Application of Neural Network Technique to improve the location specific forecast of temperature over Delhi from MM5 model

S. K. ROY BHOWMIK, SANKAR NATH, A. K. MITRA and H. R. HATWAR*

India Meteorological Department, New Delhi, India

* *India Meteorological Department, Pune, India*

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e mail : skrb.imd@gmail.com

सार – भारत मौसम विज्ञान विभाग अल्प अवधि अधिक समय मान (72 घंटों तक के) में दिल्ली के अधिकतम और न्यूनतम तापमान का पूर्वानुमान लगाने के लिए सांख्यिकीय मार्गदर्शन के रूप में एम. एम. 5 निदर्श के सीर्ध मॉडल आउटपुट (2 मीटर की ऊँचाई तक तापमान) का उपयोग कर रहा है। अधिकतम और न्यूनतम तापमान के लिए निदर्श के सीधे मॉडल आउटपुटों के आँकड़ों के निष्पादन से यह पता चला है कि निदर्श के पूर्वानुमान के कौशल विशेषकर न्यूनतम तापमान के लिए पर्याप्त रूप से सही है। निदर्श पूर्वानुमान को आगे और सुधारने के लिए न्यूरल संजाल (एन. एन.) के साथ– साथ समाश्रयण तकनीकों का उपयोग किया गया है ताकि अधिकतम और न्यूनतम तापमान के लिए निदर्श के सीधे निदर्श आउटपुट की क्रमबद्ध त्रुटियों को कम किया जा सके। इसका अध्ययन करने से यह पता चला है कि न्यूरल संजाल अभिगम और समाश्रयण तकनीक दोनों अधिकतम और न्यूनतम तापमान की पूर्वानुमान के कौशल को सुधारने में सक्षम हैं। इस पद्धति की स्वतंत्र नमूने से जाँच करने पर दैनिक संशोधित पूर्वानुमान सतत रूप से प्रेक्षणों के निकट पाए गए हैं। ये पद्धतियाँ प्रचालनात्मक अनुप्रयोग के लिए आशा के अनरूप पाई गई हैं।
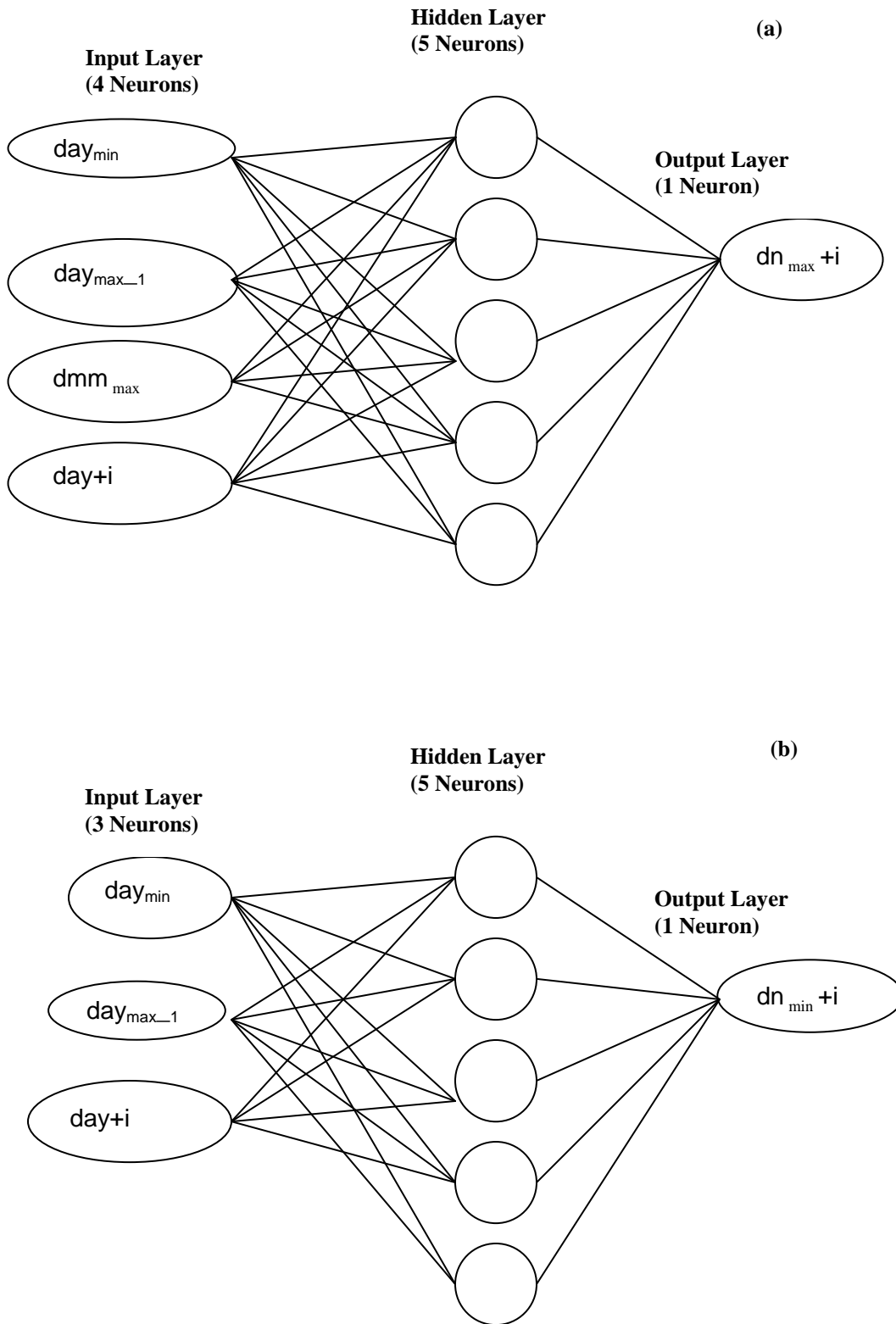
ABSTRACT. India Meteorological Department (IMD) has been using direct model output (2 meters height temperature) of MM5 model as numerical guidance for forecasting maximum and minimum temperature of Delhi in short range time scale (up to 72 hours). Performance statistics of the direct model outputs of the model for maximum and minimum temperature show that forecast skill of the model is reasonably good, particularly for the minimum temperature. For further improving the model forecast, Neural Network (NN) as well as regression techniques are applied so that the systematic errors of the direct model output of the model for maximum and minimum temperature could be reduced. The study shows that both Neural Network approach and regression technique are capable to improve the forecast skill of maximum and minimum temperature. Daily modified forecasts are found persistently closer to the observations when the method is tested with the independent sample. The methods are found to be promising for operational application.

Key word – Location specific forecast, Neural network, MM5 model.

1.   Introduction

There is a growing demand for the accurate forecasting of maximum and minimum temperature for a metropolitan city like Delhi. Some of the traditional methods available for forecasting maximum and minimum temperature of a station are: (a) Model Output Statistics (MOS), (b) Synoptic, (c) Persistence and (d) Statistical. MOS guidance is a method by which one may attempt to estimate or quantify synoptic and meso scale features associated with reference to change of temperature (Klein and Hammons, 1975). Unfortunately, the statistical

guidance from the current operational Numerical Weather Prediction (NWP) model has the basic inability to provide adequate boundary layer information for reliable prediction in short range time scale (up to 72 hours). Persistence forecast has good chance of success but fails during the transition period of flow pattern. Efforts are made by several researchers (Singh and Jaipal, 1983; Raj, 1989; Vashisth and Pareek, 1991; Attri *et al*., 1995; Dimri *et al*., 2002; Chakraborti, 2006 etc.) to develop statistical technique of multiple linear regression analysis for predicting maximum   and minimum temperature of a station using other meteorological parameters as

**Hidden Layer
(5 Neurons)**

(a)

**Input Layer
(4 Neurons)**

day_{min}

day_{max_1}

dmm_{max}

day+i

**Output Layer
(1 Neuron)**

$dn_{max} +i$

**Hidden Layer
(5 Neurons)**

(b)

**Input Layer
(3 Neurons)**

day_{min}

day_{max_1}

day+i

**Output Layer
(1 Neuron)**

$dn_{min} +i$

Figs. 1 (a&b). Illustration of neural network method for (a) maximum (b) minimum temperature forecast

predictors. As temperature of a place depends on several factors, these statistical models are not adequate for operational applications. India Meteorological Department (IMD) has been using MM5 model direct output as numerical guidance for operational forecasting of maximum and minimum temperature of Delhi in short range time scale (up to 72 hours). The inherent limitation to any NWP model is that it neglects small scale effects and it approximates complicated physical processes and interactions. Also, model loses skill because of the growth of the inevitable uncertainty in the initial conditions.

During recent years, the technique of Neural Network (NN) has drawn considerable attention from research workers as it can handle the complex and non-linear problems better than the conventional statistical techniques (Hagan *et al*., 1996). The technique has been widely applied to many meteorological problems, such as predicting tornadoes (Marzban and Stumpf, 1996), damaging winds (Marzban and Stumpf, 1998), thunderstorms (McCann, 1992), quantitative precipitation (Hall *et al*., 1999; Kuligowski and Barros, 1998; Koizumi, 1999), Typhoon intensity (Balk and Paek, 2000), long-range monsoon precipitation (Wu *et al*., 2001) and even prediction of surface ozone (Guha Thakurta, 1999).

In this paper, NN technique and conventional statistical regression technique are applied to improve the direct model outputs (forecasts) of maximum and minimum temperature of Delhi from the MM5 model.

2. Data sources and methodology

The MM5 model at IMD is run at the horizontal resolution of 45 km with 23 sigma levels in the vertical and the integration is carried out for 72 hours forecast over a single domain covering the area between Lat. 30° S to 45° N and Long 25° E to 125° E. Initial and boundary conditions are obtained from the National Centre for the Environmental Prediction (NCEP) Global Forecast System readily available in the Internet at the resolution of $1° \times 1°$ Lat./Long. The direct model output of highest and lowest temperature at 2 meters height of the MM5 model at the model grid close to Delhi (Safdarjung Airport) during the forecast period 24 hours, 48 hours and 72 hours are respectively considered as the forecasts (day-1, day-2 and day-3) of maximum and minimum temperature. The geographical location of Safdarjung Airport is at Lat. 28.35° N and Long. 77.12° E. The corresponding nearest model grid (Lat. 28.14° N / Long. 77.17° E) has the vector difference of 7 km only.

Daily maximum temperature based on direct model outputs (2 meters height) of 24 hours (day-1), 48 hours (day-2) and 72 hours (day-3) forecasts of the MM5 model for the period from 1 April to 30 September, 2006 and the corresponding maximum temperature observations of Safdarjung Airport are used to develop the techniques. The independent sample data for the period from 1 October to 31 October 2006 are used to test the techniques.

For the minimum temperature daily data for the period from 1 January to 28 February and 01 November to 24 December 2006 and the corresponding minimum temperature observations are used for developing the methods and the independent data sample for the period from 25 December 2006 to 23 January 2007 are used to validate the methods.

2.1. *Neural network technique*

In general, a neural network is a computer model consists of a set of nodes and a set of interconnections between them. A node is composed of individual processing elements called neurons. The neurons are connected by links that have weights associated with them. A neural network consists of multiple layers of neurons interconnected with neurons in other layers. These layers are referred to as the input layer, hidden layer(s), or output layer. The inputs and the interconnection weights are processed by a weighted summation function to produce a sum that is passed to a transfer function. The output of the transfer function is the output of the neurons. A neural network is trained with input and output pattern examples. It then constructs a nonlinear numerical model of a physical process in terms of network parameters.

To develop the technique we have used a three layer neural network with 4-5-1 and 3-5-1 network architecture respectively for maximum and minimum temperature forecasts as illustrated in Figs. 1(a&b). The transfer function used here is a sigmoid function and the most popular back propagation learning algorithm is used to train the network (Hagan *et al*., 1996).

In the Figs. 1(a&b), the layers 1, 2, and 3 represent the input layer, the hidden layer and the output layer respectively. In case of maximum temperature, the neuron of the input layer is represented by current day observed minimum temperature (day$_{min}$), previous day observed maximum temperature (day$_{max\_1}$), MM5 model 12 hours

forecast based on current day 0000 UTC initial conditions (dmm_{max}) and MM5 model day $+ i$ ($i = 1,2,3$) maximum temperature forecasts (day-1, day-2, day-3) based on 0000 UTC initial conditions of the day. The neuron for output layer is represented by $dn_{max} + i$, respectively for $i = 1,2,3$. Similarly for the minimum temperature, the neuron of the input layer is represented by current day observed minimum temperature (day_{min}), previous day observed maximum temperature (day_{max_1}), and MM5 model day $+ i$ ($i = 1,2,3$) minimum temperature forecasts (day-1, day-2, day-3) based on 0000 UTC initial conditions of the day. The neuron for output layer is represented by $dn_{min} + i$, respectively for $i = 1,2,3$.

These 4(3) data of maximum temperature (minimum temperature) are normalized, so that they can be applied to sigmoid function. These 4(3) days data constitute the input vector $X = (x_1, x_2, \ldots, x_{4(3)})^T$

The number of nodes in hidden layer is determined during network architecture design and adjusted to achieve best network performance (here it is 5 numbers). Finally the neuron in output layer is the corresponding maximum (minimum) temperature final forecasts (day-1, day-2 and day-3).

The activation unit z_h of the hidden layer neuron h is calculated by the following equation:

$$z_h = \sum_{m=1}^{m=4(3)} W_{mh} X_h$$

Where $W_{mh} = (w_{1h}, w_{2h}, \ldots, w_{4h(3h)})$ is the weight vector between the input and hidden layers. Then the activation unit z_h of the hidden layer neuron h is passed through a sigmoid function to generate the output $\delta(z_h)$ of neuron h of the hidden layer:

$$\delta(z_h) = \frac{1}{\left(1 + e^{-zh}\right)}$$

The activation unit y_n of the nth neuron of the output layer is calculated

$$y_n = \sum_{h=1}^{h=5} W_{hn} \delta(Z_h)$$

which is passed through the sigmoid function to get the output $\delta(y_n)$ of the output layer neuron

$$\delta(y_n) = \frac{1}{\left(1 + e^{-y_n}\right)}$$

The signal $\delta(y_n)$ is compared with the desired output O_n to generate an error estimate $e_n = [O_n - \delta(y_n)]$, from which mean square error ε is computed over the entire training set. To minimize ε, the weights are modified. The gradient of ε with the weights between hidden and output layer neuron is

$$\frac{\partial \varepsilon}{\partial w_{hn}} = -e_n \delta\left(y_n\right) \left[1 - \delta(y_n)\right] \delta\left(z_h\right)$$

So the updated weights of hidden to output layer neurons are

$$w'_{hn} = w_{hn} + \eta \left(-\frac{\partial \varepsilon}{\partial w_{hn}}\right)$$
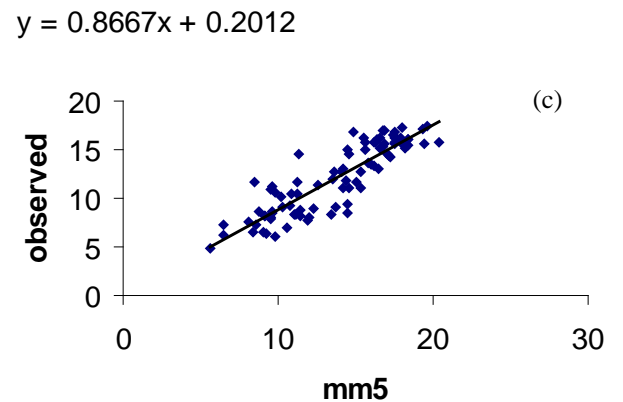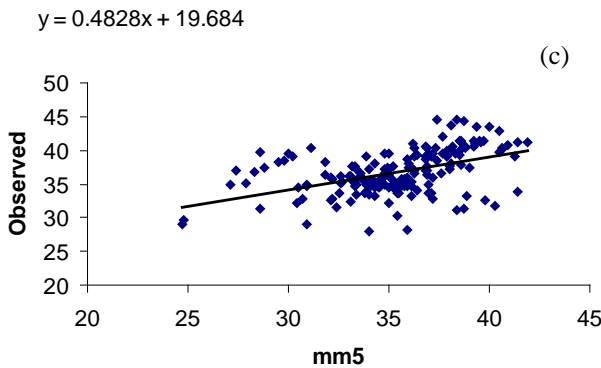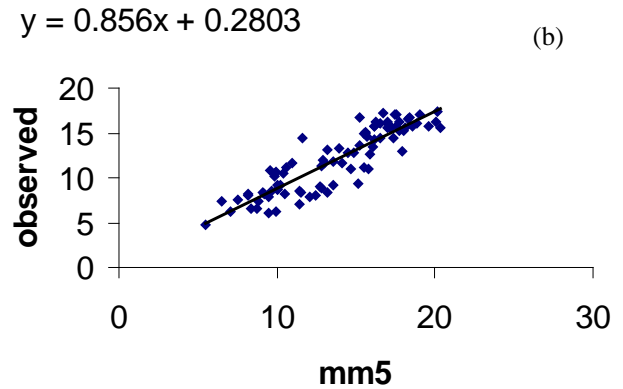
where η is the learning rate.

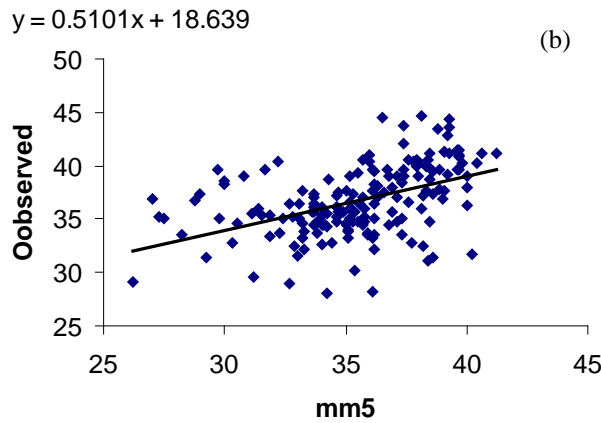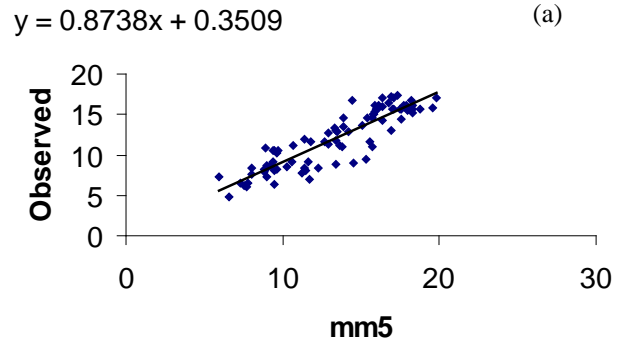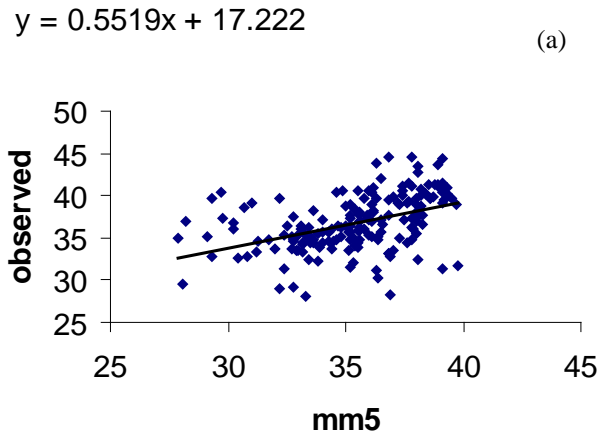The gradient of ε with the weights between input and hidden layer neuron is

$$\frac{\partial \varepsilon}{\partial w_{mh}} = -\sum_{n=1}^{n=4(3)} \left\{e_n \delta\left(y_n\right) \left[1 - \delta(y_n)\right] \delta\left(z_h\right) w_{hn}\right\}$$
$$\left\{\delta(z_h)\left[1 - \delta\left(z_h\right)\right] \times_m\right\}$$

So the updated weights of input to hidden layer neurons are

$$w'_{mh} = w_{mh} + \eta \left(-\frac{\partial \varepsilon}{\partial w_{mh}}\right)$$

Daily maximum temperature based on direct model outputs (2 meters height) of 24 hours (day-1), 48 hours (day-2) and 72 hours (day-3) forecasts of the MM5 model for the period from 1 April to 30 September, 2006

y = 0.5519x + 17.222

(a)

y = 0.8738x + 0.3509

(a)

y = 0.5101x + 18.639

(b)

y = 0.856x + 0.2803

(b)

y = 0.4828x + 19.684

(c)

y = 0.8667x + 0.2012

(c)

Figs. 2 (a-c). Regression curve of maximum temperature (°C) for the forecast period (a) 24 hours, (b) 48 hours and (c) 72 hours. The *X* axis is maximum temperature based on model output of MM5 model and *Y* axis is the corresponding observed maximum temperature

Figs. 3 (a-c). Regression curve of minimum temperature (°C) for the forecast period (a) 24 hours, (b) 48 hours and (c) 72 hours. The *X* axis is minimum temperature based on model output of MM5 model and *Y* axis is the corresponding observed minimum temperature

is taken as signal to the input layer neurons. Training was done with the help of corresponding observation and then finally the results were validated with another set of sample data for the period from 1 October to 31 October 2006.

For the minimum temperature daily data for the period from 1 January to 28 February and 01 November to 24 December 2006 has been used as the training sample and the data for the period from 25 December 2006 to 23 January 2007 is used as the independent sample to test the technique.
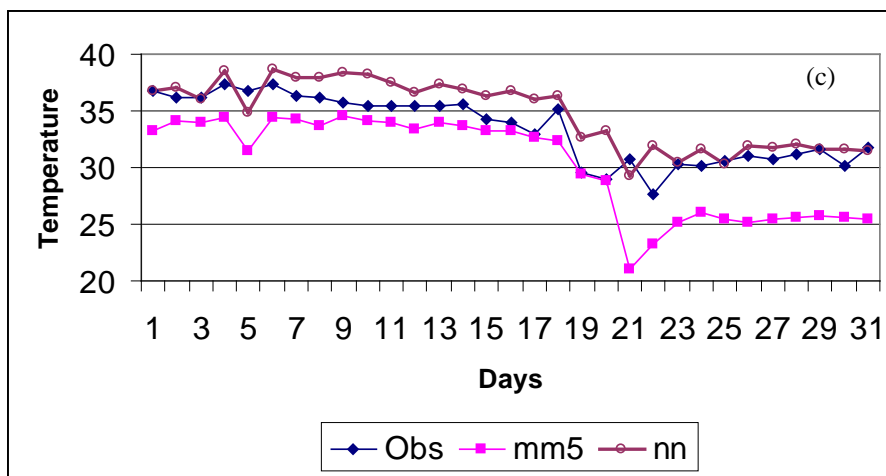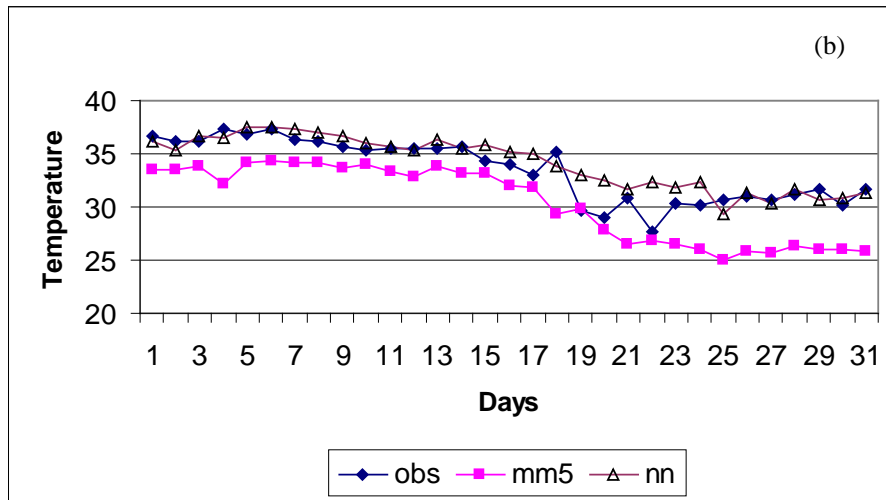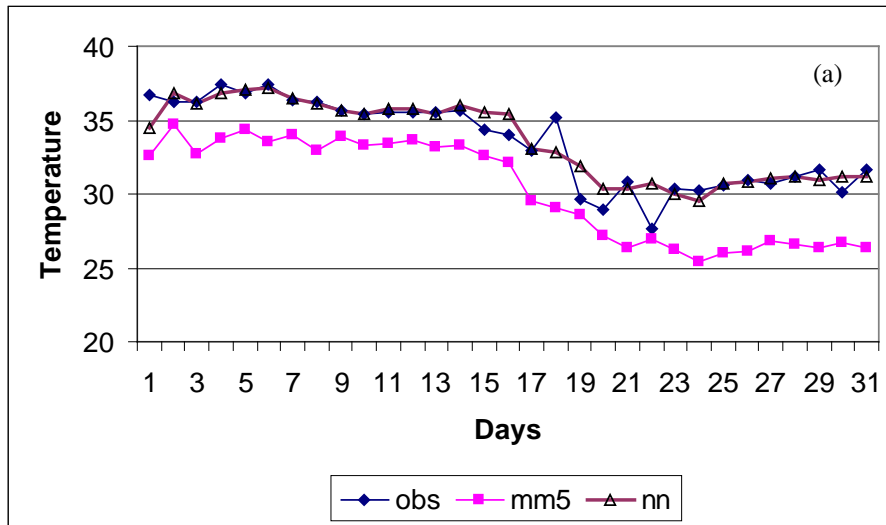
Figs. 4 (a-c).   Inter comparison of maximum temperature (°C) based on MM5 model, NN
technique and observation for the month of October, 2006 for the forecast period
(a) 24 hours, (b) 48 hours and (c) 72 hours
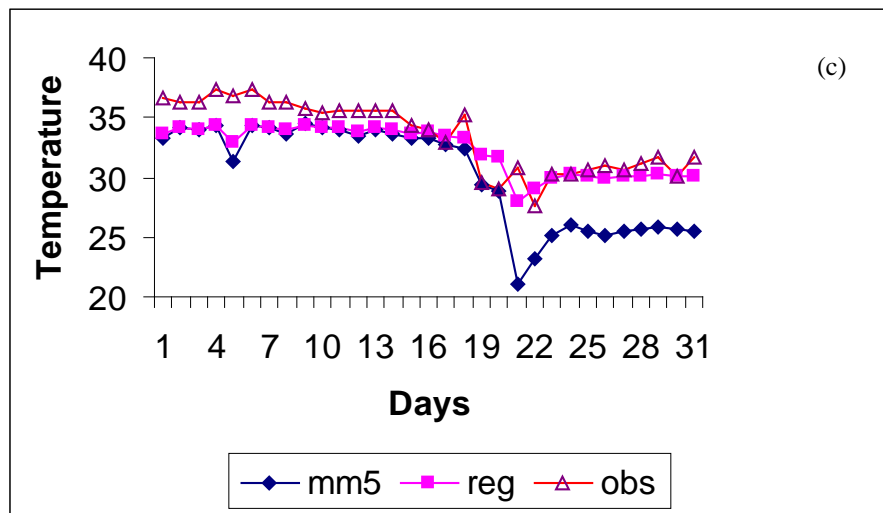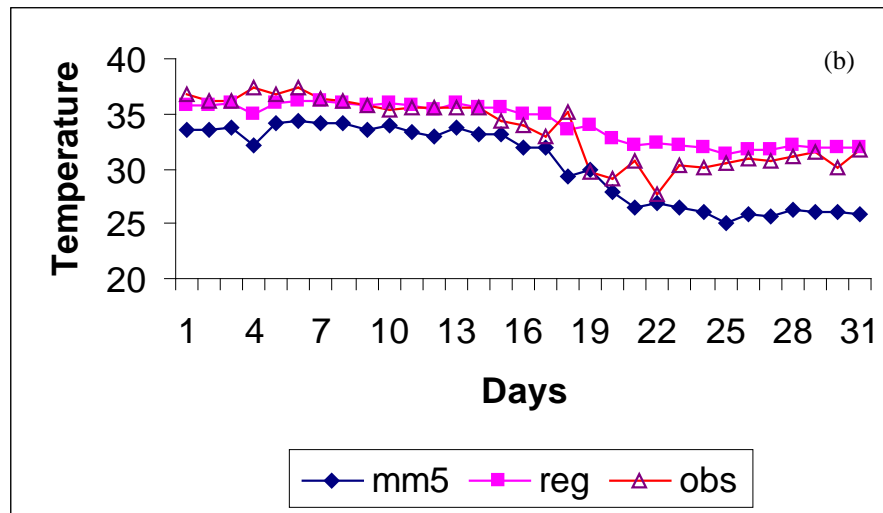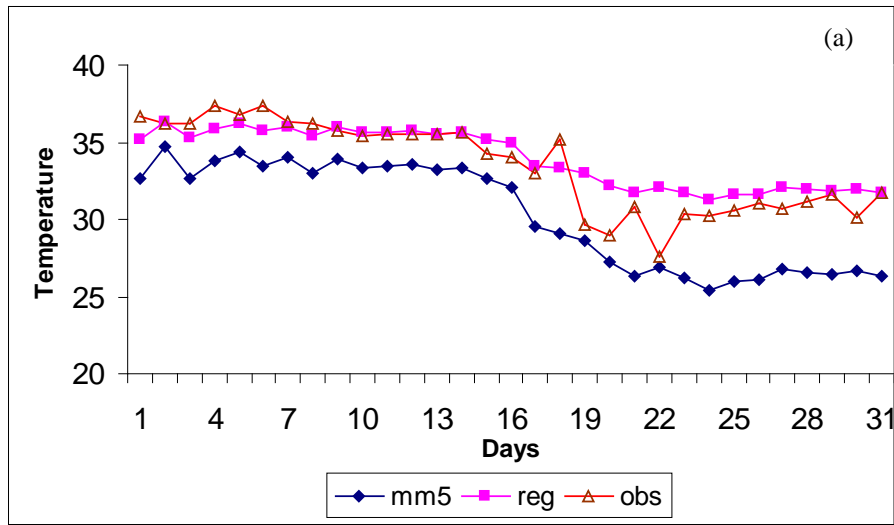
Figs. 5 (a-c).   Inter comparison of maximum temperature (°C) based on MM5 model, regression technique and observation for the month of October, 2006 for the forecast period (a) 24 hours, (b) 48 hours and (c) 72 hours

TABLE 1

**Performance statistics for maximum temperature (°C) forecasts for the
independent data sample (and for the training data sample)**

	MM5			NN			Statistical		
	24 hrs	48 hrs	72 hrs	24 hrs	48 hrs	72 hrs	24 hrs	48 hrs	72 hrs
CC	0.44	0.47	0.47	0.93	0.88	0.88	0.91	0.88	0.87
				(0.72)	(0.72)	(0.67)	(0.44)	(0.47)	(0.47)
MAE	2.6	2.6	2.6	0.69	1.1	1.6	1.1	1.2	1.6
				(1.6)	(1.7)	(1.8)	(2.2)	(2.3)	(2.2)
RMSE	3.4	3.5	3.6	1.0	1.5	1.9	1.5	1.7	1.9
				(2.2)	(2.3)	(2.4)	(2.9)	(2.9)	(2.9)

TABLE 2

Monthly mean errors for maximum temperature (°C) forecast

	MM5			NN			Statistical		
Months	24 hrs	48 hrs	72 hrs	24 hrs	48 hrs	72 hrs	24 hrs	48 hrs	72 hrs
Apr	-5.4	-5.0	-5.1	-0.4	-0.4	0.3	-2.7	-2.4	-2.3
May	-2.1	-1.3	-1.7	-0.8	-0.5	0.6	-1.9	-1.7	-1.9
Jun	-0.7	-0.8	-1.0	-0.1	0.1	-0.4	-0.2	-0.4	-0.5
Jul	0.9	0.6	0.5	0.5	-0.1	-0.8	2.0	1.8	1.8
Aug	-0.5	-0.1	-0.4	-0.5	-0.6	0.0	1.1	1.2	1.2
Sep	-0.8	-1.0	-1.0	0.1	0.3	0.6	1.3	1.1	1.3
Oct	-3.2	-3.1	-3.2	0.1	0.7	1.3	-0.5	-0.7	1.2

The number of transfer function has been examined in constructing the network architectures. It is found that using a tan-sigmoid transfer function to propagate to the hidden layer and a linear transfer function to propagate to the output layer in a three-layer back propagation architecture gives the optimum network performance for the type of data we used in this study. The training algorithm (rule) is the basic Levenberg-Marquardt method, which is the standard method for the minimization of mean square error criteria. The process of updating of weights is iterated until the error between the derived and actual output becomes less than a predefined small value 10^{-5}. The model convergence is achieved at the learning rate of 0.4 for the maximum temperature and at 0.2 for the minimum temperature model with number of 1000 set of epochs for both the models.

2.2. *Conventional statistical regression technique*

(a) *Maximum temperature*

Fig. 2 (a) shows a scatter diagram which explains a regression equation relating observed maximum temperature and MM5 24 hours direct model output for maximum temperature based on the same training sample data set. The regression relation for the maximum temperature can be written as :

$$Y = 0.5519x + 17.222 \qquad (1)$$

where Y is the modified forecast of maximum temperature (24 hours) and x is the corresponding model output in °C.

TABLE 3

**Performance statistics for minimum temperature (°C) forecasts for the
independent data sample (and for the training data sample)**

	MM5			NN			Statistical		
	24 hrs	48 hrs	72 hrs	24 hrs	48 hrs	72 hrs	24 hrs	48 hrs	72 hrs
CC	0.89	0.89	0.88	0.81	0.85	0.73	0.73	0.78	0.76
				(0.93)	(0.92)	(0.91)	(0.89)	(0.89)	(0.88)
MAE	1.63	1.94	1.97	0.76	0.74	1.0	1.0	1.0	1.2
				(0.98)	(1.0)	(1.1)	(1.2)	(1.2)	(1.3)
RMSE	2.1	2.4	2.4	1.0	0.94	1.3	1.3	1.3	1.5
				(1.3)	(1.3)	(1.5)	(1.6)	(1.6)	(1.7)

Similarly, the regression equations for the 48 hours [Fig. 2(b)] and 72 hours [Fig. 2(c)] modified forecasts of maximum temperature are respectively

$$Y = 0.5101x + 18.639 \qquad (2)$$

$$Y = 0.4828x + 19.684 \qquad (3)$$

(b) *Minimum temperature*

Figs. 3 (a-c) shows scatter diagrams which explain regression equations relating observed minimum temperature and MM5 hours direct model output (24 hours, 48 hours and 72 hours) for minimum temperature based on the same training sample data set. The regression equations for the improved minimum temperature forecasts based on the scatter diagrams are given below:

$$Y = 0.8738x + 0.3509 \qquad (4)$$

$$Y = 0.856x + 0.2803 \qquad (5)$$

$$Y = 0.8667x + 0.2012 \qquad (6)$$

3. Performance statistics
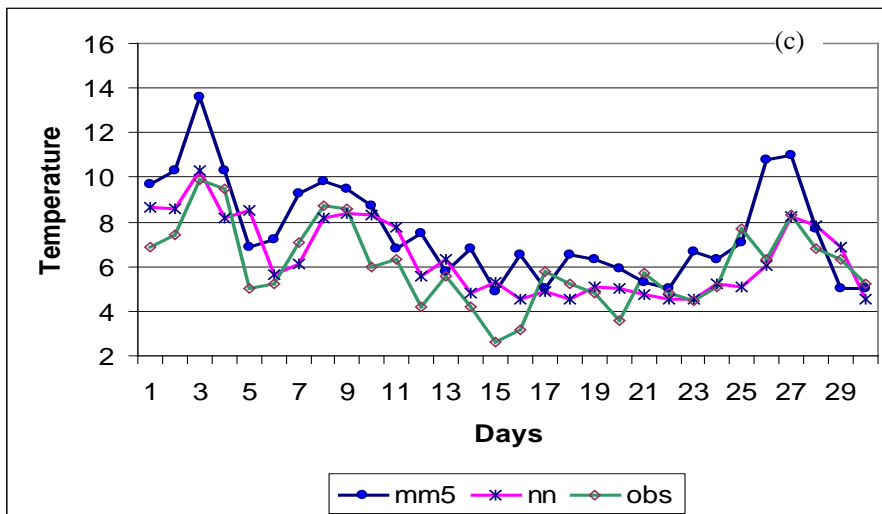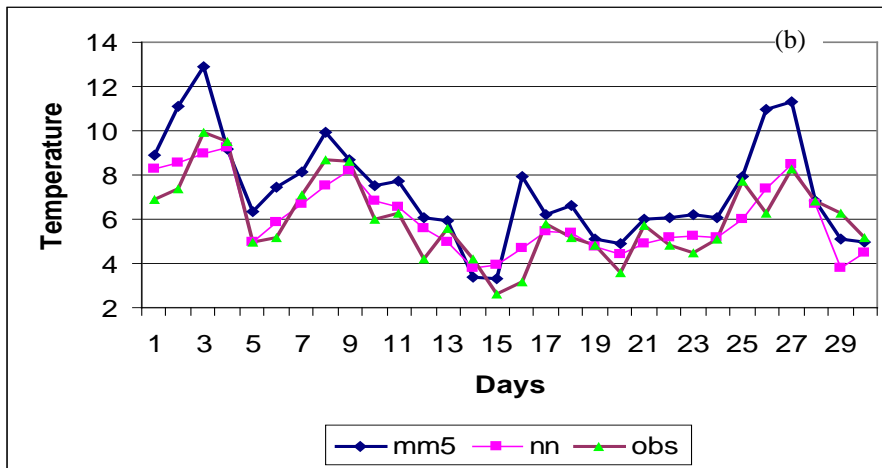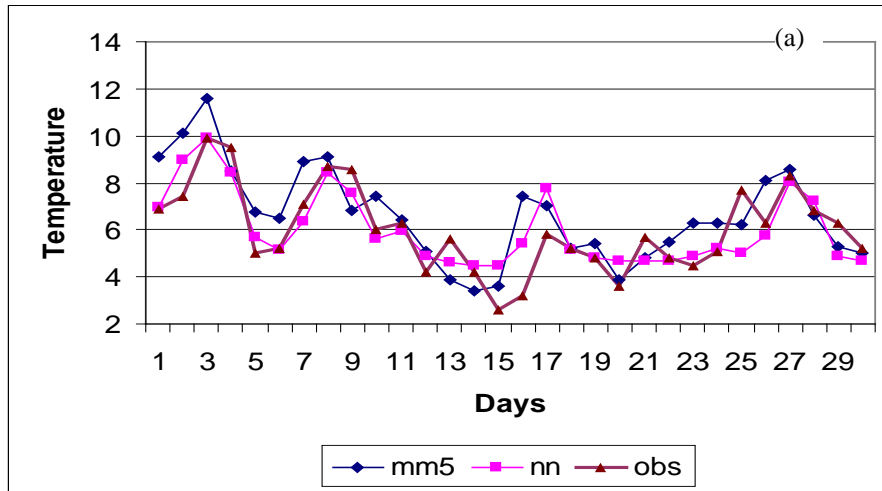
(a) *Maximum temperature*

Table 1 presents performance statistics for maximum temperature on the basis of direct model outputs of MM5

model, after applying neural technique and regression technique. The figures within bracket indicate results based on training sample and figures without bracket are the results with the independent sample. The results of skill score show that for the MM5 model (direct model output) Correlation Coefficient (CC) ranges from 0.44 to 0.47, Mean Absolute Error (MAE) is 2.6° C and Root Mean Square Error (RMSE) varies from 3.4 to 3.6° C.

The performance statistics of the model for the training sample and the independent sample after applying NN technique reveal that with the application of NN technique, improvement is achieved in the forecast skill. CC ranges between 0.67 & 0.72 for the training sample and from 0.88 to 0.93 for the independent sample. MAE is 1.6 to 1.8° C for the training sample and 0.69 to 1.6° C for the independent sample. RMSE is also found to be reduced significantly. RMSE ranges between 2.2 & 2.4° C for the training sample and 1.0 to 1.9° C for the independent sample.

The performance statistics of the model for the training sample and the independent sample after applying regression technique show that in this case CC remains same as MM5 model for the training sample and the CC ranges from 0.87 to 0.91 for the independent sample. MAE remains around 2.2° C for the training sample and 1.1 to 1.6° C for the independent sample. RMSE is 2.9° C for the training sample and 1.5 to 1.9° C for the independent sample.

Figs. 4(a-c) presents an inter-comparison of maximum temperature based on direct model output and NN output against daily observation in all the 24 hours, 48 hours and 72 hours forecasts respectively for the

Figs. 6 (a-c).   Inter comparison of minimum temperature (°C) based on MM5 model, NN technique
and observation for the period   from 25 December 2006 to 23 January 2007 for the
forecast period (a) 24 hours, (b) 48 hours and (c) 72 hours
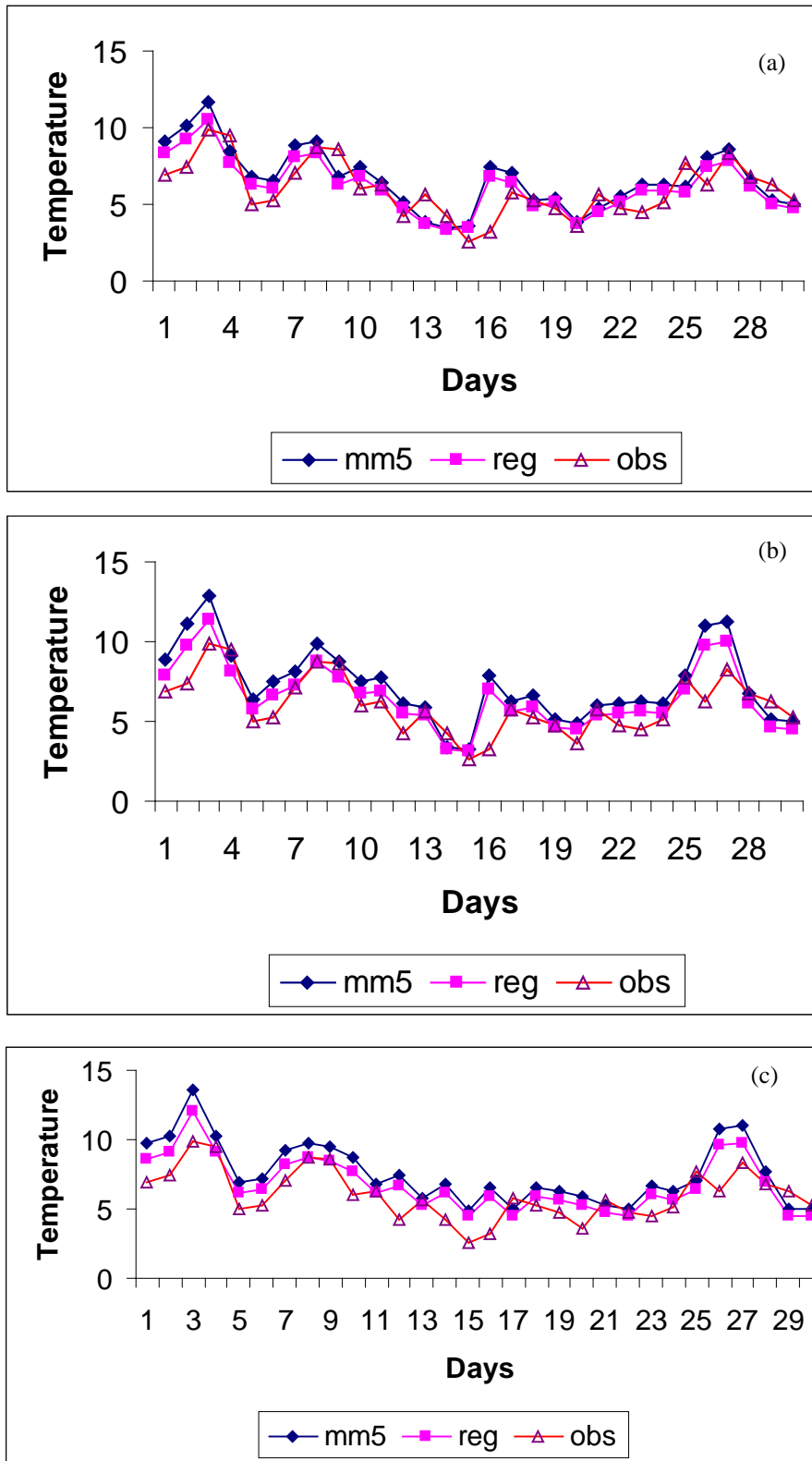
Figs. 7 (a-c). Inter comparison of minimum temperature (°C) based on MM5 model, regression technique and observation for the period from 25 December 2006 to 23 January 2007 for the forecast period (a) 24 hours, (b) 48 hours and (c) 72 hours

TABLE 4

Monthly mean errors for minimum temperature (°C) forecasts

Month	MM5			NN			Statistical		
	24 hrs	48 hrs	72 hrs	24 hrs	48 hrs	72 hrs	24 hrs	48 hrs	72 hrs
Jan 2006	2.6	2.4	2.2	0.6	0.1	0.0	1.6	1.5	1.2
Feb 2006	2.3	2.6	2.2	0.2	0.3	0.1	0.6	0.6	0.3
Nov 2006	0.7	1.0	1.4	-0.1	-0.0	0.0	-0.7	-0.7	-0.4
Dec 2006	0.9	1.2	1.3	-0.3	-0.4	-0.4	0.0	0.0	0.1

independent data period. It shows that NN technique could provide daily forecasts closer to observations, persistently at all the three forecast periods. But forecast values are slightly on the higher side (over-estimation).

Figs. 5(a-c) presents an inter-comparison of maximum temperature based on direct model output and regression output against daily observation for the 24 hours, 48 hours and 72 hours forecasts respectively for the independent data period. It shows that regression technique could provide daily forecasts closer to observations in all the three forecast periods. In this case also values of regression are usually on the higher side against observation.

Table 2 shows monthly mean errors (forecast-observed) of maximum temperature forecasts by direct MM5 model output, NN technique and regression technique for the months April to October based on the training sample. The result shows that except July, in all other months MM5 model under-estimates maximum temperature. Maximum under-estimation takes place in April (5° C), followed by October (3° C)   and May (around 2° C). In other months error is less than 1° C. In July model slightly overestimates (0.5 to 0.9° C) maximum temperature.   Daily mean errors become considerably smaller with the application of NN as well as regression technique. These features are noticed in all the three forecast periods. For the month of April, mean error becomes around 0.4° C against 5° C for the corresponding MM5 direct output and around 2.5° for the regression technique.

(b)   *Minimum temperature*

Table 3 presents performance statistics for minimum temperature on the basis of direct model outputs of MM5

model, after applying neural technique and regression technique. The figures within bracket indicate results based on training sample and figures without bracket are the results with the independent sample. The results of skill score show that for the MM5 model (direct model output) CC ranges from 0.88 to 0.89, MAE remains between 1.63 & 1.97° C and RMSE ranges from 2.1 to 2.4° C.

The inter-comparison reveals that the performance of the direct model output of minimum temperature is considerably better than that of maximum temperature. In general, the model has warm bias for the minimum temperature and cold bias for the maximum temperature.

The performance statistics of the model for the training sample and the independent sample after applying NN technique reveals that with the application of NN technique considerable improvement is achieved in the forecast skill. CC is found to vary from 0.91 to 0.93 for the training sample and from 0.73 to 0.81 for the independent sample. MAE varies from 0.98 to 1.1° C for the training sample and 0.74 to 1.0° C for the independent sample. RMSE is found to range between 1.3 & 1.5° C for the training sample and from 0.94 to 1.3° C for the independent sample.

The performance statistics of MM5 model for minimum temperature forecasts after applying the regression technique for the training period data set and for the independent data set shows that in this case, CC remains same as MM5 model for the training sample and ranges around 0.75 for the independent sample. MAE remains around 1.2° C for the training sample and around 1.0° C for the independent sample. RMSE is around 1.7° C for the training sample and varies from 1.3 to 1.5° C for the independent sample.

An inter-comparison of minimum temperature based on direct model output and NN output against daily observation for the 24 hours, 48 hours and 72 hours forecast respectively for the independent data period is illustrated in Figs. 6(a-c). The result shows that the NN technique could provide daily forecast closer to observation in all the three forecast periods and values are always between observed value and direct model output values.

Figs. 7 (a-c) presents an inter-comparison of minimum temperature based on direct model output and regression output against daily observation for the 24 hours, 48 hours and 72 hours forecast respectively for the independent data period. It shows that regression technique could provide daily forecast closer to observation in all the three forecast periods.

Table 4 shows monthly mean errors of minimum temperature forecasts by direct MM5 model output, NN technique and regression technique. In this case, the MM5 model over-estimates minimum temperature and maximum over-estimation takes place in the month of January and February (2.2 to 2.6° C). During November and December the magnitude of over-estimation varies from 0.7 to 1.4° C. In this case also daily mean errors become considerably smaller with the application of NN as well as regression technique for all the three forecast periods.

4.   Conclusions

Following conclusions are drawn from this study:

(*i*)   Performance of the MM5 model in predicting daily minimum temperature of Delhi is superior to that of maximum temperature. The results of this study shows that the MM5 model has cold bias for maximum temperature forecast and warm bias for minimum temperature forecast.

(*ii*)   With the application of NN technique to the time series of direct model outputs of maximum and minimum temperatures against corresponding observations, significant improvement is noticed in the forecast skill for both maximum and minimum temperature. Similar improvement is also noticed with the regression technique.

(*iii*) Daily modified forecasts are found closer to the observations when the method is tested with the independent sample.

The method with one season data has shown sufficiently promising results for operational applications. As we do more and more days of forecasts, we can pass the datasets of the forecast periods to the training period, thus increasing the length of the training period. It remains to be seen what further improvement in the prediction skill is possible from the use of neural network for each month (instead of entire season) on the basis of the longer training period data. The future work would also require to increase the forecast period up to medium range (5 to 7 days) from the use of global model outputs and to extend the work for many such stations as required for the district level integrated agro-advisory services. It is worth to be mentioned that in this direction work is already initiated by IMD.

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