

Predicting Reservoir Evaporation Using Artificial Neural Network

Kharat Pallavi¹, Shetkar Rajeev²Research Scholar, Department of Civil Engineering, Government Engineering College, Aurangabad, Maharashtra,
India¹Associate Professor, Department of Civil Engineering, Government Engineering College, Aurangabad, Maharashtra,
India²

ABSTRACT: The hydrological cycle comprises of various complex processes involved in it and every process is important in planning and management of water resources projects. The prediction of various parameters of the hydrological processes is very difficult due to the stochastic nature. Estimating evaporation from surface water usually requires data that are not easily measurable or available it has a nonlinear relationship with meteorological parameter. Evaporation is a complex process and is influenced by several metrological parameters. The purpose of this study is to develop an Artificial Neural Network model for evaluating the evaporation with available scarce data of NathSagar Reservoir located in Marathwada Region of Maharashtra. The feed forward back propagation network with one hidden layer has been utilised to construct the model. Different networks with different number of neurons were evaluated. Correlation coefficient (R^2) and Root mean square error (RMSE) were employed to evaluate the accuracy of the proposed model. The study shows the best model for evaporation estimation is ANN-2 (4-9-1) with a correlation coefficient (R^2) of 0.974 and the root mean square value (RMSE) of 1.276. It is also observed that ANN-4 (2-10-1) provides acceptable results with (R^2) of 0.972 and (RMSE) of 1.281 for this NathSagar Reservoir of Maharashtra.

KEYWORDS: Artificial Neural Network, Daily evaporation, estimation, NathSagar Reservoir.

I. INTRODUCTION

Evaporation is the process whereby liquid water moves from an evaporating surface to the atmosphere as water vapour. Evaporating surfaces include open bodies of water (e.g. lakes, reservoirs, ponds and streams), saturated soil surfaces and water intercepted on vegetation. Evaporation estimation is a necessary component in water resources planning, design, and operation and management studies. Among the various components of the hydrological cycle, evaporation is the most difficult one to estimate owing to the complexity involved in it. Every Year a sizable amount of water is lost from open bodies in the form of evaporation hence its estimation is important. Pan evaporation method has been widely used because of its simplicity, but the number of measuring stations is limited compared with stations available for measurement of other hydrological parameters. Therefore, it is necessary to develop some alternative method to estimate the evaporation rates using meteorology data, which are either easily available or easier for measurements. The rate of evaporation depends on factors such as solar radiation, air temperature, relative humidity, wind speed, atmospheric pressure, nature of evaporating surface and water quality.

The methods for determining evaporation can be classified as Direct and Indirect methods. The direct method is by using the pan evaporimeter. The indirect methods include empirical method (Kohler et al., 1995), empirical temperature based method (Thornthwaite 1948; Blaney Criddle 1950), water budget method (Guitjens, 1982), energy budget method (Fritschen, 1966), mass transfer method (Harbeck, 1962), a combination method based on physical processes such as (Penman, 1948; Monteith, 1965). It is difficult to select the most appropriate evaporation measurement technique or method for a given project. From studies it is observed that the pan evaporation-based methods, mass transfer based equations have a tendency to under estimate evaporation (Hossein et.al, 2013). In few

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

studies evaporation is estimated using simple equations involving solar radiation and maximum air temperature data and they are recorded at the lake weather station site or at headquarters (Wossenu Abtew, 2001).

Various studies have been conducted to determine the dominating factors and its effect on evaporation. The solar radiation and the mechanism of transporting the vapour from the water surface has a great effect (Chow et al., 1988) on evaporation. Singh (1992) observed that vapour pressure deficit, temperature, barometric pressure, humidity and wind speed as the controlling factors while, Gupta (1992) pointed out that relative humidity, wind velocity, and temperature of water and atmosphere are the climatic factors controlling evaporation. Sensitivity analysis shows that the estimated evaporation is most sensitive to changes in water temperature (Knapp H. et al., 1984). In general the factors controlling the phenomenon are site specific and also the studies used different data sets as per the availability hence the results are not globally acceptable.

Recently, encouraging results using neural networks models in the field of evaporation have been obtained (Bruton et al. 2000; Sudheer et al. 2002; Terzi and Keskin 2005; Keskin and Terzi 2006; Kisi 2006; Tan et al. 2007; Kisi 2009; Tabari et al. 2009; Shirsath and Singh 2010; Guven and Kisi 2011; Shiri et al. 2011; Shiri and Kisi 2011; Kim et al. 2012). Results from a study in China using neural network model show that the correlation coefficient between the evapo-transpiration calculated by FAO56 method and predicted with a hidden layer of ten nodes is 0.993 with error 1.67%. Moreover, the use of weather factors wind speed, average temperature, dew point and maximum temperature as input variables, and a hidden layer of three nodes in the back propagation can predict evapotranspiration with $R = 0.98$, and error 1.35% (Sheng Feng Kuo et al., 2011). Linear genetic programming is also used and found suitable for daily pan evaporation modelling using available climatic data. The daily climatic data, air temperature, solar radiation, wind speed, pressure and humidity were used as inputs (Aytac Guven and Ozgur Kisi (2011)

The application of ANN models in evaporation estimation is now being widely used (Sungwon Kim, et al (2013)). An artificial neural network is inspired by the structure of the brain which suits best for complicated tasks (Haykin s. 1994). Most of the studies use locally trained ANN models in evaporation estimation which are in better agreement with the results obtained by other methods (Keskin, M. and Terzi, O. (2006). These locally developed models have limitation of global validity. However, some studies attempted to develop ANN models with global validity. This could be achieved either by developing ANN model to map Evaporation process both in space and time or by incorporating data from several locations to train the ANN. (Kumar et al., 2011). For the semi arid region of Iran five models with various combinations of daily meteorological variables, relative humidity, air temperature, solar radiation, wind speed and precipitation were developed to evaluate degree of effect of each of these variables on evaporation. The comparison of models estimates showed that model with sigmoid activation function with all input parameters performed best in prediction of daily evaporation (Hossein Tabari et al. 2010).

Increasing temperature is able to enhance evaporation as generally expected. However, the contribution of temperature rising to evaporation was offset, by the impact of the wind speed, according to its significant decrement and high sensitivity with evaporation. Therefore, evaporation has declined while climate warming has increased in China (Yunhe Yin et al., 2010). Studies are also undertaken for evaporation reduction, it is observed that shades suspended above a water surface and covers floating on a water surface provide the highest evaporation reduction efficiency. Of these two, floating covers were considered as most practical and economical, because of their greater durability and elimination of the need for an expensive supporting structure (Keith R. Cooley, 1983)

Artificial Neural Network (ANN)

Artificial Neural Network was first introduced as a mathematical aid (McCulloch et al., 1943). They were inspired by the neural structure of the brain. A neural network functions as a replica of human brain. It has the capability of handling complex nonlinear relationships between inputs and output datasets. The main processor of artificial intelligence based-models is Neuron. They are arranged in groups called layers. The basic structure of a network usually consists of three layers: the input layer, the hidden layer and the output layer. The architecture of an ANN is designed by weights between neurons, a transfer function that controls the output generation in a neuron, and learning laws that define the relative importance of weights for input to a neuron.

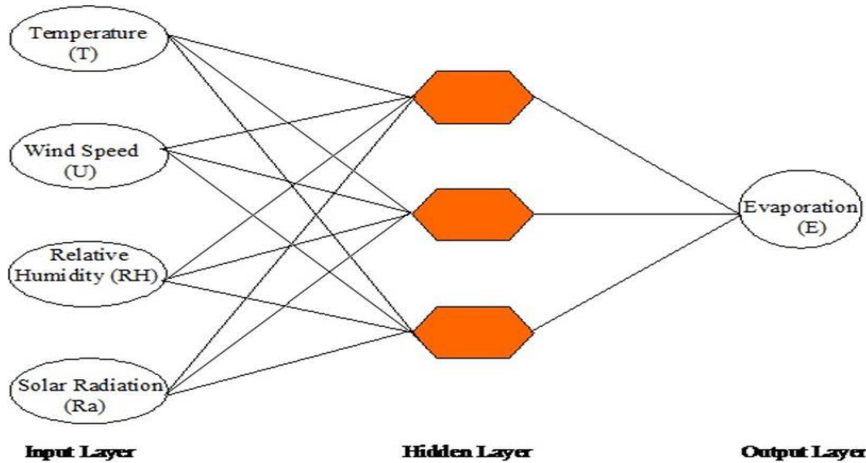


Figure 1. The Basic Structure of ANN model

There are a wide variety of algorithms available for training a network and adjusting its weights. In this study, an adaptive technique momentum Levenberg–Marquardt based on the generalized delta rule was adopted.

Let x_i ($i = 1, 2, \dots, n$) are inputs and w_i ($i = 1, 2, \dots, n$) are respective weights. The net input to the node can be expressed as

$$net = \sum_{i=1}^n x_i w_i$$

The net input is then passed through an activation function $f(\cdot)$ and the output y of the node is computed as

$$y = f(net)$$

Sigmoid function is the most commonly used nonlinear activation function which is given by

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

In this study, a type of feed forward back propagation network multilayer back propagation is explored, as it is the most popular type used in hydrology (Dawson and Wilby, 1998).

II. RELATED WORK

Study Area

The project under study is Nath Sagar Project also called as Jayakwadi Project located (19°29'8.7" N latitude and 75°22'12"E longitude) in Marathwada region of Maharashtra, India. Figure 2 shows the location of the study area. The Jayakwadi project is one of the largest irrigation projects in the state of Maharashtra. It is a multipurpose project. The water is mainly used for irrigation in the drought-prone Marathwada region of the state. It also provides water for drinking and industrial use. Jayakwadi is one of the largest earthen dams in Asia. Its height is approx 41.30 m and length of 9,998 m (10 km approx) with total storage capacity 2,909 MCM (million cubic meters) and effective live storage capacity is 2,171 MCM. The total catchment area of dam is 21,750 km². The Nath Sagar reservoir formed by Jayakwadi Dam is fed by the Godavari and Pravara rivers the reservoir is about 55 km long and 27 km wide. Total submergence area due to the reservoir is approx 36,000 hectares.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

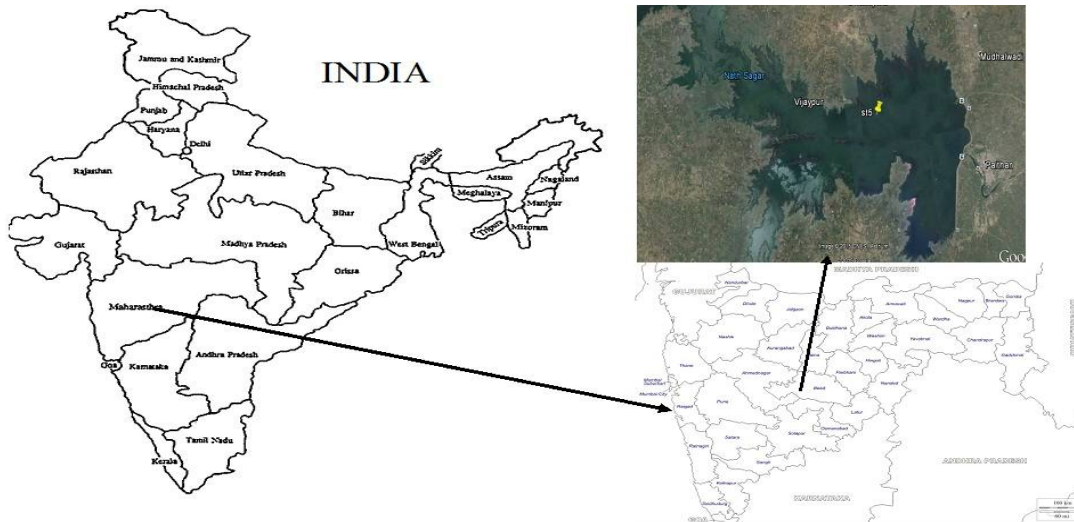


Figure 2. The Location of NathSagar Reservoir

Data Acquisition

The metrological data of the Nath Sagar reservoir is acquired from the Indian Metrological Department, Pune. The metrological data includes maximum and minimum air temperature, relative humidity, wind speed, sunshine hours and evaporation. Table 1. shows the meteorological data and their descriptive statistics for the reservoir under study.

Table 1. Descriptive statistics of the Nath Sagar Reservoir

Sr no.	Variables*	Units	Minimum Observed	Maximum Observed	Mean	Standard Deviation
1	Maximum Air Temperature	°C	19.20	43.30	32.67	4.17
2	Minimum Air Temperature	°C	5.40	30.80	18.88	4.94
3	Wind Speed	Km/hr	1.00	23.50	6.94	4.13
4	Sunshine Hours	Hours	0.19	11.80	7.55	2.73
5	Relative Humidity	%	13.50	98.50	56.36	19.33
6	Evaporation	mm/day	0.20	20.40	4.18	2.13

The study area has mean temperature about 32.67°C, mean wind speed about 6.94Km/hr, mean relative humidity of 56.36% and mean evaporation of 4.18mm/day. Daily records from 2000 to 2006 are used for studying reservoir evaporation.

III. MATERIAL METHOD

Considering the significance of individual meteorological parameter, the study revealed that the highest value of correlation coefficient and lowest root mean square error is obtained for evaporation with maximum temperature, followed by using relative humidity and sunshine hours (Table2). While the lowest correlation coefficient is obtained with wind speed, which mean intensity of wind speed does not influence the evaporation significantly in this case. The effect of temperature, wind speed and sunshine hours was found to be positive; whereas a negative correlation exists

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

between evaporation and relative humidity (that is evaporation decreases with increase in relative humidity). It is important to take into account the combined influence of all the meteorological parameter on evaporation.

Table 2. Statistical analysis of the weather data

Sr. No.	Variables	Units	Minimum	Maximum	Correlation coefficient with evaporation
1	Maximum Air Temperature	°C	19.20	43.30	0.76
2	Minimum Air Temperature	°C	5.40	30.80	0.37
3	Wind Speed	Km/hr	1.00	23.50	0.27
4	Sunshine Hours	Hours	0.19	11.80	0.43
5	Relative Humidity	%	13.50	98.50	-0.50
6	Evaporation	mm/day	0.20	20.40	1.00

The input combinations used to estimate evaporation for reservoir are maximum and minimum temperature (°C), Wind Speed (Km/hr), Sunshine hours (Hours), and Relative humidity (%). The daily metrological data recorded at Pategaon metrological station for a period from 2000 to 2006 is used (2557 data sets). Different structure of artificial neural network is used with different combination of data for estimation of daily evaporation. Four years data (1760 data sets) are used for training and two year data (767 data set) data are used for testing ANN models.

The input layer contains the input variables temperature, relative humidity, sunshine hours and wind speed. Four ANN models are proposed ANN1, ANN2, ANN3 and ANN4 having five, four, three and two input variables respectively. The selection of variables is done on the basis of correlation coefficient. The highest correlation value neglecting the sign enters first in the model (Table 3.) and the variable with the lowest correlation value leaves first. The hidden layer neurons were selected between 2 to 12. The output layer contains the evaporation.

Different ANN architecture is tried using these inputs and hidden layers to find an appropriate model structure for each input and hidden layer combination. The ANN models are then tested and the results are compared by means of correlation coefficient and root mean square error statistics.

Table 3. ANN Input Data Structure

Sr. No.	Model	Max. Temp	Relative Humidity	Sunshine Hours	Min. Temp.	Wind speed
1	ANN-1	I	I	I	I	I
2	ANN-2	I	I	I	I	-
3	ANN-3	I	I	I	-	-
4	ANN-4	I	I	-	-	-

For best fit ANN model in present study multilayer perception with one hidden layer and with a sigmoid activation function is used as it provided better results for this data set. Other user-defined parameters used were momentum learning rate and step size = 0.1, momentum = 0.700, hidden layer nodes = 8 and iterations = 1000. These values were obtained after a number of trials by using different combination of these parameters carried out on data set.

IV. EXPERIMENTAL RESULTS

The correlation coefficient and the root mean square error values of the developed values are given in Table 4. ANN-1 model with five inputs gives a correlation coefficient of 0.89 and the root mean square value of 1.581. ANN-2 model with four inputs gives a correlation coefficient of 0.974 and the root mean square value of 1.276. ANN-3 model with three inputs gives a correlation coefficient of 0.89 and the root mean square value of 1.539. ANN-4 model with two inputs gives a correlation coefficient of 0.972 and the root mean square value of 1.281.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

Table 4. Performance and Evolution of Models

Sr. No.	Model	(i/p-hidden-o/p)	R ²	RMSE
1	ANN-1	(5-8-1)	0.892707	1.581067
2	ANN-2	(4-9-1)	0.974774	1.276934
3	ANN-3	(3-9-1)	0.894942	1.539764
4	ANN-4	(2-10-1)	0.972538	1.281376

From the table the highest value of correlation coefficient and minimum root mean square error suggests the suitability of ANN-2 model. ANN-4 model has close results to ANN-2 model. The inputs and the hidden layers in the models are different. ANN-2 has a combination of temperature; relativity humidity and sun shine hours where as ANN-4 model has a combination of only maximum temperature and relativity humidity with nine and ten hidden neurons respectively.

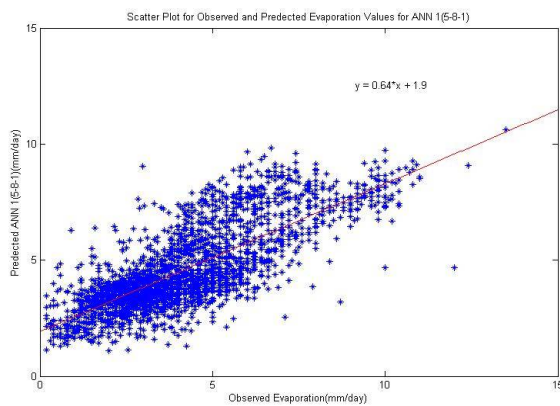


Figure 3. Scatter Plot for Observed and Predicted Evaporation Values for ANN-1 (5-8-1)

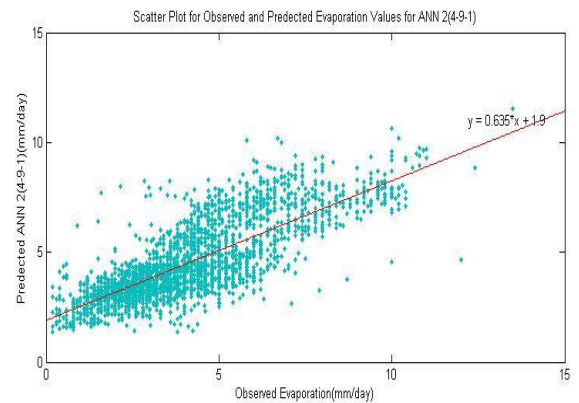


Figure 4. Scatter Plot for Observed and Predicted Evaporation Values for ANN-2 (4-9-1)

Figures 3, 4, 5 and 6 show the comparison of the observed and the predicted values of the ANN models. The highest value of correlation coefficient and minimum value of root mean square error suggests the suitability of ANN-2 model for the reservoir.

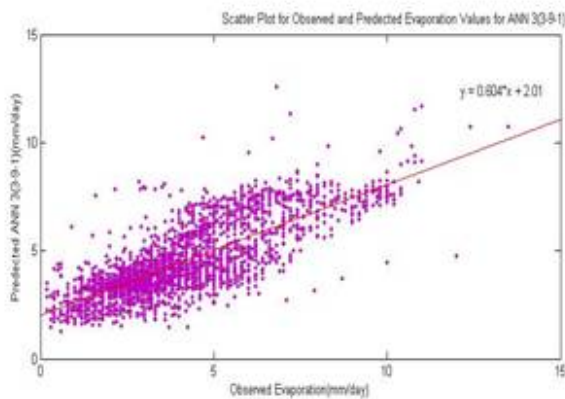


Figure 5. Scatter Plot for Observed and Predicted Evaporation Values for ANN-3 (3-9-1)

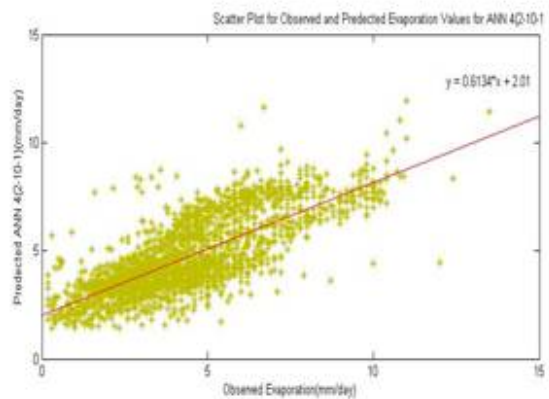


Figure 6. Scatter Plot for Observed and Predicted Evaporation Values for ANN-4 (2-10-1)

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

The present study discusses the application and the usefulness of artificial neural network based model for estimation of daily evaporation over a region. The results are encouraging and suggest the usefulness of neural network based modelling technique in better prediction of evaporation. This study also concludes that a combination of maximum and minimum temperature, relative humidity and sunshine hours as input variable to the model perform better in predicting evaporation. In addition the combination of maximum temperature and relative humidity also gives good prediction of evaporation and can be used in the absence of other data.

REFERENCES

- [1.] Aytac Guven and Ozgur Kisi, "Daily pan evaporation modeling using linear genetic programming technique.", *Irrig. Sci.*, vol. 29, pp.135–145, 2011.
- [2.] Bruton JM, McClendon RW, Hoogenboom G., "Estimating daily pan evaporation with artificial neural networks" *ASAE* vol. 43, no.2 pp.491–496, 2000.
- [3.] Caudill M., "Neural networks primer, part I". *AI Expert*, December, pp. 46–52, 1987.
- [4.] Chow, V., D. Maidment and, L. Mays, "Applied Hydrology." N.Y.: McGraw-Hill Pub., 1988.
- [5.] Gupta, B., "Engineering Hydrology." Jain, India: N.C., 1992.
- [6.] Guven A, Kisi O., "Daily pan evaporation modeling using linear genetic programming technique." *IrrigSci.*, vol.29, no.2, pp.135–145, 2011.
- [7.] Harbeck G., "A practical field technique for measuring reservoir evaporation utilizing mass-transfer theory." *U.S. Geol. Surv.*, vol.272, no.E, pp.101–105, 1962.
- [8.] Haykin S., "Neural networks and learning machines, 3rd edn." Prentice Hall, NJ., 2009.
- [9.] Hecht-Nielsen R., "Neuro computing." Addison-Wesley Publishing Company, Reading, 1990.
- [10.] Hossein Tabari, Safar Marofi, Ali-Akbar Sabziparvar, "Estimation of daily pan evaporation using artificial neural network and multivariate non-linear regression.", *Irrig.Sci.*, vol. 28 pp.399–406, 2010.
- [11.] Hossein Tabari, Mark E. Grismer, Slavisa Trajkovic, "Comparative analysis of 31 reference evapotranspiration methods under humid conditions", *Irrig. Sci.*, vol. 31, pp.107–117, 2013.
- [12.] Keith R. Cooley, "Evaporation Reduction: Summary of Long Term Tank studies.", *J. Irrig. Drain Eng.*, vol.109, no.1, pp. 89-98, 1983.
- [13.] Keskin ME, Terzi O., "Artificial neural networks models of daily pan evaporation.", *J Hydrol. Eng.*, vol.11, no.1, pp. 65–70, 2006.
- [14.] Keskin, M. and Terzi, Ö. "Artificial Neural Network Models of Daily Pan Evaporation." *J. Hydrol. Eng.*, vol.11, no.1, pp. 65-70, 2006.
- [15.] Kim S, Shiri J, Kisi O., "Pan evaporation modeling using neural computing approach for different climatic zones." *Water Resour. Manag.*, vol.26, no.11, pp. 3231–3249, 2012.
- [16.] Kisi O., "Daily pan evaporation modelling using a neuro-fuzzy computing technique." *J. Hydrol.*, vol.329, pp. 636-646, 2006.
- [17.] Kisi O., "Daily pan evaporation modelling using multi-layer perceptrons and radial basis neural networks." *Hydrol. Proc.*, vol.23, pp.213-223, 2009.
- [18.] Knapp, H., Yu, Y., and Pogge, E. "Monthly Evaporation for Milford Lake in Kansas." *J. Irrig. Drain Eng.*, vol.110, no.2, pp.138-148, 1984.
- [19.] Kohler MA, Nordenson T, Fox W., "Evaporation from pans and lakes." *U.S. Dept. Commerce, Weather. Bureau. Res.* pp. 38, 1955.
- [20.] Kumar M, Raghuvanshi N.S., Singh R., "Artificial neural networks approach in evapotranspiration modeling: a review", *IrrigSci.*, vol.29, pp.11–25, 2011.
- [21.] McCulloch W. S. and Pitts W., "A Logical Calculus of the Ideas Immanent in Nervous Activity." *Bulletin of Mathematical Biophysics*, vol. 5, pp.115-133, 1943.
- [22.] Penman H., "Natural evaporation from open water, bare soil and grass.", *Proc. Roy. Soc. London* Vol.193, pp.120-146, 1948.
- [23.] Sheng-Feng Kuo, Feng-Wen Chen, Pei-Yu Liao, Chen-Wuing Liu, "A comparative study on the estimation of evapotranspiration using backpropagation neural network: Penman–Monteith method versus pan evaporation method", *Paddy Water Environ.*, vol. 9, pp.413–424, 2011.
- [24.] Shiri J, Dierickx W, Pour-Ali Baba A, Neamati S, Ghorbani M A., "Estimating daily pan evaporation from climatic data of the state of Illinois, USA using adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN)." *Hydrol Res.*, vol.42, no.6, pp.491–502, 2011.
- [25.] Shiri J, Kisi O., "Application of artificial intelligence to estimate daily pan evaporation using available and estimated climatic data in the Khozestan Province (Southwestern Iran)." *J Irrig Drain Eng.*, vol.137, no.7, pp.412–425, 2011.
- [26.] Shirsath P, Singh A., "A comparative study of daily pan evaporation estimation using ANN, regression and climate based models." *Water Resour. Manag.*, vol.24 pp.1571-1581, 2010.
- [27.] Singh, V., "Elementary Hydrology." NJ, U.S.A.: Prentice Hall Inc., 1992.
- [28.] Sudheer KP, Gosain AK, Rangan DM, Saheb SM., "Modelling evaporation using an artificial neural network algorithm." *J. Hydrol. Proc.*, vol.16, pp.3189-3202, 2002.
- [29.] Sungwon Kim & Jalal Shiri & Ozgur Kisi & Vijay P. Singh "Estimating Daily Pan Evaporation Using Different Data-Driven Methods and Lag-Time Patterns", *Water Resour Manage*, vol.27, pp.2267–2286, 2013.
- [30.] Tabari et al., "Estimation of daily pan evaporation using artificial neural Network and multivariate non-linear regression". *IrrigSci.*, vol.28, no.5, pp.399–406, 2010.
- [31.] Terzi O, Keskin ME., "Evaporation estimation using gene expression programming." *J Appl Sci* vol.5, no.3, pp.508–512, 2005.
- [32.] Wossenu Abtew, "Evaporation Estimation for Lake Okeechobee in South Florida" *Journal of Irrigation and Drainage Engineering*, vol. 127, no.3, pp. 0140–0147, 2001.
- [33.] Yunhe Yin, Shaohong Wu, Gang Chen and Erfu Dai, "Attribution analyses of potential evapotranspiration changes in China since the 1960s." *Theor. Appl. Climatol.*, vol. 101, pp.19–28, 2010.