Journal of Hydroscience and Hydraulic Engineering
Vol. 17, No.2 November, 1999, 37-50

COMPARISON OF INTEGRATED ARTIFICIAL NEURAL NETWORK WITH TIME SERIES MODELING FOR FLOOD FORECAST

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SYNOPSIS

This study presents a flood forecasting procedure by integrating LTF(Linear transfer function), ARIMA(Auto regressive integrated moving average) model and ANN(Artificial neural network), we call it integrated ANN model. The proposed procedure allows one to accurately forecast the flood discharges at a downstream gauging station. For illustrative purposes, the proposed integrated procedure and a stand-alone ARIMA model are applied to Wu-Shi basin, Taiwan. The simulated results obtained from these two models are then compared in this study.

INTRODUCTION

Time series ARIMA (Auto Regressive Integrated Moving Average) models have been extensively used in hydrology and water resources to model the annual and periodic hydrologic time series since the early 1960's (4). These models have highly promising hydrological application because [I] the auto-regressive form has an intuitive type of time dependence (the value of a variable at the present time depends on the values at previous times), and [II] they are relatively easy to be applied. In this study, we adopt the SCA (1) (Scientific Computing Associations) statistical system to construct ARIMA based flood forecasting models of Wu-Shi basin, Taiwan.

In flood prevention analysis, reference points are normally located on a densely populated region at the downstream. These tributaries affect the mainstream in watershed encompassed tributaries. Therefore, this study constructs a flood forecasting model capable of accurately representing the complex relation between downstream and upstream. The artificial neural network (ANN) makes such a consideration.

ANN, a means of solving nonlinear dynamic problems, can accurately represent an internally complex relation between input and output variables (8). In light of above concern, this study presents a flood discharge forecasted model by applying an artificial neural network to identify the relationships between the flood discharges at downstream and upstream gauging stations.

ANN has been successfully applied to forecast flood discharge. M.L. Zhu and M. Fujita (7) forecasted the hourly discharge in flooding events by ANN. Although obtaining acceptable results, their investigation lacked a systematical procedure to determine an appropriate number of neurons for an input layer of ANN, thereby limiting the range of forecasting time step to the next three forecasting hours; Therefore, their model can be viewed as a preliminary application for flood forecasting.

Hsu et al. (2) recommended that a forecasting model should design many ANN combinations having different numbers of neurons at input, hidden and output layers to simulate daily discharge. Their investigation then used RMSE(root-mean-square error), AIC(Akaike's information criterion), and BIC(Bayesian information criterion)to select the optimal combination. However, their models could not objectively determine the number of processing units in input layer owing to some anticipated assumptions may mislead the selection of the optimal combination.

Huang (3) also adopted AIC and BIC criteria to establish ANN hourly discharge forecasting models. However, their models did not have a fixed structure for all hourly forecasting because each model had its own design (Different forecasting range requires different ANN model).

Above investigations generally rely on a subjective means of designing ANNs and select the optimal one by RMSE, AIC and BIC. However, their methodologies lack an objective means of selecting the input elements. Therefore, this study estimates the impulse response weights of gauging stations of a watershed by LTF and performs a parameter significance T-test for impulse response weights, thereby allowing us to determine an appropriate number of processing units in input layer of ANN.

With historical data used as the only input data, forecasting range for those models is limited as well. To obtain a fixed ANN structure and extend the forecasting range, this study integrates the ARIMA and ANN as a hybrid watershed ANN flood forecasting model. The proposed method only uses the historical data when forecasting the discharge of the next hour, while the time series ARIMA model provides the predicted input values (upstream discharges) for the next several hours.

More specifically, this study integrates three methods, LTF, time series ARIMA model and ANN, to accurately forecast the flood discharges for a downstream gauging station, we call it integrated ANN model. For illustrative purposes, the model proposed herein is applied to Wu-Shi basin in which the results obtained the forecasted discharge of the next one to three hours are satisfactory. The simulated results obtained from integrated ANN model and stand-alone ARIMA model are compared.

METHODOLOGY

Artificial Neural Network

ANN consists of many artificial neurons (commonly referred to as processing units or nodes). The output signal is determined by the algebraic sum of the weighted inputs, i.e.,

$$Y_i = f\left(\sum_i W_{ij} X_i - \theta_j\right) \tag{1}$$

where, Y_i : output signal of the node ;

f : transfer function ;

W_{ij} : weights of the node ; Wij is the connection from the ith neuron in the input layer to the jth neuron in the second or hidden layer.

X_i : input signals ;

θ_j : bias;

ANN has two faces of neural processing: [I] Learning process, in which all knowledge in ANN is encoded in the interconnection weights which are determined through learning process from a set of examples, and [II] Recalling process, in which the recalling process attempts to retrieve the information, based on the weights obtained from learning process, and to forecast the output data of new examples. Besides, the learning process can be categorized into two types: [i] Supervised learning (also referred to as learning with a teacher). Supervised learning gradually adjusts the weights of the ANN, thereby minimizing the error signal between the known answers and the responses of ANN. [ii] Unsupervised learning, which does not rely on an external teacher. Without a known answer, this approach is expected to identify features, categories or class memberships in the input data and associate them with the corresponding outputs (8).

After introducing basic structure and neural processing, this study describes the characteristics of a neural network. The characteristics of neural network can be summarized as follows: [I] Parallel distributed processing: neural network has a highly parallel structure which lends itself immediately to parallel implementation; [II] Fault tolerance: neural network has a highly fault tolerance. A negligible amount of wrong information, if exists in input data, can still reach a collective decision. Although some nodes lose their efficacy, neural network does not stop working; and [III] Learning and adaptation: the neural network can be trained and adapted using the information from the system without a prior knowledge of the system. It provides a model-free controller design approach to cope with complex systems. It can be adapted on-line as well.

Back-propagation network (BPN), a widely used neural networks, contains three layers (Fig 1): input (receives the input signals from the external world), hidden (represents the relation between input layer and output layer), and output (releases the output signals to the external world) layers. The appropriate number of hidden layer nodes in this study are determined by the following rule: (the number of input layer nodes + the number of output layer nodes)/2. Belonging to supervised learning, BPN gradually adjusts its weights, thereby minimizing the error between the known answers and actual responses (8).

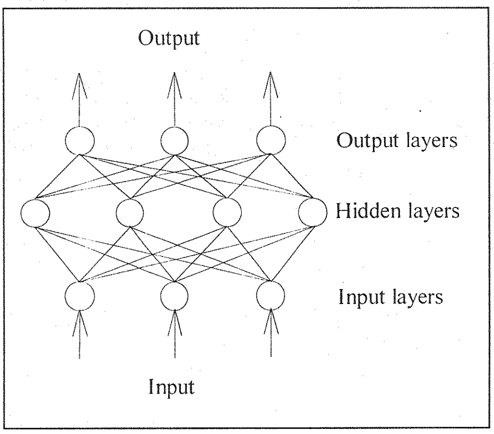

Fig. 1 Structure of back-propagation network

Linear Transfer Function

If the time series of interest, say X_t, is related to one or more other time series, a model called linear transfer function (LTF), can be constructed. Such a model uses the information content in these other time series to help forecast X_t. In addition, LTF applies the least-squares method to estimate the impulse response weights and can be expressed as follows:

$$Y_t = C + (\upsilon_0 + \upsilon_1 B + \upsilon_2 B^2 + \ldots\ldots + \upsilon_\ell B^\ell) X_t + a_t \qquad (2)$$

where B denotes the backward shift operator; Y_t represents the output time series; X_t is the input time series; C denotes the constant; a_t represents the white noise process; and the unknown weights $(\upsilon_0, \upsilon_1, \upsilon_2, \ldots\ldots, \upsilon_\ell)$ are called the impulse response weights (4). In this study, we estimate impulse response weights of every gauging station of a watershed by LTF and evaluate those weights by parameter significance T-test. Those processes are proposed in this study to determine the appropriate number of network input elements.

ARIMA

This study designs a representative ANN structure for fixed numbers of input layer processing and extends the range of the forecasting time step. Therefore, time series ARIMA model at every upstream gauging station is constructed to provide the data for the input layer of ANN in future forecasting. Box and Jenkins proposed ARIMA in 1976, which is capable of representing characteristics and meanings of stationary, non-stationary, and seasonal time series. The structure of ARIMA consists of auto regressive, moving average, and mixed processes:

$$\phi(B)\nabla^d Y_t = \theta(B) a_t \qquad (3)$$

where Y_t denotes the time series; B represents the backward shift operator and $B\,Y_t = Y_{t-1}$; $B^s Y_t = Y_{t-s}$; a_t is the white noise process and $a_t \sim N.D.(0, \sigma_a^2)$, N.D. is normally distributed with mean zero and variance σ_a^2 ; ∇^d is difference operator , and $\nabla^d Y_t = (1-B)^d Y_t$, $\phi(B) = (1-\phi_1 B - \ldots\ldots \phi_p B^p)$; $(\phi_1, \ldots\ldots, \phi_p)$ is autoregressive parameters and $\theta(B) = (1-\theta_1 B - \ldots\ldots \theta_q B^q)$; $(\theta_1 \ldots\ldots \theta_q)$ is moving average parameters (4).

In this study, we apply the SCA(Scientific Computing Associations)(1)(see appendix – SCA) statistical system to construct/develop the time series ARIMA models.

STATEMENT OF THE APPLICATION

Data Arrangement

The Wu-Shi basin, as depicted in Fig 2, is selected herein for testing the time series ANN model with Chien-Feng Bridge as the upstream gauging station (as gauging stations of tributaries, His-Nan Bridge of Da-Li River and Nan-Gang Bridge of Mao-Luo River), and Da-Du Bridge as the downstream gauging station. Five scenes of flood events were selected, as summarized in Table1 (6).

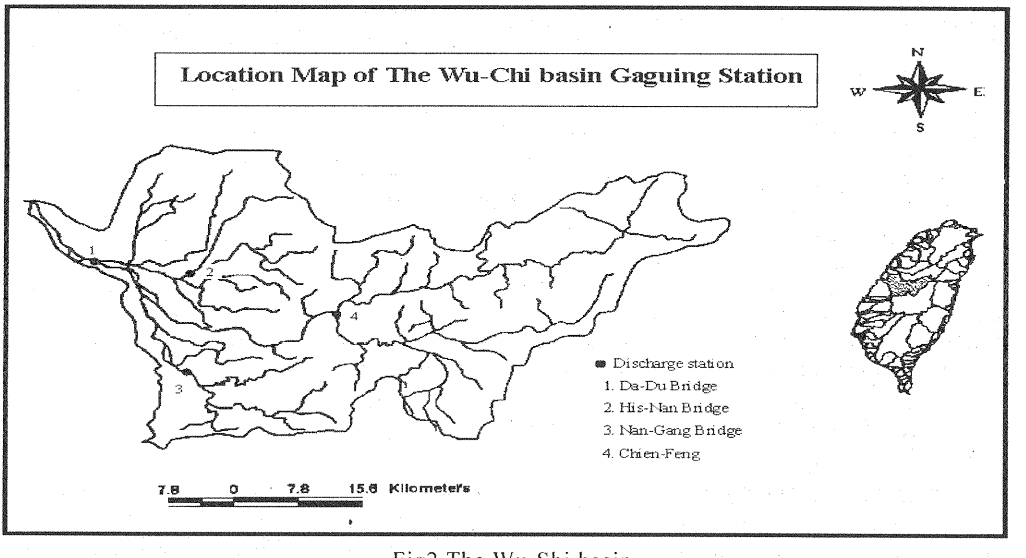

Fig2 The Wu-Shi basin

Table. 1 Flood events in this study

No.	Date	Cause of Flood Events	Peak (cms[m³/sec])	Uses
1	1993.5.26	Storm	1780	learning ; calibration
2	1993.6.2	Storm	2430	learning ; calibration
3	1990.4.16	Storm	1850	verification (recalling)
4	1992.7.6	Storm	2100	verification (recalling)
5	1992.8.30	Baoli(Typhoon)	2810	verification (recalling)

Construction of Integrated ANN Model

First, representative time steps of every gauging station are chosen by the following procedures:

1. Wu-Shi basin has an average velocity of 4.95m/sec and the time of concentration of 5.8 hours (5). Therefore, in this study, one to five time steps are selected as the candidate of the representative time steps of every gauging station.
2. Next, impulse response weights of one to five time steps of every gauging station are calculated by LTF and proceed parameter significance T-test of impulse response weights, i.e. in Table 2. If the absolute value of the T value of any time step exceeds 1.96, it indicates this time step is significance in statistics and should be adopted as input neuron in the model.

Table. 2 Parameter significance T-test of impulse response weights

Time Steps	His-Nan Bridge (T VALUE)	Nan-Gang Bridge (T VALUE)	Chien-Feng Bridge (T VALUE)	Da-Du Bridge (T VALUE)
1	**1.35**	**-3.67**	**4.90**	**1.97**
2	**1.45**	**3.03**	**-3.30**	**-2.70**
3	0.64	0.04	**3.35**	**2.25**
4	0.33	1.40	-1.44	-1.41
5	1.54	-0.51	-1.60	-0.69

3. According to the T-test, the representative time steps are 1~2 time steps for Nan-Gang Bridge, 1~3 time steps for Chien-Feng Bridge, 1~3 time steps for Da-Du Bridge. However, all T values of His-Nan Bridge are smaller than 1.96. Finally, 1~2 time steps are selected herein as the representative time steps of the His-Nan Bridge by comparison (T values of 1~2 time steps are larger than 1, but those of 3~4 time steps are smaller than 1)and physical meaning (If the velocity of flood is smaller than 4.95m/sec, the traveling time of flow between His-Nan Bridge and the downstream gauging station is within 3 hours).

According to above results, the number of input layer nodes are three ($I'_{t-1}, I'_{t-2}, I'_{t-3}$) for His-Nan Bridge, three ($I''_{t-1}, I''_{t-2}, I''_{t-3}$) for Nan-Gang Bridge, four ($I_{t-1}, I_{t-2}, I_{t-3}, I_{t-4}$) for Chien-Feng Bridge, and four ($O_{t-1}, O_{t-2}, O_{t-3}, O_{t-4}$)for Da-Du Bridge. The sum of all input layer nodes is 14 while the number of the output layer nodes is single (O_t) . The appropriate number of hidden layer nodes is nearly 8. Finally, input vector (x_i) and objective vector (T) are shown as follows:

$$x_i^T = \left(I'_{t-1}, I'_{t-2}, I'_{t-3}, I''_{t-1}, I''_{t-2}, I''_{t-3}, I_{t-1}, I_{t-2}, I_{t-3}, I_{t-4}, O_{t-1}, O_{t-2}, O_{t-3}, O_{t-4}\right) \quad (4)$$

$$T = O_t$$

where ,

x_i^T : the transposed input vector of x_i

$I'_{t-1}, I'_{t-2}, I'_{t-3}$: inflow discharge of His-Nan Bridge , "t-i" is previous i hours of t hour.

$I''_{t-1}, I''_{t-2}, I''_{t-3}$: inflow discharge of Nan-Gang Bridge

$I_{t-1}, I_{t-2}, I_{t-3}, I_{t-4}$: inflow discharge of Chien-Feng Bridge

$O_{t-1}, O_{t-2}, O_{t-3}, O_{t-4}$: outflow discharge of Da-Du Bridge

O_t : outflow discharge of t hour of Da-Du Bridge

With determined processing number for each layer, learning training process is displayed by the following organizational flow chart Fig 3.

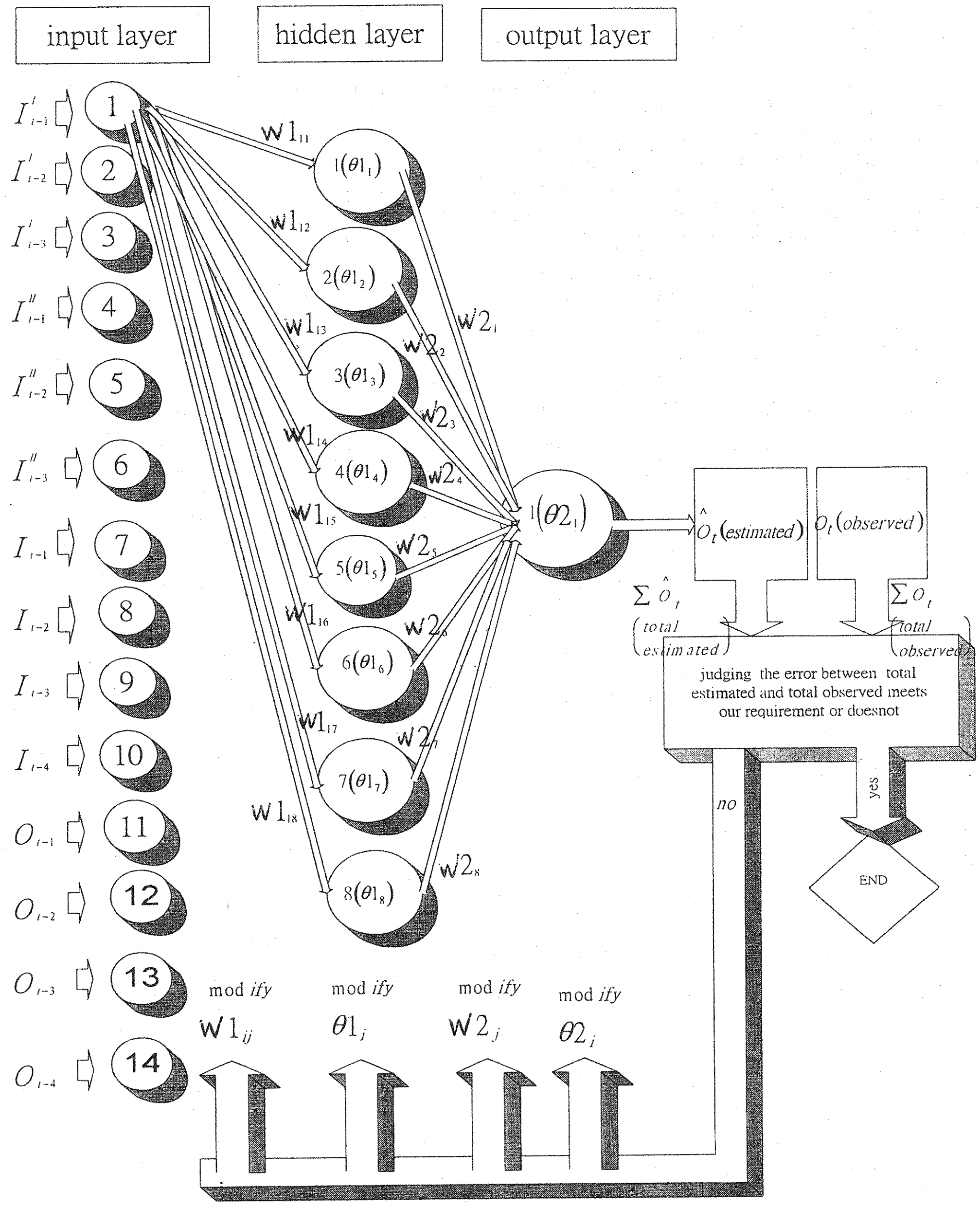

Fig. 3 Organizational flow chart of learning training process

The first two flood events (May 26, 1993 and June 2,1993) are adopted as a learning data set with requirements with respect to accuracy of the learning process, i.e. error function (Error function is expressed as follows: $E=(1/2)\sum_j (T_j - O_j)^2$ where Tj is target output; Oj is network output.) is less than 0.1. With ultimate actual accuracy E=0.0844 (illustrated in Fig 4), the learning training process helps us obtain representative weights and biases.

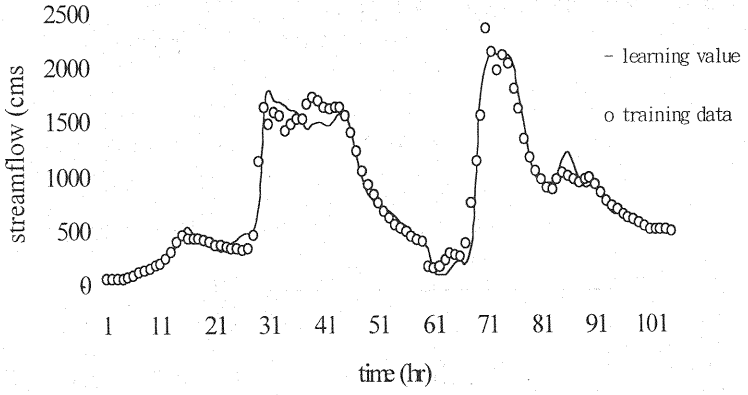

Fig. 4 Results obtained from learning process (May 26,1993 and June 2,1993).

[Data 1~59 of this fig belong to the first event (May 26,1993).]

[The others belong to the second event (June 2,1993).]

Via these parameters, the recalling process can be designed to accurately forecast the outflow discharge in the next hour. When proceeding with the outflow discharge forecasting in the next several hours, the predicted discharges at the upstream gauging stations are required. In this study, we construct a time series ARIMA models at every upstream gauging station and every gauging stations of tributaries to provide the forecasting discharges which are input data for forecasting at downstream outflow of the next several hours. Time series ARIMA models at every gauging station can be estimated as follows:

(1) Verify whether if the learning data set at every gauging stations of tributaries and upstream are stationary series. If not, try successively for the appropriate orders of differentiation until the stationary behavior is achieved.

(2) With stationary series, proceed to estimate the auto-regressive process of order p and moving average process of order q. Then establish any probable forecasting models at every gauging station by combining different p,q items and obtaining each BIC (Bayesian information criterion) value.

By BIC rule (if the model has the smallest BIC value than others, it means the model which has the best performance in forecasting than others), the optimal forecasting models at every gauging station and their representative p,q items can be obtained. After p,q items and their parameters have been confirmed, a decision can be made of the time series ARIMA models at every gauging station.

Above relative information and parameters needed can be obtained by SCA statistical system. The time series ARIMA models at every gauging station and the flow chart of integrated ANN model are expressed as follows:

His-Nan Bridge $\nabla Y_t = 0.5876\nabla Y_{t-1} + 0.2962 + a_t - 0.2578 a_{t-1} - 0.2450 a_{t-2}$ (5)

Nan-Gang Bridge $\nabla Y_t = 1.4375\nabla Y_{t-1} - 0.7087\nabla Y_{t-2} - 0.0421 + a_t - 0.5005 a_{t-1}$ (6)

Chien-Feng Bridge $\nabla Y_t = 0.4213\nabla Y_{t-1} + 1.6117 + a_t - 0.1737 a_{t-1} + 0.3337 a_{t-2}$ (7)

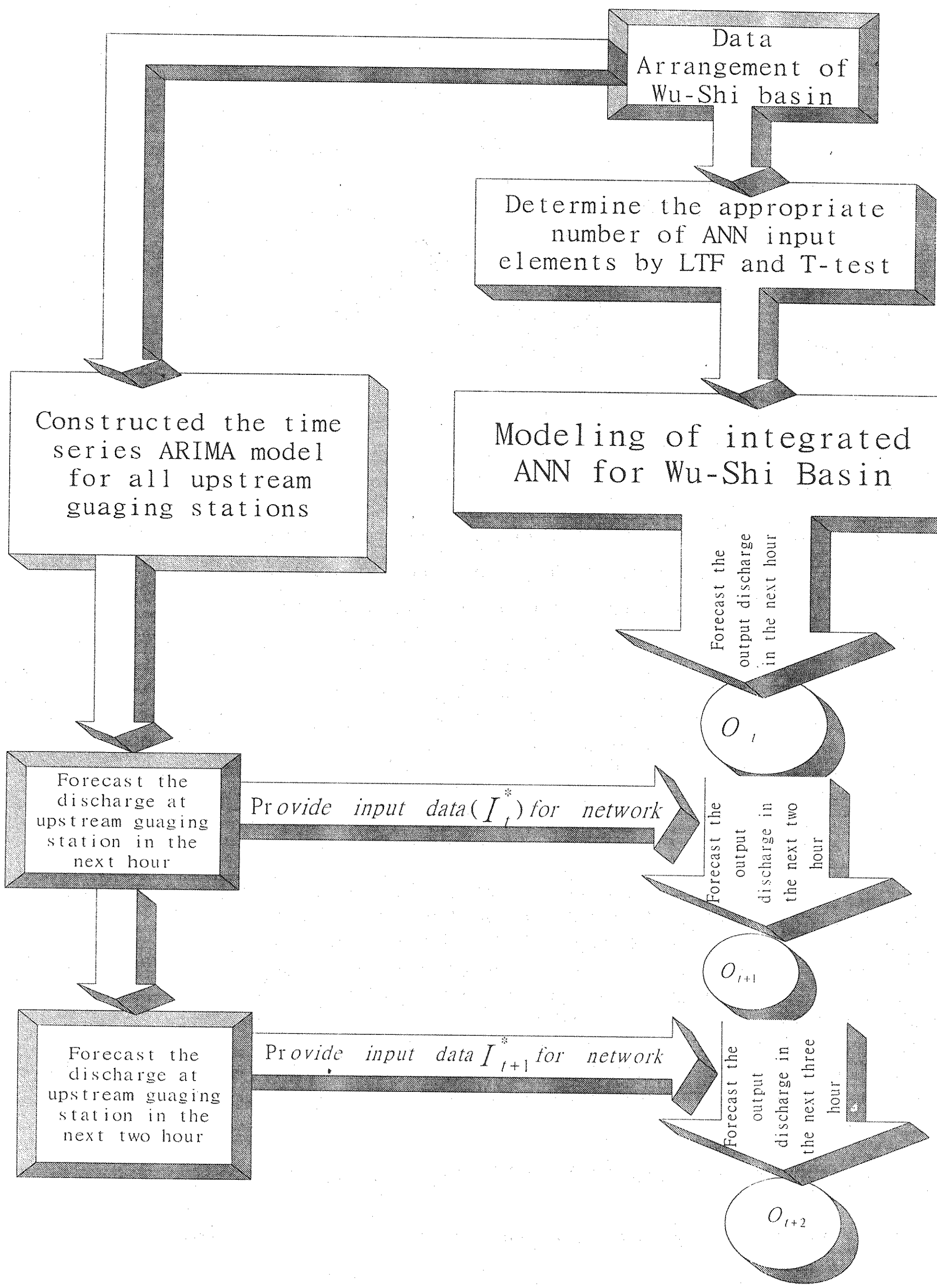

Fig. 5 The flow chart of integrated ANN model

Criteria of Comparing the Models

Three indicators are used herein to evaluate the proposed model's accuracy:

(Ⅰ) Coefficient of efficiency, CE

$$CE = 1 - \frac{\sum(Q_{obs} - Q_{est})^2}{\sum(Q_{obs} - \bar{Q}_{obs})^2} \tag{8}$$

where Q_{est} denotes the estimating flood discharge (cms); Q_{obs} represents the observed flood discharge (cms); and $\bar{Q}_{obs}$ is the mean value of the observed flood discharge (cms). The closer value of CE to 1 implies a more accurate model.

(2) Error of peak discharge, EQ_P

$$EQ_p = \frac{Q_{pest} - Q_{pobs}}{Q_{pobs}} \tag{9}$$

where Q_{pobs} and Q_{pest} are the peak discharges of flood of observation and estimation, respectively. The lower value of EQp implies a more accurate model.

(3) Error of time to peak, *ETp*

$$ET_p = T_{pest} - T_{pobs} \tag{10}$$

where T_{pest} and T_{pobs} denote the times to peak discharge of estimation and observation, respectively. The smaller value of ETp implies a more accurate prediction of occurrence of peak discharge.

CALIBRATION AND VERIFICATION

According to the calibration results (Table 3), the average value of CE is 0.961 and the average value of EQp is 0.071. For ETp, the second flood events (in June 2,1993) is within 1 hour, while the first one (in May 26, 1993) is up to 8 hours for the close discharges of eight hours before and after the peak. Overall, the calibrated results of the proposed model are satisfactory.

Table. 3 Calibrated results

No.	Date	Cause of Flood Events	Peak (cms)	CE	EQp	ETp 【hr】
1	1993.5.26	Storm	1780	0.9699	0.0379	-8
2	1993.6.2	Storm	2430	0.9522	-0.1054	1

Table4 indicates that the average value of CE is 0.894, the average value of EQp is 0.075, and the average value of ETp is within 2 hours for the verified results at the next hour. However, the average values of CE are 0.663 and 0.509, the average values of EQp are 0.093 and 0.118, and the average values of ETp are within 2.75 and 4 hours for the next two and three hour, respectively. Obviously, the above results are acceptable. However, the verified results at the next three hours are not as satisfactory as those at the next one and two hours, but still have acceptable simulations in terms of the trend of outflow hydrograph.

Table. 4 Verified results

No.	Date	Cause of Flood Events	Peak (cms)	Forecasting hours 【hr】	CE	EQp	ETp 【hr】
3	1990.4.16	Storm	1850	one	0.9259	0.0298	1
				two	0.7204	0.0622	2
				three	0.5954	0.1779	3
4	1992.7.6	Storm (Peak 1)	2000	one	0.9209	-0.0550	2
				two	0.6358	0.0200	3
				three	0.3764	0.1750	4
4	1992.7.6	Storm (Peak 2)	2100	one	0.9209	-0.0644	1
				two	0.6358	-0.0950	1
				three	0.3764	-0.0335	4
5	1992.8.30	Baoli	2810	one	0.8070	-0.1531	4
				two	0.6601	-0.1950	5
				three	0.6894	-0.1924	5

From the calibrated and verified results, we can infer that the integrated ANN model is practical for flood forecasting in Wu-Shi basin.

Besides, the simulated results for verification in final typhoon event (in August 30, 1992) are worse than the other events because the peak discharge of final event is 2810cms and the numbers of discharges over 2000cms are seven. However, the maximal discharge of the learning sample is 2430cms and the numbers of discharges over 2000cms for learning sample are three. Being a disadvantage of supervised learning, the proposed model cannot accurately forecast the discharge over the range of the learning sample.

Comparison of models

This study also proceeds with flood forecasting at the next one ~ three hours by the ARIMA model at Da-Du Bridge as follow:

$$\text{Da-Du Bridge} \quad \nabla Y_t = 0.2234\nabla Y_{t-1} + 4.8829 + a_t + 0.3860 a_{t-1} \qquad (11)$$

Finally, this study compares the results between these two models (the time series ARIMA model at downstream gauging station and the integrated ANN model) from Tables. 5~7. In CE, they are not difference obviously in the performance of CE compared Time series ARIMA model with integrated ANN model. However In EQp, although the time series ARIMA model for downstream gauging station is better than the integrated ANN model in general, it appears more likely to under-estimate the peak discharge. In the practice of flood damage reduction, the under-estimation of peak discharge will incur serious damage for inhabitant at downstream area. In ETp, They are not difference obviously in the performance of ETp compared Time series ARIMA model with integrated ANN model.

Table.5 Verified results of two models (CE)

No.	Date	Cause of Flood Events	Peak (cms)	Forecasting hours 【hr】	integrated ANN model (CE)	time series ARIMA model (CE)
3	1990.4.16	Storm	1850	one	0.9259	0.9027
				two	0.7204	0.6890
				three	0.5954	0.4171
4	1992.7.6	Storm (Peak 1)	2000	one	0.9209	0.9217
				two	0.6358	0.7712
				three	0.3764	0.5949
4	1992.7.6	Storm (Peak 2)	2100	one	0.9209	0.9217
				two	0.6358	0.7712
				three	0.3764	0.5949
5	1992.8.30	Baoli	2810	one	0.8070	0.9210
				two	0.6601	0.7583
				three	0.6894	0.5302

Table. 6 Verified results of two models (EQp)

No.	Date	Cause of Flood Events	Peak (cms)	Forecasting hours 【hr】	integrated ANN model (EQp)	time series ARIMA model (EQp)
3	1990.4.16	Storm	1850	one	0.0298	-0.0264
				two	0.0622	-0.0261
				three	0.1779	-0.0233
4	1992.7.6	Storm (Peak 1)	2000	one	-0.0550	-0.0492
				two	0.0200	-0.0578
				three	0.1750	-0.0573
4	1992.7.6	Storm (Peak 2)	2100	one	-0.0644	0.0174
				two	-0.0950	-0.0347
				three	-0.0335	-0.0331
5	1992.8.30	Baoli	2810	one	-0.1531	-0.0133
				two	-0.1950	-0.0146
				three	-0.1924	-0.0131

Table.7 Verified results of two models (ETp)

No.	Date	Cause of Flood Events	Peak (cms)	Forecasting hours 【hr】	integrated ANN model (ETp)	time series ARIMA model (ETp)
3	1990.4.16	Storm	1850	one	1	2
				two	2	3
				three	3	4
4	1992.7.6	Storm (Peak 1)	2000	one	2	1
				two	3	2
				three	4	3
4	1992.7.6	Storm (Peak 2)	2100	one	1	1
				two	1	2
				three	4	3
5	1992.8.30	Baoli	2810	one	4	1
				two	5	2
				three	5	3

CONCLUSION AND DISCUSSION

This study presents a novel flood forecasting procedure by integrating LTF(Linear transfer function) 、ARIMA(Auto regressive integrated moving average) model and ANN(Artificial neural network). Based on the results presented herein, we conclude the following: Compared with previous investigations, our design of the model proposed herein not only has a simple structure but also does not contain the anticipated hypothesis. On account of the satisfactory results at the next one hour through the next three hours of flood forecasting, we believe that the integrated ANN model, which consists of ANN, LTF and ARIMA model, is appropriate for watershed flood forecasting.

In this section, then we compare the differences in model construction, selection of the input elements and application between the time series ARIMA model and the integrated ANN model.

1. Model construction

   The construction of the time series ARIMA model is relatively simple. While, the integrated ANN model is complex because it consists of ANN, LTF and ARIMA model.

2. Selection of the input elements

   The time series ARIMA model analyses the characteristics of the time series by autocorrelation function (ACF) and partial autocorrelation function (PACF) to select several kinds of possible combinations, each having different numbers of the input elements; In the integrated ANN model, we propose the linear transfer function method and parameter significance T-test to determine the number of network input elements.

3. Modeling Considerations

   The time series ARIMA model can only discuss the characteristics of single gauging station because it only conducts analysis on the historical trend of the variable. On the other hand, the design of the integrated ANN model considers the input to output relationship between at the upstream and downstream gauge stations. Restated, the integrated ANN tries to simulate the mechanism of the flood routine for the selected watershed.

ACKNOWLEDGMENTS

The authors would like to thank the National Science Council of the Republic of China for financially supporting this research under Contract No. NSC 87-2211-E035-019. The anonymous reviewers are also appreciated for their constructive comments.

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APPENDIX – NOTATION

The following symbols are used in this paper:

a_t	= white noise process;
B	= backward shift operator;
C	= denotes the constant;
f	= transfer function ;
$I'_{t-1}, I'_{t-2}, I'_{t-3}$	= inflow discharge of His-Nan Bridge , "t-i" is previous i hours of t hour;
$I''_{t-1}, I''_{t-2}, I''_{t-3}$	= inflow discharge of Nan-Gang Bridge;
$I_{t-1}, I_{t-2}, I_{t-3}, I_{t-4}$	= inflow discharge of Chien-Feng Bridge;
$O_{t-1}, O_{t-2}, O_{t-3}, O_{t-4}$	= outflow discharge of Da-Du Bridge;
O_t	= outflow discharge of t hour of Da-Du Bridge;
Q_{est}	= estimating flood discharge (cms);
Q_{obs}	= observed flood discharge (cms);
Q_{pobs}	= the peak discharges of flood of observation ;
Q_{pest}	= the peak discharges of flood of estimation;
T_{pest}	= the times to peak discharge of estimation ;
T_{pobs}	= the times to peak discharge of observation, respectively;
W_{ij}	= weights of the node ;
X_i	= input signals ;
X_t	= input time series;
x_i^T	= the transposed input vector of x_i ;
Y_t	= output time series;
Y_i	= output signals ;
∇^d	= difference operator;
$(\phi_1 \ldots\ldots, \phi_p)$	= autoregressive parameters;
$(\theta_1 \ldots\ldots, \theta_q)$	= moving average parameters;
θ_j	= bias; and
$(\upsilon_0, \upsilon_1, \ldots\ldots, \upsilon_l)$	= impulse response weights.

APPENDIX – SCA

SCA *Scientific Computing Associates*

The SCA Statistical System was designed and developed by Lon-Mu Liu with the assistance of the SCA programming staff. The SCA statistical system used to Forecasting and Time Series Analysis (Liu, L.M. : Forecasting and time series analysis using the SCA statistical system, Scientific Computing Associates, U.S.A., 1992.). The SCA System is also available for use on personal computers having A DOS. OS/2 or Macintosh operating system. The Scientific Computing Associates Corporation (SCA) provides several self-contained modules in its statistical software system. At present, the SCA Statistical System includes the **SCA-UTS** module for univariate time series analysis and forecasting, the **Extended UTS** module for univariate time series analysis and forecasting with automatic outlier detection and adjustment, the **SCA-MTS** module for econometric modeling and forecasting, the **SCA-ECON/M** module for econometric modeling and forecasting, the **SCA-GSA** module for general statistical analysis, and the **SCA-QPI** module for industrial quality and process improvement.

(Received December 4, 1998 ; revised March 8, 1999)