Research on electric vehicle-supercapacitor hybrid system participates in the application of tracking PV project output

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Abstract
With the increase in new energy power generation and the continuous augment in the penetration rate of electric vehicles, it is of crucial importance to use electric vehicles as energy storage devices to promote the consumption of new energy. Aiming at the uncertainty of electric vehicles, this paper proposes a method based on multiobjective optimization for electric vehicle-supercapacitor hybrid energy storage system to track PV project output. The hybrid system consists of electric vehicles and supercapacitor. Electric vehicles and supercapacitors supplement the deviation of PV actual power and predicted power by charging and discharging. The electric vehicle is regarded as a nonspecific way to label a piece of equipment that can store energy. First and foremost, on the basis of traditional method of predicting PV output, a PSO-BP prediction method based on PCA is proposed to improve the accuracy of PV output prediction. Secondly, according to the different characteristics of electric vehicles and supercapacitors, the empirical mode decomposition (EMD) method is used to decompose the deviation that the hybrid energy storage system needs to bear with the purpose of initially allocating the energy. Furthermore, a multiobjective optimization model is established for the precise energy distribution of the hybrid energy storage system, and the NSGA-III algorithm is used to solve it. Ultimately, the data of a domestic PV power station are used for simulation. After optimized control, the result shows that the standard deviation of the system output is reduced from 1967 to 75.77. The research in this article provides a theoretical basis for the application of electric vehicle virtual energy storage technology in the field of auxiliary new energy grid connection.

KEYWORDS
consumption of renewable energy, electric vehicle, hybrid energy storage system, track PV project output
1 | INTRODUCTION

With the increasingly prominent environmental and energy problems, the proportion of renewable energy represented by PV is increasing year by year. However, the randomness and uncertainty of PV power generation reduce the reliability of PV power generation and the stability of power grid. Therefore, it is particularly important to accurately predict PV power generation and take certain measures to deal with its randomness and uncertainty, which can provide support for the development of PV industry.

At present, the error can be minimized in most cases when predicting PV output power. However, due to the influence of many factors like weather, large errors also occur from time to time. In response to these situations, energy storage systems are used to solve the problem. The application of energy storage system in the field of PV power generation can not only improve its stability and reliability, but also greatly increase the PV utilization rate.

Barelli et al. developed a dynamic model of the overall microgrid including PV and energy storage to implement the energy storage system preliminary sizing and a suitable management algorithm. Guo et al. proposed a wind-PV-thermal energy storage hybrid system with an electric heater, which can provide a new way to reform conventional small-scale thermal power plant. Akagi et al. proposed a multipurpose control and planning method for energy storage systems to cope with the increase of large-scale PVPs in distribution networks. It can be seen that energy storage systems are of great significance to power systems. However, energy storage is currently expensive, so that large-scale applications are restricted.

Currently, the number of electric vehicles is increasing year by year. While electric cars are idle, 95% of the time according to the statistics of the State Grid Corporation. Regarding the idle electric vehicle as an energy storage unit and guiding it to participate in the auxiliary services of the power system can give full play to the role of electric vehicle power batteries, which can improve the stability of the grid and profit car owners. At present, most countries and regions have carried out research on virtual energy storage of electric vehicles. Yi et al. took the alternative energy storage effect of EVs into consideration. Zhu et al. regarded the controllable loads as “virtual energy storage system”. Then, these models are integrated into a scheduling model for regional integrated energy system. Wu et al. proposed a hierarchical distributed control strategy in this paper for mobile energy storage clusters considering the life loss of each EV’s battery. The control strategy realized the two-way communication of energy between EVs and the power grid, and ensured the optimal economical dispatch for the mobile energy storage system. Dong et al. proposed a high-performance and robust linear quadratic regulator-proportional integral derivative controller for frequency regulation in a two-area interconnected smart grid with a population of plug-in hybrid electric vehicles.

It can be seen by combing the existing research on electric vehicles that the current research is mainly limited in its participation in power grid frequency regulation, peak shaving, and so on. Therefore, in order to make up for the lack of current research, this study introduces the virtual energy storage of electric vehicles into the application scenario of tracking PV project output. At the same time, different types of energy storage have different characteristics, corresponding to various applicable conditions.

Reasonable control of charging and discharging process can not only improve the life of energy storage but also improve the economic benefits. In practical applications, the output required by energy storage is different in power and frequency changes, and it is difficult for a single energy storage to adapt to changing working conditions. Therefore, in this paper, super capacitors and electric vehicles make up a hybrid energy storage system to study the feasibility of hybrid energy storage systems in order that PV project output can be tracked. A hybrid energy storage energy distribution optimization control method based on EMD decomposition is proposed considering the energy storage characteristics and applicable working conditions of electric vehicles. First, the PV output power is predicted. The principal components analysis (PCA) is used to extract the principal components of the factors that may affect the PV output power, and then the PSO-BP model is used for training to predict the future PV output power. The planned output curve is formulated based on the forecast data, and the deviation that the hybrid energy storage system needs to bear during the actual grid connection process is obtained. Electric vehicles are suitable for low frequency and high energy, while super-capacitors are suitable for high frequency and low energy. According to the characteristic, the deviation that the hybrid energy storage system needs to bear is decomposed by the EMD method.

After that, a multiobjective optimization model is established. On one hand, the model considered the deviation between planned output and actual output of hybrid energy storage. On the other hand, it considered the difference between the actual output of an electric vehicle and the low-frequency component, as well as the difference between the actual output of the supercapacitor and the high-frequency component.

Eventually, a simulation based on the data of a PV power station proves that it is theoretically feasible for the electric vehicle-supercapacitor hybrid energy storage system to participate in tracking PV project output. Besides, the simulation results show that the output scheme of the
hybrid energy storage system optimized by the NSGA-III algorithm can reduce the average absolute error of the deviation between the actual output of the PV energy storage system and the planned output of the PV system up to 42.7 kW, under the premise of ensuring the optimal performance of the hybrid energy storage system. The research can provide a theoretical basis for the hybrid energy storage system with electric vehicles to assist the grid connection of new energy.

2 | FORECAST OF PV OUTPUT POWER

The predicted value of PV power generation power is an important basis for the power grid dispatching center to issue PV output plans. Therefore, improving the accuracy of the predicted value can reduce the assessment of new energy stations by the power grid dispatching department. Moreover, accuracy prediction is of great significance to coordinate and cooperate with PV generation and thermal power generation, the efficient formulation of dispatching plans, and the reduction of the impact of PV grid connection on the grid.\textsuperscript{20} What’s more, accurate prediction of PV power generation is also the basis for achieving optimal control among electric vehicle-supercapacitor hybrid systems, PV power generation, and grid load. This section analyzes the historical data of PV power plants and establishes a PV power prediction model based on the PCA-based PSO-BP neural network algorithm.

FIGURE 1 PSO-BP forecast flow chart

FIGURE 2 PSO-BP prediction model structure diagram
PSO-BP neural network

The particle swarm optimization algorithm can be used to solve complex optimization problems. In this article, the PSO algorithm optimizes the weights and thresholds in the BP neural network, that is, the weights and thresholds are “particles”. The optimization process is setting initial values, initializing population and evolution speed, calculating fitness, position update and speed update, population optimal and global optimal update, and the final result is obtained through repeated iterations. The prediction flow chart is shown in Figure 1.

The input of the prediction model in this paper includes PV panel output (kW) (output) data, ambient temperature (°C), dew point (°C), instantaneous value of total radiation (W/m²), instantaneous value of scattered radiation (W/m²), direct 15 input data such as instantaneous radiation value (W/m²), wind direction (°), wind speed (m/s), voltage (V), current (A), reflectivity, light transmittance, etc. The structure diagram of the prediction model is shown in Figure 2.

Taking the data of a PV power station in China from July 1 to July 31 as an example, the data sampling interval is 1 min, the first 30 days are used as training data, and the last day is used as test data. After 1000 iterations, the predicted output power is obtained as shown in Figure 3.

Principal component analysis

According to the technical requirements for connecting PV power station to power system (GB/T 19964-2012), the forecast error of PV grid connection shall not be higher than 15%. The error predicted by the above method is 4%. Although it meets the requirements, in order to reduce the pressure of the energy storage system, it is necessary to reduce the forecast error. It can be seen from the Section 2.1 that some factors may have little or no impact on the PV output power. At the same time, various factors may also have some correlations with each other. Therefore, the input dimensions of the prediction model are numerous and redundant, which may cause such problems as extending model learning time, reducing efficiency, and reducing prediction accuracy.

In order to make up for the shortcomings of the above prediction models, PCA is used to transform the linearly related factors in the original multidimensional data into new independent parameters before inputting the raw data into the PSO-BP prediction model. The obtained variables are arranged in order of variance value from largest to smallest. The total variance is unchanged during the transformation process. The new variable dimension is less than the original dimension, but it can still explain the original variable, which is the so-called principal component. It is a comprehensive index that explains the different influencing factors of the original PV output power. Therefore, the PCA method can be applied to reduce the dimensionality of the input data. For a matrix with \( p \) factors affecting PV output and \( n \) observations, it can be expressed as follows:

\[
X = \begin{bmatrix}
X_{11} & \cdots & X_{1p} \\
\vdots & \ddots & \vdots \\
X_{n1} & \cdots & X_{np}
\end{bmatrix}
\]  

(1)

In the above formula, \( p = 15 \) and \( n = 1440 \). The PCA method recombines \( p \) influencing factors that may be relevant into a set of uncorrelated PV output power influencing factors. The specific steps are as follows:
2.2.1 The original data are standardized, and the formula is as follows

\[ X_{ij} = \frac{x_{ij} - \overline{x}_j}{S_j} \]  

(2)

In the above formula, \( i = 1, 2, \ldots, n; j = 1, 2, \ldots, p; \)
\( \overline{x}_j = \frac{1}{n} \sum_{i=1}^{n} x_{ij} \) is the mean value of the \( j \)-th influencing factor; \( S_j = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_{ij} - \overline{x}_j)^2} \) is the matrix standardized by the standard deviation of the \( j \)-th influencing factor.

2.2.2 Calculation of the correlation coefficient matrix

According to the matrix obtained in (1), the correlation coefficient matrix \( R \) is calculated:

\[
R = \begin{bmatrix}
  r_{11} & r_{12} & \cdots & r_{1p} \\
  r_{21} & r_{22} & \cdots & r_{2p} \\
  \vdots & \vdots & \ddots & \vdots \\
  r_{p1} & r_{p2} & \cdots & r_{pp}
\end{bmatrix}
\]  

(3)

In the above formula, \( r_{ij} (i, j = 1, 2, \ldots, p) \) is the correlation coefficient between \( X_i \) and \( X_j \) in the original influencing factors, and \( r_{ij} = r_{ji} \), which is calculated by the following formula:

\[
r_{ij} = \frac{\sum_{k=1}^{n} (x_{ki} - \overline{x}_k)(x_{kj} - \overline{x}_j)}{\sqrt{\sum_{k=1}^{n} (x_{ki} - \overline{x}_k)^2(x_{kj} - \overline{x}_j)^2}}
\]  

(4)

2.2.3 Calculation of eigenvalues and eigenvectors

Calculate the eigenvalues \( (\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0) \) and eigenvectors \( (r_1, r_2, \ldots, r_p) \) of the matrix \( R \), where \( r_j = [r_{j1}, r_{j2}, \ldots, r_{jp}]^T \); at this time, each principal component can be expressed as follows:

\[
\begin{cases}
  Y_1 = r_{11} \% \overline{x}_1 + r_{12} \% \overline{x}_2 + \cdots + r_{1p} \% \overline{x}_p \\
  Y_2 = r_{21} \% \overline{x}_1 + r_{22} \% \overline{x}_2 + \cdots + r_{2p} \% \overline{x}_p \\
  \quad \vdots \\
  Y_p = r_{p1} \% \overline{x}_1 + r_{p2} \% \overline{x}_2 + \cdots + r_{pp} \% \overline{x}_p
\end{cases}
\]  

(5)

In the formula, \( Y_1, Y_2, \ldots, Y_p \) are the 1, 2, …, \( p \)-th principal components, respectively.

### Table 1

| Number | Eigenvalues | Contribution rate (%) | Cumulative contribution |
|--------|-------------|-----------------------|-------------------------|
| 1      | 5.6522      | 37.6812               | 37.6812                 |
| 2      | 1.8695      | 12.4635               | 50.1448                 |
| 3      | 1.4211      | 9.4739                | 59.6186                 |
| 4      | 1.1865      | 7.9103                | 67.5290                 |
| 5      | 1.0258      | 6.8389                | 74.3678                 |
| 6      | 0.9894      | 6.5959                | 80.9637                 |
| 7      | 0.9028      | 6.0187                | 86.9825                 |
| 8      | 0.6788      | 4.5254                | 91.5079                 |
| 15     | 0.0242      | 0.1611                | 100.0000                |

2.2.4 Calculation of eigenvalues and eigenvectors

The contribution rate of the eigenvalue \( \lambda_j (j = 1, 2, \ldots, p) \), that is, the information contribution rate of the principal component \( Y_j \), is calculated as follows:

\[
b_j = \frac{\lambda_j}{\sum_{k=1}^{p} \lambda_k}
\]  

(6)

The cumulative information contribution rate of the first \( k \) principal components \( Y_1, Y_2, \ldots, Y_k \) is as follows:

\[
a_k = \frac{\sum_{j=1}^{k} \lambda_j}{\sum_{j=1}^{p} \lambda_j} (k = 1, 2, \ldots, p)
\]  

(7)

The larger the value of \( a_k \), the closer the expression of the first \( k \) principal components to the original influencing factors \( [X_1, X_2, \ldots, X_n] \). If \( a_k \) reaches 90%, it can be considered that the \( k \) principal components basically contain all the information about the factors affecting PV output. Therefore, the first \( k \) principal components are selected to replace the original 15 variables to predict the PV output power.

The formula for calculating the comprehensive score is as follows:

\[
Z = \sum_{i=1}^{k} b_i Y_i
\]  

(8)

This section uses MATLAB to analyze the principal components of the original data, and the results of PCA are shown in Table 1.
It can be seen from Table 1 that the cumulative contribution rate of the first 8 principal components has exceeded 90%, so the first 8 principal components are selected to represent the original data. The scores of the original data under these 8 principal components are used as the input of the PSO-BP prediction model. Keeping the time series, data sampling interval, and output variables unchanged, the structure diagram of the improved forecasting model is shown in Figure 4.

The PV output power predicted by the improved model is shown in Figure 5.

The prediction result shown in Figure 5 is obtained by adding the PCA algorithm on the basis of PSO-BP. Comparing the prediction results in Figure 5 and Figure 3, it can be found that after using the PCA algorithm, the deviation between the predicted output and the actual output becomes smaller. This section uses mean absolute deviation (MAD) and root mean square error (RMSE) to compare and analyze the prediction errors before and after the PCA method, as shown in Table 2.

From the error comparison in the above table, it can be seen that the principal components of the original data can greatly reduce the prediction error, improve the prediction accuracy, and reduce the cost of energy storage tracking output.

3 | FORMULATION OF PV DISPATCHING PLAN

The power grid dispatching department formulates the planned output curve according to the predicted output value of the PV power station. According to the technical requirements for connecting PV power station to power system (GB/T 19964-2012), the time interval for the power grid dispatching department to issue dispatching instructions is 15 min. Therefore, it is necessary to process the point with a time interval of 1 min when formulating the PV planned output, that is, taking the average of the predicted values in every 15 min as the planned PV output within the scheduled time period. Figure 6 shows the
planned output curve based on the PV output power predicted in Section 2.2.

Due to the unstable PV output, the electric vehicle virtual energy storage-supercapacitor hybrid energy storage system needs to make up for the deviation between the planned output and the actual output. The output curve of the hybrid energy storage system tracking PV project output through calculation is shown in Figure 7.

It can be seen from Figure 7 that there is a certain deviation between the planned PV output and the actual output. The purpose of using a hybrid energy storage system is to make up for this deviation and achieve the purpose of high-quality PV grid-connected operation. However, reasonable arrangements for charging and discharging the electric vehicle-supercapacitor hybrid energy storage system can greatly improve the economics of the hybrid energy storage system.

4 | HYBRID SYSTEM ENERGY DISTRIBUTION

4.1 | Initial distribution of energy

Situations are different in the process of electric vehicle-supercapacitor hybrid energy storage system tracking PV project output. When the actual PV output power is greater than the output plan, the hybrid energy storage system absorbs electric energy. When the actual PV output power is less than the output plan, the energy storage system releases electric energy. The purpose of the hybrid system action is to meet the scheduling requirements.

Different types of energy storage in hybrid energy storage systems have different characteristics. In applications, in order to avoid great damage to the electric vehicle battery caused by frequent charging and discharging, supercapacitors are used to compensate the high frequency part of the deviation between the planned PV output and the actual output, and the electric vehicle is used to compensate for the low frequency part of the deviation. In this paper, EMD method is used to decompose the deviation by frequency. The deviation and the high- and low-frequency components obtained after decomposition are shown in Figure 8.

It can be seen from Figure 8 that the output of electric vehicles is relatively smooth, and the output of supercapacitors has relatively large fluctuations, which can achieve the purpose of giving full play to their respective advantages. However, in practical applications, there is a certain randomness in the end time and daily mileage of electric vehicles. It cannot be guaranteed that electric vehicles can fully meet the above low-frequency parts. Also, supercapacitors may be limited by their own SOC and charge and discharge power when being used. Therefore, at this time, the deviation between the planned PV output and the actual output cannot be optimally compensated by the hybrid energy storage system.

4.2 | Multiobjective optimization model for accurate energy distribution of hybrid energy storage system

In order to avoid the above distribution method that only considers high- and low-frequency power to reduce the accuracy of PV project output, the behavioral characteristics
of electric vehicles and the capacity and power constraints of supercapacitors need to be considered. Ideal output of hybrid energy storage system under different conditions is shown in Table 3.

Among them, $x_l(t)$ and $x_h(t)$ are the low-frequency components and high-frequency components in Figure 8, respectively. $P_{EV_{\text{control}}}$ and $P_{PC_{\text{control}}}$ are the ideal output for electric vehicles and supercapacitors, respectively. $P_{EV_{\text{max}}}$, $P_{EV_{\text{min}}}$, $P_{PC_{\text{max}}}$, and $P_{PC_{\text{min}}}$ are the upper and lower limits of the output power of electric vehicles and supercapacitors, respectively. $P_{EV_{C}}$ and $P_{PC_{C}}$ are the energy borne by the electric vehicle for the super capacitor and the energy borne by the super capacitor for the electric vehicle, respectively.

In addition, the purpose of the hybrid energy storage system to track PV project output is to minimize the deviation between the planned PV output and the actual output, which is expressed by the formula (9)

$$\min f_1 = \sum_{i=1}^{96} \left[ P_{EV} + P_{PC} - (P_{\text{plan}} - P_{\text{real}}) \right]^2$$ (9)
In the formula, $P_{EV}$ is the actual output of electric vehicles, $P_C$ is the actual output of supercapacitors, $P_{plan}$ is the planned output of PV, and $P_{real}$ is the actual output of PV.

Moreover, the minimum mutual compensation power between the electric vehicle and the super capacitor is the second objective function to achieve the goal of accurately tracking PV project output, as shown in formula (10)

$$\min f_2 = \sum_{i=1}^{96} (P_{EV} - P_{EV}^{control})^2$$  \hspace{1cm} (10)

This paper uses the behavioral characteristics of electric vehicles introduced in reference 25 to do further research. This research uses a supercapacitor with a rated voltage of 800 V and a rated capacity of 15 F. The constraints of supercapacitors are as follows:

$$\begin{align*}
p_{C_{min}} & \leq P_C(t) \leq p_{C_{max}} \\
SOC(t) & = SOC(t-1) + \int_{t-1}^{t} P_C dt \\
SOC_{min} & \leq SOC(t) \leq SOC_{max}
\end{align*}$$ \hspace{1cm} (11)

In the formula, $SOC_{max}$ and $SOC_{min}$ are the upper and lower limits of the SOC value of the supercapacitor.

4.3 Solving multiobjective optimization model based on NSGA-III algorithm

In practical engineering applications, the NSGA-III algorithm is commonly used to solve multiobjective optimization models. The output optimization model of the hybrid energy storage system in this paper is a multiobjective optimization problem. This paper needs to minimize the deviation of the high- and low-frequency components from the output of supercapacitors and electric vehicles, but it needs to meet the charging and discharging power constraints of the electric vehicle itself and the charging and discharging station. Therefore, this paper uses the NSGA-III algorithm to solve the model.

The NSGA-III algorithm uses cross-mutation operations to generate progeny populations. First, the individual target fitness of the population is calculated. And then the nondominated sorting method is used to divide the combined parent and offspring populations into different nondominated layers. The flow chart of NSGA-III algorithm is shown in Figure 9.

Since the PV output at night is 0, in order to reduce the amount of calculation in the optimization process, the data between 5:00–20:00 is selected for optimization. In the optimization process, the population size is set to 30. After 1000 iterations of the two objective functions using the NSGA-III algorithm, the optimized solution is shown in Figure 10.

This paper uses the TOPSIS method to find the optimal solution from a set of solutions obtained. Through calculation, the 27th solution stands out. At this time, the output of electric vehicles and supercapacitors are shown in the following figure.

It can be seen from Figure 11 that, considering the deviation between the planned output and the actual output and the time, capacity, and power characteristics of the hybrid energy storage system, the output of electric vehicles and supercapacitors is shown in the figure above. It is calculated that the difference in the planned output of the PV energy storage system tracking is the smallest if the electric vehicle and the super capacitor work as shown in the figure above. Figure 12 shows the deviation curve between the total output of the PV energy storage system and the PV project output of tracking.

The above figure shows that when the mathematical model established in this paper is used and the mathematical model established is solved by the proposed method, the average absolute error of the deviation between the actual output of the PV energy storage system and the planned output of the PV can be reduced to 42.7 kW.
Figure 10: The solutions of the two objective functions obtained by NSGA-III optimization.

Figure 11: Accurate distribution curve of hybrid energy storage system output.

Figure 12: The curve of the PV energy storage system error curve and the error of PV project output of tracking.
The above research greatly overcomes the instability of PV power generation, improves the power quality of the power system, and ensures the high-quality output of PV power generation.

5 | CONCLUSIONS

In order to make full use of idle electric vehicles and improve the consumption level of new energy, this paper proposes a method to track PV project output by using a hybrid energy storage system composed of electric vehicles and supercapacitors, and establishes a multiobjective optimization model for energy distribution in the energy storage system. The method proposed in this paper can effectively improve the reliability of PV grid connected and provide a certain theoretical reference for electric vehicles as an energy storage device to assist new energy grid connected. The main conclusions of this paper are as follows:

- In PV output forecasting, based on the traditional method of predicting PV output, the introduction of PCA method can improve the accuracy of the forecast. To be more specific, the mean absolute deviation (MAD) dropped from 60.83 to 33.1; the root mean square error (RMSE) dropped from 38.6 to 11.16.

- The EMD method is used to decompose the deviation between the actual output of PVs and the planned output. According to the different characteristics of electric vehicles and supercapacitors, low-frequency components are allocated to electric vehicles and high-frequency components are allocated to supercapacitors, which can improve the life and economy of energy storage system.

- The NSGA-III algorithm is used to solve the established multiobjective optimization model of the precise energy distribution of the hybrid energy storage system, which effectively realizes the mutual compensation of electric vehicles and supercapacitors. The problem that electric vehicles or supercapacitors cannot completely independently bear low-frequency components and high-frequency components is solved. The goal of minimizing the deviation between the total output of the PV energy storage system and the planned output is achieved.

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**How to cite this article:** Zhao S, Zhou L, Zhang Q, et al. Research on electric vehicle-supercapacitor hybrid system participates in the application of tracking PV project output. *Energy Sci Eng*. 2022;10:120–131. [https://doi.org/10.1002/ese3.1013](https://doi.org/10.1002/ese3.1013)