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Maximum and minimum temperature prediction over western Himalaya using artificial neural network

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सार – पूर्वाभिमुखी दिशा की ओर चलने वाले सिनॉप्टिक मौसम तंत्र, जिसे पश्चिमी विक्षोभ (डब्ल्यू. डी.) कहते है, के कारण पश्चिमी हिमालय में शीत ऋतु (नवम्बर से अप्रैल) के दौरान हिम के रूप में बड़ी मात्रा में वर्षण होता है। यह वर्षण इकट्ठा होता जाता है जिससे हिमस्खलन का खतरा हो जाता है। हिमस्खलन के आरंभ होने में तापमान की महत्वपूर्ण भूमिका होती है। अतः अधिकतम और न्यूनतम तापमान का पूर्वानुमान हिमस्खलन के पूर्वानुमान के लिए काफी सहायक रहेगा। इस अध्ययन में पश्चिमी हिमालय क्षेत्र में विभिन्न वेधशालाओं के प्रेक्षित सतही मौसम विज्ञान आँकड़ों का उपयोग करके अधिकतम और न्यूनतम तापमान का पूर्वानुमान करने के लिए एक अरैखिक पद्धति, कृत्रिम न्यूरल संजाल (ए. एन. एन.) का उपयोग किया गया है। ए. एन. एन. बहुत से इनपुट और एक अथवा अधिक आउटपुट के बीच आनुभाविक संभावित अरैखिक संबंध का निर्धारण करने के लिए अभिकल्पनात्मक प्रभावी तरीका उपलब्ध कराता है। इस अध्ययन में बैक प्रोपेगेशन लर्निंग एलगोरिथ्म का उपयोग संजाल के प्रशिक्षण के लिए किया गया है। प्रशिक्षण की प्रक्रिया में इनपुट और आउटपुट के बीच संबंध का पता लगाया है अर्थात अंतिम भार का आकलन किया गया है। संजाल को व्यवस्थित करने के लिए लगभग 25 वर्षों के पुराने आँकड़ों का उपयोग किया गया है और व्यवस्थित किए गए संजाल का उपयोग पाँच शीत ऋतुओं (2005–06 तथा 2009–10) के तापमान का पूर्वानुमान करने के लिए किया गया है। न्यूनतम और अधिकतम तापमान के तदनुरूप वर्ग माध्य मूल त्रुटियों (आर. एम. एस. ई.) का आकलन किया गया है। स्वतंत्र सेट के लिए क्रमशः आर. एम. एस. ई. 2.18 से 2.48 और 1.99 से 2.78 का अंतर रहा ।

ABSTRACT. Due to eastward moving synoptic weather system called Western Disturbance (WD), Western Himalaya receives enormous amount of precipitation in the form of snow during winter months (November to April). This precipitation keeps on accumulating and poses an avalanche threat. Temperature plays an important role for the initiation of avalanches. Therefore, prediction of maximum and minimum temperature may be quite helpful for avalanche forecasting. In the present study Artificial Neural Network (ANN), a non-linear method is used for the prediction of maximum and minimum temperature using surface meteorological data observed at various observatories in Western Himalaya region. ANN provides a computational efficient way of determining an empirical possible non-linear relationship between a number of input and one or more outputs. In present study back propagation learning algorithm is used to train the network. In the training process the relationship between input and output is extracted *i.e.*, final weights are computed. Past data of about 25 years is used for training the network and trained network is used for temperature prediction for five winter seasons (2005-06 to 2009-10). Root mean square errors (RMSE) corresponding to maximum and minimum temperature are computed. For independent data set RMSE vary from 2.18 to 2.48 and 1.99 to 2.78 for maximum and minimum temperatures respectively.

Key words – Avalanche, ANN, WD, Back propagation, Mountain meteorology.

1. Introduction

Western Himalaya receives good amount of snow during winter due to western disturbances. This region is badly affected by snow avalanches during this period. Avalanche forecasting is one of the best methods to mitigate avalanches. A number of snow and meteorological parameters are required to develop avalanche forecast models. Maximum and minimum temperatures are very important parameters to assess avalanche danger. Therefore, predicted/estimated values of maximum and minimum temperature in advance may help a lot in assessing avalanche danger and developing avalanche forecast models.

TABLE 1

Three layer artificial neural network architecture

No of inputs	6
No of hidden layers	1
No of hidden nodes	4
No of outputs	1
Learning rate	0.5
Momentum	0.3
Acivation function	Sigmoid transfer function $f(x) = (1+e^{-x})^{-1}$

Generally, two methods are used to forecast weather (*i*) the empirical approach (*ii*) the dynamical approach (Maqsood *et al*., 2004). The first approach is based upon the occurrence of analogous and is often referred as analogous forecasting. This approach is useful for predicting local scale weather if good number of recorded cases is available. The second approach is based upon equations and forward simulations of the atmosphere and referred to as computer modeling. The dynamical approach is useful for modeling large scale weather phenomenon and may not predict short term weather efficiently. Though usually the dynamical prediction of meteorological parameters using NWP is followed, prediction of maximum and minimum temperature using Artificial Neural Network (ANN) technique is preferred here due to its simplicity with the available resources.

A number of studies have been done for prediction of maximum and minimum temperature. Mohanty, *et al*., (1997) applied multiple regression technique to forecast maximum and minimum temperatures at Delhi. Adya, (1998) presented the effectiveness of neural network in forecasting and prediction. Guhathakurta, (1999) used neural network technique for short term prediction of air pollution. Richardo and Palutikof (1999) simulated daily temperature over Portugal using neural network. Sahai *et al*., (2000) applied ANN technique with error back propagation algorithm to provide prediction of Indian summer monsoon rainfall on monthly and seasonal basis. Marzben, (2003) post processed the temperature forecast of the ARPS by neural network. Dimri and Mohanty (2007) used statistical-dynamical models for site and time specific prediction of maximum and minimum temperature. Hayati and Mohebi, (2007) used ANN for temperature forecasting in Iran. Joshi and Dimri (2008) used artificial neural network for location specific prediction of precipitation using surface parameters. Singh *et al*., (2008) used analogue method for prediction of surface weather parameters. De (2009) applied ANN to forecast maximum and minimum temperature in the summer monsoon months over India.

TABLE 2

Principal observatories considered for study

Station	Altitude (m)	No of data points (training set)	No of data points (test set)
Kanzalwan	2440	3273	895
Haddan Taj	3080	3174	885
Gulmarg	2800	3479	904
Stage II	2650	2158	902

TABLE 3

Meteorological parameters considered for prediction of maximum and minimum temperature

Parameter	Time of observation
Maximum temperature (T_x)	1730 hr (previous day)
Minimum temperature (T_n)	0830 hr
Dry bulb temperature (T)	0830 hr
Av wind speed (ws_{avg})	Average of last 24 hr
Cloud amount (cla)	0830 hr
Precipitation amount (mm)	0830 hr

In the present study ANN is used for prediction of maximum and minimum temperature at four different surface observatories in Western Himalaya. Maximum and minimum temperature at a specific location depends upon the topographic conditions of the area. Surface parameters observed at each location are used for prediction of temperature at that location.

2. Study area and data

Four representative observatories (road axes/sectors), Kanzalwan (Bandipur-Gurez axis - BG), Haddantaj (Nogaon-Kaiyan axis - NK), StageII (Chowkibal-Tangdhar axis - CT) and Gulmarg (Gulmarg sector) are considered for the study. These observatories represent the climatic and weather conditions of the region and are nodal centers for forecasting avalanche hazards. Further, these sectors are considered as they represent different geographical and climatic conditions of the western Himalaya. Western Himalaya has complex topography. Broadly, it comprises different mountain ranges oriented in North-West, South-East direction. These ranges are Pir-Panjal, Great Himalayan, Zanskar, Laddakh and Great Karakoram range. The winter weather system interacts with these ranges and modifies the intensity and distribution of precipitation.

TABLE 4 (a)

Statistics corresponding to training set

Station	Temperature	Observed SD	Predicted SD	Observed mean	Predicted mean	CC	PP
Kanzalwan	Maximum	5.16	4.58	6.37	6.42	0.90	0.19
	Minimum	5.35	4.91	-6.48	-6.49	0.91	0.16
Haddan Taj	Maximum	4.48	3.94	2.94	2.93	0.88	0.23
	Minimum	4.48	4.01	-5.4	-5.41	0.89	0.20
Gulmarg	Maximum	4.77	4.43	4.76	4.75	0.93	0.14
	Minimum	4.46	4.12	-5.22	-5.22	0.92	0.15
Stage II	Maximum	5.30	4.96	6.25	6.24	0.94	0.12
	Minimum	4.23	3.91	-2.24	-2.24	0.93	0.14

TABLE 4(b)

Statistics corresponding to test set

Station	Temperature	Observed SD	Predicted SD	Observed mean	Predicted mean	CC	PP
Kanzalwan	Maximum	5.77	4.90	6.07	5.89	0.92	0.16
	Minimum	5.33	4.69	-5.72	-5.14	0.89	0.21
Haddan Taj	Maximum	4.77	4.07	4.30	3.80	0.87	0.25
	Minimum	4.95	4.11	-5.54	-5.65	0.89	0.21
Gulmarg	Maximum	5.06	4.59	5.88	5.79	0.87	0.24
	Minimum	4.92	3.95	-4.87	-4.52	0.83	0.32
Stage II	Maximum	5.21	4.58	6.03	5.72	0.91	0.18
	Minimum	4.56	3.79	-2.49	-1.61	0.92	0.19

The data set consists of data from winter (Nov-Apr) 1985 to winter 2009-10. Six important surface weather parameters (continuously available for all stations) given in Table 3 are taken as input parameters. Data prior to winter 2005-06 is used to train the network and trained network is tested with independent data set of five winter seasons, from 2005-06 to 2009-10. The total number of data points for Kanzalwan, Haddan Taj, Gulmarg and Stage II are 4168, 4059, 4383 and 3060 respectively. The altitude, number of data points for training and independent test data set for different stations are given in Table 2.

3. Methodology

ANN is a computational structure modeled loosely on biological processes. ANNs explore many competing hypotheses simultaneously using a massive parallel network composed of non-linear relatively computational elements interconnected by links with variable weights. It is this interconnected set of weights that contains the knowledge generated by the ANN. ANN is useful in the situations, where underlying processes/relationships may display chaotic properties. ANN does not require any prior knowledge of the system under consideration. This

TABLE 5(a)

Root mean square error (RMSE) for training set

Station	Temperature	Root mean square error	Standard deviation
Kanzalwan	Maximum	2.22	5.16
	Minimum	2.15	5.35
Haddan Taj	Maximum	2.13	4.48
	Minimum	2.01	4.48
Gulmarg	Maximum	1.77	4.77
	Minimum	1.73	4.46
Stage II	Maximum	1.86	5.30
	Minimum	1.59	4.23

TABLE 5(b)

Number of days with error in different range for training set

Station	Temperature	Total days	Number of days with error in different ranges					
			0-1	1-2	2-3	3-4	4-5	>5
Kanzalwan	Maximum	3273	1255	920	542	308	137	111
	Minimum		1249	1045	540	245	91	103
Haddan Taj	Maximum	3174	1270	908	530	254	125	87
	Minimum		1353	1022	505	164	60	70
Gulmarg	Maximum	3479	1602	1060	516	200	66	35
	Minimum		1660	1084	469	163	65	38
Stage II	Maximum	2158	955	646	321	151	60	25
	Minimum		1044	737	276	73	19	10

method being highly flexible, can handle any kind of chaotic change in the relevant input data. In the present study a three layer network with single hidden layer is trained using back propagation learning algorithm. The developed network structure is shown in Table 1.

4. Result and discussions

Six important surface weather parameters are taken as predictors. Corresponding to these parameters ANN model is trained for maximum and minimum temperature prediction in one day advance and tested on independent data set of five winters. Time series of temperature is analyzed and found that there is a large variation in both maximum and minimum temperature. The analysis for both maximum and minimum temperature is given as following.

4.1. *Maximum Temperature*

The maximum temperature varies from -7 to 24, -11 to 17, -7.0 to 20 and -7.5 to 22 ºC for Kanzalwan, Haddan

TABLE 6(a)

Root mean square error (RMSE) for independent test set

Station	Temperature	Root mean square error	Standard deviation
Kanzalwan	Maximum	2.34	5.77
	Minimum	2.46	5.33
Haddan Taj	Maximum	2.40	4.77
	Minimum	2.24	4.95
Gulmarg	Maximum	2.48	5.06
	Minimum	2.78	4.92
Stage II	Maximum	2.18	5.21
	Minimum	1.99	4.56

TABLE 6(b)

Number of days with error in different range for independent test set

Station	Temperature	Total days	Number of days with error in different ranges					
			0-1	1-2	2-3	3-4	4-5	>5
Kanzalwan	Maximum	895	357	241	153	78	36	30
	Minimum		353	247	134	75	38	48
Haddan Taj	Maximum	885	277	269	177	99	33	30
	Minimum		358	225	507	82	41	26
Gulmarg	Maximum	904	350	270	140	69	32	43
	Minimum		317	255	151	73	39	69
Stage II	Maximum	902	379	274	129	71	24	25
	Minimum		388	269	129	70	25	21

Taj, Gulmarg and Stage II respectively for winter period. Thus, there is a large variation in the maximum temperature. The standard deviation (SD) of maximum temperature corresponding to training set is 5.16 and 4.58 for observed data and ANN model predicted data for Kanzalwan station. The SD for independent test data set corresponding to observed and ANN predicted data are 5.77 and 4.90 for the same station. The observed mean and predicted mean of maximum temperature corresponding to training set are 6.37 and 6.42 while for test set the values are 6.07 and 5.89 for Kanzalwan. Thus, the SD and mean of the predicted values of maximum temperature are quite close to that of observed values. This indicates a good prediction by the ANN model. The correlation coefficient (CC) between observed and predicted values is found to be 0.90 and 0.92 corresponding to training and test sets. To check the performance of the model, performance parameter (PP) (ratio of mean square error and the variance of the observed values) is also calculated. For the same station

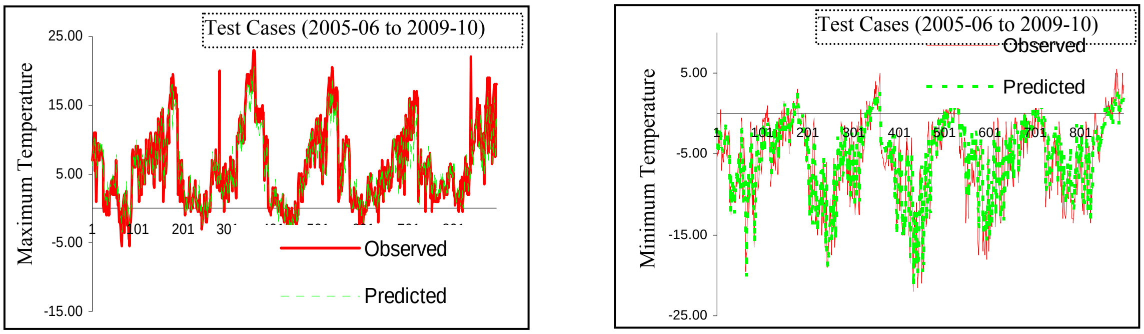

Fig. 1 (a). Observed *vs* predicted temperatures for Kanzalwan

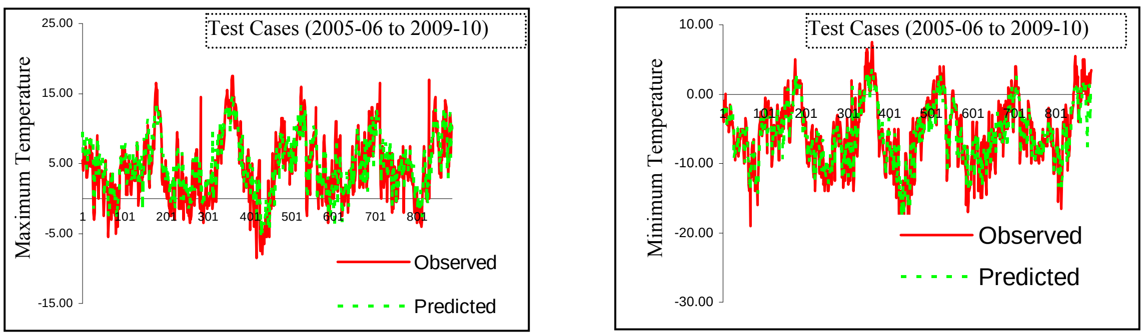

Fig. 1 (b). Observed *vs* predicted temperatures for Hadantaj

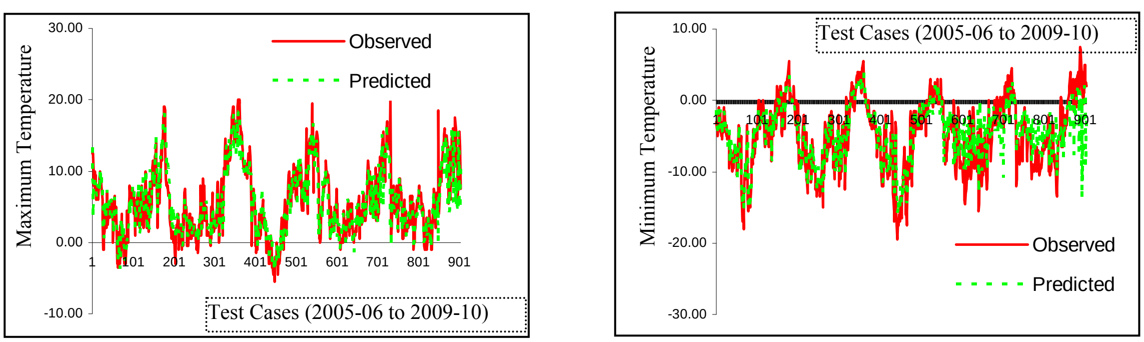

Fig. 1 (c). Observed *vs* predicted temperatures for Gulmarg

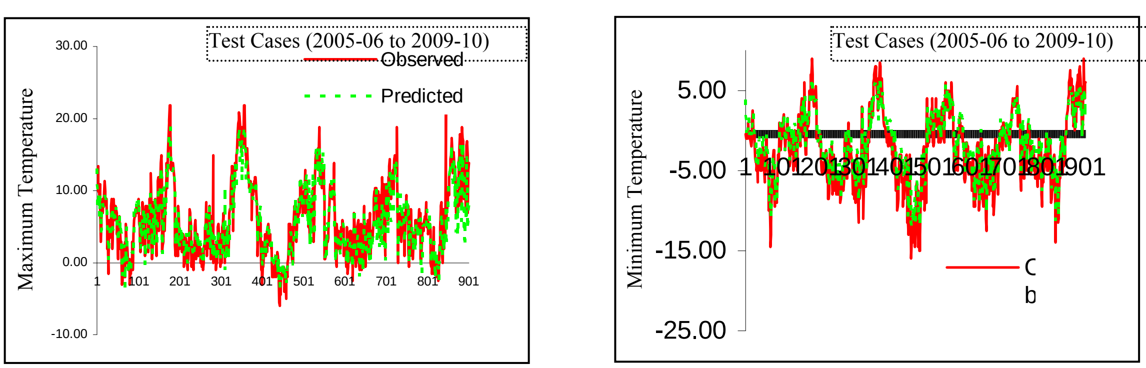

Fig. 1 (d). Observed *vs* predicted temperatures for Stage II the value of PP is 0.19 and 0.16 corresponding to training and test set. For a good prediction CC should be closer to 1 and PP should be near to zero. Similar statistics has been calculated for all stations and is given in Tables 4(a&b) for training and test set respectively.

Again to verify the temperature forecast root mean square error (RMSE) is calculated corresponding to training and test set. RMSE for different stations are given in Table 5(a) and Table 6(a). RMSE corresponding to maximum temperature varies from 1.86 to 2.22 and 2.18 to 2.48 for training set and test set respectively. RMSE is less than the SD for maximum temperature corresponding to the test data set, which indicates the good performance of the ANN model.

Table 5(b) and 6(b) give the total number of days with error in 6 different categories (0-1, 1-2, 2-3, 3-4, 4-5 and >5° C) for training and test data set respectively. For Kanzalwan total data points for test set are 895 out of which 66.81 % are predicted within error range of ± 2° C. Only 30 days are predicted with error greater than 5° C. For Haddan Taj, Gulmarg and Stage II, percentage of the days with error of 2° C is 61.69%, 68.58% and 72.39% respectively.

4.2. *Minimum temperature*

The range of minimum temperature is -25 to 7, -27 to 9.5, -19 to 7 and -16 to 11 for these stations. During the winter season the minimum temperatures are generally below 0° C. Lowest minimum temperatures are found in January-February. The standard deviation (SD) of minimum temperature corresponding to training set is 5.35 and 4.91 for observed data and ANN model predicted data for Kanzalwan station. The SD for independent test data set corresponding to observed and ANN predicted data are 5.33 and 4.69 for Kanzalwan. The observed mean and predicted mean of minimum temperature corresponding to training set are -6.48 and -6.49 while for test set the values are -5.72 and -5.14 for Kanzalwan. Thus, the SD and mean of the predicted values of minimum temperature are also close to that of the observed values. The correlation coefficient (CC) between observed and predicted values is found to be 0.91 and 0.89 corresponding to training and test sets. The value of PP is 0.16 and 0.21 for training and test set. Statistics for all stations is given in Tables 4(a&b).

RMSE corresponding to minimum temperature varies from 1.59 to 2.15 and 1.99 to 2.78 for training set and test set respectively. RMSE for minimum temperature is also less than the SD for test set showing good performance of the ANN model. For Kanzalwan, Haddan Taj, Gulmarg and Stage II percentage of the days with error of 2° C is 67.03%, 65.87%, 63.27% and 72.83% respectively. Figs. 1(a-d) show observed *vs.* predicted maximum and minimum temperature curve for all stations.

5. Conclusions

In present study an ANN model for maximum and minimum temperature forecast at four locations in western Himalaya is developed using six surface meteorological parameters. Three layer feed forward network with a non-linear differentiable sigmoid transfer function is used. RMSE for forecast and skill score are computed for both maximum and minimum temperatures. RMSE is close to 2° C, though there is a large fluctuation in maximum and minimum temperature over the region. With independent test data set the model could predict up to 72% of days with an error of 2° C. There are some limitations in this technique as there is no definite rule to decide the number of hidden nodes and value for learning rate and momentum; however ANN can be used as an effective tool for temperature forecasting at specific station location. This may help in assessing likely avalanche danger situation.

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