

The strategy of building a flood forecast model by neuro-fuzzy network

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Abstract:

A methodology is proposed for constructing a flood forecast model using the adaptive neuro-fuzzy inference system (ANFIS). This is based on a self-organizing rule-base generator, a feedforward network, and fuzzy control arithmetic. Given the rainfall-runoff patterns, ANFIS could systematically and effectively construct flood forecast models. The precipitation and flow data sets of the Choshui River in central Taiwan are analysed to identify the useful input variables and then the forecasting model can be self-constructed through ANFIS. The analysis results suggest that the persistent effect and upstream flow information are the key effects for modelling the flood forecast, and the watershed's average rainfall provides further information and enhances the accuracy of the model performance. For the purpose of comparison, the commonly used back-propagation neural network (BPNN) is also examined. The forecast results demonstrate that ANFIS is superior to the BPNN, and ANFIS can effectively and reliably construct an accurate flood forecast model. Copyright © 2005 John Wiley & Sons, Ltd.

KEY WORDS flood forecast; neuro-fuzzy; artificial neural network; BPNN; ANFIS

INTRODUCTION

Taiwan, with its tropical climate and high mountain watersheds all over the island, is susceptible to natural disasters such as floods and debris flows, which cause a great amount of damage. For this reason, building a forecast model to reduce flood damage is crucial. A key limitation of accurate streamflow forecasting is that the commonly used physical and/or statistical models still do not fully represent the complicated hydrological process (Anderson and Burt, 1985). These models are generally affected by a wide range of sensitive hydrographic and physiographic factors associated with the change of time and space. Consequently, such hydrological models are difficult to use and lack practicality in our case.

Artificial neural networks (ANNs) were created to simulate the nervous system and brain activity. In recent decades, a number of neural networks, such as the Hopfield neural network (Hopfield, 1982), the back-propagation neural network (BPNN; Rumelhart *et al.*, 1986), the recurrent neural network (Williams and Zipser, 1989), and the fuzzy neural network (Nie and Linkens, 1994), have been developed to solve a wide variety of problems (Schalkoff, 1997), demonstrating their great ability of functional mapping between input and output and generalization. One of the advantages of neural networks is their adaptive nature in dealing with nonlinear problems, such as highly complicated hydrological systems, that are difficult to formulate and solve (Chang and Hwang, 1999; Sajikumar and Thandaveswara, 1999; Chang *et al.*, 2004; Huang *et al.*, 2004). The ASCE Task Committee report (ASCE Task Committee on Application of Artificial Neural Networks in Hydrology, 2000a,b) carried out a comprehensive review of the application of ANNs to hydrology, as did Maier and Dandy (2000).

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In this study, we present a novel neuro-fuzzy approach, i.e. the adaptive neuro-fuzzy inference system (ANFIS), for flood forecasting. The motivation lies primarily in evaluating the feasibility of applying a hybrid scheme to the problem, thereby providing an alternative to fuzzy and neural approaches. It is assumed that the streamflow series can be estimated by using a set of if–then rules that relate future streamflows based on antecedent streamflows. The rules are extracted from the historical data sets (input–output patterns) through a self-organizing fuzzy clustering method. The predicted values into the future are inferred from those rules with a fuzzy reasoning model. To verify its applicability and suitability, the longest river in Taiwan, the Choshui River, was chosen as the study area, and the BPNN was also used for comparison. In the following, the methodology of constructing the ANFIS and BPNN models for streamflow forecasting is presented. The theorem, network structure, and parameter estimating algorithms are described first. Next, a presentation of the study watershed and available data is given. The data sets are analysed to identify the useful input variables and then the flood forecast models are constructed through ANFIS.

METHODOLOGY

This study proposes a methodology for constructing a flood forecast model using ANFIS. For the purpose of comparison, the commonly used BPNN is also examined. ANFIS is based on a fuzzy inference system with the supervised learning scheme of a multilayer feedforward network. Through some self-organizing fuzzy clustering method, such as the subtractive clustering method, fuzzy if–then rules can be extracted from numerical data to provide the fuzzy reasoning processes of the ANFIS. These algorithms are described first, and then we briefly describe the architectures and learning algorithms of the popular BPNN model.

The ANFIS

Intelligent computation methods, i.e. ANNs and fuzzy inference, are state-of-the-art technology that resembles the human thinking process in decision making and strategy learning; they are well recognized for their outstanding ability in modelling complex systems. Recently, there has been a growing interest in integrating the ANN and fuzzy inference; as a result, neuro-fuzzy networks have been developed. A neuro-fuzzy network combines the semantic transparency of fuzzy if–then rules with the learning capability of neural networks. This flexible framework is widely recognized, because it not only provides a tool for accurate nonlinear modelling, but also is able to learn from the environment (input–output pairs), self-organize its structure, and adapt to it in an interactive manner. For this reason, we propose the use of the ANFIS methodology (Jang, 1993) to self-organize the network structure and to adapt parameters of the fuzzy system for flood forecasting.

Architecture and algorithm. The ANFIS is a multilayer feedforward network that uses neural network learning algorithms and fuzzy reasoning to map an input space to an output space. With the ability to combine the verbal power of a fuzzy system with the numeric power of a neural system adaptive network, ANFIS has been shown to be powerful in modelling numerous processes, e.g. motor fault detection and diagnosis (Altug *et al.*, 1999), power systems dynamic load (Djukanovic *et al.*, 1997; Oonsivilai and El-Hawary, 1999), and real-time reservoir operation (Chang and Chang, 2001; Chang *et al.*, 2005).

For simplicity, we assume the fuzzy inference system under consideration has three inputs (x_1 , x_2 and x_3) and one output (y). The architecture of ANFIS consists of five layers (Figure 1), and the functions corresponding to nodes of the same layer are similar. Each input has two rules (A1 and A2, B1 and B2, C1 and C2) in the first layer (input nodes), which can generate eight rules in the second layer (rule nodes). A brief sketch of the operations of the five layers is given in the following.

Layer 1, input nodes: each node of this layer generates membership grades to which they belong to each of the appropriate fuzzy sets using membership functions.

$$O_{1,i} = \mu_{A_i}(x_1) \quad (1)$$

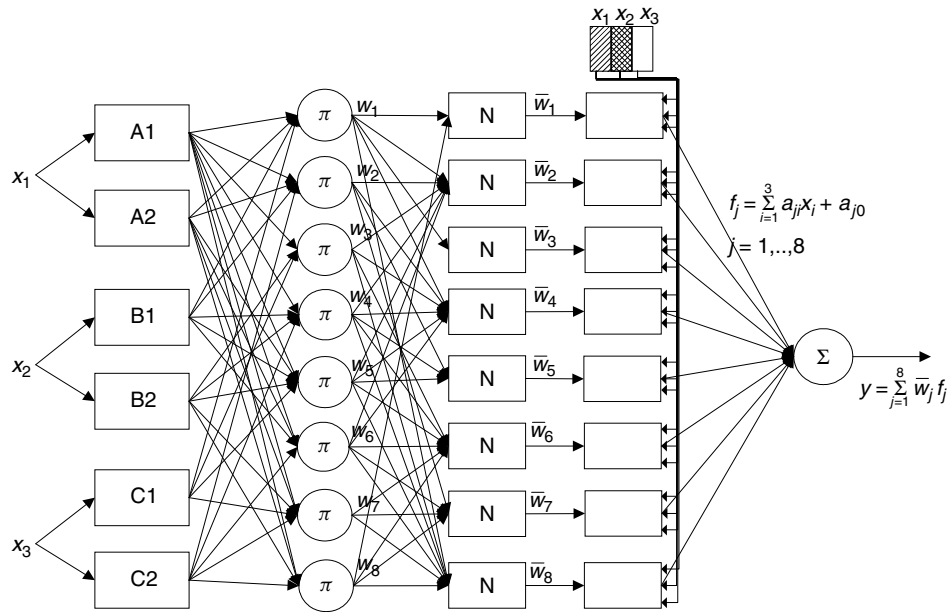


Figure 1. The architecture of ANFIS

$$\begin{aligned} O_{1,i+2} &= \mu_{B_i}(x_2) \text{ for } i = 1, 2 \\ O_{1,i+4} &= \mu_{C_i}(x_3) \end{aligned} \quad (2)$$

where x_1 , x_2 and x_3 are the crisp inputs to node i , and A_i , B_i and C_i are the linguistic labels characterized by membership functions μ_{A_i} , μ_{B_i} and μ_{C_i} respectively.

Layer 2, rule nodes: in this layer, the AND or the OR operator is applied to obtain one output that represents the result of the antecedent for that rule, i.e. firing strength. Hence, the outputs $O_{2,m}$ of this layer are the products of the corresponding degrees from layer 1.

$$O_{2,m} = w_m = \mu_{A_i}(x_1) \times \mu_{B_j}(x_2) \times \mu_{C_k}(x_3) \quad m = 1, \dots, 8; i, j, k = 1, 2 \quad (3)$$

Layer 3, average nodes: in this layer, the main objective is to calculate the ratio of each i th rule's firing strength to the sum of all rules' firing strength. Consequently, $\bar{w}_i$ is taken as the normalized firing strength.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_{i=1}^8 w_i} \quad i = 1, \dots, 8 \quad (4)$$

Layer 4, consequent nodes: in this layer, the first-order Sugeno fuzzy model (Takagi and Sugeno, 1985) is considered as a fuzzy inference system. Hence, the node function of the fourth layer computes the contribution of each i th rule toward the total output, and the function defined as

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i \sum_{j=1}^3 a_{ij} x_j + a_{i0} \quad i = 1, \dots, 8; j = 1, \dots, 3 \quad (5)$$

where $\bar{w}_i$ is the i th node's output from the previous layer. The a_{ij} are the coefficients of this linear combination.

Layer 5: output nodes: the single node computes the overall output by summing all the incoming signals. Accordingly, the defuzzification process transforms each rule's fuzzy results into a crisp output in this layer.

$$O_{5,1} = \sum_{i=1}^8 \bar{w}_i f_i = \frac{\sum_{i=1}^8 w_i f_i}{\sum_{i=1}^8 w_i} \quad (6)$$

This network training is based on supervised learning. Our goal is thus to train adaptive networks to be able to approximate unknown functions given by training data and then find the precise value of the above parameters.

The distinguishing characteristic of the approach is that ANFIS applies a hybrid-learning algorithm, the gradient descent method and the least-squares method, to update parameters. The gradient descent method is employed to tune premise nonlinear parameters, whereas the least-squares method is used to identify consequent linear parameters.

Subtractive fuzzy clustering. In the ANFIS model, each input variable, which varies within a range, might be clustered into several class values in layer 1 to build up fuzzy rules, and each fuzzy rule would be constructed through several parameters of membership function in layer 2. Accordingly, as the number of rules is increased the number of parameters that need to be determined becomes enormous. To solve this problem, we use subtractive fuzzy clustering to establish the rule base relationship between the input and output variables. The algorithm for implementing the subtractive fuzzy clustering into the ANFIS model can be found in Chang and Chang (2001). After several different influence clustering radii are evaluated, each forecasting model adopts the appropriate number of rules (Table I). It appears that the subtractive fuzzy clustering significantly reduces the number of rules, where all forecasting models only need a small number of rules.

BPNNs

The BPNN is the most popular and widely used neural network today. It is trained by using supervised learning; so, the goal of this algorithm is to decrease global error. To obtain the optimal values of the connected weights such that the energy function is a minimum, the standard BP algorithm searches the error surface by using the steepest descent method. The connected weights are adjusted by moving a small step in the direction of the negative gradient of the energy function at each iteration. Details of the standard BP algorithm can be found in the literature (Rumelhart *et al.*, 1986). There are two major disadvantages to applying the BPNN: the number of hidden nodes must be determined through trial and error, and the initial setting for the connecting

Table I. The number of rules and adjusted linear and nonlinear parameters of the ANFIS models investigated

Model		Rules	Parameters	
			Nonlinear	Linear
Runoff-1	One step	10	30	70
	Two steps	5	15	35
Runoff-2	One step	7	21	49
	Two steps	7	21	49
Rainfall-runoff	One step	7	21	56
	Two steps	6	18	48

weights could influence the network performance significantly. To overcome these problems, we investigated the BPNN through a different number of hidden nodes, and for each case the model was performed with a great number of initial settings of the connecting weights.

STUDY WATERSHED AND MODELLING

To illustrate the practical application of the forecasting models, the Choshui River is used as a case study. The Choshui River is the longest river in Taiwan and is renowned for its dark and muddy water. The river originates from the highest peak of Mt Hohuan and east peak of Mt Hohuan at about 3220 m altitude. The river winds 186.6 km, and the watershed, which extends from the mountains (elevation 3220m) to sea level, drains an area of 3157 km². Within this area, the average slope is 5.3%. The catchment receives an average of 2459 mm of rainfall each year; however, the rainfall is uneven. Typhoons, accompanied by torrential rainfall, which usually occur in the summer, are mainly responsible for the floods. Consequently, flood forecasting becomes one of the most important tasks of hydrologists. The administration regions, where the stream passes, include four counties. There is a population of about 0.6 million living in this area. The abundant water resources and particular geographic characteristics of the Choshui River nurture a diversified socioeconomic culture.

The available data

There are two water-level gauging stations and 10 rain-gauging stations in this river basin, which were recently equipped with automatic recorders and wireless transmitters (Figure 2 and Table II). Consequently, real-time flow forecasting becomes a reality. There were 23 typhoon (or heavy rainfall) events recorded in the period 1992 to 2002, as published by the Water Resources Agency (WRA), Taiwan. The hourly rainfall and water levels of the gauging stations are used. A total of 1998 data sets are obtained.

The data for the 23 events were divided into three independent subsets: the training, validating, and testing subsets. The training subset includes 1554 sets of data, the validating subset has 222 sets, and the testing subset



Figure 2. Location of gauging stations (▲: water level; ●: rain stations) in the Choshui River, Taiwan

Table II. Collected hourly data of typhoons or storm events for the years 1992 to 2002

Data set	Amount of data	Events	Specific events
Training	1554	17	
Validating	222	3	Typhoon Gloria (1996) Typhoon Winnie (1997) Typhoon Maggie (1999)
Testing	222	3	Typhoon Ryan (1995) 0527 Storm (1999) Typhoon Kai-Tak (2000)

also has 222 sets (Table II). First, the training subset is used to build networks and to adjust the connected weights of the constructed networks. Then, the validating subset is used to simulate the performance of the built models to check their suitability for generalization, and the best network is selected for later use. The testing data set is then used for final evaluation of the selected network performance. It is worth mentioning that the testing set must be unseen by the model in the training and validating phases.

The important input variables and forecasting models

One of the most important tasks in developing a satisfactory ANN forecasting model is the selection of the input variables, which determines the architecture of the neural network and significantly influences the stability and reliability of the network performance. Similar to most of the time-delay neural networks, which use time delays to learn the salient features of the input patterns and to perform temporal processes, we first investigate the time-delay (or the persistence) effect. Owing to the steep slope and small territory of our study watershed, the travel times of the flow from the rain gauging stations to the water-level gauging stations are only a couple of hours. And the travel time of the flow between the upstream and downstream gauging stations is less than 3 h. Consequently, the inputs of the model would only include the antecedent rainfall and/or water-level information between adjacent values for up to 3 h before the current time.

Figure 3 demonstrates the linear relationship between future and antecedent water levels. It shows the persistence effect of current water level versus several previous water levels ($t - 1$, $t - 2$, and $t - 3$) at the Ziuchian Bridge gauging station. It appears that the water level of t versus $t - 1$ is closely related (Figure 3a), i.e. the current water level can be estimated by using the water level of the previous step with no significant error. As one might expect, the persistence effect is decreased (Figure 3b and c) and the effect of rainfall is increased as the time step is increased. Figure 4 shows two hydrographs of the current water level of the Ziuchian Bridge gauging station versus (1) the current water level and (2) the $t - 3$ water level of the Chunyun Bridge gauging station. Because the datum of these two stations is different, in Figure 4 the water level of Chunyun (upstream) station is on the left-hand side of the ordinate and the water level of Ziuchian (downstream) station is on the right-hand side of the ordinate. Chunyun Bridge gauging station is located about 26 km upstream from Ziuchian Bridge gauging station, and the travel time of flow is about 2 or 3 h. As we can see from Figure 4, when we shift three time-steps of water level at the Chunyun Bridge gauging station, the shape and peak of four flood events in Ziuchian Bridge and Chunyun Bridge gauging stations seem well matched. This information provides an important message for estimating the amount and time of a peak flow arrival to the Ziuchian Bridge gauging station.

As mentioned above, the persistence effect and the upstream flow value are important information for flood forecasting; consequently we implemented three previous water levels of the Ziuchian Bridge gauging station ($ZC(t - 1)$, $ZC(t - 2)$, $ZC(t - 3)$) and several previous upstream water levels ($CY(t - 2)$, $CY(t - 3)$, and $CY(t - 4)$ of the Chunyun Bridge gauging station) as inputs to construct the ANFIS models. The first ANFIS model used the original water level values as input and was named Runoff-1. Because the water level in a natural river can be significantly different after a flood event, one way to solve the time variability problem

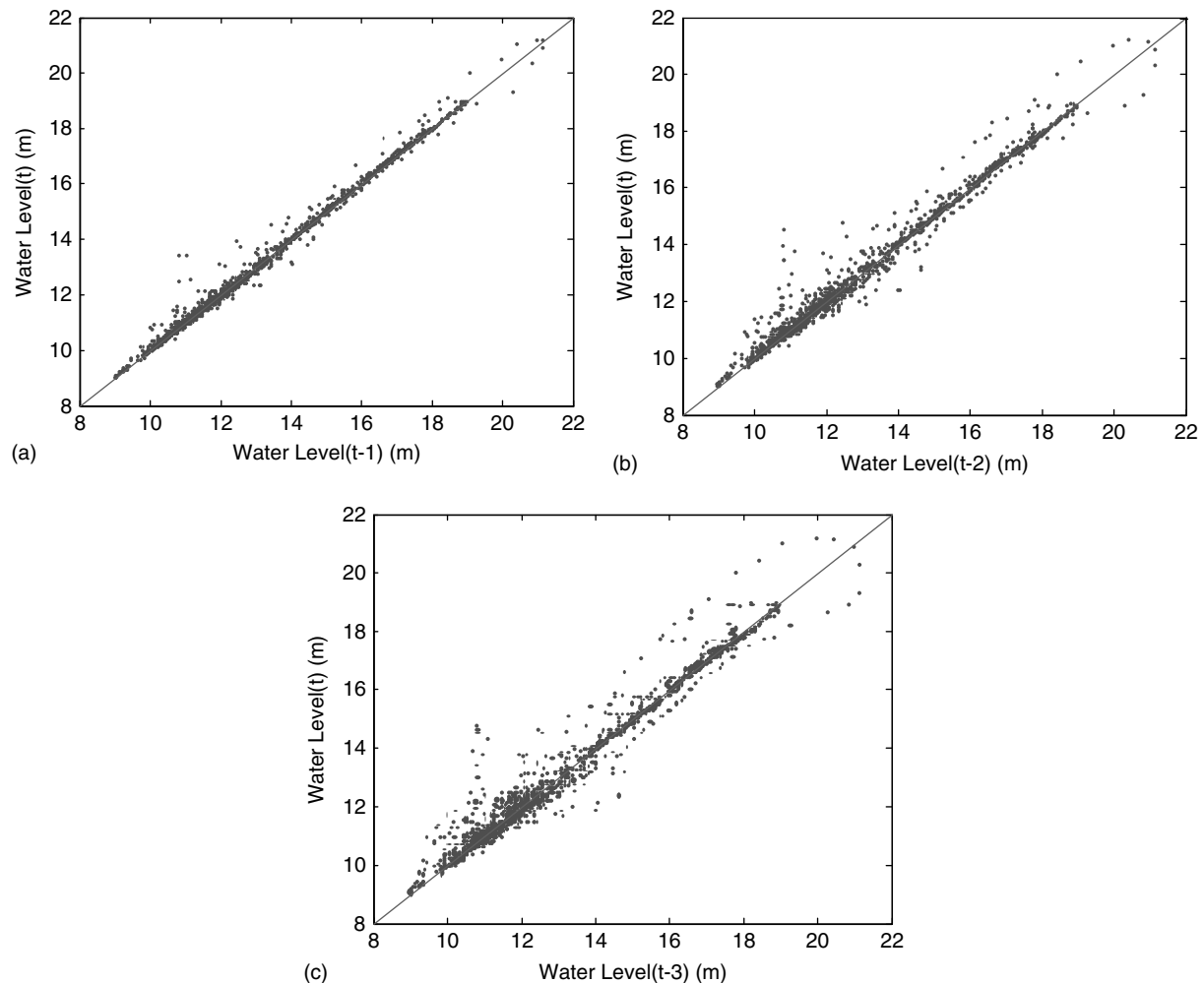


Figure 3. Comparison of current (t) and previous hourly ($t - 1$, $t - 2$, $t - 3$) water-level station (a) t versus $t - 3$, (b) t versus $t - 2$, (c) t vs. $t - 1$ at Ziuchian Bridge gauging station

is by using the difference operation, which has frequently been used to remove the nonstationarity of a time series (Salas *et al.*, 1985). Our second ANFIS model uses the differential values between two consecutive time steps (e.g. $\Delta ZC(t) = ZC(t) - ZC(t - 1)$ and $\Delta CY(t) = CY(t) - CY(t - 1)$, etc.) as input, and is referred to as Runoff-2 in the following.

There are several rain-gauging stations in the upstream part of the watershed (Figure 2). Owing to the tropical climate and high mountain watershed, the rainfall amount and pattern are significantly different in both storm events (time) and stations (space), and the travel distances and times of flow from each rain-gauging station to the Ziuchian Bridge gauging station are different and cannot be properly estimated. As we know, any individual rain-gauging station does not have a significant effect on the water level. To investigate the effect of each rain-gauging station, the hourly rainfall at six stations versus the water level at Ziuchian Bridge gauging station is plotted in Figure 5. It appears the concurrent water level at Ziuchian Bridge versus rainfall at all six gauging stations was almost randomly distributed. We also investigated the relationship between the differential water level values versus rainfall at all six stations, but similar results were found. Apparently, the great variation in rainfall distributions in both time and space influence the time of concentration significantly.

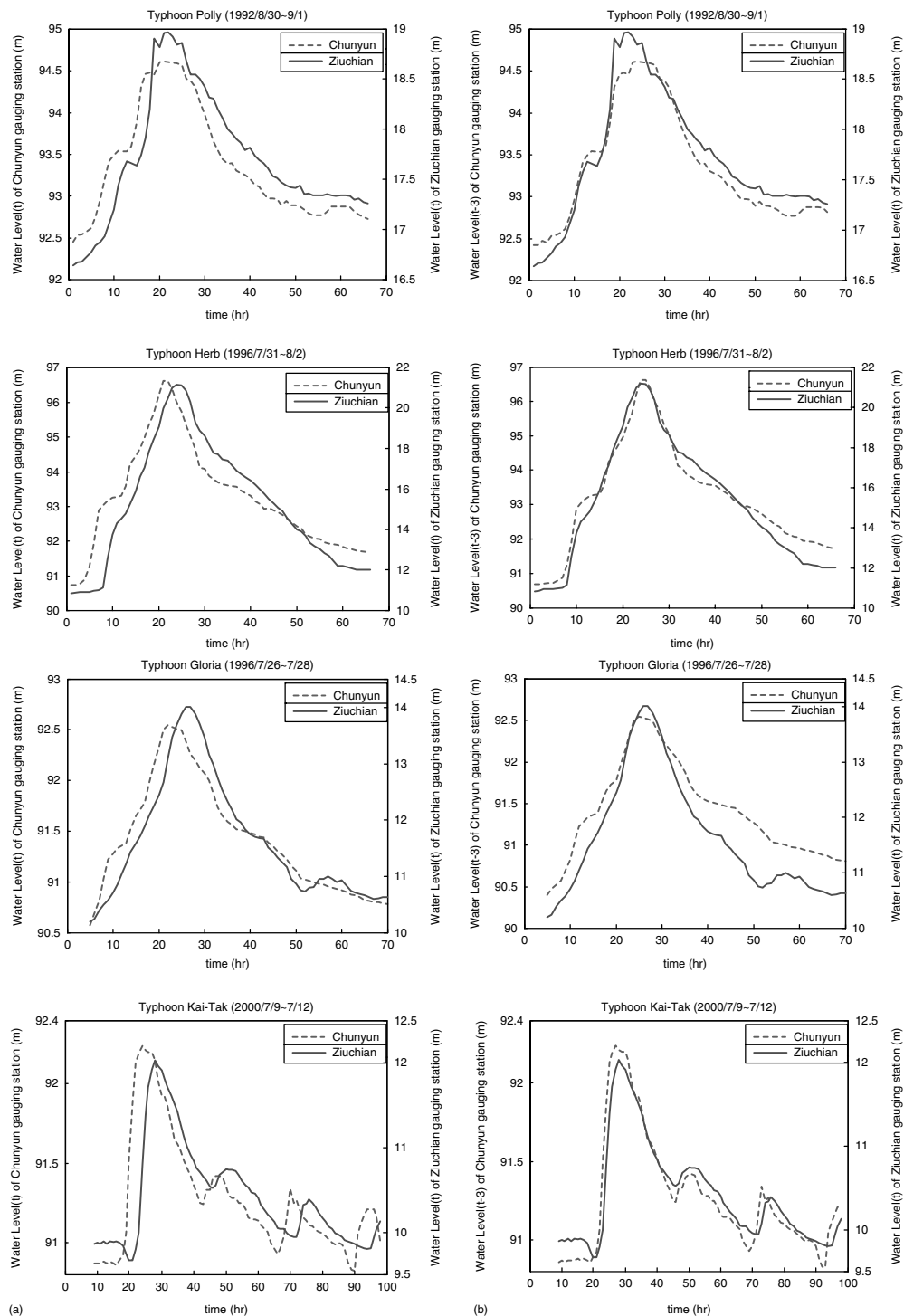


Figure 4. Observed water level at current water level of Ziuchian versus (a) current water level and (b) $t-3$ water level of Chunyun gauging stations

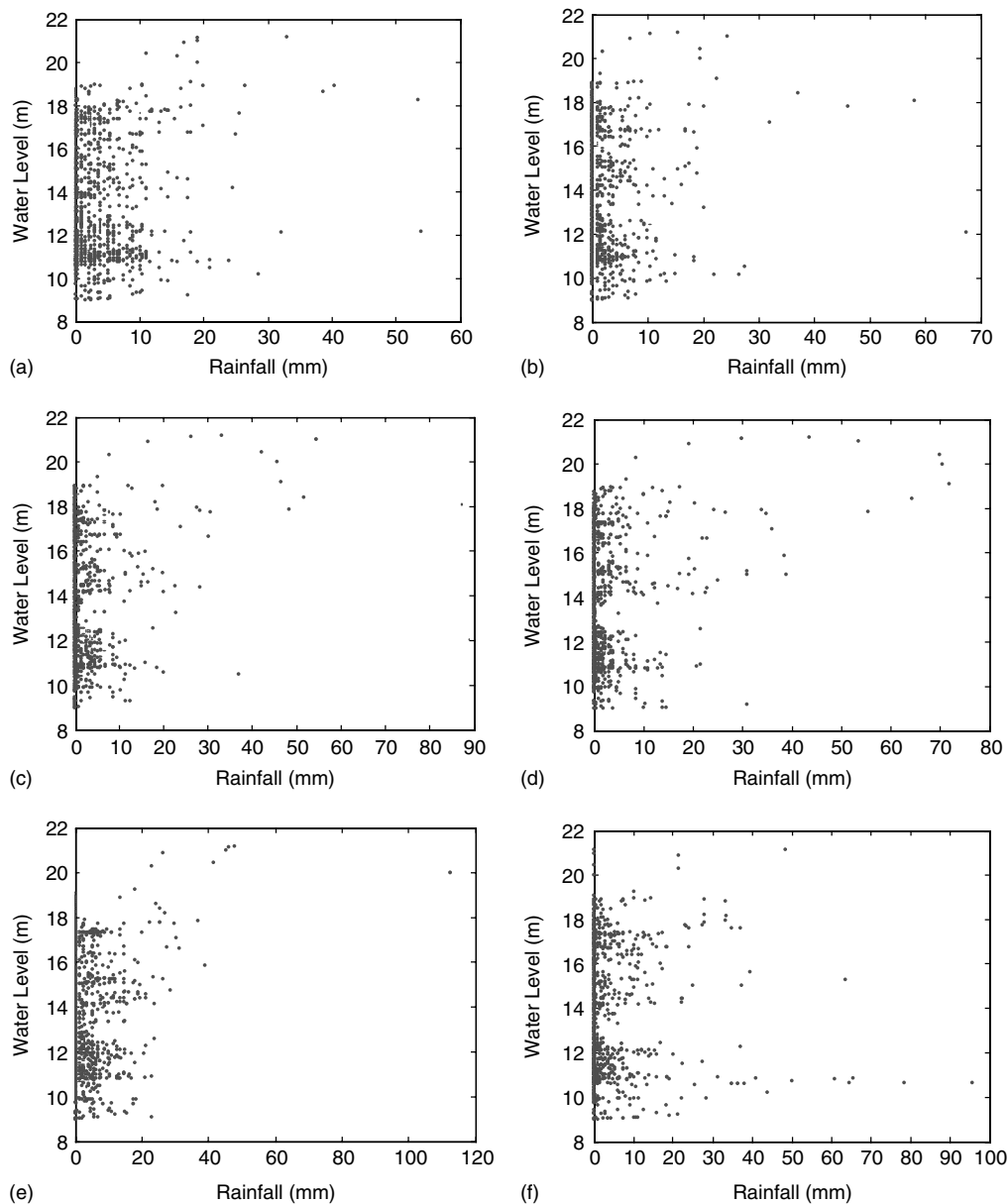


Figure 5. Comparison of current water level at Ziuchian Bridge gauging station and current rainfall at (a) Tsueyfen, (b) Tanta, (c) Chingyun, (d) Shinyi, (e) Shigauko and (f) Tuntou gauging stations

Because the effect of rainfall on the water level varied with time at all six rain-gauging stations and could not be identified as a solid relation (as matter of fact, it is more like a noise), the information on rainfall amount at each individual station is, hence, not used as input. Otherwise, we would encounter a very complex model.

Instead of using individual rain-gauge information, we investigated the lumped rainfall effect on the downstream water level. The lumped rainfall was obtained by using the weighted sum of the 10 rain-gauging stations shown in Figure 2. Although the lumped rainfall would lose the individual information for a particular rain-gauging station, it also can filter the noise generated by an individual rain-gauging station. Figure 6

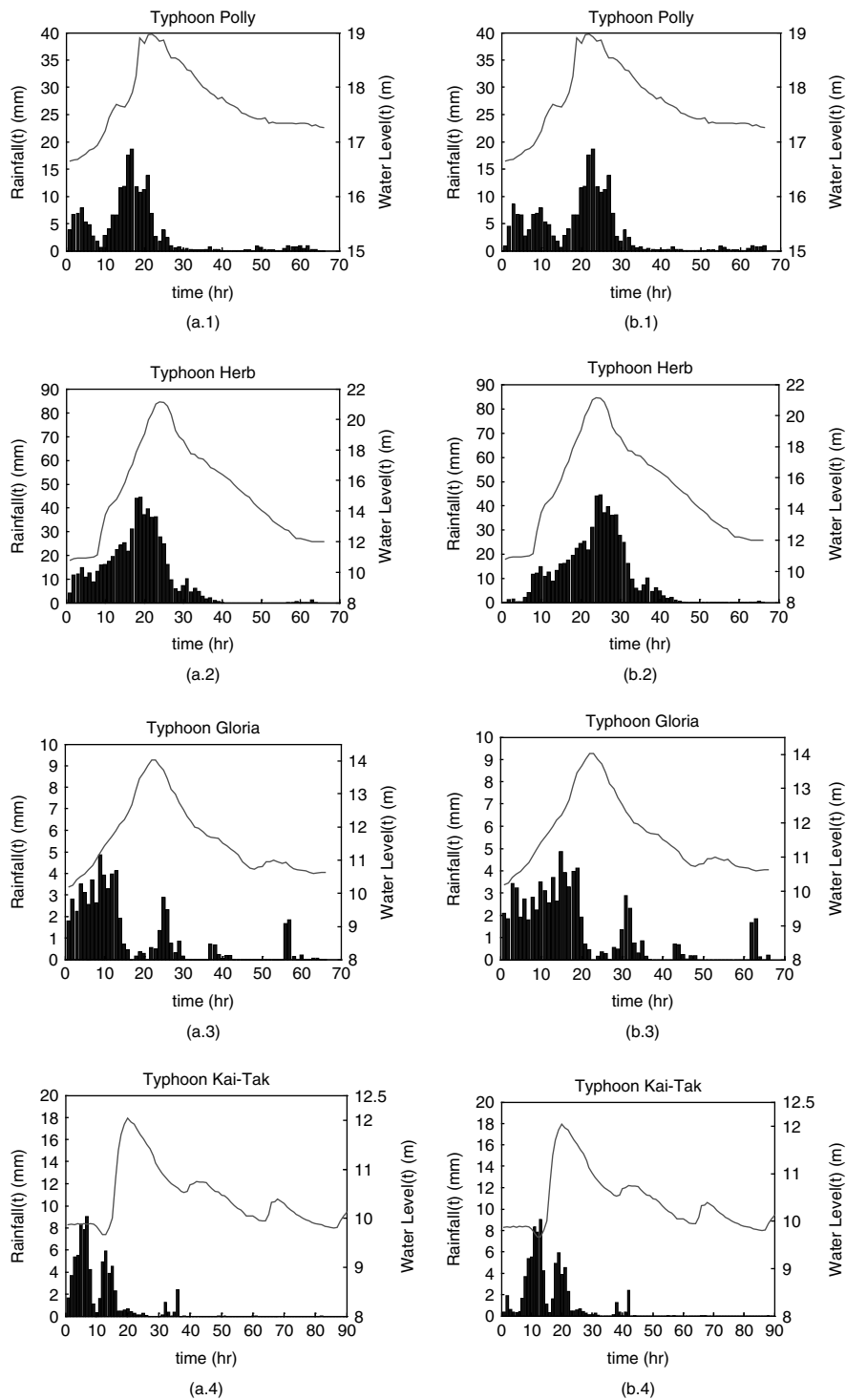


Figure 6. Observed water level at current water level of Ziuchian Bridge versus (a) current and (b) $t-5$ weighted sum of 10 rain gauging stations

Table III. Input variables of the models investigated

Model	Ziuchian Bridge	Chunyun Bridge	Weighted sum of rainfall
Runoff-1	$t - 1, t - 2, t - 3$	$t - 2, t - 3, t - 4$	—
Runoff-2	$\Delta(t - 1), \Delta(t - 2), \Delta(t - 3)$	$\Delta(t - 2), \Delta(t - 3), \Delta(t - 4)$	—
Rainfall-runoff	$\Delta(t - 1), \Delta(t - 2), \Delta(t - 3)$	$\Delta(t - 1), \Delta(t - 2), \Delta(t - 3)$	$t - 5$

shows the relationship between the watershed's average rainfall histogram with the water-level hydrograph of Ziuchian Bridge gauging station in four different typhoon events. It is easy to find that there is a significant relation. As we move the rainfall histogram forward 5 h, the pattern and peak of the rainfall histogram and water-level hydrograph seem well matched. This information provides another important message for flood estimation. Consequently, several previous average rainfalls of the watershed ($AR(t - 4)$, $AR(t - 5)$, $AR(t - 6)$) are used as input and termed the Rainfall-runoff model. The model inputs (Table III) and output can be represented as follows:

Runoff-1, with original water-level patterns of Ziuchian and Chunyun stations as input variables

$$ZC(t + i) = f(ZC(t - 1), ZC(t - 2), ZC(t - 3), CY(t - 2), CY(t - 3), CY(t - 4)) \quad (7)$$

Runoff-2, with differential water-level patterns of Ziuchian and Chunyun stations as input variables

$$\Delta ZC(t + i) = f(\Delta ZC(t - 1), \Delta ZC(t - 2), \Delta ZC(t - 3), \Delta CY(t - 2), \Delta CY(t - 3), \Delta CY(t - 4)) \quad (8)$$

Rainfall-runoff, with average rainfalls of this watershed and differential water-level patterns of Ziuchian and Chunyun stations as input variables

$$\Delta ZC(t + i) = f(AR(t - 5), \Delta ZC(t - 1), \Delta ZC(t - 2), \Delta ZC(t - 3), \Delta CY(t - 2), \Delta CY(t - 3), \Delta CY(t - 4)) \quad (9)$$

The results

The criteria of mean square error (MSE), mean absolute error (MAE) and the goodness of fit with respect to the benchmark (G_{bench}) (Nash and Sutcliffe, 1970; Seibert, 2001) are used for evaluating the performance of the models. These are defined as

$$\text{MSE} = \frac{\sum_{i=1}^n (\hat{Q}_i - Q_i)^2}{n} \quad (10)$$

$$\text{MAE} = \frac{\sum_{i=1}^n |\hat{Q}_i - Q_i|}{n} \quad (11)$$

$$G_{\text{bench}} = 1 - \frac{\sum_{i=1}^n (\hat{Q}_i - Q_i)^2}{\sum_{i=1}^n (Q_i - \tilde{Q}_i)^2} \quad (12)$$

Table IV. Comparison of one-step ahead water level forecasting among the standard BPNN and ANFIS models (in the Runoff-1 case)

Model	Training			Validating			Testing		
	MSE	MAE	G_{bench}	MSE	MAE	G_{bench}	MSE	MAE	G_{bench}
ANFIS	0.0081	0.0518	0.77	0.0057	0.0486	0.70	0.0028	0.0400	0.69
BPNN (mean)	0.0116	0.0573	0.67	0.0060	0.0506	0.68	0.0049	0.0487	0.47
BPNN (minimum)	0.0102	0.0541	0.71	0.0055	0.0483	0.70	0.0039	0.0412	0.58

Table V. The performance of one-step and two-steps ahead water-level forecasting among the Runoff-1, Runoff-2 and Rainfall-runoff models

Model		Training			Validating			Testing		
		MSE	MAE	G_{bench}	MSE	MAE	G_{bench}	MSE	MAE	G_{bench}
Runoff-1	One step	0.0081	0.0518	0.77	0.0057	0.0486	0.70	0.0028	0.0400	0.69
	Two steps	0.0294	0.0994	0.74	0.0221	0.0868	0.68	0.0103	0.0765	0.69
Runoff-2	One step	0.0060	0.0451	0.83	0.0059	0.0490	0.68	0.0026	0.0347	0.72
	Two steps	0.0203	0.0810	0.82	0.0195	0.0875	0.71	0.0081	0.0598	0.75
Rainfall-runoff	One step	0.0059	0.0450	0.84	0.0052	0.0467	0.72	0.0024	0.0331	0.74
	Two steps	0.0198	0.0802	0.82	0.0184	0.0848	0.73	0.0079	0.0586	0.76

where Q_i is the observed value at the i step, $\hat{Q}_i$ is the forecasted value at the i step, and $\tilde{Q}_i$ is the previous observed value at the i step, e.g. $\tilde{Q}_i = Q_{i-1}$ for 1 h ahead forecasting and $\tilde{Q}_i = Q_{i-2}$ for 2 h ahead forecasting in our case.

For the three different data sets (i.e. training, validating and testing sets), Table IV gives the comparative results of the two models (ANFIS and BPNN) in the Runoff-1 case. Because the number of hidden nodes and initial values of the connecting weights in the BPNN could significantly influence the final results (i.e. convergence to different local optimums), in this study we tried a different number of hidden nodes (i.e. from 1 to 10 nodes—a total of 10 cases), and for each case the network was trained by using the training data set with 50 different initial sets for the connected weights. Then, we chose as the best network the one whose average MSE of these 50 sets in the validating sets was the minimum value. Our extensive experiments indicate that the BPNN with six hidden nodes produces the best result in this study case. For the assessment of the BPNN performance, the average result and the best performance of these 50 sets by using the BPNN (with six hidden nodes) are summarized in Table IV. The ANFIS produces a very small error (MSE and MAE) and a high goodness of fit (G_{bench}) for the one-step ahead water-level forecasting in all three different data sets. The best BPNN model (among the 50 initial sets of the connected weights) also produces very nice results in both training and validating cases, whereas it only produces fair results in the testing case. The results of the average performance of the BPNN models (with 50 initial sets of the connected weights), i.e. BPNN (mean), also seem fine; however, the BPNN results are not as good as those of the ANFIS. It appears that both models (ANFIS and BPNN) do provide suitable results, but the ANFIS model (Runoff-1) has a better performance than the BPNN in terms of smaller MSE, MAE, and higher G_{bench} , especially in the testing set. These results demonstrate that the ANFIS model is superior to the BPNN, both in applicability and ability.

The ANFIS model is further investigated for its performance on one-step and two-steps ahead forecasting by using different input patterns (Runoff-2 case) or adding more input information (Rainfall-runoff case). Table V presents the results of the ANFIS models (Runoff-1, Runoff-2 and, Rainfall-runoff). It is easy to see that the ANFIS models, in general, provide very accurate and quite stable performance for both one-step and

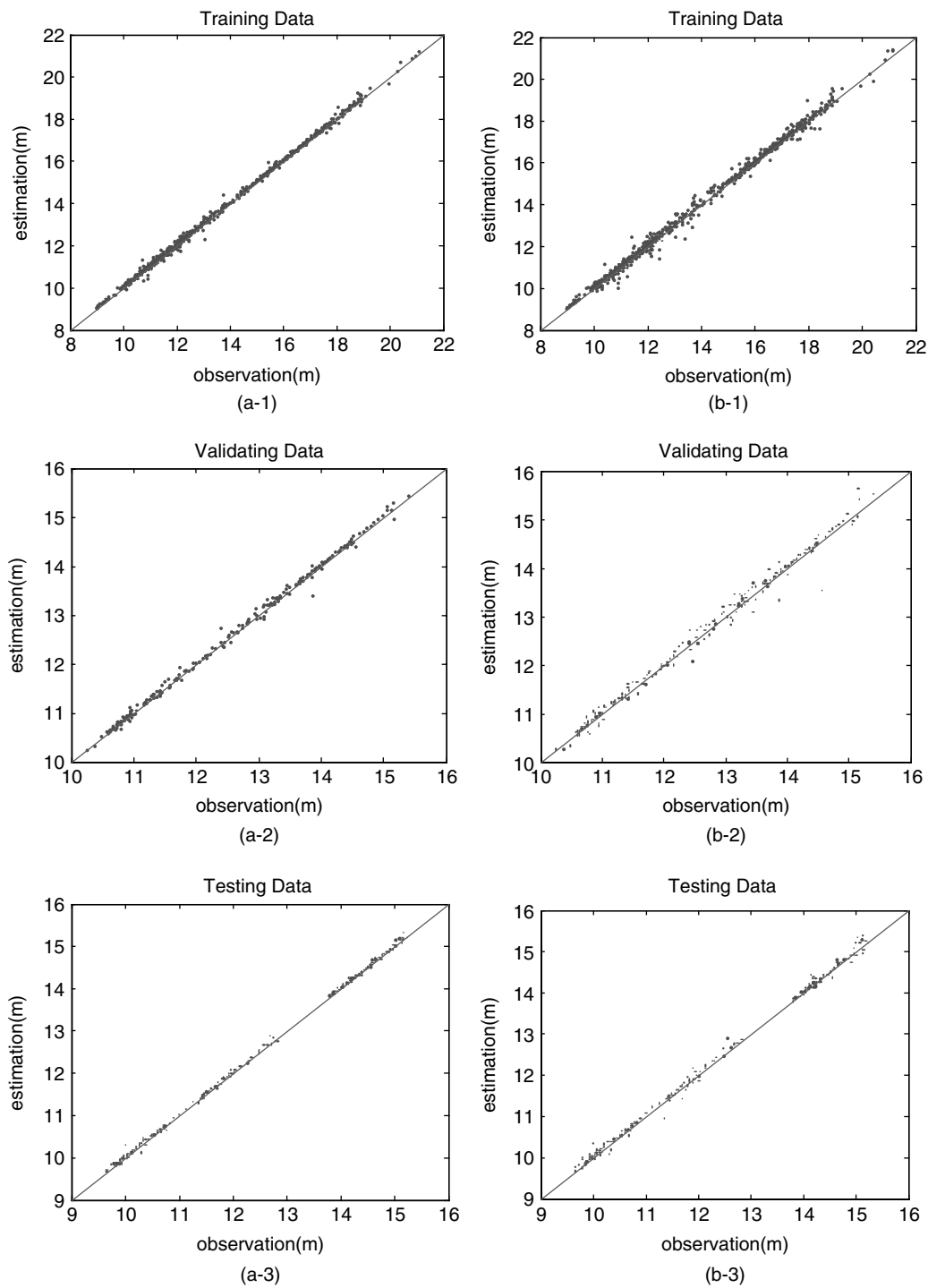


Figure 7. Comparison of observed and (a) one-step ahead, (b) two-steps ahead water level of the Rainfall-runoff model during different phases (training, validating and testing)

two-steps ahead forecasting, where the results of the MSE and MAE are very small in all three stages (training, validating and testing sets). Among these models, the Runoff-2 model is slightly better than the Runoff-1 model, and the Rainfall-runoff model provides the most accurate results. These results can be interpreted as (1) a downstream water level can be suitably estimated by just using several of the previous downstream and upstream water levels as input to the ANFIS model; (2) adding the watershed average rainfall information in addition to water-level information could slightly enhance the forecasting accuracy.

To provide an impression of the accuracy of prediction by using the ANFIS Rainfall-runoff model, a scatter plot of observed versus model predicted water level (one-step ahead and two-steps ahead) in the three different data sets is presented in Figure 7, and an observed and forecasted hydrograph of the typhoon Kai-Tak event is shown in Figure 8. All the points in Figure 7a, i.e. one-step ahead, appear to fall nicely around the line of agreement, and in Figure 7b, i.e. two-steps ahead, they fall suitably around the line of agreement. These results indicate the accuracy and reliability of the model presented herein.

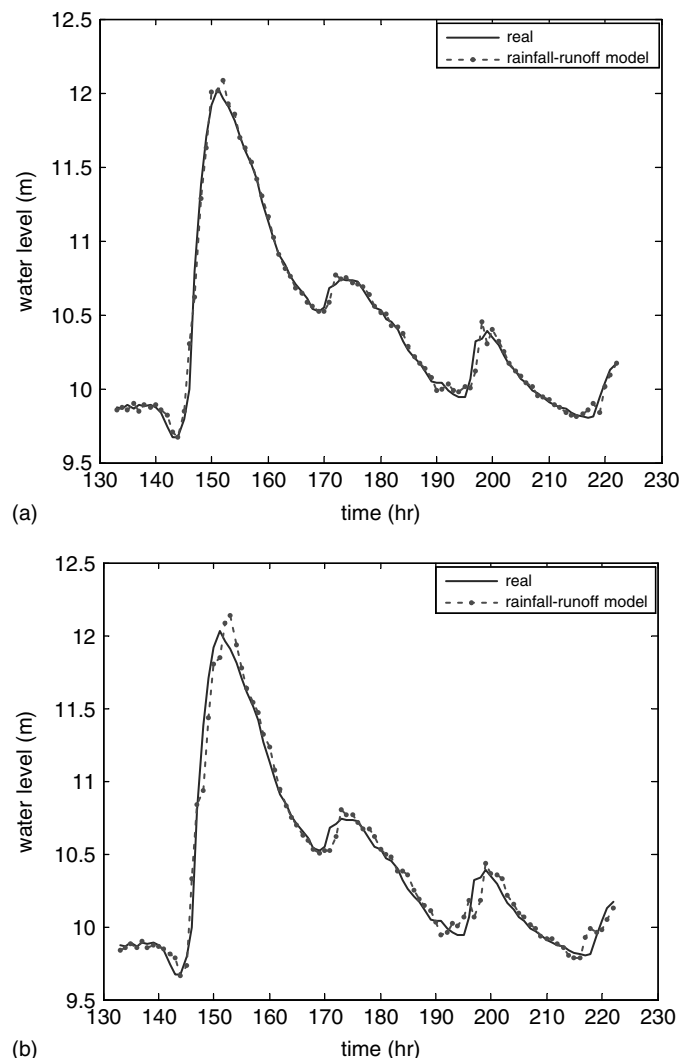


Figure 8. An enlarged peak flow of Typhoon Kai-Tak (testing result) for (a) one-step ahead and (b) two-steps ahead forecasting versus observed water level

CONCLUSIONS

Neural networks have a complex connection structure and simple computing elements that provide a great ability to learn by example and to generalize. In the last few decades, a great number of researches regarding the application of ANNs in water resources problems have demonstrated their applicability. Nevertheless, there are a few of problems that might limit their applicability. One major problem is lack of data. A river basin usually has many rain and water-level gauging stations, and it is easy to build up a forecasting model by means of regression or ANN approaches. However, if we only have a limited number of data sets, the models built might only be good for the training sets due to overtraining and could not be used for future events. One way to solve this problem is to identify the crucial inputs and then reduce the input dimensions. This is especially important in developing a satisfactory ANN forecasting model. Based on 23 flood events in the Choshui River, we find that the persistence effect and the upstream flow information are crucial for flood forecasting. The effect of rainfall on the water level varies from time to time in all rain gauging stations and cannot be identified as a solid relation, whereas the watershed's average rainfall provides other useful information for flood forecasting.

After identifying the important inputs, we proposed the ANFIS for constructing the flood forecasting models. The ANFIS is an integration of a neural network and fuzzy arithmetic. For the purpose of comparison, the BPNN model was also performed. Compared to BPNN, the principal advantage of the proposed method is that the ANFIS can automatically construct a rainfall-runoff model and estimate the needed parameters by an approach converging to an optimal solution. The comparative results obtained by the BPNN and ANFIS provide evidence that the ANFIS can offer a higher degree of reliability and accuracy than BPNN in flood forecasting.

For further investigation, three ANFIS models, based on different input information, were built to perform one- and two-steps ahead flood forecasting. The results show that: (1) a downstream water level can be suitably estimated by just using several of the previous downstream and upstream water levels as input to the ANFIS model; (2) using the differential values, which could remove the nonstationarity of a time series, could provide better performance than the original values; and (3) adding the watershed average rainfall information in addition to water-level information would enhance the forecasting accuracy. The ANFIS models, in general, provide very accurate and quite stable performance for both one-step and two-step ahead forecasting, where the results of MSE and MAE are very small in all three stages (training, validating and testing sets).

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