(IJISE) 2018, Vol. No. 8, Jul-Dec **e-ISSN: 2454-6402, p-ISSN: 2454-812X**

EMPLOYABILITY OF NEURAL NETWORKING AND TIME SERIES MATRIX IN DEVELOPING AN EFFICACIOUS WIND SPEED AND WIND POWER PREDICTION MODEL

Harshit Yadav

Student, Bal Bharati Public School, Dwarka, New Delhi

ABSTRACT

This paper examines the forecast for wind power and wind speed. The test information is gathered at a breeze control station in 30 seconds interim. A period arrangement display and a neural system expectation show are connected for anticipating the breeze speed and wind control forecasts. The exhibitions of expectation of various time focuses are thought about.

Keywords*-Power prediction; wind speed prediction; time series model; neural networks.*

I. INTRODUCTION

As the expanding in vitality request, impressive research has been led in the reasonable vitality, including wind, sun based vitality, to supplant the old restricted non-renewable energy source sort of vitality. There is a long history for use of wind vitality. As of now, it has been understood that the breeze power might be a fundamentally traded vitality for the age of power. Wind control forecast is basic to control framework unwavering quality and dealing with inconstancy of the produced power [1]. Now a forecast of wind turbine parameters is imperative to the expectant control of wind turbines and web-based observing. In this paper, we center around the fleeting breeze speed expectation and window control forecast models.

The double exponential smoothing time-series model is employed in the wind speed prediction. A neural network model is applied to predict the wind power. The predicted results from both models are compared to the measurement data collected in a wind power station. The comparisons indicate that the neural network model may provide better prediction performance than the time-series model. However,the time-series model has a lower computational complexity.

The paper is organized as follows. Section II introduces the time-series model. The damped trend method is employed to construct the wind speed prediction model. The simulations for the wind speed predictions in different time intervals are compared. Section III introduces the neural networks model for the wind power prediction. The results are also compared with different inputs in the simulation part. Section IV concludes this paper.

II. TIME-SERIES WIND SPEED PREDICTION

MODEL

1. General model

Time series model arises in many different data such as second-by-second frequency of signals, or minute-by-minute wind speed at a power station, hourly numbers of parents at hospital, daily numbers of ships at harbor. Time series is a set of sequential data collected by the same time intervals [2-4]. Time series model prediction use the past data to predict the future values, which can be expressed as follows:

$$\hat{y}_{t+T} = f(y_t, y_{t-T}, \ldots y_{t-nT}) \quad (1)$$

where $f(\ldots)$ denotes the time series prediction model function that maps the observations to prediction, t denotes the time instant, y^t+T denotes the predicted value at time t+T, T is the sampling time interval, n is the index of samples, yt ,yt–T ,Ă yt–nT denote the observations at time instants t, t — T, … , t — nT.

2. Prediction accuracy

Before introducing the prediction models, we present the measure of the prediction accuracy for the models. The matter of measuring the accuracy of predictions from numerous procedures has been a contestable issue. We summarize some of the ways here. A more thorough discussion is given by Hyndman and Koehler . When comparing forecastprocedures on a single series, we prefer the mean absolute error (MAE) as it is easy to understand and compute. However, itcannot be used to make comparisons between series as it makes no sense to compare accuracy on different scales. Mean absolute percentage error (MAPE) have the advantage of being scale-independent, and so are frequently used to compare forecast performance between different data sets. MAE and MAPE are expressed as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_t - y_t| \quad (2)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left|\frac{\hat{y}_t - y_t}{y_t}\right| \times 10 \quad (3)$$

3. Damped trend time-series model

Various time-series models have been studied for short-term predictions. In this paper, we use the damped trend method, which is one of the extended simple double exponential smoothing of time series models [5]. Double exponential smoothing (DES) is a commonly used model for forecasting the time series based on the past observed value and exponential decreasing weights. Gardner and McKenzie proposed a modification of Holts linear method to allow the damping of trends. This method is expressed as follows:

$$l_t = \alpha y_t + (1 - \alpha)(l_{t-T} + \$ b_{t-T}) \quad (4)$$

$$b_t = þ(l_t - l_{t-T}) + (1 - þ)\$ b_{t-T} \quad (5)$$

$$\hat{y}_{t+T} = l_t + \$ b_t \quad (6)$$

where lt is the level of the prediction at time t, bt is the growth of the prediction at time t, α, þ and $ are the smoothing weights which adjust the predicted value to approach the target value. In the wind speed predictions, vt–T is the last state of the wind speed, vt–nT is

the last n state of the wind speed, and they are used in the initialization for the model, in which the initial level component lO and the initial growth component b0 are considered to be set. We choose lO and b0 as follows:

$$l_O = v_{t-T} \quad (7)$$

$$b_O = \frac{\sum_{n=-5}^{-2} v_{t-nT} - \sum_{n=-4}^{-1} v_{t-nT}}{4} \quad (8)$$

Implementation of Damped Trend Method includes the training and prediction phases.

First, the best parameters a, þ and need to be trained using the past observation data. The equations (4)-(6) and initialization equation (7)-(8) are applied to the training data set in obtaining the prediction. The MAPE is then calculated by the prediction and observation. Parameters a, þ and are further optimized by minimizingthe MAPE. The optimized parameters are used to predict the future values by equation (4)-(8).

4. The Performance of time-series model in Wind Speed Prediction

The measurements of wind speed are obtained at a wind power station at Kansas State in 2012. Other measurements including wind power, volts, rpm are also recorded. The measurements are recorded in 30 seconds time interval. To reduce the cost in measurements, wind speed readings are recorded as integers. The measurement data is pre-processed by removing the negative power in the shutting down period of the wind rotor. To train the parameter a, þ×, and , we use 60,000 instances of data to adjust the smoothing weights and then to predict the wind speeds at the next 20,000 time instances. The best parameters of damped trend method are α = 0.6249, þ×= 0.6247, and = 0.2630. Fig.1 - Fig.4 show the wind speed predictions at the time point t+30s, t+60s, t+90s and t+120s. Only 200 data points are plotted in the figures. Table I summarizes the estimation accuracy of the wind speed model. From the table, the mean absolute percentage error is 0.0556, 0.0885, 0.1038, 0.1298 at time point t+30s, t+60s, t+90s, t+120s. It is about 3% growth after every 30s. As the prediction time goes further to the future, the error of prediction increases.

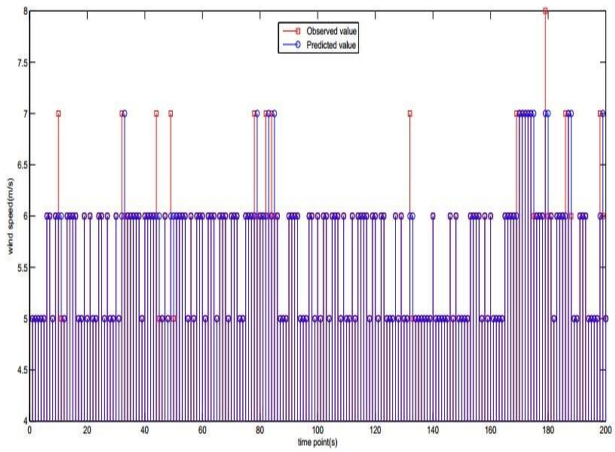

Fig.1 Wind speed prediction att+30s

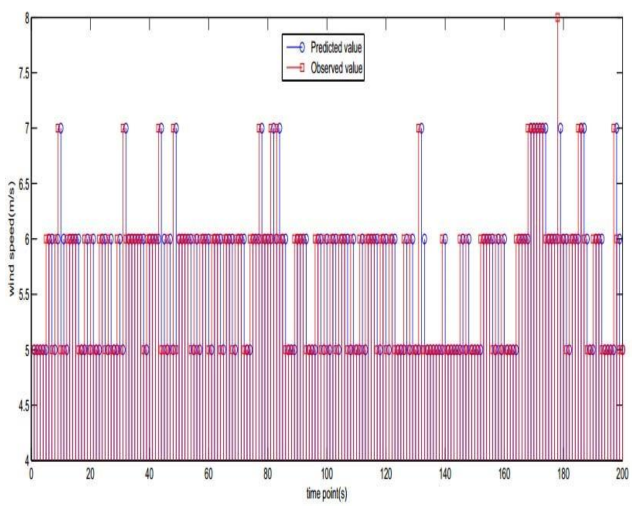

Fig.2 Wind speed prediction at t+60s

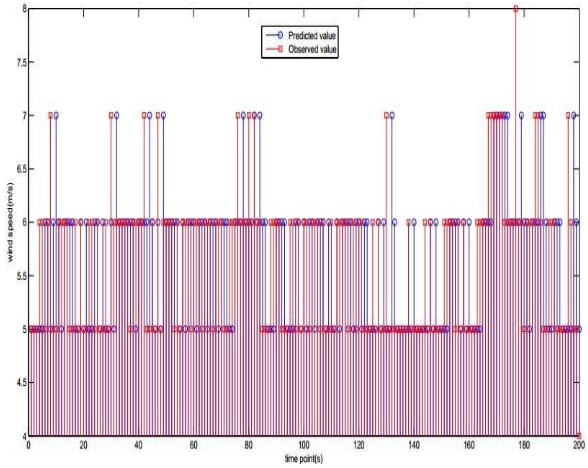

Fig.3 Wind speed prediction at t+90s

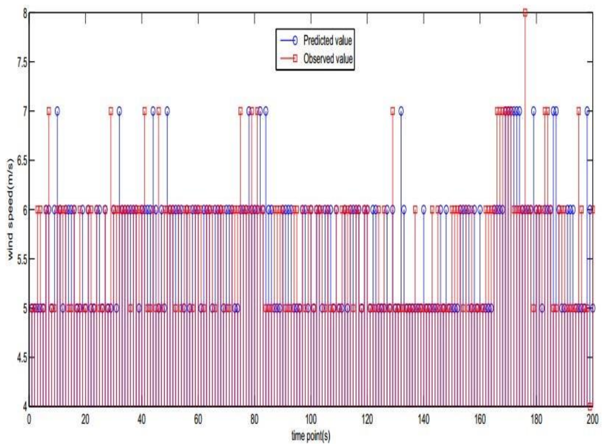

Fig. 4 Wind speed prediction at t+120s

TABLE I. THE ERRORS OF THE WIND SPEED PREDICTION

Time point	MAE	MAPE
t+30s	0.2808	0.0556
t+60s	0.5025	0.0885
t+90s	0.6327	0.1038
t+120s	0.7802	0.1298

(IJISE) 2018, Vol. No. 8, Jul-Dec **e-ISSN: 2454-6402, p-ISSN: 2454-812X**

III. WIND POWER PREDICTION MODEL

In this section, we discuss a wind power prediction model using the neural networks. Neural networks model is an algorithm that is constructed by many neurons. Every neuron is a computational unit and they are connected by different weights of connection. The neural networks model is built by three parts: inputs layer, hidden layers and outputs layer. Mapping is concerned with the forward pass through the network, during which the outputs are computed from the inputs [6-9]. This calculation is performed in two situations: when the network is trained and when it is used. We put the data into the network and get the results comparing to the observations, and then the weights are adjusted by the neural network. When the progress is repeated many times, the weights can be adjusted to the final value. After the weights are obtained, the test data could be used to predict.

1. The proposed neural network model

To develop the neural network model for the wind power prediction, let Pt be the wind power value we want to predict, Pt–T is the last observed wind power value, vt is the wind speed in current value, mt is rpm of wind rotor in current

value. The wind power is predicted by wind speed, rpm and past state of wind power observations. The model is expressed as

$$P_t = f(P_{t-T}, v_t, m_t) \quad (9)$$

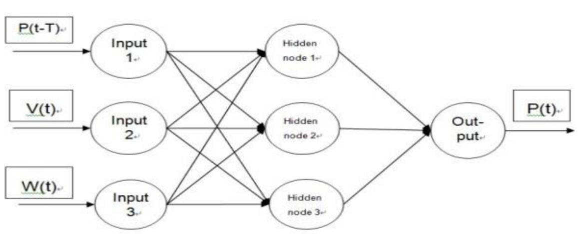

Fig. 5 Structure of Neural Networks

We use the sigmoid function to be the mapping function. The sigmoid functionis expressed as follows:

$$g(x) = \frac{1}{1+\frac{1}{e^x}} \quad (10)$$

Fig.5 shows the structure of the neural networks model. There are three input nodes, three hidden nodes and one output node. The prediction for the wind power Pt at time t is given by

$P_t = g(v)$ (11)

$v = \Sigma_{j=1}^{J} b_j u_j$ (12)

$u_j = g(h_j)$ (13)

$h_j = \Sigma_{i=1}^{I} a_{ij} s_i$ (14)

Where i and j are the indices of the input nodes and hidden nodes, and in our model, I=J=3, s are the input values, and s =P , s =v and s = m , function g(.) is the mapping function which is used between the hidden nodes and output.

Here, we use the sigmoid function g(x)

When x

ex

increase from -5 to 5, the sigmoid function g(x) is a linear function whose value is between 0 to 1. The sigmoid function approaches to 1 when x increase to positive infinity and approach to 0 when x decrease to negative infinity. hj is the input values at the j-th hidden node, uj is the input values at the j-th hidden node obtained by the sigmoid function, v is the weighted sum of the components in u, aij and bj are the weights in the different branches. Given the inputs at a time instant, we use the (14) to compute the inputs for the hidden nodes. The results are passed to the sigmoid function, and (12) is used to compute the output by the value mapped by the sigmoid function. The prediction is obtained using (11).

To implement the neural network, we pick the training data and obtain the optimal weights to minimize the MAPE. The optimization is performed by iterations and a maximum number of iterations is set by the learning law in neural network. The learning law provides a method to train the weights to reduce the prediction errors. The core of the learning law is minimizing the partial derivatives of the error with respect to the weights. The learning law equations are shown as follows:

$d_n = \Sigma_{n=1}^{N} \left(\frac{\delta E_n}{\delta m_n}\right)_n$ (15)

$c_n = -s d_n$ (16)

$m_n = m_{n-1} + c_n$ (17)

where m is the number of the iteration of the training, dn is the derivative of the error with respect to the weights in epoch m, En is the MAPE in epoch m, mn is the weights including aij and bj , ‹ is the parameter controlling the weights change, cn is the weight change at the end of epoch m. Once the maximum number of iterations is determined, the learning law will modify the weights to the best value for the network.

2. The performance of the neural network model in wind power prediction

In this section, the performance of the wind power prediction using the proposed neural network is presented. We use 60,000 data to train the weights and after that, 20,000 data as test data. For the input wind speed, we consider two types of data: the measured values and the predicted values using the time-series model, and compare the results. Fig.6 and Fig.8 are the prediction at the time interval t+30s, t+60s using the measured wind speeds. Fig.7 and Fig.9 are the prediction at the time interval t+30s, t+60s using the predicted wind speeds. Table II presents the errors using these two wind speed inputs. The MAPE using the predicted wind speeds at time point t+30s is more 6.75% than that using the measured wind speeds, and MAPE of the former at time point t+60s is more 7.32% than the latter. The prediction errors increase for both inputs, as the prediction time moves further to the future.

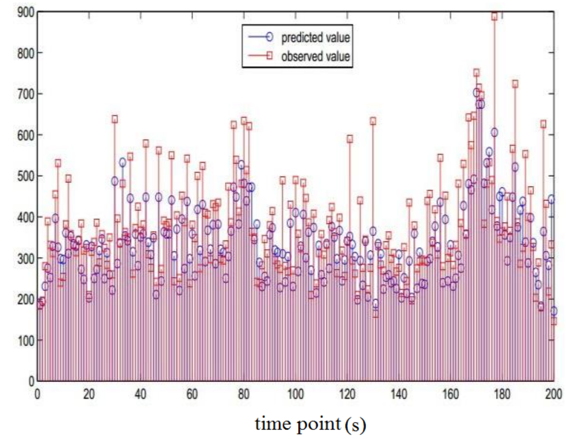

Fig. 6 Wind power prediction at t+30s by the observed wind speed data

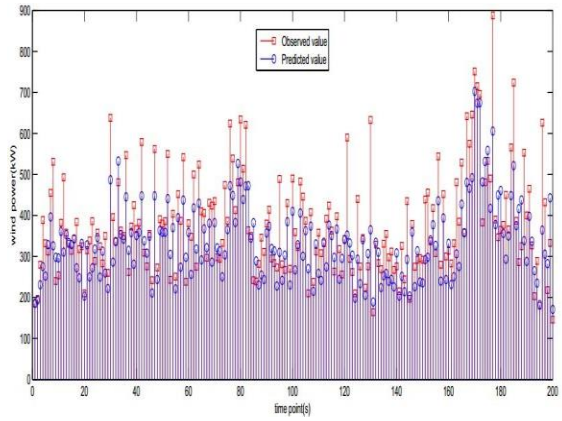

Fig. 7 Wind power prediction at t+30s by the predicted wind speed data

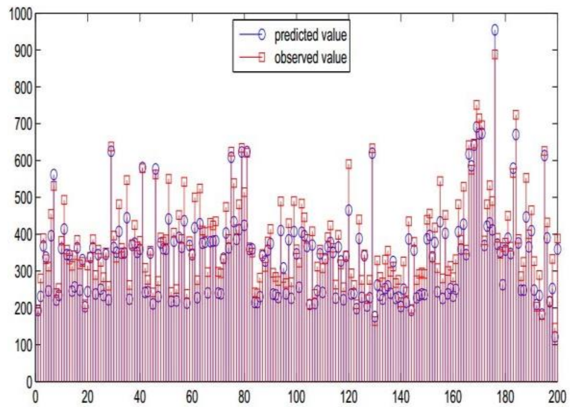

Fig. 8 Wind power prediction at t+60s by the observed wind speed data

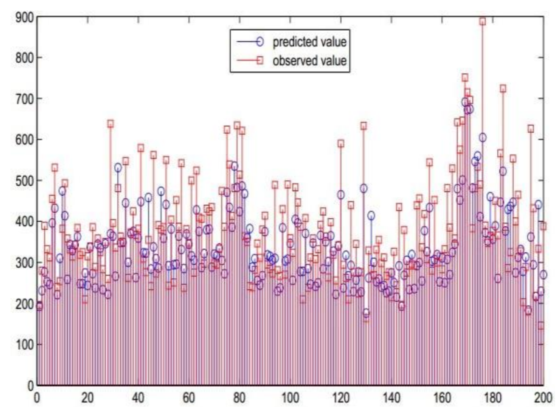

Fig. 9 Wind power prediction at t+60s by the predicted wind speed data

TABLE II: THE ERRORS OF THE WIND POWER PREDICTION

Time point	**Observed value as input**	**Predicted value as input**
t+30s MAE	0.0062	0.0162
t+30s MAPE	0.0356	0.0837
t+60s MAE	0.0078	0.0176
t+60s MAPE	0.0382	0.0908

IV. CONCLUSION

In this paper, a time-series model for wind speed prediction and a neural network model for wind power prediction were presented. In the time-series model, we discussed the damped trend method for the wind speed prediction using three parameters a, þ×and . In the neural network model, the wind power was predicted using three inputs: wind speed, rpm, and the past measured power levels. Simulations indicated that both models provided satisfactory performance in terms of MAE and MAPE. For the future prospects, we plan to apply our results in the short-term prediction to long-term prediction, in addition, we will consider a more general prediction model which cooperates different system optional conditions and locations.