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Impact of Car Arrival/Departure Patterns on EV Parking Lot Energy Storage Capacity

Sıtkı GUNER
Istanbul Arel University
Istanbul, Turkey
sguner@arel.edu.tr

Aydogan OZDEMIR
Istanbul Technical University
Istanbul, Turkey
ozdemiraydo@itu.edu.tr

Gorkem SERBES
Yildiz Technical University
Istanbul Turkey
gserbes@yildiz.edu.tr

***Abstract*— Development and implementation of electrified transportation systems, particularly those that integrate with renewable-based vehicle charging systems are supposed to continue attracting the interest of the researchers in the future. Electric utilities have to develop integrated solutions to take the advantage of the opportunities that transportation electrification offers, in addition to design and planning of their supply needs. In this context, storage capacity of electric vehicles (EVs) offer a new and effective distributed storage capacity for evolving power grids. It is clear that an effective storage can be achieved by aggregating the single EVs. Commercial car parks and parking lots of several public and private companies can be used for these purposes. This paper presents improved car arrival/departure patterns to asses more realistic storage capacity models for an EVPL. Real car arrival/departure data of a representative PL, provided by The Chief Management of Istanbul Car Parking Corporation is used in the studies. In addition, future car arrival/departure patterns are estimated using the available data and PL storage capacity is obtained for those future patterns.**

Keywords— Distributed Energy Resources, Electric Vehicle, Parking Lot, Monte-Carlo Simulation, Kernel Density Estimator

I. INTRODUCTION

Smarter electric power networks have been accelerated all around the world during the last decades. In this context, electric vehicles, EVs, serve as mobile storage unit alternatives in smart grid environment. EVs, are probably the newest member of electrical transportation system. Furthermore, increasing use of EVs may be facilitated to the emission reduction and penetration of renewable energy sources.

In order to use EVs as a spinning reserve alternative for the power system, they should operate at discharging phase which is named as vehicle-to-grid (V2G) operation mode. According to [1], private vehicles are averagely driven only one hour in a day and they are parked during most of the day time. Therefore, they can be used to supply the power system through V2G hardware as a distributed energy resources, DERs, during the peak-load periods. Additionally, they can be used to facilitate the penetration of wind power as charging at off-peak (night) times.

Individual effects of EV are limited because of the modest battery capacity whose range is between 12 kWh to 65 kWh. At this point, in order to enhance the amount of the stored energy, parking lots (PLs) play a crucial role as an aggregator of individual EV capacities. Moreover, diversification of energy resources in a smart grid is an important issue for better grid management. Hence injecting the stored energy of PL at peak-load periods enables the improvement of the reliability as well as voltage profiles of the distribution grid.

In recent years, the number of studies about EV PLs has been dramatically increased. The most important reason of this occasion is the developments in control and protection facilities in smart grid era enabling the bidirectional power flow so thus the increased penetration of distributed energy facilities. Due to the fact that the EVs generally charge at off-peak (night) times, EV PLs increase the integration of more renewable energy resources (RESs) [2 - 4]. This gives a chance to participate more wind power which is more efficient during the night times. Also, intelligent PL models are proposed to maximize the integration EVs and RESs [5] – [11]. In these works, stochastic optimization algorithms were developed to determine the optimal time intervals for charging/discharging operation modes of EVs. The basic and the common target of these studies was to sell the stored energy in EVs with the best prices [12].

PLs, aggregating the EVs improve the importance of EVs' stored energy. Furthermore, PLs are generally close to Park and Ride (P/R) regions or intensive working areas which increases the importance of PL support to the distribution grid. At this point, optimum allocation problem of EV PLs was investigated in several studies which focus on the newly constructed PLs [13], [14]. Although several electrical, mechanical, environmental etc. requirements are considered for the new PL designs, existing PLs have already been built according to urban planning issues of the municipalities and are not expected any economic benefits. Hence, increasing the contribution of existing PLs for the quality improvement of power grid supply is an important task as designing a new one.

Stochastic storage capacity model of an existing PL is presented in a recent paper using real-time data [15]. Furthermore, sensitivity of the storage capacity with respect to travel statistics of the cars and to some other probabilistic parameters were investigated in [16]. Moreover, the model is revised in accordance with the future expectations for city urban planning and travel behavior of the community. The results showed that EV PLs can effectively be used as DERs after the midday hours for the current driving patterns. However, future driving patterns for more electrified mass transportation is expected to shift the V2G period to the morning times. On the other hand, sensitivity analysis showed that the arrival/departure pattern had major role affecting the available storage capacity of PL; whereas charging/discharging rate of EV batteries and SoC of the batteries had secondary effects. Therefore, more realistic storage capacity of an EVPL could only be achieved using improved models for car arrival and departure times.

This paper is therefore devoted to the improved modeling of car arrival/departure patterns of EVs. Real car arrival/departure data of a representative PL, provided by The Chief Management of Istanbul Car Parking Corporation (ISPARK) is used in the studies. Data analysis showed that arrival times could be represented by a single probability density function whereas the departure times could not. Therefore, a kernel density estimation (KDE), is employed

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to the parking duration of the cars [17]. In addition, future car arrival/departure patterns are extracted from the data and PL storage capacity is obtained for those future patterns. Sequential Monte Carlo simulations are implemented in the studies.

The rest of the paper is organized as follows: In the second part, parking lots and some details of representative PL data are explained. The third chapter is devoted to the methodology of the simulation process. The fourth chapter presents the simulation results for the PL and finally the conclusions are summarized in Chapter 5.

II. PARKING LOTS

In metropolitan cities, like Istanbul, due to high population density, there are many PLs whose car capacity is about 400-500 cars. Hence, EV PLs will give cheaper and more reliable option at the peak-load durations for grid management in the future. Therefore, determination (estimation) of the storage capacity of EV PLs is a prior task for the future planning of power grid as well as real time pricing issues.

The storage capacity of PL depends on some parameters, such as, uncertain behavior of the drivers, arrival/departure times of the cars, travel distance of the cars before arriving to the PL, state of the charge (SoC) of the batteries, battery charger details etc. According to [16], car arrival/departure pattern is the most important parameter to assess the realistic available storage capacity of EV PLs. Therefore, statistical data of car arrival/departure times has a crucial importance to determine the stochastic modeling of the diversity of EVs in the PL.

22-weekday statistical data of a sample PL in Istanbul is used in this study. Car capacity of this PL is 500 cars and it is a closed P/R place located at a subway station. Arrival/departure data format of the data provided by ISPARK is given in Table 1. This raw data is processed and scaled to fit more appropriate probability distribution function for car arrival/departure times. The detailed information of these processes is given in the next section.

Table 1. ARRIVAL/DEPARTURE TIME FORMAT OF THE DATA PROVIDED BY ISPARK

Arrival Date	Arrival Time	Departure Date	Departure Time
8.12.2014	08:55:20	8.12.2014	18:46:18
8.12.2014	08:54:51	8.12.2014	21:16:44
8.12.2014	08:52:34	8.12.2014	18:24:18

The travel distance covered before arrival to the PL, battery capacity of an EV, and energy expenditure of EVs directly affect the SoC of the battery of EVs arriving at the PL. The SoC of an EV before arrival to the PL is modeled by a random variable and each EV is assumed to be fully charged at night before starting their travel. Battery capacity, and energy expenditure of EVs differ according to the brands as well as according to their manufacturing years. Nowadays, battery capacity and energy expenditure of EVs in Turkey are between 12 kWh to 65 kWh and 0.18-0.25 kWh/km, respectively. However, there are no any relevant data for the statistics of these parameters. Hence, both of these parameters of an EV are assumed to be constant values and are specified as 25 kWh and 0.23 kWh/km, respectively. In [18], the average travelled distance of an EV before arrival to the PL is reported as 50 km/day according to the survey for İstanbul.

III. SIMULATION METHODOLOGY

In order to obtain stochastic storage capacity of the PL, deterministic and stochastic parameters that will be used in using MC simulation should be determined first. These parameters and the treatments are explained step by step below.

As mentioned before, this study is based on the statistical data of a PL having a total capacity of 500 cars. Half of the parking locations are assumed to be equipped with V2G hardware. Note that, the PL capacity is expressed as a percentage of total capacity, and therefore can easily be adopted for different capacities and different percentage of available V2G hardware.

ISPARK statistics for 22 weekdays in December 2014 is used to model the arrival/departure times of the cars. First stage of the study involves the identification of the appropriate time intervals that will be used in the simulations. Car mobility between 7:00 a.m. to 00:00 am was found to be reasonable since the distributed capacity of the PL was not intended to be used during the night time. Car arrival times from 7:00 a.m. to 00:00 am is clustered in different time bins. Among them, 15-minute is found to be a reasonable value, providing the desired accuracy. Arrival times of the cars in a weekdays for sample period is given in Fig. 1 in terms of 15-minure bins. The data is sorted and aggregated in order to obtain the average number of cars arriving to the PL at each time bin of a weekday. Consequently, a data cluster representing the stochastic characteristic of the car arrival was obtained.

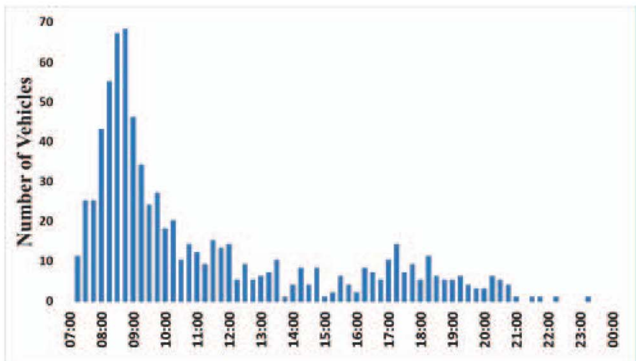

Fig. 1: Arrival times of the cars in a weekday for the sample period.

Then, in order to obtain the departing-time behavior of the EVs for each arriving-time bin, the related arriving-time bin's departing time-axis is also divided into 15-minute time bins and the vehicle departing times are assigned to each proper bin. Fig. 2, shows this type of representation, where the parking duration statistics is shown with respect to the arrival times of the cars.

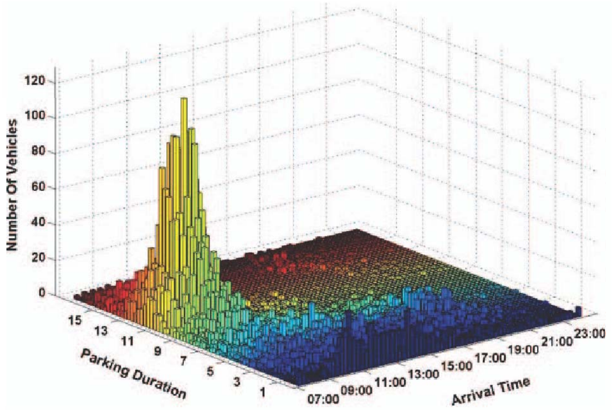

Fig. 2: Parking duration versus arrival time statistics of the parking lot

The departure time statistics are somehow more dispersed when compared with the arrival times. It is mainly because of the different parking durations of the car owners having different aims of parking. For example, the cars arriving during the morning times are generally belong to the people who prefer using mass transportation (subway) to their works after parking their cars in the PL. Therefore, those cars park all the day, up to the arrival of the owners by mass transportation. On the other hand, the cars arriving after 9:00 a.m. belong to the people who are not supposed to work during the day time (housewives, retired person etc.). This second group of cars generally park for shorter durations. Consequently, it is better to use two-dimensional statistics for departure time, more preferably for parking duration and departure time models will be constructed separately for each car arrival time bin. On the other hand, car arrival time bins are aggregated for this purpose, in order to limit the number of models.

Second stage of the study is devoted to fit appropriate probability distribution functions for the random arrival and the departure times (parking durations) of the cars for 07:00 a.m.-11:59 p.m period of a working day. Firstly, various distribution functions in MATLAB is fitted for the car arrival data set. The performance of each distribution functions is compared in terms of several statistical performance measures. Sum square error (SSE), R-squared, and root-mean squared error (RMSE) are used for fitting performance indices. The results are given in Table 2. It is clear that two-parameter Weibull distribution, exponential distribution and Lognormal distribution are found to provide reasonable performances. Among them, two-parameter Weibull distribution function is selected in order to simulate the car arriving times along a weekday for the representative PL.

Table 2. FITTING PERFORMANCE FOR ARRIVAL DATA SET

Performance→ PDF↓	SSE	R-squared	RMSE
Weibull Dist.	0.0967	0.9783	0.0383
Exponential Dist.	0.0972	0.9782	0.0381
Normal Dist.	0.3268	0.9267	0.0704
Lognormal Dist.	0.0959	0.9785	0.0381

Weibull distribution is a 2-parameter probability density function (PDF) as given in Eq.(1), where α and β denote the shape and the scale parameters. By car arrival data set, the most appropriate α and β values are found to be 0.9831 and 16.8, respectively.

$$f(x) = \frac{\alpha}{\beta}\left(\frac{x}{\beta}\right)^{\alpha-1} e^{-\left(x/\beta\right)^{\alpha}} \tag{1}$$

On the other hand, the performance of probability density function, PDF, fitting for the departure times is not found to be as successful as in arrival times. That is, a single PDF does not provide intended accuracy to represent the departure times for all the intended duration of a weekday. For example, a Normal PDF is found to provide satisfactory results for the cars arriving during the morning bins (07:00- and 09:00 a.m.), which indicates that the cars arriving during the morning bins depart around 6.00 p.m. However, after 09:00, which is the major part of the day, a single parametric distribution is not found to provide satisfactory accuracy. Therefore, a kernel density estimation (KDE), which is a nonparametric estimation of the probability density function of a random variable, is employed. The random variable is chosen as parking duration for providing better results when compared to departure times. KDE is a data smoothing problem where inferences about the population are made, based on a finite data sample. It is defined by a smoothing function and a bandwidth value that controls the smoothness of the resulting density curve. The kernel density estimator given in Eq.(2) is the estimated probability density function (pdf) of the random variable.

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{x-x_i}{h}\right) \tag{2}$$

where n is the sample size, $K(\cdot)$ is the kernel smoothing function, h is the bandwidth and x_i is the sample data points. In our study, Gaussian kernel is used as a smoothing function and 1 is chosen for the bandwidth.

The last stage of the study is to obtain the stochastic storage capacity of the PL with the following deterministic and random parameters. Note that random parameters are expressed with their probability density functions, which are derived from the data. Deterministic parameters are either specified by ISPARK or assumed to be deterministic due to lack of relevant statistical data.

- The number of initial cars at 7.00 a.m.: N_0 ; Normal (μ=26 cars, σ= 4 cars). Those cars are assumed to be fully charged at 7:00 a.m.,
- The number of initial EVs at 7.00 a.m.: Binary (1=EV, 0=ICE),
- The number of daily arriving/departing cars to the PL from 7:00 to 23:59 : $Total_{car}$; Normal($\mu = 710$, σ= 20)
- Car capacity of the parking lot = 500 cars; 250 of them is equipped with V2G and G2V hardware.
- Arrival time: t_{arr} ; Weibull (α =0.9831, β = 16.8),
- Parking duration: t_{dur}; Kernel distribution,
- Departure time: $t_{dep} = t_{arr} + t_{dur}$,
- The type of arriving/departing cars: $type_{EV}$:Binary (1=EV, 0=ICE),
- Battery capacity of an EV = 25 kWh,
- Energy expenditure of each EV = 0.23 kWh/km,
- Maximum charging power = 12.5 kW,
- Travelled distance of an EV before arriving to PL: Normal(μ=30 km, σ= 15 km),
- SoC of EVs when arrived to the PL: SoC_{arr} ; Normal(μ= 70%, σ= %15),

- SoC of EVs when departing from PL: Fully charged (%100).
- Each arriving EV to the PL is charged immediately, if there is an available place equipped with V2G hardware.: Exponential (α= 1.956 1/h),

These parameters are used in MC simulation to determine the available storage capacity of the sample EV PL. MC simulation is iterated for one thousand times while the operating policies of the PL is assumed as;

- An arriving car will be let in the PL regardless of its type, if there is a vacant place.
- Since EV and ICE parking locations can be used interchangeably when there is vacant parking place in one of them, the uppermost number of EVs in the parking lot part where there are V2G operating facilities is 250.
- If the PL is full (there are 500 vehicles at the PL), a new incoming car will be admitted after the departure of the first car.

IV. Simulation Results

Average available storage capacity of the PL at each day hour is shown in Fig. 3, in terms of a percentage of the uppermost capacity, i.e. 250*25 kWh, of the lot. The results show that 90 % or greater storage capacity of the PL can be injected to the power grid during midday peak-load period. Furthermore, storage capacity of the PL that can be used even at 5 p.m. is still greater than 70%. It is clear that the distributed storage capacity of the park can be used during 10.00 a.m. - 5 p.m. with respect to power market conditions, whenever required.

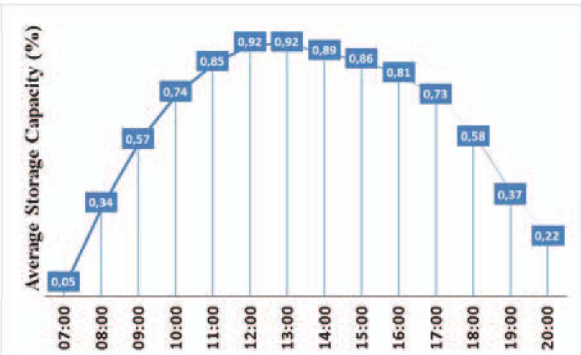

Fig. 3: Average available capacity of the PL

The basic difference between the model used in [16] is the application of the kernel density estimation for car parking duration, so does the departure time. The results show that kernel density estimator based novel model has provided more robust and realistic storage capacities of the PL. Fig. 4 shows the difference between the results of the two models for each hour. Assuming that the parking lot storage capacity can be used for 10 am-5 p.m period, the new improved model provides 3-6 % less capacity than the one reported in [16].

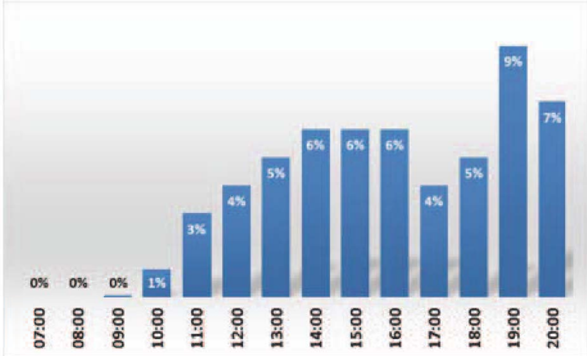

Fig. 4: The differences between the results of the proposed model and the one used in [16]

As mentioned in [16], arrival/departure data of the PL is the indicator of current transportation style and driver behavior. According to available records, there are so many cars arriving at the PL after 10:00 a.m. and these late arrivals prevent the effective usage of the storage capacity of the PL during morning times. Therefore, PL storage capacity is generally available after 12:00 a.m. However, it is expected that the arriving and departing times in the near future will concentrate to the morning and evening times, respectively. This expectation is based on the two important facts. The first one is the change in the driver preferences to use more mass transportation instead of using their cars. It is because of increasing costs of the individual driving as well as increasing traffic jam in Istanbul day by day. The second important reason will be the incentives of the distribution utilities for the sake of to smoother daily load patterns.

Future estimation of the PL capacity is performed using a revised arriving car patterns of ICE vehicles given in [19], and car departure patterns where the arrival time is smoothed by kernel estimator. The new hourly average storage capacity is shown in Fig. 5, together with the current one and with the one reported in [16].

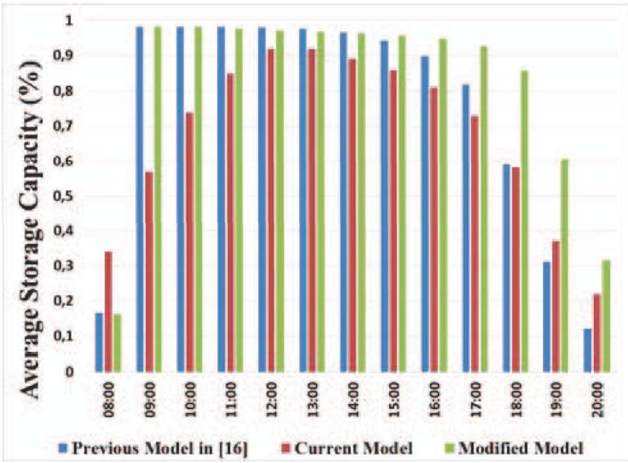

Fig. 5: Comparison between three models

It is clear that the future estimations using the proposed method are more or less the same with the reported ones in [16] up to 3 p.m.. However, the proposed improved model shows that the available storage capacity car capacity is higher than those reported in [16] and it can effectively be used up to 6 p.m. In summary, distributed storage capacity of the PL can be used all the day from 9 a.m. to 6 p.m. if the expected driver behavior changes and expected utility incentives are provided. The results also states that the EV penetration and PL distributed capacity integration are positively correlated with the mass transportation of the cities.

V. Conclusions

This paper has presented improved modeling of car arrival/departure patterns of EVs which provides more robust and realistic storage capacities for an EV PL. Car parking durations so do the car departure times are revised using kernel density estimator according to car arrival times. Real car arrival/departure data of a representative PL, provided by The Chief Management of Istanbul Car Parking Corporation (ISPARK) is used in the studies. In addition, future car arrival/departure patterns are extracted from the data and PL storage capacity is obtained for those future patterns. The results are compared with of the ones reported in [16]

The results show that PL distributed storage capacity can be used all the day from 9 a.m. to 5 p.m. if agreed with the costumers. However, realistic storage capacities are 3-5 % less than the ones reported in [16] for the current patterns. On the other hand, increasing mass transportation in the city and expected incentives of the distribution utilities will increase both the duration and the amount of available storage capacities. In addition to noon peaks in summer rime, PL storage capacity can also be an important alternative for the evening peaks in the winter, especially at the initial part of it.

Note that this study does not take into account any transmission and economical limits. Hence, the results may require some modifications if there are similar limits.

VI. Acknowledgment

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References

[1] W. Kempton, V. Udo, K. Huber, K. Komara, S. Letendre, S. Baker, D. Brunner, and N. Pearre, "Test of vehicle-to-grid (V2G) for energy storage and frequency regulation in the PJM system", 2009, http://www.udel.edu/V2G/resources/test-v2g-in-pjm-jan09.pdf

[2] M. Honarmanda, A. Zakariazadeha, and S. Jadida, "Self-scheduling of electric vehicles in an intelligent parking lot using stochastic optimization", Journal of the Franklin Institute, Vol. 352, Issue 2, pp. 449-467, February 2015.

[3] M. Honarmanda, A. Zakariazadeha, and S. Jadida, "Integrated scheduling of renewable generation and electric vehicles parking lot in a smart microgrid", Energy Conversion and Management, Vol. 86, pp. 745-755, October 2014.

[4] U. C. Chukwu and S. M. Mahajan, "V2G parking lot with PV rooftop for capacity enhancement of a distribution system", IEEE Transactions on Sustainable Energy, Vol. 5, No. 1, pp. 119-127, January 2014.

[5] M. Honarmanda, A. Zakariazadeha, and S. Jadida, "Integrated scheduling of renewable generation and electric vehicles parking lot in a smart microgrid," Energy Conversion and Management, vol. 86, pp. 745-755, Oct. 2014.

[6] M. Honarmanda, A. Zakariazadeha, and S. Jadida, "Self-scheduling of electric vehicles in an intelligent parking lot using stochastic optimization," Journal of the Franklin Institute, vol. 352, no. 2, pp. 449-467, Feb. 2015.

[7] M. S. Kuran, A. C. Viana, L. Iannone, D. Kofman, G. Mermoud, and J. P. Vasseur, "A smart parking lot management system for scheduling the recharging of electric vehicles" IEEE Trans. on Smart Grid, vol.6, no.6, pp. 2942-2953, Nov. 2015.

[8] M. Honarmand, A. Zakariazadeh, and S. Jadid, "Optimal scheduling of electric vehicles in an intelligent parking lot considering vehicle-to-grid concept and battery condition," Energy, vol. 65, pp. 572-579, Feb. 2014.

[9] M.F.Shaaban, M. Ismail, E.F. El-Saadany, and W. Zhuang,"Real-time PEV charging/discharging coordination in smart distribution systems", IEEE Trans. on Smart Grid, vol. 5, no. 4, pp. 1797-1807, July 2014.

[10] M. S. Kuran, A. C. Viana, L. Iannone, D. Kofman, G. Mermoud, and J. P. Vasseur, "Smart parking lot management system for scheduling the recharging of electric vehicles", IEEE Trans. on Smart Grid, vol. 6, no. 6, pp. 2942-2953, November 2015.

[11] M. Jannati, S.H. Hosseinian, B. Vahidi, and G. Li, "A significant reduction in the costs of battery energy storage systems by use of smart parking lots in the power fluctuation smoothing process of the wind farms", Renewable Energy, vol. 87, no.1, pp.1-14, October 2015.

[12] C. Hutson, G.K. Venayagamoorthy, and K.A. Corzine, "Intelligent scheduling of hybrid and electric vehicle storage capacity in a parking lot for profit maximization in grid power transactions", in Proc. Energy 2030 Conference Energy 2008.

[13] N. Neyestani, M.Y. Damavandi, M. Shafie-Khah, J. Contreras, and J.P.S. Catalão, "Allocation of plug-in vehicles' parking lots in distribution systems considering network-constrained objectives," IEEE Trans. on Power Systems, vol. 30, no. 5, pp. 2643-2656, Sep. 2015.

[14] M. Rahmani-Andebili and G.K. Venayagamoorthy, "SmartPark placement and operation for improving system reliability and market participation," Electric Power Systems Research, vol. 123, pp. 21-30, June 2015.

[15] S. Guner and A. Ozdemir, "Distributed storage capacity modelling of EV parking lots", International Conference on Electrical and Electronics Engineering, ELECO 2015, pp.359-363, Bursa Turkey, 26-28 November 2015.

[16] S. Guner and A. Ozdemir, "Stochastic energy storage capacity model of EV parking lots", submitted.

[17] E. Alpaydin, "Introduction to machine learning", 2. Edition, MIT Press, 2010.

[18] B. Yagcitekin, M. Uzunoglu, A. Karakas, and M. Vurgun, "Assessment of a car park with electric vehicles", 4th International Conference on Power Engineering, Energy and Electrical Drives, Istanbul, Turkey, 13-17 May 2013.

[19] E. Pashajavid and M.A. Golkar, "Placing parking lot of plug-in electric vehicles within a distribution grid considering high penetration level of photovoltaic generation", Integration of Renewables into the Distribution Grid CIRED 2012 Workshop, Lisbon, Portugal, 29-30 May 2012.

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