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Assessment of radial basis and generalized regression neural networks in daily reservoir inflow simulation

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ABSTRACT

In this study, two different type of Artificial Neural Networks (ANNs) were analyzed in simulating the daily inflow into Taleghan reservoir in Iran. These types include: General Regression Neural Network with standardized inputs (GRNN1) and with non-standardized inputs (GRNN1), and Radial Basis Networks with standardized inputs (RBN1) and with non-standardized inputs (RBN2). An iterative algorithm was designed to assess different architecture of these models. Results revealed the potential of these models, as suitable tools for simulating the daily reservoir inflow. Also, it was concluded that multiday averaging can improve the simulation results considerably.

Introduction

Information about the parameters defining water resources availability is a key factor in their management which improves the operation policies for water resources systems. One of the most important parameters in this area is river streamflow. Moreover, climate change impact assessment studies often need models capable in simulating river streamflow on a daily time basis. The modeling of streamflow time process has essentially followed two approaches (Razavi and Araghinejad 2009): empirical and statistical simulation of the hydrological system. In the first approach, the hydrological system is described by theoretical and/or empirical (physical) relationships (e.g. Garrote and Bras 1995), whereas, in the statistical approach, the objective is to develop a model in order to represent the most relevant statistical characteristics of the historical series (Araghinejad et al. 2006).

Artificial Neural Networks (ANNs)

Many statistical-based methods are used to model and forecast streamflow time series. In the recent years, Artificial Neural Networks (ANNs), have been widely studied and applied to simulate and forecast the hydrological variables (Hsu et al. 1995; Coulibaly et al. 2001; Razavi and Karamouz 2007; Altunkaynak 2007; Razavi and Araghinejad 2009; Ahmed and Sarma 2007; El-Shafiel et al. 2007).

Radial Basis Neural Network (RBN)

The radial basis function approach traces its roots from the work of Powell (1987), whose use as an alternative tool to learning in neural networks is particularly suited to multivariable interpolation given irregularly positioned data points. Their use in neural networks has found applications in solution of classification problems, function approximation, noisy interpolation, and regularization (Ke´gl et al. 2000) in various engineering fields due to their advantages over traditional multilayer perceptrons (Kagoda et al. 2010), namely faster convergence, smaller extrapolation errors, and higher reliability (Girosi and Pogio 1990). In hydrology and considering the complex nature of the rainfall–runoff process which is usually highly non-linear, the most suitable neural networks for modeling the process should have the ability to approximate any continuous function. The RBF technique provides good generalization ability with a minimum number of nodes to avoid unnecessarily lengthy calculations, in comparison with multilayer perceptron networks (Moradkhani et al. 2004). The architecture of radial basis function neural networks consists of an input layer, one hidden layer and one output layer. Each node in the hidden layer evaluates a radial basis function on the incoming input. In this study, the radial basis function applied was the Gaussian function and the neural network output was then evaluated as the weighted linear summation of the radial basis functions.

General Regression Neural Network (GRNN)

General Regression Neural Networks (GRNNs), falls into the category of probabilistic neural networks. This neural network like other probabilistic neural networks needs only a fraction of the training samples a backpropagation neural network would need. The use of a probabilistic neural network is especially advantageous due to its ability to converge to the underlying function of the data with only few training samples available. The additional knowledge needed to get the fit in a satisfying way is relatively small and can be done without additional input by the user. This makes GRNN a very useful tool to perform predictions and comparisons of system performance in practice. GRNN consists of four layers namely, input layer, pattern layer, summation layer and output layer (Singh and Deo 2007). The first layer is fully connected to the second pattern layer, where each unit represents a training pattern and its output is a measure of the distance of the input from the stored patterns. Each pattern layer unit is connected to the two neurons in the summation layer: S-summation neuron and D-summation neuron. The S-summation neuron computes the sum of the weighted outputs of the pattern layer while the D-summation neuron calculates the unweighted outputs of the pattern neurons.

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The connection weight between a neuron in the pattern layer and a S-summation neuron is the target output value corresponding to given input pattern. For D-summation neuron, the connection weight is unity. The output layer only divides the output of each S-summation neuron by that of each D-summation neuron, yielding the predicted value corresponding to an unknown input vector. The operation of the D-summation neuron includes a parameter called the spread factor, whose optimal value is often determined by trials (Kim et al. 2003). More information can be found in Specht (1991) and Tsoukalas and Uhrig (1997).

Models Specification and Calibration

As mentioned above, this study has focus on two different types of ANN models: General Regression Neural Network with standardized inputs (GRNN1) and with non-standardized inputs (GRNN1), and Radial Basis Networks with standardized inputs (RBN1) and with non-standardized inputs (RBN2) (Table 1).

Calibration parameters of these networks is limited to choose the spread values (0.1 to 2000 with variable intervals). Larger spread values result in smoother function approximation. To fit data very closely, a spread value smaller than the typical distance between input vectors should be used (MATLAB 2008).

Case Study and Data Preprocessing

Taleghan reservoir dam, located in the nearly central part of Iran, is considered as the case study and its daily inflow time series is used in the analysis. In order to prepare data for introducing to the models, the inflow time series (March 2006 through April 2011) was divided between two data sets for calibration (60%) and validation (40%).

Application of the Models

An iterative algorithm was designed in MATLAB for calibration and validation of the considered models. The performances of the models were compared using well-known statistics: Mean Absolute Error (MAE, Eq. 1) and Root Mean Squared Error (RMSE, Eq.2). We normalized these statistics by dividing them by the mean of the observed values.

$$MAE^* = \frac{1}{\bar{Q} \times n} \sum_i^n = 1 \left| Q_i - S_i \right| \qquad (1)$$

$$RMAE^* = \frac{1}{\bar{Q}} \sqrt{\frac{1}{n} \sum_i^n = 1 \left(Q_i - S_i \right)^2} \qquad (2)$$

where, Q_i : observed value on day i, S_i : simulated value on day i, n: the number of days, and $\overline{Q}$: the mean of the observed values.

Using different combinations of inputs (precipitation and mean temperature lags) were analyzed. In the following tables, the signs "P" and "T" represent daily precipitation and mean temperature lags, respectively. They include lags 0 through lags 3. For example, PPPTT means the inputs include precipitation from two days ago until the current day and temperature of the last day and the current day.

Results and Discussion

Daily Simulation

Table 2 shows the best 10 models of in Group 2 selected by the iterative algorithm. All the best model-input combinations are RBN2-PPT according to the RMSE* statistic. This tables shows that the effect of precipitation is more than the effect of temperature, since more precipitation signs (i.e. lags) are presented among the best input combination.

The best GRNN model appears in the 56th place in the ranking of Group 2 according to the RMSE* statistic (Table 3). As it can be seen, the performance of the best RBN and GRNN models are comparable and there is no considerable difference between them. Moreover, precipitation signs appear more than temperature signs in this table. Table 4 compares the statistics of the best models of each type.

The best models are very capable in simulating the mean values of the time series (Table 5). But, the main deficiency is related to the simulation of standard deviation (Std) and Maximum values. Almost all the models studied here are not good at regenerating the Std (and Maximum) values of the time series and it can be seen from this table that all the models underestimate the Std values (Table 5, the last column).

Figures 1 shows the scatter plots of the simulated inflows versus the observed inflows using the best models for the whole period along with the 1:1 line. Figure 1 demonstrates that the scatter plot of the RBN model is to some extent closer to the 1:1 line as compared to the GRNN model. Also, this is obvious in this figure that both models are incapable in simulating the peak flows.

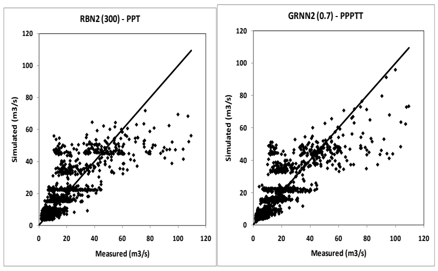

Figure 1. Observed .vs. Simulated inflows: Group 2 (values in the parenthesis are the spread values)

10-Day-Average Simulation

As mentioned above, the models are nearly incapable of simulating the Std and Maximum values of the time series. So, there is way to cope with such a deficiency: using multiple day averages. In water resource management, specially the issues related to reservoirs, it is common to use multi day averages (specially monthly averages). Thus, we assess the performance of the best models (Table 6) after performing a 10-day averaging on the simulated time series. These results show that multiday averaging operation on the simulated values of the studied ANN models can considerably improve the statistics.

Summary and Conclusion

This study compared the performance of two different types of ANN models in simulating the daily reservoir inflow values using daily precipitation and mean temperature data. Results showed that RBN and GRNN models are more capable in simulating the daily time series and regenerating the mean and std values of the time series. Moreover, we analyzed the effect of multiday (10-day) averaging on the quality of the simulations. It was concluded that this operation can improve the models performance, because of some deficiencies which were detected in simulating the Std and Maximum values of the time series by all the studied models. It can be suggested that more studies should be carried out in this field and more model types with different input combination must be analyzed to select the best model for each case study.

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Table 1. Description of models and calibration process

Network Name	Abbreviation	Description of Calibration Process
General Regression Neural Network	GRNN1	Spread values between 0.1 to 2000 with standardized inputs
	GRNN2	Spread values between 0.1 to 2000 with non-standardized inputs
Radial Basis Networks	RBN1	Spread values between 0.1 to 2000 with standardized inputs
	RBN2	Spread values between 0.1 to 2000 with non-standardized inputs

Table 2. Simulation statistics of the best models of Group 2

Rank	Inputs	Model	Spread	R2			RMSE*			MAE*		
				Train	Test	All	Train	Test	All	Train	Test	All
1	PPT	RBN2	300	0.82	0.94	0.84	0.68	0.46	0.68	0.39	0.30	0.38
2	PPT	RBN2	350	0.81	0.94	0.83	0.69	0.47	0.69	0.39	0.30	0.39
3	PPT	RBN2	400	0.81	0.94	0.83	0.70	0.47	0.70	0.40	0.30	0.39
4	PPT	RBN2	450	0.81	0.93	0.83	0.71	0.48	0.70	0.40	0.31	0.39
5	PPT	RBN2	500	0.81	0.93	0.83	0.71	0.48	0.70	0.40	0.31	0.39
6	PPT	RBN2	550	0.81	0.93	0.83	0.71	0.48	0.70	0.40	0.31	0.39
7	PPT	RBN2	600	0.81	0.93	0.83	0.71	0.48	0.70	0.40	0.31	0.39
8	PPT	RBN2	650	0.81	0.93	0.83	0.71	0.48	0.70	0.40	0.31	0.39
9	PPT	RBN2	700	0.81	0.93	0.83	0.71	0.48	0.70	0.40	0.31	0.39
10	PPT	RBN2	750	0.81	0.93	0.83	0.71	0.48	0.70	0.40	0.31	0.39

Table 3. Simulation statistics of some acceptable models of Group 2

Rank	Inputs	Model	Spread	R2			RMSE*			MAE*		
				Train	Test	All	Train	Test	All	Train	Test	All
56	PPPTT	GRNN2	0.7	0.85	0.93	0.86	0.61	0.49	0.63	0.33	0.30	0.34
57	PPT	GRNN2	0.7	0.82	0.93	0.84	0.67	0.49	0.68	0.37	0.31	0.37
58	PPT	GRNN2	0.8	0.82	0.93	0.83	0.68	0.49	0.68	0.37	0.31	0.37
59	PPT	GRNN2	0.9	0.81	0.93	0.83	0.68	0.49	0.69	0.38	0.31	0.38
60	PPTT	RBN2	300	0.80	0.93	0.82	0.73	0.49	0.72	0.40	0.31	0.39
61	PPT	RBN2	100	0.81	0.93	0.83	0.69	0.49	0.69	0.39	0.32	0.39
62	PT	RBN2	350	0.80	0.93	0.82	0.72	0.49	0.71	0.40	0.32	0.40
63	PT	RBN2	400	0.80	0.93	0.82	0.72	0.49	0.71	0.40	0.32	0.40
64	PPT	RBN2	20	0.82	0.93	0.84	0.68	0.49	0.68	0.37	0.32	0.38
65	PPT	RBN2	25	0.82	0.93	0.84	0.68	0.49	0.68	0.38	0.32	0.38

Table 4. Comparison of the statistics of the best models

Inputs	Model	TrFunc	Nn / Spread	R2				RMSE*				MAE*			
				Train	Valid	Test	All	Train	Valid	Test	All	Train	Valid	Test	All
PPT	RBN2	--	300	0.82	0.94		0.84	0.68	0.46		0.68	0.39	0.30		0.38
PPPTT	GRNN2	--	0.7	0.85	0.93		0.86	0.61	0.49		0.63	0.33	0.30		0.34

Table 5. Comparison of the Mean and Std values of the best models

Model	Mean								Std							
	Train		Valid		Test		All		Train		Valid		Test		All	
RBN2	13.99	14.86	13.99	14.86	13.99	14.86	13.99	14.86	16.28	14.88	16.91	15.32	16.91	15.32	17.04	14.97
GRNN2	14.03	14.63	14.03	14.63	14.03	14.63	14.03	14.63	16.32	14.96	16.84	14.99	16.84	14.99	17.05	15.13

Table 6. Comparison of the statistics of the best models after 10-day averaging

Inputs	Model	TrFunc	Nn / Spread	R2	RMSE*	MAE*	R2	RMSE*	MAE*
				Test	Test	Test	All	All	All
PPT	RBN2	--	300	0.99	0.25	0.20	0.87	0.59	0.33
PPPTT	GRNN2	--	0.7	0.99	0.25	0.20	0.89	0.55	0.30