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Research on the Vehicle Routing Problem of Multi-Vehicle Types Electric Vehicles Considering Piecewise Linear Charging and Load Impact on Energy Consumption

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ABSTRACT

With the introduction of policies such as green logistics and green supply chains, the application of electric vehicles in logistics distribution is becoming increasingly widespread. This paper starts from the vehicle routing problem of multi-vehicle types electric vehicles, introduces a non-linear charging strategy, and uses piecewise linear functions to fit the non-linear charging process. We propose a vehicle routing problem for multi-vehicle types electric vehicles considering piecewise linear charging and load impact on energy consumption, and construct a mixed integer programming model. An adaptive large-scale neighborhood search algorithm is designed to conduct experiments on small and large-scale instances to verify the performance of the model and algorithm.

KEYWORDS

Multi-vehicle types; Electric vehicle routing problem; Piecewise linear charging; Load impact on energy consumption; Adaptive large-scale neighborhood search algorithm

1. INTRODUCTION

With the continuous development of technology and the diversification of consumer habits, the position of China's logistics industry is increasingly prominent. According to statistics released by the State Post Bureau, in 2022, China's express delivery volume reached 110.581 billion pieces, and business revenue reached 1.03323 trillion yuan. At the same time, the total social logistics costs show a continuous growth trend, with transportation costs accounting for as high as 54%. To achieve the important goals of peaking carbon emissions and carbon neutrality, policy support and technological innovation have become necessary conditions. In this context, the development of green logistics is particularly important, and the application of electric vehicles in logistics has become an important means to promote green logistics. European countries and the Chinese government are committed to promoting the development of new energy vehicles, and regions such as California and Germany have also introduced relevant policies to support the development of new energy vehicles. Electric vehicles have advantages such as zero emissions, high efficiency, and low operating costs, but they also face challenges such as insufficient charging facilities.

Felipe and his team[1] proposed a problem called Green Vehicle Routing Problem with Partial Recharging (GVRP-PR). In the process of vehicle charging, in addition to considering the charging time and location, it is also necessary to pay attention to the charging amount. Montoya et al.[2] divided the charging process of electric vehicles into two stages. In the first stage, the charging rate is constant, and the battery level increases linearly with time until the terminal voltage reaches a specific maximum value; in the second stage, the current decreases exponentially, the terminal voltage remains constant, and the rate of change of battery level decreases over time. Based on the use of partial charging, a mixed integer linear programming problem for the nonlinear electric vehicle routing problem is established. Kancharla and Ramadurai[3] proposed a nonlinear charging and load-related discharge EVRP, allowing electric vehicles to access charging stations multiple times without repeating nodes. The optimization objective function in this paper is to minimize driving time, the number of stops at charging stations, and charging time, while considering nonlinear charging time, and using the ALNS algorithm to solve this problem. Behnke et al.[4] considered the impact of vehicle load on path carbon emissions and studied the vehicle routing problem of minimizing carbon emissions of heterogeneous vehicles and roads. They proposed a column generation algorithm, which has an acceleration effect in fast heuristic algorithms and branch-and-price algorithms, and is of reference value for optimizing urban transportation networks. Liu et al.[5] extended the two-level vehicle routing problem considering load-related unit transportation costs and unit emissions of mixed vehicles and multiple warehouses, minimizing transportation costs and emissions.

Through a comprehensive review of the literature, we can observe that both domestically and internationally, there is a considerable wealth of research on electric vehicle routing optimization, and numerous research results have been achieved. These studies provide solid theoretical support for the problem of multi-vehicle type electric vehicle routing optimization considering piecewise linear charging and the impact of load on energy consumption. However, there is relatively little research on how the energy consumption rate of electric vehicles is affected by vehicle load, and there has been no in-depth discussion on the interrelationships and effects of these factors. At the same time, the above-mentioned studies basically use single vehicle single path, and mostly adopt simple full charging or linear charging strategies, without considering more realistic nonlinear charging strategies. Therefore, this paper starts from the vehicle routing problem of electric vehicles, considering the impact of load on the energy consumption rate of electric vehicles and the nonlinear charging process according to the actual characteristics of electric logistics vehicles, and uses piecewise linear charging to fit the charging process, constructs a mixed integer programming model, designs algorithms, and verifies them.

2. PROBLEM DESCRIPTION AND MODEL CONSTRUCTION

The distribution scenario constructed in this paper is assumed that there is only one distribution center, and electric vehicles of the same type provide services to customers at different locations. The electric vehicles maintain a constant speed and must return to the distribution center after completing the task. The vehicle load cannot exceed its maximum capacity, and the load at the customer point upon arrival should meet the customer's demand. The arrival time at the customer point should meet the customer's time window requirements. The time window is set as a hard time constraint on the acceptable service time for the customer. If the vehicle arrives earlier than the customer's time window, it needs to wait, and if it arrives later than the time window, it cannot provide distribution services to the customer. The electric vehicles adopt a linear charging method with a fixed charging rate, and the power consumption rate is composed of a fixed power consumption rate and a power consumption rate influenced by the load. The vehicle needs to ensure sufficient power to reach the next node during the driving process. There is only one charging method at the charging station, which can serve multiple electric vehicles simultaneously, and the electric vehicles reach full power after each charging.

2.1. Basic Assumptions

The combinatorial optimization problem of the electric vehicle routing problem with segmented linear charging and power consumption rate influenced by load is an NP-hard problem, which is complex to model in practical scenarios. To facilitate the mathematical modeling, this paper makes the following assumptions:

(1) Two different types of electric vehicles provide services to customers at different locations. The vehicles depart from the distribution center and must return to the distribution center after completing the delivery task.

(2) The vehicle load cannot exceed its maximum capacity, and the load at each customer point upon arrival should meet the demand of the current customer point.

(3) The arrival time at the customer point should meet the customer's time window requirements. This paper sets the time window as a hard time constraint on the acceptable service time for the customer in the delivery scenario, and if the vehicle arrives earlier than the customer's time window, it needs to wait, and if it arrives later than the time window, it cannot provide distribution services to the customer.

(4) The electric vehicles maintain a constant speed during the delivery process, and need to ensuresufficient power to reach the next node. The range of the electric vehicles is modeled as a segmented linear charging method, and the power consumption rate during discharge is composed of a fixed power consumption rate and a power consumption rate influenced by the load.

(5) There is only one charging method provided at the charging station in the logistics network, and a charging station can serve multiple electric vehicles simultaneously. This paper adopts a segmented linear charging strategy, and the electric vehicles reach full power after each charging.

2.2. Symbol explanation

Table 1. Model Variable Explanation

Variable Name	Definition
xij	0-1 variable, equal to 1 if the electric vehicle passes through arc (i, j)
ui	Remaining load capacity of the electric vehicle when arriving at customer point i
ti	Time when the electric vehicle arrives at customer point i
yi	Remaining battery level of the electric vehicle when arriving at customer point i
Si	Charging duration of the electric vehicle at charging station i

Table 2. Model Variable Explanation

Variable Name	Definition
D = {0, N + 1}	0-1 variable, equal to 1 if the electric vehicle passes through arc (i, j)
F = {f1, f2, … , fm}	Remaining load capacity of the electric vehicle when arriving at customer point i
EV = {ev1, ev2, … , evk}	Time when the electric vehicle arrives at customer point i
V = {v1, v2, … , vn}	Remaining battery level of the electric vehicle when arriving at customer point i
V0 = 0 ∪ V	Charging duration of the electric vehicle at charging station i
VN+1 = V ∪ N + 1	Collection of starting distribution centers and customer points
Vp = F ∪ V	Terminate the collection of distribution centers and customer points
V0p = 0 ∪ F ∪ V	Collection of charging stations and customer points
VpN+1 = F ∪ V ∪ N + 1	Collection of starting distribution centers, charging stations, and customer points

Variable Name	Definition
V0pN+1 = 0 ∪ F ∪ V ∪ N + 1	Collection of distribution centers, charging stations, and customer points
B0	Fixed usage cost of electric vehicle
B1	The operating cost per unit distance of electric vehicles
C	The rated cargo capacity of electric vehicles
v	The speed at which an electric vehicle travels at a constant speed
Q	Rated capacity of electric vehicle batteries
Qi	battery level upon arrival at the charging station
R(t)	charging function
g	Fixed charging rate of electric vehicles
h	Fixed power consumption rate of electric vehicles
p	The power consumption rate affected by the load capacity of electric vehicles
qi	customer point i's needs
si	Service duration for customer point i
dij	The distance between dij customer points i and j
tij	time from customer point i to j
[ei, li]	The time window within which customers can accept services

2.3. Construction of Charging Process Mode

As the terminal voltage and current of the battery change with time during the charging process, the charging process function is nonlinear. The charging process is usually divided into two stages: in the first stage, the charging current is constant, and the battery capacity increases linearly with time until the terminal voltage of the battery reaches a specific maximum value; in the second stage, the terminal voltage is constant, and the current gradually decreases to avoid battery damage. In this stage, the battery capacity increases in a concave shape over time. Due to the influence of factors such as current, voltage, self-recovery, and temperature, it is difficult to simulate the charging process by designing a model. Therefore, this study refers to the method of Zuo et al. [15] and regards the battery's State of Charge (SoC) as a concave function R(t) of the charging time, which can be replaced by a set of continuous secant lines, as shown in Figure 1, from SoC=0 to SoC=100%. Each secant line is represented by a pair of slopes Kr and intercepts Br.

As shown in Figure 3., when the charging time is T, the amount of electricity calculated by the function R(t) is SoC2, while the actual charging amount is SoC1, and SoC1 is greater than SoC2. Therefore, the function R(t) can ensure that the calculated solution is feasible in practice. In addition, using more tangent lines will make the piecewise linear approximation more accurate.

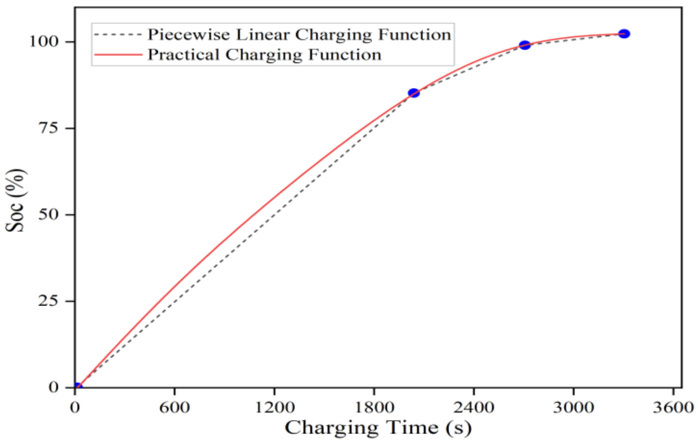

Figure. 1 Nonlinear Charging Process Graph and Fitting Function Graph

2.4. Special Signs

$$\min \quad B_0 \sum_{j \in V_p} x_{0j} + B_0' \sum_{j \in V_p} x'_{0j} + B_1 \sum_{i \in V_{0p}} \sum_{j \in V_{pN+1}} d_{ij} x_{ij} + B_2 \sum_{i \in V_{0p}} \sum_{j \in F} S_j x_{ij} \tag{1}$$

$$\sum_{j \in V_p} x_{0j} = \sum_{j \in V_p} x_{jN+1}, \forall j \in V_p \tag{2}$$

$$\sum_{j' \in V_{0p}, j' \neq i} x_{j'i} - \sum_{j \in V_{pN+1}, i \neq j} x_{ij} = 0, \forall i \in V_p \tag{3}$$

$$\sum_{j \in V_{pN+1}, i \neq j} x_{ij} = 1, \forall i \in V \tag{4}$$

$$\sum_{j \in V_{pN+1}, i \neq j} x_{ij} \leq 1, \forall i \in F \tag{5}$$

$$q_j \leq u_j \leq u_i - x_{ij} q_i + C(1 - x_{ij}), \forall i \in V_{0p}, j \in V_{pN+1}, i \neq j \tag{6}$$

$$0 \leq u_j \leq C, \forall j \in V_{0pN+1} \tag{7}$$

$$0 \leq y_j \leq y_i - d_{ij}(hx_{ij} + pu_j) + Q(1 - x_{ij}), \forall i \in V, j \in V_{pN+1}, i \neq j \tag{8}$$

$$0 \leq y_j \leq Q - d_{ij}(hx_{ij} + pu_j), \forall i \in F \bigcup \{0\}, j \in V_{pN+1}, i \neq j \tag{9}$$

$$t_i + x_{ij}(s_i + \frac{d_{ij}}{v}) - l_0(1 - x_{ij}) \leq t_j \leq l_j, \forall i \in V_0, j \in V_{pN+1}, i \neq j \tag{10}$$

$$t_i + x_{ij} \frac{d_{ij}}{v} + S_i - (l_0 + gQ)(1 - x_{ij}) \leq t_j \leq l_j, \forall i \in F, j \in V_{pN+1}, i \neq j \tag{11}$$

$$R(S_i) = Q - Q_i, \forall i \in F \tag{12}$$

$$t_0 = e_0 \tag{13}$$

$$e_i \leq t_i \leq l_i, \forall i \in V_{pN+1} \tag{14}$$

The objective function (1) represents minimizing the total cost, which includes the fixed cost, path travel cost, and charging cost of the electric vehicle. The charging cost is related to the charging time of the electric vehicle at the charging station. Constraint (2) represents the balance of the incoming and outgoing flow of the distribution center. The total number of vehicles dispatched from the starting distribution center 0 should be consistent with the total number of vehicles returned to the terminating distribution center N+1, that is, all dispatched distribution vehicles are ultimately recovered. Constraint (3) represents the balance of the incoming and outgoing flow of the customer node or charging station node Constraint (4) indicates that each customer node is only accessed once, and there is only one vehicle and one direction leaving each customer node. Constraint (5) indicates that a single charging station can provide charging services for multiple vehicles simultaneously. Constraint (6-7) is the vehicle capacity constraint, which means that the cargo volume when departing from the distribution center must meet both the total path demand and the vehicle capacity limit, and the cargo volume when arriving at each node should meet the node demand. Constraint (8-10) is the vehicle power constraint, and the remaining electricity is related to the remaining electricity of the previous node, the fixed path consumption, and the load consumption. It is necessary to meet the vehicle battery capacity limit while ensuring that there is enough electricity to reach the next node, and the electric vehicle's electricity after passing through the charging station from the distribution center or on the way is in a fully charged state. Constraint (10-14) is the time when the electric vehicle arrives at each node in a hard time window, which is earlier than the time window and requires waiting, and later than the time window. Upon arrival, services cannot be provided to that node. Constraints (10) and (11) indicate that the time tj to reach node j is related to the arrival time ti, service time si or charging time Si of the previous node i, as well as the path length dij of that segment. The calculation method for the charging time of the vehicle at charging station node i is based on the formula listed in constraint (12). Constraint (13) indicates that the unified departure time t0 of the electric vehicle at the starting distribution center is the upper bound e0 of the distribution center time window, while constraint (14) indicates that the time to return to the terminating distribution center should meet the time window requirements of the distribution center.

3. IMPROVED ADAPTIVE LARGE NEIGHBORHOOD SEARCH ALGORITHM DESIGN

In order to obtain a satisfactory electric vehicle logistics distribution plan in a limited time, based on the nature of the problem, this chapter proposes an adaptive large neighborhood search algorithm suitable for solving the problem studied in this paper. Specifically, the initial solution generation algorithm, the ideas of 8 destruction and repair operators, charging station adjustment strategy, targeted vehicle exchange operator, 2 different operator selection mechanisms, 2 solution acceptance criteria, and diverse operator weight update rules, and algorithm termination conditions are described in detail.

The method used to construct the initial solution in this paper is the k-insertion method. First, all customer nodes are considered unvisited, and the initial path is set to an empty path. In each iteration, the algorithm tries to insert unvisited customer nodes into all possible positions in the current path and selects the insertion position with the minimum cost. This process is repeated k times to select from multiple candidate insertion positions.

3.1. Operator Design

The operators used in the improved adaptive large neighborhood search algorithm designed in this paper are divided into customer node destruction operators, customer node repair operators, and charging station adjustment operators according to node type and function.

3.1.1. Customer Node Destruction Operator

After constructing an initial feasible solution, the current feasible solution's customer nodes are removed using a destruction operator and added to the unassigned list. The customer node destruction operators used in this study include random destruction operator, random path destruction operator, Shaw destruction operator, and worst destruction operator.

Random destruction operator: This operator randomly selects from all customer nodes, with each customer node having an equal probability of being selected.

Random path destruction operator: This operator randomly selects a path from the current feasible solution and moves all customer nodes in the selected path to the unassigned list.

Shaw destruction operator: This operator randomly selects a customer node and disrupts the current solution by removing the node and reinserting other nodes to further explore the solution space.

Worst destruction operator: This operator determines the worst customer node by calculating the cost increase of the node and removes it to disrupt the current solution.

3.1.2. Customer Node Repair Operator

The customer node repair operator runs after the destruction operator is executed, and the customer nodes stored in the set of customer nodes to be repaired are reinserted into the path. Charging stations are reasonably inserted during the customer repair process to meet the path's power requirements. The repair operator aims to effectively jump out of the previous neighborhood space, provide more choices for optimizing subsequent solutions and further optimize the current solution by searching in different neighborhood spaces' depth.

The customer node selection operators used in this study include random selection operator, greedy selection operator, and regret value selection operator.

Greedy repair operator: The greedy repair operator assigns unassigned customer nodes to the path one by one to repair the unassigned nodes in the current state.

Random operator: The random customer node repair operator randomly assigns unassigned customer nodes to existing paths or new paths to repair unassigned nodes in the current state.

Regret value repair operator: The regret value operator determines the optimal insertion position by calculating the cost change of each customer node inserted in each path and calculating the regret value. Then, the insertion position is sorted according to the regret value size, and the customer node is inserted into the best position.

Best position repair operator: In the given path list, find the optimal insertion position for the customer node to minimize the cost change after insertion.

3.1.3. Vehicle Exchange Operator

In the multi-vehicle electric vehicle routing problem, after the repair operator is executed, the vehicle exchange operator is used to further improve the current solution. The operator checks whether the current route can be accommodated by a smaller vehicle. If so, the vehicle type of the current route is changed to a smaller vehicle to further reduce costs.

3.1.4. Charging Station Adjustment Operator

After the customer nodes in the current solution are destroyed and repaired, the path of the solution may not meet the power constraints, so it is necessary to adjust the charging station nodes in the path to make the current solution feasible. After the customer node destruction and repair operations on the original feasible solution are completed, the charging station node destruction is performed to remove redundant charging stations. A redundant charging station is a charging station that can be removed, and the path is still feasible after removal. After removing the redundant charging station, there are two charging station insertion operators:

Charging station random destruction: The charging station random destruction operator randomly selects a charging station node on the path and removes its adjacent customer nodes before and after to disrupt the current solution.

Charging station random repair: The charging station random repair operator randomly repairs the path's power by recording the remaining power of the vehicle when it reaches each node. When the power is insufficient at a certain node, it means that a charging station needs to be inserted before the node to repair the power to meet the power constraint.

3.2. Operator Adaptive Mechanism

One of the main features of the improved adaptive large neighborhood search algorithm designed in this paper is the use of an adaptive mechanism to select operators to improve the algorithm's solving efficiency.

3.2.1. Operator Scoring Mechanism

The operator scoring mechanism in the adaptive large neighborhood search algorithm directly evaluates the performance of the operator during the iterative search process. The higher the score of an operator, the better the operator performs in this search phase, and the higher the likelihood that the operator will be adaptively selected in the subsequent computational iterations.The score for a particular operator is initialized to 0 at the beginning of each search phase s.

3.2.2. Operator Adaptive Weight Adjustment Mechanism

In this paper, the alpha-UCB rule is employed to select the destruction and repair operators that participate in each iteration. This is different from the traditional roulette wheel selection method, as the alpha-UCB rule first divides the operators into different groups and then selects the operators to participate in the iteration according to the grouping.

In contrast to the approach presented in this paper, the operator selection method under comparison is the classical roulette wheel selection. Herein, a brief overview of the roulette wheel operator selection mechanism is also provided. The fundamental concept of the roulette wheel selection mechanism entails assigning corresponding areas on the wheel to the candidate options based on their selection probabilities. Randomly spinning the pointer of the roulette wheel ensures an equal chance for the pointer to land on any position. However, options with larger areas on the wheel have a higher likelihood of being selected.

3.2.3. Acceptance criteria for solutions

In this study, the simulated annealing acceptance criterion was chosen as the acceptance criterion for solutions. This criterion accepts new solutions with a probability that depends on the difference between the new and current solutions, as well as a temperature parameter that controls the probability of accepting worse solutions. This approach allows the algorithm to explore the solution space more extensively and avoid getting trapped in local optima.

This article also refers to Dueck's record to record travel (RRT) reception criterion as the final solution reception criterion. The basic idea of the RRT algorithm is to maintain a best record and maintain the travel from record to record during the search process. In each iteration, the algorithm attempts to change the current solution through neighborhood operations and compares it with the current best solution after the change. If the new solution is better than the current best solution, it is considered as the new current best solution and the record is updated. But even if the new solution is worse than the current optimal solution, it may still be accepted with a certain probability in order to continue exploring in the solution space.

3.2.4. Algorithm termination conditions

In the adaptive large neighborhood search algorithm, there are four widely used termination conditions, which are based on the number of iterations of the algorithm, running time, the number of iterations without improved solutions, and the lower limit of simulated annealing temperature. This study used two termination conditions for the algorithm, and as long as one of the termination conditions is met, the algorithm immediately stops iteration.

The first termination condition is that the running time of the adaptive large-scale neighborhood search algorithm reaches the upper limit.

The second termination condition is that the adaptive large-scale neighborhood search algorithm does not have a new optimal solution within the set number of consecutive iterations, that is, the algorithm converges.

4. NUMERICAL EXPERIMENT

4.1. Small scale examples

This article uses Python language for experimental programming, and the computer is configured with Intel Core i7-7700HQ 2.8GHz, 4-core, and 8GB of memory. The algorithm is solved using Python language in the PyCharm compiler for model algorithm experiments.

The EVRP problem is an extension of the VRP problem and belongs to the NP hard problem. Due to the difficulty in solving large-scale cases using precise algorithms and optimization solvers within an acceptable time range, it is usually necessary to design efficient heuristic algorithms to solve such problems. Although the application of precise algorithms and optimization solvers in practical problems is limited, they can verify the effectiveness of problem models and heuristic algorithms by solving small-scale examples. This article aims to verify the effectiveness of the constructed problem model and the solving effect of the designed ALNS algorithm by comparing the solution obtained by the Gurobi optimization solver within 3600 seconds with the running results of the ALNS algorithm.

Table 3. Small scale examples

AC	Gurobi			ALNS			Gap%
	RN	RC	RT	RN	RC	RT	
C101-5	3	322.765	10.68	3	322.765	0.059	0.00
C103-5	3	280.695	12.73	3	280.695	0.076	0.00
C206-5	4	275.165	36.84	4	275.165	0.05	0.00
C208-5	1	298.38	83.72	1	298.38	0.038	0.00
r104-5	1	254.061	1273.38	1	254.061	0.042	0.00
r105-5	2	265.951	3600	2	265.951	0.128	0.00
r202-5	1	179.362	3600	1	179.362	0.024	0.00
r203-5	2	290.866	3600	2	290.866	0.077	0.00
rc105-5	3	422.899	3600	3	421.803	0.04	-0.26
rc108-5	3	471.655	3600	3	443.786	0.074	-6.28
rc204-5	1	328.999	3600	1	328.999	0.099	0.00
rc208-5	2	288.842	3600	2	288.842	0.031	0.00
c101-10	4	545.725	3600	3	530.758	0.293	-2.82
c104-10	5	494.445	3600	3	473.788	0.263	-4.36
c202-10	4	563.510	3600	3	551.488	0.272	-3.87
c205-10	3	442.148	3600	3	442.148	0.311	0.00
r102-10	4	443.155	3600	3	429.372	0.08	-3.21
r103-10	3	363.116	3600	2	311.955	0.305	-16.40
r201-10	3	430.587	3600	3	415.946	0.314	-3.52
r203-10	1	420.612	3600	1	380.99	0.297	-10.40
rc102-10	4	596.038	3600	4	596.038	0.358	0.00
rc108-10	4	525.784	3600	3	488.1024	0.363	-7.72
rc201-10	3	458.029	3600	3	452.241	0.595	-1.28
rc205-10	3	429.074	3600	3	492.074	0.326	0.00
c103-15	4	800.627	3600	3	694.025	0.66	-15.36
c106-15	2	479.037	3600	2	479.037	1.136	0.00
c202-15	4	761.012	3600	3	605.588	1.507	-25.68
c208-15	3	656.817	3600	2	653.875	0.653	-0.45
r102-15	6	735.387	3600	5	679.278	0.775	-8.26
r105-15	5	595.423	3600	4	566.422	1.457	-5.12
r202-15	3	689.745	3600	4	621.503	0.683	-10.98
r209-15	3	574.564	3600	3	555.379	0.525	-3.46

rc103-15	6	587.956	3600	5	714.011	0.684	-20.16
rc108-15	6	853.753	3600	5	771.65	1.113	-10.64
rc202-15	4	776.767	3600	4	675.098	0.727	-15.06
rc204-15	3	760.630	3600	3	703.896	0.554	-8.06

Table 3 shows that the ALNS algorithm and Gurobi solver have the same solution results in 14 examples, verifying the correctness of the ALNS algorithm proposed in this paper. Especially in small-scale cases, the ALNS algorithm has shown good solving performance. In the remaining 22 examples, the ALNS algorithm outperformed Gurobi, with a cost advantage of up to 25.68%. In terms of solution time, the ALNS algorithm is significantly faster than Gurobi. For small-scale cases, the average solution time is less than one second, and the fastest time to obtain the optimal solution is only 0.024 seconds. Therefore, it can be expected that the ALNS algorithm will be efficient in large-scale calculations.

4.2. large scale examples

Table 4. Large scale examples

AC	Smll+Big car		Small		Big	
	RN	TC	RN	TC	RN	TC
c101-100	23	3433.66	24	3497.23	21	3655.46
c102-100	22	3414.3	22	3476.37	20	3469.37
c103-100	20	3351.41	24	3490.96	18	3483.98
c104-100	21	3356.17	23	3383.96	19	3491.67
c105-100	20	3405.02	21	3496.01	18	3460.99
c106-100	21	3448.13	23	3456.18	20	3463.21
c107-100	22	3452.52	23	3483.33	20	3506.22
c108-100	21	3448.81	23	3440.32	18	3465.02
r101-100	21	3068.49	24	3161.67	18	3455.46
r102-100	20	2853.36	22	2989.82	17	3069.37
r103-100	18	2766.32	24	2862.86	15	3156.29
r104-100	17	2743.25	23	2816.39	15	2790.04
r105-100	19	2880.33	21	3000.06	15	3420.51
r106-100	16	2818.28	19	2848.69	13	3205.27
r107-100	17	2740.49	20	2838.48	15	3121.06
r108-100	14	2828.35	18	3013.33	10	2843.57
r109-100	16	2968.76	19	2971.66	13	3140.84
r110-100	14	2851.27	17	2813.85	11	2927.62
rc101-100	22	3827.34	24	3805.71	18	4199.36
rc102-100	21	3725.76	22	3809.46	16	4155.05
rc103-100	20	3696.35	24	3491.08	16	3794.22
rc104-100	20	3534.12	23	3501.97	17	3531.19
rc105-100	17	3632.57	21	3608.42	14	3937.84
rc106-100	20	3659.17	23	3658.66	18	3979.99
rc107-100	19	3359.65	23	3512.28	16	3576.10
rc108-100	17	3444.21	20	3492.81	14	3554.05

It was found that in the vast majority of cases, the cost of using multiple vehicle models to participate in delivery tasks is lower than that of using a single vehicle model to participate in delivery.

Although the cargo capacity of small car models is relatively small, for small-scale distribution tasks or situations with low cargo volume, small car models can leverage their cargo carrying efficiency and better adapt to changes in cargo volume. At the same time, the unit energy cost of small cars is relatively low. In contrast, large vehicle models have stronger cargo carrying capacity and endurance, and can transport more goods at once. However, due to the small battery capacity and short range of small car models, they may need to be charged more frequently, which increases energy costs and delivery time.

The use of hybrid electric vehicles can achieve distance optimization and reduce no-load rate. Large vehicle models can be responsible for long-distance transportation, while small vehicle models can be responsible for short distance delivery. This can better utilize the high-speed and efficient characteristics of large vehicles, reducing time and energy consumption during long-distance transportation. At the same time, small car models can undertake delivery tasks with relatively small customer demands, reduce the situation of empty driving, and improve delivery efficiency.

4.3. Solution effect and cost analysis of different effects of load on power consumption rate

It is generally believed that electric vehicles with a larger load capacity have a higher power consumption rate. Driving the same distance under the same conditions, electric vehicles with a larger load capacity will generate greater power consumption. In order to verify the importance of the power consumption rate affected by load on the routing problem of electric vehicles, this section takes the c101 and rc101 cases of 100 customer points as examples, and calculates the cost composition of path distribution schemes with power consumption rates of 0, p, 1.1p, 1.2p, 1.3p, etc. affected by load, and analyzes the impact of different degrees of load on power consumption on logistics path planning for various types of cases.

Table 5. analysis of different effects of load on power consumption rate

AC	c101		r101		rc101	
	RN	TC	RN	TC	RN	TC
0.0×p	16	2127.38	16	1928.86	18	2227.13
1.0×p	23	3433.66	22	3135.24	25	3743.85
1.1×p	25	3533.28	24	3353.72	25	3794.22
1.2×p	24	3677.51	25	3501.97	27	3937.86
1.3×p	26	3820.46	25	3753.85	18	4118.55
1.4×p	27	4113.37	24	3921.36	20	4389.63
1.5×p	27	4260.58	25	3993.65	20	4599.62
1.6×p	28	4362.16	26	4132.73	18	4848.13
1.7×p	28	4688.27	27	4373.99	18	5001.06
1.8×p	28	4816.15	27	4585.56	19	5213.36

The distribution path costs under different degrees of influence of load on power consumption are shown in Table 5. It can be seen that the results of different types of calculation examples show that the solution without considering the p 'value has much lower number of paths and total distribution costs than the solution considering load power consumption. Therefore, if the influence of load on power consumption is ignored in research, the results obtained are not accurate enough and will have significant limitations in practical applications. It can also be seen that in different types of cases, as p 'increases, it greatly affects the range of the vehicle in a loaded state. The decrease in range capacity leads to finding optimal feasible solutions by increasing the number of vehicles and charging times when planning distribution plans, resulting in an increase in the total cost of the distribution plan. Therefore, when planning the path of electric vehicles, it is necessary to consider the power consumption rate affected by customer demand and vehicle load.

5. SUMMARY

Taking electric vehicle logistics distribution as the research object, a multi vehicle electric vehicle routing problem considering segmented linear charging and the influence of load on power consumption rate is proposed; Based on the characteristics of the problem, a mixed integer linear programming model was established with the goal of minimizing fixed vehicle costs, vehicle operating costs, charging costs, and power consumption costs. An improved adaptive large-scale neighborhood search algorithm was designed to solve the problem, and the effectiveness of the model and algorithm was verified through numerical experiments. In addition, the analysis of experimental results shows that the cost of multi vehicle delivery is lower than that of single vehicle delivery; It has been proven that considering the impact of load on power consumption is of great significance in the optimization of electric vehicle paths. Based on the research results of this article, future research will consider more practical power consumption patterns, construct a more realistic mathematical relationship between load capacity and power consumption rate, and solve more practical electric vehicle path optimization problems, providing more reference basis for the formulation of distribution plans for logistics enterprises.·

REFERENCES

[1] Felipe Á, Ortuño M T, Righini G, et al. A heuristic approach for the green vehicle routing problem with multiple technologies and partial recharges[J]. Transportation Research Part E: Logistics and Transportation Review, 2014, 71: 111-128.

[2] Montoya A, Guéret C, Mendoza J E, et al. The electric vehicle routing problem with nonlinear charging function[J]. Transportation Research Part B: Methodological, 2017, 103: 87-110.

[3] KANCHARLA S R, RAMADURAI G. Electric vehicle routing problem with non-linear charging and load-dependent discharging[J/OL]. Expert Systems with Applications, 2020, 160: 113714.

[4] BEHNKE M, KIRSCHSTEIN T, BIERWIRTH C. A column generation approach for an emission-oriented vehicle routing problem on a multigraph[J/OL]. European Journal of Operational Research, 2021, 288(3): 794-809. DOI:10.1016/j.ejor.2020.06.035.

[5] LIU D, KAISAR E I, YANG Y. Physical Internet-enabled E-grocery delivery Network: A load-dependent two-echelon vehicle routing problem with mixed vehicles[J/OL]. International Journal of Production Economics, 2022, 254: 108632