Lecture Notes in Computer Science, Vol. 3612, 2005, pp. 1152-1161

Long-Term Prediction of Discharges in Manwan Hydropower using Adaptive-Network-based Fuzzy Inference Systems Models

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Abstract

Forecasting reservoir inflow is important to hydropower reservoir management and scheduling. An Adaptive-Network-based Fuzzy Inference System (ANFIS) is successfully developed to forecast the long-term discharges in Manwan Hydropower. Using the long-term observations of discharges of monthly river flow discharges during 1953-2003, different types of membership functions and antecedent input flows associated with ANFIS model are tested. When compared to the ANN model, the ANFIS model has shown a significant forecast improvement. The training and validation results show that the ANFIS model is an effective algorithm to forecast the long-term discharges in Manwan Hydropower. The ANFIS model is finally employed in the advanced water resource project of Yunnan Power Group (http://202.118.74.192:7001/YNProject/index.jsp).

Key words: Long-term prediction; Discharge forecast; Fuzzy inference system; ANFIS; ANN

1. Introduction

Accurate time and site-specific forecasts of streamflows and reservoir inflow are required for effective hydropower reservoir management and scheduling. In the past few decades, a wide range of hydrologic models has been proposed for this purpose. Conventionally, factor analysis and hydrological analysis methods such as historical evolution method, time series analysis, multiple linear regression method and so forth, are used to forecast the long-term discharges. Nowadays, time series analysis and multiple linear regression method are the two most commonly used methods. The time series analysis is based on the decomposition of various factors into trend and cycle. After 1970s, autoregressive moving-average (ARMA) models proposed by Box et al. [1] are also widely used. Since 1990s, artificial neural network (ANN) [2,3], based on the understanding of the brain and nervous systems, is gradually used in hydrological prediction. In this paper, the potential of the adaptive-network-based fuzzy inference system (ANFIS) [4-7], first developed by Jang (1993), in hydrological prediction will be discussed and evaluated. This approach has been tested and evaluated in the field of signal processing and related areas.

The past few years have witnessed a rapid growth in the number and variety of applications of fuzzy logic and fuzzy set theory, which were introduced by Zadeh [22]. The applications range from consumer products such as cameras, washing machines, and microwave ovens to industrial process control, medical instrumentation, decision-support systems, and portfolio selection. An apparent recent trend relates to the use of fuzzy logic in combination with neurocomputing and genetic algorithms. In general, fuzzy logic, neurocomputing, and genetic algorithms might be viewed as principal constituents of soft computing. Among various combinations of methodologies in soft computing, the most interesting applications offer an appropriate combination of fuzzy logic and neurocomputing. It results in a hybrid system that operates on both linguistic descriptions of the variables and the numeric values through a parallel and fault tolerant architecture. This effective method, ANFIS, has been successfully applied to many problems such as prediction of workpiece surface roughness [8], pesticide prediction in ground water [9] and validation in financial time series [10]. Specially, the neuro-fuzzy system for modeling hydrological time series was presented by Nayak et al. [11].

2. Fuzzy inference system

2.1. Fuzzy rule-based models

The process of fuzzy inference involves membership functions, fuzzy logic operators, and if-then rules. Fuzzy inference systems (FIS) have been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision. The basic structure of a FIS consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database which defines the membership functions (MF) used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules to derive an output (see Fig. 1). FIS implements a nonlinear mapping from its input space to the output space. This mapping is accomplished by a number of fuzzy if-then rules, each of which describes the local behavior of the mapping. The parameters of the if-then rules (referred to as antecedents or premises in fuzzy modeling) define a fuzzy region of the input space, and the output parameters (also termed consequents in fuzzy modeling) specify the corresponding output. There are three types of fuzzy inference systems in wide use: Mamdani-type [12], Sugeno-type [13-14] and Tsukamoto-type [15]. These three types of inference systems vary somewhat in the way outputs are determined.

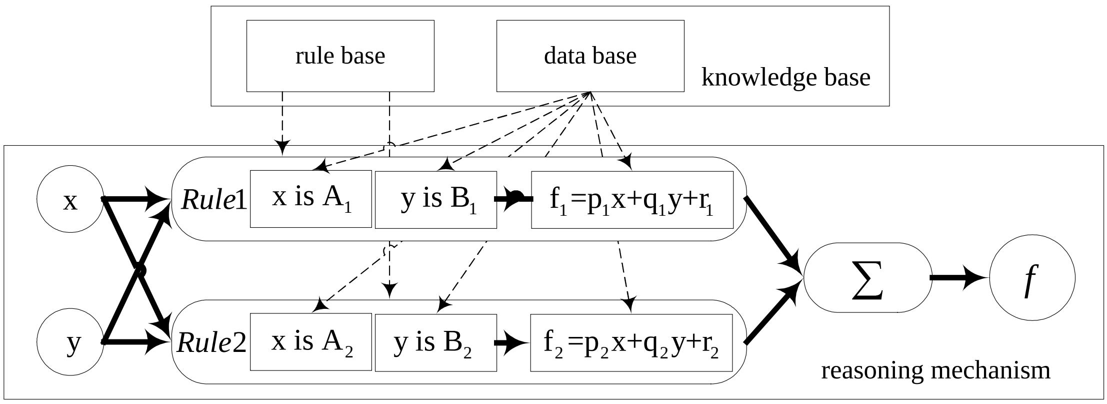

Fig.1. Fuzzy inference system (first-order Sugeno)

2.2. Sugeno models

The Sugeno model (or Takagi-Sugeno model) was proposed by Takagi and Sugeno [14]. A typical rule in a Sugeno fuzzy model has the form:

If x is A and y is B, then z = f（x， y）

where A and B are fuzzy sets of antecedent, and z = f（x， y）is the precise function. Usually, z = f（x，y）are polynomials of input variables x and y. In the first-order Sugeno model, the function z = f（x， y）is a first-order polynomial of the input variables. For a zero-order Sugeno model, the output level z is a constant. For instance, consider that the FIS has two inputs x and y and one output z and, for the first-order Sugeno fuzzy model, a typical rule set with two fuzzy if-then rules can be expressed as:

Rule 1:If x is A_1 and y is B_1， then $f_1=p_1x+q_1y+r_1$

Rule 2:If x is A_2 and y is B_2， then $f_2=p_2x+q_2y+r_2$

Figure 2 illustrates the fuzzy reasoning mechanism for this Sugeno model to derive an output function (f) from a given input vector [x, y]. The Sugeno fuzzy inference system is computationally efficient and works well with linear techniques, optimization and adaptive techniques. It is extremely well suited to the task of developing a FIS using the framework of adaptive neural networks which is termed an ANFIS.

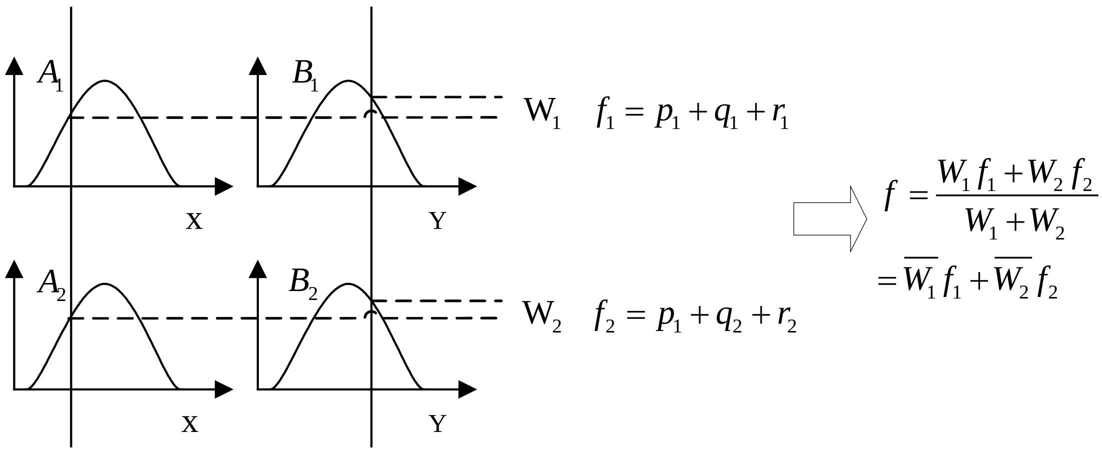

Fig.2. First-order Sugeno fuzzy model

3. ANFIS

3.1. ANFIS architecture

This neuro-fuzzy network is a five-layer feed forward network that uses neural network learning algorithms coupled with fuzzy reasoning to map an input space to an output space. The ANFIS architecture is shown in Figure 3, and an introduction of the model is as follows.

Layer1: input nodes

Each node in this layer generates membership grades of an input variable. The node output $O_{1,i}$ is defined by:

$$O_{1,i} = \mu_{A_i}(x),\ i=1,2 \quad \text{or}$$

$$O_{1,i} = \mu_{B_{i-2}}(y),\ i=3,4$$

where x (or y) is the input to the node; A_i (or B_{i-2}) is a fuzzy set associated with this node, characterized by the shape of the MFs in this node and can be any appropriate functions that are continuous and piecewise differentiable such as Gaussian, generalized bell shaped, trapezoidal shaped and triangular shaped functions. Assuming a generalized bell function as the MF, the output $O_{1,i}$ can be computed as,

$$\mu_A(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b}}$$

where { a_i , b_i , c_i } is the parameter set that changes the shapes of the MF with the maximum equal to 1 and the minimum equal to 0; and { a_i , b_i , c_i } are called premise parameters.

Layer 2: rule nodes

Every node in this layer multiplies the incoming signals, denoted as Π, and the output $O_{2,i}$ that represents the firing strength of a rule, is computed as,

$$O_{2,i} = w_{A_i}(x)\mu_{B_i}(y),\ \ i=1,2$$

Therefore, the outputs $O_{2,i}$ of this layer are the products of the corresponding degrees from layer 1.

Layer 3: average nodes

The node of this layer, labeled as N, computes the normalized firing strengths as,

$$O_{3,i} = \overline{w} = \frac{w_i}{w_1 + w_2},\ \ i=1,2$$

Layer 4: consequent nodes

Node i in this layer computes the contribution of the ith rule towards the model output, with the following node function:

$$O_{4,i} = \overline{w_i} f = \overline{w_i}(p_i + q_i + r_i)$$

where $\overline{w_i}$ is the output of layer 3 and { p_i , q_i , r_i } is the consequent parameter set.

Layer 5: output nodes

The single node in this layer computes the overall output of the ANFIS as:

$$\text{overall output} = O_{5,1} = \sum \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

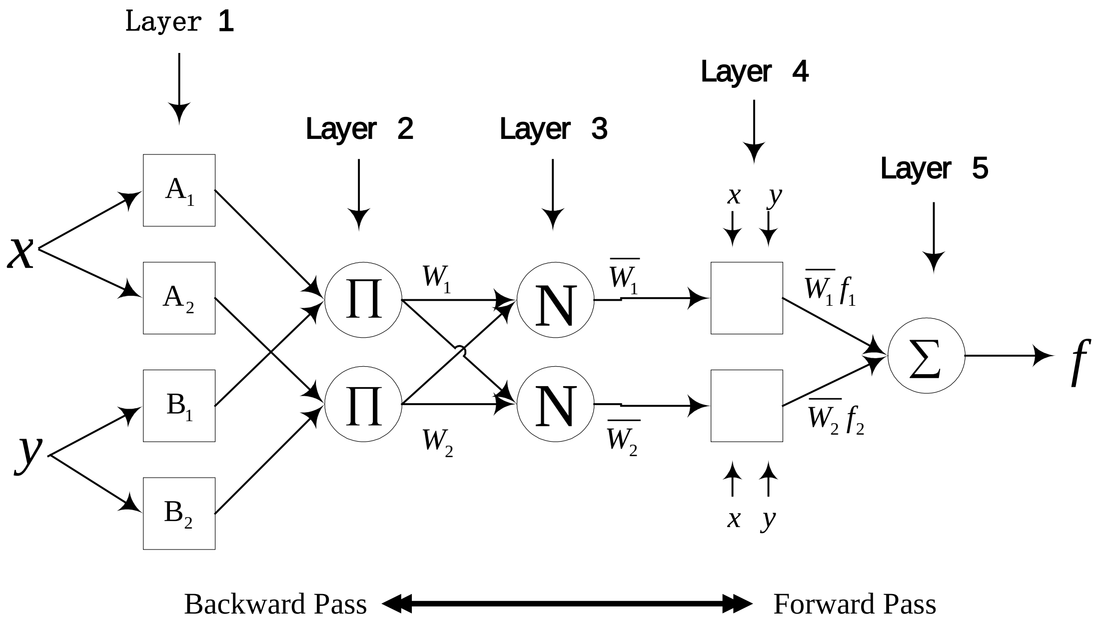

Fig.3. ANFIS architecture

3.2. Hybrid learning algorithm

The ANFIS architecture consists of two parameter sets for optimization: the premise parameters { a_i , b_i , c_i },which describe the shape of the MFs, and the consequent parameters { p_i , q_i , r_i },which describe the overall output of the system. From the ANFIS architecture shown in Fig.3, it can be seen that when the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters. In symbols, the output f in Fig.3 can be rewritten as

$$f=\overline{w}_1 f_1+\overline{w}_2 f_2$$
$$=(\overline{w}_1 x\ p_1)+(\overline{w}_1 y)\ q_1+(\overline{w}_1)\ r_1+(\overline{w}_2 x)\ p_2+(\overline{w}_2 y)\ q_2+(\overline{w}_2)\ r_2$$

which is linear in the consequent parameters $p_1, q_1, r_1, p_2, q_2, r_2$. Therefore, a hybrid learning algorithm combines the backpropagation gradient descent and the least squares estimate method, which outperforms the original backproagation algorithm [16]. The consequent parameters are updated first using the least squares algorithm and the antecedent parameters are then updated by back propagating the errors that still exist. Specifically, in the forward pass of the hybrid learning algorithm, node outputs go forward until layer 4 and the consequent parameters are identified by the least squares method. In the backward pass, the error signals propagate backward and the premise parameters are updated by gradient descent. Table 1 summarizes the activities in each pass. More details about the hybrid learning algorithm can be found in Jang and Sun [6].

Table.1. Two passes in the hydrid learning procedure for ANFIS

	Forward pass	Backward pass
Premise parameters	Fixed	Gradient descent

Consequent parameters	Least-squares estimate	Fixed
Signals	Node outputs	Error signals

4. Study area and data used

The Manwan Hydropower in the Lancangjiang River is selected as the study site. The Lancangjiang River is a large river in Asia, which originates from the Qinghai-Tibet Plateau, penetrates Yunnan from northwest to the south and passes through the Laos, Burma, Thailand, Cambodia and Vietnam, ingresses into the South China Sea at last. The river is about 4,500 miles long and has a drainage area of 744,000 square miles. The Manwan Hydropower merges on the middle reaches of the Lancang River and at borders of Yunxian and Jingdong counties. The catchment area at the Manwan dam site is 114,500 square miles, the length above Manwan is 1,579 miles, and the mean elevation is 4,000 miles. The average yearly runoff is 1,230 cubic meters per at the dam site. Rainfall provides most of the runoff and snow melt accounts for 10%. Nearly 70% of the annual rainfall occurs from June to September.

The monthly flow data from January 1953 to December 2003 (presented in Figure 4) are studied. The data set from January 1953 to December 1998 is used for training whilst that from January 1999 to December 2003 is used for validation. In the modeling process, the data sets of river flow were normalized to the range between 0 and 1 as recommended by Masters [17].

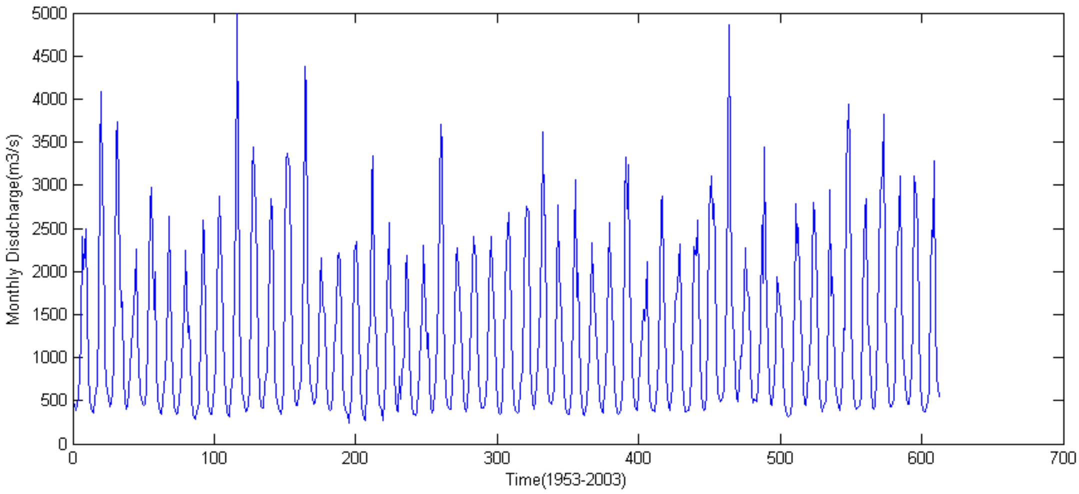

Fig.4. Monthly discharge of the Manwan Reservoir(unnormalized)

5. Application of ANFIS to flow prediction in Manwan

5.1. Model development and testing

There are no fixed rules for developing an ANFIS, even though a general framework can be followed based on previous successful applications in engineering. The goal of an ANFIS is to generalize a relationship of the form of

$$Y = f\left(X^n\right)$$

where X^n is an n-dimensional input vector consisting of variables $x_1, \ldots, x_i, \ldots, x_n$, and

Y is the output variable. In the flow modeling, values of x_i may be flow values with different time lags and the value of Y is generally the flow in the next period. However, the number of antecedent flow values that should be included in the vector X^n is not known a priori. An ANFIS model is constructed initially with one antecedent flow in the input vector. The input vector is then modified by successively adding flow at one more time lag, and a new ANFIS model is developed each time. With the increase of the input vectors adding from one to six, Six ANFIS models were developed as follows:

$$\text{Model } n \quad Q_t = f\,(Q_{t-1}, \;, \; Q_{t-n}) \quad n=1, \;,6$$

where Q_t corresponds to the river flow at time t.

The model performance is examined by means of the following indices:
(1) The coefficient of correlation (CORR) given by:

$$\text{CORR}=\frac{\frac{1}{n}\sum_{i=1}^{n}(Q_o(i)-\overline{Q_o})(Q_f(i)-\overline{Q_f})}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_o(i)-\overline{Q_o})^2} * \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_f(i)-\overline{Q_f})^2}}$$

where $Q_o(i)$ and $Q_f(i)$ are, respectively, the observed and forecasted discharge and $\overline{Q_o}$, $\overline{Q_f}$ denotes the mean of them, and n is the number data points considered.

(2) The root mean square error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_f(i)-Q_o(i))^2}$$

5.2. Results and discussions

Table 2 shows the performance indices of ANFIS form model 1 to model 6, which are developed in Section 5.1, using the Gaussian membership function and the trapezoidal membership function respectively. The membership function of every input parameter within the architecture can be divided into two areas, i.e. small and large areas. The results indicate that model 3, which consists of three antecedent flows in input, showed the highest CORR and minimum RMSE during validation regardless of the adoption of Gaussian membership function or trapezoidal membership function for the ANFIS. It is selected as the best-fit model for describing the flow of the Manwan Hydropower. To demonstrate the effect of choice of membership function on the model performance, the triangular membership function (TRIMF), the trapezoidal membership function (TRAPMF), the generalized bell membership function (GBELLMF), the Gaussian membership function (GAUSSMF), the Gaussian combination membership function (GAUSS2MF), the spline-based membership function (PIMF) and the sigmoidal membership function (DSGMF) for the ANFIS structure are tested using model 3, and the results are presented in Table 3. It is showed that, the TRAPMF performs the best with the highest CORR and minimum RMSE during validation, and the GAUSSMF performs the worst.

Table.2. CORR and RMSE for different models

Model	GAUSSMF				TRAPMF			
	Training		Validation		Training		Validation	
	RMSE	CORR	RMSE	CORR	RMSE	CORR	RMSE	CORR
1	0.11843	0.78539	0.13043	0.77773	0.11889	0.78348	0.12958	0.78156
2	0.090325	0.88157	0.10475	0.86359	0.09186	0.87722	0.10694	0.85762
3	0.075927	0.91793	0.099208	0.87957	0.075795	0.91823	0.097094	0.88877
4	0.06605	0.93861	0.13718	0.78263	0.067406	0.93597	0.10266	0.87995
5	0.061604	0.9469	0.14105	0.78515	0.065892	0.939	0.16199	0.72977
6	0.058825	0.9518	0.41629	0.38461	0.060644	0.94868	0.27504	0.58358

Table.3. CORR and RMSE for model 3 with different MFs

MF	Training		Validation	
	RMSE	CORR	RMSE	CORR
TRIMF	0.079641	0.9093	0.097281	0.88339
TRAPMF	0.075795	0.91823	0.097094	0.88877
GBELLMF	0.075036	0.91993	0.10304	0.86983
GAUSSMF	0.075927	0.91793	0.099208	0.87957
GAUSS2MF	0.074961	0.9201	0.098256	0.88327
PIMF	0.075463	0.91898	0.98573	0.88652
DSGMF	0.07424	0.92169	0.99168	0.87999

5.3. Result comparison with ANN Model

ANN model has been widely applied in flow prediction. The main advantage of the ANN approach over traditional methods is that it does not require information about the complex nature of the underlying process under consideration to be explicitly described in mathematical form. Hence, an ANN model is constructed using the same input parameters to the ANFIS model 3 to compare the performance of them in this case. A scaled conjugate gradient algorithm [18,19] is employed for training, and the hidden neurons are optimized by trial and error. The final ANN architecture consists of 3 hidden neurons. In order to have the same basis of comparison, the same training and verification sets are used for both models. The performances of ANN and ANFIS during training period and validation period are respectively presented in Figure 5 and Figure 6, and the performance indices of them is showed in Table 4. It is demonstrated that, when employed for flow prediction in Manwan, ANFIS exhibits some advantages over ANN model. During validation, the correlation coefficient of ANFIS model is 0.88877, which is larger than its counterparts of ANN model (0.87766). Moreover, the RMSE of ANFIS model is 0.097094, which is much smaller than that of ANN model (0.099927).

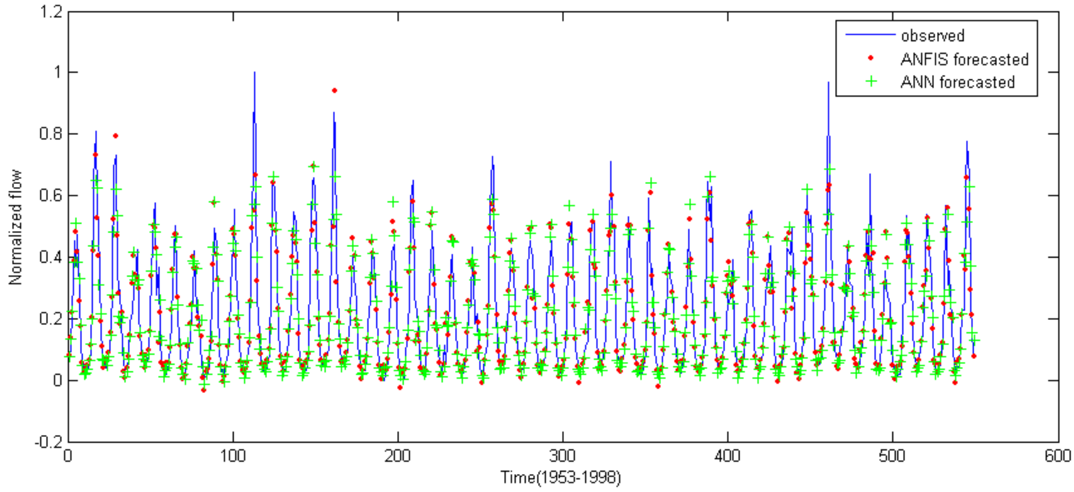

Fig.5. ANFIS forecasted, ANN forecasted and observed flow during training period

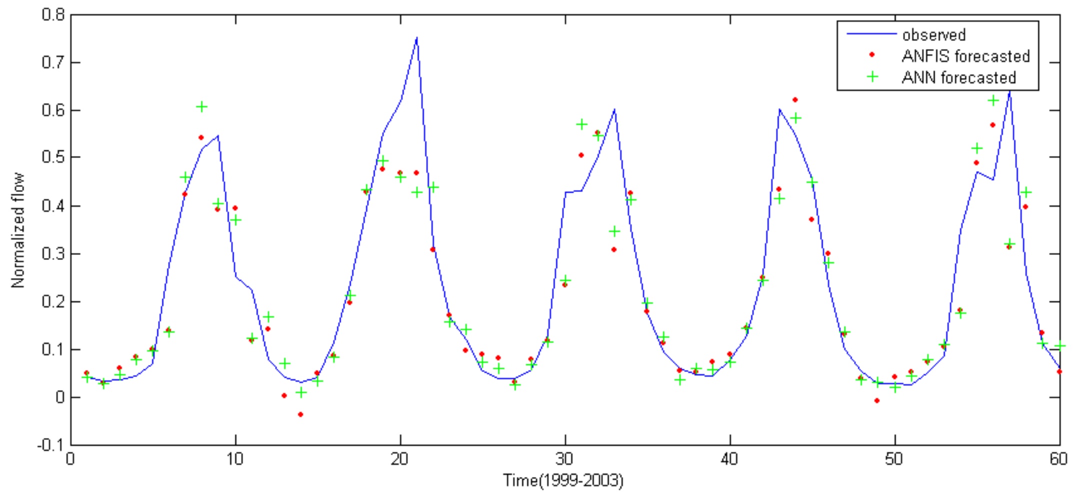

Fig.6. ANFIS forecasted, ANN forecasted and observed flow during validation period

Table.4. Performance indices of ANN and ANFIS models

	Training		Validation	
	RMSE	CORR	RMSE	CORR
ANFIS	0.075795	0.91823	0.097094	0.88877
ANN	0.080755	0.90662	0.099927	0.87766

6. Conclusion

In this study, an ANFIS model is used to predict long-term flow discharges in Manwan based on historical records. Data from January 1953 to December 1998 and from January 1999 to December 2003 are used for training and validation in monthly flow predictions, respectively. The results indicate the ANFIS model can give good prediction performance. The correlation coefficients between the prediction values and the observational values are 0.88877 and 0.91823 for validation and training, respectively. The adoption of different membership functions for ANFIS show that the TRAPMF performs the best in long-term prediction of discharges in Manwan Hydropower consisting of three antecedent flows in input. It is found, through result comparison with an appropriate ANN model, that the ANFIS model is able to give more accurate prediction. This demonstrates its distinct capability and advantages in identifying hydrological time series comprising non-linear characteristics.

7. Acknowledgement

This research was supported by the National Natural Science Foundation of China (No. 50479055) and the Internal Competitive Research Grant of Hong Kong Polytechnic University (G-T592).

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