

Flood Risk Prediction for a Hydropower System using Artificial Neural Network



Nurul Najwa Anuar, M. Reyasudin Basir Khan, Jagadeesh Pasupuleti, Aizat Faiz Ramli

Abstract: Hydropower scheme would experience issue relating to high flooding especially at low lying area due to extreme raining season. To mitigate the potential risk of flooding and improve the hydroelectric regulation, a flow prediction is needed to estimate the discharge of water flow at hydroelectric reservoirs. Artificial Neural Network (ANN) model were used in this research to forecast the water discharge of hydroelectric station. The discharge flow predictions were made based on fore bay elevation, inflow and the discharge of water flow. Elman Neural Network architecture was selected as ANN method and its performance was evaluated by considering the number of hidden nodes and training methods. ANN model performance were 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 indicate that ANN model showed the best applicability for discharge prediction with small performance metric.

Keywords: Hydropower, Artificial Neural Network, Elman Neural Network, Flow prediction

I. INTRODUCTION

Hydropower is the renewable energy source that non-polluting and environmentally friendly [1]. Hydropower not only generate the electricity, it also provide the essential service for water management [2]. Despite the storage hydro that give advantage to human society, hydropower also has high risk. For instance, hydropower system has high spillage due to the extreme raining season. Consequently, high flooding occur at the low-lying area [3]. In order to mitigate the potential risk of flooding at the downstream, streamflow forecasting is required to estimate the hydropower discharge. Streamflow forecasting is very important for hydroelectric project design, water resource operation, and minimize the effect of extreme climate on the environment [4]. Many methods have been applied to forecast the flow discharge throughout the years.

Previously, statistical methods such as multiple regression models, simple regression model, and auto regressive moving average (ARMA) had been applied for hydrological forecasting purpose [4]. However, statistical model unable to produce high prediction accuracy [5]. In addition, several prediction techniques such as Hybrid Support Vector Machine [6], Wavelet Neural Network (WNN) [7], Adaptive Neuro Fuzzy Inference System (ANFIS) [8], and Wavelet Artificial

Neural Network (WANN) [9] had been developed for streamflow forecasting. Recently, ANN method had been applied to solve the hydrological problem [10]. ANN is a computing model that is design to imitate the human decision making [11]. ANN model had been widely used in hydrological system due to its capability to identify the nonlinear relationship without require any explicitly instruction as traditional statistical [12], [13]. ANN has been successfully used in some of hydrological problems such as streamflow forecasting [4], [12], [14]–[17], rainfall-runoff prediction [18]–[20], flood prediction [5], [10], [21] and forecast water level [22], [23]. In addition, ANN model also capable for tidal level forecasting [24], snowmelt forecasting [25] and prediction of power production [26]. Ghorbani et al. proposed ANN model to forecast river flow at Iran. Their work concluded that ANN model shows better performance than SVM model for monthly river flow [27]. Yaseen et al developed two ANN model, which is Radial Basis Function Neural Network (RBFNN and Feed Forward Back Propagation Neural Network (FFNN) to forecast streamflow in Malaysia. Their research illustrates ANN model yields difference performance where the RBFNN model generate higher accuracy than FFNN model in streamflow prediction [13].

This work developed an ANN model based on Elman Neural Network as a prediction method. Data collected such as fore bay elevation, inflow and discharge flow were used as input variable to forecast the hydropower discharge This study also aim to investigate the effect of the training method and the number of hidden neurons on ANN model performance. ANN performance is evaluated using performance parameters such as MSE, RMSE, MAE and SSE. The rest of this paper is organized as follows: Data collection, ANN modelling and performance metric are presented in the Methodology section. Meanwhile, all the result collected are discussed in result and discussion section. Finally, the conclusion summarizes the findings of ANN based hydropower discharge prediction.

II. METHODOLOGY

Data Collection

Forebay Elevation (mSLE), pickup inflow (m³/s) and the water discharge (m³/s) were used as input parameter to forecast the hydropower discharge.

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Forebay elevation specify as the reservoir water level. All these data were collected from period 2008 until 2011 through data sharing from TNB Research (Power Plant Optimization, Generation Unit). The data from the period 2008 until 2010 were applied to train the model while the data 2011 were applied for validating the models. Each of the data set were analyzed and plot since the data set are too numerous and complicated

to be described adequately. It is easier to interpret relationship between the data set by illustrate it into the graph. Figure 1 shows the Fore bay elevation in 2008. The figure indicates that reservoir water level is decreasing in small quantity from January to early of December. Meanwhile, Figure 2 presents the hydropower inflow in 2008. Based on Figure 2, the water that flow into the hydropower is quite high on early of December. The hydropower discharge in 2008 is illustrated in Figure 3. Figure 3 demonstrates that hydropower discharge almost reached 350 m³/s on January.

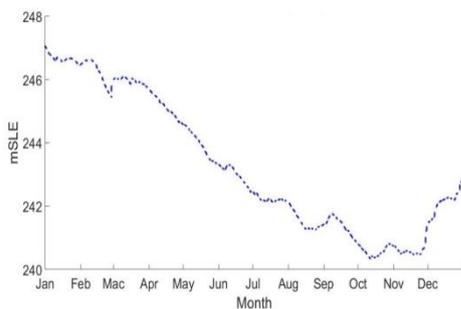


Fig. 1 Fore bay elevation

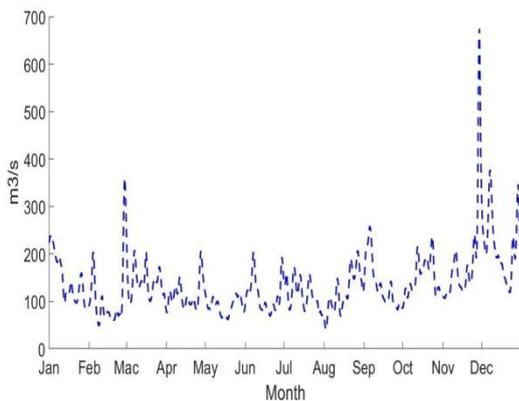


Fig. 2 Inflow

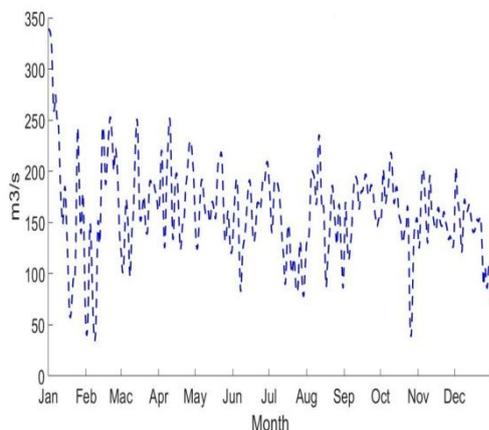


Fig. 3 Discharge Flow

ANN Model

ANN is known as powerful tool that identify the nonlinear relationship between data set of input and output. The ANN architecture used in this study is Elman Neural Network. The architecture of Elman neural network commonly has three layers, which is input layer, hidden layer and output layer. Figure 4 illustrate the architecture of Elman Neural Network. The structure of Elman Neural Network is different with Feed Forward Back Propagation where it had the feedback connection from the hidden layer that allow the network to recall the previous sign. The existence of feedback connection effected the network learning capability. As shown in Figure 4, the input layer of Elman network is separated into two parts which is true input value ($x(t)$) and context value ($z(t)$). Context value copy the hidden neuron from the earlier time step. Both context and true input value activate the neuron in hidden layer. However, for initial state only true input value can contribute in activating the hidden neuron. The hidden neurons are fed backward to the context layer at the time the hidden neuron is fed forward to the output layer. In addition, the neuron in the hidden layer has its additional information due to the time delay unit. The additional information can be used for the upcoming time step that resulted in nonlinear dynamic behavior. Thus, Elman Neural Network had an essential and explicit dynamic memory.

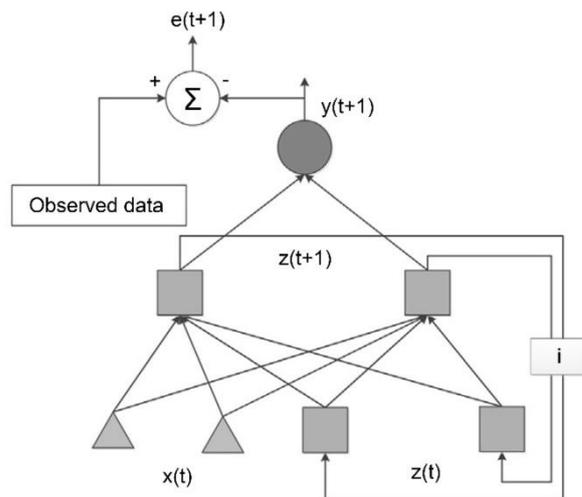


Fig. 4 Structure of Elman Neural Network

Where $y(t+1)$ is the output value. The output and the actual value will be compared, and error value will be calculated which is $e(t+1)$ where i represent the value of 1 until n . The goal of this research also to investigate the impact of the training algorithm and the number of hidden neuron towards ANN model performance. In this study, two training algorithms were used which is Levenberg-Marquardt and Bayesian Regularization. Levenberg-Marquardt algorithm usually train faster than Bayesian Regularization algorithm, but it requires more memory. Levenberg-Marquardt algorithms training will automatically end when the performance of generalization stops increase as indicate in the performance metric.

Bayesian Regularization algorithm usually train in long time but resulted with good generalization particularly for noisy or tough set of data. In this work, several number of hidden neurons were selected which is 11, 13, 15 and 17 to evaluate the performance of ANN model. ANN architecture also needs to specify the transfer functions for both hidden and output layer. This work applied hyperbolic tangent sigmoid functions for hidden and output layer. The hyperbolic tangent sigmoid function is bounded between -1 and 1 and as shown in Eq. (1);

$$y = \frac{2}{1+e^{-2x}} - 1 \tag{1}$$

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

Evaluation of ANN Model Performance

ANN model performances were evaluated using some performance metric. MSE, RMSE, MAE and SSE were commonly used to evaluate the time-series prediction. The performance measures were mathematically expressed as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i) \tag{2}$$

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

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \tag{4}$$

$$SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \tag{5}$$

Where y_i and \hat{y}_i is the actual and predicted value for the entire i th training vector while n is the observed data of the model.

III. RESULTS AND DISCUSSIONS

ANN model was applied in this research where Elman Neural network method were selected for flow prediction. Reservoir water level, discharge and inflow were used as input parameter to forecast the hydropower discharge. ANN model performance was evaluated with different training method and the number of hidden neurons. Table 1 demonstrates the ANN models performance for the training period. The result indicates that Elman Neural Network showed better performance when Bayesian Regularization were used as training algorithm with 13 as hidden neuron. Usually, Bayesian Regularization algorithm takes more computational time than Levenberg-Marquardt when training the ANN model. However, Bayesian Regularization generate better result in generalization especially for tough or noisy set of data. The result indicates that the number of the hidden neuron highly give impact on the ANN performance. Table 1 illustrates that ANN model performance decreased when big number of hidden neurons were used. Heuristic method is the ideal technique to find the optimum number of hidden neurons. As shown in Table 1, the lowest error obtain on performance metric were 357.54, 18.91, 6.3601 and 9.4028x10⁶ respectively.

Table. 1 Ann model training performance

| Architecture | Performance Function | Algorithm | Number of Neuron | | | |
|--------------|----------------------|-----------|-----------------------|-----------------------|-----------------------|-----------------------|
| | | | 11 | 13 | 15 | 17 |
| Elman | 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 |

Figure 5 shows the best training performance of ANN model when applied Bayesian Regularization as the training algorithm and 13 as the number of hidden neuron. The result indicate that best training performance was 357.5413 at epoch 1000.

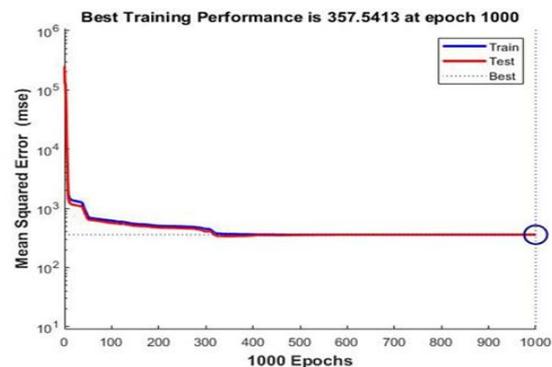


Fig. 5 Training Performance

Test Session

Figure 6 demonstrate the hydropower discharge prediction for test session. Elman network in this test session applied Bayesian Regularization as training method and 13 as hidden neurons. The figure demonstrates the differences between predicted and the actual discharge value. The result indicates the applicability of Elman Neural Network to forecast the hydropower discharge especially in high peak. However, the predicted discharge not accurately forecasted at the lower peak as shown on January and December. Besides, the figure also shows that the predicted discharge is slightly deviated on the middle of March and April. Elman Neural Network capable to forecast the water discharge since it is the type of Recurrent Neural Network that had the dynamic behavior. Its output not only depend on the current input but also on the earlier states of the network. Moreover, it keeps the information of hidden neuron as additional information for the future reference. Elman Neural Network that involve both feedback connection and dynamic element had an essential power memory, which is suitable for non-linear hydrologic modelling. In addition, hyperbolic tangent sigmoid transfer function gives high impact to the output response, thus, making it performs well in discharge forecasting. The hyperbolic tangent sigmoid transfer function has the greater response than sigmoid function since it have the bigger slope. Hence, it can produce nonlinear response and differentiate between small variations in the input parameter. Moreover, the hyperbolic tangent sigmoid function had a positive response for positive input while negative response for negative input. Figure 7 shows the differences between prediction and actual value. The result shows that error between actual and predicted value is slightly high in January and December month due to the inaccuracy of discharge prediction. As a result, the potential risk of flooding at the lower stream can be identify through the hydropower discharge prediction. Figure 8 showed the potential flood risk at the downstream throughout the year. Figure 8 indicate that flooding may occur at the low-lying area in the month of March, April, May, June and December.

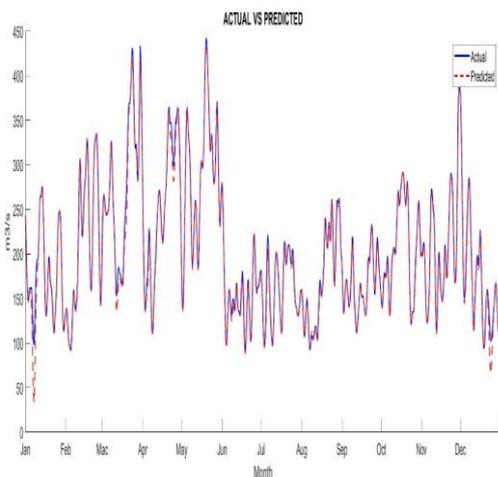


Fig. 6 Flood prediction

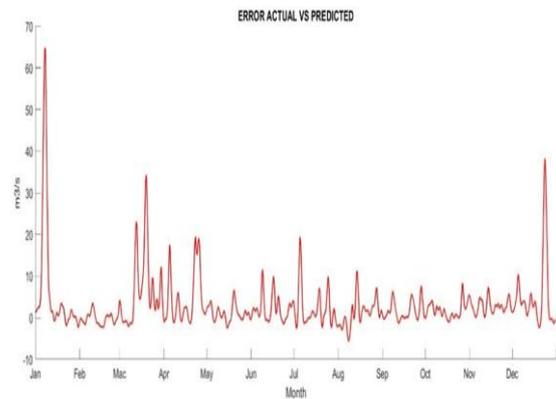


Fig. 7 Error Value

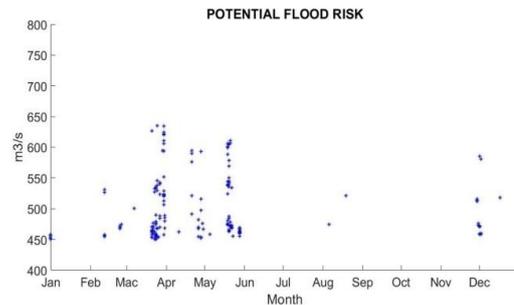


Fig. 8 Potential Risk of Flooding

IV. CONCLUSION

In conclusion, ANN model was used to forecast the discharge at the hydropower station. Elman Neural Network capable to perform discharge prediction with small error. The results indicates that ANN model showed higher accuracy in prediction based on Bayesian-Regularization as training algorithm. In addition, hidden neuron has high impact on the performance of ANN model. Variation of hidden neuron produce different ANN model performance. The results demonstrates that ANN model has lower performance when has high hidden neuron value. Nevertheless, the optimal number of hidden neuron was 13 that generates overall best performance. The potential risk of flooding at the low-lying area can be identified via hydropower discharge prediction. Hence, the hydropower discharge prediction can be used to mitigate the risk of flood at the downstream.

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