Electric Vehicles Charging Scheduling Strategy Considering the Uncertainty of Photovoltaic Output

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Abstract: The rapid development of electric vehicles and distributed generation bring new challenges to security and economic operation of the power system, so the collaborative research of the EVs and the distributed generation have important significance in distribution network. Under this background, an EVs charging scheduling strategy considering the uncertainty of photovoltaic(PV) output is proposed. The characteristics of EVs charging are analysed first. A PV output prediction method is proposed with a PV database then. On this basis, an EVs charging scheduling strategy is proposed with the goal to satisfy EVs users' charging willingness and decrease the power loss in distribution network. The case study proves that the proposed PV output prediction method can predict the PV output accurately and the EVs charging scheduling strategy can reduce the power loss and stabilize the fluctuation of the load in distributed network.

1. Introduction

The energy crisis could drive to the development of renewable energy, especially photovoltaic(PV). The PV output would change with weather, and could cause the large fluctuation of the voltage [1-2]. At the same time, the development of electric vehicles(EVs) could have been payed more attention. As a new type of electric power load, the charging load of EVs is random and intermittent. Large-scale EVs charging will change the current load conditions and increase the peak-valley gap of load and it will also affect the stable operation of the distribution network [3-5]. In order to reduce the influence of large-scale EVs access to distribution network, the EVs charging behavior should be guided to improve the reliability and economy of operation in distribution network. Meanwhile, EVs can be considered to consume the PV output. Therefore, it is of great significance to study the coordinated scheduling of EVs and PV in the distribution network.

At present, many scholars around the world have done a lot of research on the EVs charging scheduling. In [6], the EVs charging priority is set up according to the difference of the parking duration of the EVs. In [7], the charging time of EVs is scheduled to increase the utilization rate of feeder terminal load and decrease the power loss in distribution network at the same time. In [8], the multi agent system is used to schedule EVs charging for the aim of peak shaving and three phase equilibrium. In [9], the real-time load management system is proposed to reduce the voltage drop and power loss when EVs are charged. However, all of the studies mentioned above didn’t take EVs user's
willingness into account when making the charging scheduling strategy. Besides, the state of charge (SOC) of EVs in these studies is set to 100% or some fixed values [10] or some existing laws [11], which is inconsistent with the actual EVs travel law. EVs charging load is related to the initial SOC and the parking duration in fact. At the same time, EVs are mainly concentrated in some first-tier cities in China, where the household charging pile is less. The only choice where EVs users can charge their EVs is public charging station for charging, and the charging time is always limited. Most of studies mentioned above used the U.S. national household travel survey statistics [12-14] to describe EVs users’ travel characteristics, which is inconsistent with actual travel characteristics in first-tier cities in China. Therefore, the charging scheduling strategy with the actual EVs users’ travel data and fully considering the initial SOC and the parking duration of EVs is proposed to satisfy EVs users’ willingness.

The coordinated scheduling of EVs and PV mainly considers the coordination among the EVs, PV and the load in order to satisfy EVs users’ charging willingness, improve the utilization rate of PV and stabilize the load fluctuation in distributed network. However, few studies about the coordinated scheduling of EVs and PV have been published. In [15], an EVs charging algorithm, which is applied for smart homes/buildings, is designed to determine the optimal schedules of EV charging based on PV output prediction. However, EVs users’ willingness and the load in distribution network aren’t considered in [15].

In a word, an EVs charging scheduling strategy based on PV output prediction is proposed in this paper. Firstly, the structure of distribution network and the characteristics of EVs charging based on the actual measured data are illustrated in Section 2. A PV output prediction method is proposed in Section 3. An EVs charging scheduling strategy is proposed in Section 4. A case study based on Section 2 to Section 4 is introduced in Section 5. The conclusion of the paper and the future work is introduced in Section 6.

2. Structure of distribution network and related model

2.1. Structure of distribution network

With the development of the new energy technologies and electric vehicles, the penetration level of the PV is likely to be higher. Figure 1 shows the general structure of the distribution network including EVs and PV.

![Figure 1. Structure of distribution network](image)

There are 11 nodes in distribution network in this paper and the EVs and PV are involved in node 7. The EVs charging load, PV output and the load in distribution network are concentrated in the energy dispatching center. The charging scheduling strategy of EVs is proposed to achieve energy balance in distribution network with both EVs and PV.

2.2. The characteristic of EVs charging
The probability density of the arriving time, the departure time and the SOC can be acquired by statistical actual measured data in office areas from Beijing university, as shown in Fig. 2 and Fig. 3. The sampling rate of the vehicle data is real-time, but in order to simplify, the statistical data is counted by per hour.

**Figure 2.** Probability density of the arriving time, the departure time

**Figure 3.** Probability density of the SOC of EVs

### 3. Photovoltaic output prediction

PV output will affect the implementation of the EVs scheduling strategy. To formulate the proper scheduling strategy, it is necessary to predict PV output in advance.

Before PV output prediction, a photovoltaic database is established according to the seasons and the meteorological characteristic of PV output. Based on the actual measured data of PV, of which the capacity is 35kW, the PV output can be divided into three categories according to the type of weather: sunny, cloudy and rainy day. The day in clear to overcast is often regarded as a sunny day, the day cloudy to sunny is often regarded as a cloudy day. The weather forecast information is derived from a public weather forecast website [16].

The database includes two parts: seasonal classification and meteorological classification, as shown in Fig. 4.

**Figure 4.** The photovoltaic database

Because of the large amount of information in database, the information of similar days in database can help enhance the accuracy of PV output prediction. Euclidean distance, which is used to calculate the similarity of temperature, is obtained as (1):

$$d_i = \sqrt{\sum_{j=1}^{2} (Y_j - X_{ij})^2}, \quad i = 1, 2, \cdots, n$$ (1)

Where, $n$ denotes the number of days in database, $d_i$ denotes the Euclidean distance, $Y_1$, $Y_2$ are the highest and lowest temperature of the predicted day, and $X_{i1}$, $X_{i2}$ are the highest and lowest temperature of the day in database.

Rank the Euclidean distance from small to large, the top k Euclidean distance can be selected as the original samples. The BP (Back Propagation) neural network algorithm [17-19], composed of multiple input layers, multiple hidden layers, and multiple output layers, is a kind of error back propagation
neural network. Each layer has a certain number of neurons in BP neural network algorithm, as shown in Figure 5.

In this paper, the samples in BP neural network are simulated and trained so the PV output can be calculated, as shown in Fig.6.

![Figure 5](image1.png)  
**Figure 5.** The structure of BP neural network

![Figure 6](image2.png)  
**Figure 6.** Flowchart of the BP neural network

4. Electric vehicle charging scheduling strategy

4.1. Strategy

Electric vehicle charging scheduling strategy based on photovoltaic prediction is introduced and formulated.

Step 1, determining whether the vehicle is scheduled for charging or not, in $t$ hour.

Determining whether each EV is scheduled for charging or not according to the necessary SOC level for commute considering the service life of the battery and the traffic jam and the time to stay of EVs in the charging station. The EVs are divided into 3 types.

- **Type 1:** The initial SOC of EVs is greater than the necessary SOC level for the commute.
- **Type 2:** The initial SOC of EVs is less than the necessary SOC level for the commute, and the time to the necessary SOC level for the commute is less than the parking time.
- **Type 3:** The initial SOC of EVs is less than the necessary SOC level for the commute, and the time to the necessary SOC level for the commute is greater than the parking time;

The type 1 and type 2 are available to participate the scheduling strategy, type 3 is not to participate in it. The detailed flowchart is shown in Figure 6, where the $SOC_D$ denotes the SOC to the necessary SOC level for the commute, the $T_D$ denotes the time to the necessary SOC level for the commute, and the $T_S$ denotes the parking time.

Step 2, formulating different scheduling for three types of vehicles

- **Schedule 1:** For the type 1 of the EVs, the charged EVs battery capacity can meet the necessary SOC level for the commute, and then the actual start charging time of EVs is not necessary to the entering time of EVs. That means, the type 1 EVs can participate the scheduling strategy without any constraints. Therefore, more controllable and flexible scheduling plan may be applied for type 1 EVs.

- **Schedule 2:** For the type 2 of the EVs, the charged EVs battery capacity cannot meet the necessary SOC level for the commute and the parking time is longer than the time to the necessary SOC level for the commute. The type 2 EVs need to charge the EV battery until the SOC level becomes the necessary SOC level for the commute after entering the EV charging station. Then, the type 2 EVs can participate the scheduling strategy. Therefore, the controllable and flexible scheduling plan may be applied for type 2 EVs only after the SOC level is $SOC_D$.

- **Schedule 3:** For the type 3 of the EVs, the EVs cannot participate scheduling strategy. Therefore, type 3 EVs are out of scope for the scheduling strategy.

Both the PV output and power grid should be taken into account when charging scheduling is planned. The PV output provide power to EVs if the charging load of EVs is less than or equal to the PV output, otherwise the PV output is totally used for EVs charging and the lacking power is provided
by grid. The Particle swarm optimization (PSO) algorithm is used to optimize the charging time of EVs.

Step 3, in $t+1$ hour, updating the network. The new schedule is made for new EVs, or the current scheduling continues.

According to the charging scheduling mentioned above, the PV output can be used for EVs charging, and reduce the negative impact to the distribution network when EVs and PV access to the grid at the same time. The charging scheduling is shown in figure 7, where $N_C$ denotes the number of EVs in hour $t$.

Figure 7. Flowchart of optimal scheduling

4.2. **Optimal scheduling model**

Set if each EV is charged or not in every hour as the variable, so the status of each EVs can be expressed as $x_{i_c} = (x_{i_c1}, x_{i_c2}, \ldots, x_{i_ct})$, $t = 1, 2, \ldots, 24$, where $x_{i_ct}$ can be obtained in (2).

$$x_{i_ct} = \begin{cases} 
0, & \text{EV isn't charged in hour } t \\
1, & \text{EV is charged in hour } t 
\end{cases} \quad (2)$$

The objective is minimizing the active power loss of distribution network, as shown in (3).

$$\min P_{loss} = \min \sum_{t=1}^{24} P_{lt} \quad (3)$$

Where, $P_{loss}$ denotes the total active power loss of distribution network and $P_{lt}$ denotes the active power loss of distribution network every hour.

There are some constraint conditions. The sum charging time of each EV can be calculated as (4).

$$\sum_{t=1}^{24} x_{i_ct} = T_a \quad (4)$$

Where, $T_a$ denotes the actual charging time.

5. **Case Study**

140kW PV system is installed in load 1 shown in Figure 1 and 100 vehicles are selected randomly as the research samples. Take May 31th, when the weather is sunny and the maximum and minimum temperature are 30 °C and 20 °C, as an example. 5 similar days are selected as the training samples from the database. Figure 8 shows the PV output calculated with neural network algorithm, which is called prediction output.
As shown in Fig. 8, PV output calculated with neural network algorithm is similar to the actual PV output, which proves prediction output is relatively accurate.

In general, the commute distance for residents in Beijing city is about 40km for a round trip [20], so about 30% of the electricity is needed in a round trip if the battery capacity of EV is 25.6kWh. Besides, for a prolonged battery life of EVs, the SOC of EVs is no less than 20% [21]. 10% of the electricity is reserved for traffic jam. In a word, the \( SOC_D \) is set to 60% in consideration of what is said above.

The PSO algorithm is used to optimize the charging time of EVs. The power loss in distribution network is reduced by 377.9W compared to original charge. Figure 9 shows the charging load of EVs in this case study with and without the charging scheduling strategy of EVs. As shown in Figure 9, the charging scheduling strategy is based on the charging time shifting on the premise of meeting the demand of EVs users.

77 of 100 EVs can be scheduled according to the charging scheduling strategy. Figure 10 shows the charging scheduling of first five EVs. Figure 11 shows the daily load curve in the distribution network only with PV, with PV and original EVs and with PV and optimal EVs. As shown in Figure 11, from the time 6:00 to 18:00 when PV output is available, the original charging load of EVs are concentrated in the daytime when the load is high while the optimal charging load of EVs are transferred to the daytime when the load is lower, which makes the load curve in distribution network smoothly.

**6. Conclusion**

Different weather types lead different PV output, so a PV output prediction method considering the different weather types is proposed in this paper firstly. The PV output prediction is closer to the actual output with the method mentioned above. Accurate PV output prediction is a premise of the charging scheduling strategy of EVs. The EVs charging load with charging scheduling strategy decreases the peak load of the daily load curve and the power loss in distribution network compared with the original EVs charging load. The paper provides a reference for energy optimization management in distribution network.
Acknowledgement
This work is supported by the National Natural Science Foundation of China (51677004) and the Fundamental Research Funds for the Central Universities (2016JB061).

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