京都大学防災研究所年報 第 55 号 B 平成 24 年 6 月
Annuals of Disas. Prev. Res. Inst., Kyoto Univ., No. 55 B, 2012

Integrated Models in the Lower Part of Chao-Phraya River Basin for an Early Flood Warning System

Supatchaya CHUANPONGPANICH(1), Kenji TANAKA,
Toshiharu KOJIRI and Phatcharasak ARLAI(2)

(1) Graduate School of Engineering, Kyoto University
(2) Research Center of Sustainable Water Resources and Disaster Mitigation Management, Nakhon Pathom Rajabhat University, Thailand

Synopsis

Chao-Phraya river basin is the most important river basin in Thailand that produces the main country products; therefore, flood can make loss to the national economy. In this study, the mathematical models have been applied to prepare flood information for an early flood warning system. HEC-RAS is applied for discharge and water level simulation in the main channel of Chao-Phraya River with unsteady state condition; consequently, it required data in the upstream, downstream and lateral boundary that can be estimated by Artificial Neural Networks (ANNs), Harmonic Analysis and Multiple Linear Regressions, respectively. HEC-RAS model calibration obtained 80% of correlation coefficient; besides, boundary data estimations can achieve the satisfied accuracy. Furthermore, the integrating of river flow model and boundary models obtained satisfied verification result during June to November, 2011. Thus, the integrated model can provide 4 days ahead of flood forecasting information.

Keywords: flood forecasting, Chao-Phraya, River flow model, integrating models

1. Introduction

Flood is a natural phenomenon of Chao-Phraya river basin because there are four sub-basins in the upper part and two huge dams that are influent to discharge in Chao-Phraya River. Therefore, flood forecasting information is necessary for dam operation planning and flood mitigation in this area. Although many researchers attempted to study about flood in this region, flood forecasting information still needs to improve the accuracy for a real time warning system. In 2000, Weesakul and Thammasittirong applied and developed AIT River Network model in the Chao-Phraya river delta with acceptable agreement flood forecasting results in 1980, 1983 and 1995. Moreover, HEC-RAS that is applied for river flow model in this study had been developed in Chao-Phraya River by Visutimeteegorn et al. (2007) and his study aimed to analyze the effects on the upstream flood inundation in 1995. Whereas, the historical flood magnitude in 2006 is higher than in 1980, 1983 and 1995; therefore, in this study, the data in 2006 were selected for model calibration to improve flood forecasting information. In addition, the model is verified with the data in 2011. Finally, the main objective of this study is providing and improving flood information for an early flood warning system.

2. Study area and Scope of work

Chao-Phraya river basin covers Thailand's land area of 20,125 sq.km and 372 km of length of Chao-Phraya river. It starts from the meet point of northern four sub-basin in Nakhon Sawan to the Gulf of Thailand in Samuth Prakarn. About 85% of the total runoff occurs in the months of July to December. Therefore, this period is used for model calibration.

HEC-RAS model is applied to simulate the flow in the channel of Chao-Phraya river to provide flood prediction information for an early flood warning system with unsteady state upstream and downstream boundary conditons. The upstream boundary of the model that is located at the meet point of northern four sub-basin (C.2) is estimated by ANNs model with back propagation method. The downstream boundary of the model is located at Fort Chula gaging station (C.54) at the river mouth just at the sea in the Gulf of Thailand. Because the water level at Fort Chula is influenced by the upstream of river discharge and the tidal wave from the sea, Harmonic Analysis method is applied at Fort Chula gaging station for prediction of water level at this gaging station. In addition, the lateral boundary of HEC-RAS model that is the flow from river branches (R.1, R.2, R.3, R.4 and R.5) are also added to the model. All boundary conditions are shown in Fig. 1. and the boundary condition information is shown in Table 1.

3. Theoretical consideration

In this study, the mathematical models that are written in the following information have been applied and integrated to prepare flood information for an early flood warning system.

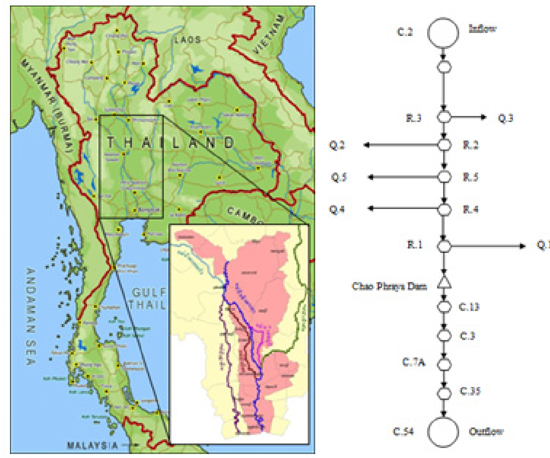

Fig. 1 Boundary condition of river flow model

3.1 River flow model

Hydrologic Engineering Center River Analysis system (HEC-RAS) model is referring to the theory of one-dimensional river analysis for steady flow water surface profile computations and unsteady flow simulation. In this study, the application of HEC-RAS model is based on unsteady flow simulation which can be explained by two main equations.

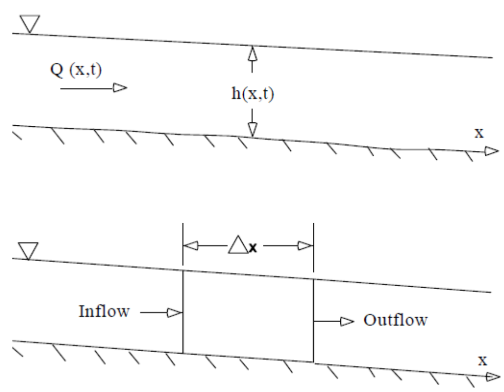

Fig. 2 Elementary control volume

Table 1 Boundary condition information

Sta.	*River*	*Name*	*Boundary Condition*
C.2	Chao-Phraya	Nakhonsawan	Discharge
C.54	Chao-Phraya	Fort Chula	Water level
Dam	Chao-Phraya	CH dam	Controlled gates
R.1	Chainat-Ayutthaya	Maharat	Water level
R.2	Makhamtao-Uthong	M-U	Water level
R.3	Chainat-Pasak	Manorom	Water level
R.4	Noi	Boromatad	Water level
R.5	Tachean	Poltep	Water level

(1) Continuity equation

The elementary consideration of control volume is shown in Fig. 2. The distance x is measured along the channel. At the midpoint of the control volume the flow and total flow area are denoted *Q(x,t)* and *AT*, respectively. The total flow area is the sum of active area A and off-channel storage area S. The continuity equation can be written as equation 1.

$$\frac{\partial A}{\partial t}+\frac{\partial S}{\partial t}+\frac{\partial Q}{\partial x}-q_1=0 \tag{1}$$

Where x is distance along the channel, t is time, Q is flow, A is cross-sectional area, S is storage from non-conveying portions of cross section and q_1 is lateral inflow per unit distance.

(2) Momentum equation

The momentum equation states as shown in equation 2, the rate of change in momentum is equal to the external forces acting on the system for a single channel.

$$\frac{\partial Q}{\partial t}+\frac{\partial (VQ)}{\partial x}+gA\left(\frac{\partial z}{\partial x}+S_f\right)=0 \tag{2}$$

Where g is acceleration of gravity,is S_f friction slope and V is velocity.

3.2 ANNs

Artificial Neural Network (ANNs) is an information processing model that is stimulated by the biological nervous systems. The processes of ANNs back propagation method are shown in Fig.3 for upstream discharge forecasting.

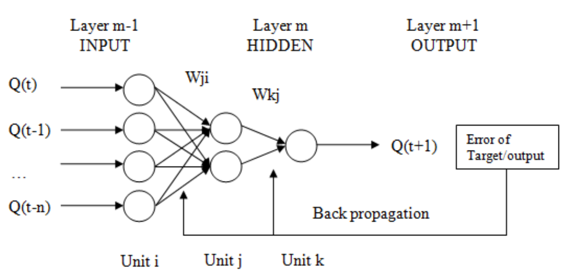

Fig. 3 ANNs Back Propagation Method

For this method, there are two main steps that are forward pass and backward pass. Firstly, data will be normalized for converting all in the same unit. Defining parameters, learning rate range should be 0.1-0.3, momentum rate range should be 0.1-0.5 and the selected activation function is sigmoid function. Also, weighting inputs random initialization should be -1 to 1. Secondly, the model running will use an error from forward pass for adjusting the new weight in backward pass, and the new weight will be used in the new forward pass iteration until the calculation reaches to the stopping criteria with 10,000 iterations that are enough to obtain the minimum error.

3.3 Tide analysis

The tide analysis that is called Harmonic Analysis purposes to determine the amplitude and phase (tidal harmonic constants) of the individual cosine waves. The partial tide corresponding to a single tidal constituent is represented by the following equations,

$$\eta_r(t)=a_0+\sum_{i=1}^{N}a_i\sin\left[\frac{2\pi t}{T_i}+\delta_i\right] \tag{3}$$

where a is the mean sea level, N is the total number of constituents a_i, δ_i and T_i are the amplitude, phase and period of the i^{th} constituent. The values of a_0, a_i, δ_i can be determined for each corresponding values of T_i using the information that are obtained from tidal records.

3.4 Linear regression analysis

Regression analysis is a statistical technique that efforts the relationship between two or more variables using a straight line. The variables are Criterion Variable (Y) and Predictor Variable (X). For the river branch data, there are two predictor variables from rainfall and water level relate to one criteria variable; therefore, the multiple linear regression method has been applied in this model. It can be written in the mathematical equation as;

$$Y=\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_nX_n+\varepsilon \tag{4}$$

where intercept and coefficients, $\beta_0, \beta_1, \beta_2, \ldots, \beta_n$

can be estimated by least squares method, and ε is an error. In the least-squares model, the best-fitting line for the observed data is calculated by minimizing the sum of the squares of the vertical deviations from each data point to the line. The residuals, ε are the difference between the observed and fitted values; hence, the sum of the residuals is equal to zero.

3.5 Statistical evaluations

The statistical evaluation functions can evaluate the calibrated and forecasted accuracy. They can perform the reliability of flood information which is simulated by integrating models for an early flood warning systems. Therefore, there are three kinds of statistical functions that have been calculated in this study to evaluate the accuracy of models.

(1) Correlation coefficient (r)

The correlation coefficient is a measure how well the relationship between two variables of the predicted values and actual values. The correlation coefficient is a number between 0 and 1. If there is no relationship between the predicted values and the actual values the correlation coefficient is 0. The correlation coefficient equation is shown in the equation 5.

$$r = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{5}$$

(2) Mean Absolute Error (MAE)

Mean Absolute Error is an average of the difference between an estimated value and observed value to evaluate the simulated data, without considering their direction. It measures accuracy for continuous variables. The formula of this calculation is shown in equation 6.

$$MAE = \frac{\sum_{i=1}^{N}|X - Y|}{N} \tag{6}$$

(3) Root Mean Square Error (RMSE)

Root mean square error (RMSE) is an error measure from the differences between values predicted by a model or an estimator and the observed values. The RMSE equation is shown in equation 7.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y - X)^2} \tag{7}$$

(4) Efficiency Index (EI)

The efficiency index is a ratio between calculated value and observed value. The efficiency index equation is shown in Eq. 8.

$$EI = \frac{\sum_{i=1}^{N}(X - \overline{X})^2 - \sum_{i=1}^{N}(X - Y)^2}{\sum_{i=1}^{N}(X - \overline{X})^2} \tag{8}$$

Where X is measured value, $\overline{X}$ is average of measured value, Y is calculated value, $\overline{Y}$ is average calculated value and N is number of data.

4. Results

HEC-RAS model is applied for the river flow simulation in the main channel to provide flood forecasting information to an early flood warning system with unsteady state condition and it needs some boundary data in the upstream, downstream and lateral flow from river branches. Hence, ANNs, Multiple Linear Regression and Harmonic Analysis are applied for estimating upstream discharge, river branch water level and downstream water level.

4.1 HEC-RAS

There are two parts of calibration that are parameter calibration and inline structure water release calibration.

(1) Parameter calibration

Before HEC-RAS is ready for flood forecasting, model is needed to calibrate the water level. There are five parameters have been calibrated that are Manning's n roughness coefficient in main channel, Manning's n roughness coefficient in floodplain, Free flow discharge coefficient, Submerge flow discharge coefficient and Discharge coefficient when the gate opening exceeding the flow subscribed by c_w, n_r , n_f , c_f and c_s The typical parameter values are recommended by

Visutimeteegorn (2006) as shown in Table 2. Finally, the statistical evaluations of parameter calibration are 0.68m of RMSE and 90% of EI. Also, the correlation coefficient is about 80%. Thus the model can be estimated an accurate water level and the results of water level are shown in Fig. 5 - Fig. 10 and the gage locations are shown in Fig. 4.

Table 2 The selected typical parameter values

Parameter	***Typical Value***	***Range***	***Reference***
n_r	0.025	0.025-0.060	
n_f	0.055	0.035-0.160	
c_f	0.5	0.4-0.8	
c_s	0.6	0.6-0.8	
c_w	0.6	0.6-0.8	US Army (2010)

Fig. 4 The gage location of calibrated results

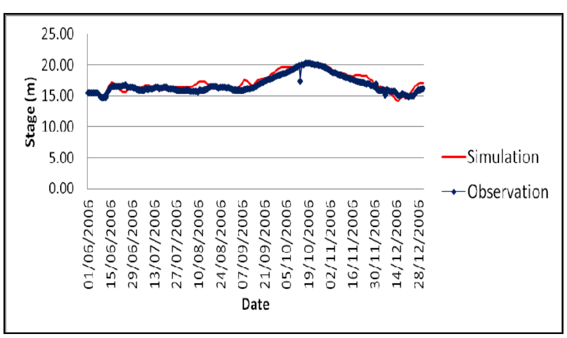

Fig. 5 Calibrated result at Manorom

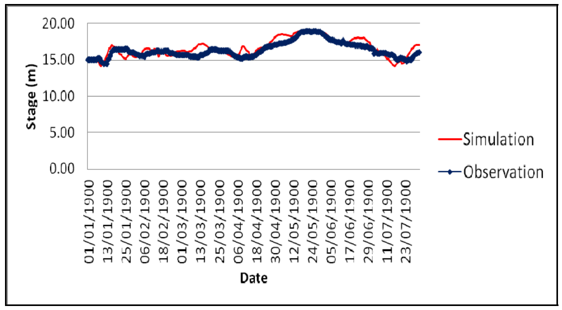

Fig. 6 Calibrated result at Makhamtao-Uthong

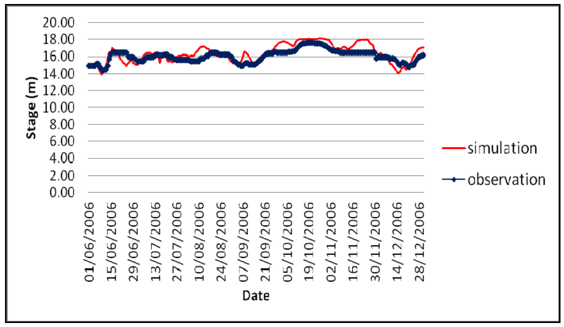

Fig. 7 Calibrated result at Maharat

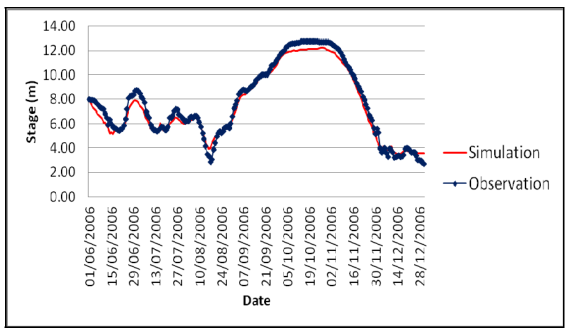

Fig. 8 Calibrated result at Ban Bangpudsa

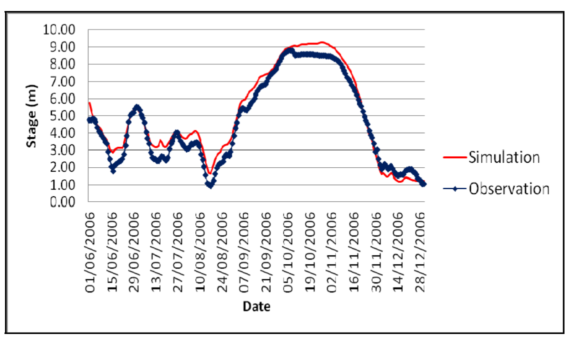

Fig. 9 Calibrated result at Ban Bangkaew

(2) Inline structure calibration

There is the inline structure, Chao-Phraya dam that is located at the Chao-Phraya River. It has 16 radial gate openings with 7.50m height and 12.50m width. The maximum water release is about 3,300 CMS; however, it is controlled to release only

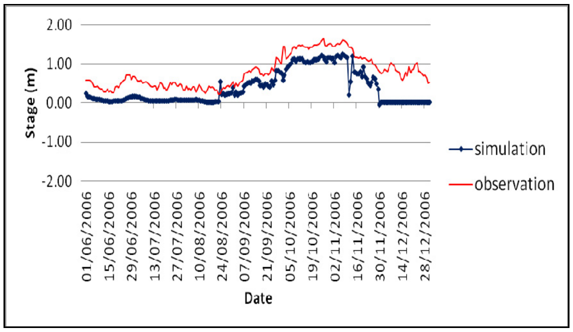

Fig. 10 Calibrated result at Memorial Bridge

2,500 CMS for protecting the effect in downstream areas. Also, the different water level between upstream and downstream should not be exceeded 10m.

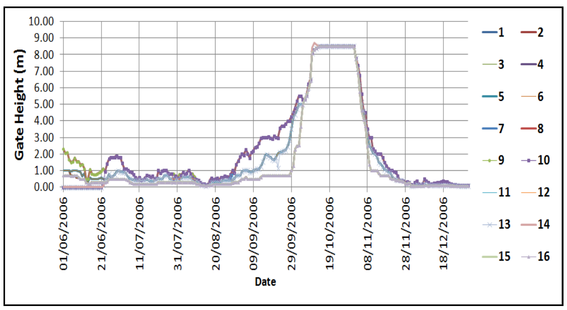

Fig. 11 Chao-Phraya dam gate operation graph

Referring to the historical data in Fig. 11 of the flood control period during June to December, 2006, the model assumed that the gate is automatic controlled. The open rate of 16 dam gates is specified from the positive slope of dam gate operation graph; while, the negative slope of the graphs are shown the close rate of dam gates. Moreover, each gate has the different maximum and minimum opening operation. Finally, the gate control rules are added to inline structure part of HEC-RAS model to simulate the water level for flood warning system. The result of water release calibration from the downstream of Chao-Phraya dam station (C.13) by using the specified control rules from the historical data is shown in Fig. 12. When the observed data and simulated data are compared by statistical evaluation equation; therefore, MAE is 0.617m and EI is 94%. Thus, the results can be acceptable.

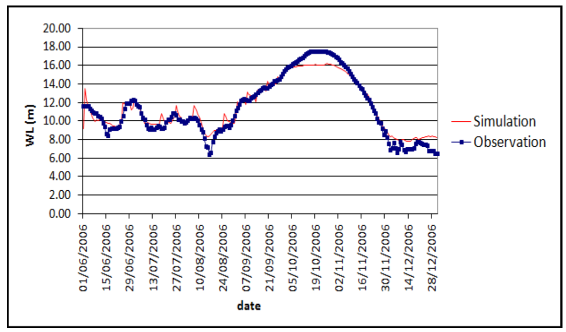

Fig. 12 Calibration result at Chao-Phraya dam station (C.13)

4.2 Upstream boundary data estimation

Chao-Phraya collects discharge from four upper sub-basins, 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 for the downstream reaches of the Chao-Phraya river is not an easy effort. Therefore, Artificial Neural Networks (ANNs) is applied to

Table 3 Different training cases of ANNs

case	*runoff station (input)*								*output*
	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)	C.2 (t)
1	O	O	O	O	O	O	O	O	O
2	O	O	X	X	X	X	O	O	O
3	O	O	O	X	O	X	O	O	O
4	O	O	O	O	O	O	X	X	O
5	X	X	O	O	O	O	O	O	O
6	X	X	O	O	O	O	X	X	O

Note: O used, X non-used

estimate the appropriate upstream river discharge for use in the upper boundary condition of the integrated river flow model.

The upstream river discharge estimation has been done with the data from June to December, 2006 by ANNs model. There are six training cases with the different travel time from the station to C.2 as shown in Table 3 and the gage station locations are shown in Fig. 13. The best result of ANNs training process is in case 3 with 6 nodes of river discharge input data from Bhumibhol dam (D.1), Sirikit dam (D.2), W.4A, Y.17, N.67 and P.17 gage stations. The number of hidden node in hidden layer is 6 nodes, and the number of node in output layer is 1 node from gage station C.2. The statistical evaluation results of this network are 99% of Efficiency Index and 55.952 of Root Mean Square Error. Therefore, this network is selected for runoff forecasting in the upper boundary condition of HEC-RAS model.

After the suitable network is obtained the selected network will be set for river discharge forecasting as shown in Table 4. Lastly, the trend of forecasted accuracy is reducing for the next time step as shown in Table 5. In addition, ANN network 7-14-1 means the number of input node in input layer is 7 nodes, the number of hidden node in hidden layer is 14 nodes and the number of output in output layer is 1 node.

Table 5 Forecasting results

day	*ANN* **Network**	*EI%*	*MAE (cms)*	*RMSE*
t+1	7-14-1	99	29.93	92.56
t+2	8-16-1	98	150.13	327.58
t+3	9-18-1	93	272.15	579.25
t+4	10-20-1	91	334.52	652.75

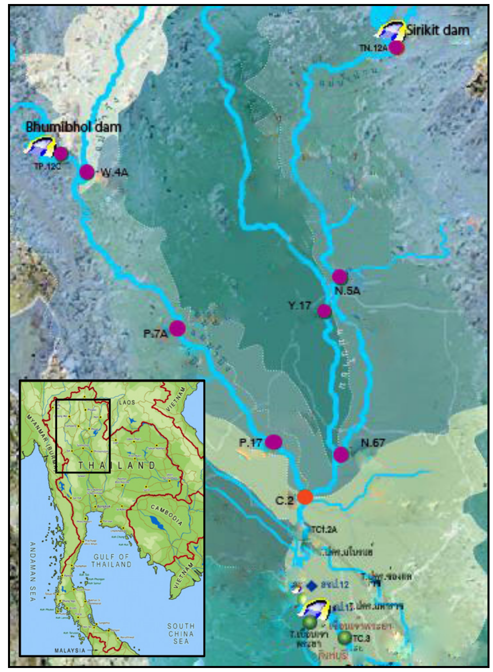

Fig. 13 Runoff stations for ANNs

4.3 Downstream boundary data estimation

The downstream boundary of the model is located at Fort Chula gaging station at the river mouth just at the sea in the Gulf of Thailand. The water level at Fort Chula is influenced by the upstream of river discharge and the tidal wave from the sea. Therefore, Harmonic Analysis method is applied at Fort Chula gaging station for estimation of water level at this gaging station. In this analysis, the number of constituents and the tidal length records are determined to achieve the best tidal forecasting for 7 days ahead in 2006. The number of harmonic analysis constituents varies from 4 to 8 constituents and the record length varies from 7 to 80 days. Therefore, Fig. 14 shows the comparison of Root Mean Square Error

Table 4 River discharge forecasting by ANNs

Forecasting date	***runoff station (input)***										
	D.2 (t-4)	D.1 (t-3)	W.4A (t-3)	Y.17 (t-2)	N.67 (t-1)	P.17 (t-1)	C.2 (t)	C.2 (t+1)	C.2 (t+2)	C.2 (t+3)	C.2 (t+4)
1	O	O	O	O	O	O	O	result			
2	O	O	O	O	O	O	O	O	result		
3	O	O	O	O	O	O	O	O	O	result	
4	O	O	O	O	O	O	O	O	O	O	result

(RMSE) of Harmonic Analysis for various record length and number of constituents. The comparison of Root Mean Square Error (RMSE) and Efficiency Index (EI) of

Harmonic Analysis at Fort Chula station, the result of 4 constituents (N=4) for 35 days record length showed the smallest RMSE and highest EI, 0.178m and 96%, respectively.

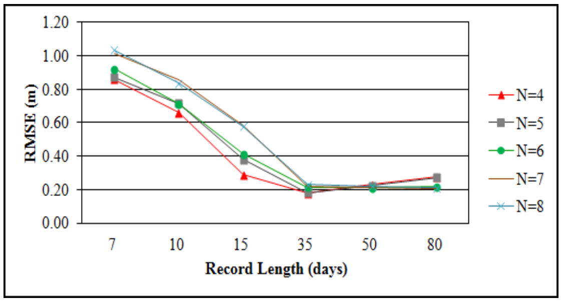

Fig. 14 RMSE comparison of Harmonic Analysis at Fort Chula in 2006

Furthermore, harmonic analysis of water level in the Gulf of Thailand is based on the four main tide constituents that are:

(1) Principal lunar *M2* with a period of 12.4206 hours.

(2) Principal solar *S2* with a period of 12.0000 hours.

(3) Luni-solar declinational *K1* with a period of 23.9346 hours.

(4) Large lunar declinational *O1* with a period of 25.8194 hours.

All principle constituents are explained in the appendix. Finally, the forecasting evaluation of various day ahead, the seven days ahead forecasting is obtained with satisfactory results. Therefore, this harmonic model shows a forecast of hourly tidal data for 7days ahead with 87% of EI as shown in Fig. 15. The longer period ahead of prediction or forecasting shows increasing error of forecast especially at the peaks and troughs of the tidal fluctuation.

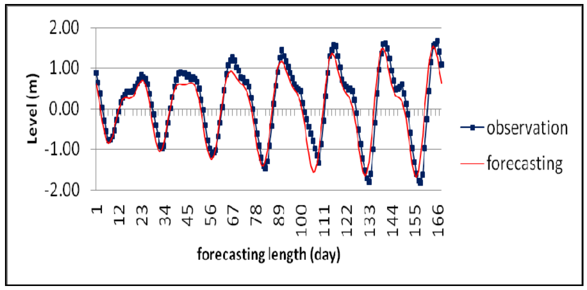

Fig. 15 Results of tidal level forecasting

4.4 Lateral boundary data estimation

The lateral boundary data or river branch data of river flow model are controlled by regulator which connects to the main river channel. Therefore, Linear Regression method is applied for the lateral boundary data estimation to estimate the river branches water level. The linear regression equations are defined from multiple regressions with two predictors from upstream water level of a regulator and rainfall from the nearest rain gage stations to estimate downstream water level of each river branch regulator. The estimated water level evaluations of the river branch are shown in Table 6. The average correlation coefficient of five river branches is 73% and the results of estimated water level are shown in Fig. 16 – Fig. 20.

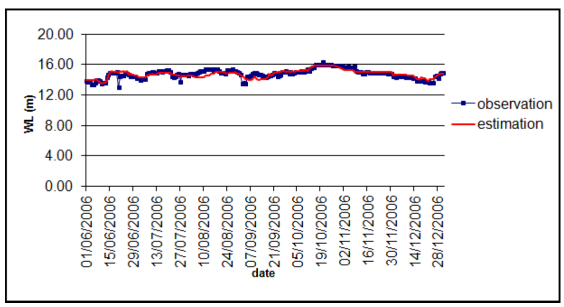

Fig. 16 The estimation results at R.1

Table 6 Water level estimation in the river branch results

Sta.	*River*	*Name*	*r*	*MAE*
R.1	Chainat-Ayutthaya	Maharat	0.81	0.368
R.2	Makhamtao-Uthong	M-U	0.78	0.284
R.3	Chainat-Pasak	Manorom	0.68	0.476
R.4	Noi	Boromatad	0.70	1.049
R.5	Tachean	Poltep	0.66	0.702

5. Model verification

The verification of river flow model has been done during June to November, 2011. The results are shown in Fig. 21 with 1.026m of RMSE and 94% of correlation coefficient at Ban Bangpudsa station (C.3). In the figure, the simulated flood duration shift from observation 4 days, and it starts from 10th October until 8th November, 2011; whereas, the observed flood duration is 6th September to 14th November, 2011.

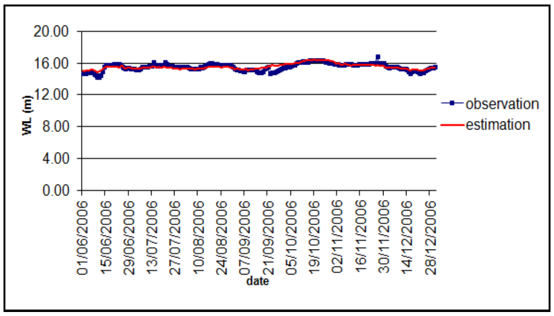

Fig. 17 The estimation results at R.2

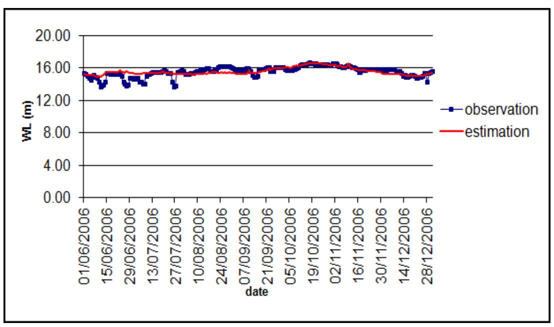

Fig. 18 The estimation results at R.3

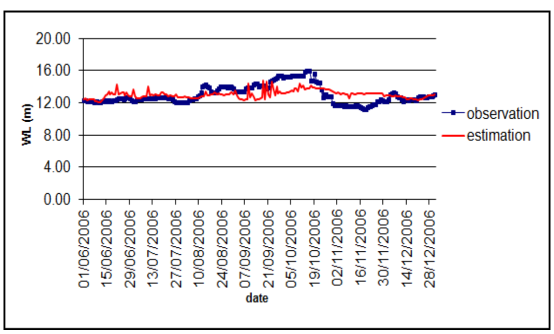

Fig. 19 The estimation results at R.4

Also, there is small flood in the simulation of Fig. 22, and the flood peak is different from observed stage 0.40m at Ban Bankaew station (C.7A) with 0.353m of RMSE and 97% of correlation coefficient.

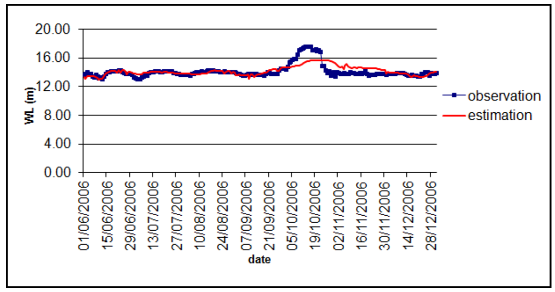

Fig. 20 The estimation results at R.5

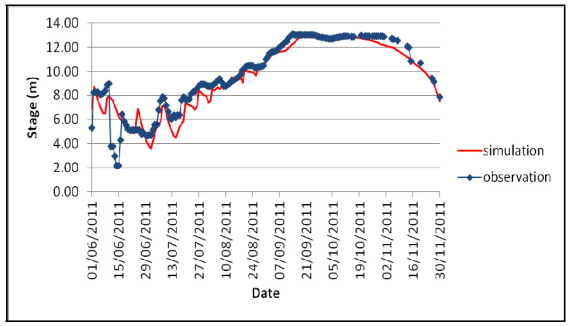

Fig. 21 Verification results at C.3

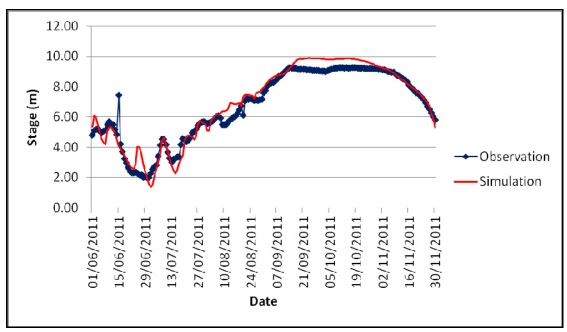

Fig. 22 Verification results at C.7A

6. Flood forecasting

The estimated boundary data models and HEC-RAS are integrated to forecast the water level in the Chao-Phraya River for 4 days ahead, and the observed rainfall data are utilized for the integrated model. For the real time warning system, it provides the daily forecasted information and the evaluations of forecasted results are shown in Fig. 23 - Fig. 30. The correlation coefficient of water level itself in the main channel stations which are C.7A and C.35 can obtain fairly accuracies as shown in table 7. Moreover, the evaluation of correlation coefficient by evaluate in terms of "change from initial value" that is subscribed by Δ(t+n), can obtain the fairly accuracy as shown in table 8. Thus, the trend of forecasting accuracy is decreasing when the time step is increasing. For the comparison of forecasting results and observation results are changing by different seasons. In the start of rainy season during August to September, the change of water level forecasting is much fluctuated. Furthermore, the water level during rainy season, September to October is under estimated (negative deviation values) in time step t+1 (one day ahead forecasting); in contrast, next time steps from one day ahead are almost over estimated (positive deviation values). Especially, during the peak of flow at the middle of October, the trend of forecasting is increasing when the time step is increasing. The reason is the travel time in the model might be later than in the real situation. Then, the model should be adjusted for the suitable time step of forecasting. Thus, improvement of accuracy and extension of forecasting time should be developed in the future work.

Table 7 The correlation coefficient of water level

station	correlation coefficient			
	t+1	t+2	t+3	t+4
C.7A	0.989	0.969	0.959	0.952
C.35	0.975	0.962	0.950	0.935

Table 8 The correlation coefficient by change from initial value

station	correlation coefficient			
	Δ(t+1)	Δ(t+2)	Δ(t+3)	Δ(t+4)
C.7A	0.758	0.665	0.610	0.540
C.35	0.629	0.611	0.564	0.500

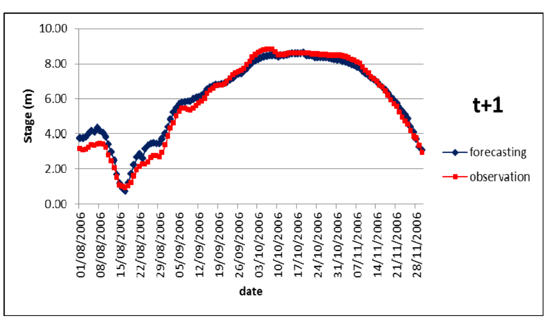

Fig. 23 Forecasting result of C.7A at time t+1

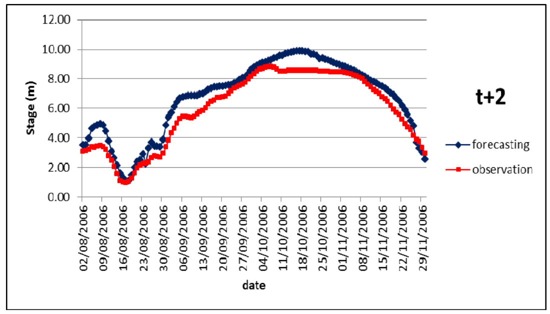

Fig. 24 Forecasting result of C.7A at time t+2

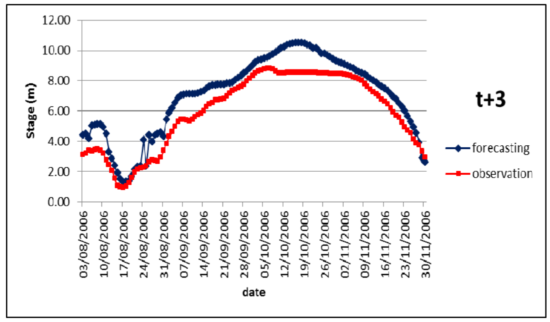

Fig. 25 Forecasting result of C.7A at time t+3

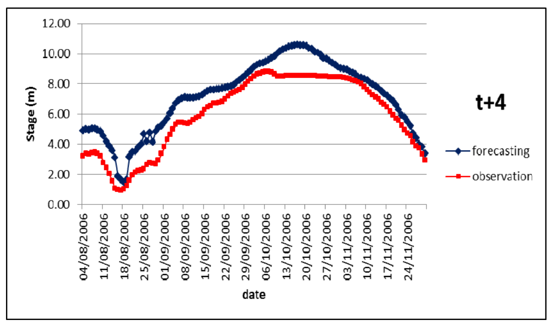

Fig. 26 Forecasting result of C.7A at time t+4

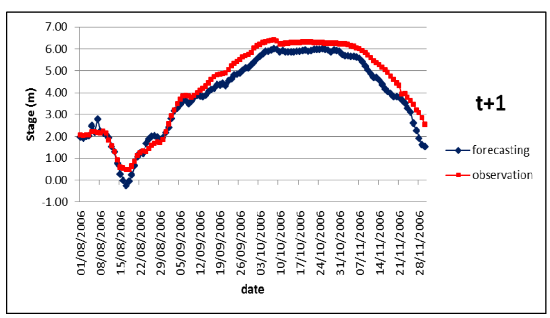

Fig. 27 Forecasting result of C.35 at time t+1

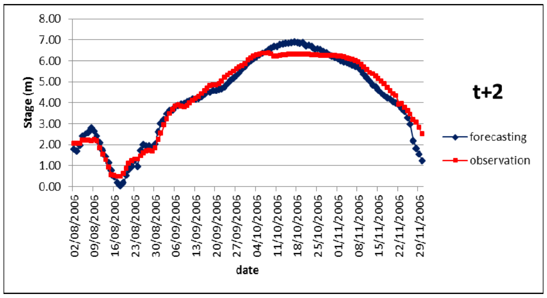

Fig. 28 Forecasting result of C.35 at time t+2

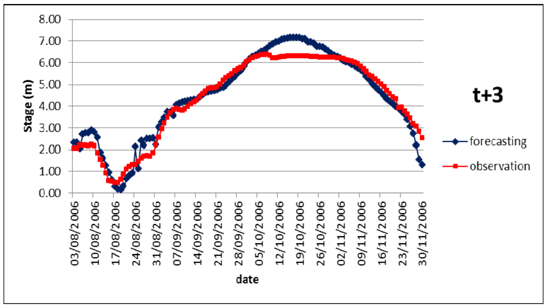

Fig. 29 Forecasting result of C.35 at time t+3

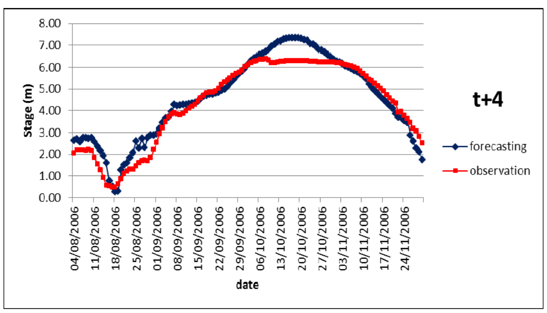

Fig. 30 Forecasting result of C.35 at time t+4

7. Early flood warning system

The flood inundation information can predict the flood magnitude from water which exceeds the river capacity. Chao-Phraya river basin always flood because of overbank flow; especially, the critical part of Chao-Phraya River mainly in a storm season. Finally, an early flood warning system can monitor the flood duration and magnitude; however, it needs to improve for more reliable flood information. Therefore, an early flood warning system procedure is shown in Fig. 31.

From Fig. 32, the capacity of Chao-Phraya River at Chao-Phraya dam downstream station (C.13) is about 2,900cms; meanwhile, the maximum discharge is 4,188cms in October 19th, 2006. Therefore, an observed maximum flood inundation volume in 2006 is 1,759MCM (Fig. 33) during October 5th to November 4th, 2006.

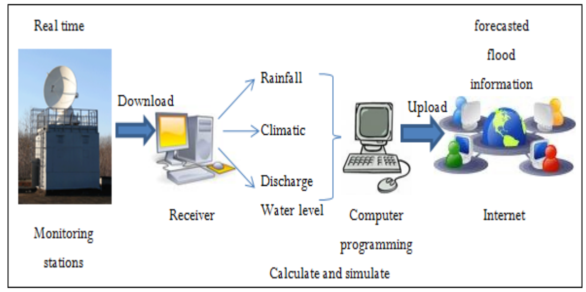

Fig. 31 An early flood warning system

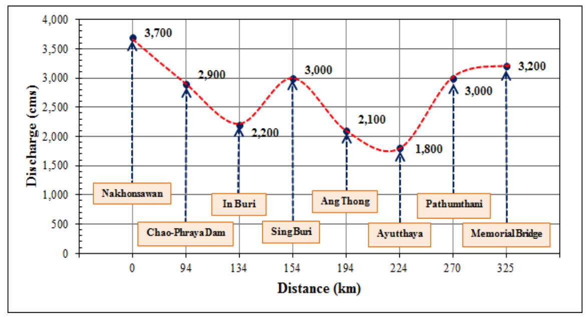

Fig. 32 Capacity of Chao-Phraya River (Source: Ang Thong Irrigation Project)

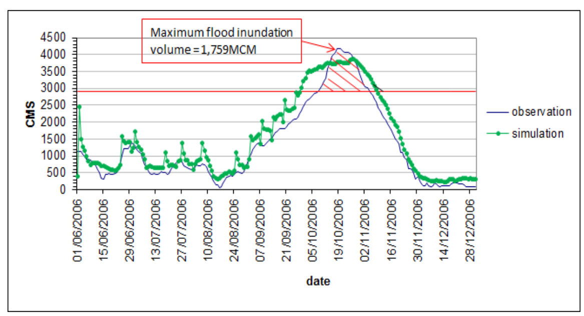

Fig. 33 Observed discharge at C.13

For the simulated data in 2006, the maximum discharge is 3,874cms in October 26th, 2006. September 29th to November 8th, 2006 is the flood duration that discharge exceeded the river capacity. The simulation of river discharge in 2006 showed the maximum discharge is under estimating comparing with the observed data about 7% and the simulation of flood duration is longer than observation. Finally, an early flood warning system can monitor the flood duration and magnitude; however, it needs to improve for more reliable flood information.

8. Conclusions

The statistical evaluation of river flow model calibration and boundary estimation in the upstream by ANNs and downstream by Harmonic Analysis are satisfactory. However, the Multiple Linear Regression can estimate the fairly satisfied accuracy of water level in the river branches. Moreover, the trend of flood forecasting by integrated model is changing by seasonal and the accuracy is decreasing when the time step is increasing. The integrated model still needs to improve the accuracy and extend the time of forecasting information. Therefore, the future plan of the study will use the forecasted rainfall data from the coupling model of land surface process and cloud resolving storm simulator, namely CReSiBUC model to improve the accuracy of flood information and extend the time of forecasting. Finally, the reliable flood information will be monitored on the real time flood warning system of Nakhon Pathom Rajabhat University server.

Acknowledgements

The authors are grateful to Water Resources Research Center (WRRC) of Kyoto University and Research Center of Sustainable Water Resources and Disaster Mitigation Management (RCSWM) of Nakhon Pathom Rajabhat University for cooperation to develop an early flood warning system, Global Center of Education (GCOE) and Research on Human Security Engineering for Asian Megacities (HSE) of Kyoto University for field trip financial supporting, Asian Institute of Technology (AIT) for the Harmonic Analysis program and data supporting; and also to Royal Irrigation Department (RID) and Thai Meteorological Department (TMD) for data supporting.

References

Defant, A. (1961). Physical oceanography, Vol. 2, Pergamon Press, New York.

US Army Corps of Engineers. (2010). HEC-RAS River Analysis System; User's Manual version 4.1. From http://www.hec.usace.army.mil/.

Visutimeteegorn, S., et al. (2007). Effects on the upstream flood inundation caused from the operation of Chao Phraya Dam. Songklanakarin Journal. Sci. Technol, Vol. 29, No.6, pp.85-98.

Weesakul, S., Thammasittirong, S. (2000). Operational Flood Forecasting for Chao Phraya River Delta, the Chao Phraya Delta: Historical Development, Dynamics and Challenges of Thailand's Rice Bowl, pp. 267-270.

Appendix

Table A1 Principal tidal constituents (Defant, 1961)

Name	Symbol	Period (hr)
Luni-solar diurnal	K_1	23.9346
Principal lunar diurnal	O_1	25.8194
Principal lunar	M_2	12.4206
Principal solar	S_2	12.0000
Larger lunar elliptic	N_2	12.6582
Luni-solar semidiurnal	K_2	11.9673
Larger lunar evectional	ν_2	12.6258
Variational	μ_2	12.8719
Smaller solar elliptic	L_2	12.1918
Larger solar elliptic	T_2	12.0164
Lunar elliptic second order	$2N_2$	12.9055
Smaller lunar evectional	λ_2	12.2216
Principal solar diurnal	P_1	24.0658
Larger lunar elliptic	Q_1	26.8677

(Received June 7, 2012)

洪水早期警報システムのためのチャオプラヤ川下流域統合モデル

Supatchaya CHUANPONGPANICH[(1)]・田中賢治・小尻利治・Phatcharasak ARLAI[(2)]

[(1)]京都大学大学院工学研究科
[(2)] タイ国ナコンパトムラジャパット大学持続可能水資源および減災管理研究センター

要　旨

チャオプラヤ川流域は国内生産の大部分を生み出すタイ国で最も重要な流域であるため，チャオプラヤ川の洪水はタイ国の経済に多大な損失をもたらす。本研究では，早期洪水警報のための洪水予測情報を提供するために，数値モデルが適用された。非定常流条件でHEC-RASがチャオプラヤ川本川の洪水流計算に適用される。この結果、上流端、下流端，側方流の境界条件が必要となるが，これらはそれぞれ ANN，調和解析，多重線形回帰により推定される。河道のパラメータ，河道内流量調整施設（チャオプラヤダム）のキャリブレーションにおいて，相関係数が 0.8 以上，境界条件の推定精度も相関係数 90%以上が達成された。さらに本モデルを 2011 年の洪水に適用したところ，1 日先，2 日先，3 日先予測でそれぞれ 98%, 96%, 95%の精度が得られた。

キーワード：洪水予測，チャオプラヤ川，河道流モデル，統合モデル