WATER LEVEL PREDICTION IN NAN RIVER, THAILAND USING WAVELET NEURAL NETWORK

Somchit Amnatsan[*]
MEE09209

Supervisor: Prof. A. W. Jayawardena[**]

ABSTRACT

Accurate prediction of water levels in a river is an important factor for effective flood prevention and mitigation. In this study, Artificial Neural Networks (ANNs) with Wavelet Decomposition has been applied to predict water levels in Nan River of Thailand at N.64 and N.1 gauging stations. These stations are located in Nan province of Thailand. A feed forward neural network with early stopping method of training is adopted to train and generalize the network in order to prevent the network from overfitting the training data. Discrete wavelet analysis is used as the data pre-processing technique to decompose the input data into their detail (high frequency) component and approximation (low frequency) component. The Haar wavelet, the simplest and the oldest of all wavelets (Vidakovic and Mueller 1991) is used to decompose the data in this study. Both original and decomposed data are used as the input of the ANN model. The integration of wavelet analysis and ANN is called the wavelet neural network (WNN) model. Beside the ANN and WNN models, the recurrent neural network (RNN) model is experimented. The performance of the ANN, WNN and RNN models are evaluated by several statistical indicators. The comparison of model performance indicators between the ANN, WNN and RNN models for the same input pattern indicates that the WNN model provides the best model performance. Most of model performance indicators are improved to their optimum values in the application of WNN models for all input patterns. In conclusion, the hybrid model between the artificial neural network (ANN) and the wavelet analysis can be successfully applied to predict water levels in Nan River of Thailand. The adopted discrete wavelet analysis that decomposed the input data before feeding into ANN models can significantly improve the performance of models resulting in the more accurate prediction of water levels which can be employed for flood warning in the study area.

Keywords: Artificial Neural Network, Discrete Wavelet Analysis, Multilayer Perceptron, Back Propagation, Haar Wavelet

INTRODUCTION

Floods are a part of nature. They occur every year in many parts of the world claiming human lives and causing large scale property damages. To prevent and mitigate flood consequences, many structural measures such as dams, levees, etc., have been constructed. However, the past experience from many countries indicates that the structural measures alone cannot effectively overcome flood problems. Moreover, some structural measures tend to increase flood damage in case of their malfunction and the false sense of

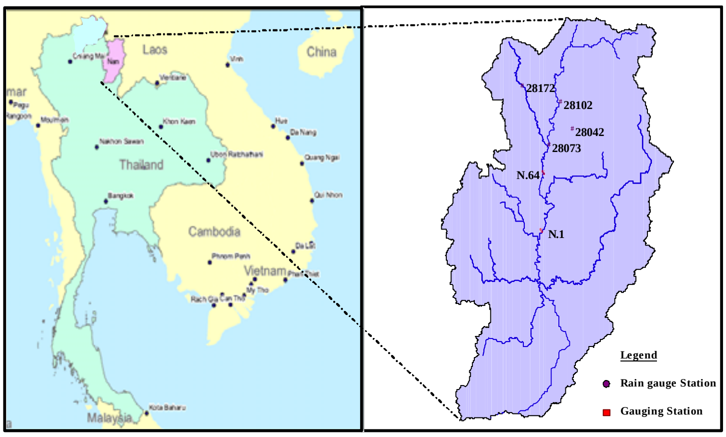

Figure 1: River system in Nan province and locations of gauging stations

[*] Irrigation Engineer, Regional Irrigation Office 2, Royal Irrigation Department, Thailand.
[**] Research and Training Advisor
International Centre for Water Hazard and Risk Management (ICHARM), Public Works Research Institute (PWRI), Tsukuba, Ibaraki, Japan.

security of people on such structures. Due to these experiences, several non-structural measures have been researched and employed in practice to enhance the effectiveness of structural measures in flood prevention and mitigation. In the case of riverine floods, the effectiveness of flood countermeasures is greatly dependent on the information of water levels in the river so that it is of great interest for the researchers to develop a model that is capable of accurately predicting the water level in a river. In this study, Artificial Neural Networks (ANN) with Wavelet Decomposition has been applied to predict the water levels in Nan River at N.64 and N.1 gauging stations. The selected gauging stations are located in Nan province of Thailand. This province is situated in the upper part of Nan River basin. The watershed area at the selected stations N.64 and N.1 are 3,476 and 4,560 km^2 respectively. The area of Nan province is the northern mountainous terrain which renders this region prone to water-related disasters such as flash flood, landslide and debris flow. Floods that occur in this area are usually of the riverine type due to heavy rainfall in the upstream watershed. Figure 1 shows the river system in Nan province and the locations of gauging stations.

DATA

Daily water levels and rainfall data are collected manually by the Royal Irrigation Department (RID) of Thailand. Water levels at N.64 gauging station and rainfall at four upstream rain gauge stations from 1/4/1994 to 31/3/2010 are used for the prediction of water levels at station N.64. Water levels at N.64 and at N.1 gauging stations from 1/4/1995 to 31/3/2009 are utilized for the prediction of water levels at station N.1. The data are separated into three parts for training, validation and testing of models. Table 1 summarizes the data used in different phases of simulation in this study.

Table 1: Summary of used data in training, validation and application phases of simulation

Station	**Coordinate**		**Total data range**	**Training range**	**Validation range**	**Testing range**
	Latitude	**Longtitude**				
N.64	19º 00′ 32″ N	100º 47′ 19″ E	1/4/1994 to 31/3/2010	1/7/1996 to 31/12/2007	1/4/1994 to 30/6/1996	1/1/2008 to 31/3/2010
N.1	18º 46′ 26″ N	100º 46′ 56″ E	1/4/1995 to 31/3/2009	1/4/1997 to 31/3/2007	1/5/1995 to 31/3/1997	1/4/2007 to 31/3/2009

THEORY AND METHODOLOGY

The adopted methodology starts from performing the cross correlation between rainfalls and water levels and autocorrelation of water levels for different lag-time. The objective of this analysis is to determine the input patterns of the neural networks. The next step is the development of the computer program for the neural network models. This computer program is validated for its reliability before applying with real data. After the validation of the computer program, the model is applied with the ordinary real data. During this application, the sensitivity of models to activation functions, learning rate and momentum term is tested to find the optimum network structure. The optimum network structure is kept to use with all input patterns which is determined from the correlation analysis. The optimum number of hidden neurons is tested for each input pattern during this application. The wavelet analysis is employed as the data pre-processing technique to improve the accuracy of ANN model. In this step, the ordinary data are decomposed into their approximation (low frequency) components and detail (high frequency) components by the discrete wavelet transform. The wavelet decomposed data which have the same number of data sets as the ordinary data are then fed as inputs of neural network model. The ANN model which uses the wavelet decomposed data as inputs is called the wavelet network model (WNN). The recurrent neural network (RNN) is experimented in this study in order to compare its prediction capability with the conventional ANN model and WNN model. The same sets of input data are used in this experiment. The performances of ANN, WNN and RNN models are then compared by using several statistical indicators as shown in Table 2. The model which provides the best performance is selected for the prediction of water levels in the study locations.

Table 2: Statistical indicators used in this study

Performance Index	Correlation Coefficient (r)	Root Mean Square Error (RMSE)	Efficiency Index (EI)	Coefficient of Determination (CD)
Equation	$\frac{\sum_{i=1}^{N}(P_i-\overline{P})(O_i-\overline{O})}{\sqrt{\sum_{i=1}^{N}(P_i-\overline{P})^2\sum_{i=1}^{N}(O_i-\overline{O})^2}}$	$\sqrt{\frac{\sum_{i=1}^{N}(O_i-P_i)^2}{\mathrm{N}}}$	$1-\frac{\sum_{i=1}^{N}(O_i-P_i)^2}{\sum_{i=1}^{N}(O_i-\overline{O})^2}$	$\frac{\sum_{i=1}^{N}(P_i-\overline{O})^2}{\sum_{i=1}^{N}(O_i-\overline{O})^2}$
Unit	Dimensionless	Same as O & P	Dimensionless	Dimensionless
Optimal value	1.0	0.0	1.0	1.0
Range	-1.0 to 1.0	≥ 0.0	> -∞ and ≤ 1.0	> 0.0 and ≤ +∞

Artificial neural network model: The model adopted in this study is the multilayer perceptron (MLP) feedforward network. Typically, the network consists of the input layer, one or more hidden layers of computation nodes, and an output layer of computation nodes. In this study, the network consists of only one hidden layer and its structure is shown in Figure 2. The network is trained in a supervised manner with the error back-propagation algorithm. The error back-propagation algorithm has two activities of working process, i.e. activities in the forward pass and activities in the backward pass.

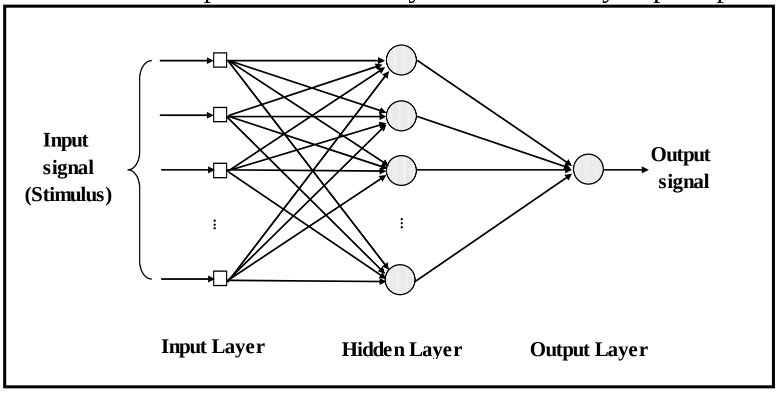

Figure 2: Structure of neural network in this study

The activities in the forward pass begin with the presentation of input and desired output data to the network. The next step is the calculation of the induced local field and output signal in hidden and output layers. The induced local field $v_j(n)$ for neuron j in the hidden and output layers can be calculated as:

$$v_j(n)=\sum_{i=0}^{I} w_{ji}(n)x_i(n) \tag{1}$$

where $x_i(n)$ is the input signal of neuron i in the input layer, $w_{ji}(n)$ is the synaptic weight of neuron j in the computation layer. For i = 0, $x_0(n)$ = +1 and $w_{j0}(n) = b_j(n)$ is the bias applied to neuron j in the computation layer. The output signal of neuron j in the computation layer is:

$$y_j(n)=\varphi_j(v_j(n)) \tag{2}$$

where $\varphi_j(\bullet)$ is the activation function. The network in this study is designed to have only one output neuron in the output layer and the output signal of the output neuron in output layer is denoted as $o(n)$. After the output signal of the output neuron in output layer is calculated, the error signal is then computed as:

$$e(n)=d(n)-o(n) \tag{3}$$

where $d(n)$ is the desired response of n^{th} pattern of training data set.

The backward activities then start from the output neuron in output layer. The instantaneous value $E(n)$ of the total error energy of output neuron and the average squared error energy for the network with single output neuron in the output layer are calculated as:

$$E(n)=\frac{1}{2}e^2(n) \tag{4}$$

$$ASE(n) = \frac{1}{N}\sum_{n=1}^{N} E(n) \qquad (5)$$

where N denote the total number of patterns in the training set. The weights and biases are updated from this error using the delta rule as shown by (Haykin, 1998):

$$\Delta w_{ji}(n) = \alpha \Delta w_{ji}(n-1) + \eta \delta_j(n) y_i(n) \qquad (6)$$

where η is the learning rate and α is the momentum term. The activities of back propagation algorithm are stopped when the stopping criteria is met. In this study, the network will be stopped if the absolute rate of change $AASE$ in the average squared error (ASE) per epoch is sufficiently small which can be expressed as:

$$AASE = \left| ASE(n) - ASE(n-1) \right| \leq 0.000000001$$

Wavelet Analysis: The discrete wavelet transform is employed in this study to decompose the input signal into its approximation (low frequency) and detail (high frequency) components before feeding into the ANN. The discrete wavelet transform is composed of decomposition and reconstruction processes as shown in Figure 3 (Misiti et al., 2009). The wavelet decomposition process involves filtering and downsampling the original signal and yields the approximation and detail coefficients. The wavelet reconstruction process consists of upsampling and filtering the approximation and detail coefficients. The results of the reconstruction process are the approximation and detail components which are then used as inputs of the ANN.

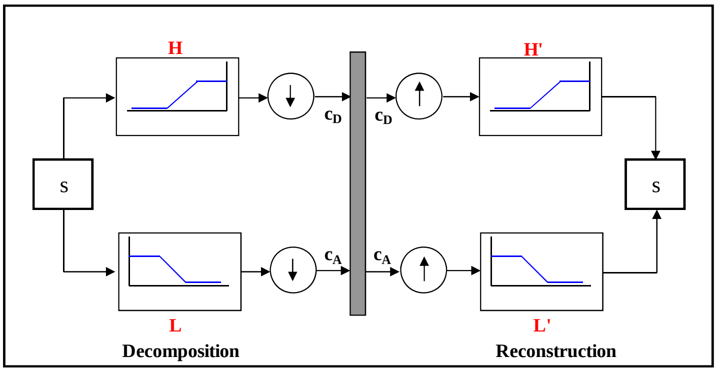

Figure 3: Decomposition and reconstruction process

Recurrent neural network: This network architecture is experimented in this study. Recurrent neural networks are fundamentally different from feedforward architectures that they not only operate on an input space but also on an internal state space (Bodén, 2001). The state space enables the representation of temporally/sequentially extended dependencies over unspecified intervals as described by the following equation:

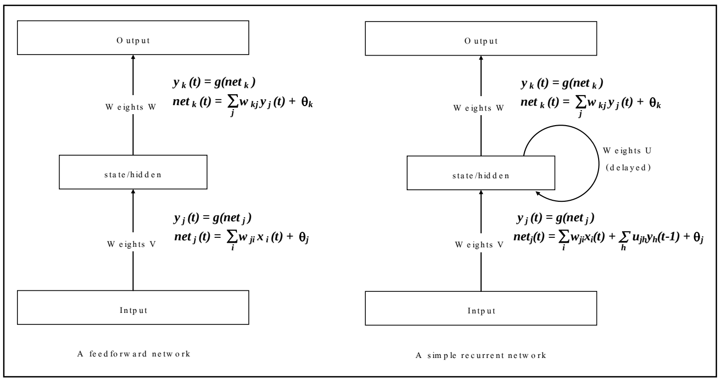

Figure 4: Comparison between a feed forward network and a simple recurrent network

$$y(t) = G(s(t)) \qquad (7)$$

$$s(t) = F(s(t-1), s(t-2), \ldots, s(t-\tau), x(t)) \qquad (8)$$

where τ is the number of previous presentations. The comparison of an ordinary feedforward network and a simple recurrent network is illustrated in Figure 4 (Bodén, 2001).

RESULTS AND DISCUSSION

Table 2 shows the model performance of ANN, RNN, WNN and WRNN models for the prediction of 1-day lead time water level at station N.64. The WRNN model is the RNN model which uses the wavelet-decomposed data as the input. The abbreviation NHN in the table denotes the number of hidden neurons in hidden layer and the number in the bracket following the number of hidden neurons in the case of the recurrent network is the number of recurrent time step used in RNN. The number of hidden neurons and recurrent time step shown in the table is the number that gives the best model performance for each model. Comparison between the ANN and WNN models indicates that most of the model performance indicators except the coefficient of determination in validation period of some input patterns of the WNN model are closer to their optimum values than those of the ANN model. The application of RNN usually improves the coefficient of determination but deteriorates other performance indicators. The comparison between WNN and WRNN models indicates similar result as the case between ANN and RNN model, that is, the WRNN model usually improves the CD but deteriorates other model performance indicators. The application of models to predict 1-day lead time water levels at gauging station N.1 indicates the same result as shown in Table 3. The comparison of model performance indicators suggests that the WNN model is the best choice for the prediction of water levels in the study area because it always improves performance indicators for all input patterns. This improvement is confirmed with the relationship and time series plots between observed and predicted water levels at station N.1 shown in Figure 5.

Table 2: Model performance for prediction of 1-day lead-time water levels at station N.64

Input pattern	Model	NHN	Model performance											
			Training				Validation				Testing			
			RMSE	r	EI	CD	RMSE	r	EI	CD	RMSE	r	EI	CD
R4_WL1	ANN	5	0.3535	0.9561	0.9142	0.9142	0.4857	0.9437	0.8906	0.8777	0.3503	0.9618	0.9234	0.8498
	RNN	**2(1)**	**0.3649**	**0.9532**	**0.9086**	**0.9085**	**0.5123**	**0.9403**	**0.8783**	**1.0116**	**0.3570**	**0.9613**	**0.9205**	**0.9368**
	WNN	4	0.3061	0.9673	0.9357	0.9367	0.4210	0.9580	0.9178	0.9265	0.3369	0.9648	0.9292	0.9733
	WRNN	**4(1)**	**0.3129**	**0.9658**	**0.9328**	**0.9324**	**0.4371**	**0.9559**	**0.9114**	**1.0045**	**0.3451**	**0.9645**	**0.9257**	**1.0301**
R4_WL2	ANN	4	0.3567	0.9553	0.9127	0.9108	0.4874	0.9433	0.8898	0.8841	0.3481	0.9624	0.9244	0.8468
	RNN	**2(3)**	**0.3570**	**0.9552**	**0.9125**	**0.9116**	**0.5517**	**0.9367**	**0.8588**	**1.1476**	**0.3657**	**0.9588**	**0.9165**	**1.0212**
	WNN	2	0.2917	0.9703	0.9416	0.9412	0.4114	0.9624	0.9215	0.8169	0.3116	0.9697	0.9394	0.8844
	WRNN	**2(3)**	**0.2924**	**0.9702**	**0.9413**	**0.9402**	**0.4317**	**0.9563**	**0.9136**	**0.9724**	**0.3377**	**0.9665**	**0.9288**	**1.0265**
R4_WL3	ANN	2	0.3434	0.9587	0.9190	0.9195	0.5220	0.9358	0.8736	0.9658	0.3493	0.9635	0.9239	0.8117
	RNN	**2(3)**	**0.3470**	**0.9578**	**0.9173**	**0.9170**	**0.5017**	**0.9425**	**0.8832**	**1.0055**	**0.3397**	**0.9640**	**0.9280**	**0.9207**
	WNN	2	0.2596	0.9766	0.9537	0.9523	0.3890	0.9670	0.9298	0.8331	0.2710	0.9770	0.9542	0.9161
	WRNN	**2(3)**	**0.2582**	**0.9768**	**0.9542**	**0.9536**	**0.3782**	**0.9692**	**0.9337**	**0.8132**	**0.2839**	**0.9756**	**0.9497**	**0.9369**

Table 3: Model performance for prediction of 1-day lead-time water levels at station N.1

Input pattern	Model	NHN	Model performance											
			Training				Validation				Testing			
			RMSE	r	EI	CD	RMSE	r	EI	CD	RMSE	r	EI	CD
LU1_LD2	ANN	2	0.3037	0.9661	0.9333	0.9311	0.3809	0.9503	0.8891	1.0809	0.3513	0.9605	0.9048	1.1280
	RNN	**3(1)**	**0.2997**	**0.9670**	**0.9350**	**0.9310**	**0.4017**	**0.9365**	**0.8767**	**0.8493**	**0.3617**	**0.9486**	**0.8991**	**0.9197**
	WNN	6	0.2512	0.9769	0.9543	0.9536	0.2875	0.9706	0.9368	0.9734	0.3260	0.9723	0.9180	1.1725
	WRNN	**6(1)**	**0.2330**	**0.9802**	**0.9607**	**0.9606**	**0.2693**	**0.9719**	**0.9446**	**0.9527**	**0.3168**	**0.9687**	**0.9226**	**1.1761**
LD2	ANN	2	0.3327	0.9591	0.9200	0.9187	0.3725	0.9462	0.8940	0.8348	0.3185	0.9603	0.9218	0.8868
	RNN	**2(2)**	**0.3430**	**0.9565**	**0.9149**	**0.9144**	**0.3850**	**0.9420**	**0.8867**	**0.9309**	**0.3341**	**0.9561**	**0.9139**	**0.9067**
	WNN	5	0.2575	0.9757	0.9520	0.9509	0.2645	0.9732	0.9465	0.9021	0.2716	0.9730	0.9431	1.0311
	WRNN	**5(1)**	**0.2501**	**0.9771**	**0.9547**	**0.9517**	**0.3402**	**0.9586**	**0.9115**	**0.7623**	**0.2968**	**0.9669**	**0.9321**	**0.8431**
LD3	ANN	4	0.3263	0.9607	0.9230	0.9221	0.3628	0.9487	0.8995	0.8684	0.3061	0.9633	0.9278	0.8998
	RNN	**4(1)**	**0.3395**	**0.9574**	**0.9166**	**0.9156**	**0.3759**	**0.9446**	**0.8921**	**0.9125**	**0.3151**	**0.9611**	**0.9235**	**0.8962**
	WNN	4	0.2624	0.9748	0.9502	0.9495	0.2883	0.9684	0.9366	0.9903	0.2914	0.9778	0.9346	1.1771
	WRNN	**4(1)**	**0.2708**	**0.9731**	**0.9470**	**0.9468**	**0.2957**	**0.9677**	**0.9332**	**1.0283**	**0.3085**	**0.9773**	**0.9267**	**1.2171**

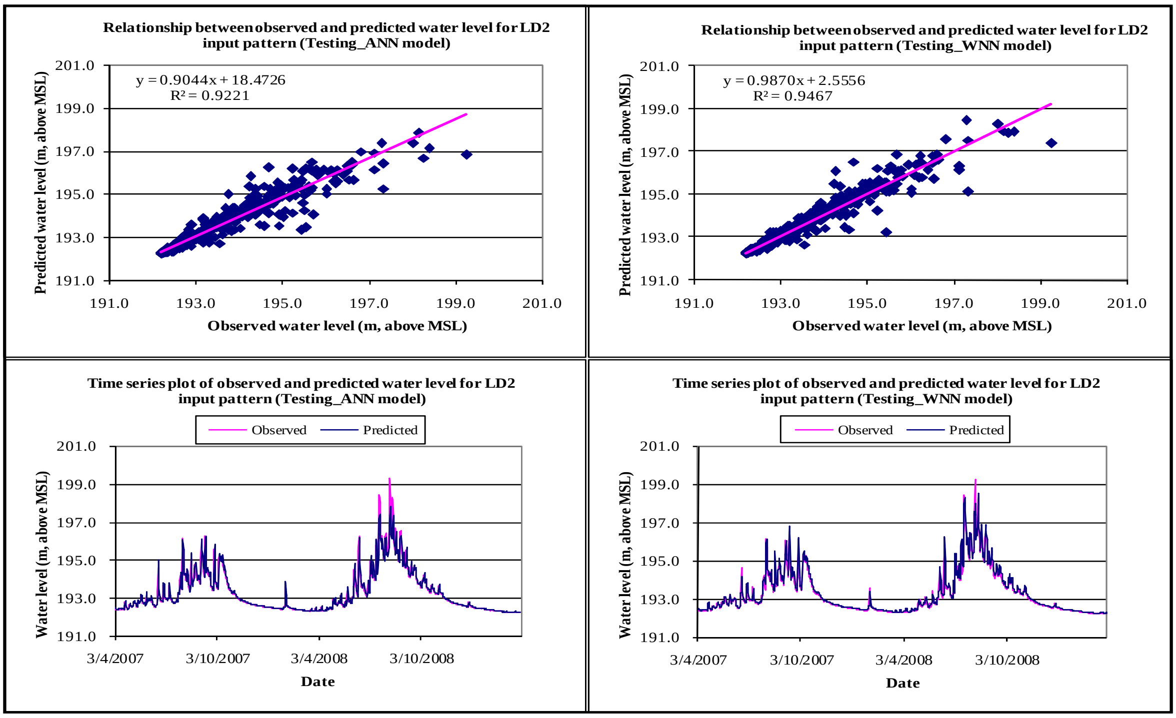

Figure 5: Relationship between observed and predicted water levels at station N.1 of ANN and WNN models in testing period of input pattern LD2

CONCLUSIONS

The hybrid model between the artificial neural network (ANN) and the wavelet analysis which is called the "wavelet neural network (WNN)" model can be successfully applied to predict water levels in Nan River of Thailand. The adopted discrete wavelet analysis that decomposed the input data before feeding into ANN models can significantly improve the performance of models resulting in more accurate prediction of water levels which can be employed for flood warning in the study area.

RECOMMENDATION

In this study, 1-level of wavelet decomposition and the Haar wavelet which is the simplest wavelet function are employed to decompose the input data of the WNN model. Since there are several wavelet functions which can be used for wavelet decomposition, it is interesting to study the effect of the use of different wavelet functions and different levels of decomposition on the accuracy of WNN model.

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