Application of Artificial Neural Networks for Reservoir Inflow Forecasting

Varawoot Vudhivanich*, Santi Thongpumnak, Nimit Cherdchanpipat, Areeya Rittima and Nattaphun Kasempun

ABSTRACT

This study showed the application of the Artificial Neural Networks in forecasting the reservoir inflow. Two cases were studied, (1) single reservoir inflow forecasting and (2) multi-reservoir inflow forecasting. The problems were formulated as daily, weekly and monthly inflow forecast. There were 4 types of model namely A, B, C and D according to the levels of data used as the input variables to the ANNs. Model A used all available data of that reservoir. Model B used the data having relatively high correlation with the reservoir inflow such as the first 3 lags of reservoir inflow, stream flow, rainfall and some meteorological data. Model C used only the first 3 lags of the reservoir inflow and stream flow data. Model D used the first 3 lags of reservoir inflow, stream flow and rainfall data. The 4 reservoirs namely Mun Bon, Lam Chae, Lam Phra Phloeng and Lam Takong reservoirs in Upper Mun basin, Nakhon Ratchasima province, were selected as the case study. Feed forwards back propagation algorithm was selected for the study. One to 3 hidden layers with different ANNs parameters were experimented. Two to 3 hidden layers were suitable for single reservoir problem while 1 to 2 hidden layers were suitable for multi-reservoir problem. Sigmoid transfer function was used in all the models. The initial weight, learning rate and momentum were in the ranges of 0.80-0.90. However they were not sensitive to prediction performance. For single reservoir forecasting, models A and B showed better performance (R^2) than models C and D. The monthly model showed the better result than the weekly and daily models. For multi-reservoir forecasting, the performance of the 4 models was not different. Model C was recommended since it required less data. The training and testing performance of daily, weekly and monthly models were not much different in case of multi-reservoir.
Key words: artificial neural networks, forecasting, reservoir inflow, Upper Mun basin

INTRODUCTION

Reservoir inflow forecasting is an important task in reservoir operations. An effective reservoir inflow forecasting enables the reservoir operators to get the accurate information for decision making in planning and operating the reservoirs. With accurate and reliable forecast of inflow, flood and drought damages and inefficient utilization of water resources can be reduced. However, an accurate and reliable inflow forecast is usually difficult to obtain, particularly for a long lead time.

The artificial neural networks (ANNs)

Department of Irrigation Engineering, Faculty of Engineering at Kamphaengsaen, Kasetsart University, Kamphaengsaen Campus, Nakhon Pathom 73140, Thailand.

* Corresponding auther, e-mail: fengvwv@ku.ac.th

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are now becoming more and more popular in hydrological forecasting. ANNs is apart of artificial intelligence (AI) which has been widely applied in many fields. It is also called a machine learning algorithm or natural intelligent system. ANNs is a computational system that resembles the performance characteristics of the biological neural networks of the human brain (Vudhivanich, 2001). It is in the class of black box model which inputs, outputs and functional performance are known, whereas the internal process is unknown or irrelevant. ANNs are information processing system that are composed of a number of neurons and interconnections between these neurons. The neurons are arranged in group called layer. Commonly, the basic ANNs architectures consist of three layers namely input layer, hidden layer and output layer. The most different characteristics of ANNs are their capability to recognize the patterns from the example outputs by the automatic weight adjustments. The selection of the best fit model is accomplished by a trial and error process (Tokar, 1996).

Since 1990s, the successful applications for hydrological forecasting by means of ANNs techniques have been extensively carried out in water resource engineering. Tokar and Markus (2000) presented ANNs approach with back-propagation algorithm for rainfall-runoff modeling. In Thailand, the hourly water levels and discharges in Chao Pharaya River were forecasted for flood control study in tidal area by ANNs with back propagation algorithm (Tingsanchali and Manusthiparom, 2001). The ANNs with neuro-genetic algorithm was developed to forecast water level for flood warning system in Hat Yai district (Supharatid, 2002). The artificial neural networks model was also developed to forecast the daily, weekly and monthly inflow of Lam Takong reservoir (Vudhivanich and Rittima, 2003) and the four reservoirs in the Upper Mun basin (Vudhivanich *et al.*, 2004). Additionally, ANNs was also applied for runoff forecasting in Lam Phachi river basin (Phathravuthichai and Vudhivanich, 2003). Most of the mentioned researches used feed forwards back propagation algorithm with sigmoid transfer function in forecasting where the result is satisfactorily.

In this paper, the ANNs model was developed for the reservoir inflow forecasting to benefit the reservoir operations. Four reservoirs namely Mun Bon, Lam Chae, Lam Phra Phloeng and Lam Takong reservoirs in Nakhon Ratchasima province were selected as the case study.

MATERIALS AND METHODS

Required data

(1) The daily, weekly and monthly inflow of Mun Bon reservoir during 1995-2000, Lam Chae reservoir during 1999-2002, Lam Phra Phloeng reservoir during 1992-2000 and Lam Takong reservoir during 1987-2000.

(2) The streamflow data of station M.49B near Mun Bon reservoir during 1995-2000, M.81 near Lam Chae reservoir during 1999-2002, M.145 near Lam Phra Phloeng reservoir during 1992-2000 and M.89 near Lam Takong reservoir during 1992-2000.

(3) The daily, weekly and monthly rainfall data as follows;

- Mun Bon reservoir: station 25293 (Chok Chai), 25112 (Khon Buri), 25152 (Ban San Chao Pho School) during 1995-2000.

- Lam Chae reservoir: station 25093 (Chok Chai), 25112 (Khon Buri) and 25152 (Ban San Chao Pho School) during 1999-2002.

- Lam Phra Phloeng reservoir: station 25511 (Lam Phra Phloeng), 25102 (Pak Thong Chai), 25093 (Chokchai) and 25152 (Ban San Chao Pho School) during 1987-2000, station 25751 (Ban Wang Ta-Khian Thong) and 25781 (Ban Tha Nam Sab) during 1992-2000.

- Lam Takong reservoir: station 25541 (Lam Takong), 25062 (Sung Noen), 25013 (Muang), 25612 (Agriculture Office), 25644

(Lam Takong watershed research station), 25650 (Chok Chai 4 farms) and 25272 (Pak Chong agrometeorological station) during 1992-2000.

(4) The daily, weekly and monthly meteorological data of Nakhon Ratchasima station including the temperature, pressure and relative humidity during 1992-2002.

Methods

(1) Preliminary checking the abnormality and inconsistency of the data via time series plots and filling in the missing data by the distance weighted method.

(2) Determing the autocorrelation and cross correlation matrices of the data in order to identify the tentative ANNs input structures for daily, weekly and monthly inflow forecast for both a single reservoir and multi-reservoir inflow forecasting.

(3) Training and testing the ANNs model by adjusting the number of hidden layers, number of neurons in hidden layer, ANNs parameters such that the performance efficiency in term of R^2 would be acceptable. Selecting 80% of the records for training and using the remainder, 20% of the records, for testing.

Description of the study area

Upper Mun basin is situated in the northeast of Thailand covering the total area of 37,970 km^2 in three provinces namely Nakhon Ratchasima, Buri Ram and Surin provinces as shown in Figure 1. Upper Mun basin is a subbasin of Mun River basin. It covers about 54.5% of the Mun River basin area. This basin is composed of four main reservoirs; Mun Bon(MB), Lam Chae(LC), Lam Phra Phloeng(LP) and Lam Takong(LK) reservoirs. All of them are located in Nakhon Ratchasima province.

These reservoirs have been operated by Royal Irrigation Department (RID) mainly for irrigation and municipality purposes. Most of the water in the four reservoirs have been used for irrigation. The four reservoirs have the combined storage capacity of 836 mcm which can supply water to 353,650 rai of irrigable area in Mun Bon, Lam Chae, Lam Phra Phloeng and Lam Takong irrigation projects. The basic data of the four reservoirs are shown in Table 1.

In addition, Mun Bon reservoir has allocated 0.0025 mcm per month of water for Charakae Hin sub-district municipality, Khon Buri district and 0.40 mcm per month for the

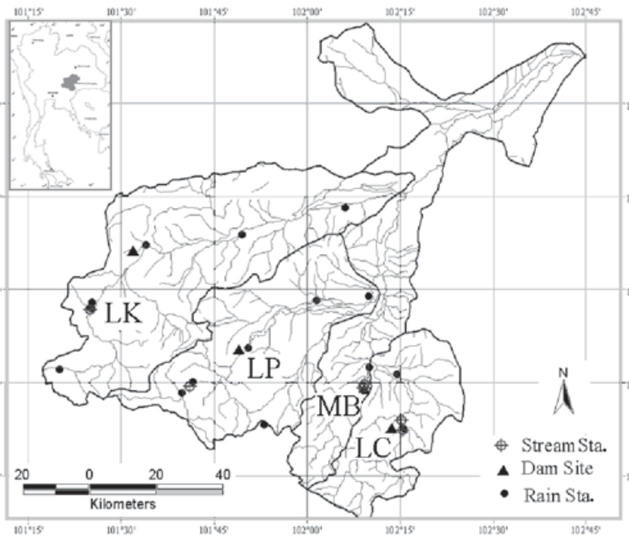


Figure 1 Location map of Upper Mun basin.

downstream control. Lam Chae reservoir has allocated 5.13 mcm per month for the downstream control. Likewise, the amount of 1.93 and 2.04 mcm per month are diverted from Lam Phra Phloeng and Lam Takong reservoirs, respectively, for municipal water supply of Nakhon Ratchasima province. However, the municipal water requirements are only small percentages of the irrigation water requirements.

RESULTS AND DISCUSSION

Preliminary analysis of data

The cross correlation analysis between the reservoir inflow and the other input variables including stream flow, rainfall and meteorological data showed that in general there was some correlation between the inflow of each reservoir and the mean humidity at stations 43201 and 431401. The inflow of Lam Phra Phloeng and Lam Takong reservoirs was highly related to the stream flow at station M.89 and M.145 with the correlation coefficient of 0.79 and 0.70 respectively but the correlation with rainfall was not good, correlation coefficients of 0.11-0.24. However, the inflow of Mun Bon and Lam Chae reservoir were fairly related to the rainfall at station 25112 and 25152 with the correlation coefficient of 0.23 and 0.32, respectively.

The autocorrelation or serial correlation analysis showed that, for Mun Bon and Lam Chae reservoirs, the autocorrelation coefficients of daily inflows were highly significant upto the first 30 days lag. The autocorrelation coefficients were in the range of 0.17-0.82 and 0.42-0.85 for Mun Bon and Lam Chae reservoirs, respectively. The first 7 days lag autocorrelation coefficients were between 0.24-0.73 for Lam Phra Phloeng inflow, 0.35-0.78 for Lam Takong inflow, 0.33-0.75 for the M.145 streamflow and 0.38-0.79 for the M.89 streamflow.

Eighty percent of entire records were selected as the training data set for ANNs and the other 20% were used as the testing data set. The description of data selected for training and testing is shown in Table 2.

Reservoir inflow forecasting model formulation

In this study, four types of ANNs inflow forecasting models namely model A, B, C and D were developed for both single reservoir and multi-reservoir inflow forecasting. Each type of the model was divided into daily, weekly and monthly model. Single reservoir model was designed to forecast the inflow at one step ahead (lead time equal to 1) or inflow (t+1) of each reservoir. Multi-reservoir model could forecast the inflow at one step ahead of the four reservoirs simultaneously. The autocorrelation and cross correlation of the data were used to identify the model inputs in preliminary formulation of the forecasting model.

The four single reservoir models were developed to use different levels of inputs. Model A used all available data of that reservoir. Model B used the data having relatively high correlation with the reservoir inflow such as the first three lags of reservoir inflow, stream flow, rainfall and some meteorological data. Model C used only the first three lags of the reservoir inflow and stream flow data. Model D used the first three lags of reservoir inflow, stream flow and rainfall data. Phien *et al.*(2000) forecasted the daily river flow of one day lead time (Q_{t+1}) of several stations including Srinakarind and Khao Laem reservoirs in Mae Klong river basin, Thailand, and the Chukha reservoir in Bhutan using the lag zero and lag one of flow (Q_t, Q_{t-1}) and those of rainfall (R_t, R_{t-1}) as the input variables. Anmala *et al.*(2000) used the artificial neural networks for forecasting the watershed runoff in Kansas, USA. Monthly precipitation and temperature formed then inputs, and the monthly average runoff was chosen as the outputs. However this study proposed some more input variables, the first three lags of reservoir inflow and other high correlated variables. Similarly, there were four types of the multi-

Table 1 The basic data of the four reservoirs in Upper Mun basin.

Basic data	MB	LC	LP	LK
1. Catchment area (km^2)	454	601	807	1,430
2. Annual rainfall (mcm)	1,047	1,039	1,112	920
3. Annual inflow (mcm)	98	218	158	223
4. Storage capacity(mcm)	141	275	110	310
5. Irrigable area (rai)	44,600	113,750	67,760	127,540
6. Municipality & downstream control (mcm/month)	0.4025	5.13	1.93	2.04

Table 2 The training and testing data set.

Reservoir	Available data	Training data set	Testing data set
1. Mun Bon	Apr 1995-Jan 2000	Apr 1995-Dec 1998	Jan 1999-Jan 2000
2. Lam Chae	Jan 1999-Mar 2002	Jan 1999-Feb 2001	Mar 2001-Mar 2002
3. Lam Phra Phloeng	Jul 1992-Mar 2000	Jul 1992-Dec 1998	Jan 1999-Mar 2000
4. Lam Takong	Jul 1992-Mar 2000	Jul 1992-Dec 1998	Jan 1999-Mar 2000

reservoir forecasting models A, B, C and D which used the same levels of input data to the single reservoir model. The multi-reservoir model utilized more information on cross correlation coefficients among the reservoir inflow which was one of the advantages. However, the multi-reservoir model required more computational time than the single reservoir model for training. The detail input variables of ANNs reservoir forecasting models A, B, C and D are shown in Table 3.

Training and testing of ANNs forecasting model

The multi-layer feed forward neural networks with back propagation algorithm was selected for this study. Sigmoid transfer function was used in all the models. The initial weight (IW), momentum (M) and learning rate (LR) were initially set between 0.80-0.90. The number of epochs for training varied between 10,000 to 100,000 depending on the performance efficiency (R^2) of the training. There were no fixed rules for designing the structures of ANNs, number of hidden layers and number of neurons in hidden layers. Many times the best fit model was accomplished by trial and error processes. The optimal ANNs design was considered from the best performance training and testing by using R^2.

- **Single reservoir forecasting model**

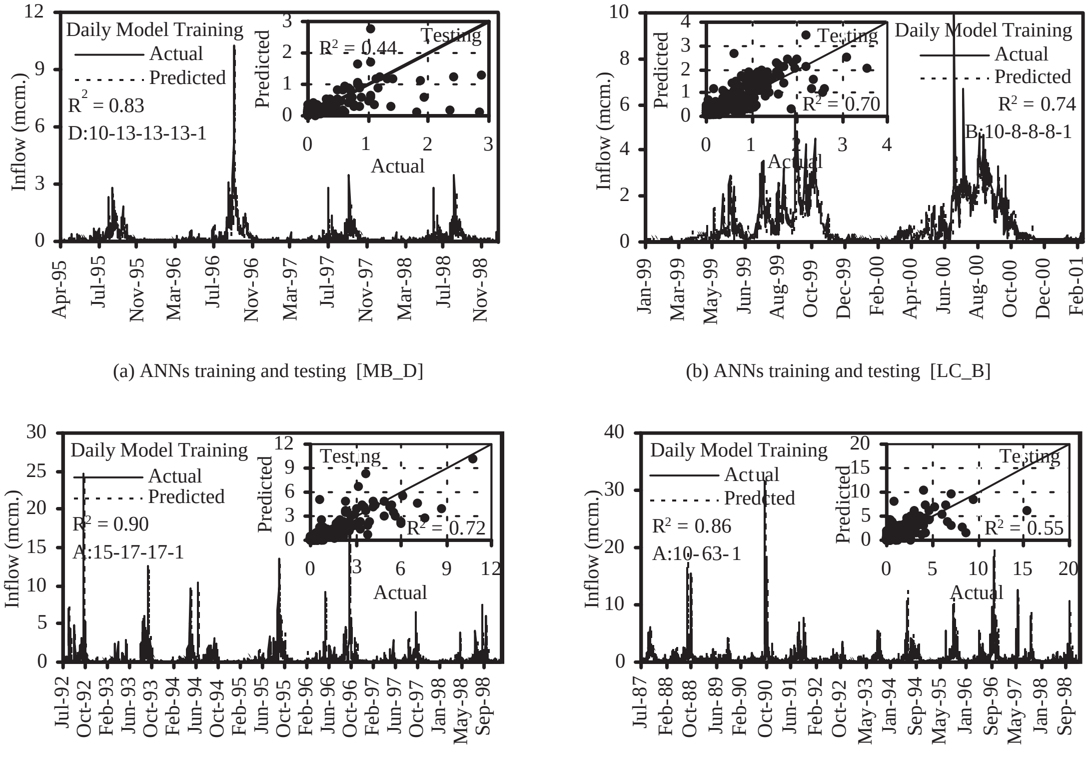
The ANNs structures and the training parameters of the best fit single reservoir forecasting models are presented in Table 4. The time series plot of the actual inflow and the predicted or forecasted inflow were compared for the daily, weekly and monthly models in Figures 2 to 4, respectively. The best fit models were models A and B. The number of hidden layers varied between one to three layers but mostly 2 to 3 layers. The number of neurons in hidden layers varied considerably from one model to the others. The models were trained by 80% of the data. The training result showed that all the ANNs models could produce an acceptable result in reservoir inflow forecasting especially the monthly model. The monthly model of all the reservoirs showed the better performance than the weekly and daily models. The R^2 of monthly, weekly and daily models were 0.95, 0.88 and 0.83, respectively, for Mun Bon; 0.90, 0.73 and 0.74 for Lam Chae; 0.93, 0.89 and 0.90 for Lam Phra Phloeng and 0.97, 0.96,

Table 3 Detail input variables of different reservoir inflow forecasting models.

Reservoir forecasting model	Single reservoir																Multi-reservoir			
	MB				LC				LP				LK							
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
Target output / Input variables	$Inflow_{MB}(t+1)$				$Inflow_{LC}(t+1)$				$Inflow_{LP}(t+1)$				$Inflow_{LK}(t+1)$				$Inflow_{MB}(t+1)$	$Inflow_{LC}(t+1)$	$Inflow_{LP}(t+1)$	$Inflow_{LK}(t+1)$
$Inflow_{MB}(t)$	•	•	•	•													•	•	•	•
$Inflow_{MB}(t-1,t-2,t-3)$			•																•	
$Inflow_{LC}(t)$					•	•	•	•									•	•	•	•
$Inflow_{LC}(t-1,t-2,t-3)$							•												•	
$Inflow_{LP}(t)$									•	•	•	•					•	•	•	•
$Inflow_{LP}(t-1,t-2,t-3)$											•								•	
$Inflow_{LK}(t)$													•	•	•	•	•	•	•	•
$Inflow_{LK}(t-1,t-2,t-3)$																			•	
Flow89(t)													•	•	•	•	•	•		•
Flow89(t-1,t-2,t-3)															•					
Flow145(t)									•	•	•	•					•	•		•
Ra25093(t)	•	•			•	•		•									•	•		•
Ra25102(t)																				
Ra25112(t)	•	•		•	•	•		•									•			•
Ra25152(t)	•	•		•	•	•		•	•	•							•	•		•
Ra25272(t)													•	•			•	•		•
Ra25511(t)									•	•		•								
Ra25521(t)	•	•		•																
Ra25612(t)													•	•			•	•		•
Ra25644(t)													•							
Ra25650(t)													•				•	•		•
Ra25751(t)									•	•							•	•		•
Ra25781(t)									•	•							•	•		•
Ra25272(t-1,t-2,t-3)																•				
Ra25511(t-1,t-2,t-3)												•								
AvgRH431201(t)	•	•		•	•	•			•	•							•	•		
AvgRH431301(t)																				
AvgRH431401(t)	•	•		•	•	•											•	•		
MinRH431301(t)													•	•			•			
MaxRH431301(t)													•	•			•			
MinTemp431201(t)	•	•		•	•	•			•								•			
MinTemp431301(t)													•	•			•			
MinTemp431401(t)	•	•		•	•	•			•								•			
MaxTemp431201(t)	•	•		•	•	•			•								•			
MaxTemp431301(t)													•	•			•			
MaxTemp431401(t)	•	•		•	•	•			•								•			
AvgTemp431201(t)	•				•				•								•			
AvgTemp431401(t)	•				•				•								•			
AvgPres431201(t)	•				•				•	•							•			
AvgPres431301(t)																				
AvgPres431401(t)	•				•				•								•			

Table 4 Training and testing result of ANNs models for single reservoir forecasting.

Reservoirs	Structures of ANNs					R^2	
	Models	Structures	IW	M	LR	Training	Testing
(1) MB							
Daily	MB_D	10-13-13-1	0.9	0.9	0.9	0.83	0.44
Weekly	MB_B	11-6-6-6-1	0.9	0.9	0.9	0.88	0.45
Monthly	MB_B	11-4-4-4-1	0.9	0.9	0.9	0.95	0.50
(2) LC							
Daily	LC_B	10-8-8-8-1	0.9	0.9	0.9	0.74	0.70
Weekly	LC_B	10-8-8-1	0.9	0.9	0.9	0.73	0.74
Monthly	LC_B	10-3-3-3-1	0.9	0.9	0.9	0.90	0.79
(3) LP							
Daily	LP_A	15-17-17-17-1	0.8	0.8	0.8	0.90	0.72
Weekly	LP_A	15-10-10-10-1	0.8	0.8	0.8	0.89	0.74
Monthly	LP_A	15-5-5-5-1	0.8	0.8	0.8	0.93	0.82
(4) LK							
Daily	LK_A	10-63-1	0.9	0.9	0.9	0.86	0.55
Weekly	LK_A	10-14-14-1	0.9	0.9	0.9	0.96	0.59
Monthly	LK_B	8-5-5-5-1	0.9	0.9	0.9	0.97	0.80



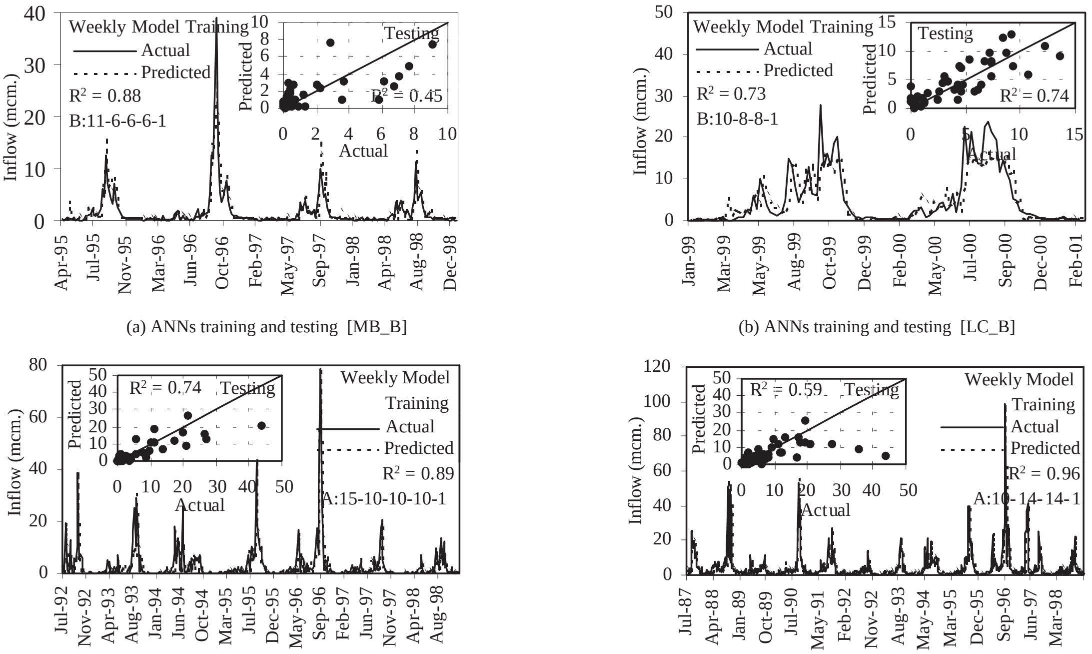
(a) ANNs training and testing [MB_D]

(b) ANNs training and testing [LC_B]

(c) ANNs training and testing [LP_A]

(d) ANNs training and testing [LK_A]

Figure 2 Comparison of the actual and predicted inflow of selected ANNs daily models.



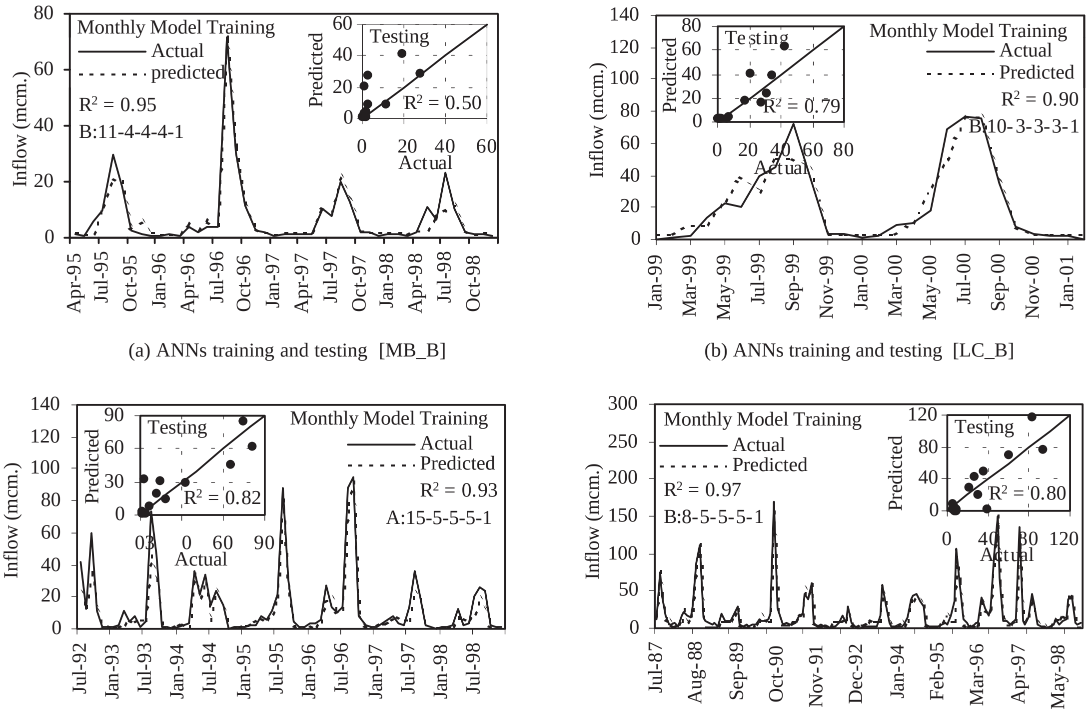
(a) ANNs training and testing [MB_B]

(b) ANNs training and testing [LC_B]

(c) ANNs training and testing [LP_A]

(d) ANNs training and testing [LK_A]

Figure 3 Comparison of the actual and predicted inflow of selected ANNs weekly models.



(a) ANNs training and testing [MB_B]

(b) ANNs training and testing [LC_B]

(c) ANNs training and testing [LP_A]

(d) ANNs training and testing [LK_B]

Figure 4 Comparison of the actual and predicted inflow of selected ANNs monthly models.

0.86 for Lam Takong. Lam Takong showed the highest performance in comparison to other reservoirs.

In general, the performance of this study was comparable to the study of Phien e*t al*.(2000), where the efficiency index or R^2 of daily flow forecast for both Srinakarind and Khao Laem reservoirs and Chukha reservoir were above 0.82 for calibration and 0.70 for validation of the model. The study of Anmala *et al*.(2000) showed R^2 of one month flow forecast of El Dorado watershed in Kansas, USA, to be 0.74 for the training set (from 1948-1955), 0.66 for the validation set (from1956-1963), and 0.61 for the testing set(from 1964-1993). Atiya and Shaheen(1999) used the backpropagtion algorithm neural networks for forecasting the river flow of Nile river in Egypt. The multistep ahead forecasting was employed by using 10-day and one month time steps. The normalized root mean square (NRMS) was used as the forecast performance indicator instead of R^2. The NRMS was less than 0.60 in most cases. The one step forecast performed better than the multistep.

The remainder 20% of the data were used for model testing. Although the testing phase showed R^2 lower than the training phase, most of the R^2 were above 0.50 and more than half of them

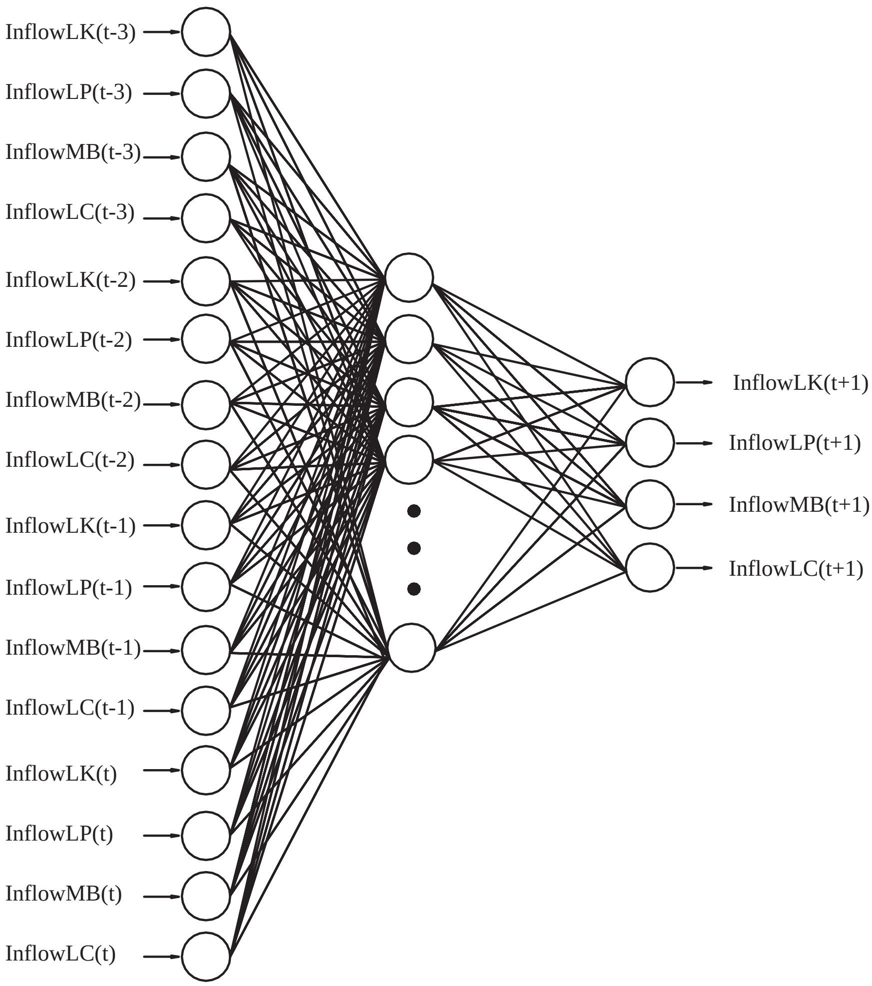


Figure 5 ANNs model C for multi-reservoir inflow forecasting.

were above 0.70. The testing result was quite satisfactorily.

However, it appeared from Figures 2 to 4 that there was higher forecasting error during the peak reservoir inflow than other periods. There were the common characteristics in all the daily, weekly and monthly models. If one would like to improve the accuracy of peak inflow forecast, one should develop the ANNs model for the peak inflow period in particular. It was also observed that the training parameters including the learning rate, initial weights and momentum were not sensitive to the prediction performance.

- **Multi-reservoir forecasting model**

The multi-reservoir inflow forecasting models A, B, C and D were experimented on daily, weekly and monthly data of Mun Bon, Lam Chae, Lam Phra Phoeng and Lam Takong reservoirs to find the best fitted ANNs models. The ANNs structure of model C is shown in Figure 5 as an example. The experiment covered one to three hidden layers with different neurons in each layer. The result of training and testing the ANNs showed that two hidden layers for daily and weekly models were indifferent from three hidden layers while one hidden layer for monthly model was indifferent from two and three hidden layers. The result showed that sigmoid transfer function was acceptable. The structures of selected models for multi-reservoir inflow forecasting are show in Table 5. The R^2 from training was in the ranges of 0.49 to 0.98 but mostly above 0.80. This indicated good training performance as shown in Figure 6. The R^2 from testing was acceptable in general. It was in the ranges of 0.17 to 0.64 except Mun Bon reservoir where the R^2 was very low due to high variation of Mun Bon inflow during test period. The monthly model showed that, in general, the performance of multi-reservoir ANNs model as indicated by R^2 was not as good as the single reservoir model because the data available for training and testing were shorter. The data of the four reservoirs were available in different periods. For example, the inflow were available from 1995-2000, 1999-2002, 1992-2000 and 1987-2000 for Mun Bon, Lam Chae, Lam Phra Phloeng and Lam Takong, respectively. Thus only the data of

Table 5 Training and testing result of ANNs multi-reservoir forecasting model.

Models	Parameters			Structures	R^2 training				R^2 testing			
	IW	M	LR	of ANNs	MB	LC	LP	LK	MB	LC	LP	LK
Daily												
A	0.8	0.8	0.8	28-22-22-4	0.72	0.81	0.84	0.82	0.02	0.57	0.32	0.29
B	0.8	0.8	0.8	15-18-18-4	0.69	0.80	0.83	0.80	0.06	0.64	0.41	0.28
C	0.8	0.8	0.8	16-18-18-4	0.74	0.83	0.81	0.82	0.05	0.63	0.34	0.24
D	0.8	0.8	0.8	14-18-18-4	0.68	0.80	0.82	0.81	0.05	0.64	0.33	0.27
Weekly												
A	0.8	0.8	0.8	28-13-13-4	0.82	0.87	0.68	0.63	0.05	0.59	0.21	0.48
B	0.8	0.8	0.8	15-10-10-4	0.66	0.73	0.49	0.51	0.08	0.57	0.20	0.51
C	0.8	0.8	0.8	16-10-10-4	0.89	0.98	0.89	0.92	0.05	0.39	0.21	0.58
D	0.8	0.8	0.8	14-10-10-4	0.88	0.96	0.92	0.94	0.15	0.54	0.40	0.54
Monthly												
A	0.8	0.8	0.8	28-21-4	0.96	0.77	0.89	0.84	0.04	0.51	0.19	0.56
B	0.8	0.8	0.8	15-14-4	0.91	0.85	0.85	0.88	0.04	0.22	0.23	0.17
C	0.8	0.8	0.8	16-14-4	0.50	0.69	0.78	0.89	0.05	0.43	0.24	0.63
D	0.8	0.8	0.8	14-14-4	0.71	0.78	0.84	0.88	0.08	0.36	0.32	0.27

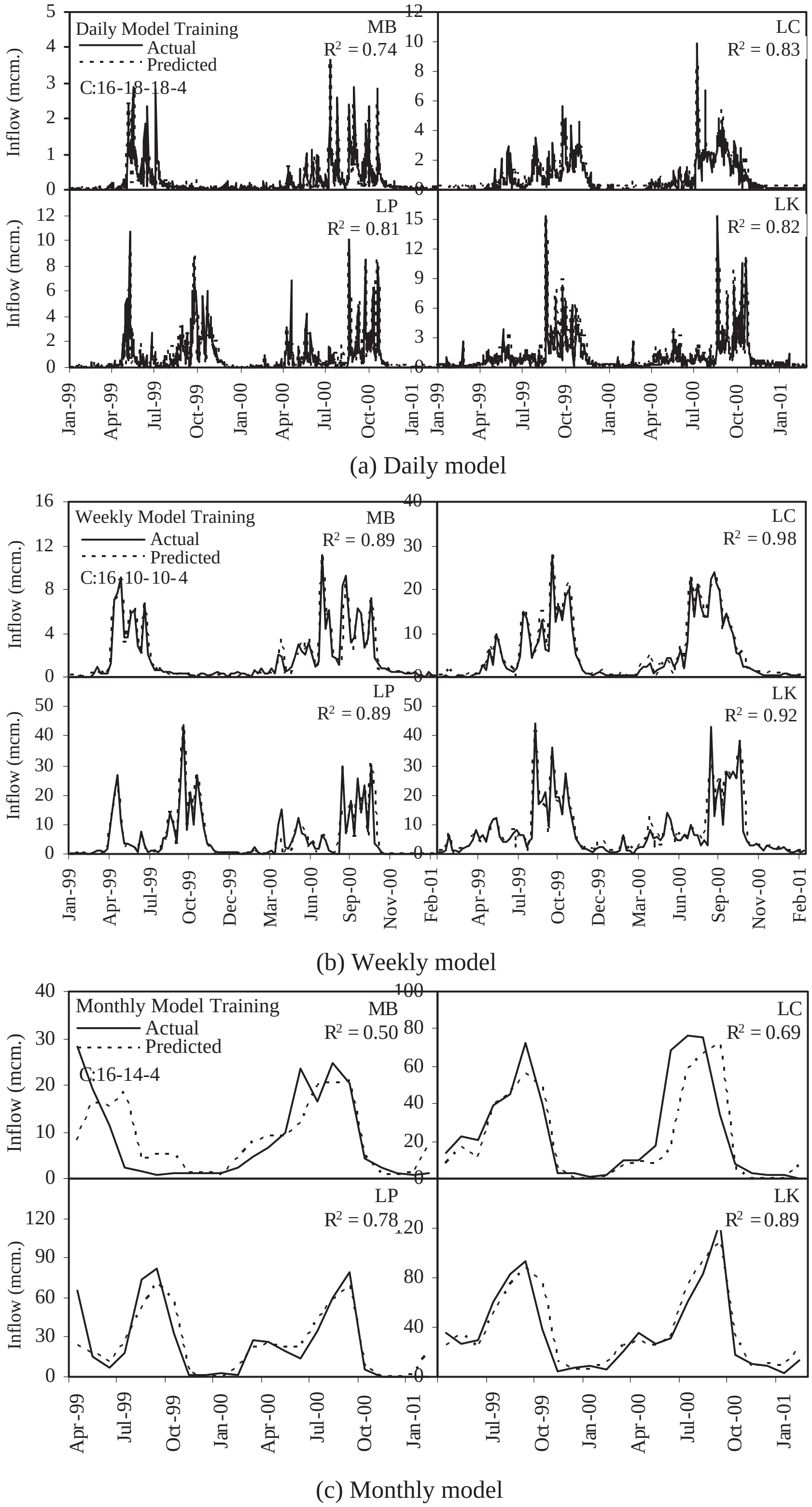


Figure 6 Comparison of the actual and predicted inflow of ANNs model C.

1999-2000 could be used for training and testing the multi-reservoir ANNs model.

It was difficult to distinguish which of the models A, B, C and D was the better one by R^2 in Table 5. Some models gave good result for some reservoirs. Model C used less data, only the reservoir inflow and stream flow, was more attractive than the other models. Moreover, the performance of daily, weekly and monthly models were not much different. Theoretically, the ANNs multi-reservoir model should provide the better result, but it was not true for this case due to the limited data. The multi-reservoir problem required a lot longer training time than the case of single reservoir, particularly the case of daily model. This could be the disadvantage of the ANNs multi-reservoir.

CONCLUSIONS

For single reservoir forecasting, models A and B showed better performance (R^2) than models C and D. The monthly model showed the better result than the weekly and daily models. For multi-reservoir forecasting, the performance of the four models was not different. Model C was recommended since it required less data. The training and testing performance of daily, weekly and monthly models were not much different in case of multi-reservoir. However, the multi-reservoir problem required a lot longer training time than the single reservoir problem, particularly the case of daily model. This could be the disadvantage of the ANNs multi-reservoir inflow forecasting. In general, the single reservoir inflow forecasting showed the better result.

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