A PREDICTION MODEL FOR WIND ENERGY BASED ON ARTIFICIAL NEURAL NETWORK WITH EXTEND KALMAN FILTER

Bopit Chainok [a,*], Wachairapond Permpoonsinsup [b], Satean Thunyasrirut [a],
Santi Wangnipparnto [a]

[a]*Faculty of Engineering, Pathumwan Institute of Technology, Bangkok, 10330, Thailand*
[b]*Faculty of Science and Technology, Pathumwan Institute of Technology, Bangkok, 10330, Thailand*

Received 7 March 2017; Revised 23 June 2017; Accepted 4 July 2017

ABSTRACT

This paper presents a prediction model for wind energy based on artificial neural network (ANN) with extend Kalman filter (EKF). ANN is a mathematical model to solve the nonlinear problems. The EKF technique is used to update weights in the training processes. The considerate data for training set data are on short-term observations during November to December 2016 which is gathered up from the database (PITWeatherDB). 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 it has a remarkable improvement in the model prediction skill.

KEYWORDS: *Wind energy; Artificial neural network; Extend kalman filter*

* Corresponding authors; e-mail: bbopitt@gmail.com ,Tel: +668-1457-9009

INTRODUCTION

Wind energy is known as one of cleanest and most sustainable [1] renewable energies. Nowadays, wind turbines have been installed and used in many countries to produce electrical power. These turbines are installed in spacious rural areas far from major cities, where the electricity is required. The cost of this wind energy production could be reduced if these wind turbines, could be installed in high building, and managed, closer to the larger cities such as Bangkok. However, there are various factors that cause unstable winds, which in turn influences the management of the wind power. Artificial neural network (ANN) is one technique has been used to predict wind energy. ANN is a mathematical model for representing the biological nervous system of human brain. ANN composes of topology and training algorithm for adjusting weights. There are many algorithms to train ANN. Krok [2] used Kalman filter to updated ANN for removing unnecessary connection inside the network. Palma et al. [3] have studied the potential benefits of non-linear state space in neural networks for real time identification with EKF. Galanis et al. [4] used a non-linear functions in classical Kalman filter algorithms on the improvement of regional weather forecasts. Babazadeh et al. [1] have applied wind speed variables and Gaussian noise into prediction model in measuring of wind speed and Kalman filtering is used as the prediction method. As mentioned the researches, this paper is to develop a mathematical model based on ANN to predict wind energy. For optimizing weights, EKF is applied.

THEORY

Artificial neural network

ANN is the biological neuron nervous system which simulates the human brain [2]. The topology of ANN can be seen as Fig.1.

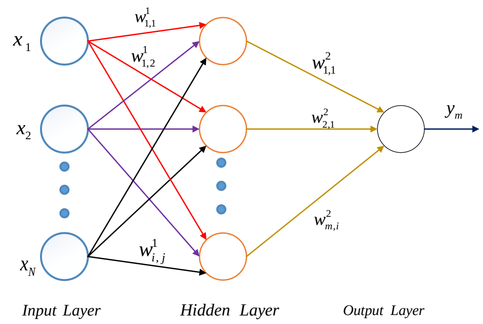


Fig. 1 Artificial neural network.

There are three layers, namely, input, hidden and output layers. In the input layer, let x be input vector and N be the number of input neurons. The input vector can be defined as.

$$\mathbf{x}=[x_1,...,x_N] \tag{1}$$

The connection weight vector, $\mathbf{w}_{ij}^{1}$ between the input neuron, i^{th} and hidden neuron, j^{th} and the number of hidden layer, M can be written as

$$w_{ij}^{q}=\begin{bmatrix} w_{11}^{1} & w_{12}^{1} & .. & w_{1N}^{1} \\ w_{21}^{1} & w_{22}^{1} & .. & w_{2N}^{1} \\ .. & .. & .. & .. \\ w_{M1}^{1} & w_{M2}^{1} & .. & w_{MN}^{1} \end{bmatrix} \tag{2}$$

where i = (1, 2, …, N), j = (1, 2, …, M)

The net input between i^{th} and j^{th} neurons can be calculated by the combination of input neuron and weight vector including biases. It can be written as

$$y_j=f^1(\sum_{i=1}^{N} x_i^1 w_{ij}^1+b_j^1) \tag{3}$$

where f^1 is transfer function, b_j^1 are biases.

The output network can be formulated as

$$y_k=f^2(\sum_{j=1}^{M} f^1(\sum_{i=1}^{N} x_i w_{ij}^1+b_j^1)w_{jk}^2+b_k^2) \tag{4}$$

where k = (1, 2, …, K), b_k^2 are biases.

To calculate the net input between the layer, the activation functions are applied such as sigmoid transfer function, $f_{logsig}(net_i)$ and tangent sigmoid transfer function, $f_{tansig}(net_i)$. They can be defined as (5) and (6), respectively.

$$f_{logsig}(net_i)=\frac{1}{1+exp(-net_i)} \tag{5}$$

$$f_{tansig}(net_i)=\frac{2}{(1+exp(-2net_i))-1} \tag{6}$$

where net_i is a net input.

Wind power energy

To generate electricity from wind turbine, the wind power can be defined as

$$P=\frac{1}{2}C_p\rho AV^3 \tag{7}$$

where P is the wind power, ρ is the air density, and C_p is the the Betz limit, which maximal possible equal 16/27, A is wind turbine blade area, and V is wind speed.

Extended Kalman filter

Kalman filter is a non-linear system that is applied to develop and algorithm for a linear system. It has been still popular for research and applications [2]. Extended Kalman filter (EKF) is developed to improve the convergence of Kalman filter. In this regards, EKF is used to update new weights for ANN. Following in EKF based on weights optimization algorithm, the new weights can be constructed by Eq.8.

$$w_{k+1}^{i}=w_k^i+K_k\left[t_k-f_k(w_k,x_k)\right] \tag{8}$$

The matrix $\mathbf{H}_k^i$ should be obtain by calculating the Jacobian. It can be written as

$$\mathbf{H}_k^i=\frac{\partial \mathbf{f}}{\partial \mathbf{w}^i} \tag{9}$$

Kalman gain matrix, K_k^i is given as

$$K_k^i=P_kH_k^i\left[\sum_{j=1}^{g}(H_k^j)^T P_k^j H_k^j+R_k\right]^{-1} \tag{10}$$

Approximate error covariance matrix, P_{k+1}^i can be derived as

$$P_{k+1}^i=(I-K_k^i(H_k^k)^T)P_k^i+Q_k^i \tag{11}$$

where P_0 and R_k are symmetric positive definite matrices, Q_t is a symmetric positive semidefinite matrix, P_k is error covariance matrix in previous state.

Performance of prediction model

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

$$SSE=\sum_{i=1}^{n}(t_k-y_k)^2 \tag{12}$$

$$MSE=\sum_{i=1}^{n}\left(\frac{t_k-y_k}{n}\right)^2 \tag{13}$$

$$RMSE=\sqrt{\sum_{i=1}^{n}(\frac{t_k-y_k}{n})^2} \tag{14}$$

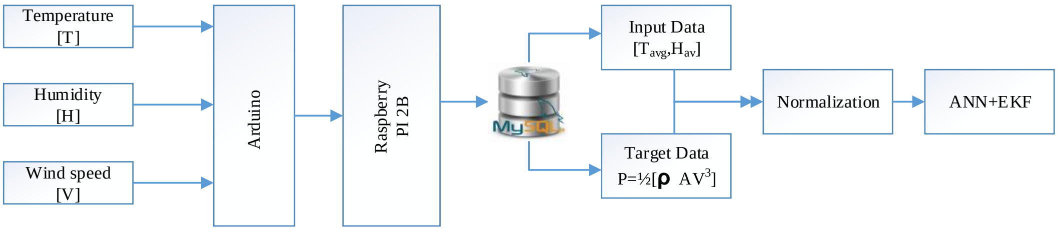
where t_k is target data, y_k is output network data, n is an input number.

EXPERIMENT AND DISCUSSION

Implementing of output network wind turbine on the urban building in Bangkok of Thailand, the system of wind turbine consists of wind sensor and microcontroller that is shown as Fig. 2 (a) and (b), respectively.

(a)

(b)



(c)

Fig. 2 (a) wind sensor (b) microcontrollers (c) system diagram.

Table 1 Sensor Specificationd

Wind Speed Sensor	Wind Direction Sensor	Temp&Hum DHT22 Sensor
Unit : m s^{-1}	Unit : m s^{-1}	Unit : Celsius and %
Supply : 24 V	Supply : 24 V	Supply : 5 V
Output Signal : mA	Output Signal : mA	Output Signal : Digital

Table 2 Server Specification

Raspberry PI 2B
OS : Raspbian GNU/Linux 8.0 (jessie)
DB : MySQL 5.5.52-0+deb8u1 - (Raspbian)
Web : Apache/2.4.10 (Raspbian)

Table 3 Model setting

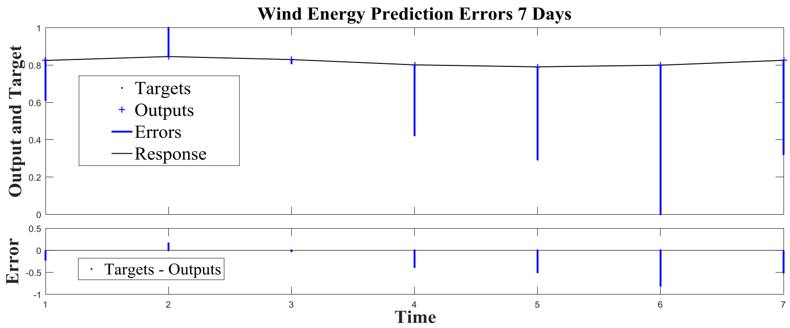
Parameter	Value
ANN topology	2-8-1, 2-10-1
Transfer function	$f_{logsig}(net_i)$, $f_{tansig}(net_i)$
Studied days	3, 5, 7, 10, 15 and 31 (During Nov-Dec, 2016)
Performance	SSE, MSE and RMSE
Correlation (R)	[-1, 1]
Constants in EKF	A = 1, P = 100 and 1, Q = 0.1 and R = 0.001

Table 3 shows the initial parameters. The weather data on urban building during November to December, 2016 are stored in the database (PITWeaterDB). The time frequency is minutely. The data for ANN are selected as 3, 5, 7, 15 and 31 days. The proposed topologies are designed as 2-8-1 and 2-10-1. In consequence, the transfer function is applied $f_{logsig}(net_i)$ and $f_{tansig}(net_i)$. Table 4. illustrates experimental results of prediction models.

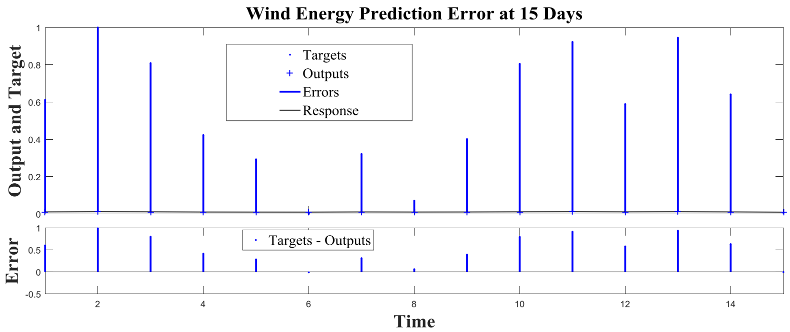
Table 4 Experimental results of prediction models

Model	Days	Topology	SSE	MSE	RMSE	R
1	3	2-8-1	0.2389	0.7168	0.4888	0.8377
2	3	2-10-1	0.1554	0.4661	0.3942	0.9764
3	5	2-8-1	0.1528	0.7639	0.3909	0.9794
4	5	2-10-1	0.2843	1.4214	0.5332	0.9872
5	7	2-8-1	0.2234	1.5641	0.4727	0.8467
6	7	2-10-1	0.3311	2.3174	0.5754	0.8511
7	15	2-8-1	0.3270	4.9049	0.5718	0.8238
8	15	2-10-1	0.2509	3.7634	0.5009	0.8676
9	31	2-8-1	0.0681	2.1114	0.2610	0.9939
10	31	2-10-1	0.1447	4.4858	0.3804	0.9858

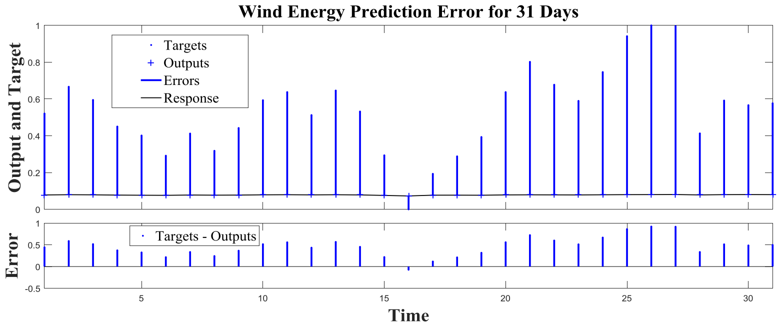
Table 4 shows the results. The weather data on urban building during November to December, 2016 are stored in the database (PITWeaterDB). The time frequency is minutely. The data for ANN are selected as 3, 5, 7, 15 and 31 days. The proposed topologies are designed as 2-8-1 and 2-10-1. In consequence, the transfer function is applied $f_{logsig}(net_i)$ and $f_{tansig}(net_i)$. Table 4. illustrates experimental results of prediction models. Among the results based on the two topology, Model 9 and 10 is the best according to regression (R) nearly 1 with 31 days while Model 2 is the best according to RMSE with 3 days.



(a) Wind energy prediction error for 7 days.



(b) Wind energy prediction error for 15 days.



(c) Wind energy prediction error for 31 days.

Fig. 3 The error between output of prediction model and measured data.

Fig. 3 (a), (b) and (c) demonstrate the errors between the output of prediction model and measured data of model number 3, 5 and 10, respectively.

CONCLUSION

In this paper, ANN is applied to predict the wind power energy. The topology in proposed method is divided in 2-8-1 and 2-10-1. In the training process, EKF is used to optimize weights for update a new weights in iteration time for ANN. The training set data consist of input data, temperature and humidity, from PITWeatherDB, and measured data which are defined by theory. The experimental results show that the 2-10-1 topology is highest performance. Therefore, the prediction model based on EKF can capably predict the wind power on urban building. According to regression closely one and SSE, RMSE, and MSE closely zero.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge faculty of engineering, Pathumwan institute of technology for supporting the facilities and industrial computer technology department, Nakhon Pathom Rajabhat University for supporting the hardware.

REFERENCES

[1] H. Babazadeh, W. Gao, L. Cheng, J. Lin, An Hour Ahead Wind Speed Prediction by Kalman Filter, IEEE Power Electronics and Machines in Wind Applications (PEMWA), University of Denver, 16–18 July 2012, 1–6.
[2] A. Krok, The Development of Kalman Filter Learning Technique for Artificial Neural Networks, JTIT. 4 (2013) 16–21.
[3] L. Palma, P. Gil, J. Henriques, A. Dourado, H. Duarte-Ramos, Applicatioin of an Extended Kalman Filter for On-line Identification with Recurrent Neural Networks, The 7th Jornadas Hispano-Lusas de Ingenieria electrica Madrid, Madrid, 4–6 July 2001, 1–6.
[4] G. Galanis, P. Louka, P. Katsafados, G. Kallos, I. Pytharoulis, Applications of Kalman filters based on non-linear functions to numerical weather predictions, ANGEO. 24 (2006) 1–10.