Optimal Coordination of EV Charging through Aggregators under Peak Load Limitation Based DR Considering Stochasticity

İbrahim Şengör, Ayşe Kübra Erenoğlu, and Ozan Erdinç
Dept. of Electrical Engineering
Yildiz Technical University
Istanbul, Turkey
{isengor, erenayse, erdinc}@yildiz.edu.tr

Akın Taşcıkaraoğlu
Dept. of Electrical and Electronics Engineering
Mugla Sitki Kocman University
Muğla, Turkey
akintascikaraoglu@mu.edu.tr

João P. S. Catalão
INESC TEC and FEUP, Porto, C-MAST/UBI, Covilha, and INESC-ID/IST-UL, Lisbon, Portugal
catalao@fe.up.pt

Abstract—Demand response (DR) provides enormous opportunities to distribution system operators so as to conduct the power system in a sustainable manner. Due to the increasing penetration of electric vehicles (EV) in the power system, the necessity of enhancing flexibility has gained importance in the charging operation process. With the aid of the smart grid concept and DR programs, more flexible grid operations are provided. In this study, an optimal day-ahead EV charging strategy through electric vehicle parking lots (EVPL) aggregators is intended for the purpose of maximizing the load factor during daily operation. Furthermore, the behavioral uncertainty of EVs and peak load limitation based DR programs are also taken into account in the devised model. In order to reveal the effectiveness of the proposed EVPL aggregator energy management strategy, various case studies are performed, and credible results are reported.

Keywords—energy management, EV parking lots, aggregator, demand response, stochastic programming, load factor.

NOMENCLATURE

The sets, parameters, and decision variables used throughout the study are listed below.

ABBREVIATIONS

DR	Demand response
EV	Electric vehicle
GHG	Greenhouse gas
LSE	Load serving entity
EVPL	Electric vehicle parking lot
PLL	Peak load limitation
SoE	State-of-energy

SETS

t	Period of the day index in time units [min].
s	Set of scenarios.
n	Set of aggregators.
k	Set of EVPLs.
m	Set of EVs.

PARAMETERS

CE_m^{EV}	Charging efficiency of EV h.
CR_m^{EV}	Charging rate of EV h [kW].
$P_t^{imposed}$	Peak power limit demanded by LSE during period t [kW].
$SoE_{n,k,m,s}^{EV,ini}$	Initial SoE of EV m in EVPL k under aggregator n for scenario s [kWh].
$SoE_m^{EV,max}$	Maximum SoE of EV m [kWh].
$SoE_m^{EV,min}$	Minimum SoE of EV m [kWh].
$SoE_{n,k,m}^{EV,des}$	Desired SoE of EV m in EVPL k under aggregator n at the departure time [kWh].
$T_{n,k,m,s}^a$	Arrival time period of EV m to EVPL k under aggregator n for scenario s.
$T_{n,k,m,s}^d$	Departure time period of EV m to EVPL k under aggregator n for scenario s.
ΔT	Time granularity [mins].
π_s	Probability value of scenario s.

DECISION VARIABLES

$P_{s,n,k,m,t}^{EV,ch}$	Charging power of EV m in EVPL k under aggregator n during period t for scenario s [kW].
$P_{s,t}^{grid}$	Power drawn from the grid during period t for scenario s [kW].
$P_{s,n,t}^{agg}$	Total charging power of aggregator n during period t for scenario s [kW].
$P_{s,n,k,t}^{EVPL}$	Total charging power of EVPL k under aggregator n 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].
$SoE_{s,n,k,m,t}^{EV}$	SoE of EV m in EVPL k under aggregator n for scenario s [kWh].

I. INTRODUCTION

A. Motivation

The share of electrical energy in the energy sector has increased dramatically owing to its environmentally friendly nature, its less harmful structure to human health, and sustainability issue [1].

Because of the rise of electricity use, management of the power system has been a critical commitment in order to provide sustainability. Thanks to the smart grid concept, demand-side management is also taking a key role as much as generation facilities to enhance the flexible operation of the power system [2].

The transportation sector is also shifting towards to electric-based types so that the widespread of electric vehicles (EV) is undeniable. According to the published report [3], it is expected to be over 150 million total of plug-in hybrids and battery electric vehicles worldwide by 2040.

Yet another crucial report [4] is about environmental impacts of transportation. It is stated that the transportation sector is responsible for 23% of current global energy-related greenhouse gas (GHG) emissions in 2017. As an outcome, in the light of the many reports not referred here, it is expected that the number of EV parking lots will increase in near future. In this context, aforementioned concerns gather the attention on the coordination of EVs charging operation in parking lots.

B. *Literature overview*

There are several recent studies in the literature considering smart charging strategies in EV parking lots under an aggregator framework and this concept has been comprehensively investigated from different points of view by various researchers around the world. Among them, Guo et al. [5] developed a non-cooperative Stackelberg Game approach for the energy trading process between EV aggregator and EVs with the aim of providing optimal energy-price scheduling strategies thanks to the bidirectional energy and information flow between parties. Vehicle to grid (V2G) technology has been taken into account within the concept of demand response (DR) through which it is possible to sell surplus energy from EVs while considering battery degradation and energy transmission losses. To address uncertain nature of EVs, different types, brands and state-of-energy (SOE) of EVs were randomly selected. Also in [6], a dynamic aggregator-EVs system was proposed as a stochastic-based optimization problem where EVs are centrally controlled by an aggregator in regulation services with using V2G facility of the parked EVs. Nonetheless, it was indicated that [5] aimed to maximize own profits of each player while [6] targeted at maximizing the long-term social welfare of the system; however, load factor and parking lot aggregator under aggregator architecture were not taken into consideration. Shukla et al. [7] presented the intelligent aggregator scheme to schedule EVs charging process in large parking lots with the objective of reducing dynamic load variation and increasing load factor as well as satisfying EV's charging requirements. On the other hand, the stochasticity caused by EVs' arrival/departure times and the DR programs were neglected in that paper. Rezai et al. [8] suggested an online intelligent energy management strategy in order to coordinate EV charging process in a smart parking lot while maximizing EV owners' satisfaction. However, a major criticism of this study is that the power system constraints and any DR program were not taken into account.

Sharma et al. [9] suggested a multi-objective optimization problem for scheduling EVs' charging-discharging pattern in the parking lot by taking into consideration variable market prices and EV mobility. The main targets of the study are to maximize aggregator's profit, to minimize EV's charging cost and lastly to maximize EV's departing with target (desired) state-of-charge. Moreover, different case studies were conducted to demonstrate the effectiveness of the suggested concept in terms of satisfying the objectives. Nevertheless, no attempt was made to investigate DR programs' impact on the power grid together with the importance of load factor. A conceptual framework was presented in [10] for integrating a large amount of EVs into the power system. It suggested a hierarchical management structure to control EVs charging behavior in a wide area to operate the grid with less stressed and improved voltage profiles. Furthermore, it is possible to participate in electricity market for aggregator along with communicating distribution system operator (DSO) by transmitting variable price information and also the other units capable of exchanging data with transmission system operator (TSO) to ensure technical system requirements. Although this was one of the most comprehensive studies, the stochasticity of EV habits and load factor were neglected in this framework. Chen et al. [11] presented an integrated eVoucher program in order to utilize typical flexible loads, such as parking lots with highly penetrated EVs, energy reduction capability in DR strategies and to encourage aggregators to be an active participant in real-time retail electricity market.

It is worthy to note that the frequency-deviation in power system can be reduced as well as providing economic benefits to consumers thanks to this proposed framework. On the other hand, the uncertain behavior of arrival time of EVs and the load factor were not taken into account. The authors in [12] developed a comprehensive model in which aggregator has distributed energy sources, load retailers and parking lot under its structure. This framework provides opportunities for the aggregator to actively participate in the energy transaction market by taking advantages of load management axioms and enables to maximize its profit in the upper level while parking lot aims to maximize its own profit in lower level.

Although the various uncertainties caused by EVs such as arrival, departure, and duration of stay in the parking lot were considered, load factor was not even touched in this study. Furthermore, the role of aggregators in electricity markets was investigated in [13] and [14]. There are many comprehensive relevant studies emphasizing the importance of coordination of EV charging operations from different points of view such as [15], [16], and [17] that reviewed the EV parking lots interaction with renewable energy sources. More detail reviews devoted to the topic can also be found in [18], [19], and [20].

These aforementioned references along with many other studies not referred here have provided important insights into parking lot management and EV aggregation in order to enhance system performance within the concept of the smart grid. However, none of them considered parking load (PL) aggregator architecture which is actually the significance of this study and also load factor maximization was not investigated widely yet together with taking into account uncertain features of EVs.

C. *Contributions and organization*

A linear programming model of EV charging coordination through aggregators that include different electric vehicle parking lots (EVPLs) is proposed by considering the uncertain behavior of EVs in a stochastic manner. The main objective of the propounded EVPL aggregator energy management concept is to maximize the load factor of a region composed of different aggregators during the day period. The contributions of the study can be detailed as follows:

- An optimal EV charging coordination of a region through EVPL aggregators is presented. The uncertainty of the EV behavior such as arrival time and remaining SoE is conducted by generated scenarios based on driving cycles.
- Peak load limitation based DR programs are introduced into EVPL aggregators during the maximization of load factor which is the first time in the literature.

The rest of paper is organized as follows: the relevant mathematical background of both the EV motion and devised energy management model are detailed in Section II. Afterwards, Section III provides the declarations of case studies and the discussion of results. Finally, concluding remarks and future work are presented Section IV.

II. METHODOLOGY

The block diagram of devised EVPL aggregators' energy management model is presented in Fig. 1. It can be seen from the mentioned figure that the proposed energy management model administrates the charging operation of EVs in different EVPL under different aggregators in distribution system operator point of view.
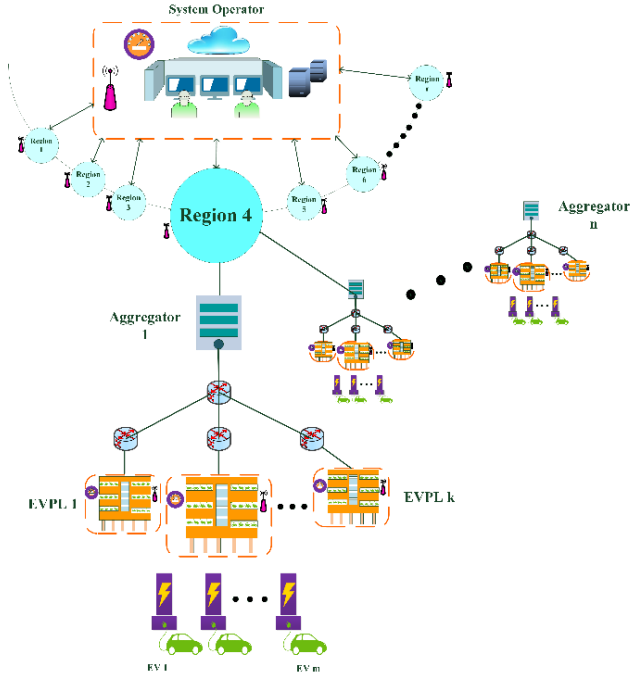
Fig. 1. The block diagram of devised EVPL aggregator model.

Also, a DR strategy demanded by load-serving entity (LSE) and uncertain behavior of EVs are also considered. A crucial drawback for performing this type of frequent charging transactions is battery degradation. It is worthy to remind that the battery degradation is not taken into account throughout the study.

The rest of this section describes the mathematical background of both the EV motion and the devised energy management strategy, respectively.

A. Mathematical Background of EV motion

In order to obtain the scenarios for arrival time of EVs and remaining state-of-energy (SoE) belongs to each EV, mathematical model of EV motion is utilized by considering different driving cycles.

The mathematical background of an EV motion can be modeled based on Newton's one dimensional motion law. The forces that have impact on EV motion during the trip are demonstrated in Fig. 2.

Moreover, the total traction force expression is given in (1). The total traction force is obtained by 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 [21].

$$F_t(t) = m_v \frac{dv(t)}{dt} + F_a(t) + F_r(t) + F_g(t) + F_d(t) \quad (1)$$

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

$$F_r(t) = m_v \cdot C_r \cdot g \cdot cos(\alpha) \quad (3)$$

$$F_g(t) = m_v \cdot g \cdot sin(\alpha) \quad (4)$$

Equations (2), (3), and (4) state the aerodynamic drug force, the rolling friction force, and the gravity force. 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.
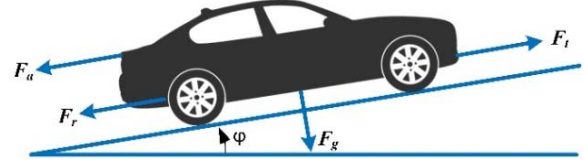

Fig. 2. Forces acting on the EV motion.

It is worthy to underline that the force caused by acceleration will be negative if the vehicle is slowing down.

$$\frac{dv(t)}{dt} = \frac{v(t) - v(t-1)}{\Delta T} \quad (5)$$

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 (5), which in turn gives the average acceleration. ΔT is the time granularity that must be in *seconds* in (5).

In (6), $P(t)$ 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 (7).

$$P(t) = \frac{P_v(t)}{\eta_d} \quad (6)$$

$$P_v(t) = v(t) \cdot F_t(t) \quad (7)$$

B. Devised EVPL aggregator energy management model

The devised EVPL aggregator energy management model is analyzed as an optimization problem in this study. The objective of the problem is to maximize load factor of a region that includes different aggregators during EV charging operation. The main purpose of resulting in maximizing load factor is to provide the most effective use of power system assets as much as possible.

Equation (8) refers the objective function adopted in devised EVPL aggregator concept. Nonetheless, (8) cannot be solved by using linear programming techniques due to the nonlinear structure of the classical expression of load factor term.

$$max \sum_s \pi_s \frac{P_s^{grid,avg}}{P_s^{grid,max}} \quad (8)$$

Regarding this fact, in order to prevent this nonlinearity, the objective function is evolved to the version represented in (9) which serve the same purpose.

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

Equations (8) and (9) are composed of the probability value (π_s) of the scenarios, maximum power drawn from the grid ($P_s^{grid,max}$) and average power drawn from the grid ($P_s^{grid,avg}$) by the region for scenario *s*. In addition, these mentioned variables are calculated by using (10) and (11). It should be noticed that $P_s^{grid,max}$ value in (10) will be minimized naturally because the objective function is to minimize the difference between the maximum and average power draw from the grid. The expression $card(t)$ in (11) refers the cardinality of the time set.

$$P_s^{grid,max} \geq P_{t,s}^{grid}, \quad \forall s, \forall t \quad (10)$$

$$P_s^{grid,avg} = \frac{\sum_t P_{t,s}^{grid}}{card(t)}, \quad \forall s \quad (11)$$

Equation (12) states the total demanded power from the grid by the region that includes different EVPL aggregators ($P_{s,n,t}^{agg}$). In (13), it is described that the total charging power of aggregator n composed of different EVPLs during period t for scenario s. Total power for each EVPL ($P_{s,n,k,t}^{EVPL}$) is obtained by summation of charging power of EVs ($P_{s,n,k,m,t}^{EV,ch}$) that charged in EVPL k in (14).

$$P_{s,t}^{grid} = \sum_n P_{s,n,t}^{agg}, \qquad \forall s, \forall t \tag{12}$$

$$P_{s,n,t}^{agg} = \sum_k P_{s,n,k,t}^{EVPL}, \qquad \forall s, \forall n, \forall t \tag{13}$$

$$P_{s,n,k,t}^{EVPL} = \sum_m P_{s,n,k,m,t}^{EV,ch}, \qquad \forall s, \forall n, \forall k, \forall t \tag{14}$$

Charging power of each EV ($P_{s,n,k,m,t}^{EV,ch}$) cannot be greater than the charging capacity of related charging station and this constraint is provided by (15). Equation (16) presents the SoE variations of an EV during the charging transactions. Herein, related expression describes the SoE of EV m after it reaches to EVPL k under the aggregator n during period t for scenario s ($t > T_{s,n,k,m}^a$). In (17), before the charging operation ($t = T_{s,n,k,m}^a$) of EV m, SoE of related EV is designated by initial SoE of EV ($SoE_{s,n,k,m}^{EA,ini}$) that is associated with the scenario s.

$$P_{s,n,k,m,t}^{EV,ch} \leq CR_m^{EV}, \quad \forall s, \forall n, \forall k, \forall m, t \in [T_{n,k,m,s}^a, T_{n,k,m,s}^d] \tag{15}$$

$$SoE_{s,n,k,m,t}^{EV} = SoE_{s,n,k,m,t-1}^{EV} + P_{s,n,k,m,t}^{EV,ch} \cdot CE_m^{EV} \cdot \Delta T,$$
$$\forall s, \forall n, \forall k, \forall m,$$
$$t \in [T_{n,k,m,s}^a, T_{n,k,m,s}^d] \tag{16}$$

$$SoE_{s,n,k,m,t}^{EV} = SoE_{s,n,k,m}^{EA,ini}, \qquad \forall s, \forall n, \forall k, \forall m, \quad t = T_{s,n,k,m}^a \tag{17}$$

In order to satisfy EV owners' charging demands, SoE of an EV is assumed to be desired at fully charged when it departures by (18). In (19), it is stated that the SoE of an EV can be taken as a value between the maximum and the minimum battery capacity. It should be underlined that to prevent charging transactions when EVs are not in any EVPL, (20) is introduced into the propounded formulation.

$$SoE_{s,n,k,m,t}^{EV} = SoE_{n,k,m}^{EV,des} \qquad \forall s, \forall n, \forall k, \forall m, \quad t = T_{s,n,k,m}^d \tag{18}$$

$$SoE_m^{EV,min} \leq SoE_{s,n,k,m,t}^{EV} \leq SoE_m^{EV,maks}, \forall s, \forall n, \forall k, \forall m, \forall t \tag{19}$$

$$SoE_{s,n,k,m,t}^{EV} = 0, P_{s,n,k,m,t}^{EA,ch} = 0, \qquad \forall s, \forall n, \forall k, \forall m,$$
$$t \notin [T_{n,k,m}^{geliş}, T_{n,k,m}^{gidiş}] \tag{20}$$

Lastly, in order to enhance operational flexibility for distribution system operators, peak load limitation based DR strategy is adopted in the proposed model. In (21), peak load limit imposed by load-serving entity (LSE) restricts the each aggregators' peak power demand during charging operations. Moreover, the power consumption of each EVPL is limited equally by introducing of (22). It is worth underlining that EV owners have already accepted to participate in a DR program.

$$P_{s,n,t}^{agg} \leq P_t^{imposed}, \qquad \forall s, \forall n, \forall t \tag{21}$$

$$P_{s,n,k,t}^{EVPL} \leq \frac{P_t^{imposed}}{card(k)}, \quad \forall s, \forall n, \forall k, \forall t \tag{22}$$

III. TEST AND RESULTS

Providing maximum load factor for a region during daily operation is the main objective of the study. Together with the uncertain behavior of EV owners such as arrival time and remaining SoE, peak load limitation (PLL) based DR strategy is taken into consideration in the scope of the study.

To reveal the feasibility of the proposed model, it is assumed that there are 3 different aggregators in a region and each of them controls 2 different EVPLs.

In total, 200 EVs that have different SoE level and arrival times are scheduled to charge their batteries.

A. Input Data

In this study, 10 different types of EV are evaluated throughout the simulations. Electrical specifications of considered EVs are listed in Table I. Each EV has different initial SoE and arrival time with respect to the 8 different scenarios that are generated by using 8 different driving cycles given in Table II. The mentioned driving cycles are utilized to obtain differently initial SoE level and arrival time via MATLAB/Simulink [22].

The arrival time distribution in a day period based on the generated 8 different scenarios is depicted in Fig. 3. It should be underlined that the related demonstration is obtained for 100 EVs for the sake of clarity. It can also be deduced from Fig. 3, EVs are parked in an EVPL between 7 am and 7 pm, which means that realistic scenarios are generated.

B. Case Studies and Results

The devised EVPL aggregator management concept is modeled in GAMS v.24.1.3 and has been solved by CPLEX v.12 [34]. Moreover, in order to evaluate the effectiveness of the proposed model, following case studies are conducted.

- *Case-1:* No peak load limitation for aggregators and EVs are not restricted by means of departure time.
- *Case-2:* Each aggregator is limited 30 kW peak power by LSE and EVs are not restricted by means of departure time.

TABLE I. ELECTRICAL SPECIFICATIONS OF CONSIDERED EVS

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

TABLE II. CONSIDERED DRIVING CYCLES TO GENERATE SCENARIOS

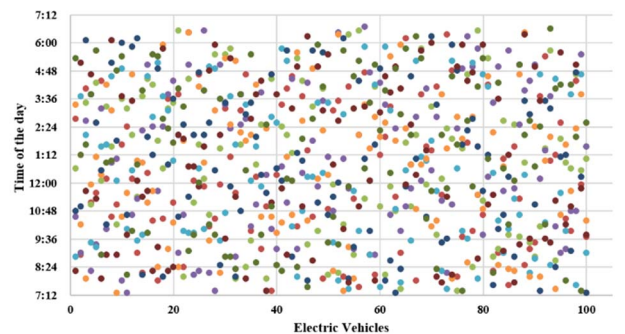| Driving Cycles [33]	Journey Time (s)
UDDS	1370
EPA IM240	240
FTP	1875
HDUDD	1060
HWFET	765
US06	600
EUDC	400
LA92	1435

Fig. 3. The arrival times distribution in a day period for 100 EVs based on the generated 8 scenarios.

- *Case-3:* Each aggregator is limited 60 kW peak power by LSE and EVs are restricted to leave at between the time of the minimum full charge and 12 am.
- *Case-4:* Each aggregator is limited 60 kW peak power by LSE and EVs are restricted to leave at between the time of the minimum full charge and 10 pm.
- *Case-5:* Each aggregator is limited 30 kW peak power by LSE and EVs are restricted to leave at between the time of the minimum full charge and 12 am.
- *Case-6:* Each aggregator is limited 30 kW peak power by LSE and EVs are restricted to leave at between the time of the minimum full charge and 10 pm.

The term "the time of the minimum full charge" represents that necessary time period to fully charge the battery after EVs immediate plugged-in. It is worth underlining that all EV owners are assumed to depart with the full SoE level from an EVPL. Due to consideration of 200 EVs, hundreds of results are obtained at the end of the optimization. Therefore, some selected results are presented and discussed for clearer representation.

In Fig. 4, the total power consumption of EVPL-1 which is under the aggregator-1 for selected 3 scenarios is illustrated. Impacts of scenarios on the power pattern are clear; while peak power for scenario-4 occurs at 11.45am, this is around 10.30 pm for scenario-8. It can also be seen from the mentioned figure that each aggregator is imposed a peak power limit of 60 kW so each of EVPL is restricted by 30 kW between 12 pm and 2 pm.

Moreover, the amount of PLL has also noticeable impacts on the drawn power profile. Regarding this, 30 kW PLL and 60 kW PLL are imposed on each aggregator between 12 pm and 2 pm. In Fig. 5, the drawn power from the grid by aggregator-3 for scenario-5 is depicted. As can be clearly seen, for the PLL imposed by 30 kW, the devised management system is pressured during charging operations of the EVs in related EVPLs. Therefore, while the peak power of the case imposed by 30 kW PLL (dashed line) is over 120 kW, the other one is about 100 kW.

However, to show the importance of departure time on the daily power pattern, the total drawn power of aggregator-1 for scenario-1 under different departure time constraints is plotted in Fig. 6. Together with different departure time constraints, 30 kW PLL is also considered in the above-mentioned case. It can be deduced from the figure that tight time period for charging operations has a remarkable negative impact on the power profile. Especially, if there is not any constraint related to the departure time, the devised management system can reduce the gap between the maximum and minimum power consumption which is clearly seen with the continuous grey line in Fig. 6.

Figure 7 demonstrates the SoE variation with respect to the charging power of Nissan Leaf that is charging in EVPL-1 under the aggregator-2 for scenario-6. While column charts represent the charging power for the related time period, the line graph shows the SoE level. It is obviously seen that between 1.15 pm and 1.45 pm, for instance, there is no consumption for charging operation and the SoE level remains constant in this period which means the proposed model works correctly.

The comparison of evaluated case studies is detailed in Table III. It can be deduced from the table that base case can be accepted as the worst case since there is no energy management concept. Case-1 represents the best case due to including none of PLL and departure constraints, which means increasing the load factor by the rate of 146.3%.
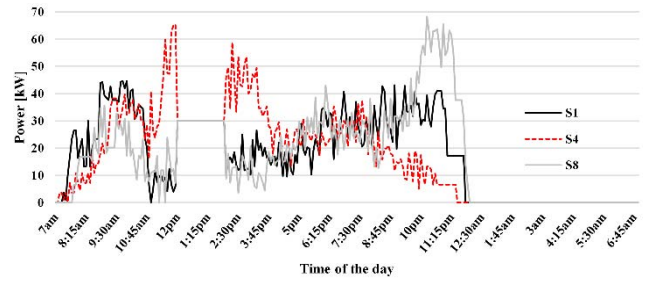

Fig. 4. Total power consumption of EVPL-1 under the aggregator-1 for different scenarios.
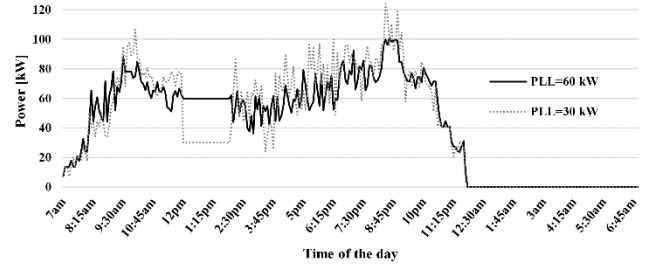

Fig. 5. The drawn power from the grid by aggregator-3 for scenario-5 under different peak power limitation.
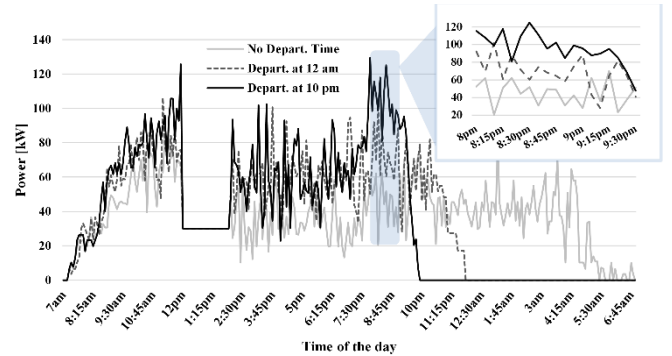

Fig. 6. Total power drawn from the grid by aggregator-1 for scenario-1 under different departure time constraints.
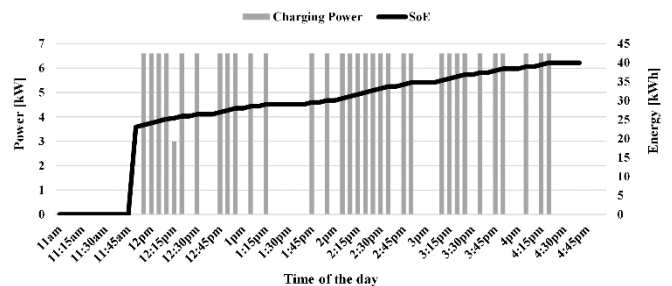

Fig. 7. SoE variation of Nissan Leaf with respect to the charging power of the EV charging station in EVPL-1 under aggregator-2 for scenario-6.

TABLE III. COMPARISON OF CASE STUDIES

Case Studies	Peak Power Limit	Departure Time Constraint	Load Factor	Increase Rate
Base Case	--	--	0.371	-
Case 1	--	--	0.914	146.3%
Case 2	30 kW	--	0.867	133.7%
Case 3	60 kW	12 am	0.631	70.1%
Case 4	60 kW	10 pm	0.540	45.5%
Case 5	30 kW	12 am	0.570	53.6%
Case 6	30 kW	10 pm	0.493	32.8%

In order to clarify the effect of PLL, Case-2 should be compared with Case-1, in which 30 kW PLL causes a reduction in load factor by the rate of 5.14%. Moreover, with the comparing Case-3 with Case-4, it can be observed how different departure constrains affect the load factor. In addition, even if both of Case-3 and Case-4 are imposed 60 kW PLL, the load factor is increased according to the base case by 70.1% and 45.5%, respectively. Furthermore, the amount of PLL has discernible impacts on the objective of the problem. As can be seen in Table III, comparison of Case-4 and Case-6 can be evaluated so as to reveal the effect of PLL amount that causes a rise in load factor by the rate of 45.5% and 32.8%, respectively.

IV. CONCLUSION

In this study, with the aim of maximizing the load factor, the optimal coordination of EVs' charging operations oriented energy management model through EVPL aggregators was propounded. The uncertainty of arrival time and initial SoE level for each EV were taken into account in a stochastic programming approach. In addition, a peak power limitation based DR strategy was evaluated by creating case studies. As a consequence, thanks to the high load factor values, other power system assets can be utilized with the maximum capacity by the coordination of EVs' charging operation. Even if the departure time of EVs was constrained with the tight time period and also the peak power limitation was implemented with the rate of 60 kW by LSE, the load factor was increased by 32.8% according to the base case. It is the evidence that the proposed model has undeniable effects on load factor maximization. The PLL are imposed equally to each EVPL under the aggregators in the study; however, this may not be practicable in real-life. Regarding this, authors may extend this research including load flow calculations among the aggregators so that the PLL amount can be obtained for each EVPL, as a future work.

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