

# Aggregation Model-Based Optimization for Electric Vehicle Charging Strategy

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**Abstract**—This paper presents an aggregation charging model for large numbers of electric vehicles (EVs). A genetic algorithm (GA) is employed to obtain the stochastic feature parameters of the aggregation model, and a charging strategy based on the aggregation model is developed to reduce the power fluctuation level caused by EV charging. In addition, an updatable optimization method is proposed to track the variation of the EV charging characteristics. The proposed charging strategy and optimization method are validated by the simulation results.

**Index Terms**—Aggregation model, electric vehicle, optimal charging, parameter estimation, stochastic distribution.

## I. INTRODUCTION

**E**LECTRIC vehicles (EVs) are expected to play a major role in the road transport system since the energy crisis and environmental problems are being more and more urgent in recent years. However, a large number of EVs connected to distribution network may result in the significant increasing of the peak load, which can cause the distribution grid overloaded [1], [2]. Since the load features of EVs are mainly influenced by the charging characteristics of the EV batteries and the time of EV switching on and off, the studies on EV load have been increasingly focused on these two aspects [3], [4].

Accurate dynamic modeling of battery is typically considered for the control of EV drive system [5]–[7]. However, the aggregation charging features of large numbers of batteries are usually investigated in the scale of hours. The short-term detailed dynamic features of the batteries may be ignored in the EV load studies where a simple controlled voltage source in series with a constant resistance is more convenient [8]–[12].

In comparison with the battery charging, the distributed feature of EV plug-in/off time has more significant effect on the aggregation load characteristic when the number of EV is large. In order to reduce the peak load, a charging management system

(CMS) with the optimal charging strategies should be employed for EV charging [13]–[18]. A charging regulation algorithm for unidirectional vehicle-to-grid (V2G) is developed in [13] to modulate the set point of charging rate called the preferred operating point (POP) for each EV. Moreover, based on a forecast of future electricity prices, the dynamic programming method is used in [14] to find the economically optimal solution for the vehicle owner to optimize the charging time and energy flows.

To consider the uncertainty and the limits on the random variables about the parking time and initial state-of-charge (SOC), a truncated normal distribution is suggested in [15] and [16] to represent the parking time, and the initial SOC is modeled as a random variable of log-normal distribution [15], [17]. Then based on the simulation of the random variables above, an estimation of distribution algorithm (EDA) based charging algorithm is used in [15] to intelligently allocate electrical energy to EVs. However, the above charging management algorithms are usually applied to an office parking deck in a city, in which the pattern of vehicle arrival time is different from the one in a parking lot of a residential district. Furthermore, the objective of optimization in these applications is typically to maximize the average SOC for all vehicles at the next time step, rather than minimizing the impact on the grid as its first objective, which makes the charging strategy different.

This paper addresses the optimization issue of EV charging from the perspective of the impact on distribution system peak load. The stochastic features of the charging procedure in a typical residential district in China are mainly considered. In addition, an updatable optimization method is proposed to track the variation of the charging characteristic for practical applications.

The paper is organized as follows. Section II presents an aggregation model of an EV charging station. The parameter estimation method for the aggregation model with a case study is discussed in Section III. Section IV proposes the charging strategy for CMS, including its optimization method. The updating strategy for the aggregation model and the charging-control parameters are presented in Section V. The conclusions are summarized in Section VI.

## II. AGGREGATION MODEL OF EV CHARGING STATION

### A. Single EV Charging Model

A typical EV charger consists of a rectifier, a low-pass filter and a dc-dc converter, as shown in Fig. 1 [18]–[21]. The battery is connected to the output of the dc-dc converter.

To obtain better ac-dc converting performance, the diode rectifier can be replaced by the power factor correction (PFC) circuit which can improve the charger power factor to 97%–99%

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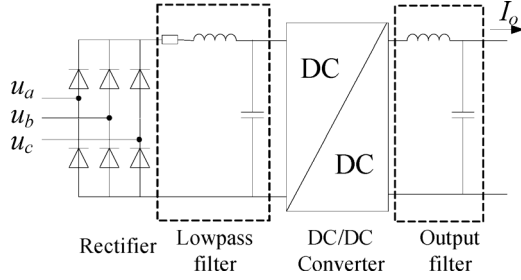


Fig. 1. Schematic diagram of EV charger.

[19], [20]. As a result, the reactive power of the charger is far less than the active power. In addition, the efficiency of the dc-dc converter including the low-pass filter is commonly higher than 96% [21]. Therefore, the reactive power of the charger and the loss of dc-dc converter can be ignored to simplify the EV modeling. By this means, the charging model of single EV can be represented by the active power characteristic of the EV battery during the charging process.

Lithium battery is used for study in this paper as it is the prevailing EV battery at the current stage. The lithium battery model is described as follows [12], [22]:

$$V_{\text{batt}} = E_0 + \frac{KQ}{0.1Q + It} \cdot i - \frac{KQ}{Q - It} \cdot It + Ae^{-B \cdot It} + R \cdot i \quad (1)$$

$$It = [1 - \text{SOC}_0] \cdot Q - \int_0^t idt, \quad 0 \leq It \leq Q \quad (2)$$

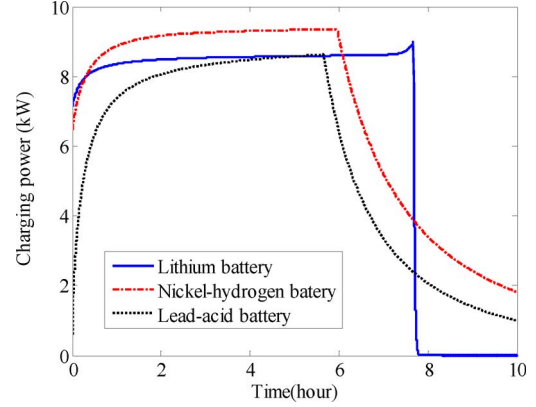
where  $V_{\text{batt}}$  is the terminal voltage of the battery;  $i$  is the charging current;  $Q$  is the nominal capacity of the battery;  $R$  is the internal resistance of the battery;  $K$  is a polarization constant of battery;  $E_0$  is the constant electric potential of the battery;  $A$  and  $B$  are the constants of the exponential section of the battery charging;  $It$  is the extracted capacity of the battery;  $\text{SOC}_0$  is the initial state-of-charge (SOC) of the battery.

The meanings of the right part items in (1) are explained as follows [12], [22].  $E_0$  is the constant electric potential of the battery. The second item represents the impact of the polarization resistance. The third item is a non-linear voltage concerning the polarization voltage that changes with the actual charge of the battery in the initial rise part of battery charging. The fourth item represents the end part in the exponential section of the end battery charging term. The fifth item is the voltage loss on the internal resistance of the battery.

Usually, the given parameters of a battery are the battery rated voltage  $U_n$  (unit: V) and the battery capacity  $Q$  (unit: Ah). The relations between  $U_n$ ,  $Q$  and the parameters  $E_0$ ,  $K$ ,  $A$ ,  $B$ ,  $R$  in (1), (2) are expressed in (3) [12], [22].

$$\begin{aligned} E_0 &= 1.0834U_n, & K &= 0.005645U_n/Q, & A &= 0.08496U_n, \\ B &= 60.0619/Q, & R &= 0.01U_n/Q \end{aligned} \quad (3)$$

In this paper, the rated voltage and the capacity of a single lithium battery are set to  $U_n = 316.8$  V and  $Q = 200$  Ah based on the current EV battery specification in China [23], [24].


 Fig. 2. Charging power curves of 3 types of batteries with  $U_n = 316.8$  V and  $Q = 200$  Ah.

The two-stage charging of constant-current and constant-voltage is a common approach to extend battery service life. The three types of batteries with the same parameters  $Q = 200$  Ah and  $U_n = 316.8$  V, including lead-acid battery, nickel-hydrogen battery and lithium battery, are charged by the way of constant-current and constant-voltage charging from 0 remaining capacity to the full capacity. The constant charging current is 25 A which will be used in all the following cases. The charging power curves are simulated by using the battery models in Matlab/Simulink as shown in Fig. 2.

The characteristic of lithium battery is significantly different from that of the other two. Based on (1), the charging current indicates the charging speed and the charging voltage exhibits the SOC level of lithium battery. When the large charging current is applied, the SOC value will increase fast and it will reach a high SOC level after the charging voltage hits the maximum value. This SOC level is mainly affected by the maximum charging voltage value.

The constant voltage charging stage of lithium battery lasts a very short time with respect to the constant current-charging stage and charging current decays to 0 sharply. However, the constant voltage charging stages of the other two types of batteries are much longer remarkably. Therefore, to concentrate on the main characteristics of the EV charging and simplify the calculation, the constant voltage charging process could be ignored in the study of lithium battery charging characteristics and modeling.

The power of the lithium battery model can be calculated as follows on the assumption that only the constant-current charging process is involved and the charging current  $i$  is a constant  $I_C$ .

First, calculate the parameters  $E_0$ ,  $K$ ,  $A$ ,  $B$ ,  $R$  from  $Q$  and  $U_n$  according to (3).

Then, when  $V_{\text{batt}} < U_{\text{batt\_max}}$ ,  $i$  is equal to  $I_C$  which is the constant charging current.  $V_{\text{batt}}$  can be calculated according to (1) and (2), where  $U_{\text{batt\_max}}$  is the maximum allowable charging voltage for battery. For lithium battery,  $U_{\text{batt\_max}} = 1.164U_n$  [12], [22].

When  $V_{\text{batt}} \geq U_{\text{batt\_max}}$ , let  $i = 0$  and  $V_{\text{batt}} = U_{\text{batt\_max}}$ .

The battery charging power during charging is:

$$P = V_{\text{batt}} \cdot i \quad (4)$$

Hence, if the  $\text{SOC}_0$ ,  $Q$  and  $U_n$  of the lithium battery are given, the charging power of battery can be simulated according to (1)–(4).

### B. Aggregation Charging Model for a Parking Lot

The arrival time of the EVs at the charging station in the parking lot of a residential district is a random variable and follows a certain stochastic distribution determined by the pattern of vehicle usage. In practice, the behavior of the vehicle arriving at a parking lot can be described as a Poisson Process [25], [26]. Poisson process is the most basic independent increment random process that accumulates the number of random event occurrences, which meets the following three conditions [27]:

- $N_0 = 0$ ;
- $N_t$  is a process with independent increments, i.e., for any  $0 < t_1 < t_2 < \dots < t_N$ , that the increment of  $N_t$  in the interval  $(t_i, t_{i+1})$ ,  $N_{t_{i+1}} - N_{t_i}$  is independent of each other,  $i = 1, 2, \dots, n - 1$ ;
- For any  $t > 0, s > 0$ , the increment  $N_{t+s} - N_s \sim \text{Poisson}(\lambda)$ , i.e., the probability is

$$P(N_{s+t} - N_s = k) = \frac{(\lambda t)^k e^{-\lambda t}}{k!}, \quad k = 0, 1, 2, \dots \quad (5)$$

In (5), the parameter  $\lambda$  represents the times that the random event happens per unit time, which determines the frequency of EVs arriving at the parking lot.

According to the characteristics of the Poisson process,  $\mathbf{N}_{\text{car}}$ , an array of the number of EVs that arrive at the parking lot, can be predicted for each time segment.

In this paper, it is assumed that the same type of battery is used in the EVs with the same battery parameters, and the charging process for EVs begins from the time when EVs arrive at the charging station without any charging control. The starting time of charging for an EV is denoted by  $T_{\text{start},i}$ .  $T_{\text{start},i}$  can be calculated by the index number of time segments of the arrival time (i.e., the index number in the  $\mathbf{N}_{\text{car}}$  array) and the time segment length  $T_{\text{step}}$  ( $T_{\text{step}}$  is 5 minutes in this paper).

In general, the EV charging power load is a part of the total power load of a residential district and usually appears at night after people drive back home. So the time studied in this paper is from 18:00 P.M. to 6:00 A.M. of the next day. Considering the actual situation of a residential district, the time can be divided into 2 sections for different density of coming vehicles. The rush hour, 18:00 P.M. to 20:00 P.M. is the peak time of the EV arriving for charging (called the first section), when more than half of the EVs return. From 20:00 P.M. to 24:00 P.M. is the lower arriving density period (the second section), when the remaining vehicles return. That means the arrival time of EVs in a parking lot follows the two-section Poisson distribution. In each section, the average number of vehicles arrived per unit time  $\lambda$  is apparently different from each other.

In addition, the randomness of initial SOC of EVs for charging depends on the individual EV owners. The truncated normal distribution for initial SOC is used here [15]–[17], since SOC has a finite support [0, 100%].

Based on the analysis above, simulation of aggregation characteristic of charging station can be described as follows:

- According to the characteristic of the Poisson distribution, the number series of EV arriving in each time segment for the two sections of EVs arriving time are represented as follows.

$$\begin{aligned} \mathbf{N}_{\text{car}_1} &= [n_{11}, n_{12}, \dots, n_{1L}] \\ &\sim \text{Poisson}(\lambda_1), \quad L = \frac{T_1}{T_{\text{step}}} \end{aligned} \quad (6)$$

$$\begin{aligned} \mathbf{N}_{\text{car}_2} &= [n_{21}, n_{22}, \dots, n_{2M}] \\ &\sim \text{Poisson}(\lambda_2), \quad M = \frac{T_2}{T_{\text{step}}} \end{aligned} \quad (7)$$

$$\mathbf{N}_{\text{car}} = [\mathbf{N}_{\text{car}_1}, \mathbf{N}_{\text{car}_2}] \quad (8)$$

where  $T_1, T_2$  are the lengths of the first and second time sections.  $L$  and  $M$  are the total numbers of the first and second sections.  $\lambda_1$  and  $\lambda_2$  are the Poisson distribution parameters of the first and second sections.  $n_{1i}$  and  $n_{2i}$  are the number of vehicles for each section ( $1i < L, M$ ).  $\mathbf{N}_{\text{car}_1}$  and  $\mathbf{N}_{\text{car}_2}$  are the Poisson distribution series of the first and second sections that vehicles arrive.  $\mathbf{N}_{\text{car}}$  is the total series of vehicle distribution.

- Generate the initial SOC series of normal distribution.

$$\text{SOC}_0 = [\text{SOC}_1, \text{SOC}_2, \dots, \text{SOC}_{N_T}] \sim N(\mu, D) \quad (9)$$

where  $\mu$  is the average of the SOC of the EV batteries,  $D$  is the standard deviation of the SOC,  $\text{SOC}_0$  is the initial SOC series of all the EVs for charging,  $N_T$  is the total number of the EVs for charging.

$$N_T = \sum_{i=1}^L n_{1i} + \sum_{i=1}^M n_{2i} \quad (10)$$

- Charging load power of EV.  
According to  $\text{SOC}_0(i)$  of the  $i$ th EV, the charging load power,  $P_{EV,i}$  of the EV is calculated by (1)–(4).
- The total load of a charging station.

According to the respective charging start time  $T_{\text{start},i}$  of each EV, and by arranging the start time of the charging power of the EVs, the actual charging power of the  $i$ th EV is:

$$P_i(t) = \begin{cases} 0 & t < T_{\text{start},i} \\ P_{EV,i} & t \geq T_{\text{start},i} \end{cases} \quad (11)$$

Each charging power of the EVs can be added together to get the total load of the charging station:

$$P_{\text{EVstation}} = \sum_{i=1}^{N_T} P_i(t) \quad (12)$$

Hence, the aggregation charging power model for a parking lot can be computed by the above 4 steps. The aggregation characteristic of charging load is mainly determined by the 6 important parameters  $\lambda_1, T_1, \lambda_2, T_2, \mu, D$ . The 6 parameters, which describe the random characteristics of the charging load, are called the aggregation characteristic parameters of EV charging.

TABLE I  
PARAMETERS OF AGGREGATION CHARGING MODEL FOR SIMULATION

	$\lambda_1$ (car/5min)	$T_1$ (hour)	$\lambda_2$ (car/5min)	$T_2$ (hour)	$\mu$	$D$
Value	13.33	2.0	1.67	4.0	30.0%	0.1

### III. PARAMETER ESTIMATION FOR EV AGGREGATION MODEL

#### A. Estimation Method for EV Aggregation Model

Generally speaking, the 6 parameters of the aggregation EV charging model can be obtained from the statistic of the charging data. Furthermore, some special measure equipment such as the device in [28] is needed to record the SOC of each EV and other data for each charger device. However, the statistic method is inconvenient when the number of EVs is large and the EVs have different charging characteristics, i.e., different type, capacity, etc. Since the charging power curve is intensively influenced by the 6 parameters, there is another convenient way to obtain the 6 parameters by measuring the daily total charging power curve of charging station.

Unlike the conventional parameter estimation algorithms [29]–[31], the aggregation characteristic parameters of charging stations are affected by many random variables. The load power of charging station is also a random process. Even with the same set of parameters of aggregation charging model, we can get different results of load power satisfying the same laws of certain stochastic properties. In traditional gradient-based parameter estimation algorithms (such as the Gauss-Newton method and the Levenberg-Marquardt method) [32], the descent direction of cost function is always considered as the searching direction. However, the cost function of the aggregation model has randomness due to the random process in the model. Even at the same search direction, the cost function may show randomly positive or negative increment, which makes it hard to find the search direction.

Stochastic search strategy is an effective way to solve this kind of stochastic optimization problems, which overcomes its random output of the model through a random search. Genetic algorithm (GA) is one of the stochastic optimization algorithms. The random search through a certain number of populations can avoid or reduce the interference of individuals from the random output of the model [33]–[35]. In this paper, GA is used for estimating the aggregation parameters of the EV charging station.

In the following implementation of the utilized GA, the initial population  $N_0 = 100$ , the maximum generation  $N_g = 100$ , crossover fraction = 0.8, the method of mutation is “adaptive feasible” [35], the selection method is “stochastic uniform” [35]. The cost function of the aggregation model, which is also the GA fitness function, is defined as follows.

$$J(\alpha) = \frac{1}{N} \sum_{i=0}^{N-1} (P_{EV_i}(\alpha) - P_{mi})^2 \quad (13)$$

where  $N$  is the total sampling points of the charging curve,  $P_{EV_i}$  is the  $i$ th point calculated power value of aggregation model under the parameter of  $\alpha$ ,  $P_{mi}$  is the  $i$ th point value of measured

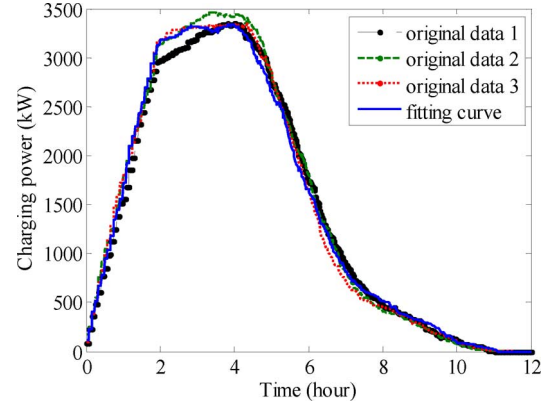


Fig. 3. Fitting curves of the charging power.

active charging power,  $\alpha = [\lambda_1, T_1, \lambda_2, T_2, \mu, D]$  is the vector of aggregation characteristic parameters.

Multiple charging power curves can be used together to estimate the aggregation model of the days related to these curves. This will reduce the impact of stochastic process on the parameter estimation. The cost function then can be described as follows:

$$J(\alpha) = \frac{1}{K \cdot N} \sum_{j=1}^K \sum_{i=0}^{N-1} (P_{EV_i}(\alpha) - P_{mi,j})^2 \quad (14)$$

where  $K$  is the number of charging power curves,  $P_{mi,j}$  is the  $i$ th point value of the  $j$ th measured active charging power curve, the other parameters are the same as those in the previous equations.

#### B. Parameter Estimation Case

For a middle sized residential district with 2000 vehicles (hypothetically, all are EVs), we assume there are approximate 20–30% EVs (about 400–600 EVs) for charging in the parking lot every day, which can be referred to the Mini-E field test in Berlin [36]–[38].

Assume that three measured charging power curves of a parking lot are simulated by the aggregation charging model in Part B of Section II. The battery parameters of each EV are  $U_n = 316.8$  V and  $Q = 200$  Ah. The initial SOC of EVs for charging in the parking lot follow the normal distribution with  $\mu = 30\%$  and  $D = 0.1$ . The distribution of the arrival time of EVs follows the two-section Poisson distribution. The parameters of the aggregation charging model is showed in Table I, which is used to simulate the measured charging power curve of a parking lot as the original data. There are totally 400 EVs for charging in this case.

The GA method is applied to estimate the aggregation characteristic parameters of the EV charging. The time span from 0 to 12 hours corresponds to 18:00 P.M. to 6:00 A.M. of the next day (0 represents the beginning at 18:00 P.M., 12 represents the end at 6:00 A.M. on the next day).

The estimated results of EV charging station aggregation parameters are listed in Table II. The fitting curves are shown in Fig. 3. The Best fitness and the Mean fitness of GA with log scale in the estimation process are shown in Fig. 4.

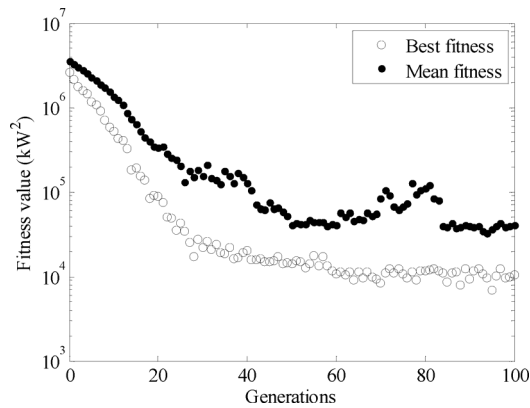


Fig. 4. Fitness values of generations in estimation process.

TABLE II  
ESTIMATED RESULT OF AGGREGATION PARAMETERS

	$\lambda_1$ (car/5min)	$T_1$ (hour)	$\lambda_2$ (car/5min)	$T_2$ (hour)	$\mu$	$D$
Real Value	13.33	2.0	1.67	4.0	30.0%	0.1
Estimated Value	12.26	2.16	1.54	3.86	30.83%	0.13

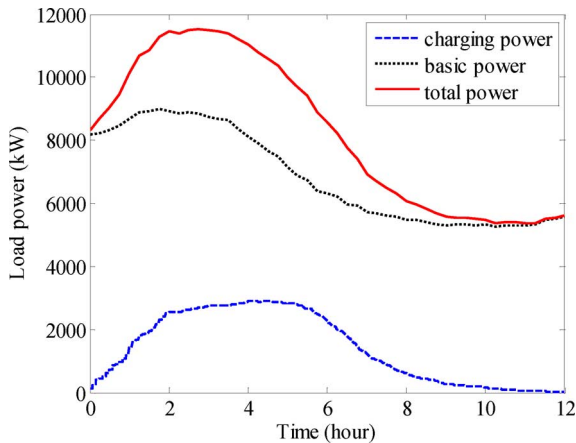


Fig. 5. Basic load and EV charging load in a residential district.

The results of Figs. 3 and 4 show that the error of using GA to establish aggregation charging model is acceptable and the estimation method is effective.

#### IV. OPTIMIZATION METHOD FOR EV CHARGING STRATEGY

The dotted curve in Fig. 5 shows the basic power load of a residential district except the EV charging load, which was sampled from a southeast coastal city in China. The time span from 0 to 12 hours also corresponds to 18:00 P.M. to 6:00 A.M. of the next day. The charging power of EVs, which is simulated with the parameters in Table I, is given in Fig. 5. However, without the control of the EV charging, the charging power load may significantly increase the peak and overload the electricity grid.

##### A. Charging Strategy of EVs

Based on Fig. 5, the most intuitive and simplest charging strategy is to change all EVs centralized at midnight. However, if the charging power of the parking lots is large enough

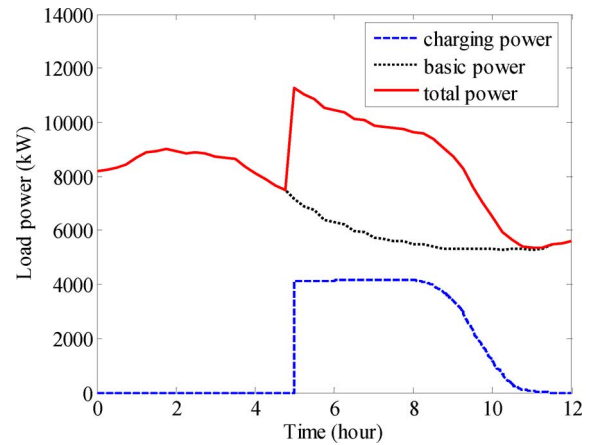


Fig. 6. Total power load of the residential district while changing all EVs centralized at midnight.

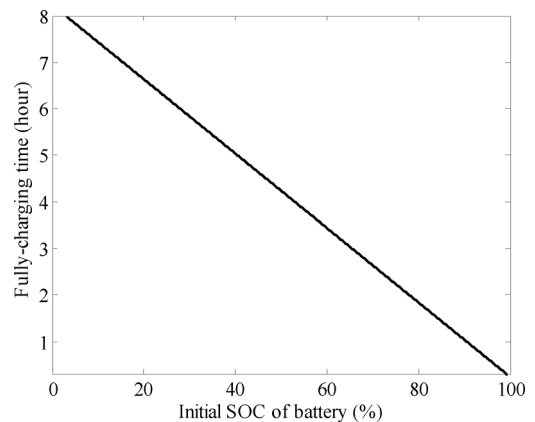


Fig. 7. The relation of the fully-charging time and the initial SOC of battery.

and comparable to basic load, as shown in Fig. 6, it will cause evening peak for the total power load.

To reduce the power difference of peak and valley, a charging management system (CMS) with a suitable optimization strategy is necessary for the parking lots to minimize the fluctuation level of power load which is impacted by the EV charging power [39], [40].

The charging strategy of EVs must guarantee that every vehicle should be charged to full capacity before 6:00 A.M. in the next morning as possible. This requires that the beginning time of charging must be restricted by the relation of the fully-charging time and the initial SOC of the EV battery. Fig. 7 shows an example of the relation based on the parameters of EV battery in Section II.

According to Fig. 7, it will take about 8 hours to charge an empty battery to the full state. The relation between the fully-charging time and the initial SOC of battery is linear. So the relation can be described as follows.

$$T_{\text{charge}} = (1 - \text{SOC}_0) \cdot 8 \quad (15)$$

where  $\text{SOC}_0$  is the initial SOC of the battery,  $T_{\text{charge}}$  is the fully-charging time for the battery with  $\text{SOC}_0$ .

The full charging time for an EV could be calculated based on the initial SOC of battery of the EV by (15). Since the power valley of basic load curve is after 23:00 and the power is almost declining thereafter, as shown in Fig. 6, a better way to charge

the EVs is to plug in them in the last time period before 6:00 A.M. . Thus the starting time of the EV charging could be determined according to (15) to make the charging of EV finished at exactly 6:00 A.M..

However, if all EVs are charging at 5:00 A.M.–6:00 A.M., this may potentially cause a peak at this time. In order to prevent the charging power peak from the case at time of 5:00 A.M.–6:00 A.M. or the case at time of 23:00 P.M. in Fig. 6, some EVs would be charged in 18:00 P.M. to 23:00 P.M. conditionally. This could also be a kind of special service to provide prior charging for the need of some EV with higher payment. The amount of EVs charged during 18:00 P.M. to 23:00 P.M. can be reasonably limited less than a number, which is represented by  $N_{lim}$ . Furthermore, the initial SOC of the EV must meet a certain range, e.g., less than a threshold SOC ( $SOC_{cr}$ ), which means the EV need longer time to charge. Vehicles whose initial SOC is greater than  $SOC_{cr}$  or whose number has exceeded  $N_{lim}$  in 18:00 P.M. to 23:00 P.M. are arranged to be charged at a proper time based on the relation between the fully-charging time and the initial SOC of battery by (15).

In summary, the charging strategy for the CMS is as follows.

- 1) If the initial SOC of the arrived EV is less than  $SOC_{cr}$  and the number of EV is also fewer than  $N_{lim}$ , the EV can be charged immediately.
- 2) If the initial SOC of the arrived EV is less than  $SOC_{cr}$  while the number of EVs is greater than  $N_{lim}$ , the EV can be arranged to begin charging at a later and proper time which is defined as the later charging start time and is represented by  $T_{later\_start}$ .
- 3) Otherwise, the EV will be shifted after  $T_{later\_start}$  to charge and the starting time of charging should be calculated based on (15). If the calculated starting time is earlier than the arrival time of the EV, the arrival time should be used as the actual starting time of charging. If the starting time is earlier than  $T_{later\_start}$ , it should be set to  $T_{later\_start}$ .

### B. Optimization of Charging Strategy

The limited amount for the EVs charging in 18:00 P.M. to 23:00 P.M. ( $N_{lim}$ ), the threshold SOC ( $SOC_{cr}$ ) and the later charging start time ( $T_{later\_start}$ ) are the parameters to control the charging of the EVs. The goal of the optimization is to minimize the impact on the power fluctuation from EV charging by adjusting the charging-control parameters  $N_{lim}$ ,  $SOC_{cr}$  and  $T_{later\_start}$ . To describe the fluctuation level of the power curve, we define the power fluctuation level (PFL) index as follows.

$$\text{Index}_{PFL} = (P_{max} - P_{min})/P_{average} \quad (16)$$

where  $P_{max}$  is the maximum total power in the interested time period,  $P_{min}$  is the minimum total power, and  $P_{average}$  is the average total power.

Thus, the PFL index of total power curve with no optimization in Fig. 5 is 0.741, which is calculated by (16).

The total power in (16) is separated into the basic power and the charging power. The basic power comes from the load prediction for the next day. The charging power is calculated based

TABLE III  
PARAMETERS OF AGGREGATION MODEL

	$\lambda_1$ (car/5min)	$T_1$ (hour)	$\lambda_2$ (car/5min)	$T_2$ (hour)	$\mu$	$D$
Value	20	2.0	2.5	4.0	30.0%	0.2

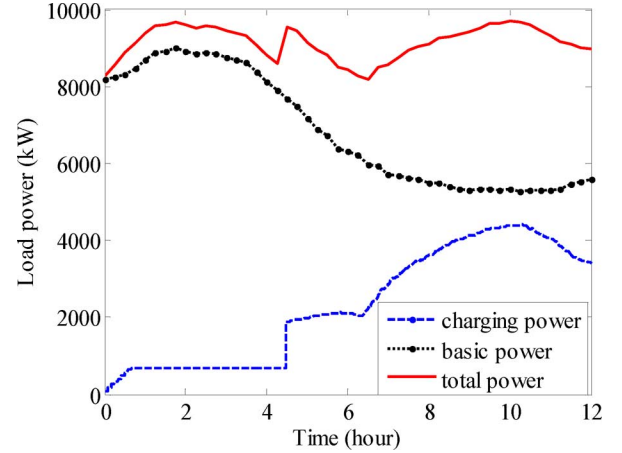


Fig. 8. Total power curve with optimization.

on the charging strategy with the parameters  $N_{lim}$ ,  $SOC_{cr}$  and  $T_{later\_start}$ .

The cost function of the optimization for the charging strategy is

$$J = \min \text{Index}_{PFL}(N_{lim}, SOC_{cr}) \quad (17)$$

This optimization problem is also a stochastic optimization problem because of the random process of the aggregation model of EV. Therefore, we use GA to solve the problem and the reason is the same as that in Section III-A. The parameters of the GA method are also described in Section III-A. The goal is to find the best  $N_{lim}$ ,  $SOC_{cr}$  and  $T_{later\_start}$  for the EV charging strategy to minimize the power fluctuation level of the residential area.

### C. Case Study

For a middle sized residential district with 2000 EVs, we assume there are approximately 30% EVs (about 600 EVs) for charging in the parking lot every day.

The battery parameters of each EV are  $U_n = 316.8$  V and  $Q = 200$  Ah. The distribution of the arrival time of EVs follows the two-section Poisson distribution. Their initial SOC of batteries are under normal distribution. The parameters of the aggregation charging power model are listed in Table III.

Then the GA method presented in part B of this section is used to estimate the optimization  $N_{lim}$ ,  $SOC_{cr}$  and  $T_{later\_start}$ . The optimization results are shown in Table IV and Fig. 8, as well as the power fluctuation level index ( $\text{Index}_{PFL}$ ) with and without optimization.

The charging strategy and the optimization method proposed in this paper can reduce the power fluctuation level of the total power of the residential district greatly from 0.7410 to 0.1706. In contrast to Fig. 5, if the charging strategy is applied in the

TABLE IV  
RESULT OF OPTIMIZATION

Parameters	Value
$N_{ctr}$	81
$SOC_{cr}$	26.56%
$T_{later\_start}$	4.48 hours (10:29pm)
$Index_{PFL}$ with optimization	0.1706
$Index_{PFL}$ with no optimization	0.7410

CMS, the negative impact of the EVs charging will be alleviated deeply as shown in Fig. 8.

## V. UPDATING STRATEGY FOR AGGREGATION MODEL AND CHARGING CONTROL

### A. Assumption

The aforementioned optimization method and the charging strategy are quite effective when the charging characteristics of the parking lot are time-invariant. However, in reality those characteristics are time-variant. In order to maintain the effectiveness of the charging control, a method is required to update the parameters of the aggregation charging model constantly to track the variation of the charging characteristics.

The characteristics of the EV charging depend on the pattern of the vehicle usage, which is related to the people's life styles, personal habits, working schedules and social networks. Generally, these factors are relatively steady and will change slowly, which means the characteristics of the charging will not suddenly change with the same pattern. Therefore, we have the following assumption about the characteristics of the EV charging: the stochastic characteristics of the EV aggregation charging model on the previous day of the same pattern are almost the same as what they are on the current day.

### B. Updating Strategy

Usually, the estimation of the aggregation charging model requires the complete charging data from 18:00 P.M. to 6:00 A.M. in a day. Based on the assumption, the estimation results from the data of the previous day can approximately represent the characteristics of the aggregation charging model on the current day. Therefore, the updating strategy for the aggregation charging model can be running in a daily loop.

Furthermore, the effects of the optimization method and the charging strategy strongly depend on the accuracy of the aggregation charging model. The parameters of the aggregation charging model estimated from the original charging power (the charging curve in Fig. 5) determine the final effect of the optimization. However, once the charging strategy is applied in the CMS, the shape of charging curve changes from the curve in Fig. 5 to the curve in Fig. 8.

Since the parameter estimation of the aggregation charging model is based on the original charging power curve (as shown in Fig. 5) without charging control, it is not applicable due to the shape changing of the EV charging curve. Because both the charging strategy and the control parameters are known, intuitively we could use the daily charging power curve (as shown in Fig. 8) when considering the effect of the charging control to estimate the parameters of the aggregation charging model.

GA is used to validate the approach. The charging power data in Fig. 8 is used as the measured data of the charging power.

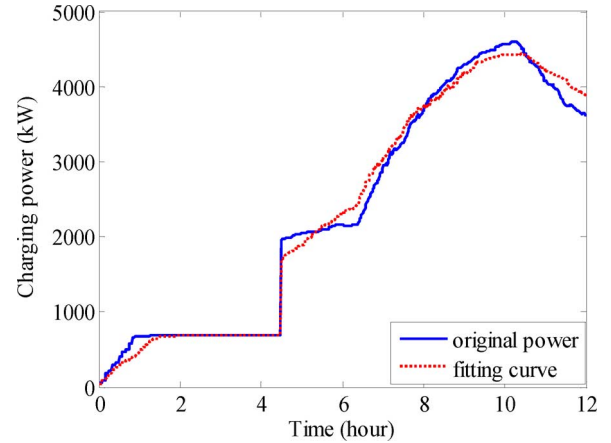


Fig. 9. Fitting charging power curves with 6 parameters estimated.

TABLE V  
ESTIMATED RESULT OF AGGREGATION PARAMETERS

	$\lambda_1$ (car/5min)	$T_1$ (hour)	$\lambda_2$ (car/5min)	$T_2$ (hour)	$\mu$	$D$
Real Value	20	2.0	2.5	4.0	30.0%	0.2
Estimated Value	5.523	5.687	7.179	2.190	11.67%	0.285

The results are listed in Table V and the fitting curve is shown in Fig. 9.

The results of the parameter estimation in Table IV are not well as expected. But the error of the curve fitting is much less than it appears. The reason is that, the early arrived vehicles delayed to be charged in the midnight cannot be distinguished from the vehicles actually arrive and are charged in the midnight. However, these two situations with the same charging power curve correspond with different values of parameters of the aggregation charging model.

Therefore, it is difficult to directly estimate the parameters of the aggregation model from the charging power curve with charging control.

It is still possible to obtain the parameters using a combination of multiple methods.

First, since  $T_1$  and  $T_2$  are the relatively fixed variables, they can be obtained from the statistic of the historical data of the vehicles arrival time. Second,  $\lambda_1$  and  $\lambda_2$ , representing the average amount of arrived EVs per unit time, can be obtained by counting the number in  $T_1$  and  $T_2$  by the CMS automatically, which is usually quite accurate and easy to realize. At last,  $\mu$  and  $D$  are estimated by using the daily charging power curve (as shown in Fig. 8) with considering the effect of the charging control.

The simulation also uses the charging power data in Fig. 9. Assume  $T_1 = 2$  and  $T_2 = 4$  according to the actual situation in Section II. Let the count number be  $N_1$  in  $T_1$ ,  $\lambda_1$  equals to  $N_1/T_1/12$  (car/5 min).  $\lambda_2$  can be obtained similarly. The values of  $\lambda_1$  (19.875) and  $\lambda_2$  (2.521) are calculated from CMS and the calculation error is less than 1%.

The accuracy of the estimation results of  $\mu$  and  $D$  are adequate as listed in Table VI. Fig. 10 shows much better fitting results compared to that in Fig. 9.

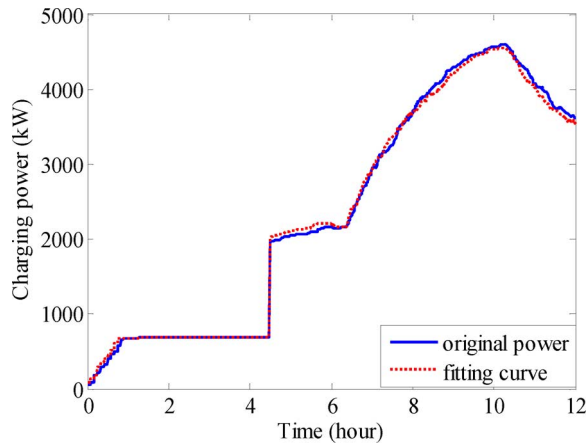


Fig. 10. Fitting charging power curves with 2 parameters estimated.

TABLE VI  
ESTIMATED RESULT OF AGGREGATION PARAMETERS

	$\lambda_1$ (car/5min)	$T_1$ (hour)	$\lambda_2$ (car/5min)	$T_2$ (hour)	$\mu$	$D$
Real Value	20	2.0	2.5	4.0	30.0%	0.2
Estimated Value	19.875	-	2.521	-	30.74%	0.207

In summary, the daily updating strategy for the aggregation model and the charging-control parameters is proposed as follows.

- Step 1: From every day 18:00 P.M., count the numbers of arrived vehicle in  $T_1$  and  $T_2$  periods in the CMS, and calculate the  $\lambda_1$  and  $\lambda_2$ .
- Step 2: Estimate  $\mu$  and  $D$  by using the charging power curve of previous day while considering the effect of the charging control. And update the parameters of the aggregation model.
- Step 3: To minimize the power fluctuation level based on the updated aggregation model, optimize  $N_{lim}$ ,  $SOC_{cr}$  and  $T_{later\_start}$ .
- Step 4: Update  $N_{lim}$ ,  $SOC_{cr}$  and  $T_{later\_start}$  in the CMS before 18:00 P.M. on the current day.

### C. Future Extension

The assumption in part A of this section may not be valid in some special circumstances and the characteristics of the charging may change suddenly. For example, the pattern characteristics are different for weekdays and weekends (or holidays). Emergencies or special events may also change the pattern characteristics. In order to improve the updating strategy, a special process for these special cases should be applied in the updating strategy.

One of the solutions is to distinguish the situations of the charging as weekday pattern, weekend pattern, holiday pattern, emergency pattern, etc. The estimation of the aggregation model based on the daily charging power curve runs on a daily basis. The pattern will first be detected before updating the parameters of the aggregation model. The daily updating of the aggregation model only continues in the same charging situation pattern. The pattern change can be detected by large errors on

the fitting charging power curve or marked by calendars. Once the pattern has changed in two consecutive days, the best suitable parameters will be obtained by searching from the same pattern in historical data. Then the next steps of optimizing and updating  $N_{lim}$ ,  $SOC_{cr}$  and  $T_{later\_start}$  will be the same as the steps in part B. The extended updating strategy based on daily pattern classification can be investigated in the future.

## VI. CONCLUSION

In this paper, an EV aggregation charging model for a parking lot is presented to describe the stochastic feature of the charging characteristics. The parameters of the aggregation model can be estimated using genetic algorithm based on the original charging power curves of the parking lot. We proposed a charging strategy with two charging-control parameters  $N_{lim}$ ,  $SOC_{cr}$  and  $T_{later\_start}$  for the CMS and an aggregation model-based optimization method to minimize the influence of the EV charging. An updatable optimization method is introduced to fit the change of charging power curve as the applying of the charging strategy. The simulation results show the updatable optimization method is effective for estimating the parameters of the aggregation model and adjusting the control-parameters of the charging strategy, so that the power fluctuation level of the residential district can be reduced. The updating strategy can also be extended to consider different daily patterns in the future.

In addition, some factors such as the average SOC of users, the line losses, the ancillary services provided by EVs and so on, are not considered in the optimization process of the proposed charging strategy. Next the effect of the proposed strategy on these factors will be studied for the investigated situation. The multi-objective optimization problem will be formulated by considering the above factors and an improved charging strategy will be proposed to solve this problem.

## REFERENCES

- [1] S. Shao, M. Pipattanasomporn, and S. Rahman, "Challenges of PHEV penetration to the residential distribution network," in *Proc. 2009 IEEE Power Energy Soc. Gen. Meet.*, Calgary, AB, Canada, Jul. 2009, pp. 1–8.
- [2] L. Dow, M. Marshall, L. Xu, J. R. Agüero, and H. L. Willis, "A novel approach for evaluating the impact of electric vehicles on the power distribution system," in *Proc. 2010 IEEE Power Energy Soc. Gen. Meet.*, Minneapolis, MN, USA, Jul. 25–29, 2010, pp. 1–6.
- [3] K. Qian, C. Zhou, M. Allan, and Y. Yuan, "Modeling of load demand due to EV battery charging in distribution systems," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 802–810, May 2011.
- [4] J. Taylor, A. Maitra, M. Alexander, D. Brooks, and M. Duvall, "Evaluation of the impact of plug-in electric vehicle loading on distribution system operations," in *Proc. 2009 IEEE Power Energy Soc. Gen. Meet.*, Calgary, AB, Canada, Jul. 2009, pp. 1–6.
- [5] G. Capizzi, F. Bonanno, and G. M. Tina, "Recurrent neural network-based modeling and simulation of lead-acid batteries charge-discharge," *IEEE Trans. Energy Convers.*, vol. 26, no. 1, pp. 435–443, Mar. 2011.
- [6] J. Jang and J. Yoo, "Equivalent circuit evaluation method of lithium polymer battery using bode plot and numerical analysis," *IEEE Trans. Energy Convers.*, vol. 26, no. 1, pp. 290–298, Mar. 2011.
- [7] C. R. Gould, C. M. Bingham, D. A. Stone, and P. Bentley, "New battery model and state-of-health determination through subspace parameter estimation and state-observer techniques," *IEEE Trans. Veh. Technol.*, vol. 58, no. 8, pp. 3905–3916, Oct. 2009.
- [8] Z. M. Salameh, M. A. Casacca, and W. A. Lynch, "A mathematical model for lead-acid batteries," *IEEE Trans. Energy Convers.*, vol. 7, no. 1, pp. 93–98, Mar. 1992.

- [9] M. Casacca and Z. M. Salameh, "Determination of lead-acid battery capacity via mathematical modeling techniques," *IEEE Trans. Energy Convers.*, vol. 7, no. 3, pp. 442–446, Sep. 1992.
- [10] C. M. Shepherd, "Design of primary and secondary cells—Part 2 an equation describing battery discharge," *J. Electrochem. Soc.*, vol. 112, no. 7, pp. 657–664, July 1965.
- [11] O. Tremblay, L. A. Dessaint, and A. I. Dekkiche, "A generic battery model for the dynamic simulation of hybrid electric vehicles," in *Proc. 2007 IEEE Veh. Power Propulsion Conf.*, pp. 284–289.
- [12] *Matlab R2009b Help Document: Battery—Implement Generic Battery Model* version 7.9.0.529 (R2009b), The Mathworks, Inc., Natick, MA, USA, Aug. 12, 2009.
- [13] E. Sortomme and M. A. El-Sharkawi, "Optimal charging strategies for unidirectional vehicle-to-grid," *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 131–138, Mar. 2011.
- [14] N. Rotering and M. Ilic, "Optimal charge control of plug-in hybrid electric vehicles in deregulated electricity markets," *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1021–1029, Aug. 2011.
- [15] W. Su and M. Y. Chow, "Performance evaluation of an EDA-based large-scale plug-in hybrid electric vehicle charging algorithm," *IEEE Trans. Smart Grid*, to be published.
- [16] C. Guille and G. Gross, "The integration of PHEV aggregation into a power system with wind resources," in *Proc. Bulk Power Syst. Dyn. Control Symp.*, Aug. 1–6, 2010, pp. 1–9.
- [17] P. T. Staats, W. M. Grady, A. Arapostathis, and R. S. Thallam, "A statistical method for predicting the net harmonic currents generated by a concentration of electric vehicle battery chargers," *IEEE Trans. Power Del.*, vol. 12, no. 3, pp. 1258–1266, Jul. 1997.
- [18] M. S. W. Chan, K. T. Chau, and C. C. Chan, "Modeling of electric vehicle chargers," in *Proc. 24th Annu. Conf. IEEE Ind. Electron. Soc. (IECON'98)*, vol. 1, pp. 433–438.
- [19] M. Etezadi-Amoli, K. Choma, and J. Stefani, "Rapid-charge electric-vehicle stations," *IEEE Trans. Power Del.*, vol. 25, no. 3, pp. 1883–1887, Jul. 2010.
- [20] H. M. Zhang, Y. K. Sun, and Y. H. Huang, "Research of 60 v/3 kW lithium power and its charge circuit based on DSP," *Power Supply Technol. and Its Appl.*, no. 11, pp. 143–149, 2007.
- [21] C. Y. Xia, K. Liu, and Y. Guo, "Implementation of a bi-directional dc/dc converter in the electric vehicle," *Power Electron.*, vol. 40, no. 1, pp. 70–72, 2006.
- [22] O. Tremblay and L. A. Dessaint, "Experimental validation of a battery dynamic model for EV applications," *World Elect. Veh. J.*, vol. 3, May 13–16, 2009, EVS24, Stavanger, Norway.
- [23] D. Y. Yu, H. L. Huang, M. Lei, X. Lin, B. Zhang, and X. S. Han, "CO<sub>2</sub> reduction benefit by coordinated dispatch of electric vehicle charging and wind power," *Autom. Elect. Power Syst.*, vol. 36, no. 10, pp. 14–18, 2012.
- [24] Nevfocus, New Energy Vehicle Database: BYD E6 [Online]. Available: [Online]. Available: <http://www.zjjw.com.cn/a/database/chundiaodong/2010/0609/171.html>
- [25] C. Farkas, K. I. Szabó, and L. Prikler, "Impact assessment of electric vehicle charging on a LV distribution system," in *Proc. 3rd Int. Youth Conf. Energetics*, Leiria, Portugal, Jun. 7–9, 2011.
- [26] E. Munoz and E. Ruspini, "Using fuzzy queuing theory to analyze the impact of electric vehicles on power networks," in *Proc. WCCI 2012 IEEE World Congr. Comput. Intell.*, Brisbane, Australia, Jun. 10–15, 2012.
- [27] M. P. Qian, J. Ye, and S. T. Xiao, *Stochastic Mathematics*. Beijing, China: Higher Education Press, 2004, pp. 100–114.
- [28] M. Shahriari and M. Farrokhi, "State of health estimation of vrla batteries using fuzzy logic," in *Proc. Electr. Eng. (ICEE) 2010 18th Iranian Conf.*, May 11–13, 2010.
- [29] L. Ljung, *System Identification: Theory for the User*, 2nd ed. Upper Saddle River, NJ, USA: Prentice-Hall PTR, 1999, pp. 203–234.
- [30] J. Nocedal and S. J. Wright, *Numerical Optimization*. New York: Springer, 1999, pp. 100–131, 259–266.
- [31] D. P. Mandic, "A generalized normalized gradient descent algorithm," *IEEE Signal Process. Lett.*, vol. 11, no. 2, pp. 115–118, Feb. 2004.
- [32] S. C. NG, S. H. Leung, C. Y. Chung, A. Luk, and W. H. Lau, "The genetic search approach. A new learning algorithm for adaptive IIR filtering," *IEEE Signal Process. Mag.*, vol. 13, no. 6, pp. 38–46, Nov. 1996.
- [33] J. A. Vasconcelos, J. A. Ramirez, R. H. C. Takahashi, and R. R. Saldanha, "Improvements in genetic algorithms," *IEEE Trans. Magn.*, vol. 37, no. 5, pp. 3414–3417, Sep. 2001.
- [34] A. E. Eiben, R. Hinterding, and Z. Michalewicz, "Parameter control in evolutionary algorithms," *IEEE Trans. Evol. Comput.*, vol. 3, no. 2, pp. 124–141, Jul. 1999.
- [35] *Matlab R2009b Help Document: Genetic Algorithm and Direct Search Toolbox* version 7.9.0.529 (R2009b), The Mathworks, Inc., Natick, MA, USA, Aug. 12, 2009.
- [36] D. Westermann, M. Agsten, and S. Schlegel, "Empirical bev model for power flow analysis and demand side management purposes," in *Proc. Int. Symp. Modern Elect. Power Syst. (MEPS)*, Wroclaw, Poland, Sept. 20–22, 2010, pp. 1–6.
- [37] M. Agsten, M. Ifland, S. Schlegel, and D. Westermann, "Utilizing battery electric and plug-in hybrids for smart grid operation techniques," in *Proc. 2011 IEEE Power Energy Soc. Gen. Meet.*, Detroit, MI, USA, Jul. 24–29, 2011, pp. 1–5.
- [38] M. Agsten, S. Schlegel, and D. Westermann, "On the optimization of the load of electric vehicles," in *Proc. 18th IFAC World Congr.*, Milano, Italy, Aug. 28–Sep. 2 2011, pp. 13673–13678.
- [39] C. Huston, G. K. Venayagamoorthy, and K. A. Corzine, "Intelligent scheduling of hybrid and electric vehicle storage capacity in a parking lot for profit maximization in grid power transactions," in *Proc. IEEE Energy 2030 Conf.*, Atlanta, GA, USA, Nov. 17–18, 2008, pp. 1–8.
- [40] A. Y. Saber and G. K. Venayagamoorthy, "Optimization of vehicle-to-grid scheduling in constrained parking lots," in *Proc. 2009 IEEE Power Energy Soc. Gen. Meet. (PES'09)*, Calgary, AB, Canada, Jul. 26–30, 2009, pp. 1–8.

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