Joint Route Selection and Charging Discharging Scheduling of EVs in V2G Energy Network

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Abstract—Thanks to the advantages of zero carbon dioxide emissions and low operation cost, the number of on-road electric vehicles (EVs) is expected to keep increasing. They usually get charged through charging stations powered by either the grid or renewable plants. Due to the potential difference in electricity price between the grid and the renewable plants, an EV may purchase electricity at charging stations powered by renewable plants, and then discharge the surplus energy in the battery to the grid, to gain profits and enhance the overall renewable energy utilization. In this work, we aim to optimize the route selection and charging/discharging scheduling to improve the overall economic profits of EVs, taking into account the constraints, including the time-varying energy supply caused by the intermittent generation of renewable energy, the limited number of charging piles in a charging station, and the traveling delay tolerance of EVs. Firstly, a time-expanded vehicle-to-grid graph is designed to model the objective and related constraints. Then, we apply an AI-based A* algorithm to find K-shortest paths for each EV. Finally, a joint routing selection and charging/discharging algorithm, namely, K-Shortest-Paths-Joint-Routing-Scheduling (KSP-JRS), is proposed to minimize the total cost of EVs by maximizing their revenue from energy discharging under time constraints. The proposed approach is evaluated using the real traffic map around Santa Clara, California. The simulation, with different numbers of testing EVs, shows the feasibility and superiority of the proposed algorithm.

Index Terms—Vehicle-to-grid, renewable energy, route selection, charging/discharging, vehicular energy network.

I. INTRODUCTION

COUNTLESS vehicles powered by the fossil fuel are continuously releasing greenhouse gases, causing environmental pollution and climate change in this century. According to statistics, oil demands will continue to rise by 54% by 2035. In order to cope with the pollution and exhausting of the fossil fuel, clean energies, including electricity, have received great supports from governments recently. A large number of charging stations are built in cities to stimulate the utilization of EVs [1]. However, with the rising number of EVs, high penetration levels of EVs may cause the risk of overload of the grid [2], [3].

Vehicle-to-grid (V2G) [4], [5] technology is proposed to utilize the two-way energy transmission between a charging station and an EV, where the EV can offload its surplus energy to the grid. Thus, EVs which carry batteries with high storage capacity can be regarded as energy transporters in the city, and help alleviate the energy shortage at peak hours in the power grid. Like charging, however, discharging of a large number of EVs to the power grid can also bring challenges in terms of load stability and energy supply quality since unmanaged and self-determined EV discharging can cause burst power injections, overloads, and voltage fluctuations [6].

New technologies have enabled efficiency improvement in generating electricity from renewable sources, such as wind power and solar power. By 2018, renewable energy consumption had accounted for 26% of world energy consumption [7]. In some cities, both types of charging stations powered by the renewables or the grid are built. Energy plants powered by renewable energy have demonstrated better economical efficiency on account of the integration of renewable energy with traditional grids. Generally, EVs can enjoy less cost for charging at charging stations powered by renewable energy than those powered by the traditional grid [8]. Therefore, EVs can trade energy for profit in stations powered by the traditional grid because of the price difference. However, the electricity price can vary [9] from place to place, which needs to be taken into consideration. Moreover, with the continuous advancement of charging technology, the time spent on charging and discharging is dropping. Thus, the time cost of charging is outweighed by the revenue that users get from trading electricity.

Although the problem of minimizing the travel cost for EVs has been discussed in many previous works, such as minimizing the distance traveled or joint routing and charging optimization [10], [11], they fail to consider the discharging ability of EVs [4] which can bring profit. Some work utilizes discharging behaviors of EVs, however, only at fixed locations [6] and ignoring waiting queue at stations [12]. Ref. [13] uses HMM (Hidden-Markov-Model) to model queueing delays at stations without taking the competition between scheduled EVs into

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account, which makes the method not practical. Furthermore, this scenario is not similar to those on charger deployment of wireless rechargeable networks with mobility consideration, since the location of stations is arbitrarily given and the decision variables are EV route selection and charging/discharging scheduling.

In this paper, we consider a vehicular energy network consisting of two types of charging stations located at some key traffic intersections in the urban area, i.e., charging stations powered by renewable energy (denoted as R), and those powered by the traditional grid (denoted as G). EVs inside the network can be charged at R-type stations and sell residual energy to G-type stations, so as to earn revenue. The goal is achieved by choosing optimal routes and making optimal charging/discharging decisions at each R-type/G-type station (e.g., waiting, charging, discharging, passing) for EVs, under the constraints of time-varying power supply, charging space availability, as well as the individual delay tolerance. The contributions of this paper are mainly three-fold:

1) To our best knowledge, this is the first work that jointly optimizes EVs' path selections and charging/discharging decisions considering both renewable and grid stations with limited charging spaces and supplied power. We aim to minimize the total cost of EVs by maximizing the revenue of them while satisfying the restrictions on their traveling time.

2) We first model the system using a time-expanded V2G graph. A number of practical factors, such as travel time constraints, limited spaces at charging stations, time-varying energy supplies, detours and waiting behaviors of EVs are captured in this time-expanded graph. Next, the large-scale nonlinear mixed integer programming problem originated from the constraints is solved by two steps based on new decision variables we designed. The first step is to find the possible routes for each EV, then the second step is to minimize the cost of all EVs based on the possible routes.

3) To calculate routes more efficiently, we use the artificial intelligence-based A* algorithm to solve the first sub-problem, and then apply the integer linear programming on the second sub-problem. We design an algorithm that can automatically decide the manual parameter K, to decrease computational cost. We evaluate the proposed algorithm based on the urban traffic map of Santa Clara, California, to demonstrate the actual performance of our algorithm.

The remainder of the paper is organized as follows: In Section II, we review the related work. System model and problem formulation are presented in Section III. The KSP-JRS solution is proposed in Section IV. Then, in Section V, simulations are concluded on the urban traffic map of Santa Clara, California to evaluate the performance. Finally, Section VI concludes this work.

II. RELATED WORK

Optimal routing and charging of vehicles has been studied in many literatures [14]. Reference [15] aims to determine the best route from the start point to the destination for each EV to satisfy the welfare of passengers (in terms of travel time and distance), while maximizing the energy efficiency (by reducing charging cost), subject to some constraints (e.g., charging station availability). The problem is solved as a mixed-integer quadratically constrained programming problem. In another literature [11], an en-route charging navigation resorting to a joint charging and routing optimization is considered, which is different from traditional route planning work tending to find a shortest path. From another aspect, price control is used to motivate drivers to follow the coordination of the charging scheduling [16]. In [17], charging decisions are made according to the current information in the grid.

Above works only consider the one-way charging from stations to vehicles. As the vehicle-to-grid technology has enabled energy transfer from vehicles to the grid, the energy flow is becoming bidirectional. Together with the advancing of the vehicle-to-vehicle energy exchange, a concept called vehicular energy network (VEN) is proposed in [18] to improve the efficiency of the energy delivery system. A more extensive work considers vehicle-to-home, vehicle-to-vehicle and vehicle-to-grid is further discussed in [19]. Since EVs have energy storage and controllable loads, they can discharge to the grid to help smooth the fluctuations [20]. In [21], authors aim to schedule the elastic load in the time domain, such as EVs, to minimize the power fluctuation in the power grid. By exploiting both spatial and temporal coordinations, the authors present an online EV charging/discharging strategy considering range anxieties [3]. A complete solution methodology to multi-EVs pick up and delivery routing problem that considers G2V charging and V2G discharging has been discussed in [13].

As EVs can discharge electricity to the grid, they have been employed as means of energy transporting in some works, especially for charging stations enabled with renewable energy harvesting capabilities, in order to improve the utilization of renewable energy [22]. The work focuses on maximizing energy delivery efficiency, and model the energy route problem as network flow, as well as solving it using the bipartite graph. Wang *et al.* propose a blockchain based secure incentive scheme for energy delivery in VEN. To improve the efficiency of energy transmission, it may also apply a store-n-forward strategy, such as an intermediate energy storage or throwbox [23]. Under the uncertainty of EV arrivals rate, electricity prices and renewable energy supply, the authors propose an Lyapunov optimization-based online algorithm to fulfill the charging demands of EVs with the minimal purchase of energy from the grid [24]. Li *et al.* aim to maximize the overall EV charging energy in a power distribution system, given the voltage drop and maximum charging power constraint. The routing problem for EV charging coordination among charging stations is also considered under the EV range of anxiety constraints [25].

There are few works that have considered the scenario where EVs can sell their additional energy for profit [26]. V2V trading is one of them and assures that an EV can trade energy with another EV efficiently [27]. To trustfully find a potential trading partner, the scheme in [28] can be adopted. In [29], authors utilize EVs on the road to advertise EV charging station. The objective
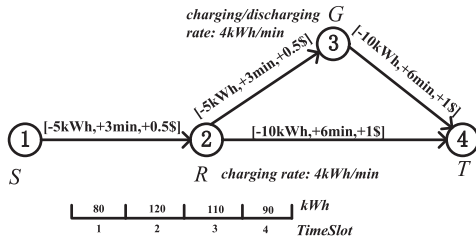
Fig. 1. An illustration of the V2G network for EVs.

is to maximize the profit of recruited EV and charging stations. There is an interesting work [30], which uses user owned EV to charge at work and then compensate to the household usage according to the time-based electricity pricing where the price is predetermined. This only reduces the energy cost of the user himself.

The major difference between this paper and existing works is that we consider two types of charging stations and aim to maximize revenue of EVs by selling redundant energy purchased at renewable charging stations to the grid. The action is optimized by choosing optimal routes and making optimal decisions at each station under practical constraints.

III. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, a simple example is used to illustrate two problems the paper aims to solve. As shown in Fig. 1, each node represents a charging station. There is an EV which travels from node 1 to node 4 and the maximal traveling time allowance is 30 minutes. We set a weighted vector on each directed edge to indicate cost (energy cost, time cost, economic cost) of an EV passing through this road segment. In this example, both charging rate and discharging rate are 4 kWh/min. Charging fee in node 2 is 0.1 $/kWh, and selling price in node 3 is 0.25 $/kWh. The maximum power supply of the charging station fluctuates with time due to the uncertainty of renewable energy. E.g., node 2 can provide (80, 120, 110, 90) kWh energy in time slot (1, 2, 3, 4) respectively. If the car chooses the shortest path, the route is [1,2,4]. Then, this journey will cost 1.5$ and 9 minutes. If this EV chooses another route, it spends 14.4$ (12 kWh/min · 12 min · 0.1 $/kWh) and 12 minutes on charging at node 2 and then spends 6 minutes on selling part of its own energy at node 3 to earn 18$ (12 kWh/min × 6 min × 0.25 $/kWh). Finally it reaches the destination (node 4). The economic cost of this route is −1.6$ (0.5$ + 0.5$ + 1$ + 14.4$ − 18$), and the EV is still able to arrive at the destination within 30 minutes. Comparing these two driving schemes, we find that only considering the shortest path for EVs in V2G network is not the optimal choice, especially when those EVs have sufficient travel time. EVs can purchase cheap electricity at R-type charging stations and sell some at G-type charging stations to earn profit, which can effectively reduce the final travel cost.

A. System Model

As illustrated above, we consider a set of EVs traveling from one location to another in the city, they will go through

a few charging stations, in which some are powered by renewable energy, the others are connected with the grid. Along the journey, each EV may choose when, where and how much to charge/discharge from/to charging stations. Electricity from renewable sources is cheaper because it costs less to produce, whereas electricity from the grid is more expensive. EVs can earn money by buying some electricity at renewable charging stations and selling it to the grid. The price of selling one unit of power to grid is lower than buying one unit of power from the grid. Nowadays, vehicles are not only transportation means, the connected vehicle paradigm is to empower vehicles to be communication and computation means [31]. Therefore, they definitely have some spare time during their trips. The purpose of our paper is to find a strategy that minimizes the total cost of EVs by maximizing the sum of revenue of all EVs and ensure that each EV reaches its destination within its maximum tolerance time.

Before starting to solve this problem, we define some objects in the proposed V2G traffic network.

Charging Station: It can be divided into two types, one powered by renewable energy (denoted as R-type), and others connected to the traditional grid (denoted as G-type). EVs can purchase electricity either from R-type or G-type, but can only sell electricity to G-type. Therefore, there are three kinds of behaviors at charging stations, i.e., charging at R-type, charging at G-type and discharging at G-type. EVs can also choose not to stay at the charging station, which is represent by passing through waiting node of the charging station.

Charging Space: Each charging station i is accompanied by a fixed number of charing spaces, denoted by $Park^i$. When the number of EVs arriving at the charging station exceeds the upper limitation of parking spaces, some late arrival vehicles have to wait outside until there are parking spaces available.

Power Supply: The amount of electricity supplied by the charging station varies with time. We denote the maximum electricity supplied by station i in the j time slot by Pow_j^i. One of the reasons is that the source of the renewable energy station itself is unstable, and because of the high and low peaks of traffic in the city, the inventory power of the power station will have obvious fluctuations.

Waiting Queue: If the charging station does not have enough space or sufficient power in a period of time, some EVs may be scheduled to wait outside or detour based on the calculated decision. The waiting process do not increase economic costs but time. In order to simplify the problem, we do not limit the size of the waiting queue, because in this scenario, the problem also concerns delay tolerance and the algorithms consider load balancing of all charging stations. Therefore, the vehicle will not stay in the waiting queue indefinitely unless the power supply load of city grid reaches the upper limitation.

EV: The vehicle car has an upper limit for energy storage, and has initial energy E_{init}^{car} at the beginning, and each vehicle has the maximum tolerated travel time $Delay_{max}^{car}$. In this paper, the charging rate of EVs at the charging station is fixed, donated as Pow^{car}, where subscript car represents different EV.

Start point and destination: We denote the starting point and destination by $Start$ and T. EVs can buy and sell power at $Start$ and T, if they are charging stations.
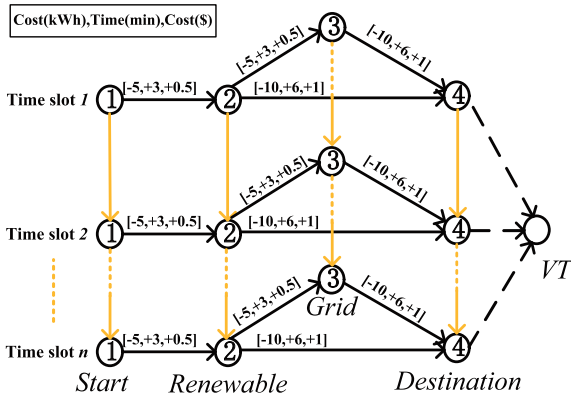
Fig. 2. An illustration of the time-expanded V2G network that is generated by the time expansion of Fig. 1. Each row of nodes is a different instance of the network at different time slots. *Start* and *VT* are starting node and virtual destination of an EV, respectively. *Renewable* and *Grid* represent renewable charging stations and grid charging stations, respectively.

Road: When an EV is running on the road, it consumes power and accumulates the traveling time. Without loss of generality, we assume the road is one-way only. After an EV leaves one station, it will not be able to find a path back to this point, so the road map is loop-free. We use a weighted vector $[Cost_{energy}, Cost_t, Cost_{dollar}]$ with three elements to describe the EV's energy loss, time-consumption, and profit changes on this road.

According to the above definition, we are going to abstract the problem into a graph problem. Since the number of available charging slots and the available energy of the power station are related to time, we must expand the time in the static image to establish a time-expanded graph.

B. Time Expanded V2G Network

Considering a large number of EVs in a city which have different start points and destinations, we want to optimize their travel expenses, by developing a joint optimized travel plan for them. Since the routing decisions of the EVs cross over a period of time, we need to expand the static network topology into a time expanded graph. In Fig. 2, we create an instance of the expanded network graph on each time slot from Fig. 1. $node_i$ is expanded into a vector $[node_i^1, node_i^2, \ldots, node_i^n]$. Superscripts and subscripts represent different time slots and node name, respectively. Each time slot is 3 minutes. The yellow vertical directional edge presents duration of an EV staying at the charging station. VT is a virtual node which is created to facilitate the operation of the algorithm. Here we can find several edges between node 4 and VT because node 4 is the actual destination for an EV. If another EV wants to go to node 3 as destination, there will be several edges from 3 to VT instead. So the time-expanded graph can be used for represent multiple pairs of start nodes and destinations.

In Fig. 2, we finally build the time-expanded network based on the previously mentioned definition. Yellow directed edges represent EVs staying at the station for one time slot. For each edge, we use a weighted vector to describe the loss of
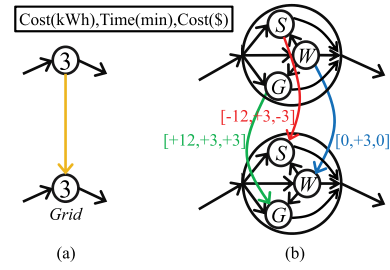

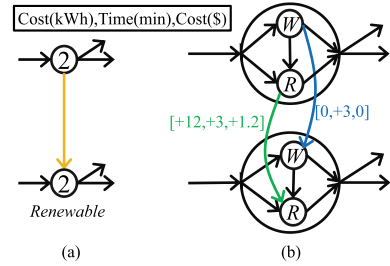Fig. 3. The node expansion of charging station powered by traditional power grid.

Fig. 4. The node expansion of charging station powered by renewable energy.

energy, time and money, i.e. $[Cost_{energy}, Cost_t, Cost_{dollar}]$. Their values are fixed numbers. Here we use a simple example to illustrate how an electric car can reduce traveling cost by selling energy. If absolute energy loss of passing through an edge is greater than the remaining energy of the EV, the EV will not choose to pass through this edge.

In fact, the EV does not necessarily get charged when it passes a charging station. It may be waiting or selling energy, so the yellow directed edges in Fig. 2 represent the merger of the three behaviors (charging, selling, waiting). The behavior of detouring is represented by passing through node W. The detailed explanation of the yellow line is shown in Fig. 3 and Fig. 4.

Fig. 3(a) is a part taken from time-expanded graph Fig. 2. Fig. 3(b) is a more specific model display of Fig. 3(a). In Fig. 3(b), we can extend a grid station node into three node instances namely S(selling), W(waiting) and G(charging). When an EV enters a grid charging station, if there are charging piles available, the EV will enter the child node S or G. The green edge and red edge in Fig. 3(b) represent that an EV is charging or selling energy in the time slot, respectively. An EV sells redundant electricity to the grid at charging station 3 between the time slot 2 and the time slot 3. This EV will earn 3 dollars, consume 12 kWh energy and 3 minutes. On the other hand, if there is no charging pile available, the EV will wait at child node W along the blue directed edge in Fig. 3(b) until there are idle charging piles available, then it enters the G or S from W. Similarly, the behaviors of EVs in renewable stations can be extended into two sub-nodes named W(waiting) and R(charging). In Fig. 4(b), the green edge and blue edge mean that an EV is charging energy or waiting, respectively. By

TABLE I
USEFUL NOTATIONS

Variables	Description
V	The set of all cars
Z	The set of all nodes in the time-expanded graph
H	The set of all directed edges between different time instances of charging stations in the time-expanded graph $H \in Z$
$Start$	The start node of one EV
VT	Virtual destination node of the time-expanded graph of one EV
ω_e	Economic cost of passing through edge e
x_e^{car}	The 0/1 variable that indicates whether an EV named car passes edge e
$in(j)$	The set of incoming edges of the node j
$out(j)$	The set of outcoming edges of the node j
y_i^{car}	The current remaining power when the EV named car travels to node i
$Elec_e$	The energy cost of passing through edge e
$Park_{max}^e$	The maximum number of charging piles of the charging station to which the edge e linked
Pow_{charge}^{car}	The charging rate of an EV named car
$Pow_{discharge}^{car}$	The discharging rate of an EV named car
Pow_{supply}^e	The maximum power supply of charging stations to which the edge e linked
Pow_{cap}^e	The maximum power capacity of charging stations to which the edge e linked
E_{car}^{max}	The maximum battery capacity of an EV named car
w_i	Economic cost of path i
r_i^{car}	The 0/1 variable that indicates whether EV named car select route i
A_{car}	The route set of an EV named car.
$R(e)$	The route set that each route includes edge e.
E	The set of all edges the in time-expanded graph.
t^{car_i}, n^{car_i}	t^{car_i} and n^{car_i} are actual travel time and maximum tolerance time of car_i, respectively.

establishing such a time-expanded graph, the dynamics of the entire network graph are accurately represented.

C. Problem Formulation

Given the time expanded V2G network graph, our objective is to find a global route scheduling and charging/discharging decisions for a set of EVs to minimize the total cost by trading electricity. The objective subjects to charging space constraints and energy supply constraints. For each selected route of any EV, its traveling time should be within the tolerance time. The variables used in this paper is shown in the Table I. Here we describe the objective function as shown in Eq. (1):

Min:

$$\sum_{car \in Z} \sum_{e \in E} \omega_e \cdot x_e^{car} \qquad (1)$$

where x_e^{car} indicates whether an edge e in the network is selected for an EV's route. $x_e^{car} \in \{0, 1\}$. ω_e represents the economic cost when an EV (car) passes through edge e along its route. This objective function is constrained by the following equations.

Route Continuity

For route continuity, the in-degree is equal to the out-degree in intermediate nodes. This concept of routing is very common

in the graph theory.

$$\sum_{e \in in(j)} x_e^{car} - \sum_{e' \in out(j)} x_{e'}^{car} = \begin{cases} -1 & j = Start \\ 0 & \forall j \in \{Z \backslash Start, VT\} \\ 1 & j = VT \end{cases} \qquad (2)$$

where $in(j)$ and $out(j)$ are in-degree road set and out-degree road set, respectively. The in-degree of node VT in the route is one more than its out-degree. Similarly, the out-degree of node VS in the route is one more than its in-degree.

Conservation of Energy

To describe the transmission of energy in the time-expanded graph, we denote y_j^{car} as the remaining power when the car arrives at node j. i is one of the parent nodes connected to j. The remaining energy of an EV at node j is equal to the remaining energy when the EV is at parent node i (i.e. y_i^{car}) plus the energy consumption $Elec_e$ which can be negative or positive. Equation (3) describes how the carried electricity changes when an EV leaves node i for j,

$$\sum_{e \in in(j)} y_i^{car} \cdot x_e^{car} + \sum_{e \in in(j)} Elec_e \cdot x_e^{car} = y_j^{car} \qquad (3)$$

where x_e^{car} denotes whether or not we choose edge e for the car, which has an integer value of 0 or 1.

We can only select one road e to pass between node i and j, therefore, we introduce the following Equation (4) to represent this constraint.

$$\sum_{e \in in(j)} x_e^{car} = 1 \qquad (4)$$

where $in(j)$ is in-degree node set of j. We notice that there are two variables multiplied by the other in Equation (3), i.e. x_e^{car} and y_i^{car}, which makes the constraints nonlinear and tricky to be solved by using the general solver.

Routing Feasibility

$$\sum_{car \in V} x_e^{car} \leq Park_{max}^e \quad \forall e \in H \qquad (5)$$

$$\sum_{car \in V} Pow_{charge}^{car} \cdot x_e^{car} \leq Pow_{supply}^e \quad \forall e \in H \qquad (6)$$

$$\sum_{car \in V} Pow_{discharge}^{car} \cdot x_e^{car} \leq Pow_{cap}^e \quad \forall e \in H \qquad (7)$$

$$0 \leq y_i^{car} \leq E_{car}^{max} \quad \forall i \in Z \quad \forall car \in V \qquad (8)$$

$$x_e^{car} \in \{0, 1\} \quad \forall car \in V \qquad (9)$$

Time Constraint

$$t^{car_i} \leq n^{car_i}, size(E) \propto \max\{n^{car_1}, n^{car_2}, \dots, n^{car_h}\} \quad (10)$$

Here we define the upper and lower bounds of the variables in routes. Eq. (10) represents that the actual travel time t^{car} of the vehicle cannot exceed its maximum travel time n^{car}. The maximum tolerance travel time determines the maximum time slot and thus it determines the size of the time-expanded map. Equations (5) and (6) indicate charging space limitation

and the maximum energy supply between two adjacent time slots for each charging station. If a charging station does not have available charging space or energy in a period of time, which means the green edge is fully used, the proposed method will not schedule other EVs to stay at this charging station. Equation (7) represents that the power sold by EVs cannot exceed the capacity of the charging stations. Equation (8) describes carried electricity of each EV cannot be negative or greater than its storage. Equation (9) represents that each decision variable x_e^v is an integer variable. According to the above definition, the problem has been completely abstracted, we can find that this is an integer programming problem with quadratic constraints. The number of quadratic constraints is $Z * K * Cars$. This will cost a lot of time to calculate and even fail to find out the optimal solution even if the network scale is small.

Therefore, we try to change the way of the problem expression to find out a more suitable solution for this scene. In the following part, we are going to propose a two-step method to solve the joint optimal routing and charging/discharging problem.

IV. ROUTING CALCULATING AND JOINT ROUTE SCHEDULING

Considering again the formula description in the previous section, we find that the combination of formulas except Equation (3), actually describes the joint optimal shortest path problem in the acyclic network with negative weights and linear resource constraints (i.e. limited charging space and energy supply of charging station). Inspired by the idea of calculating co-flow in the data center network [32], we find that using the complete set of paths as candidate solution spaces can effectively solve joint routing scheduling and charging/discharging decision problem. Then, we can split the objective into two sub-problems, one for calculating K shortest path set with energy conservation and resource constraints, and the other for jointly solving optimal routing for multi-EVs. As Artificial Intelligence has been applied in many works [33], we also use it in calculating k-shortest path set in Section IV-A and integer programming for joint optimal routing selection in Section IV-B, respectively. Algorithm 3 provides a comprehensive overview of how the two algorithms work together. In order to decide suitable parameter K of the k-shortest path algorithm, we design a search algorithm Algorithm 4 that automatically determines the parameter K in Section IV-D.

Algorithm 3 solves routing selection and charging/discharging decision for each EV to maximize the overall revenue based on each *k-shortest* path set of every EV we calculated in Algorithm 1. Algorithm 3 first constructs a time-expanded graph to describe the entire scenario in line 1. Then, in line 3, the multiple constrained K-Shortest-Paths (*KSP*) problem combined Yen's algorithm (Algorithm 1) with A* algorithm (Algorithm 2) is solved. Next, a simple integer programming problem is going to be solved at line 6. Finally, the optimal joint route scheduling is accomplished. The full procedure is interpreted in Section IV-C.

Algorithm 1: K-Shortest Constrained Path Algorithm(KSP).

Input: Pow_{supply}^{car}, Pow_{cap}^{car} $Park_{\max}^e$, $Elec_e$, ω_e, $cars$ $number$, Map, $E_{initial}$, K, $Start$, $Destination$, $E_i^{\max}$.
Output: The K-shortest routes of an EV from the start node to destination.
1: Initial set A, B = $\emptyset$, $graph = Map$, l=1
2: Add the first shortest path calculated by A* algorithm to set A.
3: Reset the graph and copy $A[l]$ to $path$
4: **for** $l = 2 : k$ **do**
5:    **for** each node j in the route $path$ **do**
6:      $rootpath \leftarrow path(source, j)$
7:      **for** each $route$ in A **do**
8:        **if** $route(source, supr)==rootpath$ **then**
9:          delete $graph(j, j + 1)$
10:     $subpath \leftarrow$ A* search$(j, sink)$
11:     **if** $subpath$ meets the traveling time constraint and energy conservation **then**
12:        $sp \leftarrow rootpath + subpath$
13:     **else** break
14:     **if** sp does not exist in B **then**
15:        Add sp to B
16:     l_{th} route $\leftarrow minsort(B)$
17:     add l_{th} route to A
18:     $path \leftarrow A[l]$
19: **return** A

Algorithm 2: A* Search Algorithm (A*).

Input: *Map*, *Start*, *Destination*, **heuristic**.
Output: The shortest route of an EV from the start node to destination.
1: Initialize the vector **gscore** and **fscore** with default value of Infinity.
2: Put start node into **openset**.
3: Set **gscore**[$start$] and **fscore**[$start$] to zero.
4: **while** $openset$ is not empty **do**
5:    $current \leftarrow$ the node with lowest **fscore** value in **openset**.
6:    **if** $current == Destination$ **then**
7:      **return** shortest route
8:    remove the $currrent$ in **openset**
9:    **for** each $neighbor$ of $current$ **do**
10:     $tentativegscore \leftarrow$ **gscore**[$currentnode$] + distance(current, neighbor).
11:     **if** tentative gscore $<$ **gscore**[$neighbor$] **then**
12:       **gscore**[$neighbor$] $\leftarrow$ tentative **gscore**
13:       **fscore**[$neighbor$] $\leftarrow$ tentative **gscore** + **heuristic**[$neighbor$].
14:       **if** $neighbor$ is not in **openset** then
15:         Put $neighbor$ into **openset**
16: **return** the shortest route

Algorithm 3: K-Shortest Constrained Path - Joint Route Scheduling for Multi-EVs (KSP-JRS).

Input: Pow_{supply}^{car}, Pow_{cap}^{car} $Park_{max}^e$, $Elec_e$, ω_e, $cars$ $number$, Map, $E_{initial}$, K, $Start$, $Destination$, E_i^{max}.

Output: Route set of all EVs with total cost.

1: Build the time-expanded graph $Graph$ based on the road map.
2: **for** num of cars **do**
3: 　　Use Algorithm 1 (K-shortest Constrained Path Algorithm) to calculate alternate route set A_{car} for each EV car.
4: 　　Assign binary variable r_i^{car} for each element in A_{car}.
5: 　　Combine all set A_{car} to $\mathbb{A} = \{A_1, A_2, \ldots, A_n\}$
6: 　　Solve the optimization problem in Equation (12) by solving the integer programming.
7: 　　**return** $[\{R|\overline{r}^1, \overline{r}^2, \ldots \overline{r}^{cars}\}, SumProfit]$. Each element r^i in set R is the selected route for EV i. $SumProfit$ is the total economic cost of all EVs.

A. K-Shortest Constrained Path Algorithm

The algorithm proposed in this section is to solve the sub-problem 1, that is, calculate the EV's k-shortest paths which satisfy the resource constraints and the time constraints.

Process to obtain a set of paths has been widely studied in many literatures. The most classic algorithms are depth-first search (*DFS*) and breadth-first search (*BFS*). However, both of them cannot be applied to search all paths between two points because of exponential time complexity. Actually, we do not really need to calculate all possible paths from the starting point to destination. Users may not be satisfied with one route that has low profit and high time consumption, although traveling time may not exceed the tolerance time. In other words, plenty of routes between $Start$ and VT should not be considered during the joint route scheduling. Inspired by this idea, we use K-Shortest Path (*KSP*) algorithm to reduce the size of the possible path set. Here we use Yen's algorithm (a kind of *KSP* algorithm) combined with A* algorithm to calculate a more meaningful route set.

We first briefly introduce some of the two shortest path algorithms as the background knowledge.

1) Yen's Algorithm: Yen's algorithm can compute *K-shortest* loop-free paths between two nodes in an acyclic graph [34]. Algorithm 1 explains in detail how to calculate the K optimal path set that meets resource constraints.

2) A Search Algorithm:* A* search algorithm is an intelligent algorithm for calculating the shortest path between two points in a weighted graph. It is widely used for path planning problems in 2-D planes. The key of the algorithm is to set a heuristic function, which is used to calculate the estimated distance from the current location to the destination. In two-dimensional planar scenes, the heuristic function is usually set to Manhattan distance or Euclidean distance. In our scenario, since we are using an abstract time-expanded map, we need to use new heuristic function to estimate distance to the end point for each charging station in advance, and their estimated

distance should not be overestimated in order to calculate the appropriate shortest route. We assume that an EV initially has enough energy but not unlimited and do not consider charging on-road. The estimated distance from a charging station to the destination is the total economic cost, which the EV continues to reach the destination along the shortest path based on the current power and then sells all the remaining power in the destination, as shown in Eq. 11:

$$heuristic_i^{car} = (y_i^{car} - sp_{i,dst}) * (price_{rnew} - price_{grid}) \tag{11}$$

in which heuristic distance of station i of car is calculated. y_i^{car} is the remaining power of an EV car in station i. $sp_{i,dest}$ is the minimum energy cost of driving from i to the destination dst without considering power constraints. $price_{rnew}$ and $price_{grid}$ are price of charging in renewable stations and grid stations, respectively. In line 6 of Algorithm 1, we use A* search algorithm (Algorithm 2) to calculate the shortest path between the $Start$ node and VT.

In Algorithm 1, set A and B store all *i-shortest* routes and possible routes, respectively. The $i - th$ shortest route will be calculated from line 4 to line 17. In line 11, the sub-path which is obtained in line 10 will be judged whether the constraints are satisfied. If the traveling time or carried energy exceeds the bound of the constraints, this sub-path will be dropped.

B. Joint Route Scheduling

After Algorithm 1 being executed, each EV has obtained its *k-shortest* paths. In this section, we explain in detail the operation performed in line 4–7 in Algorithm 3. We first let r_i^{car} be the variable which indicates whether to choose the route i in the route set A_{car} of EV car. Then we can obtain variable vector $\mathbb{R} = \{r_i^{car}, \forall car \in V, \forall i \in A_{car}\}$. The objective is to minimize the total cost of all EVs that travel from the source to destination. Now we rebuild the abstract formulation of this problem based on the integer variable vector $\mathbb{R}$. The new math formulation of this problem is as follows:

Min:

$$\sum_{car \in V} \sum_{i \in A_{car}} w_i \cdot r_i^{car} \tag{12}$$

Subject to:

$$\sum_{i \in A_{car}} r_i^{car} = 1 \quad \forall car \in V \tag{13}$$

$$\sum_{car \in V} \sum_{i \in R(e)} r_i^{car} \leq Park_{max}^e \tag{14}$$

$$\sum_{car \in V} \sum_{i \in R(e)} Pow^{car} \cdot r_i^{car} \leq Pow_{max}^e \tag{15}$$

$$r_i^{car} \in \{0, 1\} \tag{16}$$

This is an integer linear programming that has $\sum_{car \in V} |A_{car}|$ variables and $|V| + (2|R| + 3|G|) * Slots * 2$ linear constraints. $R(e)$ in Equation (14), (15) is a subset of the A_{car} that each route contains the edge e.
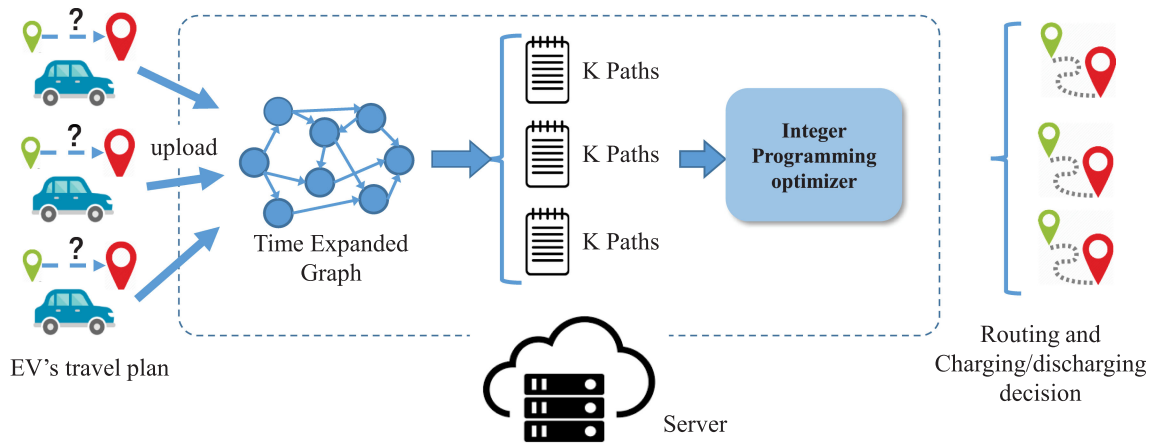
Fig. 5. Procedure of joint routing scheduling and charging/discharging decision algorithm.

C. The Procedure of Joint Routing Scheduling and Charging/Discharging Algorithm

Fig. 5 shows the workflow of the proposed algorithm. Firstly, each EV sends the start location, destination and delay constraints to the central controller (server). Secondly, the server uses Algorithm 1 to calculate the feasible top K optimal routes for each EV based on the time expanded graph which is constructed inside the server. The route here in the time expanded graph represents the real road mixed with charging/discharging decisions. At last, the server calculates an appropriate route for EV through the integer programming optimizer which is as line 6 in Algorithm 3 based on the route sets we get in the second step. In the next section, we are going to explain the effect of parameter K and the way to choose it.

D. The Parameter K of K-Shortest Path

Since the vector A_{car} represents all possible paths that the EV *car* will take from its starting point to the destination within the time allowance, we will get a very large number of vector collections. This makes the calculation of joint route scheduling very difficult. However, the optimal route is often among the top routes in the list. Therefore, regarding these K paths, the time spent in the calculation will be greatly reduced. KSP-JRS algorithm and the algorithm using the complete route set can both calculate the total cost of all EVs and routing scheme. However, the supported maximum number of EVs by the two algorithms are different. We use the parameter *gap* to represent this difference. The higher the K, the smaller the *gap*, with the increasing in the calculating time, and vice versa. In practice, some EVs may not be able to reach their destinations on time due to insufficient route plans, if k is too small. Once the K is calculated appropriately, we can reduce the amount of calculation and get the optimal path scheduling scheme simultaneously. Thus, we propose an algorithm Algorithm 4 to determine the parameter K for each case.

If Algorithm 4 is not possible to calculate a routing scheme for all EVs (line 3), with the expansion of K (line 4), it will succeed eventually. The result of the algorithm is equivalent

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Algorithm 4: KSP-JRS Using Auto-Determined K.

Input: Pow_{supply}^{car}, Pow_{cap}^{car} $Park_{max}^{e}$, $Elec_{e}$, ω_{e}, $cars$ $number$, Map, $E_{initial}$, K, S, T, E_{i}^{max}, k_{ini}^{car}

Output: Parameter K of each EV, Optimal routing scheme, Optimal total economic cost

1: Input the time-expanded graph based on the map. $k^{car} = k_{ini}^{car}$.

2: Calculate the joint routing scheme based $k_{ini}^{car} * cars$ route set using Algorithm 3.

3: **while** Calculate the joint routing scheme by using Algorithm 3 unsuccessfully **do**

4:     $newk^{car} = k^{car} * 2$

5:     Expand the size of A_{car} from k^{car} to $newk^{car}$.

6: Use the binary search to find k_{opt}^{car} between $newk^{car}$ and k^{car}, then all vehicles can be scheduled successfully by Algorithm 3 using the parameter k_{opt}^{car}.

7: **return** k_{opt}^{car} of each EV, routing scheme, total economic cost.

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to the optimal solution calculated by the algorithm using the complete route set. In order to obtain K more accurately, we use a binary search between K in the $(n-1)th$ iteration and the nth iteration.

V. EXPERIMENTS AND ANALYSIS

A. Experiment Setting

We test the algorithm on a traffic map near Santa Clara, California, as shown in Fig. 6. The data is synthetic based on the real highway data of the suburban area in California, USA. In order to verify the correctness of the proposed KSP-JRS algorithm, we set up 5 types of EVs and each has a different start-destination pair, travel time constraint, battery capacity and initial power, as given in Table II. These EVs are randomly deployed in the map in each simulation. The traffic volume is a parameter of the experiment, ranging from 50 to 250. In the traffic network diagram, we use a directed acyclic graph,
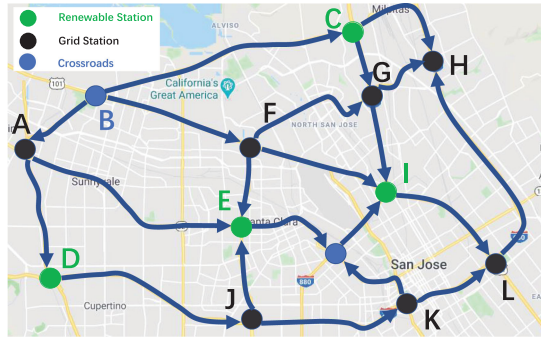
Fig. 6. The traffic network graph near Santa Clara.

TABLE II
PARAMETERS OF THE TYPES OF EVs IN THE SIMULATION

| Car Type	Battery Capacity (kWh)	Initial Energy (kWh)	Max Travel Time (min)	Start Node	End Node
1	100	100	48	B	L
2	65	30	39	D	I
3	110	75	42	C	L
4	90	60	54	A	H
5	100	75	36	D	K

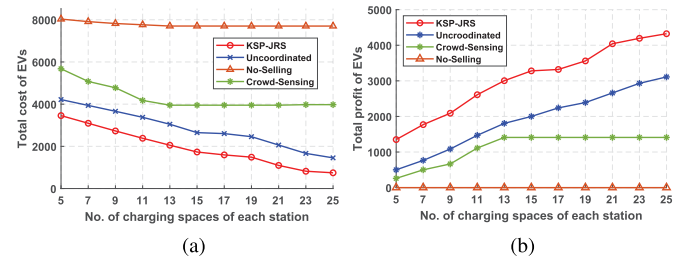Fig. 7. Cost and profit of EVs. (a) Total cost of EVs. (b) Total profit of EVs.

Fig. 8. Cost and profit of 150 EVs with the increasing number of charging spaces in each station. (a) Total cost of 150 EVs. (b) Total profit of 150 EVs.

and randomly place 7 charging stations, among which 4 are renewable energy powered. We use black and green nodes to represent grid charging stations and renewable energy charging stations, respectively. The energy consumption due to detour can be predicted using velocity, like the method in [35] and [36]. Scheduling and decisions are conducted in a time slot-based manner, and each time slot is 3 minutes long. The duration of each simulation is 20 time slots in total, which guarantees all EVs will finally reach their destinations.

In our experimental scenario, we consider that the total energy supply of charging stations dynamically changes along the time scale. Each charging station has a limited number of charging piles and a waiting queue. Electric vehicles will consume time and energy while driving, waiting, charging and discharging. We set an upper energy supply limit that fluctuates over time for each charging station. To highlight the advantages of the proposed algorithm, three representative strategies are used for comparison. In the first one, called *uncoordinated*, each EV selects its own optimal route independently (may cause big queuing delay at some popular stations). The second one *crowd-sensing*, proposed in [6], only allows EVs discharge energy at destinations for profit. The last one, titled *no-selling*, only focuses on minimizing traveling cost without selling any of its energy.

B. Performance Evaluation

Our goal is to minimize the cost of EVs while complying with their maximal travel time tolerance. We first compare the total cost of our algorithm with other three strategies. Fig. 7(a) shows that the cost of four strategies grows with the increasing number of EVs in the network, and the total cost of KSP-JRS
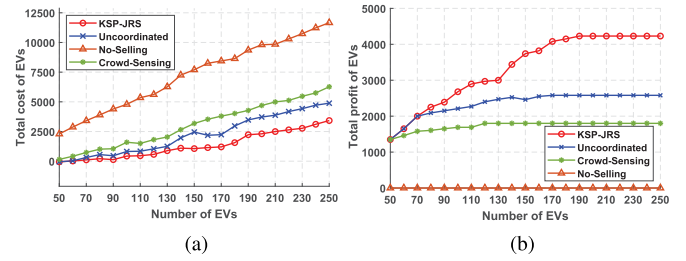
algorithm is the lest. Fig. 7(b) shows the profit of the four scheduling strategies against the number of EVs. The total profit of EVs increases with the number of EVs, and the profit gap between these algorithms grows wider until the overall number of EVs reaches 170. This is because the charging stations in the network are already running at full load. In that case, newly coming EVs are not able to either get charged nor discharged within their travel time allowance. In terms of *uncoordinated* and *crowd-sensing* strategies, this moment will come early, since without scheduling, many EVs may gather at a few popular charging stations, spending a lot of time in waiting. Therefore, their spare time is wasted. As shown in the figure, increasing charging spaces can alleviate this phenomenon. *No-selling* strategy shows ZERO profit because energy is not traded for benefit. The proposed KSP-JRS algorithm gets the highest revenue and almost 60% higher than that of *uncoordinated*.

Fig. 8(a) shows the total cost for 150 EVs with the increasing number of charging spaces in each station. *No-Selling* and *Crowd-Sensing* are not sensitive to the change of charging spaces because EVs do not sell electricity during the trip. The proposed algorithm can achieve the lowest cost with the increasing number of charging spaces compared with the others, which shows the effectiveness in improving the utilization of the charging stations. Fig. 8(b) shows that more charging spaces can meet the charging/discharging needs of EVs and help EVs gain more profit. However, the profit of EVs will be fixed when charging spaces are saturated. KSP-JRS demonstrates the best performance that surpasses the runner-up by over 30%.

In Fig. 9, each cross of a row (represented by letters) and a column (represented by numbers) represents an instance of a station in a given time slot in the city traffic network. C, D, E, I are charging stations powered by renewable energy. B is a
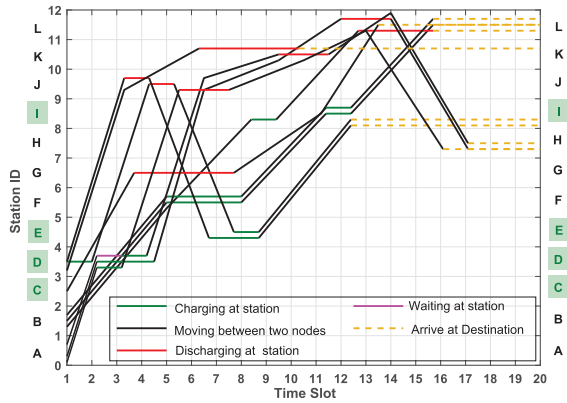
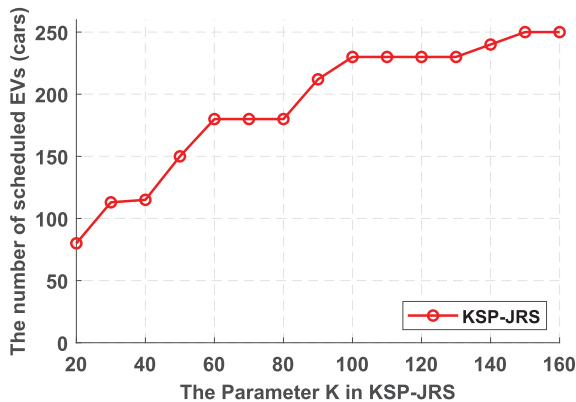Fig. 9. Joint routing selections calculated by KSP-JRS.

Fig. 10. The maximum number of EVs that the network can afford calculated by KSP-JRS using different values of the parameter K.

their trip. Therefore, there is an upper bound for the number of EVs that the system with parameter K can support. However, as the parameter K is gradually increased, KSP-JRS algorithm can support the same number of EVs which is the actual maximal capacity of the traffic network.

VI. CONCLUSION

In this paper, we have proposed a joint route selection and charging/discharging decision algorithm to minimize the cost of all EVs in a vehicular energy network. A time-expanded V2G network is constructed to model the behavior of EVs, travel time constraints and limited resources of charging stations. The problem is solved by two steps, i.e., route calculation and joint optimization. In order to reduce the calculation time, we determine the parameter K automatically through binary search in the proposed KSP-JRS method. Simulation results show that joint route scheduling and charging/discharging decision can significantly increase the total revenue of EV groups. The proposed model can effectively simplify the problem and provide a personalized route decision for each EV, thus helping reduce the operation cost of EVs and increase utility of renewable energy in real-life applications. For the future work, we will study distributed route selection and charging scheduling of EVs, where each EV makes its own decision based on the estimation.

crossroad and others are grid stations. Each route in Fig. 9 is a mixture of black, pink, red and green lines. The black line segment represents that the EV departs from one node to another node. The red line segment represents that an EV is selling electricity at a charging station powered by the grid. The green line segment represents the charging behavior. And the pink line segment represents that an EV is waiting at a charging station. For example, an EV wants to leave node A for H in the network as shown in Fig. 6. Its maximal travel time tolerance is 54 minutes. According to our joint optimal route scheduling, this EV takes 3 minutes for passing through road (A, D), then it gets charged at station D for 2 time slots due to cheaper price of renewable energy. Afterwards, it passes through J at $6th$ time slot and K at $9th$ time slot, and sells redundant energy in station L between 12 and $14 - th$ time slot. Finally, it arrives at the destination H by traveling through road segment (L, H), and the whole traveling time consumption is 51 minutes. We can see that there are three cars at station D between 2nd and 3rd time slot, among which one EV has to wait for an available charging space, represented by the pink line.

To reduce the overhead in route calculation, we use the KSP algorithm obtained by the A* algorithm, and then search the most suitable size of K to achieve the optimal scheduling. In Fig. 10, we can see that when K is small, some EVs cannot select the appropriate path in its own routing set to complete

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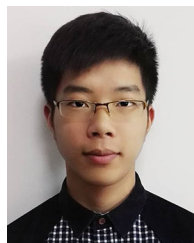
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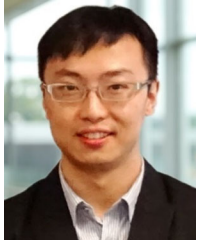
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