Behaviour-based Distributed Energy Management for Charging EVs in Photovoltaic Charging Station

Amro Alsabbagh, Dongxiang Yan, Songyang Han, Yandong Wang, Chengbin Ma*
Univ. of Michigan-Shanghai Jiao Tong Univ. Joint Institute,
Shanghai Jiao Tong University, Shanghai, P. R. China
amro.alsabbagh@sjtu.edu.cn, dongxiangyan@sjtu.edu.cn, hansongyang@sjtu.edu.cn, wangyd@sjtu.edu.cn, chbma@sjtu.edu.cn

***Abstract*—Behaviour-based distributed energy management for charging electric vehicles (EVs) in photovoltaic (PV) charging station (CS) has been introduced in this paper. Based on the provider or consumer of the power, CS and EVs are modeled as independent players with different preferences. The energy distribution problem is modeled as a noncooperative stackelberg game and the existence of equilibrium among players is proofed at each control instant. Update of Charging powers of EVs in a distributed fashion is implemented through utilising the learning-based consensus network. Static and dynamic analyses are shown in simulation. Moreover, different behaviours of the EVs' drivers to the discount on the power price offered by the station is also showed. All the previous results proof the effectiveness and workability of the proposed energy management.**

***Index Terms*—Distributed energy management; PV charging station; Electric vehicle; Game theory; Consensus network.**

I. Introduction

Environmental pollution concerns have motivated the focus on renewable energy sources (REs) and electric vehicles (EVs). Apart from their advantages, difficulties arise from dealing with them. Fluctuations and intermittent of photovoltaic generation and limitation of onboard battery capacity along with the heavy load of EVs penetration are the main concerns [1]. For the first point, adding energy storage system (ESS) could be a proper solution. While for the second, supporting a distributed infrastructure of charging points with the ability of switching from grid-tied mode (GTM) to islanded mode (IM) could be a reasonable choice. There are various conflicts and uncertainties related to such field of work. Unpredictable solar irradiation, onboard battery capacity, incoming of EVs with their initial SOCs are the main within others. So, developing energy management in charging stations (CSs) to support satisfied charging service for costumers is inevitable. On contrary of relaxed mode of charging EVs in homes, fast charging technology is one of the requirements in public charging areas to achieve a full-charged battery in a short time. This will increase their penetration impacts, lower the solution keys and shorten the freedom in the system. Due to the competing behaviour within the costumers and the conflict between them and the power provider, avoiding the rising complexity cannot be bypassed. Taking all the above mentioned, evolving a proper energy strategy is a crucial challenge.

Energy management problem (EMP) for charging EVs has been vastly studied in recent years [2]-[8]. Basically, EMP in this field can be categorized into centralized and decentralized. Regarding the first, [2] has developed a control strategy in industrial/commercial EV charging park. Reducing the entire daily cost of charging PHEVs along with scheduling them was the aim. [3] has discussed a rule-based energy strategy for charging station. Controlling the energy flux and evaluating its impact on the main grid was the objective. A heuristic rule-based strategy to reduce the impact on the grid and to allocate EVs' powers in a commercial building has introduced in [4]. Concerning the decentralized, it has the main advantages of minimizing the communication bandwidth and computational efforts as well as allowing flexibility over reconfigurable system [5]. [6] has proposed a decentralized strategy for EV charging station. The objective was to efficiently charge EVs. A simple prefixed way is utilised regardless the preferences of EVs. The system works only in the grid-tied mode, thus the pros and cons of working in the islanded mode haven't studied. [7] has conducted an optimal allocation of the available charging power in EV charging station. Charging powers of EVs are designed to minimize the total charing cost regardless of their own characteristics. [8] has designed a coordinated distributed method to charge EVs in a smart community. Avoiding overloads and maximizing customer preferences was the objective. Although, due to the privacy and selfishness of EVs cooperation cannot be guaranteed to be existed.

To the best knowledge of the authors, including components' behaviours in the preferences will give better performance in the system and make it more close to the daily life conditions. To this aim, the proposed power dispatch adopts different agents' behaviours i.e., EV's driver along with the station's owner and reflects it in their preferences. Moreover, due to the uncertainties in the renewable energy system and features and behaviours of EVs/drivers, choosing the distributed management is much efficient in such these applications. Finally, because of the selfish attitude in charging EVs, utilising the game theory tool is a perfect match to solve the decision making problem here [9]. Accordingly, a noncooperative stackelberg game is employed to dispatch power between selfish and individual players. Below are the paper's contribution points,

- Distributed: no centralized controller is required.
- Flexible: breakdown-free against single point of failure.
- Novel: inserting the behaviours of EVs'drivers and station's owner under waiting condition in the charging station.

II. System Structure and Model

The main components of the charging station are photovoltaic System (PVS), battery energy storage system (BESS), grid system (GS), station load and a fleet of EVs (FEVs) which are illustrated in Fig. 1. Each unit is connected to the DC-bus through a compatible converter. To assure the voltage stability of the DC-bus, one of the connected devices supposed to work at the voltage control mode. Although the proposed charging station system has many components, from the service point of view it can be conceptually divided into two parts, the provider i.e., the charging station and the consumer i.e., the fleet of EVs.

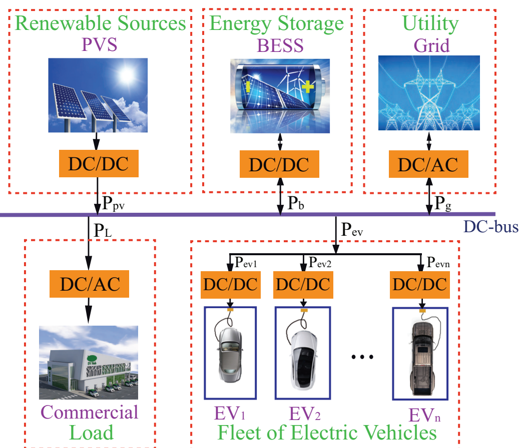

Fig. 1. System Structure of the charging station

A. Components and Objective Function of Charging Station

1) Photovoltaic system: which is composed of PV panels and DC/DC converters. In general, PVS can work in three different modes i.e, current, voltage and standby. In the current mode and to fully utilise the irradiation profile, the maximum power point tracking (MPPT) algorithm is implemented in its related converters. The model of PV panel which relies on the temperature and irradiation can be derived as in [10]. To make the output power from PV more realistic, weather irradiance profile should match the daily life one as much as possible. To this aim, beta distribution is selected to model the solar irradiance uncertainty [11].

2) Grid system: even though PVS is the main supplier of power in CS, GS plays a role in filling the lack of power during peak hours or meanwhile abnormal weather i.e, cloudy days. The main grid is connected to DC-bus through bi-directional DC/AC inverter with proper transformer. Similar to PVS, GS can also work in the three mentioned modes.

3) Station load: when the charging station has a specific working time each day, its household load behaviour will be similar to that one in a commercial company. Thus, a real-world office building profile is considered [12]. It should be noted that any type of load profile such as residential, industrial, etc., can also be applied.

4) Battery energy storage system: composed of battery tank and bi-directional DC/DC converter. Its model can be achieved through its equivalent circuit model [13]. Similar to PVS and GS, BESS can work on the three discussed modes. The main benefit of BESS is to buffer the power and utilise it during the intermittent or lack of renewable energy along with filtering its dynamic. As a result, the dominant control loop for it is maintaining the DC-bus voltage level.

5) Objective Function: as a profitable service, the preference here is to increase the revenue gained by selling power to EVs. This payoff can be indicated through the price of total power derived either from PVS or supported by the grid. Although of its valuable benefit to fill in the shortage of generated power, power loss in the inverter and transformer could be the drawback of the ancillary power from utility. This could be with higher impact or even inefficient when there is a small number of plugged in EVs in CS. Another hurdle is the changeable price from utility which may modify untimely the incentives for the drivers to charge their EVs. As a result, CS would like to work on the islanded mode in such these situations. So, CS can select one of two working modes, i.e, IM or GTM, to maintain higher profit and lower maintenance cost. Thus, the economically/behavioural-based utility function of the station is to maximize (1).

$$u_s = \begin{cases} -|P_{all}| & N \leq N^{th} \ \& \ SOC_b \geq SOC_b^{th} \quad IM \\ C.\sum_{i=1}^{N} P_i & Otherwise \quad GTM, \end{cases} \tag{1}$$

$$P_{all} = P_{pv} + P_b - P_l - \sum_{j=1}^{N} P_i, \tag{2}$$

where N is the number of plugged-in EVs, N^{th} is the threshold number of the plugged-in EVs, SOC_b is the SOC of BESS, SOC_b^{th} is the SOC threshold of BESS, C is the unit price of power, and P_{pv}, P_b, P_l, $\sum_{j=1}^{N} P_i$ are the powers of PVS, load, BESS, and summed of EVs powers, respectively. As it can be seen, CS switches to IM when there is low number of EVs under charging along with sufficient amount of power in BESS. At this mode, CS tries to balance the total power in the system without the assistance from grid. Meanwhile at GTM, CS seeks the profit maximization aim.

To make CS more independent i.e., prolong its ability to work on the islanded mode, the following two tips should be borne in mind. Number of PV modules is to meet the total load demand. BESS's capacity should hold the cumulative differences between the generated and consumed powers.

B. Fleet of Electric Vehicles

1) Model and uncertainties: since this paper focuses on charging EVs, each EV can be considered as a battery with DC/DC converter i.e., on-board battery with charger. The procedure used for modeling BESS can also be used here [13]. As it is introduced before, the more data profile models match the daily life ones, the more stable and efficient system is achieved. Types of EVs i.e., capacities, coming to CS is highly diverse, i.e., passenger cars, vans, etc. Also, their initial SOCs, i.e., previous trip and EV's driver incentives are stochastic. As a result, it is more convenient to model these important uncertainties to enhance the performance of the system. Gaussian distribution is the most suitable function to model these uncertainties [14]. Fig. 2 shows the distribution of both EVs' capacities and initial SOCs.

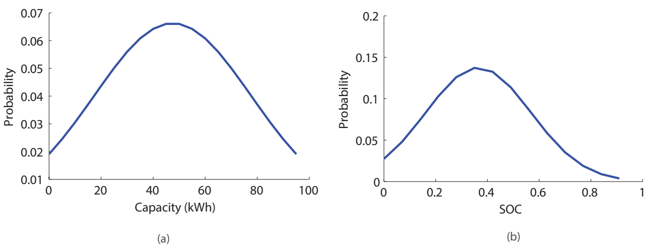

Fig. 2. (a) Capacity distribution of coming EVs. (b) SOC distribution of coming EVs

2) Objective function of EV's driver: this paper tries to model different behaviours of EV's driver. Herein, it is sorted into three types, namely, rich driver (RD), comfortable driver (CD), and poor driver (PD). The idea behind can be explained in the interest and response of each. For the rich kind, the driver has the thirst for charging his/her EV as much as possible, while has less care about the discounted price offered by CS. Meanwhile, the poor driver has the sensitive response to the discounted price proposed from CS. Comparing with the previous two kinds, the comfortable driver lies in between them. Accordingly, the utility function can be divided into two parts. The first indicates for the behaviour with respect to the charging power, while the second cares about the discount on price offered by the station. In either behaviour, the driver wants to maximize his/her charging power in the exist of discount from the station, thus driver tries to maximize (3).

$$u_i = \begin{cases} (-\frac{1}{2}SOC_i P_i^2 + P_i^d P_i).(\frac{e^{\tau-1}-1}{e^{\tau^{max}-1}-1}+1) & RD \\ (-\frac{1}{2}SOC_i P_i^2 + P_i^d P_i).(\frac{\tau-1}{\tau^{max}-1}+1) & CD \\ (-\frac{1}{2}SOC_i P_i^2 + P_i^d P_i).(\frac{ln(\tau+e-1)-1}{ln(\tau^{max}+e-1)-1}+1) & PD, \end{cases} \quad (3)$$

$$0 \leq P_i \leq P_i^{max} \quad (4)$$

where, SOC_i is the state of charge of EV's battery, P_i^d is the desired charging power of the on-board battery, P_i is the charging power of EV, ψ_i is the incentive (the value of the second term of the utility), τ is the discount on the price, and P_i^{max} equals $\psi_i.P_i^d$ the maximum charging power of the on-board battery. The controller for each EV in each charging pole receives information from the battery management system of EV i.e., SOC and maximum and charging station i.e., discount. For better understanding of the format of the utility functions, table I classifies the function form for the charging power and incentive parts of each driver behaviour.

TABLE I
FUNCTION FORM OF CHARGING POWER AND INCENTIVE PARTS IN EACH DRIVER UTILITY

Driver type	Rich	Comfortable	Poor
Charging power part	quadratic	quadratic	quadratic
Incentive part	exponential	linear	logarithmic

To catch the clue behind choosing the form of functions for the two parts of each driver type with respect to their interests, Fig. 3 is dedicated for this purpose.

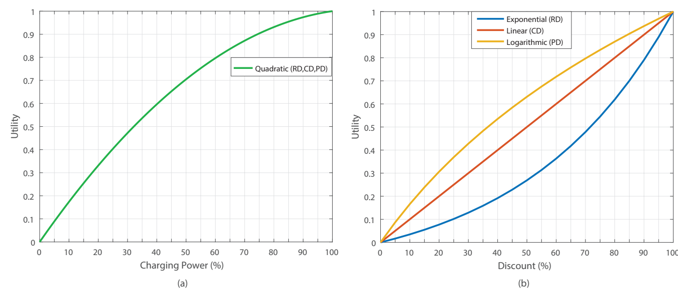

Fig. 3. (a) Driver's preference with respect to charging power. (b) Drivers' preferences with respect to discount.

III. DISTRIBUTED ENERGY MANAGEMENT STRATEGY

From the control strategy point of view, the problem is modeled as a noncooperative generalized stackelberg game. Number of coming EVs along with their SOCs may change at each control instant (i.e., independent stages). In this game, the station is designed to be the leader since it has the advantage of accessing all the charging poles, while EVs as followers. The proposed distributed energy management strategy relies on the generalized noncooperative game and the consensus network-based learning algorithm. For better understanding of their functionalities in the system, it is more convenient to show its envisioned hierarchical structure in Fig. 4. Here, two layers are shown, the physical and the cyber layers besides the in-between control mapping. The first one represents the physical system dynamics, while the second depicts such communications between the nodes (i.e., components).

A. Generalized Noncooperative Game

Determining the charging powers of EVs in the station at each time instant is the energy management problem in this paper. It can conceptually be divided into two stages. The first, relies on the station, is to determine the available power for charging EVs and the discount on price. The available power value will be the common constraint for all EVs. Afterwards, in the second stage, EVs will distributively set their charging powers.

1) First Stage: In either working mode of the station i.e., IM or GCM, it should support the available amount of power for charging EVs i.e., P_{ava} which lies between the lower and

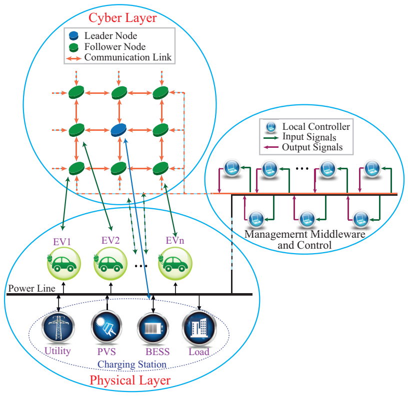

Fig. 4. The conceptual hierarchy scheme of the system.

upper bounds P_{ava}^{min} and P_{ava}^{max}, respectively.

$$P_{ava} = \begin{cases} P_{pv} + P_b - P_l & GIM \\ P_g + P_{pv} + P_b - P_l & GCM, \end{cases} \tag{5}$$

$$P_{ava}^{min} \leq \textstyle\sum_{i=1}^{N} P_i \leq P_{ava} \leq P_{ava}^{max}, \tag{6}$$

$$P_g = P_g^{cap} \frac{N}{N^{cap}} (1 - SOC_b), \tag{7}$$

$$P_b = -(SOC_b - SOC_b^{min}) P_b^{max}, \tag{8}$$

where P_g is the power supported from the grid, P_g^{cap} is the capacity power of the grid, N^{cap} is the capacity of charging poles in the station, SOC_b is the BESS state of charge, SOC_b^{min} is the minimum allowed state of charge of BESS, and P_b^{max} is the maximum power of BESS. As it can be seen, there is always more power in GCM because of the help from the grid. Moreover, the power supported from the BESS is proportional to its state of charge. On the other hand, the real price charged by the station is dynamics and related to the basic price with the discount,

$$C = \frac{C_b}{1 + \frac{N_q}{N_q^{cap}}} = \frac{C_b}{\tau}, \tag{9}$$

where N_q is the number of EVs in the queue, C is the discounted price, C_b is the basic price, τ is the discount, and N_q^{cap} is the capacity of the queue. The discount supported by the station comes from its condition as shown in Fig. 5. The station offers discount on the price when there are EVs waiting in the queue, i.e., no vacant charging poles (CPs), to incentivize the plugged-in EVs to charge by higher power to leave early i.e., allow vacant poles for waited EVs.

2) Second Stage: Since the game is treated as noncooperative game thus, all players are selfish and try to increase their own preferences. The leader i.e., station tries to maximize its profit through changing the basic price, while the followers i.e., EVs try to charge at higher powers with respect to their incentives. The noncooperative power distribution among EVs is a generalized Nash equilibrium problem (GNEP). In this paper, the distributed charging algorithm to find GNE is based on Karush–Kuhn–Tucker (KKT) conditions of optimality and

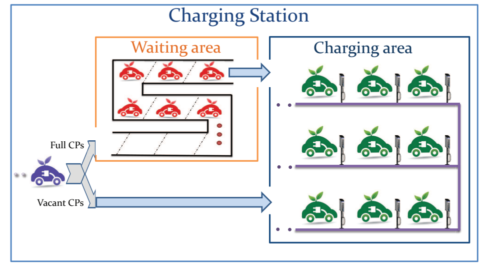

Fig. 5. Working mechanism in the charging station

Lagrange multipliers method. The general optimization problem for each player i.e., EV as well as KKT conditions are shown as follows,

$$\begin{aligned} OBJ: \quad & f_{min} = -u_i \\ S.t. \quad & g = \textstyle\sum_{i=1}^{N} P_i - P_{ava} \leq 0, \end{aligned} \tag{10}$$

$$L_i(P_i, \lambda_i) = -u_i + \lambda_i g, \tag{11}$$

$$\frac{\partial L_i}{\partial P_i} = -\nabla_{P_i} u_i + \lambda_i \nabla_{P_i} g = 0, \tag{12}$$

where λ_i is the Lagrange multiplier of each player. The most socially stable equilibrium is of interest and can be reached by making all λ_is have the same value [15]. Since GNEP is convex—convexity of the objective function along with a linear inequality constraint, KKT necessary conditions are sufficient. The relaxed solution ($\lambda = 0$) and the constrained one ($\lambda \neq 0$) at the most socially stable state can be derived as follows under simplified case (given the discount a unit value),

$$P_i^* = \begin{cases} \frac{P_i^d}{SOC_i} & \lambda = 0 \\ \frac{P_{ava} - \sum_{j=1}^{N} \frac{P_j^d}{SOC_j} + P_i^d \sum_{j=1}^{N} \frac{1}{SOC_j}}{SOC_i \sum_{j=1}^{N} \frac{1}{SOC_j}} & \lambda \neq 0, \end{cases} \tag{13}$$

Hence, the existence of GNE is proofed. After forming the derivative of the utility function (F) and its jacobian (JF),

$$F = -\frac{du_i}{dP_i} = \begin{pmatrix} (SOC_1 P_1 - P_1^d) \\ \vdots \\ (SOC_n P_n - P_n^d) \end{pmatrix}, \tag{14}$$

$$JF = \begin{pmatrix} SOC_1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & SOC_n \end{pmatrix}, \tag{15}$$

it is evident that JF is positive definite on P_i, and so, F is strictly monotone. Therefore, GNEP confesses a unique global equilibrium solution.

B. Consensus Network

The aim in the proposed decentralized control is to let each player updates its demand repetitively until a uniform value of all λ_is is obtained. To this end, the concept of the consensus network is utilised [8]. Because of the distributed nature, there is an individual controller for each player who shares i.e., communicates, only its own control variable (λ_i) with its neighbours rather than revealing all its parameters. Herein, one of the system's nodes assists in reaching the power equilibrium state by tuning its parameters corresponding to the power mismatch i.e., violating (10). Without loss of generality, it will be indexed as "1". The proposed consensus-based distributed power management (CDPM) algorithm for a single stage of the whole procedure is shown. Where, each local controller at a node executes its belonging part. At the first step, an initialization of all λ_is have been done with zero values to give maximum charging powers to EVs. Then, the consensus phase takes place which pursues to converge all the values of λ_is to a single one. This can be achieved by updating each node's λ_i utilizing the sum of weighted differences between this node's λ_i and its neighbors' λs as in line 3. Where N_i is the neighbors set of node i, and $w_{i,j}$ is the connectivity strength between node i and j which should be chosen in the range $[0\ 1/n]$ to insure the intended convergence. When the convergence is achieved, the power distribution among the players will be assigned accordingly within the local boundaries. Afterwards, the validity of the common constraint will be checked. The algorithm will reach the Nash equilibrium the time the constraint is satisfied. Otherwise, an iterative procedure takes place carrying modification on the λ_1 as a translation of the power mismatch as in line 13. It is worth to mention that the values of ε_0 are ε_1 are user defined, with better resolution at lower values sacrificing more iterations to reach convergence.

Algorithm CDPM

I. Initialization

1: $\lambda_i(0) = 0$; $\forall i \in N$

II. Consensus Phase

2: **while** $\delta\lambda_i > \varepsilon_0$ **do** ; $\forall i \in N$

3: $\quad \lambda_i(k+1) = \lambda_i(k) + \sum_{j \in N_i} w_{i,j}(\lambda_j(k) - \lambda_i(k))$

4: $\quad P_i = \frac{P_i^d - \frac{1}{\psi_i}\lambda_i(k+1)}{SOC_i}$

5: $\quad P_i = min(max(P_i, P_i^{max}), 0)$

6: **end while**

III. Checking Constraint

7: **if** $||\sum_{i=1}^{N} P_i - P_{ava}|| \leq \varepsilon_1$ **then**

8: Terminate

9: **else**

10: Continue

11: **end if**

V. Tuning 1's Parameters

12: $P_1(k+1) = P_1(k) - k_p(\sum_{i=1}^{N} P_i - P_{ava})$

13: $\lambda_1(k+1) = \psi_1(P_1^d - SOC_1 P_1)$

VI. Go back Step II

IV. Simulation Results and Analysis

A. Specifications of the Charging Station and EVs

Most of the charging station parameters are listed in table II. The mentioned capacity of EV is just the mean value and the real values follow the normal distribution as EVs'SOC with mean value of 0.4. The number of coming EVs is assumed to be 100 per day according to Poisson distribution. Fast charging technology is adopted in the charging station with tunable charging rate 0.5 C to 1 C. Working time for the station is from 7 a.m. until 10 p.m i.e., 0∼900 min.

TABLE II
SPECIFICATIONS OF THE CHARGING STATION AND EVS

Parameter Capacity	PVS	Grid	BESS	Charging/Waiting areas	EV
Value	1200 kWp	1 MW	2000 kWh	15/5 pole/lot	50 kWh

B. Static and Dynamic Power Dispatch

The workability of the game theory based control and consensus algorithm during single stage is showed in the static case. The chosen instant time is at 60 min when six EVs are plugged in for charging. Fig. 6 shows the convergence of λ_is under a given P_{ava}. Here, λ_1 is tuned according to the mismatch power and λ_2 to λ_6 are identical. As it can be seen, the convergence is fast enough to be implemented in applications which proofs the efficiency of both game theory and the consensus network algorithm. Power distribution of

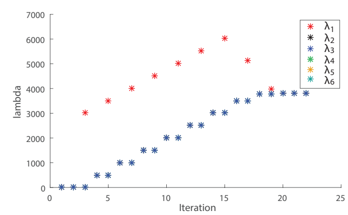

Fig. 6. Number of iterations for convergence of λ_is.

EVs with other parameters are shown in table III. Since the the required powers of EVs are less than the available power, all EVs are charging at their maximum powers. It can be seen clearly that low-SOC with high capacity will be charged at higher power.

TABLE III
POWER DISTRIBUTION AT INSTANT TIME 60 MIN.

	EV_1	EV_2	EV_3	EV_4	EV_5	EV_6
Capacity (kWh)	49	43	46	41	54	51
SOC (%)	0.39	0.40	0.35	0.31	0.37	0.33
P_i (kW)	24.4	21.3	22.8	20.2	26.9	25.4

Parameter	P_{pv}	P_b	P_{ava}	Mode
Value	114.67 (kW)	166.96 (kW)	291.34 (kW)	IS

Showing the whole charging procedure of 100 EVs meanwhile the working time of the station is relatively messy. Hereinafter, the game theory based power distribution of the previous six EVs are presented which can be extended to the rest. It can be concluded from Fig. 7 (a) that each EV is charging according to its preference under the specific SOC and P_i^{max} at each control instant. The charging state remains until it reaches the final demanded SOC. It is clear that SOC rate is proportional to charging rate. In Fig. 7 (b) rather than showing the dynamics in the whole day, only the station working time period is illustrated. First, the generated power of PVS is showed which matches the beta distribution discussed before. Then the condition of the coming EVs in the charging and waiting areas are illustrated which follows poisson distribution is illustrated. Moreover, Due to the waiting EVs, the station offers a discount translated into different incentive values in the three types of drivers. To illustrate the affect of the incentive on the different type of EV drivers, Fig. 7 (c) is depicted. Here, EV1, EV2 and EV3 are chosen, similarly to EV1, EV3 and EV5 in part (a), to represent RD, CD and PD, respectively. Three scenarios are dedicated C1, C2 and C3 which adopt the incentive range of 'non', 'lowest value' and 'highest value', respectively. As it can be seen, at C2, the increment in charging rate of EV3 is the highest then EV2, EV1 which are compilable with the drivers' behaviours. At C3, all EVs have the same rate of increment in charging, since it is the extreme high value of incentive. SOC response has a compilable results with what have just explained in the power response. Showing the powers of BESS and P_{ava}, BESS's SOC, the station modes, scalability study and others are of great interest which is kept for future extension of the paper due to the current limitation.

V. Conclusion

This paper proposed a behaviour-based distributed energy management for charging EVs in PV. The power distribution problem was modeled as a noncooperative stackelberg game. The station was designed as leader while EVs as followers with different preferences. The existence of the equilibrium among them was proofed at each control instant. The learning-based consensus network was utilised to reach the equilibrium in a distributed way. In the simulation section, static and dynamic analysis along with behaviours of the EVs' drivers to the discount on the power price offered by the station were showed. Effectiveness and workability of the proposed energy management were proofed through the results.

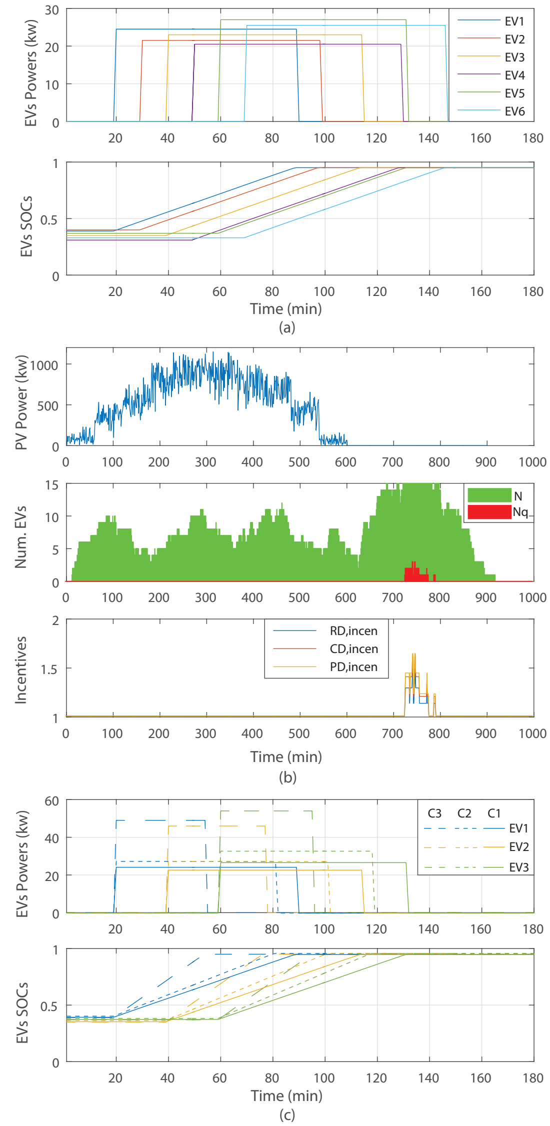

Fig. 7. (a) Power response and SOC response for EVs. (b) PV Power, number of EVs in the charging/queue areas and incentive values. (c) Charging power levels with SOCs at different incentive values

References

[1] D. B. Richardson, "Electric vehicles and the electric grid: A review of modeling approaches, impacts, and renewable energy integration," *Renewable and Sustainable Energy Reviews*, vol. 19, pp. 247–254, 2013.

[2] A. Mohamed, V. Salehi, T. Ma, and O. Mohammed, "Real-time energy management algorithm for plug-in hybrid electric vehicle charging parks involving sustainable energy," *IEEE Trans. Sustain. Energy*, vol. 5, pp. 577–586, April 2014.

[3] C. Capasso and O. Veneri, "Experimental study of a dc charging station for full electric and plug in hybrid vehicles," *Appl. Energy*, vol. 152, pp. 131–142, 2015.

[4] N. Liu, Q. Chen, J. Liu, X. Lu, P. Li, J. Lei, and J. Zhang, "A heuristic operation strategy for commercial building microgrids containing evs and pv system," *IEEE Trans. Ind. Electron.*, vol. 62, pp. 2560–2570, April 2015.

[5] L. Gan, U. Topcu, and S. H. Low, "Optimal decentralized protocol for electric vehicle charging," *IEEE Trans. on Power Syst.*, vol. 28, no. 2, pp. 940–951, 2013.

[6] J. P. Torreglosa, P. García-Triviño, L. M. Fernández-Ramirez, and F. Jurado, "Decentralized energy management strategy based on predictive controllers for a medium voltage direct current photovoltaic electric vehicle charging station," *Energy Convers. Manage.*, vol. 108, pp. 1–13, 2016.

[7] Y. Xu, "Optimal distributed charging rate control of plug-in electric vehicles for demand management," *IEEE Trans. Power Syst.*, vol. 30, no. 3, pp. 1536–1545, 2015.

[8] N. Rahbari-Asr and M.-Y. Chow, "Cooperative distributed demand management for community charging of phev/pevs based on kkt conditions and consensus networks," *IEEE Trans. Ind. Informat.*, vol. 10, no. 3, pp. 1907–1916, 2014.

[9] A. M. Colman, *Game theory and experimental games: The study of strategic interaction*. Elsevier, 2016.

[10] J. Zhang, K. J. Li, M. Wang, W. J. Lee, H. Gao, C. Zhang, and K. Li, "A bi-level program for the planning of an islanded microgrid including caes," *IEEE Trans. Ind. Appl.*, vol. 52, pp. 2768–2777, July 2016.

[11] S. Talari, M. Yazdaninejad, and M.-R. Haghifam, "Stochastic-based scheduling of the microgrid operation including wind turbines, photovoltaic cells, energy storages and responsive loads," *IET Generation, Transmission & Distribution*, vol. 9, no. 12, pp. 1498–1509, 2015.

[12] http://en.openei.org/datasets/files/961/pub/

[13] H. Yin, C. Zhao, M. Li, C. Ma, and M. Y. Chow, "A game theory approach to energy management of an engine-generator/battery/ultracapacitor hybrid energy system," *IEEE Trans. Ind. Electron.*, vol. 63, pp. 4266–4277, July 2016.

[14] R. C. Leou, J. H. Teng, and C. L. Su, "Modelling and verifying the load behaviour of electric vehicle charging stations based on field measurements," *IET Gener. Transm. Distrib.*, vol. 9, no. 11, pp. 1112–1119, 2015.

[15] W. Tushar, W. Saad, H. V. Poor, and D. B. Smith, "Economics of electric vehicle charging: A game theoretic approach," *IEEE Trans. Smart Grid*, vol. 3, pp. 1767–1778, Dec 2012.