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Optimal Energy Management of EV Parking Lots under Peak Load Reduction Based DR Programs Considering Uncertainty

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***Abstract*—Demand response (DR) programs offer tremendous opportunities to those who have concerns about the future of energy. Since the DR strategies facilitate new technologies to take part in the power systems, the idea of spreading of electric vehicles (EVs) attracts the researchers around the world. In this study, an optimal energy management strategy for EV parking lots considering peak load reduction (PLR) based DR programs is built in stochastic programming framework, denoted by EV parking lot energy management (EV-PLEM). The proposed EV-PLEM aims to maximize the load factor during the daily operation of an EV parking lot taking into account the uncertain behavior of EVs such as arrival and departure times together with the stochasticity of the remaining state-of-energy (SoE) of EVs when they reach the parking lot. A set of case studies is conducted to validate the effectiveness of the suggested EV-PLEM concept, and credible results and useful findings are reported for the cases in which the EV-PLEM is implemented.**

***Index Terms*—Energy management, EV parking lots, demand response, stochastic systems, user interfaces.**

NOMENCLATURE

The abbreviations, sets and indices, parameters along with variables used in this study are alphabetically given in following tables. The others non-listed are explained where they first appear.

TABLE I
ABBREVIATIONS

DR	Demand response
EV	Electric vehicle
GHG	Greenhouse gas emissions
LSE	Load serving entity
PLEM	Parking lot energy management
PLR	Peak load reduction
RFID	Radio frequency identification
SoE	State-of-energy

TABLE II
SETS AND INDICES

h	Set of electric vehicles.
s	Set of scenarios.
t	Period of the day index in time units [min].

TABLE III
PARAMETERS

CE_h^{EV}	Charging efficiency of EV h.
CR_h^{EV}	Charging rate of EV h [kW].
$P_t^{desired}$	Desired power in PLR during period t [kW].
$P_{t,s}^{ref}$	Reference power during period t for scenario s [kW].
$SoE_h^{EV,ini}$	Initial SoE of EV h for scenario s [kWh].
$SoE_h^{EV,max}$	Maximum SoE of EV h [kWh].
$SoE_h^{EV,min}$	Minimum SoE of EV h [kWh].
$SoE_h^{EV,des}$	Desired SoE of EV h at the departure time [kWh].
$T_{h,s}^a$	Arrival time period of EV h for scenario s.
$T_{h,s}^d$	Departure time period of EV h for scenario s.
ΔT	Time granularity.
π_s	Probability value of scenario s for reference power profile.
t_1	Starting period of the PLR oriented DR
t_2	Ending period of the PLR oriented DR

TABLE IV
VARIABLES

$P_{s,h,t}^{EV,ch}$	Charging power of EV h during period t for scenario s [kW].
$P_{s,t}^{grid}$	Power drawn from the grid during period t for scenario s [kW].
$P_s^{grid,avg}$	Average power drawn from the grid for scenario s [kW].
$P_s^{grid,max}$	Maximum power drawn from the grid for scenario s [kW].
$P_{t,s}^{ref}$	Reference power during period t for scenario s [kW].
$SoE_{s,h,t}^{EV}$	SoE of EV h during period t for scenario s [kWh].

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I. INTRODUCTION

A. Motivation and Background

DUE to the gradually increase of energy demand, electricity industry needs to be upgraded majorly so as to meet the related demand in an efficient and economic manner.

In particular, the rising penetration of renewable energy systems on the generation side on account of environmental concerns has begun to constitute uncertainty on the demand side as well as the generation side.

In this context, it has recently become a significant field of study to consider the demand side as a source of flexibility in modern power system operation thanks to the smart grid paradigm [1]. Another innovation provided by smart grid is to facilitate the integration of electric vehicles (EVs) into the power system in daily-life. The spread of EVs has accelerated even more in the last decade because of providing less greenhouse gas emissions (GHG) and more efficient use of energy.

One of the revealed report claimed that the transportation industry accounts for 14% of total GHG emission in 2010. Furthermore, it is supposed to be doubled by 2050 in [2]. Yet another report [3] announced that the transportation sector is liable for 23% of current global energy-related GHG emissions in 2017. As indicated in [3], EV stock has exceed 2 million all around the world and the inevitable rising on number of EVs will further proceed unceasingly. In addition to valuable pros of EVs, this increase brings undeniable concerns with it for the power system operation. As an outcome, the aforementioned circumstances draw attention for associating energy management approach with the charging operations of EVs by designing a parking lot energy management concept [4], [5].

B. *Relevant Background*

In recent years, the topic of scheduling of charging operation in EV parking lots is followed and also contributed by various researchers around the world. Shafie-khah et al. [6] proposed a model considering both price-based and incentive-based demand response (DR) strategies in order to derive optimal strategies for EV parking lots. Furthermore, the uncertainties of arrival time of EVs and electricity markets were taken into account. Nonetheless, it was stated that the objective function of the designed model was to maximize the profit of EV parking lot; however, load factor was not noticed during the operation.

Both [7] and [8] investigated an optimal parking lot planning. While [7] considered power loss and voltage profile, the rising of reliability in distribution network was aimed in [8]. Although the proposed models were performed under various DR programs, stochasticity of EV habits and load factor were also not noticed in those papers. Reference [9] evaluated the allocation of EV parking lots in a distribution system to minimize system costs by taking into account restrictions regarding power system in a stochastic manner. It should be stated that the importance of load factor and DR programs were neglected in the proposed method.

Akhavan-Rezai et al. [10] presented a real-time energy management system to enhance the participation of EV parking lots to DR programs. The aim of the suggested model was to maximize the delivered energy and minimize the cost of energy. Besides, arrival time and energy demand of the EVs were also considered in a stochastic manner. Nevertheless, load factor for daily operation was neglected in that paper.

Jannati and Nazarpour [11] developed an optimal energy management model for an EV parking lot containing local generators and renewable energy sources.

It was stated that the proposed model aims to minimize the operation costs of upstream grid, local generators along with charging and discharging cost of EV parking lot under different case studies. On the other hand, uncertain behavior of arrival time of EVs and the load factor were not taken into account.

Also in [12], a management system was designed to operate EV charging in an EV parking lot based on prioritizing EVs so as to determine the charging order by considering the departure times and SoE of EVs. Nonetheless, the power system constraints and any DR program were not included in [12].

Heydarian-Forushani et al. suggested a two-stage stochastic programming approach for a system including flexible components such as DR, energy storage systems, and EV parking lots in order to cope with the uncertain nature of market operations and with high penetration of renewable energy sources [13]. It was underlined that the ramp market on a sub-hourly basis was modeled in first time and flexibility tools were considered comprehensively. However, significance of load factor to enhance benefit of using the power system components was not evaluated.

Farzin et al. investigated the increase of the reliability of the renewable-based distribution system during a malfunction. Moreover, EV parking lot was assumed as a power source with the vehicle-to-grid option [14]. It was stated in contributions that the uncertain charging habits of EV owners were modeled based on real data; however, consideration of load factor and implementation of a DR strategy were not even touched.

Zhang and Li [15] compared day-time charging case in an EV parking lot near commercial places with night-time charging case in an EV parking lot for a residential building in order to prove the impacts on energy cost. The arrival and departure times and the initial SoE of EVs were taken into account in a stochastic manner by dynamic programming framework. It is worthy to note that load factor for scheduling of EV parking lot and any DR strategy were not evaluated in that study.

Awad et al. suggested an optimization model for optimal usage of solar-based renewable energy system and energy storage systems as well as for defining the optimal charging price for EV parking lot's owner. It was stated that the main objective of the optimization problem was to rise the profit from the EV charging while satisfying the technical restrictions. Neither load factor nor any DR program were taken into account in favor of the power system [16].

Lastly, there are many comprehensive literature studies emphasizing the significance of energy management of EV parking lots from different points of view such as [17] and [18] that reviewed the EV parking lots interaction with renewable energy sources. More detail reviews devoted to the topic can also be found in [19], [20], and [21].

Aforementioned studies along with many other studies that cannot all be referred in this study considered the topic from different points of view so as to enhance the efficient use of energy based on smart grid paradigm in EV parking lots. However, none of them considered simultaneously the implementation of a peak load reduction (PLR) oriented DR program and the consideration of load factor maximization (which is a crucial factor for effective and efficient use of power system assets) together with the several uncertainty sources in the energy management of an EV parking lot.

C. *Contributions*

In this study, a linear programming model of a parking lot energy management concept denoted by EV parking lot energy management (EV-PLEM) is proposed with the objective of investigating the operation of charging EVs in the parking lot.

Because the arrival time and the initial SoE of EVs before the charging are generally unpredictable, the propounded EV-PLEM strategy is evaluated by using a stochastic approach to dispose of the aforementioned concerns.

The main objective of the EV-PLEM system is to maximize the load factor to enhance the beneficial usage of other power system components. The novelties of the paper can also be highlighted as follows:

- The stochasticity of arrival time related to the EVs and uncertain behavior of initial SoE of EVs before charging are considered by using different driving cycles, resulting in eight different scenarios for reference power profiles for EV parking lot.
- The PLR based DR program is performed in an optimization problem, which aims to maximize the load factor for the first time in the literature.
- An interactive interface is developed to provide a more user-friendly tool for EV owners to facilitate the charging operation in parking lots.

D. Organization

The remainder of paper is organized as follows. The mathematical model of motion and the proposed EV-PLEM model are expressed in Section II. Thereafter, the Section III describes the case studies and provides discussions on the related results. Finally, concluding remarks and future studies are presented in Section IV.

II. Methodology

The demonstration of the proposed (EV-PLEM) strategy is shown in Fig. 1. As can be seen from Fig. 1, the energy management concept manipulates the charging operation of the EVs by considering the DR strategy demanded by the load serving entity (LSE) and by maximizing load factor to support operation and planning of the power system. The significant obstacle for carrying out this type of charging operation strategies is to provide participants of EV owners in these irregular charging operations due to the battery degradation. It is worth underlining that the battery degradation is neglected during the charging transactions in this study. The rest of this section gives the details about the mathematical background of an EV motion and the proposed EV-PLEM model.

A. Mathematical Model of EV Motion

In order to obtain reference power scenarios for EV parking lot, the mathematical model of EV motion is used by considering different driving cycles. It is also acquired that how much SoE belong to the EV will remain when it reaches to the parking lot by using this motion model. The mathematical details relevant to the EV motion will be analyzed in this subsection. The mathematical model of EV motion can be analyzed by using Newton one dimensional motion law. It should be stated that not only road topology affects the consumed power, but also the characteristics of EVs have great influence on the motion.

In (1), $P(t)$ represents the electrical power demand of the EV in period *t*, in *watt*; $P_v(t)$ is mechanical power demand in period *t*, in *watt*, and η_d is the drive efficiency. $P_v(t)$ is obtained by multiplying vehicle speed $v(t)$ in *m/s* in period *t*, and total traction force $F_t(t)$ in *Newton* acts on the EV in period *t* in (2).

$$P(t) = \frac{P_v(t)}{\eta_d} \tag{1}$$

$$P_v(t) = v(t) \cdot F_t(t) \tag{2}$$

Fig. 2 depicts the forces that have effects on the EV motion during the trip to the parking lot. Moreover, the total traction force expression is given in (3). The total traction force is obtained by the summation of aerodynamic drug force, $F_a(t)$, rolling friction (resistance) force, $F_r(t)$, the force caused by the gravity when driving on non-horizontal roads, $F_g(t)$, the disturbance force that summarizes all other effects, $F_d(t)$, and lastly the force by the acceleration of the vehicle [22].

$$F_t(t) = m_v \frac{dv(t)}{dt} + F_a(t) + F_r(t) + F_g(t) + F_d(t) \tag{3}$$

$$F_a(t) = \frac{1}{2} \cdot \rho \cdot A \cdot C_x \cdot v(t)^2 \tag{4}$$

$$F_r(t) = m_v \cdot C_r \cdot g \cdot cos(\alpha) \tag{5}$$

$$F_g(t) = m_v \cdot g \cdot sin(\alpha) \tag{6}$$

Equations (4), (5), and (6) state the aerodynamic drug force, the rolling friction force, and the gravity force, respectively. Herein, A expresses front surface of the vehicle in m^2, C_x and C_r represent the drag coefficient and rolling resistance coefficient, respectively. α, g, ρ, and m_v are road slope in *rad*, gravity of earth in m/s^2, air density in kg/m^3, and mass of the vehicle in kg, respectively. It is worthy to underline that the force caused by acceleration will be negative if the vehicle is slowing down.

Furthermore, $F_g(t)$ will be negative if the vehicle goes downhill. Besides, the expression of acceleration $\frac{dv(t)}{dt}$ can be simply obtained by the difference between consecutive values of $v(t)$ divided by the time step as in (7). ΔT is the time granularity that must be in *seconds* in (7).

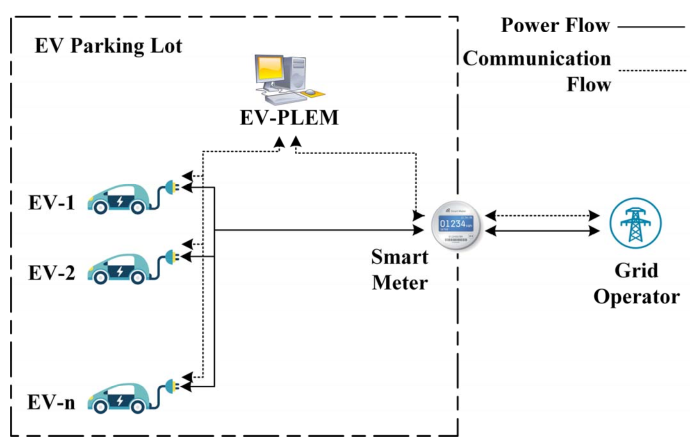

Fig. 1. The proposed energy management strategy for EV parking lot.

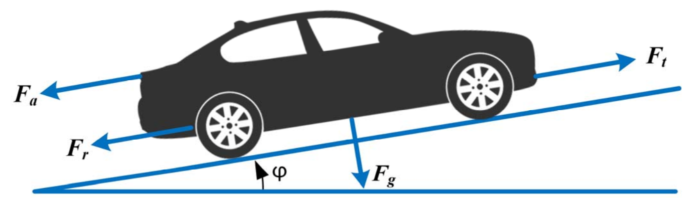

Fig. 2. Forces acting on the EV motion.

$$\frac{dv(t)}{dt} = \frac{v(t) - v(t-1)}{\Delta T} \tag{7}$$

B. EV Parking Lot Energy Management Model

The proposed EV-PLEM system is modeled as an optimization problem in this study. The objective of the energy management strategy is to maximize the load factor. In other words, the objective is to obtain benefit from the capacity of power system components in the most effective manner as much as possible at all time periods of the day.

Eq. (8) reflects the objective function adopted in the EV-PLEM strategy proposed in the study.

$$max \sum_s \pi_s \frac{P_s^{grid,avg}}{P_s^{grid,max}} \tag{8}$$

Due to its nonlinear structure, Eq. (8) cannot be solved by using linear programming techniques. Regarding this fact, the objective function is rearranged to serve the same purpose, maximizing the load factor, as indicated in (9). It should be noted that (9) naturally results in the maximization of the load factor defined in (8), by maximizing the numerator and minimizing the denominator in (8) in order to minimize the subtraction in (9).

$$min \sum_s \pi_s \left(P_s^{grid,max} - P_s^{grid,avg}\right) \tag{9}$$

Equation (9) is composed of the probability value (π_s) of the related reference power consumption for EV parking lot and the difference between the maximum power drawn from the grid ($P_s^{grid,max}$) and the average power drawn from the grid ($P_s^{grid,avg}$) during the scenario s. Furthermore, these variables are obtained via (10) and (11).

$$P_s^{grid,max} \geq P_{t,s}^{grid}, \qquad \forall s, \forall t \tag{10}$$

$$P_s^{grid,avg} = \frac{\sum_t P_{t,s}^{grid}}{tot(t)}, \qquad \forall s \tag{11}$$

It should be reminded that in related expressions, $P_s^{grid,max}$ is minimized naturally by the solution technique since the aim is to minimize the difference between $P_s^{grid,max}$ and $P_s^{grid,avg}$. Besides, even if (8) is an inequality constraint, $P_{t,s}^{grid}$ cannot take a value above the maximum value. Herein, the power drawn from the grid ($P_{s,t}^{grid}$) is equal to the sum of charging power of EVs ($P_{s,h,t}^{EV,ch}$) in parking lot.

$$P_{s,t}^{grid} = \sum_h P_{s,h,t}^{EV,ch}, \qquad \forall t, \forall s \tag{12}$$

Equation (13) describes that the charging power for each EV cannot be greater than the charging station capacity of the related EV.

$$P_{s,h,t}^{EV,ch} \leq CR_h^{EV}, \qquad \forall s, \forall h, t \in \left[T_{h,s}^a, T_{h,s}^d\right] \tag{13}$$

Equation (14) expresses the relationship between the SoE of the EV for the previous time interval ($SoE_{s,h,t-1}^{EV}$) and charging energy supplied from the grid ($P_{s,h,t}^{EV,ch} \cdot CE_h^{EV} \cdot \Delta T$) in order to obtain the SoE of the EV for each time interval.

$$SoE_{s,h,t}^{EV} = SoE_{s,h,t-1}^{EV} + P_{s,h,t}^{EV,ch} \cdot CE_h^{EV} \cdot \Delta T, \quad \forall s, \forall h, t \in \left[T_{h,s}^a, T_{h,s}^d\right] \tag{14}$$

As far as the initial SoE values of EVs are concerned, after journey of the EV to the parking lot, remaining SoE of the EV is assumed as initial SoE of the EV ($SoE_h^{EV,ini}$) for the charging operation by (15). It is worthy to highlight that the initial SoE of EV should be considered as a variable to perform the journey stochasticity of EVs according to the related scenarios.

$$SoE_{s,h,t}^{EV} = SoE_{s,h}^{EV,ini}, \qquad \forall s, \forall h, t = T_{h,s}^a \tag{15}$$

In order to take end-user comfort into account, SoE of the EV ($SoE_{s,h,t}^{EV}$) at the departure time is achieved to be equal to the desired SoE value of the EV ($SoE_{s,h,t}^{EV,desired}$) by using (16). Moreover, the SoE of the EV is restricted in allowed maximum SoE capacity of EV ($SoE_h^{EV,max}$) as indicated in (17).

$$SoE_{s,h,t}^{EV} = SoE_{s,h,t}^{EV,desired}, \qquad \forall s, \forall h, t = T_{h,s}^d \tag{16}$$

$$SoE_{s,h,t}^{EV} \leq SoE_h^{EV,max}, \qquad \forall s, \forall h, \forall t \tag{17}$$

It should be noted that designated variables for each EV should not be any value when they are not in parking lot. In order to satisfy this constraint, therefore, (18) is defined in the proposed EV-PLEM model.

$$SoE_{s,h,t}^{EV}, P_{s,h,t}^{EV,ch} = 0, \qquad \forall s, \forall h, t \notin \left[T_{h,s}^a, T_{h,s}^d\right] \tag{18}$$

Lastly, it should be clarified that the reference power patterns are provided for management of the charging interactions of EV-PLEM under the PLR based DR events. The uncertainty of the reference power pattern is related to arrival time and remaining SoE level of each EV. In order to conduct the EV-PLEM under a PLR based DR strategy, (19) is modeled. Thus, reducing the charging power of the EVs according to the reference power profile ($P_{t,s}^{ref}$) at the level demanded ($P_t^{desired}$) by the LSE is achieved. It is worthy to underline that regarding PLR based DR program, the interaction between EV owners and parking lot operator are not evaluated in this study. It is assumed that EV owners have already accepted to participate in the DR program. It should be recalled that there cannot be any peak curtailment if the reference power is equal to zero, hence (20) restricts the proposed model in this manner.

$$P_t^{desired} \leq P_{t,s}^{ref} - P_{s,t}^{grid}, \qquad \forall s, \forall t \in [t_1, t_2] \tag{19}$$

$$P_{s,t}^{grid} = 0, \forall P_{t,s}^{ref} = 0, \qquad \forall s, t \in [t_1, t_2] \tag{20}$$

III. Test and Results

With the aim of maximizing load factor along with the evaluation of stochasticity of the initial SoE of EVs and uncertainty of the arrival time for each EV to the parking lot, the energy management of the EV parking lot is modeled by using linear programming. The proposed EV-PLEM strategy is tested in GAMS v.24.1.3 software with commercially available solver CPLEX v.12 [23]. It should also be clarified that the reference power profiles for the EV parking lot are obtained via MATLAB/Simulink [24]. Input data and relevant results to the different cases will be analyzed in following subsections, respectively. The key challenge for implementing the proposed EV-PLEM can be the computational burden. But, even for the longest case, it takes only 0.18 s to solve the devised EV-PLEM using a Dual Core Laptop with 2.5 GHz CPU and 8 GB RAM, which can give an insight of the computation time required for the methodology.

A. Input Data

In this paper, 10 different commercially existing EV types and 8 dissimilar driving cycles are taken into account.

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Furthermore, 10 different vehicles of each type of EV model that have different arrival time and initial SoE in order to reach more appropriate assessments with the real life are evaluated. Table V covers the whole EV models analyzed in this study along with their electrical characteristics.

As mentioned before, in order to consider the stochasticity of the arrival time of EVs to the parking lot and uncertainty regarding the initial SoE of EVs, 8 different driving cycles [35] detailed with the journey times in Table VI are utilized. The reason for using different drive cycles is that each of the drive cycles represents the different external factors that have impacts on the power consumption of an EV. Therefore, at the end of every drive cycle, each of EVs will have different initial SoE level when they arrive at the parking lot, just before the charging operation.

In Fig. 3, the reference power patterns based on generated scenarios by using driving cycles for an EV parking lot are shown. For a clearer representation, another subfigure is demonstrated between 1 pm and 4 pm for scenarios 5, 6, and 7.

To obtain more realistic scenarios, 8 different driving cycles (i.e., 8 different scenarios) and a total of 100 EVs including 10 different models are taken into account in the study. The distribution of the arrival times relevant to each EV for each scenario is shown in Fig. 4.

It can be seen in the demonstration that EVs are assumed to use the parking lot between 7 am and 7 pm throughout the day, thereby, it can be approved that the generated scenarios are close to real-life.

TABLE V
ELECTRICAL CHARACTERISTICS OF ELECTRICAL VEHICLES

EV Types	Battery Capacity [kWh]	Charging Rate [kW]
Volkswagen E-Golf [25]	36	7.2
BMW i-3 [26]	33	7.7
Mercedes B-Class [27]	28	10
Tesla Model-S [28]	100	10
Fiat 500E [29]	24	6.6
Ford Focus Electric [30]	23	6.6
Kia Soul EV [31]	27	6.6
Mitsubishi i-MiEV [32]	16	3.6
Chevy Volt [33]	18	3.6
Nissan LEAF [34]	40	6.6

TABLE VI
CONSIDERED DRIVING CYCLES TO GENERATE REFERENCE POWER PROFILES FOR EV PARKING LOT

Driving Cycles [35]	Journey Time (s)
UDDS	1370
EPA IM240	240
FTP	1875
HDUDD	1060
HWFET	765
US06	600
EUDC	400
LA92	1435

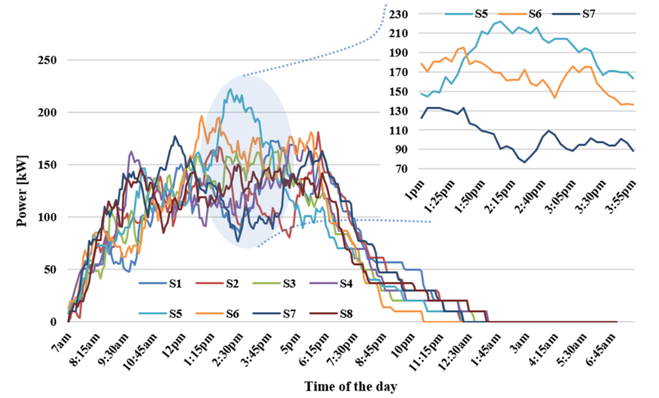

Fig. 3. The generated scenarios for reference power profiles for EV charging.

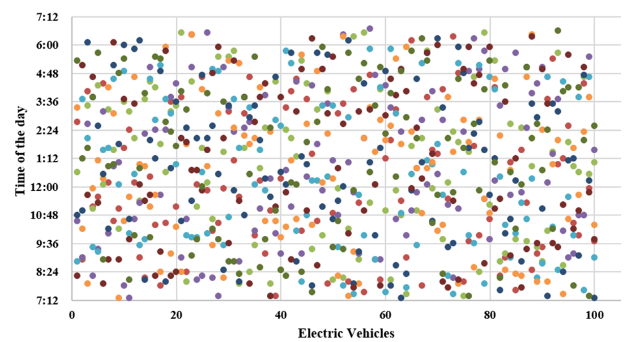

Fig. 4. The distribution of arrival times in the day for 100 EVs according to the 8 different scenarios.

B. *Simulation and Results*

The performance of EV-PLEM model has been examined by considering base case along with 7 different case studies. The evaluated case studies are listed below:

- *Case-1:* No peak load reduction is demanded by the LSE and EVs are free to depart after the time of the minimum full charge without any time constraint.
- *Case-2:* 30 kW peak load reduction is demanded between 1 pm and 3 pm by the LSE and EVs can be departed between the time of the minimum full charge and 12 am.
- *Case-3:* 30 kW peak load reduction is demanded between 1 pm and 3 pm by the LSE and EVs can be departed between the time of the minimum full charge and 10 pm.
- *Case-4:* 30 kW peak load reduction is demanded between 1 pm and 3 pm by the LSE and EVs can be departed between the time of the minimum full charge and 8 pm.
- *Case-5:* 70 kW peak load reduction is demanded between 1 pm and 3 pm by the LSE and EVs can be departed between the time of the minimum full charge and 12 am.
- *Case-6:* 70 kW peak load reduction is demanded between 1 pm and 3 pm by the LSE and EVs can be departed between the time of the minimum full charge and 10 pm.
- *Case-7:* 70 kW peak load reduction is demanded between 1 pm and 3 pm by the LSE and EVs can be departed between the time of the minimum full charge and 8 pm.

The time of the minimum full charge is obtained by considering the difference between the maximum SoE of the EV and the initial SoE of the EV immediately before charging. Besides, the arrival time of the EV to the parking lot, the rate of charge, together with the capacity and the efficiency of the charging station of relevant EV are the components of the calculation. It should also be indicated that all the EVs' owners are assumed to be willing to depart from the parking lot with the maximum SoE. There are 100 EVs with different arrival and departure times in addition to SoE of EVs under 8 case studies evaluated in this study. This means that hundreds of results are obtained. Therefore, it is worthy to underline that the assessments of the graphical results are conducted based on some selected cases and scenarios for the sake of clarity. Selected results are determined to manifest the impacts of the mentioned variables most prominently.

Fig. 5 shows the power drawn from the grid for each scenario in Case-4. It is obvious that generated scenarios have remarkable impacts on the drawn power pattern. It can also be understood from the mentioned figure that after the LSE demanded peak load reduction between 1 pm and 3 pm, the charging power profile is affected directly.

In order to clarify the effects of different case studies on the power drawn from the grid for EVs charging, all cases can be observed for one selected scenario and Fig. 6 is illustrated in this context. It should be mentioned that the impacts of departure time restrict have great influence on the power pattern rather than peak load curtailment demand. A subfigure is demonstrated in Fig. 6 so as to show up the impact of peak load reduction based DR strategy as the effect of DR is eliminated when the SoE of EVs reaches a certain level. In order to take an attention on significance of the departure time constraint for EV-PLEM system, however, Case-1 can be compared with the others in Fig. 6. It can be concluded that thanks to disposed of time constraints the EV-PLEM system can schedule the charging operations in a more flexible fashion.

The variation of the SoE of a Volkswagen type EV and the drawn power from the grid are presented for a short time interval in Case-5 during Scenario 1 in Fig. 7. It is obvious in Fig. 7 that after introducing of peak load reduction demand of the LSE, the power drawn from the grid is curtailed and the charging of the EV is stopped for a while.

Table VII encapsulates the comparison of the base case along with 7 different cases analyzed in this study according to the main objective of the proposed EV-PLEM strategy. It can be deduced from Table VII that base case can be accepted as the worst case since there is no energy management concept. Case-1 that includes neither DR strategy nor departure time restrict provides the best load factor value at the end of the day. As seen in the mentioned table, with the introduction of the EV-PLEM, load factor has increased to 0.9293 almost equal to 1 with the increase rate of 150.3%.

Case-2 reveals the effect of PLR demanded by LSE in first. Moreover, comparing Case-2 with Case-3, and Case-4, it can be observed how the dissimilar departure time constraints affect the objective of the EV-PLEM.

It is obvious that after demanding PLR by LSE, the EV-PLEM system is restricted to shed the charging load of EVs. Even there are departure time and PLR restrictions, in Case-2, Case-3, and Case-4, EV-PLEM has raised the load factor by the rate of 70.3%, 45.8%, and 19.6%, respectively.

As a result of variations on departure times, the load factor value is getting smaller gradually since EV-PLEM has a limited area in a day period for scheduling.

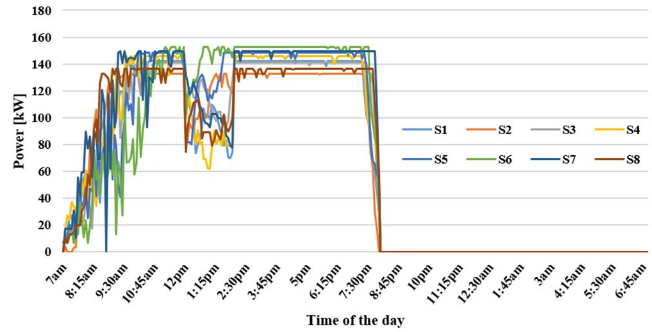

Fig. 5. The power drawn from the grid to charge EVs in parking lot for each scenario in case-4.

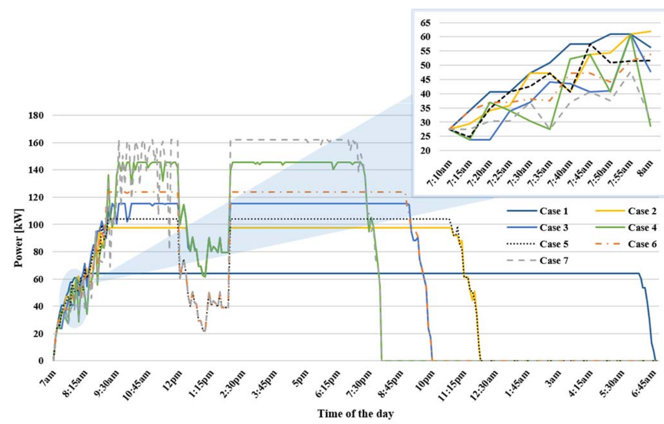

Fig. 6. The power drawn from the grid for scenario 4 in each case study.

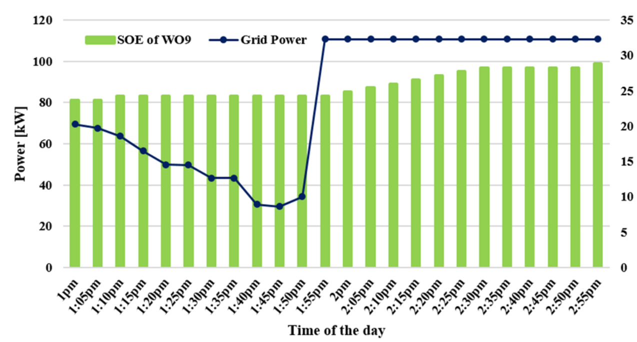

Fig. 7. The SoE variation of Volkswagen E-Golf number 9 and the power drawn from the grid for scenario 1.

TABLE VII
COMPARISON OF DIFFERENT CASE STUDIES

Case Studies	Amount of PLR	Departure Time Constraint	Load Factor	Increase Rate
Base Case	--	--	0.3712	-
Case 1	--	--	0.9293	150.3%
Case 2	30 kW	12 am	0.6322	70.3%
Case 3	30 kW	10 pm	0.5413	45.8%
Case 4	30 kW	8 pm	0.4442	19.6%
Case 5	70 kW	12 am	0.6020	61.6%
Case 6	70 kW	10 pm	0.5133	38.2%
Case 7	70 kW	8 pm	0.4087	10.1%

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When it comes to Cases 5, 6, and 7, the increase of amount of PLR demanded by LSE is also quite influential on arranging of the load factor. It can be deduced from the above-mentioned implications that Case-7 has the smallest load factor which is equal to 0.4087 by the rate of 10.1% in comparison with Base Case due to high power demand and restrain time to charging operation of EVs. The comparison of the Case-1 and Case-7 reveals the effects of the departure time and PLR constraints on the load factor maximization evidently, in which it can be seen that the mentioned constraints decrease the load factor by the rate of 56%.

In order to reflect the impacts of the PLR based DR on the devised EV-PLEM strategy, additional cases are provided, namely Case-8, Case-9, and Case-10, which are with different departure time constraints (12am, 10pm, 8pm, respectively) but no PLR limit is demanded by the LSE. The relevant results are given in Fig. 8 where the DR period is further zoomed to enable a better comparison.

As seen, when PLR limit is not imposed, a reduction may be observed in peak load between t_1 and t_2 in some cases compared to the reference power curve. However, it is not guaranteed to achieve a certain lower level of reduction in peak demand when PLR limits are not imposed. Thus, the reason for applying PLR limits here is to obtain a certain amount of reduction in peak load during stressful conditions for the grid, rather than a reduction amount that is uncertain from the lower bound point of view. The PLR limit oriented constraints impose a lower bound for the reduction that is decided by upper hierarchical levels of grid operation.

C. Interactive User Interface for EV Parking Lots

The abovementioned EV-PLEM concept is modeled for the LSE and EV parking lot operators; however, the new-generation parking lots need to be adopted to also EV owners. Therefore, a user-friendly interactive interface is developed for EV owners as a mobile phone application in the scope of this work. The operation diagram of the user interface is illustrated in Fig. 9 and the following bullets summarize this process step by step.

When the EV owner arrives the parking lot and plugs the EV to the charging station, the EV-PLEM recognizes it and sends notification to the mobile app of the end user via radio frequency identification (RFID) based communication. Afterwards, via the mentioned mobile app, the EV-PLEM offers two options to the user, which are named as pick up on a specific date and time or pick up at desired SoE level, as shown at the top of Fig. 10.

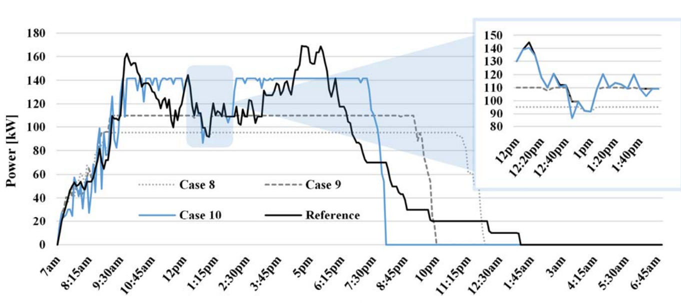

Fig. 8. Analysis of the impacts of neglecting PLR limits on EVPL operation (DR period further zoomed).

Operation steps of the interactive user interface

1. EV owner plugs the EV to charging station,
2. EV-PLEM notices the EV via RFID,
3. EV-PLEM sends a notification to the mobile app of EV owner,
4. EV owner chooses the proper option as time or charging,
5. EV-PLEM makes the decision for charging operation based on the EV owner's request,
6. The mobile app shows the pick-up date or battery level.

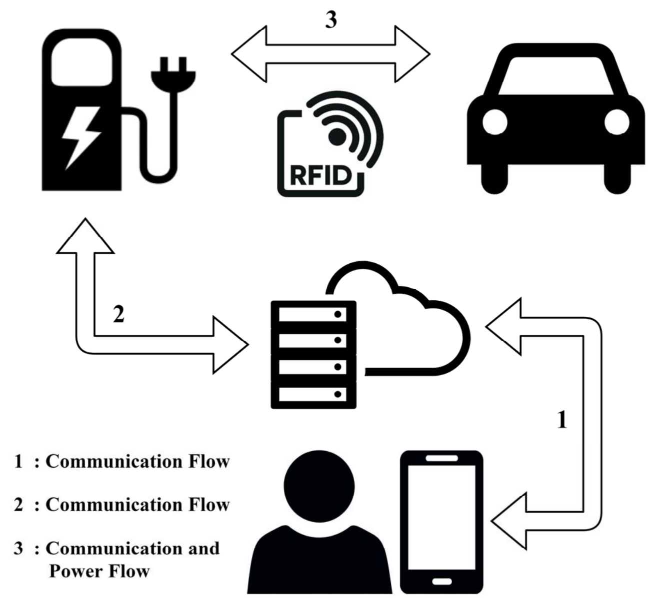

Fig. 9. The block diagram of interactive interface for EV owners.

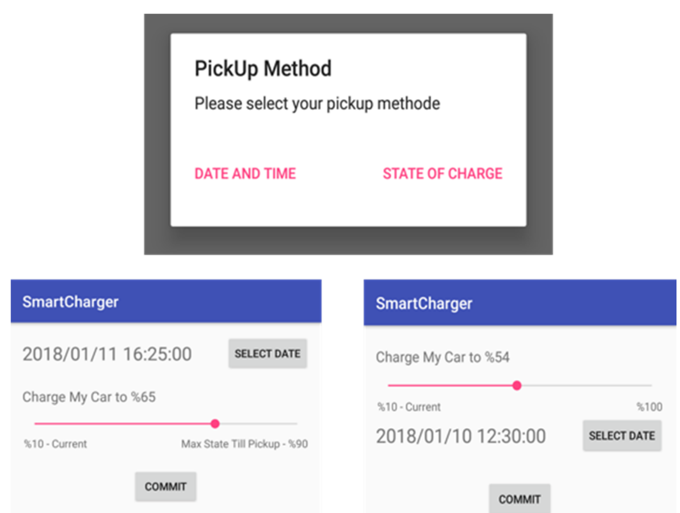

Fig. 10. User interface of options asked to the EV owners.

The user who has priority on date will choose the option called date and time. After determining the pick-up date and time, application sends data to cloud and asks for maximum possible SoE for showing it on the user interface. Then, the user can only select above the current and below the maximum possible SoE level as the desired departure SoE value. Another choice for the user who has time constraint is to pick up the EV at a desired SoE level.

When the user select SoE option, the application will ask for SoE level and then calculate the proper date for departure considering the grid loads. First, the nearest appropriate time is shown for the specified SoE level the user desires. Besides, EV owner can determine a later time for picking up the EV. The interactive interface of the aforementioned options can be seen at the bottom part of Fig. 10.

IV. Conclusion

For the purpose of reducing the dependence on fossil fuels and providing flexibility for LSEs thanks to the bi-directional energy flow, EVs and their management have a key role for the new power system. This study proposed an EV-PLEM strategy based on a linear programming framework, aiming to maximize the load factor during the daily operation of an EV parking lot under the peak load reduction based DR program. The arrival and departure time, together with the remaining SoE of EVs just before charging operation were evaluated in a stochastic manner in this study. Eight different driving cycles and ten different commercially available EV models (100 EVs in total) were considered during the generation of scenarios to increase the accuracy of the suggested EV-PLEM. It should be highlighted that bi-directional power flow was not considered in the scope of this study. Thus, EV-PLEM system managed the charging operation of EVs in the parking lot. Moreover, several case studies were performed by considering different departure time constraints and a different amount of demand power for peak load reduction by the LSE to validate the effectiveness of the designed concept. It should also be underlined that an interactive interface for EV owners was developed in order to simplify them to be adjusted to new generation parking lots in this study. The results showed that the load factor, which is a significant parameter to take advantage of other power system components in an effective way, can be improved by using the proposed EV-PLEM. For the case in which no energy management strategy is implemented, assumed as the worst and base case, the load factor obtained was as 0.3712. In order to illustrate the impacts of the EV-PLEM strategy, the base case was compared with Case-1 in which the load factor is at the maximum level equal to 0.9293 by the increase rate of 150.3% due to not considering either departure time or any PLR constraints. Cases 2, 3, and 4 were created to show the effects of the departure time variation with 30 kW peak load reduction based DR program. One of the astonishing results was that the departure time plays a key role to arrange the load factor during the scheduling of the charging operation. Further, Cases 5, 6, and 7 were explored to observe how the load factor will response to the change in the amount of demanded power for PLR, which was desired to be 70 kW. The best option to show up the impacts of the departure time and PLR constraints is the comparison of Case-7 with Case-1, in which the decrease rate of the load factor is 56%. In the light of these results, it can be deduced that increasing the amount of PLR also causes extra stress on the EV-PLEM system during the load factor maximization. In this study, the aforementioned EV-PLEM model constructed using linear programming was examined by considering just the charging operation of EVs. This research may be extended by including bi-directional power flow thanks to the vehicle-to-grid feature, and also considering the battery degradation due to the irregular charging operation as a future work.

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