Indian Journal of Fundamental and Applied Life Sciences ISSN: 2231– 6345 (Online)
An Open Access, Online International Journal Available at www.cibtech.org/sp.ed/jls/2015/03/jls.htm
2015 Vol. 5 (S3), pp. 692-701/Fereydooni and Sadeghi
Research Article

USE OF HYBRID WAVELET-NEURAL AND WAVELET NEURO-FUZZY MODEL IN SIMULATION OF RATE OF FLOW OF RIVER (STUDY CASE: FAHLIAN RIVER)

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ABSTRACT
Runoff is one of the basic hydrological variables and its forecast (forecast) plays an important role in fields such as optimum utilization of water resource systems, supply needs, reduction of loss of flood, drought, etc. By increasing population and economic activities in the main floodplains and rivers, importance of this issue increases. Determination and forecast of rivers' flow give complete and valuable information to managers and authorities to control and manage resources and supply water needs. In this research with the purpose of simulating runoff at Batoon Station, Falhian River located in Fars Province, by using wavelet theory (identification of signals and separation of error signals) input data information was extracted; then presented as inputs of neural artificial and neuro-fuzzy networks. As compared, in correlation coefficient (R^2) and the root mean square error (RMSE), wavelet neuro-fuzzy model (RMSE=0.0227, R^2 = 0.8945) has been come to better results in comparison with wavelet neural model (RMSE= 0.0090, R^2 = 0.8661).

Keywords: *Wavelet Neuro-Fuzzy, Wavelet Neural, Simulation, Fahlian River, Runoff*

INTRODUCTION
To achieve an appropriate utilization planning from the existing water resources, forecast of water quantity, which means rate of input flow to the dam reservoirs, is a fundamental instrument in optimum management of water resources which can be useful for allocation of water in a useful district appropriately. Thus, by accurate forecasts of flow, in producing hydroelectric (hydropower) systems, seasonal planning for irrigation of farmers, it is resulted to the preservation of favorable flows in dehydration years and more efficient of flood control measure. The necessity for forecast of River's rate of flow in civil works, in order to plan for the use of dam reservoirs, organizing river and flood warning are necessarily felt. Increasing population and economic activities in the main floodplain and rivers, the importance of this issue is increased as well.
Rainfall-runoff is one of the most complicated hydrological processes which is entirely complicated and non-linear. Hydrologists, for many years, are tried to find out how can be transformed rainfall to runoff for forecast of flood. Large number of parameters and lack of sustainability of characteristics of watersheds and models of precipitation, are further complicated this issue. Using statistical, hydraulic and hydrological models have had a long history in discussion on rainfall-runoff forecast. Considering problems and weak points which existed in conceptual and statistical models, a model needs to perform mapping operations with input and output parameters. Some common (regular) techniques, used in modeling hydrological time series, are assumed relation between variables linear and failed in modeling non-linear phenomenon. In the recent two decades, it is focused on the use of extra search methods due to presenting a clear relation between variables. Among these methods, intelligent models such as neural artificial networks, hybrid neural-fuzzy or theory of wavelet can be indicated. Extension of the use of intelligent models as new methods and as powerful and reliable tool for associating complicated data without any previous knowledge from their relation has drawn engineers' attention to various areas including estimation and forecast of river's flow. In recent years, extensive researches have been carried out in modeling and forecast of hydrological bilan (result) components specially rate of flow of rivers by using neural-artificial networks, Neuro-fuzzy inference system and theory of wavelet around the world such as followings:

Kisi (2007), by using four training algorithm including: 1) Conjugate Gradient Algorithm, 2) Cascade Correlation Algorithm, 3) Levenberg-Marquardt Algorithm, 4) Back-propagation Algorithm, was predicted short-term flow with a one-day time horizon at hydrometry station of flow of North Pilet River located in Colorado State of America with neural artificial networks method. The results are shown that Levenberg-Marquardt training algorithm is the most rapid and accurate training algorithm due to time and accuracy, while back-propagation algorithm needs more time and repetition. Later, this research is shown that back propagation training algorithm in comparison with the other three training algorithms have less accuracy in daily forecasts. Nabizadeh *et al.*, (2011) estimated daily intelligent rate of flow by utilizing Adaptive neuro-fuzzy inference system. In this research, three parameters of daily precipitation, temperature, and rate of flow of Lighvan Chay watershed (drainage area) were used for forecast of daily flow of Lighvan River. Evaluation of predicted results by using different criterion including Nash-Sutcliffe criterion, is shown that ANFIS model has high accuracy (C_{NS}= 0.979) and quantitative error (RMSE = 0.041) in forecast and this method can be employed as an efficient and accurate method for the forecast of river flow. Darabi and Fereydooni (2013) were stimulated rate of flow of Ghareaghaj River by using Intelligent ANFIS Neuro-fuzzy model. In this research, using a fuzzy system on basis of adaptive neural networks and considering available data from Ghareaghaj River, network training (training) has been done. For validation, ANFIS model with GAUSS membership function was elected as the best model with the least error by applying a part of data and results of ANFIS model with various membership functions and by using statistical tests such as R2, RMSE, MSE, and SSE. Shafaei (2011) forecasted daily flow of Venyar Station by using wavelet Hybrid and neural network. The results obtained from transform of wavelet – neural network were compared with a results derived from application of neural network selected ANN and as it shown wavelet-neural network method is predicted further days with acceptable correlation in comparison with neural network method. Maroofi *et al.*, (2012) examined simulation of daily flow using neural artificial and neural-wavelet networks (Study case: Barandoozchay River). The results are proposed an appropriate efficiency and high accuracy of neural – wavelet model in comparison with neural artificial network in forecast of river flow.

MATERIALS AND METHODS

Region of Study Case

Fahlian River is located in Mamasani, Fars Province. In accordance with the original source this river is known as Zohreh River.

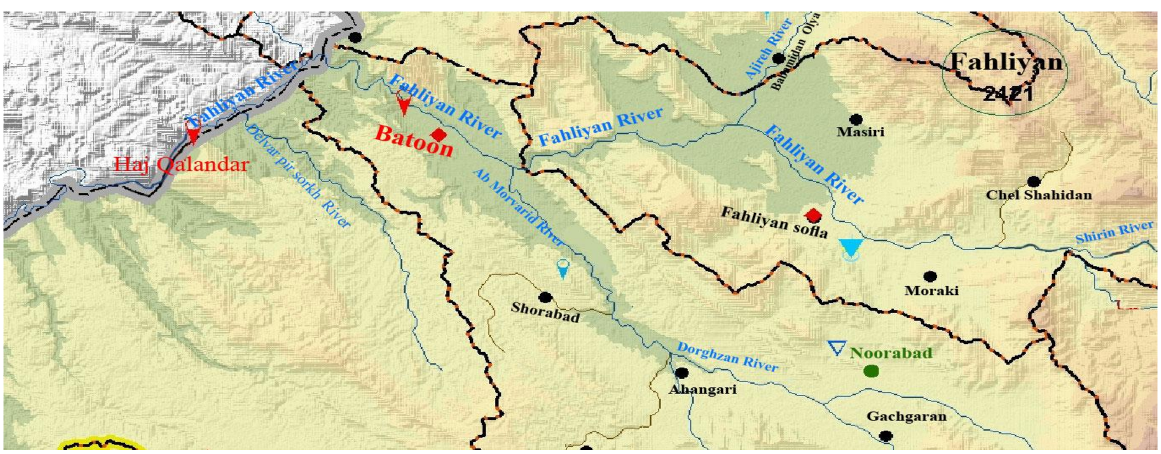

Figure 1: Status of Batoon Station on Fahlian River

At eastwards of watershed, Zohreh River is flown. The flowing surface water of Ardakan and Noorabad cities are gathered and flown into Zohreh River. Length of Fahlian River is 170 km. and its regional watershed is an area of 8700 sq/km. River has permanent water and water regime is rain-snow. At its eastwards, major part of water flow is fed by melting snow and in south-north regions fed by rain. Annual water yield of Fahlian is 155 million M^3 in average. Moment water yield in Kosangian has been measured at 24 M^3/S in average and measuring data have been gathered from hydrometry, ombrometer, evaporimeter stations and temperature of Regional Water Organization of Kazeroon (Studies in west of Fars) during seventeen years.

Neural – Artificial Networks

Neural-artificial network is a system of neural biological networks-based; in other word, inspired from neural biological networks. Neural artificial networks are successfully used in hydrology fields from the early decade of 1990 up to present such as modeling rainfall-runoff, predicting river flow, modeling underground waters, water quality, predicting precipitation, etc.

A) Forward Neural Networks

Neural artificial networks include a series of interconnected neurons; every series of these neurons is called layer. These networks are formed from an input layer, one or several hidden layers and an output layer. Form and connection of neurons in different layers has been made various structures in neural artificial networks. If in a neural network, output of each neuron only connected to the neurons on the next layers, it is called forward neural network. Figure 1 is shown an overview of multi-layer forward neural network.

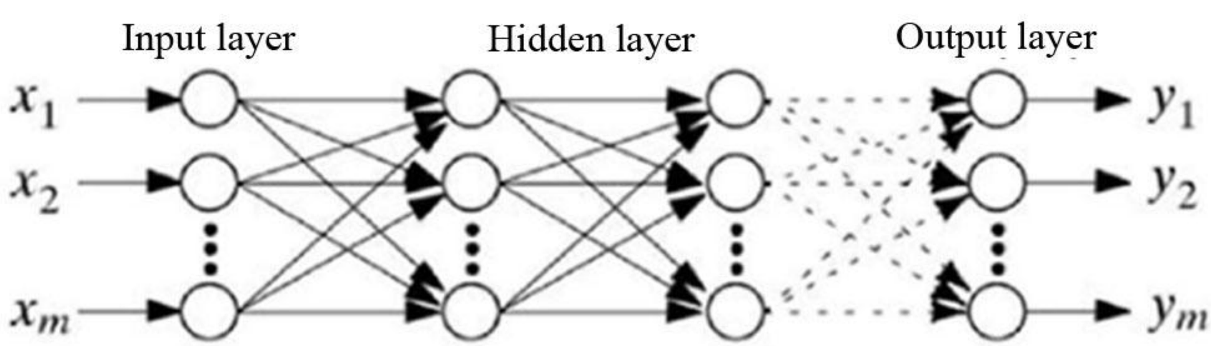

Figure 2: Overview of Multi-layer Forward Neural Network: Kim (2008)

B) Activity Functions

Total of weighted inputs (net input) is transformed to an output value through an activity function. In output layer we can use a linear function, but however, this function is not proposed in hidden layer because the efficiency of the network is decreased and is not able to solve non-linear problems. Whereas most of issues are non-linear in a real world, it is necessary to apply non-linear functions in hidden layers. Sigmoid and hyperbolic tangent linear functions are the most common activity functions (Kamerozamen *et al.*, 2006).

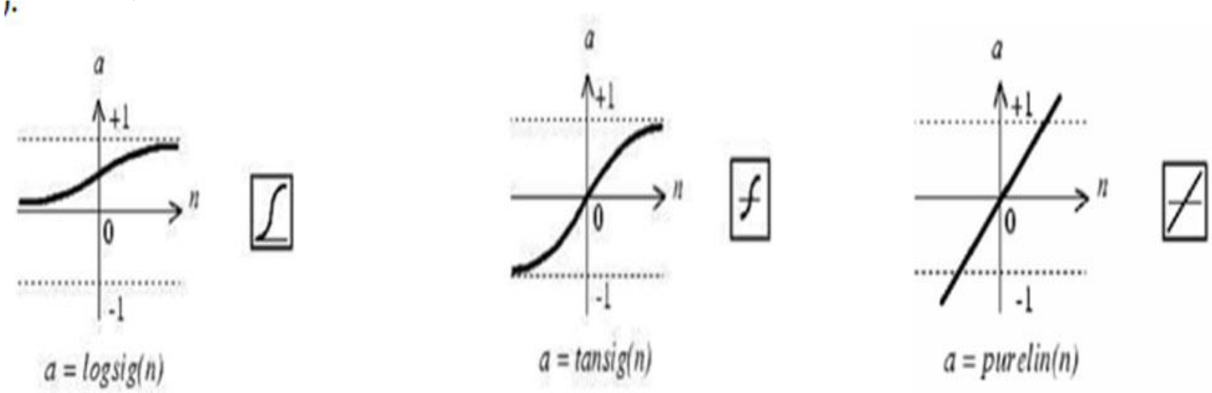

Figure 3: From right to left: *, Hyperbolic tangent driving function, log-sigmoid driving function**

C) Error Back Propagation Training Algorithm

One of the most popular back propagation neural networks is multilayer perceptron (MLP) with error back propagation training algorithm which has been used in modeling and nonlinear process mapping. Figure 3 is presented back propagation training algorithm in three-layer perceptron neural network.

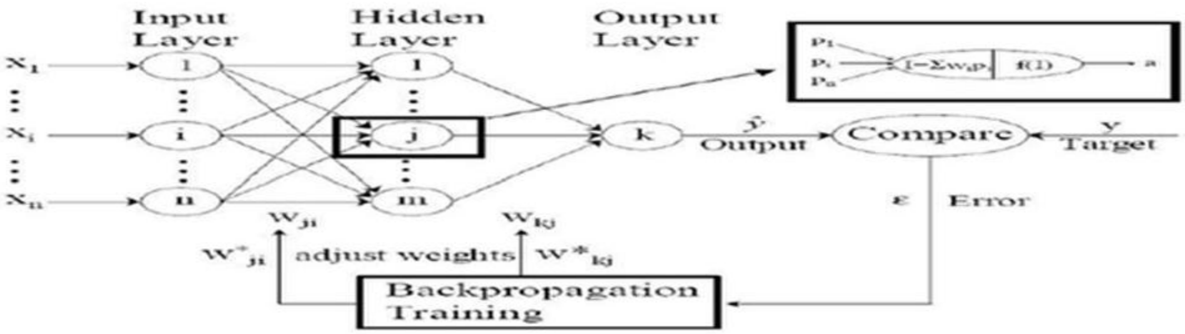

Figure 4: Overview of Back Propagation Training Algorithm in 3-layer Percentron Neural Network: Kim & Valdes

Wavelet Analysis

The word wavelet means ripple. The reason of using the work ripple is for its limitation and small length and the word wave is used for its oscillating nature. Wavelets have three characteristics: finite oscillation (fluctuation), quick return to zero in its domain, zero average (mean). Analysis of wavelet is focused on a small area and is an appropriate instrument for examining non-static and transient phenomena.

Although there are many wavelet functions, selecting an appropriate wavelet function for analysis would be difficult. To select a proper wavelet the following points shall be observed:

1) Approximation of a wavelet function to a reviewing signal

2) Usefulness of wavelet in selection transform (some of wavelets are behaved only by a special transform).

3) Considering properties of wavelets concerning nature and characteristics of reviewing signals.

In this research Haar Wavelet Function was used for analysis of input matrix lines to wavelet-ANNs and Wavelet-ANFIS models.

Two types of wavelet transform are:

1) Continues Wavelet Transform (CWT)

2) Discrete Wavelet Transform (DWT)

Continues Wavelet Transform: Continues Wavelet Transform is an appropriate instrument for the analysis of robust signal. Robust signal is a signal with a series of various frequencies with wide range and many changes and fluctuations. Operation of this function is almost similar to discrete transform and its difference is in the analysis of details in every step of signal analysis in a way that in each step of analysis, not only approximation part of signal is not analyzed, but also details part is separated into two new approximation and details parts. This is caused the extraction of all domain and signaled frequencies and brought out more complete information of signal for its analysis (Sharifi 2013).

Discrete Wavelet Transform: Discussing Discrete Wavelet, due to difficulty in computing c values for each a and b ($-\infty < b < +\infty$, $-\infty < b < +\infty$, $a > 0$), these coefficients shall be estimated in special points to decrease complicated computations. For example, techniques used in this regard, are based on Discrete Wavelet Transform.

In discrete transform, wavelet transform is only performed for a subset of scales and statuses. If scale and status are selected on power-based (dual scale and status), analysis of signal is more rapid and enough accurate. By the said transform, primary data are turned to wavelet and divided into two groups. The first group called approximation, has a low frequency and represents general trend of available data. This group plays an important role in computations. The second group called details, has a high frequency and

low period and represents finite changes in data. In time series there is a signal named "S" which can be divided into two A and D signals.
As you are seen in figure, we can divide S to two A_1 and D_1 signals; A_1 again can be divided into A_2 and D_2, … this can be done as long as D value is zero or close to zero.

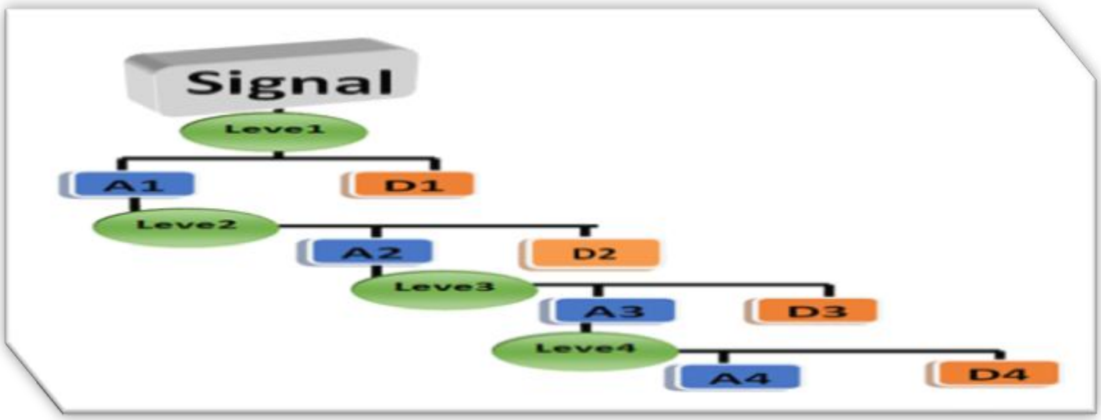

Figure 5: Signal Division

Algorithm and Structure of Adaptive-Network-Based Fuzzy Inference System (ANFIS)
Architecture of ANFIS is consisting of five layers which are explained below in brief:
Layer 1: input nodes
Layer 2: nodes of Laws
Layer 3: mean of nodes
Layer 4: results of nodes
Layer 5: output nodes
In this research, for fuzzy – neural evaluation, MATLAB software, which is known as strong software for complicated and computational analysis, is used. To simplify explanation of these networks, it is assumed that there is a fuzzy system with two inputs of x and y and an output Z and it also assumed that this system includes two rules presented by Takagi-Sugeno method and following equations:
Rule (Law) 1: if x is A_1 and y, is B_1, then: $f_1= p_1x+q_1y+r_1$
Rule 2: if x is A_2 and y is B_2, then: $f_2 = p_2x+q_2y+r_2$
In this status, an inference motor, type three which has been presented in part "a" of this figure, has been used. Equivalent structure of ANFIS has been shown in part "b" of the same figure.

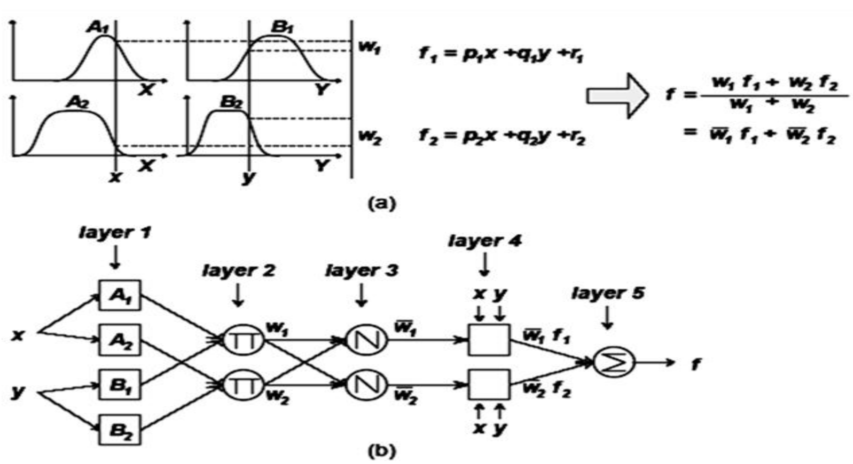

Figure 6: a) Fuzzy (type three) b) Equivalent to its ANFIS (type three)

Functions of each group are similar in each layer. We will present and examine each layer of this network later.
Layer 1:
Each one of existing nodes in this layer is in a form of square with the following function:
$O^1_i = \mu A_i(x)$ (1)
where x is input to node i and A_i is a lingual quantity. $\mu A_i(x)$ might typically be selected in a scope of [0, 1] and bell-shaped that its maximum is in point (1) and is gradually spread up to zero level. General figure of bell-shaped function is as following:

$$\mu A_i(x) = \frac{1}{1+\left[\left(\frac{x-a_i}{a_i}\right)^2\right]^b} \quad (2)$$

Gussian Function is definitely used for this purpose as following:

$$\mu A_i(x) = \exp\left[-\left(\frac{x-c_i}{a_i}\right)^2\right] \quad (3)$$

where c_i and a_i are regulator parameters of a function and as soon as the values of these parameters are changed, its bell-shaped will be transformed in appropriate with these changes.
Layer 2:
Each node in this layer is in a form of a circle detected by π. In nodes of this layer input signals multiplied and applied as output for the next layer. For example:

$$\omega_i = \mu_{A,i}(x) * \mu_B(y), i = 1,2 \quad (4)$$

Output of each node is identified weight of each rule.
Layer 3:
Each node in this layer is in a form of circle which has been represented by N. In this layer, i'n node defined relation of i'n weight of rule to the sum of all rules.

$$\varpi_i = \frac{\omega_i}{\omega_1 + \omega_2}, i = 1,2 \quad (5)$$

To simplify the definition, outputs of this layer are presented as normal weight.
Layer 4:
Each i node in this layer is in a form of square with the following function:

$$O^4_i = \varpi_i f_i = \varpi_i(p_i x + q_i y + r_i) \quad (6)$$

where ω_i is an output of layer 3 and { p_i, q_i, r_i} are regulator parameters. Parameters of this layer are final parameters; they generate final results and send them to the output.
Layer 5:
The only node existing in this layer is in a form of circle and creates final output by using the sum of all input signals; it means:

$$O^5_i = \sum_i \varpi_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \quad (7)$$

Thus, by defining layers of this network, an adaptive network will be examined which is corresponding with type three of fuzzy systems (Takagi-Sugeno).

Neural Network and ANFIS Analysis by using data produced in Wavelet Analysis

Useful data Extracted from wavelet analysis is applied as input data for neural network and ANFIS. It is assumed that by doing so and filtering non-useful signals, besides increasing the speed of neural network analysis and ANFIS, models evaluation criterion and RMSE will developed optimally as well.

Evaluation Indexes

To evaluate performance of estimation models used in this research, correlation coefficient statistical indexes (R^2), root mean square (RMSE) is used as following:

$$R^2 = \left(\frac{\sum_{i=1}^{n} (Q_{i,obs} - \bar{Q}_{obs}).(Q_{i,sim} - \bar{Q}_{sim})}{\sqrt{\sum_{i=1}^{n} (Q_{i,obs} - \bar{Q}_{obs})^2 . \sum_{i=1}^{n} (Q_{i,sim} - \bar{Q}_{sim})^2}} \right)^2 \quad (8)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Q_{i,sim} - Q_{i,obs})^2}{n}} \quad (9)$$

In these equations, $Q_{i,obs}$ is observation value of rate of flow in in time pitch, $Q_{i,sim}$ is computational value of rate of flow at the same time, n is number of time pitches, Q_{obs} and Q_{sim} are respectively mean of observation and computational values.

RESULTS AND DISCUSSION

Considering the objectives of this research, we measure rate of flow after normalization and arrangement of data (From 21 Mar 1996 to 20 Mar. 2014) as input data for neural artificial networks (80% for training and 20% for network test) and results derived from neural artificial networks with existing real results with evaluation scales, correlation coefficient and root mean square error and at the next step, we use different patterns for simulation of rate of flow by using neuro-fuzzy networks. And among different patterns for simulation of rate of flow, we select the best pattern (by using evaluation scales) and finally compare the better model of rate of flow with better model of neural artificial networks and present the best simulation.

Input Patterns used in this Research

1st input pattern Q (e_{t-1}), Q (q_{t-1}): Using rate of flow and evaporation with a time delay as an input
2nd input pattern Q (p_{t-1}), Q (q_{t-1}): Using rate of flow and rainfall with a time delay as an input
3rd input pattern Q (p_{t-1}), Q (q_{t-1}): Using rate of flow and temperature with a time delay as an input
4th input pattern Q (q_{t-1}): Using rate of flow with a time delay as an input
5th input pattern Q (p_{t-1}), Q (q_{t-1}): Using evaporation and temperature with a time delay as an input
6th input pattern Q (p_{t-1}), Q (q_{t-1}): Using temperature and rainfall with a time delay as an input

Table 1: Simulation by Wavelet Neural Method (Results derived from simulation based on the second input pattern)

MLP	Layer	Neuron			Function	R-training	R-validation	R-test	R-all	R-Corrcoef	R-rmse
		Input	Middle	Output							
1	2	4		1	TANSIG	0.8062	0.6310	0.7538	0.7213	0.8534	0.0066
2	2	1		1	TANSIG	0.7476	0.7580	0.6823	0.6845	0.7911	0.0060
3	2	3		1	TANSIG	0.8646	0.6862	0.7255	0.8477	0.8158	0.0113
4	2	6		1	TANSIG	0.9144	0.5398	0.9101	0.8771	0.8661	0.0090
5	2	8		1	TANSIG	0.9228	0.9139	0.7681	0.8539	0.7591	0.0068
6	2	10		1	TANSIG	0.7747	0.7104	0.6816	0.7636	0.7455	0.0169
7	2	14		1	TANSIG	0.9437	0.7764	0.9055	0.8798	0.8467	0.0083
8	2	17		1	TANSIG	0.9134	0.6810	0.7212	0.8426	0.4216	0.0039
9	2	20		1	TANSIG	0.8986	0.7551	0.3627	0.7475	0.8107	0.0124
10	2	2		1	LOGSIG	0.7734	0.9152	0.8326	0.7846	0.8652	0.0145

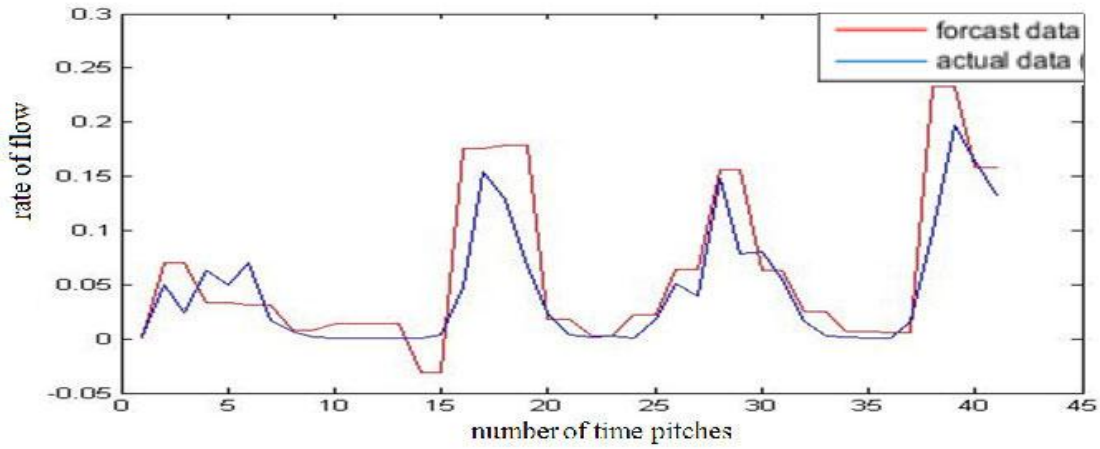

Figure 7: Comparison of results, the best simulation model and real values for the 2nd input pattern

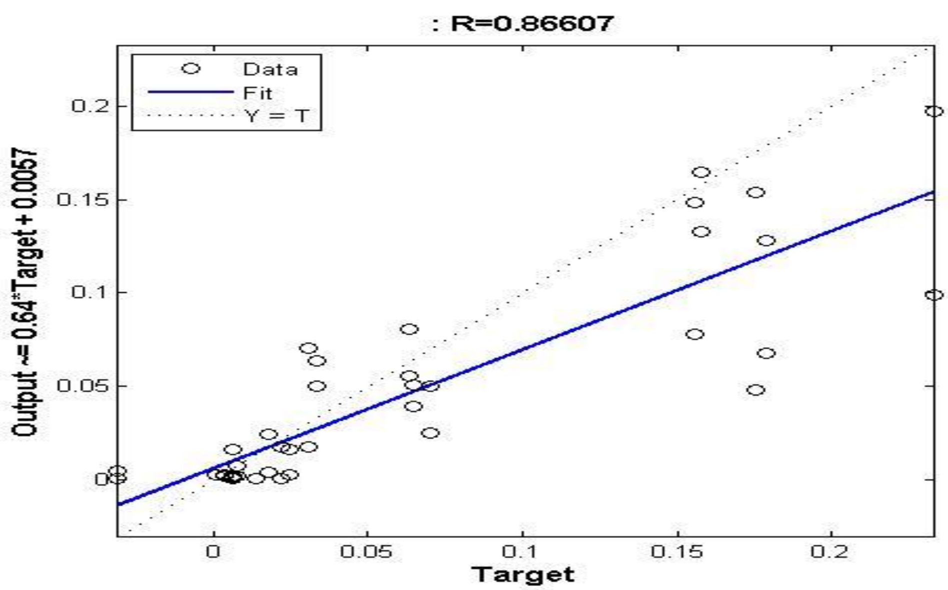

Figure 8: Simulation Target Function Diagram against real results for the 2nd pattern

Table 2: Simulation by Wavelet-Neuro-Fuzzy Method (Results derived from simulation by Wavelet-Neuro-fuzzy method according to the 1st input pattern)

ANFIS	Function	No. of membership functions	Repetition	R-corrcoef	RMSE
1	GAUSSMF	3 3 3 3	30	0.8799	0.0225
2	GAUSSMF	2 2 2 2	30	0.8698	0.0238
3	GAUSSMF	2 2 3 3	30	0.8405	0.0257
4	GAUSSMF	3 2 3 3	30	0.8713	0.0242
5	GAUSSMF	4 4 3 4	30	0.8765	0.0242
6	GAUSSMF	5 2 4 2	30	0.8777	0.0240
7	GAUSSMF	3 5 3 2	30	0.8844	0.0229
8	GAUSSMF	5 4 3 3	30	0.8945	0.0227
9	GAUSSMF	3 4 3 5	30	0.8887	0.0230
10	GAUSSMF	2 3 5 4	30	0.8721	0.0239

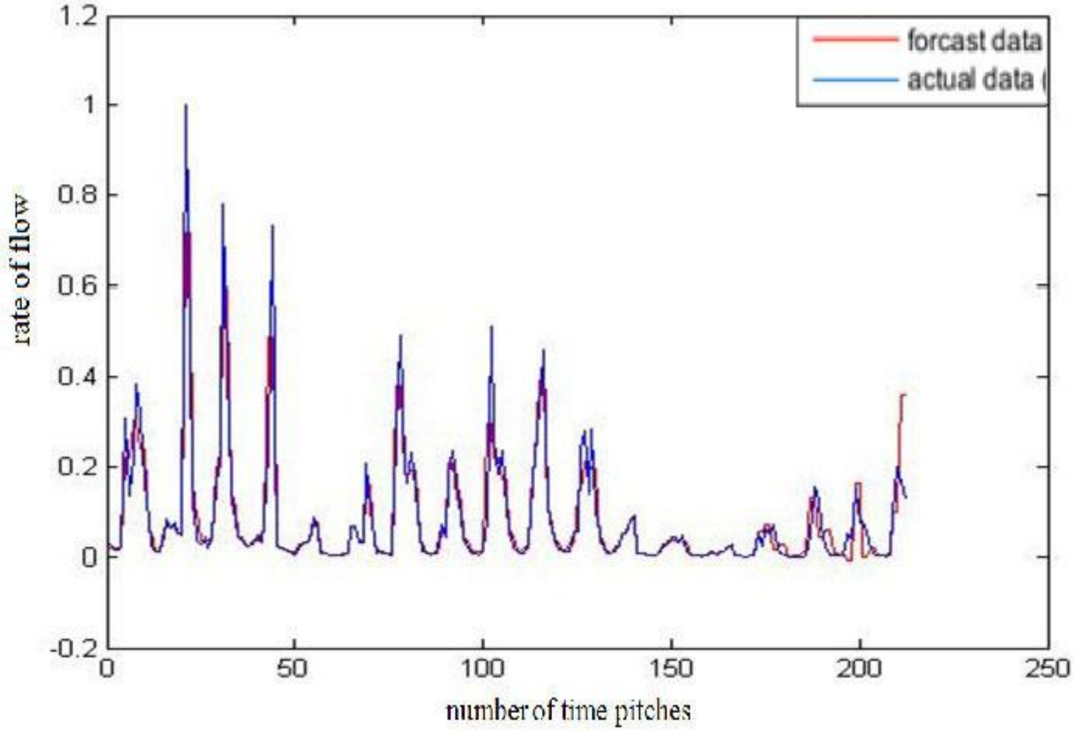

Figure 9: Comparison of results of the best simulation model and real values for the 1st input pattern

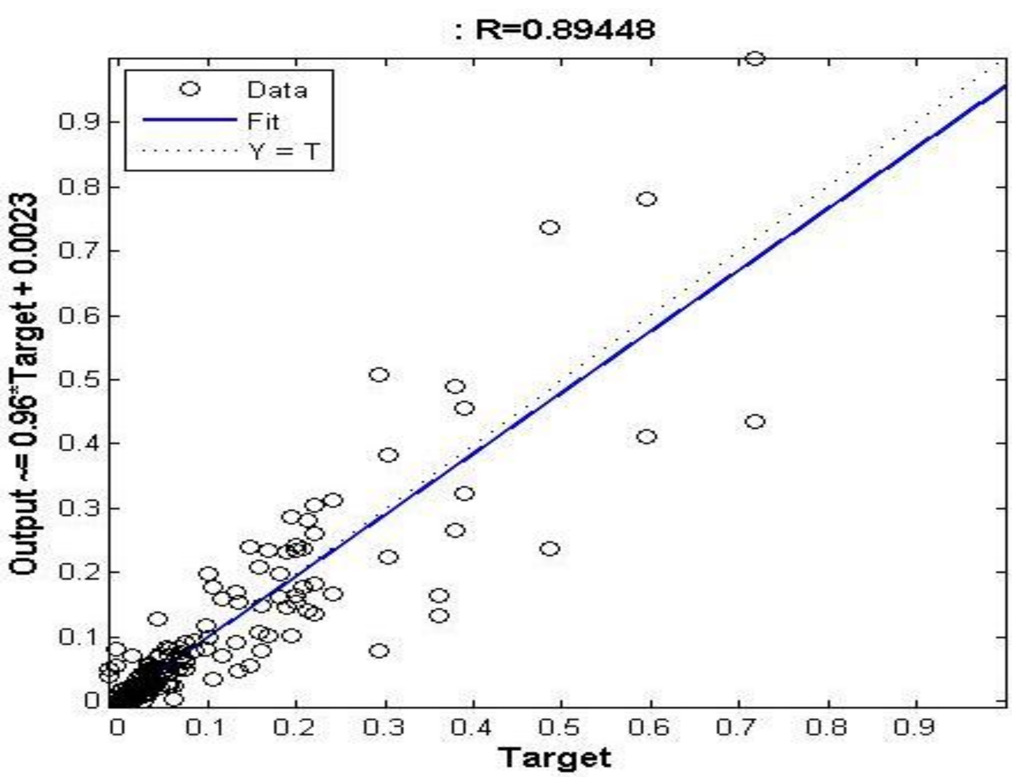

Figure 10: Simulation Target Function Diagram against real results for the 1st pattern

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Table 3: Evaluation of Neural Artificial Models and Neuro-fuzzy Networks (Comparison of Wavelet Neural and Wavelet Neuro-fuzzy Models)

	Wavelet-ANNs		Wavelet-ANFIS		
		RMSE		**RMSE**	**Better model**
Rate of flow	0.8661	0.0090	0.8945	0.0227	Wavelet-ANFIS

Conclusion

Using more inputs caused that in wavelet neural, stimulated model has had better results in all cases. Therefore, it is obvious that by having more different data, results can be approached to the main results. By comparing simulation of rate of flow by using wavelet neural and wavelet neuro-fuzzy we can make a conclusion that wavelet-neuro-fuzzy model has better and more acceptable results than a wavelet-neural model. Finally, we can select wavelet neuro-fuzzy model for simulation of rate of flow as a better model.

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