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Research Article

DISCHARGE PREDICTION OF DASHTBAL HYDROMETRIC STATION OF KOR RIVER WITH COMBINING ARTIFICIAL NEURAL NETWORK AND WAVELET THEORY AND COMPARING THE RESULTS WITH ANFIS MODEL

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ABSTRACT
Over the past years, necessary predictions for managing surface water resources have significant importance especially in hot and dry areas which suffer from raining shortage. In this regard the amount of Discharge passed through is considered as the main factors for predicting the amount of surface water due to they are the main power supply of water behind dams. In this research, powerful model was created through combining Artificial Neural Networks with Wavelet Theory used for predicting Discharge of Dashtbal Station located on Kor River. Comparing the results obtained from this hybrid model with ANFIS, showed that Neural- Wavelet Model performs slightly better than ANFIS model if its structure parameters can be adjusted sufficiently.

Keywords: *Neural Networks, Wavelet Theory, ANFIS, Discharge Prediction, Dashtbal Station, Kor River*

INTRODUCTION
Rivers are accounted for the main part of flow surface water. Discharge of rivers is varied during year and these variations depend on different factors including: temperature, humidity, evaporation and raining of the mentioned region. Discharge of river is described as the amount of water passed (liter/ time "second") through transverse cross section of river.

Among new methods for predicting natural phenomena in Hydrology Science, Artificial Neural Networks, Wavelet analysis and ANFIS can be pointed.

ANFIS Model and Wavelet Theory used for predicting developmentally were structured so that can solve the weaknesses of neural networks namely getting trapped in local minimum. Among several researches used ANFIS for predicting, we can point out to Flournsho and his colleagues (Folorunsho and Iguisi, 2012); Zounematand Teshnehlab, 2007).

The improvement of results of final model was verified comparing with other prediction models. Hybrid Wavelet- Neural Model applied as the main model in this study as well as ANFIS Model. This instrument breaks the fundamental time series into subseries with different frequencies and in different levels. Wavelets are included in mathematical functions used for analyzing continuous signal or discrete signal into its frequency elements.Among several techniques for using wavelet theory and combining it with other models we can focused on studies of (Partal and Kisi, 2007); Wang and Lee, 1998); Nourani *et al.*, 2011).

In this study, hybrid wavelet – neural model was applied for predicting monthly average Discharge of Kor River, statistical information of this river was obtained from Dashtbal Hydrometrics Station. For comparison, hybrid ANFIS Model was also implemented and examined upon related data collection.

MATERIALS AND METHODS

Region and Data Collection of Study

The study region location is the river basin dam of Dourodzan, located in Fars Province with the area of 9650 Km. Dashtbal Hyrometric Station Water Output established on Kor river enters to this dam. The station is located geographically at 30.02 North Degree and 52.961 East Degree. Figure 1 shows geographical location of the region.

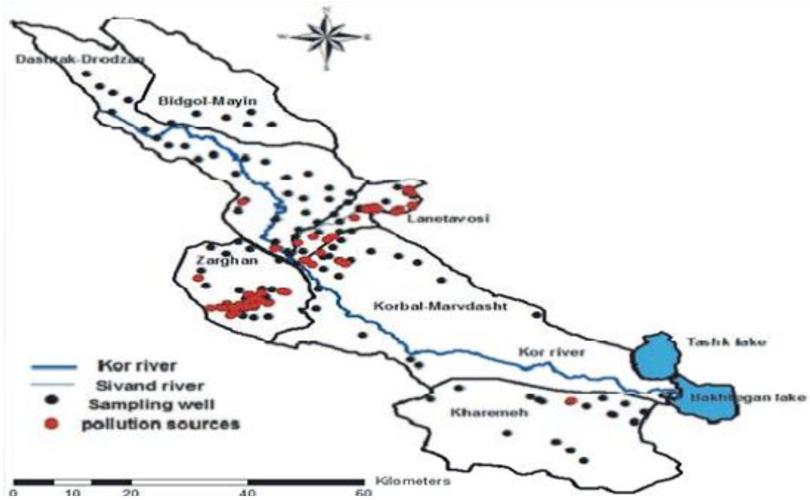

Figure 1: Range of consideration area

The used data collection related to month average statistical was measured at Dashtbal Station. This collection includes four types of various data as raining, temperature, evaporation and Discharge of Koru river as month average. These data was measured from the beginning of Oct., 1998-99 to the end of Sep. 2008-09,so each feature of data included 132 amount during 11 years of month average statistical.

Wavelet Analysis

Wavelet Decomposition: Often Hydrologic Processes are considered as variable problems dependon times called time series. Already, Fourier Transforms (FT) and inverse Fourier Transforms were used for analysis of these types of series.

These transforms were able to transform time domain into frequency domain and conversely. But these transforms require very complex calculations and increase the time order of the algorithm. Also understanding these problems and complex mathematical processes were difficult. Another main problem of FT was that it couldn't able to show at which times each frequency happens. For example, consider two different time series each one has same frequencies, but happens at different times. The shape of each signal would be different, but the FT of both would be same.

Because the FT can just tell us what frequencies are in the signal and can't provide the information about the times of happening of them. Wavelet analysis is considered as effective method in ground of Signals and non-stationary time series over last decade (Li *et al.*, 1997; Wang *et al.*, 2002).

In an overall view, the purpose of applying a mathematical transform on a signal such as wavelet decomposition is to obtain additional information that is not accessible in the primary raw signal. Time domain representation oaf signal is not the best way to describe its features.

In many cases, useful information is available within the frequency content of the signal which is known as the so-called frequency spectrum. Wavelet Analysis is capable of showing the analysis of one signal in three dimensions of Frequency, Time and Amplitude.

So, it can define the time of each frequency, unlike Fourier Transforms. Continuous Wavelet Transformation is described as follows:

$$\mathrm{CWT}_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{+\infty} x(t).\psi\left(\frac{t-\tau}{s}\right) dt \qquad (1)$$

Where τ,s are scale and transform parameters respectively. Signal decomposes into two sub signals namely details and approximation in each level. In the following level sub signal of approximation is decomposed into two sub signals. This process continues recursively to specified depth.

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It can be seen that output coefficients of Low-pass filter follow the primary form of signal, these coefficients are called approximation. Also output coefficients of high-pass filter include the details of high frequencies of the signal and these are called details.

Used Wavelet Functions: Applied wavelet functions of this study includes: (haar, 1910), Daubechies 4 (Daubechies, 1992) and Gaussian wavelets. Figure 2 shows the figures of three wavelets.

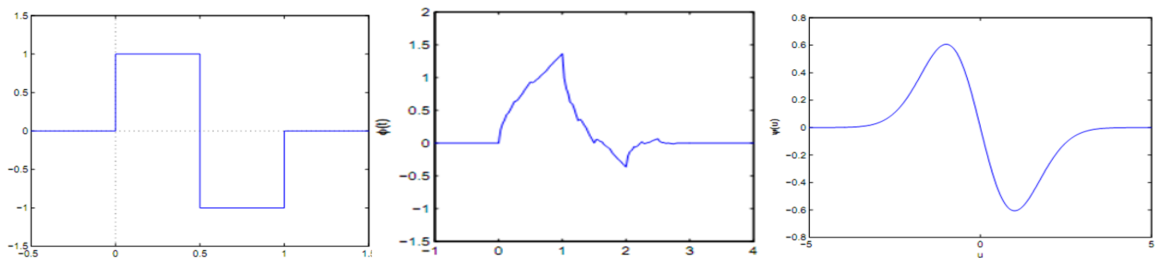

Figure 2: Wavelet functions, from the left Haar, Daubechies 4 and Gaussian waveletes respectively

Hybrid Neural-Wavelet Network Model

The structure of wavelet-neural network is very similar to a multi-layer neural network. Like a feed-forward network, it commonly takes some inputs in the input layer, has a hidden layer and its output layer is one or multi linear summer.

The applied method used in this study to creation a hybrid wavelet-neural model, includes two separated steps which output of first step is equal to input of second step.

At the first step, the signals related to problem is decomposed, analyzed and its proper coefficients are chosen through the wavelet analysis and built-in tools of MATLAB. At the second stage, calculated coefficients are injected to input layer of a perception neural network. In addition, observed output of each sample is obtained through two steps firstly; wavelet coefficients of discharge signal related to next month of current input record was obtained and is placed as output of neural network. Providing values of both input and the output neurons of the neural network corresponding to each sample, it can be applied the propagation training algorithm learning phase of the neural network. As mentioned before, data collection has four features including: discharge, temperature, evaporation and raining. Their statistics has been used by monthly average. Before any implementation, each one of four features became normalized in [0 1] range and then transformed into the signal of time series.

Fig. 3 shows two normalized time series during 132 months for temperature and discharge features. Then, each time series separately decomposed into four levels as a signal within time domain. Each decomposed wavelet, fitted on a function so coefficients of each wavelet obtained. Finally, selected wavelet coefficients assigned for any feature as an input in input layer of the perception neural network. Training of the network performed by 75% of the data, and the trained network was examined with 25% of remained data.

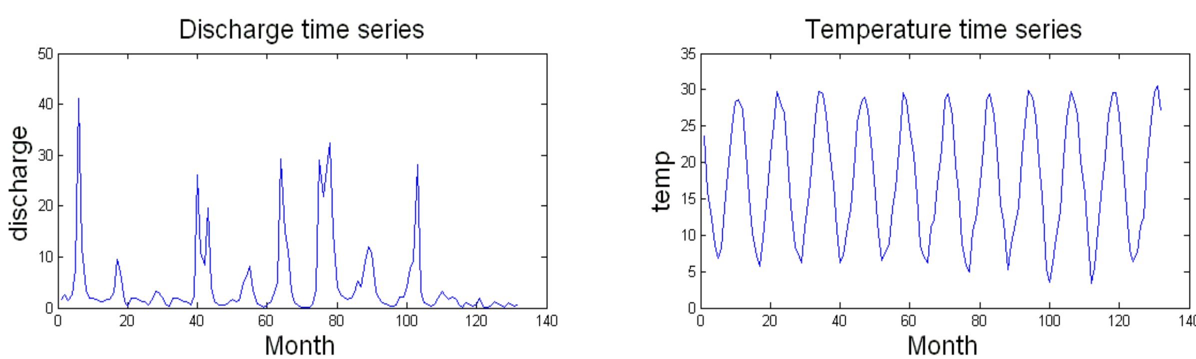

Figure 3: Time series of the discharge and temperature

RESULTS AND DISCUSSION

The reason for selecting the four levels of decomposition of signals is that the decomposed signals of fourth and third levels are very similar to each other, so the sub-signals at the higher levels of decomposition couldn't provide further information. In the second step of implementation of the hybrid model (perception neural network), the output expected was considered as the next month discharge, i.e. (t+1). Providing four average features of present month, it is expected that output of Discharge related to next month can be predicted. At the first step, several models were obtained by changing three types of wavelet function, number of neurons of hidden layer of neural network from 5 to 20 by step 5 , and Losing activation function in this layer. Also, after finding superior neuron of hidden layer, due to more exploration two neurons less and also more than superior neuron was investigated.Any model was investigated based on three Evaluation criteria: Mean Squared Error (MSE), Mean of Relative Error (MRE) and Coefficient of Determination (R^2).

Results in form of Table

Table (1) shows the best results of each of Hear, Daubechies 4, and Gussianwavelet functions over the different neurons. It was not possible to show all of decomposed levels in one table because of multiplicity of various cases and here just showed the best case of any wavelet function.

It should be mention that the results of table 1 related to each of wavelet functions is on sigmoid function (Losing).Regarding to this table; Hear wavelet at the second level and five neuron at the hidden layer of neural network have gained the best result with coefficient of determination equal to 0.918. Haar is known as the first discovered wavelet and due to its simplicity, discontinuity and non derivative features less favors to use.

Table 1: Best results of hybrid neural-wavelet model on Haar, Daubechies and Gaussian wavelet

Gaussian Third Decomposed Level					**Daubechies Third Decomposed Level**					**Haar Second Decomposed Level**					
21	**20**	19	15	10	20	**16**	15	14	10	15	10	6	**5**	4	**#Hidden Neurons**
0.059	**0.058**	0.060	0.060	0.063	0.069	**0.062**	0.068	0.071	0.071	0.097	0.089	0.09	**0.089**	0.094	MSE
0.035	**0.033**	0.036	0.037	0.039	0.044	**0.039**	0.041	0.045	0.047	0.071	0.063	0.066	**0.061**	0.068	MRE
0.946	**0.948**	0.943	0.941	0.933	0.931	**0.936**	0.931	0.930	0.925	0.909	0.916	0.916	**0.918**	0.903	R^2

Daubechies 4 wavelet has 4 coefficients so it is more complex and stronger respect to Harr. This wavelet can properly extract and use many specifications and hidden information of the signals.

Regarding to table 1, Daubechies 4 has gained the best result with coefficient of determination equal to 0.936,while it applies 16 neuron at hidden layer of neural network. It shows that this wavelet is able to effectively utilize more number of neurons than Harr wavelet.

Inaddition to coefficient of determination criteria, the other two criteria of MSE and MREhave minimum value with this same number of neuron and in this regard, coordinated with coefficient of determination. By comparing the best results of both Daubechies 4 and the Gaussian wavelets, it is determined that the operation of Gaussian wavelet is better. Like Daubechies 4, Gaussian wavelet has gained the best values at third level of decomposition.

While the used number of effective neuron in Gaussian wavelet equals to 20 and it shows that Gaussian Wavelet provides more information in comparison to Daubechies 4 for the input layer of Percpetron neural Network.

Gaussian Wavelet has coefficient of determination equal to 0,948 and also error has gained minimum value in comparison to two other wavelet functions.Final results shows that the quality of outputs depend on inputs of neural network in first layer and in fact inputs of neural network are the same as outputs of wavelet analysis model.

Comparing the Results Of Hybrid Neural-Wavelet Model With ANFIS And Percpetron Neural Network

Hybrid Adaptive Neuro-Fuzzy Inference System (ANFIS) and Neural Networks are chosen to make comparison which was related to hybrid wavelet – neural model. The results of ANFIS created over built-in Genfis1 Model including parameter of membership functions. Gaussian and triangular membership functions are the best and most common used among all membership functions in ANFIS model.

Table 2 shows the results of Applying ANFIS with Gaussian and triangle membership functions with 3, 4 and 5 number of them in their domain.

Table 2: ANFIS and Neural Network results

		Gaussian			**Triangular**	**Membership Functions**
5	**4**	3	5	4	3	**#mf's in ANFIS**
0.935	**0.937**	0.933	0.933	0.924	0.919	R2
20	15	11	10	**9**	5	**#Hidden Neurons**
0.859	0.865	0.870	0.868	**0.871**	0.763	R2

As shown in Table 2, Gaussian function gives the best result for ANFIS model. The best coefficient of determination related to hybrid wavelet- neural model equals to .948. While the best value that ANFIS has obtained equals to .937. It can be said that providing Gaussian wavelet function and enough effective number of hidden neurons in wavelet- neural model, it performs slightly better than ANFIS and neural network. Of course, it should be noted that result of ANFIS is better than many other case results of wavelet- neural model. As the final result, hybrid wavelet – neural model is considered better than ANFIS and neural network Model if proper parameters be selected.

Conclusion

In this essay, strong hybrid model was used as name Wavelet- Neural Model to predict the monthly average Discharge (Discharge) obtained from 11 year statistics of Dashtbal Hydrometric Station located over Kor River. This model included several parameters such as type of wavelet function, type of activation function and number of neurons of hidden layer in neural network.

Different models of hybrid model were made through the permutation of these parameters. Best model was selected based on the maximum coefficient of determination criteria. The best model was related to Gaussian wavelet with losing activation function while 20 neurons of hidden layer were applied. It obtained coefficient of determination equal to .948 in third level of decomposition. Daubechies 4 was slightly weaker than Gaussian wavelet. Also, Haar wavelet was the weakest wavelet function with more difference.

Comparing the results showed that whatever the effective neurons in hidden layer be more, the higher prediction power of the hybrid model is presented. Moreover, by implementing the Hybrid ANFIS Model and Neural Network and applying them over consideration data collection, the results according to coefficient of determination criteria were obtained. By comparing three models, it is proved that the hybrid Wavelet –Neural model would perform better than ANFIS and Neural Network Models, if the proper parameters be selected.

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