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Modeling of Relative Humidity Using Artificial Neural Network

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Abstract

This paper presents a relative humidity predictions using feedforward artificial neural network (FFNN). Relative humidity values obtained from weather records for Malaysia are used in training the FFNNs. The prediction of the relative humidity is in terms of Sun shine ration and cloud cover. However, three statistical parameters, namely, mean absolute percentage error, MAPE, mean bias error, MBE, and root mean square error, RMSE are used to evaluate the neural networks. Based on results, the proposed neural network gives accurate prediction of hourly relative humidity whereas the MAPE, RMSE and MBE values in predicting hourly relative humidity are 5.08%, 5.8 and -0.041, respectively. While the MAPE values for the daily and monthly predicted values are 2.66% and 0.57%.

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Introduction

Relative humidity is a term used to describe the amount of water vapor in a mixture of air and water vapor. It is defined as the partial pressure of water vapor in the air-water mixture, given as a percentage of the saturated vapor pressure under those conditions. The relative humidity of air thus changes not only with respect to the absolute humidity (moisture content) but also temperature and pressure, upon which the saturated vapor pressure depends. Relative humidity is often used instead of absolute humidity in situations where the rate of water evaporation is important, as it takes into account the variation in saturated vapor pressure. The humidity of an air-water vapor mixture is determined through the use of psychrometric charts if both the dry bulb temperature and the wet bulb temperature of the mixture are known. These quantities are readily estimated by using a sling psychrometer. However, the artificial neural networks (ANN) can be used as an alternative method for calculating the relative humidity (Khatib, 2010, Khaitb, 2010(1), Kumar, 2011).

Recently the artificial neural network is employed for modeling metrological variables such as wind speed, ambient temperature and solar radiation. An artificial neural network (ANN) approach is considered for wind speed prediction after observing the statistical of mean monthly and daily wind speed in Jeddah, Saudi Arabia (Mohandes, 1998). A comparison of various time series forecasting approaches was done for predicting mean hourly wind speed data (Sfetsos, 2000). A recurrent ANN is also applied for predicting long-term wind speed and power forecasting (Barbounis, 2006, Barbounis, 2007). In (Bilgili, 2007), ANN is applied for wind speed prediction of a target station using reference stations' data. In (Aksoy, 2004), a new wind speed data generation scheme based on the wavelet transform is introduced and compared to the existing wind speed generation methods. However, in recent years, artificial neural networks (ANNs) have been used in ambient temperature prediction for locations with different latitudes and climates (Tasadduq, 2002, Abdel-Aal, 2004, Altan, 2009). In (Tasadduq, 2002), ANN was used for predicting hourly mean values of ambient temperature. A full year hourly values of ambient temperatures were used to train a neural network model for a coastal location, Jeddah, Saudi Arabia. The ANN requires only one temperature value as input to predict the temperature for the following day. In (Abdel-Aal, 2004), a modern machine learning technique including ANN were applied for the next-day and next-hour ambient temperature prediction. The alternative abductive networks approach was considered for developing hourly models for next-day and next-hour temperature forecasting, both with and without extreme temperature forecasts for the forecasting day, by training hourly temperature data for 5 years and evaluating the data for the 6th year. A multilayer perceptron network consisting of 3 input neurons, 6 hidden neurons and 1 output was developed for daily ambient temperature prediction in Denizli, south-western Turkey (Altan, 2009). The training of the ANN was done by using the Levenberg–Marquardt feed-forward back propagation algorithm with temperature values for Turkey over three years while records of the fourth year were used in testing the network. All the methods in (Tasadduq, 2002, Abdel-Aal, 2004, Altan, 2009) used previous values of ambient temperatures for the location to forecast the current ambient temperature. However, these methods are considered not valid for sites where there are no ambient temperature measuring instruments because of dependence on the previous ambient temperature value.

As for solar energy prediction work, In (Mohandes, 1998) the ANN was used to estimate the global solar radiation for selected sites in Saudi Arabia. 41 stations data were employed for this propose where 31 locations were used for tainting the network while 10 were used for testing purposes. The authors used the multi-layer feed forward neural network (MLPFF) while the back propagation algorithm was used for training the developed model. The developed network consists of 4 inputs, 10 neurons in one hidden layer (no optimization method mentioned) and one neuron in the output layer. The inputs of the developed network are The latitude, longitude, altitude and sunshine duration. However, the authors use the MAPE for evaluating the developed algorithm. The average MAPE was 12.6 %. In (Mohandes, 2000) an ANN model is developed to predict the global solar radiation for sites in Oman in terms of location, month, mean pressure, mean temperature, mean vapor pressure, mean relative humidity and mean sunshine duration. A multilayer feed forward is used in this research and trained by a back propagation algorithm. The MAPE for the developed model as reported by authors is 7.3%. In (Alawi, 1998) the authors have used ANNs to predict solar radiation in areas not covered by direct measurement instrumentation. The input data to the network are the location, month, mean pressure, mean temperature, mean vapor pressure, mean relative humidity, mean wind speed and mean duration of sunshine. The ANN model predicts solar radiation with an accuracy of 93% and mean absolute percentage error of 7.3. In (Mohandes, 2000), three solar energy modeling techniques were employed for estimating solar energy on a horizontal surface in Saudi Arabia. These modeling techniques are radial basis ANN, MLP ANN and classic regression model. The back propagation algorithm we used to train the developed ANNs which supposed to have 10 neurons at the hidden layer. The developed ANNs have four inputs which are latitude, altitude, longitude and sun shine ratio, however, the authors of this research claimed that the radial Basis ANN was the best in estimating solar energy on a horizontal surface among the proposed techniques.

However, litter work is presented regarding the relative humidity and therefore, Tthe main objective of this research is to present a novel ANN model for predicting hourly relative humidity for Malaysia. This work is done based on the long term metrological data for Kuala Lumpur.

Relative Humidity prediction using ANN

Figures 1 shows the feed-forward neural network (FFNN) diagram for relative humidity prediction. The FFNN is a fully connected, three layer, feed-forward, perceptron neural network. Here, "fully connected" means that the output from each input and hidden neuron is distributed to all of the neurons in the following layer and also the values only move from input to hidden to output layers with no values fed back to the earlier layers.

The FFNN which is kind of multi layer perceptron networks has an input layer where a vector of predictor variable values is presented to. The input layer standardizes these values so that the range of each variable is -1 to 1. The input layer distributes the values to each of the neurons in the hidden layer. In addition to the predictor variables, there is a constant input of 1.0, called "the bias" that is fed to each of the hidden layers; the bias is multiplied by a weight and added to the sum going into the neuron. However, the hidden layer represents the phase where the value from each input neuron is multiplied by a weight, and the resulting weighted values are added together to produce a combined value. The weighted sum is fed into a transfer function, which outputs a value. The outputs from the hidden layer are distributed to the output layer. The value from each hidden layer neuron is multiplied by a weight, and the resulting weighted values are added together producing a combined value. The weighted sum is fed into a transfer function, which outputs a value. These values are the outputs of the network (Mehrotra, 1996).

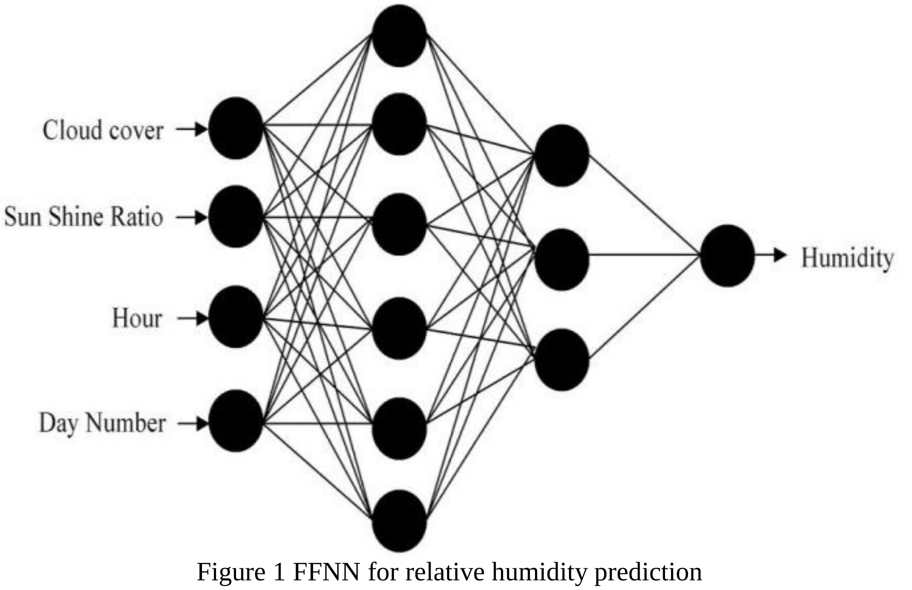

Figure 1 FFNN for relative humidity prediction

MATLAB was used to developed and train the FFNN model. The developed FFNN model has 4 inputs which are day number (month and day), hour, sun shine ratio and cloud cover. These inputs generate the relative humidity which is the output of the FFNN.

ANN evaluation criteria

To evaluate the proposed FFNN, three error statistics were considered; the mean absolute percentage error (MAPE), mean bias error (MBE) and root mean square error (RMSE). MAPE is a measure of accuracy in a fitted time series value in statistics, specifically trending. It usually expresses accuracy as a percentage, and is defined by the formula:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{I-I_p}{I} \qquad (1)$$

where I is the actual value and Ip is the forecast value. The difference between I and Ip is divided by the actual value I again. The absolute value of this calculation is summed for every fitted or forecast point in time and divided again by the number of fitted points n. This makes it a percentage error so one can compare the error of fitted time series that differ in level. In addition, Most ANN models being evaluated quantitatively and ascertain whether there is any underlying trend in the performance of the ANN models in different climates using MBE and RMSE. MBE is an indication of the average deviation of the predicted values from the corresponding measured data and can provide information on the long term performance of the models. A positive MBE value indicates the amount of overestimation in the predicted global solar radiation and vice versa. On the other hand, RMSE provides information on the short term performance and is a measure of the variation of predicted values around the measured data. It indicates the scattering of data around the linear lines. Moreover, RMES shows the efficiency of the developed network in predicting a future individual values, large positive RMES means big deviation in the predicted value form the real one. However, MBE and RMSE are given as follows

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(I_{P_i} - I_i) \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(I_{P_i} - I_i)^2} \quad (4)$$

where I_{P_i} is the predicted value, I_i is the measured value and n is the number of observations

Results and discussion

The taken weather data contains 8769 records for Sebang , Selangor, Malaysia for the year 2005 .6561 (January to September) records were used to train the developed network, while 2208 records were used to test the network. Figure 2 shows the hourly predicted relative humidity results in which the prediction accuracy is considered high since the MAPE, RMSE and MBE are 5.08%, 5.8 (6.7%) and -0.041 (0.048%). Figures 3 and 4 show the daily and monthly averages of the predicted values in which the daily average MAPE is 2.66% while the monthly average MAPE is 0.57%

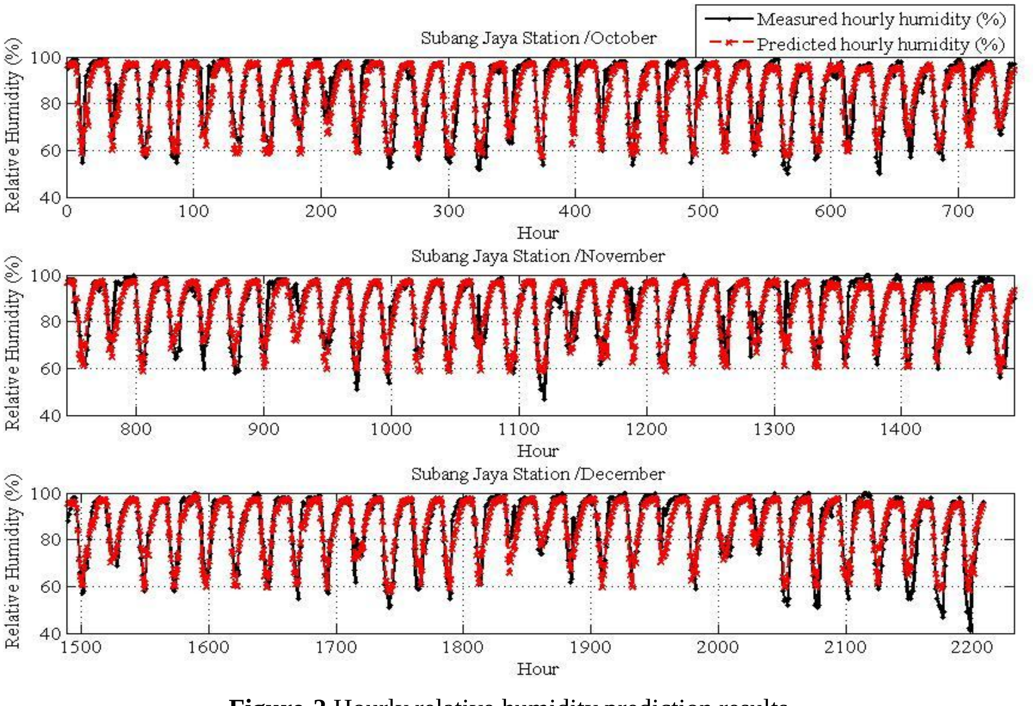

Figure-2 Hourly relative humidity prediction results

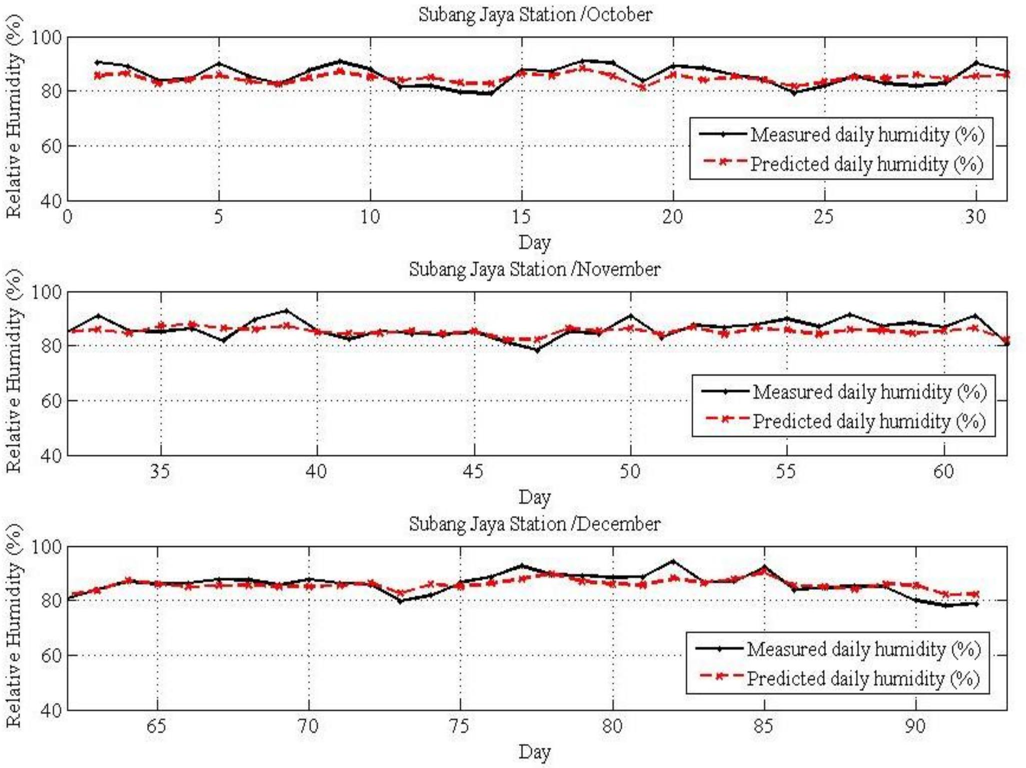

Figure-3 Daily average relative humidity values

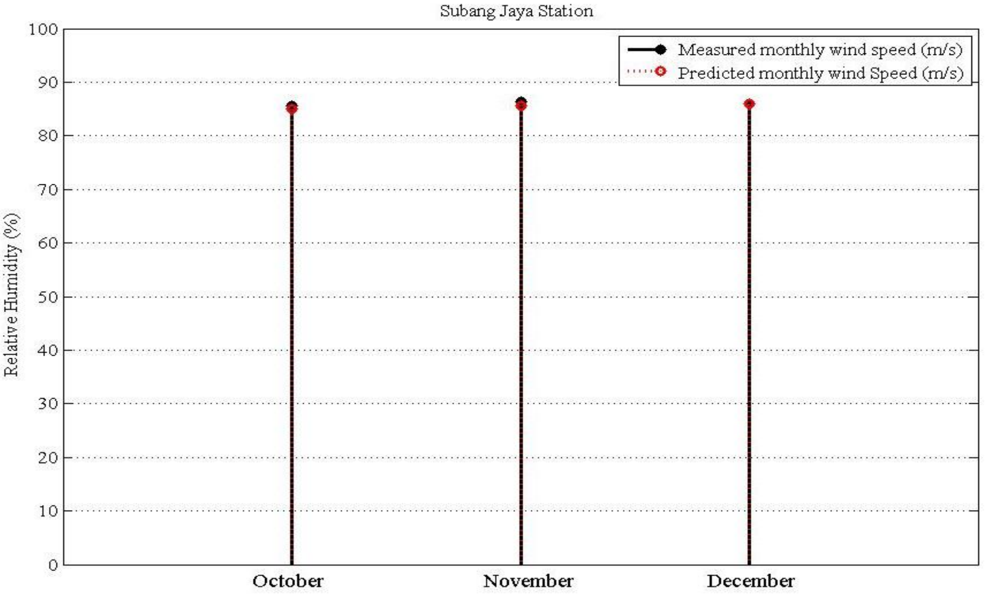

Figure-4 Monthly average relative humidity values

Conclusion

Predictions for relative humidity for Malaysia was made using the feedback forward neural network. For the prediction, the average daily and monthly relative humidity values were calculated from the predic ted hourly values. The FFNN results for predicting hourly relative humidity gave MAPE, RMSE and MBE values for predicting hourly relative humidity were 5.08%, 5.8 (6.7%) and -0.041 (0.048%). However, the MAPE values for the daily and monthly predicted wind speed values were 13.04% and 4.8%. Meanwhile, the MAPE values for the daily and monthly predicted relative humidity values were 2.66% and 0.57%.

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