Analysis of the Usefulness of Very Short-Term Wind Power Forecasting Models

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Abstract

Wind power prediction is a useful tool for mitigating the risk that intermittent and variable wind power poses to the electric grid's dispatch. Ultra-short term wind power prediction typically operates on a time scale of minutes to hours, so it may enable power grid dispatching in real-time and ensure the safe, stable, and cost-effective functioning of the electric power system. The ultra-short term wind power forecast model is established using three algorithms: BP, SVM, and RBF. Three actual wind farms located in different parts of China were given wind power predictions using the projected models, and the applicability of each model was evaluated by comparing the varied expected outcomes. Additionally, in order to analyze the expected inaccuracy brought on by various time spans, the wind farm with the highest predicted efficiency was utilized as an example. The overall forecast findings indicate that seasonal and wind farm characteristics will affect the yearly fluctuation of prediction error. The RMSE of predicting power exhibits a rising pattern as the time span increases.

1 Introduction

Large scale wind power into grid will pose a great threat to the secure and stable operation of power system, while accurate wind power prediction is an effective way to solve this problem [1]. The ultra-short term wind power forecasting can give technical supports to power grid dispatching as well as the operation and management of wind farms, and then guarantee the reasonable operation of power system [2].

The ultra-short term wind power forecasting provides the predicted results from zero to four hours, and should be updated every fifteen minutes, which make higher demands on the forecasting precision and computational efficiency [3]. China has a large territory and complicated geographic and geomorphic conditions, and is vulnerable to the short-time extreme weather. Besides, the constructions of wind farm take on a character of large-scale centralized, so the meteorology and topography between different regions will have mutual influence and constraint. All of the above factors bring severe challenges to the improvement on the forecasting precision and efficiency of ultra-short term wind power forecasting. Therefore, exploring the applicability of different ultra-short term wind power forecasting methods are of great significance.

The ultra-short term load prediction consists of three links [4], namely the processing of pseudo historical load data, the sifting of prediction samples and prediction algorithm. At present, the ultra-short term wind power prediction is mainly realized by statistical models. The frequently used forecasting methods [5] are primarily made up of time series method, Kalman filters, autoregressive moving average, artificial neural network and support vector machine.

The widely used BP-ANN!SVM! RBF-ANN algorithms were applied separately to establish ultra-short term wind power prediction models, and a one-year wind power prediction was carried on in three actual wind farms of China. Moreover, the monthly predicted error was calculated to analyse the impact of different meteorology, topography conditions and time scale on the predicted precision, which lays foundation for the optimization and improvement of wind power forecasting system..

2 Algorithm research and model establishment

The build of these three prediction models (BP, SVM and RBF) are all based on MATLAB simulation platform, and also with the help of neural network toolbox and SVM toolbox, the detailed implementation steps are as follows.

Back Propagation Neural Network Model

Back Propagation (BP) [6] is a multilayer feed forward neural network, acquired by error backward propagation algorithm, and it's one of the most widely used neural network models. The basic BP algorithm adopt the supervision way of learning, it turns the mapping problem between input and output into a highly nonlinear optimization problem, and then to minimizing the error function. The basic idea of BP is to divide the learning process into signal forward-propagating and error back propagating. The work procedure of BP model is described by figure 1.

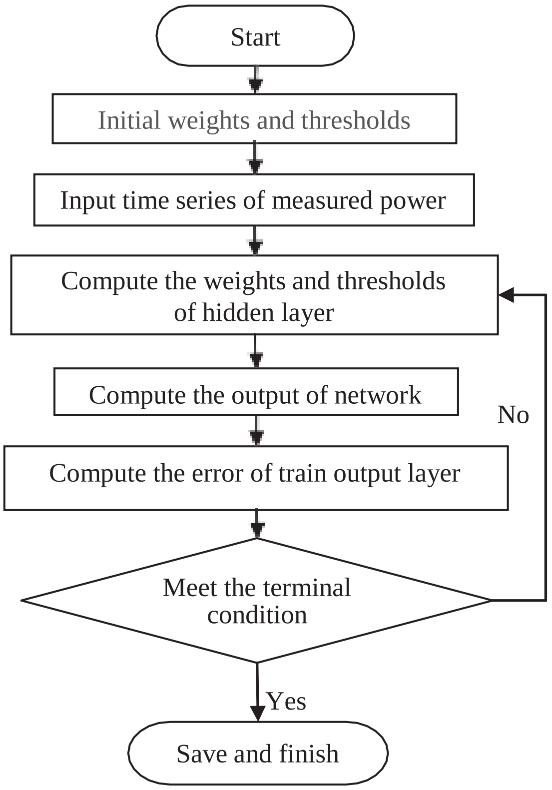


Fig 1: the work procedure of BP

Support Vector Machine Model

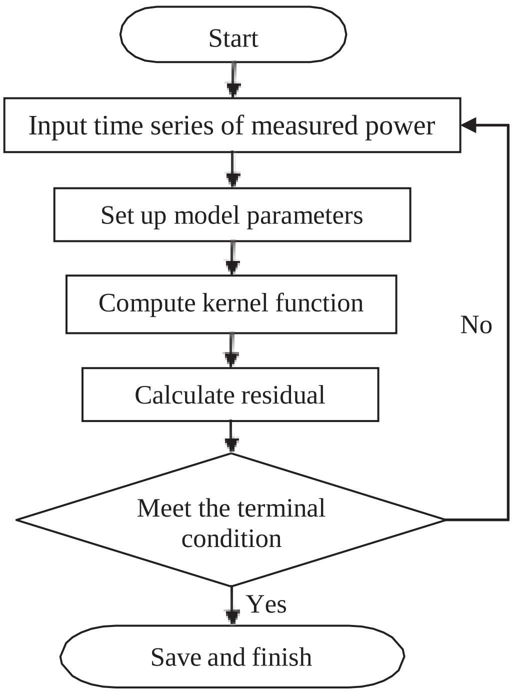


Fig 2: the work procedure of SVM

Support Vector Machine (SVM)[7] is a learning method which based on empirical risk minimization principal, and turn the process into solving the problem of quadratic programming, so the expression of SVM is the only optimal solution of the overall situation. The kernel functions which meet Mercer condition correspond to the inner product of transformation space, after the nonlinear transformation, and then realize the linear regression. The work procedure of SVM model is described by figure 2.

Radial Basis Function Model

Radial Basis Function (RBF) neural network [8,9] is some kinds of the same as BP, and it's also a feed forward neural network. RBF includes input layer, hidden layer and output layer, it has simple structure and concise training procedure. What's more, it can approximate any nonlinear function. The detailed process of obtaining the nonlinear relationship between input and output is shown as figure 3.

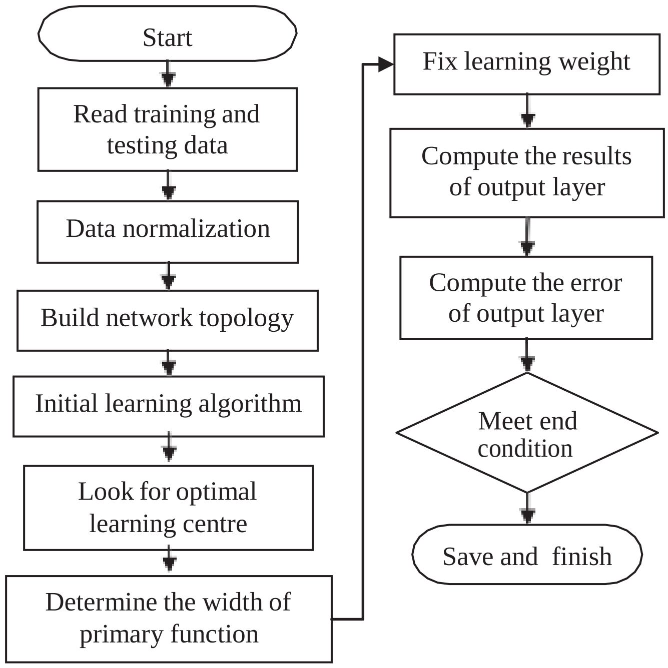


Fig 3: the work procedure of RBF

3 Technique route of wind power prediction

In the whole process of wind power prediction, with the help of measured wind power data in historical time series, each algorithm was used separately to carry on 4 hours ahead ultra-short term wind power prediction. In order to reduce the data amount, the time interval was transformed from 5min to 15min, and there are 4 data in every hour. In the process of modelling, the relevant pre-processing was done as follows.
(1) By means of calculating the average value, the time interval of power data was turned from 5min to 15min.
(2) To deal with existing breakpoints data: as for the power data with a small amount of breakpoints, using the average value of adjacent moment to complete; as for the data with a large amount of breakpoints, the breakpoints should be delete and the data should be regrouped.

(3) Take the wind power of the former 16 time points(4h) as input, and take the wind power of the latter 16 time points(16h)as output.
(4) Both of the input and output data were divided into training and testing samples, and to forecast the wind power of 12 months in the whole year.

4 Analysis of actual Examples

The data and index of modelling

Description of wind farms

Three wind farms were chosen to serve for the research of those three ultra-short term prediction models' applicability. Wind farm 1(WF1) and Wind farm 2(WF2) are located in Hebei province of China, the typography of these two wind farms is complex and the difference of elevation is big, the gross installed capacity of WF1 and WF2 are 100.5MW and 150WM. Wind farm 3(WF3) is located in the coastal mud flat of Jiangsu province in China, and it was built according to the east, middle and west orientation of the wind farm, the gross installed capacity is 201MW.

Index of error evaluation

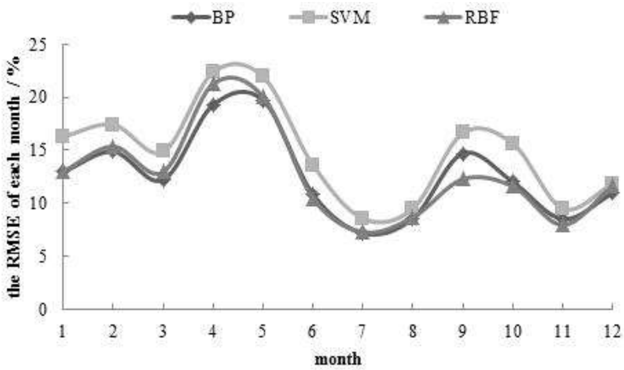
BP, SVM and RBF models were adopted separately to carry on wind power prediction in three wind farms of China. In order to inspect the accuracy of predicted results in general, the root mean squared error (RMSE) is chosen as the index of error evaluation [10]. The computation formula of RMSE is shown as equation (1).

$$RMSE = \frac{1}{P}\sqrt{\frac{\sum_{i=1}^{N}(y_i^{'} - y_i)^2}{N}} \qquad (13$$

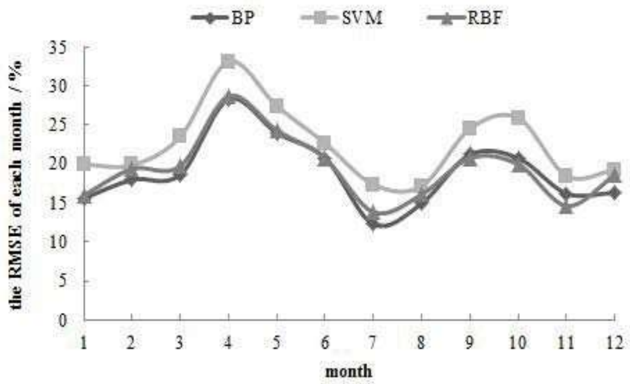
Where:

$y_i^{'}$ - predicted power of time point i, y_i - measured power of time point i, N - the number of prediction samples, P - the gross installed capacity of wind farms.

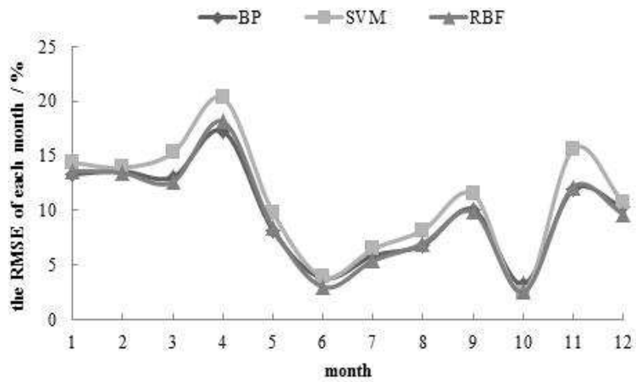
Applicability contrast of three models



(a3Wind Farm 1



(b3Wind Farm 2



(c3Wind Farm 3

Fig 4: Monthly RMSE variation of 16 forecasting time points

To begin with, the data samples that affected by the factors of power limited and wind turbine maintenance should be get rid of. Then take the 12 month as predicted units, and divide the data into training and testing samples, the ratio of training and testing is four to one. The input and output of the forecasting model are the measured power of the former 16 time point and the latter 16 time points separately.

Apply the three prediction model into real wind farms, and calculate the average error value in sixteen forecasting time points of twelve months. As to each wind farm, the annual error variation curve of sixteen forecasting time points can be obtained, shown as fig4 (a), (b), (c).

From fig.4, we can know that the prediction results of different wind farms not only have difference but also have something in common.

The common aspects of prediction effect act as follows. As for those three wind farms, the SVM model performs worst with no exception, while BP and RBF models have similar prediction effect and they all behave better than SVM. Forecasting error is the highest in spring (March to May) and lowest in summer (June to August), the other seasons are in the middle level.

The different aspects of prediction effect perform as follow. WF3 has the best forecasting precision, and the average RMSE of sixteen time point are all under 20%. WF1 has a slightly worse performance, the monthly RMSE are all around or below 15% except April and May. WF2 has the worst predicted accuracy, the RMSE of April reach up to 33.1%. What's more, the six curves correspond to WF1 and

WF2 take on almost the same variation trend, but the RMSE curve of WF3 has a sudden drop in October, which as low as 2.5%.

Some individual months have relatively high forecasting errors, and the main reasons of this phenomenon are as follows: the high error months have fluctuated short time variations, and the wind speed correlation is low between the former four hours and the latter four hours, thus weaken the learning ability of prediction model and decrease the prediction accuracy.

Prediction results of different time span

According to the prediction results of three wind farms, take the wind farm which has the highest forecasting precision as the typical example to do research, and make an analysis on the error characters of BP, SVM and RBF models.

As for WF3, the wind power prediction models are built based on BP, SVM and RBF algorithm, and the RMSE of predicted power on sixteen time points were calculated separately, collect the power data on the last prediction point of each hour, namely the RMSE on the fourth, eighth, twelfth and sixteenth prediction time points. The forecasting RMSE on each prediction points of those three models are displayed as table 1 (a), (b), (c).

Table 1: Statistics of monthly RMSE on each prediction point

(a) BP model

Month	RMSE of predicted power/%			
	fourth	eighth	twelfth	sixteenth
1	7.86	13.98	17.70	20.00
2	9.41	14.65	17.09	19.00
3	8.49	13.18	16.90	19.88
4	13.62	18.29	20.89	23.19
5	5.84	8.35	10.44	11.65
6	2.50	3.70	4.77	6.08
7	5.30	6.17	6.75	6.87
8	5.48	7.07	8.25	8.70
9	7.01	10.63	12.67	14.38
10	2.14	3.30	4.14	4.94
11	8.30	12.08	14.93	17.38
12	6.65	10.32	13.23	15.81

(b) SVM model

Month	RMSE of predicted power/%			
	fourth	eighth	twelfth	sixteenth
1	9.73	16.01	18.03	19.84
2	11.55	14.98	16.02	17.34
3	10.87	15.95	19.43	22.11
4	17.52	20.85	22.92	26.22
5	6.58	10.19	13.00	14.07
6	2.50	3.93	5.01	6.25
7	6.00	6.84	6.89	7.24
8	6.63	8.28	9.80	10.85
9	7.71	11.69	14.67	17.17
10	1.80	2.68	3.09	3.47
11	12.53	16.03	18.13	19.39
12	7.43	10.24	13.71	16.36

(c) RBF model

Month	RMSE of predicted power/%			
	fourth	eighth	twelfth	sixteenth
1	7.71	14.24	18.45	21.11
2	9.44	14.73	17.10	18.42
3	8.13	12.88	16.51	19.57
4	14.29	19.07	21.99	24.91
5	5.75	8.63	11.01	12.17
6	2.06	3.07	3.75	4.44
7	4.97	5.67	6.14	6.27
8	5.38	7.34	8.54	9.16
9	6.90	10.44	12.50	13.89
10	1.62	2.52	3.24	3.92
11	8.48	12.33	15.31	18.03
12	6.22	9.60	12.63	15.32

As can be seem from table 1 (a), (b), (c), The results show that, as for these three models, the RMSE variation curves of different time span present similar distribution, namely the RMSE of predicted wind power will increase with the increase of time span (from the fourth to the sixteenth point). The higher average forecasting error is, the higher error of every single predicted point, which is the same with low error situation. That is to say, the forecasting errors of those sixteen prediction points have the same annual variation trend.

By analysing the forecasting error of single prediction point, it can be seen that January and April still possess the highest error. BP model preforms the best, following closely is RBF model and SVM model has the worst prediction performance. In terms of these three models, the forecasting errors on the sixteenth point are all beneath 20% apart from January, March and April.

Calculate the RMSE deviation of the first and the sixteenth point, and draw the error deviation annual variation curves of three prediction models, which is shown as figure 5.

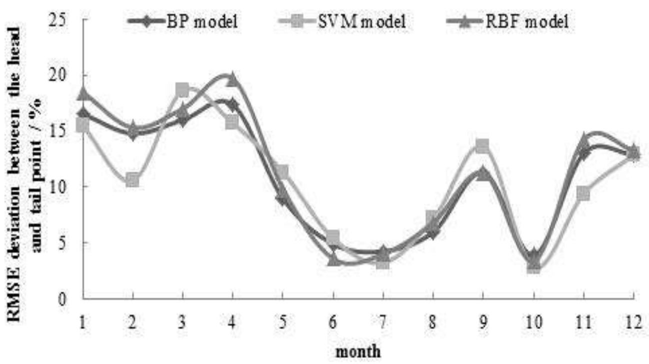


Fig 5 Three model's annual variation of RMSE deviation between the head and tail point

The conclusion can be drawn from figure 5, for these three models, the RMSE deviation of predicted power between the head and tail time point have approximate values, and also have the same annual variation trends. Of which, from January to April, the RMSE on the head and tail points has the most obvious variation, and the fluctuation magnitude range from 15% to 20%, the highest one may reach 19.7%. The RMSE deviation of May, September, November and December is a bit less, which range from 10% to 15%. June to August and October has the least head and tail error deviation, which vary from zero to 5%, and the minimum value is 2.8%. In spring and winter, wind speed changes frequently, and so does the output power of wind turbines, which made the predicted results of each predicted time points have poor correlation. So the prediction accuracy has a big difference between the head and the tail prediction point. Similarly, in summer and autumn, the wind speed changes gently and has a strong regularity, thus the prediction accuracy of head and tail points are approximate to each other.

5 Conclusion

Three ultra-short term wind power prediction models were established based on BP, SVM and RBF algorithm. In order to validate the applicability of different forecasting models, they were applied to three different wind farms in China. Via the calculation and analysis of the prediction results, the following conclusions can be drawn.

(1) The prediction results of different wind farms not only have difference but also have something in common. The SVM model performs worst with no exception, while BP and RBF models have similar prediction effect.

(2) In terms of different wind farm, the prediction results of ultra-short term wind power prediction act as that spring has the maximum forecasting error and summer has the minimum one.

(3) For a single wind farm, the RMSE of three models' forecasting power increases with the extension of time span.

(4) Due to seasonal wind speed variation, the prediction accuracy deviation between the head and the tail prediction point has a big difference in spring and winter, while has a small difference in summer and autumn.

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