THE EFFICIENCY OF USING DIFFERENT OF LEARNING ALGORITHMS IN ARTIFICIAL NEURAL NETWORK MODEL FOR FLOOD FORECASTING AT UPPER RIVER PING CATCHMENT, THAILAND

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Abstract- This paper presents the result of exploration the efficiency of 12 learning algorithms; Levenberg-Marquardt (LM), Bayesian Regularization (BR), BFGS Quasi-Newton (BFG), Resilient Backprogagation (RP), Scaled Conjugate Gradient (SCG), Conjugate Gradient with Powell/Beale Restarts (CGB), Fletcher-Powell Conjugate Gradient (CGF), Polak-Ribiere Conjugate Gradient (CGP), One Step Secant (OSS), Variable Learning Rate Gradient Descent (GDX), Gradien Descent with Momentum (GDM), Gradient Descent (GD) in artificial neural network model by forecast flood at 6 and 12 hour in advances. In addition, to compare the algorithms performance, different number of hidden nodes by 1, 50%, 75% and 100% of the number of input variables and selecting input variables with different input determination techniques; Cross correlation (C), Stepwise regression (S), Genetic algorithms (G) and combination between C and S (CS) are included in this study.In conclusion, LM and BFG are the best algorithm for flood forecasting at 6 butfor 12 hour is only BFG with different input variables and number of hidden nodes as the maximum of R^2 value are 0.99 and 0.97 respectively.

Index terms- Artificial neural network, Upper River Ping, Flood forecasting, Thailand

I. INTRODUCTION

There are many types of learning algorithm in artificial neural network that are available in the MATLAB such as Levenberg-Marquardt (LM), Bayesian Regularization (BR), BFGS Quasi-Newton (BFG), Resilient Backprogagation (RP), Scaled Conjugate Gradient (SCG), Conjugate Gradient with Powell/Beale Restarts (CGB), Fletcher-Powell Conjugate Gradient (CGF), Polak-Ribiere Conjugate Gradient (CGP), One Step Secant (OSS), Variable Learning Rate Gradient Descent(GDX), Gradien Descent with Momentum (GDM), Gradient Descent (GD)[1]and different type has different ways to update the network weights and biases. Beale et al [1] have investigated 9 types of learning algorithms (LM, BFG, RP, SCG, CGB, CGF, CGP, OSS and GDX)with 6different problems of data set (SIN, Parity, Engine, Cancer, Cholesterol and Diabetes) and found that different types of learning algorithms had different performance with different problemsor Chaipimonplin and Vangpaisal[2, 3] compared LM and BR for flood forecasting at Mun Catchment and concluded that BR and LM had similar performance but BR forecasted better than LM at the flood peak. However, the study of Chaipimonplin[4] concluded LM is better than BR at the peak stage for flood forecasting at Upper River Ping.

The recent research for flood forecasting at P.1 station, Upper River Ping of exploration the different types of learning algorithms are Chaipimonplin[5] investigated 7 learning algorithms (GDX, BFG, LM, BR, OSS, SCG and RP)and concluded that for the best learning algorithm for flood forecasting at 6 and 12 hr is LM and BR respectively, in addition, Chaipimonplin[6]who continued to investigate learning algorithmsfrom Chaipimonplin[5]by adding 3 more algorithms (CGP, CGB and CGF) and concluded that all 10 algorithms have similar performant except GDX. Moreover, LM and BR are suitable flood forecasting at 6 and 12 hr particularly when forecast the big flood and the first flood event of the season. However, other floods such as second flood event or small flood, the best algorithm for 6 hr is CGP and BR, LM, BFG and SCG are suitable algorithms for 12 hr, also the BFG is suitable for forecast at the peak stage for 6 and 12 hour in advances.

The objectives of this study are to investigate all 12 algorithms (GDM, GD, BFG, CGB, CGP, LM, RP, BR, CGF, GDX, OSS and SCG), number of hidden nodes and input determination techniques.

The key factors of making this study different toChaipimonplin's[5,6]work are more input variables (adding 2 more water level stations and creating more time lag at 1 hour interval for each station from 1-24 hr) and selecting input variable from input determination techniques.

II. STUDY AREA AND DATA

Upper Ping Catchment is located in the Northern of Thailand with 23,000 km^2. There are several of water level stations; P.1, P.21, P.67, P.75, P.4a and P.20. (Figure 1). However, only P.1, P.67, P.75 and P.20 are selected for this study due to all 4 stations are at the main river and available in hourly data. Therefore, total 100 input variables are from 4 stations at time t, t-1, t-2,…, t-24.

Figure 1: Study area.
Source: Hydrology and water management center for upper northern region [7]

Between years 2005-2011, 9 flood event (5 big and 4 small)occurred, 5 events in 2005, 2 event in 2006 and 2 events in 2011(Figure 2).

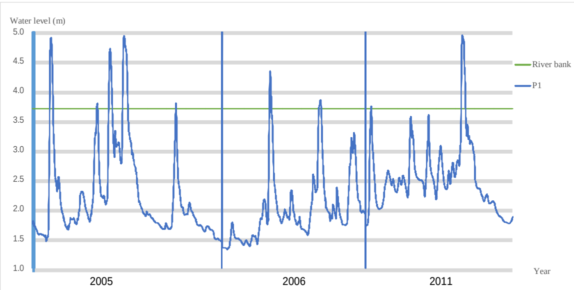

Figure 2: Flood events at P.1 station.

III. ARTIFICIAL NEURAL NETWORK MODEL DEVELOPMENT

All 9 flood events are divided for learning data (2005-2006) and testing data (2011) and model development focuses on flood forecasting at 6 and 12 hour in advances. For the suitable number of input variables will be selected by four techniques (Cross correlation-C, Stepwise regression-S, Combination between cross correlation and stepwise regression-CS and Genetic algorithms-G). Technique C, S and CS are in SPSS and G is in WEKA. The combination technique (CS) is applying all remaining input variable from technique C to be selected by technique S. All remaining input variables for t+6 and 12 hr shown in Table 1 and 3, respectively.

Model architecture structures are depended on number of input variables and hidden nodes. Numbers of hidden nodes are based on number of input variables by 1, 25%, 50%, 75% and 100%(Table 2 and 4).

Table 1. Input variable selections t+6

P.1	C	CS	G	S	P.67	C	CS	G	S
t	X	X	X	X	t				X
t-1	X		X		t-1				
t-2	X	X	X	X	t-2				
t-3	X		X		t-3				X
t-4	X				t-4			X	
t-5	X				t-5			X	X
t-6	X	X	X		t-6				
t-7	X		X		t-7			X	
t-8	X		X		t-8				
t-9	X		X		t-9				
t-10	X	X			t-10				X
t-11	X		X		t-11				
t-12	X				t-12				
t-13	X	X	X		t-13				
t-14					t-14				
t-15			X		t-15				
t-16					t-16				
t-17				X	t-17				
t-18					t-18				
t-19					t-19				
t-20					t-20				
t-21					t-21				
t-22					t-22				
t-23					t-23				X
t-24					t-24				
P.75	**C**	**CS**	**G**	**S**	**P.20**	**C**	**CS**	**G**	**S**
t	X	X	X	X	t			X	X
t-1	X	X	X		t-1				
t-2	X				t-2			X	
t-3	X				t-3				
t-4	X		X		t-4			X	
t-5	X				t-5			X	
t-6	X				t-6			X	
t-7	X				t-7			X	X
t-8	X				t-8				
t-9	X	X			t-9				
t-10	X	X			t-10			X	
t-11					t-11				
t-12			X		t-12				X
t-13					t-13				
t-14					t-14			X	X
t-15				X	t-15			X	
t-16			X		t-16			X	
t-17					t-17				
t-18			X		t-18				X
t-19				X	t-19			X	
t-20					t-20				
t-21				X	t-21				
t-22					t-22			X	X
t-23					t-23				
t-24					t-24				X
Total						25	9	32	19

Table2. Number of hidden nodes.

t+6	No. of hidden node				
	1	**25%**	**50%**	**75%**	**100%**
C	1	7	13	19	25
CS	1	3	5	7	9
G	1	8	16	24	32
S	1	5	10	15	19

Table 3. Input variable selections t+12

P.1	C	CS	G	S	P.67	C	CS	G	S
t	X	X	X	X	t			X	X
t-1	X		X		t-1			X	
t-2	X	X	X	X	t-2			X	X
t-3	X				t-3				
t-4	X				t-4				X
t-5	X	X			t-5			X	
t-6	X		X		t-6				X
t-7	X	X	X		t-7				
t-8					t-8				
t-9			X		t-9				
t-10					t-10				X
t-11					t-11				
t-12			X		t-12				X

t-13					t-13				
t-14					t-14				
t-15					t-15				
t-16					t-16				
t-17					t-17				
t-18			X	X	t-18				X
t-19					t-19				
t-20					t-20				
t-21			X		t-21				
t-22					t-22				
t-23					t-23				
t-24				X	t-24				
P.75	**C**	**CS**	**G**	**S**	**P.20**	**C**	**CS**	**G**	**S**
t	X	X	X	X	t			X	X
t-1	X	X	X		t-1			X	
t-2	X		X		t-2			X	X
t-3	X				t-3				
t-4	X	X		X	t-4				
t-5			X		t-5			X	
t-6			X		t-6			X	
t-7				X	t-7			X	
t-8					t-8			X	X
t-9					t-9				
t-10			X		t-10			X	
t-11				X	t-11			X	X
t-12			X		t-12				
t-13					t-13				X
t-14					t-14				
t-15				X	t-15				
t-16			X		t-16			X	
t-17					t-17				
t-18					t-18				
t-19					t-19			X	X
t-20					t-20				
t-21					t-21				
t-22				X	t-22				
t-23					t-23				
t-24					t-24			X	X
Total						13	7	33	24

Table4. Number of hidden nodes.

t+12	No. of hidden node				
	1	**25%**	**50%**	**75%**	**100%**
C	1	3	6	9	13
CS	1	2	3	5	7
G	1	8	16	24	33
S	1	6	12	18	24

For evaluated model performance, it is based on the result of forecasting 6 and 12 hr.

R-squared statistic (Coefficient of Determination; Pearson's r squared)[8]

$$\mathrm{RSqr} = \left[\frac{\sum_{i=1}^{n}(Q_i - \bar{Q})(\widehat{Q_i} - \tilde{Q})}{\sqrt{\sum_{i=1}^{n}(Q_i - \bar{Q})^2 \sum_{i=1}^{n}(\widehat{Q_i} - \tilde{Q})^2}}\right]^2$$

Where Q_i is the observed value at time i

$\widehat{Q_i}$ is the modelled value at time i

$\bar{Q}$ is the mean of the observed data

$\tilde{Q}$ is the mean of the modelled data

IV. RESULTS

For t+6 hour, all learning algorithms forecast similar by having R^2 value between 0.99-.098 except GDM, GDX and GD(Figure 3). Moreover, BR has the highest value 0.99 at 1 hidden node, then values tend to decrease when increasing hidden nodes as the lowest value is 0.75 with hidden node is 100% of input variable.

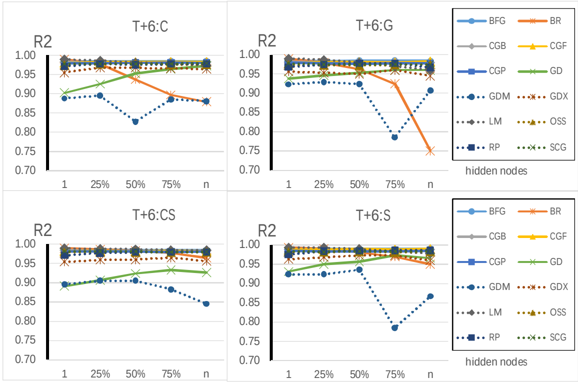

Figure 3:R^2 values for 12 learning algorithms with different number of hidden nodes at t+6 hr.

Hydrographs in Figure 4 show some results at 6 hr of BR, LM, BFG, GDM, GDX and GDalgorithms of C technique with 1 hidden node. It is obvious that BR, LM and BFGforecast similar result with the actual water level. In contrast, GDM, GDX and GD could not performance well at the big flood event.

For the best flood forecasting R^2 values (0.99) represent that BFG and LM are the best performance for all input determination techniques. However, the recommend number of hidden nodes should not greater than 50% of number of input variables.

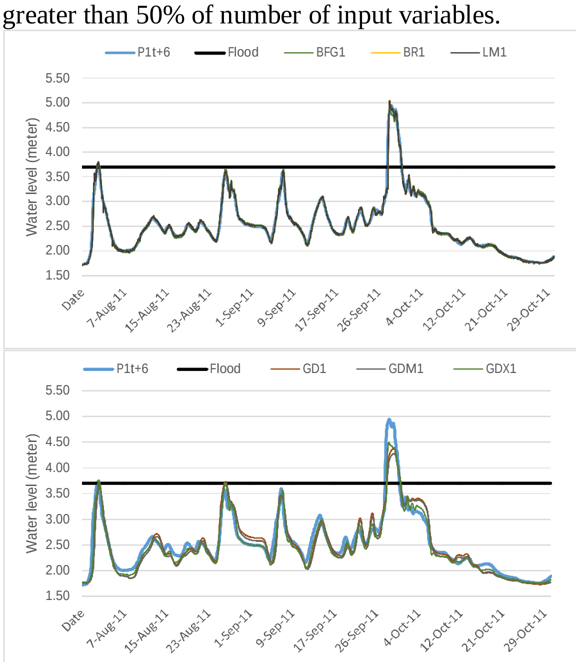

Figure 4:Hydrographs at t+6 hr.

Increasing number of hidden nodes seems to be no effected with model performance particularly learning algorithms BFG, CGB, CGP, CGF, OSS and SCG.

The performance pattern of t+12 hr is also similar with t+6 hr as GDM, GDX and GD are the worst performance and the best algorithms are LM, BR and BFG with one hidden node withR^2 value is 0.97 but for the overall results BFG seems to be the recommendation choice because it has not much effect when changing number of hidden nodes with the range of maximum R^2 value is 0.94-0.97 (Figure 5).

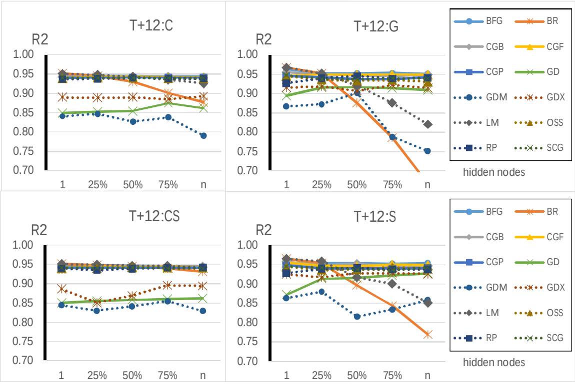

Figure 5:CE and R2 value for 12 learning algorithms with number of different hidden nodes, t+12.

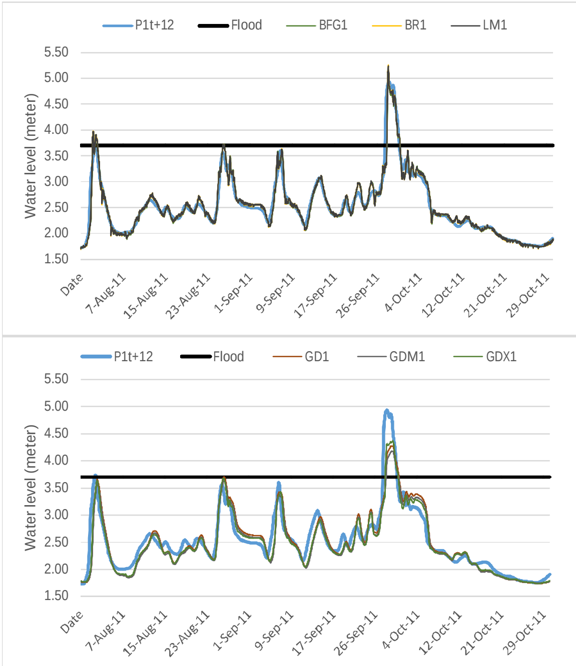

Figure 6: Hydrographs at t+12.

For results of C technique with 1 hidden node at 12 hr, again, the hydrographs of GDM, GDX and GD are the worst performance while, It is clearly that BR, LM and BFGforecast very similar each other (Figure 6)

CONCLUSION

To sum up, all 12 learning algorithms seem to be similar performance but for the best performance of learning algorithm for flood forecasting with different input variables and number of hidden nodes have no effect with the BFG and LM learning algorithms performance at 6 hr and only BFG at 12 hr. In the other hand, GDM, GDX and GD have the lowest R^2 value.

To compare the result with related study [5,6]that concluded that LM and BR are the best algorithms for flood forecasting 6 and 12 hr, however, in this studyBR is not the best algorithm it is because BR performance depends on input variable and number of hidden node.

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