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Temperature Forecasting for Dar Es Salaam City Using Artificial Neural Network

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Abstract:- Knowing about future climate and weather is important for planning and decision making. Thus temperature forecasting is vital since it helps to determine future weather and consequently climate. The main focus of this paper was to develop a model capable to forecast the seven-days-ahead temperature of Dar es Salaam city in Tanzania by using Artificial Neural Network. In this study, a temperature prediction model with multilayer feedforward neural network architecture was developed and applied to predict the temperature. Three combinations of daily data of maximum and minimum temperature, sunshine hours, air pressure, relative humidity and wind speed for the year 2007 – 2015 were used as training data set and the same data for the year 20016 – 2017 was used as testing data set for the model. Levenberg Marquardt learning algorithm was used to train the model. The performance of the model was measured by using root mean square error (RMSE), mean bias error (MBE) and coefficient of determination (R^2). The results revealed that the model with input data of relative humidity, minimum and maximum temperature, wind speed, air pressure, and sunshine hour, and 5 hidden neurons performed well with MBE=0.429 ℃, RMSE=0.569℃ and R^2=0.967. The model managed to forecast the seven-days-ahead temperature with minimum prediction error in the range of 0.04 - 1.03 ℃. Thus the model developed by using Artificial Neural Network can be considered as an appropriate tool for predicting the temperature of Dar es Salaam city.

I. INTRODUCTION

Knowing about future climate and weather is important for planning and decision making. Thus temperature forecasting is vital since it helps to determine future weather and consequently climate. Temperature forecasting as part of weather prediction involves the application of science and technology to predict the state of temperature for a future period in a specific location. Accurate and precise temperature forecasting is still a challenging task due to the dynamic nature of the atmosphere.

In recent years most of the meteorological stations in the world have adopted the use of Numerical Weather Prediction (NWP) and statistical methods, with the combination of image data collected by weather satellites to predict the future trend of temperature. In view of standards that have to be considered when selecting a prediction method; nature of the time series to be predicted, cost and accuracy, it is noted that satellite-based system is expensive, require complete support system and uses generalized information from a wide range of geographical area which does not give accurate results for predicting the temperature of a specific location. This has led to the temperature results communicated to the public to have limited information about the uncertainty (Darj et al., 2015; Tolstykh & Frolov, 2015).

Though NWP has been extensively used in temperature prediction, it is still limited by the availability of numerical weather prediction products (Paras, 2007). Again, the use of the NWP method in the prediction of temperature is restricted by the random nature of the atmospheric physical variable (Chang et al., 2010). The random nature of the atmosphere poses a difficult situation in establishing the initial conditions of the atmosphere which are essentially needed in temperature prediction. On the other hand, the uses of statistical methods to predict temperature do not give accurate result since they are centered on the assumption of linear time series; thus cannot identify the non-linear pattern of atmospheric temperature time series.

Artificial Neural Network (ANN) has been found to be a promising tool to be used in temperature forecasting because it can handle complex and nonlinear physical variables of the atmosphere. It makes a few assumptions compared with statistical methods and exhibits rapid information processing (Mohita, 2012). It uses the principle of parallel massively machine based on actual biological neuron simplification. ANN also can develop a mapping of input and output which can be used to predict desired output as a function of suitable inputs (Nagendra, 2006). These features of ANN are well suited to the problem of temperature prediction. Therefore this study aimed at developing a temperature forecasting model for Dar es Salaam city by using the ANN technique.

II. MATERIALS AND METHODS

A. Source of Data

The historical meteorological data of maximum and minimum temperature (℃), sunshine hours, air pressure (hPa), relative humidity (%) and wind speed (Knots) of Dar es Salaam city from 2006 to 2017 were obtained from Tanzania Meteorological Agency (TMA). Dar es Salaam city is located at 6.7924^o S 39.2083^o E along the Indian Ocean on the eastern coast of East Africa.

B. Development of Temperature Prediction Model

The temperature prediction model based on ANN was developed by using the procedures shown in figure 1.

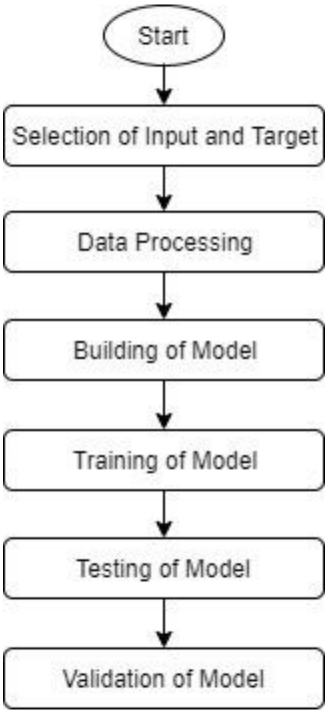

Fig 1:- Procedures for developing a temperature prediction model

➢ *Selection of Input and Target of the model*

Three combinations of input data of year, month, day, minimum temperature (Tmin), maximum temperature (Tmax), wind speed (WS), relative humidity (RH), pressure (P), rainfall (RF) and sunshine hour (SSHR) were formed as shown in table 1. These combinations were used as input of the model. Furthermore, the year, month and day were also used as input to help the network in learning the temporal variations. The daily temperature was taken as the target of the model.

Input	Combination of input	Target
1	Day, month, year, Tmin, Tmax, WS, RH and P	Daily Temperature
2	Day, month, year, Tmin, Tmax, WS, RH, P and SSHR	Daily Temperature
3	Day, month, year, Tmin, Tmax WS, RH, P and RF	Daily Temperature

Table 1:- Input parameters and target of the model

➢ *Data Processing*

The historical meteorological data were portioned into a training set (2006 – 2015) and testing set (2016 – 2017). The missing data were substituted with an average nearby data. The data set was normalized by using **mapstd** function in MATLAB R2016(a). It normalizes the training set and target set into zero mean and unity standard deviation. This was intended to scale the data set into small range so as to speed up the learning phase and to prevent weights from being overly adjusted.

➢ *Building the model*

The temperature prediction model with feedforward neural network architecture was developed to predict the temperature for Dar es Salaam city by using MATLAB R2016(a). The model comprised three layers; input layer, hidden layer and output layer. The number of neurons in the hidden layer was chosen by using a forward approach, with the focus on minimization of prediction errors (Panchal & Panchal, 2014). In this approach, the selection begins with two neurons and then increased during training until a minimum prediction error was obtained. The minimum prediction error was recognized by using a hidden neuron with minimum MBE and RMS.

Levenberg Marquardt learning algorithm was used to train the model. It is commonly used in training multilayer feedforward neural networks, since it has high speed and well-suited with a variety of problems than other common algorithms (Kişia & Uncuoğlu, 2005). The transfer functions which were used in the transformation of neurons in the hidden and output layer of networks were hyperbolic tangent and linear transfer function represented by equations 2.2 and 2.3 respectively. The hyperbolic tangent transfer function was used in the hidden layer to enable the nonlinearity of hidden neurons and to scale the output of hidden neurons into a range of -1 to +1. The linear transfer function was used to generate the unbounded output of the model.

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad \ldots\ldots(2.2)$$

$$f(x) = x \quad \ldots\ldots(2.3)$$

Where x represent the input.

➢ *Training and testing of the model*

The model was trained by using three combinations of input data of seven previous days for the year 2007 – 2015 and then tested by using the data of the year 2016 – 2017. The performances of the model were measured by using Root Mean Squared Error (RMSE), Mean Bias Error (MBE) and Coefficient of Determination (R^2), defined by equations 2.4, 2.5 and 2.6 respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i^*\right)^2}$$

……………………………………………………………….(2.4)

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i^*\right)$$

……………………………………………………………………….(2.5)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - y_i^*\right)^2}{\sum\left(y_i - y_m^*\right)^2}$$

………………………………………………………………..(2.6)

Where y_i is actual temperature value, y_i^* is predicted temperature value, y_m^* represent the average temperature of the data set and n represent a number of samples.

➢ *Validation of the model*

In this case, the first seven days meteorological data for March, June, September and December of 2017 were used as input to the model for forecasting the seven-days-ahead temperature; 8th to 14th of the same months and year. The four months were used in order to assess the suitability of the model for predicting future temperatures in different seasons; March equinox, June solstice, September equinox, and December solstice. The predicted temperatures by the model in those four months were compared with their corresponding actual temperatures.

III. RESULTS AND DISCUSSIONS

The results of this study are presented in the form of graphs of accurate weather forecasting. Figure 2 shows the performance of the model with the variation of the number of neurons in the hidden layer by using input data of year, month, day, wind speed, minimum and maximum temperature, relative humidity, and air pressure. It can be noted from the figure that the performance of this model in terms of MBE, RMSE, and R^2 is varying randomly with the number of neurons in the hidden layer. The model portrayed the minimum prediction error at 3 neurons with MBE=0.444 °C and RMSE=0.609 °C . The maximum prediction error is noted at 11 neurons with MBE=0.626°C, MBE=0.865°C, and R^2=0.899.

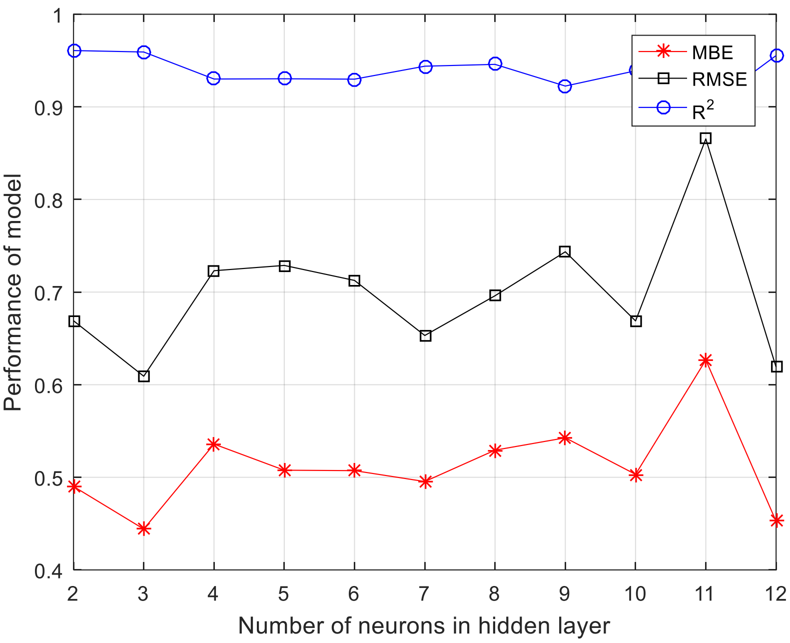

Fig 2:- Performance of model with input 1

Figure 3 shows the performance of the model using input data of year, month, day, relative humidity, minimum and maximum temperature, wind speed, air pressure, and sunshine hour. The figure demonstrates that MBE, RMSE, and R^2 vary randomly continually with the number of neurons in the hidden layer. The minimum prediction error of the model occurred at 5 neurons with MBE=0.388°C, RMSE=0.536°C and R^2 =0.967. The maximum prediction error was observed at 12 neurons with RMSE=0.816°C

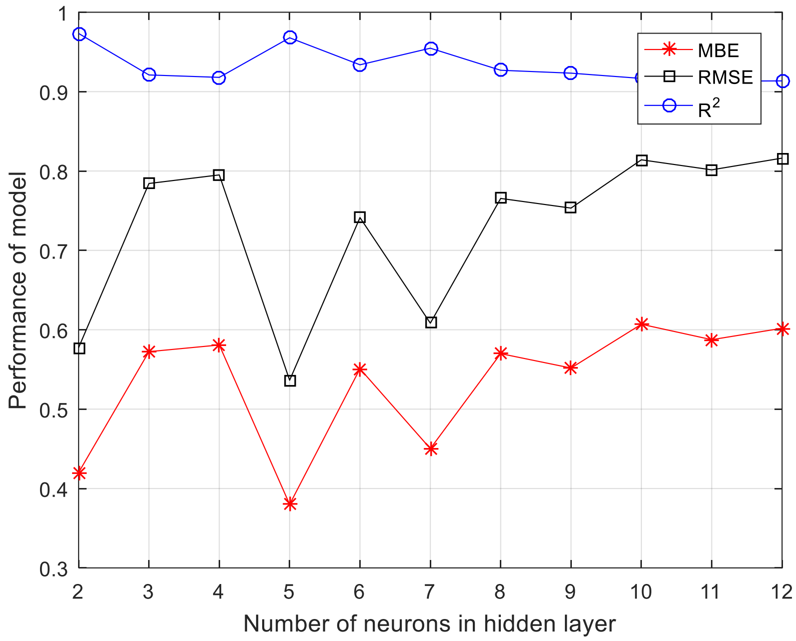

Fig 3:- Performance of Model with input 2

Figure 4 shows the performance of the model by using input data of year, month, day, relative humidity, minimum and maximum temperature, wind speed, air pressure, and rainfall. The figure outlines that MBE, RMSE, and R^2 vary randomly with the number of neurons in the hidden layer. The minimum prediction error of the model is observed at 4 neurons with MBE=0.429℃, RMSE=0.569℃, R^2=0.962 and the maximum prediction error occur at 10 neurons with MBE =0.586℃, RMSE=0.808℃ and R^2=0,897.

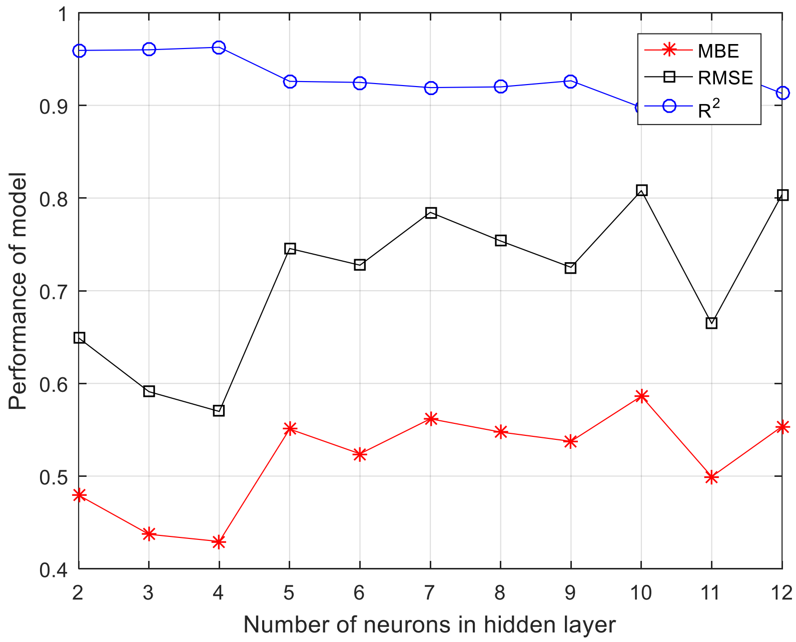

Fig 4:- Performance of the model with input 3

Figure 5 shows the performance comparisons of the model against the inputs. It is observed from the figure that the model with input 2 portrays minimum MBE and RMSE compared to other inputs. Therefore, the model with input data of year, month, day, relative humidity, minimum and maximum temperature, wind speed, air pressure, and sunshine hour, 5 hidden neurons is considered as the best model for temperature forecasting of Dar es Salaam city.

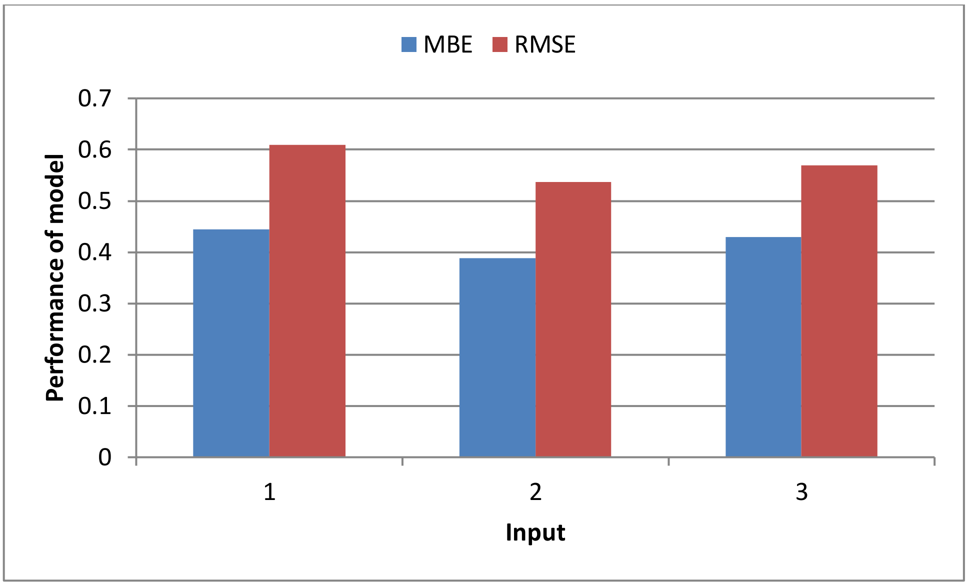

Fig 5:- Performance comparisons of a model with inputs

According to Saba, et al (2017) the best model for weather forecasting is one that has minimum prediction error. Furthermore, the higher value of R^2 indicated by this model shows good agreement between predicted and actual temperature. This result agrees with the study by Singh and Tiwari (2017) and also a study by Doreswamy and Vastrad (2013).

The model managed to predict the daily temperature with minimum MBE and RMSE since it was supplied with a suitable training set, an appropriate number of hidden neurons, suitable training algorithms and significant input parameters (Abhishek et al., 2012; S.R Devi et al., 2016). However, the performance of the model can be improved by increasing the training set, higher-order neural network and hybrid neural network (Ghazali, Ismail, Husaini, & Samsuddin, 2012; Saba et al., 2017).

Figures 6-9 show the comparison of the predicted and their corresponding actual temperatures by the model. The figures demonstrate that in both four months, the model managed to predict the temperature with minimum prediction error. The prediction errors depicted by the model in predicting the seven-days-ahead temperature in the four months are shown in table 2.

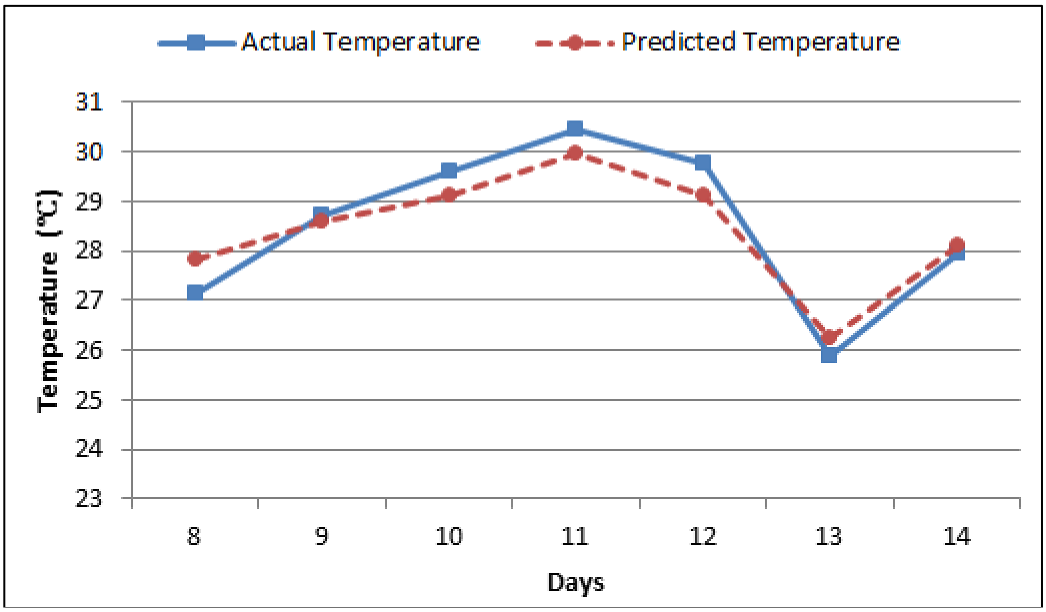

Fig 6:- Temperature forecasting for March 2017

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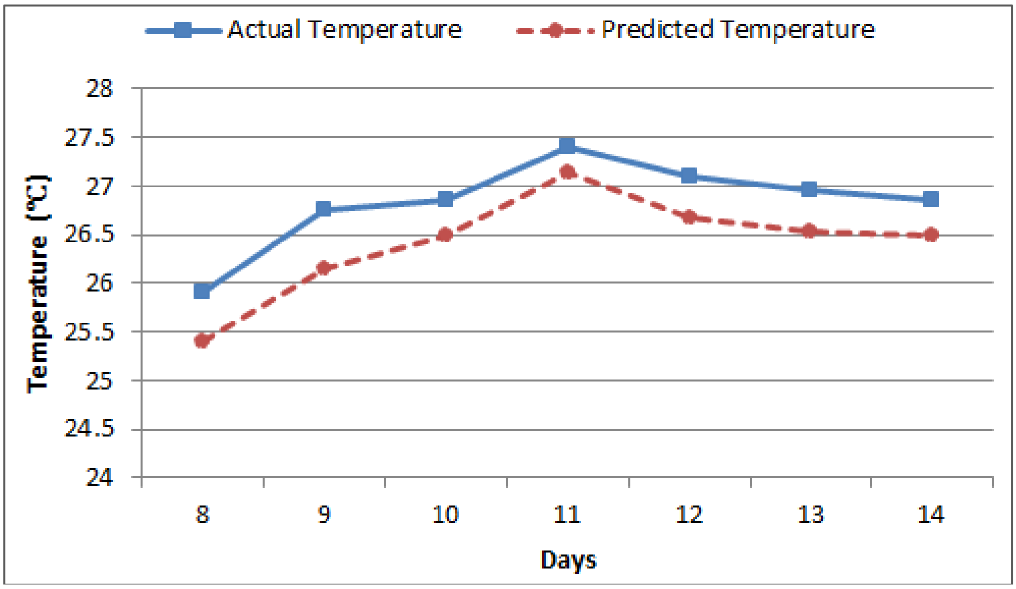

Fig 7:- Temperature forecasting for June 2017

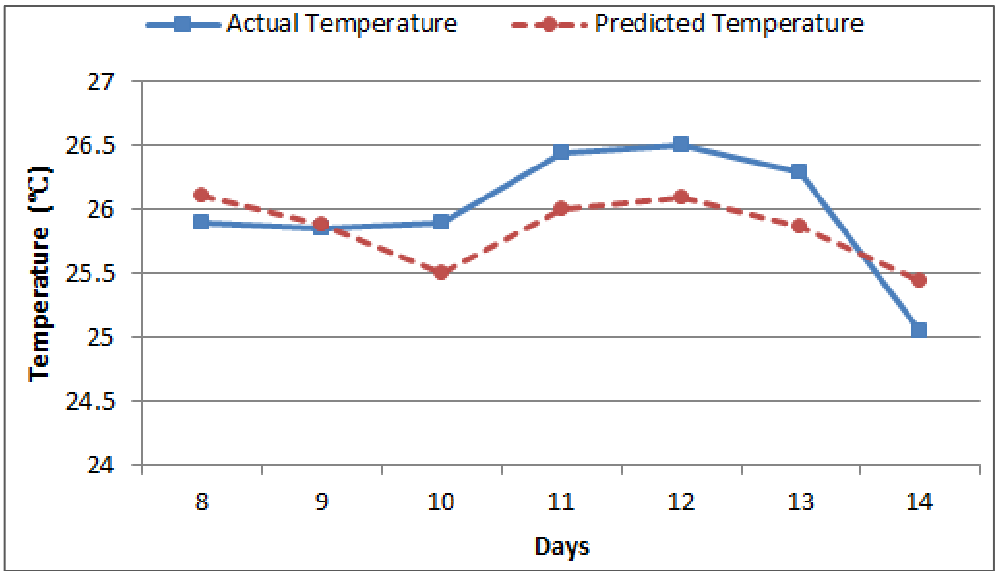

Fig 8:- Temperature forecasting for September 2017

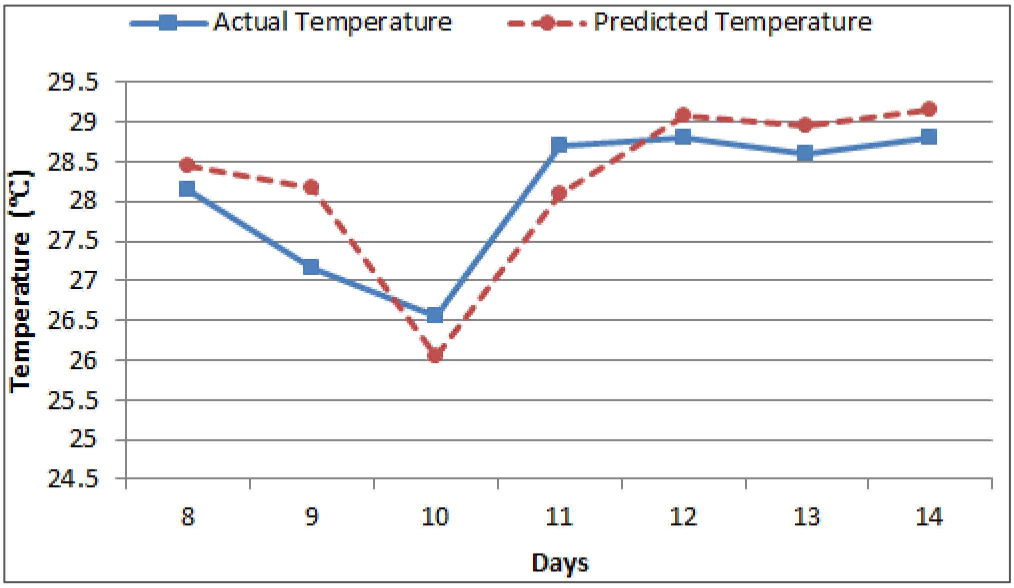

Fig 9:- Temperature forecasting for December 2017

	Prediction error (℃)			
Day	March 2017	June 2017	September 2017	December 2017
8	0.64	0.50	0.21	0.29
9	0.13	0.60	0.04	1.03
10	0.49	0.36	0.40	0.50
11	0.50	0.25	0.45	0.60
12	0.62	0.43	0.40	0.29
13	0.34	0.42	0.42	0.35
14	0.14	0.36	0.39	0.35

Table 2:- Prediction error of the model

The prediction error in the four months lies in the range of 0.04-1.03 ℃. These lower prediction errors indicate that there is a small difference between the predicted and actual temperature, thus the model managed to predict the seven-days-ahead temperature of Dar es Salaam city.

IV. CONCLUSIONS

The results of this study revealed that the developed temperature forecasting model can generate a forecasting of temperature with minimum errors and the best forecast result is obtained by using a model with inputs of year, month, day, relative humidity, minimum and maximum temperature, wind speed, air pressure, and sunshine and 5 hidden neurons. The developed model has reasonable prediction accuracy and good performance. For this reason, the developed model by using ANN is considered as an appropriate tool for forecasting the temperature of Dar es Salaam city.

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