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Application of artificial neural networks for the wind power prediction in Nakhon Pathom

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Abstract

This paper uses weather data from the Thai Meteorological Department (TMD), Nakhon Pathom Weather Station [1]. Weather information includes wind speed, wind direction, temperature, humidity, and atmospheric pressure. Average data sets were collected on daily basis for 9 months, from January 2017 to September 2017 and converted to a database. Artificial neural networks (ANN) are used to estimate wind power. The mean square error (MSE) is used for measured ANN performance. The experimental results show that the topology of the 3 neurons in the input, 10 neurons in the hidden layer, and a neuron node output is trained by Levenbergï Marquardt algorithm (LM). It has maximum regression and minimum MSE.

Keywords: wind power prediction, wind energy, artificial neural network

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1. Introduction

Wind is a natural source of energy, and can be used indefinitely [2]. Nowadays, wind turbines have been installed, and used to change wind power to mechanical energy, thus producing electrical power. However, wind power is unstable and un-storable. Therefore, the amount of electricity produced directly from wind power, is impossible to measure. One of the most useful tools for attaining the measurement of electrical power attained wind power is the Artificial Neural Network (ANN); a mathematical model for solving non-linear functions. ANN is employed to estimate electrical power [3]. Chainok et al. [4] had collected climate data from high-rise buildings in Bangkok, which are approximately 25 meters high. The frequency of collection is every 1 minute. The collected data includes wind speeds, wind direction, temperatures, and relative humidity. Following the above data collection, the ANN model was used to estimate the electrical power produced by wind turbines that have a diameter of 1.5 meters. Furthermore, the LM was used to train and MSE was used to evaluate efficiency of ANN. Chainok et al. [5] had modified training procedure from LM to Extended Kalman Filter (EKF), and, used MSE, Sum Square Error (SSE) and Root Mean Square Error (RMSE) to evaluate efficiency of ANN. The result of the experiment found that the estimation of wind power energy has more accuracy. Dong et al. [6] use the ANN to forecast the wind power of wind plant in China not only checks the correctness of ANN ensemble based on the principal components analysis (PCA) to forecast wind power but also proves it has a better accuracy and will not cause ñoverfittingò phenomenon. Tebello Mathaba et al. [7] presents a short-term prediction scheme of wind power from wind speed data using Least-Square Support Vector Machines (LS-SVM). Develops different LSSVM models that make use of atmospheric temperature and take advantage of the periodicity of the wind speed data. Results show that atmospheric temperature and using the periodic trend improves the predictions accuracy over the persistence model. The proposed models predict wind power within an error margin of 20% of rated power, 85% of the time. Jinxuan LI et al. [8] presents an ultra short-term wind power prediction method for future four hours is presented and a prediction model based on BP neural network is established. Some experiments are performed. The results show that the prediction method is feasible and has an important reference value for similar wind power prediction system. This paper used data sets from the Nakhon Pathom Weather Station. The datasets were collected daily and included wind speed, wind direction, temperature, humidity, and atmospheric pressure, then develop a mathematical model based on ANN to predict wind energy.

2. Materials and methods

2.1 Artificial neural network is a mathematical model. For information processing with connection-oriented computing. A connectionist to simulate the neural network in the human brain with the aim of creating tools that are capable of learning patterns recognition and knowledge deduction as well as capabilities. Contained in the human brain. The topology of ANN can be seen as figure 1.

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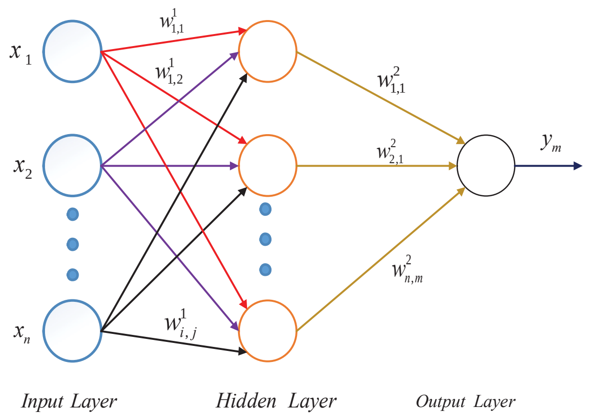

Figure 1 Artificial neural network

From figure 1 ANN is tree layers, input, hidden and output layers. In the input layer, let $\boldsymbol{x}$ be the input vector and N be the number of input neurons. The input vector can be defined as

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

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

$$\mathbf{w}^1_{ij} = [w^1_{11}, \dots, w^1_{NM}] \tag{2}$$

where $i = (1, 2, \dots, N)$, $j = (1, 2, \dots, M)$

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

$$y_j = f^1\left(\sum \quad\right) \tag{3}$$

where f^1 is transfer function, b^1_j are biased.

The output network can be formulated as

$$y_k = f^2\left(\sum_{j=1}^{M} \sum_{i=1}^{N} x_i w^1_{ij} + b^1_j w^2_{jk} + b^2_k\right) \tag{4}$$

where k = (1, 2, …, K), 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.

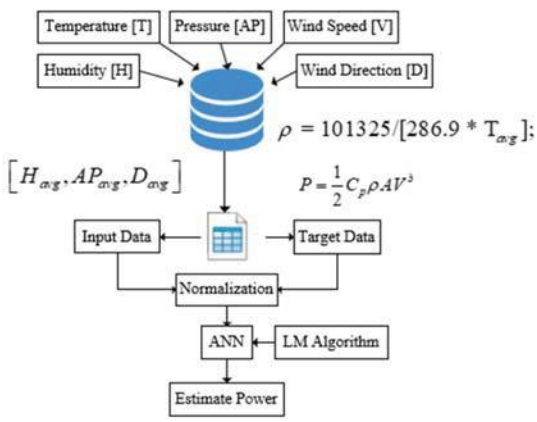

Figure 2 System diagram

2.2 Wind power energy to generate power energy from a wind turbine, the wind power can be defined as

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

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

2.3 Evaluate efficiency of ANN

To measure the error between the output network and the measurement data, the mean of squares error (MSE) which used.

$$MSE = \sum_{i=1}^{n} \left(\quad \right)^2 \tag{8}$$

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

2.4 Wind power estimation method

The input data are from the 3 variables that are humidity, wind direction, and atmospheric pressure. The target data, which have two variables that are temperature and wind speed. From (7), the energy in daily is calculated. Suppose that radius blades of a wind turbine are 2 meters. The atmospheric variables data are averaged every day for 9 months. Average wind direction, average humidity, and average atmospheric pressure are calculated. Data are normalized. The system diagram is shown in figure 2.

Table 1 Model setting

Parameter	Value
Network type	Feed forward back propagation
Training function	Levenberg-Marquardt
Adaption learning function	Gradient descent with momentum weight and bias learning function
Performance function	Mean squared normalized error performance function

Table 2 Experimental models

Model	Topology	Transfer Function Layer I	Transfer Function Layer II	MSE	Regression
1	3-2-1	TANSIG	TANSIG	0.075	-0.059
2	3-2-1	TANSIG	LOGSIG	0.690	-0.033
3	3-2-1	LOGSIG	TANSIG	0.167	0.320
4	3-2-1	LOGSIG	LOGSIG	0.642	-0.025
5	3-4-1	TANSIG	TANSIG	0.156	0.392
6	3-4-1	TANSIG	LOGSIG	0.666	-0.043
7	3-4-1	LOGSIG	TANSIG	0.114	-0.108
8	3-4-1	LOGSIG	LOGSIG	0.628	0.000
9	3-8-1	TANSIG	TANSIG	0.039	0.521
10	3-8-1	TANSIG	LOGSIG	0.656	0.000
11	3-8-1	LOGSIG	TANSIG	0.048	0.380
12	3-8-1	LOGSIG	LOGSIG	0.628	0.005
13	3-10-1	TANSIG	TANSIG	0.013	0.746
14	3-10-1	TANSIG	LOGSIG	0.635	-0.028
15	3-10-1	LOGSIG	TANSIG	0.030	0.700
16	3-10-1	LOGSIG	LOGSIG	0.706	0.010

3. Results and discussion

The weather data during January to October 2017 are converted in the database. The time-frequency is average daily. The proposed topologies are designed as 3-2-1, 3,4,1, 3,8,1 and 3-10-1. The transfer function is applied $f_{logsig}(net_i)$ and $f_{tansig}(net_i)$. Table 1. shows the initial parameters of ANN.

Table 2. illustrates experimental results of prediction models. Among the results based on the 4 topologies, Model 13 is the best according to regression (R) nearly 1 and best MSE.

4. Conclusions

In this paper, ANN is applied to predict the wind power energy. The topology in the proposed method is divided in 3-2-1, 3-4-1, 3-8-1 and 3-10-1. In the training process, LM is used to optimize weights for update a new weight in iteration time for ANN. The training set data consist of input data, humidity, wind direction and pressure, and target data which are defined by theory. The experimental results show that the 3-10-1 topology is the highest performance. Therefore, the prediction model based on LM can capably predict the wind power.

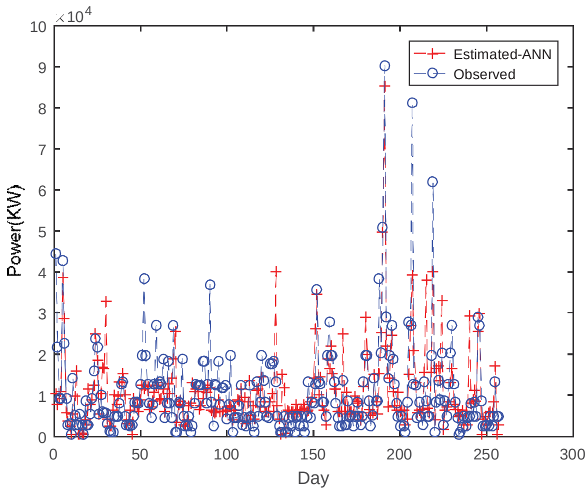

Figure 3 Comparison of observed and estimated of model 13 data

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