New Regression models for Estimation daily temperature of Karachi and its Neural Network analysis

Adeel Tahir [1,2*], Muhammad Ashraf [1], Mamnoon Akhter[3], Zaheer Uddin[2], Muhammad Sarim[4]

[1]Department of Physics, Federal Urdu University of Arts Science and Technology, Karachi

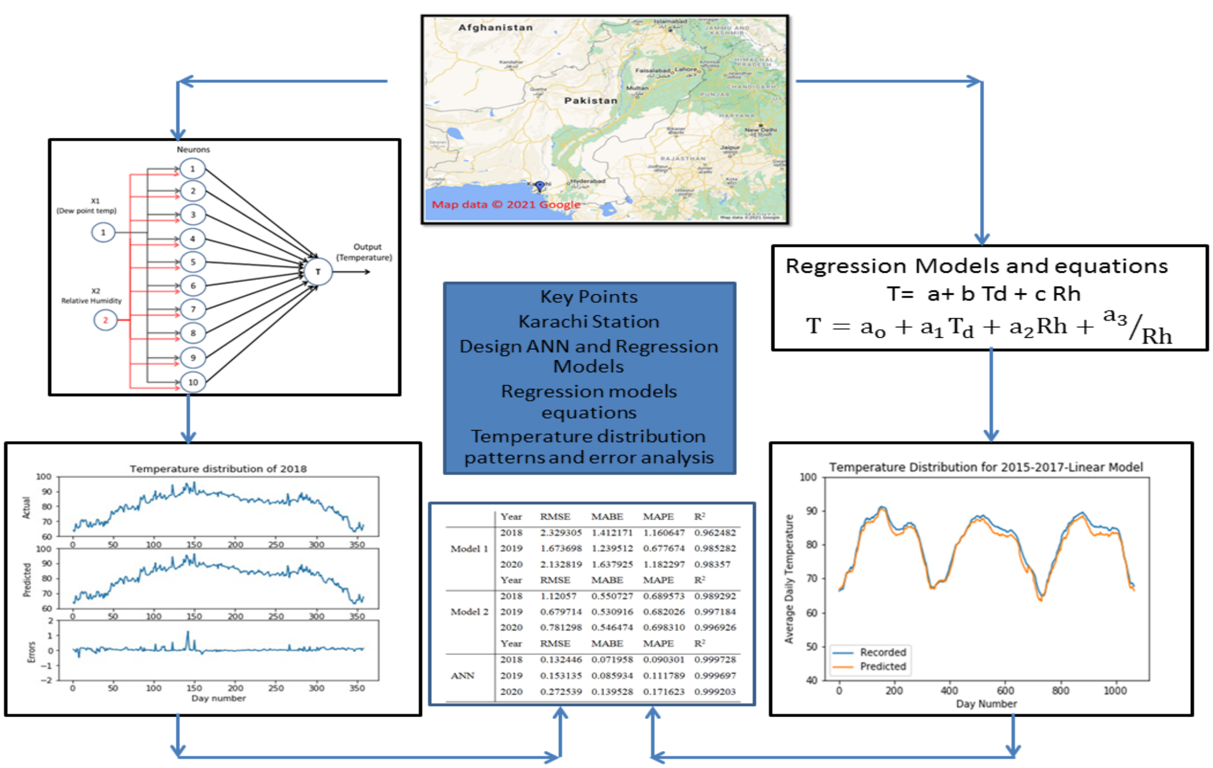
[2]Department of Physics, University of Karachi, Karachi,

`[3]Department of Applied Physics, University of Karachi, Karachi,

[4]Department of Computer Science, Federal Urdu University of Arts Science and Technology, Karachi

Correspondace Author : Adeel Tahir, adeel.tahir@fuuast.edu.pk

GRAPHICAL ABSTRACT



	Year	RMSE	MABE	MAPE	R^2
Model 1	2018	2.329305	1.412171	1.160647	0.962482
	2019	1.673698	1.239512	0.677674	0.985282
	2020	2.132819	1.637925	1.182297	0.98357
	Year	RMSE	MABE	MAPE	R^2
Model 2	2018	1.12057	0.550727	0.689573	0.989292
	2019	0.679714	0.530916	0.682026	0.997184
	2020	0.781298	0.546474	0.698310	0.996926
	Year	RMSE	MABE	MAPE	R^2
ANN	2018	0.132446	0.071958	0.090301	0.999728
	2019	0.153135	0.085934	0.111789	0.999697
	2020	0.272539	0.139528	0.171623	0.999203

ABSTRACT

This study presents the determination of the average daily temperature distribution for Karachi city. Artificial Neural Network (ANN) has been used to predict the average daily temperature of 2018, 2019, and 2020. Two regression models (linear and non-linear) were also developed. These models are based on relative humidity and dew points. Karachi's six-year environmental datasets were used for the case study location and to establish temperature distribution models. In ANN three years, temperature data (2015-2017) was used to train and validate the ANN model. The same data was used to find the regression coefficients of each model. Both models and ANN are then used to estimate the average daily temperature of years 2018-2020. The statistical errors are also calculated for comparison and to evaluate the performance of both models; an excellent agreement was found between recorded and ANN estimates. Both regression models predict average daily temperature with reasonable uncertainties. However, the non-linear regression model predictions are better. The results show that the models provide a good prediction of temperature distribution.

Keywords : Neural network, Regression, Karachi, Mathematical modeling, temperature distribution

1. Introduction

Climate changes influence the environment and play an essential role in daily routine life. The change can be predicted by gathering information, observing, and forecasting weather events over the years (Ukhurebor et.al 2017). The climatic change depends on solar radiation flux, cloudiness, longitude, and latitude (McHugh et.al 2015). Temperature is an important parameter that affects different weather elements such as dew point temperature, precipitation, humidity, clouds, and atmospheric pressure (Pondyal et. al 2011). The moisture in the air can easily be measured by relative humidity and dew point temperature (Iqbal 2011). The performance of metals, processing food, biological items, and electrical devices are also affected by relative humidity (Lawrence, M. G. 2005). Solar radiation, ambient temperature, and dew point are the factors whose combination influences relative humidity (Geerts, B. 2003) . For human comfort, thunderstorms probability, rain, fog, and frost forecasting, Meteorologists adopted dew point temperature irrespective of relative humidity (Eludoyin et al 2014, Tanabe, S. et. al 1994). At lower atmosphere pressure, the dew point greater than 60°C shows intense thunderstorm probability (Górnicki et al 2017). When relative humidity is less than 10% and air temperature ranges from 50 to 60^{o}F, the negative dew point is observed in a semiarid environment (Yousif et. al 2013). At the same time, 13 to 20^{o}F dew point temperature is critical and leads to cold nights with possible difficulty in keeping room temperatures above critical levels. At dew point below zero, the moisture content in the air is less. Besides precipitation, dewfall and direct water vapor adsorption are the main mechanisms that add water to the soil (Ukhurebor et. al 2017). It is believed that world advancement has made an ordinary person's life more comfortable, but it is a fact that this advancement has caused global temperature to rise. The estimated global warming trend is 2°C per century (Salinger, M. J. 2005). In the last century, in climatic variation research, the focus was the variation of surface air temperature. In Pakistan, the air temperature has been studied since 1882 (Pondyal et. al 2011). It is found that Normal distribution fits well on temperature distribution and a temperature increase from 0.3°C to 1.0°C in the twentieth century.

Bayesian analysis computational technique shows that the average annual mean temperature for 1882-1960 is less than the period 1961-2000 (Agam et. al 2006).

Monthly, seasonal, and annual observations were used to study the pattern of maximum and minimum temperatures of 39 weather stations in Pakistan. Two statistical tests (Sen's slope and Mann-Kendall) were used to classify the slopes and magnitude of the climate change trend. The statistical study examined the potential variations in the maximum and minimum temperature patterns. The maximum and minimum temperatures for 2030 and 2060 is forecast using a statistical downscaling climate prediction model (SimCLIM). With the median Representative Concentration Pathway (RCP-6.0) for potential predictions in SimCLIM, an ensemble of 40 General Circulation Models (GCMs) was used. In February and March, a positive trend from 0.06 to 0.51 °C, whereas in Balochistan and northern areas of Pakistan negative trend from −0.06 to −0.30°C temperature has been observed (Amin et al 2018). Variation in Karachi temperature was studied from 1947 to 2005 (59 years) by evaluating time series data of mean annual maximum, mean annual minimum, and mean annual temperature. Taking anomalies into account and using linear regression analysis, an increase of around 4-6°C was suggested (Sajjad et. al 2009) . Temperature rise raises the saturation pressure exponentially and impacts the air strength of water vapor retaining (Gong et. al 2006) . Moisture in the air can be estimated by relative humidity R_H and dew point temperature T_d. A simple thumb rule for approximating moist air conversion is that if $R_H > 50\%$, a decrease of 5% in R_H causes 1°C decrease in T_d (Lawrence, M. G. 2005). Relative humidity (R_H) is the ratio between the amount of water the ambient air holds and the amount it could have when the air is saturated with water vapor at the same temperature. Therefore, it can be expressed as the ratio between the actual vapor pressure (e_a) and saturation

(e_s). The saturation vapor pressure from the ambient temperature and the real vapor pressure from the dew point temperature (T_d) can be calculated using empirical formulas.

$$e\,(T) = 0.6108\ \exp\left(\frac{17.62\ T}{T + 273.3}\right)$$

An empirical model to estimate dew point (T_d) by parameters daily minimum (T_{min}) and daily maximum (T_{max}) temperature and the estimated daily potential evapotranspiration ratio to annual precipitation ($EF = I_{EP,\ day}/I_{P,\ ann}$) by Kimball.

$$T_d = T_{min}\{-0.127 + 1.121\,(1.003 - 1.444EF + 12.312\,EF^2 - 32.766\,EF^3)$$
$$+ (0.00006\,(T_{max} - T_{min})\}$$

Another model developed by Sboarina and Cescatti (2004) to measure dewpoint temperature (Td) using daily minimum (T_{min}) and daily maximum (T_{max}) and daily mean (T_{mean}) temperature.

$$T_d = T_{min} - k\,(0.45\,T_{max} - 0.55\,T_{mean} - T_{min})$$

k is a site-specific constant (Gunawardhana et. al 2017, Al-Muhyi et. al 2016).

2. Study Area

Karachi is Pakistan's first, the world's twelfth largest city and capital of Sindh province situated at geographical location (latitude) 24° 51' 39.4776" N and (longitude) 66° 59' 25.8036". It is located south coast of Pakistan and covers an area of around 3,527 km² (Figure 1).

Figure1 Geographical location of Karachi, Pakistan (Google Maps. Retrieved Jan 2021)

(Google Maps. Retrieved Jan 2021, from https://www.google.com/maps/@24.920064,67.1055872,11z)

Karachi is Pakistan's most cosmopolitan region, with a linguistic, ethnic, and religious diversity that makes it one of the world's most secular and socially liberal cities. Karachi serves as a transportation center due to its location in the Arabian Sea. It hosts Pakistan's two largest seaports, the Port of Karachi and Port Bin Qasim, and its busiest airport, Jinnah International Airport (Karachi – The dominant Culture. Retrieved December 2020, from History Pak,com: https://historypak.com/karachis-dominant-culture).

Karachi has an arid climate with a long "Summer Season" moderated by the Arabian Sea's oceanic impact. May and June are the hottest months where the temperature reaches around 43°C. Spring and Autumn in Karachi have a short period. The monsoon rainfall receives from July to September. Almost 7 inches per annum is average rainfall. Winters are moderate, with temperatures as low as 5°C in January. Karachi has a tropical climate with hot summers and mild winters. Due to its geographical location, Karachi is the most important city of Pakistan and neighboring countries.

3. Methodology

3.1 Artificial Neural Network

The prediction of average daily temperature, like other meteorological is important for different sectors, an industry of renewable energy, agriculture, and everyday life of a common man. Water contents in the soil also depend on temperature, which directly affects processes like seed germination, plant growth, etc. In designing houses, hospitals, etc., the variation in daily temperature is also considered. Scientists and researchers in forecasting temperature have employed various methods. Artificial Neural Network is one of them. In Artificial Neural Network, the computer learns the behavior of the input data and performs several tasks to train a machine. Once the machine is trained efficiently, the output data is predicted (Agatonovic 2000, Malone, T. F. 1955, Maqsood et al 2004). In this study, ANN is used to predict the average daily temperature of Karachi city. The architecture of ANN used in this study is shown figure 2.

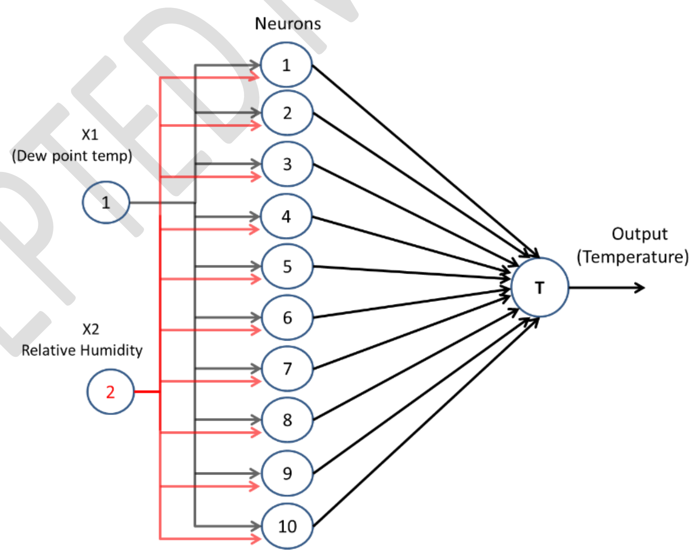


Figure 2 Feedforward neural network with 10 Neuron

There are two inputs which are dew point and relative humidity, to estimate the temperature. This prediction model is developed on MATLAB, which is a three-layered feed-forward network. The input layer contains two neurons without any hidden layer, 10 neurons are included in the hidden layers. Hidden layer neurons have sigmoidal transfer function while neuron in output layer has linear transfer function. The output of the only neuron in the output layer represents Estimated temperature T, and it is given by

$$\mathrm{T} = \sum_{\mathrm{i}=1}^{10} \mathrm{w_i H_i} + \mathrm{B} \tag{1}$$

Where bias B=0.47363 and weights w_i are given in Table 1.

Here, H_i can be calculated by the following equation

$$\mathrm{H_i} = \frac{1}{1 + \mathrm{e}^{-\mathrm{E_i}}} \tag{2}$$

E_i can be calculated using the following formula,

$$\mathrm{E_i} = \mathrm{W_{1i}X_1} + \mathrm{W_{2i}X_2} + \mathrm{b_i} \tag{3}$$

Where X_1 and X_2 represent inputs dew point and humidity, respectively. b_i is the bias associated with an ith neuron of the hidden layer, and W_{ji} is the branch's weight connecting ith neuron and jth input.

3.2 Multiple Regression Models

Two multiple regression models (see equations 4 and 5) are suggested in which a predictor of a dependent variable (average daily temperature) is given as a function of two independent variables. The independent variables are dew point and relative humidity. The first model is linear, and the second model is non-linear functions of these independent variables. The data is divided into two parts, and each part consists of three years. The first part of the data (2015-2017) is used to establish models. The second part of the data (2018-2020) is used to validate the models. The models are established by regression analysis. In equation (4) a, b, c and in equation (5) a_o, a_1, a_2 and a_3 are regression coefficients. T is the average daily temperature, T_d is the average dew point, and Rh is the relative humidity. Temperature and relative humidity are inversely proportional to each other. On a clear calm day, as time pass the temperature increase and relative humidity decrease (Abed et. al 2018). Similarly, temperature increases in the summer season and relative humidity decreases for one full year, and vice versa in the winter season (How Temperature & Humidity are Related. Retrieved December 2020, from Science: https://sciencing.com/temperature-ampamp-humidity-related-7245642.html).

Model 1: (linear model)

$$T = a + bT_d + cRh \tag{4}$$

Model 2: (Non-linear model)

$$T = a_o + a_1 T_d + a_2 Rh + {}^{a_3}/_{Rh} \tag{5}$$

The Adaptive Neuro-Fuzzy Inference System (ANFIS) and Artificial Neural Networks (ANNs) models were designed to evaluate the monthly air temperature based on latitude, longitude, and altitude at 30 different weather stations of Iran. The monthly model data of 20 and 10 weather stations were used for training and testing, respectively (Kisi et. al 2014). Hietaharju presented a dynamic model for the prediction of indoor temperature in a building. Their model used the precursor method; the precursors were indoor and outdoor temperatures earlier (Hietaharju et. al 2018). Alvares et al. monthly mean air temperature for Brazil used latitude, longitude, and height of the site as independent variables in their regression model (Alvares et. al 2013). In modeling temperature, Wang et al. considered strong seasonality of the temperature distribution and used the sine function of time in days in their model (Wang et. al 2015).

4. Statistical Errors for Validation of Regression Analysis

The Mean Square Error (MSE), Mean Absolute Error (MABE), Mean Absolute Percent Error (MAPE), and R- square are calculated to check the validity of regression analysis results.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(T_{c.i} - T_{m.i})^2 \tag{6}$$

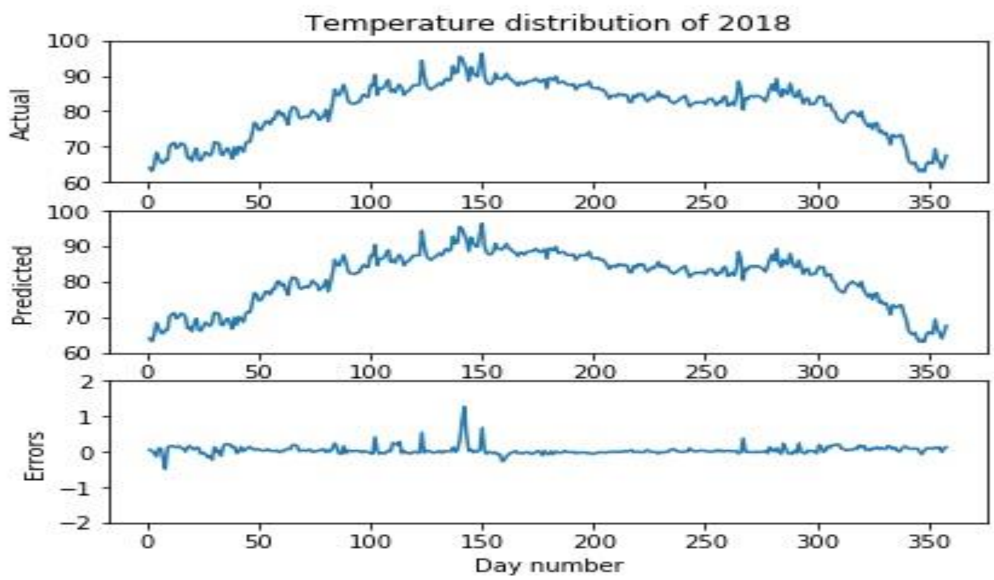
$$\mathrm{MABE} = \frac{1}{n}\sum_{i=1}^{n}|T_{c.i} - T_{m.i}| \tag{7}$$

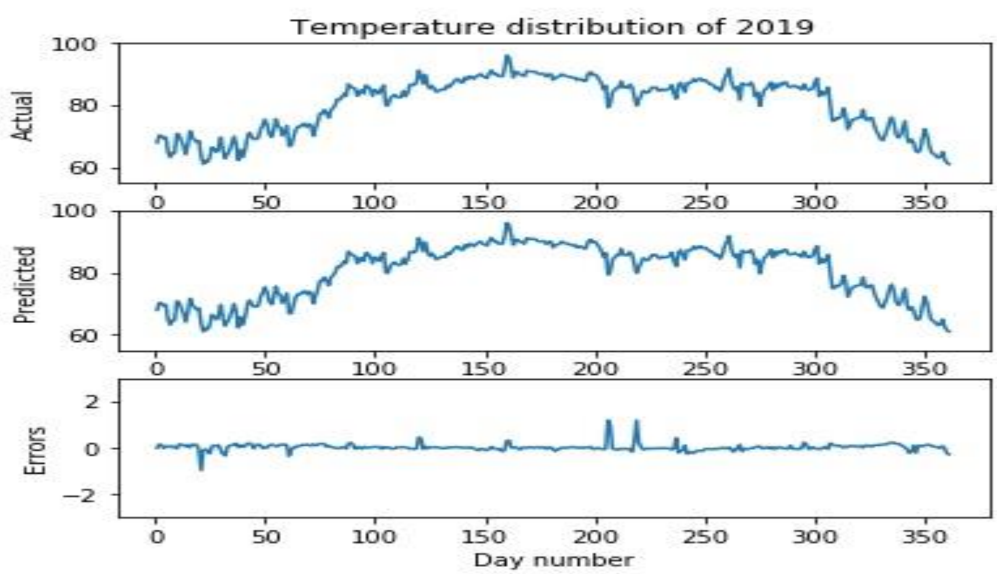
$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(T_{c.i} - T_{m.i})}{T_{m.i}}\right| x100 \tag{8}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(T_{c.i} - T_{m.i})^2}{\sum_{i=1}^{n}(T_{c.i} - \overline{T_m})^2} \tag{9}$$

5. Result and Discussion

In this study, ANN is used to estimate the average daily temperature. Neural Network consists of two input variables (dew point and relative humidity), a hidden layer with 10 neurons, and the output variable (Average daily temperature). The network is trained using 1092 data (2015-2017) points (average daily temperature, dew point, and relative humidity) using Levenberg–Marquardt algorithm (Kişi, Ö. 2007). 764 out of these 1092 samples were used to train this network, while 164 were used for validation and testing. We used backpropagation algorithm and Levenberg Marquardt gives faster conversion for this algorithm. Later this trained network was used to estimate the 1086 values of temperatures of 2018 to 2020. Predicted and actual values along with errors are plotted in figure. 3. The Weights W_1 and W_2 of the neuron that connects different nodes are determined and presented in Table 1. Table also gives the bias values in equation (3). The bias 'B' in equation 1 is found to be 0.47363. The weights w_i at nodes connecting neurons in the hidden layer and out are also given in Table 1. The seasonal variations were removed using moving average method by taking running averages of 25 values.





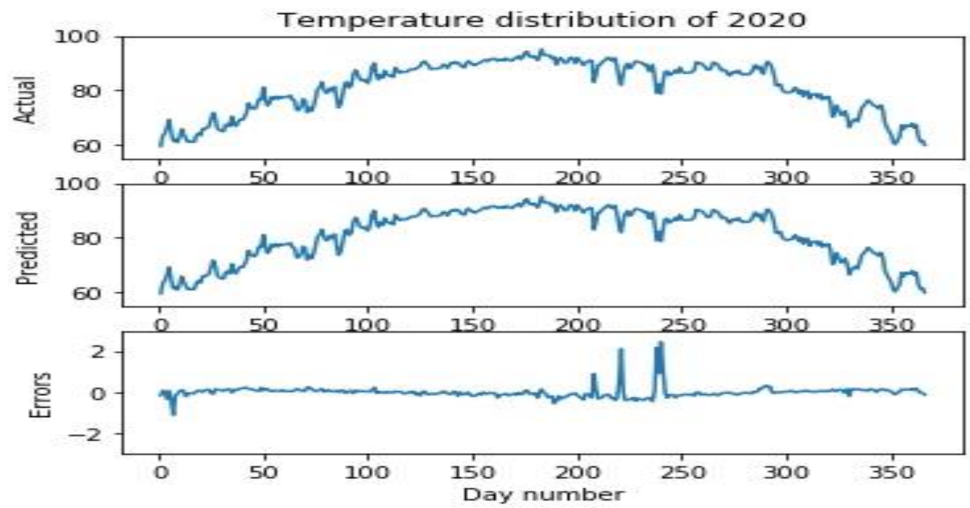


Figure 3 Comparison of predicted and actual average daily temperature of Karachi for the years 2018-2020

Table 1: Weights of the input variable, and neurons and bias associated with the neurons.

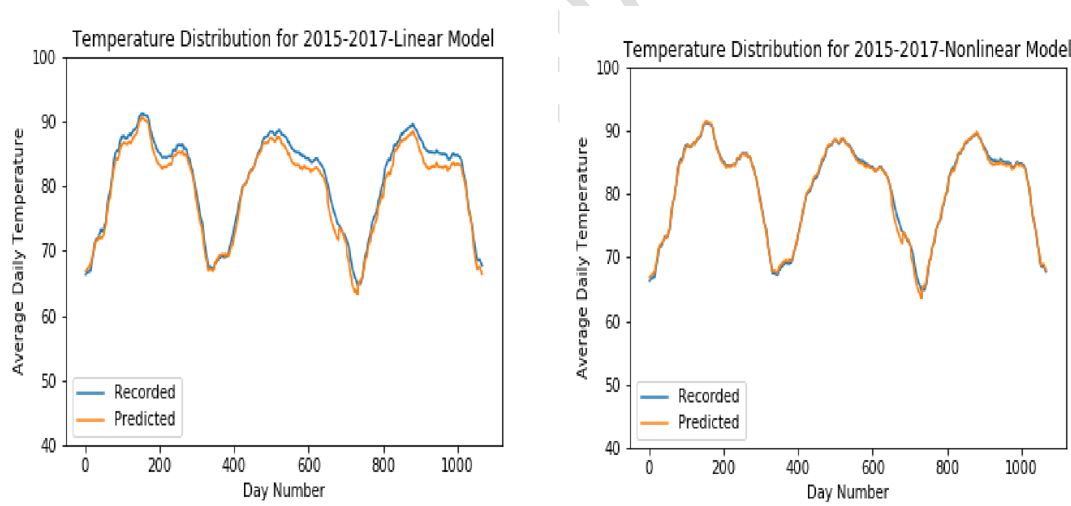
I	W_{1i}	W_{2i}	w_i	b_i
1	4.060232	5.971542	0.021858	-8.46554
2	-1.59832	-10.87	0.003273	3.03792
3	-6.36445	4.554757	0.002988	3.226254
4	7.620068	0.648445	0.001072	-2.4725
5	1.652472	3.545221	0.00681	-0.42737
6	-0.22734	1.347246	0.716058	-0.54587
7	3.392446	5.748316	0.002744	1.983417
8	0.584383	-0.59251	3.050216	-0.21358
9	-0.26117	3.264822	-0.8349	3.474654
10	-2.25312	3.579778	-0.79087	-6.10823

Two multiple regression models are suggested for the average daily temperature distribution. Six years of environmental data is used to establish and validate the two models. The first part of the dataset is also used to find the regression coefficients. These coefficients are substituted in equations 4 and 5 (see equations 10 and 11). For further validation, statistical errors are calculated, and the performance of the models is compared. These errors include Mean Square Error (MSE), Mean Absolute Error (MABE), Mean Absolute Percent Error (MAPE), and R- square. The best model was identified by predicting temperature distribution for 2018-2020 and comparing the associated errors with the models.

$$\mathrm{T} = 50.02922 + 1.043707\mathrm{T_d} - 0.63266\mathrm{Rh} \tag{10}$$

$$\mathrm{T} = 34.72128 + 1.076365\mathrm{T_d} - 0.48742\mathrm{Rh} + {}^{302.5679}/_{\mathrm{Rh}} \tag{11}$$

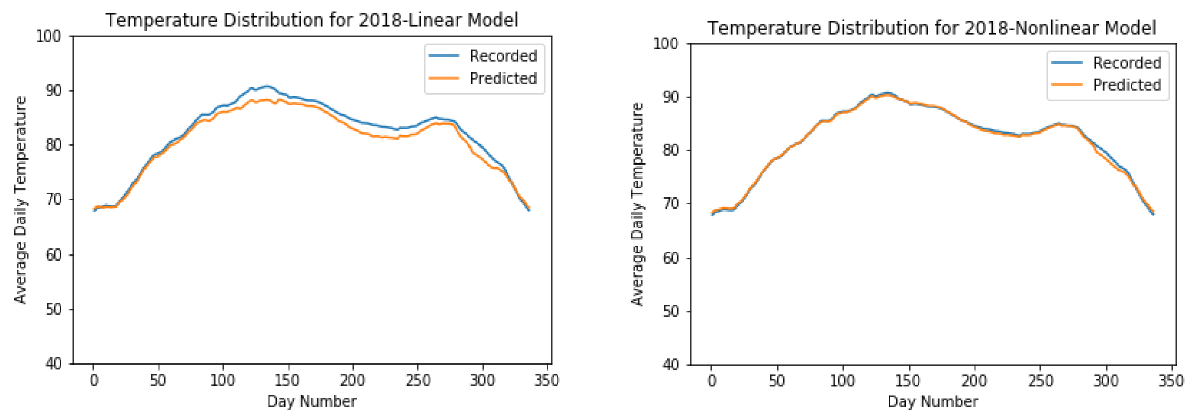
Figure 4 Shows measured and predicted temperature distributions for 2015-2017 by (a) model 1 and (b) model 2. The regression coefficients are determined by multiple regression analysis,



(a) (b)

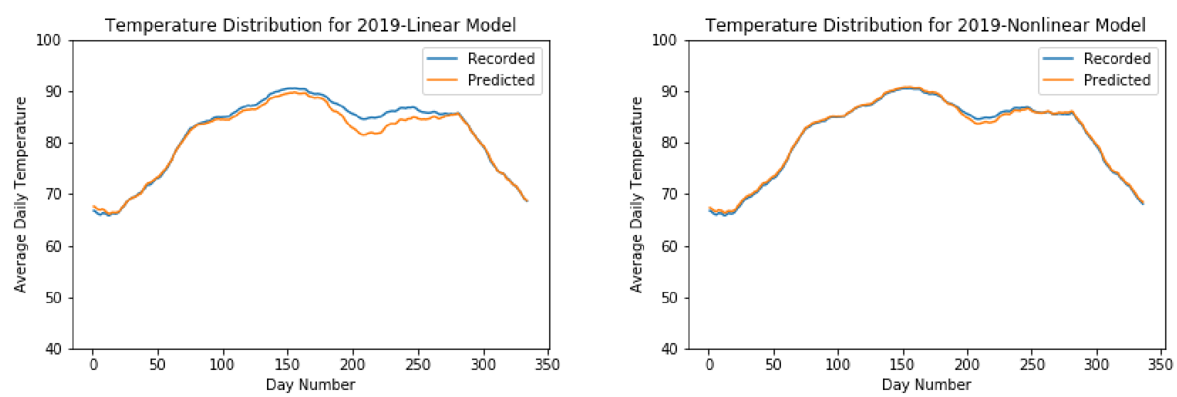
Figure 4 The recorded and predicted temperature distribution (by (a) model 1 and (b) model 2) for the years 2015-2017.

and these coefficients are then employed to predict temperature distribution for 2018-2020 (see figure 5-7). Similarly, model 2 was used to find the regression coefficients from the temperature distribution of 2015-2017 (see figure. 4). The coefficients are employed to estimate temperature distribution for 2018-2020 (see fig. 5-7).



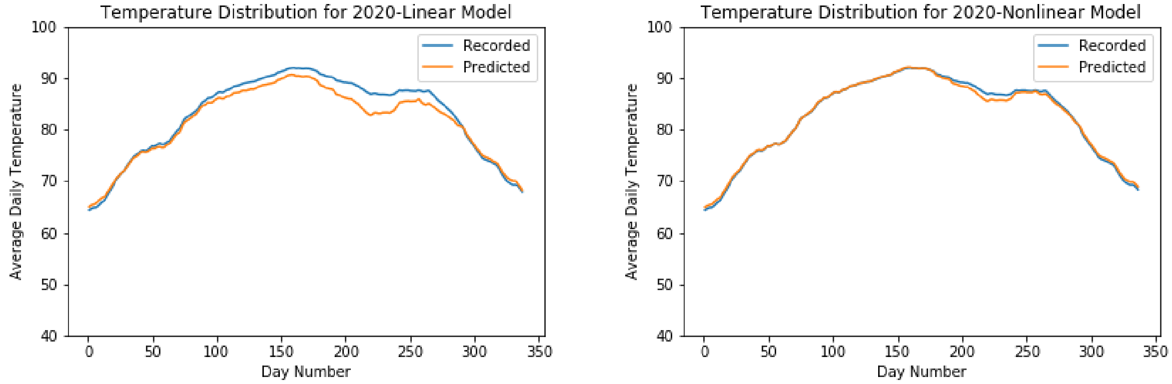
(a) (b)

Figure 5 The recorded and predicted temperature distribution (by (a) model 1 and (b) model 2) for 2018.



(a) (b)

Figure 6 The recorded and predicted temperature distribution (by (a) model 1 and (b) model 2) for 2019.



(a) (b)

Figure 7 The recorded and predicted temperature distribution (by (a) model 1 and (b) model 2) for 2020

Table 2: Statistical Errors in the predicted temperature distribution of 2018-2020 for model 1, model 2, and ANN

	Year	RMSE	MABE	MAPE	R^2
	2018	2.329305	1.412171	1.160647	0.962482
Model 1	2019	1.673698	1.239512	0.677674	0.985282
	2020	2.132819	1.637925	1.182297	0.98357
	Year	RMSE	MABE	MAPE	R^2
	2018	1.12057	0.550727	0.689573	0.989292
Model 2	2019	0.679714	0.530916	0.682026	0.997184
	2020	0.781298	0.546474	0.698310	0.996926
	Year	RMSE	MABE	MAPE	R^2
	2018	0.132446	0.071958	0.090301	0.999728
ANN	2019	0.153135	0.085934	0.111789	0.999697
	2020	0.272539	0.139528	0.171623	0.999203

Table 2 shows statistical errors in ANN and both regression models. The statistical errors RMSE, MABE, and MAPE, are the lowest in ANN. The coefficient of determination between predicted and actual average daily temperatures is highest for ANN. The maximum absolute difference between measured and calculated temperature by model 1 was greater than 6.23^{o}F in 2019 and 7.80^{o}F for the year 2020. Whereas the corresponding difference for model 2 was found to be 2.30^{o}F for 2019 and 2.04^{o}F for 2020. The statistical errors correspond to models are listed in table 2. The table clearly shows that all four statistical errors for model 2 are less than those for model 1. Both temperature distribution and statistical error predictions indicate that model 2 is better than model 1, and it predicts more reliable temperature values for Karachi city.

The persistence models work well when weather patterns change very little, and features on the weather maps move very slowly. It shows the best result for short-term forecasting (2 to 4 days) or where the weather parameters slightly change; otherwise, it's invalid. Accuracy of weather forecasting is better for a short period as compared to an extended period. According to the National Oceanic and Atmospheric Administration (NOAA), around 80% accurate forecast is observed for the next 5 days, whereas it becomes 50% for the next 10 days. Furthermore, precise forecasting depends on the geographical location and atmosphere since the weather is non-linear and complex. Some mathematical models are designed to estimate the weather parameters whose accuracy can be justified by statistical error values (Persistence Method. Retrieved November 2020, from http://ww2010.atmos.uiuc.edu/(Gh)/guides/mtr/fcst/mth/prst.rxml).

6. Conclusion

In this study, we modeled the Average daily temperature distribution for Karachi, Pakistan. The study was divided into two parts. In the first part, we used ANN, in which we trained the machine on temperature variations for the years 2015-2017. The input variables were dew point and relative humidity; ANN had one hidden layer consists of 10 neurons. The output was an average daily temperature. The weights and biases obtained after training were used to predict the average daily temperature for three years (2018 to 2020). The predictions by ANN were excellent. The errors are ±1 for the years 2018, 2019, whereas the errors for 2020 are in the range ±2. The Average daily temperature can be found through ANN with two independent variables, dew point, and relative humidity. This fact is used in the development of two regression models, one of them is linear (model 1), and the other is a non-linear (model 2) multiple regression model.

In both models, the regression coefficients were calculated from daily average temperature data of 2015-2017. These coefficients are then employed in models 1 and 2, and predicted temperatures for 2018-2020. To check the validity of ANN and regression models, statistical errors RMSE, MABE, and MAPE are calculated. The coefficient of determination is also estimated to study the correlation between predicted and actual temperatures. The RMSE, MABE, and MAPE are lowest in ANN (between 0 and 0.3), whereas the same errors have the highest model 1 (between 0 and 3). These errors for model 2 are less than 1, except for 2018, i.e., 1.12057. It is also clear from the figures 5-7 that the overlapping of graphs of actual and predicted temperatures is suitable for model 2 compared to model 1. We conclude that ANN indicates the best results out of three studies and suggests that model 2 can predict Karachi's daily average temperature.

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