Pure Electric Logistics Vehicle Distribution Path Optimization Study with Time Window

Wenjia Xu¹⁺, Zhiyong Zhang² and Lixin Miao³

¹ Department of Industrial Engineering, Tsinghua University, Beijing, China 2 College of Economics and Trade, South China University of Technology, Guangzhou, China ³Research Center on Modern Logistics Graduate School at Shenzhen, Tsinghua University, Shenzhen, China

Abstract. With the awareness of energy saving and sustainable development realized, the pure electric vehicles (EVs) have received more and more attention in the field of logistics distribution. In this paper, we analyze the research background and significance of pure electric logistics vehicle distribution, construct the distribution path optimization model of customer point with time window (Electric Vehicles Routing Problems with Time Window, EVRPTW). A mixed integer planning model is built with node constraint, load constraint, remaining power constraint, and time window constraint of customer point. Take the total cost of minimizing the sum of fixed cost, transportation cost and time window penalty cost as the objective. A domain search-based hill-climbing algorithm is added to the traditional genetic algorithm to generate an improved genetic algorithm solution model with enhanced local search capability to obtain more accurate solutions to large-scale complex problems.

Keywords: pure electric logistics vehicle, time window penalty cost, EVRPTW, improved genetic algorithm.

1. Introduction

With the rising oil prices in recent years, the distribution cost of logistics and transportation industry using traditional fuel vehicles will continue to increase, the construction of green freight distribution system has become an inevitable trend of development. Electric Vehicles (EVs) are gaining more and more attention in the field of logistics distribution because of their good environmental protection and energy adjustment effect. Based on the characteristics of urban logistics distribution in the field of new energy, it is important to reasonably optimize the distribution path scheme of pure electric logistics vehicles to improve the distribution efficiency and reduce the operation cost. Conrad and Figliozzi considered the electric vehicle path planning problem with the objective function of minimizing cost under time window [1]. BtilentCatay and MerveKeskin considered the short charging time and insufficient charging of electric vehicles, established an integer planning model for the vehicle path problem with time window, used a large-scale adaptive neighborhood search algorithm to solve [2]. Schneider et al. extended the GVRP to argue that the charging time is linearly related to the energy consumed, the vehicle is replenished at a specific charging station, and a new benchmark problem is proposed based on the Solomon calculus [3]. Hiermann, Puchinger et al. optimized the objective considering a multi-model fleet problem and constructed the model with the minimum sum of travel range and vehicle usage cost, where the vehicle is able to replenish energy at the charging station [4]. Goeke and Schneider consider a hybrid fleet with conventional internal combustion vehicles based on the previous EVRPTW, which considers a more realistic energy consumption process related to speed, loading and road slope [5]. Chao Chen applied the non-dominated ranking multi-objective genetic algorithm (NSGA-II) to solve the multi-objective optimization problem for single yard based pure electric bus vehicle scheduling [6].

On basis of classification and analysis of the pure electric logistics vehicle's own characteristics, considering the customer point time window, specifically combined with the actual development of

⁺ Corresponding author. Tel.: +18122137546;

E-mail address:xuwj19@mails.tsinghua.edu.cn

Shenzhen, the study of pure electric logistics vehicle VRP can enrich the theoretical study of pure electric logistics vehicle dispatching problem to a certain extent.

	Conrad&	Btilent	Schneider	Hierman	Goeke
	Figliozzi	Et al	Et al	Et al	Et al
Vehicle load	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Customer	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
requirements					
Energy Limit	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Time Window	\checkmark	×	\checkmark	\checkmark	\checkmark
Energy change	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Energy	Customer points	Car parks	Charging station	Charging station	Chargingstation
replenishment position					
Mixed vehicles	×	×	×	$\checkmark 1$	$\checkmark 2$

Table 1: Comparison table of factors considered in literature studies of some EVRP problems

a. <1: the same vehicle type with different load limits; <2: different vehicle types, including pure electric vehicles and internal combustion engine vehicles

With the promotion of just-in-time production method, logistics enterprises often encounter the situation that customers require restrictions on delivery time. The time periods that customers require goods to be delivered is the time window, which can be divided into hard time window, soft time window and mixed time window. The road traffic condition in urban distribution has been in dynamic change, it is difficult to ensure that all customer point goods can be delivered within the time window, if the pure electric logistics vehicles in the distribution process charging, but also produce a relatively long charging time. Therefore, it is more appropriate to adopt soft time window for the vehicle scheduling problem of pure electric logistics vehicles, which avoids the situation that hard time window may have no solution. In this paper, we mainly consider the soft time window problem. The longer the violation of the time window the larger the penalty cost, which is expressed here as a linear function.



Fig. 1:Hard (left) and soft (right) time window problem

2. EVRPTW optimization model study

G = (V, A) is a directed graph consisting of a point set and an edge set, V denotes the set of all points (customers, charging stations and distribution centers), A denotes the set of arcs. Under the satisfaction of each constraint, the distribution route containing $v = \{0, 1, 2, ..., n + 1\}$, $A = \{(i, j) | i, j \in V, i \neq j\}$ is sought such that the total cost including fixed cost, transportation cost and time window penalty cost is minimized. The vehicle can go to the charging station to replenish its power, and the route optimization problem provides the optimal charging plan for it. Based on the description of the problem and assumptions, the required parameter notation of the model is defined below.

2.1. Collection.

V: the set of all points, including the set of distribution centers, customer points, charging stations, etc., $V = C \cup S \cup O$

C: the set of customer points.

S: the collection of charging stations.

K: the collection of pure electric logistics vehicles, denoted by the subscript k.

0: distribution center o, single distribution center.

2.2. Variables.

 d_{ij} : the distance from point *i* to point *j*, where $i, j \in V$;

 t_{ij} : the travel time of the pure electric logistics vehicle point *i* to point *j*, where $i, j \in V$;

 u_{ik} : the actual weight of the pure electric logistics vehicle k at the point i, and $i \in V, k \in K$

Q: the rated capacity of the battery of the pure electric logistics vehicle k.

U: the rated weight of the pure electric logistics vehicle k.

 u_i : the demand of goods at the customer's point, and $i \in C$

r: the transportation cost per unit distance of pure electric logistics vehicle k.

h: Electricity consumption per unit distance of pure electric logistics vehicle k.

 E_i : the earliest service time requested by the customer point, $i \in C$;

 L_i : the latest service time requested by the customer point. $i \in C$;

 C_o : unit fixed cost of pure electric logistics vehicle k.

 C_e : the time penalty coefficient of the pure electric logistics vehicle for arriving at the customer's point ahead of schedule.

 C_d : time penalty factor for delayed arrival of the pure electric logistics vehicle k at the customer point i.

 S_{ik} : the service time of the pure electric logistics vehicle k at the customer's site.

 T_s : charging time of pure electric logistics vehicles k at charging stations.

 λ : load utilization factor.

 μ : minimum capacitance rate.

 p_{ik}^{1} : the remaining power of the pure electric logistics vehicle k at the point of arrival

 p_{ik}^2 : the remaining power of the pure electric logistics vehicle k when it leaves the point.

 T_{ik} : time of the pure electric logistics vehicle to the point.

 X_{ijk} : the variable is 0-1; 1 when the electric logistics vehicle arrives at the point and 0 otherwise.

2.3. Mathematical model of EVRPTW

Fixed cost

$$C_c = kC_o, k \in K \tag{1}$$

Transportation cost

$$C_r = r, \sum_{k \in K} \sum_{i \in V} \sum_{j \in V, j \neq j} d_{ij} X_{ijk}$$
⁽²⁾

Time window penalty cost

Penalty costs $C_{P_{ik}}$ for distribution centers for violating customer point-in-time windows are expressed as

$$P_{ik} = \begin{cases} C_e \times max(E_i - T_{ik}, 0) & E_i > T_{ik} \\ 0 & E_i \le T_{ik} \le L_i \\ C_d \times max(T_{ik} - L_i, 0) & T_{ik} > L_i \end{cases}$$
(3)

The total time window penalty cost is

$$\mathcal{L}_{P_{ik}} = \sum_{k \in K} \sum_{i \in C} P_{ik} = \sum_{k \in K} \sum_{i \in C} C_e \times max(\mathbf{E}_i - \mathbf{T}_{ik}, \mathbf{0}) + \sum_{k \in K} \sum_{i \in C} C_d \times max(\mathbf{T}_{ik} - \mathbf{L}_i, \mathbf{0})$$
(4)

 $C_{P_{ik}}$ is the time window penalty function. The time window restriction for customer service means that specific operations such as unloading and handling can only be performed during this time after arrival. When the vehicle arrives at the customer earlier than scheduled, the company is compensated per unit of time; when the vehicle arrives at the customer later than scheduled, the company is compensated for the penalty cost per unit of time. The above functional expression can also be expressed as

$$P_{ik} = C_e \times max(\mathbf{E}_i - \mathbf{T}_{ik}, 0) + C_d \times max(\mathbf{T}_{ik} - \mathbf{L}_i, 0)$$
(5)

2.4. Constraint conditions

The range of an electric vehicle, which refers to the maximum continuous driving range after a full charge, is mainly limited by the battery capacity. The remaining charge constraint, which is essentially the driving range during discharge, can be converted from the maximum economic driving range constraint of the vehicle path problem for conventional vehicles.

Load constraint

Combined with the discussion of the load capacity utilization factor in Shenzhen, the statistical analysis of the load capacity of the existing pure electric logistics vehicles in Shenzhen shows that based on the rated load capacity of 80% of the pure electric logistics vehicles in Shenzhen today, the actual load capacity will not exceed 70% of the rated load capacity, i.e. $\lambda = 0.7$.

$$0 \le u_i \le \lambda U, \forall k \in K, j \in C$$
(6)

$$u_{jk} \le u_{ik} - q_j X_{jik} + U(1 - X_{jik}), \forall i, j \in K, i \neq j, k \in K$$

$$\tag{7}$$

Residual power constraint

The remaining power constraint is a description of the constraint on the remaining power of the vehicle's battery at each node. The range of electric vehicles is relatively short, and the range of pure electric logistics vehicles commonly used for logistics and distribution in Shenzhen is between 100km and 200km. The remaining mileage constraint needs to be considered in the pure electric vehicle problem. Each of the following equations represents the different constraints on the remaining battery power of the vehicle arriving at the customer point and the charging station, ensuring that the electric vehicle is in a normal driving condition for the entire trip.

$$p_{ik}^{1} \le p_{ik}^{2} - hd_{ij}X_{jik} + Q(1 - X_{jik})$$
(8)

$$p_{ik}^2 = Q, i \in O \cup S \tag{9}$$

$$p_{ik}^1 > \mu Q, \forall i \in V, k \in K$$
⁽¹⁰⁾

$$p_{ik}^1 = p_{ik}^2, \forall j \in V, k \in K$$
(11)

Time window constraint

The customer point time window requirement is known. If the delivery vehicle cannot arrive within the target time window, the company needs to pay a certain price. Meanwhile, as the pure electric logistics vehicle allowed to be charged several times on the way, charging time will be incurred at the charging station. Based on the time window penalty linear function analyzed above, the formula is expressed as

$$P_{ik} = C_e \times max(\mathbf{E}_i - \mathbf{T}_{ik}, 0) + C_d \times max(\mathbf{T}_{ik} - \mathbf{L}_i, 0)$$
(12)

$$\mathbf{E}_i \le \mathbf{T}_{ik} \le \mathbf{L}_i \,, \forall \mathbf{j} \in \mathbf{V}, \mathbf{k} \in \mathbf{K} \tag{13}$$

$$\mathbf{T}_{0k} = \mathbf{0}, \mathbf{k} \in \mathbf{K} \tag{14}$$

$$\mathbf{t}_{ij} = \mathbf{d}_{ij} / \boldsymbol{v}, \forall \mathbf{i}, \mathbf{j} \in \mathbf{V} \tag{15}$$

In this paper, the model is further improved by introducing the load utilization factor λ and the minimum capacitance rate μ based on the existing ones. For the load constraint, considering the charging demand of pure electric logistics vehicles to charging stations and the cautiousness of consumer use (e.g., mileage anxiety), the load efficiency decreases, and the actual load weight of the vehicle from the distribution center is between 0 and the rated load weight * load utilization factor. For the residual power constraint, to avoid irreversible damage to the battery caused by deep discharge, it is necessary to ensure that the residual power at each node on the distribution route reached by the vehicle is greater than the minimum electric capacity and the rated battery capacity minimum capacitance rate, i.e., greater than the minimum electric capacity. The minimum capacitance rate varies according to the electric vehicle discharge performance.

3. Algorithm design and solution

3.1. Improved genetic algorithm

In this chapter, based on the previous research, the improved genetic algorithm is generated for the pure electric logistics vehicle distribution path optimization problem with time windows by considering the addition of the hill climbing algorithm with strong local search capability to the genetic algorithm. The hillclimbing algorithm is based on the genetic algorithm so that the improved algorithm has both global and local search capability and improves the overall search accuracy. The improved genetic algorithm copes with the shortcomings of the traditional genetic algorithm in terms of local search capability more efficiently, and thus obtains better solutions than the traditional genetic algorithm. In addition, the robustness of the improved hybrid genetic algorithm is enhanced to a certain extent. In addition, the genetic operator selection is performed by combining elite strategy with roulette wheel, and the co-arrangement convergence under the selected elite retention strategy can find the global chromosome optimum. Adaptation is used to evaluate individual merit, partial matching method for crossover, and finally multiple permutation variants to solve the EVRPTW model problem.

3.2. Hill-climbing operation

The optimal chromosome individual searched globally by the genetic operation is subjected to several hill-climbing operations to strengthen the local search capability of the solution algorithm to replace the original individual.

Step1: Select the initial solution X_0 , record the current optimal solution $X_{best} = X_0$, such that $P = N(X_{best})$.

Step2: When $P = \emptyset$ then go to step 4; otherwise select the X_{best} solution from $P = N(X_{best})$, go to step 3.

Step3: If X_{now} the objective function value of the objective function $f(X_{best}) < X_{best}$ value of, then make $f(X_{best}), X_{best} = X_{now} P = N(X_{best})$, otherwise $P = P - X_{now}$ go to step 2. Step4: Output the calculation result and stop.

Step4. Sulput the calculation result and stop.

4. Calculation solution and analysis

This case study investigates a Shenzhen company's terminal distribution station located in Futian District, which provides replenishment services to convenience stores and supermarkets. The number of customer points is numerous, by integrating the customer points that are close to each other, 20 of them are randomly selected from the customer points of this enterprise as the sample for case analysis, the distribution of customer points is simulated approximately, their locations are randomly distributed on the road network, and the distribution area located in the range of 10KM*10KM. The social charging facilities in Futian District of Shenzhen City are well built with many nodes. For the convenience of calculation and solution, five social charging points with more convenient traffic are randomly selected as the rechargeable points in the distribution process. The distance between customer points is approximated by the distance between two points D(i, j) to simulate the shortest path in the urban road network. Distribution vehicles may pass through distribution centers, customer points and charging stations are represented by S1 to S5. The coordinates of customer points and charging stations are shown in Table III. The locations of distribution centers and some charging stations are shown in Figure 2.



Fig. 2:Schematic diagram of the location of distribution center A and some charging stations at the end distribution station

Table 1: Charging station coordinates

Serial number	1	2	3	4	5
X	25	30	20	32	35
Y	15	9	20	19	10

The pure electric logistics van has a relatively short mileage, the characteristics of "less batch" and "more batch" of urban distribution are suitable for end-distribution transportation in cities. In this case, the time window limitation of customer points is considered, and two time points are randomly selected as the time window range for each customer point. The daily time window of each customer point is relatively fixed, but the demand of goods is not fixed. The pure electric logistics vehicle starts from the end distribution site A, serves the customer points in a certain visiting order, and returns to the starting point after completing the distribution task.

Serial		X		Y	Demand	Customer Point Time Window	Rejection time
number							
1		26.4		9.45	30	(8:00-12:00)	14:00
	7						
2		30.0		10.1	25	(6:00-10:00)	12:00
	7		4				
3		33.3		13.3	55	(6:00-10:00)	12:00
	9		7				
4		35.2		14.2	30	(8:00-12:00)	14:00
	7		4				
5		32.0		10.0	15	(6:00-10:00)	12:00
	0		4		_		
6	-	35.4		17.0	40	(6.00-10.00)	12:00
Ū	7		2	1710			12100
7	,	25.7	-	15.1	25	(6:00-10:00)	12:00
,	9	25.1	0	15.1	25		12.00
8		26.6	0	123	30	(6.00, 10.00)	12:00
0	0	20.0	Q	12.5	50	(0.00-10.00)	12.00
0	0	24.0	0	10.1	20	(8.00 12.00)	14.00
9	5	24.0	2	16.1	20	(8:00-12:00)	14:00
	3	27.5	2	17.2	25	((00 10 00)	12.00
10	2	27.5	0	17.3	25	(6:00-10:00)	12:00
	3		8	10.4		(0.00.10.00)	11.00
11		33.5	_	13.4	35	(8:00-12:00)	14:00
	2		5			(
12		29.4		18.1	30	(8:00-12:00)	14:00
	1		3				
13		32.1		12.5	50	(8:00-12:00)	14:00
	1		1				
14		21.2		11.0	45	(10:00-14:00)	14:00
	5		4				
15		24.1		9.76	20	(8:00-12:00)	16:00
	7						
16		34.0		19.0	35	(8:00-12:00)	14:00
	0		9				
17		22.2		14.5	40	(6:00-10:00)	16:00
	1		0				
18		23.3		17.3	45	(6:00-10:00)	18:00
	4		2				
19		31.4		9.23	23	(8:00-12:00)	18:00
	5						
20		34.2		10.2	20	(6:00-10:00)	18:00
	3		1				
			<u> </u>		1		·

Table 2: Customer coordinates, demand, customer point time windows and rejection times

The optimal cost is 1262.6827 and the mileage is 161.8401. Elapsed time is 11.6869. The trend of the algorithm fitness value is shown in Figure 3.



Fig. 3:Trend graph of the change of the algorithm fitness value

As can be seen from the adaptation trend graph, the iteration curve drops sharply in the beginning stage, and the adaptation value drops to around 1500 at around 30-50 times. As the algorithm continues, the curve tends to level off, and the optimal solution can consider to be obtained at close to 200 times. After comparing the results of 50 operations, the one with the best calculation result is selected as the solution result. The optimal distribution scheme obtained has 8 distribution sub-paths, which means that 8 pure electric logistics vehicles are needed, and the total distance driven by 8 pure electric logistics vehicles in the process of goods distribution is 161.8km. the best path distribution scheme at this time is shown in Figure4



Fig. 4:Schematic diagram of the optimal distribution path

Through the results obtained from the simulation, the final distribution network optimization scheme obtained in this paper has 8 distribution paths, using 8 pure electric logistics vehicles, as shown in Figure 5-8. Under the parameter setting of this example, the total driving distance of the pure electric logistics vehicle is 161.8km. Compared with the original Shenzhen express delivery G enterprises, 10 pure electric logistics vehicles can be reduced to 8. After the distribution scheme optimization, the pure electric logistics vehicles can be reduced by 2 units, and the idle rate is reduced by 20%. By reasonably planning the distribution path, the utilization rate of logistics vehicles can be increased and the satisfaction of customer points with time windows can be improved. The distribution process of each pure electric logistics vehicle is described in terms of the access order of each customer point in the path.

Table 3: COMPARISON OF THE ECONOMICS OF TRADITIONAL AND PURE ELECTRIC LOGISTICS
VEHICLES

Vehicle Type	Pure Electric Logistics Vehicle	Conventional Fuel Logistics Vehicle	
Range (km)	245	-	
Maximum economic driving rang		245	
Average daily operating mileage (km) 120	120	
Fuel consumption per 100 km (lite	ers, 100 km) -	14	
Electricity consumption per 100 k	km (kWh, 100 km) 41	-	
Price of oil	-	6.5	
Electricity price	0.6	-	
Daily operating costs (yuan)	29.52	109.2	
Annual operating costs (yuan)	10627.	2 39312	
Maintenance and repair costs	2000	15000	
Annual operating costs	12627.	2 54312	
Years of operation	4	4	
Total cost after 4 years	50508.	8 217248	
Cost savings in 4 years	166739	9.2 -	

5. Summary

The fuel cost saved in the whole life cycle is estimated to reach about 174,000 yuan/vehicle, 10 vehicles totaling 1.74 million yuan, saving 1.04 million yuan and reduce 33.52%. It reflects the economic superiority of pure electric logistics vehicles in the field of urban end distribution compared with traditional fuel vehicles. From a whole life cycle perspective, the cost of electric logistics vehicles is significantly smaller than that of fuel logistics vehicles. At the same time, it also reduces carbon dioxide and other pollutant emissions, which is conducive to the sustainable development of logistics and distribution. The Shenzhen government should also continue to promote the transfer of subsidies from the acquisition to the operation of the link and continue to strengthen the financial support for infrastructure. Give electric logistics vehicles access and stopping convenience policy, time-sharing and staggered reasonable planning, optimize and improve the policy system of urban distribution vehicles. Pay attention to the synergy of policies, working together to promote the use of new energy logistics vehicles.

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