Scientific Research Publishing

Automatic Driving Material Handling Vehicle Station Location and Scheduling Mathematical Modeling and Analysis

Qi Zhang[1], Qiaozhen Zhang[2*]

[1]School of Mathematical Sciences, Nankai University, Tianjin, China
[2]The Key Laboratory of Pure Mathematics and Combinatorics, Ministry of Education, Key Laboratory for Medical Data Analysis and Statistical Research of Tianjin, Laboratory for Economic Behaviors and Policy Simulation, School of Statistics and Data Science, Nankai University, Tianjin, China
Email: 1093436597@qq.com, *zhangqz@nankai.edu.cn

Abstract

Traditional material handling vehicles often use internal combustion engines as their power source, which results in exhaust emissions that pollute the environment. In contrast, automated material handling vehicles have the advantages of zero emissions, low noise, and low vibration, thus avoiding exhaust pollution and providing a more comfortable working environment for operators. In order to achieve the goals of "peaking carbon emissions by 2030 and achieving carbon neutrality by 2060", the use of environmentally friendly autonomous material handling vehicles for material transportation is an inevitable trend. To maximize the amount of transported materials, consider peak-to-valley electricity pricing, battery pack procurement, and the construction of charging and swapping stations while achieving "minimum daily transportation volume" and "lowest investment and operational cost over a 3-year settlement period" with the shortest overall travel distance for all material handling vehicles, this paper examines two different scenarios and establishes goal programming models. The appropriate locations for material handling vehicle swapping stations and vehicle battery pack scheduling schemes are then developed using the NSGA-II algorithm and ant colony optimization algorithm. The results show that, while ensuring a daily transportation volume of no less than 300 vehicles, the lowest investment and operational cost over a 3-year settlement period is approximately 24.1 million Yuan. The material handling vehicles follow the shortest path of 119.2653 km passing through the designated retrieval points and have two shortest routes. Furthermore, the advantages and disadvantages of the proposed models are analyzed, followed by an evaluation, deepening, and potential extension of the models. Finally, future research directions in this field are suggested.

1. Introduction

In order to achieve the goals of "carbon peak by 2030" and "carbon neutrality by 2060", the development of new energy electric vehicles is an important approach to energy conservation and emission reduction. Traditional material handling vehicles typically use internal combustion engines as their power source. However, the exhaust emissions produced by this power source contribute to environmental pollution. Additionally, internal combustion engines require a fuel supply, which incurs high costs and is also susceptible to fuel price fluctuations. Moreover, the noise and vibration generated by internal combustion engines can have negative effects on the work environment and the health of operators. In contrast, environmentally friendly automated material handling vehicles possess features such as zero emissions, low noise, and low vibration, thus avoiding exhaust pollution and providing a more comfortable working environment for operators. Furthermore, electric material handling vehicles utilize batteries as their energy source, obtaining energy through charging, which is more convenient and cost-effective. Therefore, using environmentally friendly autonomous electric vehicles for material transportation is an inevitable trend [1]. It is worth noting that electric vehicles have limited energy storage, which restricts their driving range, and therefore, the construction of charging facilities must be considered. However, setting up numerous charging and swapping stations can lead to increased social costs, so it is essential to consider the time cost of charging and swapping batteries. This involves the rational location selection of charging and swapping stations under a predetermined number of stations [2] [3]. Currently, there have been many studies on the planning of electric vehicle charging stations both domestically and internationally, but most of them focus on the interests of power companies and do not comprehensively consider various charging needs and social factors affecting electric vehicle charging [4]. In 2020, the National Development and Reform Commission and the Ministry of Transport issued the "Notice on Further Reducing Logistics Costs and Implementing Measures", calling for the active development of green logistics and promoting the greening and reduction of packaging and logistics equipment. Logistics companies should adjust their development strategies in accordance with their own business characteristics and development directions, actively adapting to the green transformation of the logistics industry. Therefore, centralized collaborative delivery is an important decarbonization method, which can improve the overall loading speed and vehicle utilization rate of environmentally friendly

automated material handling vehicles, while reducing empty driving, lowering logistics company operating costs and investments. This paper takes into account multiple parameters, such as peak-to-valley electricity pricing, construction costs of charging and swapping stations, and automatic battery swapping equipment costs, to establish a multi-objective programming model. The aim is to determine optimal station locations and scheduling schemes that ensure the minimum transportation volume and lowest investment and operational costs over a 3-year settlement period. The NSGA-II algorithm [5] and ant colony optimization algorithm are employed to solve the proposed model and provide more reasonable scheduling schemes.

2. One Pickup Point and One Delivery Point Model

In material transportation, the simplest scenario involves having only one pickup point and one delivery point. Considering multiple parameters such as peak-to-valley electricity pricing, construction costs of charging and swapping stations, and automatic battery swapping equipment costs, it is crucial for logistics companies to find optimal locations for stations and scheduling schemes to ensure the minimum transportation volume and the lowest investment and operational costs over a 3-year settlement period.

From a mathematical perspective, this is a multi-objective linear programming problem. By establishing a multi-objective programming model, the dual-objective linear programming problem can be transformed into a sequential single-objective linear programming problem. The two objective functions to be minimized are the minimum power consumption and the lowest total investment cost while satisfying the condition of minimum daily transportation volume. The NSGA-II algorithm is utilized to solve this problem effectively.

2.1. Cost Analysis

2.1.1. Peak-to-Valley Electricity Pricing Analysis

Peak-to-Valley electricity pricing is a new pricing category implemented for urban residents' electricity consumption. It involves two types of electricity usage: peak electricity consumption and off-peak electricity consumption. Typically, a 24-hour day is divided into two time periods: 8:00 to 22:00, consisting of 14 hours, referred to as the peak period, with a peak electricity price of 0.568 Yuan/kWh; and 22:00 to the next day's 8:00, consisting of 10 hours, known as the off-peak period, with an off-peak electricity price of 0.288 Yuan/kWh. Based on the peak and off-peak electricity prices, the charging and discharging schedules of material handling vehicles can be economically allocated. The mathematical models for peak and off-peak electricity prices are as follows:

$$f_p(t) = \begin{cases} p_v, & t_{a1} \le t \le t_{a2} \\ p_p, & t_{b1} \le t \le t_{b2} \\ p_f, & \text{others} \end{cases} \tag{1}$$

In the equations, p_v represents the off-peak electricity price, p_P represents the peak electricity price, p_f represents the flat electricity price, $[t_{a1}, t_{a2}]$ represents the off-peak electricity price period during one day, $[t_{b1}, t_{b2}]$ represents the peak electricity price period during one day, and others represent the flat electricity price period.

2.1.2. Battery Pack Cost Analysis

Assuming that all battery packs have the same model and cost, let's denote the cost of one battery pack as u. As mentioned in the problem, each material handling vehicle requires 6 battery packs. Therefore, the total cost of battery packs for one material handling vehicle is 6u. Since there are a total of 900 material handling vehicles, the overall cost of purchasing battery packs is 900u.

2.1.3. Charging and Swapping Station Costs

The costs of charging and swapping stations for electric material handling vehicles mainly include the construction costs, operational costs, and carbon emissions costs.

1) Construction Costs of Charging and Swapping Stations: The construction costs of charging and swapping stations include infrastructure expenses and equipment costs. According to relevant information, infrastructure expenses mainly cover the costs of business buildings and road construction. The equipment costs include charging equipment, battery swapping machines, and other necessary facilities for the charging and swapping processes.

2) Operational Costs of Charging and Swapping Stations: The operational costs of charging and swapping stations mainly include employee wages, equipment maintenance costs, land lease costs, and other ongoing expenses related to the day-to-day operation of the stations.

3) Carbon Emissions Costs: When electric material handling vehicles travel to charging and swapping stations, they consume electricity, and the production of this electricity may result in carbon emissions. We can calculate the environmental impact of material handling vehicles' journey to the swapping station by factoring in carbon emissions costs into the planning model for charging and swapping station location. This approach helps to consider and account for the environmental consequences of the transportation process and encourages the adoption of sustainable practices in material handling operations.

2.2. Model Establishment

Based on the comprehensive consideration of the aforementioned factors, we have established the following objective functions:

1) Objective Function 1: Minimize Power Consumption Load.

Let's assume the peak-to-valley electricity pricing periods are [9:00, 17:00] and [17:00, 21:00]. During the off-peak electricity pricing period, all material handling vehicles are fully charged to meet their energy requirements. In the peak electricity pricing period, they perform the discharging work, which can lead to

higher economic benefits. Let Z represent the minimum power consumption load. The objective function can be formulated as follows:

$$\min Z = L_T\left(t_{a1}, t_{a2}, t_{b1}, t_{b2}\right).\tag{2}$$

The constraints are as follows:

$$\begin{cases} t_{b1} < t_{b2}, \ t_{b1}, t_{b2} \in [9,17] \\ t_{a1} < t_{a2}, \ t_{a1}, t_{a2} \in [0,9] \end{cases}\tag{3}$$

2) Objective Function 2: Minimum Investment and Operational Costs Over 3 Years

Let's assume i represents the demand point where the material handling vehicles are located, with a total of m demand points; j represents the candidate locations for charging and swapping stations; h_i represents the battery swapping demand at demand point i for electric vehicles; k represents the level or capacity of the swapping station, $k \in \{1,2,3\}$; F_{bk} represents the construction cost of a swapping station at level k; F_{rk} represents the annual operational cost of a swapping station at level k; represents the distance between demand point i and swapping station j; P_{co2} represents the carbon emissions price, which is the price for trading CO_2 emissions in carbon markets; represents the carbon emissions coefficient per unit distance traveled by electric vehicles; e_{elec} represents the greenhouse gas emission factor for the supply of electricity at charging terminals, it quantifies the average carbon emissions produced per unit of electricity generated during the charging process; E_{1km} represents the average energy consumption of an electric vehicle per 1 kilometer of travel; represents the conversion efficiency. The objective function is as follows:

$$\min F = C_1 + C_2 + C_3 + C_4 .\tag{4}$$

The constraints are as follows:

$$\begin{cases} C_1 = \sum_j \sum_k F_{bk} X_{jk} \\ C_2 = 3\sum_j \sum_k F_{rk} X_{jk} \\ C_3 = 1095 P_{co2} e_{co2} \sum_i \sum_j h_i d_{ij} Y_{ij} \\ C_4 = 900u \\ e_{co2} = \dfrac{e_{co2} E_{1km}}{\eta} \\ T_{ang} \geq 60m \\ d_{ij} \leq 10 \\ X_{jk} \in \{0,1\}, \forall j \in J, k \in K \\ Y_{ij} \in \{0,1\}, \forall i \in I, j \in J \end{cases}\tag{5}$$

Here are the constraints, C_1 represents the construction cost of the swapping station; C_2 represents the operational cost of the swapping station; C_3 represents the carbon emissions cost of electric vehicles; C_4 represents the cost of purchasing battery packs; the 5th equation represents the calculation formula for the

carbon emissions coefficient per unit distance traveled by electric vehicles; the 6th equation represents the constraint for the minimum daily transportation quantity; the 7th equation represents the distance constraint between material handling vehicles and swapping stations (distance between pickup and delivery points is 10 km).

2.3. Solving the Model Based on the NSGA-II Algorithm

The Non-Dominated Sorting Genetic Algorithm (NSGA) is a method based on Pareto-optimal solutions. This algorithm performs a non-dominated sorting of individuals into different layers based on their dominance relationships before executing the selection operator [5]. The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is an improved version of the non-dominated sorting method. Compared to NSGA, NSGA-II introduces a fast non-dominated sorting method, reducing the computational complexity. It replaces the fitness sharing strategy with the proposed crowding distance and crowding distance comparison operators. These operators are used as winning criteria in comparisons among individuals at the same level after fast sorting. This allows individuals in the approximate Pareto front to extend to the entire Pareto front and achieve a more uniform distribution. NSGA-II also incorporates an elite strategy [6], combining the parent population with the offspring population and letting them compete together for the next generation is more favorable for preserving the excellent individuals from the parent population to the next generation. Through the non-dominated sorting of all individuals in the population, the best individuals are not lost, thus improving the overall quality of the population.

Specific algorithm flow is shown in Figure 1.

The performance of the NSGA-II algorithm is influenced by the adjustment of parameters, such as crossover probability, mutation probability, and population size. In the NSGA-II algorithm, both the crossover operation and mutation operation require setting probabilities, namely the crossover probability and mutation probability. For a population of "size", perform the crossover operation "size/2" times and the mutation operation "size" times. In each operation, a random number is generated and compared with the given probability. If the random number is smaller than the given probability, the operation continues; otherwise, it exits. The crossover operation takes two individuals from the population in order of their ranking (according to the individual's number) and performs the crossover operation. Each time the crossover operation is executed, it is also necessary to determine whether to conduct the crossover operation by comparing the generated random number with the given crossover probability. By continuously adjusting the parameters, a set of individuals belonging to non-dominated rank 1 can be found as the optimal solution.

2.4. Solution Results

The peak electricity price is set at 3.118 Yuan/(kWh), and the off-peak electricity

price is 1.089 Yuan/(kWh). The price of one battery pack is 10,000 Yuan, so the total cost of the battery pack for one vehicle (including 6 battery packs) is 60,000 Yuan. The total cost for 900 vehicles in the swapping stations to purchase battery packs is 9 million Yuan. The construction cost of a charging and swapping station is approximately 2.5 million Yuan, with a distribution cost of around 1.92 million Yuan per year and an operational cost of around 1.21 million Yuan per year.

After applying the NSGA-II algorithm to ensure a minimum daily transportation quantity of 300 vehicles, the minimum investment and operational cost over a 3-year settlement period is found to be 24.1 million Yuan. The fitness value change curve is shown in **Figure 2**.
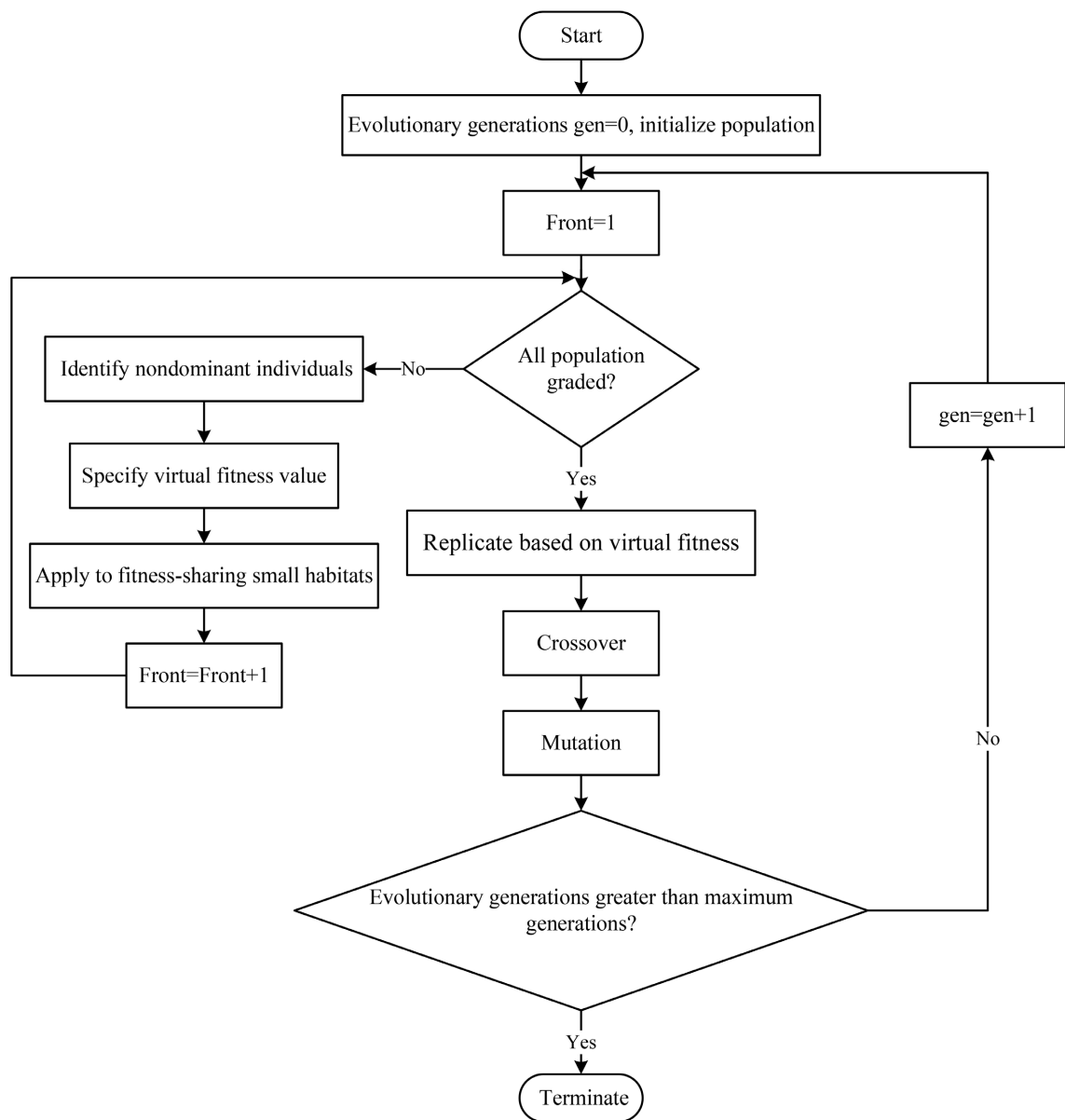

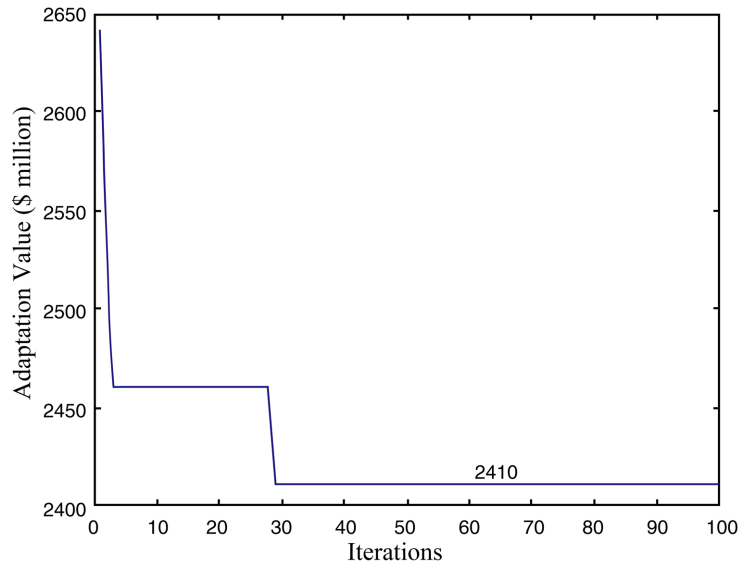**Figure 1.** Flowchart of NSGA algorithm.

Figure 2. Fitness value change curve.

3. Multiple Pickup Points and Single Delivery Point Model

3.1. Model Analysis

When there are multiple pickup points and a single delivery point, knowing the distances between the delivery point and each pickup point, as well as the distances between any two pickup points, is equivalent to knowing the positions of the swapping station, multiple pickup points, and a single delivery point. It can be considered as multiple material handling vehicles departing from the swapping station, traveling to the pickup points to pick up the goods, and then traveling to the delivery point for unloading. In this case, the material handling vehicles are no longer moving on both sides of the road, but following the driving routes, as shown in **Figure 3** [7].

In **Figure 3**, P_i represents the pickup points, D represents the delivery point. Let d_{ij} represents the distance between pickup point i and pickup point j. X_{kij} indicates whether material handling vehicle k travels from pickup point i to pick up point j, where $X_{kij} = 1$ if it does and $X_{kij} = 0$ otherwise; $\Delta^+(i)$ represents the set of arcs departing from pickup point i, $\Delta^-(j)$ represents the set of arcs returning to pick up point j; $N = V \setminus \{0, n+1\}$ represents the set of pickup points and the delivery point, k represents the set of distribution vehicle. Therefore, the following mathematical model is established:

$$\min \sum_{i \in K} \sum_{(i,j) \in A} d_{ij} X_{kij} , \tag{6}$$

$$\text{s.t.} \begin{cases} \sum_{k \in K} \sum_{j \in \Delta^+(i)} X_{kij} = 1, \forall i \in N \\ \sum_{j \in \Delta^+(i)} X_{kOj} = 1, \forall k \in K \\ \sum_{i \in \Delta_-(j)} X_{kij} - \sum_{i \in \Delta^+(j)} X_{kij} = 0, \forall k \in K, \forall j \in N \\ \sum_{i \in \Delta_-(n-1)} X_{k,i,n+1} = 1, \forall k \in K \\ X_{kij} \in \{0,1\}, \forall k \in K, \forall (i,j) \in A \end{cases} \tag{7}$$
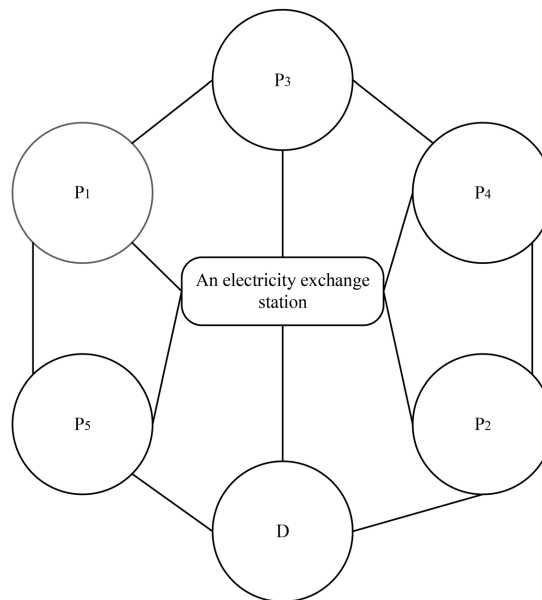
Figure 3. Connectivity graph between the swapping station and pickup points.

In the above equation, the first constraint restricts each pickup point to be assigned to only one path, and the remaining constraints represent the flow restrictions of material handling vehicle k on the paths.

3.2. Solving the Model Based on Ant Colony Optimization Algorithm

Ant Colony Optimization (ACO) is a probabilistic algorithm used to find optimized paths in graphs, inspired by the foraging behavior of ants in nature. When ants search for food, if they encounter an unexplored intersection, they will randomly choose a path to proceed while releasing pheromones related to the path length. Ants leave a volatile hormone, known as pheromones, on the paths they have traveled. The role of pheromones is to inform other ants about the information of the optimal path. When subsequent ants encounter the same intersection again, they have a higher probability of choosing the path with a higher pheromone concentration. This process forms a positive feedback loop [8]. Therefore, in a situation with a finite number of solutions, ants tend to follow the path with a higher accumulation of pheromones. Ants that find the shortest path will return to the nest early, leaving more pheromones on the pat [9]. Due to the higher accumulation of pheromones on the shortest path, more ants will choose this path, eventually allowing the entire colony to find the shortest path between the food source and the nest [10].

As shown in **Figure 4**, in the sequence (1) - (2) - (3), as time passes, ants move in the direction of higher pheromone concentration. Within the same time frame, the pheromones left on the shorter path increase. As a result, more ants are attracted to the shorter path. Eventually, as more ants pass through a certain path, the subsequent ants tend to choose this path [11]. In the end, all ants will follow this path as their route.
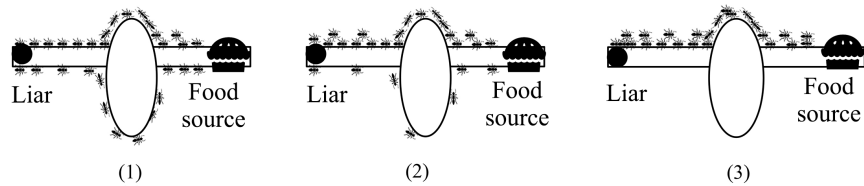
Figure 4. Ant movement path map.

The two essential steps of the Ant Colony Optimization algorithm are path construction and pheromone updating [12]. In ant colony optimization algorithms, multiple parameters need to be adjusted to find the best solution, including the number of ants, pheromone evaporation rate, and pheromone deposition intensity. Each parameter has a different role, and the optimal parameter settings need to be found through trial and optimization. The number of ants is one of the important parameters that affect the algorithm's performance. For small-scale problems, we typically set the number of ants between 50 and 100, for medium-scale problems, we can set it around 200 - 300, and as for large-scale problems, we can set it at around 500 - 1000. The pheromone evaporation rate is a parameter that controls the rate at which pheromones evaporate. For small-scale problems, we can set the evaporation rate around 0.2; for medium-scale problems, we can set it around 0.3; for large-scale problems, a higher evaporation rate is generally required and can be set between 0.4 - 0.5. The pheromone deposition intensity represents the strength of pheromone updating, controlling the amount of pheromones released by ants on the path. For small-scale problems, the intensity can be set around 1; for medium-scale problems, we can set it around 2; for large-scale problems, we can set it between 2 - 3; the Ant Colony Optimization algorithm flowchart is shown in the **Figure 5** [13].

3.3. Model Conclusion

During the model simulation, the parameters were set as follows: the initial number of ants was 75, α value was 1, β value was 5, the pheromone evaporation factor ρ was 0.85, the constant Q for updating pheromone concentration was 5, and the maximum iteration was set to 100. By using the Ant Colony Optimization algorithm, the shortest path was found to be 119.2653 km. The variation of distance during iterations is shown in **Figure 6**.

Meanwhile, the optimal delivery route map is shown in **Figure 7**.

From the above figure, it can be observed that there are two shortest paths for the material handling vehicle to travel:

One of the routes is as follows: [Route 1] $0 \rightarrow 5 \rightarrow 1 \rightarrow 3$.

The other route is as follows: [Route 2] $0 \rightarrow 2 \rightarrow 4 \rightarrow 7 \rightarrow 6 \rightarrow 8 \rightarrow 16 \rightarrow 14 \rightarrow 9 \rightarrow 10 \rightarrow 12 \rightarrow 11 \rightarrow 13 \rightarrow 15 \rightarrow 0$.

4. Model Evaluation and Generalization

4.1. Advantages

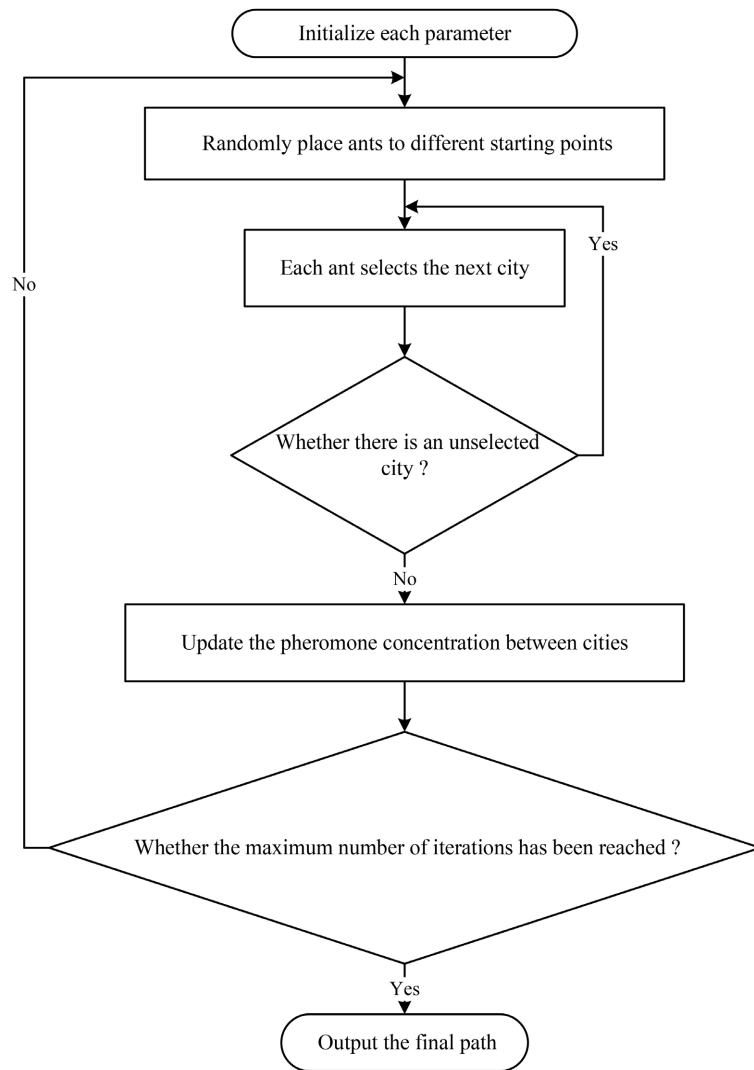1) Utilization of linear programming models simplifies the problem, and the

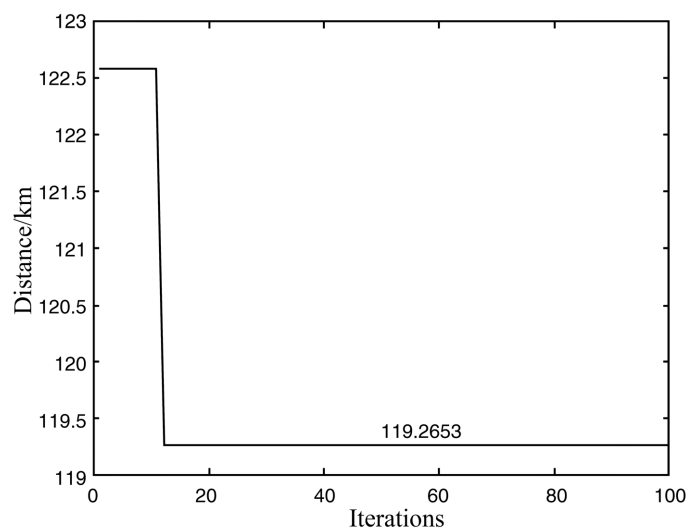**Figure 5.** Ant colony optimization algorithm flowchart.

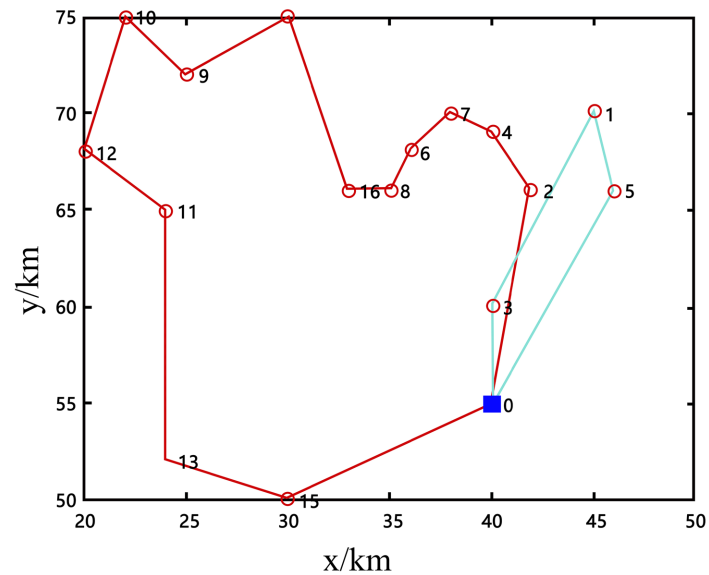**Figure 6.** Distance iteration variation graph.

Figure 7. Optimal solution route map.

linear programming objective function allows for finding maximum, minimum, and critical values. This facilitates discussions on different vehicle-battery dispatching strategies for various scenarios; employing multi-objective programming models simplifies the problem and makes the solution process more straightforward;

2) The use of graph theory models in combination with the Ant Colony Optimization algorithm streamlines the solving process and provides more intuitive results.

4.2. Shortcomings and Limitations of the Model

1) During the data collection process, differences in data acquisition methods and statistical approaches may lead to certain conclusions lacking practical validation, potentially impacting the experimental results;

2) During the data collection process, differences in data acquisition methods and statistical approaches may lead to certain conclusions lacking practical validation, potentially impacting the experimental results;

3) Shortcomings and limitations of the model: Due to insufficient data to support, the parameter values in the modeling process of this study are subject to a considerable level of subjectivity. Future research plans to accumulate more relevant empirical data, continuously refine the model, and enhance computational accuracy to better validate the applicability value of the model.

4.3. Model Generalization

The various model algorithms presented in this paper can be suitably applied to optimization problems in other engineering fields. For instance, the NSGA-II algorithm used for solving in this study is not only applicable to the material handling vehicle scheduling problem but also useful in other domains such as

path planning, production scheduling, and more. It can efficiently and effectively solve diverse models and optimization challenges across different engineering applications.

5. Conclusions

This article starts with graphical simulations and combines with the characteristics of the power grid to focus on the last part of transporting goods. It analyzes the selection of charging and swapping stations and battery scheduling using models of extreme value problems and software like MATLAB. The implementation of the scheduling plan and the selection of charging and swapping stations are objectively and macroscopically depicted. The influence of different battery swapping methods during vehicle travel on the swapping process is considered, evaluating the fleet's status (empty or loaded) during swapping. Multiple dimensions of cost calculations, including time cost, charging, and swapping prices, are considered, establishing a new multidimensional planning system.

Furthermore, this article simplifies the path map based on the attributes and characteristics of multiple pickup points and a single delivery point, considering two influencing factors, and efficiently searches for optimal paths using the ant colony algorithm.

From the results of the model, it can be seen that using electric vehicles for material transportation indeed simplifies the transportation process. However, it is important to note that this study is based on certain assumptions. On the one hand, using environmentally friendly automatic electric vehicles for material transportation is a developmental trend. On the other hand, in formulating electric vehicle scheduling plans, it is necessary to consider the time cost of charging and swapping batteries, leading to the proposal of new vehicle transportation site selection and scheduling problems, which are necessary for advocacy, development, and limitations.

Due to space limitations, this paper cannot select particular examples to quantitatively verify the economic index functions of the impacts of charging and discharging on the power grid's reliability, voltage quality, and the reduction of harmonic pollution. Therefore, future research directions involve selecting appropriate conditions and examples for verification, and improving the economic comparison index functions.

Currently, the automatic material handling vehicle industry in China is still in the development stage, and domestically produced batteries have a relatively short lifecycle, potentially facing a high scrappage rate issue. Therefore, for discarded batteries that have reached their service life, it is necessary to establish a market-oriented battery recycling network to improve energy utilization efficiency, save costs, protect the environment, and reduce heavy metal pollution.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Si, S.K. and Sun, Z.L. (2015) Mathematical Modelling Algorithms and Applications. 2nd Edition, National Defense Industry Press, Beijing. (in Chinese)

[2] Zhou, L. (2012) Research on Electric Vehicle Charging and Switching Station Sitting Planning Layout. Master's Thesis, Shandong University, Jinan. (in Chinese)

[3] Shen, Y.D. and Chen, C. (2021) A Review of Research on Electric Bus Scheduling Problems. Logistics Science and Technology, **44**, 62-66. (in Chinese)

[4] Xu, Z.Y. (2014) Research on Optimal Decision-making and Operation Mode of Electric Vehicle Charging and Battery Swap Station Considering Multiple Demands. Master's Thesis, Zhejiang University, Hangzhou. (in Chinese)

[5] Zheng, X. and Ma, L. (2020) An Improved NSGA-II Algorithm for Multi-Objective Nonlinear Optimization. *Microelectronics & Computer*, **37**, 47-53. (in Chinese)

[6] Feng, S. and Ai, Q. (2007) Application of Improved NSGA-II Algorithm with Elite Strategy in Multi-objective Reactive Power Optimization. *Transactions of China Electrotechnical Society*, **22**, 146-151. (in Chinese)

[7] Zeng, S., Dai, X., Hu, X. and Teng, G.H.W. (2022) Path Optimization Design of Dispatched Vehicles Based on Ant Colony Algorithm. *Automation & Instrumentation*, **37**, 89-93+98. (in Chinese)

[8] Lu, Z. (2018) Research on WSN Routing Based on Improved Ant Colony Algorithm. Master's Thesis, Anhui University of Science and Technology, Huainan. (in Chinese)

[9] Lin, Y., Wu, J. and Fan, S. (2012) Channel Allocation Optimization Model and Simulation Based on Ant Colony Algorithm. *Science Technology and Engineering*, **12**, 6016-6020. (in Chinese)

[10] Sun, Q. and Wang, D. (2008) Optimization Parallel Ant Colony Algorithm with Particle Swarm Features. *Computer Engineering*, **34**, 208-210. (in Chinese)

[11] Xu, M. (2006) Research on Self-Organized Network Routing Technology Based on Ant Colony Algorithm. Master's Thesis, National University of Defense Technology, Changsha. (in Chinese)

[12] Liu, H. (2010) Improvement of Ant Colony Optimization Algorithm and Its Application in TSP, Master's Thesis, Chongqing University, Chongqing. (in Chinese)

[13] Dai, T. (2022) Application of Improved Ant Colony Algorithm in Vehicle Routing Optimization Problem. *Journal of Nanyang Institute of Technology*, **14**, 35-38. (in Chinese)