A novel dynamic pricing scheme for a large-scale electric vehicle sharing network considering vehicle relocation and vehicle-grid-integration☆

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ABSTRACT

With promising benefits such as traffic emission reduction, traffic congestion alleviation, and parking problem solving, Electric Vehicle (EV)-sharing systems have attracted large attentions in recent years. Different from other business modes, customers in sharing economy systems are usually price sensitive. Therefore, it is possible to shift the usage of shared EVs through a well-designed Dynamic Pricing Scheme (DPS), with the objective of maximizing the system operator's total profit. In this study, we propose a novel DPS for a large-scale EV-sharing network to address the EV unbalancing issue and satisfy the vehicle-grid-integration (VGI) service based on accurate station-level demand prediction. The proposed DPS is formulated as a complex optimization problem, which includes two Price Adjustment Level (PAL) decision variables for every origin-destination pair of stations. The two PALs are employed to affect the EV-sharing demand and travel time between each station pair, respectively. Physical and operational constraints from both EV demand and VGI service aspects are also included in the proposed model. Two case study are conducted to validate the effectiveness of the proposed method.

1. Introduction

1.1. Background

In recent years, more and more customers who used to purchase products, have now started to rent them with the emerging of sharing economy. The most popular sharing business models include bike sharing, vehicle sharing, and room sharing (Yuan and Shen, 2019). Vehicle sharing is one of the sharing economy modes, which has the potentials of alleviating traffic congestion and parking space problems. In a recent study, Yu et al. (2019) investigated a Bi-Objective Green Ride-Sharing Problem (BGRSP) and found a trade-off between two objectives: minimize carbon emission and maximize the average ride profit so that every driver's interest can be satisfied. Recently, with promising benefits in reducing fossil fuel consumption and carbon emissions, Electric Vehicle (EV) sharing has attracted increasing attentions in both academia and industry. Especially, considering a typical motorized passenger vehicle emits about 4.7 metric tons of carbon dioxide per year (US EPA, 2016), many vehicle systems have been seeking to use EVs to provide mobility services. Switching to EV represents a natural evolution of moving towards sustainable means of transport (Gambella et al., 2018).

There are three kinds of business models that are commonly offered by car-sharing providers, namely round-way, one-way, and free-floating way. In the round-way vehicle sharing system, customers are required to return vehicles to pick-up stations. A one-way system allows users to pick up and drop off vehicles at different sites offered by the vehicle sharing provider. As the most flexible service, a free-floating system allows users to return the vehicle at any idle parking spot under the area controlled by the car-sharing provider. In EV-sharing services, the one-way system is commonly adopted, in which customers can pick up and return vehicles at specific sites where recharge infrastructures locate (Gambella et al., 2018). In one-way vehicle sharing systems, the imbalance distribution of vehicles is a challenging task from the system operational level that has attracted wide attentions from researchers. The task for providers and operators is to react to actual demand situations and initiate vehicle re-locations between the stations before shortages occur and customer satisfaction levels drop (Jorge and...
This has been studied and solved in many different ways. One solution is the operator-based strategies, in which staff operations are scheduled to relocate the vehicles to high demand stations by optimization control parameters and key performance indicators (Jorge et al., 2014; Nourinejad et al., 2015; Li et al., 2018; Balac et al., 2019). The other solution is the user-based strategies, in which the relocation is implemented by customers and the system relocates the imbalanced distribution of vehicles in the network by encouraging customers to change their trips at some kinds of rewards. The vehicle imbalancing problem is more complicated in the case of EV-sharing, where the travel range depends on the level of charge of the vehicles (Bruglieri et al., 2014).

To design an efficient EV-sharing system, some studies focus on estimating the willingness of the public about EV-sharing. Kim et al. (2015) conducted a survey to identify factors that may affect participants’ attitudes towards car ownership and EV-sharing program participation. Some studies aim at solving the location problem of EV charging infrastructure (Frade et al., 2011). Besides that, for one-way EV-sharing systems, the common vehicle imbalance problem has also attracted a lot of attentions (Bruglieri et al., 2014; Lin, 2018).

Furthermore, considering customers in sharing economy systems are usually price sensitive (Kumar et al., 2018; Shen et al., 2019), Dynamic Pricing Scheme (DPS) is an essential component in EV-sharing systems. Previous study developed a DPS which can maximize the system profit by reducing vehicle (Jorge et al., 2015), e.g., charging higher prices for the trips that increase imbalance and lower prices for trips that improve the balance. However, this study only focuses on traditional gas vehicles. For EV-sharing systems, factors from multiple domains, i.e., transportation and power systems, need to be considered. The simultaneous charging activities may cause stability problems to distribution grids in residential areas (Flath et al., 2013). Yang et al. (2015) proposes a new optimal EV route model considering the fast-charging and regular-charging under the time-of-use price in the electricity market, which took into account factors from both transportation and power systems. Kempston and Tomic (2005) develop equations to evaluate revenue and costs for EVs to supply electricity to three electric markets (peak power, spinning reserves, and regulation). Similarly, the charging capacity of an EV-sharing station should also be taken as a variable to formulate the DPS.

Another element that the literature has not been well investigated in the EV-sharing system is the station-level demand prediction. Traffic demand/state prediction has been a hot topic in other transportation systems for optimal transportation management, such as bike-sharing demand prediction (Lin et al., 2018a; Regue and Recker, 2014), traffic speed prediction (Lin et al., 2015), border crossing demand prediction (Lin et al., 2018b), and so on. Accurate station-level demand predictions not only enable the relocation of the EVs, but also allow the scheduling of the Vehicle-Grid-Integration (VGI) services. For example, if there will be a significant margin above charging/discharging for a longer time, the price can be adjusted accordingly. In recent years, the development of artificial intelligence and deep learning models has shown very satisfying performances in many traffic demand prediction studies. With the accumulation of EV-sharing demand data, station-level demand prediction should be included in the dynamic pricing model.

1.2. Contributions of this work

This study proposes a novel DPS in a large-scale EV-sharing network considering EV relocation and VGI problems. A graph convolution neural network model (GCNN) with Data-driven Graph Filter (DDGF) model is applied for the station-level EV-sharing demand prediction (Lin et al., 2018a). On the basis of station-level EV demands, we formulate the DPS problem as an optimization model which has two decision variables, namely two Price Adjustment Level (PALS) for every origin-destination pair of stations. The two PALS are tuned to affect the EV-sharing demands and travel times between every origin-destination pair in the network. The proposed model can also consider the requirement from both EV relocation and VGI scheduling to maximize the system profit. The findings provide valuable insights to the operations management of the emerging one-way EV-sharing systems.

The rest of the paper is organized as follows. The next section introduces related work about EV relocation and VGI. The novel DPS optimization model that considers the constraints from the EV relocation and the VGI scheduling is then presented. Following that, a case study is proposed to demonstrate the proposed DPS model. The paper concludes with a discussion of the findings and future research directions.

2. Literature review

2.1. EV relocation

One-way car sharing systems brings convenience to customers comparing with the round-way one, but at the same time induce significant operational challenges due to possible demand-supply imbalance at different stations. To solve the imbalance problems, it requires the service providers to solve the conflict between the positioning of vehicles “at the right place and time” and the freedom for customers to return vehicles where and when they want. This kind of imbalance issue apparently increases the relocation cost (move the vehicles from low demand parking point to high demand parking point), and reduces the service quality of car-sharing systems such that some users have to wait for available vehicles. Comparing with traditional vehicle-sharing systems, EV-sharing systems are more environmentally friendly with rapid development in battery and EV technologies. Furthermore, the emerging autonomous and connected electric vehicles (ACEV) car sharing system can further enhance the system by reducing operation cost and providing safe and efficient mobility services (Li et al., 2016; Xu et al., 2018). However, the imbalanced and dispersed vehicle distributions problem also gets more complicated in EV-sharing systems. For example, one different constraint, the stochasticity in vehicles’ level of charge that limits the available travel distance and time for the customers, needs to be considered. Previous studies on the vehicle relocation problem can be split into two groups: operator-based strategies and user-based strategies respectively.

For operator-based strategies, vehicles are relocated mainly by system operators. Kek et al. (2009) solved the imbalance problem of car sharing system by proposing a three-phase optimization-trend-simulation model. The model found the optimal vehicle relocation strategies in the first phase, then disaggregate the strategies into a set of practical operating parameters (e.g., staff activities, relocation technique, relocation thresholds). In the last phase, the effectiveness of the operating parameters was evaluated via simulation. Besides vehicle relocation, Nourinejad et al. (2015) also took into account of the staff relocation strategies in the car sharing problem. To jointly optimize these two sets of decision variables, an integrated mathematical model was developed to minimize the total cost of the car-sharing system. By making a survey how to define the decision problems related to the vehicle relocation issue, and consider their division into multistage approaches, Illgen and Hock (2019) conduct a detailed review on how to model the relocation problem in one-way traditional car-sharing system. For EV-sharing systems, a more complicated operation planner was proposed by Lee and Park (2014) according to the actual distribution of EVs. They also proposed a three-step EV relocation model, in which the first step is to choose the relocation strategy, the second step is to compute the demand for relocation, and the last step is to schedule the staff operations. Considering specific characteristics of EVs, the consumption and recharging process of EV batteries were taken into account when solving the relocation problem for operating hours by Gambella et al. (2018).

For user-based strategies, customers are encouraged to relocate vehicles. Di Febraro et al. (2012) developed a discrete event model.
that performed well in planning the optimal user-based relocation strategy. By using this method, the absolute difference between the number of available vehicles and user reservations can be minimized in a specified time period. Jorge et al. (2014) proposed a two-step model to increase the profitability in a one-way car-sharing system, in which the first is a mathematical model to optimize the vehicle relocation operations, and the other is a simulation model to study different real-time relocation policies. Considering the limitation of EVs charging level feasibility, Boyaci et al. (2017) developed an optimization framework for the operational planning problem of one-way EV-sharing systems, which is able to decide on the relocations of EVs, movement of personnel and accepting/rejecting rental requests. Based on the above reviewed studies, this paper examines the EV-sharing systems with proposal of a novel DPS.

2.2. Vehicle-grid-integration

Because of the battery’s restriction, EVs need to recharge for future trips. Boyaci et al., (2015) introduced a bi-objective Mixed Integer Programming (MIP) model to simulate the recharging waiting time. Assume the consumption of an EVs’ battery is a linear function, Bruglieri et al. (2014) developed a Mixed Integer Linear Programming (MILP) to maximize the total number of requests served. Zhang et al., 2018a also proposed an ant colony (AC) algorithm to solve the Electric Vehicle Routing Problem (EVRP) by assuming EVs need recharges after each trip. Furthermore, the time-dependent energy price also causes a dynamic cost for EVs travelling in different time periods, as well as an opportunity to sell energy back to grid (Wichmann et al., 2019). Zhang et al., 2018b pointed out that by integrating EVs and grid, the effectiveness of EV-sharing as a promising sustainable transportation solution could be further enhanced. Sovacool et al. (2017) insisted that vehicle-grid-integration (VGI) is able to benefit both the electric power system and the transportation system by linking each other. According to reviewing literature above, the majority of VGI studies only focus on technical aspects of VGI (e.g., the potential of V2G systems to facilitate load balancing, minimization of electricity costs including environmental goals as constraints, and integration of renewable energy into the grid), only a few studies directly investigate the role of consumer acceptance and driver behavior within such systems, and barely any studies address the need for institutional capacity and cross-sectoral policy coordination.

2.3. Pricing strategy for vehicle sharing systems

Pricing is a stable reference of the company that practices a table of prices that should be tailored to the existing consumer preferences and the operational constraints of the company (Jorge et al., 2015). Jorge et al. (2015) proposed a method a Mixed Integer Non-Linear Programming (MINLP) model to maximize profit for optimally setting the trip prices in one-way carsharing systems and show how it can be useful for profit maximization by reducing vehicle fleet imbalance. Following that, taking into account the vehicle relocation and personnel assignment, Xu et al. (2018) develop a mixed-integer nonlinear and non-convex programming model to maximize the profit of operators by determining the electric vehicle fleet size, trip pricing, and strategies of vehicle relocation in one-way carsharing system. Near recently, Giorgionea et al. (2019) propose an availability-based dynamic pricing scheme (price depends on vehicle availability in booking stations) for round-trip carsharing system and conduct a comparison study with a fixed pricing policy scheme. The results indicate that when the dynamic pricing is applied there is a light decrease in the number of bookings and people with low value of time tend to abandon the carsharing mode in favor of other modes of transportation. This paper also explore pricing schemes while the model is totally different from the above studies.

3. Methodology

In this section, we first briefly introduce the graph convolutional neural network for station-level EV demand predictions. On the basis of accurate predictions, the rest part of the section then introduces the dynamic pricing scheme. The notation used to formulate the model (sets, data and decision variables) are summarized as follows: Table 1

3.1. Graph convolutional neural network

Comparing with traditional Convolutional Neural Network (CNN) (Shen and Chan, 2017) which can be applied straightforwardly only in grid structured data such as image and video, Graph Convolutional Neural Network (GCNN) is applicable for data lying on irregular domains. Previous studies have applied GCNNs for station-level bike-sharing demand prediction in a large-scale network (Lin et al., 2018a), and have shown that GCNNs outperform other state-of-the-art models. In this study, we extend the GCNN models from bike-sharing systems to EV-sharing systems. More details of GCNN methodology can be found in Lin et al. (2018a). Here we briefly introduce the basic idea of the GCNN:

Suppose we have a graph $G = (K, S, \delta, A)$, where $K$ is the number of vertices, e.g., $K$ stations in a EV-sharing system; signal $S \in \mathbb{R}^{K \times K}$ is a matrix that each row is the EV demands from previous $d$ time steps for every station; $\delta$ is a set of edges, $A \in \mathbb{R}^{K \times K}$ is the adjacency matrix, and entry $A_{ij}$ encodes the correlation between two EV stations. The task is to predict future EV demands $\hat{S}_{K \times d}$, where $H$ is the prediction horizon.

Previous studies show that the definition of the adjacency matrix $A$ impacts the prediction performance of GCNNs. The hidden correlation between two stations is difficult to be captured with predefined spatial distance or travel time. The GCNN model with data-driven graph filter (DDGF) (Lin et al., 2018a) can learn the adjacency matrix $A$ automatically in order to generate the most accurate predictions. Each layer in the GCNN-DDGF model includes two steps. For the graph convolution step, the signal vector at each station will be either amplified or attenuated, and linearly combined with signals at other vertices weighted proportionally to the learned degree of their correlations. The feed forward step will calculate the signal vectors at vertices of the next layer. Fig. 1 shows one example for the layerwery calculation in GCNN-DDGF.

3.2. The dynamic pricing scheme in a large-scale EV-Sharing network

On one aspect, based on station-level demand predictions provided by the GCNN-DDGF model, we can find an optimal PAL between each pair of stations such that the profit of operating the system is maximized; on the other aspect, we can find another optimal PAL such that the profit of VGI services in each station is maximized while take into account the parking time and electricity price. Electricity price forecasting in different stations and different time periods are of importance to the pricing scheme especially when the EV-sharing scale is large. The Panel Cointegration and Particle Filter (PCPF) model (Li et al., 2013) which utilizes information of both the inter-temporal dynamics and the individuality of interconnected regions, was adopted in this study to maximize profits from these two aspects while detailed description of the techniques is beyond the scope of this paper.

Different from other business modes, customers in sharing economy are usually price sensitive, which indicates users of sharing EVs can be motivated by a well-designed DPS to take part in the operation management. The DPS in a large-scale EV-Sharing network proposed in the study is a time-varying price matrix contains two PALs between each Origin-Destination pair of stations. PAL1 = $P_{ij}$/P0 aims at encouraging the EV movements between a set of stations to maximize the profit of a one-way EV-Sharing network during a given period. PAL2 = $P_{ij}$/P0 aims at affecting the travel time based on a trade-off between profit.
Table 1
Definition for notation.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>K' = (1,...,k,...K)</td>
<td>Set of Stations.</td>
</tr>
<tr>
<td>V' = (1,...,v,...V)</td>
<td>Set of sharing EVs.</td>
</tr>
<tr>
<td>T' = (1,...,t,...T)</td>
<td>Set of time instants in the operation period.</td>
</tr>
<tr>
<td>Γ' = (1,...,i,...I)</td>
<td>The set of time intervals in the operation period.</td>
</tr>
<tr>
<td>X = (1,...,k,...k,...k,...k)</td>
<td>Nodes of a time-space network combining the K stations with the T time intervals, where k represents station k at time instant t.</td>
</tr>
<tr>
<td>A = {k_\text{1}, k_\text{t}, ...}</td>
<td>Set of arcs over which vehicles move between stations k and ( j ), ( \forall k, j \in K' ), between time instant t and t + 1, ( \delta_1^{kj} ).</td>
</tr>
<tr>
<td>A = {k_\text{1}, k_\text{t}, ...}</td>
<td>Set of arcs that represent vehicles stocked in station k, ( k \in K' ), from time instant t to time t + 1.</td>
</tr>
<tr>
<td>C_{\text{inv}}</td>
<td>The maintenance cost of each vehicle per unit time driven.</td>
</tr>
<tr>
<td>C_{\text{mp}}</td>
<td>The cost of maintaining one parking space per day.</td>
</tr>
<tr>
<td>C_{\text{d}}</td>
<td>The depreciation cost of one vehicle per day.</td>
</tr>
<tr>
<td>P0</td>
<td>The current carsharing price for all Original-Destination pairs of stations at any time instant.</td>
</tr>
<tr>
<td>( D_{0,k_1k_{t+1}}^{ij} )</td>
<td>Number of customer trips from stations k to j from instant t to instant t + 1, ( \delta_1^{ij} ), ( \forall k_\text{1}, k_{t+1} \in A_1 ) for the reference price.</td>
</tr>
<tr>
<td>( \delta_1^{ij} )</td>
<td>Travel time, in time instants, between stations k and j when departure time is t, ( \forall k, \in X, j \in K' ) for the reference price.</td>
</tr>
<tr>
<td>( P_{0,ij} )</td>
<td>The current carsharing price per time step driven from stations k to j when departure time interval is ( i_t ), ( \forall k \in X, j \in K' ), i ( \in I' ) for the reference price.</td>
</tr>
<tr>
<td>( \delta_1^{ij}<em>{k_1k</em>{t+1}} )</td>
<td>The state that the vehicle v is connected in the parking lot at station k from time instant t to time t + 1, ( \forall v \in V', (k_1k_{t+1}) \in A_2 ) for the reference price.</td>
</tr>
<tr>
<td>B_v</td>
<td>The nominal battery capacity of vehicle v, ( \forall v \in V' ).</td>
</tr>
<tr>
<td>B_{\text{v}}'</td>
<td>The upper threshold of SOC of battery.</td>
</tr>
<tr>
<td>B_{\text{v}}''</td>
<td>The lower threshold of SOC of battery.</td>
</tr>
<tr>
<td>P_{\text{EL}}_Z</td>
<td>The electricity price (€/KWh) in zone Z at time interval i, ( \forall z \in Z', i \in I' ).</td>
</tr>
<tr>
<td>P_{\text{EL}}_Z</td>
<td>The capacity price (€/KWh) in zone Z at time interval i, ( \forall z \in Z', i \in I' ).</td>
</tr>
<tr>
<td>R_{\text{EL}}_Zc</td>
<td>The average ratio of the actual energy dispatched for regulation and the total power available.</td>
</tr>
<tr>
<td>S_k</td>
<td>Size of station k, ( \forall k \in K' ), where size refers to the number of parking spaces.</td>
</tr>
<tr>
<td>( n_k )</td>
<td>Number of available vehicles at station k at time instant, ( \forall k \in X ).</td>
</tr>
<tr>
<td>( V_{kk+1} )</td>
<td>Number of vehicles stocked at each station k from time instant t to time t + 1, ( \forall (k,k_{t+1}) \in A_2 ).</td>
</tr>
<tr>
<td>( \text{SOC}_v^i )</td>
<td>The state of charge of vehicle v at instant t, ( \forall v \in V' ).</td>
</tr>
<tr>
<td>( \text{Cap}_k )</td>
<td>The contracted capacity available at station k at instant t.</td>
</tr>
<tr>
<td>( \delta_1^{ij}<em>{k_1k</em>{t+1}} )</td>
<td>The time that the vehicle v is connected in the parking lot at station k from time instant t to time t + 1, ( \forall v \in V', (k_1k_{t+1}) \in A_2 ) after the price is varied.</td>
</tr>
<tr>
<td>( \delta_1^{ij}<em>{V</em>{kk+1}} )</td>
<td>The round up time (in hours) that the vehicle v in the parking lot at station k from time instant t to time t + 1, ( \forall v \in V', (k,k_{t+1}) \in A_2 ).</td>
</tr>
<tr>
<td>( \text{V2P}_{\text{kt+1}} )</td>
<td>The power that the vehicle v is discharged to the parking lot at station k per minute from time instant t to time t + 1, ( \forall v \in V', (k,k_{t+1}) \in A_2 ).</td>
</tr>
<tr>
<td>( \text{V2P}_{\text{kt+1}} )</td>
<td>The power that the vehicle v is charged from the parking lot at station k per minute from time instant t to time t + 1, ( \forall v \in V', (k,k_{t+1}) \in A_2 ).</td>
</tr>
<tr>
<td>( D_{0,k_1k_{t+1}}^{ij} )</td>
<td>Number of customer trips from stations k to j from instant t to instant t + 1, ( \delta_1^{ij} ), ( \forall k_\text{1}, k_{t+1} \in A_1 ) after the price is varied.</td>
</tr>
<tr>
<td>( \delta_1^{ij} )</td>
<td>Travel time, in time instants, between stations k and j when departure time is t, ( \forall k, \in X, j \in K' ) after the price is varied.</td>
</tr>
<tr>
<td>PAL1</td>
<td>PAL per time step driven between stations k and j when departure time period is ( i_t ), ( \forall k \in X, j \in K', i \in I' ).</td>
</tr>
<tr>
<td>PAL2</td>
<td>PAL driven the travel time between station k and j when departure time period is ( i_t ), ( \forall k \in X, j \in K', i \in I' ).</td>
</tr>
</tbody>
</table>

From EV-sharing services and VGI services according to the electricity prices during a given period.

The dashed line is the learned adjacency matrix A. Each color in Fig. 1(a) represents a feature vector for that vertex. Through Step 1 the graph convolution, the mixed color at each vertex in Fig. 1(b) represents the feature vector are combined with those from other vertices on the basis of the learned A. Through Step 2 the feed forward operation, the new color with a background pattern represents the new feature vector at each node in Fig. 1(c). Programming (MINLP) model is formulated to search the optimal combination of the two PALs to maximize the profit of operation system by considering EV relocation and VGI services.

EV-Sharing Demand, in this model, varies according to a simple elastic behavior. The new demand \( D_{0,k_1k_{t+1}}^{ij} \) results from applying the price elasticity \( E_{\text{Demand}} \) to a reference demand \( D_{0,k_1k_{t+1}}^{ij} \) that exists for price P0. The expression is:

![Fig. 1. Layer-wise calculation of GCNN-DDGF model.](image-url)
We assume that there are inverse proportional relationship between the varies in Sharing EV travel time and the varies in sharing EV parking lot connection time $\delta_{i,k_{i+1}}$. The expression is:

$$\frac{\delta_{i,k_{i+1}}}{\delta_{i,j}} = \frac{\delta_{0,j}}{\delta_{0,k_{i+1}}}$$  \hspace{1cm} (3)

Therefore, we have

$$\delta_{i,k_{i+1}} = \frac{\delta_{0,j}}{\delta_{0,k_{i+1}}} \times P0 \times E_{Time}$$  \hspace{1cm} (4)

Using the above notation, the model is formulated as follows:

$$\text{Max} \theta = \sum_{k_{i},k_{i+1} \in A_{k}} \left( R_{k_{i}k_{i+1}} \right) \sum_{i \in V} \sum_{k \in K} \left( R_{i,k} \right) \sum_{t \in T}$$  \hspace{1cm} (5)

The DPS model assumes that the estimated value of the price elasticity of demand is known and do not change during the operation period. Therefore, the decision variables $D_{c_{i}}$ and $\delta_{i,j}$ are considered known when the MINLP solver is searching the optimal combination of PALs. Using the optimal combination of PALs, the 2 stations EV-sharing network is able to achieve a profit of 287.59€ during 1 h’s operation. Not surprisingly, we find that the adjusting directions of the same PALs from station 1 to station 2 and from station 2 to station 1 are opposite. It indicates that the movements of EVs from station 1 to station 2 will be encouraged because PAL1(1–2) lowering the carsharing price, and the travel time from station 1 to station 2 is expected to be shortened as PAL2(1–2) will lead to a higher price. That is to say the DPS would encourage EVs move to station 2 faster. Besides, some interesting observations include: i) the adjusting directions of the two PALs between each origin-destination pair of stations are opposite. For example, if the system operator applies PAL1(1–2) only, the adjusted car sharing price from station 1 to station 2 will enjoy a 10% discount, however, PAL2(1–2) will raise the price up to 120%; ii) PAL2 has a more dominant impact on the adjusted price than PAL1. It can be seen easily because the adjusting directions based on the composite PAL and the PAL2 are always the same, e.g., 108% and 120% for trips from station 1 to 2, and 88% and 80% for trips from station 2 to 1; iii) The mean of the adjusted car sharing prices from station 1 to 2 and from station 2 to 1 is $(\€0.324/min + \€0.264/min)/2 = \€0.294/min$, which is 90% of the price in the previous study (Jorge et al., 2015), then change the value of $E_{Time}$ as $-0.8$, $-1.0$, $-1.2$, $-1.7$ or $-2$ to investigate the impact of $E_{Time}$ on the profit of the operation network.

It is worth noting that $D_{c_{i}}$ and $\delta_{i,j}$ can be predicted from the previous works proposed by the authors. For the consideration of simplicity, we assume these values are given.

With these data and parameters, the DPS model is implemented for a “two stations and one hour” case, which is shown in Fig. 2. The computation results are given in Table 3, where PAL1(1–2) and PAL2(1–2) denote the PALs for trips from station 1 to station 2, PAL1(2–1) and PAL2(2–1) denotes the PALs for trips from station 2 to station 1.

### Table 3: Computation results of DPS model.

<table>
<thead>
<tr>
<th>PAL1(1–2)</th>
<th>PAL2(1–2)</th>
<th>PAL1(2–1)</th>
<th>PAL2(2–1)</th>
<th>Profit (€/hour)</th>
</tr>
</thead>
<tbody>
<tr>
<td>90%</td>
<td>120%</td>
<td>110%</td>
<td>80%</td>
<td>287.59</td>
</tr>
<tr>
<td>Composite PAL (1–2)</td>
<td>Composite PAL (2–1)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>108%</td>
<td>88%</td>
<td></td>
<td></td>
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<table>
<thead>
<tr>
<th>Adjusted car sharing price (1–2)</th>
<th>Adjusted car sharing price (2–1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>€0.324/min</td>
<td>€0.264/min</td>
</tr>
</tbody>
</table>

### Table 2: Data/Parameter values in the computation experiments.

<table>
<thead>
<tr>
<th>Data/Parameters</th>
<th>Value</th>
<th>Reference</th>
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<tbody>
<tr>
<td>$c_{i}$</td>
<td>€0.007/min</td>
<td>Wang et al. (2011)</td>
</tr>
<tr>
<td>$c_{i}$</td>
<td>€0.007/min</td>
<td>Jorge et al. (2015)</td>
</tr>
<tr>
<td>$c_{i}$</td>
<td>€0.007/min</td>
<td>Jorge et al. (2015)</td>
</tr>
<tr>
<td>$p_{0}$</td>
<td>€0.3/min</td>
<td>Car2go (2018)</td>
</tr>
<tr>
<td>$B_{v}$</td>
<td>30 KWh</td>
<td>Nissan Leaf (2018)</td>
</tr>
<tr>
<td>$\delta_{0,j}$</td>
<td>95%</td>
<td>Kempton and Tomić (2005)</td>
</tr>
<tr>
<td>$\delta_{0,j}$</td>
<td>50%</td>
<td>Kempton and Tomić (2005)</td>
</tr>
<tr>
<td>$P_{i}^{i}$</td>
<td>€0.0032/KWh</td>
<td>Nord Pool (2018)</td>
</tr>
<tr>
<td>$R_{i}^{i}$</td>
<td>10%</td>
<td>Nord Pool (2018)</td>
</tr>
<tr>
<td>$E_{Demand}$</td>
<td>−1.5</td>
<td>Jorge et al. (2015)</td>
</tr>
<tr>
<td>$E_{Time}$</td>
<td>−1.5</td>
<td>−1.5</td>
</tr>
<tr>
<td>$D_{0,j}$</td>
<td>predicted by GCNN model</td>
<td>Lin et al. (2018a)</td>
</tr>
<tr>
<td>$PEL_{i}$</td>
<td>predicted by PCPF model</td>
<td>Li et al. (2013)</td>
</tr>
</tbody>
</table>

is close to the original carsharing price €0.3/min. From this point of view, the customers will enjoy a slightly discount by the DPS.

We then change the values of $E_{Time}$ from $-0.8$ to $-2$ with a step of $0.2$ to investigate the impact of $E_{Time}$ on the profit of the operation network. Fig. 3 shows the statistics of best solutions found during each of the runs. It can be seen that PAL2(1–2) raised the prices much heavily while PAL2(2-1) lower the prices at most all the time.

As shown in Table 4, the elasticity influences the results achieved by the algorithm when reference parameters are used. Very good results can be obtained when the demand does not significantly depend on the price, as can be seen for the elasticity $E_{Time} = -1.2$ (the best profit found is 308.24€ during the 1-h operation). In this case, both Composite PALs are lower than the original carsharing price, which means all customers enjoy a discount in the network according to the DPS. It can be easily explained by the economics fact that a relatively low elasticity and discounted prices attract more customers to move to the destination faster. Besides, it is of interest to observe that the lowest profits are registered for the lowest elastic problem we considered, where the worst solution has a profit of 278.60€ for the operation hour. The average of all cases is 292.52€. In general, when the price elasticity falls within the interval $(-1,0)$, changes in price are considered to have a relatively small effect on the quantity of the demand. In this case, the service providers can raise prices without affecting consumers’ travel time. The low profit achieved can be explained that the in-elasticity unable to increase the connected time in parking lots so that the profit from VGI services cannot be increased.

Note that the objective function (20) in the proposed DPS model is an MINLP problem which is not easy to solve by traditional branch and cut algorithms. Some MINLP solver software tools are capable of solving this type of problem for both concave and non-concave formulations, but the search space of our problem is much larger than that these solvers can tackle. With only two stations and one time period, if PALs vary from 80% to 120% with 0.1 increments, our calculation shows the number of possible solutions for this problem would be 625.

In order to obtain more sensitivity analysis and findings, the “four stations and three hours” case study is further conducted and the details are shown in Appendix A.

5. Conclusion

EV-sharing is an emerging transportation mode that can help to alleviate many transportation issues such as traffic congestion, traffic emission, and so on. A novel dynamic pricing scheme for EV-sharing systems is proposed in this study. Problems from both transportation system and energy system are considered in the proposed pricing scheme. For the former, station-level EV demand is predicted through a graph convolutional neural network with data-driven graph filter that can learn hidden correlations between stations to improve prediction performances; For the latter, the vehicle-grid-integration is considered. The proposed DPS has been tested on two case studies, named the “two stations and one hour” and the “four stations and three hours”, respectively. Computation results show that the proposed DPS can effectively maximize the system profit by considering both vehicle relocation and VGI scheduling.

More specifically, we suggest that the proposed DPS is able to work well in a large scale EV-sharing network and assist system operator to utilize the optimized prices set to harvest its largest profit. Key findings from our case studies can be summarized as:

1. The operator of a carsharing system can raise the EV-sharing prices higher with the help of the proposed DPS in some arcs with larger stations without rejecting customers. But for arcs with only small size stations, the prices can only be adjusted to a limit extend;
2. When applying the proposed DPS, the MBE (imbalance level of the sharing EV system) is cut down from 40% to 20% while the average EV-sharing price is increased by 40%;
3. The diverse distribution of the composite PAL enables the DPS to take advantage of the market power to alleviate imbalance of vehicles across all the stations as well as to affect the travel times in different routes;
4. The average travelling time decreases in most cases with the increase of EV-sharing cost. It indicates that: I) the system operator prefers to serve more trips with short distances; II) the electricity prices at this time period are considered high enough for EVs to

![Image](image_url)

**Table 4** Computation results of different $E_{Time}$

<table>
<thead>
<tr>
<th>$E_{Time}$</th>
<th>PAL1 (1–2)</th>
<th>PAL2 (1–2)</th>
<th>Composite PAL (1–2)</th>
<th>PAL1 (2–1)</th>
<th>PAL2 (2–1)</th>
<th>Composite PAL (2–1)</th>
<th>Profit (€/hour)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$-0.8$</td>
<td>100%</td>
<td>120%</td>
<td>120%</td>
<td>100%</td>
<td>90%</td>
<td>90%</td>
<td>308.24</td>
</tr>
<tr>
<td>$-1$</td>
<td>80%</td>
<td>120%</td>
<td>96%</td>
<td>80%</td>
<td>90%</td>
<td>72%</td>
<td>283.18</td>
</tr>
<tr>
<td>$-1.2$</td>
<td>90%</td>
<td>100%</td>
<td>90%</td>
<td>90%</td>
<td>90%</td>
<td>81%</td>
<td>308.24</td>
</tr>
<tr>
<td>$-1.5$</td>
<td>90%</td>
<td>120%</td>
<td>108%</td>
<td>110%</td>
<td>80%</td>
<td>88%</td>
<td>287.59</td>
</tr>
<tr>
<td>$-1.7$</td>
<td>100%</td>
<td>110%</td>
<td>110%</td>
<td>100%</td>
<td>80%</td>
<td>80%</td>
<td>290.69</td>
</tr>
<tr>
<td>$-2$</td>
<td>80%</td>
<td>80%</td>
<td>64%</td>
<td>110%</td>
<td>90%</td>
<td>99%</td>
<td>286.77</td>
</tr>
<tr>
<td>Average</td>
<td>93%</td>
<td>102%</td>
<td>98%</td>
<td>103%</td>
<td>93%</td>
<td>85%</td>
<td>292.52</td>
</tr>
</tbody>
</table>

Fig. 3. Computation results of different $E_{Time}$. 
improve the overall profit via providing VGI services in the stations for staying longer time;

(5) It is worth noting that electricity prices in this case study consist of both electricity price and capacity price. In this case, the system operators are able to receive paybacks once their sharing EVs connected to the grid, because EVs provide ancillary services to the power grid based on the capacity of their batteries. This part of incoming may differ significantly in different cities subjected to different electricity market rules;

(6) When the elasticity of $E_{Time}$ is high enough, more trips with short distances become a popular pattern of the EV-sharing system. However, when the elasticity exceeds a threshold, the profit of each trip cannot be increased anymore as the cost per trip is fixed;

(7) In all cases with different values of $E_{Time}$, the profit for rebalancing service is negative and the values are relatively stable while the profit from VGI services is positive and varies according to the change of $E_{Time}$ significantly. The proposed DPS tend to adjust the dynamic pricing set to optimize the total profit.

Appendix A. Four stations and three hours case study

The proposed DPS model is applied into a “four stations and three hours” case study. In this sharing EV network, there are 100 sharing EVs moving among 4 stations which sizes are: $Z_1 = 40; Z_2 = 20; Z_3 = 30; Z_4 = 10$. Other parameters values are same as in the “two stations and one hour” case study, which have been listed in Table 2. It should be noted that there is no any study that specifically address the calculation of carsharing elasticity of travel time $E_{Time}$, we firstly assume $E_{Time} = E_{Demand} = -1.5$ based on the previous study (Jorge et al., 2015), then change the value of $E_{Time}$ as -0.1, -0.8, -1.2, -1.5, -1.7, -1.9, -5 to investigate the impact of $E_{Time}$ on the operations in the sharing EV network.

A. Analysis of EV sharing Prices

When $E_{Time} = E_{Demand} = -1.5$, the variations of PAL1s, PAL2s, and composite PALs (composite PAL = PAL1* PAL2) from 5PM to 7PM in the 12 routes among 4 stations can be observed in Fig. 1. In each arc, PAL1s and PAL2s are shown as the light pink columns and dark pink columns, respectively. Most of the PALs are larger than 1 so that the composite PALs (denoted by the red lines) usually lied above both PAL1s and PAL2s. In another words, the EV-sharing prices are raised in most cases. Another interesting observation from Fig. 4 is that, except the composite PALs in the route (2,3) (refer to from station 2 to 3), others varied relatively dramatically over time. Furthermore, variation directions of the composite PALs over times in the 2 routes of each arc are opposite at most cases. For example, the composite PAL in the route (2,4) goes up from 5pm to 6pm, then goes down from 6pm to 7pm, while the one in the route (4,2) varies in a different way. To analysis further, the average composite PALs from 5PM to 7PM in each arc is listed as followed: arc(1,2) = 1.45, arc(1,3) = 1.48, arc(1,4) = 1.33, arc(2,3) = 1.45, arc(2,4) = 1.39, arc(3,4) = 1.33. It's interesting that low prices are all seen in arcs contain station 4, which is the smallest one among all stations. And the highest price 1.48 is found in the arc between station 1 and 3, which are the two largest ones in the system. The results indicate that a larger size station with plenty parking lots buffer enables the system operator to raise prices without rejecting customers. The system operator would without doubt to raise the price as much as possible, but price increase causes falls in the demand. When unreasonably high prices are applied, the demand drops to a certain low level or even zero by force of the elasticity. And if the available EVs in the station are too few it would reject potential customers, which is the case that the system operator don't want to see. To sum up, the arc with large station has more room to adjust its according EV-sharing prices while others can only adjust to a limit extend. By the help of the proposed DPS, the system operator can utilize the optimized prices set to harvest its largest profit.

The variations trends of PAL1s and PAL2s can be seen clearly in Fig. 5 by applying the 2nd order polynomial curve fitting (the regression equations are shown on the top right corner), that is, PAL1’s trend decreased gradually while PAL2’s trend increased rapidly. The lowest (0.94) and highest (1.38) value of PAL1 and can be found in route (4,3) at 5PM and route (3,2) at 6PM, respectively. The lowest (0.94) value of PAL2 can be found in route (4,1) at 5PM, route (2,3) and route (3,4) at 6PM. The highest (1.40) value of PAL2 can be found in route (3,2) at 7PM.

![Fig. 4. PAL1s, PAL2s, and Composite PALs from 5PM to 7PM in 12 routes among 4 stations.](image-url)
Both the lowest (0.98) and highest (1.81) value of the composite PAL can be found in route (3,1) and route (2,3) at 7PM. It is noted that only three composite PALs are less than 1 and the mean of composite PALs is as high as 1.40. Not surprisingly, the system operator would take the opportunity to improve its overall profitability by setting the optimal combination of PALs set. Although the trend curve of the composite PAL looks much smooth and steady in Fig. 6 comparing with the PAL1 and PAL2 ones, the standard deviation of the composite PAL set is 0.25, which is higher than PAL 1’s (0.14) and PAL2’s (0.15). The diverse distribution of the composite PAL enables the DPS to take advantage of the market power to alleviate imbalance of vehicles across all the stations as well as to affect the travel times in different routes.
B. Analysis of the impacts of PALs on the demand

To analyse the impacts of PALs on the demand, all variations of demand over times in the 12 routes are shown in Fig. 7. In the small Fig of each route, the light gray column denotes D0s while the dark gray one denotes D1s after applying the according composite PALs which is shown in the red line. Besides, the PAL1 is also plotted in blue lines as a reference. In order to evaluate the effect of the proposed DPS on alleviating the imbalance situation in the EV sharing system, the MBE (Mean Balancing Error) proposed by N. Wang et al. (2018) was adopted. Applying the proposed DPS, the MBE has been cut down from 40% to 20% while the average EV-sharing price has been increased by 40%.

When we look at the small Fig in each route, although the composite PALs are the final ones which applied to the customers, the PAL1s are much related to the demand variations. It is clearly that when the PAL1 is less than 1, the demand climbs up and its adjustment level follows PAL1’s variation according, vice versa. The Highest adjustment level 67% is recorded in the route (2,1) at 7PM and the lowest one 5% are found in the route 3.
(3,1) and route (2,4) at 7PM. It is noted that in most cases operator takes advantage of the opportunity to improve the profitability by applying the composite PALs to raise up the EV-sharing prices. For example, if customer choose to ride the EVs in the route (4,1) at 5pm, they would have enjoyed a slightly discount 0.99 if only PAL1. However, the customer needs to pay 5% more under the proposed DPS. It is worth noting that there is not only transportation reason but also VGI reason for the variation of a station’s demand over time.

C. Analysis of the impacts of PALs on the travelling time

To analyse the impacts of travel on the travelling time, all variations of the travelling time from 5PM to 7PM in the 12 routes are shown in Fig. 8. In the small Fig of each route, the light gray column denotes T0s while the dark gray one denotes T1s after applying the according composite PALs which is shown in the red line. Besides, the PAL2 is also plotted in green lines as a reference. It is interest to observe that the average travelling time decreases in most cases with the increase of EV-sharing cost. It indicates that: 1) the system operator prefers to serve more trips with short distances; 2) the electricity prices at this time period are considered high enough for EVs to improve the overall profit via providing VGI services in the stations for staying longer time. It is worth noting that electricity prices in this case study consist of both electricity price and capacity price. In this case, the system operators are able to receive paybacks once their sharing EVs connected to the grid, because EVs are providing ancillary services to the power grid based on the capacity of their batteries. This part of incoming may differ significantly in different cities with different electricity market rules.

![Fig. 8. Impacts of PALs on the travelling time from 5PM to 7PM in the 12 routes.](image)

Similar to the case in variation of demand, although the composite PALs are the final ones which applied to the customers, the PAL2s are much related to the travelling time variations. It is clearly that when the PAL2 is less than 1, the average travelling time last for longer, vice versa. It is noted that in most cases and the system operator takes advantage of the opportunity to improve the profitability by applying the composite PALs to raise up the EV-sharing prices. For example, the customer would have enjoyed a 5% discount on the unit price in the route (4,2) at 6pm if only PAL2 was applied. However, the customer needs suffer a composite PAL 1.07 under the proposed DPS. It’s worth noting that the average travelling times decreases significantly (> 20%) over two third of the routes. The Highest adjustment level 59% are recorded in the route (3,2) and route (4,2) at 7PM and the lowest one – 2% are found in the route (3,1) at 7PM.

<table>
<thead>
<tr>
<th></th>
<th>5PM</th>
<th>6PM</th>
<th>7PM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>–24%</td>
<td>–30%</td>
<td>–30%</td>
</tr>
<tr>
<td>2</td>
<td>–24%</td>
<td>–30%</td>
<td>–30%</td>
</tr>
<tr>
<td>3</td>
<td>–24%</td>
<td>–30%</td>
<td>–30%</td>
</tr>
<tr>
<td>4</td>
<td>–24%</td>
<td>–30%</td>
<td>–30%</td>
</tr>
</tbody>
</table>

D. Analysis of the impacts of price elasticity on the Profit

To analyse the impacts of price elasticity on the profit of the operation network, we tested the proposed DPS with different values of $E_{\text{Time}} = [-0.1, -0.8, -1, -1.2, -1.5, -1.7, -1.9, -5]$. As shown in Table 7, the elasticity influences the results achieved by the proposed DPS when reference parameters are used. Very good results can be obtained when the travelling time nearly not depend on the price, as can be seen for the elasticity $E_{\text{Time}} = -0.1$ (the best profit found is 1,619 € during the 3-h operation). In this case, the mean of composite PALs 1.39 is relatively high among all cases, which means all customers need to pay more for every minute they are riding the sharing EVs. It can be easily explained by the economics fact that the low elasticity (near inelasticity) enables service providers to raise prices without rejecting customers. Considering that there are several alternative transportation tools available, it is impossible that an EV sharing system can achieve such low $E_{\text{Time}}$ value.
Besides the near inelasticity case, it is observed that the total profit of the EV sharing system increases as $E_{\text{Time}}$ goes up till $E_{\text{Time}} = -1.8$. It indicates that the average travelling time decreases more and more significantly with the increase of elasticity. When the elasticity is high enough, more trips with short distances become a popular pattern of the EV sharing system. However, when the elasticity passes a threshold, the profit of each trip cannot be increased anymore as the cost per trip is fixed. It is worth noting that in all cases, the profit for rebalancing service is negative and the values are relatively stable while the profit from VGI services is positive and varies according to the change of $E_{\text{Time}}$ significantly. The possible reason may be the profit of providing the VGI services during these three hours are higher than the ones of rebalancing. From the results, it can be concluded that the proposed DPS tend to adjust the dynamic pricing set to optimize the total profit.

### Appendix B

$$R_{DS} = (P_k^i - C_m) \times D_{k_i|s_j} \times \delta_{k_i|s_j} \sum_{k \in K} Z_k - C_v \sum_{k \in K} \alpha_k + K \sum_{k \in K} \beta_k$$

$$R_{\text{VGI}} = PEL^i \times \delta_{k_i|s_j} \times (V_{k|s_j}^{V|s_j} - G_{v|s_j}^{V|s_j}) + \min \left( \frac{\text{Cap}_{k|s_j}^{i}}{V_{k|s_j}^{i}} \right) \times \left( PEC_k^i \times \delta_{k_i|s_j} + PEL_k^i \times \delta_{k_i|s_j} \right)$$

Subject to,

$$D_{k_i|s_j} \geq D_{0k_i|s_j} + \frac{E_{\text{Demand}} \times D_{0k_i|s_j} \times (P_{0w} - P_0)}{P_0} - 0.5 \right \{ k_i|s_j \} \in A_i, z, w \in Z', i \in I'$$

$$D_{k_i|s_j} \leq D_{0k_i|s_j} + \frac{E_{\text{Demand}} \times D_{0k_i|s_j} \times (P_{0w} - P_0)}{P_0} + 0.5 \right \{ k_i|s_j \} \in A_i, z, w \in Z', i \in I'$$

$$D_{0k_i|s_j} \geq 0$$

$$V_{k|s_j} + \sum_{j \in K} D_{k_i|s_j} = \sum_{j \in K} D_{j|i|s_j} + V_{k|s_j}, \forall \ k \in X$$

$$a_{uv} = V_{k|s_j} + \sum_{j \in K} D_{k_i|s_j}, \forall \ k \in X$$

$$Z_k \geq 0, \forall \ k \in X$$

$$D_{k_i|s_j} \in \mathbb{N}^0, \forall \ k \in X$$

$$P_{0w} \in \mathbb{R}^0, \forall \ z, w \in Z', i \in I'$$

$$V_{k|s_j} \in \mathbb{N}^0, \forall \ (k|s_j) \in A_2$$

$$a_{uv} \in \mathbb{N}^0, \forall \ k \in X$$

$$Z_k \in \mathbb{N}^0, \forall \ k \in K'$$

$$\delta_{k_i|s_j} \geq \frac{\delta_{0k_i|s_j} \times P_0}{P_0 + (P_{0w} - P_0) \times E_{\text{Time}}} - 0.5 \right \{ k_i|s_j \} \in A_i, z, w \in Z', v \in V', i \in I'$$

$$\delta_{k_i|s_j} \leq \frac{\delta_{0k|s_j} \times P_0}{P_0 + (P_{0w} - P_0) \times E_{\text{Time}}} + 0.5 \right \{ k_i|s_j \} \in A_i, z, w \in Z', v \in V', i \in I'$$
\[ \frac{\partial V_{kkt}}{\partial t} \times P_0 \geq 0 \]

\[ P_0 + \left( \frac{P_j}{q_j} - P_0 \right) \times E_{\text{Time}} \]

\[ V_{G}^k + V_{G}^k = 0 \]

\[ 0 \leq V_{G}^k + \delta_{kkt} \leq \frac{C_A}{V_{kkt}} \]

\[ 0 \leq V_{G}^k + \delta_{kkt} \leq \frac{C_A}{V_{kkt}} \]

\[ \text{SOC}_{v}^k + \frac{V_{G}^k \times \delta_{kkt}}{B_v} \leq B_v^{\text{LT}} \]

\[ B_v^{\text{LT}} \leq \text{SOC}_{v}^k - \frac{V_{G}^k \times \delta_{kkt}}{B_v} \]

The objective function (6)–(7) is to maximize the total profit $\theta$ of the one-way car-sharing service, taking into consideration the revenue from i) the relocation services, including the trips paid by clients, vehicle maintenance costs, vehicle depreciation costs, station maintenance costs, and relocation costs; ii) the VGI services, including the charging cost or discharging income, revenues from spinning reserves and regulation services.

Equations (8)–(18) are constraints related to the EV relocation services. Constraints (8) and (9) compute the demand resulting from considering the price change. Given that this demand is a continuous function of price, we use two inequalities to ensure that $D$ will be integer. Constraints (10) ensure that the demand resulting from the application of price elasticity to the reference demand is positive. Constraints (11) ensure the conservation of vehicle flows at each node of the time–space network. Constraints (12) compute the number of vehicles at each station $k$ at the start of time instant $t$, assuming that vehicles destined to arrive at station $k$ at time instant $t$ arrive before vehicles leave from the same station at time instant $t$. Constraints (13) guarantee that the size of the station at location $k$ is greater than the number of vehicles located there at each time instant $t$. Expressions (14)–(16) set the variables domain.

Equations (19)–(26) are constraints related to the VGI services. Similar to Constraints (8)–(10), Constraints (19) and (20) compute the Sharing EV parking lot connection time resulting from considering the price change while (21) regulate the price elasticity. Constraints (22) ensure that the simultaneous charging and discharging at the same period is not a feasible operation for an EV. Constraints (23) and (24) guarantee that the spinning reserves and regulation services each EV provided is in compliance with the nominal power of the charging infrastructure. Constraints (25) and (26) ensure that EV battery operates within acceptable limits.

References


Sovacool, B.K., Axsen, J., Kemp, W., 2017. The future promise of vehicle-to-grid (V2G)


Zhang, Y., Li, M., Shen, S., 2018b. On the values of vehicle-to-grid electricity selling in electric vehicle sharing. Available at: SSRN: https://ssrn.com/abstract=3172116,