Evaporation Estimation Using Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference System Techniques

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Abstract

Accurate estimation of potential evaporation has been of a great as its importance is obvious 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 complicated nature of the evaporation process and the data availability. For this purpose, artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS) models were developed to forecast monthly potential evaporation in Pantagar, U.S. Nagar (India) based on four explanatory 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 revealed that the models were able to well learn the events they were trained to recognize. Moreover, they were capable of effectively generalizing their training by predicting evaporation for sets of unseen cases. These encouraging results were supported by high values of coefficient of correlation and low mean square errors. It has been found that ANN and ANFIS techniques have good performances (for the test data set, correlation coefficient for ANN is 0.9236 and root mean square error is 0.9863 and for ANFIS correlation coefficient is 0.9562 and root mean square error is 1.2812. Between ANN and ANFIS, ANFIS model is slightly better albeit the difference is small. Although ANN and ANFIS techniques seem to be powerful, their data input selection process was done by trial and error method.

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. According to Linsely et al (1988) radiation is by far the most important single factor affecting evaporation and Chow et al (1988) reported that in addition to solar radiation, the mechanism of transporting the vapour from the water surface has also a great effect. Vapour 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, temperature of water and atmosphere are the climatic factors on which evaporation awfully depends . 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

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techniques such as artificial neural networks and adaptive neuro fuzzy inference system techniques to estimate evaporation.

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

Materials and Methodology

Artificial neural networks

ANN was first introduced as a mathematical aid by McCulloch and Pitts (1943). They were inspired by the neural structure of the brain. The application of ANN is based on their ability to mimic the human behaviour and neural structure to construct a good approximation of functional relationships between past and future values of a time series. It describes a nonlinear relationship between the input and output of a complex system using historic process data. 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. 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.

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, 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. 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.

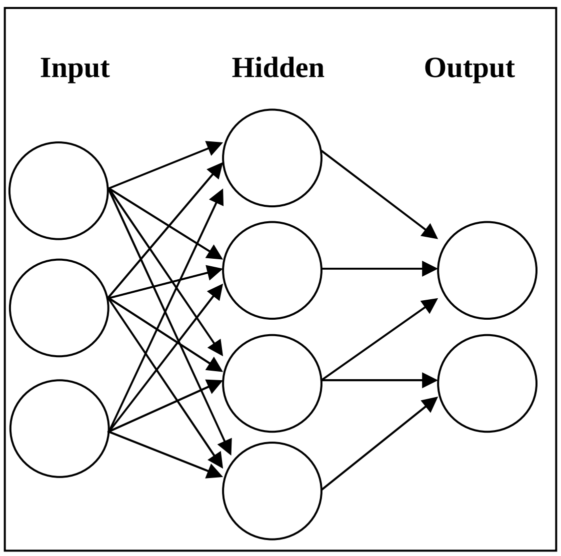

Figure 1: Architecture of multilayer feed forward neural network

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

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

Eq. 1

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

$$y=f\left(net\right)$$

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

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

Eq. 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.

Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

Adaptive Neuro Fuzzy Inference System (ANFIS) is a fuzzy mapping algorithm that is based on Tagaki-Sugeno-Kang (TSK) fuzzy inference system (Jang et al., 1997 and Loukas, 2001).ANFIS is integration of neural networks and fuzzy logic and have the potential to capture the benefits of both these fields in a single framework. ANFIS utilizes linguistic information from the fuzzy logic as well learning capability of an ANN for automatic fuzzy if-then rule generation and parameter optimization.

A conceptual ANFIS consists of five components: inputs and output database, a Fuzzy system generator, a Fuzzy Inference System (FIS), and an Adaptive Neural Network. The Sugeno- type Fuzzy Inference System, (Takagi and Sugeno, 1985) which is the combination of a FIS and an Adaptive Neural Network, was used in this study for rainfall-runoff modeling. The optimization method used is hybrid learning algorithms.

For a first-order Sugeno model, a common rule set with two fuzzy if-then rules is as follows:

Rule 1: If x_1 is A_1 and x_2 is B_1, then $f_1=a_1x_1+b_1x_2+c_1$.

Rule 2: If x_1 is A_2 and x_2 is B_2, then $f_2=a_2x_1+b_2x_2+c_2$.

where, x_1 and x_2 are the crisp inputs to the node and A_1, B_1, A_2, B_2 are fuzzy sets, a_i, b_i and c_i $(i = 1, 2)$ are the coefficients of the first-order polynomial linear functions. Structure of a two-input first-order Sugeno fuzzy model with two rules is shown in Figure 1 It is possible to assign a different weight to each rule based on the structure of the system, where, weights w_1 and w_2 are assigned to rules 1 and 2 respectively and f = weighted average

The ANFIS consists of five layers (Jang, 1993), shown in Figure 3.

The five layers of model are as follows:

Layer1: Each node output in this layer is fuzzified by membership grade of a fuzzy set corresponding to each input.

$$O_{i,1} = \mu_{Ai}\left(x_1\right) \qquad i = 1,2$$

or

$$O_{i,1} = \mu_{Bi-2}\left(x_2\right) \qquad i = 3,4$$

Eq. 3

Where, x_1 and x_2 are the inputs to node i *(i = 1, 2 for* x_1 *and i = 3, 4 for* x_2*)* and x_1 *(or* x_2*)* is the input to the i^{th} node and A_i *(or* B_{i-2}*)* is a fuzzy label.

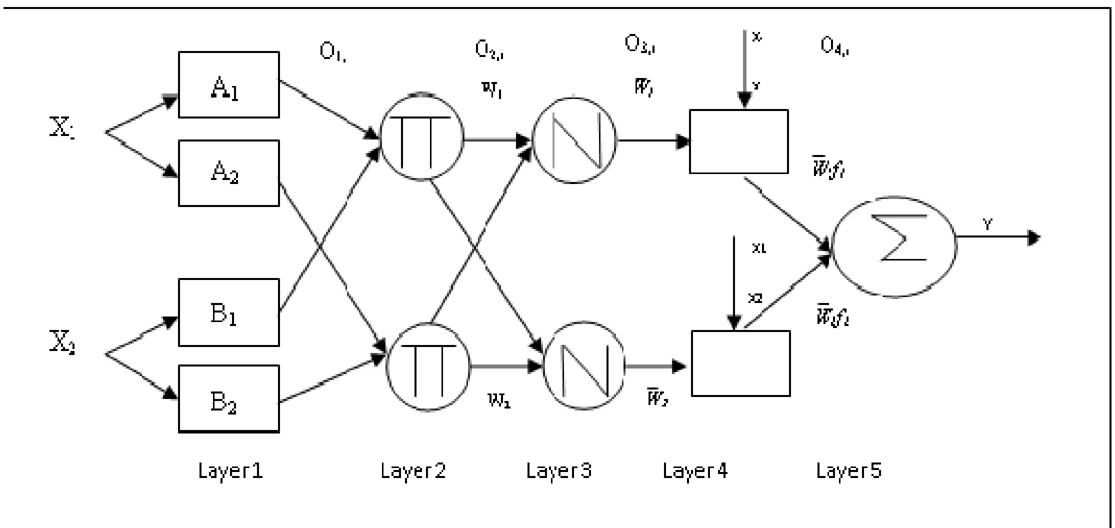

Figure 2: ANFIS architecture

Layer 2: Each node output in this layer represents the firing strength of a rule, which performs fuzzy, AND operation. Each node in this layer, labelled Π, is a stable node which multiplies incoming signals and sends the product out.

$$O_{2,i} = W_i = \mu_{Ai}\left(x_1\right)\mu_{Bi}\left(x_2\right) \qquad i = 1,2 \qquad \textbf{Eq. 4}$$

Layer 3: Each node output in this layer is the normalized value of layer 2, i.e., the normalized firing strengths.

$$O_{3,i} = \overline{W_i} = \frac{w_i}{w_1 + w_2} \qquad i = 1,2 \qquad \textbf{Eq. 5}$$

Layer 4: Each node output in this layer is the normalized value of each fuzzy rule. The nodes in this layer are adaptive .Here $\overline{W_i}$ is the output of layer 3, and $\{a_i, b_i, c_i\}$ are the parameter set. Parameters of this layer are referred to as consequence or output parameters.

$$O_{4i} = \overline{W}_i f_i = \overline{W}_i (a_i x_1 + b_i x_2 + c_i) \qquad i = 1, 2 \qquad \textbf{Eq. 6}$$

Layer 5: The node output in this layer is the overall output of the system, which is the summation of all coming signals.

$$Y = \sum_1^2 \overline{W}_i f_i = \frac{\sum_1^2 W_i f_i}{\sum_1^2 W_i} \qquad \textbf{Eq. 7}$$

In this way the input vector was fed through the network layer by layer. The two major phases for implementing the ANFIS for applications are the structure identification phase and the parameter identification phase. The structure identification phase involves finding a suitable number of fuzzy rules and fuzzy sets and a proper partition feature space. The parameter identification phase involves the adjustment of the premise and consequence parameters of the system.

Optimizing the values of the adaptive parameters is of vital importance for the performance of the adaptive system. Jang et al. (1997) developed a hybrid learning algorithm for ANFIS to approximate the precise value of the model parameters. The hybrid algorithm, which is a combination of gradient descent and the least-squares method, consists of two alternating phases: (1) in the backward pass, the error signals recursively propagated backwards and the premise parameters are updated by gradient descent

, and (2) least squares method finds a proper set of consequent parameters (Jang et al., 1997). In premise parameters set for a given fixed values, the overall output can be expressed as a linear combination of the consequent parameters.

$$AX = B \qquad \textbf{Eq. 8}$$

Where, *X* is an unknown vector whose elements are the consequent parameters. A least squares estimator of *X*, namely *X**, is chosen to minimize the squared error $\|AX - B\|^2$. Sequential formulas are employed to compute the least squares estimator of *X*. For given fixed values of premise parameters, the estimated consequent parameters are known to be globally optimal.

Study Area and Model Application

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.

Results

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 1). While the lowest correlation coefficient 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). 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, both by ANN as well as ANFIS.

Table 1: 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

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.

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

For 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. For ANFIS, model structure identification was done by subtractive clustering with a cluster radius of 0.5 and hybrid learning algorithm was used for model parameter identification. There were 50 iterations used for ANFIS model.

Table 2: Performance evolution of model on training and testing period

Models	Training period		Testing period	
	ANFIS	ANN	ANFIS	ANN
Correlation coefficient	0.9731	0.9311	0.9562	0.9236
Root mean square error	0.6715	1.070	1.2812	0.9863

The correlation coefficient and root mean square error values of each model in the training period as well as in testing period are given in Table 2. It can be seen from the table that the ANFIS model with 0.5 cluster radius has the highest correlation coefficient 0.9731 in training period as well as 0.9562 in testing period and value of root mean square error for ANFIS model in training period is 0.6715 and in testing period it is 1.2812. In case of ANN model correlation coefficient for training period is 0.9311 and for testing period is 0.9236. The value of root mean square error for ANN model for training period is 1.070 and for testing period it is 0.9863. It is clear from Table 2 that ANFIS outperformed over ANN model in case of training data sets for both stastical parameters root mean square error and correlation coefficient but in case of testing period correlation coefficient of ANFIS model are better to ANN and root mean square value of ANN is smaller to ANFIS model.

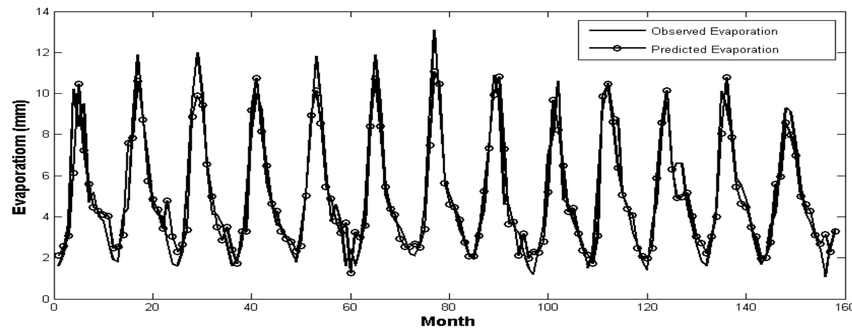

Figure 3: Observed and predicted monthly evaporation for ANN model in training period

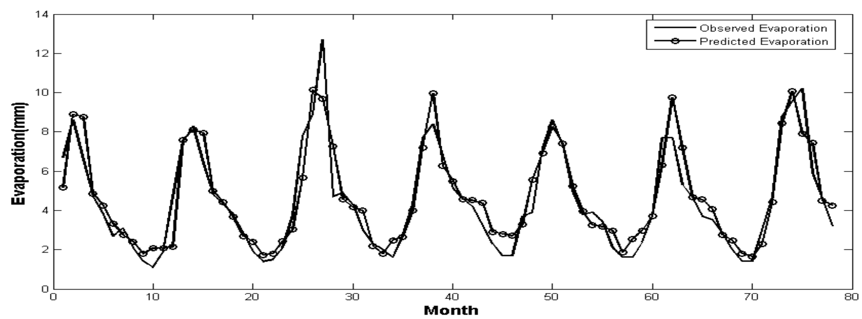

Figure 4: Observed and predicted monthly evaporation for ANN model in testing period

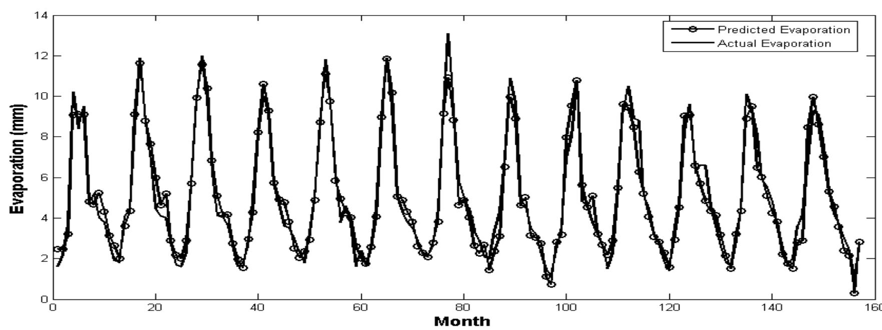

Figure 5: Observed and predicted monthly evaporation for ANFIS model in training period

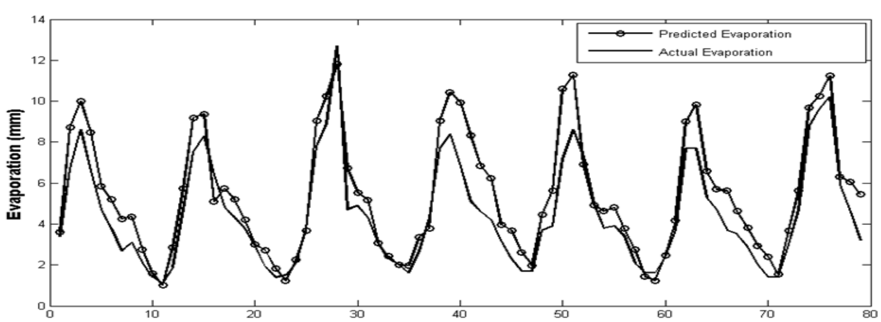

Figure 6: Observed and predicted monthly evaporation for ANFIS model in testing period

The observed and estimated values of evaporation are shown in Figure 3 and Figure 5 for training period with ANN and ANFIS models respectively. In case of testing period observed and estimated values of evaporation are shown in Figure 4 and Figure 6 for ANN and ANFIS models respectively. Visual inspection of figures shows that, there is a fairly good agreement between the estimated and the observed evaporation values, and overall shape of the plot of estimated evaporation is similar to that of the observed evaporation for both models. But by visual observation it is concluded that ANFIS model is slightly better than ANN for evaporation estimation in case of Tarai region of Pantnagar.

Conclusion

The present study discusses the application and usefulness of artificial neural network and adaptive neuro fuzzy inference system based modelling approach in predicating the evaporation losses over a region. Both soft computing techniques performed well but ANFIS outperformed over ANN. The ANFIS model is more flexible than the ANN model considered, with more options of incorporating the fuzzy nature of the real-world system. 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 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.

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