Forecasting model of Chao Phraya river flood levels at Bangkok

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Abstract: *Hourly flood forecasting is necessary in coastal rivers and estuaries for the purposes of flood control and mitigation. The water level is greatly affected by the movement of the tidal waves that continually fluctuate and by the upland flood discharge. The interference of the tidal backwater with the upstream flow of the river increases flood stages that enlarge flood plain inundation areas and increase potential flood damages.*

A neural network model with a back-propagation algorithm (BP) is applied for forecasting hourly water levels in the Chao Phraya River at Bangkok Memorial Bridge (Station C4) which is located about 48 km from the river mouth. The considered river reach is from the river mouth at Fort Chula (km 1) to Bang Sai (km 112). The river flow is mainly influenced by the effects of the upstream discharge at Bang Sai, the tide levels at Fort Chula. The neural network model is calibrated and verified based on the observed hourly flood level data during high stages in 1998. The accuracy of flood forecast is evaluated by using a statistical performance index and is found to be very satisfactory. The results of this study encourage further applications of the neural network model for hourly tidal discharge forecasting in the Chao Phraya river and in other rivers under different topographical and flow characteristics.

1 Introduction

The Chao Phraya River Basin is the largest basin in Thailand. Rising among the northern mountains of the country, it flows through fertile rice fields and the Bangkok Plain, then pours into the Gulf of Thailand. Its catchment basin is about 163,000 km^2, which is almost 1/3 of the area of the whole country. Approximately 50% of the drainage area of the Chao Phraya River Basin lies in the hills and mountains, with the remaining half in the flat alluvial plains of the Central Valley. The average yearly rainfall is about 1,200 mm in the northern region and 1,350 mm in the Central Valley. The peak is in September and 85% of the total flood volume is attained in the months of May to October during the Southwest Monsoon. The months of November through April are dry months with less than 15 % of rain. The basin, particularly the delta in the downstream reach, has been the focus of much agricultural production and urban development. However, recurrent floods have inflicted serious damage to the basin,

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particularly the delta area. Formulation of a flood forecasting system is therefore necessary in order to cope up with flood damage problems.

Many flat areas with coastal rivers are centers of development, high-density communities and developed economy such as Bangkok, the capital of Thailand. The Bangkok Memorial Bridge is situated about 48 km from the mouth of the Chao Phraya River. In Bangkok, frequent flooding is usually caused by the combined effects of high discharges of the Chao Phraya River from the north, high tides at the river mouth and heavy rainfall in the city. The present study is limited to the flood levels in the tidal reach of the Chao Phraya River from Fort Chula (km 1) near the Chao Phraya river mouth up to Bang Sai gaging station (km 112) (see Figure 1).

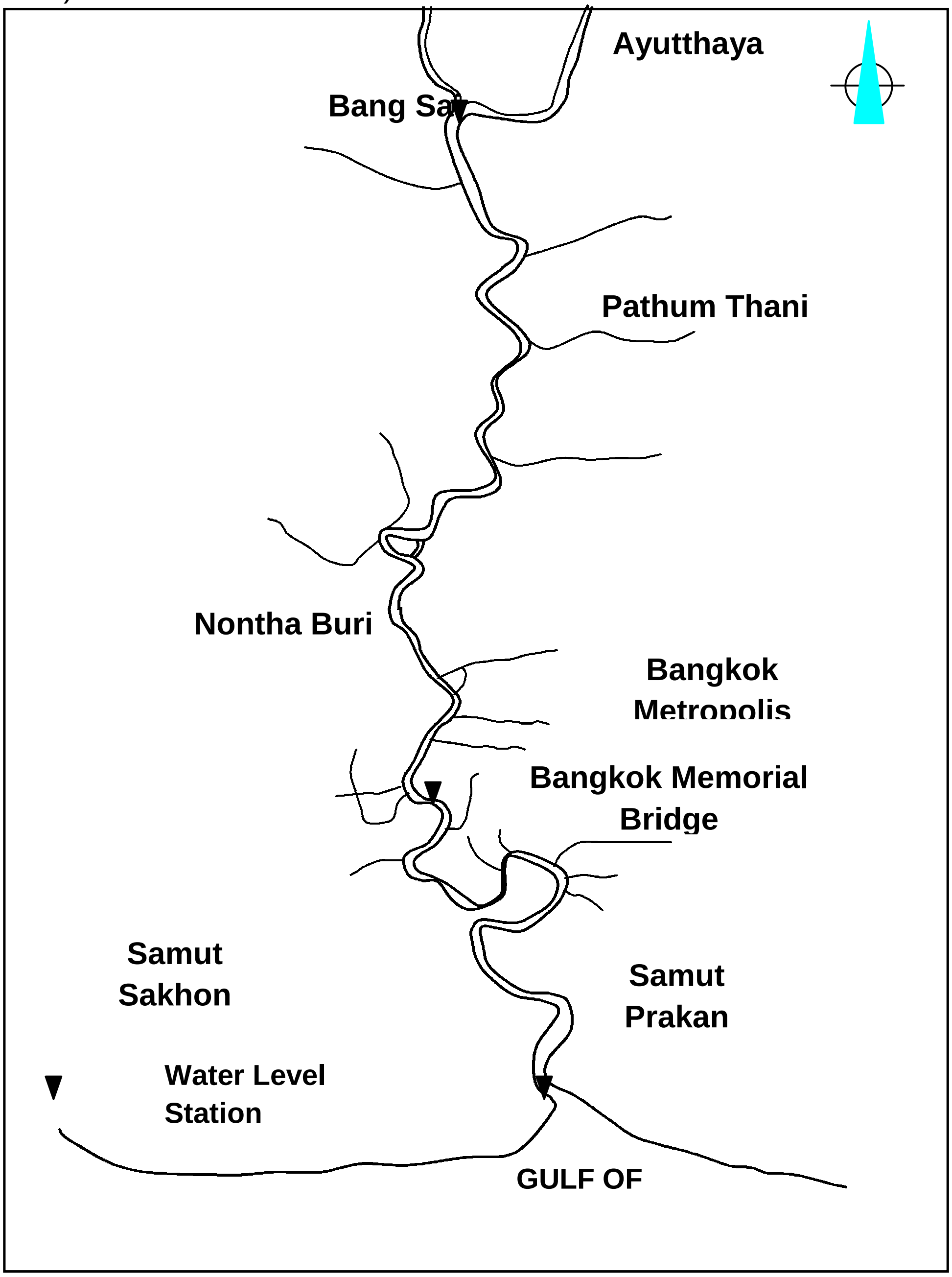


Figure 1: Tidal reach of Chao Phraya river from Bang Sai to the river mouth at Fort Chula

Hourly streamflow forecasting in tidal rivers has been carried out using various models such as the use of unsteady flow models by Tingsanchali (1982 and 1996) and JICA(1988 and 1998). Recently, neural networks have been successfully applied to hydrology for rainfall forecasting in space and time (French et al., 1992) and for river flow prediction (Karunanithi et al., 1994 and Tingsanchali and Gautam, 2000). A well known method of supervised learning of neural networks called Back-Propagation (BP) (Rumelhart et al., 1986 and 1988) has been found effective in flood forecasting problems (Zhu and Fujita, 1994; Tingsanchali and Gautam, 2000). The main objective of this study is to develop a neural network model for forecasting hourly flood water levels of the Chao Phraya River at Bangkok Memorial Bridge.

2 Neural network model structure

Artificial Neural Networks (ANNs) are being used increasingly to predict and forecast water resources variables. Based on the consideration of the hydrological processes (Dooge, 1974) divides hydrological models into three categories- physically based distributed models, lumped conceptual models and black box models. Neural Network models which inherently involves mapping of input and output vectors can be considered as a black box model. Such black box models can be considered of little significance in enhancing the understanding of hydrological and hydraulic processes, nevertheless, in operational hydrology their usefulness can be paramount. The excessive requirement of field data in the case of physically based distributed models and the large number of parameters and subsequent difficulty in calibration in the case of lumped conceptual models render such models less suitable in operational flood forecasting use. This is the reason why simple black box or storage based models found to be used extensively as flood forecast models.

Several algorithms of neural network model exist. However, back propagation which belongs to supervised learning algorithm that performs a gradient descent search in weights space using generalized delta rule is often reported in applications (Minn and Halls, 1986). Back Propagation (BP) networks were developed by Rumelhart and McClelland (1986 and 1988) for learning associations between input and output patterns using more than a single layer perception, which overcomes some limitations of a single-layer perception (no hidden layer). A three layer feed forward neural network model is shown in Figure 2. Any BP network is based on a supervised learning technique that compares the actual output from output units to the target or specified output and then readjust the weights backward in the network. The same input is presented to the network in the next iteration, so the actual output will be closer to the target output.

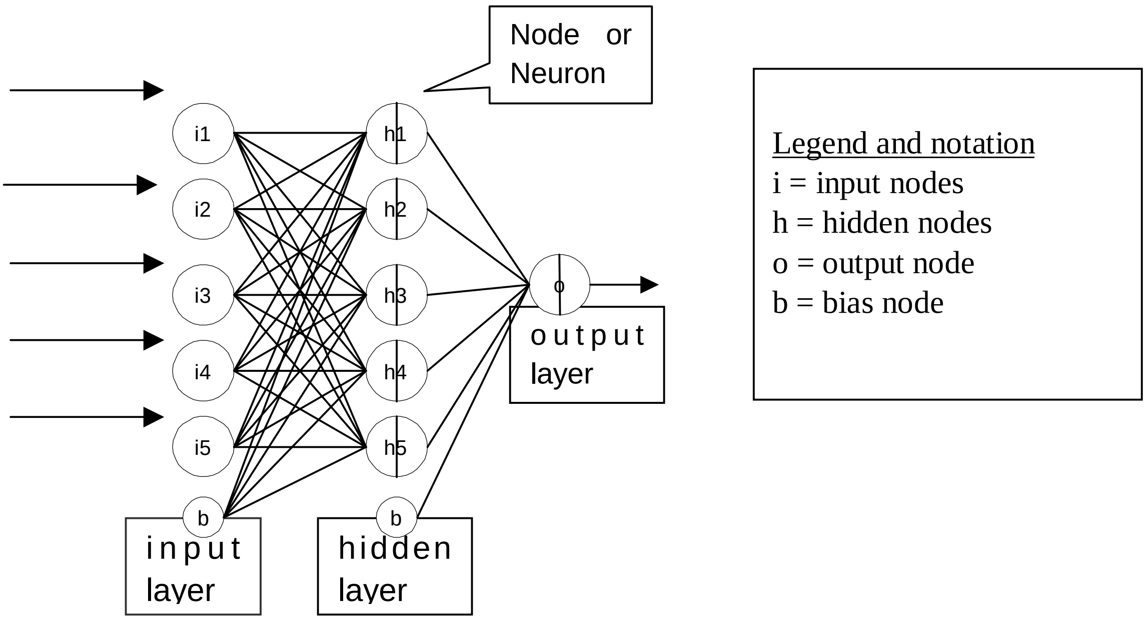


Figure 2 A typical three layer neural network model

3 General Structure of Neuron

A node or neuron of a hidden layer is characterized by two functional activities, namely,

- Activation in which all the weighted inputs are summed up yielding what is known as activation of the neuron
- Transfer in which the activation of the neuron is transferred into outputs with the aid of appropriate type of functions such as logistics, linear and step functions.

One of the basic requirements of the BP training is that the transfer function be continuous and differentiable. The sigmoid logistic non-linear function which fulfills the above requirement and which has a simple derivative making the implementation of algorithm easier (Minn and Halls, 1996) is often used. The sigmoid function has the value ranging between 0 to 1. The logistic function, which is a commonly used transfer function in NN, transforms the weighted input into an output. The characteristic of the sigmoid function can be graphically illustrated in Figure 3.

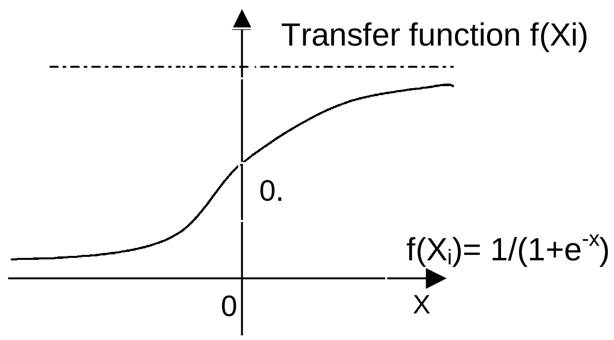


FIGURE 3: SIGMOID NON-LINEAR TRANSFER FUNCTION

The standard back propagation training algorithm is as followed

1. Initialize all weights and bias factors to small random values.
2. <u>Forward pass</u>: Present input vector *(I_1, $I_{2,...,}$ I_{no})* and specify the desired output *(t_1, $t_{2,...,}$ t_{n1})*
3. For layer m = 1,2,…,l:

According to Figure 4, we can compute $N_{j,m}$,the activation of neuron j in layer m

a.

$$N_{j,m} = \sum_{i=1}^{n_{m-1}} W_{ji,m} \cdot O_{i,m-1} + \theta_{j,m} \qquad (1)$$

where $O_{i,0} = I_i$

t_j = target value of neuron j in output layer

$O_{j,m}$ = output of neuron j in layer m

$\theta_{j,m}$ = bias value for neuron j in layer m

$W_{ji,m}$ = synaptic weight between node j in layer m and node i in layer m-1

n_m = number of neuron in layer m

b. Compute the output $O_{j,m}$ of the j^{th} unit in the layer m

$$O_{j,m} = \frac{1}{1+e^{-N_{j,m}}};\ j = 1,2,...,n_m \qquad (2)$$

4. Compute the final output $(O_{1,1}, O_{2,1}, ..., O_{n1,1})$ and compared with the desired output *(t_1, $t_{2,...}$ t_{n1})*. If the difference is acceptable, the process is terminated and the system has learned. Otherwise, continue to next step. When the number of epochs is reached while the difference is not acceptable, the convergence is not attained. One should try with a new set of initial values, or even modify the structure of the network.

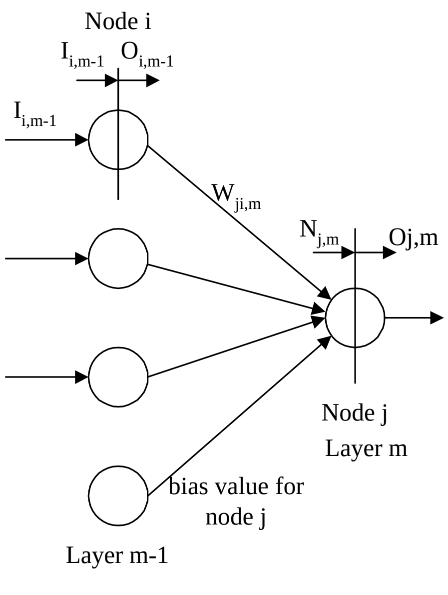


Figure 4 Transfer of inputs of layer m-1 to a nodal output of layer m

5. Backpass: For layer m = l, l-1, l-2, …., 1

Let $\delta_{j,m}$ = the value of δ for neuron j in layer m

a. We can compute the following

For output layer m $\delta_{j,m} = O_{j,m}(1-O_{j,m})(t_j - O_{j,m});$ (3a)

For hidden layer m $\delta_{j,m} = O_{j,m}(1-O_{j,m})\sum_{k=1}^{n_{m+1}} W_{kj,m+1}\delta_{k,m+1}$ (3b)

b. Compute the weight increments:

$$\Delta W_{ji,m}(n+1) = \eta \cdot \delta_{j,m} \cdot O_{i,m+1} + \alpha \cdot \Delta W_{ji,m}(n) \quad (4)$$

where η = learning parameter

α = momentum constant

$\Delta W_{ji,m}(n)$ = weight change between node j in layer m and node i at n iteration

$\Delta W_{ji,m}(n+1)$ = weight change between node j in layer m and node i at n+1iteration

$O_{i,m-1}$ = $I_{i,m}$

n = number of iteration (n = 1,2,3,…)

c. Compute the new values of the weights:

$$W_{ji,m}(n+1) = W_{ji,m}(n) + \Delta W_{ji,m}(n+1) \quad (5)$$

where

$W_{ji,m}(n)$ = weight value between node j in layer m and node i at n iteration

$W_{ji,m}(n+1)$= weight value between node j in layer m and node i at n+1 iteration

6. Go to step 2.

In a neural network architecture, the output node represents the water levels and discharges to be forecasted. The hidden nodes, which are the internal part of the system, enable to learn the non-linear relationship between the output and input. The parameters on which the forecast value depends with some function represent the input nodes. The training time is directly dependent on the size of the network, the larger the network size, the longer the training time. The training process depends on number of input units, number of hidden units and convergence criteria. To make the problem simple, an architecture with three layers is used, i.e, input layer, hidden layer and output layer. The small number of hidden nodes may not able to train the network and a very large number of hidden nodes pose difficulty to the training but may also weaken the effective learning strength of the networks. Therefore the determination of the hidden layers and nodes is made by the trial and error process depending on the condition of the problem. The basic way in which back propagation is trained is that a set of input and output patterns is given in the training phase of back propagation. The system transfers the input to output based on initially randomly selected weights using the defined activation function. The system output is then compared with training set output and the difference between these two is what to be minimized in the so called “training phase” which is identical to “calibration” of the conceptual models.

The weights leading into the output node and weights leading to the hidden nodes are adjusted backward so that the correction in error is propagated backward in an iterative process until the system converges after a predefined acceptable limit. The network is then said to be trained.

4 Model application

The input data of the BPNN model are the observed hourly upstream water levels at Bang Sai, the observed hourly downstream water levels at Fort Chula. The hourly measured water level data at Station C4 were used as the target water levels in the BPNN model calibration and verification for forecasting the water levels at this station. During high flood periods, it was found that the effect of local inflows to the river is very small compared to the river discharges and hence can be neglected.

By considering the data in 1998, the calibration (training) and verification (testing) of the model is carried out for the flood level data at Station C4. The highest flood water level in October 1998 is used in the model training to assure that the calibrated parameters of the model can really represent the highest flow condition. The flood data in August 1998 is used in the model testing

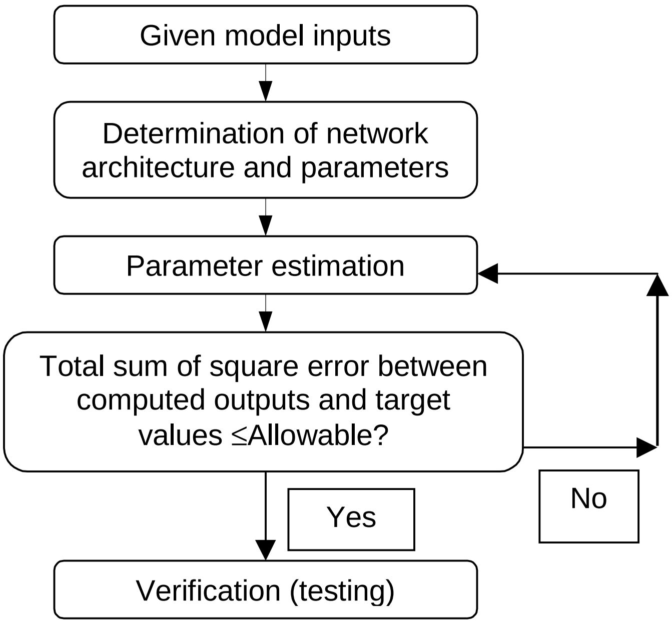


Figure 5 Steps in training and testing NN model

The data used consist of two sets: one for training and the other for testing the model.. As the BPNN Model uses Logistic Activation Function on which its output lies in the interval [0,1] (Figure 3) , the original data is linearly transformed to the interval [0.05,0.95] before inputting to the network. Interval [0.05,0.95] is chosen instead of interval [0,1] because Logistic Activation Function is an asymptotic function, so it neither reaches the value 0 nor 1.

4.1 Input data processing

Let a and A are the minimum and maximum values of the data series respectively; then an actual value X_t is transformed to the interval [0.05,0.95] using the formula:

$$X_t' = \frac{0.9(X_t - a)}{A - a} + 0.05 \qquad (6)$$

where X_t is the actual value, a is the minimum value, A is the maximum value and X_t' is the transform value

4.2 Output data processing

Once the most suitable network is found, the output results from the neural network are transformed back into their original value by the equation:

$$X_t = \frac{(A - a)(X_t' - 0.05)}{0.9} + a \qquad (7)$$

The model is trained starting with some small randomly generated weights. After the predefined target error of 0.05 for 90% of all patterns is reached, the training process is stopped and the weights are saved. These weights and the same NN architecture of the model are utilized in the verification (testing) phase. The momentum parameter β was fixed at 0.5 while the learning parameter η was varied from 0.2 to 0.03 at the final stage.

5 Results and discussions

Two network architectures were tried. One is a three layer network with five input nodes, five hidden nodes and one output node. Another is with ten input nodes, five hidden nodes and one output node. It is found that the latter network yields a better accuracy than the first one and the computation time is within acceptable limit. Therefore the second network (10-5-1) as shown in Figure 6 is selected in this study for forecasting hourly water levels and discharges and is also shown in Table 1.

TABLE 1 FUNCTIONAL RELATIONSHIPS FOR ONE-HOUR AHEAD FORECASTING HOURLY WATER LEVELS AND DISCHARGES

Case	Functional Relationship	Network Architecture
Water level	W'(t+1)=f[B(t),B(t-1),F(t),F(t-1),U(t),U(t-1),D(t),D(t-1),W(t),W(t-1)]	10-5-1
Discharge	Q'(t+1)=f[B(t),B(t-1),F(t),F(t-1),U(t),U(t-1),D(t),D(t-1),Q(t),Q(t-1)]	10-5-1

5.1 Water level and discharge forecasting by the BPNN model

The formulation of hourly water level or discharge forecasting is simple as the output expressed is functionally dependent on the hourly observed input data which are the observed hourly water levels at Bangsai, Bangkok Memorial Bridge (Station C4) and Fort Chula.

The BPNN model was used for water level and discharge forecasting at Station C4. For one-hour ahead, the model parameters are set for training procedures for various study cases. The target error of 0.05 is set for all study cases. The value of learning parameter is equal to 0.02 while the momentum rate is equal to 0.95.

Model Performance

The NN model performance was evaluated both qualitatively by the visual comparison of the simulated and observed hydrographs and quantitatively using the performance statistical index namely the Model Efficiency (EI) (Nash and Sutcliffe, 1970). The model efficiency is given by,

$$EI = \frac{SR}{ST} \tag{8}$$

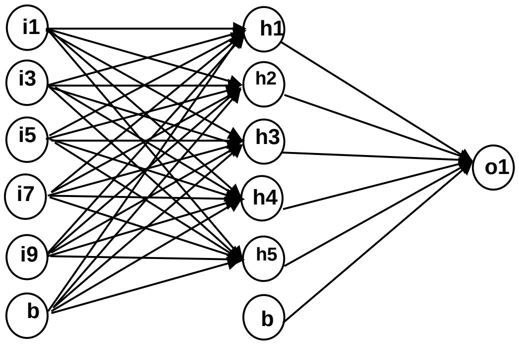
$$SR = ST - SE \tag{9}$$

$$ST = \sum_{i=1}^{N} (Q_i - \overline{Q})^2 \tag{10}$$

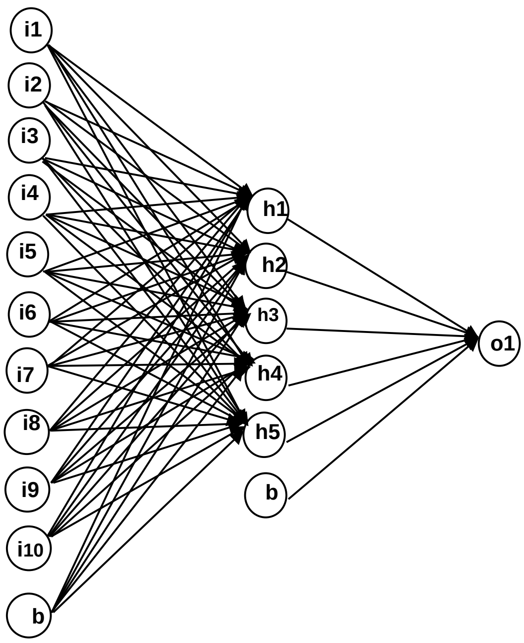
$$SE = \sum_{i=1}^{N} (Q_i - F_i)^2 \tag{11}$$

where, SR is the variation explained by the model, ST is the total variation of the discharge in training stage, SE is the sum of square of the differences between the forecasted data F and the observed data Q, subscript i refers to time i, $\overline{Q}$ is the mean value of observed value, $\overline{Q} = \frac{1}{N}\sum_{i=1}^{N} Q_i$, N is the number of data points.

By varying the time sets of the input nodes of the BPNN model for training the networks, the present and past one-hour data give more accuracy than only the present input data. The differences of EI values between two cases are significant therefore the present and past one-hour data were defined as the input nodes. The results of forecasting hourly water levels and discharges are shown in Figure 7. The past data of more than one hour are not used as the additional input node in this study because the increase in the computational time and the efficiency index is not significant. The efficiency index is found to range from 95.1 to 98.9 for model training and testing. The model performance is found to be satisfactory.



One-hour ahead water level forecasting BPNN(5-5-1)



One-hour ahead water level forecasting BPNN(10-5-1)

Legend and Notation

i1= B(t)
i2= B(t-1)
i3= F(t)
i4= F(t-1)
i5= U(t)
i6= U(t-1)
i7= D(t)
i8= D(t-1)
i9= W(t)
i10=W(t-1)
i11=Q(t)
i12=Q(t-1)
o1=W'(t+1)
or =Q'(t+1)
i= input node
b= bias nodes
h= hidden nodes
o= output nodes
B= water level at Bang Sai
F= water level at Fort Chula
U= upstream local inflow
D= downstream local inflow
W=water level at Station C4
W'=forecated water level at Station C4
Q= observed discharge at Station C4
Q'=forecasted discharge at Station C4
t= 1 hour time step, present time t

FIGURE 6 NETWORK ARCHITECTURES FOR FORECASTING OF HOURLY FLOOD WATER LEVELS OR DISCHARGES

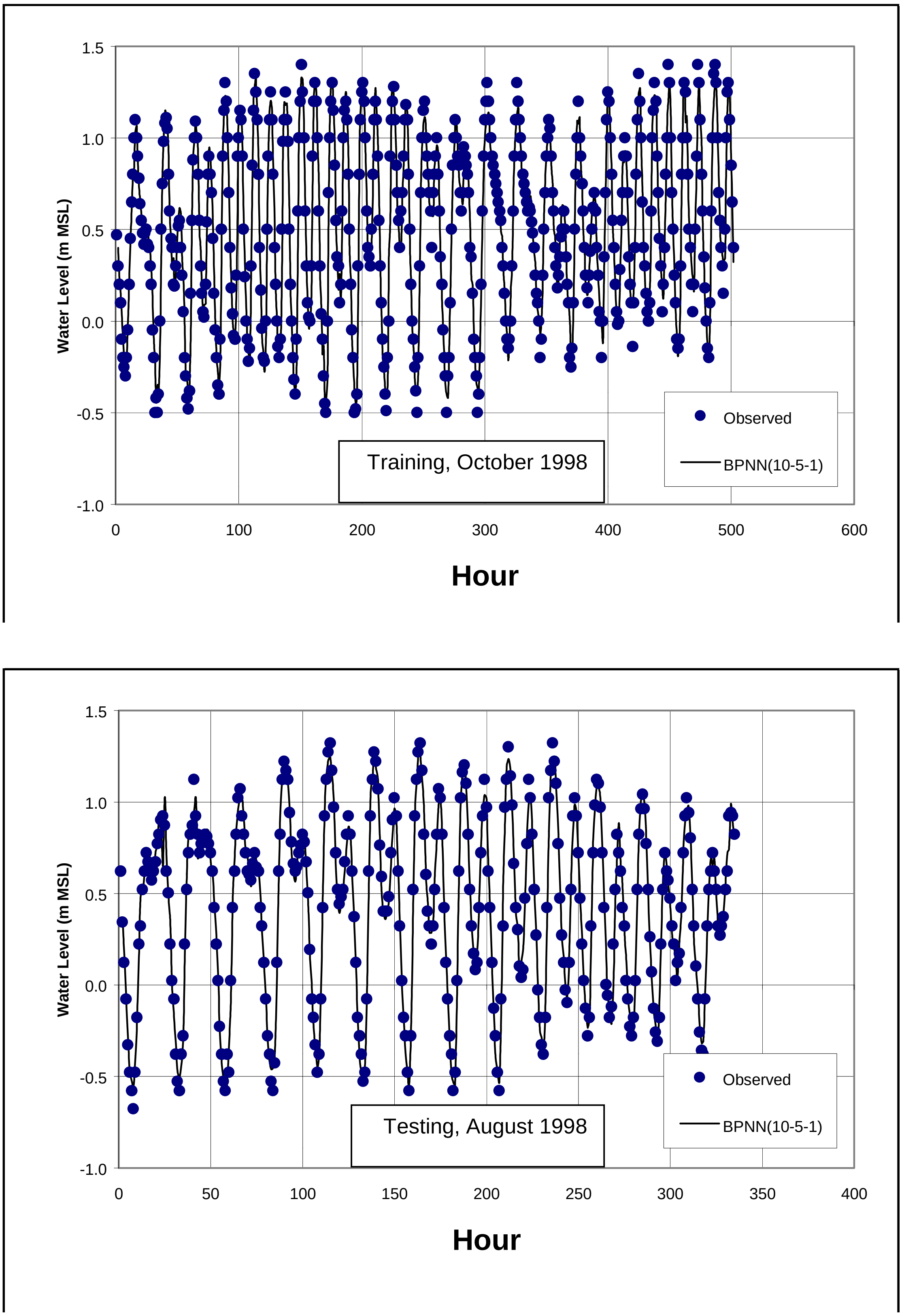


FIGURE 7 FORECASTING OF HOURLY FLOOD LEVELS OF CHAO PHRAYA RIVER AT BANGKOK MEMORIAL BRIDGE STATION C4, MODEL TRAINING IN OCTOBER 1998 AND MODEL TESTING IN AUGUST 1998

6 Conclusions

A neural network model with back propagation algorithm for flood forecasting was developed in the tidal reach of the Chao Phraya river at the Bangkok Memorial Bridge (gaging station no. C4). The model developed was found to perform very well in both calibration (training) and verification (testing). The efficiency index of the model forecasting results is found to range from 95-99 percent. The neural network model is however still dominated by trial and error process in many aspects. It is important to mention that the selection of the network architecture significantly influences the output performance of the model and the computational time. The model requires water level or discharge data but not the topographical data. A study is being conducted to use the neural network model to forecast hourly water levels and discharges for more time steps ahead in the Chao Phraya river.

More studies are encouraged to apply neural network models for flood forecasting in other tidal rivers of different characteristics so that the models can be applied with confidence in operational flood forecasting and warning.

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