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Flood Forecasting with Machine Learning Technique on Hydrological Modeling

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Abstract

Urban flooding is a major problem in Thailand. An essential countermeasure towards better flooding management is to forecast flood water levels in the real-time manner. Most existing early warning systems (EWS) in Thailand contain a lot of miscalculations when they face with real situations. Towards prediction improvement, this paper presents hydrological modeling augmented with alternative five machine learning techniques; linear regression, neural network regression, Bayesian linear regression and boosted decision tree regression. As the testbed system, the so-called MIKE-11 hydrologic forecasting model, developed by Danish Hydraulic Institute (DHI), Denmark, is used. To test error reduction in runoff forecasting, the water-level records during 2012-2016 data are used for training and the derived model is tested on the record of 2017, in the experiments.

Keywords: Flood forecasting; Machine learning; Yom river

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1. Introduction

The flooding problem in Thailand normally happens due to heavy rainfall which overflows from the Yom River in the middle of the rainy season in the floodplain area between the middle part and the lower part of the basin, especially in Sukhothai, Phitsanulok, Phichit, and Nakhon Sawan Provinces. Furthermore, after the problem of flooding happens, it is then followed by drought occurring in the dry season. Besides this, due to many non-negotiable problems of landowners at the dam site, local people have resisted the plan for the dam construction [13]. As a result, the construction of a huge dam for challenging flood and drought problems in the upstream area of this river is not possible.

This study focuses on the natural river without human buildings. The study area is the main basin in Thailand, the Chao Phraya basin. We focused on the Yom River, one of four headwaters of the Chao Phraya River, which flows from north to south. There are 7 significant water stations located from the upper Yom River to Sukhothai City, namely Y.20, Y.1C, Y.6, Y.3A, Y.33, and Y.4. Station Y.1C is the flood monitoring station of this area. The study aimed at forecasting runoff at Y.1C station then used the results to predict water levels at Y.4 in Sukhothai City. [10]

From a previous study [6], it was found that some machine learning techniques, for example, Bayesian linear regression, Neural Network, Decision Forest, Boosted Decision Tree and Linear Regression can be used for forecasting errors. In this study, a machine learning technique to forecast errors in runoff simulations was developed. It was expected that the hybrid model based on MIKE11 and a machine learning technique could give better runoff forecasting than only a single model MIKE11 [15].

A current warning system in Thailand is presented in Figure1. However, there are many limitations in the current flood forecasting system. The implementation of flood preparedness and planning is only one level, not a full system. There is also a weakness in the database system involved in risky areas; therefore, it is not complete enough. It is important to plan for the readiness of the disaster to minimize damage, especially in urban areas with high economic importance. The development of a flood preparedness system is to make it more effective in responding to flood disasters in a timely manner. This system is needed to be the center of information for Sukhothai Province, which holds the main responsibility for flood forecasting. It can also be used in planning decision-making for actions to be taken before the disaster. During and after the disaster, the system must be easily accessible for people to use to alleviate flooding as well. Sukhothai Province, one of the provinces that has experienced flooding over the past 10 years, has a flooded area at Kong Kra Klang, which is a water catchment area where villagers do fishing in the rainy season. It is also flooded in the areas of Pak Mueang, Muang and Thanee Districts. Sukhothai Province is located in Muang District, and it is a commercial area, which is situated along the main riverbanks. At present, there is a flap nearly 2 meters high built in front of Sukhothai City Hall to prevent flooding [9].

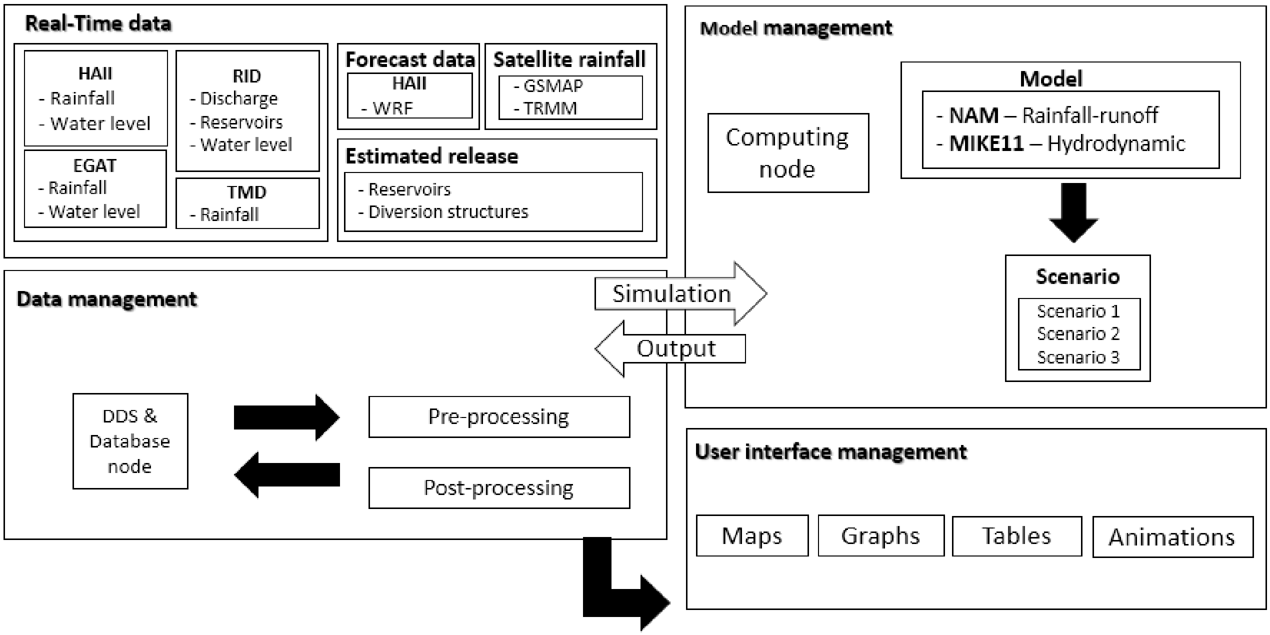

Fig. 1The current flood warning system in Thailand.

The main problem of many canals is their connection. Some six-bay canals also lack water delivery capacity and excess water flows down the old river. The canals also have many branches and in some of them the water cannot pass by. Some areas of the canals are taken and occupied by public enterprises and some of them are very wide. Nowadays, there are some small canals within canals and some drains are higher than the water level. Therefore, some cannot drain the water effectively. Besides this, there are many water sources from all directions flowing into Sukhothai Province. The Yom River flows from Phrae while it receives water from the Ping River from Kamphaeng Phet Province, and then all the water flows to Khiri-Mart District in Sukhothai. In addition, Sukhothai also receives a lot of water from the Mae Tha Phae Reservoir at Sri Satchanalai District and from West Mae Mok Reservoir at Wiang Mok in Thin District, Lampang Province. Consequently, it is very necessary to have good water management and stable EWS in this area [1].

At present, the flood monitoring systems and stakeholders in Thailand include HAII Hydro and Agro Informatics Institute, RID Royal Irrigation Department, EGAT Electricity Generating Authority of Thailand and TMD Thai Meteorological Department.

2. MIKE 11

The MIKE11 model or forecasting model is a model used to calculate the level of water or a stream flowing at a point of interest at the location of a waterway station at the time specified by the model. MIKE11 has a special ability to adjust the results of the calculation. It is the same as the NAM / HD water meter model with the measured value (Observe). The user only specifies the time of forecast (TOF), which determines the time required to prepare the hydrological data for the model, and the time-period for which the forecast is to be made. Each time the water is called Runtime. It is divided into two time-periods, which are then divided into TOF times. [2].

- Hindcast Period the TOF is a time-sensitive, hydrologic period. Measurement data from all stations, if the data are accurate and reliable, the forecast period is very accurate as well.
- Forecast Period the TOF is a time-period in which the model estimates the boundary value, i.e. the amount of rain or flow during the forecast period. The model is used as a boundary condition.

Equation use in MIKE NAM are Semi – Empirical as below;

$$P_N = U - U_{max} \quad (1)$$
$$QOF = P_N \times CQ_{OF} \frac{L/L_{max} - TOF}{1-TOF} \quad (2)$$
$$QIF = U \times \frac{1}{CQ_{IF}} \times \frac{L/L_{max} - TIF}{1-TIF} \quad (3)$$
$$Inf. = P_N - Q_{OF} \quad (4)$$
$$G = (P_N - Q_{OF}) \times \frac{L/L_{max} - TG}{1-TG} \quad (5)$$
$$DL = (P_N - QOF) - G \quad (6)$$
$$BF = (GWLBF_O - GWL) \times \frac{S_y}{CK_{BF}} \quad (7)$$
$$Q_t = OF_t + IF_t + BF_t \quad (8)$$

PN = Excess water (mm.); U = Water content in surface storage (mm.); Umax = Water contain in surface storage (mm.); QOF = Overland flow (m^3/s); CQOF = Overland flow runoff coefficient (0-1);L = Water content in root zone storage(mm.); Lmax = MaxWater content in root zone storage(mm.); TOF = Root zone threshold value for overland flow (0-0.99); QIF = Interflow (m^3/s); CKIF = Time constant for routing interflow (hr.); TIF = Root zone threshold value for interflow (0-0.99); Inf. = Infiltation; G = Percolation; TG = Portion of infiltration increase in root zone; BF = Baseflow (m^3/s); CKBF = Time constant for routing base flow (hr.);Sy = Specific yield of groundwater reservoir; GWLBF0 = Threshold groundwater depth for baseflow; GWL = Groundwater table below the ground surface

3. A Study area and data used

The Yom River is the main river that flows throughout the basin with its direction from north to south. It has a total length of 735 km with an annual mean rainfall of 1,195 mm and the river flow of 3,657 million cubic meters. Index river serial no. is Thailand – 4 and is located in the northern part of Thailand at N15° 45' 35" ~ 19° 25'24" E 99° 16' 34" ~100° 40' 51. The river area is 23,616 km2. The length of the mainstream is around 700 km. Its origin point is at Mt. Phi Pannam. Its highest point is at Pong District in Pha Yao Province (1,916 m) and has an outlet at the Nan River. Its lowest point is 0 m at the river mouth. Its main geological features are Pre-cambrian to Paleozoic, Granite, Gneiss and Limestone. The main tributaries of the Yom River are the Kuan River (852km2), the Phee River (1,094 km2), the Ngao River (1,800 km2), the Mok River (1,313 km2), the Rumphan River (966km2) and the Lower Yom River (11,208 km2). There are two main reservoirs in the area, namely Mae Mok Reservoir (96 x 106 m3, 1993) and Tha Pare Reservoir (68 x 106 m3, 1993). Its annual mean precipitation is 1,087.6 mm while its annual mean runoff is 43.4 m3/s at Sri Satchanalai District in Sukhothai Province (from 1995-2011). It flows through four main provinces, namely, Prae, Sukhothai, Pichit and Phitsanulok, which have a total population of 2,768,211 (2000). Land use can be separated into forest 57.3%, agriculture & urban areas 33.7%, and water resources 9.0%. This study divided Yom basin into 2 parts. Part 1 includes Y20 and Y1C while Part 2 includes Y6, Y3A, Y33 and Y4 [14,8] Parameters used for MIKE NAM model are present in table 1.

In figure 2; show the Yom river area and its capacity at various hydrological observation station

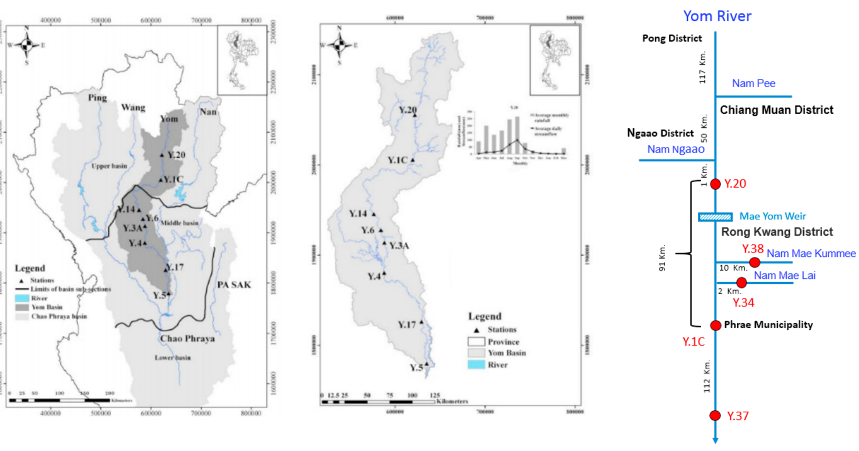

Fig. 2. The study area, the Yom river area(left) The hydrological observation stations (Right)

Table 1 Parameters used for MIKE NAM model [3,4]

Value	q	Detail	Increasing Parameter Effect	Parameter range
27	Umax	maximum water contained in surface storage	– Surface flow decreases. – Dehydration and evaporation increased. – Higher permeability to ground	10-20 mm
150	Lmax	Maximum water content in root zone storage	– Surface flow decreases. – Dehydration and evaporation increased. – Higher permeability to ground	50-300 mm
0.3	CQOF	overland flow run off coefficient	– Surface flow increases. – Lower permeability to ground	0.00- 1.00
212	CKIF	Time constant for routing interflow	– Maximize Highest Flow Rate – Minimize low Flow Rate	500- 1000 hr.
30	CK1	Time constant for routing overland flow	– Increases time of surface water	3 - 48 hr.
24	CK2	Time constant for routing overland flow	– Increasing Parameter Effect: Increases time of surface water	3 - 48 hr.
0.53	TOF	Root zone trash old value for overland flow	– Slow down start flowing point in the beginning of the flood season. – Lower permeability to ground in the beginning of the flood season – Surface flow increases in the beginning of the flood season	0.00-0.99
0.32	TIF	Root zone threshold value for interflow	– Slow down start permeating water point in the beginning of the flood season. – Lower permeability to ground – Surface flow increases	0.00-0.99
0.48	TG	Root zone threshold value for GW recharge	– Slow down start GW recharge point in the beginning of the flood season.	0.00-0.99
2481	CKBF	Time constant for routing base flow	– Maximum flow rate decreases but flow rate during drought increases	500-5000

3.1. Machine learning algorithms in this study

This study used a trial and error approach based on a previous study [6]. Eventually, it was found as follows:

3.2.1 A Linear Regression with solution method was used to create a trainer mode and the number of training epochs was set at 100. 0.0001 for L2 regularization weight.

3.2.2 A Neural Network Regression was set to 100 hidden nodes with 0.001 learning rating and 1,000 number of learning iterations. The initial learning weights diameter was 1 with a Gaussian normalizer for normalizing data.

3.2.3 A Bayesian Linear Regression was allowed unknown categorical levels with 1 for regularization weight when letting 0.1 for noise Fraction.

3.2.4 Boosted decision tree regression had a maximum number of leaves per tree set to 20 and 1 for a minimum number of samples per leaf node 10 with 0.1 learning rate and a total number of trees constructed at 100.

3.2.5 A Decision Forest Regression was used with bagging to resample method, 8 of decision trees and a maximum depth of the decision

3.2. Periods of the Study

The Chao Phraya River Basin consists of four main tributaries, namely, the Ping River, the Wang River, the Yom River and the Nan River. The Yom River is the only river that essentially has no human barriers, dams or reservoirs for managing water flow during flooding or dry seasons. The period of forecasting was in the year 2017. This model calibrates the data from the years 2012 to 2015 with the big flood in 2011 (Water year in

Thailand starts in April).

3.3. Measurement Method

The RMSE of the model prediction was used with admiration to the appraised variable. Xmodel is defined as the square root of the mean squared error:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}} \tag{9}$$

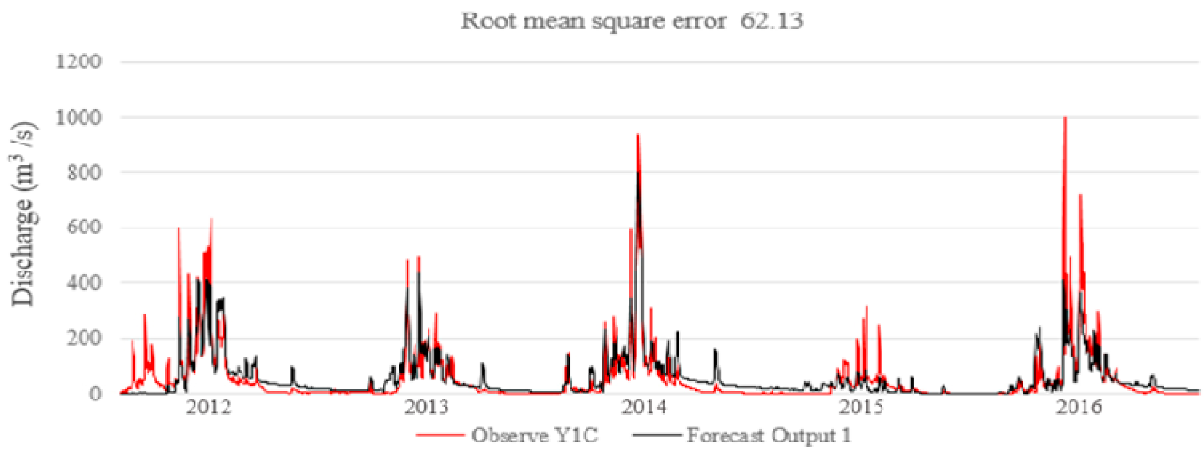

Fig. 3. Comparison between observing and forecasting in Y1C station.

4. Results and Discussion

4.1. The result of rainfall-runoff by NAM module

Figure 3 presents a comparison between observing and forecasting in Y1C station. The limitation of forecasting in Y1C station was that MIKE 11- NAM Model could not be improved to higher accuracy because the rainfall collection process was not accurate, for this reason, cause machine learning is so important to this study.

4.2. Relation between Y.1C Monitoring Station (Phrae province) and Y.4 Station (Sukhothai province)

4.2.1. Water level in Phrae province causes flood condition in Sukhothai province.
Case 1) Concerning the water level at Y.1C station, it could be predicted that within the next 34 hours, the water would flow to the city of Sukhothai. When the water level at Y.4 was increased to 6.40 meters, it made the water overflow some riverbanks in the city of Sukhothai. Case 2) When the water at Y.1C station was about 7.60 meters high, it could be predicted that within the next 46 hours, the water would flow to Y.33 at Ban Klong Tan in Sri Samrong District, Sukhothai. When the water level was increased to 10.00 meters, it led to water overflowing some riverbanks in Sri Samrong District. Case 3) When the water level at Y.1C station was about 10.60 meters, it could be predicted that within 72 hours, the water would flow to Y.3A station at Sawankhalok District. When the level was increased to 10.00 meters, it brought about water overflowing some riverbanks in Sawankhalok District. Case 4) Water overflowing some riverbanks in Si Satchanalai District could happen when the water level at Y.6 station was 9.00 meters or more. This happened in 1995. When the water level at Y.1C was about 11.73 meters, the water would reach Y.6 within about 80 hours. On average, the water level at Y.6 station was about 9.28 meters.

4.2.2. Water level and flood conditions in Sukhothai City (Y4).
Case 1) When the water level at Y.6 was 4.10 M (Water level under river bank around 5.30 M), it could be

forecasted that after around 14 hours, the water would reach Sukhothai City. The water level at Y.4 would be increasing to 6.40 M, which was the same level as the height of the riverbank (Critical level). Case 2) When the water level at Y.6 was 5.90 M (Water level under river bank around 3.50 M), within 9 hours after that, the water level at station Y.33 would be increasing to 10.00 M which is a critical level. Then the water would start to overflow the riverbanks. Case 3) When the water level at Y.6 was 7.60 M (Water level under river bank around 1.80 M), within 4 hours after that, the water level at station Y.33 would be increasing to 10.00 M. At this point, the water would start to overflow the riverbank in Sri Samrong District. Case 4) When the water level at Y.6 was 9.00 M (Water level under riverbank around 0.40 M), it would cause the water to start overflowing some riverbanks in Si Satchanalai District, especially the downstream area of station Y.6.

4.2.3. Relation between rainfall runoff in Y.1C and Y.20

The growth of the urbanization was the main cause of flooding from1952–1980. Rainfall did not relate to the water level in the Yom River. In the years 1990–2008, heavy showers of rain had an effect on the water level significantly. From 2012-2017, rainfall had had direct impacts on the Yom River water level. Only the daily average of the daily water volume and daily rainfall were used to determine the relationship between net water content and daily rainfall in the watershed as in a previous study [17].

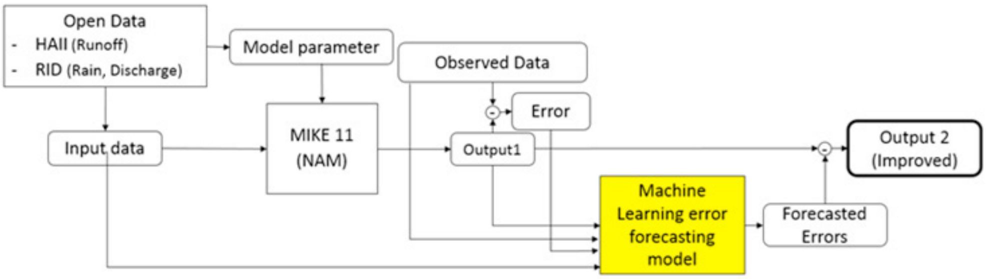

Fig.4. Conceptual Framework Reduce error in Mike 11 model process

For the Yom River, the equation between the average rain in a basin and runoff was y = 0.2088x + 80.165 at Y20 and y = 0.2042x+ 0.5783 at Y1C. The relations between rain average and net runoff was y = 1.1262x + 43.243 at Y.20 and y = 1.5825x + 4.4816 at Y1C. It was also found that the runoff from maximum rain was Y20 = 46 mm, Y1C = 37. The maximum runoff at Y20 was 246 Million cubic meters and was 289 million cubic meters at Y1C. A coefficient of the runoff in Y.20 was approximately 25.6% and in Y1C around 20.6%. The lowest amount of rainwater was 18 mm. at Y.20 and 11 mm. at Y1C. The minimum runoff was 100 million cubic meters at Y20 and 84 million cubic meters at Y1C. A coefficient of the net runoff was around 36.0% at Y.20 and was 22.0% at Y1C.

Table 2 Result comparison day in advance and algorithms

Model	RMSE						
	Day + 1	Day + 2	Day + 3	Day + 4	Day + 5	Day + 6	Day + 7
MIKE NAM (Single Model)	110.4910	126.2854	135.4931	139.9163	140.1483	140.3076	140.4256
MIKE NAM +Bayesian Linear Regression	61.8282	73.2293	84.3674	97.0711	103.3732	105.8374	109.3786
MIKE NAM + Neural Network Regression	88.2662	94.8189	107.5754	110.4444	117.1355	120.6450	116.9012
MIKE NAM + Boosted decision tree Regression	90.8732	96.7749	105.6409	117.9688	118.4499	120.7977	126.8550
MIKE NAM + Linear Regression	61.8282	73.2293	84.3674	97.0711	103.3732	105.8374	109.3786
MIKE NAM + Decision Forest Regression	91.3252	95.6893	110.8648	120.3289	121.3723	122.9555	125.9247

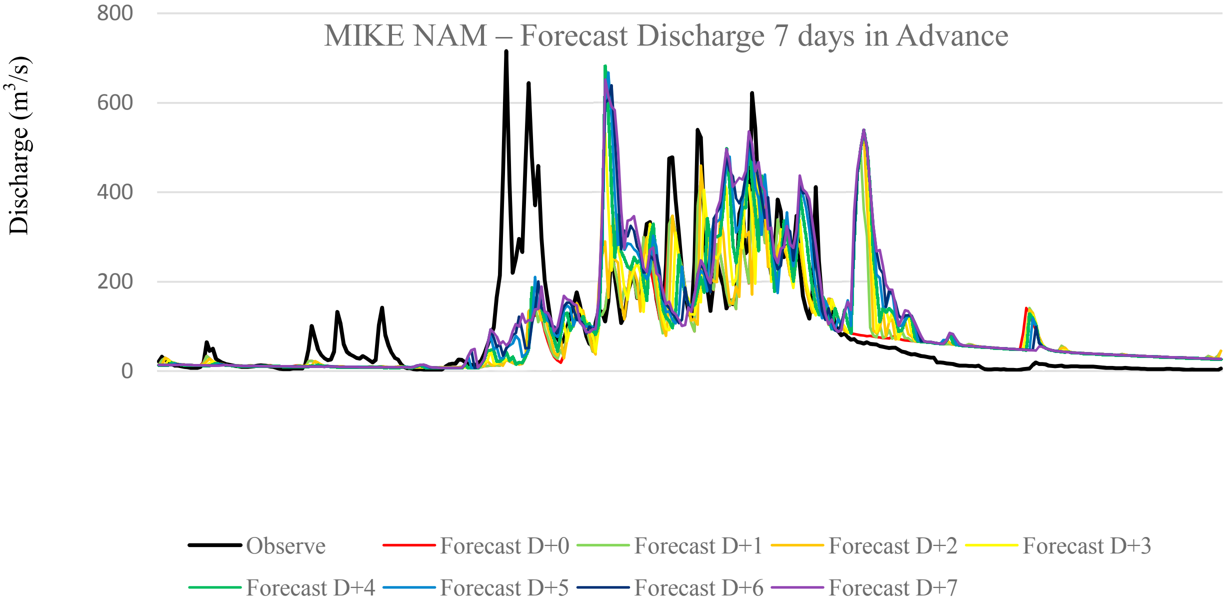

Fig. 5. Forecasting discharge result from April 2017-February 2018 from MIKE11

4.3. Using machine learning technique to improve flood prediction

A comparison between machine learning algorithms is shown in Table 2. The model was under training (2012-2016) using Machine learning model with Observe Rain Y1C, Forecast Y1C, Past Observe Q data Y1C, Observe Q Y20, Past Observe Q data Y20, Error Q20(Observe – Forecast = Error), Error Q Y1C, Rain Y20, past rain Y1C, Rain Y1C, past observe water level Y1C, observe water level Y20 and Observe water level Y1C.

As for testing the model (2017) in fig 5, almost the same data were used but observe Q Y1C, Error Q Y1C, Rain Y1C and observe water level Y1C were eliminated. The model could predict Error Y1C in the year 2017. Before applying the machine learning, error-forecasting model, RMSE was 89.05. After improving input 1 using Bayesian linear technique, it could perform a much better result.

Figure 6. 0-7 days in advance forecasting discharge result from April 2017-February 2018 from MIKE11. After simulate discharge in station Y1C then using machine learning technique to estimate error from MIKE NAM. As the first, domain expert from RID identifies several hydrological conditions into:

1. Qt-1 >= 1000m^3s^{-1} (Monitor flood)
2. Q t-1 < 1000m^3s^{-1} and Qt-1 45 m3s-1 (Normal)
3. Q t-1 < 45 m^3s^{-1} (Drought)

Flood condition due to the heavy rainfall after a period of dry weather; P_{t-1} >100 Pmov2$_{t-2}$ < 10 and Pmov3$_{t-4}$ < 5. In this study, the water level at station Y.20 was separate into QY20>=45 High, and Low is QY20 < 45.
Then apply machine learning techniques to MIKE NAM result to extract error from them using input as Forecast TEST Y1C, Past 1 day Observe Q Y1C, Observe Q Y20,Past 1 day Observe Q Y20,Error Q Y20 and Error Q Test Y1C from 2012 – 2016 and test model to find Error Q Test Y1C in 2017.

This experiment shows that rain is a significant factor in flood management in the Chao Phraya River Basin, especially the Upper Chao Phraya River, where there is no sizeable human-built construction. Thailand is in a tropical zone, but the rainfall forecasts of various organizations are almost the same, and not of high accuracy. This causes many problems in creating a flood warning model, along with the errors caused by the use of physical models for forecasting floods. This study presents the possibility of using a machine learning method.

After predicting the errors in advance, we can consider them together with physical models and make use of those results to improve the accuracy of flood forecasting. The main idea of this paper is to find the optimal configuration of a machine learning-based model and to compare the quality of the results of different machine learning techniques. The results have shown that the best algorithm in this study for seven days in advance is Bayesian linear can reduce error from MIKE 11 22.02% and 44.40% for one day in advance. Rainfall is an important key to be a predictor using MIKE11. A significant contribution of the present exploratory study is the suggestion of valuable information and methods in the modeling of urban flooding. The paper throws the problem of the limitations of the physical model and the inaccuracy of the data. It is continued from previous research studies by using the properties of some learning objects in the reviews to find and get rid of physical model errors. As a result, it was found in this study that there is a convenient way to improve the incomplete physical model.

In this study present benefits of ML in a hydrological model. Therefore, it is suggested that Thailand have an effective flood warning system, responsible agencies, and clear policy about water consumption for different groups of people. Besides this, geological data in Chao Phraya basin are presented. We found that the cause of the problems is Thai water management because there are so many organizations involved in solving flood problems, Unsynchronized actions among these organizations were perceived as the main courses to cope with the flooding. All water prediction models and the early warning systems should be calibrated in the same standard and use the same equal scales and similar indicators.

5. Conclusion and Future Works

The simulated discharges from the NAM module could be closed from the actual discharges, depending on the selection of NAM model parameters by the user and rainfall observation. The criteria for calibrating the parameters were found very important. Every approach should be considered with the same consistency. The results of analysis by MIKE 11 refer to UMAX, LMAX, CKIF, CQOF, CK1,2, TOF has affected to rainfall-runoff. If the value of UMAX and LMAX increased, the shape of hydrograph will thinner, and water accumulate is reduce. If the adjust CQOF increases, it makes the peak of discharge increases. If the alter CK1,2 increases, it has affected, the base of hydrograph is broad. If the adjust TOF increases, the peak of discharge will be decreased.

Although, data-driven modeling is a comfortable work there are limits to accuracy. For physical model even if its high accuracy but for data, preparation is high budget, and if data gathering techniques are inefficient, result from physical data is lack of precision. The purpose of Heterogeneous Modeling is to find out the error in MIKE11 and reduce it. The studies have shown that the easiest way is to minimize error in the NAM Model, but in a practical solution, we use the HD model to analyze in specific points required.

The calibration was done by comparing the computed and observed water levels and discharges at the available gauging station. The results of this model cannot use the AutoCal function because observed data not accurate. MIKE Model, Auto Calibration function not added more precision simulation result. MIKE 11 model can have computed the water level and discharges using the statistical technique in general satiation, but in flood, event Machine Learning better handle forecasting. It refers to the MIKE 11 Model with ML error forecasting model can apply studying in any case.

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