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Very Short-Term Generating Power Forecasting for Wind Power Generators Based on Time Series Analysis

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ABSTRACT

In recent years, there has been introduction of alternative energy sources such as wind energy. However, wind speed is not constant and wind power output is proportional to the cube of the wind speed. In order to control the power output for wind power generators as accurately as possible, a method of wind speed estimation is required. In this paper, a technique considers that wind speed in the order of 1 - 30 seconds is investigated in confirming the validity of the Auto Regressive model (AR), Kalman Filter (KF) and Neural Network (NN) to forecast wind speed. This paper compares the simulation results of the forecast wind speed for the power output forecast of wind power generator by using AR, KF and NN.

Keywords: Very Short-Term Ahead Forecasting; Wind Power Generation; Wind Speed Forecasting; Time Series Analysis

1. Introduction

Wind generators are rapidly gaining acceptance as some of the best alternative energy sources, and an alternative to conventional power generation. Especially due to decreasing cost of the wind generated power, it has the potential to compete with traditional power plants. However, wind speed is not constant and the power output of wind generators is proportional to the cube of the wind speed. The intermittent nature of wind makes the power output fluctuation of wind generator. In electric companies, wind speed forecasting is an important tool for utilizing the hybrid power systems with storage battery, wind generators, solar cells, etc. For example, the amount of energy stored in the battery is easily decided by forecast data. These decisions are beneficial for effective operation of hybrid power systems and consequently, their profitability depends on the technique utilized in the forecasting powers. Although the technique to forecast power output of wind generators based on wind speed prediction is regarded as an effective method in practical applications, it requires large meteorological data. In addition, although meteorological agencies or weather services will provide free data for prediction, the implementation of the above-mentioned techniques provide the order of several minutes data or hourly data. Since the data is mostly gathered over a wide area by prediction, it becomes rather difficult to determine the exact values for the order of several seconds at the installation area of a wind generator. Auto Regressive Model (AR) [1], Kalman Filter (KF) [2-4] and Neural Network (NN) [5-16] have been known that techniques are convenient in forecasting applications. It is possible to forecast wind speed by using only meteorological data. There is a valid argument: AR and KF are well known models for 1 - 3 time steps ahead forecasting. However the forecast result of using NN is usually case-by-case with the characteristic (stochastic appearance) of wind speed.

This paper describes very short-term ahead power output forecasting of wind generators based on wind speed forecasting. For the purpose of comparing the forecasting abilities of AR, KF and NN in this paper, all input data are based on the same condition. These models are constructed by using historical data on wind speed and tested for the target time. In addition, these data are observed at only one specific site. The power output of the wind generator is determined by the forecast wind speed data. The abilities of these models are confirmed by comparing the results in 1 - 30 seconds ahead forecasting.

2. Methodology and Application Model

The concept of the wind speed forecast technique is shown in **Figure 1**. In this paper, it is assumed that 1 to 30 seconds are forecast period of the wind forecasting. AR, KF and NN are constructed by making use of the historical data of 1 - 30 seconds at before 1-second. The idea is assumed that these models are constructed respectively in regard to the application of time series. It means the previous 30 seconds data reflect the trend of wind characteristic to forecast models with simple approach. After the wind speed forecasting, these three outputs are utilized for determination of power outputs of wind power generator. Explanation of AR, KF and NN are given below.

2.1. Auto Regressive Model

A common approach for modelling of time series is the AR model. The method of least-squares is applied in the estimation method of AR model. To apply the least squares method for time-varying AR model estimation, AR parameters are assumed to be time-invariant. If we want to obtain the forecast value y_{k+i}, regression coefficient a_k and residual error b_k should be determined by:

$$y_{k+i} = a_k x_k + b_k \tag{1}$$

2.2. Kalman Filter

The Kalman filter is a recursive estimator. It means that only the estimated state from the previous time step and the current measurement are needed for the current state. The first task during update of measurement is to compute the Kalman gain K_k. If estimated value $\bar{x}_k$ and covariance matrix P_k for estimate error are obtained, the next step is to measure the process to obtain observed value z_k, and update the estimated value $\hat{x}_k$ and covariance matrix P_k for posteriori estimation. This process is represented by:

$$\hat{x}_{k+1} = \bar{x}_k + K_k \left(z_k - H_k \bar{x}_k \right) \tag{3}$$

$$P_k = \left(1 - K_k H_k \right) \bar{P}_{k+1} \tag{4}$$

$$K_k = \bar{P} H_k^{\mathrm{T}} \left(H_k \bar{P}_k H_k^{\mathrm{T}} + R_k \right)^{-1} \tag{5}$$

where R is covariance for observation error, H is $m \times n$ matrix, which shows the relation between the state variable of a system and an observed value. 1 step-ahead estimation value $\bar{x}_{k+1}$ and covariance matrix $\bar{P}_{k+1}$ for estimation errors are calculated by:

$$\bar{x}_{k+1} = A_k \hat{x}_k + B_k u_k \tag{6}$$

$$\bar{P}_{k+1} = A_k P_k A_k^{\mathrm{T}} + Q_k \tag{7}$$

where A_k is $n \times n$ matrix, B_k is $n \times l$ matrix, Q_k is covariance of process error, $\bar{x}_{k+1}$ will be update of z_k after 2 steps ahead.

2.3. Neural Network

Figure 2 shows the Feed-forward Neural Network (FFNN), having l and m neurons in input layer and hidden layer respectively, and n neurons in output layer. These neurons are connected with a linear coupling, and x_1 - x_l are input data to NN. There are connection weights between each neuron. The output of the hidden neurons and output neurons are converted to nonlinear values by the sigmoid function. The sigmoid function is as follows:

$$f(x) = \frac{1}{1 + \exp(-x)} \tag{8}$$

where, x is the input data.

Back Propagation (BP) method is adopted for training the NN. Generally, BP is explained as follows. To begin with, output of the hidden neuron is transmitted to the output neuron. Then the output of the output neuron is
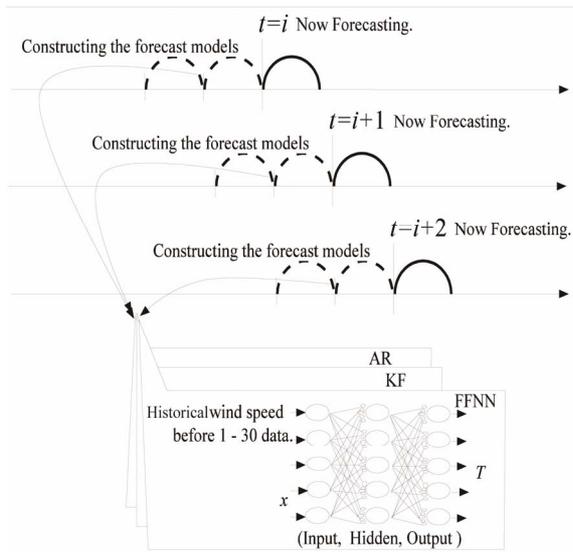
Figure 1. The concept of the forecast technique.
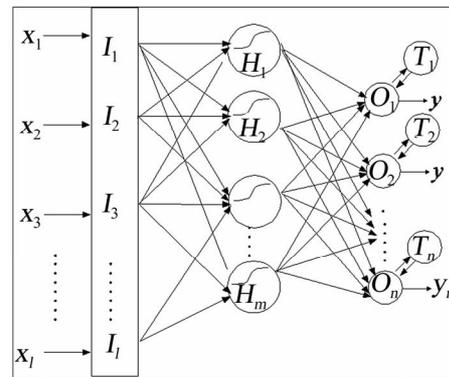
Figure 2. Neural network.

compared with target signal, *T*, as shown in **Figure 2**. Finally, to minimize the mean square error margin, each connection weight and the output value of each neuron are changed in the direction of a straight line from output layer to input layer. In this paper, Levenberg-Marquardt algorithm [17] was adopted for training each connection weight of neurons. The "momentum" and "training coefficient" terms are parameters of training; momentum promotes training speed and acts rapidly by changing each connection weight of neurons. The training coefficient parameter has to be large; however, if it is too large, the network becomes unstable. It is desired that the mean square error margin of NN model should not be unstable. The authors determined these parameters by a trial-and-error method.

3. Simulation Results

This section shows the simulation results of wind speed forecasting. Analysis results of forecasting error are also described below. The wind speed is important parameter to know the forecasted power output of wind turbine. Because of the accuracy of the forecasted power output depends on characteristic of fluctuating power output and also wind speed.

3.1. Wind Speed Forecasting

Figure 3 shows the results of 10 sec ahead wind speed forecasting at the time *t* = 121 - 900 for observation (1-second intervals), and calculates the forecast error (*MAE*, mean absolute error) by using AR, KF and NN as shown in **Figure 4**. In the case of **Figure 4**, mean value of wind speed is 14.3265 m·s^{-1}, and the variance is 3.6736 m·s^{-1}. *MAE* is given as:

$$MAE = \frac{1}{N}\sqrt{\sum_{K=1}^{N}\left(P_a^k - P_f^k\right)^2} \qquad (9)$$

where *N* is number of data, P_f^k is forecast value, P_a^k is actual value, and *k* is forecast time. In the result of using AR, the forecast error (*MAE*) is 1.6169 m·s^{-1} in 10 sec ahead, while KF and NN cause 1.6120 m·s^{-1} and 1.6047 m·s^{-1}, respectively. **Figure 4** shows the calculated *MAE* of 1 - 30 ahead wind speed forecast. In wind speed forecasting, as forecast time lengthens, forecast error increases. This phenomenon appears prominently in the result shown in **Figure 4**. There are no differences in calculated results of *MAE* with AR model, KF and NN. But the forecast results of these models vary on a case-by-case basis with the characteristic (stochastic appearance) of wind speed. In the case of AR model, **Figure 3(a)** shows that the forecast result of 10 sec ahead wind speed is influenced by gradient between forecast time and before 10 sec wind speed. In the case of NN, **Figure 3(b)** shows that the result of 10 sec ahead wind
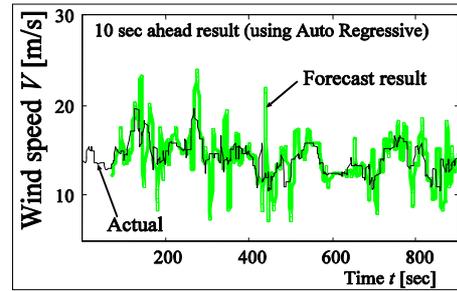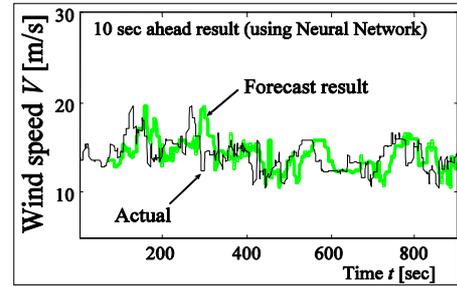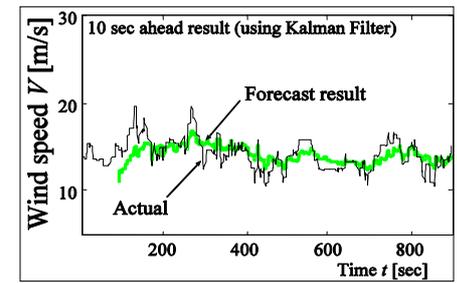
Figure 3. Simulation result for 10 sec ahead wind speed forecasting. (a) The result for using auto regressive model; (b) The result for using neural network; (c) The result for using Kalman filter.
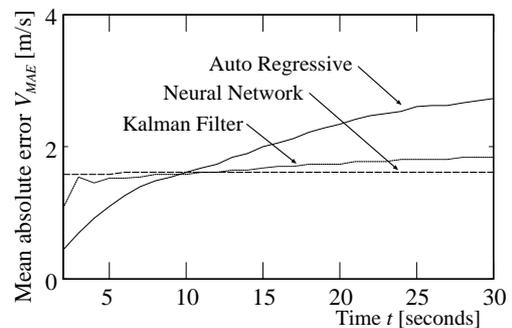
Figure 4. Mean absolute error V_{MAE} (wind speed forecasting).

speed is influenced by before 1 - 30 seconds wind speed characteristic. In the case of KF, **Figure 3(c)** shows that the 10 sec ahead forecast result is similar to the result of using AR model, but the gradient between forecast time and before 10 sec wind speed have an insignificant effect

on forecast result. In the simulation results of the fore-casted wind speed, each of these models has its own me-rits and demerits as shown in **Figure 3**. But one of the criterions to decide the forecast performance of these models is described along with forecast time as shown in **Figure 4**.

3.2. Power Spectral of Wind Speed

Figure 5 shows the power spectral of wind speed at the time t = 121 - 900 s for observation in **Figure 3**. The power spectral (Van der Hoven model [18]) is as indi-cated below. The power spectral $S_{yy}(f_k)$ for wind speed is an exponential-type Fourier transform $Y(f_k)$ calculated by observed wind speed $y(t)$. Therefore, the power spectral $S_{yy}(f_k)$ is represented by:

$$S_{yy}\left(f_k\right) = f_k \times \left|\frac{Y\left(f_k\right)}{N}\right|^2 \times T \qquad (10)$$

where $y(t)$ [m·s^{-1}] is observed wind speed, $S_{yy}(f_k)$ [m^2·s^{-2}] is the power spectral for wind speed, f_k [Hz] is frequency, T [sec] is observation time, and N is the number of data. Fourier transform $Y(f_k)$ is obtained by:

$$Y\left(f_k\right) = \sum_{t=1}^{N} y(t)\exp\left(-\frac{i2\pi kt}{N}\right)$$
$$= \sum_{t=1}^{N} y(t)\exp(i2\pi kt\Delta t); \qquad (11)$$
$$f_k = \frac{k}{N\Delta t}, \qquad k = 0,\cdots,N$$

The power spectral density is usually represented by:

$$S_{yy}\left(f_k\right) = \frac{1}{N} \times \left|Y\left(f_k\right)\right|^2, \ 0 \le f_k \le f_N \qquad (12)$$

Equation (10) supposes that wind speed has white noise properties, *i.e.*, (distribution = 1, power spectral density = 1). **Figure 5** shows that the power spectral of wind speed is low density at around 7 - 10 sec. Therefore, wind speed forecast errors of 7 - 10 sec ahead in **Figures 3** and **4** are influenced by characteristic of wind speed for
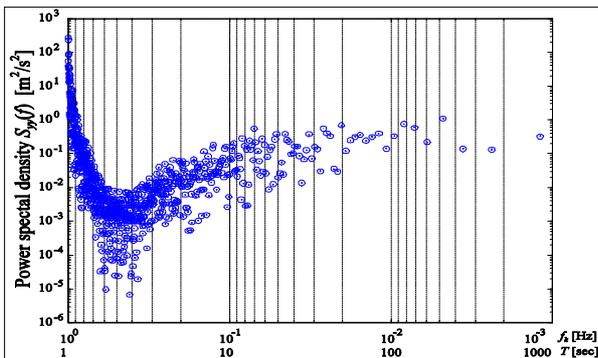
Figure 5. Power spectral density of wind speed (Van der Hoven model).

the power spectral with low density.

4. Power Output of Wind Power Generator

After the wind speed forecasting, the authors determined the power output of wind power generator. In this paper, the point under discussion was put on wind speed fore-casting. To confirm the validity of the proposed method, the authors determined the power output. It means that power output for wind generator can be forecast by using only wind speed data. The energy of the wind is kinetic energy, and kinetic energy of mass m and speed V is de-fined by $0.5\,m\cdot V^2$. Thus the wind power energy received by the swept area of the blades has the following equa-tion:

$$P = \frac{1}{2}mV^2\eta = \frac{1}{2}(\rho AV)V^2\eta = \frac{1}{2}\rho AV^3\eta \quad (13)$$

where m [kg] is mass, V [m·s^{-1}] is wind speed, η [%] is efficiency coefficient, ρ is air density 1.225 kg·m^3, and A [m^2] is swept area of the blades [3]. Power output of a typical wind turbine is generated starting at "cut-in wind speed", and not generated at over the "cut-out wind speed". Rated wind speed is different in each type of wind turbine. Usually, cut in wind speed is 3 - 5 m·s^{-1}, rated wind speed is 8 - 16 m·s^{-1}, and cut out wind speed is 24 - 25 m·s^{-1} [19-21]. In this paper, power output of wind power generator is determined by parameters shown in **Table 1** and **Figure 6**. As mentioned above, the
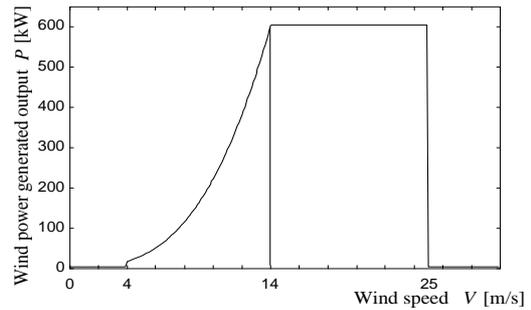
Figure 6. Power output curve of wind power generation sys-tem.

Table 1. Simulation parameters of tested wind power gene-rator.

Blade radius	21 m
Swept area of the blades	1428 m^2
Efficiency coefficient	25%
Rated wind speed	14 m·s^{-1}
Rated output power	600 kW
Cut in wind speed	4 m·s^{-1}
Cut out wind speed	25 m·s^{-1}

power output of wind power generator is determined by using only wind speed data.

Figure 7 shows the forecasting results of power output of wind power generator. The results of **Figure 8** are

(a)

(b)

(c)
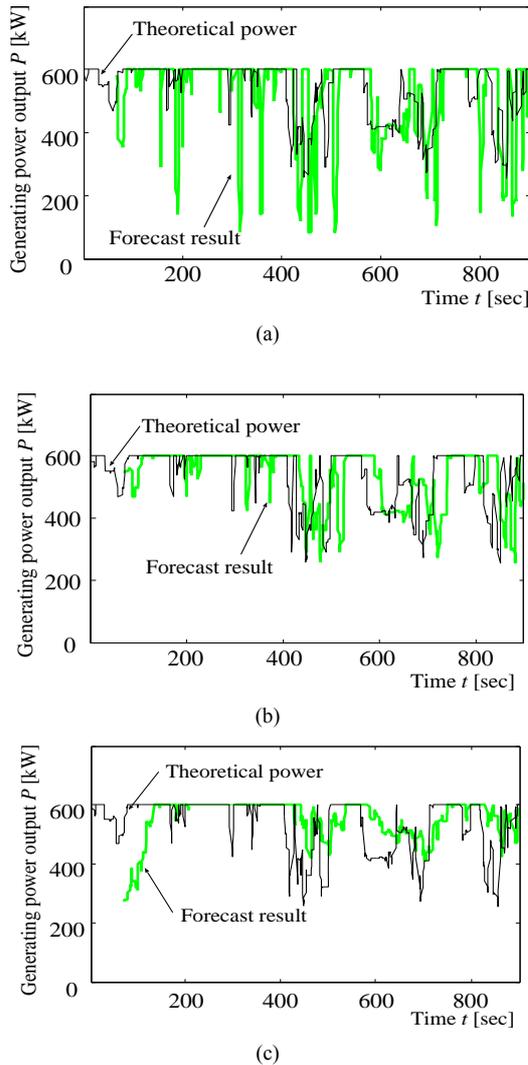
Figure 7. Simulation result of 10 sec ahead forecasting power output for wind generator. (a) The result for using auto regressive model; (b) The result for using neural network; (c) The result for using Kalman filter.
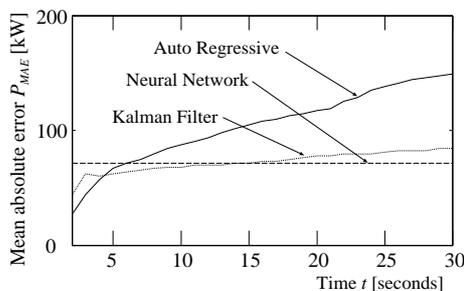
Figure 8. Mean absolute error P_{MAE} (power output for wind generator).

calculated by wind speed forecasting shown in **Figure 3**. The calculated results of *MAE* with AR model, KF and NN are similar. But for the forecast result of the power output by using AR in **Figure 7**, the forecast error is 87.0152 kW in 10 sec ahead, while the results of KF and NN are 71.4639 kW and 68.7320 kW respectively. In fact, forecast error of power output increases by increasing forecast error of wind speed. Although our data sample is relatively small (representing only 900 wind speed data), adding data would further improve the model performance.

5. Conclusion

This paper shows the generating power forecasting of wind generators based on wind speed time series analysis by using AR, KF and NN. The constructed methods do not require complicated calculations due to wind speed data. At the time of wind speed forecasting, it is possible to shorten the calculation time by using historical wind speed data. The validity is confirmed by comparing forecasting results with AR, KF and NN. It is found that the proposed method shows good performance to forecast power output of wind generator. Simulation results lead to the conclusion that it is possible to build up the following hypotheses: if wind speed data are always available, the advantage of the proposed method in this paper is the ability to forecast and estimate sequences of seconds-scale power output for wind power generations from the wind speed only.

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