on residents' living environments. Therefore, it is necessary to propose a multi-objective modeling and solution method for the location of KW transfer stations.

The main challenges in this study are as follows: (1) How do we optimize the trade-off between economic cost and negative environmental effects in the location planning for KW transfer stations? (2) For multi-objective optimization, how do we obtain as many combinations of optimal solutions as possible? (3) What are the sensitive parameters in a KW collection and transportation system? What are the relationships among these parameters, and how do they affect the location planning for KW transfer stations?

To address these questions, this paper aims to establish a methodology for the location and optimization configuration of KW transfer stations, considering the bi-objectives of cost and environmental negative effects. The objectives of this paper are as follows:

- Formulate a mathematical bi-objective model for solving the centralized location and optimization configuration problem for KW transfer stations;
- Improve the traditional multi-objective genetic algorithm to increase the quantity and quality of optimal solutions and to enhance the solution speed;
- To verify the effectiveness and efficiency of the method proposed in this paper using real-world cases and to investigate the impact of specific sensitivity parameters on the results in terms of KW transfer station locations and the optimal configuration.

Referring to the research aim and objectives, we carry out this research according to the following three aspects. Firstly, based on the characteristics of KW collection and transportation systems, a mixed-integer planning model is developed to solve the problem of the TS locations and optimal configuration. The objectives of this model are to minimize the economic costs (including construction, operation, removal, and transfer costs) and negative environmental effects. Secondly, the uncertainty of the amount of KW generated is considered, and fuzzy mathematics is used to convert the uncertain amount of garbage into a fixed value at a certain confidence level. Then, in order to address the issues of poor convergence and the tendency to fall into local optima commonly encountered by traditional multi-objective heuristic algorithms, an improved NSGA-II is adopted. In this approach, the previously fixed crossover and mutation probabilities are dynamically adjusted to decrease with the number of iterations, thereby enhancing the population diversity. This adjustment guides the population towards the global optimal solution. The effectiveness of the improved algorithm has been validated. Finally, the feasibility and validity of the proposed methodology are verified through a real-world cooperative enterprise case study. This case study yields the locations and the optimal configuration plan for a scenario with 556 collection points, 20 TS candidates, and 2 disposal sites. Additionally, a sensitivity analysis is conducted on four parameters, the fixed construction costs, the TS tank capacity, the minimum tank load rate, and the different $m/n/p$ values, providing valuable managerial insights.

The main contributions of this paper are as follows: (1) The TS locations and the optimal configuration model in this study fully consider the CT characteristics of KW, considering their cost and negative environmental effect objectives, which makes the formulated model more in line with reality. (2) The NSGA-II is improved by integrating it with the specific problem model. (3) Given the current urgent need to establish a separate collection system for MSW, it provides an excellent reference for governments and enterprises in planning and constructing a KW collection network. Additionally, it offers managerial suggestions on how to reduce the economic cost of the waste collection system and improve its collection efficiency.

The remainder of this paper is organized as follows: Section 2 focuses on the problem description. Section 3 introduces the construction of the mathematical model, while Section 4 illustrates the design of the model solving algorithm. In Section 5, the computational results and a sensitivity analysis are presented, which verify the validity and practicability of the model and the algorithm, and the effect of parameter variations within the model on the relevant objectives is discussed. A summary and conclusions are presented in Section 6.

2. Problem Description

KW recycling involves three crucial stages: front-end deposit, mid-stage CT, and end-stage disposal [31]. The recycling process is shown in Figure 1. This paper focuses on the mid-stage CT of KW, specifically the process of transporting waste from the front-end deposit points to the end-stage disposal sites. This process is divided into two subprocesses: the collection of waste and its subsequent transportation. The collection subprocess is responsible for transporting waste from deposit points to transfer stations, whereas the transportation subprocess involves moving the waste from transfer stations to disposal sites.

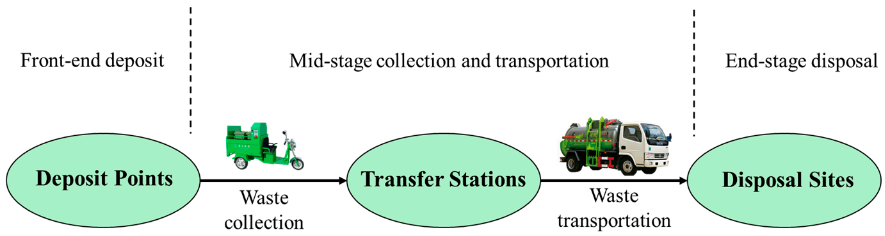

Figure 1. The recycling process of KW.

KW deposit points are varied and extensively distributed, primarily encompassing restaurants in commercial zones, snack stands in food streets, dining facilities in hotels, the cafeterias of enterprises and institutions, and garbage sorting stations in various communities, as well as markets, among other things. Given that the roads to these deposit points are typically narrow, they can only be transported to TSs using small collection vehicles (such as platform trucks, tricycles, enclosed pickup trucks, and so forth.). The primary aim of establishing TSs is to minimize the costs associated with waste CT. Situated in urban areas near deposit points, these stations function as centralized, temporary storage hubs for waste collected from nearby locations. Once the accumulated waste at a TS reaches a certain volume, it is then transported to the final disposal site using large transfer vehicles, such as large tank trucks. Therefore, TSs should be in areas with convenient traffic access to facilitate the passage of vehicles. However, the construction area for disposal sites is relatively large and carries a high risk of environmental pollution, often leading to public opposition. As a result, these facilities are generally located far from densely populated urban centers, in sparsely populated, remote suburban areas.

For a given urban area, suppose there are m KW deposit points. These points may be located at a single waste generation source, such as a restaurant, hotel, school cafeteria, or farmers' market, or they may represent a region comprising multiple adjacent waste-generating sites, such as a residential community or a commercial street/commercial complex, where the center of gravity (or centroid) of these adjacent sites is considered. Additionally, there are n KW transfer station candidates and p waste disposal sites within this urban area. The entire waste recycling logistics network structure is formed of these nodes, including deposit points, TSs, and disposal sites, as well as the collection and transfer activities between the nodes, as shown in Figure 2. The circles represent the KW deposit points, while the squares represent KW transfer stations. The green squares indicate activated candidate sites, and the gray squares indicate non-activated candidate sites. The triangles represent waste disposal sites. As shown in Figure 2, there are multiple TS candidates. KW from deposit points can only be transported to the nearest TS, while each TS can receive waste from multiple deposit points, forming "many-to-one" relationships between the deposit points and TSs. On the other hand, KW from one TS can be transported to multiple disposal sites, and one disposal site can receive waste from multiple TSs, which indicates a "many-to-many" relationship.

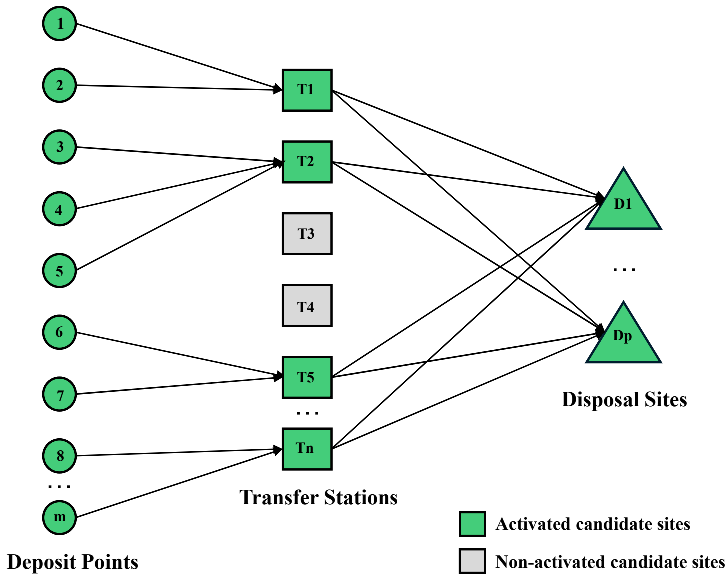

Figure 2. The collection and transportation network for kitchen waste.

The optimization decisions that will be provided by this model include the following: (1) which KW transfer station candidates should be selected; (2) the actual capacity and optimization configuration of each selected KW transfer station; (3) the determination of which TS will receive the waste from each deposit point; and (4) the determination of which disposal site will receive waste from each TS. These decisions aim to minimize both the total cost of establishing the KW transfer stations and their negative environmental effects.

3. Mathematical Formulation

3.1. Assumption

(1) Candidate sites for each TS have been identified and evaluated by the relevant authorities in terms of their environmental aspects, ensuring compliance with national and local government policies and regulations.
(2) The volume of waste generated at the KW deposit points is unknown and expressed in the form of triangular fuzzy numbers $\widetilde{q}_i = \left(q_i^L, q_i^M, q_i^U\right)$.
(3) The negative environmental effect caused by the KW bins at the deposit points and disposal sites is not considered.
(4) Assuming that the population is primarily concentrated around the deposit points, ignoring the distance between the generation points and the deposit points, that is, the deposit point is the center point of the population distribution in a local area.
(5) All KW transfer stations are equipped with tanks of an equal capacity, and the tanks must meet a certain load requirement before they can be transferred.

(6) Assuming that the distance between the deposit points and the TSs is equal to the spherical distance on Earth from each deposit point to the TS.
(7) Each transfer vehicle can transport only one tank at a time.
(8) Each tank at each TS must be transferred only once per day.

3.2. Definition of the Equations

(1) Sets

I: Nodes corresponding to KW deposit points in the area, $i \in I = \{1, 2, \ldots, m\}$;
J: Nodes corresponding to KW transfer station candidates in the area, $j \in J = \{1, 2, \ldots, n\}$;
K: Nodes corresponding to KW disposal sites in the area, $k \in K = \{1, 2, \ldots, p\}$.

(2) Parameters

C: Total cost of location planning;
U: Total negative environmental effect of location planning;
C_{max}: Maximum budget of total cost;
Q_0: Capacity of each tank in a TS;
Q_j^{max}: Maximum capacity of candidate node j;
γ: Minimum tank loading rate (a tank can only be moved once this threshold is reached);
S_k: Maximum processing capacity of KW disposal site k;
$\widetilde{q}_i$: Daily waste generation volume (an uncertain value) at KW deposit point i;
q_i^L: The most conservative estimate of the daily KW generated at deposit point i;
q_i^M: The most probable estimate of the daily KW generated at collection point i;
q_i^U: The most optimistic estimate of the daily KW generated at deposit point i;
$\widetilde{B}_i$: Daily waste generation volume (a determined value) at KW deposit point i;
α: The confidence interval for waste generation;
$long_i$: Longitude coordinate of the center of waste deposit point i;
lat_i: Latitude coordinate of the center of waste deposit point i;
$long_j$: Longitude coordinate of waste TS candidate j;
lat_j: Latitude coordinate of waste TS candidate j;
$long_k$: Longitude coordinate of waste disposal site k;
lat_k: Latitude coordinate of waste disposal site k;
Δlat_{ij}: The difference in latitude between deposit point i and TS j;
$\Delta long_{ij}$: The difference in longitude between deposit point i and TS j;
Δlat_{jk}: The difference in latitude between TS j and disposal site k;
$\Delta long_{jk}$: The difference in longitude between TS j and disposal site k;
r: Average radius of the Earth;
d_{ij}: The great circle distance from waste deposit point i to waste TS j;
D_{jk}: The great circle distance from waste TS j to waste disposal site k;
H_i: Permanent population in the vicinity of deposit point i;
a: Impact parameter of the actual capacity of the TS on negative environmental effects;
b: Impact parameter of distance on negative environmental effects;
T: Planned service life of a TS;
c_j^1: Unit fixed construction cost of KW transfer station j;
c_j^2: Unit operating cost of KW transfer station j;
$c_{vehicle}^3$: Unit transportation cost of the collection vehicle;
c_{Truck}^4: Unit transportation cost of the transfer vehicle.

(3) Decision Variables

$X_j = \begin{cases} 1, \ if \ a \ TS \ is \ located \ at \ site \ j \\ 0, \ otherwise \end{cases}$;
p_{ij}: Volume of waste transported from KW deposit point i to TS j;
s_{jk}: Volume of waste transported from TS j to disposal site k;
h_j: Number of tanks under the actual capacity of TS j;
Q_j: Actual construction capacity of each TS ($Q_j = h_j \cdot Q_0$).

3.3. A Bi-Objective Model

$$Minimize\ \boldsymbol{C} = C_1 + C_2 + C_3 + C_4 \tag{1}$$

$$C_1 = \sum\nolimits_{j \in J} X_j \cdot Q_j \cdot c_j^1 \tag{2}$$

$$C_2 = (365\mathrm{T}) \sum\nolimits_{i \in I} \sum\nolimits_{j \in J} p_{ij} \cdot c_j^2 \tag{3}$$

$$C_3 = (365\mathrm{T}) \sum\nolimits_{i \in I} \sum\nolimits_{j \in J} p_{ij} \cdot d_{ij} \cdot c_{vehicle}^3 \tag{4}$$

$$C_4 = (365\mathrm{T}) \sum\nolimits_{j \in J} \sum\nolimits_{k \in K} h_j \cdot Q_0 \cdot D_{jk} \cdot c_{Truck}^4 \tag{5}$$

The total negative environmental effect primarily includes the adverse impacts of the odors, noise, and air pollutants generated by a TS on the permanent residents in the vicinity of the TS. A reference for the calculation formula can be found in [22].

$$\mathrm{Minimize}\ \boldsymbol{U} = (365\mathrm{T}) \sum\nolimits_i \sum\nolimits_j H_i \cdot \frac{a \cdot \sum_k p_{kj} \cdot X_j}{\left(d_{ij} + b\right)^2} \tag{6}$$

subject to

$$\widetilde{q}_i = \sum\nolimits_{j \in J} p_{ij},\ \ \forall i \in I \tag{7}$$

$$\sum\nolimits_{i \in I} \sum\nolimits_{j \in J} p_{ij} = \sum\nolimits_{j \in J} \sum\nolimits_{k \in K} s_{jk} \tag{8}$$

$$Q_j = h_j Q_0,\ \ \forall j \in J \tag{9}$$

$$0 \leq Q_j \leq Q_j^{max} \cdot X_j,\ \ \forall j \in J \tag{10}$$

$$Q_j \geq \sum\nolimits_{i \in I} p_{ij},\ \ \forall j \in J \tag{11}$$

$$\sum\nolimits_{k \in K} s_{jk} \geq \gamma \cdot Q_j,\ \ \forall j \in J \tag{12}$$

$$d_{ij} = 2r \cdot arcsin\left(\sqrt{sin^2\left(\frac{\Delta lat_{ij}}{2}\right) + \cos\left(lat_i\right) \cdot \cos\left(lat_j\right) \cdot sin^2\left(\frac{\Delta long_{ij}}{2}\right)}\right),$$
$$\forall i \in I, \forall j \in J \tag{13}$$

$$D_{jk} = 2r \cdot arcsin\left(\sqrt{sin^2\left(\frac{\Delta lat_{jk}}{2}\right) + \cos\left(lat_j\right) \cdot \cos\left(lat_k\right) \cdot sin^2\left(\frac{\Delta long_{jk}}{2}\right)}\right),$$
$$\forall j \in J, \forall k \in K \tag{14}$$

$$C \leq C_{max} \tag{15}$$

$$X_j \in \{0, 1\},\ \ \forall j \in J \tag{16}$$

$$m, n, p \geq 0, integer \tag{17}$$

Equations (1)–(6) are the objective functions. Equation (1) represents the total TS location costs $\boldsymbol{C}$, including the construction cost (2), the operation cost (3), the waste collection cost (4), and the transfer cost (5), while Equation (6) represents the total negative environmental effect. Equations (7)–(17) are constraints. Equation (7) indicates that the waste generated at a deposit point is equal to the waste transported from that deposit point to the TS. Equation (8) indicates that the amount of waste transported from a deposit point to a TS is equal to the amount of waste transported from the TS to the disposal sites. Equation (9) indicates that the actual construction capacity of a TS is equal to the tank's capacity multiplied by the number of tanks. Equation (10) indicates that the actual construction capacity of a TS is greater than or equal to the minimum construction capacity of the candidate site and less than or equal to the maximum construction capacity of the candidate site. Equation (11) indicates that the construction capacity of a TS must meet the unloading requirements of the deposit points. Equation (12) indicates the transfer conditions for a TS. Equations (13) and (14) are the formulas for calculating the collection distance and the transfer distance, respectively. Equation (15) indicates that the location cost must be less than the maximum budget. Equation (16) involves the 0–1 decision variable constraint. Equation (17) indicates that the number of waste deposit points, the number of TSs, and the number of disposal sites are all integers.

4. Solution Approach

Due to the uncertainty of the amount of waste generated, this paper first uses the method of triangular fuzzy numbers to convert the amount of waste generated into a determined value. Subsequently, this paper adopts the improved NSGA-II algorithm for solving. The following introduces the deblurring method and the algorithm used in this paper.

4.1. The Defuzzification Method

To solve a multi-objective model of KW generation in an uncertain state, it is necessary to convert the fuzzy generation of waste into a determined value, that is, to carry out defuzzification processing. The triangular fuzzy number in uncertainty theory is a way to express the uncertainty of objective things. In this study, the amount of KW generated at deposit point i is $\widetilde{q}_i = \left(q_i^L, q_i^M, q_i^U\right)$, where $0 \leq q_i^L \leq q_i^M \leq q_i^U$. q_i^L represents the most conservative estimate of the amount of KW generated at deposit point i by the decision-maker (i.e., the lower bound of the triangular fuzzy number), q_i^M represents the most probable estimate, and q_i^U represents the most optimistic estimate (i.e., the upper bound of the triangular fuzzy number). The characteristic function of the triangular fuzzy demand for point i is shown in Equation (18).

$$\mu_{\widetilde{B}}(x) = \begin{cases} 0 & x \leq q_i^L \\ \frac{x - q_i^L}{q_i^M - q_i^L} & q_i^L \leq x \leq q_i^M \\ \frac{q_i^U - x}{q_i^U - q_i^M} & q_i^M \leq x \leq q_i^U \\ 0 & x \geq q_i^U \end{cases} \tag{18}$$

When converting $\widetilde{B}_i$ into a determined value, it is necessary to consider both the preferences of the decision-maker and the attribute values of the triangular fuzzy number. Therefore, after the government decision-maker sets the confidence level α, this paper adopts the strategy of converting triangular fuzzy numbers into deterministic numbers from reference [32] and uses the weighted average method to convert the fuzzy garbage production $\widetilde{q}_i$ at deposit point i into a deterministic value that can be used for solving, as shown in Equation (19).

$$\widetilde{B}_i = \varphi_1 \times q_i^L + \varphi_2 \times q_i^M + \varphi_3 \times q_i^U \tag{19}$$

Among them, $\varphi_1 + \varphi_2 + \varphi_3 = 1$, representing the weights of the most conservative, most likely, and optimistic values of the amount of waste generated, respectively. This paper adopts the most likely value method used in the study of multi-objective fuzzy transportation problems, as in reference [33]. This paper sets the confidence level $\alpha = 0.5$, with values of $\varphi_1 = \varphi_3 = 1/6$, $\varphi_2 = 4/6$. After determining the weight and the confidence level, the formula for deblurring the amount of KW generated at deposit point i, $\widetilde{B}_i$, into a determined value is shown in Equation (20).

$$\widetilde{B}_i = \frac{1}{6} \times \left[\left(q_i^M - q_i^L\right) \times \alpha + q_i^L\right] + \frac{4}{6} \times q_i^M + 1/6 \times \left[q_i^U - \left(q_i^U - q_i^M\right) \times \alpha\right] \tag{20}$$

Therefore, Equation (8) can be transformed into (21).

$$\sum\nolimits_{i\in I}\widetilde{B}_i=\sum\nolimits_{j\in J}\sum\nolimits_{i\in I}X_j\cdot p_{ij} \tag{21}$$

4.2. Introduction of the Algorithm

In this paper, two conflicting optimization objectives for the location and configuration of KW transfer stations are considered: the location cost and negative environmental effects. They are mutually constraining and exclusive, meaning that improving one objective may lead to the deterioration of the other. Therefore, these two objectives cannot reach their optimal values simultaneously. Furthermore, these two objectives are quantitatively incomparable due to the lack of a common measurement framework and physical interpretations. For multi-objective optimization, commonly used methods include the weighted sum method, the ε-constraint method, the goal programming method, and their corresponding improved versions [34,35]. The core idea of these methods is to transform the multi-objective optimization problem into a single-objective problem for solving, which cannot adequately account for the trade-offs between the objectives. Therefore, this paper employs an optimization strategy based on the Pareto-optimal solution set. The Pareto-optimal solution set aims to present as many representative non-dominated solutions as possible. To avoid becoming trapped in local optima, a genetic algorithm with global probabilistic optimization capabilities is proposed to solve the multi-objective optimization problem.

The commonly used multi-objective optimization methods based on genetic algorithms include the non-dominated sorting genetic algorithm (NSGA) and the NSGA-II. The NSGA ranks individuals in the population based on the principle of non-dominated sorting and assigns virtual fitness values through a niche-sharing technique [36]. This algorithm can obtain a uniformly distributed set of non-inferior (Pareto-optimal) solutions. However, it has several drawbacks: high computational requirements, the tendency for excellent individuals in the parent population to overlap, and the need to specify shared parameters. Addressing the shortcomings of the NSGA, the NSGA-II introduces a fast non-dominated sorting algorithm, an elite strategy, and the use of crowding distance and crowding comparison operators [37]. These improvements reduce the computational complexity of the algorithm, enable individuals in the optimal frontier to be evenly distributed across the entire Pareto domain, and ensure the diversity of the population. This makes the NSGA-II more suitable for solving bi-objective optimization problems. This paper adopts the basic framework of the NSGA-II, with initially fixed crossover and mutation probabilities that are then dynamically adjusted to decreasing values with each iteration according to the logsig function [38]. This adjustment aims to enhance the convergence of the population and direct the search towards the globally optimal solution. Furthermore, to prevent the issue of an insufficient number of optimal solutions, this paper also considers incorporating an inner loop for crossover and mutation operations to maintain the population size.

4.3. The Improved NSGA-II Process

The specific procedure of the improved NASG-II is shown in Figure 3, and the detailed implementation steps are as follows:

Step 1: Initialization. Select the integer coding method, initialize the population size of individuals set to N, randomly generate the parent population P_t, set the number of evolutionary generations $t = 0$, and set various parameters, such as the maximum number of evolutionary generations, population size, mutation probability (with dynamic adjustment rules based on a function value), etc.

Step 2: Rank the non-dominated solutions of the parent population. Use fast non-dominated sorting to rank each individual in P_t and calculate the crowding distances.

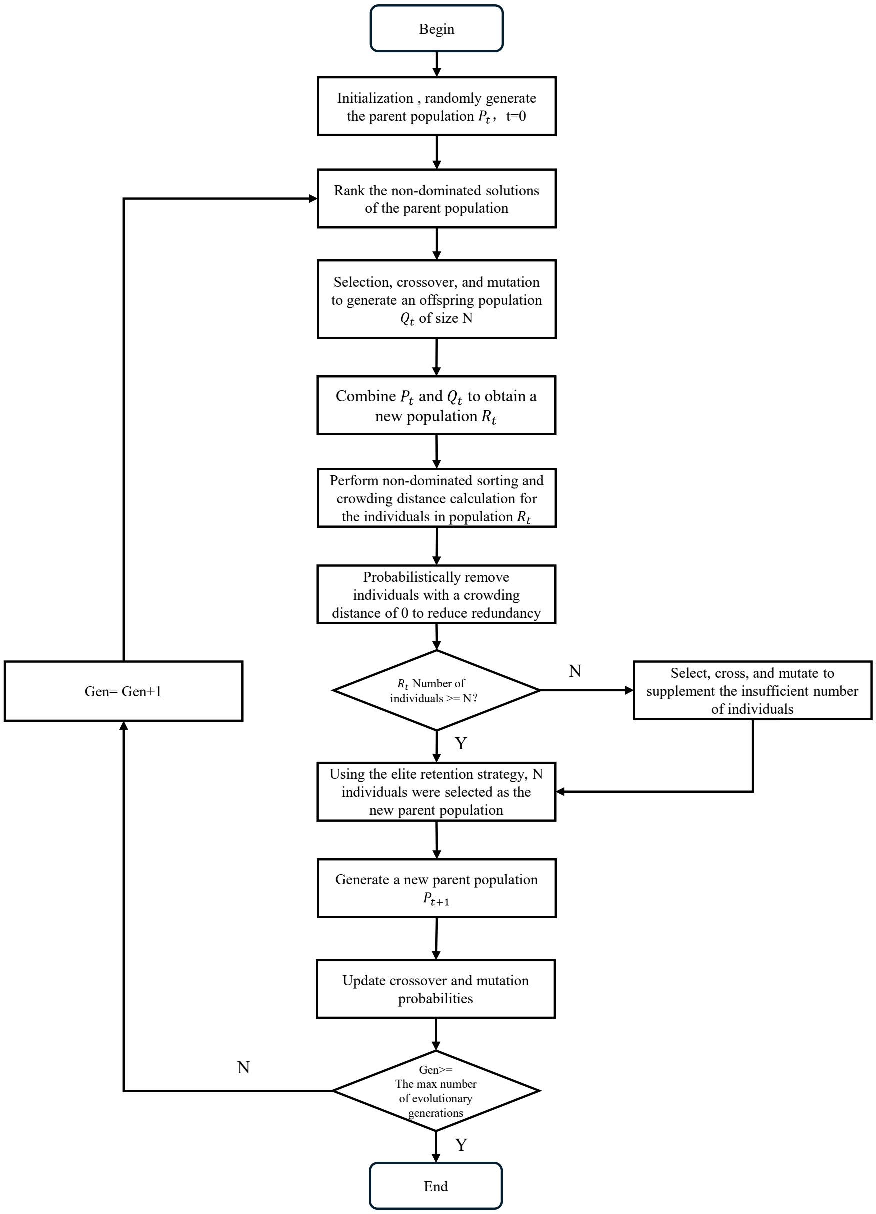

Figure 3. The process of the improved NSGA-II.

Step 3: Generate the offspring population. Apply the genetic algorithm (including selection, crossover, and mutation) to P_t to generate the offspring populations Q_t. Combine P_t and Q_t to obtain a new population R_t.

Step 4: Generate the next-generation population through an elite retention strategy. Use fast non-dominated sorting to classify each individual in R_t and calculate the crowding distances. Individuals with a crowding distance equal to 0 are probabilistically removed to reduce duplication and increase the population diversity. If the population size is insufficient after removal, perform crossover and mutation again to maintain the required size. The new generation of the parent population is then derived through the elite retention strategy, and we set $t = t + 1$.

Step 5: Dynamically adjust the crossover and mutation probabilities for the population, and then repeat Steps 3 and 4.

Step 6: Determine whether the maximum number of evolutionary generations has been reached; if so, end the run and output the result; if not, return to Step 3 and continue the iterative process until the maximum number of evolutionary generations is reached, at which point the program will terminate.

5. Case Study

5.1. Introduction of the Data Source

The test data for the model are derived from real data provided by an intelligent service management company in Zhuhai City that specializes in KW collection and transportation, in collaboration with the research team. This company is one of the largest waste CT informatization management service providers in Zhuhai, and it has undertaken 90% of the KW collection and management informatization projects in Xiangzhou District of Zhuhai City. The test data in this paper involve KW collection and transportation data from the Gongbei subdistrict in Zhuhai City, which is located in the intersection zone bordering Zhuhai and Macau. The total area of the subdistrict is 10.32 square kilometers, with a permanent population of 116,300. The Gongbei Port within this subdistrict has an average daily passenger flow of 390,000. Additionally, there are 2200 KW generation points in the area, which include commercial districts, restaurants, hotels, schools, institutional cafeterias, residential neighborhoods, and farmers' markets. The dataset includes valid daily KW generation data from 2019 to 2023 within the jurisdiction. After data extraction, filtering, correction, and merging, a final set of 556 valid deposit points was obtained. This included 379 restaurant KW generation points, 173 household KW deposit points, and 4 other KW deposit points. Each data entry provides the name of the deposit point merchant, the type of waste, longitude and latitude coordinates, and the amount of waste generated. The administrative region and the distribution of the deposit points are shown, respectively, in Figure 4. Detailed information on the 20 TS candidates available for deployment is provided in Table 1. The detailed information for the two waste disposal sites, Zhuhai Eco-environmental Protection Industrial Park and Zhuhai Sanitation Department's Lixi Landfill Plant, is shown in Table 2.

The cost parameters c_j^1, c_j^2, $c_{vehicle}^3$, and c_{Truck}^4 in the model are calculated from the historical data provided by the subdistrict office. The construction planning parameters $T, Q_0, \gamma, and\ C_{max}$ are taken from the actual construction of the subdistrict. The parameters $a,\ \ b$ for negative environmental effects are referred to from [23]. The detailed parameter values are shown in Table 3.

Table 1. Name and coordinates of TS candidates.

NO.	Name of TS Candidate	Coordinates	Q_j^{max} (ton)
0	Changsheng Road TS	(111.551453, 22.221108)	30
1	Lingxiu City TS	(113.555233, 22.241892)	30
2	Guihua North Road TS	(113.555709, 22.235375)	40
3	Lianhua North Road TS	(113.562316, 22.23351)	40
4	Bar Street TS	(113.562316, 22.232891)	20
5	Gaosha TS	(113.564918, 22.228768)	20
6	Gongbei Market TS	(113.560761, 22.229236)	30
7	Gongbei Hospital TS	(113.553198, 22.229683)	20
8	Xiawan New Village TS	(113.549183, 22.229817)	60
9	Baozhu Garden TS	(113.548132, 22.228169)	30
10	Guihua South Road TS	(113.555009, 22.227621)	50
11	Port Market TS	(113.561253, 22.225318)	20
12	Guangfa Garden TS	(113.550427, 22.225773)	30
13	Yuehai West Road TS	(113.546943, 22.237621)	90
14	Ganger Road TS	(113.541831, 22.23551)	30
15	Huaning Garden TS	(113.544289, 22.226995)	60
16	Nordic Forest Garden TS	(113.538976, 22.238678)	30
17	Yuehai Garden TS	(113.547034, 22.217712)	30
18	Qianhedong Road TS	(113.538965, 22.22804)	70
19	Hairong New Village TS	(113.535445, 22.236219)	60

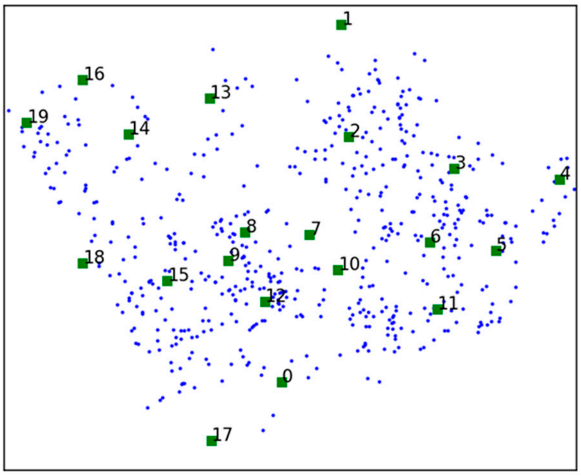

Figure 4. Distribution of KW deposit points and TS candidates within the pilot area (Blue dots represent deposit points, green squares represent TS candidates, and numbers represent numbering).

Table 2. Name, coordinates, and maximum capacity of disposal sites.

NO.	Name of Disposal Site	Coordinates	Maximum Capacity
1	Zhuhai Eco-environmental Protection Industrial Park	(113.131265, 22.207122)	800 ton/day
2	Zhuhai Sanitation Department's Lixi Landfill Plant	(113.511704, 22.316821)	20 ton/day

Table 3. Case-related parameters.

Parameter	Value	Unit	Parameter	Value	Unit
m	556	item	c_j^1	100,000	yuan/ton
n	20	item	c_j^2	22	yuan/ton
p	2	item	$c_{vehicle}^3$	50	yuan/ton*km
T	20	year	c_{Truck}^4	2.7	yuan/ton*km
a	0.025	km^2/ton	Q_0	10	ton
b	0.001	km	C_{max}	200,000,000	yuan
r	6371.393	km	γ	0.8	/

5.2. Computational Results

The computation was conducted on a computer equipped with an Intel Core i7-1260P CPU@ 2.1 GHz and 16.0 GB RAM. The models were solved using Python for coding in the Visual Studio Code 1.90.2 environment. The parameters of the improved NSGA-II were set as follows: the population size is 500, the maximum number of evolutionary generations is 150, the initial crossover probability is 0.5, and the initial mutation probability is 0.1.

The Pareto-optimal solutions computed are shown in Figure 5 and Table 4. The first point in the upper-left corner of Figure 5 corresponds to the optimal solution, numbered as 1 in Table 4, and the correspondences are in order. As can be seen in Figure 5, the negative environmental effect in the Pareto-optimal solution decreases as the cost of the site selection increases. It can be found that the value of the negative environmental effects is within the range of [3,840,520,823.80, 10,259,014,152.61], and the total location cost ranges within [74,689,849.77, 89,634,015.62], indicating costs increased by 20.01%, and negative environmental effects were reduced by 62.56%. Table 4 shows the values of the decision variables and the optimization objectives corresponding to the 23 sets of Pareto-optimal solutions obtained, including the set of Pareto-optimal solutions for the location of the TSs (the bold font indicates that the waste at the TS is transferred to Disposal Site 2), as well as the total costs and total negative effects associated with each Pareto-optimal solution.

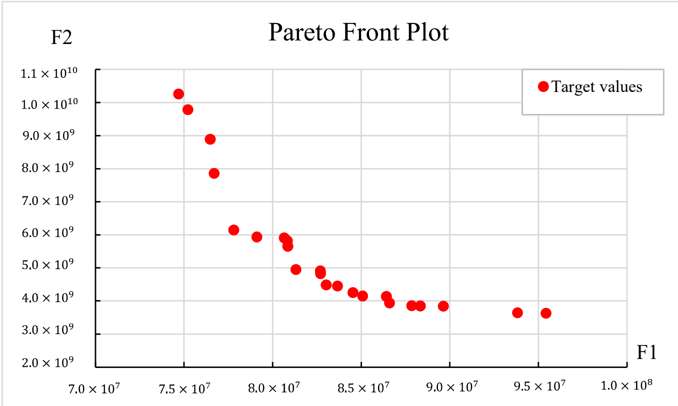

Figure 5. Distribution of Pareto-optimal front solutions (F1 reflects the total cost, and F2 reflects the negative environmental effect).

Table 4. Sets of TSs and objective values corresponding to Pareto-optimal solutions.

NO.	TS Set	F1	F2	NO.	TS Set	F1	F2
1	(0,**2**,**5**,7,8,13,18)	74,689,849.77	10,259,014,152.61	13	(**1**,13,14,17,18)	83,024,484.91	4,478,931,163.63
2	(0,2,**3**,7,**8**,13,18)	75,214,693.90	9,783,504,404.54	14	(0,**1**,13,16,17)	83,662,660.52	4,446,385,635.28
3	(0,2,3,7,11,**14**)	76,481,589.95	8,885,074,197.99	15	(**1**,14,17,18)	84,530,727.79	4,251,815,645.84
4	(0,1,4,**7**,**8**, 13, 18)	76,694,785.87	7,855,742,397.79	16	(0,**1**,16,17,18)	85,086,674.15	4,145,533,663.41
5	(0,1,4,**7**,14,18)	77,803,322.98	6,146,101,683.26	17	(**1**,13,17,18)	86,423,894.63	4,133,467,885.19
6	(1,4,**7**,14,17)	79,114,899.68	5,935,268,594.13	18	(1,17,**18**)	86,601,933.50	3,932,462,749.67
7	(0,1,4,**7**,18)	80,648,924.38	5,902,536,597.69	19	(**1**,16,17,18)	87,850,541.97	3,853,710,304.96
8	(0,1,**7**,14)	80,826,642.14	5,812,437,187.80	20	(0,**1**,17,18)	88,334,974.87	3,848,416,756.88
9	(0,1,4,7,**18**)	80,853,982.12	5,648,740,979.61	21	(1,17,**18**)	89,634,015.62	3,840,520,823.80
10	(0,**1**,4,17,18)	81,315,660.01	4,947,300,861.14	22	(1,**16**,17)	93,828,623.95	3,639,959,801.15
11	(**1**,7,13,14,17)	82,699,244.64	4,906,002,541.67	23	(1,17,**18**)	95,426,131.24	3,628,737,140.27
12	(0,**1**,14,18)	82,711,397.90	4,822,599,216.25	-	-	-	-

The distribution of the TSs and the allocation of the deposit points are shown in Figure 6. The dots in Figure 6 represent the deposit points, the squares indicate the TSs, and the numbers above the squares indicate the number of the TSs, with the different colors being used to differentiate between different scenarios in the comparison. A red circle around a square indicates that a TS is allocated to Disposal Site 2, while no red circle around a square indicates that a TS is allocated to Disposal Site 1.

By comparing the calculation results with those of the traditional NSGA-II, the improved NSGA-II proposed in this paper demonstrates certain advantages. As shown in Figure 7, the Pareto-optimal solution frontier derived by the improved NSGA-II is shifted to the left compared to the result of the traditional NSGA-II. As shown in Table 5, there are four more Pareto-optimal solutions derived by the improved NSGA-II than those from the traditional method, representing an improvement ratio of 21.05%. The computational time (taking the average of 10 calculations) of the improved algorithm is 5.28% longer compared to that of the traditional algorithm. The main reason for this is the improvement of the NSGA-II algorithm by setting the originally fixed crossover and mutation probabilities to dynamically changing values that decrease according to the logsig function. This approach increases the convergence of the population and directs the search towards the global optimal solution. Additionally, duplicate solutions are removed during the calculation process to enhance the efficiency. To prevent an insufficient number of optimal solutions being yielded during the calculation process, internal loop crossover mutation is added to maintain the population size. However, the inner loop operation will increase the time required for the crossover and mutation operations, thus extending the overall computation time. It is advisable to sacrifice a certain amount of computation time to obtain more Pareto-optimal solutions.

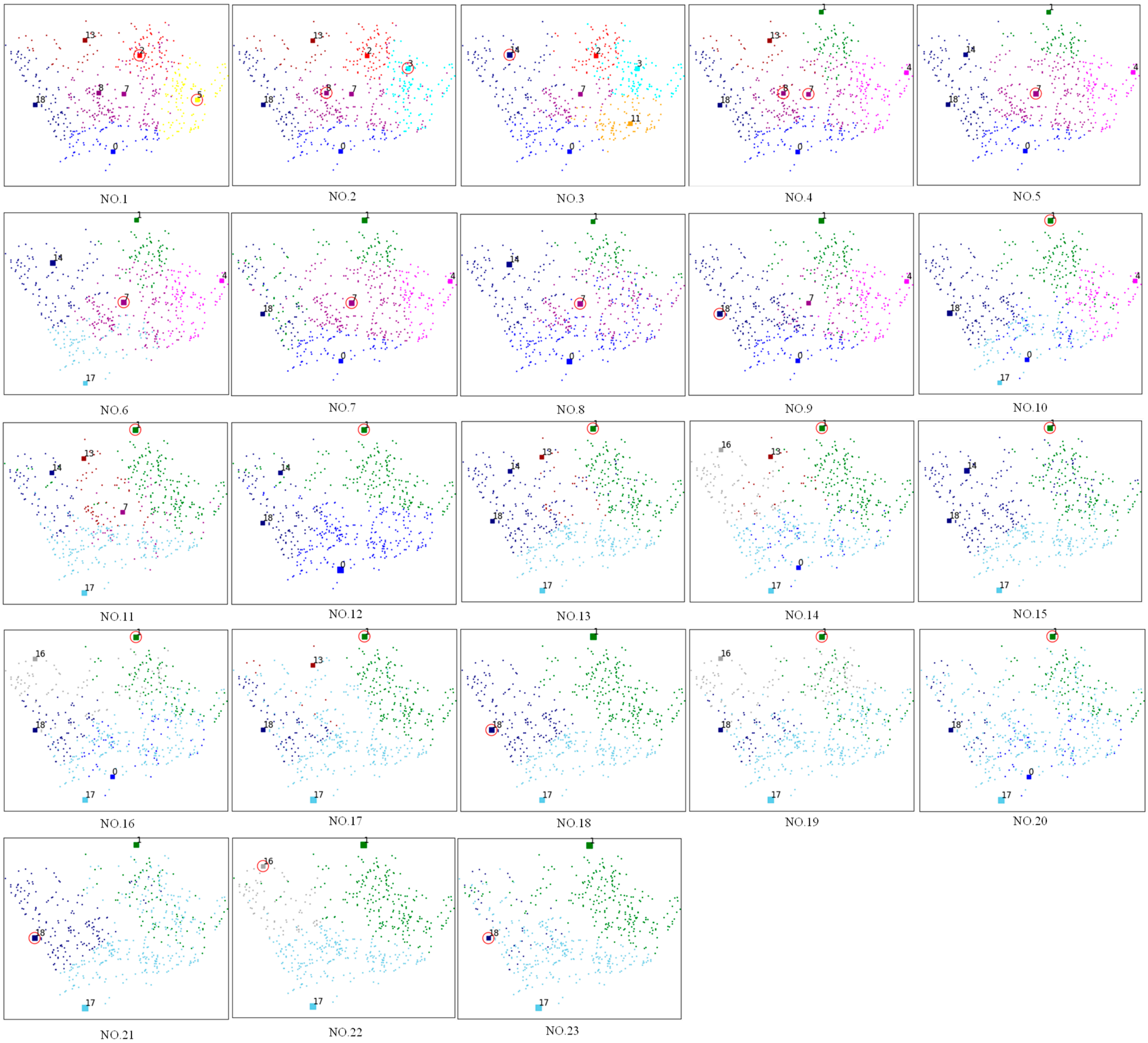

Figure 6. Distribution of the TSs and the allocation of the deposit points in the Pareto-optimal solutions.

Table 5. Comparison of the improved NSGA-II's and the traditional NSGA-II's results.

Item	Number of Pareto-Optimal Solutions	Computing Time
Traditional NSGA-II	19	239.28 s
Improved NSGA-II	23	251.91 s
Comparison of results	21.05%	5.28%

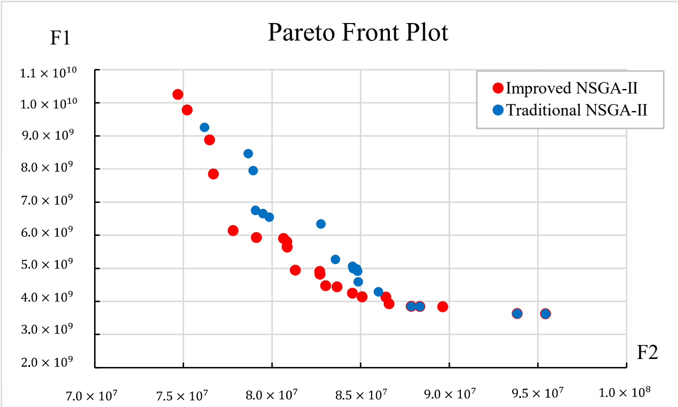

Figure 7. Comparison of improved NSGA-II and traditional NSGA-II Pareto-optimal frontiers.

5.3. Sensitivity Analysis

Factors such as the intelligence level of the TSs, the capacity of the tanks configured at these stations, the actual loading volume of the tanks at the time of transfer, and the fluctuations in waste generation play a critical role in the location and configuration of TSs. Therefore, this paper conducts a sensitivity analysis on parameters including the fixed construction cost, tank capacity, the allowable transfer thresholds, and the impact of different $m/n/p$ values. The aim is to discuss the impact of these parameters on the optimization of the site locations and configuration.

- The fixed construction cost c_j^1

The investment in intelligent equipment at a TS will significantly increase the fixed construction costs c_j^1, but at the same time, it will reduce the operating costs c_j^2 of the TS and diminish the impact factor a of its negative environmental effects. To highlight the impact of fixed construction costs, this paper assumes an inversely proportional relationship between c_j^1 and c_j^2 and a directly proportional relationship between c_j^1 and a. The effect of variations in the fixed construction costs on the location and configuration of the TSs is illustrated in Figure 8.

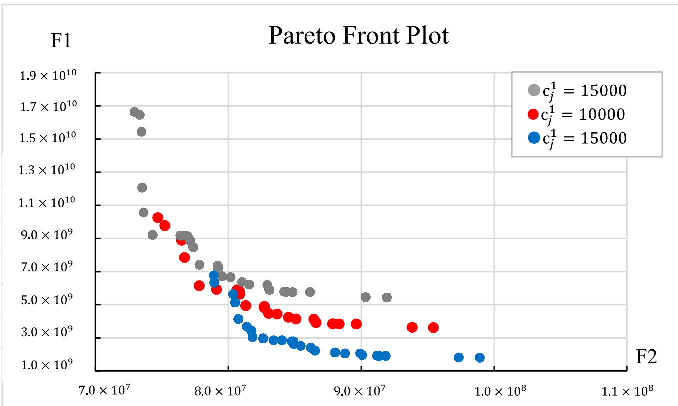

Figure 8. Comparison of different fixed construction costs of the TSs (F1 reflects the total cost, and F2 reflects the negative environmental effect).

As shown in Figure 8, it can be seen that when the input location cost is less than 8 million yuan, the Pareto-optimal solutions obtained at different fixed costs are not significantly different. However, when the investment reaches 8 million yuan, as the fixed cost increases, the Pareto-optimal frontier shifts to the lower left, and both the total cost and the total negative environmental impact decrease. This indicates that when the construction budget for the TSs exceeds 8 million yuan, decision-makers can consider selectively equipping intelligent facilities and equipment to build TSs with higher levels of intelligence.

- The tank capacity Q_0

This subsection mainly analyzes the impact of different tank capacities on the scheme proposed in this paper. As shown in Figure 9, in the case scenario of this paper, changes in tank capacity are considered to affect the transportation costs. When $Q_0 = 5T$, the optimized target result is the worst among all of the schemes. This is easy to understand: the smaller the tank capacity, the higher the unit transportation cost. However, when $Q_0 = 15T$, its unit transportation cost should be the lowest, but its optimization result is only better than $Q_0 = 5T$. On the contrary, the results are better when $Q_0 = 8T$, $Q_0 = 10T$, and $Q_0 = 12T$. This indicates that when configuring the tank, the transfer station does not necessarily choose a larger tank capacity as better, nor does it choose a smaller tank capacity as better. The capacity of the tank must be selected reasonably based on the size of each city and the distribution of the deposit points and the disposal sites. The choice of $Q_0 = 10T$ in this case is reasonable.

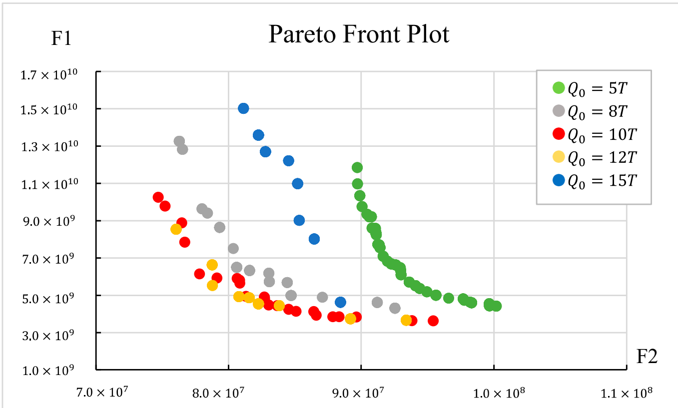

Figure 9. Pareto-optimal solutions corresponding to different tank capacities (F1 reflects the total cost, and F2 reflects the negative environmental effect).

- Minimum tank loading rate γ

To ensure the utilization rate of the tanks and reduce the empty load phenomenon during the transfer process, this paper assumes that a tank can only be allowed to transfer after it reaches the minimum loading rate. This subsection will compare different value of γ.

As shown in Figure 10, when $\gamma = 0.6,\ 0.7,$ or 0.8, the general trend is that the Pareto frontiers overlap significantly and exhibit similar tendencies, making it difficult to distinguish the differences among them. Compared with $\gamma = 0.8$, the Pareto-optimal frontier shifts to the right when $\gamma = 0.9$. This suggests that the greater the minimum loading rate required, the higher the objective values of the location cost and the negative environmental effects. Nevertheless, the Pareto-optimal frontiers are relatively similar when the minimum loading rate is 0.6, 0.7, or 0.8. It is possible that during the optimization process, although the system requires a minimum loading rate, in practice, the tanks are filled as much as possible before transport. The closer the minimum loading rate is to approximately 1, the harder it is to fully load the tank. The computational results show that $\gamma = 0.8$ is a more reasonable value.

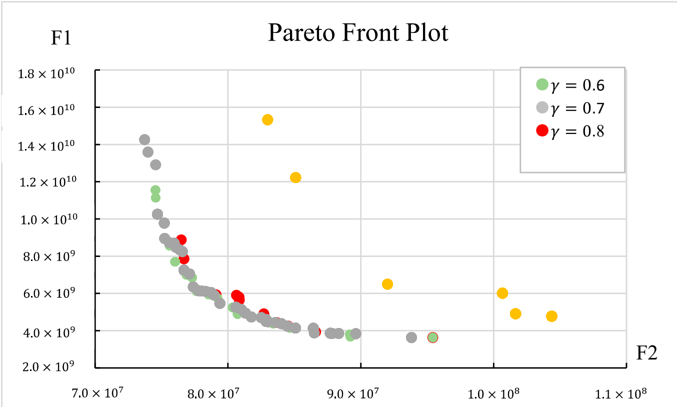

Figure 10. Pareto-optimal solutions corresponding to the different minimum loading rate of tanks (F1 reflects the total cost, and F2 reflects the negative environmental effect).

- The different $m/n/p$ values

The scale of the CT network for KW is generally related to the number of nodes. The scale of the CT network often varies among different cities or regions. To verify the applicability of the model and the algorithm proposed in this paper, different $m/n/p$ values were taken to examine the impact of the problem size on the location and optimization configuration results.

The calculation results are shown in Table 6 and Figure 11. By comparing and analyzing Table 6, the following can be concluded: (1) When the number of disposal sites is halved, the average number of optimal solutions increases by 16.04%, and the average calculation time decreases by 27.47%. (2) When the number of TS candidates is halved, the average number of optimal solutions decreases by 22.48%, and the average calculation time decreases by 1.55%. (3) When the number of deposit points is halved, the average number of optimal solutions decreases by 48.05%, and the average computation time decreases by 46.88%. From this, it can be seen that a change in the number of deposit points has the greatest impact on the time required for the model solving and the number of optimal solutions obtained. The Pareto-optimal solutions corresponding to the schemes listed in Table 6 are shown in Figure 11. The solution obtained by Scheme V is the best, while the solution obtained by Scheme IV is the worst. This indicates that reducing the number of deposit points generally leads to better optimal solutions, especially when the number of TS candidates and disposal sites is increased. Conversely, increasing the number of deposit points tends to yield worse solutions. Compared to the influence of the number of deposit points and disposal sites, the number of TS candidates has the least impact on the optimal solution sought by the model.

Table 6. Comparison of tank capacity and transfer cost.

Scenario	Value of m	Value of n	Value of p	Number of Pareto-Optimal Solutions	Computing Time (s)
I	556	20	2	23	226.38
II	556	20	1	26	176.36
III	556	10	2	15	193.00
IV	556	10	1	16	170.11
V	278	20	2	9	142.58
VI	278	20	1	12	67.16
VII	278	10	2	9	114.78
VIII	278	10	1	10	88.37

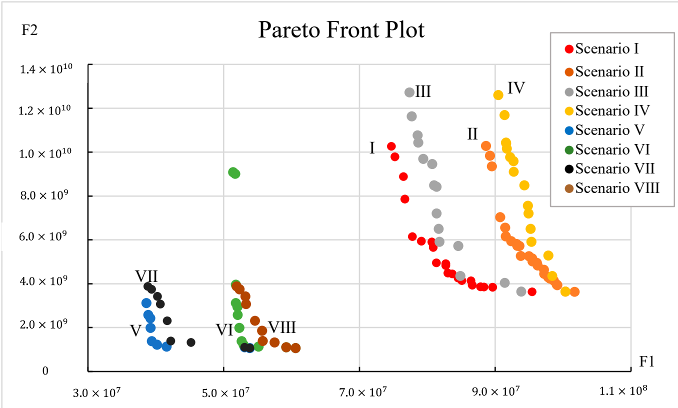

Figure 11. Distribution of Pareto-optimal solutions under different waste volumes (F1 reflects the total cost, and F2 reflects negative environmental effects).

The above analysis shows that a change in the number of deposit points has the greatest impact on the quality and calculation time of the Pareto-optimal solutions. This paper further conducts a sensitivity analysis on the change in the deposit points, taking 12 different m values. The number of TS candidates ($n = 20$) and the number of processing sites ($p = 2$) remain unchanged. When the value of m is 6116 points, the total amount of waste generated is close to the sum of the maximum construction capacity of all of the TS candidates, so a larger value of m is not considered. The relevant values and results are shown in Table 7. The number of optimal solutions and the computation time in Table 7 are illustrated in Figure 12.

In terms of the computation time, as the number of deposit points increases, the computation time noticeably lengthens. Although the data in the graph fluctuate, the overall trend continues to increase, with an average growth rate of 50%. In terms of the number of optimal solutions, as the number of deposit points increases in the interval [0, 2780] (corresponding to the garbage amount interval [35.7, 332.4]), the number of Pareto-optimal solutions obtained gradually increases. Within the interval of the number of deposit points [2780, 6116] (corresponding to a garbage amount interval of [332.4, 709.36]), as the number of deposit points increases, the number of Pareto-optimal solutions gradually decreases. It can be inferred that the model and the algorithm proposed in this paper have good adaptability for solving the location problem for small and medium-sized CT network facilities.

Table 7. Comparison of calculation results for different m values.

Value of m	Total Waste Generated (tons)	Number of Pareto-Optimal Solutions	Computing Time (s)
$m = 278$	35.73	9	142.58
$m = 556$	64.49	23	226.38
$m = 1112$	128.97	76	477.95
$m = 1668$	193.46	77	731.97
$m = 2224$	257.95	99	1284.18
$m = 2780$	322.44	206	1361.38
$m = 3336$	386.93	103	1190.64
$m = 3892$	451.41	71	1365.82
$m = 4448$	515.90	73	2138.90
$m = 5004$	580.39	48	2247.91
$m = 5560$	644.87	36	3507.89
$m = 6116$	709.36	13	4418.97

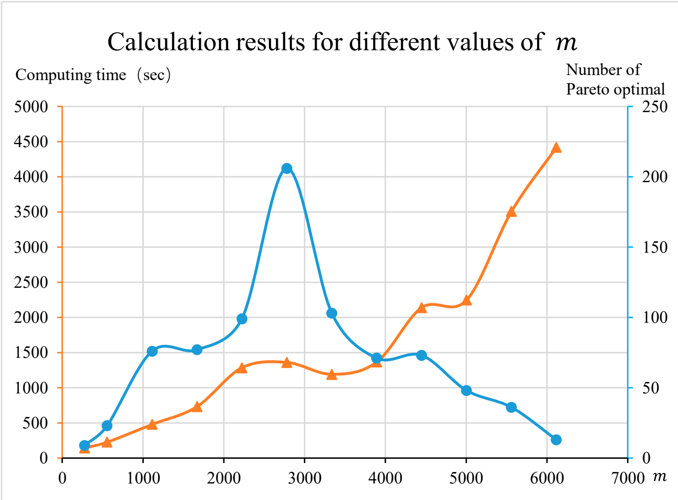

Figure 12. Trends in the variation of the calculation results for different scales (values of $\boldsymbol{m}$).

6. Conclusions

In this paper, an integer model based on the bi-objectives of the location and optimization configuration for centralized management is formulated with the objectives of minimizing the total costs and minimizing the total negative environmental effects. Then, aiming at the shortcomings of the traditional multi-objective genetic algorithm, an improved NASG-II is designed. Through the computation of a practical case study, a Pareto-optimal set of 23 non-dominated solutions was obtained. Compared with the traditional NSGA-II, the validity of the models and the algorithms proposed in this paper, as well as their feasibility, was verified. Finally, we conducted a sensitivity analysis on parameters including the fixed construction cost c_j^1, tank capacity Q_0, the minimum tank loading rate γ, and the different $m/n/p$ values, deriving certain management insights:

(1) In terms of fixed construction costs c_j^1, the higher the level of intelligence at the TS, the higher the fixed investment cost. However, this results in lower overall costs and negative environmental effects. In the decision-making process for the planning and construction of the TSs, increasing the investment in intelligent equipment or enhancing the level of intelligence at the TSs is a key consideration for decision-makers.

(2) In terms of tank capacity Q_0, a tank that is too small will result in high transfer costs. However, it is not necessarily better to use the largest available tank. The optimal configuration should be determined based on the specific context, selecting the most suitable tank size.

(3) In terms of the minimum tank loading rate γ, setting a very high value for γ during the planning process will increase the construction costs. However, setting it too low can increase management difficulties and operational costs in practice. Overall, maintaining γ at 0.8 is an important reference value for decision-making.

(4) In terms of the different $m/n/p$ values, a change in the number of collection points m has the greatest impact on the time required for model solving and the number of optimal solutions obtained. It can be inferred that the model and the algorithm proposed in this paper have good adaptability for solving the location problem for small and medium-sized CT network facilities.

Future work in this direction could consider the following aspects. On the one hand, it could involve the location and optimal configuration of the TSs taking into account different tank capacities and multiple types of transfer vehicles. On the other hand, it is also possible to consider establishing a centralized TS management platform for KW, which will jointly consider the location decisions with vehicle routing planning decisions.

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Data Availability Statement: The datasets generated during and analyzed during the current study are not publicly available.

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