Optimized prediction of solar irradiation based on MPC and ELM neural network

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Abstract. Based on the characteristics of randomness and instability of solar radiation, this paper presents an optimal prediction algorithm of solar radiation based on Model Predictive Control (MPC) and Extreme Learning Machine (ELM). Firstly, the meteorological factors directly related to solar radiation are selected to determine the input attributes; secondly, the weather forecast and historical irradiance information at the current time are used as inputs, and the irradiance at the current time is used as the output to predict the solar irradiance; finally, the MPC rolling optimization idea is used to realize the optimal processing of solar radiation prediction data. The simulation results show that MPC-ELM algorithm has smaller simulation error than other algorithms, which shows that the algorithm has more advantages.

1. Introduction

In recent years, photovoltaic power generation has become the main form of renewable energy power generation in the world. Solar energy itself is intermittent, fluctuating, and unpredictable [1]. Exploring and finding an accurate method of solar irradiance information collection and prediction is the basis for accurately predicting photovoltaic power.

At present, the common prediction methods can be divided into two categories. The first method is based on the detailed numerical weather prediction, which uses the observed numerical weather information and the physical calculation model of the radiation amount to predict the ultra-short-term solar radiation amount. In [12], a series of image processing was carried out for the ground-based cloud map to predict the solar irradiance five minutes later with the historical irradiance data. In [15], the correlation between meteorological elements and photovoltaic output power is analysed by using correlation coefficient method. Although the prediction accuracy of this kind of method is high, it needs complex satellite.
In the second category, by modelling historical data, we can simulate the change rule of irradiance, and then predict the future irradiance. For example, a Markov mathematical model is proposed in [10], and an RBF neural network prediction model is proposed in [2]. Although this method can consider all kinds of environmental factors, it usually has many disadvantages. In [13], it is pointed out that the disadvantage of the previous irradiance prediction model is that the input space dimension is too high, which makes its structure too complex and brings great difficulties to learning and training.

Based on the single-hidden layer feedforward neural networks (SLFNs) learning algorithm, Huang G.B. and others proposed the ELM, which is a kind of machine learning system or method. ELM has been proved to have a very fast learning speed in regression analysis, classification, prediction and other fields, which can overcome the problems of local minimum, over fitting and inappropriate selection of learning rate of the traditional gradient algorithm [5]. The improved GA-ELM neural network algorithm proposed in [4] optimizes the parameters, and a PCA-GA-ELM prediction model proposed in [14] avoids the influence of input weight matrix and the randomness of hidden layer deviation on the prediction accuracy of ELM, but it lacks the link of feedback correction, which will increase the prediction error of the model.

MPC is one of the only advanced control methods that has been successfully applied to industrial control. The optimization process of predictive control is not finished off-line at one time, but repeated on-line in a limited moving time interval. MPC is also a feedback control algorithm, which has strong anti-interference ability and robustness. At the same time, MPC can easily take into account a variety of constraints, and it has no specific requirements for the form of prediction model, which is suitable for the prediction of solar radiation resources including the randomness of solar radiation resources, the intermittence and volatility of photovoltaic power generation and other factors.

In this paper, the algorithm principle of ELM neural network, the rolling optimization process of MPC and the combined algorithm are introduced respectively in Section 2. In Section 3, an example is used to analyse the prediction results. Compared with other prediction algorithms, Section 4 gives a conclusion.

2. Prediction model of solar irradiance based on MPC and ELM neural network

2.1 ELM neural network principle

The typical structure of ELM is shown in Figure 1. Let the model have \(n\) input nodes, \(L\) hidden layer nodes, and \(m\) output nodes [7].

The output is:

\[
y_j = \sum_{i=1}^{L} \beta_i g(w_i \cdot x_j + b_i), j = 1, 2, \ldots, N
\]  

(1)

Assume \(\{x_j, t_j\}_{i=1}^{N} \subset \mathbb{R}^n \times \mathbb{R}^m\) is a given set of samples, \(t_j\) is the ideal output of input \(x_j\), \(N\) is the total number of sample sets. Where \(x = (x_1, x_2, \ldots, x_n) \in \mathbb{R}^n\) is the input of the neural network, \(g(x)\) is called the feature map or excitation function, \(w_i\) with \(b_i\) are the parameters of the feature map, also called node parameters in ELM, where \(w_i\) is the feature weight, \(b_i\) is the bias value of the \(i\)th hidden layer node, also known as the threshold value of the \(i\)th hidden layer node, \(y \in \mathbb{R}^m\) is the output vector, \(\beta_i = (\beta_{i1}, \beta_{i2}, \ldots, \beta_{im})^T \in \mathbb{R}^m\) is the weight vector from the hidden layer to the output layer of the \(i\)th node.

It is abbreviated in matrix form:

\[
H \beta = Y
\]  

(2)

Among them, \(H\) is the output of the hidden layer node, and \(Y\) is the component content output value of the model.

\[
H(w_1, w_2, \ldots, w_L, x_1, x_2, \ldots, x_N, b_1, b_2, \ldots, b_L) = \begin{bmatrix}
g(w_1 \cdot x_1 + b_1) & \ldots & g(w_L \cdot x_1 + b_L) \\
\vdots & \ddots & \vdots \\
g(w_1 \cdot x_N + b_1) & \ldots & g(w_L \cdot x_N + b_L)
\end{bmatrix}_{N \times L}
\]  

(3)

In ELM neural network, meteorological factors directly related to solar radiation amount need to be selected as input variables, such as cloud amount, ambient temperature and relative humidity. Then
historical radiation amount, ambient temperature, cloud amount and relative humidity are determined as input attributes [5]. In this model, the parameters with are all randomly generated. Once determined, the output matrix $H$ of the hidden layer is uniquely determined, and the output value of the ELM neural network model is also uniquely determined.

2.2 Model predictive control algorithm

The action mechanism is described as: at each adoption time, based on the current measurement information obtained, a finite-time open-loop optimization problem is solved online, and the first element of the obtained control sequence is applied to the controlled object. At the next sampling time, the above process is repeated: the new measurement value is used as the initial condition for predicting the future dynamics of the system at this time, the optimization problem is refreshed and re-solved.

In the actual process, due to the existence of non-linear, model mismatch and interference and other uncertain factors, the model-based prediction cannot be accurately consistent with the actual. The core idea of MPC is rolling optimization and feedback correction. The rolling optimization process is shown in Figure 2.

Assuming that the current system is running at time $t$, the system state at time $t$ is collected, and the output at time $t+1$ is predicted according to the state at time $t$ and the control input at time $t$. On the basis of knowing the prediction information of the system disturbance variables in the future time domain, the solar radiation resource prediction in the time domain is predicted with the objective of minimizing the error. The optimization result is only used in one control time domain, and the optimization process is repeated at $t+1$ time.

2.3 MPC and ELM neural network combined irradiation dose prediction algorithm

The MPC and ELM neural network prediction process is shown in Figure 3.

In the process of ELM prediction, the historical irradiance samples need to be divided into training set, test set and prediction set, and each input data needs to be normalized. Then the optimal number of hidden layer nodes is determined by training set and test set, and the corresponding parameters are
obtained. Finally, the parameters are applied to the prediction set to realize the prediction of n time series in the future.

At time t, determine the optimal control increment \( \Delta u(t) \), transfer \( \Delta u(t) \) to the process, advance to time \( t + 1 \), replace time t with time \( t+1 \), and then get \( \Delta u(t + 1) \), and then transfer it to the process, so as to realize rolling optimization. In the process of operation, due to the existence of model deviation and external disturbance, the predicted value will have deviation, so it is necessary to feed it back and correct the predicted value in time.

Because of the length of sunshine time, only 6:00-18:00 is selected as the prediction period, hourly prediction, so that \( n = 3 \), that is, at 5:00, according to the historical data, the elm neural network is used to predict the results of 6:00, 7:00, 8:00 and 9:00 at the next four times, and rolling optimization and feedback correction are carried out from 6:00, so 13 cycles of optimization and correction are needed in a day.

2.4 Predictive process design

2.4.1 Select historical data samples. Use the historical resource data of the existing database as the main training data for the prediction neural network model, and obtain the radiation dose and environmental factor data from 2014 to 2019. Divide the radiation dose samples into training sets, test sets and prediction sets.

2.4.2 Normalize the data. Use MATLAB software to normalize the input attributes and historically. The amount of light, ambient temperature, relative humidity, and cloud cover are mapped to \((0,1)\) for processing. Normalized formula:

\[
x_i^* (t) = \frac{x_i(t) - x_{i_{\text{min}}}}{x_{i_{\text{max}}} - x_{i_{\text{min}}}}
\]

Where \( x_i(t) \) and \( x_i^* (t) \) respectively represent the values before and after normalization of data at time \( t \), \( x_{i_{\text{min}}} \) and \( x_{i_{\text{max}}} \) represent the minimum and maximum values in the sample data.

2.4.3 Predict solar irradiance. Determine the output value of ELM neural network model, and complete the solar irradiance prediction sequence at 6:00, 7:00, 8:00 and 9:00 on the prediction day.

2.4.4 Use the idea of MPC rolling optimization, correct and evaluate. Taking the solar irradiance data and weather conditions at 6:00 as the input, using ELM model to predict the solar irradiance at 7:00, using the finite time domain optimization strategy of time rolling forward to realize the rolling prediction time by time. Realize the feedback correction. Select MAPE and RMSE to evaluate the revised prediction results [9].

3. Prediction effect analysis

This paper establishes three models (the first is BP model, the second is ELM model, the third is MPC and ELM combined model) to predict the solar radiation, and the comparison shows that the model combining MPC and ELM has higher prediction accuracy. The historical radiation data, ambient temperature, relative humidity, and cloud cover are used as the input of the model to predict the solar radiation amount on the forecast day.

Taking Nanjing as an example, the solar irradiance from 2014 to 2018 was studied and analysed. March 11, 2019, March 20, 2019, March 31, 2019 and April 8, 2019 were selected as examples for prediction. The prediction interval was one hour. Considering the length of sunshine, the weather variables and irradiance of 13 whole time points between 06:00-18:00 were selected as the daily prediction time. The predicted results are shown in Figure 4, Figure 5, Figure 6, Figure 7.

Select prediction accuracy measures to evaluate the revised prediction results:

\[
\text{MAPE} = \frac{1}{N} \sum_{t=1}^{N} \left| \frac{Y(t) - Y_m(t)}{Y(t)} \right| \\
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (Y(t) - Y_m(t))^2}
\]

(5)
Where, $Y(t)$ and $Y_m(t)$ are the measured value and predicted value respectively, and $N$ is the number of predicted time points. The error analysis period is also 06:00 to 18:00. The error analysis results are shown in Table 1.

Table 1. Error analysis of prediction results of three models.

| data   | MAPE/% | RMSE/% |
|--------|--------|--------|
|        | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
| March 11 | 43.37   | 38.96   | 26.45   | 133.13  | 76.38   | 44.77   |
| March 20 | 25.53   | 17.73   | 8.76    | 105.64  | 52.89   | 43.75   |
| March 31 | 29.56   | 24.38   | 15.44   | 103.55  | 47.48   | 38.63   |
| April 8  | 83.57   | 58.39   | 45.63   | 128.54  | 88.46   | 53.53   |

Figure 4. Prediction results of solar radiation on March 11, 2019.

Figure 5. Prediction results of solar radiation on March 20, 2019.

Figure 6. Prediction results of solar radiation on March 31, 2019.

Figure 7. Prediction results of solar radiation on April 8, 2019.

4. Conclusion

The prediction model based on the MPC-ELM neural network is proposed in this paper. Firstly, the solar irradiance of a period of time series is predicted by ELM neural network. Then, using the rolling optimization idea of MPC, the prediction value of the nearest time point is continuously used for rolling prediction with feedback correction to achieve the optimal processing of solar irradiance prediction data. This algorithm makes use of the advantages of MPC and ELM, improves the prediction accuracy, and is of great significance for accurate prediction of photovoltaic power generation. The experimental
results show that the proposed algorithm can significantly improve the accuracy of solar radiation prediction and provide the basis for the interval prediction of photovoltaic power generation.

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