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Streamflow Prediction by Applying Generalized Regression Network with Time Series Decomposition Method

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Abstrak

Precise and correct estimation of streamflow is important for the operative progression in water resources systems. The artificial intelligence approaches; such as artificial neural networks (ANN) have been applied for efficiently tackling the hydrological matters like streamflow forecasting in this study at upper Yangtze River. The objective is to investigate the certainty of monthly streamflow by applying artificial neural networks including Generalized Regression Network (GRNN). To overcome the non-linearity problem of streamflow, artificial neural networks integrated with discrete wavelet transform (DWT). Data has been analyzed by comparing the simulation outputs of the models with the correlation coefficient (R) root mean square errors (RMSE). It is found that the decomposition technique DWT has ability to improve the forecasting results as compare to single applied artificial neural networks. Moreover, all applied models are separately applies on the peak values as well which also have showed that intergrated model has more ability to catch the peak values.

Key words: *hybrid models, radial basis function neural network, desecrate wavelet transform, monthly stream flow*

1. Introduction

The necessity of creating additional and accurate time series forecast models has enforced the investigators to develop advanced approaches to model time series, which can able to resolve problems related to non-linearity. Keeping an eye on the relationship between rainfall and runoff researchers has developed numerous methods to forecast the upcoming events. Typically for discharge forecasting two types of mathematical methods can be used: streamflow models and rainfall–runoff models. In last 30 years, mathematical methods of runoff time series has been used exsessively to get the real stochastic structure of this type of hydrological process [1]. For example, the Box-Jenkins time series investigation technique includes auto-regressive (AR), moving average (MA), autoregressive moving average (ARMA), etc (Box et al., 1994).

In past few years, data-driven models, which are non-linear models have been familiarized and extensively applied and used as replacement in hydrological researches as influential and significant substitute modelling tools, such as artificial neural network (ANN). ANN has been usually applied to rainfall-runoff prediction, flood valuation and drought prediction due to its property of transformation, adaptation, self-learning and self-organization capability. The hydrological literature shows the applicability of artificial neural networks [2-6]. Artificial intelligence models have achieved success in hydrological applications [7, 8]. Though, in spite of the decent performance of ANN method when applied individually, there is still space for more improvement in their precision. Hydrological processes are considered to be random and non-stationary [9]. In this study time series decomposition named as “discrete wavelet transform” (DWT), has been appied and combined with the artificial intelligence model i.e. Generalized Regression Network (GRNN) model, for predicting monthly streamflow. Sahay and

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Srivastava suggested a hybrid model named wavelet transform-genetic algorithm-neural network model (WAGANN) to predict one-day-ahead monsoon river flows and WAGANN models are more accurate to models using original flow-time series (OFTS) for inputs [7]. The foregoing discussion suggests that a wavelet-transformed time series improves the efficiency of a forecasting model. For this reason, in this study, the constructed models are evaluated for forecasting streamflow for one-month-lead-time in the upper reaches of Yangtze River, China. The time series decomposition technique DWT is combined with the ANN models i.e. radial Generalized Regression Network (GRNN) model. The effect of DWT on streamflow forecasting is compared and the influence of high frequency components on model performance is analyzed. Two kinds of models, i.e., GRNN and DWT-GRNN are developed.

2. Research Area and Data

Yangtze River (YR) is divided into three sections, the upper section of YR is called Jinha River, which originates from Qinghai-Tibet plateau. The total length is 2316 km and covers an area of 340×103 km2, and average annual flow is about 149.8 billion m^3. Four mega hydropower plants are at present under construction; about twenty five hydropower stations are in planning. Location of Jinsha River basin and Xiangjiaba station is shown in Figure 1. To predict the streamflow of the Jinshajiang river basin at the run-off data is collected from Xiangjiaba hydrometric station, and rainfall data from 32 meteorological stations. To lessen the model inputs and the complication of the model structure, the rainfall used is average of the all above 32 meteorological stations.

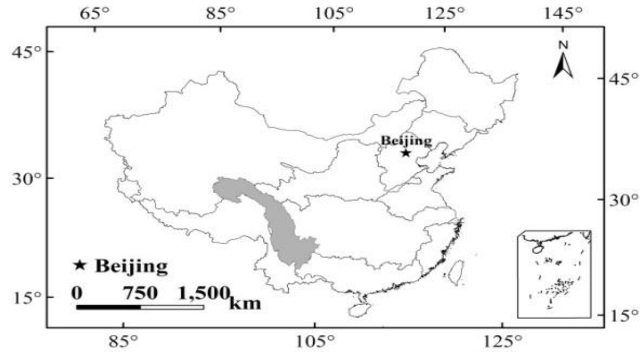

Figure 1. Location of Study Area

3. Methodology

3.1. Desceate Wavelet Transform

A wavelet is a waveform of efficiently narrow period that has an average value of “0”. The wavelets which have firmly finite extent in the time domain generally consider as discrete wavelets, else called as continuous wavelets. Wavelet investigation can expose local time and frequency information of random and non-stationary time series, so it is appropriate for streamflow process, which is consider to be highly random and contains a lot of non-linear factors. Discrete wavelet transform (DWT) creates a series of approximations or guesstimates (low-pass version) to the original signal and details (high-pass version) at altered resolution points. The basic principle of DWT is as follows Equation (1): Assume that wavelet function $\psi(t)$ is the mother wavelet satisfying $\int_{-\infty}^{+\infty} \psi(t)dt = 0$, then following wavelets $\psi_{a,b}(t)$ will be gained by reducing and escalating $\psi(t)$ scale “a: and location b”:

$$\psi_{a,b}(t) = |a|^{-\frac{1}{2}}\psi(\frac{t-b}{a}) \tag{1}$$

For the discrete time series (DTS) $f(t)$ with integer time steps, DWT in the dyadic decomposition scheme is defined as Equation (2):

$$W_\psi f(j,k) = 2^{-j/2} \sum_{t=0}^{N-1} f(t)\overline{\psi}(2^{-j}\,t - k) \quad (2)$$

Where $W_\psi f(j,k)$ is the wavelet coefficient of the discrete wavelet with $a = 2^j$,$b = 2^j k$, $\overline{\psi}(t)$ is the complex conjugate functions of $\psi(t)$, $W_\psi f(j,k)$ Reflects the characteristics of $f(t)$ in frequency and time domain at the same time. If frequency resolution of wavelet transform is high and the time domain resolution is low, j grow into big and if the frequency resolution is low and the time domain resolution is high, j turn into small.

3.2. Generalized Regression Neural Network

The Generalized Regression Network have four layers as shown in Figure 2. First the input layer, second, he radial basis layer, Third the summation layer and fourth the output layer. The input layer takes the data which then passes to the second layer for processing. The radial basis layer joins and processes the data orderly in order to get ‘‘best fit’’ relationship among the input and output variables, using the Gaussian transfer function as given in Equation (3) . The data is then passes to outline/summation neurons, where the output is amplified and passes to the output neurons. Instead of input and output layers, the only free factor, the smoothing factor plays an important role in the designing of network. This factor modifies the grade of generalization of the GRNN. If the factors value approaches to 1 means high smoothing factor which will produce strengthen path of the forecasting line, which 0 value will generate a dot-to-dot map. Smoothing factor has direct relation with the stability of network to generalize, mean if smoothing factor has greater value it degrade the error of prediction [10].

$$\varnothing(X) = \exp\left(-\frac{\|X-\mu\|^2}{2\sigma^2}\right)\sigma > 0, X \in R \quad (3)$$

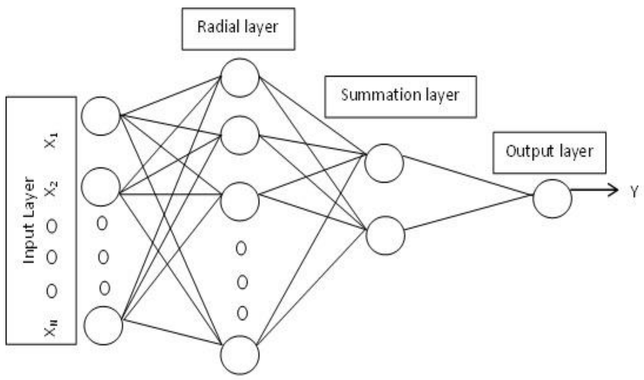

Figure 2. General Structure of GRNN

3.3. Hybrid Decomposing Neural Network

Disintegrating or decomposing ANN models are hybrid models joined with time series decomposition method. Building of hybrid models are as follows. First, appropriate inputs for models have been chosen, on the basis of auto-correlation function and the cross-correlation function of observed monthly streamflow and precipitation. Then both original observed streamflow and precipitation time series are decomposed into their sub-time series by DWT. Lastly, hybrid models DWT-GRNN-Q and DWT-GRNN-QP are built by coupling all the decomposed subseries with ANN models. Here, D1 is known as the ‘noise’ components, which is the most inconsistent and un-correlated in original observed time series. Many researchers found that by removing high-frequency component from the decomposed series, it will produce not the suitable outputs. All built models are shown in Table 1.

4. Result and discussion
4.1. Performace evaluation

To get the optimal model established in calculating streamflow at Jinsha River, different statistical indices are presented. The indices used are correlation coefficient (R) and root mean square errors (RMSE). R and RMSE, are expressed as Equation (4, 5):

Table 1. All Established Inputs

Model	Inputs
GRNN-Q	Qt-1, Qt-11, Qt-12,
GRNN-QP	Qt-1, Qt-11, Qt-12, Pt-1, Pt-11, Pt-12
DWT-GRNN-Q	Qt-1(D1-D2, A2), Qt-11(D1-D2, A2), Qt-12(D1-D2, A2)
DWT-GRNN-QP	Qt-1(D1-D2, A2), Qt-11(D1-D2, A2), Qt-12(D1-D2, A2), Pt-1(D1-D2, A2), Pt-11(D1-D2, A2), Pt-12(D1-D2, A2)

$$R = \frac{\sum_{i=1}^{N}(X_i^{sim} - X_i^{sim(mean)})(X_i^{obs} - X_i^{sim(mean)})}{\sqrt{[\sum_{i=1}^{N}[(X_i^{sim} - X_i^{sim(mean)})^2][\sum_{i=1}^{N}(X_i^{obs} - X_i^{obs(mean)})^2]}} \quad (4)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(X_i^{obs} - X_i^{sim}\right)} \quad (5)$$

where Ndenotes the number of datasets, X_i^{obs}represents the observed monthly streamflow, X_i^{sim} represents the simulated monthly streamflow.

4.2. Result Analysis

Results of ANN models i.e., Generalized Regression Network (GRNN) model integrated with DWT in validation phase (January 1992 to December 2008) are shown in Figure 3, 4, 5 and 6. R and RMSE in the calibration and validation phase are, respectively, given in Tables 2 and 3. Performance evaluator indices R and RMSE declares that GRNN-QP model, in which streamflow and precipitation used as inputs, has a superior precision as compared to the GRBP-Q model that just keeps streamflow as inputs. Then an inclusive examination requests to be prepared to expose the influence of decomposing technique on models precision on the basis of Table 3. Compare GRNN-Q, GRNN-QP, DWT-GRNN-P and DWT-GRNN-QP all of which are best models applied models in this study, it is found that the models coupled with decomposition technique achieve much better outputs than single ANN models and DWT-GRNN expands the correctness of forecasting extra-highly than GRNN-Q, GRNN-QP in both calibration and validation phase. Hence, by using decomposing technique contributes in improving performances of prediction, and decomposing technique DWT with GRNN-QP is more suitable than DWT with GRNN-Q for monthly streamflow modeling in this study.

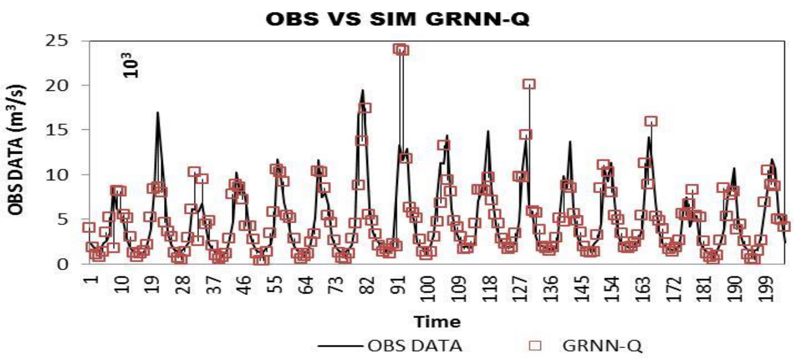

Figure 3. Flow Hydrograph OBS DATA versus GRNN-Q

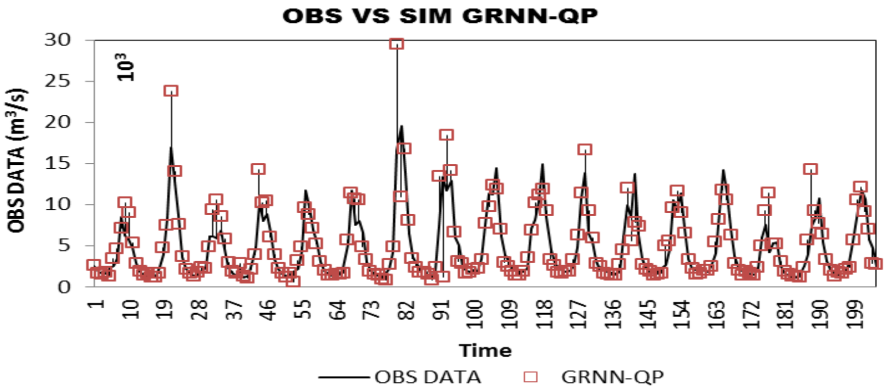

Figure 4. Flow Hydrograph OBS DATA versus GRNN-QP

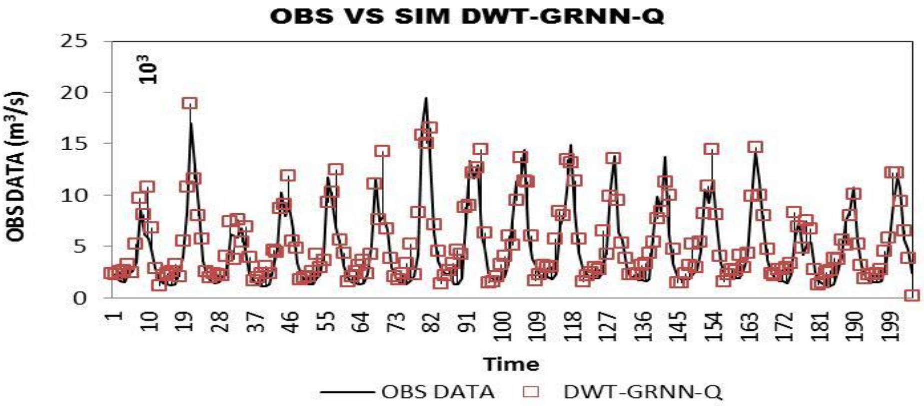

Figure 5. Flow Hydrograph OBS DATA versus DWT-GRNN-Q

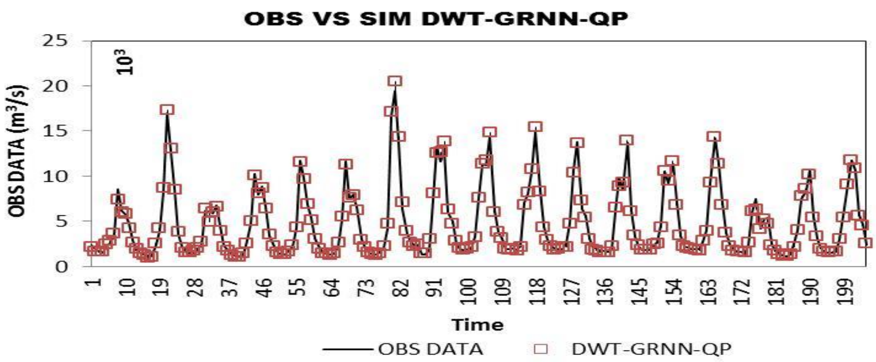

Figure 6. Flow Hydrograph OBS DATA versus DWT-GRNN-QP

5. Conclusion

Precision of monthly streamflow predicting models combine with different decomposition techniques was investigated in this paper. ANN and DWT-ANN based models were, respectively, obtained by artificial neural network, ANN, coupled with discrete wavelet transform. All models were applied with two kinds of inputs based on whether antecedent precipitation was involved, to study the effect and impact of precipitation on the prediction precision. Xiangjiaba station is the forecast station for this study, located at the Jinsha River; all

models were applied, to execute one-month-ahead streamflow prediction. Conclusion of this research as follows:
1. By adding antecedent precipitation to models as inputs, significant improvement is been shown, so to build superb model precipitation information should be taken into account.
2. Among all the applied artificial neural network models GRNN-QP, has shown better accuracy than GRNN-Q.
3. By comparing the results of GRNN-Q, GRNN-QP, DWT-GRNN-P and DWT-GRNN-QP models display that GRNN-Q gives the worst accuracy.
4. DWT possibly will expressively and significantly raise precision of monthly streamflow prediction. Meanwhile, it can be seen that DWT-GRNN-QP overtakes DWT-GRNN-Q in terms of the performance indices R and RMSE.

Table 2. Performance Evaluation of the RBFNN Models

Modle	Calibration		Validation	
	R	RMSE	R	RMSE
GR-Q	0.80	1988	0.73	2612
GR-QP	0.86	1631	0.81	2005

Table 3. Performance Evaluation of the DWT-RBFNN Models

Modle	Calibration		Validation	
	R	RMSE	R	RMSE
DW-GR-Q	0.87	1387	0.83	1877
DW-GR-QP	0.93	1041	0.89	1187

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