# Evaporation Estimation Using Artificial Neural Network

Pankaj Kumar and Ajai Kumar Tiwari

***Abstract*—Precise estimation of potential evaporation, has a great significance in many water resources applications such as management of hydrologic, hydraulic and agricultural systems. Although there are empirical formulas available for Evaporation estimation, but their performances are not all satisfactory due to the complex nature of the evaporation process and the data availability. For this purpose, artificial neural networks (ANN) models was developed to estimate monthly potential evaporation in Pantagar, US Nagar (India) based on four instructive climatic factors. Observations of relative humidity, solar radiation, temperature, wind speed and evaporation for the past 19 years and 8 months (total 236 months) have been used to train and test the developed models. Results shown that the model was able to well learn the events they were trained to recognize. These encouraging results were supported by high values of coefficient of correlation and low mean square errors. The correlation coefficient was found 0.9236 and root mean square error was 0.9863 for testing data sets.**

***Index Terms*—Artifificial neural network, evoporation estimation, prediction**

## I. Introduction

Evaporation takes place whenever there is a vapour pressure deficit between a water surface and the overlying atmosphere and sufficient energy is available. The most common and important factors affecting evaporation are solar radiation, temperature, relative humidity, vapour pressure deficit, atmospheric pressure, and wind. Evaporation losses should be considered in the design of various water resources and irrigation systems. In areas with little rainfall, evaporation losses can represent a significant part of the water budget for a lake or reservoir, and may contribute significantly to the lowering of the water surface elevation. Therefore, accurate estimation of evaporation loss from the water body is of primary importance for monitoring and allocation of water resources, at farm scales as well as at regional scales. The rate of evaporation depends on a number of meteorological factors such as solar radiation, air temperature, relative humidity, wind speed, and to some extent atmospheric pressure. Other factors are related to the nature of the evaporating surface and the quality of water. Various studies have been conducted to determine which of these factors have the dominant effect on evaporation. Radiation is by far the most important single factor affecting evaporation. In addition to solar radiation, Chow *et al*. (1988) claimed that the mechanism of transporting the vapor from the water surface has also a great effect. Vapor pressure deficit, temperature, barometric pressure, humidity, and wind speed were emphasized by Singh (1992) as the controlling factors.

Gupta (1992) pointed out that relative humidity, wind velocity, and temperature of water and atmosphere are the climatic factors evaporation awfully depends on. In summary, it has been agreed that solar radiation, wind speed, relative humidity, and air temperature have attained special consideration as the most influencing factors by most researchers.

A large number of experimental formulae exist for evaporation estimation. There are direct and indirect methods available for estimating potential evaporation from free water surfaces. Because evaporation is an incidental, nonlinear, complex, and unsteady process, it is difficult to derive an accurate formula to represent all the physical processes involved. As a result, there are new trend in using data mining techniques such as artificial neural networks techniques to estimate evaporation.

The main objectives of this study were first to investigate the potential of using ANN model to predict evaporation as affected by climatic factors. Second, is to evaluate the performance of ANN model in estimating average monthly evaporation in Pantnagar.

## II. Artificial Neural Networks

ANN was first introduced as a mathematical aid by McCulloch *et al* (1943). They were inspired by the neural structure of the brain. Fig. 1 is a general architecture of a Feed Forward ANN, with one hidden layer. Most ANNs have three layers or more: an input layer, which is used to present data to the network; an output layer, which is used to produce an appropriate response to the given input; and one or more intermediate layers, which are used to act as a collection of feature detectors. The ability of a neural network to process information is obtained through a learning process, which is the adaptation of link weights so that the network can produce an approximate output(s). In general, the learning process of an ANN will reward a correct response of the system to an input by increasing the strength of the current matrix of nodal weights.Various application of ANN in hydrology and meteorology have been implimented by researchers such as (Sudheer et. al, 2003, Firat, 2009, Kissi, 2004, Kissi 2006 and Wang, 2009).

There are several features in ANN that distinguish it from the empirical models. First, neural networks have flexible nonlinear function mapping capability which can approximate any continuous measurable function with arbitrarily desired accuracy, whereas most of the commonly used empirical models do not have this property. Second,

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being non-parametric and data-driven, neural networks impose few prior assumptions on the underlying process from which data are generated. Because of these properties, neural networks are less susceptible to model misspecification than most parametric nonlinear methods.

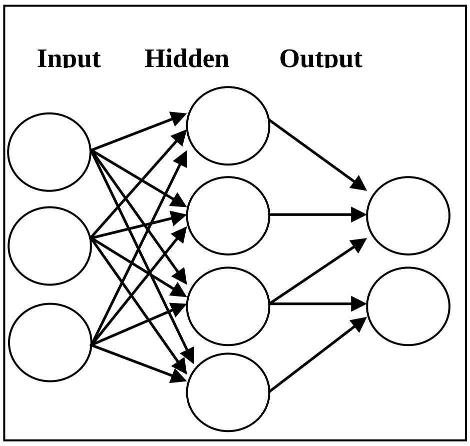


Fig. 1. Architecture of multilayer feed forward neural network

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

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

The net input is then passed through an activation function $f$ (.) 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

$$y = f(net) = \frac{1}{1+e^{-net}} \qquad (2)$$

Throughout all ANN simulations, the adaptive learning rates were used for increasing the convergence velocity. For each epoch, if the performance decreases toward the goal, then the learning rate is increased by the factor of learning increment. If the performance increases, the learning rate is adjusted by the factor of learning decrement.

## III. Study Area and Model Application

### A. *Study Area*

The weekly evaporation data for the year 1990 to 2009 (236 months) approximately 19 years and 8 months were collected from Meteorological Observatory, G.B. Pant University of Agriculture and Technology, Pantnagar, District Udham Singh Nagar, India. Pantnagar falls in sub-humid and subtropical climatic zone and situated in *Tarai* belt of Shivalik range, of foot hills of Himalayas. Geographically it is located at 29°N latitude and 79.29°E longitude and an altitude of 243.84 m above mean sea level. Generally, monsoon starts in the last of June and continues upto September. The mean annual rainfall is 1364 mm of which 80-90 percent occurs during June to September. May to June is the hottest months and December and January the coldest. The mean relative humidity remains almost 80-90 percent from mid June to February end.

### B. *Material and Methods*

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 was obtained with sunshine hours, which mean bright sunshine hours alone does appear to influence the evaporation significantly.

TABLE I: Statistical Analysis of the Total Monthly Weather Data

| S. No | Data | Maximum | Minimum | Correlation coefficient with evaporation |
|---|---|---|---|---|
| 1 | Air temperature (°C) | 32.35 | 10.45 | 0.7625 |
| 2 | Relative humadity (%) | 89 | 38.5 | - 0.640 |
| 3 | Wind velocity (m/s) | 14.2 | 0.7 | 0.6612 |
| 4 | Sunshine hours (hour) | 10.5 | 3 | 0.4931 |
| 5 | Evaporation (mm) | 13.1 | 1.1 | 1.00 |

It mean that 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).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. By various trials it was suggested 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 combinations.

The input combinations used in this application to estimate evaporation for Pantnagar station were Air temperature (°C), Relative humadity (%),Wind velocity (m/s) and Sunshine hours (hour) of a month $t$ and and Evaporation (mm) of that month $t$ was considered as output of the models.

TABLE II: Performance Evolution of Model on Training and Testing Period

| Statistical indices | Training period | Testing period |
|---|---|---|
| Correlation coefficient | 0.9311 | 0.9236 |
| Root mean square error | 1.070 | 0.9863 |

Different ANN architectures were tried using these inputs and the appropriate model structures were determined for each input combination. Then, the ANN models were tested and the results were compared by means of correlation and coefficient root mean square error statistics. 157 data sets were used for training and 79 months data were used for testing for ANN models.

For best fit ANN model in present study multilayer perceptron with one hidden layer and with a sigmoid activation function was used as it works well for this data set. Other user-defined parameters used were momentum learning rate and step size = 0.1, momentum = 0.700, hidden layer nodes = 4 and iterations = 1000. These values were obtained after a large number of trials by using different combination of these parameters carried out on data set.

### C. Results

The correlation coefficient and root mean square error values of developed model in the training period as well as in testing period are given in TABLE II. It can be seen from the table that the correlation coefficient for training period is 0.9311 and for testing period is 0.9236. The value of root mean square error for training period is 1.070 and for testing period it is 0.9863. It is clear from Table 2 that the higher values of correlation coefficients and lower values of root mean square error suggests the applicability of ANN model for evaporation estimation

## IV. Conclusion

The present study discusses the application and usefulness of artificial neural network based modeling approach in predicating the evaporation losses over a region. The results are quite encouraging and suggest the usefulness of neural network based modeling technique in accurate prediction of the evaporation. 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.

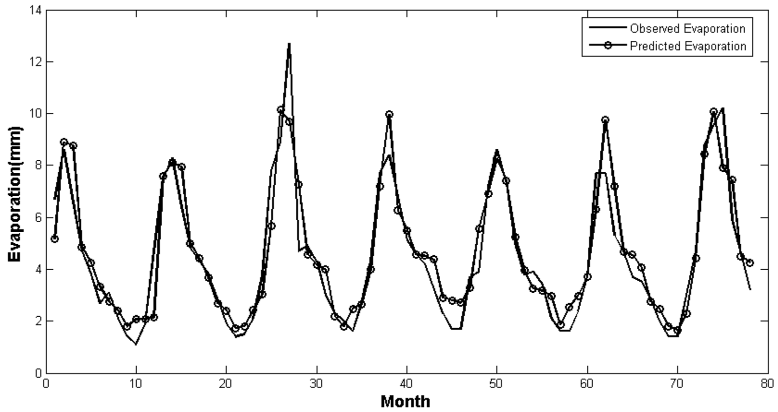


Fig. 2. Observed and predicted monthly evaporation for ANN model in testing period

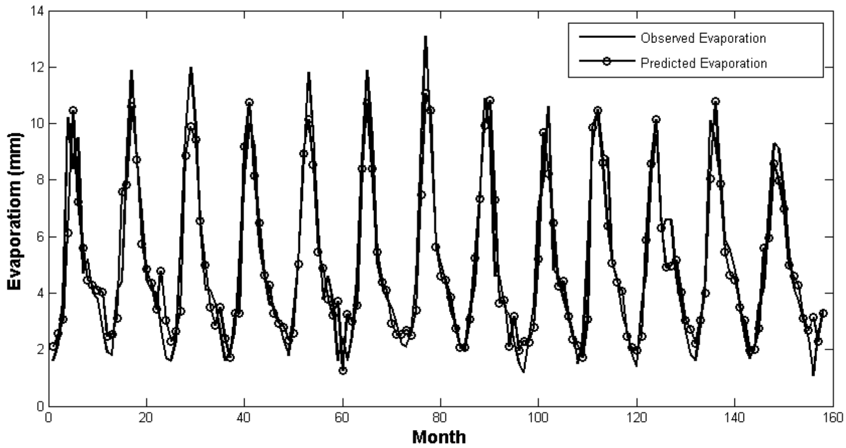


Fig. 3. Observed and predicted monthly evaporation for ANN model in training period

## References


[1] B. Gupta, 1992.*Engineering Hydrology*. Jain, India: N.C.,

[2] K. P. Sudheer, A. K. Gosain, R. D. Mohan, and S. M. Saheb, 2002. Modelling evaporation using an artificial neural network algorithm, *Hydrological Processes* 16 :3189-3202.

[3] M. Firat, M. Turan, and M. A. Yurdusev, 2009. Comparative analysis of fuzzy inference systems for water consumption time series prediction. *Journal of Hydrology* ,374 :235–241

[4] O. Kisi, 2006. Daily pan evaporation modelling using a neuro-fuzzy computing technique. *Journal of Hydrology*, 329: 636– 646.

[5] O. Kissi, 2004. River flow modeling using artificial neural networks. *Journal of Hydrologic Engg. ASCE*, 9: 60–63.

[6] V. Chow, D. Maidment, and L. Mays, 1988.*Applied Hydrology*. N.Y.: McGraw-Hill Pub.

[7] V. Singh, 1992.*Elementary Hydrology*. NJ, U.S.A.: Prentice Hall Inc.,

[8] W. S. McCulloch and W. Pitts.1943. A logic calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical and Biophysics*, 5: 115-133.

[9] W. C. Wang, K. W. Chau, C. T. Cheng, and Q. Lin, 2009. A comparison of performance of several artificial intelligence methods for forecasting monthly discharge time series. *Journal of hydrology*,374: 294-306