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Potential Flood Prediction at Downstream of Hydropower System based on ANN and Fuzzy

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Abstract:

Due to heavy raining season, hydropower scheme experience problems such as high flooding particularly at downstream zone. Hence, hydropower station required a discharge forecasting alongside flood prediction to prevent flooding at downstream area. Moreover, the discharge forecasting is important for optimization of power generation through water regulation. This paper discusses the use of Artificial Neural Network (ANN) to predict the downstream discharge pattern of a cascade hydropower station. Meanwhile, the fuzzy inference system was used to determine the potential of flood risk based on predicted discharge pattern. This study starts with data collection at a selected hydropower station. Data collected are Forebay Elevation (FBE), inflow and discharge that were used as input parameters for prediction algorithm. The Elman Neural Network architecture was used in this study for discharge predictions. Next, the optimum number of hidden neurons and training algorithm were identified. The performance of model was assessed using performance metrics such as Root Mean Square Error (RMSE), Mean Square Error (MSE), Mean Absolute Error (MAE) and Sum Square Error (SSE). The result shows ANN exhibits high performance discharge forecasting through minimal error values. Finally, Fuzzy model was used to identify the flood risk based on discharge and water level.

Keywords: *Hydropower, ANN, Fuzzy Logic, Discharge Forecasting, Elman Neural Network.*

I. Introduction

Hydropower is the sustainable power source that ecologically friendly and non-polluting [1]. Hydropower serve as power generation, and also support water management [2]. Hydropower additionally has its own risk even though offer benefits for community. For example, due to the raining season, occurrence spillage occurs at the hydropower system that causes high flooding at the downstream[3]. Therefore, discharge forecasting is required to reduce the potential risk of flooding. The capability to simulate streamflow accurately is vital for hydroelectric project configuration and applicability to reduce the impact of outrageous climate on the environment [4]. In addition, discharge forecasting is required for estimating streamflow, which is also important for water resource management.

Previously, many statistical methods had been used for hydrological prediction. For instance, auto regressive moving average (ARMA), simple regression model and multiple regression models has been used to water pattern predictions [4]. However, statistical model unable to produce an accurate prediction of discharge patterns [5]. In the past decade, numerous number of advanced prediction methods has been used to predict streamflow such as Wavelet Artificial Neural Network (WANN) [6], Adaptive Neuro Fuzzy Inference System (ANFIS) [7], Wavelet Neural Network (WNN) [8], and Hybrid Support Vector Machine [9]. ANN is a method that had been utilized to tackle the hydrological issue recently [10]. ANN is a

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computational model which is design to mimic the human being and determines the response to the information[11], [12]. It had been utilized in many hydrological model because of its capacity to distinguish the nonlinear relationship without require any additionally guidance [13], [14]. ANN model also effectively utilized in hydrology areas such as water level estimation [15], flood forecasting[5], [10], and rainfall-runoff forecasting [12], [16], streamflow prediction [17]–[20]. Furthermore, ANN model also used for power production forecasting [21], snowmelt prediction [22], and tidal level prediction [23]. Similar to this study, Hun Lee et.al proposed ANN model for streamflow forecasting. Their research demonstrates ANN can be utilized to foresee the occurrence of water release that happens in the Kapuas River that depends on precipitation and dissipation [17]. Mundher et al applied two types of ANN model for daily streamflow prediction, which is Feed Forward Back Propagation Neural Network (FFNN) and Radial Basis Function Neural Network (RBFNN). Their research shows RBFNN model capable to perform an accurate prediction of daily streamflow compared to FFNN model [14]. The author in [24] suggested the use of ANN model to investigate the capability of Support Vector Machine, RBFNN and Multilayer Perceptron (MLP) to predict the river flow. Their result demonstrates that RBF and MLP performance superior than SVM model for monthly river flow forecasting.

This research aim is to investigate the capability of ANN model as a prediction method with Elman Neural Network architecture. In order to predict the hydropower discharge, FBE, inflow and the discharge flow will be used as input parameter. Besides that, this study also aims to identify the best number of hidden neurons and training algorithm. The ANN performance are evaluate based on several performance parameters such as MSE, RMSE, MAE and SSE. In this study, fuzzy inference system will be utilized to identify the potential risk of flooding at the low-lying area based on predicted discharge pattern. The rest of this paper is organized as follows: Data Collection, ANN Model, Model Evaluation and Fuzzy Logic modeling are elaborated on Methodology section. All the result obtain on train and test session are discussed in result and discussion section. Finally, in conclusion section it summarizes the outcome of ANN model in term of hydropower discharge prediction.

II. METHODOLOGY

A. *Data collection*

In this study, the data information such as FBE, inflow and the turbine discharge were obtained from a selected hydropower station in Malaysia. FBE indicates as a forebay water level above the mean sea level while inflow is the water that flow through in the hydropower. The inputs are an hourly data obtained for four years. All the data obtained will be applied as an input variable to predict the turbine discharge. The first three years of data are used for model training and the final year data will be used as a model validation. All the data obtained will be illustrated into the graph to facilitate the data analyzation. Fig. 1a) shows the FBE in year one. The figure indicate that the water level is high especially on the middle of March and April and on the end of the year. The maximum water level of reservoir is 61.50 mSLE where it can be seen on the graph that the water level does not exceed than 60.4 mSLE. Fig. 1b) presents the inflow for year one. Fig. 1b) demonstrates that the maximum value of pick up inflow is on the middle of April. Besides, it can be seen on Fig. 1b) that the inflow is quite high on the August, September, October, November and December. The hydropower discharge in the year one is illustrated in Fig. 1c). The hydropower discharge is quite high on the end of November as shown in Fig. 1c).

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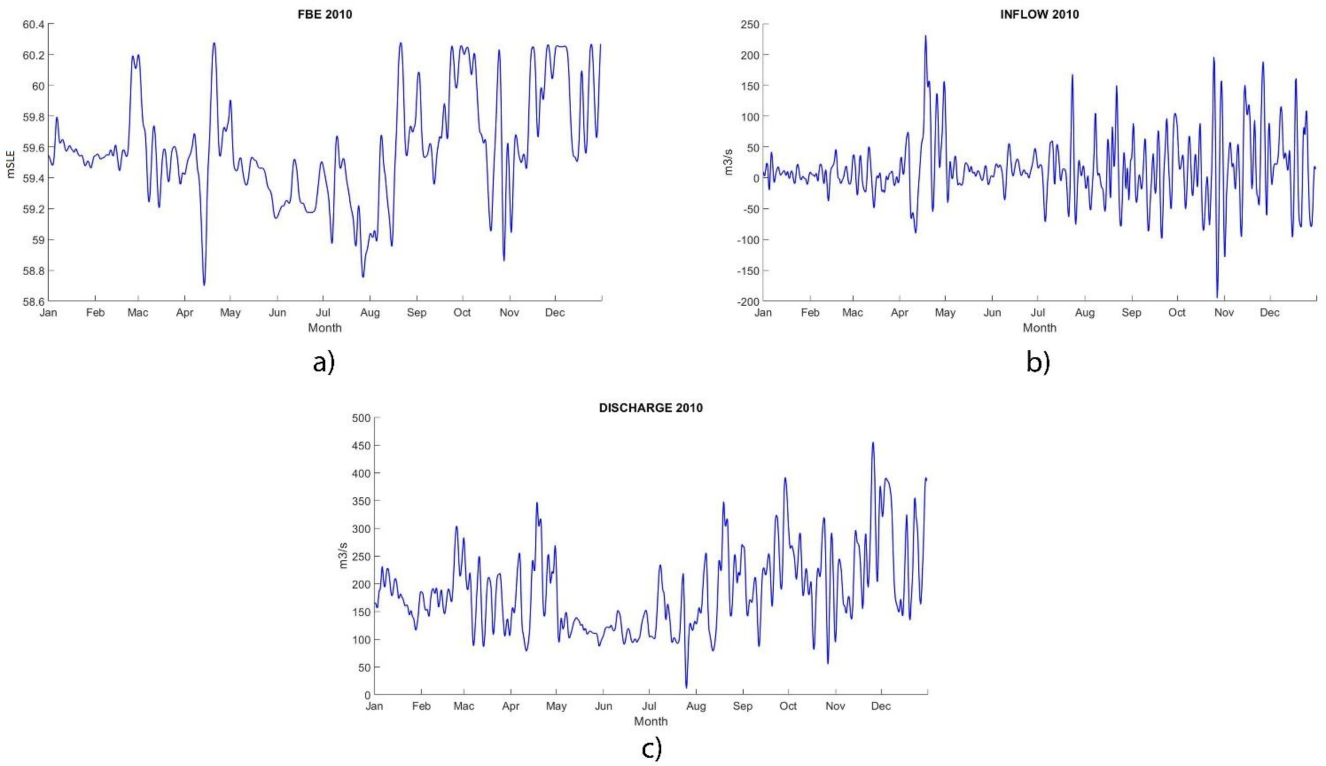

Fig. 1. a) FBE in one-year b) Inflow in one-year c) Discharge in one-year.

B. *ANN Model*

In this research, the hydropower discharge forecasting is carried out using ANN model. ANN model is computational approach which is designed to imitate the behavior of human being. It is learnt to generalize the nonlinear relationship between inputs and outputs. Elman Neural Network is among many architectures of AN. Fig. 2. illustrates the Elman Neural Network architecture where *i* indicate as 1 until *n*. The structure of Elman Neural Network has three layers, such as input layer, hidden layer and output layer. The architecture of Elman Neural Network is diverse from other type of ANN. Since, it had the feedback connection from the hidden layer that act as an additional input to network. The additional input is called as context layer. As demonstrated in Fig. 2. the network can be divided into two input which is true input units *(x(t))* and context units *(z(t)*). The observed data will be compared with the output value *(y(t+1))* and the error value will be generated *(e(t+1))*. The existence of additional input give impact on the network learning capability to produce spatial and temporal patterns. Besides, the feedback connection consists of time unit delay on each hidden neuron. Time delay unit play an important role in the network storage function and lead to nonlinear dynamical behavior.

The purpose of this study is to investigate the capability of ANN model to forecast the hydropower discharge. Also, this research aims to identify the optimum number of hidden neurons and training algorithm on the model performance. ANN model requires enough number of neurons on hidden layer. Hence, various numbers of hidden neurons were chosen in this study such as 11, 13, 15 and 17. Bayesian Regularization and Levernberg-Marquardt were the two training algorithm that applied in this research. Bayesian Regularization algorithm train in lengthy timespan however generate with great generalization especially for tough or noisy data set. Usually, Levernberg-Marquardt algorithm involves more memory than Bayesian Regularization yet train quicker in computational time. As demonstrate in the performance metric, the training of Levernberg-Marquardt will consequently end when the generalization performance stops increment. ANN model needs to specify the transfer functions for hidden and output layers. In this study, Elman Neural Network architecture applied hyperbolic tangent sigmoid as transfer function in its hidden

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and output layer. The hyperbolic tangent sigmoid function is bounded between -1 and 1 and as shown in Eq. (1);

$$y = \frac{2}{1+e^{-2x}} - 1 \qquad (1)$$

Where, *y* and *x* are the value of output and input respectively.

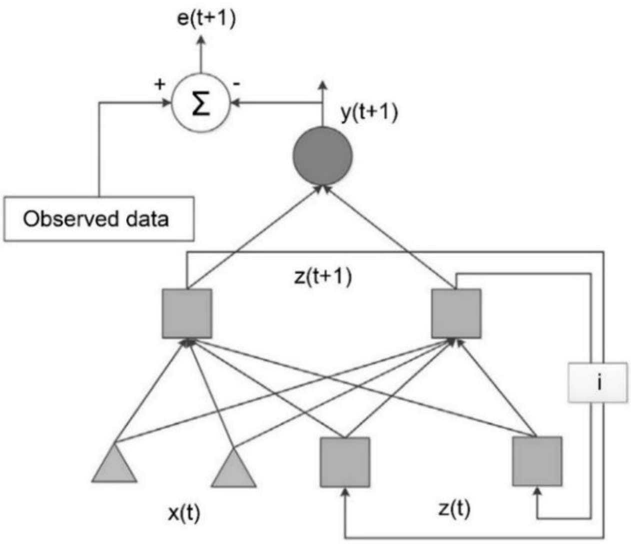

Fig. 2. Elman Neural Network architecture.

C. Model Evaluation

Various performance metric was used in this study to assess ANN model performance in terms of model accuracy. MSE, RMSE, MAE and SSE were usually applied for evaluation of time-series prediction. The performance metrics were expressed as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i) \qquad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2} \qquad (3)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i) \qquad (4)$$

$$SSE = \sum_{i=1}(yi - \hat{y}i)^2 \qquad (5)$$

D. Fuzzy Inference System

The predicted discharge obtained can be used to determine the possibility of flood risk at the lower stream through the Fuzzy Logic. The possibility of flood risk is based on river water level. Fuzzy logic is computational approach that make decision like a human being. The decision making is based on 'degrees of truth' instead of 'false or true'. For instance, Boolean system present two truth value of logic. Where, 0 represents false value and 1 represents true value. However, in fuzzy logic there is no logic for false and true value. But, possess an intermediate value too indicate which is partially false and partially true. The development of fuzzy logic comprises the formation of two things which is the membership functions and fuzzy rules. A membership function graphically represents a fuzzy set where each of elements are plotted to a membership value between 0 and 1. Fig. 3. represents the input of membership function while Fig. 4. represents the output of membership function. In this study, the input and output of membership function are the predicted discharge and river water level respectively.

The fuzzy rule also identified as the degree of fulfilment is the linguistic 'If-Then' construction. 'If-Then' constructions contain proposition that holding linguistic variable the generally form "If A then B". Where A is the premise and B is the rule consequence. The premise of fuzzy rules in this research are low, medium and heavy. While the consequences are normal, warning and potential flood. Fig. 5. demonstrates the fuzzy rule of this study where it comprises of three rules.

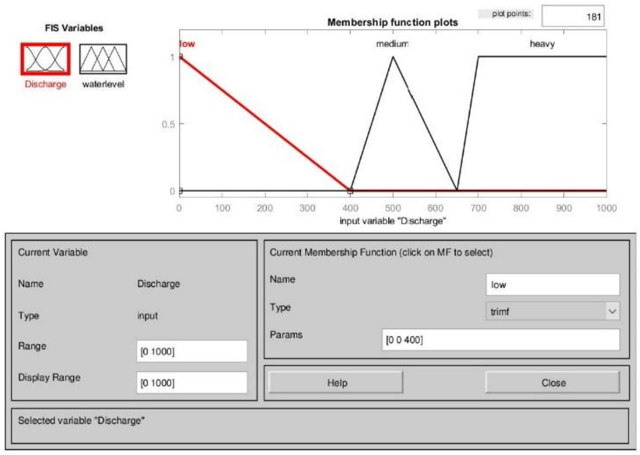

Fig. 3. Input of Membership Function.

Fig. 4. Output of Membership Function.

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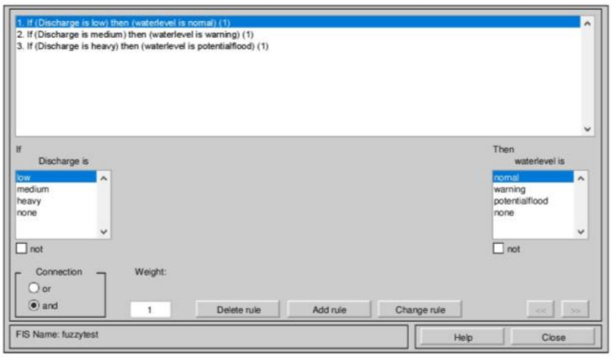

Fig. 5. Fuzzy Rules

III. RESULTS AND DISCUSSION

A. *Training Session*

In the training session, ANN model was trained to forecast the hydropower discharge using FBE, inflow and hydropower discharge as input variable. This study aims to determine the optimum number of hidden neurons and training algorithm on model performance. The result performances were evaluate using several performance metrics such as MSE, RMSE, MAE and SSE as shown in Table 1. The result demonstrates that Bayesian Regularization algorithm showed greater performance in discharge forecasting than Levernberg-Marquardt. However, from previous work it can be concluded that Bayesian Regularization algorithm train for a very long time. The number performance of ANN model highly influenced by the number of hidden neuron. As shown in Table 1, the overall optimal number of hidden neuron is 13. Minimum number of hidden neuron generate a low training performance. The performance of ANN model is improved with the great number of hidden neuron as the complexity function improve. However, setting too many hidden neurons resulted to over-fitting. The performance metric obtain were 357.54, 18.91, 6.3601 and 9.4028x106 respectively with 13 as number of hidden neuron and Bayesian Regularization as training algorithm

TABLE I. ANN model training performance

Architecture	Performance Metric	Algorithm	Number of Neuron			
			11	13	15	17
Elman Neural Network	MSE	LM	654.840	557.930	468.140	410.310
		BR	364.760	357.540	419.730	424.220
	RMSE	LM	25.580	23.620	21.640	20.250
		BR	19.100	18.910	20.490	20.600
	MAE	LM	8.173	8.258	8.210	9.057
		BR	5.943	6.360	7.698	7.478
	SSE	LM	$1.465x10^7$	$1.301x10^7$	$1.189x10^7$	$1.303x10^7$
		BR	$9.577x10^6$	$9.403x10^6$	$1.114x10^7$	$1.145x10^7$

B. *Test Session*

As shows in Fig. 6. the comparison graph between actual and predicted hydropower discharge were illustrated. The result demonstrated the capability of ANN model to do the discharge prediction particularly in maximum peak. Nevertheless, as shown in Fig. 6. the hydropower discharge on January and December not precisely predicted. Besides, the forecasted hydropower discharge on the middle of March and April were moderately deviate from actual value. In this study, Elman Neural Network was applied as ANN architecture. Elman Neural Network is one of Recurrent Neural Network, which is suitable for time series forecasting. Recurrent Neural Network that have feedback connection and time unit delay provide a great number of benefit than the static networks. In addition, Recurrent Neural Network offer a nonlinear hydrologic forecasting although with the existence of noise. Moreover, the usage of hyperbolic tangent sigmoid as transfer function highly influenced the ANN model performance. The hyperbolic tangent sigmoid that applied in hidden and output layer made a great hydropower discharge forecasting. It had a positive response for positive input while negative response for negative input. The hyperbolic tangent sigmoid function generates a great nonlinear response since due to the big slope. It also capable to distinguish between small variations at input variable. The differences value between actual and predicted were illustrated in Fig. 7. The figure demonstrate that the error values were in small deviation. However, the noticeable error value can be seen on January and December due to the imprecision of discharge forecasting. The predicted discharge obtained can be used to identify the potential of flood risk at the lower stream. Fig. 8. demonstrates the possibility of flood risk through fuzzy logic model. The increasing of hydropower discharge causes the water level at the lower stream to rise. Hence, the possibility of flood risk also increases.

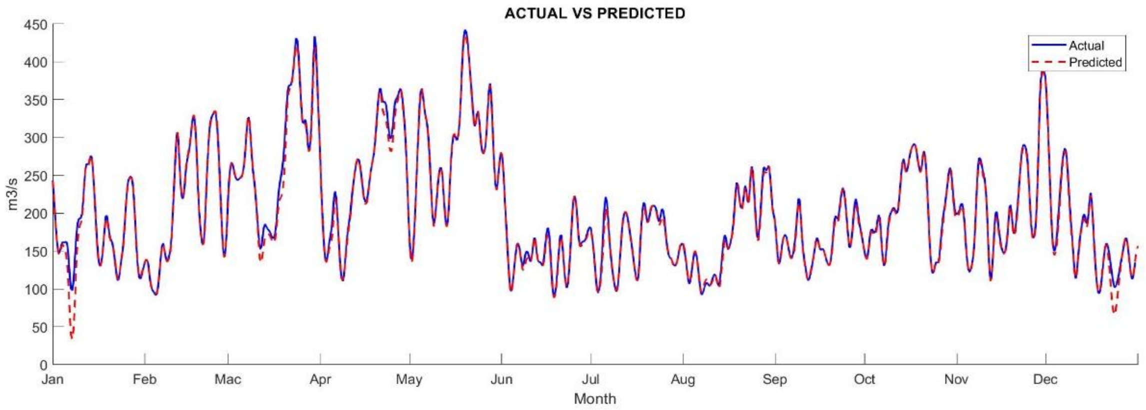

Fig. 6. Flood Prediction

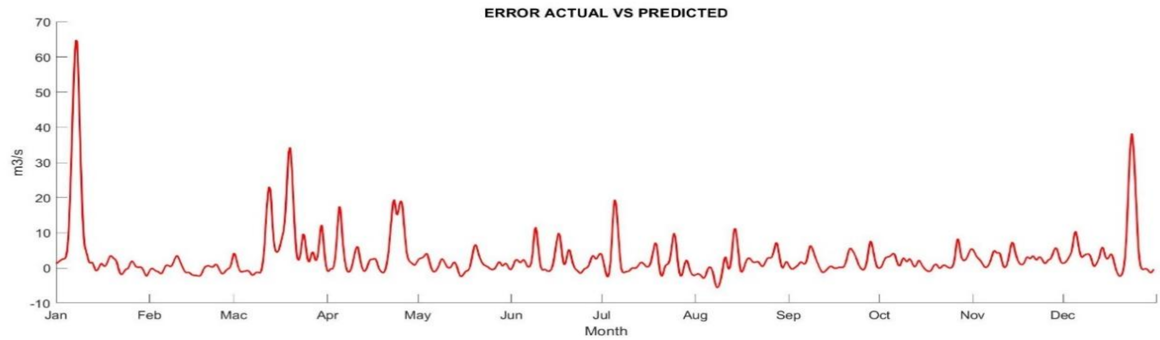

Fig. 7. Error value of flood prediction

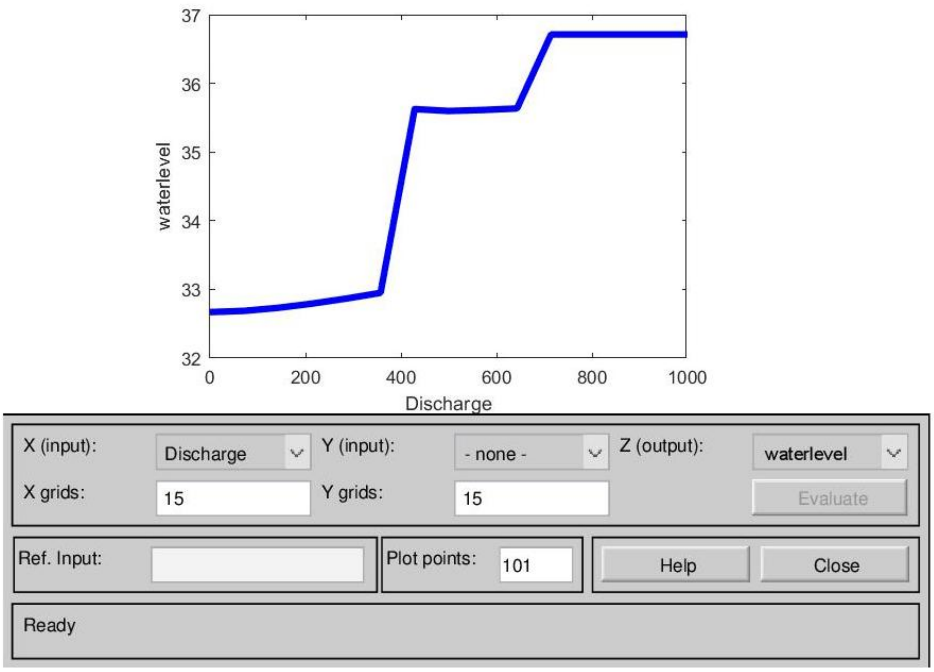

Fig. 8. Possibility of flood risk

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IV. CONCLUSION

In conclusion, the number of hidden neuron can highly influenced the model performance. Whereas the minimum number of hidden neurons generate a low performance. Therefore, the performance of model can be improve by increasing the number of hidden neurons. Nevertheless, applying too much hidden neuron can caused the model to over fit. The result also demonstrate that ANN model generate higher accuracy in term of discharge forecasting when Bayesian Regularization was applied as training algorithm. However, Bayeseian Regularization take longer computational time than Levernberg-Marquardt when training the model. Hence, the potential of flood risk at the lower stream can be determine through hydropower discharge forecasting. This study utilized the fuzzy logic model to identify the potential of flood risk that can be used to mitigate the possibility of flood at the downstream.

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