Modelling of Evaporation from a Tropical Lake using A.N.N.

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ABSTRACT

Precise estimates of evaporation rates from lakes are needed for various research and management purposes. Although a number of models exist for estimation of lake evaporation, most of them, being site specific, need to be calibrated locally or it is required to develop a region specific model. In recent years, ANNs are successfully being used to model various hydrological processes such as rainfall-runoff, stream flow forecasting, reservoir operation etc. However, there are only a handful of reported studies in the area of evaporation and no studies have been reported on tropical lakes. The present study has been taken up for a tropical lake; Lake Pichhola in Udaipur, with the objective to develop an Artificial Neural Network (ANN) Model to estimate lake evaporation and to evaluate its performance. Daily data of five years (2002-2006) have been used in the study. Based on the results of various experiments with different numbers of neurons, an ANN model with 3 neurons and 145 epochs has been selected as the best ANN architecture for the model. The performance of the model has been tested vis-a-vis a Multiple Linear Regression Model. The results of ANN are superior than the MLR model. Based on the overall performance, the ANN model is found to be reasonably suitable to estimate the evaporation from the lake.

INTRODUCTION

Estimates of evaporation rates from lakes are needed for various planning, management and research purposes. Infact evaporation may be a deciding factor in the lake water management in arid regions. Inspite of its significance, however, precise estimation of lake evaporation still remains one of the challenging tasks for the hydrologists and water resources engineers. A number of models are available for estimating lake evaporation. Energy balance method is considered to be the most accurate of all the available methods. However, estimation of energy balance terms requires intensive instrumentation, which is often not economically feasible. Use of pan data is by far the most popular method, despite its limitation. If pan data are not available, but other routinely observed meteorological data are available, then either the Penman method or multiple linear regression model or a semi empirical mass transfer model or a radiation based semi-empirical method is generally used. However, most of these models, including the Penman Model, are site specific and although it is a common practice to use them for other regions also, the results are not always satisfactory. It is, therefore, required to calibrate the models locally or develop a region specific model.

OBJECTIVES AND SCOPE

Lake Pichhola in Udaipur is a major source for drinking and domestic water supply for the people of the region. Due to improper water management, aided by heavy evaporation losses, the water availability in the lake is reducing continuously. Precise estimates of water being evaporated from a lake, is essential for various research and management purposes. A number of models for estimating lake evaporation have been developed (Rohwer, 1931; Penman, 1948; Priestly and Taylor, 1972; Kohler and Parmele, 1967, Stewart and Rouse, 1976; Morton, 1979 etc). A number of studies have been reported on their suitability to different climatic regions (Antal et al., 1973; Keijman and Koopmans, 1973; Warnaka and Pochop, 1988; Winter et al., 1995; Singh and Xu, 1997 etc). However, no evaporation studies have been reported for Pichhola Lake. Neither any model has been developed for the region, nor any existing model has been evaluated for its suitability. Since precise evaporation estimates are essential for various purposes of lake research and management, a model to be selected or developed for such estimation should be tested for its validity and performance.

Artificial Neural Networks (ANNs) are gaining popularity in diverse scientific fields such as physics, biomedical engineering, electrical engineering, computer science, acoustics, cybernetics, robotics, image processing, financing etc., in the last two decades (ASCE Task Committee, 2000). Since early nineties, ANNs are successfully being used to model the various hydrological processes. They have been used to model the rainfall-runoff process (Hsu, et al., 1995; Elshorbagy et al., 2000; Sajikumar and Thandaveswaram, 1999; Dawson and Wilby, 1998 etc), for stream flow forecasting (Danh et al., 2002; Caulibaly et al., 2001; Tokar and Markus, 2000; Tokar and Johnson, 1999; Smith and Eli,1995; Thirumalai and Deo, 1998 etc), for reservoir operation studies (Cancelliere et a., 2002; Jain et al., 1999; Neelkantan and Pundarkanthan, 2000, Raman and Chandramauli, 1996 etc.), for reservoir sedimentation studies (Kisi, 2004; Kisi, 2005 etc). However, there are only a handful of reported studies in the area of evaporation (Sudheer et al., 2003 and Kumar et al., 2002). From the limited studies reported on evaporation, it can be observed that ANNs have not been adequately explored for evaporation studies as yet. Moreover, the reported studies are for climates other than tropical. With this background in mind, the study has been taken up for estimation of evaporation from a tropical lake. The specific objectives of the study are: (i) to develop an Artificial Neural Network (ANN) Model to estimate evaporation from a tropical lake and (ii) to evaluate the performance of the ANN Model vis-a-vis other commonly used models of lake evaporation.

STUDY AREA

Udaipur is called the city of lakes. There are a number of lakes in and around Udaipur. Lake Pichhola, which is the oldest and biggest of all of them, is in particular very significant. Of the total water supply to Udaipur city, about 85% is met from Lake

Pichhola alone. Lake Pichhola is a manmade lake constructed in the 14th century. It is at the bank of this lake that the city of Udaipur was established, by Rana Udai Singh in 1560 A. D. River Sisarama is the major in-flowing stream to the lake. The catchment area of the lake is about 140 sq. km.. Most of the catchment is barren hard rock with high hills, the average height of which ranges from 650 m to 900 m. The catchment area is a semi-arid climatic region. There are three distinct seasons viz. winter (October to mid February), summer (mid February to mid June) and monsoon (mid June to September). Maximum temperature is around 43^0 C in May-June while minimum can be as low as 1.5^0 C. Most of the rainfall occurs during the monsoon months of June-September. Distribution of annual rainfall is uneven and shows large variations. Air is generally dry except for the monsoon period when the humidity is around 70%. Summer months are the driest of the year when the humidity goes to about 20-25%. Winds are generally light with some strengthening in the latter half of summer and the monsoon. Dust-storms and thunderstorms occur sometimes in the hot months of summer (Khobragade, 1996). Figure 1 shows the location map of study area. Table 1 presents the salient features of the lake.

Table 1 : Salient features of Lake Pichhola, Udaipur (Kumar and Sharma, 1991)

Parameter	Value
Longitude	$73^0 42'$
Latitude	$24^0 35'$
Altitude (m)	587
Normal rainfall (mm)	635
Storage capacity (MCF)	485
Water Spread Area (Sq. Km)*	6.96
Maximum depth (m)	8
Mean depth (m)	4.5
Maximum length (km)	3.6
Maximum width (km)	2.61
Mean width (km)	1.93
Length of shoreline (km)	12.9

* *The water spread area fluctuates annually and seasonally*

ARTIFICIAL NEURAL NETWORK (ANN)

General

An ANN is a massively parallel-distributed information processing system that has certain performance characteristics, resembling biological neural networks of the human brain. ANNs have been developed as a generalization of mathematical models of neural biology. Their development is based on the following rules (ASCE Task Committee, 2000):

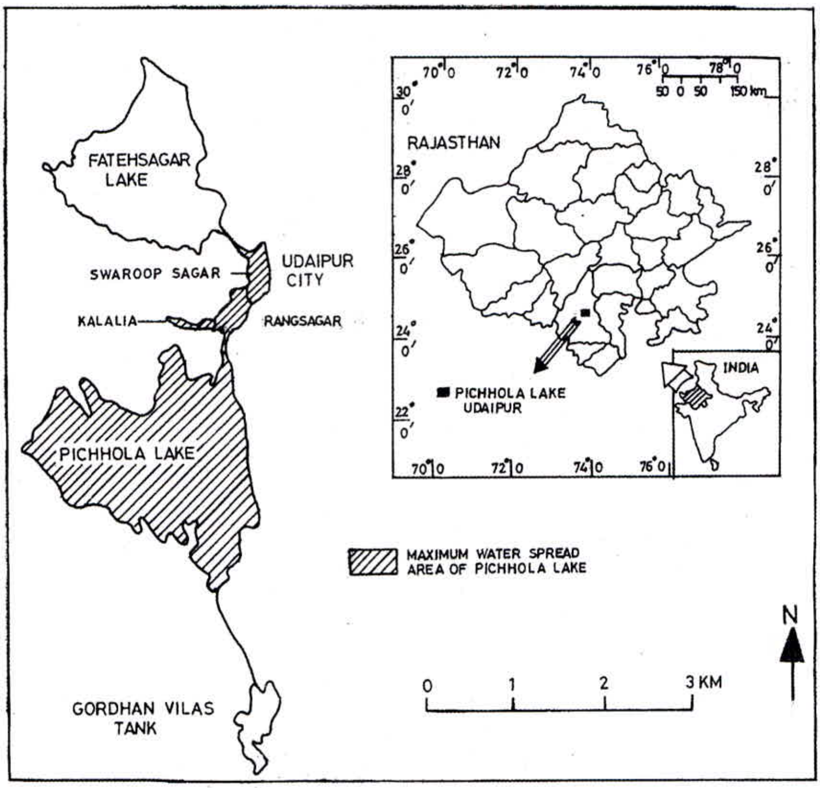

Fig. 1 : Location map of Lake Pichhola, Udaipur (Rajasthan)

1. Information processing occurs at many single elements called nodes, also referred to as neurons.
2. Signals are passed between nodes through connection links.
3. Each connection link has an associated weight that represents its connection strength
4. Each node typically applies a non-linear transformation called an activation function to its net input to determine its output signal.

A neural network is characterized by its architecture that represents the pattern of connection between nodes, its method of determining the connection weights, and the activation function (Fausett, 1994). Fig. 2 gives an overview of ANN topology. A network is made up of a number of interconnected nodes called neurons. The neurons are arranged in three basic layers-input, hidden and output. Depending upon the number of hidden layers, ANNs can be single, bi-layer or multi-layer. ANNs are also classified based on the direction of information flow and processing. In the feed forward network, information passes from input to output side. Nodes in one layer are connected to those in the next, but not to those in the same layer. Only the input nodes distribute input into the network. Thus, output of a node in a layer is only dependent on the input it receives. On the other hand, in a recurrent ANN, information flows through the nodes in both directions, from the input to the output side and vice versa. This is generally achieved by recycling previous network outputs as current inputs, thus allowing for feedback. Both feed forward and recurrent networks are common in hydrologic problems. Input layer receives the input variables. It consists of all the quantities that influence the output. Output layer consists of values predicted by the network and thus represents model output.

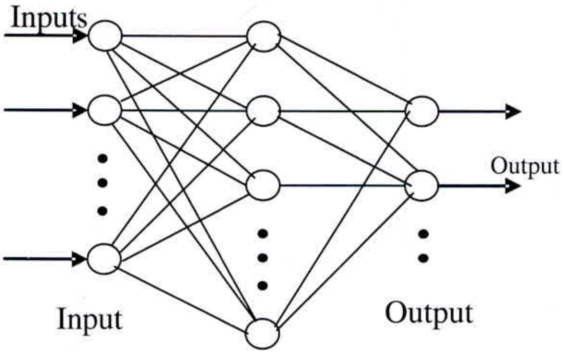

Fig. 2. A basic overview of ANN topology

The number of hidden layers, the number of input and output nodes and the number of nodes in the hidden layers, depend upon the problem. There are no fixed rules as to how many nodes should be included in a hidden layer. They are usually decided by the trial and error method. However, if there are too few nodes in the hidden layer, the network may have difficulty generalizing to problems it has never encountered before. On the other hand if there are too many nodes in the hidden layer the network may take an acceptably long time to learn anything of any value (Dawson and Wilby, 1998). The different neurons are associated with each other through the weights, which represent a factor by which any value passing into the neuron is multiplied.

A schematic diagram of a typical j^{th} node is displayed in Fig. 3. The inputs to such

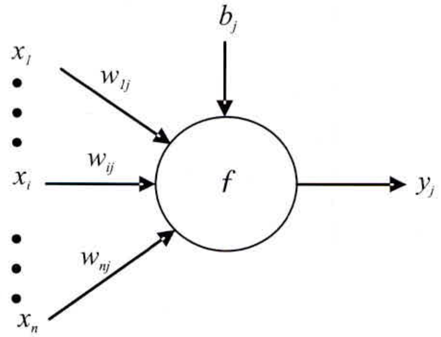

Fig. 3. Schematic diagram of Node j

a node may come from system causal variables or outputs of the other nodes, depending on the layer that the node is located in. These inputs form an input vector X = (x_1,....., x_i,...., x_n). The sequence of weights leading to the node from a weight vector W_j = (w_{1j},...., w_{ij},...., w_{nj}), where w_{ij} represents the connection weight from the ith node in the preceding layer to this node (ASCE, 2000).

The output of node j, y_j, is obtained by computing the value of function f with respect to the inner product of vector X and W_j minus bj, where bj is the threshold value, also called the bias, associated with this node. In ANN parlance, the bias bj of the node must be exceeded before it can be activated. The following equation defines the operation (ASCE, 2000):

$$y_j = f(X * W_j - b_j)$$

The function f is called an activation function. Its functional form determines the response of a node to the total input signal it receives. The most commonly used from of f(·) is the sigmoid function, given as

$$f(t) = \frac{1}{1 + e^{-1}}$$

The sigmoid function enables a network to map any non-linear process. A number of such nodes are organized to form an artificial neural network (ASCE, 2000).

$$E = \sum^{P} \sum^{p} (y_i - t_i)^2$$

Training (Learning) of the Network

In order for an ANN to generate an output vector as close to the target vector, training process (also called learning) is employed. A network trains (learns) by adjusting the weights that link its neurons

so as to find optimal weight matrices and bias vectors that minimize a predetermined error function that usually has the form (ASCE, 2000):

where,

t = component of the desired output

y = corresponding ANN output

P = number of training patterns

p = number of output nodes

NORMALIZATION AND DE-NORMALIZATION

Due to the nature of the sigmoid function used in the back propagation algorithm, it is prudent to normalize all input i.e. all input values are to be converted to the range of (0, 1) before passing them into the neural network. There is no fixed rule for normalization of the input data. There are different approaches for normalizing the data.

Due to output range of the sigmoid function, all values leaving an ANN are automatically output in a normalized form. These output values must be de-normalized to provide meaningful results. This can be achieved by simply reversing the normalization algorithm used on the input nodes.

DATA AND METHODOLOGY

Data of pan evaporation, maximum and minimum temperatures, maximum and minimum humidity, bright sunshine hours and wind velocity were initially used in the study. The data were obtained from the meteorological observatory at the college of Technology and Engineering, Maharaṇa Pratap University of Agriculture and Technology, Udaipur; which is located at about 5 kms to the east of the lake. Daily data of 5 years (2002-2006) was used. A preliminary analysis of the evaporation data was first carried out. Since the pan evaporation data is of Class a Pan covered with mesh, a correction factor of 1.144 was applied. Since monthly pan coefficients are not available for the region, pan coefficients as suggested by Abtew (2000) have been used for the study area and applying these coefficients to the observed pan evaporation data, actual lake evaporation has been obtained. The five years daily data of this observed lake evaporation is divided into two sets, one for calibration and the other for validation (testing). This has been done based on the variation in data. Standard deviations for each year data set have been found out. The data set having the maximum standard deviation (2003, 2004, 2005) has been used as training data set (calibration) so as to cover the maximum variations in the data. The remaining data set with lesser variation (2002, 2006) have been used for validation (testing the performance) purpose. The data need to be normalized before it is used for developing the ANN Model. The normalization of the data was done according to the following equation (Romesburg, 1984):

$$Z_{ij} = (O_{ij}-\min(O_{ij}))/(\max(O_{ij})-\min(O_{ij})$$

where,

Z_{ij} = standardized value of the input O_{ij}

O_{ij} = observed data of j^{th} variable

$\min(O_{ij})$ = minimum observed data

$\max(O_{ij})$ = maximum observed data

It was applied to all the individual data input variables. Simple linear correlation analysis was first carried out between the observed lake evaporation and the various hydro-meteorological variables (Table 2). Based on the correlation coefficients, maximum temperature (Tmax), minimum temperature (Tmin), maximum relative humidity (RHmax) and wind velocity, were selected as input variables for the ANN model. Minimum relative humidity (RHmin), Bright sunshine hours (BSS) and Rainfall were excluded because of insignificant correlation. Both Tmax and Tmin have been included so as to represent the average daily temperature, as temperature is the most important factor in the process of evaporation.

Table 2 : Correlation coefficients for various hydro-meteorological parameters

Variable	Tmax	Tmin	RH max	RH min	Wind	BSS	Rainfall
Lake Evap.	0.80	0.63	-0.68	-0.32	0.60	0.35	-0.07

Number of experiments were carried out with the data set. The number of hidden neurons was decided after performing these of experiments. Using the training data set, a number of ANN structures have been developed. The required ANN model (best ANN architecture) has been selected based on the training and validation performance of the model, taken together. Four criteria were used for the purpose (coefficient of correlation, model efficiency, explained variance and RMSE). Since model efficiency, correlation coefficient and explained variance criteria was more or less similar for the various ANN structures, selection was done based on the RMSE criterion only. The results of the various experiments are shown in Table 3. It can be observed from Table 3 that RMSE of training and validation do not behave in a similar manner. For example for 7 neurons while RMSE is lowest for training it is highest for validation, indicating error in validation and absence of generalization of ANN model during validation, as also observed by Sudhher et al., (2002). So, RMSE of both training and validation together was considered for selection of the best ANN architecture and based on an average performance an ANN architecture of 3 neurons and 145 epochs was selected as the optimal architecture. Although ANN architecture with 7 and 10 neurons have relatively lower RMSE values they were not selected to avoid over trained architecture. The selected ANN model (optimum ANN structure) was then run to evaluate the performance of the model.

Lake evaporation has also been estimated using a Multiple Linear Regression model involving the same variables as have been used as input parameters for the ANN model and using the same data as for the calibration of the ANN model. The model is then applied for the same data set used for the validation of the ANN model. A comparative analysis of the ANN model vis-à-vis the Multiple Linear Regression (MLR) model has been carried out. The regression coefficients for the multiple linear regression model are presented in Table 4.

Performance of ANN vis-a-vis the MLR model was evaluated based on the criteria

Table 3 : Results of ANN Model development experiments (with Training and Validation data set)

No. of Neurons	No. of Epochs	RMSE	
		Training	Validation
1	24	1.199	1.168
2	119	1.112	1.130
3	145	1.052	1.178
4	68	1.048	1.256
5	158	1.037	1.211
6	209	1.008	1.293
7	257	0.993	1.877
8	261	1.001	1.113
10	529	0.950	1.156

Table 4 : Constants for Multiple Linear Regression Model

Tmax	Tmin	RHmax	Wind
0.2945	0.036	-0.0532	0.4259

of mean absolute error (MAE), mean absolute relative error (MARE) and root mean square error (RMSE). These criteria are defined as:

$$MAE = \frac{\sum_{i=1}^{n} \left|(EC_i - EO_i)\right|}{n}$$

$$MARE = \frac{\sum_{i=1}^{n} \frac{\left|EC_i - EO_i\right|}{EC_i}}{n}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (EC_i - EO_i)^2}{n}}$$

where,

n = number of observations

EO_i = observed evaporation (lake evaporation)

EC_i = computed evaporation using various models

RESULTS AND DISCUSSION

Actual lake evaporation obtained from application of the pan coefficients to the pan data for the period 2002-2006 is shown in Fig. 4. It can be observed that in general lake evaporation is higher in the summer months of April, May and June with highest values in the month of May. This corresponds to highest air temperatures recorded in the Month of May. Lower values are recorded in the winter months of November to February with lowest being observed in the month of December. Correlation analysis (Table 2) shows that maximum temperature, minimum temperature, wind and mean relative humidity show a high coefficient of correlation. The highest correlation is observed with maximum temperature (Tmax) (r=0.80) and the lowest correlation has been observed with precipitation (r= -0.07). While maximum relative humidity is showing a higher negative correlation (r= -0.68), minimum relative humidity and bright sunshine hours are poorly correlated with the lake evaporation.

Lake evaporation estimates by the models are presented in Fig. 5. Statistical parameters of the various models are presented in Table 5. Errors in estimation of daily evaporation rates by the models are presented in Fig. 6.

It can be observed form Fig. 5 (1 and 2) that both the models fail to precisely estimate the lake evaporation. They either underestimate or overestimate the lake evaporation on daily basis. Both the models are found to underestimate the peak rates of evaporation in summer months , the degree being higher in the case of MLR model. MLR model is particularly very poor in monsoon months, the errors being almost hundred percent in this period. MLR model is also observed to highly under estimates in the winter months of December and January.

Table 5 : Statistical parameters of the models

Model	MAE	MARE	RMSE
ANN	0.845	0.238	1.178
MLR Model	1.121	0.410	1.529

Based on the criteria for comparison of the models, it can be observed (Table 5) that ANN model has relatively lower values of MAE, MARE and RMSE than the Linear Multiple Regression Model used in the study indicating relatively better performance of the ANN model. Although the values of the various statistical parameters (for example RSME value of 1.178) appear to be relatively higher, they are as per the observations made in most evaporation studies.

Error in estimation of daily evaporation rates by both the models (Fig. 6.1 and Fig. 6.2) clearly indicates that error is much higher in case of the MLR model compared to the ANN model, touching almost the 100 % error mark in many instances. Interestingly

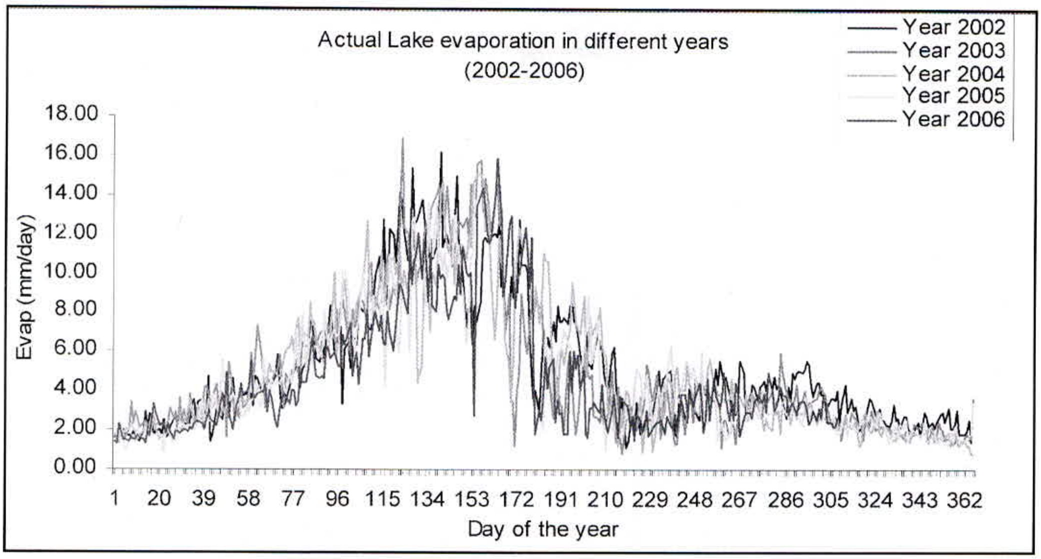

Fig. 4 : Actual lake evaporation for different years (2002-2006)

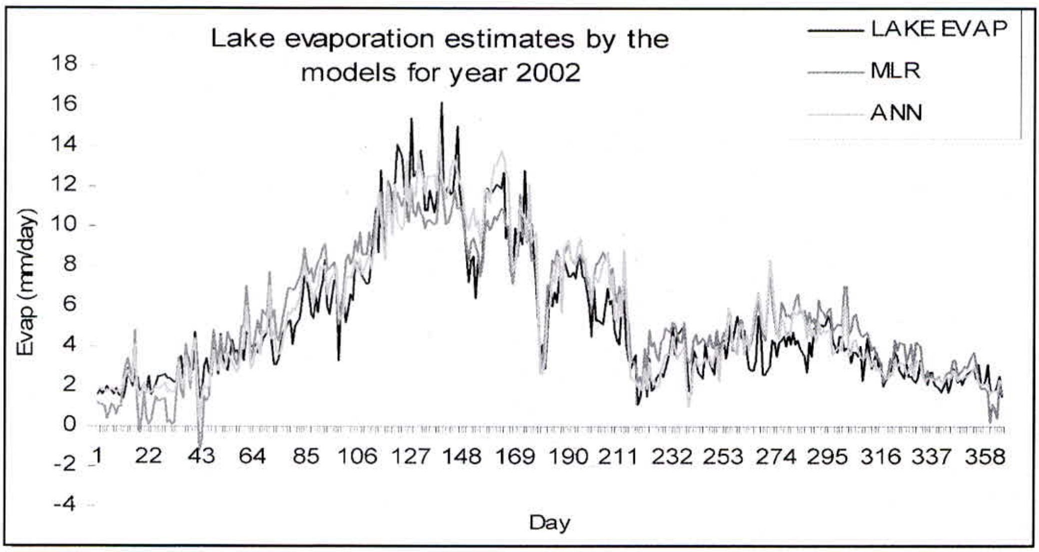

Fig. 5.1 : Lake evaporation estimates by the models for year 2002

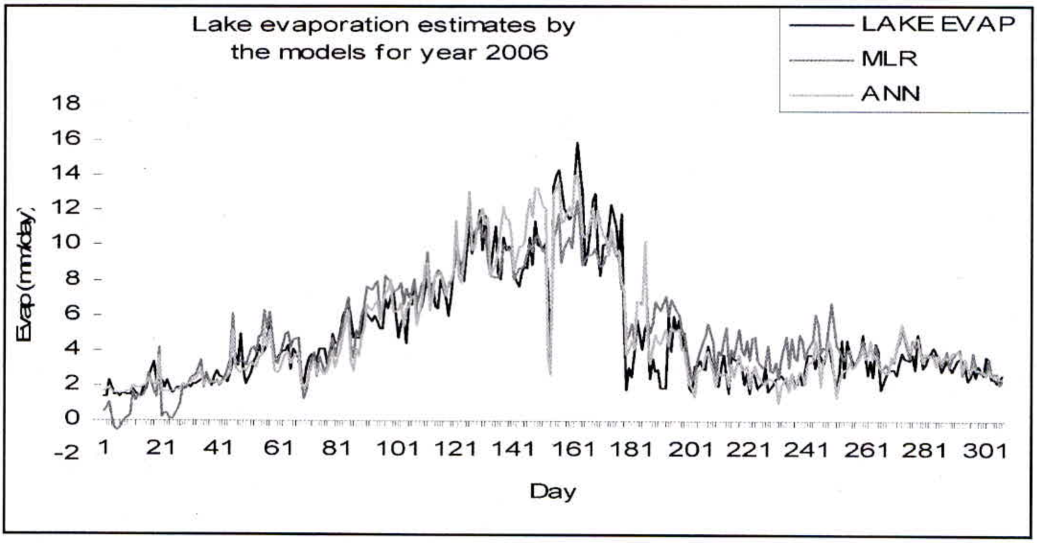

Fig. 5.2 : Lake evaporation estimates by the models for year 2006

error component is higher for monsoon months for both the models, although it is also high during the colder months for the MLR model. For the ANN model barring the shorter spells in the monsoon months, the error component is generally low and is well within the 10% (most often within 5 %) limit which is generally acceptable limit for most

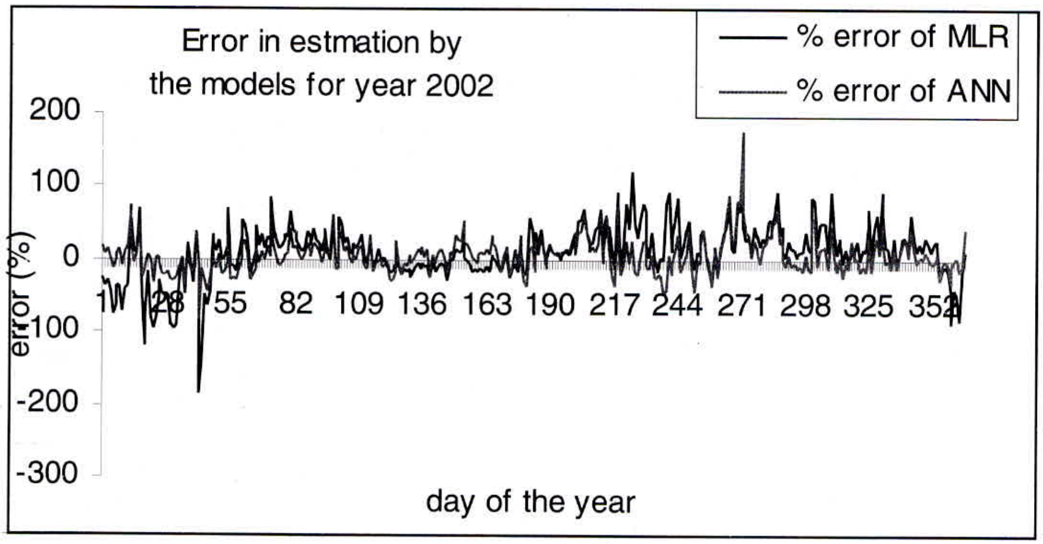

Fig. 6.1 : Error in estimation of daily evaporation by the models for year 2002

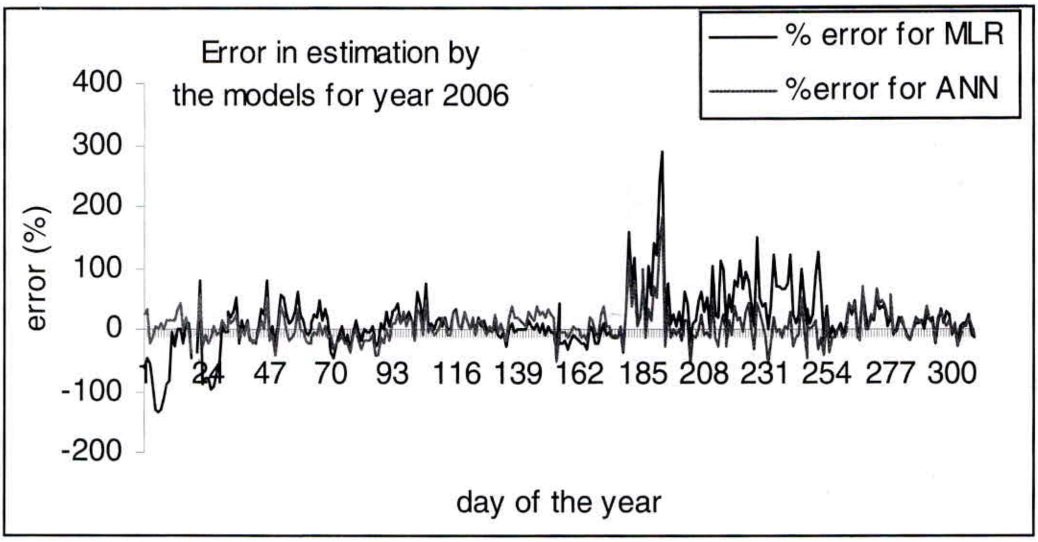

Fig 6.2 : Error in estimation of daily evaporation by the models for year 2002

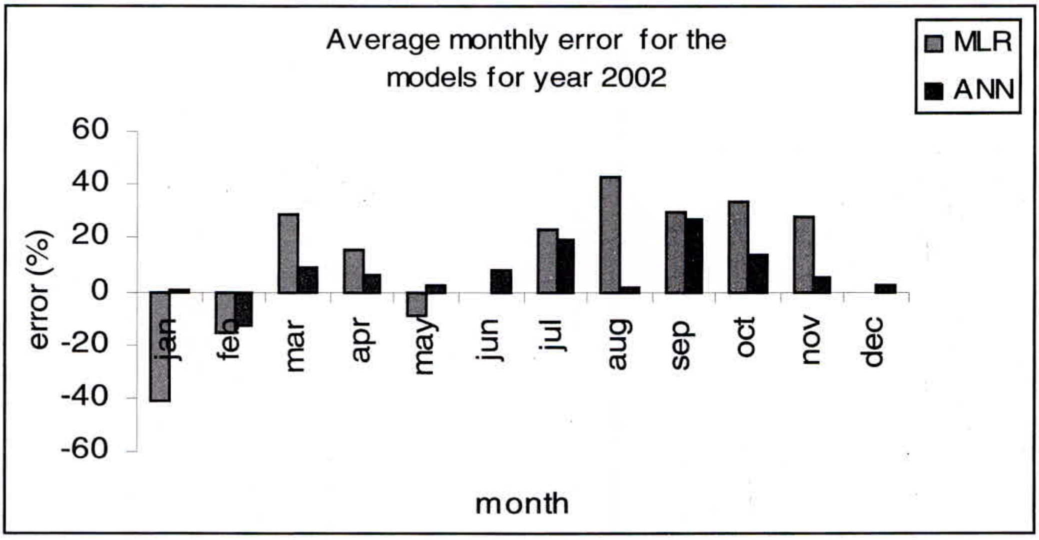

Fig. 7.1 : Average monthly error for the models for the year 2002

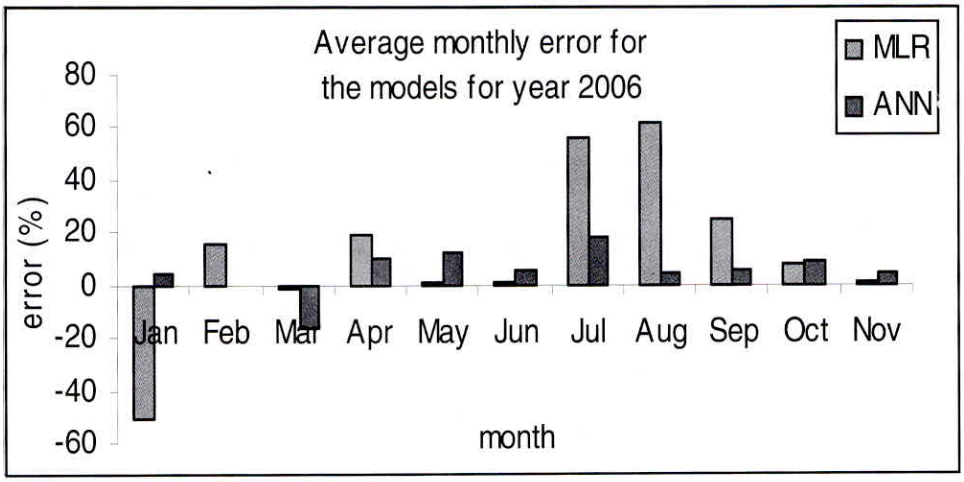

Fig. 7.2 : Average monthly error for the models for the year 2006

evaporation models. The MLR model also appears to lack consistency. While there is a high under estimation in the months of December and January a sudden over estimation is observed in the months of February to April as well as in October and November. The behavioral pattern of the models is observed to be more or less the same in both the years of model testing.

The errors reported above are for daily estimates. But for many practical purposes estimates of lake evaporation are required for monthly basis. So average monthly lake evaporation estimates have been obtained for the models from the daily estimates and error analysis has been carried for the monthly basis. Average monthly values of error for the models are presented in Fig. 7 Negative values indicate underestimation while positive values indicate overestimation. Since daily errors of underestimation and overestimation are compensated over the period of a month, a relatively better picture of error estimates for both the models can be observed in Fig. 7.

As can be observed form Fig. 7 above, on monthly basis the error of ANN model is much less compared to the MLR model for both the years. Barring the months of July and September, 2006 where the average monthly error of estimate crosses the 20% mark, for rest of the period in both the years, error is much low for the ANN model and in general below 10%. Thus based on average monthly errors also, predictability of the ANN model is fairly good.

SUMMARY AND CONCLUSIONS

An ANN Model has been developed to estimate the rates of evaporation from the Lake Pichhola in Udaipur (Rajasthan). Based on the various experiments with different numbers of neurons and epochs, an ANN model with three neurons and 145 epochs has been selected as the best ANN architecture for the model. The performance of the model has been tested vis-a-vis a Multiple Linear Regression Model. ANN model has lower values of MAE, MARE and RMSE, which were used as the criteria for comparison. The values are relatively high for both the models indicating a high degree of error. Both the models either underestimate or overestimate the daily lake evaporation, the degree being higher for the MLR model. The reason for poor performance of the models, particularly the MLR model is their inability to predict the evaporation in the monsoon months. However, the performance of ANN model in general and particularly in pre and post monsoon months is far more superior than the MLR model. The errors of ANN models are also well within the acceptable limits and are found to be far less than the general observed errors of evaporation in various studies. Based on the overall performance, the ANN model is found to be reasonably suitable to estimate the evaporation from the lake. It is definitely superior than the MLR model used in the study.

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