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ARTIFICIAL NEURAL NETWORK MODELS FOR TEMPERATURE FORECASTING IN SUNDARBAN REGION OF BANGLADESH

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ABSTRACT

Temperature is one of the major parameters in a meteorological model. Over the years, several models have been proposed to predict different weather parameters such as temperature, humidity, wind velocity, and rainfall. Recently, Artificial Neural Network (ANN) has shown fruitfulness in weather forecasting due to its capabilities of handling nonlinear weather pattern. In this study, the viability of ANN was investigated to predict temperature. ANN models were created using feed-forward back propagation algorithm. Weather data for the period 2012 to 2017 from a station of the Sundarbans region of Bangladesh, namely Mongla, was used to develop the models. The models were trained, validated and tested using the data which were preprocessed earlier through cleaning and normalization. The daily temperature prediction was conducted using different parameter settings. Finally, the performances were justified with proper statistical indices, such as the Root Mean Square Error (MSE), the Mean Absolute Percentage Error (MAPE), and regression analysis. The findings of the analysis showed 98% accuracy for Mongla station.

Keywords: Artificial Neural Networks, Sundarbans, temperature prediction, weather

INTRODUCTION

Accurate prediction of temperatures has significant impacts on various sectors of industry, agriculture, and environment. Forecasts are used by governments and industries and individuals to plan a wide range of activities like crop planting decisions, traffic control, tourism forecasting, cricket match prediction, natural disaster mitigation and many others. The aim of this paper is to develop ANN models based on the daily weather data of seven years from a station in the Sundarbans region and estimate the capability of the model in forecasting daily temperature. Sundarbans region is situated in Khulna division of Bangladesh, the biggest mangrove forest in the world. As it is a region of low elevation and near to the sea, daily temperature element plays a contributing role in understanding climate change and regional eco-environmental conditions. Accurate temperature forecasting of this region is one of the greatest challenges due to periodic change of various dynamic environmental factors which is frequently unpredictable by human effort (Arunachalam *et al.* 2015). Moreover, few attempts were made to forecast temperature of the area.

ANN contains some distinguishing features, making it ideal for forecasting. Generalization capabilities create the networks to handle unseen data, even existing certain level of noise. It is a data-driven self-adaptive method that has the ability to model non-linear relationships. Besides, ANN can work perfectly, such as for weather data, where data is abundant, but relationship may not be clear among data.

Recent literatures indicate that the ANN has been one of the most frequently used model to solve hydrogeology problems. El-Shafie *et al.* (2011) developed both Multi Linear

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Regression (MLR) and Feed Forward Neural Network (FFNN) models for predicting the rainfall and these models were applied to Alexandria, Egypt for predicting the rainfall on yearly and monthly basis. They obtained a better prediction results using FFNN compared to the MLR. Dubey (2015) developed twelve rainfall prediction models using ANN for Pondicherry, India. These models were created using three learning algorithms such as feed-forward back-propagation algorithm, layer recurrent algorithm and feed-forward distributed time delay algorithm. Saba *et al.* (2017) employed a hybrid neural model to predict the weather condition. The model exhibited both better generalization capabilities and learning abilities. Abbot and Marohasy (2012) developed a prototype using ANN and successfully employed for forecasting monthly and seasonal rainfall in Queensland, Australia.

Several works of literature also exhibit the capabilities of ANN in the forecasting of temperature. Altan Dombaycı and Gölcü (2009) developed an ANN model that can predict daily mean ambient temperatures in Denizli, south-western Turkey. They varied hidden layer neurons between 3 and 30 and obtained the best result when the number of the neurons is six. Levenberg–Marquardt (LM) feed-forward back propagation algorithms were incorporated for the training of the network. The results showed that the ANN approach was a reliable model for ambient temperature prediction. Another work on temperature prediction using the ANN model is a soil temperature prediction (Tabari *et al.* 2015). Daily meteorological data of two years were collected from two synoptic stations in Iran. The model exhibited accuracy and reliability in short-term soil temperature forecasts.

ANN model was also developed for weather prediction system in Bangladesh. Islam *et al.* (2016) have used ANN to predict monthly weather in Barisal city. The model showed a good performance and reasonable prediction accuracy in terms of monthly rainfall prediction. Rahman and Haque (2014) proposed a fuzzy-neural model for detecting the best range of wind speed. From this wind speed percentage of danger level was calculated. They claimed that this model would be viable for people in coastal area to get a better understanding of upcoming cyclone.

MATERIALS AND METHODS

Study site and data collection: The area selected for this study was Mongla (Lat: 22.60° N and Long: 89.50° E), which is situated in the Sundarbans region of Bangladesh. The input data for the station were obtained from National Weather base, one of the reliable sources for collecting weather data. The meteorological data used in this study have five parameters including temperature, dew point, humidity, wind velocity and precipitation between 2011 and 2017. Table 1 shows average annual values of these five parameters. We divided the data as input and output for ANN models.

Table 1. Average annual values of five weather parameters in the study area between 2012-2017

Parameters	Annual average value (unit)
Temperature	79.0 (Fahrenheit)
Dew Point	72.0 (Fahrenheit)
Humidity	79.6 (Percentage)
Wind velocity	1.2 (Knots)
Precipitation	0.2 (Inch)

Inputs were dew point, humidity, wind velocity and precipitation while output was temperature. Total number of daily observations from 1st August, 2012 to 4th April, 2017 for Mongla station was 1160. In the development of our model, observation was divided in such a way that first 80% was used for training, next 10% for verification and rest 10% for validation.

DATA PREPROCESSING

The raw data in this study had some missing and inconsistent values due to the complexity of weather phenomena and the data size. Therefore, the first step is to find outliers and missing values. The former were detected using box plot and the latter were filled up using mean for a given attribute. Before applying the data to the neural network, data normalization was accomplished so that the range of the data falls within 0.0 to 1.0. This transformation gave all attributes equal weights indicating appropriate for mining. The Equation 1 shows min-max normalization process that performs the task.

$$\overline{v_i} = \frac{\mathrm{v_i} - \mathrm{min_A}}{\mathrm{max_A} - \mathrm{min_A}}(\mathrm{new\_max_A} - \mathrm{new\_min_A}) + \mathrm{new\_min_A} \qquad (1)$$

Where $\mathrm{min_A}$ and $\mathrm{max_A}$are the minimum and maximum values of the time-series data of a given attribute A. Min-max normalization maps a value $\mathrm{v_i}$ of A to $\overline{v_i}$ in the range of$\mathrm{new_max_A} = 0.0$ and$\mathrm{new_min_A} = 1.0$.

NEURAL NETWORK MODELS AND LEARNING

In the present work, feed forward with the backpropagation network was constructed in order to predict the temperature. Different temperature forecasting models were implemented, with the basic architecture being the same for all the models. Each of the ANN models in this paper has an input layer which contains four neurons, at least one hidden layer whose size vary from model to model, and an output layer with one neuron. Each input neuron is connected to each neuron in the hidden layer and hidden neurons fully connected to neurons in the output neuron. Figure 1 shows a feed forward back propagation neural network with one hidden layer containing five hidden neurons. It is a challenge task to decide suitable number of hidden layers and total number of hidden neurons for model buildup. Usually, higher number of hidden layers and nodes tend the network to memorize, instead of learning and generalization and it might lead to the problem of local minima (Hung *et al.* 2009). Therefore, systematic trial and error was employed in building the models. The transfer functions for the hidden layer and output layer were sigmoid and a pure linear function respectively.

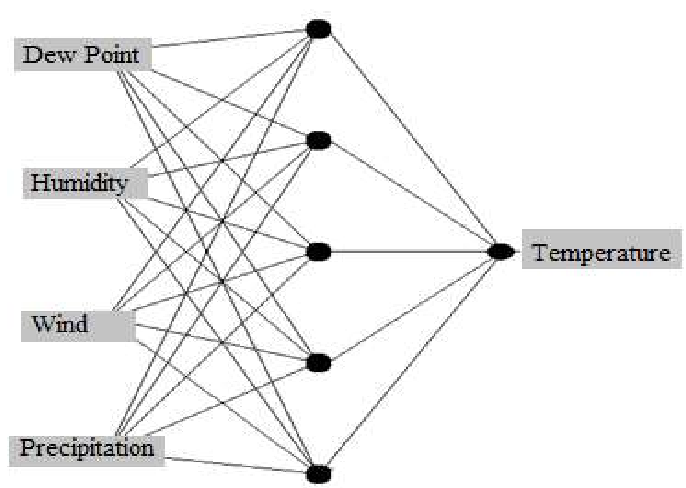

Figure 1. The Feed-Forward Neural Network Architecture used in the study.

As the number of neurons used in the input and output layers is fixed by the nature of the problem, the number of hidden layers and hidden neurons were varied for building the models. Total number of ANN models in this study were six which are summarized in Table 2. The first five models (A-E) contained only one hidden layer. Model A contained five hidden neuron, with the number of neurons increased two times each of the next models up to model E. Next three models (F-H) contained two hidden layers. In this case, the number of neurons per hidden layer for each model increased fivefold, staring from five hidden neurons.

Table 2. ANN models considered in the study

Model	Number of hidden layers	Number of Neurons per hidden layer
A	1	5
B	1	10
C	1	20
D	1	40
E	1	80
F	2	10
G	2	50
H	2	100

Supervised training was applied in this study so that the weights of the neurons are adjusted to achieve better forecasting of the desired output temperature in the input data. The network used the gradient descent with adaptive learning rate back propagation training function, which updates weights and bias values according to both gradient descent momentum and an adaptive learning rate. Adaptive learning works following way: at each epoch, new weights and biases are calculated using the current learning rate. New outputs and errors are then calculated. If the new error is lesser than the old error, the learning rate is increased. When the new error exceeds the old error by more than a predefined ratio, the learning rate is decreased. Maximum number of epochs indicate the stopping criteria for the training process. Finally, all network models were built, trained and tested using MATLAB.

Performance evaluation of ANN models

Three statistical parameters are used to evaluate the overall prediction performance of the ANN models in this study. The MeanSquared Error (MSE) is a measure of the quality of an estimator. The formula of MSE is defined in Equation 2.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2 \qquad (2)$$

The Mean Absolute Percentage Error (MAPE) is a measure of prediction accuracy of forecasting methods. MAPE is defined by the following equation:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{|O_i| - |P_i|}{|P_i|} \qquad (3)$$

We can predict the Mean Absolute Percent Accuracy (MAPA) by subtracting the MAPE from 100. By the MAPA, we can easily say the performance accuracy of the networks. The Equation 4 is used to find the MAPA value.

$$MAPA = 100 - MAPE \qquad (4)$$

Correlation coefficient (r) is defined as the degree of correlation between the predicted and observed values. This is mathematically expressed by Equation 5.

$$r = \frac{\sum_{i=1}^{n}(O_i-\overline{O})(P_i-\overline{P})}{\sqrt{\sum_{i=1}^{n}(O_i-\overline{O})^2 \sum_{i=1}^{n}(P_i-\overline{P})^2}} \qquad (5)$$

All of these equations, n is the total number of predicting temperatures, P_i is the ith temperature predicts by ANN, and O_i is the corresponding ith observation. $\overline{O}$and$\overline{P}$ are the averages for the observed and predicted values respectively.

RESULTS AND DISCUSSION

Temperature forecast accuracy of the six ANN models in testing stage (model A to H) was evaluated using Mean Square Error (MSE) and Mean Absolute Percent Accuracy (MAPA). The behavior of these parameters for the models is presented in Table 2. The performance indices showed that the first five ANN models (A, B, C, D, and E), which used only one hidden layer, yield much better results than next three ANN models (F, G, and H) with two hidden layers. This suggests that the single layer feed-forward is suitable for the proposed weather forecasting. The highest MAPA score 98.1 as well as lowest MSE value 0.000221838 was obtained in the case of the model B, since the number of hidden nodes was sufficient to memorize and learn the training data.Examination of Table 3 also reveals that when the number of hidden nodes was further increased for the subsequent models, the MAPA, in general, declined and MSE increased.

Table 3. Performance statistics of the eight ANN models for daily temperature forecasting atMongla station

Model	MSE	MAPA
A	0.001313	92.76
B	0.00012058	98.1
C	0.000221838	97.42
D	0.005009	88.07
E	0.004384	86.9
F	0.018918	65.54
G	0.019549	64.06
H	0.01911	64.72

Figure 2 shows the comparison between the observed and predicted temperature at Mongla observation using the best ANN model. The correlation between the observed temperature and model simulated temperature for the best model are also displayed in the scatter plot for the station in Figures 3. It is clear from the scatter plot that correlation coefficients is 0.99, indicating that the modelpredicts the temperature with less scatter. We can see that the data are fitted on best fit linear regression line between outputs and targets and also fitted on the perfect target line. It is obvious from the Figure 2 that the forecast value of the ANN models closely follows the corresponding observed value. This model has also the least MSE and MAPE with the performance accuracy of 98.10.

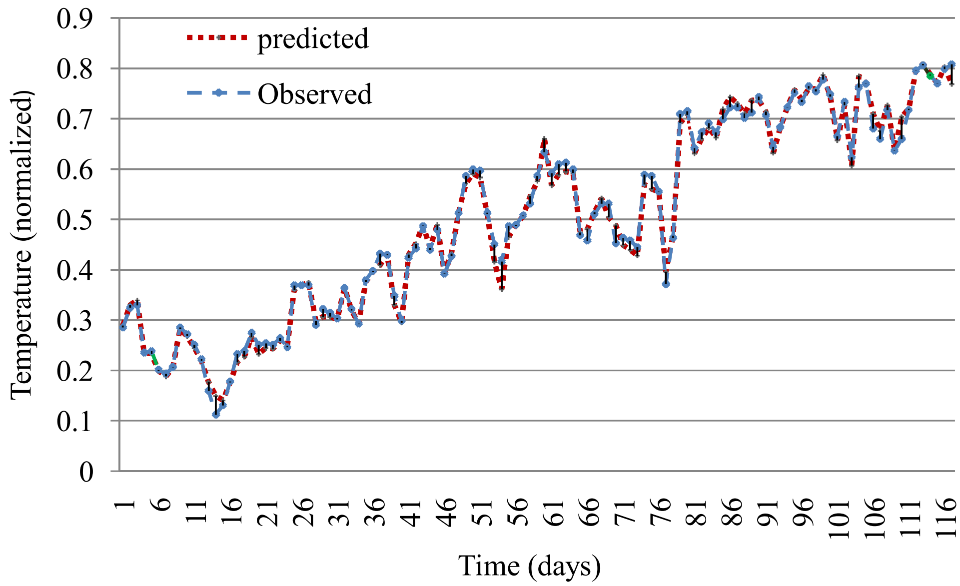

Figure 2. Comparison of observed and predicted temperature at Mongla station using a bestANN Model B in the test period.

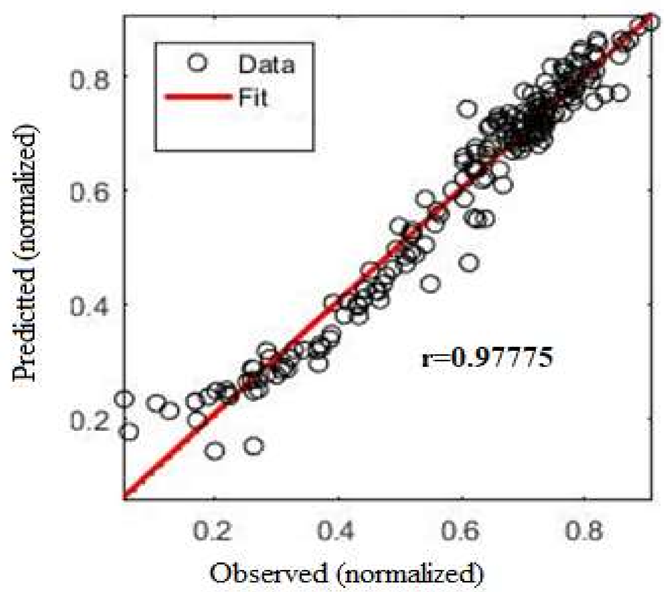

Figure 3. Scatter plot of the observed and forecasted temperature using a best ANN Model B at Mongla station in the testing period.

Figure 4 illustrates the performance of the best performing model B having the training errors, validation errors and test errors. Circle in this graph highlights the best validation performance 0.0007771 which occurs at epoch 3000. This graph shows that the train line, validation line and test line are closer at epoch 3000, which are also close to the best line indicating that the network model is trained well. Note that the low MSE value may be the result of over-fitting. It can be detected when the circle region has a large variation between the test and validation line. In this graph, the validation MSE line seems to closely follow the test MSE line, confirming no over-fitting as well as improved generalization.

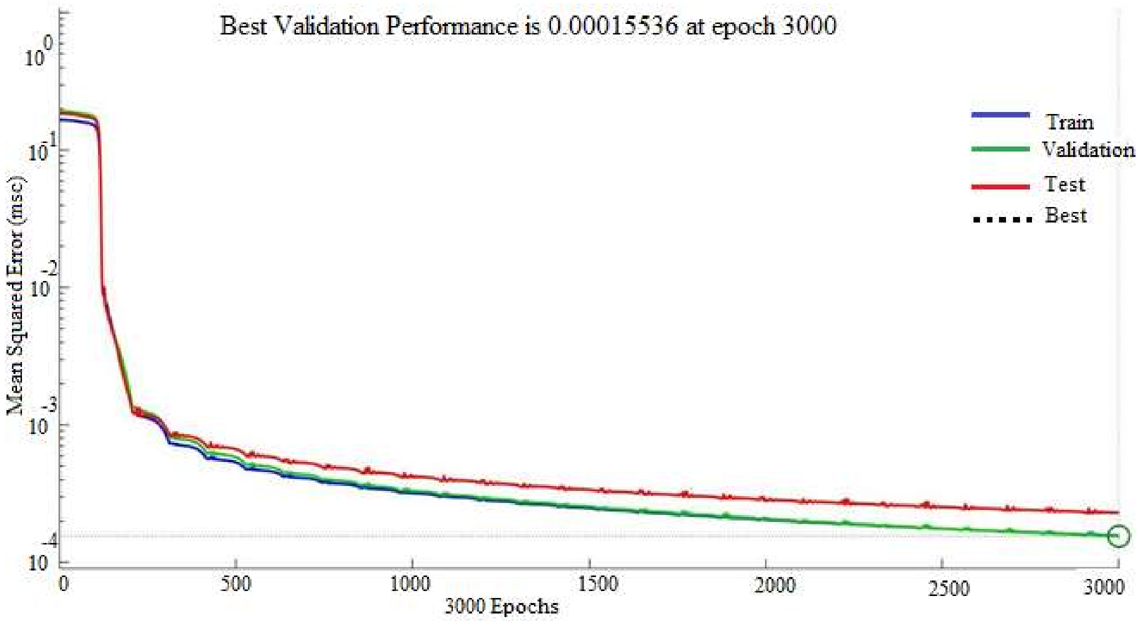

Figure 4. Performance Analysis of Training Network

CONCLUSION

In this study, back propagation neural network-based forecasting models have been developed for predicting daily temperature in the Sundarbans region. Four input vectors containing humidity, wind speed, dew point, and precipitation were employed for developing all the eight models. These models primarily differ from one another on the basis of the number of hidden layers or the number of hidden neurons. The obtained results indicate that developed ANN models are able to forecast temperature with the least error. Although used only for forecasting temperature, these ANN models have the potentiality to predict other weather parameters, such as humidity, wind speed, dew point, and precipitation. In further study, fuzzy and adaptive neural networks can be used for enhancing the prediction performance. Besides, proposed ANN models can be employed for other observing stations in Bangladesh for weather prediction.

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