INFLOW PREDICTION FOR THE UPSTREAM BOUNDARY CONDITION OF THE CHAO PHRAYA RIVER MODEL USING AN ARTIFICIAL NEURAL NETWORK

Supatchaya Chuanpongpanich[1], Kenji Tanaka[2], Phatcharasak Arlai[3],
Tawatchai Tingsanchali[3] and Manfred Koch[4]

ABSTRACT

The Chao-Phraya river basin located in the central part of Thailand is the largest river basin and it is the most productive agricultural areas of the country. Also, this river basin is highly populated, with the Chao-Phraya River flowing through Bangkok in its lower course; the ever-occurring floods of this river are frequently affecting large economic losses to the country. In this study, the river discharge that collects from four upper sub-basins is predicted to prepare the upper boundary condition for the river flow model. Also, there are two huge dams in the northern part of Thailand, Bhumibhol and Sirikit, which play an important role in the control of the discharge of the Chao-Phraya river. Artificial Neural Network (ANN) that is a mathematical model is applied for river discharge prediction for input upstream boundary condition for the integrated river flow model being prepared by NPRU research team. Thus, the simulated flow from river flow model can provide the flood prediction information for an early flood warning system for 5 days forward. The ANN is found to yield very satisfactory result for river discharge prediction.

1. INTRODUCTION

Flood is a natural phenomenon of Chao-Phraya river basin which is the main river basin of Thailand; therefore, it cause significant losses to the national economy. Chao-Phraya collects water from four upper sub-basins, namely Ping, Wang, Yom and Nan with two of them influenced significantly by the two huge reservoirs Bhumibhol and Sirikit, setting up the proper upper boundary conditions for a numerical river flow model for the purpose of establishing an early flood warning system. Therefore, Artificial Neural Networks (ANN) is applied to estimate the appropriate upstream river discharge at the meeting point of four sub-basin (station C.2) for utilizing as the upper boundary condition of the integrated river flow model for the Chao-Phraya.

This study purposes to prepare the river discharge at the upper boundary of river flow model by Artificial Neural Networks (ANN). The ANN's training process consists basically of the calculations of the weights for the synapses connecting the input variables with the subsequent

[1] Ph.D student, Disaster Prevention Research Institute, Graduate School of Engineering, Kyoto University, Japan (chuanpongpanich.supatchaya.46a@st.kyoto-u.ac.jp)
[2] Associate Professor, Water Resources Research Center, Disaster Prevention Research Institute, Kyoto University, Japan, (tanaka.kenji.6u@kyoto-u.ac.jp)
[3] Research Center of Sustainable Water and Disaster Mitigation Management, Nakhon Pathom Rajabhat University, Thailand, (arlaip@npru.ac.th)
[4] Department of Geohydraulic and Engineering Hydrology, The University of Kassel, Germany

neurons and, eventually the output variables. Here the inputs are the time-lagged (taking into account the travel times of the stream flows in the corresponding reaches) daily inflow discharges at 8 discharge stations and 4 raingage stations in the four upstream sub-basins observed between June and December, 2006, whereas the one output variable is the outflow discharge at the confluent point (station C.2), marking the inlet of the main Chao-Phraya river channel. For the estimation of the weights during this ANNs training phase the commonly used back propagation method is employed whereby, using the derivative of the objective function, i.e. the mean square error between the observed and modeled outputs, incremental learning rates of the weights are computed (back projection). The process is repeated until the mean square error is a minimum.

2. METHOD

Artificial Neural Networks (ANN) is an information processing model that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this model is the structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANN, like people, learn by example. Therefore, ANN back propagation method procedure is shown in Figure 1.

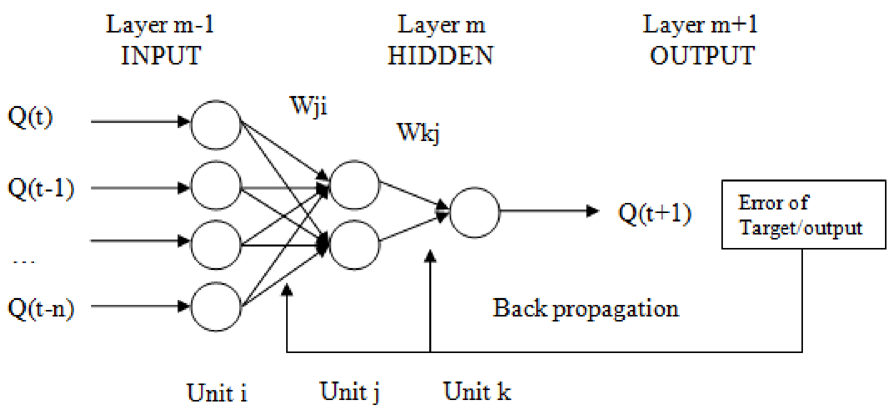


Figure 1 ANNs Back Propagation Method

The model is usually best to start with a simple network/hidden layer construction that can quickly certify the model's ability to train and learn relationships. The network is training, when convergence has been achieved and information on the quality of the model being generated. It is also likely that it will be needed to tune the training parameters so that the specified values match the training characteristics for the model.

The number of nodes and layers of hidden layer which set up in the model processing has been selected by the following information and these values suggested by Piman (2002). Furthermore, sigmoid function is applied to use for ANN back propagation, it provides to normalize a node's output response to a value between 0 and 1.

The initial weight is important for ANN in the training part because if the values are closed to the final weight, the result will be quickly convergence to the target results. In the other hand, if the initial weight is far from the final weight, the result will be divergence to target results. The initial values of weight are assume in a similar range as Piman (2002) in this study.

3. MODEL APPLICATION

There are 8 discharge monitoring stations and 4 raingage stations which are shown in Figure 2 for input to ANN and the locations are shown in table 1. For the stations no. 10 to no. 13, they are the same stations as expressing to the parentheses but they are indicated for rainfall data.

Table 1 Locations of discharge stations

No.	STA.	Location	Type of data
1	D.2	Sirikit dam, Utaradit	Daily discharge
2	D.1	Bhumibhol dam,Tak	Daily discharge
3	W.4A	Samngao, Tak	Daily discharge
4	N.5A	Muang, Pitsanulok	Daily discharge
5	Y.17	Samngam, Pichit	Daily discharge
6	P.7A	Muang, Kampheangphet	Daily discharge
7	P.17	Banpotpisai, Nakhon Sawan	Daily discharge
8	N.67	Chumsang, Nakhon Sawan	Daily discharge
9	C.2	Muang, Nakhon Sawan	Daily discharge
10	RY.6 (Y.6)	Srisatchanalai, Sukhothai	Daily rainfall
11	RP.7A (P.7A)	Muang, Kampheangphet	Daily rainfall
12	RN.67 (N.67)	Chumsang, Nakhon Sawan	Daily rainfall
13	RN.5A (N.5A)	Muang, Pitsanulok	Daily rainfall

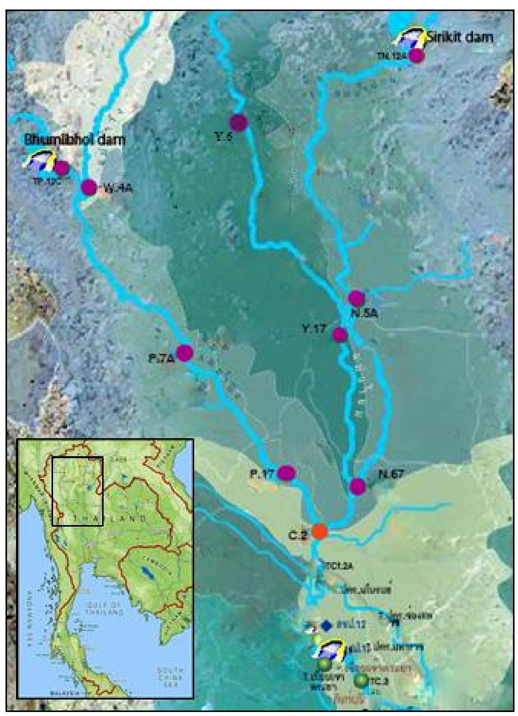


Figure 2 Monitoring stations for ANNs

There are 12 training cases of each forecasting one-day time step. The furthest station input that takes 4 days to flow to Nakhon Sawan is station D.2 at Sirikit dam; therefore, the model can predict the discharge for 5 days ahead. Moreover, the learning rate and momentum parameter which are selected to calculate in ANN are 0.01 and 0.6, respectively. Each training case is shown in the following table. The discharge at the meeting point of the four sub-basin (C.2) can be estimated by calculation of flow from previous time step discharge data from upstream stations. The ANN has been trained for discharge prediction with different cases, each using different combinations of the turned on/off stations, and the selected networks are indicated in table 2.

Table 2 Selected forecasting network (X: used, O: non-used)

output	telemetering station (input)								raingage station (input)				predicted station (input)			
C.2	D.2 (t-4)	D.1 (t-3)	W.4A (t-3)	P.7A (t-2)	Y.17 (t-2)	N.5A (t-2)	N.67 (t-1)	P.17 (t-1)	RY.6 (t-2)	RP.7A (t-2)	RN.5A (t-2)	RN.67 (t-1)	C.2 (t)	C.2 (t+1)	C.2 (t+2)	C.2 (t+3)
t	X	X	X	O	X	O	X	X	X	X	X	X	O	O	O	O
t+1	X	X	O	O	O	O	X	X	X	X	X	X	X	O	O	O
t+2	X	X	O	O	O	O	X	X	X	X	X	X	X	X	O	O
t+3	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	O
t+4	X	X	O	O	O	O	X	X	O	O	O	O	X	X	X	X

3. RESULTS

There are 10 inputs data and 20 nodes for hidden layer of the selected network for discharge prediction at the time t, and the evaluations of this network are 9.416m^3/s of mean absolute error (MAE), 99% of efficiency index (EI) this shows a high reliability of prediction with 27.817m^3/s of root mean square error (RMSE). Furthermore, the furthest station input that takes 4 days to flow to station C.2 is station D.2 at Sirikit dam; therefore, the training of discharge prediction model results are shown in table 3.

Table 3 Training of discharge prediction networks results

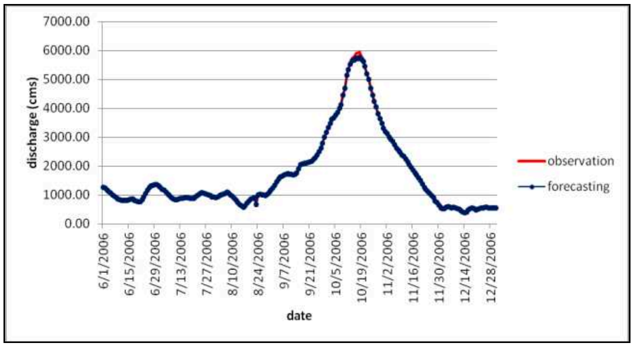
time step (day)	evaluation			
	*r**	MAE (m^3/s)	EI	RMSE (m^3/s)
t	0.999	9.416	1.000	27.817
t+1	0.999	9.887	0.999	36.551
t+2	0.999	23.043	0.998	64.231
t+3	0.998	60.405	0.994	104.443
t+4	0.999	30.758	0.997	70.006

* *r* = correlation coefficient

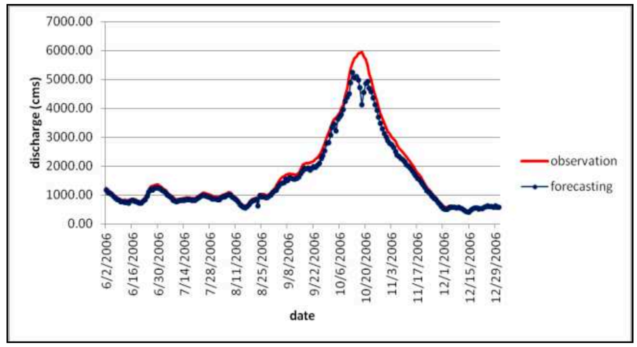
Finally, the model can predict the discharge for 5 days ahead and the results are shown in table 4, and the trend of prediction accuracy is decreasing when the time step is increasing. Thus, the inflow discharge that is predicted by ANN as shown in figure 3 will be used as upstream boundary data in the integrated river flow model that provides the flood prediction information for an early flood warning system.

Table 4 Discharge prediction results

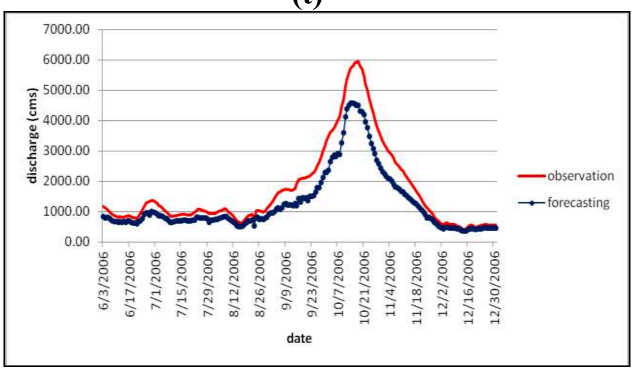
time step (day)	evaluation		
	MAE (cms)	EI	RMSE (cms)
t	9.416	1.000	27.817
t+1	165.462	0.963	267.075
t+2	442.757	0.829	575.214
t+3	403.601	0.855	531.217
t+4	365.668	0.834	569.697



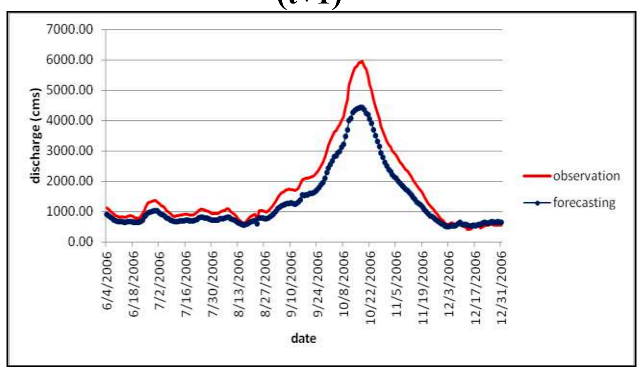
(t)



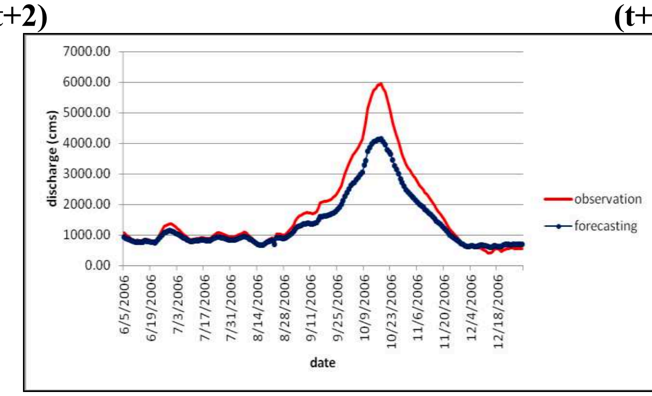
(t+1)



(t+2)



(t+3)



(t+4)

Figure 3 Forecasting results of upstream discharge at station C.2

4. SUMMARY

Flood always occurs in Chao-Phraya river basin especially, the huge magnitude of flood in 2006 requires this study for early flood warning. The lower part of Chao-Phraya river basin collects some huge discharge from the upper four sub-basins which are Ping, Wang, Yom and Nan. Also, the river discharge is controlled by two huge dams in the upper part of Chao-Phraya river basin. Therefore, the river discharge that collects from four upper sub-basins is predicted to use as the upstream boundary condition for the river flow model. There are 12 training cases of each forecasting time step. The furthest station input that takes 4 days to flow to station C.2 is station D.2 at Sirikit dam. Therefore, the model can predict the discharge at station C.2 for 5 days ahead. Finally, the trend of prediction accuracy is found decreasing when the time step is increasing. Thus, the inflow discharge that is predicted by ANN will be used as upstream boundary condition in the integrated river flow model that provides the flood prediction information for an early flood warning system.

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