IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 26 August 2022, accepted 11 September 2022, date of publication 15 September 2022, date of current version 22 September 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3206789

RESEARCH ARTICLE

Online Routing and Charging Schedule of Electric Vehicles With Uninterrupted Charging Rates

YONGSHENG CAO

Department of Information Science and Technology, East China University of Political Science and Law, Shanghai 200042, China
School of Electronic Information and Electrical Engineering, China Institute for Smart Court, Shanghai Jiao Tong University, Shanghai 200240, China

e-mail: yongshengcao@ecupl.edu.cn

This work was supported in part by the Shanghai Science and Technology Innovation Action Plan Morning Star Project (Sail Special) under Grant 22YF1411900, in part by the China Postdoctoral Science Foundation under Grant 2022TQ0210, in part by the National Social Science Fund Major Project of China on ''Legalization of Technology Standards for Public Data in China'' under Grant 21&ZD200, and in part by the National Social Science Foundation of China under Grant 20&ZD199.

ABSTRACT With the development of electric vehicle technology and the Internet of Things (IoT) technology, IoT-Based electric vehicles (IoEVs) will become a main public transposition in smart city. The increasing penetration of IoEV will have a great impact on the transportation network and power grid. In this work, we aim to study the routing and charging scheduling problem of IoEVs with the constraint of power limit. This paper proposes a clustered rolling framework and a mathematical model for the IoEVs optimal routing and charging problem to minimize the waiting time of customers and get a good converge ratio of the energy block with power limit. This framework can effectively deal with the multi-step pickup and delivery of each vehicle over the time horizon in a dynamic environment. We give a criterion to judge whether pickup and delivery tasks can be assigned to the IoEV. Then, we design a new rectangle packing method for IoEV charging dispatch with the constraint of power limit. Moreover, we consider that the charging process of IoEVs cannot be interrupted before IoEVs meet the electricity demand. We propose the IoEV Routing and Charging Algorithm and analyze its computational complexity. Simulation results show that IoEVs can offer the shuttle service to customers with the minimum waiting time and IoEV charging energy block has a good coverage ratio of the total energy block. Simulation results can verify the effectiveness of our proposed framework, compared with two benchmark algorithms.

INDEX TERMS IoT-based electric vehicle, clustered rolling framework, pickup and delivery, routing and charging, rectangle packing algorithm.

I. INTRODUCTION

One of the important options for carbon-free transportation is electrifying the transportation system by deploying the electric vehicles (EVs) [1]. IoT-Based electric vehicles (IoEVs) can transport customers more efficiently without internal combustion engines, by using artificial intelligence, next-generation battery technologies and other forth industrial revolution technologies [2]. The electrified transportation with intelligent automation driving technology will become the core part of smart city in the future metropolis [3], [4]. IoEVs can offer shuttle service and other emerging transportation network services, such as Uber, Lyft, Zipcar, and Didi. The development of IoEVs facilitates to reduce the energy consumption [5]. Accordingly, it is important to design high efficient algorithms and models to boost the utilization rate of IoEVs.

In this work, we aim study an IoEV pickup and delivery problem in a clustered rolling framework with the constraint of battery limit. We consider the one-step pickup and delivery problem when there is a customer to pick up and deliver in current time slot. Due to the different pickup and delivery service, the electricity demands of IoEVs are different. We set the charging criterion and then collect the idle IoEVs that lack electricity to charge in the charging point. We design a new rectangle packing method for IoEV charging

The associate editor coordinating the review of this manuscript and approving it for publication was Francisco Perez-Pinal.

TABLE 1. Notations.

Sets	Description
$\mathcal{K}$	Set of IoEVs
$\mathcal{N}$	Set of nodes
$\mathcal{R}$	Set of paths connecting the nodes in $\mathcal{N}$
$\mathcal{N}_1$	Set of IoEVs' starting points
$\mathcal{N}_2$	Set of AEVs' ending points
$\mathcal{N}_3$	Set of charging stations
$\mathcal{N}_4$	Set of pickup nodes
$\mathcal{N}_5$	Set of delivery nodes
$\mathcal{U}$	Set of customers
Indexs	
k	Index of IoEV
i	Index of node
j	Index of node
n	Index of energy block
Variables	
$x_{ij}^{k,u}$	Binary variable to indicator if IoEV k is scheduled to route customer u between node i and j
y_u^k	Service flag
CT_n	Charging duration time of n-th energy block
P_n	Charing rate of n-th energy block
X_n	Charging amount of n-th energy block
Parameters	
D	Routing indicator matrix
$T^{k,u}$	Time slot that IoEV k is assigned to customer u
α_k	Mileage per kilowatt hour of IoEV k
V_k	Ideal speed of IoEV k
$Q_{i,j}$	Traffic flow of node i and j
C_r	Road capacity
β, γ	Experimental parameters
$P^{\max}$	Power limit of charging station
$T^{\max}$	Time limit

dispatch with the constraint of power limit from power grid. Finally, we propose the IoEV routing and charging (ERC) algorithm to solve the routing and charging scheduling problem of IoEVs. The lightweight structure in our paper is conducive to provide the customer services immediately and efficiently. The contributions of our paper are summarized as follows.

- We propose a time-efficient service framework for IoEVs dynamic transit to formulate a pickup and delivery problem joint with IoEV charging. We aim to minimize the waiting time of customers with the IoEV charging constraints.
- We propose a clustered rolling model for IoEV pickup and delivery with the constraint of power limit. We give a criterion to judge whether pickup and delivery tasks of customers can be assigned to the IoEV. The idle IoEVs which lack electricity are collected to charge and we design a new rectangle packing method for IoEV charging dispatch with the constraint of power limit.
- We propose the IoEV routing and charging algorithm and analyze its computational complexity. Simulation results show that the IoEVs can offer the routing service to customers with the minimum waiting time. IoEV charging energy block has a good coverage ratio of the total rectangle energy block in a fixed time frame with the power limit.

The rest of this paper is organized as follows. The IoEV pickup and delivery model and the rectangle packing problem for IoEV charging dispatch are proposed in Section III. Online IoEV routing and charging algorithm in a clustered rolling framework is proposed in Section IV. The case study and performance evaluation are in Section V. Section VI concludes this paper.

II. RELATED WORK

For traditional EVs, some deterministic and probabilistic prediction methods have been studied to predict the future power demand [6]. The radial basis function neural network in a deterministic model in [7], only considered EVs' historical velocity for the prediction. Some methods are not available in the general transportation system and some are mainly utilized in simple traffic scenarios. Compared with traditional EV, IoEV is easier to perceive the surrounding environment equipped with numerous sensors, which can be fully or partially driverless [8]. Without direct human intervention, IoEVs are easy to dispatch and schedule, which is a tendency of EVs [9], [10]. The traditional centralized management method for Internet of Vehicles is difficult to solve the real-time schedule problem [11], [12]. The core models and algorithms for IoEVs sharing service in smart cities are studied to improve the routing and charging strategies. The vehicle routing problem over the time horizon can be formulated as a large scale mixed integer linear programming (MILP) problem, which is very challenged to be solved in real time [13]. The problem of a capacitated vehicle with shuttle service is studied in [14] to find a minimum route. Wang *et al.* [13] investigated a vehicle routing problem (VRP) with simultaneous delivery and pickup and time windows for five objectives in the logistics industry. Zhou *et al.* [15] proposed a decomposition-based local search algorithm for large-scale VRP with simultaneous delivery and pickup and time windows. A Hamiltonian graph-guided algorithm is designed in [16] to solve the vehicle routing problem. Deep reinforcement learning method is utilized in [17] to minimize the total travel cost of a selected EV charging station and the charging cost by the real time information. Dubois *et al.* [18] proposed an algorithm with data from the past crisis to solve this VRP for the rescue vehicles according to operation time and rapid intervention. Inspired by these researches, we can solve the pickup and delivery problem of IoEV routing with time windows.

The IoEV charging problem will become increasingly important to the stability and power quality of electricity grid with the increasing penetration of IoEVs into power systems. Some researches are studied about the stability of power grid. Zhang *et al.* [19] studied delay-tolerant charging problem of EVs at a charging station with multiple charge points, which are equipped with renewable generation. Yu *et al.* [20], [21] studied the time-based pricing mechanism for heterogeneous charging stations and the charging station allocation mechanism for EVs, and proposed a matching game framework for the charging stations allocation. ElGhanam *et al.* [22] proposed an online EV allocation algorithm with a dynamic wireless charging coordination strategy, which allocates IoEVs to the optimal dynamic wireless charging lanes. Tran *et al.* [23] proposed an energy management strategy to reduce the unexpected peak power demand, and improved the stability of power grid during peak load with vehicle-to-grid service. These works don't study the routing problem of EVs and assume that the charging rate can be changed in the charging process. The works [24] and [25] pointed out that batteries can only be charged at a fixed charging rate and cannot be intermitted during the charging process due to the limitations of current charging technology. Based on this assumption, we set the charging rate of each IoEV as a constant when IoEVs are charged at the charging point in this paper. There are some types of charging rates, which can be classified into multiple levels from the fast charging rate to the slow charging rate. Ding *et al.* [26] formulated a two-dimensional-rectangle packing problem to maximize the total profit of a battery swap station over the given time frame by finding the optimal battery dispatch with power constraints. Due to the uninterrupted charging characteristic, we can see the EV charging as a energy block and design the unintermitted constant charging problem of IoEVs as a two-dimensional-rectangle packing problem with the constraint of energy limits from power grid.

There are some works that combine the vehicle routing problem with the EV charging problem. Zuo *et al.* [27] studied the VRP of EVs with time-window with logistics maintenance optimization. Chen *et al.* [5] combined EV charging with pickup delivery problems for joint routing and charging of EVs with taking electricity price and customer satisfaction into account. Montoya *et al.* [28] extended current electric vehicle routing models to consider nonlinear charging functions with introducing planned detours to charging stations. Yao *et al.* [29] decomposed the offline EV routing problem into a master problem and some sub-problems by Benders decomposition method to increase efficiency. However, these researches don't combine the pickup and delivery problem with the unintermitted constant charging problem of IoEVs. To the best of our knowledge, few works have tried to combine the IoEV charging problem with the pickup and delivery problem to minimize the waiting time of customers with the constraint of energy limits from power grid. It is very challenging to consider multi-step pickup and delivery of each vehicle over the time horizon, which faces complicated dynamic optimization and is a NP-hard problem. The global optimization of the multi-step pickup and delivery problem is an offline optimization problem, which is not practical and difficult to solve. We aim to seek the online routing solution of IoEVs with pickup and delivery service in the rolling windows, which may have a worse performance than the offline routing solution.

III. PROBLEM FORMULATION

In this section, we first propose an IoEV pickup and delivery model and then formulate a rectangle packing problem for IoEV charging dispatch.

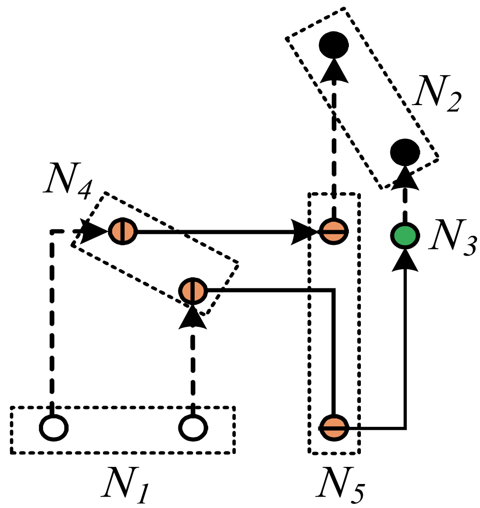

FIGURE 1. The description about all types of nodes.

A. IoEV PICKUP AND DELIVERY MODEL

We consider a set of IoEVs traveling from the starting points to different destinations in a road network, in which there are many pickups and deliveries. The road network can be described as a graph $G(\mathcal{N}, \mathcal{R})$, where $\mathcal{N}$ represents all the nodes in the network, and $\mathcal{R}$ denotes the set of paths connecting nodes in $\mathcal{N}$. In graph $G(\mathcal{N}, \mathcal{R})$, there are five types of nodes in $\mathcal{N}$, i.e., starting points of IoEVs $\mathcal{N}_1$, end points of the IoEVs $\mathcal{N}_2$, charging stations $\mathcal{N}_3$, pickup nodes $\mathcal{N}_4$ and delivery nodes $\mathcal{N}_5$, which are shown in Fig. 1. In actual case, IoEVs start from the starting points and end at the ending points. Starting points $\mathcal{N}_1$ and ending points $\mathcal{N}_2$ are certain but the number of customer is not certain and sets of pickup and delivery are scalable when we assign IoEVs to pick up and deliver the customers. The starting point and end point are special nodes because IoEVs only can flow out of the starting point and flow into the end point. We define the travel distance between nodes i and j as D_{ij}, if nodes i and j are directly connected. Notice that node i is starting point or node j is end point, $D_{ji} = \text{inf}$, which means that node j cannot flow into node i and no node can flow into starting node or flow out of the ending node. Otherwise, $D_{ij} = D_{ji}$.

$$D_{ij} = \begin{cases} D_{ji} & i, j \notin \mathcal{N}_1 \cup \mathcal{N}_2 \\ 0 & i = j \\ \text{inf} & i \in \mathcal{N}_1 || j \in \mathcal{N}_2 \end{cases} \tag{1}$$

The routing indicator matrix D can be formed by D_{ij} according to the network topology structure. A small example for six nodes which are not starting point or ending point is depicted in Fig. 2 with the corresponding matrix $\mathbf{D}$ as follows,

$$\mathbf{D} = \begin{bmatrix} 0 & D_{12} & \text{inf} & D_{14} & D_{15} & \text{inf} \\ D_{12} & 0 & D_{23} & \text{inf} & D_{25} & \text{inf} \\ \text{inf} & D_{23} & 0 & \text{inf} & D_{35} & D_{36} \\ D_{14} & D_{24} & \text{inf} & 0 & D_{45} & \text{inf} \\ \text{inf} & D_{25} & D_{35} & D_{45} & 0 & D_{56} \\ \text{inf} & \text{inf} & D_{36} & \text{inf} & D_{56} & 0 \end{bmatrix}, \tag{2}$$

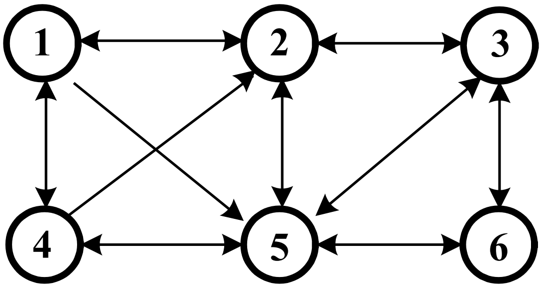

FIGURE 2. A small network topology example of 6 nodes.

We can add the nodes which are not starting point or ending point in our model and the road graph is scalable. In practical case, IoEVs can drop off the customers according to their requirement and the starting points and the ending points of IoEVs are certain when we assign IoEVs to pick up and deliver the customers.

To formulate the IoEV routing and charging problem, we define the binary variable $x_{ij}^{k,u}$ to indicate if IoEV k is scheduled to route customer u between node i and j as binary variable,

$$x_{ij}^{k,u} = \begin{cases} 1 & \text{IoEV } k \text{ is scheduled to customer } u \\ & \text{between nodes } i \text{ and } j, \\ 0 & \text{otherwise.} \end{cases} \quad (3)$$

The starting node $i \in \mathcal{N}_1$ must have only one path flowing out of it,

$$\sum_j x_{ij}^{k,u} = 1, j \in \mathcal{N}_4 \cup \mathcal{N}_5 \cup \mathcal{N}_2, \quad \forall u \in \mathcal{U},\ \forall k \in \mathcal{K}, \quad (4)$$

The end node $j \in \mathcal{N}_2$ must have only one path flowing in it,

$$\sum_i x_{ij}^{k,u} = 1, i \in \mathcal{N}_4 \cup \mathcal{N}_5 \cup \mathcal{N}_1, \quad \forall u \in \mathcal{U},\ \forall k \in \mathcal{K}, \quad (5)$$

For nodes which are neither the starting and end nodes, there is less than one path flowing out of or into the node, which satisfies the following two constraints,

$$\sum_j x_{ij}^{k,u} \le 1, \quad j \in \mathcal{N}_4 \cup \mathcal{N}_5 \cup \mathcal{N}_2, \quad i \in \mathcal{N} - (\mathcal{N}_1 \cup \mathcal{N}_2), \quad \forall u \in \mathcal{U}, \forall k \in \mathcal{K}, \quad (6)$$

$$\sum_i x_{ij}^{k,u} \le 1, \quad i \in \mathcal{N}_4 \cup \mathcal{N}_5 \cup \mathcal{N}_1, \quad j \in \mathcal{N} - (\mathcal{N}_1 \cup \mathcal{N}_2), \quad \forall u \in \mathcal{U},\ \forall k \in \mathcal{K}, \quad (7)$$

The left hand side of constraint (6) and constraint (7) can be zero, which implies that there is none IoEV passing through this node. Constraint (8) indicates that if there is an IoEV entering a node i that is neither a starting node nor an end node, it should flow out of node i afterward. Otherwise, there is no constraint on this node i.

$$-M(1 - x_{ri}^{k,u}) \le \sum_{j \in \mathcal{N}} x_{ij}^{k,u} - x_{ri}^{k,u} \le M(1 - x_{ri}^{k,u}), \quad i \in \mathcal{N} - (\mathcal{N}_1 \cup \mathcal{N}_2), r \in \mathcal{N} - \mathcal{N}_2, \quad \forall u \in \mathcal{U},\ \forall k \in \mathcal{K}, \quad (8)$$

Constraint (9) indicates that if there is an IoEV leaving a node j that is neither a starting node nor an end node, it should flow into this node beforehand. Otherwise, there is no constraint on this node j.

$$-M(1 - x_{jr}^{k,u}) \le \sum_{i \in \mathcal{N}} x_{ij}^{k,u} - x_{jr}^{k,u} \le M(1 - x_{jr}^{k,u}), \quad j \in \mathcal{N} - (\mathcal{N}_1 \cup \mathcal{N}_2), r \in \mathcal{N} - \mathcal{N}_1, \quad \forall u \in \mathcal{U},\ \forall k \in \mathcal{K}, \quad (9)$$

Constraint (10) indicates that an IoEV has supported a pickup and deliver service to one customer,

$$\sum_{j \in \mathcal{N}} x_{pj}^{k,u} + \sum_{h \in \mathcal{N}} x_{hd}^{k,u} - 2 \ge M(1 - y_u^k), \quad \forall p \in \mathcal{N}_4, \quad \forall d \in \mathcal{N}_5, , \ \forall u \in \mathcal{U},\ \forall k \in \mathcal{K}. \quad (10)$$

The sum of service flag y_u^k of customer u should be one to ensure that every customer can be served by only one IoEV,

$$\sum_{k \in \mathcal{K}} y_u^k = 1, \quad \forall u \in \mathcal{U}, \quad (11)$$

where $\mathcal{U}$ is the set of all customers. In this work, we study the case where each IoEV k can only offer service to one customer when it finishes delivering, i.e.,

$$0 \le \sum_{u \in \mathcal{U}} y_u^k \le 1, \quad \forall k \in \mathcal{K}, \quad (12)$$

where IoEV k may not offer service when $\sum_{u \in \mathcal{U}} y_u^k = 0$. Given customer u, each starting point $s \in \mathcal{N}_1(u)$ must have one way to leave from starting node s, where $\mathcal{N}_1(u)$ is the starting node set, so we have,

$$\sum_{j \in \mathcal{N}^{out}(s)} x_{sj}^{k,u} = y_u^k, \quad s \in \mathcal{N}_1(u),\ \forall k \in \mathcal{K},\ \forall u \in \mathcal{U}, \quad (13)$$

where $s \in \mathcal{N}_1(u)$ represents the starting node that has access to connect with customer u and $\mathcal{N}^{out}(s) = \mathcal{N}_{NC}^{out}(s) \cup \mathcal{N}_3^{out}(s)$ denotes all outflow nodes connected to node s. $\mathcal{N}_{NC}^{out}(s)$ and $\mathcal{N}_3^{out}(s)$ denote nodes that are not available charging nodes and are available charging nodes in $\mathcal{N}^{out}(s)$, respectively. Similarly, for given customer u, each end point $e \in \mathcal{N}_2(u)$ must have only one way to reach ending node e, where $\mathcal{N}_2(u)$ is the end node set, so we have,

$$\sum_{i \in \mathcal{N}^{in}(e)} x_{ie}^{k,u} = y_u^k, \quad e \in \mathcal{N}_2(u),\ \forall k \in \mathcal{K},\ \forall u \in \mathcal{U}, \quad (14)$$

where $e \in \mathcal{N}_2(u)$ represents the ending node that has access to connect with customer u and $\mathcal{N}^{in}(e) = \mathcal{N}_{NC}^{in}(e) \cup \mathcal{N}_3^{in}(e)$ denote the all inflow nodes connected to node e. $\mathcal{N}_{NC}^{in}(e)$ and $\mathcal{N}_3^{in}(e)$ denote the nodes that are not available charging nodes and are available charging nodes in $\mathcal{N}^{in}(e)$, respectively. When node i is neither the starting point nor the end point, inflow should equal outflow at this node, i.e.,

$$\sum_{m \in \mathcal{N}^{in}(i)} x_{mi}^{k,u} = \sum_{j \in \mathcal{N}^{out}(i)} x_{ij}^{k,u}, \quad \forall u \in \mathcal{U}, \forall i \in \mathcal{N}/(\mathcal{N}_1(u) \cup \mathcal{N}_2(u)). \quad (15)$$

In time interval τ, there are $|U(\tau)|$ customers and we know the pickup node u_p and drop-off node u_d of each customer u, where the couple (u_p, u_d) is certain if customer u is given. Then we can know the available charging node connected to the drop-off node of customer u, i.e., $\mathcal{N}_3^{out}(u_d)$. We can assign IoEV k to customer u only if the battery energy of IoEV k is enough to pick up and deliver customer u and reach the nearest charging node connected to drop-off node u_d of customer u. Then, we can formulate this criterion to judge whether IoEVs are available to support the pickup and delivery service as follows,

$$\begin{aligned} &xb^{k,T^{k,u}}\alpha_k y_u^k \\ &\quad \geq D_{i,u_p}x_{i,u_p}^{k,u} + y_u^k(D_{u_p,u_d} + \min_{j\in\mathcal{N}_3^{out}(u_d)} D_{u_d,j}) \\ &\qquad \forall u\in\mathcal{U},\quad \forall i\in\mathcal{N}/(\mathcal{N}_1(u)\cup\mathcal{N}_2(u)),\ \exists j\in\mathcal{N}_3^{out}(u_d), \end{aligned} \tag{16}$$

where $T^{k,u}$ is the time slot that IoEV k is assigned to customer u, $xb^{k,T^{k,u}}$ has a range constraint $[B_{min}, B_{max}]$, and α_k is the mileage per kilowatt hour of IoEV k. When y_u^k is 0, then $x_{i,u_p}^{k,u} = 0$ and both sides of constraint (16) are zero. Constraint (16) holds when $y_u^k = 0$. When $y_u^k = 1$, the left hand of constraint (16) is the available mileage $xb^{k,T^{k,u}}\alpha_k$ and the right hand has three parts, where the first one D_{i,u_p} represents the distance from IoEV k location to the pickup node of customer u, the second part D_{u_p,u_d} means the distance from pickup node to delivery node of customer u, which is a certain value if customer u is given, and the third part is $\min_{j\in\mathcal{N}_3^{out}(u_d)} D_{u_d,j}$, which is the minimum distance from the delivery node of customer u to the charging station. According to the linearization technology in [30], since y_u^k is a binary variable and $xb^{k,T^{k,u}}$ is a nonnegative variable, we linearize the product $xb^{k,T^{k,u}}\alpha_k y_u^k$ by introducing a new variable $r_{k,u} = xb^{k,T^{k,u}}y_u^k$ if $xb^{k,T^{k,u}}$ is bounded by a constant M. Then, we reformulate the constraint as follows,

$$\begin{aligned} r_{k,u}\alpha_k \geq\ & D_{i,u_p}x_{i,u_p}^{k,u} + y_u^k(D_{u_p,u_d} \\ & + \min_{j\in\mathcal{N}_3^{out}(u_d)} D_{u_d,j}), \forall u\in\mathcal{U}, \\ & \forall i\in\mathcal{N}/(\mathcal{N}_1(u)\cup\mathcal{N}_2(u)), \exists j\in\mathcal{N}_3^{out}(u_d), \end{aligned} \tag{17}$$

$$\text{s.t. } r_{k,u} \leq y_u^k M, \tag{18}$$

$$r_{k,u} \geq xb^{k,T^{k,u}} + M(y_u^k - 1), \tag{19}$$

$$r_{k,u} \leq xb^{k,T^{k,u}}, \tag{20}$$

$$r_{k,u} \geq 0. \tag{21}$$

The travel time between nodes i and j is decided by the travel distance, road congestion, weather and road traffic impedance. The road traffic impedance includes the density of bus stops, intersections and the saturation [31]. Considering the actual traffic conditions, we set the travel speed of IoEV k between nodes i and j as v_k,

$$v_k = \frac{V_k}{1+\beta(\frac{Q_{i,j}}{C_r})^\gamma}, \quad \forall i,j\in\mathcal{N},\ \forall k\in\mathcal{K}, \tag{22}$$

where V_k is the ideal speed of IoEV k, $Q_{i,j}$ is traffic flow of nodes i and j, C_r is road capacity, β and γ are experimental parameters from actual observations. Then the equivalent traveling time of nodes i and j can be given as follow,

$$t_{i,j} = \frac{D_{i,j}}{V_k}(1+\beta(\frac{Q_{i,j}}{C_r})^\gamma), \quad \forall i,j\in\mathcal{N},\ \forall k\in\mathcal{K}. \tag{23}$$

We set IoEV k assigned to customer u at node i at time slot $T^{k,u}$ and we need to minimize the total waiting time of customers as follows,

$$f_{ti} = \sum_{k\in\mathcal{K}}\sum_{i\in\mathcal{N}}\sum_{u\in\mathcal{U}}\left(T^{k,u} + \frac{D_{i,u_p}}{v_k}(1+\beta(\frac{Q_{i,j}}{C_r})^\gamma)x_{i,u_p}^{k,u}\right), \tag{24}$$

where D_{i,u_p} is the distance between node i of IoEV k and the pickup node u_p of customer u. For the reference time for the start node s, we set the initial time stamp of IoEV k as $T_{k,0} = 0$. IoEV k is assigned to customer u at time slot $T^{k,u}$. IoEV k can be dispatched to charge if IoEV cannot be assigned to any customer.

B. RECTANGLE PACKING PROBLEM FOR IoEV CHARGING DISPATCH

After the control center receives the signal from the customers, it will schedule IoEVs to pick up and deliver the customers in a time frame. There is a charging optimization problem of idle IoEVs, where there are two problems: when and which charging station to charge. In time slot t, the control center can make out which IoEV k is out of service, i.e., $\sum_{u\in\mathcal{U}} y_u^k = 0$. We denote the set of IoEVs out of service in time slot t as $\mathcal{H}_t$. When an IoEV is out of service, then this IoEV is qualified to be charged. By charging strategy, IoEV k sends a charging signal to the control center, which includes the requested charging amount B_k^c.

We study a two-dimensional-rectangle packing problem for the uninterrupted charging problem of IoEVs with the constraint of power limits from power grid. Due to the uninterrupted charging characteristic, we can see the EV charging as a energy block. The two-dimensional-rectangle packing problem can be efficient to solve by the optimization toolbox. IoEVs can support the pickup and delivery service when they have enough electricity. For those idle IoEVs that lack electricity, we need to do the charging schedule of IoEVs. The maximum charging rate is limited by power limit of the charging station (i.e., $P^{\max}$). We formulate our charging optimization model under a maximum allowed parking time $T^{\max}$. When it reaches the time limit $T^{\max}$, the IoEV should stop charging and leave the charging station. During the time interval $[0, T^{\max}]$, the base blocks are represented as histogram with B blocks. In Fig. 3, we show that there are a certain number of IoEVs coming to charging station during time period $[0, T^{\max}]$. Due to the limitation of current charging technology, the charging rate should be discrete in the charging process and the charging process is not interrupted until the electricity demand is met. Therefore, we skillfully consider the charging amount in a time interval of IoEV k as a rectangle energy block. The rectangle energy packing problem is challenging to solve. The $n-$th ($n \in \{1, \ldots, N\}$) type rectangle energy block can be described by a triplet (CT_n, P_n, X_n), where CT_n is the charging duration time, P_n is the charging rate and $X_n = P_n * CT_n$ is the charging amount. The IoEVs can be charged at N type of charging rates, e.g., if IoEVs charge at fast, medium and slow charging rate, $N = 3$. Furthermore, we define the left-bottom corner of the rectangle energy block of K IoEVs and B base blocks as (τ_i, h_i) to indicate the location of $K+B$ energy blocks, where τ_i is the starting time of energy block i and h_i is the maximum power of energy block i. We set the first K blocks for IoEV battery energy blocks and the rest B energy blocks are used for base blocks. The locations of B energy blocks are fixed and the left-bottom corner (τ_{K+b}, h_{K+b}) of the base load b can be expressed as follows,

$$\tau_{K+b} = T^{max} - \sum_{m=b}^{B} T_{K+m}, \quad b = 1, \ldots, B, \tag{25}$$

$$h_{K+b} = 0, \quad b = 1, \ldots, B, \tag{26}$$

where (25) and (26) show the X-axis and Y-axis relationship between τ_{K+b} and T_{K+b} about left-bottom corner of the base load b. We denote a binary variable $z_{i,n}$ that indicates whether n-th type rectangle energy block is charged at time slot τ_i. We need to guarantee that the four corners of each rectangle energy block i is within the rectangular area with allowed parking time $T^{\max}$ and power limit $P^{\max}$. The constraints can be represent in the following constraints.

$$\begin{aligned}
&\text{Left} - \text{bottom}: \\
&\quad 0 \le \tau_i \le T^{max}, 0 \le h_i \le P^{max}, i = 1, \ldots, K, && (27)\\
&\text{Left} - \text{top}: \\
&\quad 0 \le \tau_i \le T^{max}, \\
&\quad 0 \le h_i + \sum_{n=1}^{N} P_n z_{i,n} \le P^{max}, i = 1, \ldots, K, && (28)\\
&\text{Right} - \text{bottom}: \\
&\quad 0 \le \tau_i + \sum_{n=1}^{N} CT_n z_{i,n} \le T^{max}, \\
&\quad 0 \le h_i \le P^{max}, i = 1, \ldots, K, && (29)\\
&\text{Right} - \text{top}: \\
&\quad 0 \le \tau_i + \sum_{n=1}^{N} CT_n z_{i,n} \le T^{max}, \\
&\quad 0 \le h_i + \sum_{n=1}^{N} P_n z_{i,n} \le P^{max}, \quad i = 1, \ldots, K. && (30)
\end{aligned}$$

As shown in Fig. 4, the location of two energy blocks i and j has four possible non-overlapping relationship in the following expression when the packing is feasible.

$$\begin{aligned}
&h_j + H_j \le h_i \ \text{ or } \ \tau_j + W_j \le \tau_i \ \text{ or } \\
&h_i + H_j \le h_j \ \text{ or } \ \tau_i + W_j \le \tau_j \\
&\quad i = 1, \ldots, K, K+1, \ldots K+B, \\
&\quad j = 1, \ldots, K, K+1, \ldots K+B. \qquad (31)
\end{aligned}$$

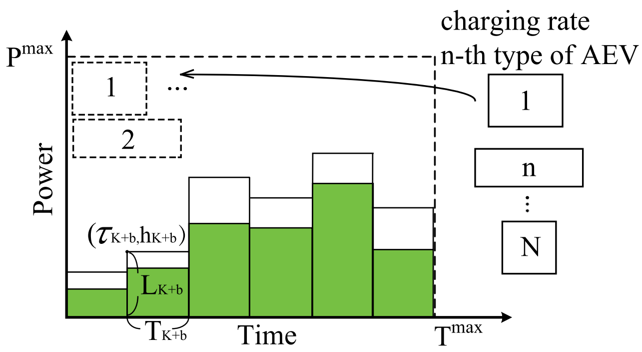

FIGURE 3. Rectangle packing problem for IoEV charging dispatch.

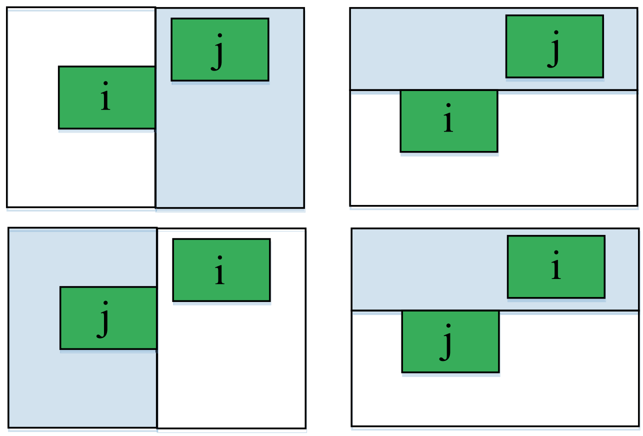

FIGURE 4. Four possibilities for two energy blocks without overlapping.

where the expressions of H_j and W_j are in the following expression,

$$H_j = \begin{cases} \sum_{n=1}^{N} P_n z_{j,n} & j = 1, \ldots, K, \\ L_{j-K} & j = K+1, \ldots, K+B, \end{cases} \tag{32}$$

$$W_j = \begin{cases} \sum_{n=1}^{N} CT_n z_{j,n} & j = 1, \ldots, K, \\ T_{j-K} & j = K+1, \ldots, K+B. \end{cases} \tag{33}$$

H_j and W_j are the length of the base load, of which the left-bottom corner is (τ_i, h_i). $L_{j-K} : j = K+1, \ldots K+B$ is the energy block of base load, which is the same description as $L_{K+b} : b = 1, \ldots, B$. The rectangle energy blocks should not be overlapped with each other. The location of two rectangle energy blocks i and j has two possibilities, where two energy blocks are not overlapped with each other over the X-axis and Y-axis. We consider that there is not queue order between the left-bottom corner (τ_i, h_i) and (τ_j, h_j) of two IoEVs i and j. The constraints of the left-bottom corner of IoEVs i and j are given as follows,

$$h_j + H_j \le h_i \ \text{ or } \ \tau_j + W_j \le \tau_i, \quad i = 1, \ldots, K, j = i+1, \ldots K+B, \tag{34}$$

It is difficult to handle the "or" constraints of h_j and τ_j in convex optimization. Therefore, we apply the big M approach [32] to reformulate the constraint (34) to make it easy to handle in convex optimization as the following expression.

$$-M_1\alpha_{i,j} + H_j \leq h_i - h_j, \tag{35}$$

$$-M_2(1-\alpha_{i,j}) + W_j \leq \tau_i - \tau_j, \quad i = 1,\ldots,K, j = i+1,\ldots K+B, \tag{36}$$

where M_1, M_2 are large numbers, $\alpha_{i,j}$ is a binary variable. If $\alpha_{i,j} = 1$, the constraint (36) is active and the constraint (35) is redundant. Otherwise, if $\alpha_{i,j} = 0$, the constraint (35) is active and the constraint (36) is redundant. Here, the number of binary variables $\alpha_{i,j}$ is $K(K+2U-1)/2$. The constraints of M_1, M_2 satisfy the following relationship,

$$-M_1 + H_j \leq h_i - h_j, -M_2 + W_j \leq \tau_i - \tau_j, \quad \text{or} \tag{37}$$

$$M_1 \geq \max_{\forall i,j}\{H_j + h_j - h_i\}, M_2 \geq \max_{\forall i,j}\{W_j + \tau_j - \tau_i\}, \tag{38}$$

Since,

$$\max_{\forall i,j}\{H_j + h_j - h_i\} \leq \max_{\forall i,j}\{H_j + h_j\} - \min_{\forall i,j} h_i\} = P^{\max}, \tag{39}$$

$$\max_{\forall i,j}\{W_j + \tau_j - \tau_i\} \leq \max_{\forall i,j}\{W_j + \tau_j\} - \min_{\forall i,j} \tau_i\} = T^{\max}, \tag{40}$$

where we can set $M_1 = P^{\max}$ and $M_2 = T^{\max}$. To satisfy the energy limits from power grid, we need to schedule as many IoEVs as possible to charge in a fixed time frame T_{max} with the power upper limit P_{max} of the charging station, which is formulated as follows,

$$f_z = \sum_{i=1}^{K}\sum_{n=1}^{N} X_n z_{i,n}, \tag{41}$$

where X_n is the charging amount of the n-th type rectangle energy block and $z_{i,n}$ is a binary variable that indicates whether the n-th type rectangle energy block is charged at time slot τ_i.

In a time frame, there are limited IoEVs connecting to charging station to charge at discrete charging rate uninterruptedly. In general, IoEV charges at discrete charging rate uninterruptedly, which may not be interrupted until the electricity demand is met. The objective function of the charging problem in (41) is to maximize the total charged energy from external grid.

IV. ONLINE IoEV ROUTING AND CHARGING ALGORITHM IN A CLUSTER ROLLING FRAMEWORK

In this section, we will discuss the solution to the online IoEV routing and charging schedule in a clustered rolling framework. The online routing and charging problem can be formulated as follows,

$$\min_{x^{k,u}_{iup}, z_{i,n}} \sum_{k\in\mathcal{K}}\sum_{i\in\mathcal{N}}\sum_{u\in\mathcal{U}} \frac{d_{i,u_p}}{V_k} x^{k,u}_{i,u_p} + \sum_{i=1}^{K}\sum_{n=1}^{N} X_n z_{i,n},$$
$$\text{s.t.}(4)-(15),(17)-(21),(25)-(36) \tag{42}$$

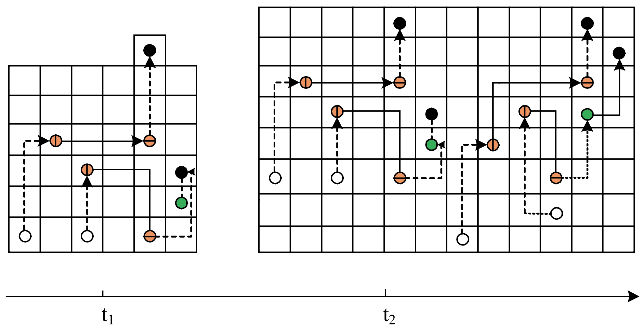

FIGURE 5. Original multi-step pickup and delivery problem of IoEVs over the time horizon.

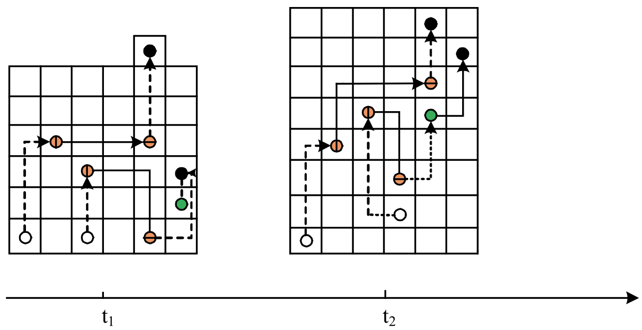

FIGURE 6. Pickup and delivery problem of IoEVs over the time horizon with the rolling windows method.

Constraints (4)-(15), (17)-(21) are from the routing part and constraints (25)-(36) are from the charging part. This optimization problem is a NP-hard problem and super large scale mixed integer linear programming, which is challenging for commercial solver such as CPLEX to solve it directly with given time limit. It would be impractical if the response time is too long. Then we propose a clustered rolling framework by dividing the whole region into several small regions based on the location of the charging stations. Due to the complexity of the IoEV routing problem, we propose a rolling framework to reduce the computational burden of multi-step pickup and delivery (MPD) problem of IoEVs over the time horizon illustrated in Fig. 5 to reformulate a pickup and delivery (PD) problem of IoEVs over the time horizon with the rolling windows method shown in Fig. 6. The white dots are IoEV's starting points, the brown dots are the couple of pickup and delivery points of customers, the dark dots are the ending points, and the green dots are the charging nodes. In time slot t_2, we need to solve a larger optimization problem in Fig. 5, compared with the optimization model in Fig. 6. Therefore, we study the routing part of this optimization problem in each current time slot by the rolling windows method.

If pickup and delivery services of customers come up one by one, it is easy to figure out the routing problem of IoEVs. We focus on the optimal routing problem that the pickup and delivery services of customers come up simultaneously. First, we generate a regional map partitioned from the whole map with clustering method, which contains some pickup and delivery nodes of customers and charging nodes. We schedule IoEVs to study the optimization problem in the small region. Second, we calculate the minimum distance from the delivery nodes of customers to all the charging stations in the regional map. Then, if the energy of IoEV k is not sufficient to reach the nearest charging station of the customer u delivery node, it cannot be arranged to customer u. Finally, we need to solve the rectangle energy packing problem to schedule these idle IoEVs to charge. We summarize the IoEV Routing and Charging (ERC) Algorithm in Algorithm 1. The flow diagram of ERC Algorithm is shown in Fig. 7. Then the computational

Algorithm 1 IoEV Routing and Charging Algorithm (ERC)

```
Initialization: Generate a regional map around the pickup and delivery node of the customer. The node set N includes starting point N_1, end point N_2, charging station point N_3. The control center can get the real-time information about the battery level and location of IoEVs.
while there is a pickup and delivery request do
    Calculate the minimum distance from the delivery point u_d ∈ N_4 of customer u to all the charging station min_{j∈N_3^out(u_d)} D_{u_d,j}.
    if the electricity of IoEV k is enough to pick up and deliver the customer u and reach the nearest charging node connected to drop-off node u_d then
        Solve problem (42) to get an optimal routing schedule
    else if there are a certain number K of idle IoEVs to charge then
        Solve the rectangle packing problem (41) for IoEV charging dispatch.
    end if
end while
```

complexity of the routing part of ERC algorithm has the following theorem.

Theorem 1: The computational complexity of the routing part of ERC algorithm is $O(\Delta\tau \cdot k_\tau n_u)$, less than that $O((k_\tau n_u)^{\Delta\tau})$ of multi-step pickup and delivery problem.

Proof: When we consider the pickup and delivery problem of IoEVs over the time horizon $\Delta\tau$, we consider there are $k_\tau \in \mathcal{K}$ IoEVs to pick up and deliver n_u customers at pickup nodes $u_p \in \mathcal{N}_4$ and delivery nodes $u_d \in \mathcal{N}_5$ in each time slot, therefore the computation complexity of this PD problem over the horizon $\Delta\tau$ is $O(\Delta\tau \cdot k_\tau n_u)$, where n_u is the number of $\mathcal{N}_4$ and $\mathcal{N}_5$. The number of $\mathcal{N}_4$ is the same as that of $\mathcal{N}_5$, where the pickup node and delivery node is a pair. When we consider MPD problem of IoEVs over the time horizon $\Delta\tau$, there are also k_τ IoEV possible routing schedule problem in the next time slot, and therefore the computational complexity of this MPD problem over the horizon is $O((k_\tau n_u)^{\Delta\tau})$. ■

If the energy of IoEV k is enough to pick up and deliver the customer u and reach the nearest charging node connected to

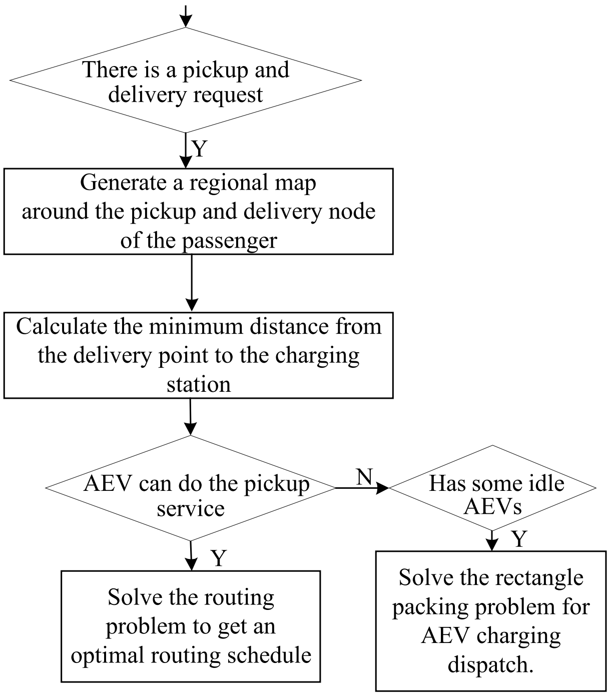

FIGURE 7. Flow diagram of IoEV optimal routing and charging algorithm.

drop-off node u_d, we can assign IoEV k to customer u. If the energy of IoEV k is not sufficient to pick up and deliver any customer and reach the nearest charging node connected to drop-off node, IoEV k cannot be arranged to support pickup and delivery service. When an IoEV is out of service, this IoEV is qualified to be charged. After checking with the charging strategy, IoEV k sends the control center a charging signal, which includes the requested charging amount B_k^c.

After the control center receives the signal from the customers, it will schedule IoEVs with plenty of electricity to pick up and deliver the customers. For the idle IoEVs with insufficient energy, there is a charging optimization problem. If there are a large number of IoEVs to charge, it will influence the stability of power grid. We consider that there are a certain number K of idle IoEVs to charge in a fixed time frame $T_{\max}$ with power upper limit $P_{\max}$ of the charging station. It is a two-dimensional rectangle packing problem for IoEV charging dispatch. We need to decide when to charge those idle IoEVs. Here, the worst-case computational complexity of IoEV charging dispatch has the following theorem.

Theorem 2: The worst-case computational complexity of two-dimensional rectangle packing problem for IoEV charging dispatch is $O\big(\Psi_x(T^{\max})\Psi_y(P^{\max})(\Psi_x(T^{\max})+\Psi_y(P^{\max}))\big)$. $\rho_\tau = [T^{\max}/CT_0]$ is the maximum number of rectangle energy block on the x-axis, where $CT_0 = \min CT_n$, $\rho = 1, 2, \ldots, \rho_\tau$ and $\rho_h = [P^{\max}/h_0]$ is the maximum number of rectangle energy block on the y-axis, where $h_0 = \min h_n$, $\rho = 1, 2, \ldots, \rho_h$. $\Psi_x(T^{\max}) \leq \sum_{\rho}^{\rho_\tau} C_{\rho+m-1}^{\rho}$, $\Psi_y(P^{\max}) \leq \sum_{\rho}^{\rho_h} C_{\rho+m-1}^{\rho}$

Proof: For a rectangle region $(T^{\max}, P^{\max})$, there are $\Psi_x(T^{\max})\Psi_y(P^{\max})$ possibilities for crosscut or vertical cut. Then the total computational complexity is $O\big(\Psi_x(T^{\max})$

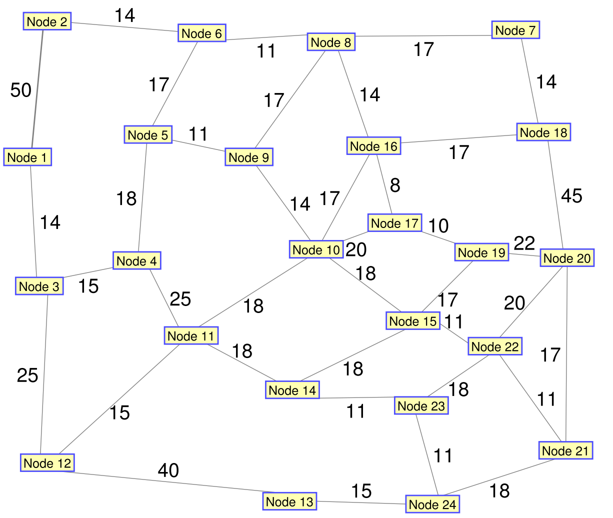

FIGURE 8. Transportation nodes of topology network.

TABLE 2. Node profile.

Start nodes	1,2,7,12,24,21,20,18,15,22
Charge nodes	4,5,10,14,16,19,22
Pickup&Dropoff	U1:{3,17},{4,22},{5,14},{23,16},{11,15},{19,10}; U2:{6,16},{12,8},{21,24},{12,3},{23,13},{9,2}

$\Psi_y(P^{\max})(\Psi_x(T^{\max})+\Psi_y(P^{\max})))$ for each recursively sub-cut after each cut. According to the definition of discrete set, the element of $\Psi_x(T^{\max})$ is obtained from the x-axis of small energy block, where there is $\sum_{\rho=1}^{\rho_\tau}(\sum_{i=1}^{m}\tau_i)^\rho$, $\rho = 1, 2, \ldots, \rho_\tau$. We know that $\sum_{i=1}^{m} CT_i\tau_i \leq T^{\max}$, the number of terms of $(\sum_{i=1}^{m}\tau_i)^\rho$ is $C_{\rho+m-1}^{\rho}$, then the number of terms of $\sum_{\rho=1}^{\rho_\tau}(\sum_{i=1}^{m}\tau_i)^\rho$ is $\sum_{\rho=1}^{\rho_\tau} C_{\rho+m-1}^{\rho}$. Therefore, $\Psi_x(T^{\max}) \leq \sum_{\rho}^{\rho_\tau} C_{\rho+m-1}^{\rho}$, $\Psi_y(P^{\max}) \leq \sum_{\rho}^{\rho_h} C_{\rho+m-1}^{\rho}$. ■

V. PERFORMANCE EVALUATION

The case studies are simulated based on a road network from a real world map. We use the real traffic flow data to generate the parameters of our proposed dynamic transit framework. We divide the total map as 20 small regions, each of which 24 nodes and 76 paths in Fig. 8. The traveling distances between nodes are given over the path. The profiles of different IoEV nodes and charging nodes are in Table 2. U1 and U2 are two groups of pickup and delivery services at two different periods. We set 200 IoEVs to support the pickup and delivery services in the total map and each region has 10 IoEVs. The capacity of IoEV battery is 35 kWh based on Jianghuai iEV7L and the maximum permitted mileage of IoEVs is 302 km [33]. The ideal speed of IoEV is assumed as 80 km/h. The traffic flow data is from [34]. We assume that the pickup and delivery services from customers are requested simultaneously. There are 10 IoEVs available to pick up and deliver the first 6 customers simultaneously in Table 2. The IoEV starting nodes are {1, 2, 7, 12, 24, 21, 20, 18, 15, 22}. The charging nodes are

TABLE 3. Route solution and waiting time.

IoEV	Waiting time (h)	Route solutions
No. 1	0.1944	1-3-4-11-10-17
No. 2	0.6125	2-6-5-4-11-14-23-22
No. 3	0.2083	12-11-14-15
No. 4	0.1528	24-23-14-15-10-16
No. 5	0.8125	21-22-15-10-9-5-4-11-14
No. 6	0.3056	20-19-17-10

TABLE 4. Number of IoEVs for charge and the total profit.

Scenarios	133kW				200kW			
	C1	C2	C3	P($)	C1	C2	C3	P($)
A	25	-	-	140	50	-	-	280
B	-	32	-	179.2	-	54	-	302.4
C	-	-	33	184.8	-	-	55	308
D	25	11	1	207.2	50	11	1	347.2

{4, 5, 10, 14, 16, 19, 22}. The pickup and delivery nodes of customers are presented as pairs, where {4, 22} indicates that the customer should be picked up at node 4 and delivered to node 22. In this simulation, we set the initial battery level of each IoEV as 80%. The travel time is estimated according to the distance shown in Fig. 8. The maximum power is set as 133 KW and the time frame is set as 12 h, which is broken down into 720 min. The charging efficiency is set to be 100%. The routing simulation runs in a Matlab environment on a general computer.

The optimal solution of U1 is that IoEV 1 at node 1 serves the pickup and delivery {3, 17} of customer 1, IoEV 2 at node 2 serves the pickup and delivery {4, 22} of customer 2, IoEV 3 at node 12 serves the pickup and delivery {11, 15} of customer 5, IoEV 4 at node 24 serves the pickup and delivery {23, 16} of customer 4, IoEV 5 at node 21 serves the pickup and delivery {5, 14} of customer 3, and IoEV 6 at node 20 serves the pickup and delivery {19, 10} of customer 6. The route solutions and waiting time of customers are shown in Table 3. The total waiting time of customers to pick up is 2.2 hours. The state of charge (SOC) of IoEV 1 to IoEV 6 are {49.54%, 39.93%, 68.08%, 58.81%, 59.80%, 70.07%}. The starting points of IoEV 1 to IoEV 6 in next step are nodes {17, 22, 15, 16, 14, 10}.The optimal solution of U2 is that IoEV 1 at node 17 serves the pickup and delivery {12, 8} of customer 8, IoEV 2 at node 22 serves the pickup and delivery {6, 16} of customer 7, IoEV 3 at node 15 serves the pickup and delivery {21, 24} of customer 9, IoEV 4 at node 16 serves the pickup and delivery {12, 3} of customer 10, IoEV 5 at node 14 serves the pickup and delivery {23, 13} of customer 11, and IoEV 6 at node 10 serves the pickup and delivery {9, 2} of customer 12. The SOC of IoEV 1 to IoEV 6 are {28.35%, 31.65%, 62.12%, 50.53%, 51.19%, 56.16%}.

IoEVs that need to charge are out of routing service. They wait in the charging station to charge when there are 37 IoEVs. We decide when these IoEVs are charged under the constraint of power limit 133 kW and time limit 12 h. We consider three charging rate: fast charging 60 kW (C1-type), medium charging 6 kW (C2-type) and slow charging 3 kW

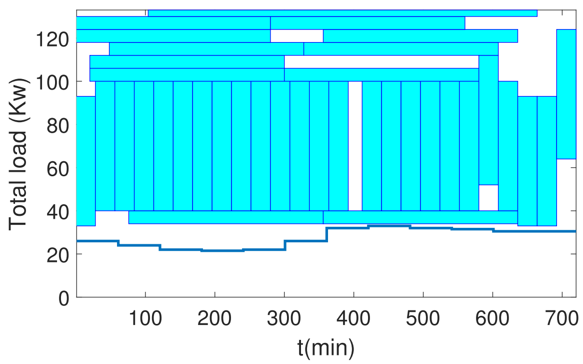

FIGURE 9. Rectangle charging for 37 IoEVs by 80% battery capacity.

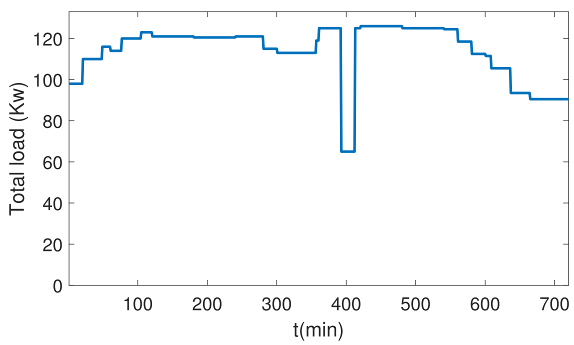

FIGURE 10. Rectangle charging for 37 IoEVs by 80% battery capacity.

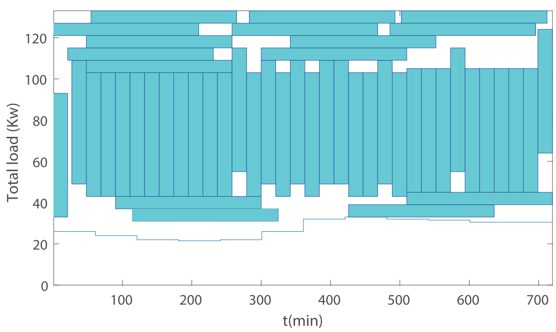

FIGURE 11. Rectangle charging for 49 IoEVs by 60% battery capacity.

(C3-type). When the SOC of IoEVs become lower than 20%, they are out of service and need to charge 80% of the battery capacity. We adopt the base load profile in South California Edsion of 12 hours from [35], which shown as the blue line in Fig. 9.

We evaluate the performance of ERC algorithm by using practical data and compare it with two benchmark algorithms as follows,

1) Lowest-level left align best fit (LLABF) algorithm [36]: LLABF algorithm considers the width-fit first rule and Height-fit first rule.

2) Bottom left fill (BLF) algorithm [37]: First, BLF places the energy block at the top-right corner and move this block to the bottom. Then BLF moves this block to the the far left and iterates until the boundary constraint is not satisfied.

TABLE 5. Performance comparison of three algorithms.

Algorithm	ERC	LLABF	BLF
Capacity (80%)	85.65%	66.35%	76.88%
Capacity (60%)	85.21%	64.16%	80.90%

The rectangle packing problem for IoEV charging dispatch is simulated in Gurobi 9.0 [38] and the result is shown in Fig. 9 and the total load is shown in Fig. 10. The left-bottom corner of each rectangle shows the optimal IoEV charging time in Fig. 9. There are 25 C1-type, 11 C2-type and 1 C3-type energy blocks. The running time for rectangle packing problem of IoEV charging dispatch is 43.67 s. We can see that the coverage ratio of available IoEV charging energy block is 85.65% from Fig. 10, where the coverage ratio is the rate of the available IoEV charging energy block to the total energy block. If IoEVs are charged by 60% of the battery capacity, the running time for rectangle packing problem of IoEV charging dispatch is 13.39 s. There are 34 C1-type and 15 C2-type energy blocks. The scheduling result for 49 IoEVs by 60% battery capacity is shown in Fig. 11 and the coverage ratio of available IoEV charging energy block is 85.21%. If we charge less, we can arrange more IoEVs to satisfy the energy limits from power grid. We need to change the planned number of IoEVs when the charging amount of IoEVs out of routing service is changed.

We set the electricity price for sale as a constant 0.2$/kWh, then the result of four charging scenarios for two power limits 133kW and 200kW are shown in Table 4. Scenario 'A' (only C1) allows the fast charging rate, scenario 'B' (only C2) allows the medium charging rate, scenario 'C' (only C3) allows the slow charging rate and scenario 'D' allows the mixed kinds of charging rates. The simulation results show that coordinating three types of charging rates can achieve the optimal charging dispatch. The optimal solution of scenario 'D' increases by 32.43%, 13.51%, 10.81% for the case where the power limit is 133 kWh and increases by 19.35%, 12.90%, 11.29% for the case where the power limit is 200 kWh, compared with that in scenario 'A', 'B', and 'C'.

For the coverage ratio of the total energy block, we compare the performance of our ERC algorithm with that of LLABF and BLF algorithms in two scenarios, which is shown in Table 5. We can see that in the scenario where EVs need to charge up to 80% of the battery capacity, the coverage ratio of the total energy block of our ERC algorithm is 85.65%. In this scenario, the coverage ratio of the total energy block of LLABF and BLF algorithm are 66.35% and 76.88%, which is 22.53% and 10.24% lower than ERC algorithm. In the scenario where EVs need to charge up to 60% of the battery capacity, the coverage ratio of the total energy block of our ERC algorithm is 85.21%. In this scenario, the coverage ratio of the total energy block of LLABF and BLF algorithm are 64.16% and 80.90%, which is 24.70% and 5.06% lower than ERC algorithm. We can see that ERC algorithm has the better performance than LLABF and BLF algorithms. Our ERC algorithm has the largest coverage ratio of the total energy block with power limits.

VI. CONCLUSION

In this work, we propose a clustered rolling framework for optimal routing and charging of IoEVs. We take the waiting time of customers and power limit of power grid into consideration. First, we divide the map into many regions by clustering method and propose a clustered rolling framework to formulate a pickup and delivery problem for customers with limited capacity of IoEV battery in a smaller region. We set the criterion to judge whether IoEVs are available to support the pickup and delivery service and IoEVs need to be charged when IoEVs are at low battery level. For the idle IoEVs, we formulate a rectangle packing problem for IoEV charging dispatch in a fixed time frame with the power upper bound to satisfy the energy limits of power grid. Finally, simulation results show that The optimal solution of scenario 'D' increases by 32.43%, 13.51%, 10.81% for the case where the power limit is 133 kWh and increases by 19.35%, 12.90%, 11.29% for the case where the power limit is 200 kWh, compared with that in scenario 'A', 'B', and 'C'. In this scenario, the coverage ratio of the total energy block of LLABF and BLF algorithm are 66.35% and 76.88%, which is 22.53% and 10.24% lower than ERC algorithm. IoEVs can offer the pickup and delivery service to customers with the minimum waiting time and available IoEV charging energy block has a good coverage ratio of the total energy block with power limits.

REFERENCES

[1] Y. Li, R. Kaewpuang, P. Wang, D. Niyato, and Z. Han, "An energy efficient solution: Integrating plug-in hybrid electric vehicle in smart grid with renewable energy," in *Proc. IEEE INFOCOM Workshops*, Orlando, FL, USA, May 2012, pp. 73–78.

[2] L. U. Khan, Y. K. Tun, M. Alsenwi, M. Imran, Z. Han, and C. S. Hong, "A dispersed federated learning framework for 6G-enabled autonomous driving cars," *IEEE Trans. Netw. Sci. Eng.*, early access, Jul. 15, 2022, doi: 10.1109/TNSE.2022.3188571.

[3] W. Wei, L. Wu, J. Wang, and S. Mei, "Expansion planning of urban electrified transportation networks: A mixed-integer convex programming approach," *IEEE Trans. Transport. Electrific.*, vol. 3, no. 1, pp. 210–224, Mar. 2017.

[4] L. Zhu, F. R. Yu, Y. Wang, B. Ning, and T. Tang, "Big data analytics in intelligent transportation systems: A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 1, pp. 383–398, Jan. 2019.

[5] T. Chen, B. Zhang, H. Pourbabak, A. Kavousi-Fard, and W. Su, "Optimal routing and charging of an electric vehicle fleet for high-efficiency dynamic transit systems," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 3563–3572, Jul. 2018.

[6] H. Wang, G. Zhou, R. Xue, Y. Lu, and J. A. McCann, "A driving-behavior-based SoC prediction method for light urban vehicles powered by supercapacitors," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 5, pp. 2090–2099, May 2020.

[7] C. Sun, S. J. Moura, X. Hu, J. K. Hedrick, and F. Sun, "Dynamic traffic feedback data enabled energy management in plug-in hybrid electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 3, pp. 1075–1086, May 2015.

[8] A. Y. S. Lam, J. J. Q. Yu, Y. Hou, and V. O. K. Li, "Coordinated autonomous vehicle parking for vehicle-to-grid services: Formulation and distributed algorithm," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 4356–4366, Sep. 2018.

[9] Y. Cao, D. Li, Y. Zhang, and X. Chen, "Joint optimization of delay-tolerant autonomous electric vehicles charge scheduling and station battery degradation," *IEEE Internet Things J.*, vol. 7, no. 9, pp. 8590–8599, Sep. 2020.

[10] D. Niyato, D. T. Hoang, P. Wang, and Z. Han, "Cyber insurance for plug-in electric vehicle charging in vehicle-to-grid systems," *IEEE Netw.*, vol. 31, no. 2, pp. 38–46, Mar./Apr. 2017.

[11] T. G. Jiang, H. Fang, and H. Wang, "Blockchain-based internet of vehicles: Distributed network architecture and performance analysis," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4640–4649, Jun. 2019.

[12] H. Xu, X. Zhou, and Z. Han, *Stackelberg Differ. Game Based Charging Control Electric Vehicles Smart Grid*, 01 2019, pp. 203–213.

[13] J. Wang, Y. Zhou, Y. Wang, J. Zhang, C. L. P. Chen, and Z. Zheng, "Multiobjective vehicle routing problems with simultaneous delivery and pickup and time windows: Formulation, instances, and algorithms," *IEEE Trans. Cybern.*, vol. 46, no. 3, pp. 582–594, Mar. 2016.

[14] T. Nishi, S. Akiyama, T. Higashi, and K. Kumagai, "Cell-based local search heuristics for guide path design of automated guided vehicle systems with dynamic multicommodity flow," *IEEE Trans. Autom. Sci. Eng.*, vol. 17, no. 2, pp. 966–980, Apr. 2020.

[15] Y. Zhou, L. Kong, Y. Cai, Z. Wu, S. Liu, J. Hong, and K. Wu, "A decomposition-based local search for large-scale many-objective vehicle routing problems with simultaneous delivery and pickup and time windows," *IEEE Syst. J.*, vol. 14, no. 4, pp. 5253–5264, Dec. 2020.

[16] H. Huang, S. Yang, X. Li, and Z. Hao, "An embedded Hamiltonian graph-guided heuristic algorithm for two-echelon vehicle routing problem," *IEEE Trans. Cybern.*, vol. 52, no. 7, pp. 5695–5707, Jul. 2022.

[17] J. Jin and Y. Xu, "Shortest path based deep reinforcement learning for EV charging routing under stochastic traffic condition and electricity prices," *IEEE Internet Things J.*, early access, Jun. 9, 2022, doi: 10.1109/JIOT.2022.3181613.

[18] F. Dubois, P. Renaud-Goud, and P. Stolf, "Capacitated vehicle routing problem under deadlines: An application to flooding crisis," *IEEE Access*, vol. 10, pp. 45629–45642, 2022.

[19] T. Zhang, W. Chen, Z. Han, and Z. Cao, "Charging scheduling of electric vehicles with local renewable energy under uncertain electric vehicle arrival and grid power price," *IEEE Trans. Veh. Technol.*, vol. 63, no. 6, pp. 2600–2612, Jul. 2014.

[20] Y. Yu, T. Song, C. Su, X. Tang, and Z. Han, "Hierarchical game for electric vehicle public charging market," in *Proc. IEEE Int. Conf. Commun., Control, Comput. Technol. Smart Grids (SmartGridComm)*, Beijing, China, Oct. 2019, pp. 1–6.

[21] Y. Yu, C. Su, X. Tang, B. Kim, T. Song, and Z. Han, "Hierarchical game for networked electric vehicle public charging under time-based billing model," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 1, pp. 518–530, Jan. 2021.

[22] E. ElGhanam, H. Sharf, Y. Odeh, M. S. Hassan, and A. H. Osman, "On the coordination of charging demand of electric vehicles in a network of dynamic wireless charging systems," *IEEE Access*, vol. 10, pp. 62879–62892, 2022.

[23] V. T. Tran, M. R. Islam, K. M. Muttaqi, and D. Sutanto, "An efficient energy management approach for a solar-powered EV battery charging facility to support distribution grids," *IEEE Trans. Ind. Appl.*, vol. 55, no. 6, pp. 6517–6526, Nov./Dec. 2019.

[24] G. Binetti, A. Davoudi, D. Naso, B. Turchiano, and F. L. Lewis, "Scalable real-time electric vehicles charging with discrete charging rates," *IEEE Trans. Smart Grid*, vol. 6, no. 5, pp. 2211–2220, Sep. 2015.

[25] M. H. Mobarak and J. Bauman, "Vehicle-directed smart charging strategies to mitigate the effect of long-range EV charging on distribution transformer aging," *IEEE Trans. Transport. Electrific.*, vol. 5, no. 4, pp. 1097–1111, Dec. 2019.

[26] T. Ding, J. Bai, P. Du, B. Qin, F. Li, J. Ma, and Z. Dong, "Rectangle packing problem for battery charging dispatch considering uninterrupted discrete charging rate," *IEEE Trans. Power Syst.*, vol. 34, no. 3, pp. 2472–2475, May 2019.

[27] X. Zuo, Y. Xiao, C. Zhu, and M. You, "A linear MIP model for the electric vehicle routing problem with time windows considering linear charging," in *Proc. Annu. Rel. Maintainability Symp. (RAMS)*, Reno, NV, USA, Jan. 2018, pp. 1–5.

[28] A. Montoya, C. Guéret, J. E. Mendoza, and J. G. Villegas, "The electric vehicle routing problem with nonlinear charging function," *Transp. Res. B, Methodol.*, vol. 103, pp. 87–110, Sep. 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0191261516304556

[29] C. Yao, S. Chen, and Z. Yang, "Online distributed routing problem of electric vehicles," *IEEE Trans. Intell. Transp. Syst.*, early access, Feb. 14, 2022, doi: 10.1109/TITS.2022.3149942.

[30] L. Fan, J. Wang, R. Jiang, and Y. Guan, "Min-max regret bidding strategy for thermal generator considering price uncertainty," *IEEE Trans. Power Syst.*, vol. 29, no. 5, pp. 2169–2179, Sep. 2014.

[31] L. Liang, Y. Yang, H. Wang, L. Huang, and X. Zhang, "Traffic impedance estimation driven by trajectories for urban roads," in *Proc. 3rd Int. Conf. Vis., Image Signal Process. (ICVISP)*. New York, NY, USA: Association for Computing Machinery, Aug. 2019, pp. 1–7, doi: 10.1145/3387168.3387209.

[32] S. Boyd, S. P. Boyd, and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[33] Jianghuai iEV7L. *Product Configuration Sheet*. Accessed: Jun. 1, 2022. [Online]. Available: http://wap.jac.com.cn/iev7/6066.htm

[34] Department for Transport. *Vehicle Counts Recorded on Major and Minor Roads*. Accessed: May 20, 2022. [Online]. Available: https://roadtraffic.dft.gov.uk/downloads

[35] A. C. Melhorn, K. McKenna, A. Keane, D. Flynn, and A. Dimitrovski, "Autonomous plug and play electric vehicle charging scenarios including reactive power provision: A probabilistic load flow analysis," *IET Gener., Transmiss. Distrib.*, vol. 11, no. 3, pp. 768–775, Feb. 2017.

[36] X. B. Jiang, X. Q. Lv, and C. C. Liu, "Lowest-level left align best-fit algorithm for the 2D rectangular strip packing problem," *J. Softw.*, vol. 20, no. 6, pp. 1528–1538, 2009.

[37] K. Daoden and T. Thaiupathump, "Applying shuffled frog leaping algorithm and bottom left fill algorithm in rectangular packing problem," in *Proc. 7th IEEE Int. Conf. Electron. Inf. Emergency Commun. (ICEIEC)*, Jul. 2017, pp. 136–139.

[38] Gurobi Optimization. (2020). *Gurobi Optimizer Reference Manual*. [Online]. Available: http://www.gurobi.com

YONGSHENG CAO received the Ph.D. degree in electronic information engineering from Donghua University, Shanghai, China, in 2021. He was a Visiting Ph.D. Student with the Department of Electrical and Computer Engineering, University of Houston, in 2020. He is currently with the Department of Information Science and Technology, School of Criminal Justice, East China University of Political Science and Law, Shanghai, China. His research interests include energy management and information safety about smart grid and road networks, the Internet of Things, network optimization, and digital forensic.