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Prediction of Lead Seven Day Minimum and Maximum Surface Air Temperature using Neural Network and Genetic Programming

(Peramalan Awalan Tujuh Hari Minimum dan Suhu Permukaan Udara Maksimum menggunakan Rangkaian Neuron dan Pengaturcaraan Genetik)

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ABSTRACT

The determination of variance of surface air temperature is very essential since it has a direct impact on vegetation, environment and human livelihood. Forecast of surface air temperature is difficult because of the complex physical phenomenon and the random-like behavior of atmospheric system which influences the temperature event on the earth surface. In this study, forecast models based on artificial neural network (ANN) and genetic programming (GP) approaches were proposed to predict lead seven days minimum and maximum surface air temperature using the weather parameters observed at the station Chennai, India. The outcome of this study stated that models formulated using ANN approach are more accurate than genetic programming for all seven days with the highest coefficient of determination (R^2), least mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE) on deployment with independent test dataset. ANN models give statistically acceptable mean absolute error of 0.59°C for lead day one in minimum temperature forecast and 0.86°C variance for lead day one in maximum temperature forecast. The study also clarified that the level of accuracy of the proposed prediction models were found to be better for smaller lead days when compared with higher lead days with both approaches.

Keywords: *ANN; GP; surface temperature; temperature forecast*

ABSTRAK

Penentuan perbezaan suhu permukaan udara adalah sangat penting kerana ia mempunyai kesan langsung pada tumbuh-tumbuhan, alam sekitar dan kehidupan manusia. Ramalan suhu permukaan udara adalah sukar kerana fenomena fizikal yang kompleks dan perilaku rawak seperti sistem atmosfera yang mempengaruhi keadaan suhu permukaan bumi. Dalam kajian ini, peramalan model berdasarkan pendekatan rangkaian neuron tiruan (ANN) dan genetik pengaturcaraan (GP) dicadangkan untuk meramalkan awalan tujuh hari minimum serta suhu permukaan udara maksimum menggunakan parameter cuaca yang dicerap di Stesen Chennai, India. Hasil kajian ini menunjukkan bahawa model yang dirumus menggunakan pendekatan ANN adalah lebih tepat daripada genetik pengaturcaraan untuk semua tujuh hari dengan pekali penentuan tertinggi (R^2), min ralat mutlak terkecil (MAE), punca min ralat kuasa dua (RMSE) dan bermakna min ralat peratusan mutlak (MAPE) pada pengerahan dengan dataset ujian bebas. Model ANN memberikan min ralat mutlak 0.59°C yang boleh diterima secara statistik untuk awalan satu hari dalam suhu peramalan minimum dan 0.86°C varians bagi satu hari dalam suhu peramalan maksimum. Kajian ini juga menjelaskan tahap ketepatan model ramalan yang dicadangkan adalah lebih baik untuk awalan hari lebih kecil jika dibandingkan dengan awalan hari lebih besar dengan kedua-dua pendekatan.

Kata kunci: *ANN; GP; peramalan suhu; suhu permukaan*

INTRODUCTION

Surface air temperature is an important weather phenomenon which has high impact on human habitation and agricultural activities on earth. Scorching heat waves, heat strokes and cold waves take many lives and affect vegetation every year. Timely and accurate forecast of temperature variations and tendency will help the people and the Government to take precautionary measures to handle very hot and cold weather. Meteorologists are also interested in the surface air temperature estimation because it affects most of the meteorological events like evapotranspiration, precipitation, wind flow, humidity and pressure. In India, information on maximum temperature will be indicated during April to June (till onset of monsoon) or minimum temperature during the period of November to February and both maximum and minimum during March and October (after withdrawal of monsoon). Temperature description need not normally be given during monsoons (southwest and northeast), but on occasions when due to subdued monsoon, the maximum and minimum temperatures deviate much from normal, temperature description may be given. However, local forecast for maximum temperature during winter can also be indicated in addition to minimum temperature if forecasters feel that such a forecast will help the users. Similarly, during summer if forecasters feel that the minimum temperature is important, local forecast for minimum temperature during summer may be issued in addition to local forecasts for maximum temperature. As the public are interested to know about the fluctuations in temperature in summer or winter, the temperature trends viz. slight fall/ rise, significant fall/ rise may be indicated in local forecast (Forecaster Guide 2008).

Researchers have devoted various techniques like linear regression, support vector machine regression algorithms (SVMr) (Ortiz-Garcia et al. 2012; Paniagua-Tineo et al. 2011), abductive network machine learning (Abdel-Aal 2004), ANN, fuzzy system, adaptive neuro fuzzy inference system (ANFIS) and GP for predicting minimum and maximum temperature. Recently, artificial intelligences (AI) techniques have been successfully used in a wide range of hydrological applications (Landeras et al. 2012).

In this work, forecast models have been created for forecasting the lead seven days minimum and maximum surface air temperature using artificial neural network (ANN) and genetic programming (GP). Minimum and maximum temperature for lead seven days were taken into account in this analysis since India Meteorological Department (IMD) provides forecast of deviation of minimum and maximum temperature for one week and forecast of minimum and maximum temperature are very essential whenever there was a high or low temperature epoch (expected to prevail for 3 days or more).

ANN is a sophisticated technique that produces significant results in nonlinear dynamic systems like hydrological forecasting (ASCE Task Committee 2000a, 2000b). Because of its robustness nature, ANN has been used in most of the hydrological forecasting processes such as rainfall-runoff (Hsu et al. 1995; Maier & Dandy 1996), ground water quality parameters estimation (Fabbian et al. 2007), ground water level simulation (Nayak et al. 2006), fog prediction in airport (Nayak et al. 2007), temperature, pressure, humidity, forecast of snowfall (Roebber et al. 2007) and precipitation prediction (Hung et al. 2009). ANN model has considerable potential for estimating monthly maximum temperature (De et al. 2011) and year round 1 to 12 h temperature prediction (Smith et al. 2009). ANN approach provides fast and accurate prediction in large and noisy dataset like weather data (De et al. 2011).

Genetic programming (GP) is a soft computing technique which can solve different kinds of problem from different fields efficiently and gives promising results in the optimization of complicated structures (Koza 1992). GP has been applied in monthly mean water demand forecast (Nasseri et al. 2011), daily reference evapotranspiration modeling (Shiri et al. 2012), modeling global temperature changes (Stanislawska et al. 2012), precipitation and stream flow prediction (Kashid et al. 2010) and in many engineering, mining and operational research problems.

DATA

The area selected for this study is Chennai, India (Latitude: 13° 4' 7.3" N, Longitude: 80° 14' 48.33" E). Chennai is a densely populated city which enjoys a tropical climate with mean annual temperature of 24.3°C to 32.9°C. The temperature is usually in the range of 13.9°C to 45°C. Since the daily surface temperature is influenced by various weather metrics observed in the surface, the atmospheric parameters recorded daily over the study area were used as predictors (listed in Table 1). The atmospheric variables used in this analysis were recorded at Regional Meteorological Centre Chennai (RMC-Chennai), a Class I surface observatory. RMC-Chennai also sustains and executes the operational suite of numerical analyses and forecast models and prepares dissemination. It records observations at 0000, 0300, 0600, 0900, 1200, 1500, 1800 and 2100 UTC using surface observing instruments (Table 1).

The observed predictor dataset for the study area Chennai has been obtained from the National Centre for Environmental Prediction (NCEP), a global repository which stores data of major weather observing stations (http://www.ncdc.noaa.gov/oa/ncdc.html). Dataset of nine years (1995-2003) was taken for analysis out of which eight years (1996 - 2003) of data were used to formulate the models and dataset of one year (1995) was used to validate the performance of the derived models. The collected predictor dataset had various flags indicating missing values, the observations with missing values were entirely dropped in this analysis.

TABLE 1. Environmental predictors used to formulate prediction models

Sl. No.	Predictor variable	Units	Instrument used to record
1	Mean temperature	°c	Thermometer
2	Mean dew point	°c	Assman psychrometer
3	Maximum sea level pressure	hPa	aneroid barometer
4	Mean visibility	km	Visibility sensor
5	Mean wind speed	km/h	Cup generator anemometer
6	Maximum wind speed	km/h	Cup generator anemometer
7	Precipitation	mm	Self recording raingauge
8[a]	Minimum temperature	°c	minimum thermometer
9[a]	Maximum temperature	°c	maximum thermometer

[a]Daily minimum temperature is used as the eighth predictor of minimum temperature prediction models and daily maximum temperature is used as the eighth predictor of maximum temperature prediction models

METHODS

ARTIFICIAL NEURAL NETWORK (ANN)

Forecasting with ANN is popular because of its capability in approximating any nonlinear function and determining prediction through learning process. In this analysis, prediction network were created with two feed-forward back-propagation neural networks, multilayer perceptron network (MLP) and radial basis function networks (RBFN).

MLP utilizes a supervised learning technique called back propagation for training the network (Rumelhart et al. 1986). Broyden–Fletcher–Goldfarb–Shanno (BFGS), an iterative algorithm suitable for solving unconstrained nonlinear optimization problems is used for training the network. One among the four activation functions logistic, hyperbolic tangent, exponential and identity were used to transform the incoming signal into an output signal.

The RBNF was also in the form of feed-forward neural network in which hidden neurons contain the radial basis function similar to the Gaussian density function, defined by a center position and a width parameter. The RBF network parameters unit centers were found using clustering algorithm, width is determined using the nearest neighbor method. The weight in the third layer is found by minimizing the sum squared error between the output and the actual data (Benghanem & Mellit 2010; Ruano et al. 2006).

The back propagation algorithm is applied as follows:

Initialize all weights and bias (a small random value) and normalize the training data; Compute the output of neurons in the hidden layer and in the output layer (net) using

$$n_i = \sum w_{ij} x_i + \theta_i, \tag{1}$$

where w_{ij}, the weight for node j to is calculated as follows:

$$w_{ij}(n+1) = w_{ij}(n) + \alpha\delta_i(n)x_j(n), \tag{2}$$

where x_j is the transformation function, $\delta_i(n)$ is the weighted sum of error, θ_i is the bias, and α is the step size; Compute the error and weight update. Weights are tuned using modified delta rule; Update all weights, bias and repeat Steps 2 and 3 for all training data; and Repeat Steps 2 to 4 until the error converges to an acceptable level.

GENETIC PROGRAMMING

Genetic programming (GP) is an evolutionary search methodology, which is capable to search in large and complicated search space. It is an expansion of genetic algorithms (GAs) which codify the result of the problem in the form computer program (mathematical expressions). GP uses tree-like individuals to represent computer program in regression problems. Like GAs, genetic programming models are based on Darwinian Theory of evolution, survival of the fittest with the three genetic operations reproduction, crossover and mutation.

GP works as follows:

Randomly generate population of candidate programs to find a computer program which is the best solution for the given task; Randomly select four programs from the population, evaluate them on the training cases, and rank them based on fitness. Fitness is calculated by fitness function, which measures the performance of each individual in a population; Create new offspring program by replacing the low performing two programs (least ranked) with high performing ones (reproduction); Randomly select a single instruction in the program, and replace it with a randomly selected instruction with mutation probability (mutation); With crossover probability, recombine the genetic material of the two copied programs by randomly selecting a subarray of instructions from each program, and exchanging it with the subarray from the other program (crossover); Iterate Steps 2 to 5 until the result converges or termination criteria is achieved.

TABLE 2. Forecast verification range proposed by Forecasts' Guide, IMD 2008

Forecast error range	Forecast results
Between ±1°C	Correct
±2°C to <±3°C	Partially correct
Greater than 3°C	Wrong

MODELS

ANN network models for minimum temperature forecast and maximum temperature forecast were created with training dataset. Two sets of predictor dataset were prepared separately one for minimum and the other for maximum. The first seven predictors are common for both dataset, minimum temperature is the eighth predictor for minimum temperature forecast dataset and maximum temperature is the eighth predictor for maximum temperature forecast data set. ANN networks were created with MLP procedure separately and with RBF identically for seven days. Based on the training and testing performance (R^2) on training dataset only one model (either MLP or RBFN network) is retailed for each day. Statistical data analysis tool Statistica 8 was used for model creation with neural network and MATLAB were used to simulate Genetic Programming. Tables 4 and 5 give the network structure and its activation functions of the networks that gave optimum results.

GP models are also developed with the following assignments. Based on Koza's (1994, 1992) works, the control parameters were assigned with the following values. The population size assigned with 500 (A larger population allows for a greater exploration of the problem space at each generation and increases the chance of evolving a solution), initial expression maximum depth is 5, selection ration is 0.05, number of generation = 20 (the evolutionary process needs to be given time; the greater the maximum number of generations, the greater the chance of evolving a solution), crossover probability P_c is 0.85 (Koza 1992 - 0.90 of the population undergoes crossover) and mutation probability P_m 0.40 (Koza's (1992) this value stays constant, at 0.40).

The modeling and simulation process is continued until optimum result is obtained. Performances of the models are validated by deploying the models with independent verification dataset. Statistical error analysis namely MAE, RMSE, mean absolute percentage error (MAPE) and correlation analysis are used as error measures for interpreting the forecast error and for validating the models efficiency. The MAE is the arithmetic average of the absolute values of the differences between the members of each pair and RMSE is the square root of average squared difference between the forecast and observation pairs. The forecast is perfect if MAE, RMSE are equal to zero. Correlation coefficient between observed and predicted value is another accuracy measure followed for validating the models.

Results and Discussion

The performance efficiency and prediction accuracy of the formulated prediction models are assessed by deploying the models with one year data (1995). After dropping the missing observations, 320 observations were used for testing.

MINIMUM TEMPERATURE FORECAST MODELS ASSESSMENT

Figure 1(a)-1(c) and Table 3 summarize the outcomes of performance analysis done on minimum temperature forecast models devised using ANN and GP techniques for lead seven days. The scatter plot (Figure 2) of observed versus predicted minimum temperature showed that ANN model for lead day one is 83% close to best-fit line drawn and fit with 65% for lead day seven whereas the GP model has 73% fit for day one and 62% for day seven, the same kind of difference persist for all seven days. The MAE for ANN models vary between 0.59ºC and 1.06ºC from lead day one over day seven. The alternative GP approach lags behind ANN models with greater mean absolute variance of 0.1ºC to 0.3ºC. (0.69ºC for day one and 1.32ºC for lead day seven). Figure 1(a) also visually conveys that RMSE is least for all seven days with ANN models. The mean absolute error percentage of ANN models is less than 5% (2.45, 3.04, 3.59, 4.09, 3.97, 4.27 and 4.42% for day one to seven, respectively), whereas GP models lag back with 0.7% more error than ANN models. The results were verified with the IMD verification criteria (Table 2). The deployment result also showed that the ANN is superior to GP in providing correct forecast. ANN model provides 83.60% of correct forecast, 16% of partial correct forecast and only 0.32% false alarm for day one.

From residual analysis (Figure 4) it is noted that ANN models are more opt and the bias is around zero for the season between October and April when the minimum forecast is essential in India. The plot of observed temperature against predicted temperature (Figure 2) shows that the models fit well with correlation coefficient(r) greater than 0.90 upto lead days three. Investigation on the results of statistical analysis confirms that ANN models provide better accuracy than GP models for all days.

MAXIMUM TEMPERATURE FORECAST MODELS ASSESSMENT

The results produced by the two techniques for maximum temperature against the observed maximum temperature

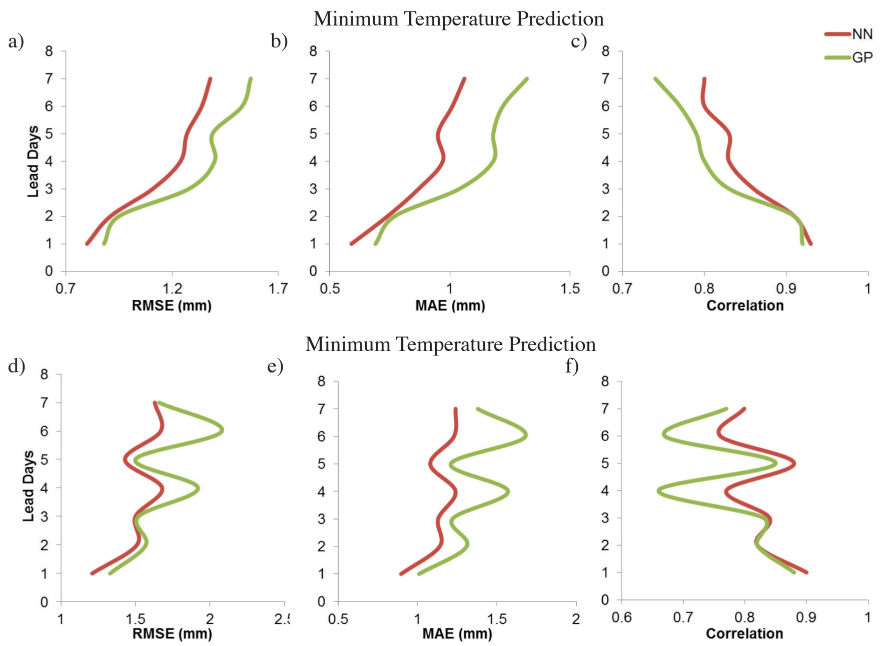

FIGURE 1. Performance comparison of ANN and GP prediction models for lead seven days

TABLE 3. Summary of performance analysis

Model	Lead Day	MAE (°C)	RMSE (°C)	MAPE (%)	R^2	Forecast verification		
						Correct (%)	Partial (%)	Wrong (%)
ANN min. temp.	1	0.59	0.81	2.44	0.87	83.60	16.09	0.32
	2	0.74	0.92	3.05	0.84	70.83	29.17	0.00
	3	0.88	1.12	3.59	0.74	64.26	34.48	1.25
	4	0.98	1.25	4.05	0.70	57.59	39.63	2.79
	5	0.95	1.27	3.98	0.69	62.96	33.33	3.70
	6	1.02	1.34	4.27	0.65	59.69	36.88	3.44
	7	1.06	1.39	4.43	0.63	58.57	37.07	4.36
GP min. temp.	1	0.70	0.89	2.86	0.85	77.29	22.08	0.63
	2	0.77	0.95	3.16	0.82	69.55	30.45	0.00
	3	1.04	1.28	4.24	0.70	55.80	42.95	1.25
	4	1.18	1.40	4.90	0.64	45.51	53.87	0.62
	5	1.18	1.39	4.94	0.63	44.14	55.56	0.31
	6	1.22	1.53	4.97	0.61	48.13	47.19	4.69
	7	1.33	1.58	5.58	0.55	42.06	55.14	2.80
ANN max. temp.	1	0.90	1.21	2.66	0.81	68.59	28.85	2.56
	2	1.14	1.52	3.46	0.68	55.59	38.66	5.75
	3	1.13	1.50	3.38	0.71	56.33	37.97	5.70
	4	1.24	1.69	3.77	0.60	54.31	39.30	6.39
	5	1.09	1.43	3.25	0.77	55.45	39.42	5.13
	6	1.23	1.68	3.78	0.59	53.87	38.71	7.42
	7	1.24	1.63	3.77	0.64	51.13	41.16	7.72
GP max. temp.	1	1.02	1.33	2.99	0.77	57.69	38.46	3.85
	2	1.31	1.57	4.00	0.68	41.53	53.99	4.47
	3	1.23	1.52	3.64	0.69	47.15	46.20	6.65
	4	1.58	1.92	4.80	0.44	36.74	53.35	9.90
	5	1.22	1.51	3.66	0.73	47.44	48.08	4.49
	6	1.69	2.08	5.28	0.45	37.74	46.13	16.13
	7	1.39	1.66	4.20	0.60	37.30	58.52	4.18

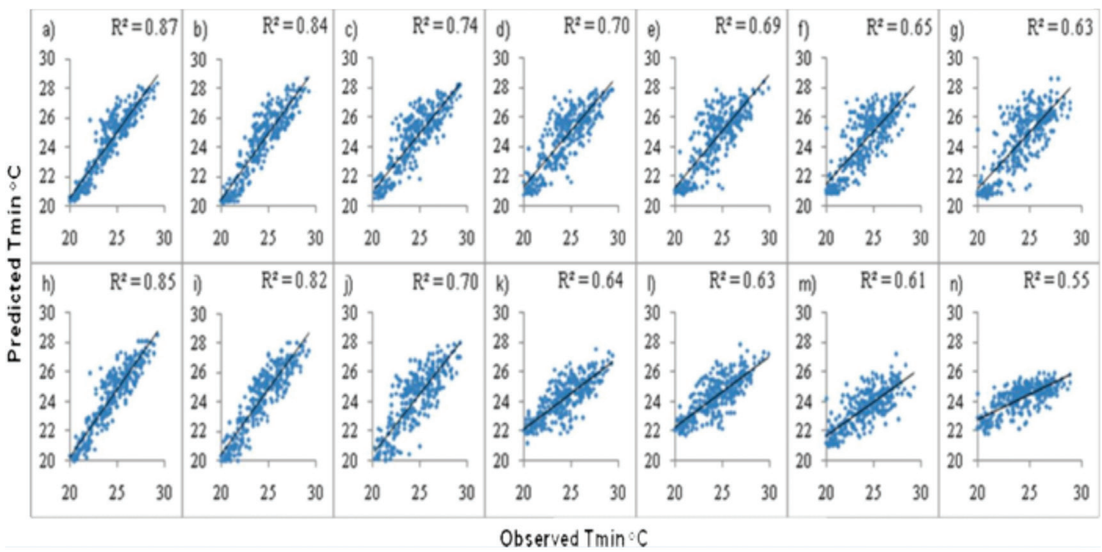

FIGURE 2. Association between observed and predicted minimum temperature (a – g) ANN models and (h – n) GP models for lead days one to seven, respectively

is shown in Figure 1(d)-1(f). Assessment on both approaches for lead day one forecast shows that ANN based models have strong correlation of 0.90 with the observed surface temperature. The forecast for remaining lead day predictions are correlated around 0.80, but the GP models have a correlation of 0.88 for the first day and the forecast skill reduces to 0.66 on lead day four and lead day six of forecasts. The correlation comparison of both approaches for seven days (Figure 1(f)) shows that the ANN maximum temperature forecast models provide much correlated prediction than GP models. The MAE and RMSE for both methods are little more than minimum temperature forecast (MAE 0.89°C and 1.01°C for day one and 1.24°C and 1.38°C for day seven in ANN and GP approaches, respectively). The mean absolute error percentage of ANN models is consistently lower than GP models particularly on days four and six (error difference more than 1%). The verification of the forecast showed that the ANN models provide considerably more correct forecast but the GP models provide more partially correct forecast. Residual analysis (Figure 5) also emphasizes that ANN performance is considerably better on higher days when compared with GP models.

Examination on the results produced by the two techniques showed that the prediction skill is better for minimum temperature than maximum temperature and the forecast has a smooth decline in prediction skill as the lead increases. It also illustrates that the prediction is better for the winter and summer (October to April) season than pre monsoon and post monsoon seasons in the study area. From Tables 4 and 5 it is noted that the MLP approach networks with hidden layer neuron varying from eight to ten has given better performance. The analysis also showed that among the parameters used, mean temperature, dew point and precipitation have the most impact and correlation on the surface air temperature. The other main significance of this work is, once the model is generated for a location and using those models, the lead seven days minimum and maximum surface air temperature can be computed with ease computation.

TABLE 4. Network structure of minimum temperature forecast

Day	Network	Training (R)	Test (R)	Hidden activation	Output activation
1	MLP 8-8-1	0.90	0.90	Tanh	Exponential
2	MLP 8-8-1	0.87	0.87	Tanh	Tanh
3	MLP 8-8-1	0.84	0.87	Exponential	Tanh
4	MLP 8-8-1	0.82	0.85	Tanh	Identity
5	MLP 8-10-1	0.82	0.83	Tanh	Identity
6	MLP 8-9-1	0.80	0.80	Logistic	Identity
7	MLP 8-10-1	0.81	0.82	Logistic	Logistic

TABLE 5. Network structure of maximum temperature forecast

Day	Network	Training (R)	Test (R)	Hidden activation	Output activation
1	MLP 8-8-1	0.92	0.94	Tanh	Exponential
2	MLP 8-8-1	0.86	0.87	Logistic	Identity
3	MLP 8-8-1	0.83	0.86	Logistic	Logistic
4	MLP 8-10-1	0.82	0.83	Tanh	Identity
5	MLP 8-10-1	0.81	0.82	Logistic	Exponential
6	MLP 8-10-1	0.79	0.82	Exponential	Exponential
7	MLP 8-8-1	0.78	0.81	Tanh	Tanh

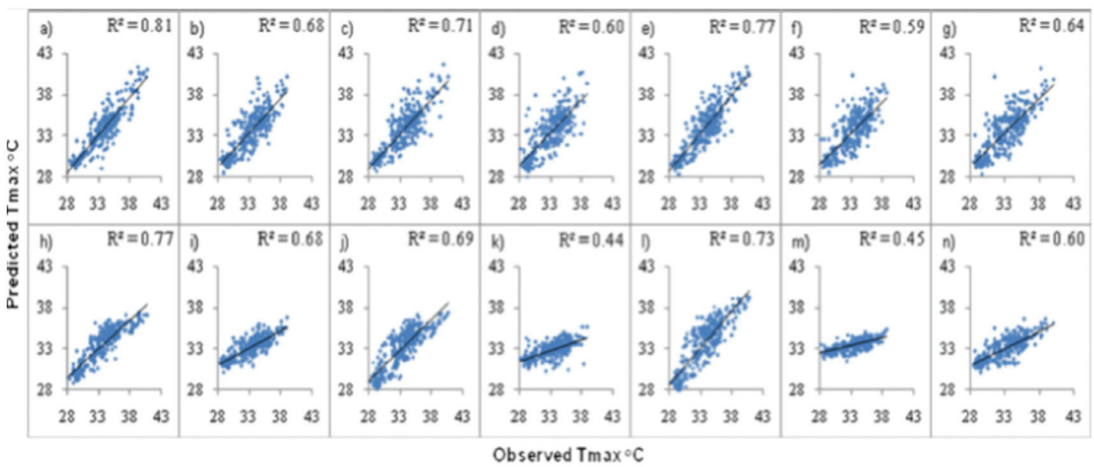

FIGURE 3. Association between observed and predicted maximum temperature (a – g) ANN models and (h – n) GP models for lead days one to seven, respectively

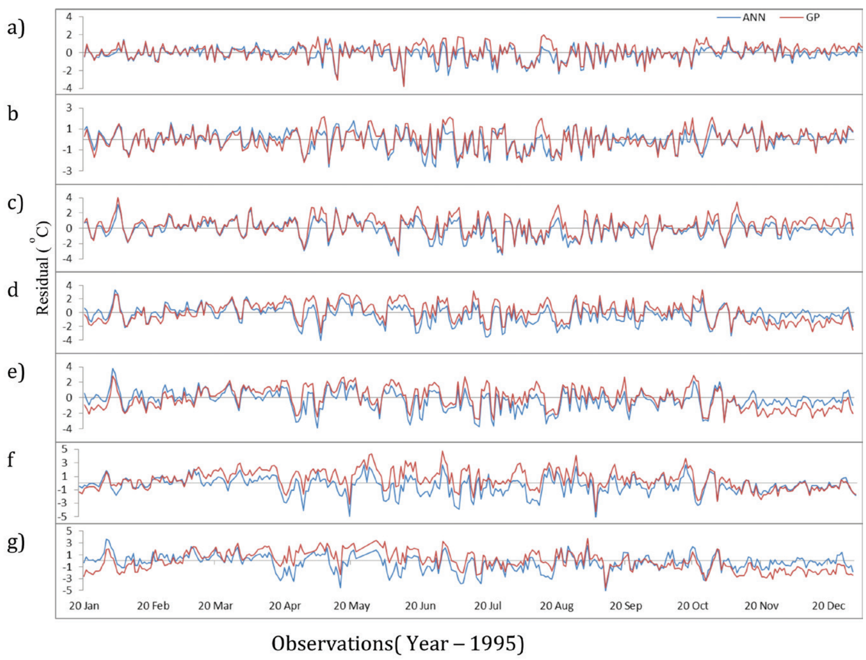

FIGURE. 4. Residual analysis of minimum temperature forecast models. 4. a. to g lead days one to seven respectively

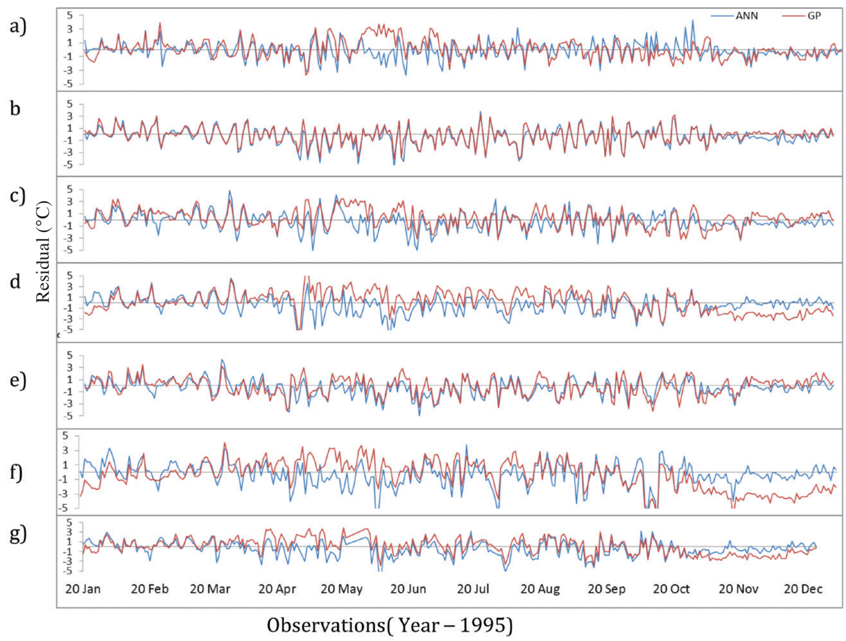

FIGURE. 5. Residual analysis of maximum temperature forecast models. 4. a. to g lead days one to seven respectively

CONCLUSION

This work has proposed surface air minimum and maximum temperature estimation models for the next consecutive seven days in densely populated urban area Chennai, India, using artificial intelligent techniques ANN and GP. ANN technique based models show promising results with MAE less than 1°C upto day five and slightly above 1°C for day six and seven in minimum temperature prediction and significant performance on maximum temperature prediction with a little higher error rate. The results of the analysis also indicate that predictability generally degrades as the time range of forecast increases. Based on the statistical analysis on the prediction models, it is concluded that although both approaches provide acceptable results, ANN model has higher prospective than the GP models in estimating minimum and maximum temperature over the study region. The prediction capability is also more in minimum temperature prediction than maximum temperature prediction. The methods employed in this study has given significant performance for least lead days but the correlation of the observed with predicted for greater lead days should be further refined.

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