Machine Learning Model Development for Water Level Forecasting at P.1 Station, Chiang Mai Province

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Abstract

This research applies machine learning models to forecast water levels at the P.1 station (Nawarat Bridge), Chiang Mai Province, both for 6 and 9 hours in advance. The objectives are to identify suitable variables and to create models for forecasting water levels at the P.1 station. The study utilizes historical hourly water level data from the P.1 and P.67 stations, combined with Moving Average (MA) and Exponential Moving Average (EMA) data covering the years from 2017 to 2024, which has amounted to a total of 66,180 records. The dataset is divided into a training set (80%) and a testing set (20%). The experiment design involves creating artificial neural network models based on historical data from one station (P.1) and two stations (P.1 and P.67). The models consist of those using only historical data, those using historical data combined with MA, and those using historical data combine with EMA, resulting in a total of 12 models. The structure of each model was optimized to achieve the best forecasting results. The results indicate that the best model for the 6-hour forecasting is the P.1_6 + P.67_6 + EMA model. This model utilizes 18 input variables, with 6 and 2 nodes in the first and second hidden layers, respectively, and 1 output node. This model achieved a Mean Absolute Error (MAE) of 0.0405, a Root Mean Square Error (RMSE) of 0.0578, and a coefficient of determination (R^2) of 0.9859. For the 9-hour forecasting, the best model is the P.1_9 + P.67_9 + EMA model, which also employs 18 input variables, with 5 and 4 nodes in the first and second hidden layers, respectively, and one output node. This model achieved a MAE of 0.0562, an RMSE of 0.0776, and an R^2 of 0.9746. Both models utilize data from two stations combined with EMA.

Keywords: Water Level Forecast, Machine Learning, Artificial Neural Network, Exponential Moving Average

1. Introduction

Flooding is considered one of the most severe natural disasters, causing significant damage to human lives, agriculture, infrastructure, and social and economic systems. Consequently, studies on flood disaster management systems and flood forecasting have gained increased importance. Accurate forecasting of flood occurrences and their progression poses a considerable challenge. Estimating water levels and flow speeds over extensive areas necessitates the integration of data, and the development of flood propagation models, which involve complex computations [1]. Water level forecasting is essential for effective water resource management and flood prevention [2]. Especially in regions like Chiang Mai, which has experienced severe flooding events, including the major flood of 2011 [3] and the 2022 flood caused by Tropical Storm "Noru". The storm led to a significant increase in the water volume of tributaries of the Ping River. The Regional Irrigation Office 1 measured and recorded the water level at the P.1 station on October 3rd, 2022, at 03:00 AM to be 4.14 meters, which was 0.44 meters above the critical water level. With continuous inflow from upstream, the water level subsequently rose up to 4.30 meters [4]. The most recent flood in the city of Chiang Mai occurred on

October 5th, 2024, when the water level of the Ping River peaked at 5.28 meters. This measurement was 1.58 meters above the riverbank level and exceeded the critical flood barrier level of 4.20 meters by 1.08 meters [5]. This situation affected key economic areas within the Chiang Mai city municipality, leading to damage to living conditions, property, businesses, and urban infrastructure. Therefore, monitoring water levels in Chiang Mai's economic zones is essential. The public can access information on water levels at the P.1 station, which is located at Nawarat Bridge, and this serves as the most important monitoring point for flood situations along the Ping River as it flows through the city of Chiang Mai. This station provides crucial indicators of flood risks that impact vital economic areas in the urban center.

Currently, the Royal Irrigation Department utilizes data from the P.67 station through a telemetry system to forecast water levels at the P.1 station. When water levels at the P.67 station reaches 4 meters, and with a flow rate of 530 cubic meters per second, it is anticipated that within 6 to 7 hours that water will overflow into urban areas, resulting in the water level at the P.1 station to overflow the riverbank. The public can monitor nearby water levels through the Chiang Mai Office of Irrigation 1's website, and the SWOC mobile application [6]. However, there is currently no advanced water level forecasting system that using machine learning models. An accurate forecasting system would significantly enhance preparedness for all stakeholders: government agencies such as the Royal Irrigation Department could issue timely flood warnings, and effectively manage reservoirs and drainage systems. Chiang Mai Municipality could also prepare pumps and flood prevention equipment in advance; Disaster response units could plan evacuations proactively; businesses would have the opportunity to safeguard their assets and inventory; hotels and tourist attractions could warn visitors and prepare appropriate responses; industrial sectors could adjust production and logistics accordingly; and residents could evacuate, move valuables to safety, stockpile essential supplies, and plan alternative routes in anticipation of flooded roads.

Presently, machine learning models play a critical role in the developing of forecasting models, particularly in the field of hydrology [7]. This study involved the collection of historical water level data from the P.1 and P.67 stations. The water levels at P.1 station exhibit a strong correlation with those at P.67 [8], as P.67 station is situated on the main river and serves as the upstream station for P.1 station, as illustrated in Figure 1.

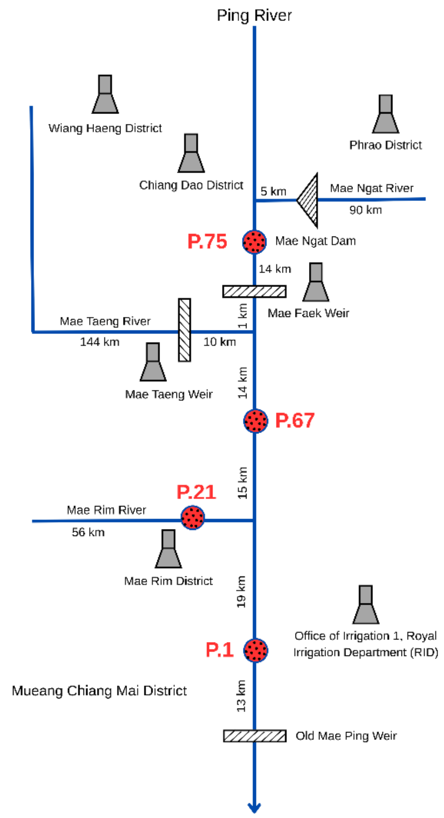

Figure 1. Hydrological diagram of the Ping River Basin [9]

Due to the geographical relationship between the two stations, the water level at the P.67 station significantly impacts the water level at the P.1 station. Consequently, data from the P.67 station is a critical variable for forecasting the water levels at the P.1 station [8]. The utilization of upstream data enhances the efficiency of forecasting models while reducing potential errors associated with relying solely on data from a single station. Therefore, data from the P.1 and P.67 stations are employed to develop an hourly water level forecasting model specifically for P.1 station, which provides forecasts at 6-hour and 9-hour intervals. The 6-hour forecast is designed to enable relevant agencies to prepare for and respond promptly to flooding events, while the 9-hour forecast serves as a mid-range projection to assist in flood disaster planning and efficient water resource management.

Additionally, time series analysis techniques were employed, specifically the Simple Moving Average (MA) and Exponential Moving Average (EMA) methods to reduce data volatility and filter out unwanted noise [10]. The MA method computes a simple average, whereas the EMA method assigns greater weight to more recent data, thereby making the forecasts more responsive to changes [11]. The MA and EMA techniques have been shown to enhance the predictive accuracy of machine learning models, as demonstrated in [12] and [13]. Furthermore, the Stepwise Regression method was employed to identify the most appropriate variables for the development of the forecasting model. This method is efficient in filtering independent variables from large datasets by considering those with the highest correlation to the outcome, and systematically adding or removing variables to determine the optimal set. This improves forecast accuracy and reduces model complexity, enabling faster and more efficient computation [14].

This research aims to develop a machine learning-based model to forecast water levels 6 and 9 hours in advance, leveraging data from MA and EMA of water levels at the P.1 and P.67 stations, along with the most up-to-date data for model creation and testing. While previous forecasting models at station P.1 employed the Moving Average (MA) approach to improve prediction accuracy [15], [16], the limitations of this method became evident during the 2024 flood event, when water levels fluctuated rapidly. To address this, this study proposes integrating EMA into the forecasting process, hypothesizing that EMA's ability to respond more effectively to rapid changes will enhance predictive accuracy. The results of this study will support the development of flood warning systems and water management strategies in the upper Ping River basin, enabling timely and effective decision-making. Additionally, the model will aid businesses in risk management, reducing asset losses, and improving operational efficiency and sustainability, particularly in transportation, goods handling, and production planning.

This research aims to study the following objectives:

To identify the appropriate variables for forecasting the water level at Station P.1 (Nawarat Bridge), Chiang Mai Province, using historical water level data from Station P.1 and P.67, as well as MA and EMA values.

To develop an artificial intelligence model for forecasting the water level at Station P.1 for 6-hour and 9-hour ahead predictions, comparing the accuracy of the model using data from a single station with the model using data from two stations, and considering the effect of using MA and EMA to enhance the model's performance.

2. Literature Review

2.1. Moving Average Techniques (MA and EMA)

Time Series Analysis is an essential tool in finance, economics, and engineering for understanding data that changes over time. Among the various techniques used, Moving Average is widely adopted to smooth out data fluctuations, making underlying trends more visible [10].

- Simple Moving Average (MA) calculates the average of data over a specific period by assigning equal weights to all data points. While simple to use and interpret, MA tends to respond slowly to data changes as it gives equal importance to all data, regardless of recency [17].
- Exponential Moving Average (EMA) assigns greater weight to more recent observations, allowing it to respond more quickly to new trends. This makes EMA particularly useful for rapidly changing data [11] such as stock prices or water levels during storms.

2.2. Application of MA and EMA in Neural Network Models

MA and EMA have been applied to enhance the performance of ANN, particularly during the preprocessing phase of time-series modeling.

- A 5-day MA combined with ANN and Particle Swarm Optimization (PSO) was implemented for stock price forecasting. The use of MA as a preprocessing technique significantly improved model accuracy [12].
- EMA was combined with Neural Networks to forecast wireless channel quality based on the Frame Delivery Ratio. The EMA-enhanced model reduced Mean Squared Error (MSE) by 20-30%, particularly in scenarios involving sudden and nonlinear signal variations [13].

2.3. Forecasting Models

- Streamflow forecasting at the Huanren station in China was investigated using both individual models-Long Short-Term Memory (LSTM), Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN)- and hybrid models incorporating signal decomposition techniques such as Empirical Mode Decomposition-LSTM (EMD-LSTM), Variational Mode Decomposition-LSTM (VMD-LSTM), and Wavelet Analysis-LSTM (WA-LSTM). LSTM showed the highest accuracy among single models, particularly during high-flow days, while VMD-LSTM outperformed other hybrid models in all performance metrics, achieving the lowest RMSE (52.14 m^3/s), the highest NSE (0.96), and the lowest BIAS (-0.002) during testing [18].

The study highlighted that signal decomposition (e.g., VMD) can effectively remove noise and isolate critical frequency components, thereby enhancing model performance significantly. Table 1 represents the strengths and limitations of the models.

Table 1 Comparison of Models

Model	Strengths	Limitations
LSTM	Excellent for time series, high accuracy, retains long-term dependencies	Complex structure, long training time
SVM	Suitable for linear/separable data, good with balanced datasets	Poor for large or nonlinear datasets, requires kernel selection
RF	Robust to noise/outliers, user-friendly, avoids overfitting	Lower accuracy in sequential data
ANN	Flexible architecture, broadly applicable, low overall bias	Sometimes less accurate for time series compared to LSTM

2.4. Water Level Forecasting at P.1 Station, Chiang Mai

Artificial Neural Networks (ANNs) were applied to forecast water levels at the P.1 station in northern Thailand using historical hourly water levels from stations P.1, P.67, and P.75, along with dam discharge data and corresponding MA values [15]. A comparison of learning algorithms-Levenberg-Marquardt (LM) and Bayesian Regularization (BR)-revealed that the LM algorithm with 75% hidden nodes provided the best performance for both 6- and 12-hour ahead forecasts.

A subsequent study compared ten ANN training algorithms, including LM, BR, Gradient Descent with Momentum and Adaptive Learning Rate (GDX), Resilient Backpropagation (RP), Broyden-Fletcher-Goldfarb–Shanno (BFG), and Scaled Conjugate Gradient (SCG) [16]. LM consistently delivered the highest accuracy for short-term forecasting (t+6 hours), followed by BR. The number of hidden nodes had minimal impact on performance, except for longer forecast horizons (t+18 hours).

2.5. Research Gap

To date, there has been no study that utilizes historical water level data from only two stations (P.1 and P.67) in combination with EMA-transformed data for short-term forecasting at station P.1. This study addresses this gap by minimizing the number of input sources while leveraging EMA to enhance the performance of an ANN. Focusing on a smaller number of well-processed inputs helps mitigate the risks associated with missing or erroneous data, thereby improving the reliability of the model. The EMA's responsiveness to short-term signal changes makes it a suitable choice for increasing model accuracy in such contexts.

This study differs from previous works [15], [16] in that it employs input data from only two stations (P.1 and P.67) and applies EMA for forecasting enhancement, whereas those studies used data from three stations-P.1, P.67, and P.75-as well as dam discharge volumes and MA of dam discharge.

3. Materials and Methods

3.1. Research Data

The hourly water level data from the P.1 and P.67 stations, collected from April 2017 to October 2024, comprise a total of 66,180 data points (Figure 2). These timeframes were selected for their completeness and reliability, characterized by nearly complete data coverage with only minimal data loss. This selection was made to minimize potential errors in calculating the MA and EMA values. Secondary data used for research purposes were collected by the Upper Northern Hydrology Center of the Royal Irrigation Department (Irrigation Office 1, Chiang Mai) [6]. Notable flooding events occurred from October 2nd to 5th, 2022, September 24th to 28th, 2024, and from October 3rd to 7th, 2024.

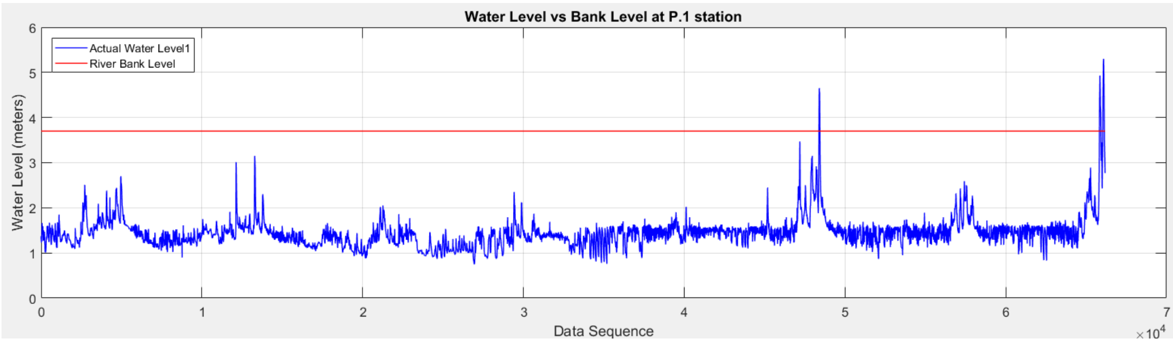

Figure 2. Hydrograph of data from April 2017 to October 2024

3.2. Research Tools

The tools used in this research include:

1) Microsoft Excel for data collection and preparation.

2) MATLAB for processing artificial neural network models.

3) SPSS for variable selection using Stepwise regression

3.3. Data Preparation

1) The water level data from the P.1 and P.67 stations were stored for the past 0 to 24 hours with variable names P1t-0 to P1t-24 and P67t-0 to P67t-24 in decimal format with two decimal places.

2) The Moving Average (MA) is a statistical method used to calculate the average water level over a specific period. This technique facilitates the identification of water level trends by smoothing out short-term fluctuations and reducing data variability. The MA method is also commonly applied in various fields, particularly in financial markets such as stocks, cryptocurrencies. MA water level data for the P.1 and P.67 stations were prepared for the past 0 to 24 hours, with each time point (t) representing the calculation of the hourly moving average of water levels over a period of *k* hours, where *k* ranges from 2 to 24. The formula for calculating the MA water level data [19] is as follows.

$$MA_{t,k}=\left(P_t+P_{t-1}+\ldots+P_{t-(k-1)}\right)/k \tag{1}$$

3) The Exponential Moving Average (EMA) is a technical analysis tool similar to the MA and is widely used in financial markets such as stocks and cryptocurrencies. While it shares similarities with the MA, a key distinction is that the EMA assigns greater weight to more recent data, allowing it to respond more quickly to changes in the dataset. Therefore, in this study, the EMA is utilized alongside historical water level data to forecast future water levels. Furthermore, the study compares the forecasting performance between using only historical water level data and using historical data in conjunction with the MA. EMA water level data for the P.1 and P.67 stations were prepared for the past 0 to 24 hours, with each time point representing the calculation of the hourly EMA of water levels over a period ranging

from 2 to 24 hours. The formula for calculating the EMA water level data [20] is as follows.

$$EMA_t=\left(P_t\times\frac{2}{n+1}\right)+EMA_{t-1}\left(1-\frac{2}{n+1}\right) \quad (2)$$

3.4. Variable selection

Variable selection was performed using Stepwise Regression [21] to create a total of 12 forecasting models from the prepared dataset.

3.5. Model Development

The machine learning models in this study were developed using an Artificial Neural Network (ANN) with a Feed-Forward Back Propagation (FFBP) technique [22]. The Feedforward Neural Network (FFNN) is a type of ANN in which data flows in one direction, from the input layer to the output layer. The input layer receives external data, with the number of neurons determined by the number of features or variables relevant to the learning and forecasting tasks. The hidden layers process the input data through the application of activation functions, such as sigmoid, tanh, and ReLU. The configuration of these layers, including the number of neurons in each, must be appropriately selected based on the specific problem under investigation. The hidden layers enable the network to model complex, nonlinear relationships, which is particularly important for tasks such as water level forecasting. The output layer provides the final prediction, with a single neuron representing the forecasted water level in this study. The training process employs the backpropagation technique, which adjusts the weights and biases within the network to minimize the discrepancy between the predicted outputs and the actual target values, ensuring optimal accuracy in the final results.

Each model in this study was constructed using the "newff" package. The parameters of each model were set as follows [15], [16], [23].

- Learning function: trainlm
- Hidden layer activation function: tanh
- Output layer activation function: purelin
- Maximum epochs: 1,000
- Learning goal (target): 1e-5

To obtain the most suitable model for each dataset, the number of nodes in the input layer for each model was determined based on the number of features, which were selected through the Stepwise Regression process. The number of hidden layers was limited to a maximum of two to prevent excessive consumption of computational resources, while still maintaining a sufficiently high level of forecasting performance. For determining the number of nodes in each hidden layer, a trial-and-error method was employed [15], [16]. The first hidden layer was assigned a range of 1 to 20 neurons, while the second hidden layer was set to none, with the number of neurons also ranging from 1 to 20, to find the most appropriate network structure.

Each dataset is divided into 80% for training and 20% for testing [24], using a chronological split method that preserves the natural time order from April 2017 to October 2024. The goal is to identify the most efficient model for forecasting 6 and 9 hours ahead. The models evaluated for performance comparison are as follows:

3.5.1 Six-Hour Ahead Water Level Forecasting Models for the P.1 station

- Data from P.1 (P.1_6)
- Data from P.1 and MA (P.1_6 + MA)
- Data from P.1 and EMA (P.1_6 + EMA)
- Data from P.1 and P.67 (P.1_6 + P.67_6)
- Data from P.1, P.67, and MA for both stations (P.1_6 + P.67_6 + MA)
- Data from P.1, P.67, and EMA for both stations (P.1_6 + P.67_6 + EMA)

3.5.2 Nine-Hour Ahead Water Level Forecasting Models for the P.1 station

- Data from P.1 (P.1_9)
- Data from P.1 and MA (P.1_9 + MA)
- Data from P.1 and EMA (P.1_9 + EMA)
- Data from P.1 and P.67 (P.1_9 + P.67_9)
- Data from P.1, P.67, and MA for both stations (P.1_9 + P.67_9 + MA)
- Data from P.1, P.67, and EMA for both stations (P.1_9 + P.67_9 + EMA)

3.6. Model Evaluation

The performance of the models was evaluated based on the following metrics

- Mean Absolute Error (MAE)

It is an indicator used to calculate the Mean Absolute Error (MAE) of forecast values compared to actual values [25], computed using the formula.

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|y_i-\hat{y}_i\right| \tag{3}$$

-Root Mean Square Error (RMSE)

It is a metric used to measure the deviation between predicted and actual values, giving more weight to larger errors by squaring the deviations before averaging and then taking the square root [25].

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2} \tag{4}$$

-R-squared (R^2)

It is a metric used to measure how well the predicted data explains the variance of the actual values [26]. It ranges between 0 and 1 and is calculated using the formula.

$$R^2=1-\frac{\sum(y_i-\hat{y}_i)^2}{\sum(y_i-\bar{y})^2} \tag{5}$$

The MAE and RMSE values should be as low as possible, while the R^2 value should be as high as possible (close to 1) to indicate that the model can explain the variability in the data effectively [27].

4. Results and Discussion

4.1. Results of Variable Selection Using Stepwise Regression

Variable selection for model development was conducted using Stepwise Regression, starting with no independent variables and progressively adding them one at a time based on their significance in explaining the dependent variable, according to predefined criteria. The results of the variable selection for each forecasting model are as follows: Model P.1_6 included 7 variables; Model P.1_6 + MA included 10 variables; Model P.1_6 + EMA included 8 variables; Model P.1_6 + P.67_6 included 16 variables; Model P.1_6 + P.67_6 + MA included 19 variables; Model P.1_6 + P.67_6 + EMA included 18 variables; Model P.1_9 included 7 variables; Model P.1_9 + MA included 8 variables; Model P.1_9 + EMA included 9 variables; Model P.1_9 + P.67_9 included 17 variables; Model P.1_9 + P.67_9 + MA included 18 variables; and Model P.1_9 + P.67_9 + EMA included 18 variables. The selected variables for each model are summarized in Table 2.

Table 2 Results of Variable Selection for Forecasting Models Using Stepwise Regression

Model	Variable Selection		
P.1_6	P1t-0	P1t-1	P1t-2
	P1t-3	P1t-12	P1t-19
	P1t-24		
P.1_6 + MA	P1t-0	P1t-1	P1t-3
	P1t-12	P1t-0_MA2	P1t-0_MA18
	P1t-18_MA24	P1t-23_MA11	P1t-24_MA3
	P1t-24_MA24		
P.1_6 + EMA	P1t-0	P1t-0_EMA2	P1t-0_EMA4
	P1t-1_EMA2	P1t-1_EMA3	P1t-12EMA24
	P1t-14_EMA20	P1t-20_EMA3	
P.1_6 + P.67_6	P1t-0	P1t-1 P1t-2	P67t-24
	P1t-3	P1t-12	P1t-19
	P1t-24	P67t-0	P67t-1
	P67t-5	P67t-6	P67t-7
	P67t-8	P67t-9	P67t-12
P.1_6 + P. 67_6 + MA	P1t-0	P1t-1_MA2	P1t-2
	P1t-3	P1t-12_MA3	P1t-13_MA22
	P1t-18_MA2	P1t-20_MA2	P1t-24_MA20
	P1t-24_MA24	P67t-0	P67t-0_MA2
	P67t-0_MA9	P67t-1_MA16	P67t-5_MA2
	P67t-7_MA2	P67t-18_MA22	P67t-24_MA5
	P67t-24_MA24		
P.1_6 + P. 67_6 + EMA	P1t-0	P1t-0_EMA23	P1t-1_EMA2
	P1t-4	P1t-2	P1t-10_EMA5
	P1t-19	P1t-20_EMA9	P1t-24_EMA3
	P1t-24_EMA24	P67t-0_EMA2	P67t-0_EMA5
	P67t-6	P67t-7_EMA6	P67t-20_EMA18
	P67t-23_EMA24	P67t-24_EMA3	P67t-24_EMA20
P.1_9	P1t-0	P1t-1	P1t-2
	P1t-3 P1t-24	P1t-12	P1t-17
P.1_9 + MA	P1t-0	P1t-1	P1t-1_MA2
	P1t-3	P1t-10_MA3	P1t-13_MA24
	P1t-21_MA11	P1t-24_MA2	
P.1_9 + EMA	P1t-0	P1t-1_EMA2	P1t-2
	P1t-4_EMA2	P1t-12_EMA24	P1t-14_EMA18
	P1t-14_EMA21	P1t-18_EMA9	P1t-24_EMA2
P.1_9 + P.67_9	P1t-0	P1t-1	P1t-2
	P1t-3	P1t-12	P1t-16
	P67t-0	P67t-1	P67t-3
	P67t-4	P67t-5	P67t-6
	P67t-7	P67t-8	P67t-9
	P67t-11	P67t-24	
P.1_9 + P. 67_9 + MA	P1t-0	P1t-0_MA2	P1t-0_MA20
	P1t-1_MA2	P1t-2	P1t-7_MA2
	P1t-11_MA6	P1t-17_MA3	P1t-24_MA7
	P1t-24_MA24	P67t-0	P67t-3_MA2
	P67t-3_MA10	P67t-5_MA2	P67t-7_MA2
	P67t-24_MA3	P67t-24_MA13	P67t-24_MA24
P.1_9 + P. 67_9 + EMA	P1t-0	P1t-1_EMA2	P1t-2_EMA14
	P1t-5	P1t-9	P1t-13_EMA_3
	P1t-17	P1t-21_EMA_12	P1t-23_EMA_5
	P67t-0	P67t-1	P67t-3
	P67t-4_EMA_8	P67t-8_EMA_2	P67t-17_EMA_3
	P67t-21	P67t-24_EMA_21	P67t-24_EMA_24

The meanings of the variables listed in Table 2 are further explained in Table 3, which provides descriptions of each variable used in the study.

Table 3 Definitions of the variables.

Variable Type	Description
Pnt-k	Water level at station *Pn* at *t-k* hours prior to the current time, where *Pn* represents the station code (i.e., P1 or P67), and *t-k* indicates the time lag of *k* hours from the present.
Pnt-k_MAp	Moving Average (MA) of the water level at station *Pn*, calculated from time *t-k* to *t-k-(p-1)*, totaling *p* values.
Pnt-k_EMAq	Exponential Moving Average (EMA) of the water level at station *Pn*, starting from time *t-k* and using *q* past values (or *q* periods).

4.2. Results of Water Level Forecasting Models for Station P.1

The Feed-Forward Back Propagation (FFBP) artificial neural network was used to develop forecasting models for the water level at the P.1 stations, both for 6-hour and 9-hour forecasts, using data from either one station (P.1) or two stations (P.1 and P.67). The models varied in terms of the number of nodes in the input layer, the number of hidden layers, the number of nodes in the hidden layers, and the number of nodes in the output layer, as shown in Table 4.

Table 4 Structures of Forecasting Models for Station P.1

Model	**Input layer**	**Hidden layer**		**Output layer**
		1	**2**	
P.1_6	7	7	-	1
P.1_6 + MA	10	6	4	1
P.1_6 + EMA	8	6	3	1
P.1_9	7	6	-	1
P.1_9 + MA	8	6	2	1
P.1_9 + EMA	9	6	2	1
P.1_6 + P.67_6	17	7	-	1
P.1_6 + P.67_6 + MA	19	6	-	1
P. 1_6 + P. 67_6 + EMA	18	6	2	1
P.1_9 + P.67_9	17	6	2	1
P.1_9 + P.67_9 + MA	19	6	1	1
P.1_9 + P.67_9 + EMA	18	5	4	1

4.3. Results of the 6-Hour Water Level Forecasting Models for Station P.1

Upon analyzing the hydrograph lines for the 6-hour forecast, as illustrated in Figures 3-5 (where the green line represents the model utilizing data from two stations, and the red line represents the model utilizing data from one station), it was determined that the model using data from two stations provided better forecast results. A comparison of the use of water level data with MA and EMA data revealed that the model employing water level data combined with MA could forecast higher peak water levels than the model using water level data alone (Figure 4, green line). However, when water level data was combined with EMA, the model's ability to forecast peak water levels improved (Figure 5, green line). Additionally, for the model using data from only one station, adding EMA data enhanced the model's performance (Figure 5, red line). Therefore, based on the hydrograph analysis, the model that combined water level data with EMA from two stations (P.1_6 + P.67_6 + EMA) was selected as the best model. This conclusion is consistent with the statistical comparison results shown in Table 5.

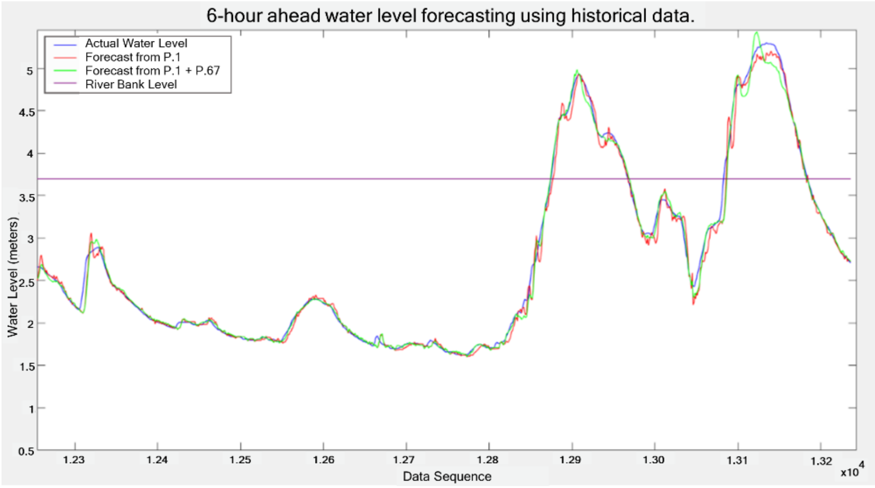

Figure 3 Comparison of the forecasting results between the P.1_6 model and the P.1_6 + P.67_6 model

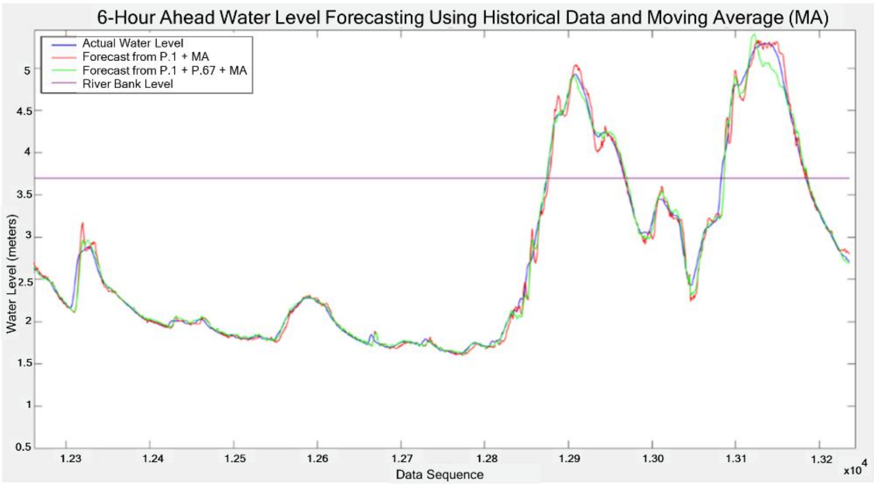

Figure 4 Comparison of the forecasting results between the P.1_6 + MA model and the P.1_6 + P.67_6 + MA model

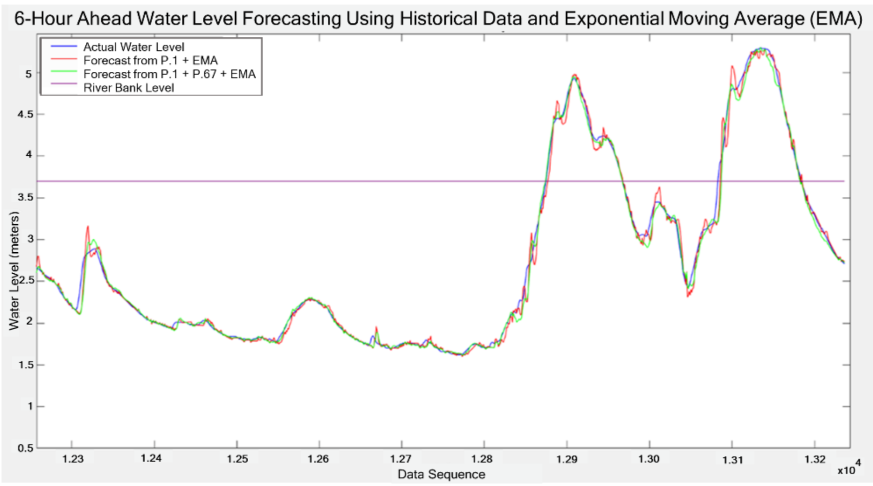

Figure 5 Comparison of the forecasting results between the P.1_6 + EMA model and the P.1_6 + P.67_6 + EMA model

4.4. Results of the 9-Hour Water Level Forecasting Model for Station P.1

The forecasting results for the 9-hour water level forecasting at the P.1 station are presented in Figure 6, where the red line represents data from one station and the green line represents data from two stations. It was observed that using data from one station provided better forecasts, particularly for predicting the peak water levels, compared to using data from two stations. However, when actual data was combined with MA and EMA data (Figures 7 and 8, respectively), it was found that the models using data from both one station and two stations showed improved performance, especially the models that used data from two stations (Figures 7-8). Adding EMA data to the two-station model continued to yield the best overall results (Figure 8), which is consistent with the statistical comparison results presented in Table 6.

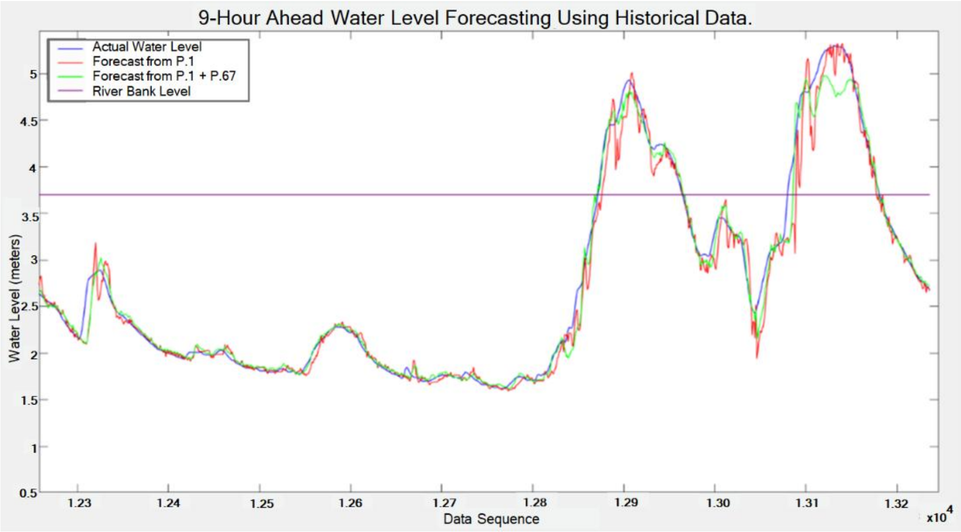

Figure 6 Comparison of the forecasting results between the P.1_9 model and the P.1_9 + P.67_9 model

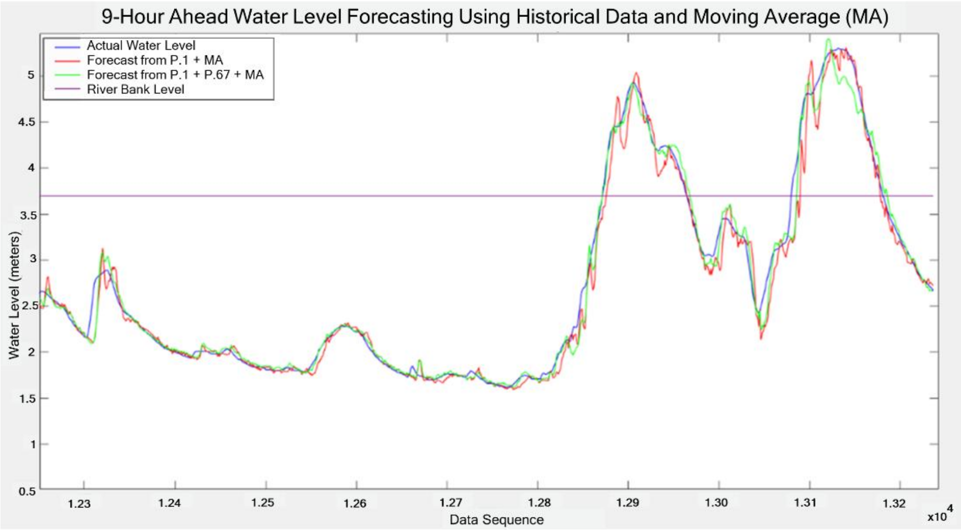

Figure 7 Comparison of the forecasting results between the P.1_9 + MA model and the P.1_9 + P.67_9 + MA model

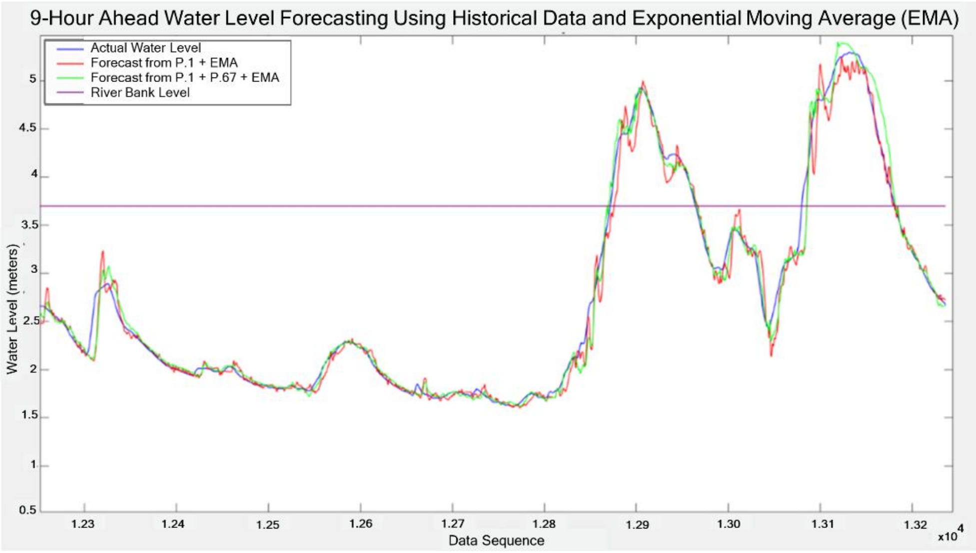

Figure 8 Comparison of the forecasting results between the P.1_9 + EMA model and the P.1_9 + P.67_9 + EMA model

4.5. Comparison of the Performance of the 6-Hour Water Level Forecasting Model for Station P.1

The results of comparing the 6-hour water level forecasting models for the P.1 station showed that the model P.1_6 + EMA performed the best for the single station (P.1), as it yielded the lowest MAE, RMSE, and the highest R^2. This was followed by the P.1_6 + MA model, and then the P.1_6 model. For the two-stations model (P.1 and P.67), the P.1_6 + P.67_6 + EMA model showed the best performance, with the lowest MAE, RMSE, and the highest R^2, followed by the P.1_6 + P.67_6 + MA model and the P.1_6 + P.67_6 model, respectively. Additionally, the models using data from two stations outperformed those using data from only one station. Therefore, the P.1_6 + P.67_6 + EMA model is considered the most suitable for forecasting the 6-hour water level at Station P.1, as shown in Table 5.

Table 5 MAE, RMSE, and R^2 values for the 6-hour water level forecasting model for Station P.1

Model	**Performance**		
	MAE	**RMSE**	**R^2**
P.1_6	0.0470	0.0679	0.9805
P.1_6 + MA	0.0461	0.0675	0.9808
P.1_6 + EMA	0.0447	0.0655	0.9818
P.1_6 + P.67_6	0.0412	0.0587	0.9854
P.1_6 + P.67_6 + MA	0.0410	0.0582	0.9857
P.1_6 + P.67_6 + EMA	0.0405	0.0578	0.9859

4.6. Comparison of the Performance of the 9-hour Water Level Forecasting Model for Station P.1

The comparison of the 9-hour water level forecasting models for the P.1 station, using data from only P.1 station, revealed that the model P.1_9 + EMA performed the best performance, with the lowest MAE, RMSE, and the highest R^2, followed by the P.1_9 + MA model, and then the P.1_9 model, respectively. For models using data from the P.1 and P.67 stations, the P.1_9 + P.67_9 + EMA model provided the best results, followed by the P.1_9 + P.67_9 + MA model, and then the P.1_9 + P.67_9 model. Additionally, the group of models using data from two stations performed better than those using data from only one station. Therefore, the P.1_9 + P.67_9 + EMA model demonstrated the best performance and is the most suitable for forecasting the 9-hour water levels at Station P.1, as shown in Table 6.

Table 6 MAE, RMSE, and R^2 values for the 9-hour water level forecasting model for Station P.1

Model	**Performance**		
	MAE	**RMSE**	**R^2**
P.1_9	0.0649	0.0939	0.9628
P.1_9 + MA	0.0657	0.0933	0.9456

P.1_9 + EMA	0.0643	0.0908	0.9652
P.1_9 + P.67_9	0.0572	0.0798	0.9732
P.1_9 + P.67_9 + MA	0.0568	0.0779	0.9744
P.1_9 + P.67_9 + EMA	0.0562	0.0776	0.9746

5. Conclusions

This study investigates the development of machine learning models for forecasting the water levels 6-hour and 9-hour ahead at the P.1 station. The primary objectives were to identify appropriate variables for forecasting water levels at the P.1 station, and to create the most suitable machine learning models for forecasting water levels at the same station for 6-hour and 9-hour periods. The results are summarized as follows:

Using data from the P.1 and P.67 stations showed better accuracy forecasting for both the 6-hour and 9-hour forecasts compared to using data from the P.1 station alone. Additionally, the inclusion of supplementary variables using EMA and MA techniques improved forecasting performance when compared to using only past water level data. Among these, EMA provided better improvement in model performance than MA.

For model development, the study used a Feed-Forward Back Propagation (FFBP) Artificial Neural Network (ANN) based on data from either one station (P.1) or two stations (P.1 and P.67). EMA and MA techniques were used to compare model performance, and variable selection was performed using Stepwise Regression.

For the 6-hour water level forecasting, the P.1_6 + P.67_6 + EMA model demonstrated the best performance, with the model structure comprising 18 input nodes; 6 and 2 nodes in the two hidden layers, and 1 output node. The model used 18 variables, including data from P.1 (P1t-0, P1t-2, P1t-4, P1t-19), EMA variables for P.1 (P1t-0_EMA23, P1t-1_EMA2, P1t-10_EMA5, etc.), data from P.67 (P67t-6, P67t-20), and EMA variables from P.67. This model achieved MAE = 0.0280, RMSE = 0.0431, and R^2 = 0.9780 for the training dataset, and MAE = 0.0405, RMSE = 0.0578, and R^2 = 0.9859 for the testing dataset. These are the best values among the models for 6-hour forecasting.

For the 9-hour water level forecasting, the P.1_9 + P.67_9 + EMA model achieved the best performance, with the model structure consisting of 18 input nodes, 4 nodes in each of the two hidden layers, and 1 output node. The model used 18 variables, including data from P.1 (P1t-0, P1t-5, P1t-9, P1t-17), EMA variables for P.1 (P1t-1_EMA2, P1t-2_EMA14, etc.), data from P.67 (P67t-0, P67t-1, P67t-3, P67t-21), and EMA variables for P.67. This model produced MAE = 0.0387, RMSE = 0.0564, and R^2 = 0.9627 for the training dataset, and MAE = 0.0562, RMSE = 0.0776, and R^2 = 0.9746 for the testing dataset. These were the best values for the 9-hour forecasting models.

In conclusion, the models for forecasting 6-hour and 9-hour water levels using past data from two stations combined with EMA performed better overall than those using past data from a single station alone or in combination with MA. Additionally, the 6-hour forecast models showed higher accuracy than the 9-hour forecast models.

For forecasting water levels at station P.1 six hours in advance, the best-performing model presented in this research utilized hourly historical water level data from two stations, P.1 and P.67, combined with the EMA of the historical water level data from both stations. This model produced forecasts consistent with the model proposed in [16], which used hourly historical data from stations P.1, P.67, P.75, and the water discharge volume from a dam, along with the MA of the dam's discharge volume. That model achieved an RMSE of less than 0.1 for 6-hour-ahead forecasting. In contrast, the study in [16] did not include a 9-hour-ahead forecast. However, the model proposed in this study still achieved an RMSE of less than 0.1 even at the 9-hour forecast horizon.

The reason why using data from two stations yields better results than using data from only one station is due to the direct correlation between P.1 and the upstream station P.67, which is located approximately 32 kilometers away. The water mass takes about 6–7 hours to travel from P.67 to P.1 [28]. Therefore, incorporating historical hourly water level data from both stations for forecasting water levels at P.1 6–9 hours in advance is likely to result in more accurate predictions compared to using data from only P.1.

In addition, using historical hourly water level data from P.1 and P.67 along with the EMA of the historical data from both stations provided better performance than using MA or raw historical data alone. This is because EMA is more responsive to short- and medium-term changes in data [11], making it suitable for trend analysis in such timeframes. EMA assigns greater weight to the most recent data and gradually reduces the weight for older data, whereas MA gives equal weight to all data points (refer to Equations 1 and 2). On the other hand, using only the historical hourly water level data from P.1 and P.67 without any smoothing technique yielded the lowest performance, as the burden of learning trends fell solely on the Artificial Neural Network (ANN). Improving the model's performance in such cases would depend heavily on adjusting the architecture and hyper parameters. Therefore, the most appropriate model for forecasting 6- and 9-hour-ahead water levels at station P.1 is the one that uses historical hourly water level data from both P.1 and P.67 combined with the EMA of historical water level data from both stations—an approach not previously reported for model development at station P.1.

Practical Applications

The forecasting model for water levels at station P.1 proposed in this study can be effectively applied to flood warning systems in the urban area of Chiang Mai Province. One of its key advantages is the simplicity of the artificial neural network (ANN) architecture, which consists of only an input layer, a hidden layer, and an output layer. This streamlined structure enables faster processing compared to models with more complex architectures, facilitating easier development into practical applications.

Furthermore, using data from only two stations helps mitigate issues related to data loss, which often arise when relying on multiple data sources and can hinder model performance. The developed model can also be integrated to enhance previously developed flood warning applications [29], improving both forecasting accuracy and the overall efficiency of the warning system.

The practical implementation of this model is expected to increase the safety of residents in Chiang Mai's urban area by providing more reliable flood warnings, thereby protecting lives and property. Additionally, it can significantly reduce the overall economic losses caused by flooding, contributing to improved quality of life and economic stability within the community.

Suggestions for Future Research

- For the 9-hour water level forecasting models, it is recommended to include data from additional upstream stations to further improve forecasting accuracy.
- It would be beneficial to experiment with combining both MA and EMA data to compare forecasting performance.
- Other variable selection techniques should be explored alongside ANN models to further enhance the water level forecasting models and compare their effectiveness.
- Consideration could be given to using other deep learning models for water level forecasting and comparing their forecasting performance with the current models.

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