Intelligent Scheduling on Electric Vehicle Routing Problem with Simultaneous Pickup and Delivery

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Abstract

In this paper, we use intelligent scheduling technique to propose an electric vehicle routing problem with simultaneous pickup and delivery (EVRPSPD) model which considers the load-dependent discharging (LD). The model aims to minimize the working time including travel time, charging time, service time, and waiting time. In small-scale problems, rational routing decisions can be obtained directly using the commercial software CPLEX. In addition, we propose an adaptive large neighbourhood search algorithm (ALNS) for this problem, which can solve large-scale problems and obtain feasible solutions in an acceptable amount of time. Our computational investigation indicates that load-dependent discharging is non-negligible for the problem.

Keywords: *intelligent scheduling, electric vehicle routing problem, simultaneous pickup and delivery, load-dependent discharging, adaptive large neighbourhood search, commercial software CPLEX*

1 INTRODUCTION

Nowadays, the carbon emissions of traditional fossil fuel vehicles account for 27% of the world's total carbon emissions [2]. Under the background that countries are committed to reducing carbon emissions to alleviate the greenhouse effect, electric vehicles, known for their zero emissions, will surely become the leader in the transportation industry [9]. Due to the battery technology that is difficult to break through in a short period of time, electric vehicles have disadvantages in terms of battery life and charging time. Faced with the above shortcomings, the electric vehicle routing model can provide a reasonable and effective solution. The electric vehicle routing problem (EVRP) is derived from the classic vehicle routing problem (VRP) and has been extensively studied by scholars from various countries recently.

Scholars from various countries mainly study unidirectional logistics [5] [11], but less research on bidirectional (reverse) logistics. Unidirectional logistics refers to considering only cargo distribution or only cargo collection, while bidirectional logistics considers both cargo distribution and cargo collection. Unidirectional logistics is widely used, but bidirectional logistics cannot be ignored. In the express service industry, main-distribution center delivers express or goods to sub-distribution center or customers, and sub-distribution centers or customers may submit some requests for sending express or goods to main-distribution center. In the sales industry, manufacturers deliver products to retailers, and retailers can negotiate the return of excess products back to the manufacturers, which is beneficial for both sides. In the manufacturing industry, the producers are responsible for the entire life-cycle of their products like industrial equipment, hardware devices, etc., which are also sent back to the manufacturing facilities to be disassembled into valuable components [10].

Goeke considers pickup and delivery into ERVPTW with a paired one-to-one service model where the requests are only for interaction between customers, not involving the depots [3]. Soysal also made efforts on the one-to-one service model. They pay attention to stochastic battery depletion and present an approximated linear formulation [8].

Although the above papers have considered both cargo and bulk cargo factors, the current electric vehicle routing problem has turned to the direction of battery

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power consumption [4] [7], where load-dependent discharging is a direction. In bidirectional logistics, electric vehicles carry goods from the depot and return to the depot with goods which means that electric vehicles are in a high cargo state for a long time. Therefore, compared with unidirectional logistics, bidirectional logistics cannot ignore the impact of cargo capacity.

Therefore, starting from the electrical vehicle routing problem with simultaneous pickup and delivery, this paper constructs the electric vehicle routing model considering the load-dependent discharging and aiming at minimizing the travel time, service time, charging time, and waiting time. The commercial solver software CPLEX is used to solve small-scale problems. When solving large-scale problems, an improved adaptive large neighbourhood search algorithm (ALNS) is proposed.

2 PROBLEM DESCRIPTION AND MATHEMATICS FORMULATION

2.1 Problem Description

A distribution center (depot) and several customers are distributed in an area, in which each customer may have both pickup and delivery requests. All customer pickup and delivery needs interact only with the distribution center. A pickup request is to pick up goods from a customer to the distribution center, and a delivery request is the reverse. Two requests from each customer may have their different time windows. In a continuous period of time, a certain number of electric vehicles need to be dispatched from the depot to visit all customer nodes to meet the corresponding pickup and delivery requests and a certain amount of service time is also considered at each customer.

During the journey, electric vehicles consume power according to the current load of cargo. When the electric vehicle has low power, it needs to visit the charging station to get charged. We define this problem as an electric vehicle routing problem with simultaneous pickup and delivery based on load-dependent discharging (EVRSPD-LD). Figure 1 presents an example solution to the problem.

We assume that the electric vehicle starts from the depot and eventually returns to the depot. If the period arrives earlier than the earliest time of the time window, it can take a certain waiting time to meet the time window constraints, but it cannot be later than the latest time of the time window.

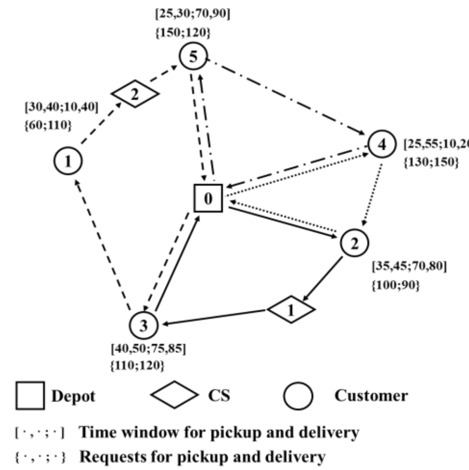

Figure 1 Example of EVRPSPD-LD

2.2 Load-dependent Discharging Mode

The Comprehensive Modal Emission Model (CMEM) was proposed by Barth and Boriboonsomsin [1] and is widely used in the calculation of the output power of various electric vehicle batteries. The calculation formula of the output power P is shown in Equation 1.

$$P = \frac{(Ma + Mg sin\theta + MgC_r cos\theta + 0.5C_d\rho Av^2)v}{1000\epsilon} \quad (1)$$

The parameters are shown in Table 1.

Table 1 Parameters in CMEM

PARM	Description	PARM	Description
v	speed (m/s)	ρ	air density (kg/m^3)
a	acceleration (m/s^2)	A	frontal surface area (m^2)
M	gross vehicle weight (kg)	C_d	coefficient of aerodynamic drag
g	gravitational constant (m/s^2)	C_r	coefficient of rolling resistance
θ	road grade angle in degrees	ϵ	vehicle drive train efficiency

Ignoring the effects of road gradient and start-stop acceleration, Equation 2 can be obtained.

$$P = \frac{(MgC_r + 0.5C_d\rho Av^2)v}{1000\epsilon} \tag{2}$$

Converting Equation 2 into a first-order linear form yields Equation 3.

$$P = \Phi_1 + \Phi_2 M \tag{3}$$

where $\Phi_1 = \frac{0.5C_d\rho Av^3}{1000\epsilon}$ is a constant and $\Phi_2 = \frac{gC_r v}{1000\epsilon}$ is the coefficient of weight, M.

The values of Φ_1 and Φ_2 can be obtained by using the data mentioned above, and the only unknown gross vehicle weight (M) is a variable in the problem formulation. Where M consists of the weight of EV (m) and the weight of vehicle loaded (u).

2.3 *Mathematics Formulation*

Unlike the unidirectional model where each customer has only one request, in this problem the customer has both a pickup and a delivery request.

The parameters in the model are shown in Table 2. The variables in the model are shown in Table 3.

Table 2 Parameters in EVRSPD-LD

n	Number of customers;
V	Set of customer requests, $V = \{1,2,\cdots,n,n+1,\cdots,2n\}$;
P	Set of pickup requests, $P = \{1,2,\cdots,n\}$;
D	Set of delivery requests, $D = \{n+1,\cdots,2n\}$;
F	Set of charging stations, $F = \{f_1, f_2, \cdots\}$;
F'	Set of charging stations and their duplicates, $F' = \{f_1, f_2, \cdots, f_1', f_2', \cdots\}$;
0, $N+1$	depot;
V_0'	$= V \cup F' \cup \{0\}$;
V_{N+1}'	$= V \cup F' \cup \{N+1\}$;
$V_{0,N+1}'$	$= V \cup F' \cup \{0\} \cup \{N+1\}$;
A	Set of arc(i,j), $i,j \in V_{0,N+1}', i \neq j$;
d_{ij}	Distance between node i and node j (km), $i,j \in V_{0,N+1}', i \neq j$;
t_{ij}	Travel time between node i and node j (h), $i,j \in V_{0,N+1}', i \neq j$;
p_i	Request for pickup of customer i, $i \in P$;
d_i	Request for delivery of customer $i-n$ (kg), $i \in D$;
C	Maximum capacity of electric vehicle (kg);
Q	Electric vehicle battery level (kWh);
g	Charging rate (kWh/h);
$[e_i, l_i]$	Time window of node i (h), $i \in V_{0,N+1}'$;
s_i	Service time of node i (h);
K	Set of electric vehicles, $K = \{k_1, k_2, \cdots\}$;
Φ_1	Discharging rate when electric vehicle is empty;
Φ_2	For every 1kg increase in the cargo, the battery discharging rate of the electric vehicle increases by Φ_2;
m	Empty weight of electric vehicle (kg);
M_c	Vehicle cost factor.

Table 3 Variables in EVRSPD-LD

x_{ij}^k	It is equal to 1 if the electric vehicle k travels between node i and node j, otherwise it is equal to 0, $i,j \in V_{0,N+1}', i \neq j, k \in K$;
u_i^k	The load of electric vehicle k before it reaches node i (kg), $i \in V_{0,N+1}', k \in K$;
Tw_i^k	Waiting time before electric vehicle k arrives at node i (h), $i \in V_{0,N+1}', k \in K$;
τ_i^k	The time for the electric vehicle k to arrive at node i (h), $i \in V_{0,N+1}', k \in K$;
v_i	Remaining power to reach node i (kWh),$i \in V_{0,N+1}, k \in K$;
Y_i	The remaining power of the electric vehicle leaving the charging station i (kWh), $i \in F'$;
θ_i	Charging time at charging station i (h),$i \in F'$;

EVRSPD-LD model

Minimize:

$$\sum_{k\in K}\sum_{i\in V_0'}\sum_{j\in V_{N+1}'} t_{ij}x_{ij}^k + \sum_{i\in V_{N+1}'} Tw_i^k + \sum_{i\in F'} \theta_i + \sum_{i\in V} s_i + \sum_{k\in K}\sum_{j\in V'} M_c x_{0j}^k \tag{4}$$

Subject to:

$$\sum_{k\in K}\sum_{j\in V_{N+1}', i\neq j} x_{ij}^k = 1 \qquad \forall i \in V \tag{5}$$

$$\sum_{k\in K}\sum_{j\in V_{N+1}', i\neq j} x_{ij}^k \leq 1 \qquad \forall i \in F' \tag{6}$$

$$\sum_{j\in V_{N+1}'} x_{0j}^k = 1 \qquad \forall k \in K \tag{7}$$

$$\sum_{j\in V'_{N+1},i\neq j} x_{ij}^k - \sum_{j\in V'_0,i\neq j} x_{ji}^k = 0$$

$$\forall i \in V', \forall k \in K \quad (8)$$

$$v_0 = Q \quad (9)$$

$$v_i - v_j - [\Phi_1(u_j^k + m) + \Phi_2]t_{ij} \geq$$
$$(-Q - [\Phi_1(C+m) + \Phi_2]t_{ij})(1 - x_{ij}^k)$$
$$\forall i \in V_0, \forall j \in V'_{N+1}, \forall k \in K, i \neq j \quad (10)$$

$$Y_i - v_j - [\Phi_1(u_j^k + m) + \Phi_2]t_{ij} \geq$$
$$(-Q - [\Phi_1(C+m) + \Phi_2]t_{ij})(1 - x_{ij}^k)$$
$$\forall i \in F', \forall j \in V_{N+1}, \forall k \in K, i \neq j \quad (11)$$

$$\theta_i = (Y_i - v_i)/g \qquad \forall i \in F' \quad (12)$$

$$\tau_0^k = 0 \qquad \forall k \in K \quad (13)$$

$$e_j \leq \tau_j^k \leq l_j \qquad \forall j \in V'_{0,N+1}, \forall k \in K \quad (14)$$

$$\tau_j^k - \tau_i^k \geq -l_0(1 - x_{ij}^k) + (t_{ij} + s_i)x_{ij}^k$$
$$\forall i \in V_0, \forall j \in V'_{N+1}, \forall k \in K, i \neq j \quad (15)$$

$$\tau_j^k - \tau_i^k \geq$$
$$-(l_0 + c_{\bar{b}})(1 - x_{ij}^k) + t_{ij}x_{ij}^k + \theta_i$$
$$\forall i \in F', \forall j \in V'_{N+1}, \forall k \in K, i \neq j \quad (16)$$

$$u_j^k - u_i^k \geq -C(1 - x_{ij}^k) + p_i x_{ij}^k$$
$$\forall i \in P, \forall j \in V'_{N+1}, \forall k \in K, i \neq j \quad (17)$$

$$C(1 - x_{ij}^k) + d_i x_{ij}^k \geq u_i^k - u_j^k \geq$$
$$-C(1 - x_{ij}^k) + d_i x_{ij}^k$$
$$\forall i \in D, \forall j \in V'_{N+1}, \forall k \in K, i \neq j \quad (18)$$

$$u_j^k \geq u_i^k - C(1 - x_{ij}^k)$$
$$\forall i \in F'_0, \forall j \in V'_{N+1}, \forall k \in K, i \neq j \quad (19)$$

$$u_0^k = \sum_{i\in P} \sum_{j\in V'_{N+1},i\neq j} p_i x_{ij}^k \qquad \forall k \in K \quad (20)$$

$$u_N^k = \sum_{i\in D} \sum_{j\in V'_{N+1},i\neq j} d_i x_{ij}^k \qquad \forall k \in K \quad (21)$$

variable domain:

$$x_{ij}^k \in \{0,1\} \qquad \forall (i,j) \in A, \forall k \in K, i \neq j$$
$$z_{ib} \in \{0,1\}, w_{ib} \in \{0,1\} \qquad \forall i \in F', b \in B$$
$$0 \leq u_i^k \leq C, 0 \leq \tau_i^k \quad \forall i \in V'_{0,N+1}, \forall k \in K \quad (22)$$
$$0 \leq y_i \leq Y_i \leq Q, \qquad \forall i \in F'$$
$$0 \leq v_i \leq Q \qquad \forall i \in V'_{0,N+1}$$
$$0 \leq \theta_i \leq C/g \quad \forall i \in F'$$

Constraint (4) states that the goal of the problem is to (i) firstly minimize the number of vehicles used; (ii) secondly minimize the total work time, including travel time, service time, charging time, and waiting time. Where M_c is a sufficiently large coefficient, $M_c = \sum_{i\in V} l_i$ can be taken in the actual solution process, where l_i is the latest arrival time in the time window. Constraints (5) guarantee that each request node can only be visited once. Constraints (6) state that each charging station and its duplicates are visited at most once. Constraints (7) ensure that each electric vehicle can only be used once. Constraints (8) construct a flow balance constraint, that is, the electric vehicle must leave the node when it visits the node. Constraint (9) indicates that the electric vehicle is fully charged when it leaves the depot. Constraints (10) construct the battery power consumption relationship when the electric vehicle departs from each request node including the depot. Constraints (11) construct the battery power consumption relationship when the electric vehicle departs from each charging station. Constraints (12) describe the charging time of the electric vehicle at the charging station. Constraints (13) conform to the general situation that the departure time is 0. Constraints (14) ensure that the moment when the electric vehicle arrives at any node complies with the time window constraint. Constraints (15) construct the arrival time relationship from all request nodes including the depot to any arrival node. Constraints (16) construct the arrival time relationship from all charging stations to any arriving node. Constraints (17) construct the cargo relationship of electric vehicles from all pickup request nodes to any arrival point. Constraints (18) construct the cargo relationship of electric vehicles from all delivery request nodes to any arrival node. Constraints (19) construct the relationship between the cargo of electric vehicles starting from all charging stations, including the depot, to any arrival node. Constraints (20) ensure that the electric vehicle can carry enough goods to be distributed when it departs from the depot. Constraints (21) ensure that the electric vehicle returns to the depot with enough cargo to be collected. Constraints (22) list the domain of the variables.

3 SOLUTION METHOD

3.1 ALNS

The adaptive large neighbourhood search algorithm (ALNS) was proposed by Ropke and Pisinger [6]. ALNS can achieve large perturbation of the solution through a variety of transformation operators so that it is not easy to fall into local optimum. In each iteration, the algorithm selects removal and insertion operators to remove and insert the current solution and form a new solution. The probability of selecting an operator is updated according to the quality of the new solution formed each time the operator is selected. The generated new and old solutions are discriminated according to the simulated annealing method (SA). The algorithm pseudocode used in this paper is **Pseudocode 1**. Among them, N_{SR} represents the charging station removal period, N_{RR} represents the path removal period, N_R and N_s respectively represent the period of updating the corresponding operator probability, and the remaining parameters will be introduced in 3.2.

3.2 Operator

The operators in ALNS are divided into removal operators and insertion operators. The removal operators include request removal (*RR*), charging station removal (*SR*), and route removal (*RR'*). Insertion operators include request insertion (*RI*) and charging station insertion (*SI*).

Request removal includes random removal, worst-distance removal, worst-time removal, and shaw removal. Worst-distance removal and worst-time removal remove the request that increases the total distance and total time respectively. Shaw removal removes requests with high correlation. The correlation R_{ij} is calculated as shown in Equation (23).

$$R_{ij} = \phi_1 d_{ij} + \phi_2 \left|e_i - e_j\right| + \phi_3 l_{ij} + \phi_4 \left|q_i - q_j\right| \tag{23}$$

If the request $i \in P$, $q_i > 0$; otherwise, $q_i < 0$. Where ϕ_1, ϕ_2, ϕ_3, and ϕ_4 are the weights, l_{ij} = -1, if request i and j are in the same route, and 1 otherwise.

Charging station removal includes random removal, worst-distance removal, worst-charge usage removal, and full charge removal. Worst-charge usage removal removes the charging station with the most power before the electric vehicle visits. Full charge removal removes a fully charged charging station.

Route removal includes random route removal (*RRR*) and greedy route removal (*GRR*), where *GRR* removes the route with the most visited nodes.

Request insertion includes greedy insertion and regret-k insertion where greedy insertion selects the best insertion position with the minimum total time and regret-k calculates the difference between the total time of the first and kth best insertions of the requests and inserts the one with the highest difference to its best position.

Charging station insertion includes greedy station insertion (*GSI*). The operator will insert the charging station between the given starting position and negative charge position, and choose the position which occurs the least time.

Pseudocode 1: ALNS heuristic method

```
For i in iteration do
  If i % N_SR == 0 then
    Select SR algorithm and remove stations
    Perform GSI to repair solution
  If i % N_RR == 0 then
    Select RRR or GRR and remove requests
    Select RI algorithm and perform GSI to repair solution if infeasible
  Else
    Select RR algorithm and remove requests
    Select RI algorithm and perform GSI to repair solution if infeasible
  Using SA criterion to accept/reject solution
  If i % N_R == 0 then
    Update the selection probability of the operators in RR and RI
  Else if i % N_s == 0 then
    Update the selection probability of the operators in SR
```

4 NUMERICAL EXPERIMENT

We design a total of 16 experimental examples with request scales of 10, 20, 40, and 80, and the number of charging stations is 2-8.

In Equation 3, we adopt the $\rho = 1.2041$, $C_d = 0.48$, $A = 2.3301$, $v = 40$, $\epsilon = 0.89$, $g = 9.81$. These values were selected such that they are close to real-world data and at the same time energy consumption for a vehicle with half-load matches the consumption rate of 125 kWh/km [4]. The battery capacity Q of the electric vehicle is 16kWh, the charging rate g is 16kWh/h, and the upper limit of the cargo capacity C is 600kg.

All numerical tests were executed on a computer with Intel Core i7-7700 @ 3.60 GHz CPU and 16 GB of RAM. The CPLEX software was IBM ILOG CPLEX Optimization Studio V12.10.0. ALNS was compiled with Python 3.7.6.

CPLEX and ALNS were used to solve the same problems. The upper limit of the solution time of CPLEX in the 10-requests case is 1200s, and the rest is 3600s. Since the ALNS solution has certain randomness, each calculation example is solved 10 times. We also set the case of considering load-dependent discharging and the case of linear discharging.

Table 4 shows the solution results of CPLEX and ALNS under the 10-requests example, where *k* represents the number of vehicles, f_{best} represents the optimal value, and *time* and $time_{avg}$ represent the CPU times of CPLEX and ALNS, respectively. The results of ALNS and CPLEX are the same, which indicate that ALNS proposed in this paper can handle this problem. In addition, it was found that the CPU time of ALNS has a great advantage over the running time of CPLEX.

Table 4 results of CPLEX or ALNS in 10-requests

ID	CPLEX			ALNS		
	k	f_{best}(h)	*time* (s)	k	f_{best}(h)	$time_{avg}$ (s)
1	3	39.19	1200	3	39.19	5.45
2	3	38.35	1200	3	38.35	4.23
3	4	36.04	1200	4	36.04	5.07
4	4	52.48	1200	4	52.48	4.62

Table 5 shows the solution results with and without load-dependent discharging, where f_{worst} represents the worst solution result in 10 times, k_{avg} represents the average number of vehicles in the 10 times, and *STD* represents the standard deviation. From the results, the problem with simultaneous pickup and delivery, power consumption based on load-dependent discharging is an important factor that cannot be ignored.

For the standard deviation of 10 solutions in ALNS, the stability without considering any situation is generally better than considering the load-dependent discharging situation. This is mainly because the use of load-dependent dynamic battery consumption rate can lead to uneven power, resulting in large deviations in charging time and working time between solutions, while the average consumption rate does not produce such results.

Table 5 The results of considering load-dependent or linear discharging

#	load-dependent discharging						linear discharging					
	f_{best}(h)	f_{worst}(h)	f_{avg}(h)	*STD*	k_{avg}	$time_{avg}$(s)	f_{best}(h)	f_{worst}(h)	f_{avg}(h)	*STD*	k_{avg}	$time_{avg}$(s)
40	92.21	99.91	95.44	2.14	7.9	64.08	87.85	106.58	95.10	5.46	7.9	62.05
	108.26	120.61	112.10	3.13	9.8	42.39	102.81	121.00	111.45	6.02	9.6	38.75
	77.94	98.71	83.27	3.10	7	87.84	77.78	87.95	83.06	3.15	6.9	98.55
	91.78	104.53	99.65	3.12	7.9	86.31	94.38	106.93	99.04	3.34	8.1	76.89
80	184.59	197.29	189.85	4.06	16.8	577.59	175.66	188.89	183.13	4.24	15.8	396.85
	193.33	208.16	201.55	5.34	17.3	600.41	185.33	203.30	195.85	4.80	16.1	517.49
	158.57	186.15	174.70	7.65	15.2	537.63	161.06	177.50	170.49	4.76	14.7	556.21
	176.25	196.20	185.08	5.66	15.1	563.95	178.71	195.49	185.56	4.66	14.9	526.34

5 CONCLUSIONS

In this paper, an electric vehicle routing problem with simultaneous pickup and delivery is constructed. The model takes load-dependent discharging as an additional constraint and aims to minimize travel time, charging time, service time, and waiting time. For large-scale problems that are difficult to solve, we propose an adaptive large neighbourhood search algorithm suitable for this problem.

The experimental results of examples of different scales show that: (i) the model constructed in this paper can describe the research problem; (ii) the ALNS proposed in this paper can better deal with the proposed problem; (iii) the load-dependent discharging has a significant impact on the route planning scheme of the simultaneous pickup and delivery problem.

Future research directions can consider the influence of driving speed, road weather conditions, etc. on the consumption rate of electric vehicles.

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