Water Level Forecasting at Bang Sai Arts and Crafts Center (C.29A) Gauge Station, Chao Phraya River Basin, Amphoe Bang Sai, PhraNakhon Si Ayuttaya Province Using NARX Network

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Abstract

This study aims to predict the water level at the Bang Sai Arts and Crafts Center (C.29A) gauge station located in the Chao Phraya River Basin, Amphoe Bang Sai, PhraNakhon Si Ayuttaya Province using NARX Network. The daily water level data at the C.13, C.3, C.7A, C.35, S.5, S.26, and C.29A gauge stations from Apr 2012 - Dec 2016 were used to develop the water level forecasting model. Data was separated in to three sets: training set, validation set, and testing set. The one-step ahead forecasting model was evaluated using mean square error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The results showed that the NARX Network using only the upstream water level gauge stations and gauge station to be predicted obtained the lowest forecasting error. Moreover, the NARX model outperformed Holt-Winters forecasting method.

Keywords: water level prediction, artificial neural network, NARX model, smoothing technique, time series

1. Introduction

Natural disasters that frequently occur in Thailand include floods, tropical storms and forest fires. Flooding, the most frequent, occurs during the monsoon season, June-September. The risks to Bangkok, in the flood plain of the Chao Phraya River, are high, with the potential for huge economic loss [1]. In 2011, Thailand witnessed its worst flooding in half a century, when the monsoon season brought unusually heavy rains, with floods spreading through the northern and central provinces of Thailand. In Bangkok, 30 districts, 27 communities, and 621,355 households were affected [2]. In the wake of the severe flooding, the government proposed strategies to prevent their reoccurrence. One of the strategies was to improve information technology (IT) to obtain real-time or frequently updated data. The IT system needs to monitor water levels to determine and maintain equilibrated water levels [3]. This data should also be shared with the public to raise awareness of water levels and the potential for flooding.

Thailand's Royal Irrigation Department (RID) is responsible for flood prevention and disaster relief. As part of this responsibility, RID monitors the water level at the Bang Sai Arts and Crafts Center Station (C.29A) gauge station in PhraNakhon Si Ayuttaya Province. As water levels at this station are keys to warning Bangkok of flood risks, an early warning system is critical.

Previous studies have applied hydrological models such as MIKE11 and Artificial Neural Network (ANN) [4, 5], for runoff forecasting. Vangpaisal and Threenat [4] showed that the performance of the ANN model depended on learning algorithms, input variables, and the number of hidden nodes. Chaipimoplin and Vangpaisal [5] found that the Levenberg-Marquardt (LM) leaning method provides better results than the Beyesian Regularization (BR) learning method. They also suggested that the water level at the upstream gauge station of the main river, as well as the water level at the gauge station to be predicted should be included as inputs in the model. However, ANN structure also depends on the data set, because different runoff behavior in the basin may require different model.

This study aims to use Nonlinear Autoregressive with eXogeneous input (NARX) model, an ANN technique, to model and forecast the water level at the Bang Sai Arts and Crafts Center Station (C.29A) and to compare our NARX model with time series models using smoothing technique.

2. Research Methodology

2.1 Data and Study Area

Figure 1 shows a map of central Thailand and the Chao Phraya River. The Chao Phraya River originates at the confluence of the Ping, Wang, Yom and Nan rivers at Nakhon Sawan. The river flows through the central plain through Bangkok into the Gulf of Thailand. At Ayutthaya, about 55 km north of Bangkok, the Pasak River joins the Chao Phraya River. Floods in Thailand are generally caused by overflowing rivers, which results in widespread flooding [6]. In 2011, the flooding began in late July, triggered by the landfall of tropical storm Nock-ten. These floods spread through the provinces of northern, northeastern, and central Thailand. Water flows in the Chao Phraya River exceeded its capacity, causing severe flooding in Bangkok. Therefore, at daily warning system is critical to forecasting runoff and preventing flooding in the lower Chao Phraya River. The flood management system monitors daily water levels at nine gauge stations. This research considered only the gauge stations in the main stream of the Chao Phraya River, thus excluding the C.36 and C.37 gauge stations. A schematic representation of the basin and the location of the seven gauge stations considered in this study are shown in Figure 2.

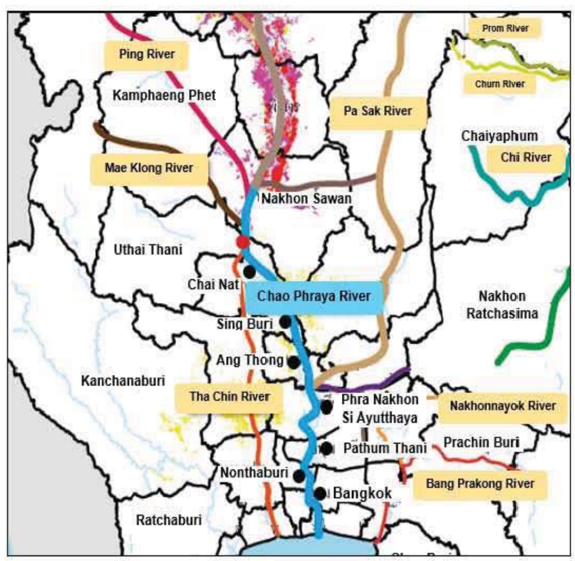

Figure 1: Map of the Chao Phraya River, the main river of Thailand [6].

Figure 2: The basin and the location of the 7 gauge stations.

The water level data collected at the selected gauge stations in this study were defined as:

- WL_{C13} — Water level at C.13 gauge station, Chao Phraya dam, Amphoe Sanphaya, Chai Nat Province
- WL_{C3} — Water level at C.3 gauge station, Ban Bang Putcha, Amphoe Muang, Sing Buri Province
- WL_{C7A} — Water level at C.7A gauge station, Ban Bang Kaew, Amphoe Muang, Ang Thong Province
- WL_{C35} — Water level at C.35 gauge station, Ban Pom, Amphoe PhraNakhon Si Ayuttaya, PhraNakhon Si Ayuttaya Province
- WL_{S5} — Water level at S.5 gauge station, Panchamathirat Uthit School, Amphoe PhraNakhon Si AyuttayaPhra, PhraNakhon Si Ayuttaya Province
- WL_{S26} — Water level at S.26 gauge station, Rama VI Dam, Amphoe ThaRua, PhraNakhon Si Ayuttaya Province
- WL_{C29A} — Water level at C.29A gauge station, Bang Sai Arts and Crafts Center, Amphoe Bang Sai, PhraNakhon Si Ayuttaya Province

The data were collected for 1,736 consecutive days – from Apr 1, 2012 to Dec 31, 2016. Normally, it takes approximately 24 hours for water to flow from the C.13 gauge station to the C.35 gauge station, and 60 hours flow from the C.13 gauge station to the C.29A gauge station. The water level data was collected by Hydrology Irrigation Center for Central Region (RID) [7].

2.2 Artificial Neural Network (ANNs)

Artificial neural networks (ANNs) have been successfully applied to a number of time series prediction. ANNs are nonlinear models that are relatively crude electronic networks of neurons based on the neural structure of the brain. The neural network consists of three layers — the input, hidden, and output layers. ANNs architecture is shown in Figure 3. This study employed a

Multilayer Perceptron Algorithm (MLP) algorithm. The training function used in the network was the Levenberg-Marquardt (LM) backpropagation method [8-10].

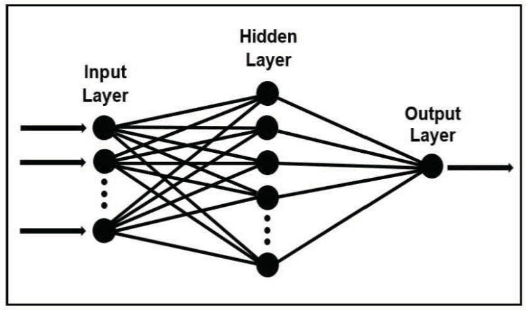

Figure 3: Multilayer Perceptron Architecture

Normally, ANNs predict one-step-ahead, or estimate the next period of a time series, without feeding back the output to the model's input data. This research focused on an incremental learning method, as the model was trained when the actual value of target variable was known. Therefore, we employed a Nonlinear Autoregressive with eXogeneous input (NARX) model, because the NARX model's input is built through two tapped-delay lines: one sliding over the input regressor and another sliding over the output regressor [8]. This research followed the equation and symbols presented in [8]. The NARX model is a discrete-time nonlinear system that can be mathematically represented as:

$$y(t+1) = f\big[y(t), \dots, y\big(t - d_y + 1\big); u(t), u(t-1), \dots, u(t - d_u + 1)\big], \quad (1)$$

where $u(t)\epsilon\mathbb{R}$ and $y(t)\epsilon\mathbb{R}$ denote the input and output of the model at discrete time step n, respectively, while d_u and d_y are the number of input delay and output delay. In vector form, it can be written as

$$y(t+1) = f[y(t); u(t)], \quad (2)$$

where $y(t)$ and $u(t)$ denote the output and input regressors, respectively. The nonlinear mapping $f(.)$ is generally unknown and can be approximated, for example, by a Multilayer Perceptron (MLP) network. The resulting network architecture is then called a NARX network [8]. The NARX network architecture is shown in Figure 4.

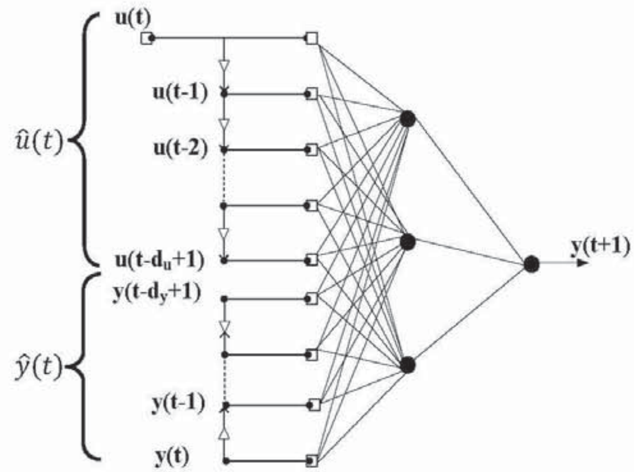

Figure 4: NARX network with d_u delayed inputs and d_y delayed outputs.

3. Experimental Setup

We evaluated the performance of the NARX network at predicting the daily water level at the C.29A gauge station. We also compared the performance of the NARX model with a time series model. We assessed trend and seasonality by using an autocorrelation plot. Since, the data contain both trend and seasonality, thus Holt-Winters forecasting technique will be used as a time series forecasting method.

3.1 Holt-Winters Forecasting Method

Holt - Winters's method can be extended to deal with time series which contain both trend and seasonal variations. In this work, we use the multiplicative Holt-Winters method and the general forecasting function is shown in equation (3).

$$\hat{Y}_{t+p} = (\hat{T}_t + \hat{\beta}_t)\hat{S}_{t-m+1} \quad (3)$$

where

$\hat{Y}_{t+p}$ is the forecast made in period t for period $t + p$,
$\hat{T}_t$ is the smoothed constant-process value for period t,
$\hat{\beta}_t$ is the smoothed trend value for period t,
$\hat{S}_t$ is the smoothed seasonal value for period t,
t is the period in which the forecast is made,
m is the number of seasonal, in this work, the seasonal pattern occurs within 15 days, thus $m = 15$,
p is the number of periods ahead to be forecast and is one-step ahead.

In Holt - Winters exponential smoothing [11], the model has the smoothing constants which are α, γ, and δ. The value of α, γ, and δ are ranged from 0 to 1. $\hat{T}_t$, $\hat{\beta}_t$, and $\hat{S}_t$ are formulated as follows:

$$\hat{T}_t = \frac{\alpha Y_t}{\hat{S}_{t-m}} + (1-\alpha)\hat{T}_{t-1}$$

$$\hat{\beta}_t = \gamma\left(\hat{T}_t - \hat{T}_{t-1}\right) + (1-\gamma)\hat{\beta}_{t-1}$$

$$\hat{S}_t = \frac{\delta Y_t}{\hat{T}_t} + (1-\delta)\hat{S}_{t-m}$$

where α is the level smoothing constant, γ is the trend smoothing constant, and δ is the seasonal smoothing constant.

To get started, initial values of the level, trend and seasonality [12], $\hat{T}_{Initial}$, $\hat{\beta}_{Initial}$ and $\hat{S}_{Initial}$ are formulated as follows:

$$\hat{T}_{Initial} = \sum_{i=1}^{m} Y_i/m, \ i = 1, 2, \dots, m$$

$$\hat{\beta}_{Initial} = \frac{\left[\sum_{j=m+1}^{m+m} Y_j - \sum_{i=1}^{m} Y_i\right]}{m^2}, i = 1,2, \dots, m; j = m+1, m+2, \dots, m+m$$

$$\hat{S}_{Initial} \quad \hat{S}_i = Y_i/\hat{T}_{Initial}, i = 1, 2, \dots, m$$

For a fair comparison, we develop an adaptive Holt-Winters model in which the parameter of the model is recomputed every time the new daily water level at gauge station C.29A is available. In an incremental learning task, we employed the concept of sliding window in which new data will be added to the training data and the oldest data will be discarded. The window size is fixed and set as the number of seasonal, $m = 15$.

3.2 Preprocessing

The data set was divided into three sets: the training set contained 1,216 days (Apr 1, 2012 – Jul 29, 2015), the validation set contained 260 days (Jul 30, 2015 – Apr 15, 2016), and the testing set contained 260 days (Apr 16 – Dec 31, 2016).

3.3 Parameters Setting

We have set the parameters of the NARX model as follows:

- Input delay and output delay varied from 1, 2, 3, 4, 5, 10, 15, 20, 25, 30, 35 to 40 days.
- Number of hidden layers was set to 1.
- Number of hidden nodes varied from 3, 5, 7, 10, 15, 20, 25 to 30.

3.4 Experiments

In this study, we conducted three experiments using different numbers of input variables:

Case I: Case I used all gauge stations. Hence, there are seven input variables – the water levels at the C.13, C.3, C.7A, C.35, S.5, S.26 and C.29A gauge stations.

Case II: Case II used only selected variables. The variables were selected by considering Pearson's correlation coefficient (r) between the water level at each gauge stations and the water level at the C.29A gauge station. The correlation coefficient between the water levels at the C.13, C.3, C.7A, S.5, S.26 and C.29A stations were computed (Table 1). We selected the water level at the gauge stations that were highly related to the water level at the C.29A gauge station (r is greater than 0.8), in addition to the water level at the gauge station to be predicted (C.29A).

Case III: Case III used only three input variables – the water level at the upstream gauge stations of the main river (C.35 and S.5) and the water level at the gauge station to be predicted (C.29A).

Table 1 Pearson's correlation coefficient between the water level at other stations and the water level at the C.29A station.

Gauge station	Pearson's correlation coefficient (r)	Decision
C.13	0.808	Include in the model
C.3	0.827	Include in the model
C.7A	0.804	Include in the model
C.35	0.550	Not include in the model
S.5	0.921	Include in the model
S.26	0.829	Include in the model

The forecasting equations for the three cases are:

$$Case\ I: WL_{C.29A}(t+1) = f\begin{bmatrix} WL_{C.29A}(t), \dots, WL_{C.29A}(t-d_y+1); \\ WL_{C.13}(t), WL_{C.13}(t-1), \dots, WL_{C.13}(t-d_u+1); \\ WL_{C.3}(t), WL_{C.3}(t-1), \dots, WL_{C.3}(t-d_u+1); \\ WL_{C.7A}(t), WL_{C.7A}(t-1), \dots, WL_{C.7A}(t-d_u+1); \\ WL_{C.35}(t), WL_{C.35}(t-1), \dots, WL_{C.35}(t-d_u+1); \\ WL_{S.5}(t), WL_{S.5}(t-1), \dots, WL_{S.5}(t-d_u+1); \\ WL_{S.26}(t), WL_{C3}(t-1), \dots, WL_{S.26}(t-d_u+1) \end{bmatrix}$$

$$Case\ II: WL_{C.29A}(t+1) = f\begin{bmatrix} WL_{C.29A}(t), \dots, WL_{C.29A}(t-d_y+1); \\ WL_{C.13}(t), WL_{C.13}(t-1), \dots, WL_{C.13}(t-d_u+1); \\ WL_{C.3}(t), WL_{C.3}(t-1), \dots, WL_{C.3}(t-d_u+1); \\ WL_{C.7A}(t), WL_{C.7A}(t-1), \dots, WL_{C.7A}(t-d_u+1); \\ WL_{S.5}(t), WL_{S.5}(t-1), \dots, WL_{S.5}(t-d_u+1); \\ WL_{S.26}(t), WL_{C3}(t-1), \dots, WL_{S.26}(t-d_u+1) \end{bmatrix}$$

$$Case\ III: WL_{C.29A}(t+1) = f\begin{bmatrix} WL_{C.29A}(t), \dots, WL_{C.29A}(t-d_y+1); \\ WL_{C.35}(t), WL_{C.35}(t-1), \dots, WL_{C.35}(t-d_u+1); \\ WL_{S.5}(t), WL_{S.5}(t-1), \dots, WL_{S.5}(t-d_u+1); \end{bmatrix}$$

3.5 Evaluation Measure

MSE, MAE, and MAPE were employed to measure the one-step ahead forecasting error of the model. MSE, MAE, and MAPE are given by equation (4), (5) and (6), respectively.

$$MSE = \frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}{n}, \tag{4}$$

$$MAE = \frac{\sum_{t=1}^{n}|Y_t - \hat{Y}_t|}{n} \tag{5}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100 \tag{6}$$

where Y_t is the actual value in period t,
$\hat{Y}_t$ is the forecast value in period t,
n is the number of periods.

4. Experimental Results

Table 2 shows the optimal number of hidden nodes and delay for each case. The number of input/output delay when considering the water level at all gauge stations (Case I) was 15 days. The number of input/output delay when using only the water level at selected gauge stations (Case II) was 3 days. The number of input/output delay when using water levels at only upstream gauge stations and gauge station to be predicted (Case III) was 15 days. In summary, the results showed that using the water levels at only upstream gauge stations and gauge station to be predicted (Case III) gave the lowest forecasting error for all measures. In addition, the training time was lower than other cases, because the number of input nodes was less.

Table 2: Water level forecasting using NARX network

Case	Input/output delay	Number of hidden nodes	MSE	MAE	MAPE	Training time (minute)
I	15	7	0.0188	0.1060	32.15%	0.09
II	3	25	0.0191	0.1052	30.69%	0.02
III	15	3	0.0180	0.1036	28.37%	< 0.01

Table 3 Comparison of MSE, MAE and MAPE between NARX and Holt-Winters

Forecasting techniques	MSE	MAE	MAPE
NARX network			
• Case I	0.0188	0.1060	32.15%
• Case II	0.0191	0.1052	30.69%
• Case III	0.0180	0.1036	28.37%
Holt-Winters exponential smoothing	0.0988	0.1934	36.08%

Table 3 shows the comparison of water level forecasting between the NARX model and the Holt-Winters model. All three NARX networks outperformed the Holt-Winters method, with lower MSE, MAE, and MAPE than the Holt-Winters. In order to show the difference between the predicted and the actual water level of all methods, we used only daily water level during 1 Sep – 15 Dec, 2016, because fluctuation appeared during this period. Figure 5 displays the predicted water level using the NARX network and the actual value of the water level at the C.29A gauge station whereas Figure 6 displays the comparison of predicted water level between the NARX model, the Holt-Winters model, and the actual value of the water level at the C.29A gauge station. Moreover, Figure 6 shows that the NARX model gave a better fit compared to the Holt-Winters model.

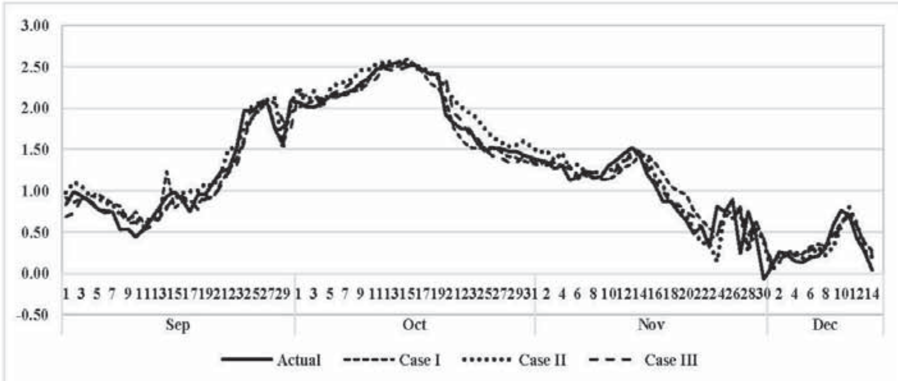

Figure 5: The water level forecast using three NARX network cases compared to the actual water level at the C.29A gauge station on the Chao Phraya River.

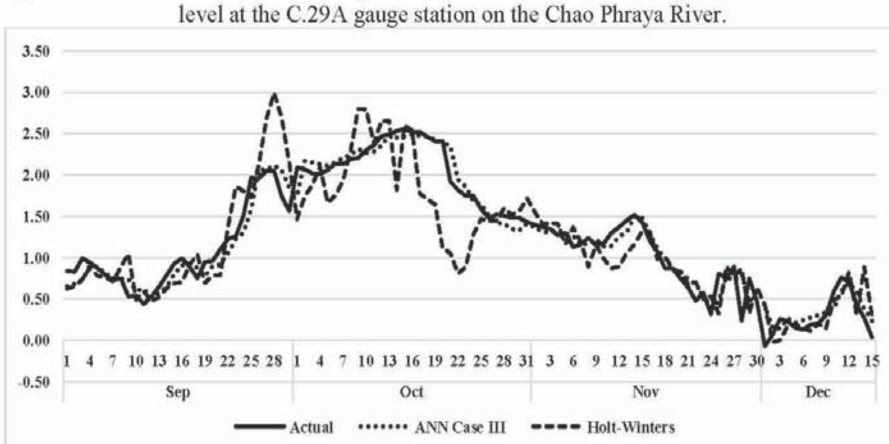

Figure 6: The water level forecast using NARX - Case III compared to the Holt-Winters model.

5. Conclusion

We applied an NARX network to forecast water levels and compared this to the traditional smoothing techniques. The results showed that the NARX model provided a lower forecasting error than the Holt-Winters model. The most appropriate structure for the NARX models was to use only the upstream water level gauge stations and gauge station to be predicted as discussed in [4]. Our results showed that the NARX network outperformed Holt-Winters forecasting method.

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