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Performance Enhancement Based on Integrated Learning and Deep Neural Networks in Ultra-Short-Term Forecasting of Wind Energy

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Abstract In order to improve the ultra-short-term prediction accuracy of wind power, this paper proposes an ultra-short-term prediction model for wind power based on integrated learning and deep neural network (Bagging-DNN). The method is based on Bagging and DNN, using Bootstrap method to generate sample sets, and training for different training subsets to obtain multiple integrated deep neural network models. By calculating the output of each model, the ultra-short-term prediction results of wind power are obtained. The analysis based on a case study of an offshore wind farm in Shanghai shows that the MAPE of this paper's model is 5.0078% and 10.9658% when predicting 1h and 4h in advance. The MAPEs are on average 2.4% and 6% smaller than those of other methods, indicating that their prediction accuracy is higher than that of other prediction models. Compared with the BP and LSTM models, the square model in this paper has a narrower width of prediction interval, shorter training time, and more superior performance. In the process of iterative training, the model in this paper has a superior fitting effect.

Index Terms wind power ultra-short-term, Bagging-DNN, integrated learning, deep neural network

I. Introduction

The main impetus for the economic development of modern society relies on electricity, which provides power for the production and development of enterprises and also facilitates the daily life of the people and improves their quality of life. In recent years, there have been a number of power outages caused by the tight supply and demand of electricity, which affected the normal planning of the state, required the state to urgently mobilize resources to maintain social order, hindered the normal production activities of enterprises, and caused a serious impact on the normal functioning of the society, resulting in a large number of economic losses, and also had a greater impact on the daily life of the residents [1]-[3]. With the gradual implementation of China's "dual-carbon" work, the use of renewable resources has been rapidly developed, and the key area for realizing the "dual-carbon" goal is the electric power sector, which needs to shift from thermal power generation to a new type of electric power system that is mainly based on clean energy generation [4], [5].

Wind energy, as the most important energy source in the future development of renewable energy, has lower carbon emissions than other renewable energy sources in the process of production and use. Compared with coal as the main energy source of thermal power generation, the carbon emissions of wind power generation in the whole life cycle is less than 11% of thermal power generation, and the land use of wind power generation is the smallest among the different forms of renewable energy power generation, and the tower required for the construction of wind power generation occupies an area of less than 200 square meters [6]-[9]. In addition to this, wind power has a relatively high power density and generates electricity for a longer period of time, making it convenient to replace thermal power in future new power systems or to complement other energy sources [10], [11]. Compared with other clean energy sources, wind power has a short construction period and high power density, and it is the main power source in the new power system in the future. Therefore, in order to ensure the smooth development of China's economy and society, and also to achieve the goal of "double carbon" with higher quality, it is necessary to realize the accurate prediction of wind power generation in the future period, so as to make timely adjustments to the power dispatch scheme of the power system according to the prediction results. Especially in the case of a sudden decrease in wind power generation, other power generation programs can be dispatched in time to ensure the stable operation of the power system, which can also promote the positioning of thermal power from the main source of energy to a guaranteed supply of energy, and promote the transformation of China's economic development and industrial structure to a low-carbon society [12]-[16]. However, under the multiple spatio-temporal effects, the wind power installation is affected by the external chaotic characteristics, showing turbulent inertia delays, and there is an anomalous situation of excessive energy aggregation within the equipment, and the correlation coefficient of power fluctuation increases in the operation process, and the error rate of the wind power ultrashort-term prediction is increasing, limiting the prediction performance [17]-[20]. In summary, in order to realize stable wind power generation, it is of great significance to improve the performance of wind power ultra-short-term prediction.

This paper focuses on combining Bagging and DNN models to propose an ultra-short-term wind power prediction method integrating deep neural networks. Taking an offshore wind farm in Shanghai area as the research object, the historical load time series data of the wind farm and its meteorological variables such as wind speed, wind direction, air pressure, air temperature and humidity are monitored and collected through the data acquisition and surveillance control system. The training sample set is constructed according to Bagging and DNN model input dimensions and output dimensions. After completing the training of the DNN model, the load time series data and its meteorological variables were input for testing, and the prediction output of each Bagging and DNN model was obtained. Comparison is made with the existing models to explore the superiority of the models in this paper.

II. Power generated by wind farms

Wind has strong intermittency and volatility, and wind power output depends on the size of the wind speed, so it also has strong intermittency and volatility. When the grid-connected wind power capacity is small, the impact of wind power fluctuations on the power system is not obvious. With the increase of wind power capacity in the power system, the impact on the power system is more and more obvious. When the grid-connected wind power capacity exceeds the wind power penetration power limit system can accept the maximum installed wind power capacity as a percentage of the maximum load of the system, it will bring serious adverse impacts to the power grid Teng [21]. Wind power disturbances brought about by wind speed variations can seriously affect the power quality of the grid, such as causing voltage fluctuations and flicker, frequency deviations, and harmonic problems, and can also have an impact on the stability of the grid and reduce the reliability of the system operation. If the wind speed and power generation of wind farms can be accurately forecast, and the characteristics of wind power are fully considered in the formulation and adjustment of the system scheduling and operation plan, the power quality of the grid can be effectively ensured, reducing the demand for system standby capacity and lowering the operating costs of the power system. This is an effective way to reduce the impact of large-scale grid-connected wind power on the power system and improve the grid-connected capacity of wind power. In addition, accurate ultra-short-term wind speed prediction for wind farms can reduce voltage and frequency fluctuations due to sudden cut-outs of wind turbines, which plays an important role in both grid-connected operation of wind farms and control of wind turbines improves the grid-connected capacity of wind power from the point of view of control of wind farms [22].

The output power of the wind turbine is:

$$P_w = \frac{1}{2} C_p A \rho v^3 \tag{1}$$

where: C_p is the rotor performance coefficient; A is the wind turbine swept area, m2; ρ is the air mass density, kg/m³; v is the wind speed, m/s; P_w is the output power, kW.

The relationship between air mass density and atmospheric pressure, temperature and relative humidity is:

$$\rho = 3.48 \frac{P}{T}(1 - 0.378 \frac{\varphi P_b}{P}) \tag{2}$$

where: P is the normal atmospheric pressure; T is the thermodynamic temperature; P_b is the saturated vapor pressure; φ is the relative air humidity.

As shown in equations (1) and (2), the fan output power is related to wind speed, temperature, humidity and pressure. Among them, wind speed is the most important factor. Among these factors, different factors affect the wind power to different degrees. Too few predictive factors can lead to a lack of information to adequately reflect changes in wind power. Too many predictors can lead to redundancy of information and high model complexity, thus decreasing robustness and generalization performance. Some of the current studies model future values of predicted power based only on historical values of wind power and do not take into account the role of the wind farm environment on wind power, which makes the model less capable of reasoning.

III. Bagging and DNN models

III. A. Bagging Model

Bagging model is an integrated learning model that generates different training subsets by autonomous sampling from a given dataset, and trains individual learners for each type of training subset. On this basis, individual learners are integrated using voting method and weighting. Studies have shown that the integrated learning method based on Bagging can effectively reduce the variance of the model output and strengthen its generalization ability [23]. The Bagging algorithm flow is shown in Figure 1.

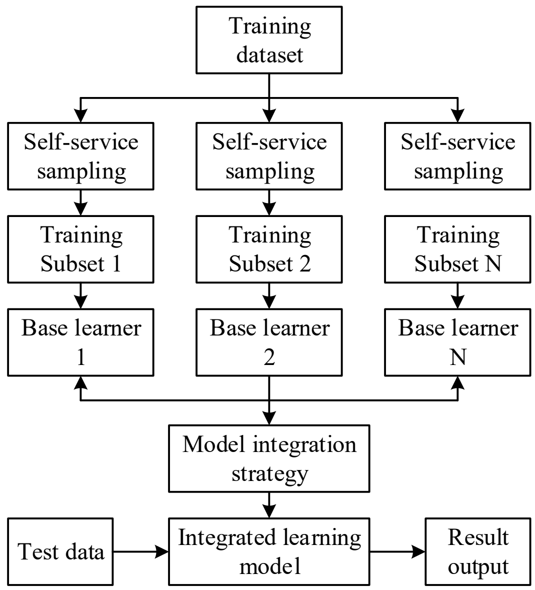

Figure 1: shows the process of the Bagging algorithm

III. B. DNN models

Deep Neural Network (DNN) model is developed on the basis of BPNN model. The traditional BPNN network model consists of input layer, hidden layer, and output layer, and the composition structure is simple.The DNN network model, compared to the BPNN model, has multiple hidden layers internally, and calculates and passes the outputs of the layers layer by layer through the connection weights, node thresholds, and their activation functions between the input layer, hidden layer, and output layer, and ultimately obtains the output value of the network. Where the input of the network is $X=\{x_1,x_2,\cdots,x_m\}$ and the output of the network is $Y=\{y_1,y_2,\cdots,y_n\}$ [24]. As a supervised training model, the training steps of DNN are summarized as follows.

STEP1: Set the number of hidden layers L, the number of nodes in each layer $p_l(l=1,2,\cdots,L)$, initialize the weights between the hidden layer, the output layer W_t, the offset vectors $b_l(l=2,3,\cdots,L)$, the learning rate η, the iteration threshold ε, and neuron activation function $f(\cdot)$. The activation function generally adopts ReLU function, tanh function, and its expression is shown in Eq. (3) and Eq. (4):

$$f(x)=\max(0,x) \tag{3}$$

$$f(x)=(e^x-e^{-x})/(e^x+e^{-x}) \tag{4}$$

STEP2: Compute the hidden layer and output layer output H_l:

$$H_l=f(z_l)=f(W_lY_{l-1}+b_l),l=2,3,\cdots,L \tag{5}$$

STEP3: Compute the loss function J, the output layer gradient δ_L:

$$J(W,b,X,Y)=\frac{1}{2}\|H_L-Y\|_2^2 \tag{6}$$

$$\delta_L=J(W,b,X,Y)\otimes f'(z_L) \tag{7}$$

STEP4: Compute the hidden layer gradient δ_l:

$$\delta_L = (W_{l+1})^T \delta_{l+1} \otimes f'(z_L), l = L-1, L-2, \cdots, 2 \tag{8}$$

STEP5: Calculate the hidden layer, output layer weight matrix W_l and offset vector b_l:

$$W_l = W_l - \eta \delta_l (H_{l-1})^T \tag{9}$$

$$b_l = b_1 - \eta \delta_l, l = 2,3,\cdots,L \tag{10}$$

STEP6: If the training process reaches the upper limit of the number of iterations or satisfies the error constraints, the training process ends. Otherwise, go to the second step.

IV. Ultra-short-term power prediction for wind power based on integrated deep neural network

IV. A. Overall framework for ultra-short-term wind power forecasting

In this paper, an ultra-short-term wind power prediction method combining Bagging and DNN modeling is proposed. The data sources are the historical measurement records from the database of the data acquisition and supervisory control (SCADA) system of a wind farm in Shanghai and the meteorological variables of the NWP model. The forecasting system uses the meteorological forecasts of the NWP model obtained near a wind farm and the actual measurement data from the database of the SCADA system of the wind farm. The proposed method is realized in two stages: in the first stage, a combined GRU and CNN prediction model is constructed with NWP meteorological variables (i.e., wind speed, wind direction, air pressure, air temperature, and humidity) as well as actual wind speed measurements recorded by the wind farm SCADA system. In the second stage, the combined Bagging and DNN model is trained under real operating conditions and maps wind power based on wind turbine wind speed and wind power generation characteristics. Finally, the Bagging and DNN models trained in the second stage are applied to obtain wind power output prediction results for the next day of the wind farm.

The performance of this approach for wind power prediction is dependent on the number of NWP models; therefore, the main focus of the study is to utilize NWP data. These data play an auxiliary role in wind power prediction, thus improving the accuracy of short-term prediction.

In the modeling process, one year of information records provided by SCADA historical measurements and NWP/WRF model historical weather forecasts are used to train the combined Bagging and DNN model. This combined Bagging and DNN model can successfully estimate the transfer function between specific input and output quantity patterns. The activation function is next used to optimize the parameters and this process continues until the prediction error reaches a suitable range.

IV. B. Ultra-short-term power prediction process for wind power

Taking the value of input dimension as 20 and the value of forecasting days h as 7, it means that the short-term load sequence and its influencing factors data of the past 21 days are utilized as inputs to the forecasting model to realize the forecasting of the short-term load profile for the next 7 days.

The steps of ultra-short-term forecasting of wind power based on integrated learning and deep neural network are as follows.

Step1 Data preparation: determine the dimension t and the number of prediction days h, construct $D(i,t), Q_d(i,h)$, and normalize it to form the overall sample set D, and the sample set is disrupted by rows.

Step2 Model preparation: set the DNN base learner parameters, and the number of base learners N.

Step3 Data sampling: utilize Bootstrap method to draw sample subsets $D_i(i=1,2,\cdots,N)$ from the overall sample set with putback.

Step4 Model training: train the base learner $M_i(i=1,2,\cdots,N)$ in parallel for different training subsets $D_i(i=1,2,\cdots,N)$.

Step5 Output phase: input the input data $D(i,t)$ for the day to be predicted and calculate the output of each base learner. On this basis, combine N base learner models and output the integrated prediction result as $O(D(i,t)) = \frac{1}{N}\sum_{k=1}^{N} M_i(D(i,t))$.

IV. C. Data processing

The prediction of wind power has to utilize multivariate time series, which can result in large quantitative differences due to differences in the scale of the different variables. Therefore, in order to more comprehensively and fairly consider the impact of each factor variable, it is necessary to normalize each variable and the wind power time series, which also allows for a quick determination of whether or not there are outliers that need to be removed. When asked, unique time points are ensured by de-duplicating data to ensure unique time points and forging missing values to fill in very simple forward points.

Due to the non-periodic trend of the weather data, the signal is transformed from non-stationary to stationary by means of first-order differencing, and wind speed, temperature, atmospheric density, and wind electric power are treated by normalizing the sample data by the limiting value, which returns the values to [-1, 1]:

$$x' = \frac{x-(x_{\max}+x_{\min})/2}{(x_{\max}-x_{\min})/2} \tag{11}$$

where: $x_{\min}$ and $x_{\max}$ are the very small and very large values of the variable, respectively.

In order for the final data results to represent their physical significance, the obtained wind power prediction data results also need to be back-normalized:

$$x = 0.5\left[x'(x_{\max}-x_{\min})+(x_{\max}+x_{\min})\right] \tag{12}$$

IV. D. Criteria for assessing errors in forecasting results

The accuracy of a load forecasting model depends on the degree of deviation between the forecast and the true value. The smaller the degree of deviation, the higher the prediction accuracy. Therefore, in order to quantitatively compare the prediction effect of the model, the mean absolute percentage error (MAPE), root mean square error (RMSE), and mean absolute error (MAE) are chosen as quantitative evaluation indexes in this paper. The definitions of each index are shown in equations (13) to (15):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{Y_t-\hat{Y}_t}{Y_t} \tag{13}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t-\hat{Y}_t)^2} \tag{14}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t-\hat{Y}_t\right| \tag{15}$$

V. Analysis of examples

V. A. Overview of the algorithm

In this paper, data from an offshore wind farm in the Shanghai region is selected for analysis, and the prediction model is trained using the June 2018 SCADA data of 34 units in this wind farm. The unit state model is trained using the relevant data of each unit 24h ago. During the neural network training, the slurry pitch angle data is added to facilitate learning the power characteristics of the units when the rated wind speed is exceeded, and the wind direction sinusoidal value to strengthen the spatial characteristics of the data.The interval sampling time of the SCADA data is 10 min, and the uniform time interval is 15 min using the method of sampling interval transformation.The SCADA data of the wind turbines may contain a large amount of abnormal and duplicate data, and inputting to the model Excessive duplicate data may complicate calculations and may lead to unnecessary output. Normalization of data is a method of transforming unprocessed data into similar scales, which helps to improve the convergence speed and prediction accuracy of model training.

V. B. Assessment of model prediction performance

V. B. 1) Comparison of prediction performance

In order to verify the advancement of the method in this paper, the model proposed in this paper is compared and analyzed with another four prediction methods, Method 1 is the traditional autoregressive sliding average (ARMA) prediction model, Method 2 is the BP neural network prediction model, Method 3 is the LSTM neural network prediction model, and Method 4 is the fluctuation law mining method, and the sample data and the prediction target data used in several methods are exactly the same. In this paper, the mean absolute percentage error (MAPE, M) and root mean square error (RMSE, R) are used as the error evaluation criteria to assess the model prediction accuracy. The wind power data provided by NREL for the whole year of 2018 are predicted with different methods for different time steps, L is also taken as 30, and the prediction results for the four seasons are shown in Table 1. By analyzing the data in the table, it can be learned that the prediction error of the method proposed in this paper is lower than that of the prediction methods exemplified by ARMA, BP, and LSTM. 4h prediction, the value of its prediction error MAPE is less than 12%, which can satisfy the industry requirements. Specifically analyzing the spring data, when predicting 1h in advance, the MAPE of this paper's method is 5.0078%, which is 2.4% smaller than the average MAPE of the comparison methods. When forecasting 4h in advance, the MAPE of this paper's method is 10.9658%, which is 6% smaller than the average MAPE of the comparative methods, which fully illustrates the superiority of the method proposed in this paper. In summary, the method proposed in this paper has a higher prediction accuracy than other prediction models in the ultra-short-term prediction of wind power, which can meet the requirements of the industry.

Table 1: Comparison of forecast results for four seasons

Step length/h	Model	Spring		Summer		Autumn		Winter	
		M%	R%	M%	R%	M%	R%	M%	R%
1	ARMA	6.8632	1.7898	4.7946	1.1919	4.543	2.5133	6.4323	4.6635
	BP	9.9676	2.3263	6.1445	1.9522	4.4338	1.5374	5.9873	2.7941
	LSTM	7.2147	2.1226	9.7427	2.9672	4.2261	1.5616	7.893	5.1976
	Wave pattern mining	5.5784	1.5516	5.4465	1.2039	3.8872	1.3741	5.8106	2.9156
	Methods of this article	5.0078	1.5149	5.1956	1.1746	3.3994	1.1764	5.1655	2.3219
2	ARMA	9.0325	2.2484	11.9031	3.287	5.6988	2.6032	10.9181	8.1443
	BP	12.1955	3.0345	10.184	2.8275	7.6027	2.2602	10.4338	6.7126
	LSTM	9.1461	2.8552	15.1919	4.1891	4.5634	1.6285	9.1695	7.1153
	Wave pattern mining	9.6025	2.7934	9.04	2.5215	5.906	2.2679	9.8195	12.175
	Methods of this article	5.1081	1.6159	9.5923	2.4641	3.7725	1.3286	8.6104	5.6337
3	ARMA	11.9527	3.1305	10.4737	4.1138	5.8398	2.8273	12.8153	11.6739
	BP	15.8903	4.4753	14.4284	3.9705	7.7638	2.4251	10.7999	16.7545
	LSTM	13.7781	3.682	19.0035	5.313	4.2252	1.5241	13.2928	12.9994
	Wave pattern mining	13.7832	4.2502	15.1657	4.4618	7.139	3.0364	13.7383	24.5003
	Methods of this article	7.1209	2.2504	10.2703	3.2053	4.2062	1.4847	9.5515	7.2118
4	ARMA	13.5833	3.7486	16.4033	5.105	12.391	3.1242	11.9644	12.3733
	BP	19.5632	4.4804	15.1672	4.9481	12.5982	3.6077	13.1152	15.3104
	LSTM	15.9605	4.5041	25.4063	7.1487	4.986	1.7898	14.0033	13.3003
	Wave pattern mining	18.8577	5.7823	18.5718	5.8243	12.5318	3.5408	16.9503	36.919
	Methods of this article	10.9658	3.1354	11.0423	2.1358	4.3915	1.5007	11.4091	10.9044

V. B. 2) Comparison of confidence interval widths

Offshore is limited by the strong uncertainty of wind power, and it is particularly important to accurately predict the upper and lower limits under a certain confidence interval of wind farm output when offshore wind farms provide frequency support for the power system. On the one hand, this helps to determine the range of power fluctuation of wind farms to ensure the safe and stable operation of the power system. On the other hand, it can be used to assess the power limit of wind farms, and then determine the power system scheduling and coordinated control instructions within the wind farms, which can help to reduce the system operating costs and improve the efficiency of wind farms.

In this section, the quantile regression function is selected as the loss function of the three algorithms, the 95% confidence interval is chosen, and all three algorithms are trained for 250 cycles, and the results of the comparison of the width of the confidence interval are shown in Fig. 2. For the 95% confidence constraint, the method of this paper and BP, LSTM two belong to the same machine learning algorithm of the

Comparison of prediction intervals. In the single machine wind power prediction, under the constraint of the same confidence level, this paper's algorithm and the BP algorithm for the first 100min of wind speed surge, the superiority is obvious, and its interval envelope better restore the real data fluctuation characteristics, and the upper boundary accurately predicts the shutdown action after 1300min. The LSTM prediction interval is wider, the envelope is smoother, and part of the wind power fluctuation information is lost, and the upper boundary of the LSTM prediction is also difficult to accurately respond to the shutdown condition after about 1300 min.

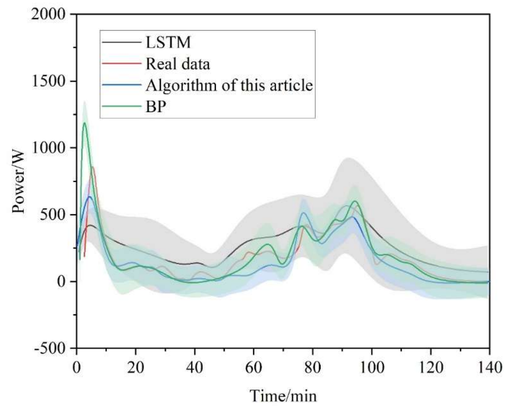

Figure 2: 95% confidence interval

Comparison of the whole field power prediction is shown in Fig. 3, LSTM adopts the method of single unit prediction and then superposition, and its prediction interval is missing important wind speed fluctuation information. In this paper's method and the BP algorithm for whole field power prediction, the envelope can still better restore the real data fluctuations, and the prediction interval of this paper's algorithm is slightly smaller than that of the BP algorithm. Whether on the single machine or the whole field prediction, the prediction interval width of this paper's method is narrower and the performance is more superior.

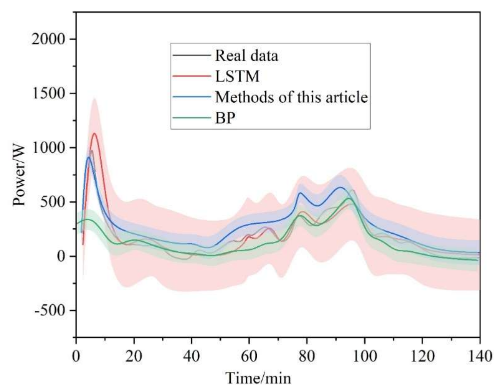

Figure 3: The total power prediction comparison of 95% confidence interval

V. B. 3) Comparison of training time

The examples in this paper are performed on a PC platform based on AMD Ryzen 7 3700X 8C-16T processor, 32GB RAM, and Nvidia GeForce GTX 1660, and the running environment is Tensorflow- gpu 2.3.0 based on python.

In this paper, the power prediction model is trained on 30 days of data, which is a long time scale data, and the high dimensional unit state data is added, which is a huge amount of training data. The results of the training time comparison between this paper's algorithm and BP and LSTM algorithms are shown in Table 2, all algorithms are trained for 250 cycles, and since the LSTM model is trained for each unit individually, the results are calculated by multiplying the training time by 34 at one time.

For engineering applications, the three methods simply use the trained model and update it periodically. For the prediction stage, all three methods can quickly produce prediction results in seconds, so only the training speed of the model is compared here. In this paper, the algorithm can reduce the model training data dimension, which significantly reduces the training time. While BP and LSTM need more than 2h training time.

Table 2: Comparison of model training time

Model	Training time/min
Algorithm of this article	18.5
BP	211.7
LSTM	162.6

V. B. 4) Number of iterations

The number of iterations refers to the number of times the algorithm traverses the entire training set while training a machine learning model. After each complete traversal of the dataset, it is called an iteration. In each iteration, the model makes predictions based on known input features and corresponding labels (or target outputs), and updates the model's parameters by comparing them with the true values. The number of iterations keeps increasing and the model gradually adjusts the parameters to minimize the loss function and improve the model's fit to the data. The more iterations, the more accurate the feature patterns and data distributions learned by the model may be, but at the same time, the risk of overfitting increases.

During training, it is common to set a maximum number of iterations or decide when to terminate training based on the convergence of the model. Choosing the right number of iterations is one of the keys to optimize the model performance, which needs to be adjusted and evaluated according to the real model training situation. The Loss curve of the model is shown in Figure 4.

It can be seen that during the iterative training of the model, the model loss function MSE decreases with the increase in the number of iterations, which meets the basic requirements of model training. When the number of iterations reaches 21, the model loss value is 0.04408, and the rate of change of the loss function curve is small thereafter. In order to prevent the model from overfitting due to over-training, and to leave a certain error margin, the number of model iterations is set to 25. The model can reach the optimal state with only about 21 iterations, which can show that using the activation function to optimize the parameters makes the model have a superior fitting effect and proves that the model is effective.

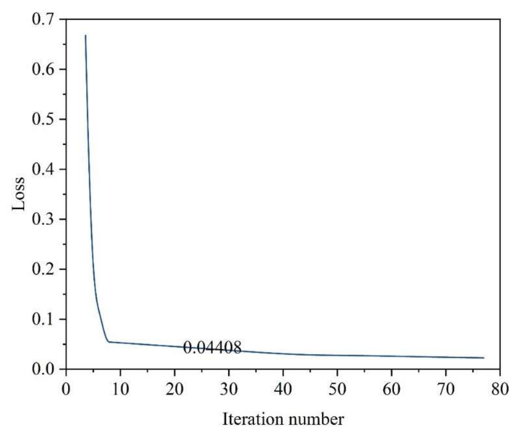

Figure 4: The loss curve of the model

VI. Conclusion

In this paper, a prediction model combining Bagging-DNN with integrated learning and deep neural network is proposed for the problem of improving the accuracy of ultra-short-term prediction of wind power. The model utilizes meteorological data as input and is processed and trained. The prediction outputs of multiple models are averaged and weighted to output the integrated prediction results. Data from an offshore wind farm in Shanghai area is selected for analysis, and the results show that

The MAPE of this paper's prediction model is on average 2.4% and 6% smaller than the MAPE of the comparative methods when compared to ARMA, BP, and LSTM prediction methods at 1h and 4h prediction. This shows that the method in this paper has certain advantages in improving the accuracy and stability of the prediction results, the width of the prediction interval is narrower, and the performance is more superior, which can be deeply studied and applied in the practice of wind farms. And by using the activation function to optimize the parameters, the fitting effect of the model can be improved.

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