An Optimal Design and Analysis of A Hybrid Power Charging Station for Electric Vehicles Considering Uncertainties

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

Dongxiang Yan
UM-SJTU Joint Institute,
Shanghai Jiao Tong Univ.,
Shanghai 200240, China
Email: dongxiangyan@sjtu.edu.cn

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

***Abstract*—The charging problem becomes prominent with the increasing number of electric vehicles. It is necessary to built charging station (CS), like the gasoline station, to satisfy the recharging and be convenient for the drivers. In this paper, a new type of charging station integrated with renewable energy source was studied. A hierarchical energy management strategy oriented to real-time application was proposed to handle the uncertainties. To determine the optimal size of the CS by considering multi-objective including economic, environment and battery energy storage system degradation, Monte Carlo simulation was adopted to solve the problem with many uncertainties. We treated battery degradation as a specific objective function. And we obtained the optimal Pareto set. The result demonstrated the optimal decision variable for CS sizing can compromise the objectives as well as realize the reasonable resource dispatch.**

***Index Terms*—charging station, electric vehicles, uncertainty, energy management strategy, optimal sizing**

I. Introduction

Recently, electric vehicles (EVs) have attracted much more attention since they use clean electricity. And large progress in lithium-ion battery propels the development of EVs. However, it is challenging that the growing number of EVs means huge charging demand and will definitely aggravate the power grid load. Traditional approach is to build more power plants for extra electric power, which is costly and brings environmental problems.

Integration with renewable energy sources such as solar and wind power is an efficient way to moderate the problem. Thus, it is necessary to research on establishing a proper electric vehicle charging station with hybrid energy source. Several papers have investigated the optimal planning or sizing of EV charging station with renewable energy source. In [1] the size of the battery storage was optimized through minimizing the total energy cost. It employed two typical irradiance scenarios and specified delivery EV charging patterns. Optimal design of an electric vehicle charging station considering various renewable energy sources with the goal of minimizing the total monetary cost was analyzed in [2]. The decision variables were the size of the PV array, size of each diesel generator, number of battery energy storage system units, and grid purchase/sell. But there was little instruction about the internal operated energy management strategy. In [3], a dynamic programming algorithm was utilized for EV charging scheduling after determining the solar power and vehicle charging demand and compared with a uncontrolled method by evaluating the economics and carbon tax. We can find that those studies treated the charging demand as fixed value to input the decision model, which neglected the uncertainties in reality.

What's more, when discussing the size optimization of the charging station, the energy management strategy should be determined among the renewables, energy storage and grid. Meanwhile, the charging strategy for electric vehicle should also be clarified. So far extensive studies on EV charging have been conducted. In [4], a globally optimal scheduling scheme for charging and discharging of electric vehicles were developed to minimize the total cost of the EVs by optimizing the total load and charging power. Dynamic programming algorithm was used in [5] to find the economically optimal solution for the vehicle owner by optimizing the charging time and energy flow and participating in ancillary service markets. However, those optimal EV charging station scheduling mentioned above require forecasted distributed generation and load demand, and the forecasts were assumed accurate in their model [6]. In addition, as number of electric vehicle increases, the computational complexity of charging management using centralized control can be dramatically high for realistic computational capability.

Therefore, decentralized charging control strategy has received much attention for EV charging because of high potential to real-time implementation. A decentralized charging scheduling was proposed in [7], where utility company broadcasts the price and EVs choose their own charging profiles, instead of being instructed by a centralized infrastructure, to achieve the objective of valley filling. Game theoretical methods are also widely used to study EV charging problem. A noncooperative Stackelberg game was built in [8], where the leader is smart grid and electric vehicles are followers, and through solving Stackelberg equilibrium electric vehicles can decide their own charging strategy while smart grid optimize its benefit. A hierarchical game approach was applied in a real-time optimal energy and reserve management of electric vehicle fast charging station which equipped with battery storage and PV cite in [9].

The previous study [10] verified that the result considering uncertainties was different from that without uncertainties. Given this background, this paper is devoted to addressing the optimal sizing for an EV charging station incorporating hybrid energy source system. A distributed game theory based charging strategy was applied to treat with the EV group charging power dispatch. And multiple decision variables were taken into account, and Monte Carlo simulation (MCS) was conducted to obtain the distribution of multi output attributes from the standpoint of economics, environment and battery aging. Finally, considering the defect of MCS which probably depends on the discrete decision variables defined by the designer, genetic algorithm based multi-objective optimization combining MCS was adopted to obtain the optimal decision variables and compared that with simply using MCS.

The remainder of this paper is organized as follows. We first detail the configuration and modeling of the EV charging station in Section II and then introduce the formulation of the game theory based charging strategy in Section III. A sizing decision model and MC simulation based algorithm are presented in Section IV. The associated analytical results and optimal size of EV charging station are discussed in Section V. Finally, conclusion is drawn in Section VI.

II. System Configuration and Modeling

A. Charging Station Configuration

The architecture of the developed grid-connected PV powered EV charging station (EVCS) in this paper is shown in Fig. 1. The key components of the EVCS are the PV system, the battery energy storage system (BESS) and a grid connection system. All these components are connected to a DC voltage bus through incorporating DC/DC converters and AC/DC inverter.

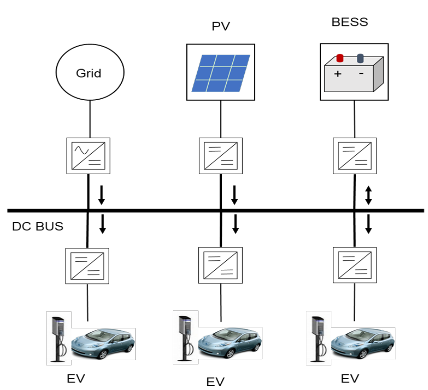


Fig. 1. Architecture of EVCS

PV system is generally the main energy source in EVCS and operates at the Maximum Power Point Tracking (MPPT) mode to maximize the utilization of the solar energy. And once confirming the PV panel size, the generated power of PV system will mainly depends on the current weather condition such as irradiation and temperature. Due to the intermittency of renewable energy sources, BESS is always used to complement the deficiency of PV panel. What's more, BESS can also abstract the excess energy from the PV system. Therefore a bidirectional DC/DC converter is used for BESS, and all of others are unidirectional converter or inverter. The function of grid-connected system is to guarantee the normal charging service for EV in some specific conditions (e.g. in the evening) where both PV system and BESS cannot satisfy the incoming EV charging demand.

B. Subsystem Modeling

1) PV system: An equivalent circuit is used to model the PV cell and detailed in [11]. Then the output current of PV can be obtained. The cell model is scaled to an PV array by connecting n_{pv} in series, thus the output power of PV system P_{pv} is calculated by following equation 1.

$$P_{pv}(k) = I_{pv}(k)U_{cell}(k)n_{pv} \tag{1}$$

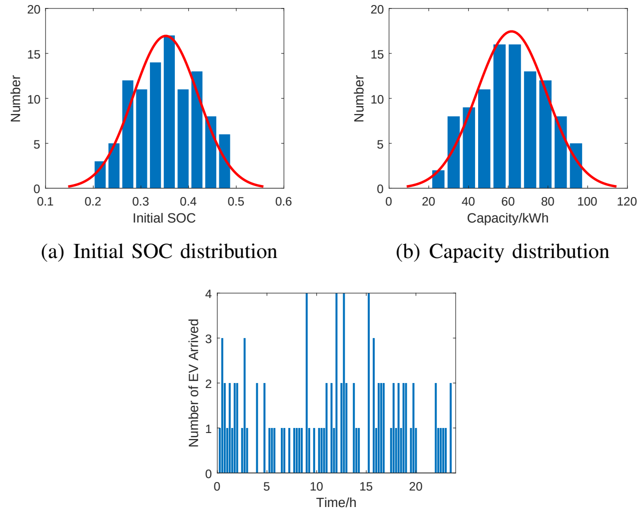
where k denotes the time instant, I_{pv} and U_{pv} represent the output voltage and the current, respectively. the MPPT mode is employed for PV system to improve the PV energy conversion efficiency.

2) BESS and EV: Batteries are used as energy storage system in the EVCS. The deterministic discrete time state of charge (SOC) equations of the battery model can be described as follows [12]:

$$SOC(k) = SOC(k-1) - \frac{\eta I_{bat}(k)\Delta t}{Q} \tag{2}$$

where η is the Coulombic efficiency, the I_{bat} represents the output current and if it is positive value, it means battery discharging in this instant and on the contrary the negative value represents charging, k denotes the time instant and δt is the sampling interval. Q is the nominal capacity of the battery. The governing equation (2) is also applied to calculate the SOC of the battery pack in EVs.

3) EV Stochastic Modeling: EVs play an uncertain role in the whole charging system and will have huge influence on the effect of energy management. To model the EV uncertainties, 4 uncertainties in EV charging demand are considered including the initial charging SOC, the battery pack capacity in EV, the amount of charging EV and the EV arriving time. Among these, Gaussian distribution model are used to model the first three uncertainties [13, 14]. And the initial SOC value is assigned with mean value $\mu = 0.35$ and standard variance $\sigma = 0.75$ between 0.2 and 0.5. Through investigating the EV market specified in the field of passenger car produced by main automotive companies, the battery pack capacity ranges from 24 kWh to 100 kWh. So the capacity model parameter is setup with $\mu = 62$ and $\sigma = 24$. EV number model is with $\mu = 100$ and $\sigma = 25$. Poisson process is used herein to model the customer arriving to charging station which is also widely used [15, 16]. Through above analysis, the four uncertain parameters are modeled. The distribution results based on 100 EVs are shown as the following Fig. 2(a) to Fig. 2(c).



(a) Initial SOC distribution

(b) Capacity distribution

(c) EV arrived distribution

Fig. 2. Uncertainty distribution of 100 EVs

C. System Modeling

When the EVCS operating, energy flow transits among different components in complex mode but power conservation should be satisfied at each instant within the whole system as follows,

$$P_{EVs}(k) = P_{grid}(k) + P_{pv}(k) + P_{BESS}(k) \tag{3}$$

where P_{EVs} is the charging demand of EVs group, P_{grid} is the output power of the utility grid, P_{BESS} is the battery charging power or discharging power and k denotes the .

III. Energy Management Strategy

A. EV Charging

Energy management strategy is needed in the system to appropriately control the energy flow among different energy components as well as determine the charging power dispatch to each EV connected with the EVCS. Meanwhile, the energy management strategy will also be used for simulation in the following section to solve the sizing problem.

As to charging power dispatch problem for EV, we adopt the game theory based energy management strategy which can refer our previous work [17], in which each EV can be treated as an independent player. They can determine their own charging powers to maximize their charging objective functions shown as following equation 4, which are utilized to describe the satisfaction level,

$$\begin{aligned} &\max \quad u_i = \frac{P_i^*}{SOC_i} ln(p_i + 1) \\ &s.t. \quad \begin{cases} \sum_{i=1}^{n} p_i \le p_{total}, & i = 1, 2, \ldots, n \\ 0 \le p_i \le P_i^*, & i = 1, 2, \cdots, n \end{cases} \end{aligned} \tag{4}$$

where i refers to the ith EV, P_i^* is the maximum allowed charging power depending on the type and capacity of the EV battery pack, p_{total} is charging limitation and is the common constraint to all EVs, and p_i is the solution after solving the equation 4.

Each EV determines its charging power to optimize its objective function 4, and the solution can be solved by Karush-Kuhn-Tucker (KKT) conditions of optimality. The detailed solve and the proof process of the existence of the Nash Equilibrium can be found in [17].

B. EVCS Energy Management Strategy

Due to the existence of uncontrolled stochastic uncertainties, it is difficult to implement an optimal approach to manage the output power ratio between the PV, BESS and utility grid. In this paper, the energy production from PV and BESS is prioritized to use for charging demand over grid energy. When the output power of PV system is enough to the EV charging demand, the excess power of PV system will be stored a certain amount of energy in the BESS for future use. If the charging demand is higher than the available power of PV, BESS will operating in the discharge mode to make up the difference amount of power. If PV production exceeds the consumption and BESS capacity, the PV will stop working. Furthermore, if both PV system and BESS still cannot satisfy the charging load, the utility grid will start to participate in the energy system to support the service availability. That is, the grid power has the lowest priority to feed the load.

IV. EVCS Sizing Decision Model

Once determining the energy management strategy, the EVCS system can operate normally to meet the expected demand. However, except the basic supporting charging service, it is also important designing an appropriate EVCS size to meet other objectives, such as minimizing the total cost, minimizing the impact on environment damage. The main factors impacting those results include the capacity size of PV, capacity of BESS, and the opening time. Obviously, the first two factors are the most direct and key factors since the size of PV and BESS directly determines the available energy for the charging load as well as the cost. Due to PV system only works in the daytime and it cannot work in the night. If opening time is extended to the night, it will increase the cost of buying electricity from grid. Hence the opening time is also a key decision variable.

In this section, three objectives are used to quantify the optimal charging station size. The first one is to minimize the total economic cost. Total cost of an EVCS component comprises 3 parts: capital investment cost C_I, operating & maintenance (O&M) cost $C_{O\&M}$, electricity cost C_E from purchasing the utility grid in the case that PV and BESS cannot meet the charging load, so total cost can be expressed as follows:

$$C_{total} = C_I + C_{O\&M} + C_E \tag{5}$$

And both C_I and $C_{O\&M}$ are comprised with PV, BESS, converters and inverters. Actually, it is difficult to obtain the exact O&M information so the general method [18] is assuming it possesses 10% of the investment cost.

Then total cost will be transformed into annualized total present cost through the present worth factor (PWF) [2]:

$$PWF_{r,N} = \frac{(1+r)^N - 1}{r(1+r)^N} \tag{6}$$

where the r is annual real interest rate (discount rate) equaling to the nominal interest rate minus the inflation rate standing the economics view [2]. And N is the EVCS project lifetime.

The daily cost $DNPC$ can be expressed as follows:

$$J_1 = \frac{(C_{total} - S) * PWF}{365} - R \tag{7}$$

where S is the salvage value, R is receive revenue from EV owner.

The second criterion considered here is to quantify the environmental impact where carbon emission is the main factor. In the EVCS, carbon emission usually comes from the power grid. And the objective function is to minimize the amount of carbon emission which can be calculated as follows:

$$J_2 = a_{CE} E_t \tag{8}$$

where a_{CE} is the carbon emission factor, and in this paper it equals 0.785 $kgCO_2/kWh$.

Except the two above criteria, battery aging is the third one considered in this paper because battery is still an expensive device and will suffer the capacity degradation with time going. Although the battery aging has been considered in a simple rough estimated form of cost in the first objective function, the accurate capacity degradation indic has been no considered independently as an objective function in optimal design of EVCS. In this work, degradation model of LiFePO4 battery developed in [19] is introduced to quantitatively calculate the capacity fade shown as follows.

$$Q_{loss} = A \exp\left(-\frac{E_a + B * C_{rate}}{RT_{bat}}\right)(A_h)^z \tag{9}$$

where Q_{loss} is denoted the percentage of capacity loss, A is the pre-exponential factor, E_a is the activation energy in $J \cdot mol^{-1}$, R is the gas constant, T is the absolute temperature, A_h is the Ah-throughput, and z is power law factor.

$$J_3 = Q_{loss} \tag{10}$$

So three objective functions above are built to explore trade-offs between different objectives. We expect to find a solution that is both cost effective, less polluting and less capacity degradation. The decision variables and other associated parameters are presented in the following Table. Those related price information of components are listed in the Table I referring to literatures [2, 20].

And the optimal EVCS size decision model can be shown as the following figure.

For those uncertainties, we use Monte Carlo simulation to draw samples from their corresponding distribution model. The Monte Carlo method is a mathematical-statistical pattern for simulating the behaviour of uncertain parameters. Given a significantly large sample size, this method can provide highly accurate results. And then the distribution of the output attribute parameter can be obtained. The average output value over large simulation under each decision variable will be used to evaluate the performance and compare with other options in the next section.

TABLE I
DATA ON DECISION VARIABLES AND OTHER INFORMATION

System	Option on size	Price	Source
PV	60,120,180,240, 300,360kW	7.5$/W	[2]
BESS	150,300,450,600, 750,900kWh	500$/kWh	[20]
Opening time	T1 (7:00-19:00), T2 (7:00-24:00), T3 (7:00-7:00 (next day))	-	-
Inverter	500kW	1000$/kW	[2]
Converter	50kW	1000$/kW	[2]
Grid energy	-	0.12$/kWh	[2]
Charge service	-	0.06	Estimated

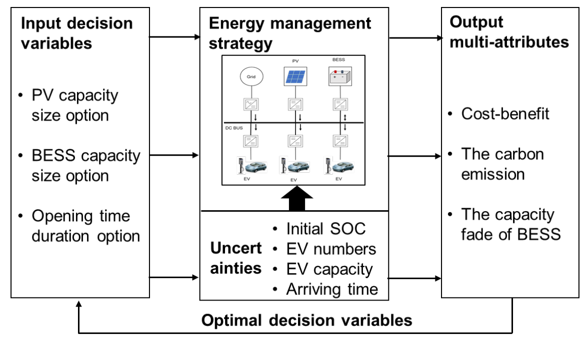


Fig. 3. EVCS decision model

V. RESULT AND DISCUSSION

The decision variables are allocated with a series of discrete value listed in Table I. Under each combination of the three variables, Monte Carlo simulation should be conducted. More simulation times are conducted, much more accurate the result is while much more computational time is consumed. Through simulation under a combination of decision variables, the corresponding distributions of evaluation indices can be obtained and also we can get the average values for each evaluation criterion.

The multi-objective optimization will provide Pareto optimal set, which includes numerous optimal solution points. For system cost, it is can be qualitatively deduced that the system cost will go up along with the increasing size of PV and BESS. On the contrary, the carbon emission generally will decline since more proportion of contribution from PV and BESS. However, the approximate linear relation is not adapted to capacity fade of BESS which depends on the matching with PV capacity. It can be proved by the simulation result using the capacity fade model shown as Fig. 4. We can observed that, under a fixed PV size, the capacity fade curve basically decreases with the BESS size increases whereas it is also affected by opening time span since longer time span will consume more battery energy. Furthermore, from the right detailed picture, it can be deduced that smaller size of BESS suffers more capacity loss, reflecting the significance of optimization of opening time duration.

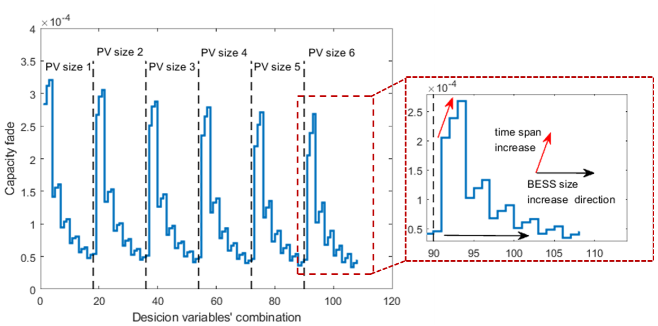


Fig. 4. Capacity fade

Due to using different units of the 3 objectives, so the normalized utility function is defined for each objective function (J_i) as follows:

$$u_i = \frac{J_i - J_i^{min}}{J_i^{max} - J_i^{min}} \tag{11}$$

where the J_i means the ith objective function.

And it is obvious that we want to minimize the u_i and the weight sum method is utilized to solve the multi objective problem as follows.

$$U = \sum_{i=1}^{3} u_i \tag{12}$$

Therefore, under a certain fixed PV size value 120kW, we can obtain the Pareto set and best trade off solutions for optimal planning of EVCS is illustrated in Fig. 5. Likewise, we can also generate other Pareto optimal set according to the PV capacity.

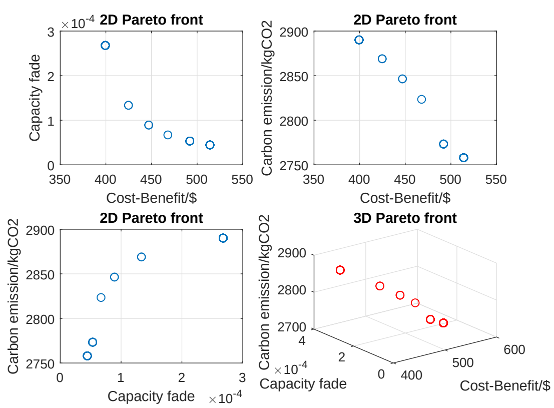


Fig. 5. 2D and 3D Pareto optimal sets and best tradeoffs in case for PV=120kW.

Considering the shortage of MCS which can only obtain the optimal solution among the given discrete determine variables, if we want to find the most optimal solution combination, numerous simulations and much narrow grid interval need be performed, which means huge amount of computational time. Genetic algorithm based multi objective function is used to search the optimal set, and the result of one simulation is shown as Fig. 6. The method obtains the optimal sizing of the EVCS components over a specified number of simulations. The optimal configuration of the EVCS ensures that minimum system cost is met with minimum carbon emission amount and minimum capacity fade of BESS.

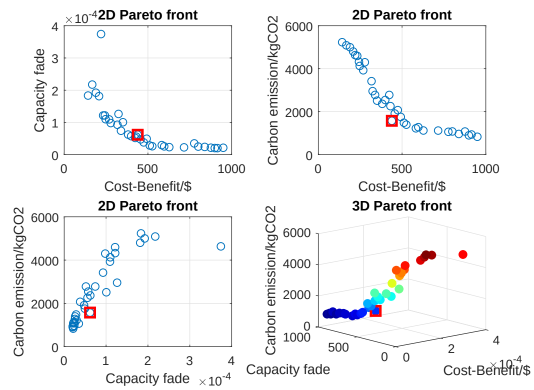


Fig. 6. 2D and 3D Pareto optimal sets and best tradeoffs using GA.

A compromise solution minimizes the normalized Euclidian distance between the potential optimal points. We solve the minimization

$$\min \sqrt{\sum_{i=1}^{3} (u_i - u_{orig})^2} \tag{13}$$

where the u_{orig} is the original point after normalization.

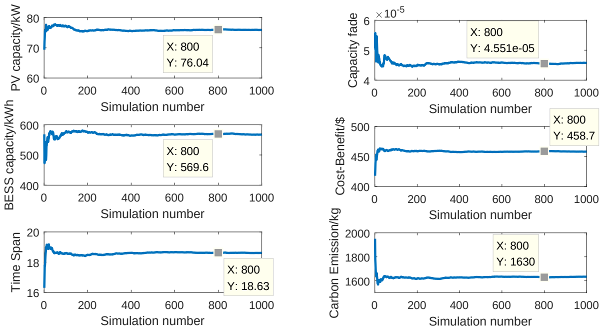
The point solved by above method is marked by the red square shape in the Fig. 6. To differentiate this point from other Pareto optimal point, we denote this point as knee point. Considering the stochastic characteristic, the stationary expectation of knee points of many simulations will be regarded as the final optimal value.

Fig. 7 shows the expected optimal values of the BESS capacity, PV capacity and opening time duration. The convergence state is almost reached after about 800 iterations.

Similarly, we can also get the knee point among the overall points using the MCS method. To compare the effect and results of two different methods, we list the corresponding optimal combination of the 3 decision variables and the optimal multi criteria value in the Tab. II.

VI. CONCLUSION

Recognizing the emerging need for planning EVCS to satisfy the increasing charging demand from EVs, in this paper a framework was proposed to optimize the size of EVCS incorporating many uncertainties. This EVCS system was composed of renewable (PV), BESS, grid-connected system, and EVs, and hierarchical energy management strategy was adopted for real-time application. To deal with the uncertainties, MCS was implemented. GA multi-objective optimization



(a) optimal decision variables (b) optimal results

Fig. 7. Expected optimal decision variables and results

TABLE II
OPTIMAL DECISION VARIABLES AND CRITERIA VALUE OF MCS AND GA

	PV /kW	BESS /kWh	Opening time/h	Cost-Benefit/$	CE /kg	Fade ($\times 10^{-5}$)
Optimal value by MCS	120	750	12	491.9	2773	5.3
Optimal value by GA	76.0	569.6	18.6	458.7	1630	4.6

technology was used to solve the multi-objective problem: minimizing total cost, minimizing carbon emission and minimizing capacity degradation of BESS. And the preliminary result showed that the capacity combination of PV with 76 kWp and BESS with 569.6 kWh could achieve optimal trade off among the three objectives.

As this study involves many aspects and assumptions, and both MCS and GA method require huge computation, to make the simulation results more convincing, variation on electricity price and sensitivity analysis will be conducted in the future.

ACKNOWLEDGEMENT

This paper was supported by Open Fund of Beijing Engineering Technology Research Center of Electric Vehicle Charging/Battery Swap, China Electric Power Research Institute.

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