International Journal of Earth, Energy and Environmental Sciences
ISSN: 2517-942X
Vol:2, No:3, 2008

Artificial Neural Network based Modeling of Evaporation Losses in Reservoirs

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***Abstract*—**An Artificial Neural Network based modeling technique has been used to study the influence of different combinations of meteorological parameters on evaporation from a reservoir. The data set used is taken from an earlier reported study. Several input combination were tried so as to find out the importance of different input parameters in predicting the evaporation. The prediction accuracy of Artificial Neural Network has also been compared with the accuracy of linear regression for predicting evaporation. The comparison demonstrated superior performance of Artificial Neural Network over linear regression approach. The findings of the study also revealed the requirement of all input parameters considered together, instead of individual parameters taken one at a time as reported in earlier studies, in predicting the evaporation. The highest correlation coefficient (0.960) along with lowest root mean square error (0.865) was obtained with the input combination of air temperature, wind speed, sunshine hours and mean relative humidity. A graph between the actual and predicted values of evaporation suggests that most of the values lie within a scatter of ±15% with all input parameters. The findings of this study suggest the usefulness of ANN technique in predicting the evaporation losses from reservoirs.

***Keywords*—**Artificial neural network, evaporation losses, multiple linear regression, modeling.

I. Introduction

EVAPORATION refers to water losses from the surface of a water body to the atmosphere. Evaporation occurs when the number of moving molecules that break from the water surface and escape into the air as vapour is larger than the number that re-enters the water surface from the air and become entrapped in the liquid. Evaporation increases with high wind speed, high temperatures and low humidity. A sizable quantity of water is lost every year by evaporation from storage reservoirs and evaporation of water from large water bodies influences the hydrological cycle. Among the hydrological cycle, evaporation is perhaps the most difficult to estimate due to complex interactions among the components of land-plant-atmosphere system [1]. This is particularly true for lakes/reservoirs when semi-arid composition gives difficulties for detailed evaporation measurement records for long time periods. Thus, it becomes necessary to develop approaches to estimate the evaporation rates from other available meteorological parameters, which are comparatively easier to measure [2].

Evaporation has been estimated from meteorological parameters through empirically developed methodologies or statistical and stochastic approaches in addition to mass-balance based formulations by many researchers [3-6]. Recently, Murthy and Gawande [7] proposed simple linear relationships between evaporation and individual meteorological parameters for predicting evaporation from reservoirs by using linear regression approach. They used field study data comprised of a single dependent variable (i.e. evaporation, E) and independent variables, describing meteorological parameters that affect evaporation, including air temperature (T), wind speed (WS), sunshine hours (SH) and relative humidity (RH). However, they hadn't considered the combined effect of all the meteorological parameters (T+ WS+SH+RH) on evaporation loss by using Multiple Linear Regression (MLR), which seems to be the major limitation of their study.

The research challenge addressed by Murthy and Gawande [7] is chosen as an example for the application of Artificial Neural Network (ANN) along with Multiple Linear Regression (MLR) for prediction of evaporation in reservoirs. Present study discusses the application of a backpropagation neural network approach in predicting the evaporation losses, as these algorithms are found to be working well in several other similar hydrological applications [2, 8-13].

The main aim of this study is to develop a suitable ANN model by considering the feed-forward back propagation learning algorithm in the estimation of daily pan evaporation from meteorological parameters and its performance comparison with simple and multiple linear regression approaches.

II. Neural Network

A neural network is a form of artificial intelligence that imitates some function of the human brain. Neural networks are general-purpose computing tools that can solve complex non-linear problems. The network comprises a large number of simple processing elements linked to each other by weighted connections according to a specified architecture. These networks learn from the training data by adjusting the connection weights [14]. There is a range of artificial neural network architectures designed and used in various fields. In this study, a feed-forward neural network with back

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International Journal of Earth, Energy and Environmental Sciences
ISSN: 2517-942X
Vol:2, No:3, 2008

propagation learning algorithm is used. The basic element of a back-propagation neural network is the processing node. Each processing node behaves like a biological neuron and performs two functions. First, it sums the values of its inputs. This sum is then passed through an activation function to generate an output. Any differentiable function can be used as activation function, *f*. All the processing nodes are arranged into layers, each fully interconnected to the following layer. There is no interconnection between the nodes of the same layer. In a back propagation neural network, generally, there is an input layer that acts as a distribution structure for the data being presented to the network. This layer is not used for any type of processing. After this layer, one or more processing layers follow, called the hidden layers. The final processing layer is called the output layer. Fig. 1 shows the structure of a commonly used back propagation neural network.

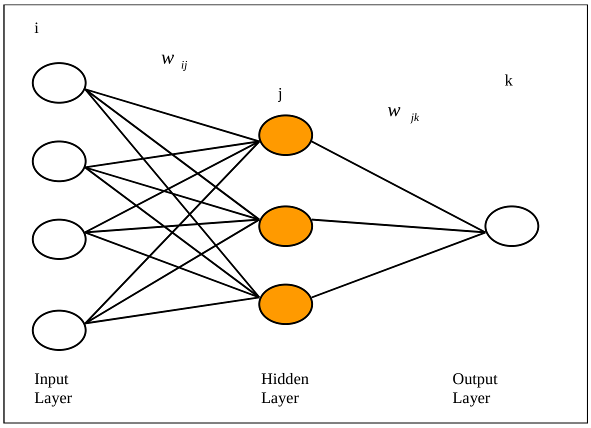


Fig. 1 Structure of a back propagation neural network

All the interconnections between each node have an associated weight. The values of the interconnecting weights are not set by the analyst but are determined by the network during the training process, starting with randomly assigned initial weights. There are a number of algorithms that can be used to adjust the interconnecting weights to achieve minimal overall training error in multi-layer networks [14]. The generalized delta rule, or back-propagation [15] is one of the most commonly used methods. This method uses an iterative process to minimize an error function over the network output and a set of target outputs, taken from the training data set. The training data consists of a pair of data vectors. The training data vector is the pattern to be learned and the desired output vector is the set of output values that should be produced by the network. The goal of training is to minimize the overall error difference between the desired and the actual outputs of the network. The process of training begins with the entry of the training data to the network. These data flow forward through the network to the output units. At this stage, the network error, which is the difference between the desired and actual network output, is computed. This error is then fed backwards through the network towards the input layer with the weights connecting the units being changed in relation to the magnitude of the error. This process is repeated until the error rate is minimized or reaches an acceptable level, or until a specified number of iterations has been accomplished.

III. Materials and Methods

The data used in the present study are taken from the study by Murthy and Gawande [7] and provided in Table I. The average weekly evaporation and meteorological data of Manasgaon (from 1990 to 2004) are collected from a reservoir in Anand Sagar, Shegaon. The evaporation data were collected for one year only; while other data as well as meteorological data for a period of fifteen year (from 1990 to 2004) was obtained from a full climatic station at Manasgaon, about 9 Km from Shegaon, lying under water resources division, Amravati Hydrology Project (Government of Maharashtra). Class *A* Pan Evaporimeter conforming I.S.:5973-1970, made up of 1mm copper sheet tinned inside and painted white outside, covered with wire mesh was used for evaporation measurements. Daily air temperature data was obtained from maximum and minimum values of thermometers housed in a Stevenson Screen conforming to I.S.:5948-1970. The mean air temperature data was obtained by averaging the maximum and minimum values. Thermo-hydrograph and dry and wet bulb thermometers located in Stevenson Screen were used to provide relative humidity values. The mean relative humidity data was obtained by averaging the maximum and minimum values. Wind speed is measured by cup cone anemometer conforming to I.S.:5912-1970. Bright Sunshine hours were measured with the help of Campbell Stokes sun shine recorder confirming I.S.:7243-1974. The weekly average data of air temperature, relative humidity, wind speed and sunshine hours was used to obtain the relationship of evaporation with these factors by Murthy and Gowande [7] in their analysis. The same weekly average off meteorological data is used for estimating evaporation rate by using ANN and MLR approaches in the present analysis.

IV. Results and Discussions

To assess the usefulness of neural network in predicting the evaporation losses, a total of 48 data were used in the present study for model building and validation. The neural network is used to calculate correlation coefficient and root mean square error (RMSE) by using cross-validation to generate the model on different combinations of the input data set in predicting the evaporation. Cross validation was used to train/test/validate the models due to the availability of small number of data sets. The cross-validation is a method of estimating the accuracy of a classification or regression model in which the input data set is divided into several parts (a number defined by the user), with each part in turn used to test a model fitted to the remaining parts. For this study, a ten-fold cross-validation was used.

One of the important factors in using a neural network for prediction of evaporation requires setting up of the appropriate user defined parameters as the accuracy of a

TABLE I
AVERAGE WEEKLY METEOROGICAL DATA OF MANASGAON (1990-2004) [7]

Month	Weeks	Evaporation (mm per day)	Mean Air Temperature (^{O}C)	Average Wind Speed (m/sec at 2 m height)	Sunshine Hours (hrs/day)	Mean Relative Humidity (%)
January	1	3.4	19.64	3.3	8.8	64.35
	2	3.3	20.29	2.9	8.3	61.35
	3	3.4	21.47	3.2	8.5	60.1
	4	3	20.86	3.8	6.9	60.45
February	1	3.4	21.99	3.5	9	59.35
	2	3.9	23.59	3.8	8.9	55.7
	3	4.3	24.52	4.4	9.1	54.25
	4	4.7	25.62	4.1	8.9	48.4
March	1	6.2	26.31	4.7	10.1	45.45
	2	5.6	26.89	4.9	8.6	45.1
	3	6.5	29.18	5	9.3	40.75
	4	5.9	30.04	5.4	8.2	40.2
April	1	8.1	31.52	5.8	10	42.55
	2	6.8	32.44	6.7	8.3	40.4
	3	8.8	33.36	6.4	9.8	38.05
	4	9.8	34.7	8	9.3	36.4
May	1	12.4	35.46	8.5	11.2	37.6
	2	11.9	34.85	9.5	10.2	44.4
	3	12.2	34.41	11.1	9.3	49.3
	4	11.2	34.68	10.3	8.3	46.6
June	1	15.3	34.05	10.7	9.4	53.3
	2	9.8	31.86	9.1	5	65.25
	3	7.5	30.07	10.4	4.1	74
	4	5.7	29.68	10.8	4.1	73.9
July	1	7.5	29.66	8.8	5.7	73
	2	5.7	29.01	9.3	3.9	77.6
	3	4.9	27.52	8.2	2.6	82.8
	4	3.3	27.37	8.1	3.4	83.95
August	1	3.9	27.1	6.7	3.2	87.65
	2	3.1	26.7	6.8	2.5	86.9
	3	2.9	26.56	6.6	2.4	86.25
	4	3	26.88	6.1	3.7	84.85
September	1	3.1	26.85	6.1	4	84.7
	2	3.3	27.43	5.4	5.6	79.3
	3	4.1	27.86	4.3	5.8	78.7
	4	4.4	28.58	2.9	6.3	78.95
October	1	4.9	27.83	2.9	8	77.5
	2	4.3	27.43	2.8	7.3	75.65
	3	4	25.65	2.2	8.8	69.25
	4	3.5	24.62	2.5	7.6	65.8
November	1	4.5	24.78	2.5	10.1	66
	2	3.5	24.47	2.5	7.4	69.35
	3	3.7	23.03	2.1	8.9	60.5
	4	3.4	22.47	2.2	8.7	58.5
December	1	3.7	20.78	2.4	9.6	61.4
	2	3.3	20.99	2.4	8.3	61.2
	3	3.3	20.21	2.5	8.1	61
	4	2.8	20.38	3.2	6.5	60.2

neural network model is largely dependent on the selection of the model parameters. The neural network requires setting up of learning rate, momentum, number of hidden layers, number of nodes in hidden layer and the number of iterations. In present study one hidden layer was used as it works well for this data set. Other user-defined parameters used were – momentum = 0.1, learning rate =0.2, hidden layer nodes = 6 and iterations = 1000. These values were obtained after a large number of trials by using different combination of these parameters carried out on used data set.

regression as obtained by Murthy and Gawande [7] have also been presented alongside in Table II.

Further, Multiple Linear Regression (MLR) approach was also applied for predicting evaporation in the reservoir by considering the influence of different combinations of meteorological parameter. Since, the major limitation of the study of Murthy and Gawande [7] was that of predicting evaporation from one meteorological parameter instead of combination of meteorological parameters. To overcome this limitation, MLR was used and results in the form correlation coefficient and root mean square error were obtained with different combinations of input parameters as well (Table II).

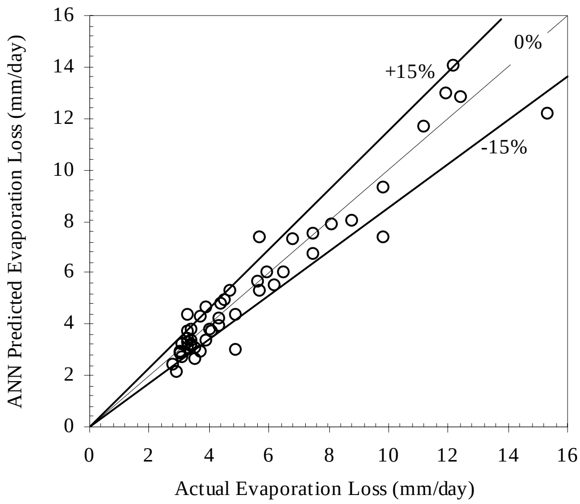
TABLE II
RESULTS WITH DIFFERENT INPUT COMBINATIONS

Input combination	Artificial Neural Network		*Linear Regression		Multiple Linear Regression	
	Correlation coefficient	RMSE	Correlation coefficient	RMSE	Correlation coefficient	RMSE
T	0.910	1.27	0.840	1.64		
WS	0.629	2.392	0.716	2.108		
SS	0.168	3.030	0.361	2.817		
RH	0.538	2.578	0.546	2.531		
T + WS	0.911	1.280			0.808	1.779
T + SS	0.926	1.156			0.891	1.375
T + WS + SS	0.954	0.937			0.949	0.954
T + WS + SS + RH	0.960	0.865			0.945	0.986

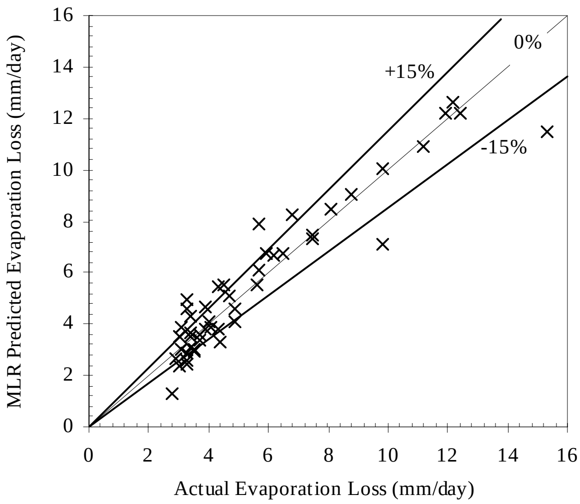
* Results of Murthy and Gawande [7]

Two parameters namely correlation coefficient and Root Mean Square Error (RMSE) values were used for the performance evaluation of the models and comparison of the results for prediction of evaporation. The higher value of correlation coefficient and a smaller value RMSE mean a better performance of the model. The results of the neural network based modeling of evaporation using different combination of input parameters with the used data set are provided in Tables II in terms of the correlation coefficient and root mean square errors. In order to present a fair comparison of the ANN approach with Murthy and Gawande [7] approach of linear regression, the results of the linear

As far as the significance of individual meteorological parameters is concerned, the study revealed that the highest value of correlation coefficient and least value of root mean square error were obtained for evaporation with air temperature, followed by using wind speed and relative humidity (Table I). While the lowest correlation coefficient



(a)



(b)

Fig. 2 Scatter plot between actual and predicted values of evaporation losses.

was obtained with sunshine hours, which mean bright sunshine hours alone does not appear to influence the evaporation significantly. The effect of air temperature, wind speed and sunshine hours was found to be positive; whereas a negative correlation exists between evaporation and relative humidity (that is evaporation decreases with increase in relative humidity). These results from the application of ANN are in concurrence with Murthy and Gawande [7].

It is a natural fact that the climatic/meteorological factors in general act in concert. Therefore, it is pertinent to take into account the combined influence of all the meteorological parameter on evaporation. The analysis (Table II), by using ANN and MLR, also support the logic as the results start improving when the combined effect of parameters is taken into account. Results from Table II suggest that a combination of temperature, wind speed, sunshine hour and humidity provides a maximum value of correlation coefficient with minimum values of root mean square error in comparison to other inputs combination, both by ANN as well as MLR. Of the two regression analysis approaches, the Artificial Neural Network provides better results in terms of predicting evaporation due to higher correlation coefficient of 0.969 along with lower root mean square error of 0.865.

Figs. 2(a) and 1(b) provides plot between actual values of evaporation loss and predicted values of evaporation from the combination of all the meteorological parameters taken together (i.e. T + WS + SS + RH) as inputs by ANN and MLR respectively. To study the scatter around the line of perfect agreement (i.e. a line at 45 degrees), two more lines in the range of ±15% error were plotted in the resulting graphs between the actual and the predicted values of evaporation loss.

Fig. 2 indicates that most of the predicted values are lying within ±15% error from the line of perfect agreement with this combination of input parameters. Thus, suggesting the usefulness of all input parameters, instead of single parameter, in modeling the evaporation from a reservoir using ANN approach. The results suggest better performances by artificial neural network as well as multiple linear regression approaches in comparison to the simple linear regression approach used by Murthy and Gawande [7]. Further, ANN is relatively more accurate than MLR in predicting evaporation losses in reservoirs from meteorological parameters (Table II).

V. Conclusion

The present study discusses the application and usefulness of artificial neural network modeling approach in predicating the evaporation losses over a reservoir. The results are quite encouraging and suggest the usefulness of neural network based modeling technique in accurate prediction of the evaporation as an alternative to the simple linear regression approach as proposed by Murthy and Gawande [7] and multiple linear regression approach as well. This study also concludes that a combination of mean air temperature, wind speed, sunshine hour and mean relative humidity provides better performance in predicting the evaporation losses. Further, this study also concludes that most of the predicted values with ANN are lying near the 45^0 line and the scatter range is within ±15% line.

Acknowledgment

Authors are thankful to Prof. S. Murthy and Prof. S. Gowande, whose evaporation dataset is used in the present modeling study.

References

[1] V. P. Singh. and C. Y. Xu, “Evaluation and generalization of 13 mass-transfer equations for determining free water evaporation,” *Hydrological Processes*, vol. 11, pp. 311-323, 1997.
[2] O. Terz and M. E. Keskn, “Modeling of daily pan evaporation,” *Appled Sc.*, vol. 5, pp. 368-372, 2005.
[3] H. A. R. D. Bruin, “A simple model for shallow lake evaporation,” *Applied Meterol.*, vol. 17, pp. 1132-1134, 1978.
[4] M. E. Anderson and H. E. Jobson, “Comparison of techniques for estimating annual lake evaporation using climatological data,” *Water Resources Res.*, vol. 18, pp. 630-636, 1982.
[5] R. B. Stewart and W. R. Rouse, “A simple method for determining the evaporation from shallow lakes and ponds,” *Water Resources Res.*, vol. 12, pp. 623-627, 1976.
[6] W. Abtew, “Evaporation estimation for Lake Okeechobee in South Florida,” *Irrigation and Drainage Eng.*, vol. 127, pp. 140-147, 2001.
[7] S. Murthy and S. Gawande, “Effect of metrological parameters on evaporation in small reservoirs ‘Anand Sagar’ Shegaon - a case study,” *J. Prudushan Nirmulan*, vol. 3, no. 2, pp. 52-56, 2006.
[8] ASCE task committee on application of ANNs in Hydrology, Artificial neural networks in hydrology, II: hydrologic applications, J. Hydraulic Engineering, ASCE, 5 (2000) 124-137.
[9] Imrie C.E., Durucan S. and Korre A., River flow prediction using artificial neural networks: generalisation beyond the calibration range, Hydrol. 233 (2000), 138-153.
[10] Zealand C.M., Burn D.H. and Simonovic S.P., Short term streamflow forecasting using artificial neural networks, Hydrol. 214 (1999), 32-48.
[11] Sudheer K.P., Gosain A.K., Mohan R.D. and Saheb S.M., Modelling evaporation using an artificial neural network algorithm, Hydrological Processes 16 (2002), 3189-3202.
[12] Braddock R.D., Kremmer M.L. and Sanzogni L., Feed-forward artificial neural network model for forecasting rainfall run-off, Environmetrics 9 (1998), 419-432.
[13] Dibike Y.B. and Solomatine D.P., River flow forecasting using artificial neural networks, Phys. Chem. Earth (B) 26 (2001), 1-7.
[14] Bishop C. M., Neural networks for pattern recognition, Oxford: Clarendon Press, 1995.
[15] Rumelhart D.E., Hinton G.E. and Williams R.J., Learning internal representation by error propagation, Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Volume 1: Foundations (ed.), Cambridge, MA: The MIT Press, 1996, pp. 318-362.