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ENERGY SAVING AND EMISSION REDUCTION OPTIMIZATION OF ENTERPRISE HAZARDOUS WASTE RECYCLING MANAGEMENT SYSTEM BASED ON HYBRID GENETIC ALGORITHM

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Abstract. This research proposes a new path planning model for hazardous waste recycling transportation to effectively manage the hazardous waste recycling transportation, improving the transportation efficiency, while considering the actual road conditions. The new model adopts the conservation algorithm and hybrid genetic algorithm, which makes the new model better meet the complex needs of hazardous waste recycling. The new approach enables optimal transportation path planning for hazardous waste recycling while ensuring safety and compliance. The results showed that the hybrid algorithm outperformed the other two algorithms in terms of path optimization, cost reduction, accuracy improvement and error reduction. The hybrid algorithm had the best path optimization effect, which can get the optimal path with the lowest cost and highest efficiency. The hybrid algorithm had the highest accuracy of 95.62%. It also had the lowest root mean square error and average percentage error, indicating that it had less error. Finally, the hybrid algorithm had the highest loss function value, which indicated that the model had the best stability and better performance. The new hybrid genetic algorithm performed better than the single traditional algorithm, which is more efficient for hazardous waste recycling.

Key words: Hazardous waste recycling; Transportation costs; Transportation efficiency; Genetic algorithm; Hybrid genetic algorithm

1. Introduction. Global climate change and environmental protection have become one of the most important challenges facing the world today. To mitigate the effects of climate change and reduce carbon emissions, more countries and enterprises have begun to take active measures. One of them is to formulate and implement dual-carbon strategy objectives [1]. Under the framework of dual-carbon strategy, the importance of corporate social responsibility is further emphasized. Enterprises need to actively participate in reducing carbon emissions and environmental protection, while striving to improve resource efficiency to minimize negative impacts on the environment [2]. Hazardous waste management is a key area that is directly related to the environmental impact and sustainability of a business. Hazardous wastes are harmful wastes generated by production and industrial activities, including chemicals, wastewater, exhaust gases and solid wastes [3]. If pollutants are not properly treated and recycled, hazardous wastes may cause serious pollution to the environment, posing a threat to public health. Therefore, effective hazardous waste management and recycling is crucial. Hybrid genetic algorithms are powerful optimization tools that have been successful in several fields, including path optimization problems [4]. In the recycling and utilization of hazardous waste in enterprises, the transport link is one of the main CO_2 emission sources. Therefore, optimizing the transportation path of hazardous waste recycling can not only improve the efficiency, but also significantly reduce carbon emissions, which is in line with the national strategic objectives. Hybrid genetic algorithm combines the global search ability of traditional genetic algorithm and the optimization features of other algorithms, which can effectively solve complex optimization problems. In hazardous waste recycling path optimization, the algorithm can be used to design optimal transport paths to reduce driving distance and time, thus directly reducing fuel consumption and CO_2 emissions. By combining the global search capability of the genetic algorithm with the fine tuning of local search techniques, the hybrid genetic algorithm can effectively solve path optimization problems in hazardous waste recycling and management systems, obtaining more efficient, environmentally friendly and economically feasible solutions. Based on this, this research aims to optimize the path planning of hazardous waste recycling to reduce the en-

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vironmental risk, improve the resource recovery rate, and reduce the operation cost. The required data for the experiment are collected through actual visit surveys. Then, the concept of multi algorithm fusion is introduced to analyze the data, improving the efficiency of hazardous waste in the transportation process. Meanwhile, it can reduce the cost and carbon emissions generated during the transportation process. This research is divided into four parts. The first part is mainly to analyze the domestic and international research. The second part is to build the hazardous waste recycling model through multiple algorithms. The third part is to prove the feasibility of the algorithm through the data analysis. The fourth part is to summarize and analyze the whole research. At the same time, route planning for hazardous waste transport is particularly important in the quest to reduce carbon emissions and improve transport efficiency. Especially in urban environments, it is crucial to avoid travelling through densely populated or ecologically sensitive areas. When planning transport routes, consideration should be given to avoiding densely populated areas such as schools, hospitals and residential areas, as well as nature reserves, water sources and other important ecologically sensitive areas. Choosing suitable routes not only reduces the accidents, but also helps to minimize the potential impact on the lives of residents and the natural environment. Starting from reducing carbon emissions, reducing transportation costs, and improving transportation efficiency, the experimental data are collected through actual visits and surveys. The concept of integrating multiple algorithms is introduced to analyze data, improving the hazardous waste transportation efficiency while reducing the costs and carbon emissions generated during transportation.

2. Related works. In domestic and international research, many scholars have achieved rich research results in the hazardous waste recycling application and hybrid algorithms. Ziye Zhao et al. introduced a hybrid algorithm in customer satisfaction and profitability improvement, which could solve the order booking and production scheduling. Therefore, based on the traditional genetic algorithm, Taboo search was introduced to optimize the parameters. The research results indicated that the introduced hybrid genetic algorithm significantly improved the efficiency while increasing the total net profit [5]. Uysal, Furkan et al. improved the traditional genetic algorithm to solve multi project scheduling problems. Among them, the original problems were assumed to set some priority order and resources. The hybrid algorithm was applied to achieve the priority relationship of different problems in the project. The research results indicated that the hybrid algorithm improved the scheduling efficiency for multiple projects [6]. Su, Bentao et al. introduced a hybrid genetic algorithm in job scheduling to reduce resource constraints and fully utilize resources. Therefore, a new hybrid genetic algorithm was designed. The research results indicated that the performance of hybrid algorithms could be effectively improved [7]. Shun-chi Yu discovered that the genetic algorithm was developed as a heuristic algorithm on many traditional problems. For some time related sequences and window settings, it could solve multi-stage workshop scheduling problems. The research results indicated that the multiple hybrid algorithms could significantly outperform other single algorithms [8].

There have also been many studies analyzing path optimization problems. Haitao Chen believed that some solid waste recycling could be carried out using image recognition technology. Therefore, a target detection network algorithm model was designed to collect and analyze data on solid objects in buildings. The research results indicated that the detection algorithm had better results in waste recycling, improving recycling efficiency [9]. Wang, Jiaqian et al. introduced the artificial intelligence into robot path planning to effectively improve the planning efficiency. Therefore, a bio-geographical optimization method based on negative gradient difference was proposed, which had strong global search ability. The research results indicated that the accuracy and optimization efficiency could be effectively improved [10]. Umesh Pandey et al. conducted a three-level optimization design for path optimization. The new optimization route could increase some production capacity. The research results indicated that the production route could be effectively improved. The production efficiency could be improved through three-level optimization design [11]. Gao, Zhaohui et al. proposed that diversity of recycling types should be considered in logistics recycling. Therefore, improving the new crossover mutation operator on traditional recycling path optimization accelerated the computational speed of genetic algorithm. The research results indicated that the new optimization algorithm could reduce the cost recovery to a certain extent. The algorithm had good stability and convergence [12]. SS Sana et al. proposed two models to explore how to provide optimal green quality at a reasonable price in an increasingly environmentally conscious economy. Model 1 examined optimal green quality and selling price for manufacturers and retailers in a double helix supply chain. Model 2 focused on price competition for alternative products and considered corporate social responsibility. The results showed that the proposed models could help business managers to develop effective strategies to achieve a win-win situation in terms of profit and environmental protection [13]. Ospina-Mateus, Holman et al. proposed a hybrid method combining the genetic algorithm and simulated annealing to analyze motorcyclists' accidents on Bogotá's roads. The method used data mining and machine learning techniques to analyze 34,232 accidents that occurred between 2013 and 2018. The results showed that the method performed well in predicting accident severity, improving the prediction accuracy by 20-21% [14]. To solve the operator mutation in genetic algorithms, Behroozi F et al. proposed a new method for operator selection. The new method uses teaching-optimized novel operators for algorithm improvement. The quality and convergence speed of the algorithm model was improved by intelligent replacement. The results showed that the new method improved the computational efficiency of the traditional genetic algorithm model [15]. Sana S S et al. proposed a mathematical model for job rotation to achieve the multi-objective optimization problem. The letter model could complete complex tasks in highly variable environments. The new non-dominated sequential genetic algorithm was applied in the letter model. The convergence was improved by changing and replacing schemes that are not very different from each other. The results showed that the letter method had better efficiency in combinatorial optimization [16].

In summary, many experts have optimized path planning and hybrid algorithms. But there is still room for improvement in this issue, such as reducing the path optimization cost and improving optimization efficiency. However, existing research mainly focuses on the efficiency and effectiveness of hybrid algorithms. There is still much room to explore the comprehensive improvement of cost reduction and transport efficiency. Especially in practical application scenarios such as hazardous waste recycling and multi-project scheduling, how to combine different algorithms to maximize the cost-effectiveness is an important in the current research. Therefore, on the basis of existing hybrid algorithms, conservation algorithms and large-scale neighborhood algorithms are introduced, aiming to enhance the computational efficiency and optimize the path planning process, and improve the overall transport efficiency while reducing the transport cost. In this way, this study hopes to fill the research gap in the existing literature on cost-effective optimization, providing a more effective solution to the hazardous waste recycling and multi-project scheduling. It is expected to improve the computational efficiency of the algorithm, thereby improving the transportation efficiency of path optimization and reducing transportation costs.

3. Materials and methods. This chapter mainly focuses on the optimization design of hazardous waste recycling path. A path optimization design algorithm model based on hybrid genetic algorithm is established. Firstly, the hazardous waste recycling is elaborated. The path optimization algorithm is improved by limiting conditions. Then, the algorithm is improved.

3.1. Optimization design of hazardous waste recycling paths for enterprises under the dual carbon strategy goal. The Path Optimization problem refers to how delivery vehicles choose the path for different quantities and types of goods delivered by distribution centers [17]. Under all delivery task conditions, the delivery path, delivery vehicles, and recycling sequence are selected to achieve minimum resource utilization and shortest path optimization. Figure 3.1 shows the constraint conditions for path optimization.

The recycling route shown in Figure 3.1 is generally constrained by time. When loading and unloading goods on a truck, the recycling route is affected by this specified action, resulting in an increase or decrease in time. The distance traveled by vehicles will to some extent constrain the truck's recycling route. New energy vehicles that typically carry out transportation operations cannot replenish energy in a timely manner for extended range like traditional vehicles. Therefore, the mileage and range of recycled cars are constrained by distance. Some customers may set a recycling time. Failure to complete the recycling task within the recycling time will result in losses for both parties. Therefore, the recycling time and effectiveness will greatly affect the optimization of the recycling path. In recycling, the path security has significant impacts on the path selection. For high-risk materials such as hazardous waste, they cannot be driven on campus, ring roads, and other routes. The loading capacity of the final vehicle transportation also limits the transportation of goods [18].

The optimization of hazardous waste recycling paths has always been a research focus for enterprises, mainly focusing on optimizing some recycling time, recycling costs, and reducing the impact of hazardous waste on society. Generally speaking, the current algorithms for optimizing the path of hazardous waste include genetic algorithm, conservation algorithm, and large-scale neighborhood search algorithm. Genetic algorithm is an

Fig. 3.1: Different constraints and limitation

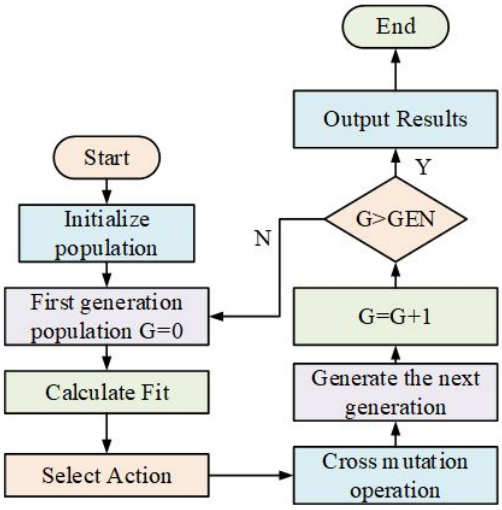

Fig. 3.2: Flow chart of genetic algorithm

algorithm that utilizes the genetic and evolutionary abilities of species in nature, as shown in Figure 3.2.

In Figure 3.2, in the genetic algorithm, the algorithm first initializes the data to form a population. Then, the fitness of the first generation population is calculated to generate the next generation. Population categories are selected, crossed, and mutated to generate the next generation of new species populations. Finally, the iterated populations are determined to determine whether they meet the new species. If they do, the optimal algorithm solution is output. If not, the population fitness is recalculated. Finally, the optimal species

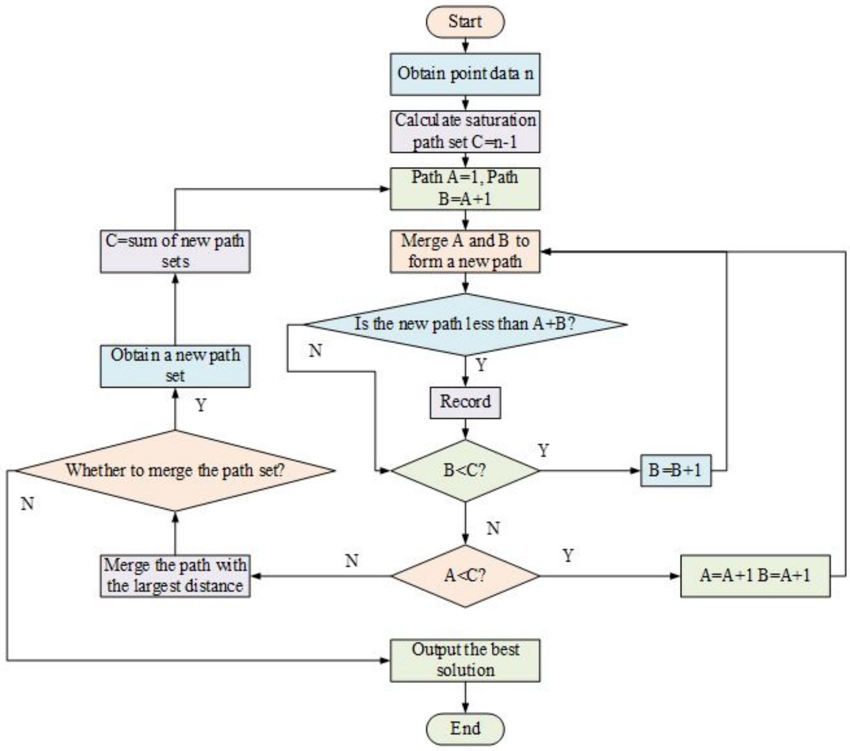

Fig. 3.3: Basic process of the saving algorithm

population is obtained. Generally speaking, genetic algorithms will retain the genetic results from the previous round until the next stage when optimizing the recycling path. However, genetic algorithms may have premature convergence. Therefore, a new saving algorithm is introduced into the recycling path for hazardous waste. The basic process of the saving algorithm is shown in Figure 3.3.

In Figure 3.3, the basic operation of the saving algorithm first confirms the point data, and then calculates the saturated recycling path. The calculated path A and path B are merged to obtain a new path. The new path size is determined to be less than A+B. If it is less than A+B, it is recorded. If not, the size of path B is directly determined to be less than the saturated path. If it is less than the path, the new path is determined by increasing the path size and merging with A again. If it meets the criteria, the size of A is determined, which is consistent with the judgment criteria for path B. If both path sizes are not less than the saturated path, the largest path in the record will be merged. Whether to merge the path set has been determined. If not merged, output the path. If there is a merge, obtain a new set of paths. At this point, the saturated path becomes a new set of paths, and then A and B paths are determined. The saving algorithm can integrate and judge any path of two paths. Therefore, the generated new path can be used as the initial solution algorithm for path optimization design in improving delivery efficiency and reducing transportation costs. Therefore, the entire problem remains at the same level, thereby reducing the premature convergence. Genetic algorithms and saving algorithms can optimize data for the early stage path selection of hazardous waste recycling path optimization problems. The large-scale neighborhood algorithm process is shown in Figure 3.4.

In Figure 3.4, large-scale neighborhood algorithms mainly perform algorithm operations through destruction and repair. The main computational process is similar to genetic algorithm. By inserting and solving the missing parts of the repair operator, the missing parts are supplemented and the optimal solution is obtained.

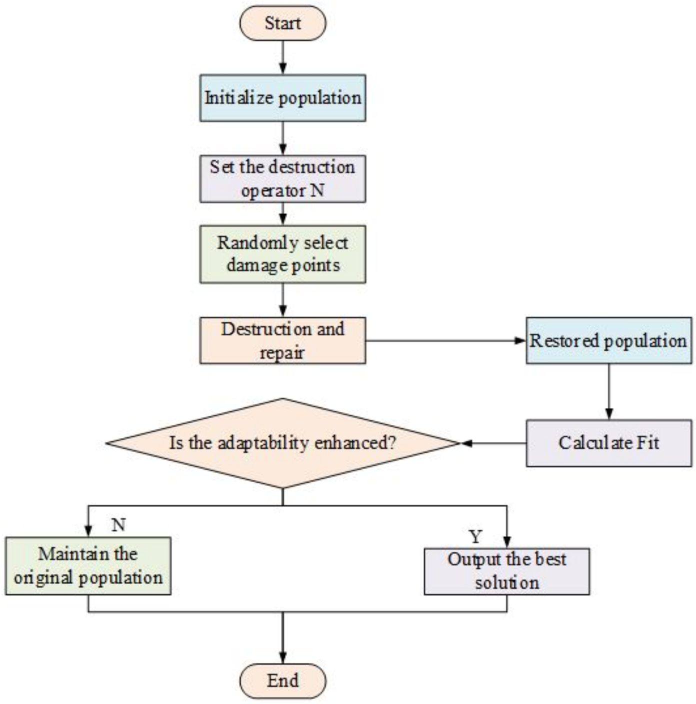

Fig. 3.4: Large scale neighborhood algorithm flow

3.2. Path optimization model construction based on hybrid genetic algorithm. Although the hazardous waste recycling is a complex transportation organization optimization process, some transportation units and transportation costs are also considered. When selecting routes and delivering vehicles for all products and hazardous waste, transportation efficiency is considered. Although carbon emissions and transportation costs are not reflected in path optimization, new carbon emissions taxes will be added to enterprises and transportation that exceed carbon emissions, which will increase transportation costs [19]. Section 2.1 has pointed out that the recycling path optimization for hazardous waste mainly considers several optimizations, including time window constraint optimization, vehicle travel distance optimization, vehicle carrying time optimization, service time optimization, etc. Therefore, the basic construction process of path optimization problems can be achieved by reducing costs and improving transportation efficiency. The transportation cost of hazardous waste includes vehicle cost, transportation cost, and time cost. The vehicle cost can is shown in equation (3.1).

$$f_1 = \sum_{k=1}^{n} c_1 z_k \tag{3.1}$$

In equation (3.1), n represents the number of recycled vehicles. f_1 represents the vehicle cost function. k represents the current recycling vehicle. c_1 represents the transportation cost of the vehicle. z_k represents vehicles involved in the hazardous waste recycling. The transportation cost of vehicles is shown in equation (3.2).

$$f_2 = \sum_{i=1}^{m} \sum_{j=1}^{m} \sum_{k=1}^{m} c_2 d_{ij} x_{ijk} \tag{3.2}$$

In equation (3.2), f_2 represents the transportation cost function of the recycling vehicle. c_2 represents the kilometer transportation cost of hazardous waste recycling vehicles. d_{ij} represents the distance from the hazardous waste recycling point i to j. x_{ijk} represents vehicle k from recycling station i to j. The time cost of the vehicle is shown in equation (3.3) [20].

$$\begin{aligned} &[Et_a, Et_b] = [e_i + \lambda, l_i + \lambda] \\ &f_3 = \textstyle\sum_{k=1}^{n}\sum_{i=1}^{m} \left\{ \begin{array}{cc} \varepsilon_1 Et_a & t_i^k < Et_a \\ \varepsilon_1 (Et_a - t_i^k) & Et_a < t_i^k < e_i \\ \varepsilon_2 (t_i^k - Et_b) & l_i < t_i^k < Et_b \\ \varepsilon_2 Et_b & t_i^k > Et_b \end{array} \right\} \end{aligned} \tag{3.3}$$

In equation (3.3), ε represents the penalty factor of time. t_i represents the time when the hazardous waste vehicle is at the hazardous waste recycling point i. e_i represents the left time window of the unit i that generates the waste. l_i represents the right time window of the unit i that generates the waste. Et_a represents the relaxation time window of the a-th recycling vehicle. λ represents the relaxation degree in the time window. Et_b represents the relaxation time window of the b-th recycling vehicle. The total cost F is calculated through fixed vehicle costs, transportation costs, and time penalty costs. Equation (3.4) shows the maximum loading capacity of vehicles transporting hazardous waste.

$$\sum_{i=1}^{m} g_i y_{ik} \leq Q \tag{3.4}$$

In equation (3.4), Q represents the maximum loading weight of hazardous waste. g_i represents the demand for hazardous waste upon arrival at station i. y_{ik}represents that the hazardous waste station i is transported by vehicle k. Equation (3.5) shows the task volume completed by each individual hazardous waste vehicle.

$$\sum_{k=1}^{n} y_{ik} = 1 \tag{3.5}$$

In equation (3.5), when fixed vehicle transportation is carried out, the cost of completing the entire transportation is expressed as 1. The unit in a recycling path is shown in equation (**??**).

$$\sum_{i=0}^{m} x_{ijk} = y_{jk}, \sum_{j=0}^{m} x_{ijk} = y_{ik} \tag{3.6}$$

Equation (**??**) indicates that the recycling paths of different recycling sites are all the same path. Equation (3.7) represents the transportation expression of the recycling vehicle for the recycling unit [21].

$$\sum_{i=0}^{m}\sum_{k=1}^{n} y_{jk} = n \tag{3.7}$$

In equation (3.7), each station has an expression for vehicle transportation. Each vehicle departs from the origin company. The transportation delivered to the corresponding company is shown in equation (3.8).

$$\sum_{i=0}^{m} x_{i0k} = \sum_{j=0}^{m} x_{0jk} \tag{3.8}$$

In equation (3.8), the cost of each vehicle during transportation is the same. When the front and back paths of hazardous waste are connected to the same hazardous waste unit, the calculation is shown in equation (3.9).

$$\sum_{i=0}^{m} x_{ipk} - \sum_{j=0}^{m} x_{pjk} = 0, p \in \{1, 2, \cdots, m\}, k \in \{1, 2, \cdots, k\} \tag{3.9}$$

In equation (3.9), the unit of hazardous waste production is expressed by a path connected expression. Within the time interval of hazardous waste generation unit i, but it cannot exceed the specified time window, as shown in equation (3.10).

$$t_i \leq l_i \tag{3.10}$$

The parameter representative values in equation (3.10) are the same as those expressed in the equation. In path planning problems, the constraint variables y_{ik}, $z_k$and x_{ijk} are between 0-1. To better simulate the variables of recycling, both early and delayed delivery to the recycling site will affect user satisfaction. Therefore, to ensure customer satisfaction in research, it is necessary to ensure customer trust, which serves as a constraint for the study. In equation (3.11), it represents the arrival time change at transportation unit i.

$$t_j = \sum_{i=0}^{m} \sum_{k=1}^{n} (\max\{e_i, t_i\} + s_j + t_{ij}) \times x_{ijk} \tag{3.11}$$

In equation (3.11), t_j represents the arrival time at the transportation unit i. The time expression from the station recycling unit to the waste production unit i is shown in equation (3.12).

$$t_{ij} = \frac{d_{ij}}{v} \tag{3.12}$$

In equation (3.12), t_{ij} represents the time from the recycling unit vehicle to the waste production unit i and to the waste production unit j. Therefore, the minimum model for hazardous waste recycling is shown in equation (3.13) [22].

$$\min F = f_1 + f_2 + f_3 \tag{3.13}$$

In equation (3.13), $\min F$ represents the minimum cost function for hazardous waste recovery. Therefore, the path recycling problem of hazardous waste is a static data problem with a single target and a time window. Traditional genetic algorithms have limitations in processing both initial and output data. Therefore, on the basis of the genetic algorithm, a saving algorithm model is introduced to optimize the preliminary data processing. Then a large-scale neighborhood algorithm is used to strengthen the genetic algorithm design to obtain a hybrid genetic algorithm.

To process computer data, initial genetic algorithm encoding is used to process path optimization data. However, genetic algorithm has some drawbacks in processing, resulting in a large amount of redundant data in the calculation process. Therefore, to improve efficiency, decimal encoding is used for data processing in hybrid genetic algorithms. To improve computational efficiency, enhance the initial population speed, increase the speed of obtaining the initial population in the early stage, the saving algorithm is used for population initialization calculations. The specific steps are shown in Figure 3.5.

In Figure 3.5, the saturation calculation method is first used to calculate the results of hazardous waste recycling for each hazardous waste generating unit vehicle without considering cost. The calculated results are summarized. Then any two paths are merged. The calculated savings values are sorted in descending order. After sorting, a save pool sequence is performed to determine whether the merged paths meet the time window requirements until a new merged path is obtained. Afterwards, the path is updated and determined to meet the loading requirements until it is calculated to meet the requirements. Finally, any two paths in the path pool are merged and calculated to determine whether the new path passes through the hazardous waste generation unit. Finally, the order in which the recycling vehicles pass is obtained.

The fitness mainly involves the current target's recovery cost, vehicle transportation cost, and time cost. The best result with the lowest cost path is obtained. To optimize the fitness, a genetic operator is added for operation. The genetic operator mainly compares the probability of the unit with the fitness degree to obtain a path with better fitness. The large-scale neighborhood algorithm mainly involves operator destruction and re-repair of the gene waste units for the parent chromosome in genetic algorithms. It mainly solves the minimum value of the target. Under the basic completion of the target conditions, the objective function is increased to

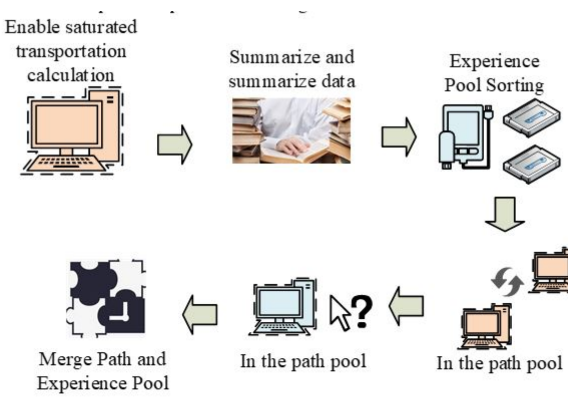

Fig. 3.5: Population optimization steps of the conservation algorithm

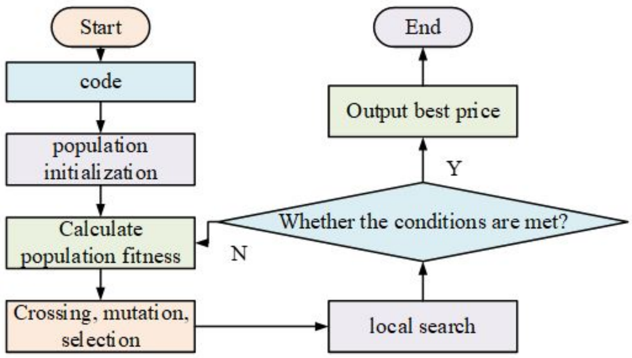

Fig. 3.6: Hybrid genetic algorithm process

reduce the adaptability of chromosomes. The convergence speed of the joint algorithm is enhanced to improve the search ability of the algorithm. The overall process of the hybrid algorithm is shown in Figure 3.6.

In Figure 3.6, the hybrid genetic algorithm first uses the saving algorithm to initialize the population. The genetic algorithm calculates the individual fitness of the population. After completing the selection, crossover and mutation operation, a large-scale neighborhood algorithm is used for local search calculation. Finally, it is determined whether the requirements of the path problem are met. If it is met, the optimal solution is output. If it is not met, the fitness is recalculated.

3.3. Materials. A hazardous waste recycling company in a city is selected as the starting point for hazardous waste recycling in the experiment. The detailed solid waste recycling data collected in the city on 18th May 2021 are analyzed and collected in a systematic data analysis. After carefully analyzing the collected data, the focus is placed on the hazardous waste category labeled HW08, which consists primarily of waste mineral oils and wastes containing mineral oils. Specifically, waste engine oil represented by 900-214-08 is a common type of vehicle waste, which is the main focus of research. Considering that the average household car needs to change about 4 litres of engine oil every 5,000 km, it can be assumed that this type of hazardous waste is relatively stable and widely distributed. This characteristic makes hazardous waste an ideal choice for detailed research and recycling.

4. Results and discussion. This chapter mainly analyzes the data of enterprise hazardous waste recycling management system based on the mixed algorithm. Some analysis data and optimization paths are compared.

Table 4.1: List of hazardous waste recycling

Hazardous waste varieties	Source of hazardous waste	Hazardous waste code	Detailed categories of hazardous waste	pollution
HW08 Waste mineral oil & waste containing mineral oil	General industry	900-214-08	Waste engine oil and transmission oil generated during equipment repair and disassembly	toxicity
				Flammable
		900-199-08	Mineral oil and sludge generated during the dismantling process of automobiles and other vehicles	toxicity
				Flammable
		900-200-08	Waste mineral oil and sludge generated during polishing and development processes	toxicity
				Flammable

Table 4.2: Comparison of parameters after path optimization of hybrid genetic algorithm

Algorithm type	vehicle number	Recycle Path	mileage(km)	Total mileage(km)	Total cost(yuan)	Timing(s)
Traditional genetic algorithm	1	0-3-7-10-11-6-2-1-0	139.7	358.2	1309.24	3.4478
	2	0-13-14-12-4-0	95.5			
	3	0-5-8-9-0	123			
Semi optimal genetic algorithm	1	0-3-7-10-11-6-2-1-0	154	340.9	1274.99	6.6751
	2	0-13-14-0	32.6			
	3	0-5-8-9-12-4-0	154.3			
Semi optimal genetic algorithm	1	0-5-7-8-11-9-12-4-0	199.8	364.4	1121.51	4.5842

The performance of the algorithm model used in the experiment is also compared with other algorithms to verify the performance.

3.1 Experimental analysis of path optimization problem based on hybrid algorithm

In the experiment, a hazardous waste recycling enterprise in a certain city is selected as the starting point for hazardous waste recycling. The pollution control platform established in the province is used to collect data and information on hazardous waste recycling from the enterprise. The current hazardous waste category is HW08. The recycling object data is solved. The specifications and categories of the recycling vehicles for this hazardous waste are the same, and the data remains roughly unchanged. Therefore, the production of hazardous waste recycling is consistent. For the convenience of data collection and calculation, hazardous waste products of this category are selected as the data analysis source. The list of hazardous waste recycling is shown in Table 4.1.

In Table 4.1, waste mineral oil such as HW08 is used as the recycling object for the current experiment. The hazardous waste generated mainly includes waste oil generated by equipment, transmission oil, and gear oil. The hazardous waste generated from 990-199-08 is mainly oil sludge and mineral oil produced during the dismantling of some cars. The waste generated with code 900-200-08 mainly consists of mineral oil and sludge generated during the polishing and ing. The main pollution of these wastes is toxicity, flammability, and explosiveness. Therefore, it needs to be recycled and treated. To compare the computational results of optimized algorithms for path optimization problems, traditional genetic algorithms, semi genetic algorithm optimization with only saving algorithm optimization, and hybrid genetic algorithm optimization are compared. The results are shown in Table 4.2.

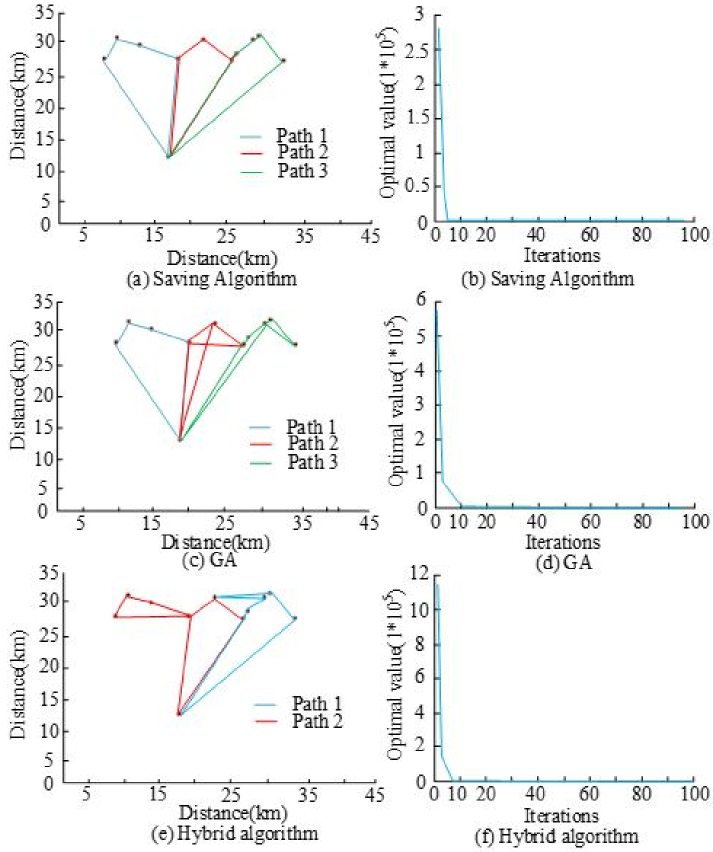

Fig. 4.1: Three algorithm paths and optimization

In Table 4.2, among the three algorithms, the hybrid algorithm increased the total mileage obtained from vehicle recycling after optimizing the path. Compared with genetic algorithm and semi optimized genetic algorithm, it increased by 6.2km and 23.5km, respectively. But the total cost of transportation decreased by 187.73 yuan and 153.48 yuan, respectively. The computational time of hybrid algorithms was relatively fast, because large-scale neighborhood algorithms were added in the later stages. The hybrid algorithm performs better than the other two algorithms in reducing costs in path optimization, CO_2 emissions can be calculated and compared under each scenario by simulating different transport routes. The path maps and optimization processes of the three algorithms are compared, as shown in Figure 4.1.

In Figure 4.1, only the hybrid genetic algorithm had fewer paths for the three algorithms, with only two paths. Meanwhile, the optimal solution value of the hybrid algorithm in solving path optimization problems was significantly higher than the other two algorithm models. From this, the hybrid algorithm could sort the existing paths reasonably to obtain the optimal solution of the path when designing path optimization, thereby making the current path the most cost-effective and efficient optimal path.

4.1. Performance analysis of the algorithm. To compare the feasibility of the hybrid algorithm, different algorithms are tested for performance. Genetic algorithm, conservation algorithm, and hybrid algorithm are selected for comparison. The testing system is Windows 10. The memory is 16GB. The CPU is i7-9800X. The test data is the current hazardous waste recycling dataset. Algorithm performance is tested and analyzed using different metrics such as Accuracy. Accuracy is one of the most intuitive performance metrics used to measure the correctness of the algorithm prediction. In algorithm performance evaluation, higher accuracy

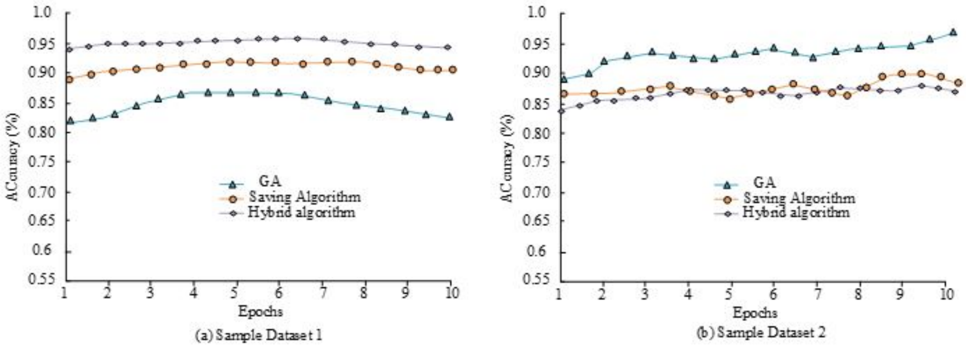

Fig. 4.2: Comparison of accuracy of three algorithms

indicates that the algorithm is more effective in prediction or classification problems. The Mean Percentage Error (MPE) measures the difference between predicted and actual values. It calculates the average prediction error and represents it as a percentage. This metric is particularly important for measuring the performance of the algorithm on continuous numerical prediction tasks. Root Mean Square Error (RMSE) measures the difference between predicted values and actual observations. RMSE gives more weight to large errors, making it a strict measure of algorithm prediction accuracy. Stability refers to the consistency of an algorithm across different datasets or across different subsets of a dataset. Even with slight changes in data, stable algorithms can still provide relatively consistent results. In practical applications, the stability of an algorithm is very important because it affects the reliability and robustness of the algorithm on new or slightly changed data. In practical applications, a single metric often fails to fully assess the performance of an algorithm. These indicator combinations can fully reflect the strengths and limitations of an algorithm from different perspectives, which improves the algorithm used in the study. The accuracy of three algorithms is compared. The accuracy is shown in Figure 4.2.

In Figure 4.2, when comparing the accuracy of the three algorithms, in dataset 1, the accuracy first increased with the increase of the sample size, and then stabilized. Finally, it decreased. From the graph, the hybrid algorithm had significantly higher accuracy than the other two algorithms. The highest accuracy value of the hybrid algorithm was 95.62%. The maximum accuracy of genetic algorithm was 85.67%, and the saving algorithm was 91.25%. From this, the accuracy of the hybrid algorithm was 9.95% higher than that of the genetic algorithm, and 4.37% higher than that of the conservation algorithm. In dataset 2, the accuracy improved with iteration, possibly because the dataset was more stable and did not exhibit bias. The actual operational errors of the three algorithms are compared, as shown in Figure'4.3.

In Figure 4.3, the three algorithms exhibited different sample error sizes in the same sample. The hybrid algorithm had the lowest error value compared to the two algorithms. The lowest RMSE was 0.185%. Compared to the 0.284% of genetic algorithm, it was 0.099% lower. Compared to the 0.245% of saving algorithm, it was 0.060% lower. The minimum average percentage error was 0.174%. Compared to the 0.346% of genetic algorithm, it was 0.172% lower. Compared to the 0.286% of saving algorithm, it was 0.112% lower. The error of the hybrid algorithm was smaller. The loss functions of the three algorithms are compared to obtain a stability comparison chart, as shown in Figure 4.4.

In Figure 4.4, the loss functions of the three algorithms gradually decreased with the increase of iteration times and then tended to stabilize. The loss function value of the hybrid algorithm was relatively high among the three algorithms. The genetic algorithm had the lowest loss function value. Among the three algorithms, the hybrid algorithm had the best algorithm stability, performing better in path optimization problems.

5. Discussion. With the increasing global concern for environmental protection and climate change, the strategic goal of "double carbon" has been proposed. In this context, the recycling and treatment of hazardous wastes generated during the production and operation of enterprises has become a key link in achieving this

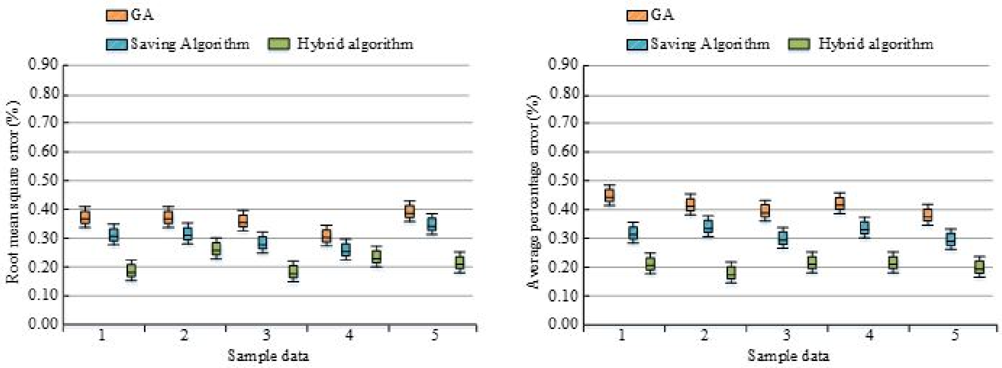

Fig. 4.3: Comparison of Errors among Three Algorithm

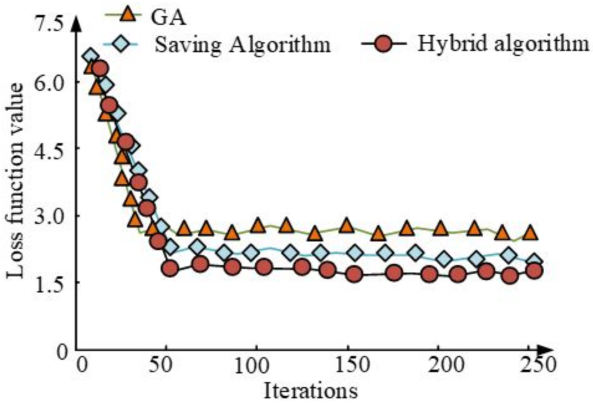

Fig. 4.4: Comparison of Loss Functions of Three Algorithms

strategic goal. Reasonable and effective management of hazardous waste recycling and treatment not only reduces environment pollution, but also promotes resource recycling, which is an important measure to achieve sustainable development. Therefore, in the selection of hazardous waste, the HW08 waste mineral oil is selected as the current experimental recycling object, because the selected hazardous waste is more common and produce more hazardous waste a. It can make the current study more universal, which is more favourable to research analysis. Meanwhile, when comparing path optimization of multiple algorithm models, compared with genetic algorithm and semi optimized genetic algorithm, the hybrid algorithm increased the total mileage after path optimization by 6.2km and 23.5km, respectively. It indicates that the hybrid algorithm can optimize the hazardous waste material path under the same conditions. It can achieve relatively good results, achieving better results in hazardous waste route management and transportation vehicle management. The paths of the three algorithms are only less than the paths of the hybrid genetic algorithm. There are only two paths. The optimal solution of the hybrid algorithm in solving the path optimization problem is significantly higher than that of the other two algorithms, indicating that the hybrid algorithm can reasonably sort the original paths to obtain the optimal solution in path optimization design. This can make the current path the most cost-effective, efficient, and optimal path. When comparing the path planning process of different hybrid algorithms, the optimal solution of the hybrid algorithm in solving the path optimization problem is significantly higher than that of the other two algorithmic models. The algorithm has fewer routes on the path optimization. This indicates that the hybrid algorithm can reduce the current driving situation of hazardous waste. Meanwhile, due to the reduction of paths, better management and planning of vehicle carrying capacity are required for transportation vehicle planning and use. This is more conducive to improving the management level of hazardous waste. When comparing the accuracy of the three algorithm models, the accuracy of the algorithm improves with the increase in the number of samples and then stabilizes. Finally, it decreases. This indicates that the model achieves maximum accuracy after increasing the number of samples. Then it decreases to indicate that the optimization effect of the model begins to decrease. It may be that the changes in the sample data, such as vehicle information, so the accuracy of the algorithm is not a stable increase in the situation. At the same time, compared to the error of the current three models, the research uses the model with the smallest error value. This indicates that the model can better optimize most of the data in sample testing when planning paths. The algorithm performance is more stable and the effect is also the best. Meanwhile, the stability of three models is compared. The stability of the model used in the study is the best, and the loss function value is the lowest, which indicates that the hybrid model used in the current path optimization is able to maintain relatively good stability. It is more beneficial to the path optimization analysis.

In summary, the model used in the study can achieve better test results when planning and analyzing the transport path of hazardous waste. Meanwhile, the model used in the study has better algorithmic stability, which is more advantageous for planning and management different paths. By optimizing hazardous waste recycling routes, it can reduce the empty and repeated trips of transportation vehicles, and reduce the total mileage traveled. This not only reduces fuel consumption and corresponding CO_2 emissions, but also lowers transport costs, achieving a win-win situation in terms of economic benefits and environmental protection.

6. Conclusion. The research mainly discusses the hazardous waste recycling in the context of dual carbon to find the most suitable path for hazardous waste recycling. According to the traditional path algorithm analysis, the advantages of each algorithm are combined to form a new hybrid genetic algorithm. Finally, the hybrid algorithm is compared for path optimization problems. The algorithm performance of the hybrid algorithm is analyzed. The experimental results showed that the hybrid algorithm increased the transportation mileage by 6.2km and 23.5km respectively compared to genetic algorithm and semi optimized genetic algorithm. But the total cost of transportation decreased by 187.73 yuan and 153.48 yuan, respectively. Simultaneously, the hybrid algorithm obtained a larger optimal value in analyzing path optimization data. There were fewer paths for transportation vehicles, improving transportation efficiency. In the performance comparison, the accuracy of the hybrid algorithm was 9.95% higher than that of the genetic algorithm, and 4.37% higher than that of the conservation algorithm. The RMSE of the hybrid algorithm was 0.099% lower than that of the genetic algorithm, and 0.060% lower than that of the saving algorithm. The average percentage error was 0.172% lower than the genetic algorithm, and 0.112% lower than the saving algorithm. The hybrid algorithm had a lower loss function descent index and more stable algorithm performance. In summary, the hybrid algorithm has a better optimization effect and higher efficiency when dealing with hazardous waste path optimization problems. After comparing several traditional algorithms, the algorithm performance is also better. Research has achieved some results in optimizing the path of hazardous waste.

This study focuses on the conversion of new energy trucks by transport companies in the context of building an ecologically civilized society and the "dual-carbon" strategy, but it does not include carbon emissions in the costing. Future trends will require companies to measure carbon dioxide in the production process and achieve carbon neutrality through carbon sinks. Carbon emissions from vehicles will be costed. The improvements are as follows. The study needs to combine the simulation of the actual carbon trading market, quote the carbon market price of the target city for cost calculation, and incorporate the carbon market price into the cost calculation function. Thus, the optimal solution reflecting cost minimization under the requirement of "carbon neutrality" is obtained. However, there are still some shortcomings in the research, such as the relatively small dataset used in the experiment. Therefore, further research will be conducted on larger and more datasets in the future.

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