

ARTIFICIAL HYBRID MODEL FOR FORECASTING WIND ENERGY BASED ON ENSEMBLE KALMAN FILTER

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Abstract

This paper presents a prediction model for wind energy based on Ensemble Kalman Filter (EnKF) Model for Prediction Wind Energy on Urban Building. Ensemble Kalman Filter is a powerful tool and is a recursive filter used to solve many variable problems. The EnKF technique is used to compare to Artificial Neural Network (ANN) technique. The considerate data are on short-term observations during January to February 2018 which is gathered up from the database. There are four meteorological parameters, namely, temperature, humidity, wind speed and wind direction. The predictive results of the prediction model and conventional ANN are compared. Finally, the experimental results show that the EnKF is a capability more than ANN.

Keywords: Wind Energy, Ensemble Kalman Filter, Prediction Wind Energy Model

Introduction

Wind energy is sustainable and infinite energy, that can produce power energy. Even so, wind energy is inconstant, discontinuous, and uncontrollable. Therefore, it causes some problem to control and manage grid system. This problem can be solved by an accurate prediction of wind energy. (Chainok *et al.*, 2017) have predicted power energy by using ANN model, which has the topology of 6-10-1,

and climate data from urban buildings in Bangkok, climate data is included; wind speed, wind direction, temperature and humidity, that results in MSE value about 0.0076. (Chainok, *et al.*, 2017) have predicted power energy from wind energy by using the same data, but applying Extend Kalman Filter (EKF) instead of Levenberg-Marquardt algorithm (LM) in ANN structure, the experimental results show

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that it has a remarkable improvement in the model prediction skill, as mentioned the researchers, this paper is to develop 2 mathematical models between ANN and EnKF to compare the result of electrical energy prediction. An alternative solution for sustainable managing of an excessive glycerol can be done by transforming glycerol to value-added products.

Materials and Methods

Wind Power Energy

A wind turbine obtains its power input by converting the force of the wind into a torque acting on the rotor blades. The amount of energy which the wind transfers to the rotor depend on the density of the air, the rotor area, and the wind speed (Wagner and Mathur, 2009). The wind power of wind turbine can be defined as

$$P = \frac{1}{2} C_p \rho A V^3 \quad (1)$$

where P is the wind power, ρ is the air density, and C_p is the wind energy utilization coefficient, which maximum value is 59.3%, A is wind turbine blade area, and V is wind speed.

The Ensemble Kalman Filter

The Ensemble Kalman Filter is a powerful tool and is a recursive filter used to solve many variable problems. The EnKF is a tool for inference in high-dimensional state-space models. The key concept of the EnKF relative to other sequential Monte Carlo methods is the use of shifting instead of reweighting in the update step, which allows the algorithm to remain stable in high-dimensional problems. In practice, the algorithm requires the choice of important tuning parameters. The state vector X can be defined as

$$X = [x_1, \dots, x_N] = [x_i] \quad (2)$$

The prior ensemble is the matrix x . Repeat the data d into an $m \times N$ matrix

$$D = [d_1, \dots, d_N] = [d_i] \quad (3)$$

where d_i is summary of the data vector d and a random vector from $N(0, R)$ matrix.

$$\hat{X} = X + K(D - HX) \quad (4)$$

where H is the observation matrix, K is Kalman gain. The EnKF algorithm as shown in Figure 1.

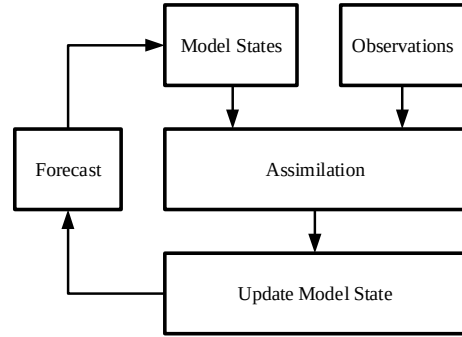


Figure 1. The EnKF algorithm

Artificial Neural Network

Artificial neural network, based on the biological nervous system, is a mathematical model to solve the nonlinear function problems (Wagner and Mathu, 2009). The structure of ANN consists of input, hidden and an output layer. The nodes of each layer must be connected by the weights. ANN models can be developed at many different nodes in the layer.

In this paper, it considerate atmospheric parameters that affect the power of the wind turbine, namely wind speed, temperature, and humidity. Therefore, the designed structure of the neural network composes of six nodes at the input layer, m nodes at the hidden layer

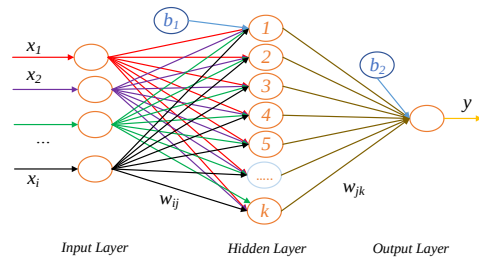


Figure 2. ANN Structure

where $m = 2, 4, 8$, and 10 and a node output layer. The structure of the neural network as shown in Figure 2.

To calculate the net input between the layer, the activation functions are applied such as sigmoid transfer function (LOGSIG) and tangent sigmoid transfer function (TANSIG). LOGSIG and TANSIG can be defined as (1) and (2), respectively.

$$f_{sig}(net_i) = \frac{1}{1 + \exp(-net_i)} \quad (6)$$

$$f_{tansig}(net_i) = \frac{2}{(1 + \exp(-2net_i)) - 1} \quad (7)$$

where net_i is a net input from the last layer to the second layer. x_i is the i^{th} net input, the weight connection between input i and hidden neuron j is w_{ij} . There are weights, w_{jk} that connect between hidden, j and output neuron, k . The net at i^{th} is calculated by the activation function, f_1 and f_2 such that the output network, y is calculated as

$$y = f_2 \left[\sum_{j=0}^m w_{jk} f_1 \left(\sum_{i=0}^n w_{ij} x_i + b_1 \right) + b_2 \right] \quad (8)$$

where n , m are the numbers of neuron in the input layer and in the hidden layer, respectively. b_1 and b_2 are biases.

Wind Power Prediction Model

The system is installed on urban buildings in Bangkok, height about 25 m from the ground. It consists of 3 sensors that collect climate data such as temperature, humidity, wind speed and wind direction data. In the data processing, training set data, input and target

data, are normalized. ANN is designed to estimate the wind power. The wind power estimation system is shown in Figure 3.

Prediction Model Performance

To measure the error between the output network and the measurement data, the mean of squares error (MSE) is estimated for measurement of how close a fitted line is to data points. The MSE is calculated as

$$MSE = \sum_{i=1}^n \left(\frac{t_k - y_k}{n} \right)^2 \quad (9)$$

where t_k is target data, y_k is output network data, n is an input number.

Experiment Data

The input data are from the 6 variables that are temperature, humidity and wind direction. Since these meteorological variables are effect to occurring wind (Wagner and Mathu, 2009). The target data have two variables that are temperature and wind speed. According to, the energy in daily is calculated. Assume that radius blades of a wind turbine are 2 m. The atmospheric variables data from Figure 3 are averaged every day for 2 months. Minimum wind speed (WS_{min}), maximum wind speed (WS_{max}), minimum temperature (T_{min}), maximum temperature (T_{max}), minimum humidity (H_{min}) and maximum humidity (H_{max}) are calculated. Data are normalized. Table 1 shows the experimental models. There is 1 type of topology, 2 activation functions. Thus, 4 models are designed. From Table 1 the mean square error (MSE) of IV ANN model which is 6-10-1

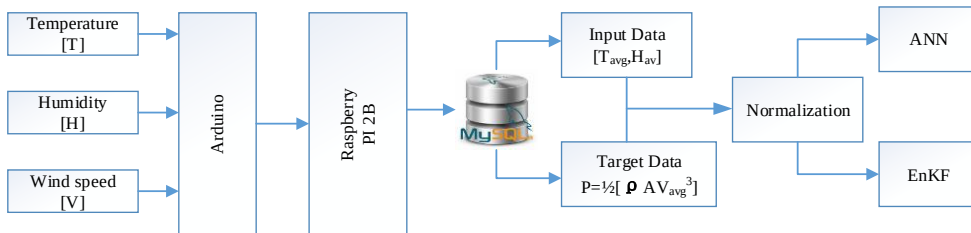


Figure 3. System Diagram

Table 1. ANN Experimental Models

Model	Topology	Transfer Function I	Transfer Function II	MSE
I	6-10-1	LOGSIG	LOGSIG	0.107
II	6-10-1	LOGSIG	TANSIG	0.096
III	6-10-1	TANSIG	LOGSIG	0.133
IV	6-10-1	TANSIG	LOGSIG	0.035

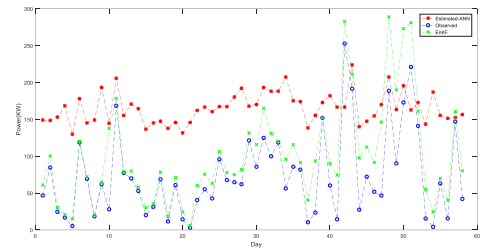


Figure 2. ANN Structure

topology, activation function in the first layer is TANSIG and in the second layer is LOGSIG, is the highest and also MSE is lowest and closed to zero.

Results and Discussion

Figure 4 demonstrate the comparison between the output of prediction model and measured data of model number 4.

Conclusions

In this paper, ANN is applied to predict the wind power energy. The topology in proposed method is divided in 6-10-1. EnKF is used to optimize weights for update a new weights in iteration time. The training set data consist of input data, temperature, wind direction and humidity, and measured data which are defined by theory. The experimental results show that the 6-10-1 topology with TANSIG in first transfer function and LOGSIG in second transfer function is highest performance. Therefore, the prediction model based on EnKF can capably predict the wind power on urban building.

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References

Chainok, B., Permpoonsinsup, W., Thunyasrirut, S., and Wangnipparnto, S. (2017). A prediction model for wind energy based on artificial neural network with extend kalman filter. *J. Mat. Sci. Appl. Ener.*, 6(2):146-150.

Chainok, B., Tunyasrirut, S., Wangnipparnto, S., and Permpoonsinsup, W. (2017). Artificial neural network model for wind energy on urban building in bangkok. 5th International Electrical Engineering Congress. 8-10 March 2017. Pattaya, Thailand, p. 33-36.

Wagner, H.J. and Mathu, J. (2009). *Introduction to Wind Energy Systems*. 1. New York: Springer.