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Prediction of wind speed and direction data by using Back-Propagation Neural Networks

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SUMMARY:
Monsoons were often the primary consideration when conducting wind environment or wind energy evaluation. Sufficient wind speed and direction data from nearby meteorological stations must be collected for statistical analyses. Shorter collection times or equipment failure cause insufficient data in some meteorological stations that cannot fully represent the characteristics of the local wind environment. This study collects historical meteorological data to input Back-Propagation Neural Network (BPNN) models with different model parameters, and input layer variables are established through training and testing. Comparison of the predicted wind speeds and directions in several combinations shows that model parameters and input layer variables shall be carefully chosen to improve the prediction accuracy. The resulting "best" model is then used to supplement the wind speeds and directions of the target stations with insufficient recorded data. It is found that the model is quite consistent with the overall trend in wind speed history comparison and is suitable for the analysis of the monsoon wind environment.

Keywords: Back-Propagation Neural Network, Wind Speed Prediction, Meteorological Data

1. INTRODUCTION

In the past, when conducting wind environment analyses, monsoons were often the primary consideration, and wind speed and direction data from nearby meteorological stations were collected for statistical analyses. However, most automatic meteorological stations in Taiwan provide insufficient data numbers to represent the local wind environment characteristics due to their shorter collection time, relocation, or instrument failure. Generally, the station needs at least ten years of wind speed data for wind environment assessments. (Hiester et al., 1979).

Artificial Neural Networks (ANNs) have been extensively used for prediction and function approximation in non-linear problems. Some researchers use ANNs to estimate wind speeds in a region with complex topography (Koo et al., 2015; Philippopoulos et al., 2012). ANNs are also used to estimate the long-term wind speeds at a candidate site (Velázquez et al., 2011) or to calibrate the cup anemometer for field measurement (Li et al., 2022).

This study utilizes the Back-Propagation Neural Network (BPNN), a typical type of ANNs. By building and comparing models with different training parameters, the number of neurons, and the combination of input variables, we attempt to find the "best" method to predict the target station's wind speeds and wind directions suit for monsoon statistical conditions.

2. METHODOLOGY

2.1. Back-Propagation Neural Networks

The learning process of BPNN includes forward and back propagation algorithms, while only one direction of the algorithm will be operated. In the learning process of BPNN, forward propagation means that the data is transmitted from the input layer to the hidden layer with calculations of weights and threshold values. Then through the transfer function, the corresponding output value of each neuron can be calculated. If output values cannot achieve target values, these values will substitute into the error function and correct weights and threshold values through gradient descent (Goh, 1995). Figure 1 shows the training process of BPNN. First, import input and target variables to the neural network, then through the backpropagation algorithm, optimal weights and thresholds are generated.

2.2 Data set Description

This study adopts the Tucheng station as the target station, and four stations adjacent to the target station are selected as training stations. The goal is to use meteorological data of training stations to train and build a BPNN model to predict the data of the target station. The relative positions of the stations are shown in Figure 2. The data collected at all stations are recorded hourly. The amount of data is 30321. In addition, the data is divided into two parts: testing data and training data, which are 30% and 70% of the total data. The training data is known, and the test data is considered the unknown value in the target station. This assumes the target station loses the test data in this period. The research process is to import the training data set of each station into BPNN to obtain the training model and then use the wind speed of one specific training station as input to predict the wind speed and direction of the target station in the test data period.

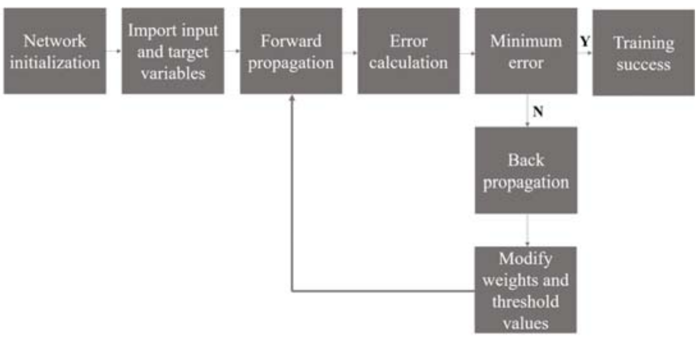

Figure 1. Training Process of BPNN

Figure 2. Locations of Tucheng Station and Adjacent Meteorological Stations

2.3 Pre-processing of Meteorological Data

In this study, monsoons are the primary consideration; therefore, the lower wind speed (U<0.5 m/s) and typhoon wind speeds are neglected. In addition, the data are normalized as follows to improve the model convergence and accuracy:

$$\hat{S} = \frac{s-(s)_{min}}{(s)_{max}-(s)_{min}} \quad (1)$$

s is the variable of the meteorological station; subscripts min and max denote the minimum and maximum value in the training data set, respectively. Hence, all variables are between 0 and 1 after normalization.

In addition, the angles θ of wind directions (between 0° to 360°) are expressed in the form of sinθ and cosθ to prevent the misjudgment of BPNN caused by significant angle differences.

3. RESULTS

Models are established considering the different combinations of input meteorological variables and the combination of input meteorological stations. The model accuracy is evaluated by Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Correlation Coefficient (denoted by R).

3.1 Combination of Input Meteorological Variables

Table 1 shows eight combinations of input meteorological variables. All variables are included in Case A1, while the other cases ignore some variables except wind speed and direction. The training results (Figure 3) show that RMSE and MAPE are lower when the neurons number increases. When all meteorological variables are involved, the error between the predicted wind speed and the target wind speed is minimized. However, the training time increases as the number of input variables grow.

Table 1. Combination of Input Meteorological Variables

Case ID	wind speed	sinθ	cosθ	temperature	humidity	atmospheric pressure
A1	v	v	v	v	v	v
A2	v	v	v	v	-	v
A3	v	v	v	-	v	v
A4	v	v	v	v	v	-
A5	v	v	v	-	-	v
A6	v	v	v	v	-	-
A7	v	v	v	-	v	-
A8	v	v	v	-	-	-

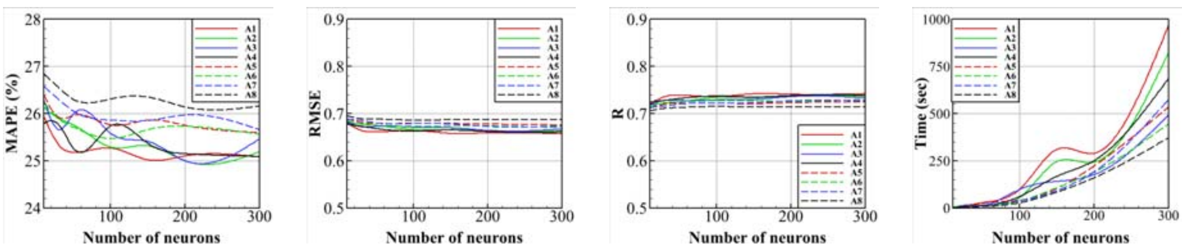

Figure 3. Comparison of Different Combinations of Input Meteorological Variables.

3.2 Combination of Input Meteorological Stations

The effect of the number of input stations on training results is also studied. The considered combinations are shown in Table 2, and all input variables are included as A1. It can be observed that increasing the number of input stations can improve the accuracy of wind speed prediction.

4. CONCLUSIONS

In this study, the wind speed and wind direction data of the Tucheng station are predicted through the BPNN. The predicting wind speed and direction accuracy are compared for eight combinations of input station variables and eight combinations of input stations. The following conclusions are made: (a) increasing the meteorological variables can improve the accuracy of wind speed prediction; (b) increasing the number of input stations can improve the accuracy of wind speed prediction; (c) The error index can achieve stability when the neurons exceed 50 according to the current study. It is found that the model is quite consistent with the overall trend in wind speed history comparison and is suitable for the analysis of the monsoon wind environment.

Table 2. Combination of Input Meteorological Stations

Case ID	Banqiao	Zhonghe	Taipei	Sanxia
B1	v	-	-	-
B2	-	v	-	-
B3	v	v		-
B4	v	-	v	-
B5		v	-	v
B6	v	v	v	-
B7	v	v	-	v
B8	v	v	v	v

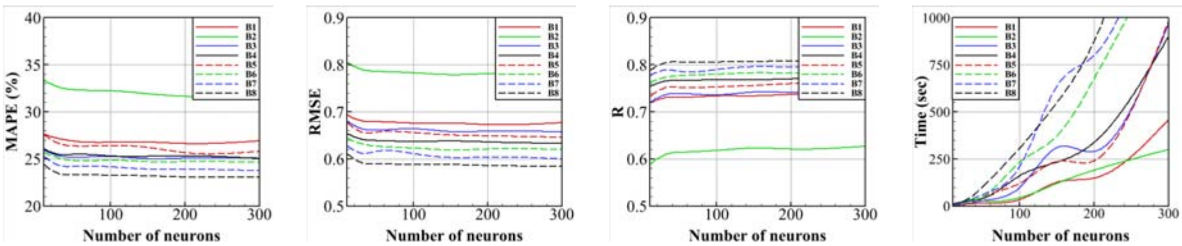

Figure 4. Comparison of Combination of Input Meteorological Stations

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