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A Survey on the Performance of Fuzzy-Neural Network at Predicting the Average Monthly Discharge of Catchment Basin Areas Having Snow Regimes

Daniel Abbasi[1], Afshin Ashrafzadeh[2], Reza Asheghi[3], Edris Merufinia[4*]

[1]*Department of River Engineering, Pars Peyab Consulting Engineers, Tehran, Iran*
[2]*Department of Water Engineering, University of Guilan, Rasht, Iran*
[3]*Department of Civil Engineering, Roudehen Branch, Islamic Azad University, Roudehen, Iran*
[4]*Department of Civil Engineering, Collage of Water Engineering, Mahabad Branch, Islamic Azad University, Mahabad, Iran*

*Corresponding author's E-mail: edris.marufynia@yahoo.com

ABSTRACT: Snow is one kind of precipitation that because of its delay in turning into runoff water is much more different from other kinds of precipitation when it comes to modeling how to turn into water. Statistical models and regression are some of the most common analytical methods which mostly, due to solving this phenomenon linearly, are presenting results with errors and are incapable of modeling over-the-time changes of the considered phenomenon with acceptable accuracy. Nowadays intellectual fuzzy and neural systems, considering their abilities at solving nonlinear and complex phenomena, have a wide use in various engineering problems especially in Hydrology. In this study, by using the abilities of fuzzy-neural networks, is tried to create a model which has the least amount of information to perform for predicting the average monthly discharge in Jajrud River. Since Jajrud River is located in a basin with a mostly snowy regime, it's meant to find a deducible relation between the average monthly discharge and information of the water equivalent of basin's snow monitoring stations.

Keywords: Average monthly discharge, Neural fuzzy network, Snow melting modeling, Jajrud catchment basin

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INTRODUCTION

Predicting rivers flow, considering its importance in water facilities design, pumping out water from rivers, scheduling the usage of dams' reservoirs, erosion control and sediment of rivers and etc., has always been an interesting topic for water resources engineers (Chow et al., 2010). Snow is a kind of precipitation that due to its delay in turning into runoff water is much more different from other sort of precipitation in regard to modeling. The snow coverage in a catchment basin affects the water balance of the basin and is an important issue in climate change of an area. Snow is a great source of water in most of the basins. Evaluating the amount of water or the water content of the snow cover and estimating the runoff water made from snow melting is one of the major topics in hydrology (Alizadeh, 2013). Snow's depth and water equivalent are very important in hydrological analysis. Normally, snow's equivalent water is not measured directly and is calculated by a relation between the density and depth of the snow. The density of snow is different in various areas. Snow density is also different in different snow coverage of the same area and also the type of precipitation. Besides, snow density is related to the conditions during the precipitation, in a way that wind makes the perceived snow denser. Point measuring of snow depth could be done by rulers or other simple measurement devices. Besides calculating the snow equivalent water is done by unstable precipitation stations point by point (Mahdavi, 2013). Regarding to the importance of predicting discharge of rivers, the usage of computer equipment and latest available innovations is necessary. Statistical, Hydraulic and Hydrological models has been used to predict rivers' flow, since mid-90's artificial intelligence such as artificial neural networks (ANNs) and fuzzy neural networks (FNN) become more common (Renner, 2009). According to the limits of conceivable fresh water, predicting flow discharge and its changes through year are fundamental concepts to schedule and manage surface water resources. Based on this, specialists are always trying to estimate rivers' discharge correctly and to make available methods more precise. Up to now, various and complex relations and algorithms, such as conceptual algorithms of precipitation-runoff, time history algorithms and hybrid algorithms, are introduced to predict rivers' stream flow (Telori, 2009). Using those relations are in many cases inconsistent with observed results due to insufficient understanding and complexity of effective factors, and in some cases results driven from various methods had a concerning and meaningful difference. The usage of implicit algorithms based on artificial neural networks, along with daily increase of computer algorithms usage through the last two decades, are widely used in studies of predicting various parameters of water resources, and specialists has always stressed on the high accuracy of this method comparing to time history algorithms. Fuzzy systems are generally able to model two types of

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uncertainty in phenomenon around the world. The first type is the uncertainty coming from the lack of human knowledge and devices to understand the complexity of a phenomenon. All the spreading quantities that are measured by averaging several points in the range are categorized in this type of uncertainty. The second is related to the opacity and implicitly of a phenomenon or being choosy about a phenomenon (Foruozan and Boroumand, 2011).

Malcher and Heidinger (2006) simulated the runoff made from snow melting in basins of Austria by using SRM model and satellite pictures of MODIS. Hong, M.A. and Guodong (2008) used SRM model to simulate the stream flow resulted from snow melting in Gunmisi River catchment basins in western China. Since they have evaluated the snow coverage area by satellite pictures, the results from this modeling illustrated that snow coverage area is related to climate change and especially temperature fall (Hong and Guodong, 2007). Chen and Adams (2006). Investigated the combination and fusion of conceptual models with artificial neural networks in regard to precipitation-runoff. Based on the combined method, locational and positional displacement of precipitation, non-homogenized rainfall characteristics and its effects on the amount of rainfall is investigated by half-spread and half-developed models of visional rainfall. Najafi et al. (2004), through a study, simulated the runoff coming from snow melting in Mahabad Dam basin using SRM model. After entering the initial data to model, simulating is done and the Hydrograph, simulated and measured, is plotted. These two Hydrographs are compared and investigated by the level of consistency, regression and volume differences. Regression and volume difference coefficient are 0.85 and -3.79 respectively. Nagler et al. (2009) by using optical images of satellite MODIS and radar images (to remove the errors resulted from long cloudy periods), has predicted the runoff made from snow melting in Otztel basin of Australia. Rajurkar et al. (2004) used nonlinear artificial neural network to simulate daily stream flow in two large-scale and small-scale basins and showed that by dividing a large basin into several smaller sub-basins, better results are conceivable. Tokar et al. (2005) reported accuracy and rapidity in achieving to results by using neural networks to predict runoff comparing to conceptual models. Turan et al. (2010) found fuzzy-neural models more efficient in compare to other intellectual neural models while using intellectual neural models techniques in estimating stream flow of rivers.

In this study it is tried to produce a model to predict the average monthly discharge of Jajrud River having the least amount of initial information to perform, by using the abilities of fuzzy neural network. Since the Jajrud River's basin is a basin with mostly snowy regime, it's meant to get a deducible relation between information of snow equivalent water in snow-monitoring stations and the resulting discharge.

MATERIAL AND METHODS

Study Area

Jajrud River is located in 30 kilometers of northeast of Tehran. Streaming from northwest to southeast and flowing from initiation point (Alborz Mountains) to lower lands, eventually pouring into Latian Dam. This river is initiated from KolonBastak in north of Darbandsar village. Meygun, Fasham, Damavand and Ahar branches join the main stream. This river with a length of 40 kilometers and 710 square meter of basin, has a steep of 4% and is a gravely, broken sandy river.

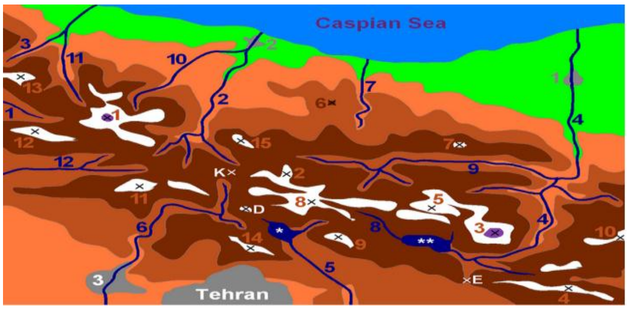

Figure1. Illustrates the geopolitical location of Jajrud River

This river, having Latian Dam on downstream, is used to supply drink water for east of Tehran besides watering farms and gardens downstream and producing hydropower (Fig2). Catchment Basins of Jajrud River is consisted of sub-basins like Garmabdar, Shemshak, Ahar, Emameh, Ghuchak Rudar, Gelukan, Kand, north and south Lavarak, Afajeh, Hezar Darreh and with the main Jajrud river.

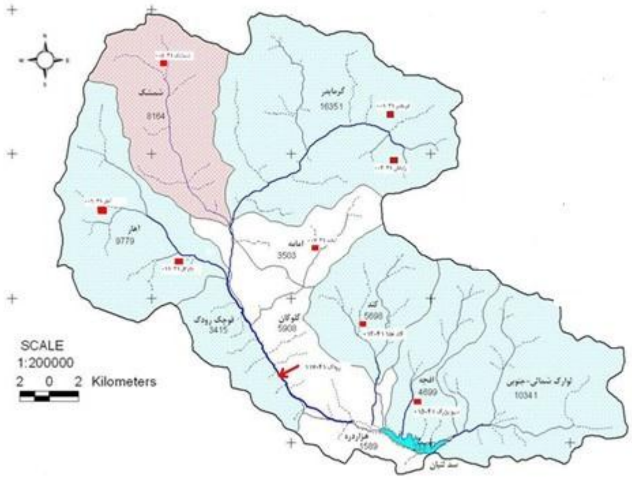

Figure 2. Jajrur River Catchment Basin

Creating water balance for Jajrud River basin and predicting the amount of runoff water reserved in Latian Dam noticing that it's a snowy regime basin, which is often done by satellite images and consuming a lot of time to produce these images and also a lot of time to separate snow covered areas from white stone areas and clouds or by the method of engineers of American Army which is an old method and is done by simple calculations has addressed snow melting issue. There are other sort of methods that normally wouldn't present a correct prediction. In this study it is tried to overcome the aforementioned obstacles of producing initial information by using fuzzy neural network.

Fuzzy Neural Network

Fuzzy neural network are good means to model nonlinear systems, which has a high degree of ability to simulate an unknown variable based on a limited variety of initiating incomplete, even with errors, data. A benefit of intellectual neural networks is to need no special function to express relations between entering data and results. Besides, these networks are able to extract the ultimate information from the available data (Schap et al., 1998). Professor LotfiZadeh has introduced fuzzy logical theory for complex systems; this theory has been used in a variety of problems with success. Rodger (1993), for the first time, considered the abilities of fuzzy theory and neural network and introduced comparative fuzzy neural deductive model (Roger, 1993). Comparative fuzzy neural deductive model is a multi-layered network, consisting of nodes and connecting arcs between nodes (Lin and Lee, 2001). In neural fuzzy network, the neural network is first used to learning and leveling the abilities and in aim to connecting the algorithm and correcting it. The part of neural network, automatically, produces fuzzy logic rules and membership functions throughout the learning period. In total, even after learning, neural network continues to correcting membership functions and the rules of fuzzy logic, in a way that learns more from its entering signals. On the other hand, fuzzy logic is used to deduce and produce an exact or non-fuzzy result (when the fuzzy variables are made) (Semnani and Hajianfar, 2010). The combination of fuzzy logic and neural network is getting more widely accepted day by day. Most of researchers in the field of artificial intelligence have followed the described method, but in this field there is still no standard model conceived that could be resulted, in a way that clarifies the offered changeability in neural networks (changes in function, number of layers, defining loop numbers, etc.).

Nevertheless, this changeability is not considered as a deficient but a strong and efficient method which is extracted from two other methods. Neural fuzzy network combines these two systems in the best way. These combined networks, address entering data and at the same time, are able to learn. Neural network, receive the real entering and resulting data, then makes new leveling and new entering-result relations, and at last produces new rules. Besides, neural network corrects the pre-receiving network based on these new rules (Statimous Kartapolous, 2011). The structure of Fuzzy neural network model is showed in fig 3 schematically.

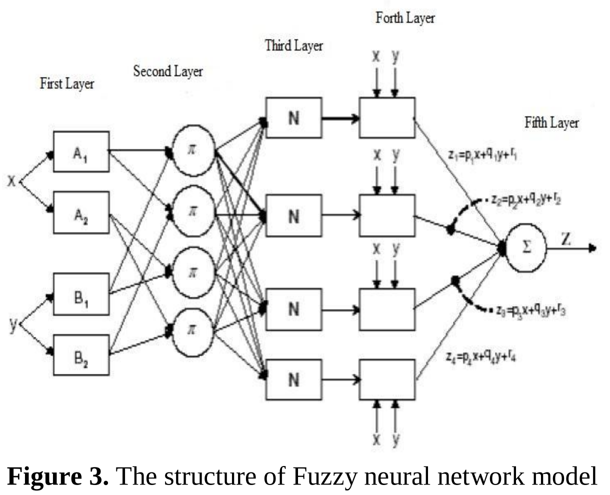

Figure 3. The structure of Fuzzy neural network model

As it is seen in the figure, the network has five layers:

First layer: this layer is the entering layer, which is applying fuzzy membership functions. The shape of membership function and their overlap is defined by operator's desire.

$$\mu_A(X) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b^i}} \quad (1)$$

Which in here X is equal to entering data.

Second Layer: in this layer the amount of signals entering to each node are multiplied to each other, and the result, which is the weight of the rules, is conceived:

$$w_i = \mu_{Ai}(X_1)\mu_{Bi}(X_2) \quad (2)$$

Third layer: the nodes of this level do the act of weigh comparing of rules:

$$\bar{W}_i = \frac{w_i}{\sum_{i=1}^{n} w_i}, i = 1,2,3,\dots,n \quad (3)$$

Fourth layer: this layer is named the layer of rules which rules are extracted from the entering data to this layer:

$$z_i = \bar{w}_1 f_i = \bar{w}_1(p_i^1 x_1 + q_i^1 x_2 + r_i^1) \quad (4)$$

Fifth layer: this is the last layer and consists of just one node. The only node of this layer's task is to summarize all the entering data to this node:

$$z = \sum_i \bar{w}_1 f_i \quad (5)$$

One of each neural fuzzy model's characteristics is the type of considered membership function for entering data. Membership functions have different types; some of them are Trapezoid, triangle, and Gaussian. One of the best fuzzy systems available is TSK, which weight average of amounts parts then rules of fuzzy. In this study, two layers is used to build fuzzy neural network. Besides the TSK system is used to build the model.

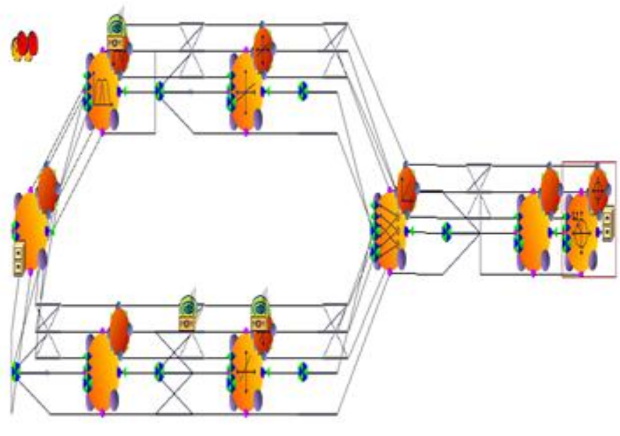

Figure 4. The direction of fuzzy neural network

Snow Equivalent Water

Snow melting supplies a major portion of basic discharge of rivers with snowy basins, in addition to that, snow has an important role in flood behavior of the river due to its depositing and melting nature. In such cases snow equivalent water is counted as the most common variable for hydrological prediction. Snow equivalent water is (22). Normally snow equivalent water (SWE) is not measured directly and is computed by a relation between density and snow depth. Snow equivalent water in a basin based on point by point information could be

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reached by the effect of snow cover height and considering a correction coefficient. By this, we can estimate or predict the catchable water from snow budget of the basin.

Normalization

Considering the vast range of data being used in this study, to normalize the algorithms the relation 6 is used:

$$X_n = \frac{X - X_{Min}}{X_{Max} - X_{Min}} \qquad (6)$$

Which in that:

X: represents the observed raw data

X_n: represents normalized data

X_{max}: represents the maximum observed raw data

X_{min}: represents the minimum observed raw data

The accuracy of the prediction is investigated by measurement and accuracy criteria. The used criteria, in general, in each of examinations are including three fundamental criteria:

A) Correlation coefficient

$$CORR = \frac{\sum_{i=1}^{n}(obs - \overline{obs}) \times (forc - \overline{forc})}{\sqrt{\sum_{i=1}^{n}(obs - \overline{obs})^2 \times \sum_{i=1}^{n}(orc - \overline{forc})^2}} \qquad (7)$$

Which $\overline{obs}$ is the average amount of observed streamflow, $\overline{forc}$ is average amount of predicted streamflow by the network, and n is equal to the number of data in examining stage. The closer the correlation coefficient is to 1, the more accurate are the results and the closer are the observed amounts and the predicted ones (23).

B) Root Mean Square Error

$$\mathrm{RMSE} = \frac{\sqrt{\sum_{i=1}^{n}(obs - forc)^2}}{n} \qquad (8)$$

When the Root Mean Square Error is closer to zero, it shows the closeness of observed amounts and calculated amounts to each other, and also the accuracy of the results in each step.

C) Coefficient of Efficiency

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(obs - forc)^2}{\sum_{i=1}^{n}(obs - \overline{forc})^2} \qquad (9)$$

The more the Coefficient of Efficiency is close to 1, it implies that the observed and calculated amounts are close together and also the accuracy of answers in each steps. In this study, considering the importance of evaluation of runoff, Coefficient of efficiency (R^2) is used.

DISCUSSION

For the fuzzy neural network 2 layers is used. Besides TSK model is used to build the model. In this study 60% of initiating information is used to train, 15% for cross validation, and 25% for test (examination). Fuzzy neural network model with 1000 and 2000 loops and 2 month delay (results conceived from neural network is used) gets tested and trained which the best results is conceived by 2000 loop and it is shown on the graphs below. The results of this study show the capability of the fuzzy neural network in predicting river runoff.

Performance	Run Off
R^2	0.659

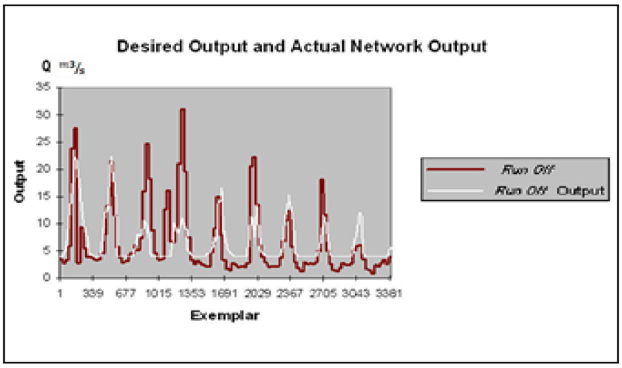
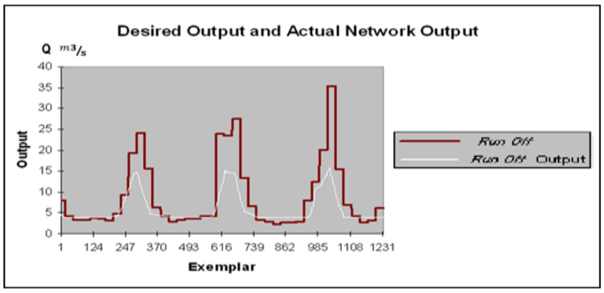


Figure 5. Comparing the predicted average monthly discharge and the observed one in data used to train the model with 2 months delay (modeling runoff with fuzzy neural network with 2 layers and 2000 loop with TSK system)



Performance	Run Off
R^2	0.894

Figure 6. Comparing the predicted average monthly discharge and the observed one in data used to test the model with 2 months delay (modeling runoff with fuzzy neural network with 2 layers and 2000 loop with TSK system).

	Type of Network	Daily Time	Best of revolution	R Train	R Test	The average percentage error in peak of Test (%)	Description
Prediction of monthly discharge	Fuzzy Neural Network	The two-month delay	1000	0.648	0.891	54.3	Fuzzy System TSK
	Fuzzy Neural Network	The two-month delay	2000	0.659	0.894	48.7	Fuzzy System TSK

Table 1. The results of average monthly discharge output from a Jajrud basin using fuzzy neural network

CONCLUSION

1-Modeling by fuzzy neural network with 2 layers and TSK system has desirable results.

2-For modeling by neural network the loop number of 5000 and for fuzzy neural network the loop number of 2000 is the best number for the model.(for basin of Jajrud)

3-Fuzzy neural network has better abilities to predict the start and finish time of peaks in compare to artificial neural network.

4-Artificial neural network and fuzzy neural network are incapable of locating the exact place of peaks.

5-Artificial neural network and fuzzy neural network are incapable of predicting the exact amounts of peaks.

6-Basic discharge of Jajrud basin (in accordance to resulted graphs) is resulted from snow melting.

7-By increasing the number of loops in fuzzy neural network better results could be achieved.

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