Proceedings of the 2006 IASME/WSEAS Int. Conf. on Water Resources, Hydraulics & Hydrology, Chalkida, Greece, May 11-13, 2006 (pp42-47)

# Reservoir inflows forecasting with artificial neural networks during typhoon period – for Shihmen Reservoir in Taiwan

AN-PEI WANG, Professor
HENG-YI LIAO, Ph D. Candidate
CHUN-YAI HUANG, Mater Graduate
Department of Civil Engineering,
Chung-Yuan Christian University
Chung-Li, Taiwan 32023, R.O.C.

*Abstract:* - A new approach based on an artificial neural network (ANN) model to forecasting flood inflow, is presented in this paper. This model contained one input, two hidden and one output layers. The hidden layers consisted of 72 neurons in first layer and 39 neurons in the other. The rainfall data of typhoons collected by ombrometer stations in the river basin is taken as the input data, and the flood inflow is the output data. Optimal weights of ANN are determined after training by the algorithm of Back-Propagation-Network (BPN) to build a model of the rainfall-runoff system. The major advantage of the ANN is that for system identification, which can be utilized for constructing a "black-box" model of the system, no particular knowledge on the physical properties of the system itself is required. In this article, after training no lagged inflows are needed, and the flood inflow can easily be estimated by the ANN model. As an example, results on forecasting the typhoon flood inflow of Shihmen reservoir in Taiwan are presented. Consequently, satisfactory results of evaluation between observed and forecasted flood inflows by using the proposed method will be shown.

*Key-Words: Artificial neural network, Back-Propagation-Network, Flood inflows, Shihmen reservoir, Rainfall-runoff model, Inflows forecasting*

## 1 Introduction

The main functions of a reservoir are not only to maintain stable supplies, but also to protect downstream from the danger of flood. However, there may be 3~4 typhoons invading Taiwan each year. The most difficult task of reservoir operation is forecasting the inflow in order to preventing failure of the reservoir. In Taiwan, since rivers flow rapidly due to their special topography, the inflow of reservoir is hard to estimate. Thus accurate inflow forecasting is quite important for on-line reservoir operation during typhoon periods. In the past, physical models were established to forecast inflows of reservoirs. However, there are numbers of physical factors that are too complex to model directly could influence the inflows.

Artificial Neural Network (ANN) has been developed for about 60 years, since the concept was first introduced by McCulloch and Pitts in 1943[11]. But, it was mostly dormant until the mid 1980s. The utilization of ANN grew rapidly and became very popular in recent years. ANN of nowadays is much more sophisticated than before and widely use in various scientific fields. ANN can be trained by the historical data and adjusted weights automatically. Since ANN has the property of adapting itself to system, it seems suitable to use ANN in handling nonlinear system such as inflows forecasting. In this paper, an ANN model was developed to simulate the property of Shihmen basin as a practical case, and establish a "rainfall-runoff" system that could offer forecasting information for reservoir operation during typhoons.

Applying ANN to civil and hydraulic engineering becomes more and more common. French et al. (1992) forecasted rainfall intensity of the next hour using back- propagation network (BPN)[4]. Hjelmfelt et al. (1993) applied ANN to simulate unit hydrograph, and the weighting matrix was taken as a unit hydrograph after training by ANN[8]. Halff et al. (1993) simulated a "rainfall-runoff" relationship by ANN[7]. Lorrai et al. (1995) also developed a "rainfall-runoff" model by BPN with 2 hidden layers[10]. Chang et al. (1998) combined CPN and fuzzy rule base to forecast inflows[1]. Chang and Chen (2001) developed a counter-propagation fuzzy-neural network model to approach the real time stream flow estimation[2]. Also, Chang et al. (2003) presents a new Radial Basin Function Neural Network (RBFNN) for water-stage forecasting in an estuary under high flood and tidal effects[3].

No matter what kind of neural network model, the inflows of past hours are needed as input data while the model is forecasting. In this article, no lagged inflows are needed after training; the model can simply estimate the flood inflow with rainfall data.

# 2 Artificial neural network model

## 2.1 Forward ANN

The structure of an artificial neuron is shown as Fig. 1. The variables $x_1, x_2, \ldots, x_i, \ldots, x_n$ are the inputs to the threshold element and the variables $w_1, w_2, \ldots, w_i, \ldots, w_n$ are the weights associated with the inputs. When $w_i$ is positive, input $x_i$ acts as an excitatory signal for the element. When $w_i$ is negative, input $x_i$ acts as an inhibitory signal for the element. The certain value of the threshold, the sum of the product of the inputs and their relative weights, decides the sensitivity of the ANN. If the summation is greater than the threshold value, an output is computed using a function *f*. The signal output y is expressed in a mathematic form as:

$$y = f\left(\sum_{i=1}^{n} x_i w_i + \theta\right)$$

$$where \begin{cases} x_i = signal\ input\ (i = 1,2,\ldots,n) \\ w_i = weight\ associated\ with\ x_i \\ \theta = threshold \\ f = a\ nonlinear\ \ function \end{cases} \tag{1}$$

The sigmoid function (*f*), a nonlinear function with values between 0 and 1, was used in this paper.

$$y_k = f(Net_y) = \frac{1}{1 + e^{-Net_y}} \tag{2}$$

The process above is how the ANN work or called the forward ANN pass.

## 2.2 Back-propagation network (BPN)

Rumelhart et al (1986) initially presented Back Propagation-algorithm Network (BPN)[12] hoping to minimize the cost function as soon as possible by gradient descent method. Generally, the type of BPN constitutes three or four layers -- an input layer, an output layer, and one or two hidden layers. Since multiplayer neural network reflects nonlinear characteristics, it has been used successfully to solve some complicated or diverse nonlinear problems. The BPN algorithm is summarized as follows:

The operation of BPN composes of two passes: a forward pass and a backward pass. All of the weights are fixed in the forward pass, but they are adjustable in the backward pass. Training a neural network in the backward pass achieves optimization most effectively by adjusting the weights and thresholds which control the cost function, and the cost function is defined as below:

$$E = \sum_k \frac{1}{2}(Y_k^* - Y_k)^2 \tag{3}$$

where E is expectation; $Y_k^*$ is the output value.

According to Delta Rule, we have

$$dP_{ji}^S = -\eta \cdot \frac{\partial E}{\partial Net_j^S}\frac{\partial Net_j^S}{\partial P_{ji}^S} = -\eta \cdot \delta_j^S \cdot X_i^{S-1} \tag{4}$$

where s is order of the layer.

When s is output layer, it becomes

$$\delta_j^S = \frac{\partial E}{\partial Net_j^S} = \frac{\partial E}{\partial Y_j^S}\frac{\partial Y_j^S}{\partial Net_j^S}$$

$$= -(Y_j^* - Y_j) \cdot f_{act-Y}'(Net_j^S) \tag{5}$$

When s is hidden layer, it becomes

$$\delta_j^S = \frac{\partial E}{\partial Net_j^S} = \frac{\partial E}{\partial X_j^S}\frac{\partial X_j^S}{\partial Net_j^S} = \frac{\partial E}{\partial X_j^S} \cdot f_{act-Y}'(Net_j^S)$$

$$\frac{\partial E}{\partial X_j^S} = \sum_k \frac{\partial E}{\partial Net_k^{S+1}}\frac{\partial Net_k^{S+1}}{\partial X_j^S} = \sum_k \delta_k^{S+1} \cdot Q_{kj}^{S+1}$$

$$\Rightarrow \delta_j^S = f_{act-Y}'(Net_j^S) \cdot \sum_k \delta_k^{S+1} \cdot Q_{kj}^{S+1} \tag{6}$$

where η is a small positive constant called the learning rate.

In order to minimize the error, we should adjust all the weights and thresholds in the opposite direction using the gradient method during training.

The forward passes or backward passes proceeds layer by layer, and they are repeated until the error of output is acceptable.

# 3 On inflow forecasting

## 3.1 Data selection

The situation of Shihmen reservoir in Tao-Yuan, Taiwan is shown in Fig. 2. The main functions of Shihmen reservoir are water supply, irrigation, hydraulic power generation, flood control and recreation. Since constructed in June 1964, it conduces both to water resource operation and economics improvement significantly in northern Taiwan.

The input and output data for the training process of the ANN model consist of upstream rainfall and reservoir inflow data in 12 typhoon events respectively. They are HOLLY (1984), NELSON (1985), ABBY (1986), SARAH (1989), YANCY (1990), ABE (1990), DOT (1990), POLLY(1992),

DOUG (1994), FRED (1994), SETH (1994), HERB (1996). All data are offered by the related government organizations in Taiwan, North Water Resource Bureau of Water Resources Agency Ministry of Economic Affairs.

The rainfall data was collected by 10 upstream ombrometer stations located in watershed of Shihmen reservoir as shown in Fig. 3. The locations of these stations are all selected by experts. The inflow data are taken from the stations on the inlet of Shihmen reservoir. The data are transmitted through simultaneous wireless system to control center, and those unreasonable data are sieved or picked out.

### 3.2 The input patterns

The input patterns include rainfall data of 10 stations, and each neuron denotes a rainfall station with 72 hours lagged data (Fig. 3).

In rainfall-runoff model in previous researches, the runoff and rainfall several hours ahead were taken as input data, and it could not only save on input data, but also converge faster during training. It seems reasonable to consider the lagged runoffs as input data; however, the lagged runoffs sometimes may not be available so that we have to establish a “rainfall-runoff” model in this paper. Then, estimating inflows without lagged data becomes a main issue. Therefore, some experiential formulas were used in this paper.

The rule of thumb help us to understand the duration of water-concentration in the study catchments: It takes about ten hours for concentration from watershed, and more than thirty hours for the peak flow to reach the reservoir. Since the whole water-concentrating period may last decades of hours, rainfall data of past 72 hours are considered to simulate the ANN model.

### 3.3 The training phase

The data of twelve typhoon events are divided into two parts -- four and eight events: the former are training patterns; the latter are verifying patterns. The two breaking conditions while training: If the value of error equal to 0.0001 or less, or the system had already been trained for 1200 times, then the training process will be stopped. For faster converging to the optimal results, the learning rate is changeable in training process. The initial learning rate is 0.95 under 900 times of training; 0.35, over 900 times. Moreover, ANN model should be retrained if it is stopped due to a wrong training before 1200 times.

### 3.4 ANN architecture

**Input layer:**

Past 72 hours rainfall data is taken as inputs; the “rainfall-runoff” model is simulated with these inputs. There are total 720 neurons in the input layer.

**Hidden layer:**

Two hidden layers, with 72 neurons in one layer and 39 in another, are established. Two hidden layers are used here in order to represent the complicated characteristics of basin. The 72 nodes of the first hidden layer denote rainfall data over 72 hours. In other words, each node is the mean of 10 rain-gauges in one hour. Actually, the first hidden layer is prearrangement of neural networks, and the second hidden layer is real hidden layer of neural networks. The nodes interwork with each other only in the second hidden layer.

**Output layer:**

There are 7 neurons in this layer, which contains $Q_t$ , $Q_{t+1}$ , … , $Q_{t+6}$, where $Q_t$ is discharges at time of t and $Q_{t+1}$ is discharges at time of t+1, and so forth. Thus, $Q_{t+6}$ is discharges at time of t+6. For better estimations, we also set up connections between these contiguous 7 neurons. Thus, $Q_{t+1}$ can be estimated based on $Q_t$ .

### 3.5 Evaluation Criteria

The performances of ANN model are evaluated and compared by the four evaluation criteria below:

1. Coefficient of Efficiency (CE):
2. Volume Error (VOER):
3. Peak Flow Error (PER) :
4. Time of Peak Flow Error (TPER) :

Positive VOER (Volume Error) denotes the excess forecasting volume; positive PER (Peak Flow Error) means an excess of peak flow, and positive TPER (Time of Peak Flow Error) means delayed peak time. Negative values denote the opposite meaning. CE (Coefficient of Efficiency) values are small or close to 1 means the model forecast well.

## 4 Results

The results are split into three sections: the training, evaluation, and the verifying sections, respectively.

The training patterns include four typhoon events, while the verifying patterns include eight typhoon events. The training patterns are used for modifying and modeling the system in this phase. A great number of hourly data of the training events are input, and the ANN system will be developed. Fig.4 displays 12 surges totally; the first 4 surges, Holly, Nelson, Abby, and Sarah, denote the results of training typhoon events, while the next 8 surges denote the results of verifying typhoon events. The figure shows the accuracy of training patterns is satisfactory.

In evaluation, Table 1 demonstrates summary of evaluations of the 4 typhoon events. Obviously, they all have nice performance in terms of CE, VER, and PER, especially Sarah. Abby is the only typhoon that has just an hour of TPER.

Since the model was trained well, the rainfall data of the verifying events could be used for simulating inflows during verifying phase. The verifying typhoon events are Yancy, Abe, Dot, Doug, Fred, Seth, and Herb. The results and evaluations of these 12 events are shown as Fig.4 and Table 2, respectively. In Fig. 4, the later 12 surges are the results of verifying events. They are very satisfactory and accurate; in particular, the notorious Herb, the most disastrous typhoon of all, has acceptable performance as well. These verifying results show that the ANN excellently forecasts the inflows of reservoir.

For further study, the ANN model was also applied to predict the inflows. When the system starts to predict, there is only one output neuron, the inflows at t, denoted $Q_t$. On the other hand, there are 6 neurons set up as output terms in predicting phase. The 6 predictions are the inflows at t+1, t+2… t+6, denoted $Q_{t+1}$, $Q_{t+2}$ …$Q_{t+6}$, respectively. The predictions at t+1, t+3, and t+6 are plotted in Fig. 5 to Fig. 7, and the evaluation at t+3 is listed in Table 3. The performances in predictions are not as marvelous as the training results, but they are good enough as the verifying results.

# 5 Conclusion

Hydraulic problems are very complicated, and it is difficult to simulate. In this study, artificial neural networks can be applied to solve tough and nonlinear hydrology problems. The ANN model simulated typhoon events well, and provides satisfactory predictions.

Without last inflows data, ANN forecasts the inflows very well and presents a pure "rainfall-runoff" model. This is the principal advantage that the pre-existing study may be lack of. The connections, another advantage of this ANN model, provide the communications of forecasting information between an output neuron and next one. Benefit by the connections, it can forecast inflows several hours later and make up the rainfall data required. ANN also has an excellent performance in big events like typhoon Herb.

Taiwan is a hilly island. According to the historical climatic data, the river flows in Taiwan change a lot during flood period and non-flood period. Although the flood period is short, the flows volume is high; comparatively, the base flows only remain in the river during non-flood period. That is to say, this is a kind of flashy basin, and the results of the model may relate to this type of basin.

This model is trained by over 2500 rainfall data from Shihmen watershed, and the ANN model exhibits good outcomes in forecasting flood inflows. It may not be appropriate for other type of basins; however, we provide a procedure how ANN simulated nonlinear hydrology problems successfully. In fact, this simulation can be applied to other types of basins only if the nodes of neural network are modified by retraining plentiful data. It is recommended that the way it is trained can be repeated in the future.

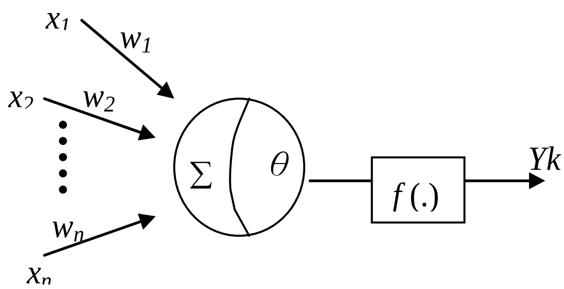


Fig. 1 An artificial neuron

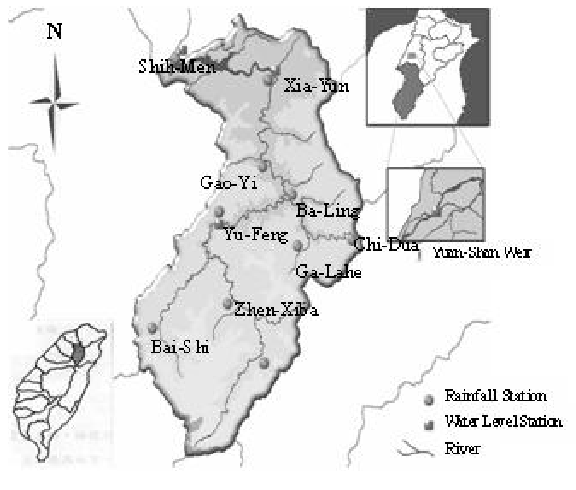


Fig. 2 Watershed of Shihmen reservoir

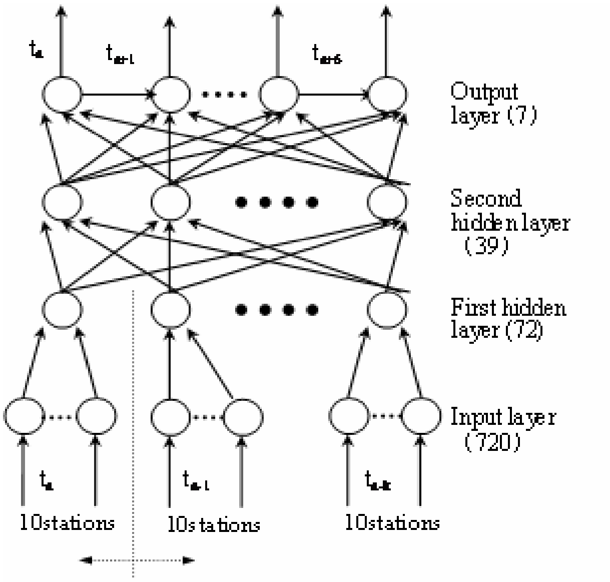


Fig. 3 Structure of network

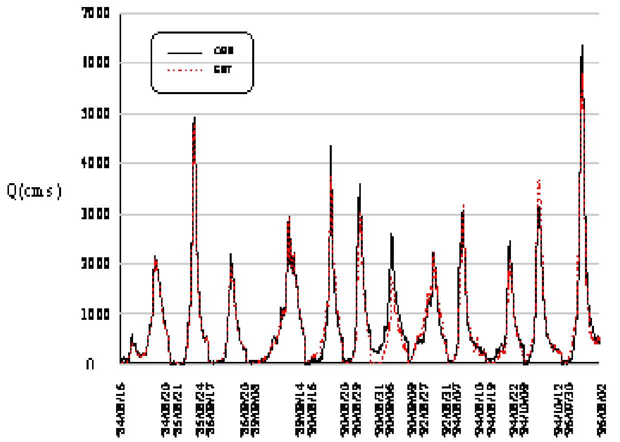


Fig. 4 Results of ANN

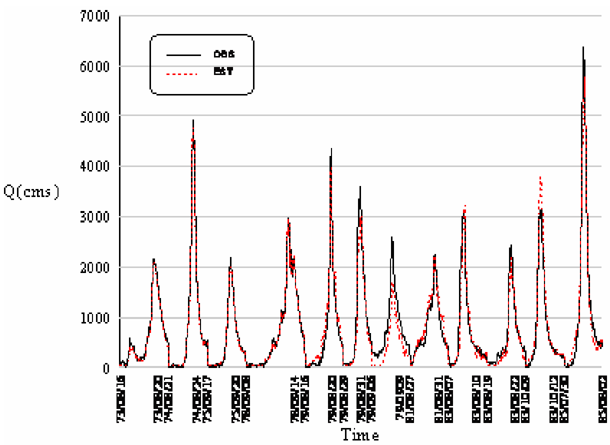


Fig. 5 Results of ANN at t+1

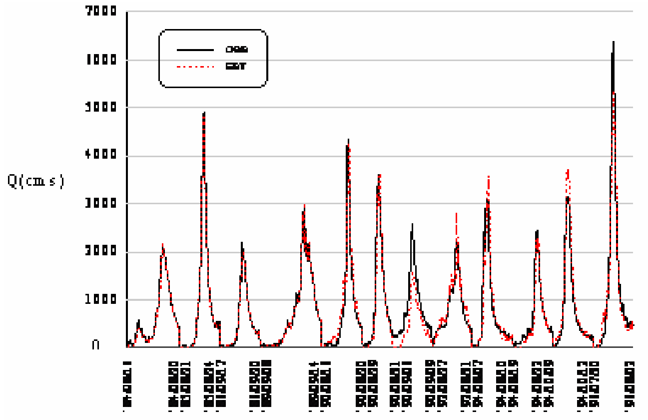


Fig. 6 Results of ANN at t+3

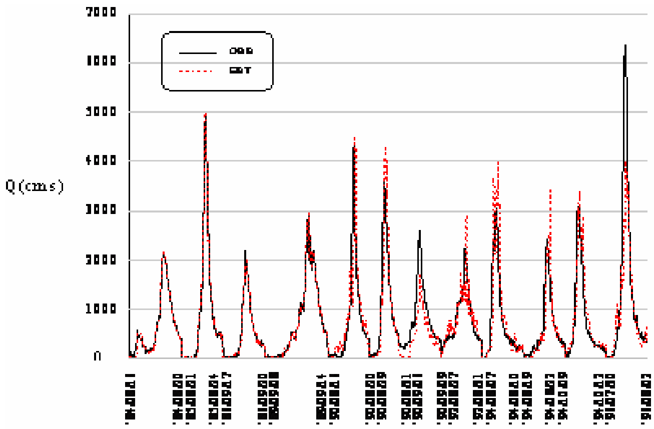


Fig. 7 Results of ANN at t+6

Table 1 Summary of evaluations of the training events

| Output at t | CE | VER | PER | TPER |
|---|---|---|---|---|
| Holly | 0.987027 | -0.081685 | -0.038716 | 0 |
| Nelson | 0.998334 | -0.024708 | -0.022029 | 0 |
| Abby | 0.992432 | 0.009325 | -0.108816 | 1 |
| Sarah | 0.99741 | -0.000831 | -0.006968 | 0 |

Table 2 Summary of evaluations of the verifying events

| Output at t | CE | VER | PER | TPER |
|---|---|---|---|---|
| Yancy | 0.95788 | 0.132614 | -0.126072 | -2 |
| Abe | 0.932645 | -0.163006 | -0.149399 | 3 |
| Dot | 0.566634 | -0.416272 | -0.320226 | 0 |
| Polly | 0.919052 | 0.119962 | -0.002607 | 0 |
| Doug | 0.917539 | -0.088812 | 0.0466538 | 1 |
| Fred | 0.91302 | -0.177201 | -0.129656 | -1 |
| Seth | 0.957526 | 0.134781 | 0.1729701 | 0 |
| Herb | 0.972328 | -0.045213 | -0.085844 | 2 |

Table 3 Summary of the result of the verifying patterns at t+3

| Output at t+3 | CE | VER | PER | TPER |
|---|---|---|---|---|
| Yancy | 0.9261 | 0.12405 | -0.027797 | 1 |
| Abe | 0.95802 | -0.0851 | -0.004953 | 3 |
| Dot | 0.56862 | -0.416 | -0.396014 | 2 |
| Polly | 0.88871 | 0.08237 | 0.2599263 | 0 |
| Doug | 0.87667 | 0.000048 | 0.1703163 | 4 |
| Fred | 0.92954 | -0.1392 | -0.071766 | -1 |
| Seth | 0.91528 | 0.17125 | 0.1938728 | 1 |
| Herb | 0.92534 | -0.1085 | -0.157996 | 2 |

*References:*


[1] Chang, F.-J., Chen, L., 1998, Real-coded genetic algorithm for rule-based flood control reservoir management. *Water Resource Management* 12, 185-198.

[2] Chang, F.-J., Chen, Y.-C., 2001. A counter-propagation fuzzy-neural network modeling approach to real time streamflow prediction. *Journal of Hydrology*, 245 (1–4), 153–164.

[3] Chang, F.-J., Chen Y.-C., 2003. Estuary water-stage forecasting by using radial basis function neural network. *Journal of Hydrology*, 270 (1-2), 158-166.

[4] French, M.N., Krajeswski W.F., Cuykendall R.R., 1992. Rainfall forecasting in space and time using a neural network. *Journal of Hydrology*. 137, 1-31.

[5] Golob, R., Stokelj, T., Grgic, D., 1998. Neural-network-based water inflow forecasting, *Control Engineering Practice*, 6 (5), 593-600.

[6] Hagan, M.T., Demuth, H.B., Beale M., 1996. *Neural Network Design*.

[7] Halff, A.H., Halff, H.M. Azmoodeh, M., 1993. Predicting Runoff from Rainfall using Neural Networks. *Proc. Eng. Hydrol.*, ASCE, NY, 760-765.

[8] Hjelmfelt, A.T., Wang, M. 1993. Runoff simulation using artificil neural networks, *Proceedings twenty-fifth Congress of the International Association for Hydraulic Research. Special Lectures*, Technical Session A, Flood and Drought, 1, 517-522.

[9] Hsu, K-L., Gupta, V.K., Sorooshian, S., 1995. Artificial neural network modelling of the rainfall–runoff process. *Water Resour. Res.* 31 (10), 2517–2530.

[10] Lorrai M., Sechi G.M., 1995. Neural nets for modelling rainfallrunoff transformations. *Water Resour. Manage*. 9, 299-313.

[11] Mcculloch, W. S., and Pitts, W., 1943. A Logical Calculus of the Ideas Immanent in Nervous Activity. *Bulletin of Mathematical Biophysics* 5: pp.115-133.

[12] Rumelhart, D.E., Hintont, G.E., Williams R.J., 1986. Learning representations by back-propagating errors. *Nature* 323, 533 – 536.

[13] Sajikumara, N., Thandaveswarab B.S., 1999. A non-linear rainfall–runoff model using an artificial neural network. *Journal of Hydrology* 216, 32–55.

[14] Torfs, P., Wojcik, R., 2001. Local Probabilistic Neural Networks in Hydrology. *Phys. Chem. Earth* (B), 26, (1), 9-14.

[15] Wang, A.P., Cheng, B.W., 1999. Fuzzy decision analysis in reservoir operation during flood period. *J. of Chinese Fuzzy Systems*, Vol. 5, No.2.