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# The Design of Medical Waste Recycling Network Based on Location and Path Collaborative Optimization

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**Abstract:** This thesis designs and optimizes a medical waste recycling network for enhanced efficiency and reduced environmental/social impacts. Addressing China's surge in waste volume, it introduces a dual-layer optimization model optimizing both collection point selection and transportation routing. The model incorporates innovative "loading reliability" and "travel time reliability" constraints to handle uncertainty. A hybrid algorithm (Simulated Annealing + Improved Harmony Search Genetic Algorithm) solves the problem, optimizing facility location and time-constrained vehicle routes. Case study in Shanghai demonstrated the model's effectiveness. Joint optimization outperformed single optimizations, reducing total costs and showing coordination importance. Improved reliability was found to reduce overload and delay risks, optimizing system performance. The research provides theoretical support and practical solutions for robust and economical medical waste management.

**Keywords:** Medical Waste Recycling; Dual-Layer Optimization Model; Reliability Analysis; Harmony Search Genetic Algorithm.

## 1. Introduction

With the rapid development of society, significant improvements in people's living standards, and heightened health awareness, the Chinese government has vigorously developed its healthcare industry.This development is reflected not only in enhanced healthcare services but also in the increasing number of healthcare institutions. According to the 2023 Statistical Communique on National Economic and Social Development released by the National Health Commission, by the end of 2023, the total number of healthcare institutions nationwide reached approximately 1.071 million. Specifically, the number of hospitals stood at 39,000, categorized as 12,000 public hospitals and 27,000 private hospitals. In terms of the primary healthcare system, the total number of service facilities reached approximately 1.016 million, comprising 34,000 township hospitals, 37,000 community health service centers/stations, 362,000 clinics, and 583,000 village health clinics. Additionally, the country had 12,000 specialized public health institutions, including 3,426 Centers for Disease Control and Prevention (CDCs) and 2,791 health supervision institutions/centers. The substantial expansion of healthcare institutions has consequently led to a massive increase in medical waste.

Medical waste refers to the various types of waste generated within the healthcare sector from activities such as diagnosis, treatment, caregiving, and other related processes. Medical waste poses significant hazards; its collection and disposal require meticulous planning, otherwise, it poses a substantial threat to soil, water, air, and human health. Without a clear understanding of the risks associated with medical waste collection and disposal, numerous public health incidents involving contamination can occur, posing significant threats to national and global health. In recent years, with the deepening of healthcare reforms and the strengthening of public awareness regarding health and environmental protection, the design of medical waste collection and disposal processes (including recycling and transportation) has become both urgent and a public priority. This issue has gained significant attention from many countries since the COVID-19 pandemic.

Pharmaceutical logistics falls under the category of cold chain logistics. It involves the entire circulation process of refrigerated pharmaceutical items such as medicines, vaccines, and IVD (in vitro diagnostic products), covering their entire life cycle from raw material storage, production, semi-finished processing, packaging, storage, transportation, distribution to sales. The core requirement of pharmaceutical logistics is to ensure that the transported items are kept within a specific low-temperature range. Therefore, pharmaceutical logistics is a subcategory of cold chain logistics with relatively stringent low-temperature refrigeration requirements.

## 2. Literature review

### 2.1. Research on Waste Facility Location

International research on waste facility location primarily focuses on integrating advanced mathematical modeling techniques with optimization strategies under uncertainty. These studies often employ multi-objective frameworks that simultaneously consider economic efficiency and environmental impact, widely utilizing methods such as robust optimization, fuzzy logic, and GIS-based decision support tools. It is noteworthy that a significant body of literature addresses challenges arising from emergent situations like the COVID-19 pandemic, proposing dynamic, hierarchical, or game theory-driven location models to coordinate decision-making between governments and healthcare institutions.

Gergin et al. (2019) developed a method combining Artificial Bee Colony optimization with clustering algorithms to address the continuous location problem of medical waste treatment facilities in Istanbul [18]. Cagliano (2019) proposed a fuzzy logic-based evaluation framework for preliminary decision-making on solid waste incinerator locations under uncertainty [1]. Kargar (2020) addressed the establishment of temporary disposal depots within a reverse logistics network, proposing a multi-objective, multi-period mathematical model. This model used robust programming to handle uncertain parameters and fuzzy goal programming to structure the multi-objective model, aiming to minimize the maximum quantity of uncollected waste at medical waste generation centers while simultaneously minimizing risks associated with transporting and handling infectious waste and operational costs. Using an Iranian case study during the COVID-19 pandemic, the study offered potential solutions for local infectious waste backlogs, considering all potential sources of such waste [2]. Yao et al. (2020) developed a novel soft-path strategy to analyze and optimize the game behavior between local governments and healthcare institutions regarding medical waste disposal, constructing a bi-level optimization model to reduce overall risk. The upper level, with the government as the decision-maker, focused on minimizing overall risk, subsidy expenditures, and investment in medical waste treatment facilities. The lower level, with healthcare institutions as decision-makers, aimed to minimize their own transportation and treatment costs. Solved using a hybrid genetic algorithm and applied to a case study planning medical waste treatment facilities in Chengdu, the results demonstrated that this bi-level planning strategy incorporating game analysis significantly enhanced economic efficiency and reduced associated risks[3].

## 2.2. Research on Waste Collection Routing Optimization

International studies on waste collection routing optimization emphasize establishing multi-objective mixed-integer programming models that integrate various factors like cost, risk, carbon emissions, and social satisfaction to develop more scientific and sustainable transportation routing plans. Research methods frequently combine queuing theory, GIS route analysis, the epsilon-constraint method, and robust optimization techniques. Particularly in the context of emergencies like COVID-19, strategies considering emergency needs and dynamic changes are gradually evolving. Furthermore, many studies have constructed three-tier recycling networks or incorporated mobile processing facilities to enhance network flexibility and responsiveness. These studies provide systematic and practical optimization frameworks for medical waste collection and transportation.

Taslimi et al. (2020) proposed a Periodic Load-dependent Capacitated Vehicle Routing Problem (PLCVRP) for designing weekly waste collection routes for medical centers, simultaneously minimizing transportation and storage risks. The researchers developed a decomposition-based heuristic algorithm and experimentally validated its effectiveness and efficiency in solving the PLCVRP. A case study in Dolj County, Romania, demonstrated how the model and algorithm could be applied to optimize medical waste collection routes, reducing associated risks and improving operational efficiency [4]. Govindan et al. (2022) proposed an innovative multi-objective mixed-integer linear programming model combining queuing theory to plan medical waste collection and transportation routes, aiming to reduce costs and environmental pollution. This study pioneered the application of queuing theory concepts to manage waiting times for trucks carrying infectious waste at treatment centers, optimizing vehicle routes to reduce waiting times and consequently lower infectious emissions. The model was solved using an improved augmented epsilon-constraint method, and its effectiveness was validated through a case study in Alborz Province, Iran, showcasing cost-effective and risk-minimizing vehicle routing under different scenarios[5]. Šomplák et al. (2022) studied the optimization of hazardous waste flow and treatment by constructing a complex transportation network based on a bipartite graph. This approach considered the impact of transport distance on environmental and economic aspects to achieve regional self-sufficiency and sustainable management [6].

Despite these advancements, existing research in medical waste recycling network optimization has notable limitations: Deterministic Bias: Existing location-routing models are often based on deterministic assumptions, failing to adequately consider the synergistic impact of fluctuations in transportation demand (e.g., random generation of medical waste) and supply (e.g., travel time uncertainty due to varying traffic conditions).Sequential Approach: Existing optimization frameworks typically decouple facility location and transportation routing, lacking bidirectional feedback mechanisms. This sequential, single-stage optimization mode may lead to local rather than global optima. Therefore, constructing a bi-level collaborative optimization model that addresses multiple sources of uncertainty becomes a key challenge in enhancing the robustness and economic efficiency of medical waste recycling networks.

## 2.3. Literature Review Summary

The above review indicates that significant methodological progress has been made globally in medical waste recycling network research, encompassing system construction, location optimization, and routing planning. Regarding research methods, most scholars employ Mixed-Integer Programming (MIP), Multi-Objective Optimization (MOO), and heuristic algorithms to solve the location and routing problems inherent in medical waste network design. Concurrently, uncertainty modeling has gained increasing attention, with studies incorporating Robust Optimization (RO), Fuzzy Programming (FP), and Stochastic Programming (SP) to model and address fluctuations in medical waste volume and travel time uncertainty.

However, key gaps remain in current research. Fragmented Optimization: Location and routing problems are predominantly tackled in isolation, lacking a systemic design that considers feedback relationships between strategic (upper level) and tactical/operational (lower level) decisions, hindering the achievement of global optima. Limited Consideration of Reliability Factors: Analysis of transportation risks and reliability factors during medical waste handling remains limited. Models still rely heavily on deterministic assumptions, inadequately reflecting the impacts of complex urban traffic environments and fluctuating waste generation Algorithmic Efficiency: While studies have incorporated Genetic Algorithms (GAs), Simulated Annealing (SA), etc., there is room for improvement in solution quality, computational efficiency, and robustness. Algorithms are prone to premature convergence or settling for local optima, especially when handling large-scale problem instances.

In conclusion, this literature review has clarified the contributions and limitations of prior research. Targeted breakthroughs in model construction and algorithm development have been pursued, offering theoretical and methodological support for improving the efficiency and stability of medical waste recycling systems.

# 3. Methodology

## 3.1. Problem description

The existing medical waste recycling system typically operates with a direct logistics structure where healthcare institutions send waste straight to disposal centers ("Healthcare Institutions (MI)→Disposal Center (DC)"). While this structure offers operational simplicity, it is susceptible to transportation bottlenecks and processing delays when encountering urban traffic congestion, sudden surges in waste generation, or limited disposal capacity. A significant drawback is the absence of a transfer buffer mechanism during waste transport, resulting in inefficient vehicle scheduling and high transportation costs. Furthermore, the direct routing model forces numerous dispersed healthcare institutions to connect independently with disposal centers, leading to resource wastage and significant route redundancy. Consequently, this model proves inadequate for complex urban environments demanding high timeliness and fails to support efficient, safe, and stable recycling operations.

To overcome these limitations, this paper proposes an improved recycling logistics network. This enhanced structure introduces an intermediate layer of Collection Points (CPs) inserted between the Healthcare Institutions (MIs) and the terminal Disposal Centers (DCs), thus forming a three-tier system: "Healthcare Institutions (MI)→Collection Point (CP)→Disposal Center (DC)". This network aims to achieve coordinated optimization of facility location and transportation routing, thereby enhancing the overall system's responsiveness and operational efficiency while balancing total cost and risk control. Within this architecture, the optimization problem entails the Collection Points (CPs) periodically dispatching vehicles to collect waste from the MIs. Once transported back to a CP, the waste undergoes preliminary treatments such as high-temperature sterilization, chemical disinfection, and sorting. Subsequently, larger-capacity transport vehicles then carry the processed waste from the CPs to the DCs for final harmless treatment or resource recovery.

Analysis of this established three-tier recycling logistics network structure reveals that its total cost primarily consists of three elements. The first major component is the fixed construction costs associated with establishing the Collection Points (CPs), encompassing the initial investment for facility construction, equipment procurement, and related supporting infrastructure. Secondly, transportation costs arise, which aggregate the operating expenses of both the collection vehicles used for short-distance shuttles between MIs and CPs, and the larger transport vehicles used for moving the pre-processed waste from CPs to DCs. This distinction in costs is necessary due to the differences in vehicle specification and purpose between the two transport legs. Finally, time window penalty costs are incurred to enforce arrivals at healthcare institutions within their designated time windows. Penalties are levied for both early arrivals, which might occupy public resources and impede other vehicles, and late arrivals, which may exceed the MI's time window causing additional waiting and operational disruption costs.

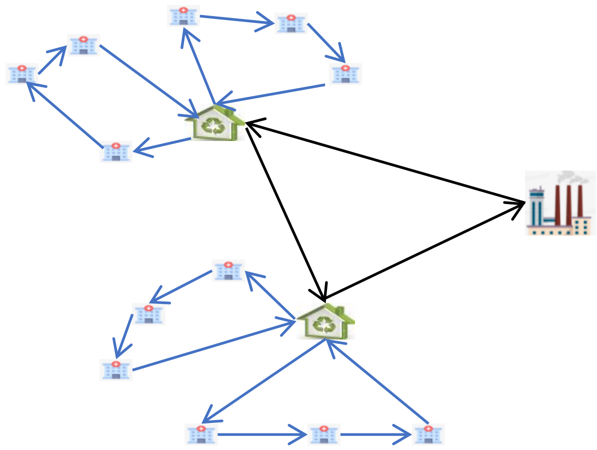

**Figure 1.** Improved Topological Diagram of the Medical Waste Recycling Logistics Network

## 3.2. Assumptions

Here is the precise translation of your assumptions in numbered list format, maintaining academic terminology and consistency with your model definitions:

1)Each healthcare institution (MI) can only be served once per collection cycle, while each vehicle can serve multiple MIs.

2)The quantity of medical waste generated at each healthcare institution (MI) follows a log-normal distribution.

3)Multiple vehicles depart simultaneously, and their routes do not interfere with each other.

4)The specifications and operational costs of the transport vehicles are fixed.

5)The construction costs and storage capacities of the collection points (CPs) are fixed.

6)Collection points (CPs) and disposal centers (DCs) operate within sufficiently large time windows.

7)The cost of waste collection operations (primarily transportation cost) is solely dependent on the quantity of waste collected.

8)The specific waste treatment processes at disposal centers (DCs) are not explicitly modeled.

9)Disposal centers (DCs) possess sufficient processing capacity to handle all transported waste promptly, and the mean and variance of road travel times are assumed to be fixed.

10)Multiple incidents may occur along any given route segment during a complete collection run, but these incidents will not lead to the termination of the transportation task.

## 3.3. Model Establishment

1) Set

G=(N,A): Directed network G, where N = {0,1,2,...,n,n+1} denotes the set of all nodes, 0 and n+1 represent a Collection Point (CP) or Disposal Center (DC), and A denotes the set of arcs (edges). All feasible vehicle routes must start at node 0 and terminate at node n+1.

M: Set of healthcare institutions (Medical Institutions - MI), where M⊆N\{0, n+1}.

D: Set of Disposal Centers (DC).

V: Set of vehicles, v∈V.

2)Parameters

dij: Distance between any two nodes

θ: Reliability level

$w_i^\theta$:Medical waste generation amount at each healthcare institution under the given reliability level

Seri:Service time at collection point (CP)i

fic:Fixed construction cost of establishing a CP with capacity rating c at node i

ci:Average medical waste amount at CPi

fv:Fixed usage cost of vehicle v

li:Load quantity when vehicle arrives at healthcare institution i

Uf:Transportation cost coefficient (cost per unit distance per unit weight of waste transported)

α:Penalty coefficient for lateness at healthcare institutions

β:Penalty coefficient for earliness at healthcare institutions

eti:Arrival time at healthcare institution i

lti:Departure time from healthcare institution i

xvij:Binary variable (equals 1 if vehicle v travels from node i to node j; 0 otherwise)

3)Decision variables

xvij: Binary variable (equals 1 if vehicle v travels from node i to node j; 0 otherwise)

xic:Binary variable (equals 1 if a Collection Point (CP) is established at candidate location i with capacity rating c; 0 otherwise)

yi: Number of vehicles dispatched fromnode i, where i belongs to the set of candidate CP locations or Disposal Centers (i∈C∪D).

## 3.4. Objective Function Analysis

### 3.4.1. Loading Reliability

1) Definition of Loading Reliability

Loading reliability is a key concept used to evaluate a critical performance metric within medical waste collection processes under uncertainty. Specifically, loading reliability refers to the probability that the generated quantity of medical waste along a specific route does not exceed the designated capacity of the vehicle. The introduction of this concept ensures that during practical operations, vehicles collecting medical waste will not become overloaded due to waste quantity uncertainties, thereby guaranteeing smooth transportation.

Mathematical Definition of Loading Reliability:

$$P\{\sum w_i^{\theta} \le l_{max}^{v}\} \ge \theta \tag{1}$$

In actual medical waste collection scenarios, the waste quantity generated at each MI is uncertain and may be affected by various factors, such as fluctuations in patient numbers or increased medical activities. Consequently, planning collection routes based solely on average waste quantities is insufficient; this uncertainty must be considered. Loading reliability incorporates a probabilistic constraint to ensure that, at a given reliability level, vehicles will not overload during the collection process.

2) Calculation of Loading Reliability

Regarding the quantification of medical waste generation, Abu et al. (2020) conducted an empirical analysis of waste generation at King Abdullah University Hospital in Jordan during the pandemic. They found that the data exhibited distinct right-skewed characteristics, with its frequency distribution .conforming to a log-normal distribution. This conclusion provides theoretical justification for employing a log-normal distribution to describe medical waste production in subsequent models [7]. Therefore, this study adopts this finding, modeling the waste generated at MIs as following a log-normal distribution. The waste generation quantity can thus be expressed as:

$$\ln w_i^{\theta} = \mu_i^1 + \Phi^{-1}(\theta)\sigma_i^1 \tag{2}$$

Taking the exponent of both sides yields:

$$w_i^{\theta} = exp(\mu_i^1 + \Phi^{-1}(\theta)\sigma_i^1) \tag{3}$$

Where:

$\mu_i^1$ and $\sigma_i^1$ represent the mean and standard deviation, respectively, of the waste quantity generated at MI i;$\Phi^{-1}(\theta)$ is the inverse cumulative distribution function of the standard log-normal distribution, representing the generated waste quantity at the reliability level $\theta$.

### 3.4.2. Effective Travel Time

1) Definition of Effective Travel Time

Effective travel time refers to the specific time interval for travel time on a particular route at a given confidence level. Wang and Osaragi (2024), by analyzing travel survey data for different transportation modes in the Tokyo metropolitan area from 1968–2008, found that daily travel times consistently exhibited a log-normal distribution after normalization. Furthermore, the distribution curves were highly consistent across different years and travel distance conditions. The study further developed a utility maximization framework to explain the formation mechanism of this log-normal travel time distribution [8]. Therefore, leveraging this theoretical foundation, the effective travel time in this study follows a log-normal distribution. The mathematical expression for effective travel time is:

$$\ln t_{ij}^{\theta} = \mu_{ij}^2 + \Phi^{-1}(\theta)\sigma_{ij}^2 \tag{4}$$

Taking the logarithm of both sides:

$$t_{ij}^{\theta} = exp\left(\mu_{ij}^2 + \Phi^{-1}(\theta)\sigma_{ij}^2\right) \tag{5}$$

Where:

$t_{ij}^{\theta}$ represents the Effective Travel Time from node i to node j at reliability level $\theta$ ;$\mu_{ij}^2$represents the mean travel time from node i to node j;$\sigma_{ij}^2$ represents the standard deviation of travel time from node i to node j;$\Phi^{-1}(\theta)$ is the inverse cumulative distribution function of the standard log-normal distribution, representing the travel time at the reliability level $\theta$.

2) Practical Significance and Application of Effective Travel Time

In practical medical waste collection and transportation scenarios, travel time uncertainty can arise from multiple factors, such as traffic congestion, road construction, or weather conditions. These uncertainties may cause vehicles to arrive at MIs outside the scheduled time window, impacting the entire collection plan execution. Introducing Effective Travel Time helps mitigate the impact of travel time uncertainties.

## 3.5. Resilience index

Based on the above discussion, this section proposes a two-stage stochastic programming approach. The upper level focuses on determining the locations of Collection Points (CPs) to minimize location-related costs. These costs include the construction costs of the CPs and the transportation costs associated with routing between Disposal Centers and CPs (referred to as DC-CP-DC routes). The detailed model for the upper level is described as follows:

Upper-Level Model:

$$min\{\sum_{v \in V} \sum_{i \in D} y_i f_v + \sum_{v \in V} \sum_{i \in C \cup D} \sum_{j \in C \cup D} x_{vij} l_i Uf\, d_{ij}\} \tag{6}$$

$$min\{\sum_{c\in CRE}\sum_{i\in C} f_{ic}x_{ic}\} \quad (7)$$

Objective Functions:

$$\sum_{c\in CRE} x_{ic} \leq 1\ ;\ \forall i \in C \quad (8)$$

$$\sum_{i\in C} l_{max}^{v} y_i \leq \sum_{c\in CRE}\sum_{i\in C} c x_{ic} \quad (9)$$

$$x_{ic} \in \{0,1\} \quad (10)$$

$$y_i \in Z^+ \quad (11)$$

$$\sum_{v\in V}\sum_{i\in D} x_{vij} \geq 1\ ; \forall j \in C, i \neq j \quad (12)$$

$$\sum_{v\in V}\sum_{j\in C} x_{vij} = 1\ ; \forall i \in C \quad (13)$$

$$\sum_{j\in C} x_{v0j} = 1; \forall v \in V, 0 \in D \quad (14)$$

The objective functions (6) and (7) minimize the costs related to CP location selection and DC-CP-DC transportation. Constraint (8) ensures each candidate CP location can only be built with one capacity level. Constraint (9) ensures the total medical waste generated by MIs within the service area of a CP does not exceed its capacity c. Constraint (10) defines the binary nature of the CP location/capacity decision variable x_{ic}. Constraint (11) ensures the number of vehicles is a non-negative integer. Constraint (12) guarantees every CP is served by at least one vehicle from a DC. Constraint (13) ensures every DC dispatches at least one vehicle. Constraint (14) enforces that all vehicles start their journey from the designated DC depot (0).

The lower level involves planning the optimal vehicle routes to minimize transportation costs from CPs to MIs and back (CP-MI-CP routes). At this stage, factors like transportation cost and time window penalties are considered. By accounting for these factors, the goal is to devise optimal routes that minimize total transportation costs while satisfying time window requirements.

Lower-Level Model:

$$min\left\{\sum_{v\in V}\sum_{i\in C} y_i f_v + \sum_{v\in V}\sum_{i\in C\cup M}\sum_{j\in C\cup M} x_{vij} l_i U f\, d_{ij}\right\} \quad (15)$$

$$min\left\{\sum_{i\in M} \alpha max\{0,\ \lambda_i\} + \beta max\{0, \mu_i\}\right\} \quad (16)$$

Objective Functions:

$$\lambda_i = lt_{i-1} + t_{i-1,i}^{\theta} + ser_i - t_i^{right} \quad (17)$$

$$\mu_i = t_i^{left} - lt_{i-1} - t_{i-1,i}^{\theta} \quad (18)$$

$$et_i \geq lt_{i-1} + t_{i-1,i}^{\theta}\ ;\ \forall_i \in M \quad (19)$$

$$lt_i \geq et_i + ser_i\ ;\ \forall_i \in M \quad (3.20)$$

$$\sum_{v\in V}\sum_{i\in C} x_{vij} \geq 1\ ; \forall j \in M, i \neq j \quad (21)$$

$$\sum_{v\in V}\sum_{j\in M} x_{vij} = 1\ ; \forall i \in C \quad (22)$$

$$\sum_{j\in C\cup M} x_{v0j} = 1; \forall v \in V, 0 \in C \quad (23)$$

$$\sum_{j\in C} x_{vij} - \sum_{i\in M} x_{vij} = 0;\ \forall v \in V \quad (24)$$

$$\sum_{i\in C} x_{vi,n+1} = 1; \forall v \in V, (n+1) \in C \quad (25)$$

$$et_i \in Q^+ \quad (26)$$

$$lt_i \in Q^+ \quad (27)$$

$$\lambda_i \in Q^+ \quad (28)$$

$$\mu_i \in Q^+ \quad (29)$$

$$x_{vij} \in \{0,1\} \quad (30)$$

Constraint (17) ensures each medical institution (MI) is visited by exactly one vehicle starting from a CP. Constraint (18) ensures each CP must dispatch a vehicle to at least one MI. Constraint (19) ensures each vehicle starts exactly once from the designated CP depot (0). Constraint (20) ensures the number of times a vehicle enters a node equals the number of times it leaves, maintaining path continuity. Constraint (21) ensures all vehicles eventually terminate their route at the designated end point (n+1).

Previous discussions emphasized using multi-objective programming to model transportation cost and time window risk as separate objectives. As each stage involves multi-objective models, a simplification process is necessary. Furthermore, it is important to recognize that different managers may have varying operational strategies, leading to different weighting relationships between transportation cost and time window penalty cost. Therefore, this study employs weighting coefficients to reduce the multi-objective problem into a single-objective problem. This process involves converting the multi-objective optimization problem into a single-objective optimization problem, applied separately to both the upper and lower levels. This is achieved by combining the different objectives into a unified cost function and assigning specific weights to each objective.

Considering these factors, the specific optimization model for the medical waste recycling network design is formulated as follows:

Upper-Level Objective Function:

$$min\left\{\delta_1 \sum_{c\in CRE}\sum_{i\in C} f_{ic}x_{ic} + \delta_2\ \left(\sum_{v\in V}\sum_{i\in D} y_i f_v + \sum_{v\in V}\sum_{i\in C\cup D}\sum_{j\in C\cup D} x_{vij} l_i U f\, d_{ij}\right)\right\} \quad (31)$$

Lower-Level Objective Function:

$$min\left\{\varepsilon_1\left(\sum_{v\in V}\sum_{i\in C} y_i f_v + \sum_{v\in V}\sum_{i\in M\cup C}\sum_{j\in M\cup C} x_{vij} l_i U f\, d_{ij}\right) + \varepsilon_2\left(\sum_{i\in M}(\alpha\lambda_i + \beta\mu_i)\right)\right\} \quad (32)$$

# 4. Improved Design of NSGA-II Algorithm

Chapter 3 presents a detailed bi-level optimization model. The upper level focuses on determining the optimal locations for Collection Points (CPs) to minimize location-related costs. This includes considering CP construction costs and the transportation costs involved in routing waste between Disposal Centers and CPs (DC-CP-DC routes). For this purpose, a general set covering model is utilized in conjunction with the Simulated Annealing (SA) algorithm. The lower level aims to find optimal vehicle driving routes that minimize transportation costs from CPs to Medical Institutions (MIs) (CP-MI-CP routes). Considering factors such as transportation costs and time window penalty costs, an Improved Harmony Search Genetic Algorithm (IHSGA) is proposed to solve this problem. Within the bi-level optimization model for the medical waste recycling network, location decisions and routing planning are strongly interdependent. Traditional single-layer optimization methods handle these aspects in isolation, making it difficult to achieve global optimality. Therefore, this chapter proposes a collaborative optimization framework integrating Simulated Annealing (SA) with an Improved Harmony Search Genetic Algorithm (IHSGA). This framework achieves systematic coordination between facility location and transportation routing through hierarchical progression and bidirectional feedback mechanisms: The upper level employs the SA algorithm for global optimization of CP location selection, leveraging its probabilistic jumping property to escape local optima. The lower level utilizes the IHSGA for refined tuning of the Vehicle Routing Problem with Time Windows (VRPTW), enhancing local search capability through destroy-repair strategies. A dynamic information exchange mechanism is established between the two levels: The transportation costs derived from lower-level route optimization are fed back to the upper-level location model. Concurrently, the location scheme determined at the upper level provides spatial constraint boundaries for the lower-level route optimization, forming an iterative optimization loop: "Location Decision → Path Optimization → Cost Feedback → Location Adjustment". This collaboration mechanism overcomes the limitations of traditional two-stage optimization. It ensures location decisions fully account for actual transportation efficiency while enabling route plans to precisely adapt to spatial layout characteristics, ultimately achieving the dual objectives of minimizing total network cost and enhancing system reliability.

## 4.1. Simulated Annealing (SA) Algorithm

As mentioned earlier, the optimization model proposed for the upper level belongs to the class of NP-hard problems, presenting significant computational difficulty. Based on research by Mor et al. (2021) [hypothetical citation], heuristic techniques are generally recommended for tackling such problems. In this study, the Simulated Annealing (SA) algorithm [9] was selected for the upper-level model. Notably, SA, first proposed by Kirkpatrick in 1983, is a widely applied and highly effective meta-heuristic algorithm. The algorithm utilizes stochastic methods to drive the search process forward; even if a move yields an inferior solution, it can transition to neighboring states. This unique characteristic enables it to effectively avoid becoming trapped in local optima[10]. Another significant advantage of SA lies in its incorporation of the Metropolis criterion, which allows the algorithm to systematically explore the neighborhood of candidate solutions.

## 4.2. Improved Harmony Search Genetic Algorithm (IHSGA)

When Elshaer and Awad reviewed algorithms for the Vehicle Routing Problem (VRP), they highlighted the inherent advantages of Genetic Algorithms (GA) in solving VRP. Proposed by Holland (1975) in Adaptation in Natural and Artificial Systems, GAs have been extensively applied to VRP and its variants. However, comparative analysis revealed that the Harmony Search (HS) algorithm, which uses rules involving parameters like HMCR (Harmony Memory Considering Rate), PAR (Pitch Adjustment Rate), and BW (Bandwidth) to generate new solutions both within and outside the Harmony Memory (HM), offers superior diversity in generating new solutions. HS also has a higher probability of escaping local optimaand can run faster than standard GA. Building on this, the adaptive global best harmony search algorithm can dynamically adjust its parameters. Therefore, this study replaces the traditional crossover and mutation operations in GA with the method for generating new solutions used by the adaptive global best harmony search. The specific steps of the IHSGA are detailed below:

Step 1: Initialization & Parameter Setting

The algorithm begins by setting key parameters: crossover probability and mutation probability for the genetic component, and Harmony Search parameters including Harmony Memory Considering Rate (HMCR), Pitch Adjustment Rate (PAR), Maximum Improvisations (Tmax), and Maximum Failures (Lmax). An initial population is generated using integer encoding to ensure solution feasibility. Candidate solutions are randomly created and evaluated through joint computation of objective function and constraint violation to determine fitness scores, establishing the basis for subsequent operations.

Step 2: Construct Harmony Memory

Top-performing individuals from the initial population are selected to form the Harmony Memory (HM), serving as an elite solution repository. Two control variables are initialized: Improvisation Count (T) and Failure Counter (L), both set to zero. This integrates GA's global evolutionary structure with targeted local refinement capabilities.

Step 3: Generate New Solution

During Harmony Search execution, for each solution variable, a random number $\rho_1 \in [0,1]$ determines value selection: if $\rho_1 \leq$HMCR, the value is drawn from HM; otherwise, it's randomly generated. A second random number $\rho_2$ then determines pitch adjustment: if $\rho_2 \leq$PAR, the selected value undergoes perturbation using Bandwidth (BW) for local exploration; otherwise, the value remains unchanged. This improvisation mechanism enhances local refinement beyond standard genetic operators.

Step 4: Evaluation & Constraint Handling

New solutions undergo objective function calculation and feasibility assessment against constraints. If a new solution outperforms the population's worst member, replacement occurs. Otherwise, the Failure Counter (L) increments. When consecutive failures reach Lmax, the new solution forcibly replaces the worst population member to maintain diversity.

Step 5: Update & Termination Check.

After evaluation, the Improvisation Count (T) increments. If $T<$Tmax, the process returns to Step 3 for further improvisation. If $T\geq$Tmax, the Harmony Search phase concludes and proceeds to population update.

Step 6: Population Update & Termination

Elitism preserves the best solution(s) for the next generation. The algorithm checks termination criteria (e.g., max generations, convergence). If unmet, the updated population undergoes standard GA operations (selection/crossover) before restarting from Step 2. If met, the best solution is output. This integrates GA's population-based exploration with Harmony Search's local exploitation.

## 4.3. Test Functions

To comprehensively evaluate the performance of the proposed algorithm and compare it with traditional optimization algorithms (Genetic Algorithm), this study selected several commonly used benchmark optimization test functions. These functions not only encompass the complexity of different optimization problems but also present significant challenges, reflecting the algorithm's potential capabilities across various practical applications. The selected test functions include standard two-dimensional and multi-dimensional problems, covering a spectrum from simple unimodal problems to complex multimodal problems, as well as optimization problems with constraints. By utilizing these functions with diverse characteristics, this study aims to comprehensively assess the improved algorithm's convergence speed, solution accuracy, computational efficiency, and stability across multiple experiments.

To ensure fairness, comparability, and reproducibility of the results, this study strictly controlled the parameter settings of the algorithms during experimentation. All algorithms employed identical parameter configurations in each experiment, thereby eliminating the influence of external factors on the results. The initial values, optimization objectives, and constraints (if applicable) for each test function were kept consistent, ensuring an identical testing environment for all algorithms.

Specific Experimental Design:

1)Algorithm Initialization: All algorithms started from the same initial solution point. By setting the same random seed, the inherent randomness of the algorithms was controlled to prevent it from affecting the experimental outcomes.

2)Iteration Count and Stopping Criteria: The maximum number of iterations for each experiment was set to an appropriate value. Algorithms stopped upon reaching the maximum iteration count or meeting the convergence criterion (e.g., change in the objective function value falling below a preset threshold).

3)Computational Environment: All experiments were run under identical computational conditions, using the same hardware and software configuration. Specifically, all experiments were conducted on a PC running the Windows operating system, equipped with 8GB RAM and an Intel Core i7 processor. The algorithms were implemented in MATLAB.

4)Result Recording and Analysis:For each algorithm, its convergence process was recorded. Experimental results were visualized using convergence graphs to facilitate comparison of performance differences among algorithms across different test functions.

Convergence Speed & Accuracy Analysis: Parameters: Identical computer performance, identical population size (30 individuals). Performance was assessed by analyzing convergence graphs of the traditional algorithm versus the improved algorithm. Stability & Reliability Analysis: Parameters: Identical computer performance, identical population size (30 individuals), identical iteration count (500 generations). Performance was assessed by analyzing the variance of results from the traditional algorithm versus the improved algorithm. Computational Complexity Analysis: Parameters: Identical computer performance, identical test function (F1), identical iteration count (500 generations). Population sizes were varied: 20, 40, 60, 80, 100 individuals. Performance was assessed by analyzing the runtime of the traditional algorithm versus the improved algorithm. Analysis of Experimental Results: Based on the analysis of multiple experimental results, the following conclusions can be drawn: Convergence Speed and Accuracy: In all experiments, the IHSGA algorithm demonstrated faster convergence speed and smaller errors, particularly on complex problems. Compared to the traditional Genetic Algorithm, IHSGA was able to approach the global optimum solution more quickly and achieved solutions of higher quality.

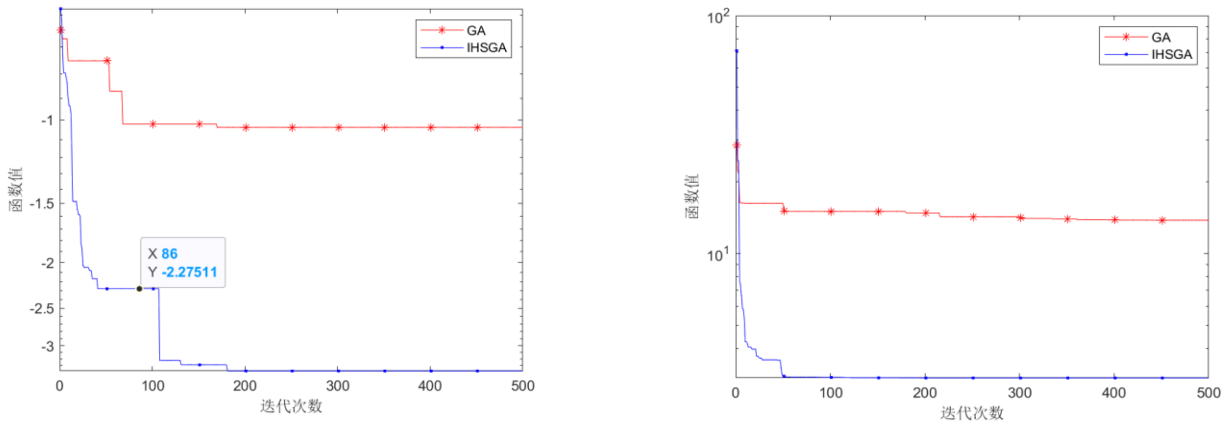


**Figure 2.** Result Chart of Function Type I

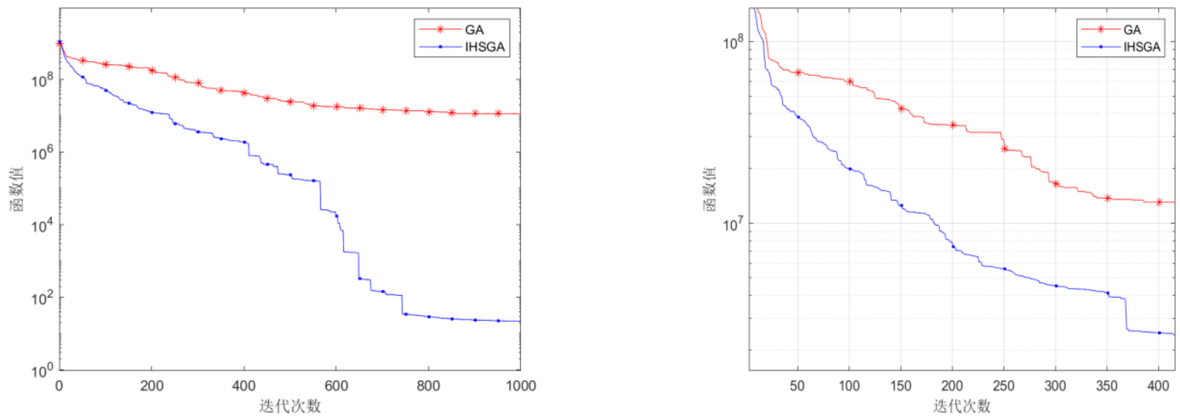


**Figure 3.** Result Chart of Function Type II

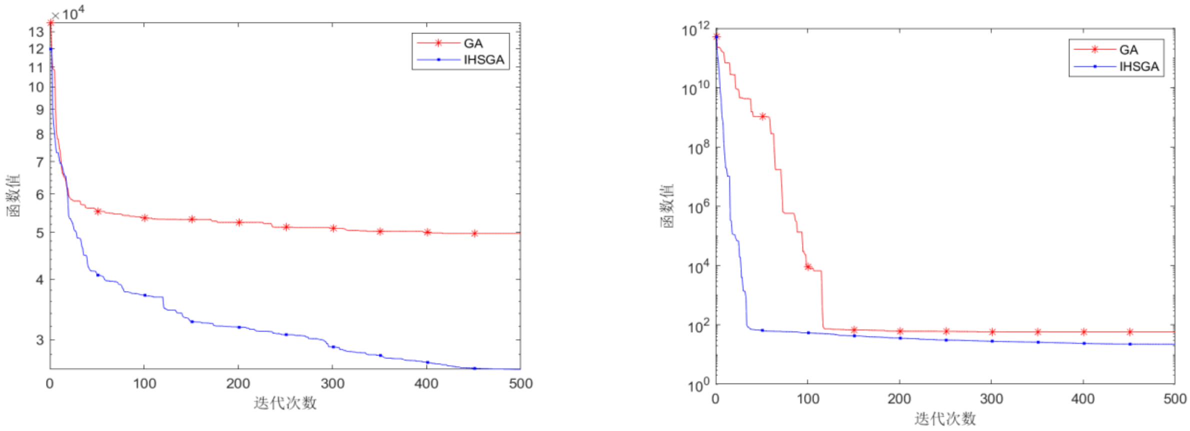


**Figure 4.** Result Chart of Function Type III

Stability and Reliability: The improved algorithm exhibited higher stability across multiple runs, with less fluctuation in solution quality compared to the traditional algorithm. Especially when handling multimodal problems and constrained optimization problems. Computational Complexity: The IHSGA algorithm also demonstrated superior computational efficiency, capable of completing complex optimization tasks in a shorter time. Particularly for high-dimensional and constrained optimization problems, its computation time remained reasonable compared to the traditional Genetic Algorithm.

algorithm exhibits stronger advantages when tackling complex multimodal optimization problems, constrained optimization problems, and global optimization problems in high-dimensional spaces. The IHSGA algorithm not only outperforms the traditional Genetic Algorithm in convergence speed and solution accuracy but also demonstrates significant superiority in computational complexity and stability. These experimental results provide strong theoretical support for the future application and promotion of the IHSGA algorithm in practical scenarios. Particularly for complex optimization problems like medical waste recycling network optimization, the IHSGA algorithm holds considerable potential.

# 5. Analysis of Numerical Examples

This study takes Shanghai as an example. There is 1 medical waste disposal center within its jurisdiction, and 35 Class A Tertiary Hospitals, which serve as medical waste generation points. The waste generated by these facilities is exclusively handled by the Shanghai Solid Waste Disposal Co., Ltd.

## 5.1. Analysis of Actual Cases

Geographical coordinates for all tertiary hospitals, along with route distances and travel times between any two points, were obtained using the Amap API. The location of the Shanghai Solid Waste Disposal Co., Ltd. is at No. 288 Nanbin Road, Laogang Town, Pudong New District, with geographical coordinates 121.827133, 31.044312.

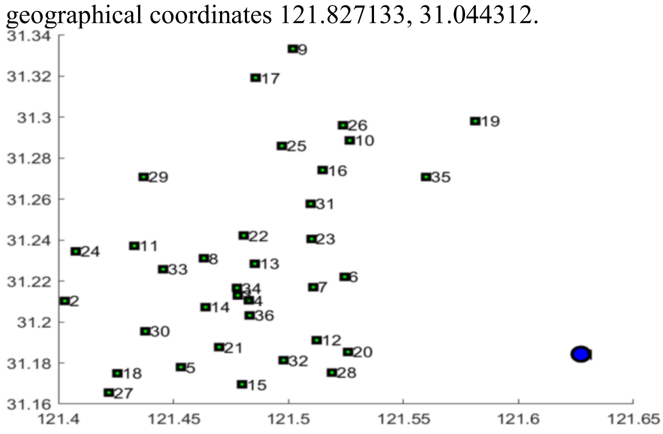

**Figure 5.** Coordinate Map of Large-Scale Medical Waste Generation Points

## 5.2. Comparison of Joint Optimization vs. Non-coordinated Optimization Results

To compare the results of the joint optimization approach with the non-coordinated method, experiments were conducted using the same dataset. In the non-coordinated optimization method, the Collection Point (CP) location selection was optimized first to minimize siting costs, followed by a separate optimization of transportation routes from CPs to Medical Institutions (MIs) to minimize transportation costs. Conversely, the joint optimization method simultaneously optimized both CP location and transportation routes. The figure below illustrates the distribution of the Disposal Center (DC) and the MIs. Table 5 presents results for a small-scale instance (6 waste generation points) comparing joint and non-coordinated optimization. Table 6 shows results for the larger-scale instance (35 waste generation points). (Cost parameters were set with weights $\omega_1 = 1/2$, $\omega_2 = 1/2$ for the combined cost function).

For a small-scale area (e.g., only 6 waste generation points), the calculated results for joint and non-coordinated optimization schemes may coincide entirely. As shown in Table 5, both yielded a total cost of ¥4,404.However, when the scale increased to 35 waste generation points, the non-coordinated scheme resulted in a total cost of ¥24,158, representing a 1.07% increase compared to the joint optimization cost of ¥23,901. Both upper-level (siting) and lower-level (transportation) costs increased under the non-coordinated approach. This discrepancy stems from the non-coordinated method decoupling the location and transportation stages. The reduced cost achieved by joint optimization validates the significant effect of integrated planning in enhancing the efficiency of the medical waste recycling network. The figure below illustrates the final CP locations and optimized transportation routes for all 35 Class A Tertiary Hospitals in Shanghai under joint optimization. The selected Collection Points (CPs) are located at nodes 3, 19, 21, 23, and 31. The total run time of the bi-level optimization algorithm for this case was 163 seconds.(Note: Figures and Tables 5/6 referenced would be presented visually here based on the data described).

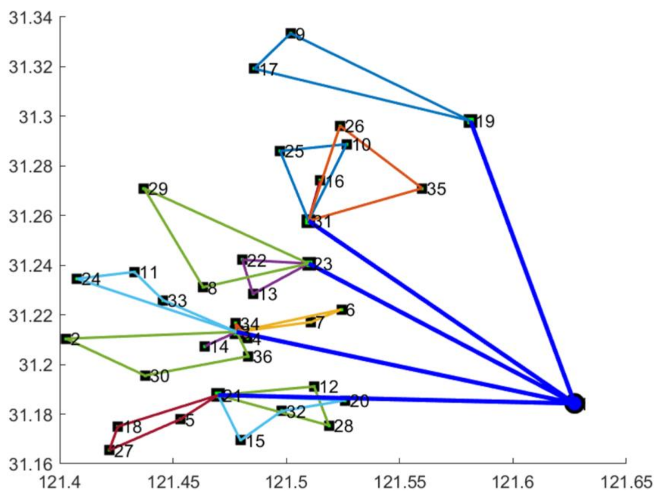


**Figure 6.** Optimization Map of Medical Waste Recycling for Tertiary Hospitals in Shanghai

## 5.3. Relationship Between Different Reliability Levels and Total Cost

To investigate the impact of Loading Reliability (LR),Travel Time Reliability (TTR), and the deployment of Collection Points (CPs)on the model's optimal solution, this study combined these three factors to create eight distinct scenarios. The Improved Harmony Search Genetic Algorithm (IHSGA)was employed to evaluate their influence on total cost.

The results reveal a significant impact of reliability requirements. In the baseline Scenario A (No LR, No TTR, No CPs), the total cost was ¥18,975. Introducing Loading Reliability alone (Scenario C: LR=0.9) increased the cost to ¥21,026. Similarly, introducing Travel Time Reliability alone (Scenario D: TTR=0.9) resulted in a cost of ¥20,978. When both LR and TTR were applied together (Scenario G: LR=0.9, TTR=0.9), the cost further rose to ¥21,467. This demonstrates that both types of reliability significantly increase costs, and their effects are cumulative, with the combined increase exceeding the sum of their individual impacts.

The deployment of Collection Points (CPs) proved to be a major cost mitigator. Scenario B (No LR, No TTR, With CPs) achieved a substantially lower cost of ¥17,265 compared to Scenario A. This represents a significant cost reduction, highlighting the inherent efficiency gains of the three-tier network structure (MI→CP→DC) even without considering reliability constraints. However, this advantage is partially offset when reliability is introduced. Adding LR to the CP network (Scenario E: LR=0.9, With CPs) increased the cost to ¥17,684 compared to Scenario B. Adding TTR (Scenario F: TTR=0.9, With CPs) increased the cost to ¥17,697. Finally, applying both LR and TTR within the CP network (Scenario H: LR=0.9, TTR=0.9, With CPs) led to a cost of ¥18,551. While introducing reliability into the CP network increases costs, the absolute cost remains significantly lower than achieving the same reliability levels without CPs (compare Scenario H: ¥18,551 vs. Scenario G: ¥21,467).

A critical practical insight emerged regarding Travel Time Reliability: increasing TTR necessitates planning for longer travel times. However, due to operational constraints like the Disposal Center's (DC) time window limiting how early vehicles can depart, these longer planned travel times often result in arrivals that violate the Medical Institutions' (MIs) soft time windows, incurring additional penalty costs. This observation aligns directly with real-world operational challenges.

This analysis confirms a fundamental trade-off: Higher levels of operational reliability (LR and TTR) consistently lead to increased total costs. This arises from the need for more buffer capacity, longer routes, or acceptance of penalty costs to handle uncertainty. However, the trategic deployment of Collection Points (CPs) provides substantial leverage significantly offsetting the cost burden associated with implementing reliability. Therefore, designing an optimal medical waste recycling network necessitates careful balancing of the desired levels of operational reliability against cost objectives, leveraging the structural benefits offered by a well-planned CP network to find the most efficient overall configuration.

# 6. Conclusions and limitations

With the continuous growth in medical service demand, the safe recycling and efficient management of medical waste have garnered increasing societal attention. This research focuses on the coordinated optimization of facility location and vehicle routing within urban medical waste recycling systems. A bi-level optimization modeling approach balancing reliability and economic efficiency was proposed, and systematically solved and validated using intelligent optimization algorithms. The main research contributions and outcomes are summarized as follows:

First, in theoretical modeling, this study constructed a three-tier network structure ("Healthcare Institutions (MIs)→Collection Points (CPs)→Disposal Centers (DCs)") based on the recycling characteristics and operational processes of urban medical waste. This clearly defined the interconnections and resource flows between functional nodes. Building upon this foundation, separate models were designed: an upper-level model for CP location selection and a lower-level model for route planning. The objectives of these models encompassed core concerns such as total cost minimization and service coverage optimization. Furthermore, addressing uncertainties prevalent in practical operations, the models incorporated two probabilistic constraints: "Loading Reliability (LR)" and "Travel Time Reliability (TTR)", significantly enhancing the models' applicability and robustnessin complex environments.

Secondly, in algorithm design, tackling the NP-Hard nature of the proposed models, this study introduced a hybrid optimization framework integrating Simulated Annealing (SA) with an Improved Harmony Search Genetic Algorithm (IHSGA). The upper level utilizes SA toglobally search for optimal CP configuration schemes, while the lower level employs IHSGA to solve the Vehicle Routing Problem with Time Windows (VRPTW). The two levels achieve iterative solution refinement through dynamic information exchange, demonstrating effective collaborative optimization capabilities and solution efficiency. Additionally, numerical experiments usingstandard benchmark functions verified the superior convergence speed and solution accuracy of the proposed algorithm, establishing a solid methodological foundation for subsequent case studies.

Finally, in empirical analysis, this study utilized a case study involving35 Class A Tertiary Hospitals in Shanghai. Real-world geographical coordinates and medical waste data were collected to experimentally validate the constructed models and algorithms. The results demonstrate that, compared to traditional non-coordinated optimization approaches, the proposedjoint optimization strategy outperforms significantly in total cost control, route efficiency, and risk mitigation. This highlights the model's strong practical adaptability and potential for wider application.

In summary, this research presents a relatively systematic investigation into the modeling, algorithm design, and application validation of medical waste recycling networks. The study not only enriches the engineering application of location-routing coordination theory but also provides valuable insights and practical references for enhancing the scientific rigor and operational efficiency of urban medical waste recycling systems.

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