A Hierarchical Distributed Energy Management for Multiple PV-Based EV Charging Stations

Jing Zhang, Yuanxing Zhang, Taoyong Li, Linru Jiang, Kang Li
*Beijing Electric Vehicle Charging/Battery Swap Engineering and Technology Research Center,
China Electric Power Research Institute Co. Ltd,
Beijing 100192, China, Email: zhangjing1@sgcc.com.cn*

He Yin
*Univ. of Tennessee, Knoxville,
TN 37996, USA
Email: hyin8@utk.edu*

Chengbin Ma
*UM-SJTU Joint Institute,
Shanghai Jiao Tong Univ.,
Shanghai 200240, China
Email: chbma@sjtu.edu.cn*

***Abstract*—A hierarchical distributed energy management for multiple photovoltaic (PV) based electric vehicle (EV) charging stations (PV-CSs) is proposed and analyzed in this paper. In the station level, PV-CSs are modelled as independent players with objectives to stabilize their average available capacity (AAC) of the storage battery tank. Meanwhile, in EV level, EV owners are modeled as players with objectives to maximize their charging power. Then a two level power distribution game is utilized to model the power distribution problem in both station and EV level. Through utilizing a consensus network based learning algorithm, a cooperative and a generalized Stackelberg equilibrium are achieved in station and EV level through a distributed fashion. One case studies, i.e., two station case, is implemented in simulation to verify the performance and effectiveness of the proposed strategy. The simulation results show that the proposed energy management has an excellent performance in both cases and comparing against stations without management.**

***Index Terms*—Distributed energy management, Game theory, multiple PV-based charging station, consensus network.**

I. Introduction

Thanks to the requirements of world energy demand, global CO_2 emissions, as well as increasing renewable energy capacity, electric vehicles (EVs) are considered as a promising solution to handle all these challenges. However, due to the limited capacity of the EV storage battery tanks, EV owners still suffer from the short EV driving range and EV charging concerns. Thus integration of renewable energy generation to EV charging stations is a strict forward solution. Among renewable energy generation units, photovoltaic (PV) panel array is commonly utilized because they can be easily implemented on the roof of the charging stations. Based on these concerns, PV-based electric vehicle charging stations (PV-CSs) are promising solutions toward both EV charging and renewable energy implementation. In addition to single PV-CS, multiple PV-CSs application is more challenging in both modeling and energy management aspects and thus is considered as target application in this paper.

The energy management problem inside a PV-based charging station is still a challenging work due to uncertainties in generation of PV, characteristics of EVs, as well as arriving time of EVs. A rule-based decision making strategy implemented in a PV-based battery switch station is introduced in [1]. The objective is to provide the battery swapping service available all the time. A pre-defined heuristic rule-based strategy is proposed to improve the self-consumption of PV energy and reduce the impact on the grid [2]. Moreover, an online-learning algorithm based control is applied to maximize the self-consumption of PV system and decide the power supplied from the power grid through scheduling strategy [3]. A decentralized energy management system is developed for regulating the energy flow among the photovoltaic system, the battery and the grid [4]. Their objectives is to achieve the efficient charging of electric vehicles (EVs). However, the charging power of EVs can not be determined by EV owners. A game theory based distributed control is applied in a PV-based charging station which can only be utilized in island system [5]. More importantly, the above literatures only discussed the energy management inside one PV-CS while the interactions among multiple PV-CSs, i.e., a microgrid network, were not taken into consideration. Instead of purchasing high-price energy from the utility company, PV-CSs may cooperate with each other to overcome the energy requirement as well as fully utilizing the renewable energy. To the best knowledge of the authors, there is no discussion about the energy management of multiple PV-CSs. However, the energy management problem for multiple microgrid has been widely studied. From economic point of view, energy trading among multiple microgrid is also widely discussed. [6] discusses a multiagent-based hierarchical energy management strategy in order to minimize the economic cost among a multiple microgrid. A multistep hierarchical optimization algorithm is implemented based on a multiagent system. [7] intends to determine the energy trading among multiple microgrid through a distributed convex optimization framework. Besides of cooperative control, deterministic and stochastic games are applied to determine the a coordinated energy management of multiple microgrids [8]. Instead of centralized energy managements, decentralized energy management strategy in both grid-connected and islanded modes is discussed and analysed [9]. However, due to the unique characteristics of the multiple PV-CSs, the above studies have not taken the physical characteristics of the energy devices as well as the preferences of the EV owners into consideration.

Considering both the physical characteristics and preferences of the PV-CSs and EV owners, this paper intends to solve the energy management problem among multiple PV-CSs and EVs through a hierarchical distributed energy management strategy. The objective of the proposed hierarchical distributed energy management strategy aims to achieve the following requirements, first, the PV-CS network should be fully supported by renewable energy sources, i.e., PVs; the entire energy management strategy should be flexible and reconfigable, i.e., robust against uncertainties in the environment; the privacy of the EV should be fully protected, i.e., no local information would be utilized to determine the charging power distribution. Game theory, a famous mathematical tool to dual with selfish players and coalitions, is utilized to model the power distribution problem for multiple stations. The energy management problem is decoupled into two level, i.e., station and EV level. In the station level, a cooperative game is utilized to determine the energy flow between neighbour PV-CSs according to their average available capacity (AAC). Note that AAC is a improved criteria comparing to SOC discussed in [10]. In the EV level, a generalized non-cooperative stackelberg game is utilized to solve the charging power distribution problem among EVs according to their status. In the simulation, a two station case is discussed and analyzed in detail.

II. System Configuration and Modeling

A. System Overview

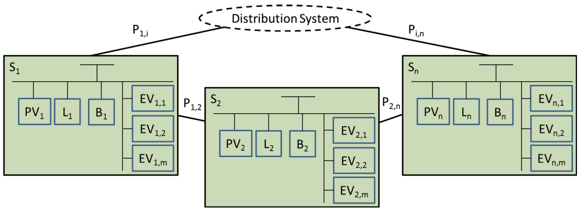


Fig. 1. The system configuration overview.

The overall system configuration of a multiple PV-CS system is shown in Fig. 1. This example system is consisted of a set of PV-CSs denoted by $\mathbf{S} = \{\mathbf{S_1}, \mathbf{S_2}, ..., \mathbf{S_n}\}$, storage batteries denoted by $\mathbf{B} = \{\mathbf{B_1}, \mathbf{B_2}, ..., \mathbf{B_n}\}$, PVs denoted by $\mathbf{PV} = \{\mathbf{PV_1}, \mathbf{PV_2}, ..., \mathbf{PV_n}\}$, loads denoted by $\mathbf{L} = \{\mathbf{L_1}, \mathbf{L_2}, ..., \mathbf{L_n}\}$, and EVs denoted by $\mathbf{EV} = \{\mathbf{EV_{1,1}}, \mathbf{EV_{1,2}} ... \mathbf{EV_{1,m}}, ..., \mathbf{EV_{n,m}}\}$ (Note that the n is the station number while m is the EV number). The distribution system means the rest of the multiple PV-CSs. Notice that the m can be different for PV-CSs with different scale. $p_{i,j}$ denotes the virtual power flow between S_i and S_j, i.e., the real power flow would directly comes from the power grid while virtual power flow would help the PV-CSs to determine the real power exchange to the power grid. Thus, in this paper, the virtual power transmitting lines are modeled exactly the same as the communication lines. Note that only the active power is discussed here while the reactive power is out of discussion in this paper.

B. Distributed Network Model

As shown in Fig. 1, the station level cyber layer of a multiple PV-CS system is represented through multiple PV-CS networks. PV-CSs here can generate a virtual power flow through virtual transmission line between each other (e.g., black solid lines here means virtual transmission lines.). Due to the purposes of simplicity, the energy loss on the transmission lines are modelled as constant efficiency, $\eta_{i,j}$. Note that since one of the objective of this energy management requires that the PV-CS network should be fully supported by PV generators, the virtual power flow would help the PV-CSs to determine the power to the grid in a distributed fashion.

The power network here can be modeled through a connected graph. In order to implement the proposed game theory based energy management, the connectivity of the graph should be guaranteed. Thus, the power network is assumed to be a simple circle here. Inside a single PV-CS, similar to the station level, the cyber layer is also treated as a connected circle in this paper.

C. Single PV-CS System Overview

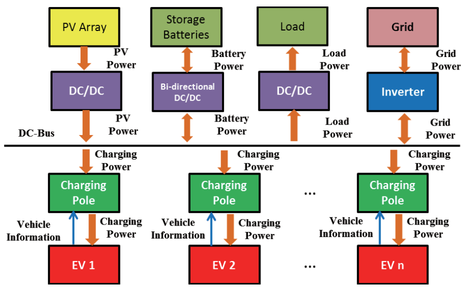


Fig. 2. The physical model of the one single PV-CS.

As shown in Fig. 2, a single DC bus topology is utilized for physical layer inside one PV-CS. The PV array, the storage battery tank, the load, the grid connect system, as well as the EV charging poles are connected to the DC bus through different kinds of converters, i.e., DC/DC converters and bidirectional inverters. Notice that, all these energy devices together with the converters can work in three mode, i.e., voltage control mode, current control mode, and standby mode. In order to maintain a stable DC bus voltage, the converter together with the storage battery tank is designed to work in a voltage control mode while other converters are working in current control mode. Notice that when the state of charge (SOC) of the storage battery tank is lower than the limitation, the grid connect system will work in voltage control mode instead of the storage battery tank.

On the other hand, the cyber layer of the proposed multiple PV-CS system can be modelled as a connected graph $G = (N, \varepsilon)$, where each node, $i \in N$, represents a station and each link $(i, j) \in \varepsilon)$ (virtual transmission line) represents a branch. The $p_{i,j}$ equal to $-p_{j,i}$ while the stations without any virtual transmission lines between them will have $p_{i,j} = 0$. And thus for each PV-CS, the real power exchange to the power grid can be represented as $p_{grid,i}$. The matrix of $p_{grid,i}$ can be represented as follows,

$$\mathbf{p_{grid}} = \begin{bmatrix} 0 & p_{1,2} & p_{1,3} & \cdots & p_{1,n} \\ p_{2,1} & 0 & p_{2,3} & \cdots & p_{2,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ p_{n,1} & p_{n,2} & \cdots & p_{n,n-1} & 0 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}. \quad (1)$$

Notice that the $p_{grid,i}$ will be controlled through the bidirectional inverter. The cyber layer inside a station applies a fixed topology. The storage battery tank, the PV panels, station loads as well as all the EVs communicate through the same transmission lines as physical layer. Note that the connectivity of the cyber system have influence on the converging speed of the proposed energy management strategy. And thus the connectivity of the cyber layer should be guaranteed.

1) EV Model: The first order EV battery equivalent circuit model is utilized to represent the physical model of the EV [11], [12]. The relationship between the charging power and the state of charge (SOC) of the EV can be written as $SOC_{EV,i,j}$. The updating matrix of $SOC_{EV,i,j}(t)$ can be represented as follows,

$$SOC_{EV,i,j}(t) = SOC_{EV,i,j}(t-1) + \triangle t \cdot \frac{p_{EV,i,j}}{C_{EV,i,j}}. \quad (2)$$

where $C_{EV,i,j}$ is the capacity of the jth EV storage battery tank in the ith PV-CS; $p_{EV,i,j}$ is the charging power for the jth EV in the ith PV-CS. Note that in the following paper, all parameters inside of the ith PV-CS and jth EV would be represented in ith PV-CS first and followed by jth EV number

Besides physical models, the EV preference model in this paper represents the satisfaction level of the EV owners. The basic idea is that the higher the charging power the higher the satisfaction level it will be. More importantly, a logarithmic function is utilized to represent the satisfaction level of the EV owner. This is because that logarithmic functions are commonly used to represent the user satisfaction level, $u_{EV,i,j}$. The matrix of $u_{EV,i,j}$ can be represented as follows,

$$u_{EV,i,j} = \frac{p_{EV,i,j,max}}{SOC_{EV,i,j}} \ln(p_{EV,i,j}+1) \quad (3)$$

$$\sum_{i=1}^{n} p_{EV,i,j,min} \leq \sum_{i=1}^{n} p_{EV,i,j} \leq p_{total,i}. \quad (4)$$

where $P_{EV,i,j,max}$ and $p_{EV,i,j,min}$ are the maximum and minimum charging power for a single EV; $p_{total,i}$ represents the total power available to all EVs in ith PV-CS. Notice that the EV owners are treated as risk-averse and thus logarithmic functions are well matching their preferences.

Since for each incoming EV, the initial SOC, capacity of the battery tank, and the incoming time is unknown, these parameters are designed as uncertainties in this paper. The initial SOC and capacity of the battery tank follows Normal distribution while the incoming time follows the Poisson distribution.

2) Storage Battery Tank Model: Again, the same equivalent circuit model is utilized to be the physical model of the storage battery tank. More importantly, the AAC of the storage battery tank model here represents the satisfaction level of the charging station administrator. Providing charging services to EVs is the responsibility for the charging station administrator. Thus, the average remaining capacity of the storage battery tank is the key parameter of the station. Again, a logarithmic function is utilized to represent the satisfaction level of the charging station administrator toward the AAC as follows,

$$AAC_{s,i} = \frac{SOC_{s,i}C_{s,i}}{n_{s,i}} \quad (5)$$

$$u_{s,i} = \ln[e-(e-1)\frac{p_{total,i}}{P_{max,i}}], \quad (6)$$

where $P_{max,i}$ is the upper boundary for the $p_{total,i}$. Notice that in order to increase the AAC of the station, it means to maximize the charging power to the storage battery tank. On the other hand, with a higher AAC of the storage battery tank, it should provide better services to EV owners which means higher charging power. And thus, the charging service quality is related to the AAC of the storage battery tank.

3) Photovoltaic Panel Array Model: The physical model of the PV panel array is consisted of radiation, temperature map as well as equivalent circuit model. The one diode equivalent circuit model is utilized because of its simplified topology and middle level accuracy. For different PV-CSs, they will use either winter and summer profiles alternatively to represent the radiation uncertainty. The PV array model here basically follows the MPPT control as well as the on-off control. For most of the scenarios, PV array is working under MPPT control while if the storage battery is fully charged, PV panel will work in standby mode, i.e., to control the DC bus voltage.

4) Sizing Problem: The sizing problem here discusses the trade-offs among storage battery tank, PV, and number of EVs. The station load model here basically follows a predefined commercial power consumption profiles considering the open and close time of the station. Based on load information as well as average incoming EVs for one single day is nearly 110, in order to work in island mode, the total energy generated from the PV panel array should be larger than the load requirement. In this regard, considering the worst case, the size of the storage battery should be the integration of the PV power profile. As shown in Table I, the standard characteristics of one single PV-CS is listed. Note that in the two PV-CS and five PV-CS case studies, the specification of one single PV-CS is exactly the same but the PV power profile would be different according to the design of these case studies.

III. Hierarchically Distributed Energy Management

A. Cooperative Game in Station Level

As mentioned in previous sections, one of the objective of this energy management is that there should be no energy exchange from the electric grid, i.e., only power source should be PVs. Thus the multiple PV-CS system can be treated as

TABLE I
SPECIFICATION OF ONE SINGLE PV-CS

Parameters	Value
Rated power of PV Cells	1200 kW
Rated capacity of an EV battery	64 kWh
Number of charging poles	20
Number of average incoming EV	110
Rated capacity of the grid-connecting system	1 MW
Capacity of the storage battery	3000 kWh

a large scaled island system. Therefore, stations should help each other to provide energy from higher one to lower one. As shown in Fig. 3, in station level, the PV-CS can be treated as an energy system with storage, generation, and load units. Thus, the power designed power exchange principle is similar to the active balancing circuit in a battery management system, i.e., the station with higher average remaining energy should provide energy flow to the entire PV-CS network while the lower one should absorb energy from the PV-CS network.

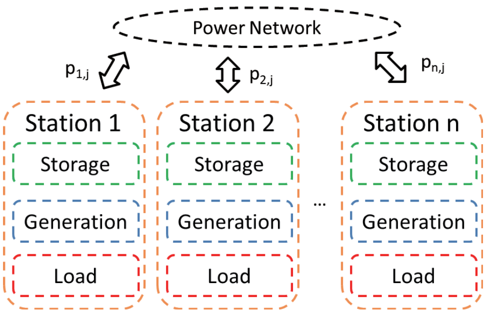


Fig. 3. The cooperative game in station level.

Thus the cooperative game in station level is designed as, $G_s = [\mathbf{S}, \mathbf{p_{EV}}, \mathbf{u_s}]$, where the players are PV-CSs, s_i, the strategy sets are virtual power exchange, i.e., $p_{i,j}$, and the utility functions are $u_{s,i}$. The learning algorithm here is designed based on consensus network through which each station can share their AAC to its neighbours. The AAC here is designed to qualify the charging availability for a PV-CS. Through comparing the AAC, the virtual power exchange can be determined at each control instant through a try and error based rule, i.e., (7). Through applying this learning algorithm, the AAC will converge to be the same, i.e., a cooperative equilibrium, which is verified in the simulation results. Notice that the control interval is designed to be fifteen minutes which can be a user defined one.

$$p_{i,j} = P_{max,i,j} \frac{AAC_{s,i} - AAC_{s,j}}{max(AAC_{s,i}, AAC_{s,j})} \tag{7}$$

where $p_{i,j}$ is the power sent from station i to station j, C_i is the capacity of the storage battery, n_i is the number of the charging poles, $P_{max,i,j}$ is the power limitation for the virtual transmission lines. Notice that the idea behind this formulator is a feedback technology. According to the difference between the average remaining capacity in S_i and S_j, the charging power is proportional to this difference.

B. Generalized Stackelberg Game in EV Level

Since the station level power exchange has been determined through the cooperative game, the EV charging power distribution can be reached through a generalized stackelberg game. In this game, the PV-CS and EV owners can be treated as a leader and followers respectively [13]. At each control instant, a rule based strategy is utilized to determine the total available power to the EVs inside ith PV-CS, i.e., $p_{total,i}$ and then a consensus network based non-cooperative game is utilized to determine the power distribution among EVs. Notice that the $p_{total,i}$ is virtually designed common constraint for all EVs in a single station.

For the leader, the AAC of the storage battery tank is utilized to determine the $p_{total,i}$. Since the objective of the charging station is to maintain the AAC level of the storage battery, the $p_{total,i}$ should be tuned accordingly. Again, a feedback rule based strategy is applied as follows,

$$p_{total,i} = p_{min,s,i}(1 + \frac{AAC_{s,i}}{AAC_{max,s,i}}), \tag{8}$$

where $AAC_{max,i}$ is the maximum remaining energy of the storage battery. The upper and lower bound of $p_{total,i}$ are $p_{min,s,i} = 0.5C_{max,i}V_{bus,i}n_i$ and $p_{max,s,i} = C_{max,i}V_{bus,i}n_i$, respectively.

Given the $p_{total,i}$, the EVs can determine their charging power in a distributed fashion. Since the charging station and EVs are treated as selfish agents here, the charging station tries to maintain the AAC of the storage battery, while the EVs intend to be charged at a higher power level. Thus the energy management problem can be treated as a non-cooperative stackelberg game. Given the objective function discussed in previous section, each EV needs to determine their charging power to optimize this objection function. The solution provided here is based on Karush-Kuhn-Tucker (KKT) conditions of optimality. For each EV, its objective function can be written as Lagrangian $L_{i,j}$,

$$L_{i,j}(p_{EV,i,j}, \lambda_{i,j}) = u_{EV,i,j} + \lambda_{i,j} G(p_{EV,i,j}), \tag{9}$$

$$G(p_{EV,i,j}) = \sum_{i=1}^{n} p_{EV,i,j} - p_{total,i}. \tag{10}$$

$\lambda_{i,j}$ is the Lagrange multiplier.

Since (9) is concave, the KKT conditions are the necessary and sufficient conditions for the existence the GNE. The KKT conditions of the ith follower's optimization problem are

$$\frac{\partial L_{i,j}}{\partial p_{EV,i,j}} = -\frac{a_{i,j}}{p_{EV,i,j}+1} + \lambda_{i,j} = 0, \tag{11}$$

$$G(p_{EV,i,j}) \leq 0, \tag{12}$$

and it is known that the KKT conditions are satisfied with [14], [15]

$$\lambda_{1,j} := \lambda_{2,j} := ... := \lambda_{n,j} := \overline{\lambda}. \tag{13}$$

Notice that if (13) holds, the GNE is the most socially stable one. When $\overline{\lambda_j} = 0$, i.e., $p_{total,i} > \sum_{i=1}^{n} p_{EV,i,j}$, it is straightforward that

$$p_{EV,i,j} = P_{EV,i,j,max} \text{ for } \overline{\lambda_j} = 0. \tag{14}$$

Otherwise, combining (11) and (13) gives the solution for non-zero $\overline{\lambda}$, i.e., a balanced decision on competing the total available power $p_{total,i}$ among the followers,

$$p_{EV,i,j} = \frac{a_{i,j}(p_{total,i}+1) - \sum_{j=1}^{n} a_{i,j}}{\sum_{j=1}^{n} a_{i,j}} \text{ for } \overline{\lambda_j} \neq 0. \quad (15)$$

$$a_{i,j} = \frac{P_{EV,i,j,max}}{SOC_{EV,i,j}} \quad (16)$$

C. Consensus Networks Based Learning Algorithm

Based on the previous discussion, in station level each PV-CS need to determine their power exchange to the neighbour stations. Meanwhile, in EV level, each EV only need $\lambda_{i,j}$ to determine their charging power, as shown in (11). If a centralized strategy is applied here, $p_{grid,i}$ and $\lambda_{i,j}$ can be determined through a central controller. While the question here is how to determine the $p_{grid,i}$ and $\lambda_{i,j}s$ in a distributed fashion. The solution provided here is applying consensus network technology. In station level, $p_{grid,i}$ will be determined through a cooperative rule based strategy. In EV level, since the required global information to assign the local optimal solution would be $\overline{\lambda_i}$. λ_i would be introduced as consensus variable for the ith EV to access the global information using a local sharing of information with neighbours based on consensus algorithms. Due to the common constraint (4), another consensus variable, i.e., δp, is utilized to guarantee that each player will follow it. Notice that, due to the leader-follower relationship, the $p_{EV,i,j}$s are available to the PV-CS. The overall flow chart of the proposed consensus algorithm is shown in Algorithm 1.

Algorithm 1 Consensus Network Based Learning Algorithm

Station Level
For each PV-CS
$p_{i,j}(k+1) = P_{max,i,j}\frac{AAC_{s,i}-AAC_{s,j}}{max(AAC_{s,i},AAC_{s,j})}$
EV Level
1.Initialization
$\lambda_{i,j}(0) = \frac{a_{i,j}}{P_{EV,i,j,max}+1}$
$\delta p = \sum p_{EV,i,j} - p_{total,i}$
2.Consensus phase
while variation of $\lambda_{i,j}(k) > 0.001$
$\lambda_{i,j}(k+1) = \lambda_{i,j}(k) + \sum_{j=1}^{n} w_{i,j}(\lambda_{i,j}(k) - \lambda_{i,j}(k)) + \eta\delta p$
$p_{EV,i,j} = \frac{a_{i,j}}{\lambda_{i,j}(k+1)} - 1$
$\delta p = \sum_{j=1}^{n} p_{EV,i,j} - p_{total,i}$
end while
3.Check phase
if $|\delta p| < \varepsilon$ **then**
Terminate, **k++**
else
Continue
end if
4.Go back to step 2

In station level, the station administrator could update the $p_{grid,i}$ through (7). In EV level, the first step is initialization where $\lambda_{i,j}s$ are determined as,

$$\lambda_{i,j} = \frac{a_{i,j}}{P_{EV,i,j,max}+1}. \quad (17)$$

The second step is the consensus phase. In this phase, the PV-CS and each EV updates δp and λ_i following the rule,

$$\delta p = \sum p_{EV,i,j} - p_{total,i}, \quad (18)$$

$$\lambda_i(k+1) = \lambda_i(k) + \sum_{j=1}^{n} w_{i,j}(\lambda_j(k) - \lambda_i(k)) + \eta\delta p, \quad (19)$$

where $w_{i,j}s$ are connectivity strengths. The $w_{i,j}s$ are always chosen within $[0, 1/n_i]$ in order to make sure that the consensus values converge to the average of the initial values of all the node. (Note that the nodes should form a connected group, i.e., there is a bidirectional path between any two nodes.) η is the step size for the δp. In the next step, the virtual vehicle will tune its $\lambda_i(k+1)$ according to the difference between the $\sum_{j=1}^{n} p_{EV,i,j}$ and $p_{total,i}$. Then it goes back to step two until the difference between the $\sum_{j=1}^{n} p_{EV,i,j}$ and $p_{total,i}$ is small enough ($\lambda_{ij}(k+1)$ for the virtual vehicle will stop changing.). After the $\lambda_{i,j}(k+1)s$ converges, each EV will update their charging power according to the $\lambda_{i,j}(k+1)$ and their charging power boundaries,

$$p_{EV,i,j}(k+1) = \frac{a_{i,j}}{\lambda_{i,j}(k+1)} - 1, \quad (20)$$

$$P_{EV,i,j,min} \leq p_{EV,i,j}(k+1) \leq P_{EV,i,j,max}. \quad (21)$$

Note that KKT multipliers for these box constrains are not considered in this paper because if the solution in (20) is out of the range, the solution will be located on the boundary. This two stage energy management will begin once any EV join the system or leave the system. If no EV joins the system, this algorithm will still work once every ten minutes. Notice that this control instant here is the decision making control instant which is different from the control instant of the DC/DC converter, i.e., 1ms.

IV. Simulation Results and Analysis

In this section,a two station case study is implemented to verify the performance of the proposed game theory based strategy.The simplest multiple PV-CS system is a two station case and thus it is chosen as the first case study here. In this case, the major difference between these two stations is that the radiation profiles come from the typical summer and winter day, respectively. In addition, the uncertainties from EV SOC, capacity and incoming time are totally different. These difference will cause the different charging power requirement and thus different AACs of the storage battery tanks.

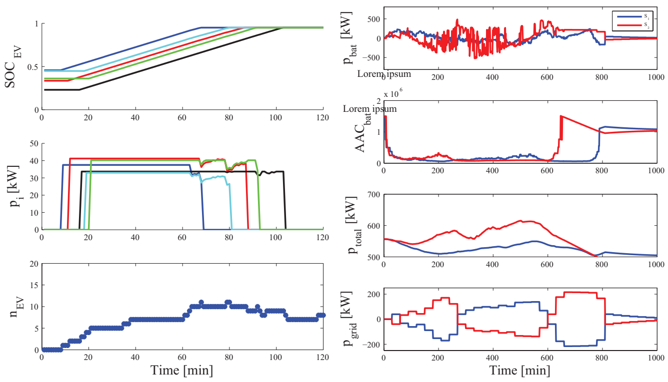
As shown in Fig. 4 (a), the response of the SOC, the charging power of the first five EVs, and the number of EV inside station are shown. It can be observed that all EVs are charged at $P_{EV,i,j,max}$ at initial time and dynamically determining their charging power distribution according to the proposed game theory based strategy. All EVs will finally be fully charged and the number of EV inside station is changing

TABLE II
THE SINGLE STATION POWER DISTRIBUTION WITH TEN EV.

EV (No.)	1	2	3	4	5	6	7	8	9	10
$p_{EV,i,j}$ (W)	3.54e04	3.65e04	2.99e04	3.62e04	3.21e04	3.92e04	3.77e04	3.65e04	4.21e04	4.22e04
$C_{EV,i,j}$ (kWh)	83.66	75.94	73.33	72.43	73.95	78.38	75.33	72.93	784.24	84.37
$SOC_{EV,i,j}$	0.84	0.74	0.87	0.65	0.82	0.45	0.59	0.25	0.34	0.41
$p_{total,2}$ (W)	5.55e05	$p_{b,2}$	1.20e05	$p_{pv,2}$ (W)	-2.55e05	$p_{grid,2}$ (W)	5.62e03			

dynamically. As shown in Fig. 4 (b), the power exchange between two stations follows the same track of the AAC difference between two station while the $p_{total,i}$s follow the track of the AACs. $p_{bat,i}$s basically cover most of the dynamic power from the PV panel systems and EVs.

As shown in Table II, the charging power distribution in station two at a random time instant is picked out. It can be observed that the charging power distribution basically follow the utility functions of EVs. The EV with higher $C_{EV,i,j}$ will be charged with high power (No.1 and No.5) while the EV with lower $SOC_{EV,i,j}$ will be charged with higher power (No.3 and No.5).



(a) (b)

Fig. 4. The simulation results for two station case.

V. Conclusions

This paper proposes a hierarchical distributed energy management for multiple PV-CSs. The power distribution problem is modelled as two level game, i.e., a cooperative game in station level and a non-cooperative Stackelberg game in EV level. The a cooperative and a generalized stackelberg equilibrium are reached a consensus network based learning algorithm. The objectives of the PV-CSs and EV owners are designed to maintain the AAC of the storage battery tank and to be charged with larger power level, respectively. In the simulation, the two stations case is implemented to verify both the effectiveness of the power distribution in EV level and the consensus network based learning algorithm. Meanwhile, a more complicated case, i.e., a five station case, is implemented to verify the station level power distribution and the performance against a comparison management.

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