Data-Driven Intelligent Management of Energy Constrained Autonomous Vehicles in Smart Cities

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Abstract. Intelligent transportation is an important component of future smart cities, and electric autonomous vehicles (EAVs) are envisioned to be the main form of transportation because EAVs can save energy, protect the environment, and improve service efficiency. With limited vehicle-specific energy storage capacity and overall constraint in the smart grid's electric load, we propose a novel intelligent management scheme to jointly schedule the travel and charging activities of the EAV fleet in one geographical area. This scheme not only schedules EAVs to meet the passengers' requests but also explores the matching problem between the energy requirement of EAVs and the deployment of charging piles in smart cities. We minimize the total cruise energy consumption of EAVs under the condition of limited energy supply while guaranteeing the quality-of-service (QoS). Network Calculus (NC) is extended to model the electric traffic flow in this paper. With the real-world electric taxi data in Beijing, simulation results demonstrate that the proposed scheme can achieve substantial energy reduction and remarkable improvements in both the order completion rate and utilization rate of the charging stations.

Keywords: Electric autonomous vehicle (EAV) · Intelligent scheduling · Network calculus (NC) · Energy consumption

1 Introduction

1.1 Motivation

Building smart cities are of great significance for sustainable development and enhancing the city's overall competitiveness, and intelligent transportation system plays a key role during this transition [1,2]. With less carbon emission and

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unified management, electric autonomous vehicles (EAVs) will replace the traditional gas-powered taxi and become the top transportation choice in future smart cities. However, there are still several challenges for the deployment of EAVs, including limited driving range, long recharging duration, inadequate charging stations, and restricted city electricity supply.

1.2 Related Work and Contributions

Intelligent management of EAVs can improve electricity utilization efficiency and alleviate the above challenges. At present, the researches on dispatching schemes for gas-powered taxis are relatively mature and have been widely used in commercial taxi platforms. Meanwhile, for autonomous vehicles (AVs), academic researchers have explored vehicle management, path planning, and unified dispatch problem. Zhang *et al.* has proposed the scheduling strategy for idle AVs [3]. Rule-based scheduling strategies were designed to divide the service area into multiple sub-areas, and the nearest idle vehicles are scheduled for the passengers. If no AV is idle in passenger's located sub-area, neighboring sub-areas will be searched [4–6]. Fagnant *et al.* used a modified Djikstra algorithm to determine the shortest path between an idle AV and a waiting passenger in the actual road network [7]. Bischoff and Maciejewski [8] simulated a city-wide replacement of private cars using autonomous taxi fleets of various sizes. Simulation results suggest that one AV could replace the demand served by ten conventional driven vehicles in Berlin. In our previous work, network calculus (NC) is adopted to model the traffic flows and the management scheme was designed for AVs to reduce the waiting and travel time for passengers [10,11].

The above literature on management has made an ideal assumption that the energy supply for each AV is unlimited. For the scheduling of EVs, however, the energy storage capacity should be taken into consideration. Tseng *et al.* used the Markov decision process to design the optimal path for electric taxis with energy constraints and maximize the profit of taxi drivers [13]. Besides, it is assumed that the EVs could charge in the nearest charging station at any time. Since the idle EAVs can also be arranged to charge, the location and status of the charging station are also significant for the management of EVs [9]. To avoid energy exhaustion before reaching the destination, Sedano *et al.* proposed a reservation plan of charging services for the electric-powered taxis [12]. To minimize the infrastructure investment, Yang *et al.* presented a data-driven optimization algorithm to allocate chargers for the battery electric vehicle (BEV) taxis throughout a city [14]. However, existing electric vehicle scheduling is affected by driver behaviors and cannot achieve large-scale unified scheduling.

From the above observations, we find that the existing work has not studied the large-scale unified scheduling of EAVs by considering both the constraint of energy storage capacity and the limited number of charging piles in each charging station. Therefore, an EAVs' intelligent management system is proposed to minimize the total cruise energy consumption of EAVs under the condition of limited energy and electric load. This intelligent management system provides a look ahead into the solution for a joint deployment of available EAVs in a more practical way. This can benefit the EAVs company for reducing the energy cost and increasing the utilization of charging piles, which can also lower the fee of passengers potentially, making it more feasible to operate the EAVs service in the market.

The contributions of the paper can be summarized as follows.

- Under the energy constraints, An intelligent management scheme to jointly schedule the travel and charging activities of the EAV fleet is proposed to minimize the total cruise energy consumption and match passengers' requests and limited charging piles.
- With EAV-specific energy storage constraints and an overall limited electric load of the urban power grid, we further propose a constrained vehicle dispatching (CVD) algorithm to solve the joint scheduling problem.
- We evaluate the proposed scheduling scheme with simulations on the collected real Beijing electric taxi dataset and demonstrate its effectiveness.

The rest of this paper is organized as follows. In Sect. 2, the collected electric taxi data are introduced along with the system model of NC on how to solve the supply and demand of EAVs for each region. Section 3 details the designed intelligent scheduling scheme of EAVs and simulations over the real electric taxis data. The results are showed and analyzed in Sect. 4. Finally, the whole paper is concluded in Sect. 5.

2 Electric Taxis Dataset and System Model

In order to facilitate the scheduling and management of EAVs, we divide the entire area into grid regions. The EAVs entering and leaving the grids is regarded as the traffic flow model by NC. Considering the limitations of EAVs energy storage and urban electric load, we obtain the energy consumption of EAVs and the location and number of charging piles to ensure all EAVs timely energy replenishment.

In this part, our captured real-world electric vehicle dataset is first introduced along with the distribution of charging stations in the selected observation area. Then, based on the trip records of EVs, the autonomous traffic flow of EAVs is modeled using the Network Calculus method, and the corresponding supply and demand of EAVs are obtained. Lastly, the energy consumption models are further derived for the subsequent energy-aware EAV scheduling.

2.1 Dataset Description

We have obtained a real-world electric taxi dataset, which contains the driving trajectory and electric taxis' behaviors in Beijing. With GPS positioning, the dataset captures 180 million real-time locations and rechargeable battery status with 10 s interval for 30 days: from June 1, 2018, to June 30, 2018, with details given in Table 1. As shown in Fig. 1, the observation area with active electric taxis is evenly divided into $N = 361$ (19×19) grid regions, each about $1\,\text{km}^2$. Without considering the behavior of the EVs inside each grid region, we simulate the entire area as a network topology for scheduling large-scale fleets, where each grid is one point. Based on the charging vehicles' location in our dataset, the number of charging piles in each region is approximated as the total number of EVs with charge state being 1, i.e., parking charge. Figure 2 displays the distribution of the number of charging stations in the indexed observation area.

Table 1. Beijing electric taxi dataset

Feature	Definition	
ID	Unique taxi identification	
Timestamp	Data recording time (second)	
Location	Longitude and Latitude	
Taxi State	0: Vacant,	1: Loaded,
	2: Parking,	3: Not in service,
	4: Charging	
Battery State	Residual electricity level (0–100)	
Charge State	1: Parking charge,	2: Driving charge,
	3: No-charging,	4: Charging finished

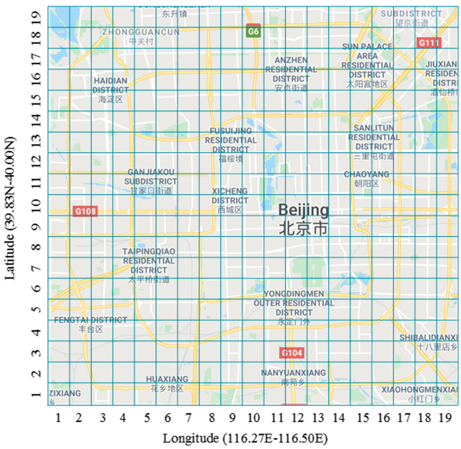


Fig. 1. The observation area with grid regions indexed from left to right and bottom to top, i.e., left bottom corner is region 1, and the top right corner is region 361.

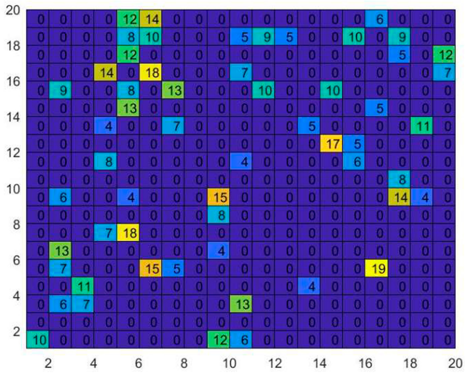


Fig. 2. The number of charging stations in the indexed regions.

2.2 EAV Flow Model

To simulate the computerized autonomous service strategy of EAVs, the NC traffic model in our prior work is extended to model the incoming new requests and outgoing served requests for EAVs [10]. Based on Min-Plus algebra and Max-Plus algebra, NC is an effective method to analyze the performance of a network router by evaluating the incoming and outgoing flows [15].

For a time-slotted system, we denote O_n^t as the optimal number of incoming requests/orders for EAVs in region n during the t-th time slot. O_n^t is borrowed from the effective bandwidth concept in NC, which is used to measure the minimum service rate while keeping the virtual delay of the flow below a predefined threshold [10].

$$O_n^t = \sup_{0<\tau'\leq\tau} (R_n^{t+1} - R_n^t) \times \frac{\tau'}{\tau' + D}, \tag{1}$$

where $\tau = 15$ min is the time duration of one time slot, and $D = 3$ min is the maximum tolerable waiting time for the passengers, we can ensure QoS of EAVs fleet by setting the threshold of D. $(R_n^{t+1} - R_n^t)$ is the number of electric taxis at the n-th region that pick up passengers during time slot t, i.e., the total number of taxis that change state from vacant to loaded.

Let S_n^t denote the number of available EAVs during time slot t in region n. To improve the utilization efficiency of EAVs, we assume that EAVs being charged at charging stations can stop charging at any time and pick up passengers.

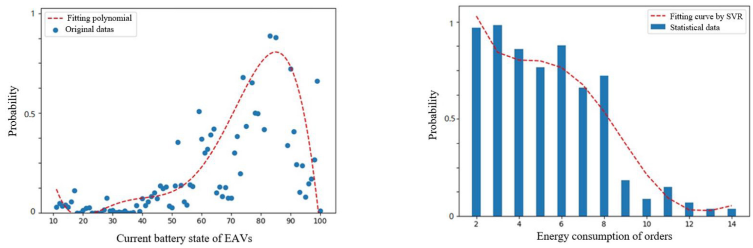
$$S_n^t = Q_n^t + C_n^t, \tag{2}$$

where Q_n^t is the total of the number of taxis that change state from loaded to vacant during the time slot t in region n, and C_n^t is the number of charging taxis.

2.3 Energy Models for EAV

We define the set of grid regions as $\mathcal{N} = \{1, \cdots, n, \cdots, N\}$, and the set of time slots as $\mathcal{T} = \{1, \cdots, t, \cdots, T\}$, where T is the total number of time slots. To efficiently schedule the EAVs, the average energy consumed by EAVs to travel from region n_1 to region n_2 is denoted by $E^t_{n_1,n_2}$, where the energy consumption for two unreachable areas is defined as ∞, and the energy consumption within each region is indicated by 0.

To design an energy-aware EAV scheduling algorithm, in addition to the travel energy model, the battery state of each EAV and the order-specific energy consumption are the other two fundamental inputs, where the first one is given in the original dataset (Table 1), while the latter can be derived by calculating the differences in battery states when driving from one location to another.



(a) The distribution of vehicles' battery state

(b) The distribution of orders' energy consumption ($n = 66$)

Fig. 3. The curve fitted by SVR (09:45 AM–10:00 AM).

The distribution of vehicles' battery state and orders' energy consumption are obtained by curve fitting the Beijing electric taxi dataset, where three weeks of data (75%) as the training set and the remaining one week (25%) for the test dataset. As illustrated in Fig. 3, the fitted curves obtained via support vector regression (SVR) can be used to estimate the EAV' battery state and travel energy consumption in the next time slot [16]. Since the battery state of the EAV cannot change much in a short period, the collected last-minute power distribution of EAVs in the previous time slot can be used as a surrogate for the current time slot of the EAVs. The distribution of the time-varying order energy consumption, however, will be estimated using the time slot-specific fitted curve, as shown in Fig. 3(b).

3 Intelligent Management System

To minimize the total energy consumption of EAVs, an energy-aware scheduling scheme is designed to control the passenger order fulfillment and charging activities of EAVs. The scheme mainly considers the energy constraints of EAVs. First, according to the remaining power of the EAVs, we match the passenger requests and EAVs to minimize the energy consumption of EAVs scheduling while ensuring the completion of the travel. Then, taking into account the urban electric load and the distribution of charging piles to schedule idle EAVs for recharging. The proposed charging scheduling method reduces energy consumption and improves the utilization of charging stations. Since the scheduling scheme will schedule EAVs independently in each time slot, we will drop the time index t in O_n^t, S_n^t, E_{n_1,n_2}^t for the following sections.

3.1 Energy-Aware Passenger Requests Scheduling

The scheduling of EAVs essentially is the matching process between vehicles and passenger requests. When considering the limited driving range and long charging time, it is critical to guarantee that the battery states of all the operating EAVs can last long enough to reach the nearest charging station after dropping off passengers at their destination. Suppose the i-th EAV is scheduled to serve the j-th passenger order, the travel energy consumption from EAV's current region n_i to the passenger's picking up location n_j is E_{n_i,n_j}. After dropping the passenger at the destination n_d, the energy consumption for EAV to reach the nearest charging station's location n_c is E_{n_d,n_c}. The matching process between the vehicles and orders has to guarantee the satisfaction of the following energy constraint.

$$B_i \geq E_j = E_{n_i,n_j} + E_{n_j,n_d} + E_{n_d,n_c} + B_0, \tag{3}$$

where B_i is the battery state of the i-th vehicle and E_j is the energy demand of the j-th order. Both B_i and E_j can be estimated using methods described in Sect. 3.1. B_0 is the lower limit of EAV's battery.

To balance the EAV supply and demand across multiple regions at each time slot, we need to match the optimal number of passenger orders $O = \sum_{n\in\mathcal{N}} O_n$ and the number of available EAVs $S = \sum_{n\in\mathcal{N}} S_n$. The matching problem is modeled as bipartite graph $(\mathcal{V}, \mathcal{P}; \mathcal{E})$.

- $\mathcal{V} = \{1, \cdots, i, \cdots, S\}$ is the set of EAVs available for dispatch at the t-th slot. Each vertex (vehicle) i has two parameters: the current battery state B_i and region n_i.
- $\mathcal{P} = \{1, \cdots, j, \cdots, O\}$ is the set of optimal orders at the t-th slot. Each vertex (order) j also has two parameters: the required energy E_j and the current region n_j.
- $\mathcal{E} = \{E_{n_i,n_j} | i \in \mathcal{V}, j \in \mathcal{P}\}$ is the energy consumed by the i-th EAV to pick up passenger j from location n_j.

At each time slot, the goal of the dispatch algorithm is to determine the minimum-weight matching between EAV $i \in \mathcal{V}$ and passenger order $j \in \mathcal{P}$ that satisfies $B_i \geq E_j$. In our problem setting, this goal can also be interpreted as finding the best action for each EAV to minimize global energy consumption in a coordinated way. We define a binary variable $x_{i,j}$ to indicate whether the vehicle i has been selected to serve the j-th order.

$$
\begin{aligned}
\max_{\{x_{i,j}\}} & \sum_{i\in\mathcal{V}}\sum_{j\in\mathcal{P}} E_{n_i,n_j} x_{i,j} \\
s.t. & \sum_{j\in\mathcal{P}} x_{ij} \le 1, \quad \forall i \in \mathcal{V}, \\
& \sum_{i\in\mathcal{V}} x_{ij} \le 1, \quad \forall j \in \mathcal{P}, \\
& (B_i - E_j) x_{i,j} \ge 0, \quad \forall i \in \mathcal{V}, \forall j \in \mathcal{P}, \\
& x_{i,j} \in \{0,1\}, \quad \forall i \in \mathcal{V}, \forall j \in \mathcal{P},
\end{aligned}
\tag{4}
$$

where the first constraint specifies each EAV can at most fulfill one customer order, and the second constraint requires that each customer's request can be answered by at most one EAV. The third constraint means for any successfully matched pair, i.e., $x_{i,j} = 1$, the energy gap between the i-th EAV and the j-th order has to be a non-negative number, i.e., the energy supply is no less than the demand.

Without considering the energy gap constraint (the third one) in Eq. (4), the Kuhn-Munkres algorithm can find the pairing between row (EAV) and column (order) over the weight matrix $\mathcal{E}$, such that the total weight (energy consumption) of the selected pairs is minimized [17]. For the constrained minimum-weight matching problem, we have designed the CVD algorithm. In the proposed CVD algorithm, we try to find maximum-weight matching for a bipartite graph with the constraint of energy supply by adding the judgement into the K-M algorithm [18] while dispatching. If the battery state of a vehicle can't satisfy the energy demand of an order, then the vehicle can't be dispatched to the order. Details given in Algorithm 1.

3.2 Grid Load-Aware Charging Scheduling

After the matching process between EAVs and orders described in the previous section, the system is left with a set of EAVs that cannot fulfill the order requirement due to insufficient energy supply. With the location information and battery state for each left-over EAV, a new approach is presented in this section on how to select the optimal charging location from the observation area.

The matching between EAV and charging station is a challenging yet practical problem, because too many EAVs charging at the same time may overload the urban power grid. To improve smart grid performance and economy, the charging schedule of EAVs is constrained by the number and the location of charging stations given in Fig. 2 as well as the capacity of the smart grid [19].

We assume that when the EAV and the matched charging station are in the same region, the energy consumed for the EAV to reach the charging location is negligible. The cross-region charging will occur only when there is no local charging station available. For the cross-region matching between the EAVs and charging stations, it can be treated as the maximum bipartite graph matching problem, similar to the algorithm designed to match EAVs and orders. In particular, we denote E_{n_i,n_c} as the travel energy consumption from the i-th EAV to

Algorithm 1. CVD algorithm

Require:

Vehicle set $\mathcal{V}$, order set $\mathcal{P}$, energy matrix $\mathcal{E}$;

Initialize node labels:

$$Label_i = \min_{j \in \mathcal{P}} E_{n_i,n_j}, \forall i \in \mathcal{V}, \text{ and } Label_j = 0, \forall j \in \mathcal{P}$$

Ensure:

The optimal assignment $\mathcal{X} = \{x_{i,j} | i \in \mathcal{V}, j \in \mathcal{P}\}$;

for all $i \in \mathcal{V}$ **do**
    Temporary variable $gap \leftarrow \infty$
    for all $j \in \mathcal{P}$ **do**
        if $Label_i + Label_j - E_{n_i,n_j} = 0$ **and** $B_i \geq E_j$ **then**
            if j has not been served **then**
                Dispatch i to j and update $x_{i,j} = 1$
            else
                Mark j and its dispatched vehicle m
            end if
        else

$$gap \leftarrow \max \left\{gap, (Label_i + Label_j - E_{n_i,n_j})\right\}$$

        end if
    end for
    if i has not been dispatched **then**
        for Marked j **do**
            $Label_i \leftarrow Label_i - gap$
            $Label_m \leftarrow Label_m - gap$
            $Label_j \leftarrow Label_j + gap$
            Repeat steps 2-23 for vehicle m
            if m could be dispatched to $j' \in \mathcal{P}$, $j' \neq j$ **then**
                Update $x_{i,j} = 1$
            end if
        end for
    end if
end for

the c-th charging pile region. To successfully match the i-th EAV with the c-th charging pile, the battery status of the EAV, i.e., B_i, has to be able to support the selected direct travel route.

$$B_i \geq E_{n_i,n_c}, \tag{5}$$

where without picking up or dropping off the passenger, the requirement on the battery status is less stringent, as compared with Eq. (3).

Similar to Eq. (4), the matching target is to minimize the EAVs' energy consumption. Suppose at each time slot, V_{opt} is the number of routes that are successfully matched by the proposed CVD algorithm, i.e., V_{opt} is the number of EAVs that are scheduled to be charged.

To avoid the overload of urban power grid supply caused by too many electric vehicles being charged at the same time, it is essential to limit the number of charging piles that can operate at the same time. We denote V_{max} as the maximum number of EAVs that can be supported by the grid for simultaneous charging.

$$V_{max} = \frac{L_{Grid}}{L_{EAV}}, \tag{6}$$

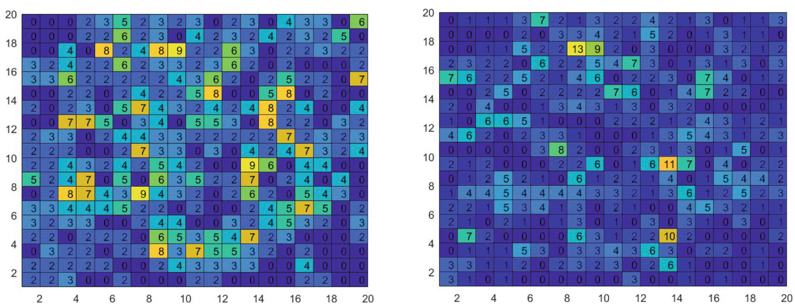
where L_{Grid} is the electric load that the smart grid can provide to the charging piles at each time slot, and L_{EAV} is the average charging power of each EAV.

With $V_{max} \geq V_{opt}$, all of the scheduled EAVs can be dispatched directly, following the matching routes. However, if $V_{max} < V_{opt}$, then, V_{max} routes with the least energy consumption will be selected from the scheduling results for dispatch.

4 Simulation Results and Analysis

4.1 The Supply and Optimal Demand of EAVs

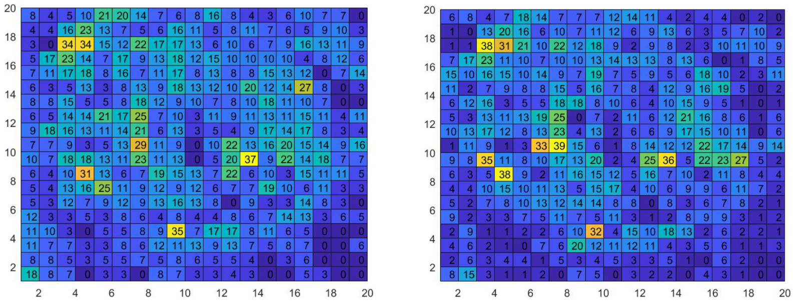
Based on the collected electric vehicle dataset in Beijing, we simulate the optimal number of demands for EAVs and the number of served requests for the n-th grid region, $n \in \mathcal{N}$. Figures 4 and 5 show the simulation results of low traffic slot (03:45 AM–04:00 AM) and heavy traffic slot (09:45 AM–10:00 AM), respectively. In addition, battery states will be assigned to the EAVs and the travel energy consumption will be given to the customer orders, based on the fitted curves in Sect. 3.1.



(a) The number of the optimal demand O_n^t

(b) The number of the served requests S_n^t

Fig. 4. Low traffic load: 03:45 AM–04:00 AM, Monday, Nov. 11, 2018.



(a) The number of optimal demand O_n^t

(b) The number of the served requests S_n^t

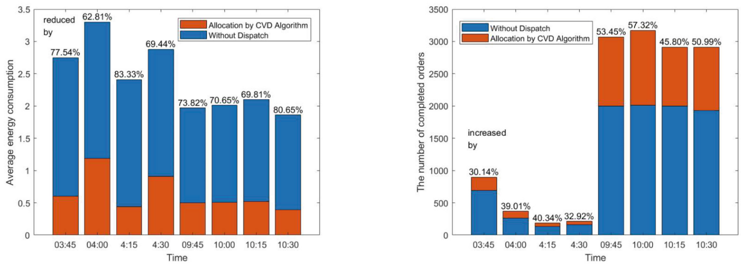
Fig. 5. High traffic load: 09:45 AM–10:00 AM, Monday, Nov. 11, 2018.

By comparing the simulation results in Figs. 4 and 5, we can notice the supply of electric taxis in Beijing is lagging behind the optimal demand. In particular, the supply is about 88.6% of demand during peak hours. Therefore, launching EAVs in the future smart city market still has a lot of potentials. Furthermore, without intervention, the taxi supply and demand in each region are unbalanced, thus vehicle resources and passengers' requirements cannot be well matched under the given QoS.

4.2 Energy-Aware EAV Scheduling

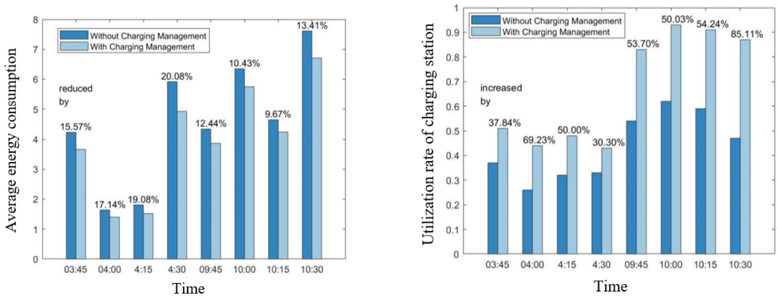
Based on the collected real-world electric vehicle dataset, we match the EAVs and customer orders for two hours with the proposed CVD algorithm. The energy spent on picking up passengers with and without dispatching are shown in Fig. 6(a) and the results indicate that dispatching can reduce energy consumption by 73.5% on average. During rush hours, Fig. 6(b) shows that the number of orders fulfilled with our allocation scheme is about 52% more than that without dispatching. Simulation results demonstrate that the proposed EAV dispatching scheme can reduce vehicle energy consumption while improving passenger satisfaction, thereby greatly increasing the operating company's revenue.

For charging scheduling, although the electric load available at the charging piles can vary with the dynamic demands on the city's smart grid, for simplicity, we set a constant load L_{Grid} = 500 MW, $\forall t \in \mathcal{T}$. Today's fast charging piles in Beijing mainly have 60–90 KW power and the average charging power is therefore set as L_{EAV} = 75 KW. The energy consumption of EAVs and the utilization rate of charging piles are shown in Fig. 7. It can be observed that charging dispatch can reduce the energy spent on cruising to the charging piles by 10–20%. Moreover, the utilization rate of charging piles is also significantly improved with the proposed charging scheduling algorithm.



(a) Energy consumption of vehicles (b) The number of completed orders

Fig. 6. EAV-order matching.



(a) Energy consumption of vehicles (b) Charging station utilization rate

Fig. 7. EAV-charging station matching.

5 Conclusion

In this paper, we propose an intelligent scheduling system for EAVs while considering the energy-related constraints. The scheduling scheme comprehensively considers the energy-constrained vehicle's order fulfillment and energy replenishment. In the designed framework, EAVs with sufficient energy supply will be matched to fulfill the customer orders, while EAVs with insufficient energy supply will be scheduled to charge at the charging station, which is powered by the urban smart grid. First, the EAVs flow is mathematically modeled using NC, the EAVs' battery states and orders' travel energy consumption are obtained via a machine learning algorithm. To minimize the total energy consumed by EAVs, we propose the CVD algorithm, based on which, the available vehicles and orders are matched with guaranteed QoS, and the charging location and EAVs are matched without violating the overall electric load in the smart grid. Simulation results show that the proposed EAVs' dispatch scheme can save cruising energy and improve both the charging station's utilization rate and the order completion rate.

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