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Optimal Routing and Charging of Electric Logistics Vehicles Based on Long-Distance Transportation and Dynamic Transportation System

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ABSTRACT

The application of electric vehicles (EVs) in the logistics industry has become more extensive. However, the mileage limitation of electric logistics vehicles (ELVs) and the long-distance distribution of ELVs have become urgent problems. Therefore, this paper proposes a long-distance distribution model for ELVs based on dynamic traffic information considering fleet mileage, distribution time and total distribution cost as the optimisation objectives, thus reasonably planning road selection and charging, and alleviating "mileage anxiety" in the long-distance distribution of ELVs. The model proposed in this paper comprehensively considers the characteristics of the high-speed and low-speed roads, the changes in road traffic flow on weekdays and non-weekdays, the time-of-use electricity price of electric vehicle charging stations (EVCSs) and uses the M/M/s queuing theory model to determine the charging waiting time. Finally, a real traffic network is taken as an example to verify the practicability and effectiveness of this model.

KEYWORDS

electric logistics vehicle; long-distance distribution; path planning; charging scheduling; M/M/s Queuing theory.

1. INTRODUCTION

With the development of the automotive industry, new energy vehicles have begun to receive the attention of the government and researchers [1]. In recent years, the national ministries and commissions have issued a series of policies to promote the penetration of new energy vehicles in the logistics field. The new energy vehicle industry development plan (2021–2035) mentions that as of 2021 the proportion of new energy vehicles in the new or updated public transport, taxi, logistics and distribution vehicles in the national ecological civilisation pilot area and critical areas of air pollution prevention and control in the public sector will not be lower than 80%. The goal has been put forward from a macro-quantitative perspective. In the context of the rapid development of new energy vehicles, ELVs are regarded as sustainable and environmentally friendly means of transportation, because they can significantly reduce harmful local emissions and global greenhouse gas emissions [2]. People have been paying more attention to EV use, aiming to build green distribution practices [3]. In the future, ELVs will gradually replace traditional fuel vehicles and become the staple of logistics distribution systems.

Compared with traditional gas stations, the number of EVCSs is still small, which also leads to the fact that they often fail to deliver commodities due to insufficient energy during transportation. This phenomenon is more significant in the long-distance distribution process. Therefore, when the number of EVCSs is insufficient, it is of great significance to carry out a reasonable path and charging planning for ELV logistics distribution and transportation. Previous studies have focused on ELV path planning and charging scheduling.

Yang et al. take the charging cost as the optimisation objective, studying the distribution path of a single electric logistics vehicle and the charging price in different periods [4]. Liu et al. [5] proposed a class of vehicle routing problems with multiple distribution centres, vehicle leasing and vehicle sharing, time window formulas and open-loop, establishing a corresponding mixed-integer programming model. Goeke considered the time window and EV pick up and delivery, developing a strategy granularity tabu search to determine charging power [6]. Deng et al. aimed at the lowest total logistics cost and the highest average customer satisfaction, and built a multi-objective optimisation model of electric vehicle logistics distribution path planning and charge-discharge management considering customer satisfaction under the power exchange mode [7]. The authors in [8] studied the impact of ambient temperature on fleet composition, energy consumption and route decision-making in the last mile distribution operation. They used an adaptive large neighbourhood search algorithm to solve large-scale examples. In [9], the authors studied a multi-site capacity constrained electric vehicle routing problem composed of two-dimensional weighted terms of customer demand and proposed a heuristic algorithm combining variable neighbourhood search algorithm and space-saving heuristic algorithm to solve the subproblem of the vehicle routing problem and packing problem. In the context of sharing economy, the urban logistics distribution routing problem of electric vehicles considering carbon tax and time of use electricity price is reflected in [10]. Li et al. proposed an optimisation model for the electric vehicle routing problem based on sharing economy. Research has been done to study the routing problems of logistics vehicles and ELVs from the aspects of time-of-use electricity price, customer demand etc. but without considering the dynamic traffic information and long-distance distribution problems [4–10].

Considering the time-dependent random traffic conditions, Bi et al. designed a dynamic electric vehicle routing problem model and proposed a hybrid rollout algorithm [11]. Yang et al. constructed an optimisation model for electric vehicle route selection and charging navigation under the time-of-use electricity price mechanism, aiming to minimise the user's total travel cost. They proposed to obtain real-time traffic conditions and charging station service information with the help of swarm intelligence sensing technology [12]. In [13], Li et al. established a dynamic road network model considering road section impedance and node impedance. They proposed a prediction method for electric vehicle charging load space-time distribution based on dynamic traffic information. The authors in [14] suggested a route planning and charging navigation strategy for electric vehicles based on real-time traffic information. According to the characteristics of urban roads, a "time flow" road resistance model was established considering road impedance and intersection node impedance. The studies [11–14] consider dynamic traffic information and long-distance path planning in electric vehicle path planning. Still there are few articles on long-distance path planning and charging scheduling of ELVs based on dynamic traffic information. During distribution on weekdays and non-weekdays, road traffic flow will change. At the same time, long-distance distribution needs to consider the characteristics and selection of high and low speed, which increases the difficulty of electric logistics vehicle path planning and charging schedule; therefore, it is of great significance to consider long-distance transportation and dynamic traffic information. Based on previous studies, this paper makes the following contributions:

1) Aiming to minimise the total distance, delivery time and total cost of logistics distribution, a path planning and charging scheduling model for long-distance distribution of ELVs is established.
2) The model considers the changes in road traffic flow on working and non-working days, as well as the effects of high-speed, low-speed and time-of-use electricity prices on driving paths and charging costs. At the same time, the m/m/s queuing theory model is used to solve the charging waiting problem.
3) The feasibility and practicability of the model are verified by a case analysis. A sensitivity analysis of several parameters is carried out to show the influence of different parameters on the path and charging selection of ELVs.

2. PROBLEM DESCRIPTION AND ASSUMPTIONS

The research background of this paper is that the electric logistics vehicle fleet participates in long-distance logistics distribution. After confirming the order, the fleet team will send suitable vehicles for distribution. Considering the randomness of the fleet vehicles and the location of the goods to be transported, the proposed model can optimally allocate each vehicle and the goods to be transported based on the starting point and destination orientation of each logistics vehicle and goods. Finally, each vehicle's driving path and charging can be reasonably planned according to different needs, such as the fastest delivery and the lowest consumption, to achieve the optimal result. Before establishing the model, the following considerations were made:

1) It is necessary to meet the loading and unloading location of the goods and deliver the goods in the shortest possible time.
2) Due to the need for long-distance delivery, it is necessary to consider the charging problem of going to the charging station during the delivery and the charging problem of high-speed driving to minimise the driving cost.
3) Driving path is to be selected according to user preferences while minimising power consumption.
4) Considering the inherent characteristics of high-speed and low-speed roads, vehicles on high-speed roads travel at high speeds and consume less time and electricity, so tolls need to be charged. There is no need to charge tolls on low-speed roads. Large traffic flow on low-speed roads leads to slow traffic and consumes more time and power.
5) The proposed optimisation model formulas include local/global formulas, such as longitudinal vehicle dynamics, EVCS congestion modelling, electric vehicle battery state of charge (SoC), road conditions etc. [15].

Considering the complexity of the model and the reality of the problem, this paper makes the following assumptions:

1) It is assumed that all vehicles in the fleet are private cars, that is, the starting and ending points of each vehicle are different, and the loading and unloading locations of each cargo piece are known.
2) The charging power of ELVs is fixed. Considering the need to deliver the goods as soon as possible, the fast-charging method is adopted here. In addition, it is assumed that each charging point's charging price in the same period is the same.
3) It is assumed that all high-speed sections are charged at a unified price. In addition, the influence of external factors (such as road slope, temperature etc.) on vehicle output power is not considered.

3. MATHEMATICAL MODEL AND LINEARISATION

According to the above considerations, the electric logistics vehicle fleet mainly considers the driving distance, delivery time and total cost (including high-speed road and charging costs) in the distribution process. The following takes these three items as the main body to establish the objective function of this model.

$$\min\left\{\omega_1\sum_{l,v}(D_l x_{l,v})+\omega_2\sum_{u,p,d,v}[y_{u,v}(t_{d,v}-t_{p,v})]+\omega_3\left[\sum_{n,v}(\xi_{n,q}pt^c_{n,v})+\sum_{f,v}(D_f z_{f,v}\varepsilon)\right]\right\} \tag{1}$$

The objective function of the model is shown in *Formula 1*, which consists of three items: the total transportation distance, the total time of distributing goods (excluding loading and unloading time), and the total cost, in which the total cost includes charging cost and high-speed charging. $\omega_1/\omega_2/\omega_3$ are the weights of the three terms, respectively; D_l is the distance of the road l; $x_{l,v}$ is a 0-1 variable parameter, the value is 1 when the vehicle v passes through the road l, and the value is 0 on the contrary; $y_{u,v}$ is a 0-1 variable index. When the vehicle v carries goods u, it is 1, otherwise it is 0. $t_{d,v}$ and $t_{p,v}$ represent the time of delivery and loading, respectively. $\xi_{n,q}$ represents the charging unit price ($/kWh) of the charging pile node n in the period q; p is the charging power; $t^c_{n,v}$ represents the charging time of the vehicle v at the node n; $z_{f,v}$ is the 0-1 variable parameter, which is 1 when the vehicle v passes through the high-speed section f, otherwise, it is 0; ε is the unit price charged for highway sections.

The model considers the path planning and charging scheduling different from the long-distance distribution of ELVs on weekdays and non-weekdays. Weekdays and non-weekdays will affect the road traffic flow, and its changes are given by *Formula 2*.

$$v_l=\gamma_{w,l}v_w+\left(1-\gamma_{w,l}\right)v_{nw},\ l\in L,\ w\in W,\ nw\in NW \tag{2}$$

In *Formula 2*, v_l represents the traffic flow of the road l; $\gamma_{w,l}$ represents a 0-1 variable parameter. In particular the value of $\gamma_{w,l}$ will be 1 for working days, and 0 on for non-working days; parameters v_w and v_{nw} represent traffic flow on working days (w) and non-working days (nw), respectively. L denotes the set of road. W and NW are the working day and non-working day sets, respectively.

$$\sum_{j=O}^{E} x_{ij} - \sum_{j=O}^{E} x_{ji} = \begin{cases} 1, i = O \\ 0, i \neq O, E \\ -1, i = E \end{cases} \tag{3}$$

Formula 3 constrains the driving of vehicles in the traffic network, where x_{ij} is a 0-1 variable; when the vehicle passes i and j, it is 1, and otherwise it is 0. O/E indicates the starting point and end point of the vehicle. When i is the starting point, the vehicle must leave the starting point; when i is the destination, the vehicle must drive to the destination, and if i is neither the starting point nor the endpoint, the vehicle will inevitably leave this node if it drives to it.

$$\sum_{l \in \psi_d^{U,L}} x_{l,v} + \sum_{l \in \psi_p^{D,L}} x_{l,v} - 2 \geq -M(1 - y_{u,v}),\ \forall u \in U,\ d \in \psi_u^D,\ p \in \psi_u^P,\ v \in V \tag{4}$$

$$\sum_{v \in V} y_{u,v} = 1, u \in U \tag{5}$$

$$t_{a,v} - t_{un,v} \leq M(1 - y_{u,v}),\ \forall u \in U,\ a \in \psi_u^a,\ un \in \psi_u^{un},\ v \in V \tag{6}$$

Formulas 4–6 are expressed by variables $y_{u,v}$, where the values of $y_{u,v}$ are either 0 or 1, to ensure that the goods at each place can be distributed. *Figure 1* illustrates the evolution of the driving process of the electric logistics vehicle for the convenience of the following explanation; it defines that the vehicle drives in the way of upstream node → road → downstream node. As shown in *Formula 4*, in order to force the electric logistics vehicle v to successfully assemble and deliver goods u ($y_{u,v} = 1$), the vehicle v must select the downstream road set ($\psi_a^{D,L}$) of the loading node and the upstream road set ($\psi_{un}^{U,L}$) of the delivery cargo node. In particular, M is a big positive number, U denotes the cargo set, V denotes the vehicle set. Parameters ψ_u^a and Ψ_u^{un} denote the loading and unloading nodes of goods u, respectively. *Formula 5* means that each cargo piece is delivered by a vehicle. *Formula 6* ensures that when the logistics vehicle is arranged to distribute the goods u, the loading completion time must be before the delivery time of the goods.

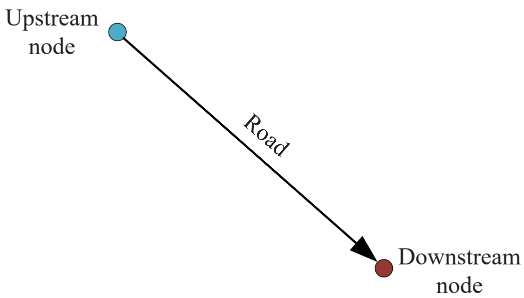

Figure 1 – Evolution of electric logistics vehicle driving process

$$t_{l,v}^T = \gamma_{l,v}\left(1 + \alpha\left(\frac{v_l}{\rho_l}\right)^\beta\right),\ \forall l \in L,\ v \in V \tag{7}$$

Formula 7 is based on the highway bureau function [16], which calculates the time consumed by vehicles passing through the road l; $\gamma_{l,v}$ is the free flow time, which determines the road travel time; α and β are constant, ρ_l is the road capacity of the road; l, v_l is the traffic flow of the road l, which can be obtained from *Formula 2*.

$$\zeta_v = (w + \partial\varpi)[\mu_f z_{f,v} + \mu_l(1 - z_{f,v})],\ \forall l \in L,\ v \in V,\ f \in F,\ u \in U \tag{8}$$

$$-M(1 - x_{l,v}) \leq \sum_{n \in \Psi_l^{U,N}} t_{n,v} + \sum_{n \in \Psi_l^{U,N}} t_{n,v}^W + \sum_{n \in \Psi_l^{U,N}} t_{n,v}^C + t_{l,v} + \sum_{n \in \Psi_{u,n}^{a,N}} t_{u,n,v}^a + \sum_{n \in \Psi_{u,n}^{un,N}} t_{u,n,v}^{un} - \sum_{n \in \Psi_l^{D,N}} t_{n,v} \leq M(1 - x_{l,v}),\\ \forall l \in L,\ v \in V,\ u \in U \tag{9}$$

$$-M(1 - x_{l,v}) \leq \sum_{n \in \Psi_l^{U,N}} SoC_{n,v} - \sum_{n \in \Psi_l^{D,N}} SoC_{n,v} - \frac{p_{l,v} t_{l,v}}{E_{max}} + \frac{\sum_{n \in \Psi_l^{U,N}} p_n t_{n,v}^C}{E_{max}} \leq M(1 - x_{l,v}),\ \forall l \in L,\ v \in V \tag{10}$$

$$t_{n,v}^a = t_u^a \varsigma_{n,v,u}^a,\ \forall n \in N,\ v \in V,\ u \in U \tag{11}$$

$$t_{n,v}^{un} = t_u^{un} \varsigma_{n,v,u}^{un},\ \forall n \in N,\ v \in V,\ u \in U \tag{12}$$

Formula 8 represents the relationship between the output power of the electric logistics vehicle and the different high-speed and low-speed sections and the cargo weight. ζ_v is the output power of the electric logistics vehicle; w represents the weight of the vehicle itself; ϖ represents the weight of the goods on the vehicle; ∂ is a constant parameter, which controls the speed of power change after the vehicles are loaded with goods; μ_f and μ_l are the power densities at high-speed and low-speed roads, respectively (kWh/t); and F is a collection of high-speed sections. *Formulas 9 and 10* represent the changes of time and state of charge (SoC) during vehicle driving. When the vehicle passes through path l, it is assumed that this vehicle drives from the upstream node of its path to the downstream node. The binary variable value $x_{l,v}$ is 1, when the vehicle passes through the road l, the time when the vehicle reaches the downstream node of the path ($\sum_{n\in\Psi_l^{D,N}} t_{n,v}$) is equal to the time when it reaches the upstream node of the path ($\sum_{n\in\Psi_l^{U,N}} t_{n,v}$) plus its charging waiting time ($\sum_{n\in\Psi_l^{U,N}} t_{n,v}^{W}$), charging time ($\sum_{n\in\Psi_l^{U,N}} t_{n,v}^{C}$), loading time ($\sum_{n\in\Psi_{u,n}^{a,N}} t_{u,n,v}^{a}$), unloading time ($\sum_{n\in\Psi_{u,n}^{un,N}} t_{u,n,v}^{un}$) and road travel time ($t_{l,v}$). Similarly, the state of charge of the vehicle arriving at the upstream node ($\sum_{n\in\Psi_l^{U,N}} SoC_{n,v}$) minus the electric quantity consumed by the road ($\frac{E_l D_l}{E_{max}}$) plus the electric quantity supplemented at the charging pile ($\frac{\sum_{n\in\Psi_l^{U,N}} p_n t_{n,v}^{C}}{E_{max}}$) is the state of charge of the downstream node ($\sum_{n\in\Psi_l^{D,N}} SoC_{n,v}$); on the contrary, if $x_{l,v}$ is 0, it is not affected by this formula. E_{max} is the maximum state of charge of the battery. *Formulas 11 and 12* restrict the time for the vehicle v to load and unload goods at the node n; $\varsigma_{n,v,u}^{a} / \varsigma_{n,v,u}^{un}$ and are 0-1 variable parameters, respectively indicating that if the node is the loading/unloading node and the vehicle loads/unloads goods u at node n, the value is 1, otherwise, it is 0, t_u^a and t_u^{un} are the loading/unloading time of goods u. The length of loading/unloading time is affected by such factors as cargo quality, shape, handling method etc., so the time needs to be determined according to the actual situation. According to our investigation of a factory, the cargo handling time is set as 0.5 h here.

The queuing rule of the charging station can be described as a single queue system, and the service organisation is designed as a parallel service system of multiple chargers [17]. According to previous research on the arrival time and charging service time of electric vehicles, because the probability distribution of the arrival time interval of electric vehicles in charging stations and charging service time will change with regions, it is assumed that the arrival time interval and charging service time of electric vehicles obey the negative exponential distribution, and there are s chargers in the charging station. Therefore, the M/M/s queuing model can be used to solve the queuing time of the charging station [18, 19].

$$\rho = \frac{\lambda}{s\mu} \tag{13}$$

$$p_0 = \left[\sum_{k=0}^{s-1} \frac{(s\rho)^k}{k!} + \frac{(s\rho)^s}{s!(1-\rho)} \right]^{-1} \tag{14}$$

$$L_{n,s}^{w} = \frac{(s\rho)^s \rho}{s!(1-\rho)^2} \cdot p_0,\ n \in N \tag{15}$$

$$t_{n,v}^{w} = \varsigma_{n,v} \frac{L_{n,s}^{w}}{\lambda},\ \forall n \in N,\ v \in V \tag{16}$$

$$\rho < 1 \tag{17}$$

$$0 \le t_{n,v}^{C} \le M \sum_{l\in\Psi_C^{D,L}} x_{l,v},\ \forall n \in C,\ v \in V \tag{18}$$

$$t_{n,v}^{C} \begin{cases} \geq 0, \forall n \in N, v \in V \\ = 0, \forall n \in N \setminus C, v \in V \end{cases} \tag{19}$$

$$t_{n,v}^{w} \begin{cases} \geq 0, t_{n,v}^{C} > 0 \\ = 0, t_{n,v}^{C} = 0 \end{cases} \tag{20}$$

Formulas 13–16 indicate the calculation process of charging waiting time, and the *Formulas 13–16* must be carried out under the conditions of *Formula 17*. *Formula 13* is used to calculate the service intensity of the queuing system (ρ), λ represents the arrival rate of vehicles arriving at the charging point in unit time, and μ represents the average utilisation rate of a single charging point. *Formula 14* calculates the probability that all charging piles are idle (p_0); s is the number of charging piles. In *Formula 15*, the average queue length ($L_{n,s}^{w}$) of the charging station is indicated. *Formula 16* calculates the average queuing waiting time ($t_{n,v}^{w}$) of vehicles v at the node n. $\zeta_{n,v}$ stands as a 0-1 variable; when the vehicle v is charging at the node n of the charging station, the value is 1, otherwise it is 0, $L_{n,s}^{w}$ is the average queuing length of the node n charging station; *Formula 18* indicates the charging behaviour of the logistics vehicle. If the vehicle does not pass through the charging pile node ($\Psi_{C}^{D,L}$), the value of $x_{l,v}$ is 0, and the charging time ($t_{n,v}^{C}$) is specified as 0; *Formula 19* indicates the nonnegativity of the vehicle's charging time at the charging station. For nodes that are not EVCSs, the charging time is limited to 0. *Formula 20* is the formula on the charging waiting time. For the charging station node, if the vehicle is charging in the charging station, the charging waiting time is greater than or equal to zero; if the vehicle is not charging here, the charging waiting time is 0.

The time-of-use electricity price of EVCSs can be regarded as a time series. $Q = \{0,1,\cdots,q,\cdots,23\}$ is defined as a set of time, $\xi = \left\{\xi_0, \xi_1, \cdots, \xi_q, \cdots, \xi_{23}\right\}$ as a collection of charging electricity price in different time. Therefore, the charging electricity price in a certain period of time at the node n can be calculated as follows:

$$\xi_{n,q} = \begin{cases} \xi_q, \forall n \in C, q \in Q \\ 0, \forall n \in N \setminus C \end{cases} \tag{21}$$

Formula 21 constrains the charging price of a certain period at the node n. When the node is a charging station node, the price of electricity is the price of the period. If the node is not a charging station node, the price of electricity at the node will not be considered, and the price of electricity is set to 0.

$$SoC_{0,v} = SoC_{max}, \ \forall v \in V \tag{22}$$

$$SoC_{min} \leq SoC_{n,v} \leq SoC_{max}, \ \forall n \in N, \ v \in V \tag{23}$$

Formulas 22 and 23 define the start of the vehicle and the state of charge of the node. *Formula 22* indicates that the vehicle v starts with the maximum capacity of the battery, $SoC_{0,v}$, which is the electric quantity at the time of departure; *Formula 23* limits the power of the car v at the node n to the minimum and maximum SoC range.

Because the *Formulas 1 and 8* contain a nonlinear term of continuous variables and binary variables, which may lead to the local optimal solution, so the expected result cannot be achieved. Therefore, a linearisation method (Big M method) is proposed in this paper to solve the problem [20].

It is assumed that parameter a is a binary variable, x is a continuous variable, and their product is y as *Formula 23*, which can be accurately replaced by *Formulas 24 and 25* [21].

$$y = ax \tag{24}$$

$$-Ma \leq y \leq Ma \tag{25}$$

$$x - M\left(1-a\right) \leq y \leq x + M\left(1-a\right) \tag{26}$$

The Big M approach has been applied in this paper to achieve the linearisation process. In the Big M method, the product of binary variables and continuous variables can be replaced by *Formulas 24 and 25*. Therefore, there is no need to discuss whether the nonlinear parameters in the formula meet the linearisation conditions when using the Big M method. This method is directly used in literature [22–24]. In this way, the model is transformed into a mixed integer linear programming (MILP) problem and the global optimality of the problem can be guaranteed by a commercial solver.

4. CASE ANALYSIS

4.1 Road network selection and parameter setting

In this paper, we use a road traffic network located in Zhejiang province, China, to demonstrate and analyse the proposed model. *Figure 2a* is the map of the studied area. *Figure 2b* is the topological network that simplifies and abstracts it into 19 nodes and 31 roads. See the attached Appendix for detailed network parameters.

The fleet sent four identical ELVs to transport four pieces of goods, and the starting and ending points of the vehicles and the goods to be transported were at different nodes. In *Table 1*, the start and end nodes of each vehicle have been identified. On the other hand, *Table 2* shows the loading and unloading nodes of the goods and the weight of each piece of good. The battery capacity and charging power of the logistics vehicle are uniformly set at 78 kWh and 80 kW. The vehicle weight is set as 5 tons. The minimum (SoC_{min}) and maximum (SoC_{max}) states of charge during vehicle operation are 0.1 and 1, respectively. The unit price of high-speed charging is 0.075 $/km.

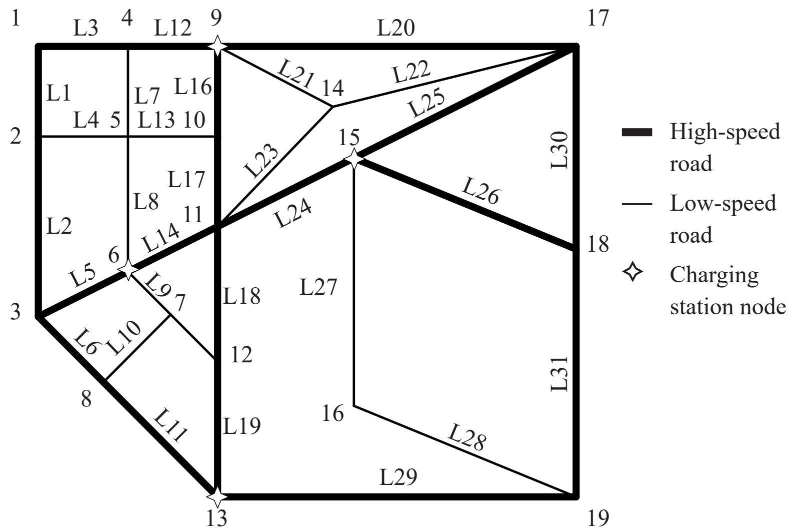

Figure 2 – Road network

Table 1 – Starting and ending nodes of electric logistics vehicles

	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4
Start node	N4	N1	N8	N16
End node	N13	N18	N17	N1

Table 2 – Loading and unloading nodes and weight of goods

	Good 1	Good 2	Good 3	Good 4
Assembly node	N5	N16	N2	N8
Unloading node	N8	N4	N18	N17
Cargo weight	4t	5t	3t	5t

4.2 Analysis of results in different scenarios

In this section, we consider the changes of vehicle travel results on working and non-working days and the impact of severe congestion on some roads on non-working days. The road traffic flow on working and non-working days is shown in the Appendix, and the time of use tariff of the charging station [25] is shown in *Table 3*.

In order to visually compare the impact of vehicle travel on route and charging on working or non-working days, the following is a separate comparison of vehicle 2's distribution results for goods 3 on working and non-working days. In order to balance the three variable parameters of the objective function, the weights of driving distance, delivery time and total cost in both scenarios are set to 1:50:1. The departure time is set at 6 a.m. on Monday and Sunday, respectively. The route planning of vehicle 2 under the two scenarios is shown in *Figure 3*. It can be seen from the results in *Figure 3* that the model changes the route from 1→2→5→10→11→15→18 to 1→ 2→3→6→11→15→18 on non-working days. This is due to a serious

Table 3 – Time-of-use electricity price of EVCSs

Period properties	Period division	Charging tariff [$/kW·h]
Peak period	10:00–15:00 18:00–21:00	0.25
Ordinary period	7:00–10:00 15:00–18:00 21:00–23:00	0.19
Valley period	23:00–7:00	0.14

increase in traffic flow on non-working days for some roads, such as scenic spots and commercial streets, with congestion occurring in routes 2→5 (road L4) and 5→10 (road L13), which results in slow traffic. The simulation results indicate that the algorithm proposed in this paper tries to avoid those roads in the optimisation process to achieve the optimal goal. If the variation of road traffic flow is not considered on non-working days, the route 1 → 2 → 5 → 10 → 11 → 15 → 18 is also adopted on non-working days. After the optimisation process, the energy surplus of the vehicle at node 11 is only 13.06%, which will not be sufficient to support the vehicle to reach the charging node 15, thus failing to complete the delivery task.

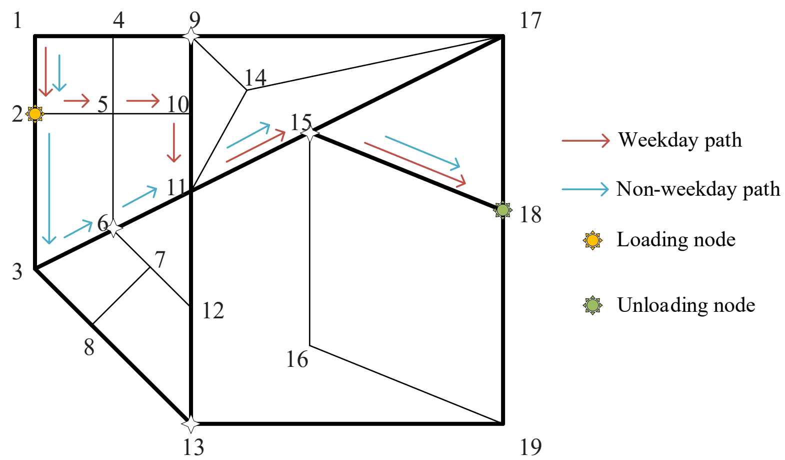

Figure 3 – Vehicle 2 route map under two scenarios

In order to visually reflect the impact of the delivery of ELVs on the results of the objective function on weekdays and non-weekdays, *Figure 4* shows the results of vehicle 2 under the distribution on weekdays and non-weekdays. According to *Figure 4*, due to the congestion of some roads on non-weekdays, the total driving distance, delivery time and total cost of vehicle 2 have increased, with the total cost increasing by a large margin. This is because the model selected high-speed roads to avoid congested roads on non-weekdays, resulting in more tolls for vehicles during their journey.

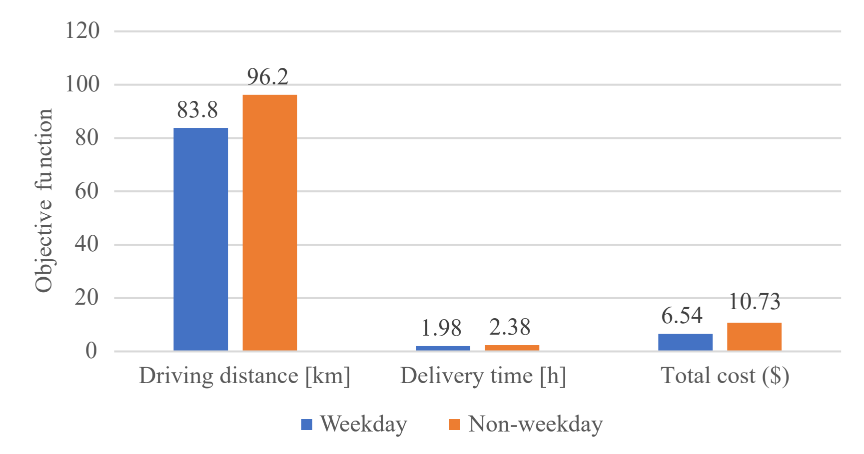

Figure 4 – Results of vehicle 2 delivery on weekdays and non-weekdays

4.3 Influence of weight change and its practical application

The choice of path in the model will vary with the change of weight. This section first analyses the results under the weight change, and then solves the practical problems according to the conclusions of the analysis.

In order to intuitively analyse the impact of weight changes, a single factor analysis is carried out here. The time weights are set as 1, 20 and 100, respectively, the distance and cost weights are set to 1, and the travel time is 6 a.m. on Monday. The delivery time under the three weights is shown in *Figure 5*.

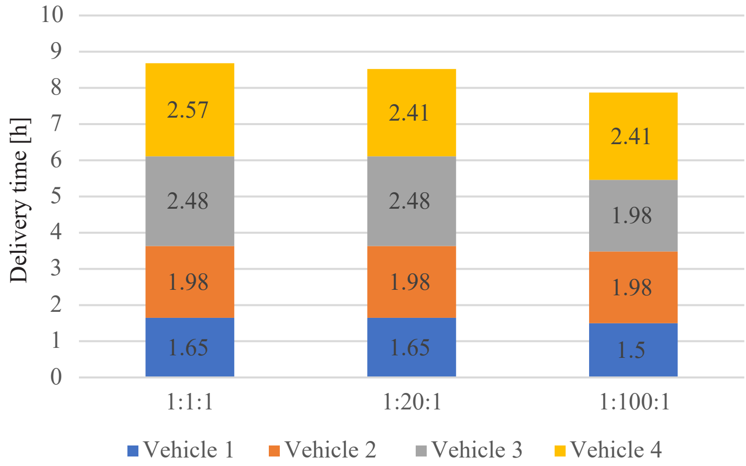

Figure 5 – Distribution time under different weights

The increase in time weight indicates that our demand for delivery as soon as possible is increased. When the weight is increased to a certain extent, the total delivery time of the team will gradually decrease. According to the results in *Figure 5*, when the time weight increases from 1 to 20, the delivery time of vehicle 4 decreases by 0.16 h. When the weight is increased to 100, the delivery time of vehicle 1 and vehicle 3 decreases by 0.15 h and 0.5 h, respectively. Moreover, the change in distribution time is due to the change of vehicle route selection. The vehicle routes based on these three weight sets are shown in *Table 4*.

Table 4 – Vehicle paths under different weights

1:1:1		1:20:1		1:100:1	
Vehicle number	Path (Node, Node)	Vehicle number	Path (Node, Node)	Vehicle number	Path (Node, Node)
1	4,5,6,7,8,13	1	4,5,6,7,8,13	1	4,5,2,3,8,13
2	1,2,5,10,11,15,18	2	1,2,5,10,11,15,18	2	1,2,5,10,11,15,18
3	8,7,6,11,14,17	3	8,7,6,11,14,17	3	8,7,6,11,15,17
4	16,15,11,10,5,4,1	4	16,15,11,10,9,4,1	4	16,15,11,10,9,4,1

According to the results in *Table 4*, for instance, the route planning of vehicle 3 is arranged as 8 → 7 → 6 → 11 → 14 → 17, when the weights of driving distance, delivery time and total cost are 1:1:1 and 1:20:1. On the other hand, the route planning of vehicle 3 is arranged as 8 → 7 → 6 → 11 → 15 → 17 when the weights are arranged as 1:100:1. Therefore, it can be seen that the simulation results of the optimisation process will vary with the change of weight. When the time weight is increased to a certain extent, the model can choose a more suitable path to reduce the delivery time. Similarly, if users prefer to consume less, they can reduce the charging and high-speed cost during the delivery process by increasing the weight of the objective function.

For the different requirements of long-distance distribution of ELVs, most of these requirements are the preference of minimum distribution time and cost. Considering the inherent characteristics of high-speed and low-speed roads, the demand for the minimum distribution time or total cost is actually the choice for high-speed or low-speed traffic. These demands are not uncommon in practice. For instance, it is necessary to deliver objects in the shortest time in the express delivery industry. On the other hand, owners of long-distance transport vehicles tend to choose low-speed roads to reduce expenses and increase profits due to the continuous increase of freight prices in recent years. These are also the practical problems to be solved by our optimisation algorithm.

The weights of the three variable parameters $\omega_1/\omega_2/\omega_3$ are set to 1:100:1 and 1:1:10, respectively, to balance the order of magnitude. The optimisation target is to minimise the total delivery time and total cost, respectively. The optimal results of high-speed and low-speed roads arrangement and related EV charging behaviour are obtained by the optimisation mechanism of the algorithm with suitable the set of weights. Then, the departure time is uniformly set at 6 a.m. on Monday. The optimisation results of the route and charging scheme with the shortest delivery time are shown in *Table 5*, and the optimisation results of the path planning and charging scheme with the lowest cost are shown in *Table 6*. Based on the simulation results in *Tables 5 and 6*, the model reasonably allocates all vehicles and goods to be transported according to the starting and ending points of vehicles and the loading and unloading points of goods.

Table 5 – Shortest delivery time scheme

Vehicle number	Path (Node, Node)	Driving distance [km]	Delivery time [h]	Charging time [h]	Charging waiting time [h]	Charging cost ($)	High-speed road spending ($)
1	4,5,2,3,8,13 (Goods 1)	68.3	1.5	0	0	0	3.62
2	1,2,5,10,11,15,18 (Goods 3)	83.8	1.98	0.12	0.09	1.78	4.78
3	8,7,6,11,15,17 (Goods 4)	73.2	1.98	0.08;0.14	0.15;0.09	0.88; 2.08	4.19
4	16,15,11,10,9,4,1 (Goods 2)	84.5	2.41	0.27;0.05	0.09;0.06	3.09; 0.7	4.26
Total		309.8	7.87			25.38	

Table 6 – Cost minimisation scheme

Vehicle number	Path (Node, Node)	Driving distance [km]	Delivery time [h]	Charging time [h]	Charging waiting time [h]	Charging cost ($)	High-speed road spending ($)
1	4,5,6,7,8,13 (Goods 1)	60.3	1.65	0;0	0;0	0	1.35
2	1,2,5,10,11,15,18 (Goods 3)	83.8	1.98	0.12	0.09	1.78	4.78
3	8,7,6,11,14,17 (Goods 4)	74.9	2.48	0.30	0.15	3.45	0.84
4	16,15,11,10,5,4,1 (Goods 2)	84.5	2.57	0.39	0.09	5.82	2.78
Total		303.5	8.68			20.8	

Shorter delivery time is necessary for the express delivery industry. The *Table 5* scheme tends to choose a high-speed road section, which not only speeds up the road passage time of vehicles, for example, vehicle 1 changes the route from 4 → 5 → 2 → 3 → 8 → 13 to 4 → 5 → 2 → 3 → 8 → 13, but directly reduces the delivery time by 0.15 hours. In addition, vehicles 3 and 4 not only shorten the road passage time but also the charging time due to the reduction of vehicle power consumption, as the charging time was reduced by 0.08 h and 0.07 h, respectively. Therefore, the total delivery time of the first scheme is 9.3% shorter than that of the second, saving 0.81 h for the express delivery fleet. On the contrary, from the perspective of the owner of a long-distance transport vehicle, the second option is more economical. By selecting as many low-speed sections as possible to reduce consumption, the charging cost is slightly increased while the high-speed toll is greatly reduced, bringing down the total cost by 18% and saving 4.38 $ for the fleet.

Based on the above practical problems in the real transportation process, this model can give the corresponding results according to the actual needs, and different schemes will bring significant benefits to users, which also shows the high applicability and practicality of the model.

5. CONCLUSION

The logistics industry freight trends and the diversity in logistics transportation determine human driving behaviour. Long-distance transportation puts forward requirements for power consumption and charging control. In this paper, an optimisation model is proposed which extends the traditional cargo delivery problem to the innovative energy-saving optimal routing and charging problem. The aim is to meet the needs of path planning and charging scheduling of long-distance distribution of electric logistics vehicles, so as to improve the performance of electric logistics vehicles in logistics distribution. At the same time, considering the dynamic changes of traffic flow with different travel scenarios and key factors such as charging prices in different periods, this paper studies the impact of travel in different time scenarios and changes the weight of the objective function alone on vehicle routing and charging schedule. In the case analysis, based on the numerical study of the actual traffic network, the results obtained by changing a certain weight of the objective function show that the model results will change as expected with the weight changing. Secondly, when the traffic changes due to the change of travel scenarios, the model can still provide users with the optimal path to ensure users' travel. Finally, based on practical problems, we studied the distribution of express industry and electric logistics vehicle owners under different objectives. The results show that the services provided by the model can reasonably reduce the distribution time or travel cost according to the pre-trip decisions to meet user needs. For the current logistics market, more owners of long-distance transport vehicles will put profits first and increase them through lower distribution cost. Therefore, a low-cost scheme may better meet the needs of and benefit most users.

In the future, the research work addressing ELV fleet logistics transportation problems will further integrate machine learning technology, so as to truly reflect the reality and improve the running speed of the model.

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基于长途运输与动态交通信息的电动物流车路径规划与充电调度

电动汽车（EV）在物流行业的应用越来越广泛，然而，电动物流车（ELV）的里程限制和长途配送问题一直是一个亟待解决的问题。为此，本文以车队行驶里程、配送时间以及配送总成本为优化目标，提出了一个基于动态交通信息的ELV长途配送路径规划与充电调度模型，对道路选择与充电进行合理规划，缓解ELV长途配送中的“里程焦虑”。本文提出的模型综合考虑了高速与低速的特性、工作日和非工作日的道路交通流变化以及电动汽车充电站（EVC）分时电价等因素，同时使用M/M/s排队论模型确定充电等待时间。最后以实际交通网络为例，验证了本模型的实用性和有效性。

电动物流车，长途配送，路径规划，充电调度，M/M/s排队论

APPENDIX

Schedule 1 – Transportation network parameters

Road	Traffic Capacity (Vehicle)	Road Length [km]	Road	Traffic Capacity (Vehicle)	Road Length [km]
L1	1667	10	L17	1578	10
L2	1701	20	L18	1634	15
L3	1612	10	L19	1599	15
L4	1020	10	L20	1612	40
L5	1588	11.2	L21	987	14.5
L6	1810	10.3	L22	956	27.9
L7	1051	10	L23	1013	18.5
L8	1003	15	L24	1586	17
L9	998	6.7	L25	1589	27.7
L10	996	10.6	L26	1546	26.8
L11	1569	18	L27	933	27.5
L12	1626	10	L28	878	26.8
L13	1060	10	L29	1454	40
L14	1569	11.2	L30	1621	22.5
L15	1008	7.4	L31	1573	27.5
L16	1604	10			

Schedule 2 – Road traffic flow on working days and non-working days

Road	Traffic Flow on Weekdays (Vehicle)	Traffic Flow on Non-Weekdays (Vehicle)	Road	Traffic Flow on Weekdays (Vehicle)	Traffic Flow on Non-Weekdays (Vehicle)
L1	456	563	L17	423	553
L2	441	557	L18	427	667
L3	488	602	L19	399	486
L4	1003	1832	L20	509	905
L5	402	933	L21	862	1474
L6	505	635	L22	844	1132
L7	1009	1212	L23	903	1965
L8	966	1163	L24	488	639
L9	811	1586	L25	441	598
L10	983	1045	L26	405	653
L11	351	477	L27	806	1000
L12	433	556	L28	723	1042
L13	960	1880	L29	303	535
L14	408	551	L30	460	577
L15	801	1022	L31	429	556
L16	412	622			