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# Hybrid Models Performance Assessment to Predict Flow of Gamasyab River

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## Abstract

Awareness of the level of river flow and its fluctuations at different times is one of the significant factor to achieve sustainable development for water resource issues. Therefore, the present study two hybrid models, Wavelet- Adaptive Neural Fuzzy Interference System (WANFIS) and Wavelet- Artificial Neural Network (WANN) are used for flow prediction of Gamasyab River (Nahavand, Hamedan, Iran). For this purpose, original time series using wavelet theory decomposed to multi time sub-signals, then these decomposed sub-signals as in input data are used in Adaptive Neural Fuzzy Interference System (ANFIS) and Artificial Neural Network (ANN) for monthly flow prediction. The obtained result shows that WANFIS model has better performance than WANN and can be used for short term and long term flow prediction. One of the weaknesses of fuzzy models is the model estimation error in minimum and maximum points. Which this problem can solve by using hybrid models of wavelet - fuzzy inference system.Also based on results of hybrid model of wavelet- network, it can be concluded that to achieve accurate estimation of the number of different intermediate layers are examined and using one intermediate layer in all conditions is not enough to achieve the best results. Generally, hybrid model of wavelet - Adaptive Neural Fuzzy Interference System have better performance in estimation of the extent points and it is better method for prediction of Gamasyab River flow.

**Keywords**: Hybrid model, Wavelet - Artificial Neural Network, Wavelet - Adaptive Neural Fuzzy Inference System, Gamasyab River, Monthly flow prediction.

## 1. Introduction

River flow prediction due to it importance in the design of hydraulic structures, withdrawals, planning and operation of reservoirs, erosion control and sedimentation in rivers from long time has been the interest of engineers. In other way, in according to the limitation of extractable fresh water resources, the more accurately prediction of flow and its changes in river length is basic planning and management of surface water resources. Therefor the experts are always tried for correct estimation of the river's flow and modification of the available methods for estimation of the flow. Until now, many patterns and equations used to predict river flows, but many of these methods due to a lack of understanding of the phenomenon, accurate results have not been obtained. In recent years with the development of neural networks in hydrology, using wavelet transform as a new method of signal analysis and time series has been considered.

Monthly modeling and predicting of river flow was used with application Wavelet neural network method and Monthly flow data from two stations (Gerdelli Station on Canakdere River and Isakoy Station on Goksudere River), in the Eastern Black Sea, Turkey.

The neuro-wavelet model improved by two methods combining, discrete wavelet transform and multi-layer perceptron (MLP) to predict monthly flow, compared with a multilayer perceptron models, multi-linear regression (MLR) and auto-correlated model (AR).

The comparison of the results revealed that the suggested model could increase the forecast accuracy and perform better than MLP, MLR and AR models (Kisi 2008). Rainfall - runoff modeling using a combination of wavelet - neural network for the Ligvan Chai (Tabriz, Iran) catchment has been studied. The results showed that the proposed model can be used to predict long-term and short-term precipitation(Nourani et al. 2009). Approach improvement based in the precipitation-runoff modeling using a combination of artificial neural network-Wavelet is performed, which shows that the model which precipitation and discharge data, as an input entered, outperformed than the model which just precipitation was entered as an input (Chua and Wong 2010). A method based on trans-form discrete wavelet and artificial neural networks to predict applied flow in seasonal river in semi-arid watershed in Cyprus were presented. Wavelet coefficients as an input Levenberg Marquardt (LM) artificial neural network models was used to predict the flow. The relative performance of the wavelet-neural network (WANN) and artificial neural network (ANN) models was compared to lead times of 1 and 3 days flow forecasting for two different rivers. In both cases, neural network-Wavelet model for flow predictions, was more accurate than artificial neural network. The results indicate that wavelet-neural network models are a promising new method of short-term flow forecasting in non-perennial rivers in semi-arid watersheds such as those found in Cyprus (Adamowski and Sun 2010). Two hybrid methods of artificial intelligence for modeling rainfall - runoff for two watersheds are presented in Azerbaijan, Iran. The first model was SARIMAX-ANN (artificial neural network- Seasonal Auto Regressive Integrated Moving Average with exogenous), and the second model was wavelet - neural network system - Adaptive Fuzzy (ANFIS). The results showed that although the proposed model can predict both short-term and long-term runoff according to seasonal effects, but the second model is relatively better. Because in this proposed model due to use of multiple scales of time-series, rainfall - runoff data has been applied as an input layer of adaptive neural network - fuzzy system(Nourani et al. 2011).

A new combination of neural networks for modeling precipitation - runoff in the basin Aq Chay Iran Presented. The model was combined of data processing methods, genetic algorithms and Levenberg Marquardt algorithm for training the neural network input. Results showed that this method has more accurately predict runoff from artificial neural networks and Adaptive Neural-Fuzzy Inference System (Asadi et al. 2013). Feature extraction method based on the Self-Organizing Map (SOM) and the combined wavelet- neural network method, was combined and presented for modeling the precipitation–runoff. Two-stage procedure to model the precipitation–runoff process of the Delaney Creek and Payne Creek Basins, Florida, USA was presented. The two-stage procedure includes data preprocessing and model building. The results proved that the proposed model leads to better outcome especially in term of determination coefficient for detecting peak points (DC peak)(Nourani and Parhizkar. 2013). Precipitation-runoff model using a combination of wavelet- neural network model is presented. According to the fitted coefficients ($R^2$) and root Mean Squared Error concluded that the hybrid model of wavelet- neural network is more efficient than the neural network and regression(Komasi 2007).

According to bad performance of the models which is used to forecast river's flow, using a combination of these models is tried to predict river flows. In this study two hybrid models are used for predicting the river flow Gamasyab (Nahavand, Hamedan, Iran) river. Two hybrid wavelet - adaptive neural fuzzy inference system and wavelet - neural network models are used and the results were analyzed to obtain the correct pattern of river's flow.

## 2. Material and Methods

### 2.1 Study Area

Verayneh Rain gauge station in the Nahavand city, is in geographical position 48 degrees 24 minutes 15 seconds East longitude and 34 degrees, 04 minutes and 32 seconds North latitude. The station was established in 1969 and has a height of 1795 meters above sea level with 521 mm long-term average annual precipitation. In this study, precipitation an flow, in 43 years period (1969-2012) were collected and obtained from Vrayneh station (Table 1). To check the homogeneity of the data, Vesej station (as an auxiliary station) and the double mass curve used which result confirmed homogeneity of our data.

Table 1 - Some climatic variables of Vrayneh station.

| climatic variable | Average | Maximum | Minimum | Standard deviation | Variance | Coefficient of Variation |
|---|---|---|---|---|---|---|
| Precipitation(mm) | 43.8 | 266 | 0.0 | 48.8 | 2385.4 | 1.1 |
| Flow($\frac{m^3}{s}$) | 3.8 | 12.93 | 1.0 | 2.3 | 5.1 | 0.6 |

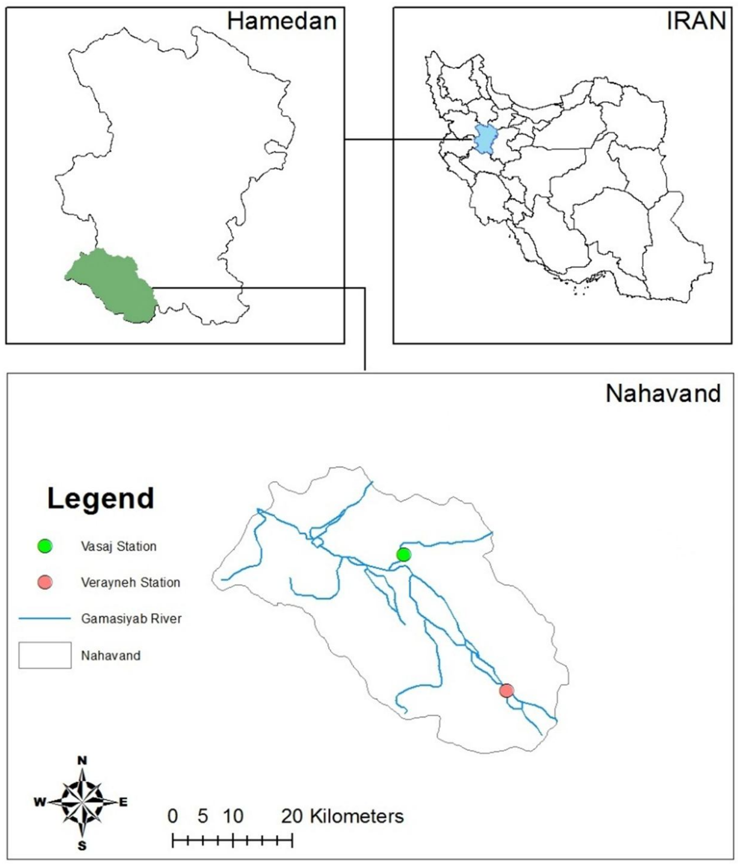



Fig.1: Location of the Nahavand, Hamedan, Iran.

Because importing raw data reduces the accuracy and speed of networks. Data normalization method is used which prevents the excessive shrinkage of the weights and avoid early saturation of the neurons. By Normalization method each number convert to a number between 0 and 1 to be applicable to the neural network function(Riad et al. 2004). The following equation was used for this work.

$$y = 0.5 + (0.5 \times (\frac{x-\bar{x}}{x_{max}-x_{min}})) \quad (1)$$

$$y = (\frac{x-x_{min}}{x_{max}-x_{min}}) \quad (2)$$

$$y = y = 0.05 + (0.95 \times (\frac{x-x_{min}}{x_{max}-x_{min}})) \quad (3)$$

Table 2. Comparison of the results of the application of normalization relations

| normalization relations | $R^2$ Train | $R^2$ Simulate | RMSE Train | RMSE Simulate |
|---|---|---|---|---|
| 1 | 0.96 | 0.76 | 0.0283 | 0.0658 |
| 2 | 0.96 | 0.74 | 0.0556 | 0.1319 |
| 3 | 0.96 | 0.74 | 0.0558 | 0.1111 |

According to table 2, using No 1 Normalized formula has lower simulation error, and has more simulation coefficient of determination, so we used formula 1 to normalization in this study. Then 75% of the data was used for training data, 25% for simulation data is considered.

### 2.2 Wavelet Transform

Wavelet theory is a method of mathematical science which the basic idea is derived from Fourier Theory that presented in $19^{th}$ century but it usage period is about one decade. The current concept of wavelet theory presented by Morlet and a team in Marcel Research Center for Theoretical Physics under the supervision of Alex Grossmann in France.

Wavelet analysis methods developed by Meyer et al. Wavelet transform is efficient mathematical transformation in the field of signal processing. Wavelets are the mathematical functions which present the scale-time shape of time series and their functions to time series analysis which include variables and non-constants. Wavelet analysis offers long-term time intervals for information which has low frequency and shorter periods for information which has higher frequency. Wavelet analysis is able to show various aspects of the different data, breakpoints and discontinuities that other signal analysis methods can’t show them.

Wavelet function is a function that has two important features of fluctuations and being in the short-term. $\psi(x)$ is the wavelet function if and only if its Fourier transform $\psi(x)$ satisfied the following condition(Mallat 1998).

$$\int_{-\infty}^{+\infty} \frac{|\psi(x)|}{|\omega|^2} d\omega < +\infty \tag{4}$$

This condition is known as an admissibility condition for the wavelet. The above equation can be considered equivalent to equation 5.

$$\psi(0) = \int_{-\infty}^{+\infty} \psi(x)\, dx = 0 \tag{5}$$

This function feature with zero average is not so limiter and many functions can be named wavelet in its base. $\psi(x)$ is the mother wavelet function that used functions in analysis, by two math practices called translation and scale during the analyzed signal, changed in the size and place.

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}} \psi\left(\frac{x-b}{a}\right) \tag{6}$$

Finally wavelet coefficient could be calculable in each signal of (b) and each value of scale of (a) by equation 7 (Mallat 1998).

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} \psi\left(\frac{t-b}{a}\right) f(t) dt \tag{7}$$

Which in equation 7, a does scale task and b does transform task. For different values of a and b, value of T obtained. Whenever T has highest positive value, the highest adjustment occurred. There is no adjustment for T equal to zero and for negative value of T, there is much difference. Wavelet functions are various.

### 2.3 Wavelet- Artificial Neural Network (WANN)

When the original time series signals was decomposed by wavelet transform and these sub-signals as inputs insert into the neural network, hybrid model of wavelet neural network is formed. Figure 2 shows the schematic view of the wavelet - neural network model with two inputs which used in this research. As you see p is precipitation and q is flow.

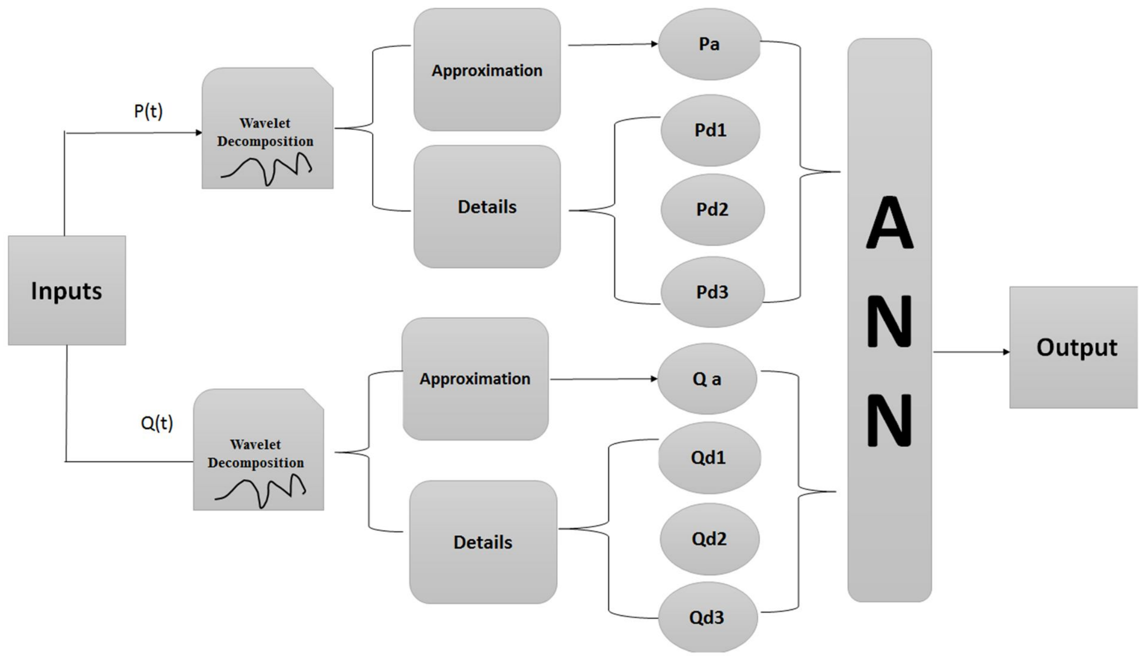



Fig.2: Schematic diagram of the WANN model.

**2.4 Adaptive Neuro-Fuzzy Inference System (ANFIS)**

ANFIS System of learning algorithms, neural network and fuzzy logic in order to design a nonlinear mapping between the input and output uses. Also due to capability in combined of linguistic power a fuzzy systems with a numerical strength of a neural network, the modeling of processes such as hydrology reservoir management and estimating suspended sediment load is very powerful(Nayak et al. 2004, Kişi 2009). Adaptive Neuro-Fuzzy based on changes in the amount and range of functions belonging to different iterations to achieve the appropriate network based on the minimum error functions. Takagi Sugeno inference method is used in the ANFIS model. The number and type of inputs, the membership functions shape are affected Neuro-Fuzzy model (Jang et al. 1997).

**2.5 Wavelet-Adaptive Neuro Fuzzy Inference System (WANFIS)**

Figure 3 shows the schematic diagram of wavelet-ANFIS model. First time series of precipitation and flow by wavelet transform decomposed and then inserted into the ANFIS model to form hybrid model of wavelet-ANFIS.

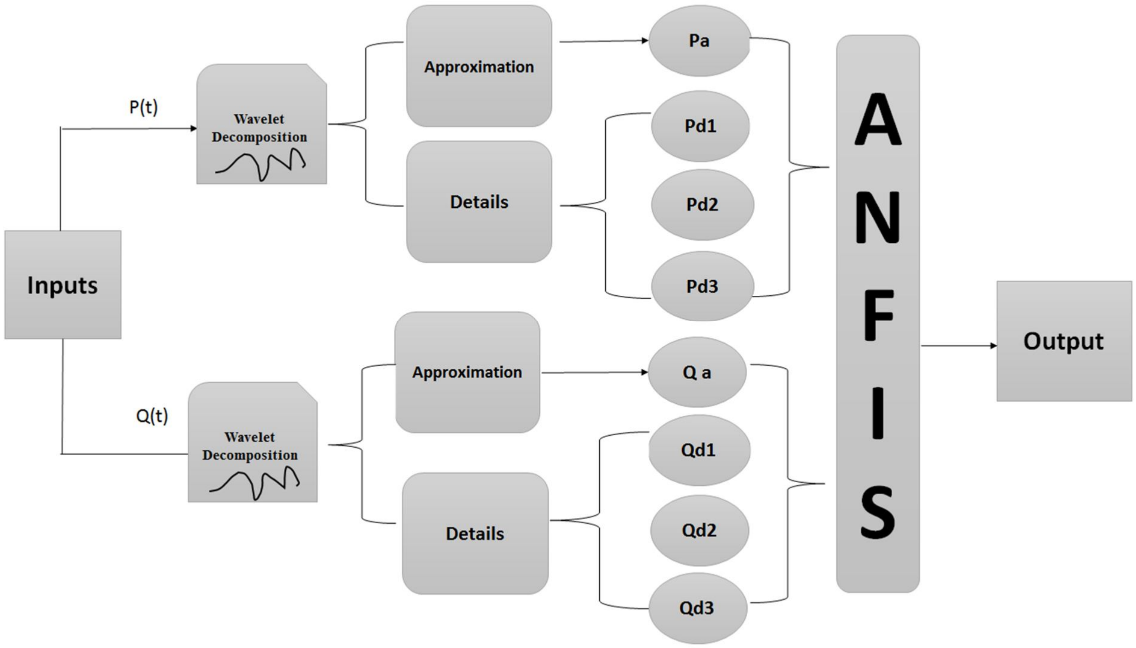



Fig.3: Schematic diagram of the WANFIS model.

### 3. Model evaluation criteria

The aim of model evaluation is to obtain the error rate of model according to the input data to train and it is based on various criteria of error calculation. In this study, the following criteria were used to evaluate the model:

1-Root mean square error or RMSE:

$$RMSE = \sqrt{\frac{\sum(Q_{obs}-Q_{pre})^2}{n}} \tag{8}$$

Where $Q_{obs}$ and $Q_{pre}$ are the observed and simulated Flow rates, respectively and n is the total number of observations.

2-Coefficient of determination or $R^2$:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Q_{obs}-Q_{pre})^2}{\sum_{i=1}^{N}(Q_{pre}-\bar{Q})^2} \tag{9}$$

Where $\bar{Q}$ the average observed flow is. Shows the degree of co-linearity between the observed and simulated time series and has a range of 0.0–1.0, with higher values indicating a higher degree of co-linearity.

3- Nash–Sutcliffe Coefficient of Efficiency or CE:

$$CE = 1 - \frac{\sum(Q_{obs}-Qp_{Pre})^2}{\sum(Q_{obs}-\bar{Q})^2} \tag{10}$$

Where $\bar{Q}$ the average is observed Flow. This measure which was introduced by Nash and Sutcliffe(1970) has a range between 1 (perfect fit) and $-\infty$. Zero or negative CE values indicate that the mean value of the observed time series could be a better predictor than the model(Talei et al. 2013)

4- Another index that is used in this research is the Akaike Information Criterion (AIC).

$$AIC = m \times \ln(RMSE) + 2(Npar) \tag{11}$$

Which based on this index each model that has lower AIC is suitable. In equation 11, m is the number of input data, Npar number of trained parameters(Nourani and Komasi 2013).

## 4. Results and Discussion

The hybrid model wavelet-neural network, first signal of input parameters using wavelet transform decomposed then sub-signals are used as inputs to the neural network. To do this, according to equation 12 as a basic recommendation, the degree of decomposition was found(Nourani, Komasi and Mano 2009)

$$L=Int[\log(N)] \tag{12}$$

In this equation, L is the proposed decomposition degree and N is the number of time series. In this study, N=516, L=2 were determined and to be more precise, 1 to 3 decomposition degree were examined. In this study, three wavelet functions were used. In Figure 4 the wavelet functions used in this study are shown(Komasi 2007). The number of neurons in the first layer depends on wavelet decomposition. The number of input neurons to the network is m (j +1) which J is the wavelet decomposition degree and m is the number of input parameters. For example, for j=1, in according to input parameters which in this study is equal to 2 (precipitation, flow), the number of input neurons is equal to 4. The output layer is also has a single neuron. The number of middle layer neurons is variable and is obtained by trial and error that in this study, the number of neurons in the middle layer varied from 3 to 20 and analyzed. Feed Forward Network is used in this study. In this case, using different training rules and different stimulus functions for different neurons of middle layers, modeling was done. For better training of the network and obtain better results, used various training rules of MATLAB software. Also, all of the transfer functions have been examined. Different structures with the obtained results are shown in Table 3.

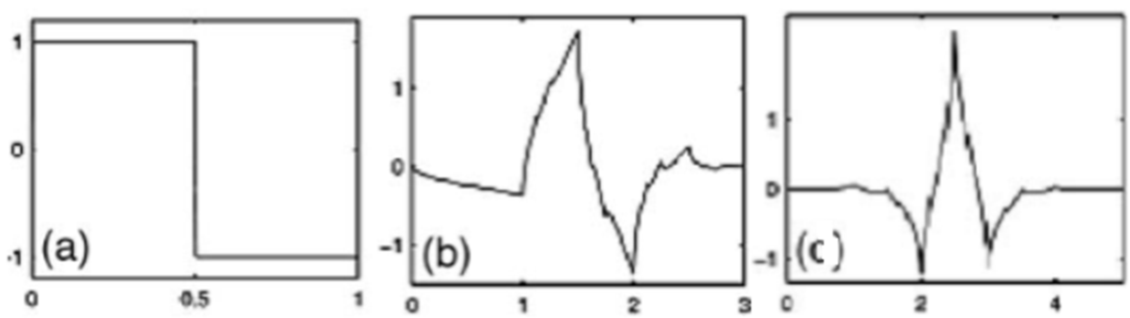



Fig. 4: a Harr wavelet. b db2 wavelet. c Coif1 wavelet.

Table 5. Result of WANN model with different mother wavelets and decomposition levels.

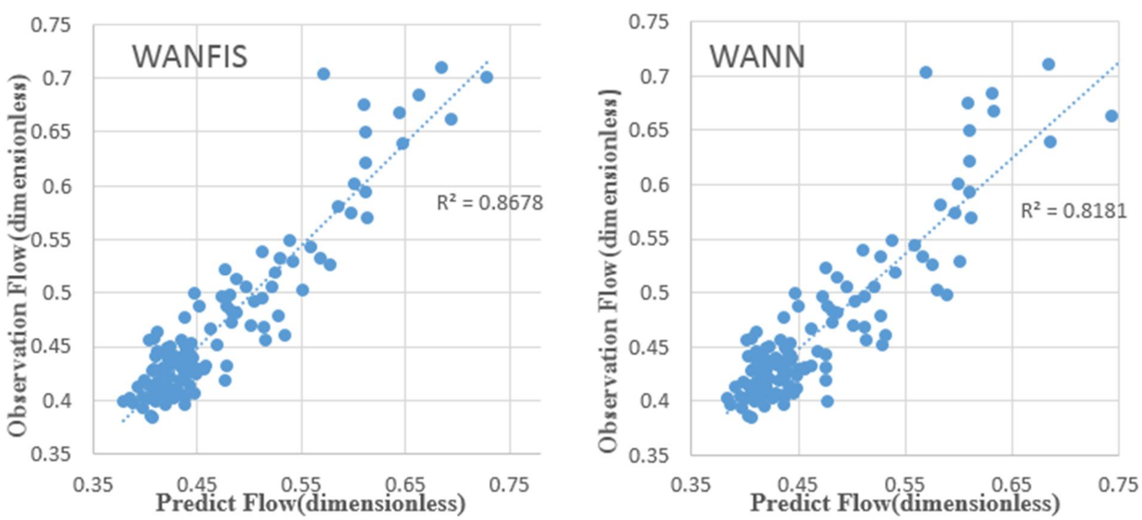
| Structure | function of transfer | Function of training | Mother Wavelet Type | Decomposition level | structure Network | $R^2$ Train | $R^2$ Simulate | RMSE Train | RMSE Simulate |
|---|---|---|---|---|---|---|---|---|---|
| 1 | tansig | Levenberg-Marquardt | Haar | 1 | 4-4-1 | 0.72 | 0.56 | 0.0516 | 0.0511 |
| 2 | tansig | Levenberg-Marquardt | Haar | 2 | 6-5-1 | 0.85 | 0.68 | 0.0277 | 0.0435 |
| 3 | tansig | Levenberg-Marquardt | Haar | 3 | 8-4-1 | 0.88 | 0.67 | 0.0341 | 0.0444 |
| 4 | tansig | Levenberg-Marquardt | Coif1 | 1 | 4-5-1 | 0.80 | 0.76 | 0.0433 | 0.0378 |
| 5 | poslin | Levenberg-Marquardt | Coif1 | 2 | 6-5-1 | 0.83 | 0.81 | 0.0399 | 0.0331 |
| 6 | logsig | Levenberg-Marquardt | Coif1 | 3 | 8-4-4-1 | 0.90 | 0.82 | 0.0312 | 0.0339 |
| 7 | satlins | Bayesian Regularization | Db2 | 1 | 4-6-1 | 0.80 | 0.67 | 0.0442 | 0.0444 |
| 8 | tansig | Levenberg-Marquardt | Db2 | 2 | 6-10-1 | 0.92 | 0.76 | 0.0283 | 0.0388 |
| 9 | satlins | BFGS Quasi-Newton | Db2 | 3 | 8-4-1 | 0.85 | 0.73 | 0.0378 | 0.0426 |

In the hybrid model of WANFIS to provide best condition to compare with the hybrid model of WANN prepared, used 3 types of wavelet function with 3 decomposition degree same as first method. The inputs are also considered same as first method to all conditions adhered for comparison. For better training of the hybrid model of WANFIS, also all the membership functions were examined. Different structures with the results are shown in Table 4.

Table 6. Result and Structures different of WANFIS model.

| structure | Mother Wavelet Type | Decomposition level | membership function | Epoch | $R^2$ Train | $R^2$ Simulate | RMSE Train | RMSE Simulate |
|---|---|---|---|---|---|---|---|---|
| 1 | Haar | 1 | Gbellmf | 20 | 0.87 | 0.78 | 0.0347 | 0.0450 |
| 2 | Haar | 2 | Dsigmf | 30 | 0.98 | 0.79 | 0.0140 | 0.0427 |
| 3 | Haar | 3 | Gbellmf | 25 | 0.90 | 0.80 | 0.0280 | 0.0396 |
| 4 | Coif1 | 1 | Primf | 25 | 0.84 | 0.77 | 0.0392 | 0.0488 |
| 5 | Coif1 | 2 | Trapmf | 15 | 0.95 | 0.85 | 0.0220 | 0.0294 |
| 6 | Coif1 | 3 | Trapmf | 20 | 0.93 | 0.87 | 0.0252 | 0.0278 |
| 7 | Db2 | 1 | Trapmf | 15 | 0.86 | 0.79 | 0.0367 | 0.0428 |
| 8 | Db2 | 2 | Trapmf | 15 | 0.98 | 0.70 | 0.0143 | 0.0628 |
| 9 | Db2 | 3 | Primf | 30 | 0.93 | 0.69 | 0.0250 | 0.1160 |

Finally, best structures in both hybrid models were compared which with the results in Table 5 are presented. Also the observed and predicted value of flow by both hybrid model are shown in Figure 5. According to predicted value and figure 5 it is concluded that the hybrid model of WANFIS in the estimation of the minimum and maximum value is better than hybrid model of WANFIS in the estimation of the minimum and maximum value is better than hybrid model of WANN. Generally, the hybrid model of WANFIS was better than hybrid model of WANN and has good ability to predicting the extent points.




a b

Fig.5: Comparison of the models used in this research,a: WANN model,b:WANFIS model.

Table 5. Comparison of different precipitation modeling

| Model Type | Stage Train | | | | Stage Simulate | | | |
|---|---|---|---|---|---|---|---|---|
| | RMSE | $R^2$ | CE | AIC | RMSE | $R^2$ | CE | AIC |
| WANN | 0.0312 | 0.90 | 0.90 | 765.06 | 0.0339 | 0.82 | 0.80 | 249.23 |
| WANFIS | 0.0252 | 0.93 | 0.93 | 764.63 | 0.0278 | 0.87 | 0.87 | 248.83 |

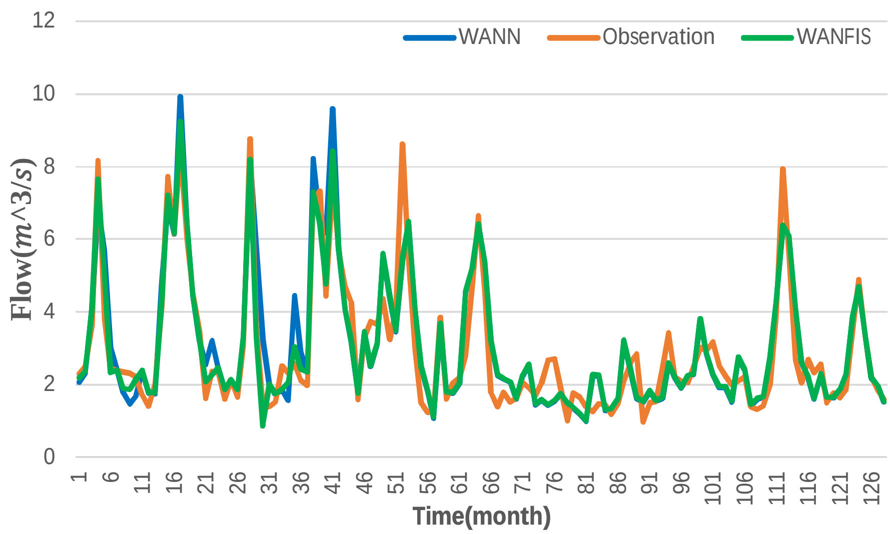



Fig.6: Comparison of the models used in this research

By comparison of figure 5 this result obtained that, although the performance of the both models is similar but WANFIS model is better to prediction of extent point. Whatever the CE index or Nash-Sutcliffe coefficient is greater that is better model. According to the results which given in Table 5, the WANFIS model has almost better performance. This is the same for the determination coefficient. Since AIC and RMSE indices is lesser, the model better. Therefor WANFIS model is better. Also the results of this study is entirely consistent with Nourani et al (2011)based on best performance of hybrid model of WANFIS than WANN.

## 5. Conclusions

In this study two hybrid models of WANN and WANFIS interference system are used for Gamasyab River's flow prediction using data of Vrayneh station. Results show that signal decomposition by wavelet incredibly increases Correlation Between estimated and observed data more than other models and prediction of flow signal occurs with more accuracy.

As various structures examined in this study it can resulted that the hybrid model WANFIS has more accuracy compared to WANN model. Also between wavelet functions, coif1 compared to other functions (i.e. Haar and Db2) has better performance. One of the weaknesses of fuzzy models is the model estimation error in minimum and maximum points. Which this problem can solve by using hybrid models of WANFIS inference system.

Generally, hybrid model of WANFIS have better performance in estimation of the extent points and it is better method for prediction of Gamasyab river flow. Also based on results of hybrid model of WANN, it can be concluded that to achieve accurate estimation of the number of different intermediate layers are examined and using one intermediate layer in all conditions is not enough to achieve the best results. Also by examination of membership functions which used in this study, it is observed that "Trapmf" Membership function have better performance than the rest of the membership functions and known as the best function in the most structures of WANFIS model.

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