Adaptive Photovoltaic Power Computer Prediction Technology Using Deep Learning and LSSVM

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Abstract. Under the background of energy Internet, the effective prediction of renewable energy output by digital means is a key link in the realization of energy Internet technology. To solve this problem, an adaptive ultra-short-term PV power prediction method is proposed. The probability density distribution of the error under different weather conditions is analysed in detail. The difference model is used to predict the PV power in different application scenarios. The decision tree algorithm is used to classify different weather conditions, and the input characteristics under different weather conditions are used differently. For sunny and rainy weather conditions, shallow LSSVM and deep confidence network models are used to predict PV output in the future. Finally, the actual PV data of a place in Henan Province is used to verify that the prediction algorithm combined with deep learning and shallow model can effectively deal with the different prediction scenarios.

1. Introduction

In recent years, energy Internet-related technologies have developed rapidly, which makes the boundaries between supply and demand of traditional energy industry change. Primary energy such as coal and oil and secondary energy such as electricity can complement each other [1-3]. One of the key technologies to realize the application of energy Internet is how to use renewable energy efficiently and make distributed generation have plug-and-play capabilities [4-5], which can be used by people at any time. In renewable energy, due to the advantages of large reserves, low cost and easy access, solar photovoltaic has been paid enough attention by researchers. At the same time, it also provides the possibility of coordinated development between energy demand and environment. In order to encourage China's photovoltaic installed capacity to continue to rise in the next few years, at the national level, a large number of scientific and technological funds will be invested and preferential policies will continue to be introduced [6].

Although solar photovoltaic has many advantages, considering the intermittence and fluctuation of photovoltaic output, large capacity integration into the grid will bring trouble to the operation and regulation, so it is particularly critical to establish an accurate prediction model. Aiming at the research of photovoltaic prediction level, the current prediction models mainly include mathematical statistical model and artificial intelligence algorithm [7-9]. Among them, reference [10] analyzes the abnormal form of the data, and uses the variational mode decomposition method to ease the non-stationary of the data, based on which the photovoltaic prediction is carried out. Reference [11] combined with isolated
forest and memory neural network for short-term prediction, the results show that this method can greatly improve the prediction accuracy and effect. In reference [12-13], considering the influence of meteorological factors in photovoltaic power prediction, a prediction method combining empirical mode decomposition with long-term and short-term memory neural network and a prediction method based on ARIMA time series are proposed. In reference [14], a dynamic combination forecasting model was established by using deep learning algorithm. Through in-depth analysis of the above models, it can be seen that although the above methods can accurately predict the photovoltaic power, the calculation is complicated, and some differences in actual conditions are not considered. The photovoltaic prediction model still needs to be further improved. It is necessary to summarize the complex input and output rules under different scenarios, especially the differences between sunny and rainy weather.

Based on the above research, this paper proposes a prediction method combining depth learning and LSSVM model adaptively. The weather types are distinguished by decision tree algorithm. For sunny and rainy weather, shallow model and deep learning model are used to predict respectively. Finally, the accuracy of the algorithm is verified by using the photovoltaic data of Zhengzhou City, Henan Province.

2. Algorithm Mechanism

2.1. Deep Belief Network Model

In the deep belief network model, the system state is generally represented by energy function, where \( v_i \) is used to describe the \( i \)-th visible neuron state and \( h_j \) is used to describe the \( j \)-th hidden neuron state [15]. The energy function \( E(v,h) \) and joint probability distribution function \( P(v,h) \) of the network are related to the state of neurons. The specific calculation process is as follows:

\[
E(v,h) = -\sum_{i=1}^{n_v} \sum_{j=1}^{n_h} w_{ij} v_i h_j - \sum_{i=1}^{n_v} a_i v_i - \sum_{j=1}^{n_h} b_j h_j
\]

\[
P(v,h) = \frac{1}{Z} e^{-E(v,h)}
\]

\[
Z = \sum_{i=1}^{n_v} \sum_{j=1}^{n_h} e^{-E(v,h)}
\]

Where, \( a_i \) -- bias information of visual unit \( i \); \( b_j \) -- bias information of hidden unit \( j \); \( w_{ij} \) -- the weight between visible neuron \( i \) and hidden neuron \( j \); \( n_v \) -- the number of visible neurons; \( n_h \) -- the number of hidden neurons. \( Z \) -- Unified distribution variable.

The optimal parameters of the model are obtained by solving the maximum log likelihood function. If the \( t \)-th input sample is represented by \( v^{(t)} \), it can be calculated by the following formula:

\[
L(\theta) = \sum_{t=1}^{T} \ln P(v^{(t)}, h) = \sum_{t=1}^{T} \left( \ln \sum_{\eta_h} e^{-E(v^{(t)}, h)} \right) - \ln \sum_{\eta_v, \eta_h} e^{-E(v, h)}
\]

\[
\theta = \arg \max \ L(\theta) = \arg \max \ \sum_{t=1}^{T} P(v^{(t)}, h)
\]

2.2. Support Vector Machine Model

Least Squares Support Vector Machine (LSSVM) was first proposed by Suykens J.A.K et al. It is based on Support Vector Machine (SVM) and uses least squares linear system to construct loss function, which
greatly simplifies the calculation process. The sample of an n-dimensional vector is represented by $(x_1, y_1), (x_l, y_l)$. And through nonlinear mapping $\Phi(x)$, the sample data is transformed from the original space $\mathbb{R}^n$ to the feature space $\Phi(x) = \left(\Phi(x_1), \Phi(x_2), ..., \Phi(x_l)\right)$. In this high dimensional space, we continue to construct the optimal decision function:

$$f(x) = w^T \Phi(x) + b$$  \hspace{1cm} (6)

Where, $w^T$ -- weight vector, $b$ -- deviation amount. According to the principle of minimizing the risk structure, the original LSSVM optimization problem can be further transformed into:

$$\min \frac{1}{2} w^T w + c \sum_{i=1}^{l} \xi_i^2 \hspace{1cm} \text{s.t.} \hspace{0.2cm} y = w^T \Phi(x_i) + b + \xi_i \hspace{0.2cm} (i = 1 \sim l)$$  \hspace{1cm} (7)

Where, $c$ -- penalty factor, $\xi_i$-- relaxation variable. At this time, the conventional Lagrange multiplier method can be used to solve the optimization problem:

$$L(w, b, \xi, \alpha) = \frac{1}{2} w^T w + c \sum_{i=1}^{l} \xi_i^2 - \sum_{i=1}^{l} \alpha_i [w^T \Phi(x_i) + b + \xi_i - y_i]$$  \hspace{1cm} (8)

Where, $\alpha_i$ -- Lagrange multiplier. The optimal case generally needs to satisfy the following conditions $\frac{\partial L}{\partial w} = 0, \frac{\partial L}{\partial b} = 0, \frac{\partial L}{\partial \xi_i} = 0, \frac{\partial L}{\partial \alpha_i} = 0$. Therefore:

$$w = \sum_{i=1}^{l} \alpha_i \Phi(x_i)$$

$$\sum_{i=1}^{l} \alpha_i = 0$$

$$\alpha_i = c \xi_i$$

$$w \cdot \Phi(x_i) + b + \xi_i - y_i = 0$$

Define the kernel function $K(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j)$, where $K(x_i, x_j)$ is a symmetric function satisfying Mercer condition. In this paper, we choose the more commonly used radial basis kernel function $K(x, x_i) = \exp \left(\frac{|x - x_i|^2}{2 \sigma^2}\right)$, where $\sigma$ is the kernel width. Then, the optimization problem of LSSVM can be transformed into:

$$\begin{bmatrix}
0 & 1 & \cdots
1 & K(x_i, x_j) + 1/c & \cdots
\vdots & \vdots & \ddots
1 & K(x_i, x_j) & \cdots & K(x_i, x_j) + 1/c
\end{bmatrix}
\begin{bmatrix}
\alpha_1 \\
\vdots \\
\alpha_l \\
\vdots \\
y_1
\end{bmatrix}
\begin{bmatrix}
b \\
y_1 \\
\vdots \\
y_l
\end{bmatrix} =
\begin{bmatrix}
0 \\
\vdots \\
y_1
\end{bmatrix}$$  \hspace{1cm} (10)

The regression function of LSSVM model is obtained:

$$f(x) = \sum_{i=1}^{l} \alpha_i K(x_i, x) + b$$  \hspace{1cm} (11)

3. Model Establishment

There are some errors in photovoltaic prediction in each scenario, and the error distribution is mainly affected by the relevant characteristics of photovoltaic output. In cloudy and other non-clear weather conditions, the clouds are randomly distributed in the sky, and the radiation intensity received by photovoltaic panels changes in a non-linear form. Therefore, the output will fluctuate greatly in a short period of time, and the shape of the output curve has strong randomness. The photovoltaic output under this type of weather conditions will be affected by multiple characteristic factors at the same time. In
the process of prediction, we should keep as many data features as possible. In this case, the deep belief algorithm based on deep learning can deeply mine the relationship between each feature, and the prediction effect is more ideal.

In the cloudless clear weather conditions, the solar radiation intensity is mainly related to time, and changes according to certain rules over time. At this time, the photovoltaic output is relatively stable, and the shape of power curve changes smoothly. In this type of weather conditions, the photovoltaic output is only related to the dominant factors such as solar radiation intensity and temperature. Good prediction results can be obtained by LSSVM through more simple calculation. Under the condition of "stable weather", the adaptive model can effectively shorten the training time by using the characteristics of output data and a small amount of mining to replace the original large amount of meteorological data. In this way, the cost is reduced on the premise of ensuring the prediction accuracy, and the prediction is easier to achieve.

Figure 1. Adaptive photovoltaic prediction model for energy Internet.

4. Example Analysis
In this paper, the data of a photovoltaic power station in Henan Province is used for verification. The installed photovoltaic capacity is 1MW, and the prediction target is the photovoltaic output in the next hour. The stable weather and unstable weather are selected respectively for analysis. The input features include light intensity, temperature, humidity, etc. The data are from the field data of photovoltaic power
Taking the relevant data from January to April 2015 as the training data, use the relevant data from May 1 to May 15, 2015 for testing. In this paper, mean relative error (MAPE) and root mean square error (RMSE) are used as the error indicators, and the calculation methods are as follows:

\[
MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{c_i - d_i}{c_i} \right| \times 100\%
\]

(12)

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (c_i - d_i)^2} \times 100\%
\]

(13)

Where \( n \) -- the number of samples in the data set; \( c_i \) -- the real value of each prediction task at time \( i \); \( d_i \) -- the prediction value of each prediction task at time \( i \). The distinction between different weather in this paper comes from the analysis of the radiation degree in numerical weather forecast. When the radiation degree changes greatly, it is judged as unstable weather, and the stable weather is judged when the radiation degree changes less.

4.1. Prediction Effect Analysis

In this paper, the prediction results of stable weather and unstable weather are analyzed respectively, so a certain day in the test set is selected for comparative analysis, and compared with the prediction results obtained by traditional neural network algorithm. Figure 2 and Figure 3 show the prediction results of different algorithms in stable and unstable weather.

![Figure 2. PV prediction analysis on stable weather.](image)
Figure 3. PV prediction analysis on unstable weather.

It can be seen from Figure 3 and Figure 4 that the prediction accuracy difference between adaptive algorithm and ANN algorithm is relatively small under stable weather. The results of photovoltaic prediction error under unstable weather are generally large, which is due to the continuous change of weather has an impact on the photovoltaic output. Compared with ANN algorithm, the adaptive learning method proposed in this paper can achieve better model training state and prediction accuracy in stable and unstable weather.

5. Conclusion
In this paper, the influence of weather conditions on the accuracy of photovoltaic output prediction is fully considered, and an adaptive learning prediction method is proposed to predict the photovoltaic output under different weather conditions. For sunny weather and rainy weather, LSSVM model and deep learning model are used to analyze, and photovoltaic output in the future is predicted. Through the prediction analysis of the actual photovoltaic data in Henan Province, it is proved that the prediction algorithm combining deep learning with shallow model can effectively deal with the differentiated prediction scenarios.

Acknowledgments
This work was financially supported by Science and technology project of China Electric Power Construction Group (2018-KJ009) fund.

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