FORECASTING THE FLOOD STAGE OF A RESERVOIR BASED ON THE CHANGES IN UPSTREAM RAINFALL PATTERN

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ABSTRACT

Flood is among the major disasters in Malaysia. Flood occurs when the existing waterways are unable to support large amounts of water during heavy rain seasons. Reservoirs have been used as one of the flood mitigation approaches in the country. A reservoir can hold excessive water to ensure water flow to the downstream area is under the safe capacity of the waterway. However, due to the needs of the society, a reservoir also serves other purposes such as water supply and recreation. Therefore, reservoir water storage should be maintained to satisfy water usage, and at the same time, the water needs to be released to reserve space for incoming water. This conflict causes problems to reservoir operators when making the water release decision. In this paper, a forecasting model was proposed to forecast the flood stage of a reservoir based on the upstream rainfall pattern. This model could be used by reservoir operators in the early decision-making stage of releasing water before the reservoir reaches its maximum capacity. Simultaneously, the reservoir water level could be maintained for other uses. In this study, the experiments conducted proved that an Artificial Neural Network is capable of producing an acceptable performance in terms of its accuracy.

Keywords: *Reservoir, flood forecasting, artificial neural network, flood stage, rainfall pattern*

INTRODUCTION

Flood is among the emergency situations that need serious attention and fast decisions from the experts in order to reduce the risk of flooding and save human lives. In Malaysia, flood is one of the catastrophes that caused by the continuous extreme rainfall event (Hadi et al., 2019). Flood management such as information and knowledge integration is one of the efforts to reduce the flood risk (Zakaria et al., 2018). However, the structural defense mechanism such as reservoir is still a vital approach. Reservoirs are used as one of the mitigation methods to reduce the direct effects of flood. In the occurrence of flood, reservoir water release decision is a critical action that takes place in the reservoir operation (Ishak et al., 2011).

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In addition to flood mitigation, most of the reservoirs in Malaysia serve other purposes such as water supply, irrigation, recreation, etc. Reservoir systems can be separated into four parts: upstream, reservoir, spillway gate, and downstream (Figure 1). Upstream is the water source or inflow of the reservoir. The upstream data is recorded at gauging and telemetric stations. The water inflow is compounded at the reservoir before it is released to the downstream water channel.

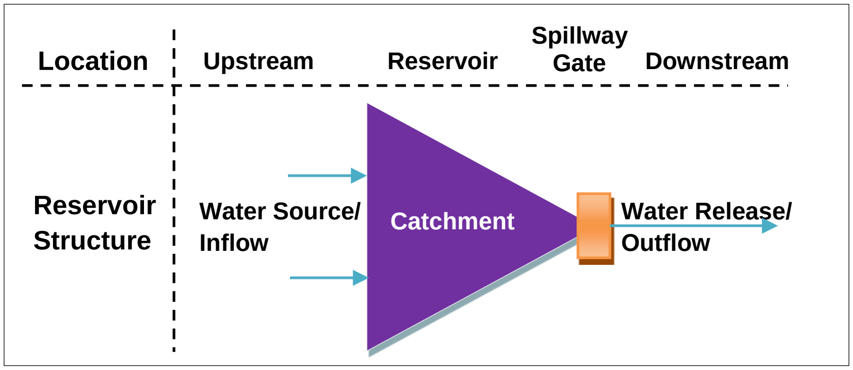

Figure 1
Conceptual model of the reservoir system (Source: Ishak et al., 2011)

Typically, the reservoir water release decision is determined by human experts (Ishak et al., 2015). The decisions are based on their past experience, current reservoir water level, and upstream inflow. The upstream inflow is observed through the magnitude of upstream rainfall and river water level. The total volume of rainfall may come from several gauging stations and their distances to the reservoir vary. Therefore, rainfall observed at those gauging stations may take different time periods to reach into the reservoir (Mokhtar et al., 2016). The spillway gate is used as an outlet for the reservoir water. Some reservoirs are equipped with an ungated spillway and some others have both types of spillways. In addition, water release decision is also crucial to reduce risk of damage on the dam structure (Pipitone et al., 2018). This paper discusses the development of the forecasting model for the reservoir's flood stage using Artificial Neural Network (ANN). The ability of ANN has been accepted by many disciplines and it is suitable for hydrological problems (Piasecki, Jurasz, & Skowron, 2015). Through the forecasting of the flood stage, the early water release decision could be determined. The flood stage is associated with the reservoir water level, where the stage is categorised as normal, alert, warning, and danger. The upstream rainfall volume and category are used as the input dataset. The data preparation is further discussed in the methodology section. The results and discussion are presented in the subsequent sections.

RELATED STUDIES

Prior studies have investigated several techniques for forecasting reservoir water level, such as ANN, Adaptive Neuro Fuzzy Inference System (ANFIS), Support Vector

Machine (SVM), and Autoregressive Integrated Moving Average (ARIMA). Hipni et al. (2013) compared the performances between SVM and ANFIS techniques. SVM's performance was superior and much better than ANFIS based on statistical evaluation. Meanwhile, Nwobi-Okoye and Igboanugo (2013) used ANN in forecasting water level and the findings were compared with ARIMA. Their findings showed that ANN produced better prediction models. Table 1 summarises some related studies on reservoir water level forecasting, types of reservoir, and techniques used. As shown in Table 1, ANN was used as the core technique in all those studies and most of the studies focused on multipurpose reservoir. Multipurpose reservoir is popular among researchers as the water release serves many purposes, such as water supply, irrigation, and recreation. On top of that, it sometimes conflicts with its function as a flood mitigation approach where the water discharge policy has to be executed in order to reduce flood risk.

Table 1
Studies on forecasting of reservoir water level

Author	Type	Technique
Rani and Parekh (2014)	Multipurpose	Neural Network - Feed Forward Backpropagation (BP) - Cascade - Elman
Hipni et al. (2013)	Multipurpose	Support Vector Machine (SVM) and Adaptive Neuro Fuzzy Inference System (ANFIS)
Valizadeh and El-Shafie (2013)	Multipurpose	Adaptive Neuro Fuzzy Inference System (ANFIS)
Nwobi-Okoye and Igboanugo (2013)	Single Purpose Hydropower	Neural Network and Autoregressive Integrated Moving Average (ARIMA)
Valizadeh et al. (2011)	Multipurpose	Adaptive Neuro Fuzzy Inference System (ANFIS)
Ishak et al. (2011)	Multipurpose	Neural Network
Chang and Chang (2006)	Multipurpose	Adaptive Neuro Fuzzy Inference System (ANFIS)

METHODOLOGY

The current study focuses on the Timah Tasoh Reservoir in Perlis, Malaysia. This reservoir is one of the reservoirs built as flood mitigation in addition to other functions. The reservoir is influenced by the upstream inflow and its water release decision is made by the reservoir operator. In this study, the upstream rainfall data of Timah Tasoh from the years of 1999–2012 was obtained from the Department of Irrigation and Drainage (DID). The rainfall data was collected from five upstream gauging stations, namely Padang Besar, Kaki Bukit, Tasoh, Lubuk Sireh, and Wang Kelian. The rainfall data was used to form three datasets. Each dataset had different input patterns but with the same target, which is the flood stage. Table 2 shows the four flood stages, i.e. normal, alert, warning, and danger. Table 3 provides the description of each dataset, while Table 4 summarises the number of instances obtained for each dataset. The number of instances for each dataset was obtained after the removal of redundancy and conflicting data.

Table 2
Flood stage of reservoir water level

Reservoir Water Level (m)	Flood Stage
< 29.0	Normal
< 29.4	Alert
< 29.6	Warning
>29.6	Danger

Table 3
Description of the datasets

Dataset	Description
Dataset 1	The rainfall pattern is determined based on the changes in rainfall volume (RV), $\Delta RV = r_t - r_{t-1}$, where r_t represents the current rainfall volume, while r_{t-1} represents the previous rainfall volume.
Dataset 2	The rainfall volume is categorised into five categories: none, light, moderate, heavy, and very heavy (Table 5). The rainfall pattern is determined based on the changes in the rainfall category (RC), $\Delta RC = c_t - c_{t-1}$, where c_t represents the current rainfall category, while c_{t-1} represents the previous rainfall category.
Dataset 3	Both rainfall category and changes in the rainfall category are used ($RC, \Delta RC$) as the input.

Table 4
Number of instances

Dataset	Number of instances
1	272
2	493
3	2047

Table 5
Category of rainfall

Rainfall Volume (mm)	Category
0	None
1-10	Light
11-30	Moderate
31-60	Heavy
>60	Very Heavy

Standard backpropagation neural network with bias, learning rate, and momentum were used to develop the forecasting model. A forecasting model was developed for each dataset. The rainfall patterns as described in Table 3 were used as the input, while the target was the flood stage of the reservoir. Each model was trained with different combinations of hidden unit, learning rate, and momentum. The aim of this procedure was to obtain the combination that gave the best result. A tool known as Waikato Environment for Knowledge Analysis, or WEKA, was used to develop the neural network model. The performance of the model was measured using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Both measurements are two of the most common metrics used to measure accuracy for continuous variables.

RESULTS AND DISCUSSION

Table 6 shows the result for each dataset after the training and testing processes. Generally, the average of predicted sample size is 90.00732601, 90.66937, and 90.52272, respectively. As shown in Table 6, Dataset 3 was selected as the best data for reservoir water level forecasting model. This is because the average of predicted sample size (Nash et al., 1970) was not too high, yet it achieved the lowest RMSE and MAE values. The value for each parameter in the neural network is shown in Table 7. This finding demonstrated that the neural system produced satisfactory results. This is in line with related studies such as Anderson et al. (1998) and Parthasarathi et al. (2010). In addition, the performance achieved by Dataset 3 reflected that the more information considered in the model, the higher the accuracy. Figure 2 shows the architecture of ANN for Dataset 3.

Table 6
Results

Dataset	1	2	3
Total no. of instances	272	493	2047
Time taken to build model	0.3 seconds	0.54 seconds	4.31 seconds
Average of predicted size	90.00732601	90.66937	90.52272
RMSE	1.0073	0.9012	0.6448
MAE	0.7812	0.715	0.5191

Table 7
Neural network default parameters

Dataset	Number of input	Hidden Unit	Learning Rate	Momentum	Epochs	threshold
1	5	3	0.3	0.2	500	20
2	5	3	0.3	0.2	500	20
3	10	5	0.3	0.2	500	20

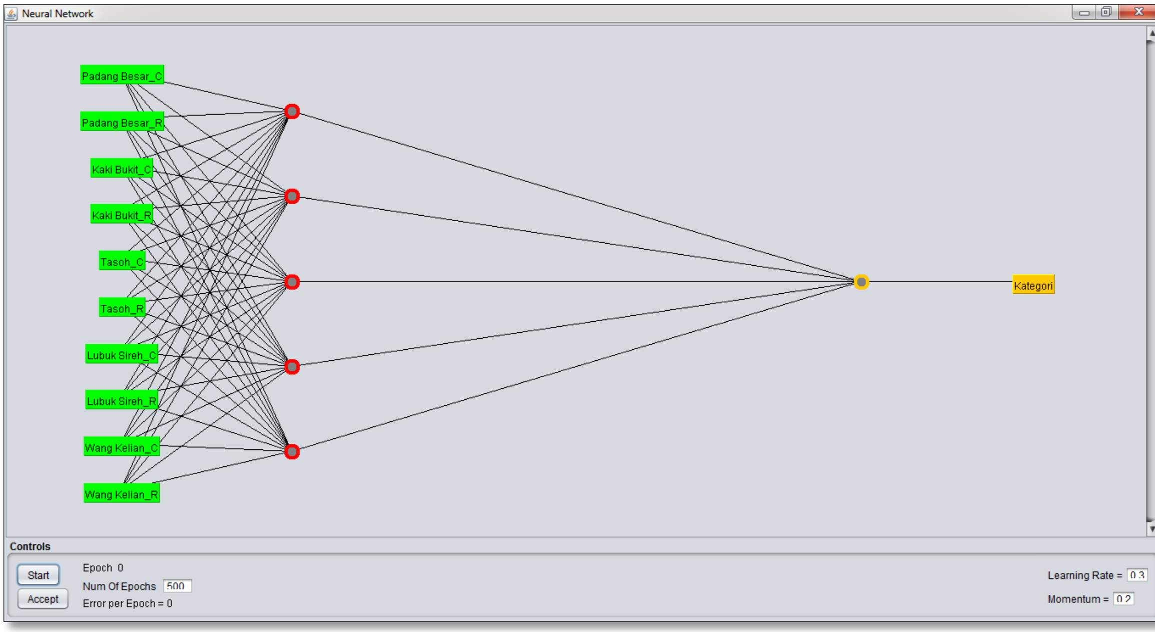

Figure 2
Neural Network Model for Dataset 3

CONCLUSION

In this study, ANN has been successfully applied to develop a forecasting model for the reservoir flood stage. Three datasets were created and tested. The dataset that represented the upstream rainfall patterns with the changes in pattern produced better results as compared to the other datasets. This showed that the changes in pattern information is vital in making the reservoir water release decision.

This finding can be used as a reference for reservoir operators when making early reservoir water release decisions. Early water release decision is crucial in order to reduce the effect of flood at downstream areas. At the same time, the reservoir should maintain its storage capacity to serve other purposes. Therefore, it is critical for the reservoir operator to execute the right decision. The proposed forecasting model can used to guide the reservoir operator to make the decision.

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