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Comparison between ANN Models and Conventional Model for Flow Discharge

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A B S T R A C T

Accurate flow discharge prediction is very important in planning, designing, operating and maintenance of water resources structures. Various models have been developed so far to identify the relation between discharge and stage. In this study, artificial intelligent approach and conventional flow discharge rating curve models are considered for predicting flow discharge (FD) in a natural river. Discharge and stage data obtained from Ahar Chai River in northwest Iran. The accuracy of the ANN models is compared with conventional model. The determination coefficient (DC), coefficient of correlation (R2) and mean normalize error (MNE) statistics are used for evaluating the accuracy of the models. Based on the comparison results, the ANN models are found to be superior alternative to the conventional model.

1. Introduction

A sufficient water supply is a concern for planners and managers of water resource systems. As presently experienced in many other countries, the condition of water resources in Iran has come to a stage where integrated action is needed to reduce over-consumption, losses, and the increasing threat of drought. Moreover, the demand on water resources has been rapidly increasing as the nation implements its development program to meet the increasing needs for irrigation, safe drinking water and industrial water. In connection to the rational water utilization program in Iran, one of the most important needs is an accurate forecasting of water supply and demand. The quality of the stage–discharge relationship or rating curve determines the accuracy of the computed discharge data [1]. Due to the large number of obscure parameters involved in this phenomenon, the theoretical governing equations may not be of much advantage in gaining knowledge of the overall process. Studies have been conducted to reduce the complexities of the problem in terms of developing practical techniques that do not require much algorithm and theory. In fact, the unique one-to-one relation between stage and discharge exists only in the ideal case of steady uniform flow [2]. The stage–discharge relationship is typically established as a single valued relationship using statistical regression analysis of stage and discharge measurements. This is developed as the best

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fit curve through the observed stage– discharge measurements. Artificial intelligence methods can be better alternatives to a curve approximation approaches. ANNs have been successfully used to directly map nonlinear complex relations and applied to different problems in water resources engineering. A significant advantage of ANN is that one need not have a well-defined process for algorithmically converting inputs to output. The ANN adapts itself to reproduce the desired output when presented with training sample input. In the past, ANN has been applied on rating curve development [3,4,5]. Tawfik et al. (1997) introduced an approach based on multilayerartificial neural network for modeling stage–discharge relationship. The data set used in this study was taken from Orang satation on the Ahar Chai River (see Figure 1). The Ahar Chai River is located in Ahar watershed in Iran. Ahar watershed with a drainage area 2426.5 km2 is located between 46º 21' and 47º 31'E longitude, and 37º18'and 38º44'N latitude. It drains a rugged area between the Kasabe Mountain and the Ghara Soo River. The Ahar Chai River flows to the Ghara Soo Riverin east of watershed.

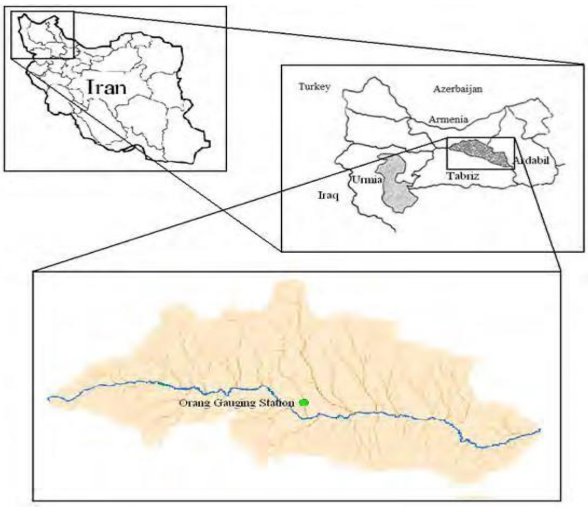


Fig.1. Ahar Chai watershed

2.Materials and Methods

2.1. FFBP Neural Networks

The feed forward neural network (FFNN) has one or more hidden layers. ANNs are massively parallel systems consist many processing elements connected by links of weights. Of the many ANN paradigms, the feed forward back-propagation network (FFBP) is by far the most popular [6]. The network is composed of layers of parallel processing elements, called neurons, with each layer being fully connected to the proceeding layer by interconnection weights. Initial estimated weight values are progressively corrected during a training process (at each iteration) that compares predicted outputs with known outputs, and back-propagates any errors to determine the appropriate weight adjustments which is necessary to minimize the errors. The detailed theoretical information about FFNN can be found in [6]. The methodology used here for adjusting the weights of FFNN model is Levenberg–Marquardt due to that this technique is more powerful than the conventional gradient descent techniques [7]. Figure 2 shows a schematic diagram of feed forward neural network architecture.

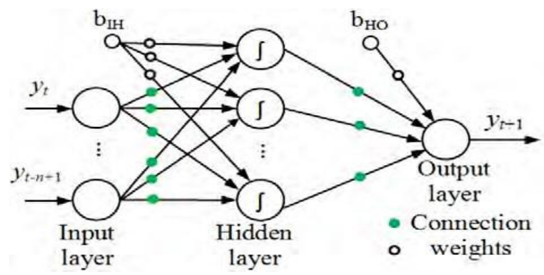


Fig 2. Topology of feed forward network.

2.2. RBF Neural Networks

The radial basis function (RBF) neural network is a multi-input, single-output forward network system consisting of an input layer, a hidden layer, and an output layer, as illustrated in Figure 3. The RBF network consists of two layers whose output nodes form a linear combination of the basis functions. The basis function in the hidden layer produces a significant nonzero response to the input only when it falls within a small localized region of the input space. It is assumed that, given N n-dimension different points $\{xi \in Rn$,i=0,1,2,..,N and N real numbers, $yi \in R$,i=0,1,2,..,N, a nonlinear function f(x) satisfying f(xi)=yi , i=1,2,…,N is called an RBF when it depends only on the radial distance r = ||x - t||, where t refers to the centre of point x.

The RBF approach chooses f from a linear space of dimension N, depending on the data points $\{x_i \in R^n, i = 0,1,2,..,N\}$. The basis of this space is chosen to be the set of functions

$$\left\{ h\left(\left\| x - t \right\|\right), (i = 0,1,2,..,N) \right\} \qquad (1)$$

Where " , " is the Euclidean norm on Rn. Therefore, the solution of the above-mentioned interpolation problem has the following form:

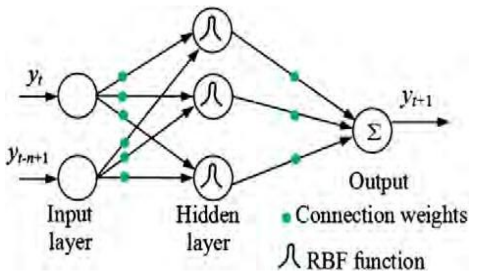


Fig 3. Topology of RBF neural network

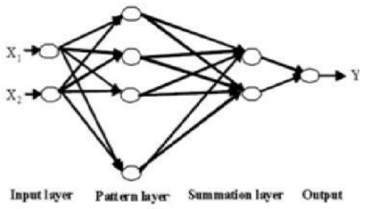


Fig 4. Schematic diagram of GRNN architecture**.**

$$f(x) = \sum_{i=1}^{N} c_i h\left(\left\| x_j - x_i \right\|\right), \ (j = 0,1,2,..,N) \qquad (2)$$

where coefficients ci can be obtained by imposing the interpolation conditions f (xi)=yi, i=1,2,…,N on the above equation. Thus, the following solution can be derived:

$$f(x) = \sum_{i=1}^{N} c_i h\left(\left\| x_j - x_i \right\|\right), \ (j = 0,1,2,..,N) \qquad (3)$$

By defining the vectors y, c and the symmetric matrix H as (y)j=yj, (c)j=cj, (H)ij=h(||xj - xi||), the coefficients ci can be obtained from c = H-1 y.

2.3. GRNN Neural Networks

General regression neural network (GRNN) can be treated as a normalized radial basic function network in which there is a hidden unit centered at every training case. By definition, the regression of a dependent variable Y on an independent X estimates the most probable value for Y, given X and a training set. The regression method will produce the estimated value of Y with a minimized root mean square error. GRNN isa method for estimating the joint probability density function of X and Y, given only training set. Because the probability density function is derived from the data with no preconceptions about its form, the system is perfectly general. The success of the GRNN depends on the selection of the appropriate smoothing factors (α) [8]. Figure 4 shows a schematic diagram of generalized regression neural network architecture.

2.4. Flow discharge rating curve

Flow discharge rating curve expresses the flow discharge, Q, at a cross-section from the river through its stage, H, as below.

$$Q_i = aH_i^b \qquad (4)$$

Where a and b are the coefficients that provide the best relationship between stage and the flow discharge. The flow discharge rating curve was fitted to the calibration data and the following equation was obtained:

$$Q = aH^b \qquad (5)$$

These parameters are generally obtained by least squares method. For a given set of Q and H data, only one solution point (a and b) values are obtained. In this case, a and b coefficients are accepted as constant through all process.

2.5. Performance criteria

Table 1-List of performance measures

	Expression
Coefficient of correlation (R^2)	$R^2 = \left[\frac{\sum_{i=1}^{n}(Q_i^o - \bar{Q}^o)(Q_i^p - \bar{Q}^p)}{\sqrt{\sum_{i=1}^{n}(Q_i^o - \bar{Q}^o)}\sqrt{\sum_{i=1}^{n}(Q_i^p - \bar{Q}^p)}} \right]$
Mean normalized error (MNE)	$MNE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left\|Q_i^o - Q_i^p\right\|}{Q_i^o} \times 100$
Determination Coefficient (DC)	$DC = 1 - \frac{\sum_{i=1}^{n}(Q_i^o - Q_i^p)^2}{\sum_{i=1}^{n}(Q_i^o - \bar{Q}^o)^2}$

Table 2. Performance evaluation criteria for Rating Curve

Evaluation parameters	MNE	DC	R^2
Rating Curve	68.54	0.3	087

Table 3. Performance evaluation criteria for models 1-5

pre-processing	No	Input	ANN Structure	Training			Testing		
				MNE	DC	R^2	MNE	DC	R^2
$0.05+0.95\frac{Xi-Xmin}{Xmax-Xmin}$	1	H_t,H_{t-1}	FFNN (2-5-1)	9.56	0.94	0.94	14.17	0.64	0.79
			RBF (s = 4)	11.98	0.94	0.94	14.42	0.66	0.79
	2	Q_{t-1},H_t,H_{t-1}	FFNN (3-5-1)	8.24	0.97	0.97	9.45	0.86	0.87
			RBF (s = 4)	6.41	0.98	0.98	7.75	0.87	0.87
	3	Q_{t-1},H_t	FFNN (2-5-1)	9	0.96	0.97	20.78	0.33	0.62
			RBF (s = 4)	8.45	0.97	0.97	19.36	0.35	0.62
	4	H_t	FFNN (1-6-1)	11.04	0.92	92	13.33	0.72	0.83
			RBF (s = 3)	10.78	0.92	0.92	12.24	0.73	0.83
	5	H_t,H_{t-1},H_{t-2}	FFNN (3-6-1)	9.89	0.96	0.97	10.42	0.85	0.85
			RBF (s = 3)	6.38	0.98	0.98	9.46	0.8	0.8

Table 4. Performance evaluation criteria for models 6-8

pre-processing	No	Input	ANN Structure	Training			Testing		
				MNE	DC	R^2	MNE	DC	R^2
$0.02+0.98\frac{Xi-Xmin}{Xmax-Xmin}$	6	H_t (year)	FFNN (1-6-1)	5.44	0.94	0.94	6.74	0.9	0.89
			RBF (s = 3)	5.72	0.94	0.94	6.35	0.89	0.88
			GRNN (s = 3)	47.57	0.03	0.8	24.46	0.19	0.81
	7	Q_{t-1},H_t,H_{t-1}	FFNN (3-5-1)	5.67	0.96	0.96	14.7	0.39	0.74
			RBF (s = 4)	4.9	0.97	0.97	60.45	0.35	0.25
			GRNN (s = 4)	48.42	0.01	0.74	22.05	0.03	0.69
	8	H_t,H_{t-1},H_{t-2}	FFNN (3-6-1)	5.07	0.97	0.97	15.98	0.35	0.63
			RBF (s = 3)	4.79	0.97	0.97	208.76	0.24	0.36
			GRNN (s = 3)	47.98	0.03	0.74	21.8	0.05	0.69

Table 5. Performance evaluation criteria for model 9

preprocessing	No	Input	ANN Structure	Training			Testing		
				MNE	DC	R^2	MNE	DC	R^2
without pre-processing	9	H_t(year)	FFNN (1-5-1)	59.74	0.1	1.00E-15	72.95	0.15	2.00E-15
			RBF (s = 4)	10.78	0.92	0.92	12.23	0.73	0.83

3.Results and discussion

In this research ANN models are applied as effective approaches to predict Qt, especially in a natural river where the relationships among physical processes are not fully understood. With respect to Tables 3, 4 and 5 the following combinations (1-9) that include different numbers of input values (Q and H) were considered in the input layer to predict the unique Q value in one day ahead at time t (Qt) in output layer. Then river stage at time t (Ht) was added. The following input parameters were chosen for the model:

H_t: stage at time step t (day)

H_{t-1}: stage at time step t-1 (one day before) Ht-2: stage at time step t-2 (two day before)

H_{t-2}: stage at time step t-2 (two day before)

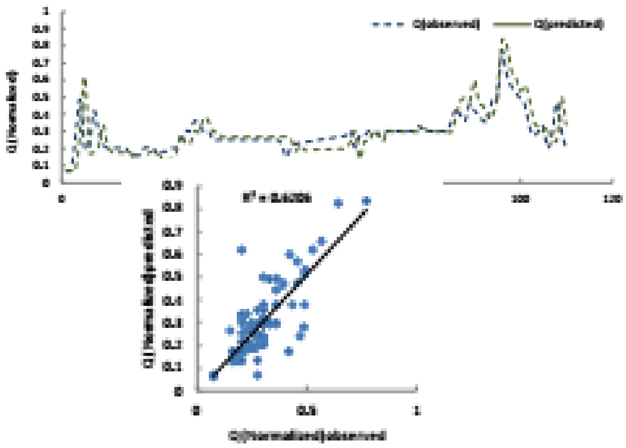
Q_{t-1}: discharge at time step t-1 (one day before)

Output: Q_t (discharge at time step t)

The models predictions are optimum if R2, DC and MNE are found to be close to 1, 1 and 0, respectively. The R2 and DC parameters clarify relation between observed and predicted values and MNE evaluates the residual between observed and predicted flow discharge (FD).The application of ANNs for predicting Qt consists of two steps. The first step is training ANNs models and the second one is testing the models. Firstly the FFNN, RBF and GRNN models were used in the modeling of Qt for all input combinations. Due to the results of GRNN and seasonally were very weak, they were not shown. Wrong data is omitted and rescaling changed. Then analyze have done with FFNN, RBF and GRNN again. The results are tabulated in Tables 3, 4, and 5.

A three layer feed forward neural network with back-propagation algorithm which contains input layer, hidden layer, and output layer was applied in this research. The standard multilayer FFNN with as few as one hidden layer using arbitrary squashing functions are capable of approximating any function from one finite dimensional space to another to any desired degree of accuracy, provided sufficiently many hidden units are available. In this sense, multilayer FFNNs are a class of universal approximates [12]. The Levenberg–Marquardt algorithm [13] was employed to train ANN models. In ANN modeling, two points are important and more attention must be paid for them, firstly the ANN architecture and secondly, training iteration number (epoch) in which appropriate selection of them can progress the model efficiency in step of verification. In addition, it prevents the ANN model to be over trained. The optimum network geometry is obtained utilizing a trial-and-error approach in which ANNs are trained with one hidden layer. Herein, the hidden layer node numbers of model was determined after trying various network structures since there is no theory yet to tell how many hidden units are needed to approximate any given function. In the training stage, the adaptive learning rates and the same initial weights were used for each ANN networks as used by Kisi [14]. The tangent sigmoid, logarithmic sigmoid and pure linear transfer functions were tried as activation functions for hidden and output layer neurons to determine the best network model. The most appropriate results were obtained from the FFNN (1,6,1) model using the logarithmic sigmoid activation functions for both hidden and output layer neurons. For the RBF applications, different numbers of hidden layer neurons and spread constants were examined in the study. The numbers of hidden layer neurons that gave the minimum mean normalize square errors (MNE) were found to be (No = 6). The spread is a constant which is selected before RBF simulation. The larger that spread is the smoother the function approximation will be. Too large a spread means a lot of neurons will be required to fit a fast changing function. Too small a spread means many neurons will be required to fit a smooth function, and the network may not generalize well. The spread that give the minimum MNE is s = 3. The spread parameter values providing the best testing performance of the GRNN was equal to s = 3. With the change of pre-processing for the best one of the combinations 1 to 6 are modeled with FFNN, RBF and GRNN again (combinations 6 to 8). The MNE, R2 and DC values of each method in the training and testing phases are given in Tables 2, 3, 4 and 5. According to tables 3, 4 and 5 in Orang station during the testing period, the FFNN and RBF configurations provided the best efficiency for combinations 6 and 7. In combinations 6 (H_t) and 7 (Q_{t}- 1,H_t,H_{t-1}) the FFNN and RBF structures were FFNN (1-6-1), RBF (s = 3), FFNN (3-5-1) and RBF (s = 4), respectively. 1, 6 and 1 neurons in input, hidden and output layers, respectively and spread parameter 3. It was displayed in Tables 3, 4 and 5 in various structures of FFNN, RBF, GRNN models, combination 6 with FFNN and RBF models provided the best results. In this combination R2, DC and MNE for FFNN and RBF were (0.9, 0.9, %6.74) and (0.88, 0.89, %6.35), respectively. In combinations 7 (in both FFNN and RBF models), 10 and 17, the above mentioned parameters were respectively (0.87, 0.86, %9.45), (0. 87, 0.87, %7.75), (0.89, 0.89, %9.7) and (0.81, 0.71, %6.41). Also it is necessary to mention that the seasonally adjusted data could not increase model performance. Without pre-processing inputs in combinations 9, results are so inaccurate. Although the GRNN gave similar statistical results in comparison with the FFNN and RBF in the training phase, the FFNN and RBF models have better accuracy than the GRNN in the testing phase. The GRNN model does not show consistency in training and test phase. Table 5 implies that the GRNN model memorizes the training data. The results of flow discharge rating curve with R2, DC and MNE (0.87, 0.3, %68.54) respectively, demonstrated that the conventional model in compression to the intelligence models was not an accurate model and not capable to predict FD. The variations of the observed and predicted FD using FFNN, RBF and GRNN for testing period in Orang station for some both of accurate and inaccurate results are shown in Figs. 5-9.

Fig 5. FD prediction by FFNN approach in



Testing period (comb. 3)

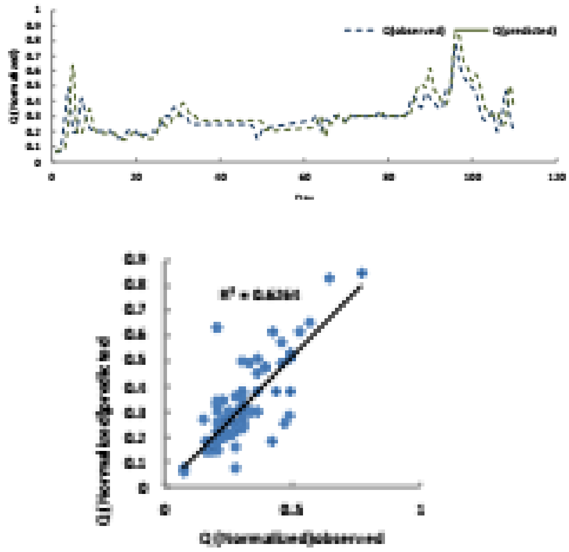


Fig 6. FD prediction by RBF approach in Testing period (comb. 3)

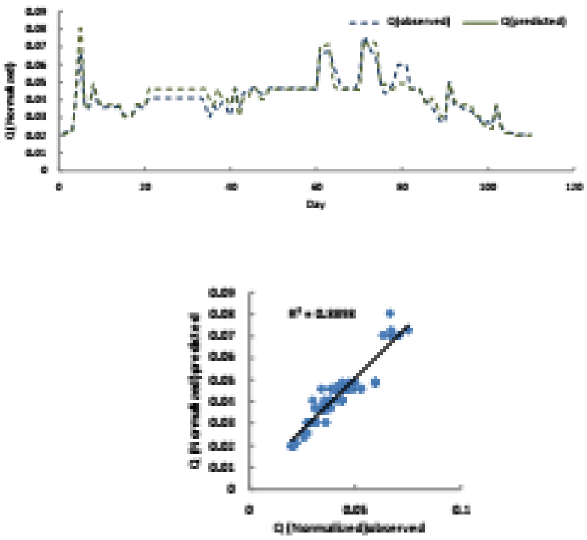


Fig 7. FD prediction by FFNN approach in Testing period (comb. 6)

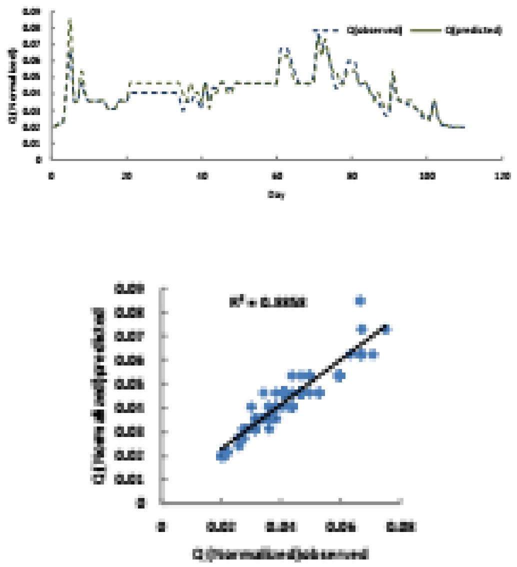


Fig 8. FD prediction by RBF approach in Testing period (comb. 6)

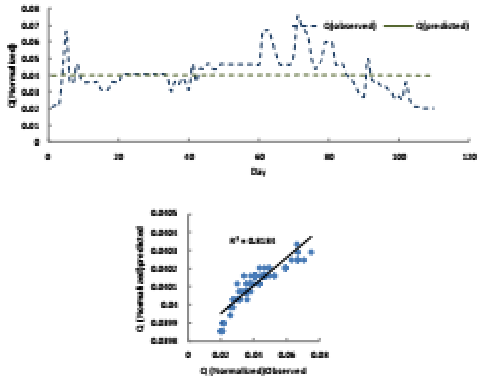


Fig 9. FD prediction by GRNN approach in Testing period (comb. 6)

4. Conclusion

Flow discharge in rivers is a complex phenomenon. The nature and motivation of traditional discharge models differ significantly. These approaches are normally able to make estimations within about one order of magnitude of the actual measurements. To overcome the complexity and uncertainty associated with flow discharge, ANN models can be applied for accurate estimation of flow discharge. In the present study, FFNN, RBF and GRNN models as expert intelligent approaches and classic rating curve were examined for simulation of flow discharge. For achieving this objective, Orang station in East Azerbaijan in Iran was considered. Comparison of the models' results indicated that the FFNN and RBF models had more ability in predicting FD comparison with rating curve technique. The GRNN model produced less accurate results than other models. It was found the ANNs models, which utilized seasonally adjusted data could not increase model performance. The FFNN and RBF estimation (combination 6) of FD were in almost perfect agreement with the measured FD. The high values of the R2, DC and MNE (0.9, 0.9, %6.74) and (0.88, 0.89, %6.35) respectively proves that FFNN and RBF models provides an excellent fit for the measured data and results suggest that the proposed FFNN and RBF models are a robust discharge predictor. The selection of input reliable data to the network has a large impact on the model accuracy. In this research using only

Ht as input data leads to more accurate results than using H_t, H_{t-1}, H_{t-2} and Q_{t-1}. Consequently, application of black box models for improving rating curve is also so useful. This study not only demonstrate a successful application of intelligent approaches as expert systems for improving flow discharge predicting of a natural river, but also suggest these models are more reliable than rating curve conventional model.

5.References

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