Neural network based prediction models for evaporation

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सार – सांख्यिकीय परिप्रेक्ष्य में, कृत्रिम न्यूरल संजालों (ANN) की, प्रामुक्ति में उनके संभाव्य उपयोग के कारण उनकी महत्ता है। इस अध्ययन में, भारत के विभिन्न स्थानों (उना, करनाल, पंतनगर, रायपुर, अनंतपुर, बंगलुरू और पटम्बी) के विभिन्न मौसम वैज्ञानिक परिवर्तिताओं अर्थात् अधिकतम तापमान (MaxT), न्यूनतम तापमान (MinT) सुबह की सापेक्षिक आर्द्रता (RHI), सायंकाल की सापेक्षिक आर्द्रता (RHII), तेज धूप के घंटों (BSH₂) और पवन गति (WS) सहित वाष्पन की प्रागुक्ति का निर्धारण करने के लिए ANNₛ आधारित मार्ग का उपयोग किया गया। सूचनाएं देने के लिए वाष्पन की प्रागुक्ति के लिए और विभिन्न स्थानों में सूचनाओं के मौसम वैज्ञानिक परिवर्तिताओं के अलग-अलग संयोजन के लिए बैकप्रोपेगेशन (BP) और कंजजगेट ग्रेडिएंट डीसेंट (CGD) के दो चरणों के एलगॉरिश्म सहित बहुस्तरीय परसेपट्रान आर्किटेक्यर (MLP) का उपयोग करते हुए ANNₛ मॉडल विकसित किए गए। परवर्ती वर्षों के लिए वाष्पन की प्राप्त की गई साप्ताहिक प्रागुक्तियां मॉडल के निकास में सम्मिलित नहीं की गई। माध्य एबसाल्यूट प्रसटेंज त्रुटि (MAPE) के आधार पर मौसम परिवर्तिताओं के भिन्न-भिन्न संयोजन के साथ विकसित किए गए मॉडलों के निष्पादन की तुलना की गई। संवेदनशील विश्लेषण से पता चला है कि माध्य तापमान और माध्य सापेक्षिक आर्द्रता वाष्पन के प्रति अधिक संवेदनशील है।

ABSTRACT. From statistical perspective, artificial neural networks (ANNs) are interesting because of their potential use in prediction. In this study, ANNs based approach has been used to assess the prediction of evaporation with meteorological variables, *viz.*, maximum temperature (MaxT), minimum temperature (MinT), relative humidity in the morning (RHI), relative humidity in evening (RHII), bright sunshine hours (BSH) and wind speed (WS) for different locations (Una, Karnal, Pantnagar, Raipur, Anantpur, Bangalore and Pattambi) in India**.** ANNs models were developed using Multilayer perceptron (MLP) architecture with two-phase algorithm of Backpropagation (BP) and Conjugate gradient descent (CGD) for prediction of evaporation as output and different combination of meteorological variables as input in different locations. Weekly predictions of evaporation have been obtained for subsequent years not included in model development. The performances of the developed models with different combination of weather variables compared based on mean absolute percentage error (MAPE). The sensitivity analysis indicated that the mean temperature and mean relative humidity are more sensitive to evaporation.

Key words – Artificial neural networks (ANNs), Backpropagation algorithm, Conjugate gradient descent methods, Mean absolute percentage error and sensitivity analysis.

1. Introduction

The knowledge of evaporation has become more and more important during the last decades because of monitoring and management of water resources and crop water requirement. The principal weather variables affecting evaporation are radiation, air temperature, humidity and wind speed. Models or procedures have been developed to assess the evaporation rate from weather variables, but most of them are based on regression models (linear and non-linear) have been widely used in studying relationship of evaporation with weather variables (as such or in some transformed forms).

Recently, artificial neural networks (ANNs) techniques have become the focus of much attention, largely because of their wide range of applicability and the ease with which they can treat complicated problems. These techniques are being successfully applied across an extraordinary range of problem domains, in areas as diverse as finance, medicine, engineering, geology, physics, biology and agriculture. From statistical perspective, neural networks are interesting because of their potential use in prediction. Models are means to capture, condense and organize knowledge. These are expressions / equations which represent relationship between various components of a system. A well tested

weather based model can be an effective scientific tool for forecasting crops in advance so that timely measures could be taken up. Various types of models / techniques have been developed for the purpose. The simplest technique forms the class of thumb rules which are based on experience. Though these do not have much scientific / theoretical background but are extensively used to provide quick forewarning. Another tool in practice is regression models that represent relationship between two or more variables so that one variable can be predicted from the other (s). Linear / non-linear regression models have been widely used in studying relationship of pests and diseases with time and weather variables (as such or in some transformed forms). Principal components and discriminant function analysis have also been explored where principal components of weather variables or discriminant scores based on linear / quadratic discriminant functions of weather variables have been used as regressors in the models. With the advent of computers more sophisticated techniques such as simulation modeling and Artificial Neural Network (ANN) have been explored. A number of simulation models have been developed all over the world for quantifying effects of various factors including weather on agriculture. These may provide a good forecast but require detailed data base which may not be available. ANN technique has recently received a great deal of attention. It is a set of simple computational units that are interconnected. As opposed to traditional model based methods, ANNs are self adaptive methods in that there are few apriori assumptions about the models for problem under study. This technique learns more from examples and captures subtle functional relationships among the data even if the underlying relationships are unknown or hard to describe. Genesis of ANN modeling and its applications appear to be a recent development. However, this field was established before the advent of computers. It started with modelling the functions of a human brain by McCulloch and Pitts in 1943, who proposed a model of "computing element" called Mc-Culloch – Pitts neuron, which performs weighted sum of the inputs to the element followed by a threshold logic operation. Combinations of these computing elements were used to realize several logical computations. The main drawback of this model of computation is that the weights are fixed and hence the model could not learn from examples. Hebb (1949) proposed a learning scheme for adjusting a connection weight based on pre and post synaptic values of the variables. Hebb's law became a fundamental learning rule in neural – network literature. Rosenblatt (1958) proposed the perceptron models, which have weights adjustable by the perceptron learning law. Widrows and Hoff (1960) proposed an ADALINE (Adaptive Linear Element) model for computing elements and LMS (Least Mean Square) learning algorithm to adjust the weights of an ADALINE

model. Hopfield (1982) gave energy analysis of feedback neural networks. The analysis has shown the existence of stable equilibrium states in a feedback network, provided the network has symmetrical weights. Rumelhart *et al.* (1986) showed that it is possible to adjust the weights of a multilayer feedforward neural network in a systematic way to learn the implicit mapping in a set of input – output pattern pairs. The learning law is called generalized delta rule or error back propagation. Cheng and Titterington (1994) made a detailed study of ANN models *vis-a-vis* traditional statistical models. They have shown that some statistical procedures including regression, principal component analysis, density function and statistical image analysis can be given neural network expressions. Warner and Misra (1996) reviewed the relevant literature on neural networks, explained the learning algorithm and made a comparison between regression and neural network models in terms of notations, terminologies and implementation. Kaastra and Boyd (1996) developed neural network model for forecasting financial and economic time series. Dewolf and Francl (1997, 2000) demonstrated the applicability of neural network technology for plant diseases forecasting. Zhang *et al.* (1998) provided the general summary of the work in ANN forecasting, providing the guidelines for neural network modelling, general paradigm of the ANNs especially those used for forecasting. They have reviewed the relative performance of ANNs with the traditional statistical methods, where in most of the studies, ANNs were found to be better than the latter. Sanzogni and Kerr (2001) developed models for predicting milk production from farm inputs using standard feedforward ANN. Chakraborty *et al.* (2004) utilized the ANN technique for predict severity of anthracnose diseases in legume crop. Gaudart *et al.* (2004) compared the performance of multilayer perceptron (MLP) and that of linear regression for epidemiological data and it was found that MLP performed better than linear regression. Kumar *et al.* (2002) studied utility of artificial neural networks (ANNs) for estimation of daily grass reference crop evapotranspiration and compared the performance of ANNs with the conventional method used to estimate evapotranspiration. Based on these results, it was found that ANN can predict evapotranspiration better than the conventional method. Das *et al.* (2002) developed MLP based forecasting model for maximum and minimum temperatures for ground level at Dum Dum station, Kolkata on the basis of daily data on several variables, such as mean sea level pressure, vapour pressure, relative humidity, rainfall, and radiation for the period 1989-95. Laxmi and Kumar (2011a,b) developed neural network model for forewarning diseases in mustard crop for different locations in India. This modeling approach with ability to learn from experience is very useful for many practical problems provided enough data are available. As

such the sophisticated techniques like simulation modeling and ANN technique have their own advantages but suffer from the drawback of large data base requirement. Thus, the uses of ANN technique for predictions of evaporation for different locations in India were attempted in this study.

2. Data

The average weekly meteorological data of for different locations, *viz.*, Karnal : (29° 68' N, 76° 98' E): 1974-2005; Bangalore (12° 58' N, 77° 38' E) : 1986-2010; Pantnagar, (28° 97' N, 79° 41' E): 1970-2008; Anantpur (14.68° N 77.60° E): 1985-2010; Pattambi (10.82° N 76.20° E): 1971-2005; Raipur (21.14° N 81.38° E): 1985-2011 and Una (31.48° N 76.28° E): 1982-2004 on maximum temperature (MaxT), minimum temperature (MinT), relative humidity in the morning (RHI) and afternoon (RHII), bright sunshine hours (BSH), wind speed (WS) and evaporation (EVAP) were procured from India Meteorological Department, Pune. In this study, the various combination of meteorological variables and its impact on evaporation were attempted. The various combination of input variable considered in this study are (*i*) mean temperature (MTEMP), mean relative humidity (MRH), bright sunshine hours (BSH) and wind speed (WS) (*ii*) MTEMP, MRH and BSH (*iii*) MTEMP and MRH (*iv*) MTEMP only.

3. Methodology

3.1. *Models based on artificial neural networks (ANNs)*

Neural networks, more accurately called Artificial Neural Networks (ANNs), are computational models that consist of a number of simple processing units that communicate by sending signals to one another over a large number of weighted connections. They were originally developed from the inspiration of human brains. In human brains, a biological neuron collects signals from other neurons through a host of fine structures called dendrites. The neuron sends out spikes of electrical activity through a long, thin stand known as an axon, which splits into thousands of branches. At the end of each branch, a structure called a synapse converts the activity from the axon into electrical effects that inhibit or excite activity in the connected neurons. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes. Like human brains, neural networks also consist of processing units (artificial neurons) and connections (weights) between

them. The processing units transport incoming information on their outgoing connections to other units. The "electrical" information is simulated with specific values stored in those weights that make these networks have the capacity to learn, memorize, and create relationships amongst data. ANNs are able to learn and generalize from experience. ANNs can identify and learn correlated patterns between input data sets and corresponding target values. After training, ANNs can be used to predict the outcome of new independent input data. ANNs imitate the learning process of the human brain and can process problems involving non-linear and complex data. The neural network model can be claimed to be 'data-driven', *i.e.*, free from any stringent model assumptions prevalent with other statistical methods. The most widely used learning algorithm in an ANN is the Backpropagation algorithm. There are various types of ANN architectures, like Multilayered Perceptron (MLP), Radial Basis Function (RBF), Kohonen etc. In the present study, neural network models using MLP architectures were developed using evaporation (EVAP) as output variables and mean temperature (MTEMP), mean relative humidity (MRH), bright sunshine hours (BSH) and wind speed (WS) as input variables.

3.2. *Activation function and number of hidden layers*

Most units in neural network transform their net inputs by using a scalar-to-scalar function called an *activation function*, yielding a value called the unit's activation. Except possibly for output units, the activation value is fed to one or more other units. Activation functions with a bounded range are often called 'squashing functions'. Appropriate differentiable function will be used as activation function. Some of the most commonly used activation functions are :

(a) The sigmoid (logistic) function

$$f(x) = \left[1 + \exp(-x)\right]^{-1}$$

(b) The hyperbolic tangent (tanh) function

$$f(x) = \left[\exp(x) - \exp(-x)\right]/\left[(\exp(x) + \exp(-x)\right]$$

(c) The sine or cosine function

$$f(x) = \sin(x) \quad or \quad f(x) = \cos(x)$$

Activation functions for the hidden units are needed to introduce non-linearity into the networks. The reason is that a composition of linear functions is again a linear function. However, it is the non-linearity (*i.e.*, the

capability to represent nonlinear functions) that makes multilayer networks so powerful. Almost any nonlinear function does the job, although for back-propagation learning it must be differentiable and it helps if the function is bounded. Therefore, the sigmoid functions are the most common choices. There are some heuristic rules for selection of the activation function. For example, Klimasauskas (1991) suggests logistic activation functions for classification problems which involve learning about average behaviour, and to use the hyperbolic tangent functions if the problem involves learning about deviations from the average such as the forecasting problem.

In general, it is strongly recommended that one hidden layer be the first choice for any practical feed forward network design. If using a single hidden layer with a large number of hidden units does not perform well, it may be worth trying a second hidden layer with fewer processing units. Neural networks with two hidden layers can represent functions with any kind of shapes. Even for problems requiring more than one hidden layer, most of the time, using one hidden layer performs much better than using two hidden layers in practice. Training often slows dramatically when more hidden layers are used. The number of local minima increases dramatically with more hidden layers. Most of the gradient-based optimization algorithms can only find local minima, thus they miss the global minima. Even though the training algorithm can find the global minima, there is a higher probability that after many time-consuming iterations, we will find ourselves stuck in a local minimum and have to escape or start over. Therefore, in the present study, hyperbolic tangent (tanh) function has been used as activation function with different number of hidden layers (one and two) for neural networks model based on MLP architecture.

4.   Learning algorithm for multilayer networks

4.1. *Back-propagation learning algorithm*

Back propagation is the most commonly used method for training multilayered feed-forward networks. It can be applied to any feed-forward network with differentiable activation functions. For most networks, the learning process is based on a suitable error function, which is then minimized with respect to the weights and bias. If a network has differential activation functions, then the activations of the output units become differentiable functions of input variables, the weights and bias. If we also define a differentiable error function of the network outputs such as the sum of square error function, then the error function itself is a differentiable function of

the weights. Therefore, we can evaluate the derivative of the error with respect to weights, and these derivatives can then be used to find the weights that minimize the error function by either using the popular gradient descent or other optimization methods. The algorithm for evaluating the derivative of the error function is known as *back propagation*, because it propagates the errors backward through the network. Multilayer feed forward neural network or multilayered perceptron (MLP) is very popular and is used more than other neural network type for a wide variety of tasks. MLP learned by back propagation algorithm is based on supervised procedure, *i.e.*, the network constructs a model based on examples of data with known output. It has to build the model up solely from the examples presented, which are together assumed to implicitly contain the information necessary to establish the relation. The architecture of MLP is a layered feed forward neural network in which the non-linear elements (neurons) are arranged in successive layers, and the information flows uni-directionally from input layer to output layer through hidden layer(s).

4.2. *Conjugate gradient descent algorithm*

The conjugate gradient method is an effective method for symmetric positive definite systems. The method proceeds by generating vector sequences of iterates, residuals corresponding to the iterates and search directions used in updating the iterates and residuals. The conjugate gradient algorithm selects the successive direction vectors as a conjugate version of the successive gradients obtained as the method progresses. Thus, the directions are not specified beforehand, but rather are determined sequentially at each step of the iteration. At step k one evaluates the current negative gradient vector and adds to it a linear combination of the previous direction vectors to obtain a new conjugate direction vector along which to move. There are three primary advantages to this method of direction selection. First, unless the solution is attained in less than n steps, the gradient is always nonzero and linearly independent of all previous direction vectors. If the solution is reached before n steps are taken, the gradient vanishes and the process terminates. Second, a more important advantage of the conjugate gradient method is the especially simple formula that is used to determine the new direction vector. This simplicity makes the method only slightly more complicated than steepest descent. Third, because the directions are based on the gradients, the process makes good uniform progress toward the solution at every step. This is in contrast to the situation for arbitrary sequences of conjugate directions in which progress may be slight until the final few steps. Although for the pure quadratic problem uniform progress is of no great importance, it is important for generalizations to no quadratic problems.

TABLE 1

Mean absolute percentage error (MAPE) for various models in different locations with various combination of weather variables

Locations	Combination of weather variables			
	MTEMP only	MTEMP and MRH	MTEMP, MRH and BSH	MTEMP, MRH, BSH and WS
Anantpur	2.87	2.40	2.23	2.15
Pantnagar	2.35	1.68	1.62	1.51
Karnal	1.26	0.81	0.85	0.49
Bangalore	1.31	0.67	0.70	0.68
Raipur	1.20	0.82	0.77	0.61
Pattambi	1.16	0.83	0.74	0.68
Una	1.11	0.75	0.71	0.66

TABLE 2

Sensitivity score (ranking) for each input variable for predicting evaporation at different locations

Locations	MTEMP	MRH	WS	BSH	Ranking of input variables
Anantpur	1.121 (2)	1.308 (1)	1.042 (3)	1.039 (4)	MRH, MTEMP, WS and BSH
Bangalore	1.427 (2)	1.681 (1)	1.520 (3)	1.051 (4)	
Pattambi	1.169 (2)	1.413 (1)	1.301 (3)	1.140 (4)	
Karnal	2.760 (1)	2.475 (2)	1.646 (3)	1.075 (4)	MTEMP, MRH, WS and BSH
Pantnagar	1.062 (1)	1.068 (2)	1.069 (3)	1.004 (4)	
Raipur	2.866 (1)	2.627 (2)	1.611 (3)	1.148 (4)	
Una	2.011 (1)	1.426 (2)	1.273 (3)	1.095 (4)	

5. Sensitivity analysis

Sensitivity analysis were also performed for ranking of input variable based on their relative contributions to output. It is a commonly used method in neural network studies for identifying the degree at which each input variables contributes to the identification of each output variables (Sharda and Delen, 2006). Sensitivity analysis attempts to provide a ranking and score of the inputs variables based on their relative contributions to model output variability and uncertainty.

6. Evaluation criterion

The performance evaluation measure considered is Mean Absolute Percentage Error (MAPE)

$$\text{MAPE} = \frac{1}{m} \sum_{i=1}^{m} \left| \frac{Y_i - F_i}{Y_i} \right| \times 100$$

where, Y_i and F_i are the observed and forecast values respectively and m is the number of observations for the hold-out data set.

7. Results and discussion

7.1. *Models based on neural networks approach*

Prediction models were developed for evaporation for Karnal, Bangalore, Pantnagar, Anantpur, Pattambi, Raipur and Una taking evaporation (EVAP) as output variables and maximum temperature (MaxT), minimum temperature (MinT), relative humidity in the morning (RHI) and afternoon (RHII), bright sunshine hours (BSH) and wind speed (WS) as input variables. The entire data have been divided into three distinct sets, *viz.* training set (70%), testing set (20%) and validation set (10%) for each locations. The training set is the largest set and is used by neural network to learn patterns present in the data. The testing set is used to evaluate the generalization ability of
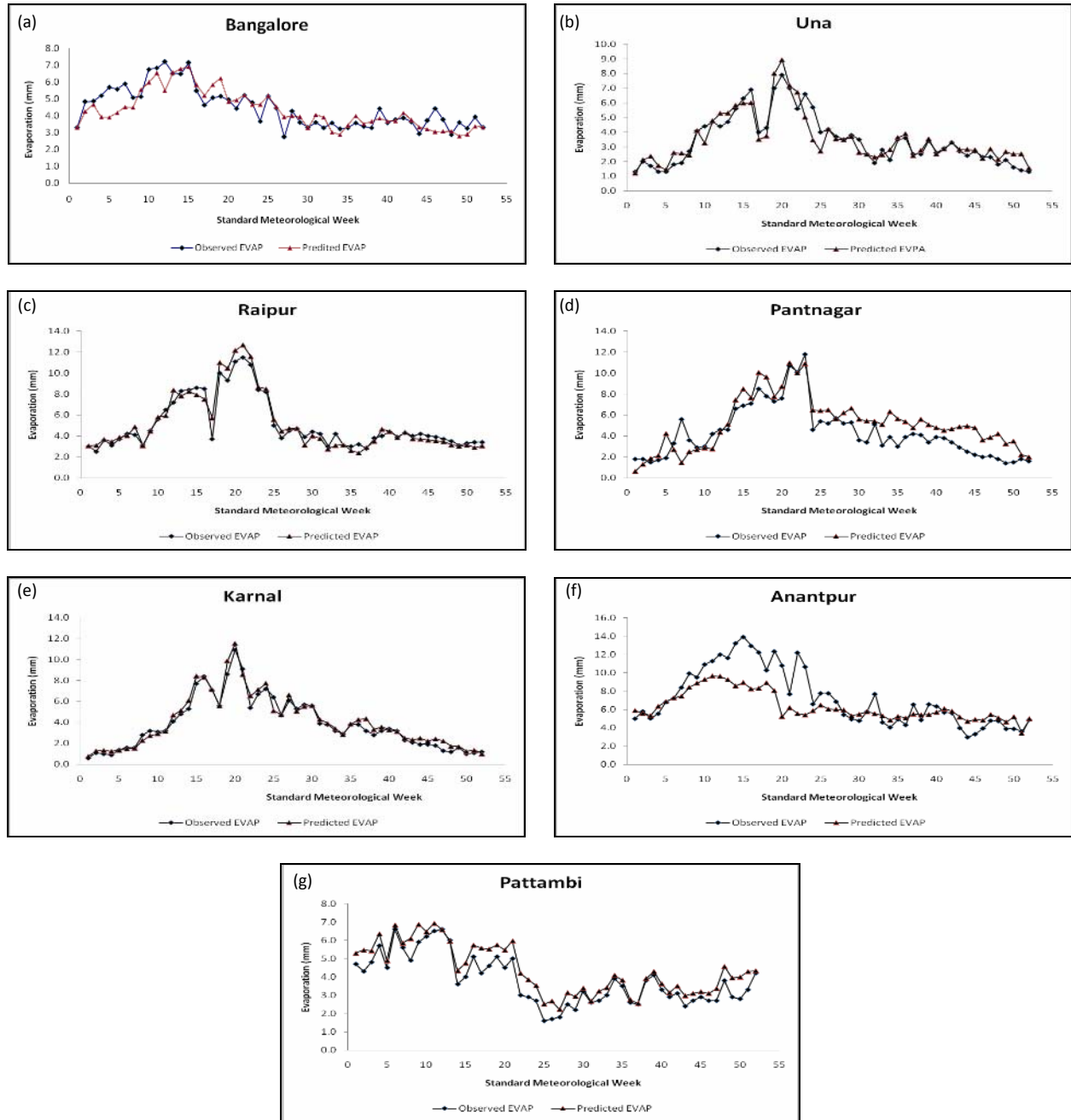
Figs. 1(a-g).   The observed and predicted evaopration based on the ANN models using MTEMP, MRH, BSH and WS as input variables for (a) Bangalore, (b) Una, (c) Raipur, (d) Pantnagar, (e) Karnal, (f) Anantpur and (g) Pattambi

a supposedly trained network. A final check on the performance of the trained network is made using validation set. In order the optimizes the architectural parameters, Multilayer perceptron (MLP) architecture with two-phase algorithm of Backpropagation (BP) and Conjugate gradient descent (CGD) based neural networks model with different hidden layers (1 and 2) and different number of neurons (3, 4 and 5) in a hidden layer with

hyperbolic function as an activation function were performed. The trained ANN models have been implemented for prediction of evaporation for subsequent cases corresponding to the years not included in the model development. The performances of various models in terms of Mean Absolute Percentage Error (MAPE) for different locations for various combinations of weather variables were obtained. The various combination of input

variables are (*i*) mean temperature (MTEMP), mean relative humidity (MRH), BSH and WS (*ii*) MTEMP, MRH and BSH (*iii*) MTEMP and MRH (*iv*) MTEMP only. The performance of four neurons with one hidden layers in MLP architecture with two-phase algorithm of Back propagation (BP) models was found to be better in most of the cases in terms of prediction error. MAPE for various models in different locations are given in given in Table 1. This table revealed that theses ANNs models with MTEMP, MRH, BSH and WS as input variables are needed for better modeling of evaporation. Sensitivity score of the models inputs based on their relative contributions to model output variability and uncertainty were also obtained for ranking of input variable. Sensitivity score for each input variable for predicting evaporation at different locations are presented in Table 2. This table indicted that the mean temperature (MTEMP) has the highest contribution followed by MRH, WS and BSH for the locations which are away from the equator while MRH has the highest contribution followed by MTEMP, WS and BSH for the locations near the equator. The weekly observed and predicted evaporation for ANNs models (using MTEMP, MRH, BSH and WS as input variables) for different locations are given in Fig. 1 which showed that the observed evaporation are in good agreement with the predicted ones.

8. Conclusions

In this study, ANNs based approach has been used to assess the prediction of evaporation with meteorological variables, *viz.*, maximum temperature (MaxT), minimum temperature (MinT), relative humidity in the morning (RHI), relative humidity in evening (RHII), bright sunshine hours (BSH) and wind speed (WS) for different locations (Una, Karnal, Pantnagar, Raipur, Anantpur, Bangalore and Pattambi) in India. ANNs models were developed using Multilayer perceptron (MLP) architecture with two-phase algorithm of Backpropagation (BP) and Conjugate gradient descent (CGD) for prediction of evaporation as output and different combination of meteorological variables as input variables for different locations. The performances of various models in terms of Mean Absolute Percentage Error (MAPE) for different locations for various combinations of weather variables were obtained. This result indicates that, MLP architecture with two-phase algorithm of Backpropagation (BP) models was found to be better in most of the cases in terms of prediction error. This result indicates that ANNs models with MTEMP, MRH, BSH and WS as input variables are performed better for prediction of evaporation. Sensitivity score of the models inputs based on their relative contributions to model output variability and uncertainty were also obtained for ranking of input variable. Sensitivity analysis showed that the mean temperature (MTEMP) has the highest contribution followed by MRH, WS and BSH.

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