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A Novel Dynamic Pricing Scheme for a Large-scale Electric Vehicle Sharing Network Considering Station-level Demand Prediction and Vehicle-Grid-Integration

Lei Lin[1], Xuran Li[2], Shuyun Ren[3]*, Shu-Chien Hsu[4], Yingying Chen[5]

[1] *Research Scientist, Goergen Institute for Data Science,*

University of Rochester, Rochester, NY, 14623, USA

[2] *Research Fellow, Department of Civil and Environmental Engineering,*

The Hong Kong Polytechnic University

[3] *Associate Professor, School of Art & Design,*

Guangdong University of Technology

[4] *Assistant Professor, Department of Civil and Environmental Engineering,*

The Hong Kong Polytechnic University

[5] *Electrical Engineer,*

Visionstream Pty Ltd Australia

ABSTRACT

With promising benefits such as traffic emission reduction, traffic congestion alleviation, and parking problems solving, electric vehicle (EV) sharing systems have attracted huge attentions. This study proposes a novel dynamic pricing scheme (DPS) for a large-scale EV-sharing network by considering station-level demand prediction and vehicle-grid-integration. The station-level demand can be predicted through a graph convolutional neural network based on data-driven graph filter which can automatically capture hidden correlations among stations. Based on accurate demand predictions, the proposed DPS aims at maximizing total system profit from EV operation and vehicle-grid-integration (VGI) services by solving a Mixed Integer Nonlinear Programming problem (MINLP). The proposed DPS can provide the optimal combination of the two Price Adjustment Levels (PALs) to maximize the profit of operation system by considering rebalancing services and VGI services. Several interesting points were found through the computation experiments of the proposed DPS.

KEY WORDS: Electric Vehicle Sharing; Graph Convolutional Neural Network; Data-driven Graph Filter; Pricing Scheme; Demand Prediction; Vehicle-Grid-Integration; Price Adjustment Levels.

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[*] Corresponding author, Tel.: +86 13560110790
E-mail address: shuyun_shara@live.cn

1. Introduction

Vehicle sharing is one of the novel business modes, which has become popular with the potential to reduce traffic congestion, decrease traffic emission and solve parking problems. 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 provide mobility services based on electric vehicles (EV).

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) proposed a maximal covering model to determine optimal location of EV charging stations, the number, and capacity of the stations. Besides that, for one-way station-based vehicle sharing system in which users can take a vehicle or a bike at one station and return it to any other station, the common vehicle imbalance problem has also attracted a lot of attentions (Bruglieri et al. 2014; Lin 2018).

Furthermore, considering customers in most sharing economy are price sensitive (Kumar et al. 2018), a dynamic trip pricing is an essential component in the EV-sharing system. Previous study developed a trip pricing methodology which can maximize the system profit by reducing vehicle imbalance (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 focused on traditional gas vehicles. For the EV-sharing system, factors from different domains, i.e., transportation and power system need to be considered. For example, the simultaneous charging activity may cause stability problems within 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 system. Kempton and Tomić (2005) develops 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 Dynamic Pricing Scheme (DPS).

Another element that has not been paid enough attention in the EV-sharing system is station-level demand prediction, which is a hot topic in other transportation systems, such as bike-sharing systems (Lin et al. 2017; Regue and Recker 2014). Station-level demand predictions enable not only rebalancing the vehicle but also scheduling the Vehicle-Grid-Integration (VGI) in practical application, which is a necessary foundation to develop the DPS. For the aspect of rebalancing the vehicle, if the destination of a trip will have a high demand in the next operation hour, a higher price can be charged to urge the user to return the EV earlier; For the aspect of scheduling the VGI, if there will have a significant margin above charging/discharging for a longer time, the price can be adjusted accordingly. This will require a model to have the capability to provide accurate predictions. In recent years, the development of artificial intelligence and deep learning models has shown very satisfying performances in many predictive tasks. With the accumulation of EV-sharing demand data, station-level demand prediction should be included in the dynamic pricing model.

This study proposes a novel pricing scheme in a large-scale EV-sharing network considering station-level demand prediction and VGI. A graph convolution neural network model (GCNN) with Data-driven Graph Filter (DDGF) model is applied for the station-level EV-sharing demand prediction. The GCNN-DDGF model has shown promising performance for station-level bike-sharing demand prediction in a large network (Lin et al. 2017). To the best knowledge of the author, the proposed scheme is the first study to develop a dynamic market based mechanism to schedule and manage EVs to satisfy demands at station-level as well as settle VGI schedules.

The rest of the paper is organized as follows. The next section introduces the novel dynamic pricing scheme in a large-scale EV-sharing network considering the station-level demand prediction and the VGI. Then, a case study is proposed to demonstrate the proposed scheme. The paper concludes with a discussion of the study findings and future research directions.

2. Methodology

In this section, we first introduce the station-level EV demand prediction model graph convolutional neural network. On the basis of accurate predictions, the rest part of the section introduce the dynamic pricing scheme.

2.1 Graph Convolutional Neural Network

Comparing with traditional Convolutional Neural Network (CNN) 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. The GCNN model conducts the convolution through the graph spectral filtering methodology. Suppose we have a graph $G = (V, x, \mathcal{E}, A)$, where V is a finite set of vertices with size N, signal $x \in \mathbb{R}^N$is a scalar for every vertex,$\mathcal{E}$ is a set of edges, $A \in \mathbb{R}^{N\times N}$ is the adjacency matrix, and entry A_{ij} encodes the connection degree between the signals at two vertices. A normalized graph Laplacian matrix is defined as

$$L = I_N - D^{-1/2}AD^{-1/2} \tag{1}$$

where I_N is the identity matrix, and $D \in \mathbb{R}^{N\times N}$ is a diagonal degree matrix with $D_{ii} = \sum_j A_{ij}$.

L is a real symmetric positive semidefinite matrix which can be diagonalized as

$$L = U\Lambda U^T \tag{2}$$

where $U = [u_0, u_1, \ldots, u_{N-1}]$; $\Lambda = diag([\lambda_0, \lambda_1, \ldots, \lambda_{N-1}])$;$\lambda_0, \lambda_1, \ldots, \lambda_{N-1}$ are the eigenvalues of L, and $u_0, u_1, \ldots, u_{N-1}$ are the corresponding set of orthonormal eigenvectors.

The spectral graph convolution consists of the following three steps:

(1) Graph Fourier Transform

Analogous to the Fourier transform which is the expansion of a signal in terms of the complex exponentials, the graph Fourier transform is defined as the expansion of a signal in terms of the eigenvectors of the graph Laplacian (Shuman et al. 2013):

$$\hat{x} = U^T x \tag{3}$$

(2) Spectral Filtering

Furthermore, the graph spectral filtering is defined as:

$$\hat{x}_{out} = g_\theta(\Lambda)\hat{x} \tag{4}$$

where $g_\theta(\Lambda)$ is a function of the eigenvalues of L.

(3) Inverse Graph Fourier Transform

The Inverse Graph Fourier Transform is given by

$$x_{out} = U\hat{x}_{out} \tag{5}$$

Merging three steps together, a spectral convolution on the graph is defined as follows:

$$g_\theta * x = U g_\theta(\Lambda) U^T x \tag{6}$$

Previous study has shown that the calculation of $g_\theta * x$can be simplified by using only the first-order polynomial of L(Kipf and Welling 2016):

$$g_\theta * x \approx \theta_0 x + \theta_1 \tilde{L} x \tag{7}$$

where $\tilde{L}$ is a rescaled Laplacian matrix, $\tilde{L} = \frac{2}{\lambda_{max}} L - I_N$, λ_{max} is the maximum eigenvalue of L.

Furthermore, Kipf and Welling (2016) approximately set $\lambda_{max} = 2$ since the neural network parameters will adapt to this change in scale during training,

$$g_\theta * x \approx \theta_0 x + \theta_1 (L - I_N) x \tag{8}$$

Replacing L with (1),

$$g_\theta * x \approx \theta_0 x - \theta_1 D^{-\frac{1}{2}} A D^{-\frac{1}{2}} x \tag{9}$$

To constrain the number of parameters to further reduce the overfitting risk, let $\theta' = \theta_0 = -\theta_1$,

$$g_\theta * x \approx \theta' (I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}}) x \tag{10}$$

When applied to the multi-layer structure, renormalization is applied at each layer to retain numerical stability:

$$I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \rightarrow \widetilde{D}^{-\frac{1}{2}} \tilde{A} \widetilde{D}^{-\frac{1}{2}} \tag{11}$$

where $\tilde{A} = A + I_N$ is the summation of the adjacency matrix of the undirected graph A and the identity matrix I_N. In another word, $\tilde{A}$ is the adjacency matrix of an undirected graph where each node connects with itself; $\widetilde{D}_{ii} = \sum_j \tilde{A}_{ij}$.

Generalizing this convolution calculation to a signal $X \in \mathbb{R}^{N \times C}$ where each vertex v_i has a C-dimensional feature vector X_i,

$$Z = \widetilde{D}^{-\frac{1}{2}} \tilde{A} \widetilde{D}^{-\frac{1}{2}} X \Theta \tag{12}$$

where $\Theta \in \mathbb{R}^{C \times F}$ is a matrix of filter parameters; $\mathrm{Z} \in \mathbb{R}^{N \times F}$ is the convolved signal matrix.

Suppose GCNN model has layers from $0, 1, \ldots$ to m from the input to the output.For each layer l, $l = 1, \ldots, m - 1$, the layer-wise calculation of GCNN model $f(X, A)$ propagates from the input to the output with the following rule:

$$H^l = \sigma \left(\widetilde{D}^{-\frac{1}{2}} \tilde{A} \widetilde{D}^{-\frac{1}{2}} H^{l-1} W^l \right) \tag{13}$$

For the output layer m, the result is:

$$H^m = \widetilde{D}^{-\frac{1}{2}} \tilde{A} \widetilde{D}^{-\frac{1}{2}} H^{m-1} W^m \tag{14}$$

where $W^m \in \mathbb{R}^{C^{m-1} \times C^m}$ are the weight parameters to be learned; $H^m \in \mathbb{R}^{N \times C^m}$ are the predictions.

To the best of our knowledge, all previous studies on GCNN require the predefinition of the graph, which means the adjacency matrix A has to be determined. Now, suppose the adjacency matrix $\tilde{A}$ is unknown; let $\hat{A} = \widetilde{D}^{-\frac{1}{2}} \tilde{A} \widetilde{D}^{-\frac{1}{2}}$, then (13) becomes:

$$H^l = \sigma \left(\hat{A} H^{l-1} W^l \right) \tag{15}$$

where $\hat{A}$ is a symmetric matrix consisting of trainable filter parameters.

Hence, the graph filter of GCNN model becomes totally data driven. From another perspective, we can view the data-driven graph filtering as filtering in the vertex domain, which avoids the three operations: graph Fourier transform, filtering and inverse graph Fourier transform.

To illustrate the GCNN model with data-driven graph filter (DDGF), Fig. 1 shows an example with three stations i, j and k. First, at Layer $(l - 1)$, the signal vectors at the three stations are $H_i^{l-1} \in \mathbb{R}^{C^{l-1}}$, H_j^{l-1} and H_k^{l-1}. From Layer $(l - 1)$ to Layer l, in step 1, the signal vector at the central station vertex is amplified or attenuated, and linearly combined with signals at other vertices weighted proportionally to the learned degree of their correlations. The signal vectors become $(\hat{A} H^{l-1})_i$, $(\hat{A} H^{l-1})_j$ and $(\hat{A} H^{l-1})_k$. In step 2, the signal vectors at vertices of the next layer l are calculated using the traditional feed-forward neural network and become $H_i^l \in \mathbb{R}^{C^l}$, H_j^l and H_k^l.

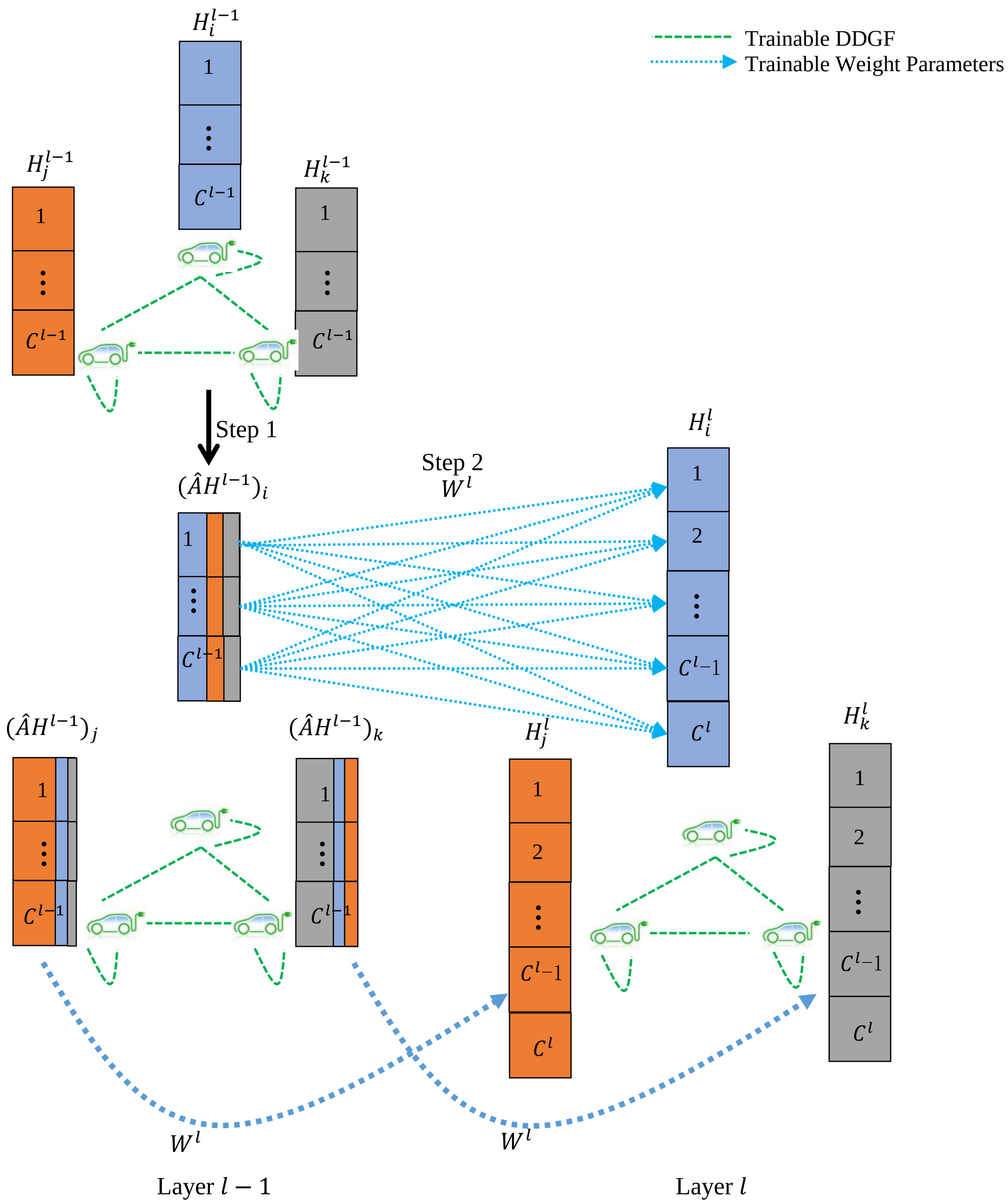

Fig. 1. Layer-wise Calculation of GCNN-DDGF Model

2.2 The Dynamic Pricing Scheme (DPS) 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 Price Adjustment Level (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 stations 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 price sensitive, that is, users of sharing EV 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. $\mathrm{PAL1} = \frac{\boldsymbol{P_{kj}^{i}}}{P0}$ 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. $\mathrm{PAL2} = \frac{\boldsymbol{P_{\delta_{kj}^{t}}^{i}}}{P0}$ aims at affecting the travel time based on a tradeoff between profit from EV-sharing services and VGI services according to the electricity prices during a given period. Thus, a mixed-integer non-linear programming (MINLP) model is formulated to search the optimal combination of the two PALs to maximize the profit of operation system by considering rebalancing services and VGI services. The notations used to formulate the model (sets, data and decision variables) are summarized as follows:

Sets:

$\mathrm{K'} = (1, \dots, \mathrm{k} \dots, \mathrm{K})$: Set of Stations.
$\mathrm{V'} = (1, \dots, \mathrm{v} \dots, \mathrm{V})$: Set of sharing EVs.
$\mathrm{T'} = (1, \dots, \mathrm{t} \dots, \mathrm{T})$: Set of time instants in the operation period.
$\mathrm{I'} = (1, \dots, \mathrm{i} \dots, \mathrm{I})$: The set of time intervals in the operation period.
$\mathrm{X} = (1, \dots, \mathrm{k_{t-1}} \dots, \mathrm{k_t}, \mathrm{k_{t+1}}, \dots, \mathrm{K_T})$: Set of nodes of a time–space network combining the K stations with the T time instants, where $\mathrm{k_t}$ represents station k at time instant t.
$\mathrm{A_1} = \left(\dots, (\mathrm{k_t}, \mathrm{j}_{\mathrm{t}+\delta_{\mathrm{kj}}^{\mathrm{t}}}), \dots\right), \mathrm{k_t} \in \mathrm{X}$: Set of arcs over which vehicles move between stations k and j,$\forall \mathrm{k}, \mathrm{j} \in \mathrm{K'}, \mathrm{k} \neq \mathrm{j}$,betweentime instant t and $\mathrm{t} + \delta_{\mathrm{kj}}^{\mathrm{t}}$.
$\mathrm{A_2} = (\dots, (\mathrm{k_t}, \mathrm{k_{t+1}}), \dots), \mathrm{k_t} \in \mathrm{X}$: Set of arcs that represent vehicles stocked in stationk, $\forall \mathrm{k} \in \mathrm{K'}$, from time instant t to time $\mathrm{t} + 1$.

Data:

C_{mv}: The maintenance cost of each vehicle per time step driven.
C_{mp}: The cost of maintaining one parking space per day.
C_v: The depreciation cost of one vehicle per day.
$P0$: The current carsharing price for all Original-Destination pairs of stations at any time instant.
$D0_{k_t j_{\mathrm{t}+\delta_{\mathrm{kj}}^{\mathrm{t}}}}$: Number of customer trips from stations k to j from instant t to instant $\mathrm{t} + \delta_{\mathrm{kj}}^{\mathrm{t}}$,$\forall (k_t j_{\mathrm{t}+\delta_{\mathrm{kj}}^{\mathrm{t}}}) \in \mathrm{A_1}$for the reference price.
$\delta 0_{kj}^{t}$: Travel time, in time instants, between stations k and j when departure time is t,$\forall k \in \mathrm{X}, j \in K'$for the reference price.
$P0_{kj}^{i}$: The current carsharing price per time step driven from stations k to j when departure time interval is i, ,,$\forall k \in \mathrm{X}, j \in K', i \in I'$ for the reference price.
$\delta 0_{\mathrm{k_t k_{t+1}}}^{v}$: The time that the vehicle v is connected in the parking lot at station k from time instant t to time $\mathrm{t} + 1, \forall v \in \mathrm{V'}, (\mathrm{k_t k_{t+1}}) \in \mathrm{A_2}$ for the reference price.
B_v: The nominal battery capacity of vehicle v, $\forall v \in \mathrm{V'}$.
$\mathrm{B_V^{UT}}$: The upper threshold of SOC of battery.

B_V^{LT}: The lower threshold of SOC of battery.
PEL_z^i: The electricity price (€/KWh) in zone Z at time interval i,$\forall z \in Z', i \in I'$.
PEC_z^i: The capacity price (€/KWh) in zone Z at time interval i, $\forall z \in Z', i \in I'$.
R_{d-c}^v: The average ratio of the actual energy dispatched for regulation and the total power available.
Z_k: Size of station k,$\forall k \in K'$, where size refers to the number of parking spaces.
a_{kt}: Number of available vehicles at station k at time instant, $\forall k \in X$.
$V_{k_t k_{t+1}}$: Number of vehicles stocked at each station k from time instant t to time $t + 1, \forall (k_t k_{t+1}) \in A_2$.
SOC_v^t: The state of charge of vehicle v at instant t, $\forall v \in V'$.
Cap_k^t: The contracted capacity available at station k at instant t.
$\delta_{k_t k_{t+1}}^v$: The time that the vehicle v is connected in the parking lot at station k from time instant t to time $t + 1, \forall v \in V', (k_t k_{t+1}) \in A_2$ after the price isvaried.
$\lceil \delta_{k_t k_{t+1}}^v \rceil$: The round up time (in hours) that the vehicle v in the parking lot at station k from time instant t to time $t + 1, \forall v \in V', (k_t k_{t+1}) \in A_2$.
$VG_v^{k_t k_{t+1}}$: The power that the vehicle v is discharge to the parking lot at station k per minute from time instant t to time $t + 1, \forall v \in V', (k_t k_{t+1}) \in A_2$.
$GV_v^{k_t k_{t+1}}$: The power that the vehicle v is charge from the parking lot at station k per minute from time instant t to time $t + 1, \forall v \in V', (k_t k_{t+1}) \in A_2$.

Decision Variables:

$D_{k_t j_{t+\delta_{kj}^t}}$: Number of customer trips from stations k to j from instant t to instant $t + \delta_{kj}^t$,$\forall (k_t j_{t+\delta_{kj}^t}) \in A_1$ after the price is varied.
δ_{kj}^t: 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.
PAL1: PAL per time step driven between stations k and j when departure time period is i,$\forall k \in X, j \in K'$,$i \in I'$.
PAL2: PAL driven the travel time between *stations* k and j when departure time period is i,$\forall k \in X, j \in K', i \in I'$.

EV-Sharing Demand, in this model, varies according to a simple elastic behavior. The new demand ($\boldsymbol{D_{k_t j_{t+\delta_{kj}^t}}}$) results from applying the price elasticity $\boldsymbol{E}_{Demand}$ to a reference demand ($\boldsymbol{D0_{k_t j_{t+\delta_{kj}^t}}}$) that exists for price $\boldsymbol{P0}$. The expression is:

$$\boldsymbol{E}_{Demand} = \frac{\frac{D_{k_t j_{t+\delta_{kj}^t}} - D0_{k_t j_{t+\delta_{kj}^t}}}{D0_{k_t j_{t+\delta_{kj}^t}}}}{\frac{P_{kj}^i - P0}{P0}} \tag{16}$$

EV-Sharing travel time, in this model, varies according to a simple elastic behavior. The travel time($\boldsymbol{\delta}_{\boldsymbol{kj}}^{\boldsymbol{t}}$) results from applying the price elasticity $\boldsymbol{E}_{Time}$ to a reference travel time($\boldsymbol{\delta 0}_{\boldsymbol{kj}}^{\boldsymbol{t}}$) that exists for price $\boldsymbol{P0}$. The expression is:

$$\boldsymbol{E}_{Time}=\frac{\frac{\delta_{kj}^{t}-\delta 0_{kj}^{t}}{\delta 0_{kj}^{t}}}{\frac{P_{\delta_{kj}^{t}}^{i}-P0}{P0}} \tag{17}$$

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 $\boldsymbol{\delta}_{\mathbf{k_t k_{t+1}}}^{\boldsymbol{v}}$. The expression is:

$$\frac{\delta_{\mathrm{k_t k_{t+1}}}^{v}}{\delta 0_{\mathrm{k_t k_{t+1}}}^{v}}=\frac{\delta 0_{kj}^{t}}{\delta_{kj}^{t}} \tag{18}$$

Therefore, we have

$$\boldsymbol{\delta}_{\mathbf{k_t k_{t+1}}}^{\boldsymbol{v}}=\frac{\delta 0_{\mathrm{k_t k_{t+1}}}^{v}\times P0}{P0+(P_{\delta_{kj}^{t}}^{i}-P0)\times \boldsymbol{E}_{Time}} \tag{19}$$

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

$$\boldsymbol{Max\theta}=\sum_{\substack{\mathrm{k_t j_{t+\delta_{kj}^t}}\in \mathrm{A_1}\\ \mathrm{k}\in \mathrm{K}'\\ \mathrm{t}\in \mathrm{T}'\\ \mathrm{i}\in \mathrm{I}'}}(\boldsymbol{R}_{DS})+\sum_{\substack{\mathrm{v}\in \mathrm{V}'\\ \mathrm{k}\in \mathrm{K}'\\ \mathrm{t}\in \mathrm{T}'\\ \mathrm{i}\in \mathrm{I}'}}(\boldsymbol{R}_{VGI}) \tag{20}$$

$$\boldsymbol{R}_{DS}=(\boldsymbol{P}_{\boldsymbol{kj}}^{\boldsymbol{i}}-C_{mv})\times \mathbf{D}_{\mathbf{k_t j_{t+\delta_{kj}^t}}}\times \boldsymbol{\delta}_{\mathbf{kj}}^{\mathbf{t}}-C_{mp}\sum_{\mathrm{k}\in \mathrm{K}'}\mathrm{Z_k}-C_v\sum_{\mathrm{k}\in \mathrm{K}'}\alpha_{\mathrm{k1}} \tag{21}$$

$$\boldsymbol{R}_{VGI}=\boldsymbol{PEL}_z^i\times \boldsymbol{\delta}_{\mathbf{k_t k_{t+1}}}^{\boldsymbol{v}}\times(\boldsymbol{VG}_v^{\mathbf{k_t k_{t+1}}}-\boldsymbol{GV}_v^{\mathbf{k_t k_{t+1}}})+\mathbf{min}\left(\mathbf{SOC}_v^t,\ \frac{\mathbf{Cap}_k^t}{\boldsymbol{V}_{\mathbf{k_t k_{t+1}}}}\right)\times \left(\boldsymbol{PEC}_z^i\times\left\lceil\boldsymbol{\delta}_{\mathbf{k_t k_{t+1}}}^{\boldsymbol{v}}\right\rceil+\boldsymbol{PEL}_z^i\boldsymbol{R}_{d-c}^{v}\times \boldsymbol{\delta}_{\mathbf{k_t k_{t+1}}}^{\boldsymbol{v}}\right) \tag{22}$$

Subject to,

$$\mathbf{D}_{\mathbf{k_t j_{t+\delta_{kj}^t}}}\geq \boldsymbol{D0}_{\boldsymbol{k_t j}_{\mathbf{t+\delta_{kj}^t}}}+\frac{\boldsymbol{E}_{Demand}\times \mathbf{D0}_{\mathbf{k_t j_{t+\delta_{kj}^t}}}\times(\boldsymbol{P}_{\boldsymbol{zw}}^{\boldsymbol{i}}-P0)}{P0}-\mathbf{0.5},\forall\left(\boldsymbol{k_t j}_{\mathbf{t+\delta_{kj}^t}}\right)\in \mathbf{A_1},\boldsymbol{z},\boldsymbol{w}\in \mathrm{Z}',\boldsymbol{i}\in \boldsymbol{I}' \tag{23}$$

$$\mathbf{D}_{\mathbf{k_t j_{t+\delta_{kj}^t}}}\leq \boldsymbol{D0}_{\boldsymbol{k_t j}_{\mathbf{t+\delta_{kj}^t}}}+\frac{\boldsymbol{E}_{Demand}\times \mathbf{D0}_{\mathbf{k_t j_{t+\delta_{kj}^t}}}\times(\boldsymbol{P}_{\boldsymbol{zw}}^{\boldsymbol{i}}-P0)}{P0}+\mathbf{0.5},\forall\left(\boldsymbol{k_t j}_{\mathbf{t+\delta_{kj}^t}}\right)\in \mathbf{A_1},\boldsymbol{z},\boldsymbol{w}\in \mathrm{Z}',\boldsymbol{i}\in \boldsymbol{I}' \tag{24}$$

$$\boldsymbol{D0}_{\boldsymbol{k_t j}_{\mathbf{t+\delta_{kj}^t}}}+\frac{\boldsymbol{E}_{Demand}\times \mathbf{D0}_{\mathbf{k_t j_{t+\delta_{kj}^t}}}\times(\boldsymbol{P}_{\boldsymbol{zw}}^{\boldsymbol{i}}-P0)}{P0}\geq \mathbf{0} \tag{25}$$

$$\boldsymbol{V}_{\mathbf{k_t k_{t+1}}}+\sum_{j\in K'}\mathbf{D}_{\mathbf{k_t j_{t+\delta_{kj}^t}}}=\sum_{j\in K':t'=\mathrm{t}-\delta_{\mathrm{kj}}^{\mathrm{t}}}\mathbf{D}_{\mathbf{j}_{t'}\mathbf{k_t}}+\boldsymbol{V}_{\mathbf{k_t k_{t+1}}},\forall \boldsymbol{k}\in \mathrm{X} \tag{26}$$

$$\boldsymbol{a_{kt}}=\boldsymbol{V}_{\mathbf{k_t k_{t+1}}}+\sum_{j\in K'}\mathbf{D}_{\mathbf{k_t j_{t+\delta_{kj}^t}}},\forall \boldsymbol{k}\in \mathrm{X} \tag{27}$$

$$\boldsymbol{Z_k} \geq \boldsymbol{a_{kt}}, \forall \boldsymbol{k} \in \mathrm{X} \tag{28}$$

$$\mathbf{D}_{\mathbf{k_t j_{t+\delta^t_{kj}}}} \in \mathbb{N}^{\mathbf{0}}, \forall \left(\boldsymbol{k_t j}_{\mathbf{t+\delta^t_{kj}}}\right) \in \mathbf{A_1} \tag{29}$$

$$\boldsymbol{P^i_{zw}} \in \mathbb{R}^{\mathbf{0}}, \forall \boldsymbol{z}, \boldsymbol{w} \in \mathrm{Z}', \boldsymbol{i} \in \boldsymbol{I}' \tag{30}$$

$$\boldsymbol{V}_{\mathbf{k_t k_{t+1}}} \in \mathbb{N}^{\mathbf{0}}, \forall (\mathbf{k_t k_{t+1}}) \in \mathbf{A_2} \tag{31}$$

$$\boldsymbol{a_{kt}} \in \mathbb{N}^{\mathbf{0}}, \forall \boldsymbol{k} \in \mathrm{X} \tag{32}$$

$$\boldsymbol{Z_k} \in \mathbb{N}^{\mathbf{0}}, \forall \boldsymbol{k} \in \mathrm{K}' \tag{33}$$

$$\boldsymbol{\delta}^{\boldsymbol{v}}_{\mathbf{k_t k_{t+1}}} \geq \frac{\boldsymbol{\delta 0}^{\boldsymbol{v}}_{\mathbf{k_t k_{t+1}}} \times P0}{P0 + (\boldsymbol{P}^{\boldsymbol{i}}_{\delta^t_{kj}} - P0) \times \boldsymbol{E}_{Time}} - \mathbf{0.5}, \forall \left(\boldsymbol{k_t j}_{\mathbf{t+\delta^t_{kj}}}\right) \in \mathbf{A_1}, \boldsymbol{z}, \boldsymbol{w} \in \mathrm{Z}', \forall \boldsymbol{v} \in \mathrm{V}', \boldsymbol{i} \in \boldsymbol{I}' \tag{34}$$

$$\boldsymbol{\delta}^{\boldsymbol{v}}_{\mathbf{k_t k_{t+1}}} \leq \frac{\boldsymbol{\delta 0}^{\boldsymbol{v}}_{\mathbf{k_t k_{t+1}}} \times P0}{P0 + (\boldsymbol{P}^{\boldsymbol{i}}_{\delta^t_{kj}} - P0) \times \boldsymbol{E}_{Time}} + \mathbf{0.5}, \forall \left(\boldsymbol{k_t j}_{\mathbf{t+\delta^t_{kj}}}\right) \in \mathbf{A_1}, \boldsymbol{z}, \boldsymbol{w} \in \mathrm{Z}', \forall \boldsymbol{v} \in \mathrm{V}', \boldsymbol{i} \in \boldsymbol{I}' \tag{35}$$

$$\frac{\boldsymbol{\delta 0}^{\boldsymbol{v}}_{\mathbf{k_t k_{t+1}}} \times P0}{P0 + (\boldsymbol{P}^{\boldsymbol{i}}_{\delta^t_{kj}} - P0) \times \boldsymbol{E}_{Time}} \geq \mathbf{0} \tag{36}$$

$$\boldsymbol{VG}^{\mathbf{k_t k_{t+1}}}_{\boldsymbol{v}} \times \boldsymbol{GV}^{\mathbf{k_t k_{t+1}}}_{\boldsymbol{v}} = 0 \tag{37}$$

$$0 \leq \boldsymbol{VG}^{\mathbf{k_t k_{t+1}}}_{\boldsymbol{v}} \times \boldsymbol{\delta}^{\boldsymbol{v}}_{\mathbf{k_t k_{t+1}}} \leq \frac{\mathbf{Cap}^{\boldsymbol{t}}_{\boldsymbol{k}}}{\boldsymbol{V}_{\mathbf{k_t k_{t+1}}}} \tag{38}$$

$$0 \leq \boldsymbol{GV}^{\mathbf{k_t k_{t+1}}}_{\boldsymbol{v}} \times \boldsymbol{\delta}^{\boldsymbol{v}}_{\mathbf{k_t k_{t+1}}} \leq \frac{\mathbf{Cap}^{\boldsymbol{t}}_{\boldsymbol{k}}}{\boldsymbol{V}_{\mathbf{k_t k_{t+1}}}} \tag{39}$$

$$\mathbf{SOC}^{\boldsymbol{t}}_{\boldsymbol{v}} + \frac{\boldsymbol{VG}^{\mathbf{k_t k_{t+1}}}_{\boldsymbol{v}} \times \boldsymbol{\delta}^{\boldsymbol{v}}_{\mathbf{k_t k_{t+1}}}}{\boldsymbol{B_v}} \leq \mathbf{B}^{\mathbf{UT}}_{\mathbf{V}} \tag{40}$$

$$\mathbf{B}^{\mathbf{LT}}_{\mathbf{V}} \leq \mathbf{SOC}^{\boldsymbol{t}}_{\boldsymbol{v}} - \frac{\boldsymbol{GV}^{\mathbf{k_t k_{t+1}}}_{\boldsymbol{v}} \times \boldsymbol{\delta}^{\boldsymbol{v}}_{\mathbf{k_t k_{t+1}}}}{\boldsymbol{B_v}} \tag{41}$$

The objective function (20-22) is to maximize the total profit $\boldsymbol{\theta}$ of the one-way carsharing service, taking into consideration the revenue from i) the rebalancing 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 (23-33) are constraints related to the rebalancing services. Constraints (23) and (24) 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 (25) ensure that the demand resulting from the application of price elasticity to the reference demand is positive. Constraints (26) ensure the conservation of vehicle flows at each node of the time–space network. Constraints (27) 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 (28) 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 (29)–(33) set the variables domain.

Equations (34-41) are constraints related to the VGI services. Similar to Constraints (23-25), Constraints (34) and (35) compute the Sharing EV parking lot connection time resulting from considering the price change while (36) regulate the price elasticity. Constraints (37) ensure that the simultaneous charging and discharging at the same period is not a feasible operation for an EV. Constraints (38) and (39) guarantee that the spinning reserves and regulation services each EV provided is in compliance with the nominal power of the charging infrastructure. Constraints (40) and (41) ensure that EV battery operates within acceptable limits.

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 $\boldsymbol{D}_{\boldsymbol{k_t j}_{\mathrm{t+\delta_{kj}^t}}}$ and $\boldsymbol{\delta_{kj}^t}$ are considered known when the MINLP solver is searching the optimal combination of PAL $\frac{\boldsymbol{P_{kj}^i}}{P0}$ and $\frac{\boldsymbol{P^i_{\delta^t_{kj}}}}{P0}$ by substituting (16-19).

3. Case study

3.1 Computation Experiments of the proposed DPS

The data studied in the computation experiments of the proposed DPS was listed in Table 1. It should be noted that there are no studies in the literature that specifically address the calculation of carsharing elasticity of travel time $\boldsymbol{E_{Time}}$, we firstly assume $\boldsymbol{E_{Time}} = \boldsymbol{E_{Demand}} = -1.5$ based on the previous study (Jorge et al. 2015), then change the value of $\boldsymbol{E_{Time}}$ as -0.8, -1.0, -1.2, -1.7 or -2 to investigate the impact of $\boldsymbol{E_{Time}}$ on the profit of the operation network.

Table 1. Data/Parameter values in the computation experiments

Data/Parameters	Value	Reference
$\mathbf{C_{mv}}$	€ 0.007/ min	Wang et al. (2011)
$\mathbf{C_{mp}}$	€0.0013/min	Jorge et al. (2015)
$\mathbf{C_{v}}$	€0.012/min	Jorge et al. (2015)
$\mathbf{P0}$	€0.3/min	Car2go (2018)[1]
$\mathbf{B_{V}}$	30 KWh	Nissan Leaf (2018)[2]
$\mathbf{B_V^{UT}}$	95%	Kempton and Tomić (2005)
$\mathbf{B_V^{LT}}$	50%	Kempton and Tomić (2005)
$\mathbf{PEC_z^i}$	€0.0032/ KWh	Nord Pool (2018)[3]
$\mathbf{R_{d-c}^v}$	10%	Nord Pool (2018)
$\boldsymbol{E_{Demand}}$	-1.5	Jorge et al. (2015)
$\boldsymbol{E_{Time}}$	-1.5	-
$\boldsymbol{D0_{k_t j_{\mathrm{t+\delta_{kj}^t}}}}$	predicted by GCNN model	Lin et al. (2017)
$\boldsymbol{PEL_z^i}$	predicted by PCPF model	Li et al. (2013)

[1] Car2go (2018) https://www.car2go.com/IT/en/
[2] Nissan Leaf(2018) https://www.nissanusa.com/vehicles/electric-cars/leaf.html
[3] Nord Pool (2018) https://www.nordpoolgroup.com/Market-data1/#/nordic/table

It is worth noting that $D0_{k_t j_{\mathrm{t+\delta_{kj}^t}}}$ and PEL_z^i 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 was implemented for a “two stations and one hour” case. The computation results are given in Table 2, 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. Composite PAL is calculated by multiplying the corresponding PAL1 and PAL2. Using the optimal combination of PALs, the 2 stations EV-sharing network is able to achieve a profit of 287.59 € during one hour's operation. Not surprisingly, we found 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 shorten 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 points can be found from the result: i) the adjusting directions of the two PALs between each origin-destination pair of stations are opposite. For example, if applying PAL1(1-2) only, the adjusted car sharing price from station 1 to station 2 will enjoy a 10% discount. But PAL2(1-2) will raise the price up; ii) PAL2 has a 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 close to the original carsharing price € 0.3/min. From this point of view, the customers will enjoy a slightly discount by the DPS.

Table 2. Computation results of DPS model

<table>
<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>
<tr><td>90%</td><td>120%</td><td>110%</td><td>80%</td><td rowspan="6">287.59</td></tr>
<tr><td colspan="2">Composite PAL (1-2)</td><td colspan="2">Composite PAL (2-1)</td></tr>
<tr><td colspan="2">108%</td><td colspan="2">88%</td></tr>
<tr><td colspan="2">Adjusted car sharing price (1-2)</td><td colspan="2">Adjusted car sharing price (2-1)</td></tr>
<tr><td colspan="2">€ 0.324/min</td><td colspan="2">€ 0.264/min</td></tr>
</table>

We then change the values of $\boldsymbol{E}_{Time}$ from -0.8 to -2 with a step of 0.2 to investigate the impact of $\boldsymbol{E}_{Time}$ on the profit of the operation network. Fig. 2 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.

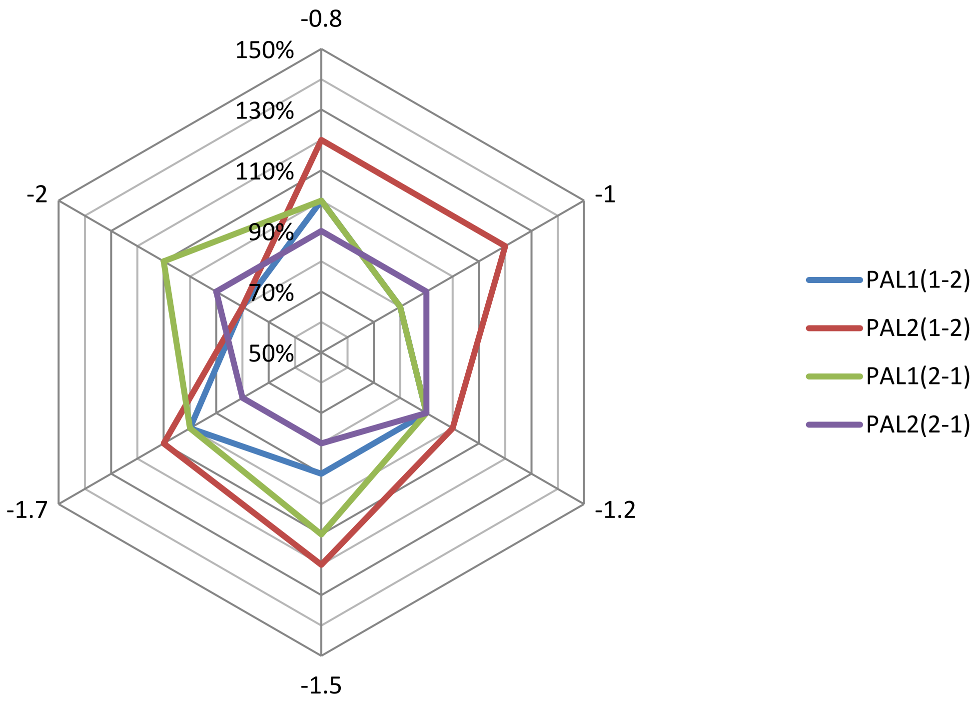

Fig. 2. Computation results of different $\boldsymbol{E}_{Time}$

As shown in Table 3, 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 $\boldsymbol{E}_{Time}$= -1.2 (best profit found is 308.24€ during one hour's operation). At this case, both Composite PALs are lower than the original carsharing price, which means all customers enjoy discount in the network by DPS. It can be easily explained by the economics fact that a relatively low elasticity and discount prices attracting more customers to move to the destination faster. Besides, it's of interest to see that the lowest profits were registered for the lowest elastic problem we considered, where the worst solution has a profit of 278.60€ during one hour's operation and the average of all cases is 292.52€. In general, when the price elasticity fall within the interval (−1, 0), changes in price are considered 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 inelasticity unable to increase the connected time in parking lots so that the profit from VGI services cannot be increased.

Table 3. Computation results of different $\boldsymbol{E}_{Time}$

$\boldsymbol{E}_{Time}$	PAL1(1-2)	PAL2(1-2)	Composite PAL (1-2)	PAL1(2-1)	PAL2(2-1)	Composite PAL (2-1)	**Profit (€/hour)**
-0.8	100%	120%	120%	100%	90%	90%	278.60
-1	80%	120%	96%	80%	90%	72%	283.18
-1.2	90%	100%	90%	90%	90%	81%	308.24
-1.5	90%	120%	108%	110%	80%	88%	287.59
-1.7	100%	110%	110%	100%	80%	80%	290.69
-2	80%	80%	64%	110%	90%	99%	286.77
Average	93%	102%	98%	103%	93%	85%	292.52

Note that the objective function (20) in the proposed DPS model is a MINLP problem which is not easily solvable by traditional branch and cut algorithms. Some MINLP solver software solutions are available to solve this type of problem for both concave and non-concave formulations, but the size of the search space of our problem is much greater 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, the number of possible solutions for this problem would be 625; For four stations and one time period, the number of possible solutions will increase to as high as 5^{24} .

4. Conclusion and Future Study

EV-sharing is an emerging transportation mode that can help to solve many transportation issues such as traffic congestion, traffic emission and so on. A novel dynamic pricing scheme (DPS) is proposed in this study to keep a large-scale EV-sharing system norally running. Both transportation system and energy system are considered in this DPS. For the former, station-level EV demand can be predicted through a graph convolutional neural network based on data-driven graph filter which can learn hidden correlations between stations to improve prediction performances; For the latter, vehicle-grid-integration (VGI) is considered. The proposed DPS is tested on a case study. The results show that the proposed DPS can effectively maximize the system profit by considering both vehicle rebalancing and VGI scheduling. For future study, considering the complexity of the problem, an advanced algorithm should be adopted to solve the DPS model more efficiently.

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