**Analysis method of the influence of electric bus optimal charging on the renewable energy power consumption**

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**Abstract.** To analyze the influence of the optimal charging of electric buses on the consumption of power generated from renewable energy sources, an optimal charging model with the electricity price revision is proposed. The revision helps to promote consistency between the charging load and renewable energy power. Then the analysis of the influence of electric bus optimal charging on the renewable energy power consumption can be achieved. Based on the revised electricity price, a 0-1 integer linear programming model for the optimal charging of electric buses is established, aiming to derive the lowest charging cost. The method takes into account the demand of buses’ drive range, continuous charging and the number of charging piles.

**1. Introduction**

Due to its incomparable advantages during energy crisis, clean energy power generation has attracted extensive attention from countries all over the world. As clean energy develops rapidly, Qinghai Power Grid shall play a pivotal role in “energy transformation”. The diverse and personalized needs of today’s users require Qinghai Power Grid to actively serve as a platform for energy distribution and conversion. As State Grid’s new “Three Functions, Two Networks” framework is deployed, Qinghai Power Grid also faces major challenges in meeting the requirements of the framework as well as in its pursuit of high-quality development. In particular, constraints on hosting capacity poses new challenges. Renewable energy has become the largest energy source for Qinghai Power Grid. As its hosting capacity has reached the maximum, there is great pressure to continue to achieve the goal of “double reduction”.

How to increase the hosting capacity of large-scale renewable energy power generation is a problem that needs an urgent solution. It should be noted that the rapid development of electric vehicles in recent years provides a resource for electrical grid load balancing with great prospective applications [1-3]. Reasonable charging guidelines for electric vehicle (EV) can not only stabilize the grid load and reduce the peak-valley difference, but also absorb excess electrical energy during the peak periods of renewable energy power generation output and improve the grid-connected capacity of renewable energy power sources. Therefore, it is of great significance to study how guidelines for the optimal charging of electric vehicles can improve the power generation and hosting capacity of renewable energy sources.
A convexified model for EV charging station scheduling is proposed in [4], which minimizes the total charging cost and the energy cost from the substation during the concerned time horizon. An intelligent charging management mechanism to maximize the interests of both the customers and the charging operator is developed in [5], aiming to promote the total utility for the charging operator subject to the time-of-use (TOU) pricing. A new efficient cutting plane method is proposed in [6], that can be used for solving charging optimization problem for both scenarios of known and uncertain electricity prices.

Some researches on the charging optimization, take Distributed Generation (DG), demand response and grid requirement into consideration. A dynamic charging scheduling scheme (DCSS) to manage the EV charging processes is designed in [7], in which the model predictive control method is employed to deal with the real-time information of EV charging requirements and the solar energy. In [8], considering EV, a detailed home energy management system structure is developed to determine the optimal day-ahead appliance scheduling of a smart household under hourly pricing and peak power-limiting (hard and soft power limitation)-based demand response strategies. The authors in [9] propose the application of a smart integration of EV charging stations in a real case scenario with DG that can guarantee the maximum exploitation of the system and its sustainability. A decentralized mechanism is developed for collaboration of EV aggregators with different type DGs in [10]. In this mechanism, that DG/EV aggregators are encouraged to adjust their price in order to improve the profit of their clients via contribution to congestion management.

The current research focuses on the optimization method of EV charging. How the optimal charging can improve the renewable energy utilization has been less well studied. To analyze the influence of the optimal charging of electric buses on the consumption of power generated from renewable energy sources, an optimal charging model with the electricity price revision is proposed. The revision helps to promote consistency between the charging load and renewable energy power. Then the analysis of the influence of electric bus optimal charging on the renewable energy power consumption can be achieved. Based on the revised electricity price, a 0-1 integer linear programming model for the optimal charging of electric buses is established, aiming to derive the lowest charging cost. The method takes into account the demand of buses’ drive range, continuous charging and the number of charging piles.

2. Division of peak and valley electricity prices by time based on the generated output characteristics of new energy

To improve the hosting capacity of electrical grids that are supplied by renewable energy sources and use the cost of charging to provide guidelines encouraging the charging of electric vehicles during peak renewable energy generation output periods, peak-valley electricity prices shall be set for electric vehicles under the existing peak-valley electricity price mechanism. A peak-valley time division method using fuzzy clustering based on the characteristics of renewable energy generation output is proposed.

Based on the basic characteristics of the DG output, the highest point on the output curve can be determined as the trough of electricity price and the lowest point as the peak of electricity price. However, other periods cannot be directly determined, so fuzzy evaluation of the membership degree of peaks and valleys in each period shall be carried out. The peak membership degree $d_p$ as in Equation 1, and the valley membership degree $d_v$, as in Equation 2, of each period are calculated respectively, and the peak-valley membership degree is used to judge the correlation between the output of each period and the peak and valley output values.

$$d_p(t) = \frac{p_{\text{max}} - p(t)}{p_{\text{max}} - p_{\text{min}}}$$

$$d_v(t) = \frac{p(t) - p_{\text{min}}}{p_{\text{max}} - p_{\text{min}}}$$
where $d_f$ and $d_g$ represent peak membership degree and valley membership degree respectively. $t$ represents the time period, $p_{\text{max}}$ and $p_{\text{min}}$ are respectively output peak value and valley value, and $p(t)$ is output of time period $t$.

Then, the membership degree shall be standardized as follows:

$$d'_f(t) = \frac{d_f(t) - \bar{d}_f}{D_f}$$ (3)

$$d'_g(t) = \frac{d_g(t) - \bar{d}_g}{D_g}$$ (4)

where, $d'_f$ and $d'_g$ are standardized membership degrees, as in Equation 3 and 4, i.e. the average values degrees in each period. $D_f$ and $D_g$ are the variance of membership degrees in each period.

The hierarchical clustering method shall be adopted for classification, and the process is as follows:

1. At the beginning, each sample is placed into one category;
2. Specify a certain measure as the distance between samples and the distance between categories, and calculating it;
3. Merge the two categories with the shortest distance into a new category;
4. Repeat step 2-3, i.e. merge the last two categories, one category at a time, until all samples are divided into three categories.

The distance between sample points shall be expressed as Euclidean distances, as in Equation 5:

$$r_{ij} = \sqrt{(d'_f(t_i) - d'_f(t_j))^2 + (d'_g(t_i) - d'_g(t_j))^2}$$ (5)

The distance between categories adopts Average Linkage: calculate the distance between each data point in the two combined data points and all other data points. The average of all distances shall be taken as the distance between two combined data points, as in Equation 6.

$$r_q = \frac{\sum_{i} \sum_{j} \left[(d'_f(i) - d'_f(j))^2 + (d'_g(i) - d'_g(j))^2\right]}{\Omega_i \Omega_j}$$ (6)

where, $\Omega_i$ and $\Omega_j$ are all sample point sets of two combinations respectively.

After the completion of clustering process, the electricity price is revised to the valley electricity price for the clustering process in the peak output period. Other periods remain unchanged.

### 3. Model for the optimal charging of electric vehicles

Among the various types of electric vehicles, electric buses have the characteristics of centralized management, high-power fast charging and obvious load regulation, which can significantly improve the power generation by renewable energy sources and the hosting capacity of their electrical grids. Therefore, this paper focuses on the impact of the optimal charging of electric buses on the power generation and hosting capacity of electrical grids which incorporate renewable energy sources.

To simplify the model, we make the following assumptions are set for the operating state of electric buses: the earliest electric bus sets off with full power, and its battery retains a certain amount of residual power to protect the battery core. Vehicles heading in both directions are charged by the charging station that is the subject of this study. Renewable energy power generation is achieved mainly through photovoltaic processes. Hence, the paper focuses on optimal charging during the operation period of electric buses. The mileage, time and power consumption of electric buses remain unchanged.

#### 3.1. Control variables

In a model where electric buses are charged in an orderly manner, the control variable is the charging state of each bus during period $t$.

It is assumed that the bus stop time matrix can be calculated from the driving routes of electric buses, as in Equation 7:
\[ \mathbf{K} = \begin{bmatrix} k_{11} & k_{12} & \cdots & k_{1n} \\ k_{21} & k_{22} & \cdots & k_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ k_{m1} & k_{m2} & \cdots & k_{mn} \end{bmatrix} \]  

(7)

where, \(k_{mn}\) indicates whether the \(m\) vehicle stops at the charging station in the \(n\) period, and the value shall be 1 or 0.

According to the docking matrix, the control variable matrix of charging and discharging are as follows, and as in Equation 8:

\[ \mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \]  

(8)

Where, \(x_{mn}\) indicates whether the \(m\) vehicle is charged in the \(n\) period. If the corresponding \(k_{mn}\) is 0, it is not a control variable. If the corresponding \(k_{mn}\) is 1, it is a control variable.

3.2. Objective function

To guide the electric bus to use the renewable energy power generation output based on the electricity price, the objective function is set as the minimum charging cost, as in Equation 9:

\[
\min f = \sum_{i=1}^{N_T} \sum_{t=1}^{N_{bus}} \left[ C(t) P_i(t) \Delta T \right] 
\]

(9)

Where, \(N_T\) and \(N_{bus}\) are the time period and the number of vehicles respectively. \(C(t)\) is the electricity price in time period \(t\). \(P_i(t)\) is the charging power of the \(i\) vehicle in time period \(t\), and \(\Delta T\) refers to each time period.

3.3. Constraints

3.3.1. Demand for driving power, as in Equation 10:

\[ s E_s E_{\min} \leq E_n \leq (s-1) E_s + E_0 \]

(10)

\[ E_n = E_0 + \Delta T \sum_{i=1}^{k_s} \eta x_i P_i(t) \]

(11)

where, \(s\) is the trip value, \(E_{\text{dis}}\) as in Equation 11, is the accumulated electric quantity before the \(s\) trip of the \(i\) vehicle, \(t_{fs}\) is the final period of stopping before the trip \(s\) of vehicle \(i\); \(E_0\) is the full electric quantity, \(\eta\) is the charging efficiency, and \(E_s\) is the average electric quantity per trip.

3.3.2. Quantity restriction of charging piles. The sum of control variables in each period is less than the number of charging piles, as in Equation 12:

\[
\forall (t) : \exists \left( \sum_{i=1}^{N_{ch}} x_i(t) \leq N_{ch} \right)
\]

(12)

where, \(N_{ch}\) is the number of charging piles

3.3.3. Continuity constraint for charging. Due to the service life of the battery, the charging process is continuous during a certain period of the docking. It is assumed that the set of docking periods \(\Omega_i\), as in Equation 13, for the \(i^{th}\) vehicle is:
Where, $\Omega_i$ is the set of docking periods for the $i$ vehicle, $N_i$ is the number of docking times for vehicle $i$, and $t_{ij}$ and $t_{lj}$ are the starting and ending times for dock $j$ respectively.

The essence of the continuous charging constraint is that the control variable indicating whether to charge does not change more than 2 times during the docking period, as in Equation 14:

$$\sum_{i \in \mathcal{G}} \left[ x_i(t) - x_i(t+1) \right]^2 \leq 2$$

(14)

However, as it is difficult to derive a non-linear solution to the model, the above formula shall be transformed and auxiliary 0-1 variables $u_i(t)$ and $v_i(t)$ are added, and the relationship between the auxiliary 0-1 variables $u_i(t)$ and $v_i(t)$ and the control variables becomes as the following Equation system 15:

$$\begin{cases} u_i(t) \geq x_i(t) - x_i(t-1) \\ v_i(t) \geq x_i(t) - x_i(t+1) \\ t \in \Omega_i \end{cases}$$

(15)

The auxiliary variable constraints are listed in Equations’ systems 16 and 17:

$$\begin{cases} u_i(t) \in \{0,1\} \\ v_i(t) \in \{0,1\} \\ \sum_{i \in \mathcal{G}} u_i(t) \leq 1 \\ \sum_{i \in \mathcal{G}} v_i(t) \leq 1 \end{cases}$$

(16)

(17)

4. Case study

The case focuses on the charging process of a bus during the driving time of a day. Buses run 40 kilometers one way, with an average speed of 20 kilometers per hour, and leaves every 10 minutes. There are 28 buses heading in both directions. The buses rest for 20 minutes after completing each trip. It is assumed that buses are fully charged at night before they start operation in the morning. Moreover, if the charging optimization is aimed at improving the power generation and consumption of energy from renewable sources, only optimal charging during bus operation times are considered. Buses depart every 10 minutes from 05:30 to 20:00 in the morning, every 20 minutes from 20:00 to 22:00, and every 30 minutes from 22:00 to 23:30. During the daily bus operation time from 05:30 to 23:30, every 10 minutes count for one period, so there are 108 periods.

The electric bus, such as the type of BYD K9, has a charging power of 250kW, a total battery power of 324kWh, a minimum remaining power of 0.15, a charging and discharging efficiency of 90% and a power consumption of 1.4kWh per kilometer. There are 4 high-power charging piles in the charging station.

Based on the electricity price in a certain region of China(such as Beijing), the flat electricity price is 0.8595 yuan (07:00~10:00, 15:00~18:00, 21:00~23:00), the peak electricity price is 1.3872 yuan (10:00~15:00, 18:00~21:00), and the valley electricity price is 0.3658 yuan (23:00~07:00).

In this case, the electric bus operated during the day is studied, so photovoltaic power generation is mainly considered for renewable energy power generation, and its typical output curve is shown in Figure 1.
Based on photovoltaic power generation output, the electricity price is revised as follows: the flat electricity price is 0.8595 yuan (07:00~10:00, 15:00~18:00, 21:00~23:00), the peak electricity price is 1.3872 yuan (18:00~21:00), and the valley electricity price is 0.3658 yuan (10:00~15:00, 23:00~07:00).

Based on the revised electricity price for optimal charging optimization, the charging power of the bus rapid charging station is shown in Figure 2. The figure shows that under the constraint of ensuring power remains sufficient for normal driving, the electric vehicle follows pricing guidelines, and the charging load is weakened during the peak period of electricity price, especially during the period when the photovoltaic output is large, while the charging load presents a trough instead.

Based on the revised electricity price for well-organized optimization of charging, the charging power of the bus rapid charging station is shown in Figure 3. The figure shows that the electricity pricing exerts significant influence on market participants. It is clear that part of the charging load moves forward to the peak period of photovoltaic output, and the characteristics of charging load and output are consistent.
For comparison, the Figure 4 shows the difference of charging power before and after the electricity price correction. According to this figure, the charging load period moves forward significantly. The calculation indicates that the charging load increases 958.33kWh in total, accounting for 16.79% of the total charging load, making great improvements to the consumption of photovoltaic power generation.

![Figure 4. Power difference before and after price correction.](image)

5. Conclusions
To analyze how much positive impact the optimal charging of electric vehicles may exert on the consumption of renewable energy power generation, the paper proposes a method of analysis to guide the load characteristics of electric vehicles to ensure consistency with the characteristics of renewable energy power generation by revising the electricity price. According to the method, the renewable energy output is classified based on cluster analysis, then the electricity price period is revised by the output classification period. On the basis of the revised electricity price, the author establishes a 0-1 integer linear programming model for the optimal charging of electric buses, aiming to achieve the lowest charging cost. The method fully takes into account the demand of the buses’ drive, continuous charging and the number of charging piles.

Based on the above method of analysis, the charging load characteristics have changed greatly, and photovoltaic power consumption has increased the total charging load of the bus rapid transit charging stations by 16.79%. Therefore, reasonable mechanisms for targeted electricity pricing may effectively enhance the hosting capacity of new energy, which is of great significance for the society. The influence of other type electric vehicles on the renewable energy power consumption will be studied in the future.

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