# River flow modeling using artificial neural networks in Kapuas river, West Kalimantan, Indonesia

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Submission date: 12-Dec-2019 09:23AM (UTC+0700) Submission ID: 1232768828 File name: Rpaper\_River\_flow\_modeling\_using\_artificial\_neural\_networks.pdf (1.61M) Word count: 1904 Character count: 9669

### River Flow Modeling Using Artificial Neural Networks in Kapuas River, West Kalimantan, Indonesia

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#### INTRODUCTION

Kapuas River is located in West Kalimantan province. Kapuas River passes across several regencies and cities in West Kalimantan. Kapuas River is 1.086 Km long while the area of Kapuas Watershed is about 100,000 Km<sup>2</sup>, which covers about 67% of West Kalimantan. Kapuas River acts as a water source used by people living around the Kapuas River to meet their needs of water. Kapuas River is also a source of water for fisheries, plantations, and other businesses. Kapuas River is also used by the surrounding community as waterway transportation for access between villages, districts and regencies around Kapuas River.

West Kalimantan which is in the tropics has two seasons, namely rainy and dry seasons. Thus, the availability of water in Kapuas River is strongly influenced by seasonal condition. In rainy season with a high amount of rainfall, Kapuas River will experience flooding. Whereas in dry season, there will be water drought in Kapuas River. Although the number of average annual rainfall in Kapuas Watershed is relatively high, but since seasonal conditions is very influential, the availability of adequate water throughout the year is difficult to obtain.

Water availability can be seen in the form of water discharge data, which can be obtained from available monthly or annual rainfall calculations that occur in catchment area. Thus, the result of water discharge calculation is also the annual or monthly water discharge data. Whereas, in an infrastructure planning, the water discharge data required are the daily water discharge. But water discharge or river flow data in long rivers, such as Kapuas River, are difficult to obtain. In addition to that, the long term river flow data of Kapuas River which are currently available are not sufficient enough, long term water discharge data which is affected by the change of rainfall and seasonal conditions are needed to identify climate change. Therefore, it is necessary to predict the river flow based on available hydrological data such as rainfall data and evaporation data. In addition to its importance as the basis for planning, the data are also needed for future maintenance of the waterworks (Abd & Sammen, 2014).

Prediction and estimation of water discharge can be done with ANN approach [1-7]. Applications of ANN approach have been widely used to predict, estimate and forecast the aspects of hydrology and water resources [8-13]. Artificial Neural Network is an artificial representation of human brain which always simulates the learning process by the human brain [14]. By using ANN approach, the prediction of river flow affected by rainfall and other seasonal

Proceedings of the 3rd International Conference on Construction and Building Engineering (ICONBUILD) 2017 AIP Conf. Proc. 1903, 100010-1–100010-7; https://doi.org/10.1063/1.5011620 Published by AIP Publishing, 978-0-7354-1591-1/\$30.00

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conditions around the observed watershed will be generated. Previous researchers have successfully modeled river flow with ANN approach in some rivers. But, there is no prediction of Kapuas river flow with a catchment area of approximately 100,000 Km<sup>2</sup>.

The modeling of rain-flow with ANN model was done by utilizing MATLAB R.2015 software [15].

#### METHODOLOGY

#### Study Area

Kapuas River is located in Kapuas Watershed, West Kalimantan Province. The watershed (Fig. 1) is located between latitude of 2° 00' S - 2° 00' N and longitude of 108° 00' E - 114° 30' E. The length of Kapuas River is 1,086 Km and the area of Kapuas Watershed is about 100,000 Km<sup>2</sup>. Figure 1 shows the location of existing rainfall station around Kapuas Watershed at Sanggau observation point. The width of Kapuas River at the measuring point is about 800 m.

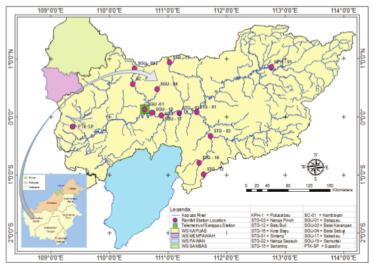


FIGURE 1. Map of Rainfall Station Location in Kapuas Watershed

#### Input and Output Variable(s)

The data available in Kapuas Watershed are rainfall and evaporation data. The data used as input are the average daily rainfall data from several rain stations in Kapuas Watershed at Sanggau observation point. The stations used are 13 stations located in Kapuas watershed (Fig. 1), which were Putussibau (KPH-1), Sintang (STG-01) Nanga Sepauk (STG-02), Nanga Pinoh (STG-03), Batu Buil (STG-12), Senaning (STG-15), Kota Baru (STG-16), Kembayan (SC-01), Sanggau (SC-04), Balai Karangan (SGU-03), Balai Sebut (SGU-04), Sekadau (SGU-17), and Semuntai (SGU-19). Average rainfall value is obtained by using Thiessen method.

Inputs on the model are as follows:

X1 (n-1) : water discharge of the previous day (Q(n-1))

 $X_{2\,(n)} \hspace{0.1 in}: \text{daily rainfall } (P_{(n)})$ 

 $X_{3(n)}$  : daily evaporation (ETo<sub>(n)</sub>)

 $X_{4(n)}$  : area of watershed (A)

While output (target); Y (n), is daily water discharge (Q).

The expected output data are daily water discharge or river flow in Kapuas River for 34 years, which is 1982 to 2015. The value of evaporation data were obtained from climatic data at Sanggau and Supadio weather stations.

#### Architectural Structure of ANN

ANN modelling in this paper uses a multilayer neural network. Training algorithm used is back propagation ANN architecture with feedforward ANN structure as shown in Fig. 2, while the ANN model and architecture model used in this study can be seen in Fig. 3.

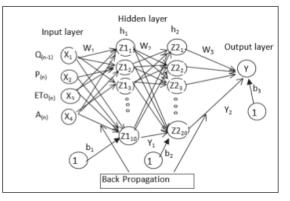


FIGURE 2. Feedforward Chart on ANN Model

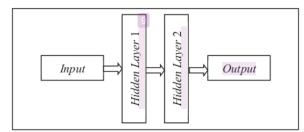


FIGURE 3. Artificial Neural System Architecture in Research

- The process occurred on each layer (hidden layer 1, hidden layer 2, output layer) are as follows:
- 1. Insert input value into hidden layer 1
  - In hidden layer 1, calculate the weighted input value by using activation function (this study used *sigmoid biner* (*logsig*) activation function).

Where,

W = weight

X = input

- B = bias
- $Z_1 = Output \text{ of hidden layer } 1 = logsig (W_1X + b_1)$
- If, y = logsig(x), then:

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

Therefore,

$$Z_1 = \frac{1}{1 + e^{-(W_1 X + b_1)}}$$
(2)

2. Pass output of hidden layer 1 to hidden layer 2.

In hidden layer 2, calculate the weighted input value by using the activation function (this study used sigmoid biner (logsig) activation function).

Where, W = weight,B = bias,  $Z_1 =$  output of hidden layer 1  $Z_2 =$  output of hidden layer 2 = logsig ( $W_2Z_1 + b_2$ ) If y = logsig(x), then

$$y = \frac{1}{1 + e^{-x}} \tag{3}$$

Therefore,

$$Z_2 = \frac{1}{1 + e^{-(W_2 Z_1 + b_2)}} \tag{4}$$

3. Pass output of hidden layer 2 to output layer.

In output layer, calculate the weighted input value by using the activation function (this study used the binary sigmoid (logsig) activation function).

Where,

W = weight

b = bias

 $Z_2 =$  output of hidden layer 2

If  $y = purelin (W_3Z_2 + b_3)$ , therefore;

$$y = \text{purelin} \left( W_3(\text{logsig}(W_2(\text{logsig}(W_1X)))) \right)$$
(5)

The value of Y obtained is the value of the network output. Total number of hidden neurons:

$$W_{1} = \begin{bmatrix} W_{11} & \dots & W_{1M} \\ W_{21} & \dots & W_{2M} \\ \vdots & \ddots & \vdots \\ W_{N1} & \ddots & W_{NM} \end{bmatrix}$$
(6)

Or it can be stated that  $W \in R^{NxM}$ Where, R = real number NxM = dimension of the matrix So that each weighted value of **b**<sub>1</sub>, **b**<sub>2</sub>, **b**<sub>3</sub>, **W**<sub>1</sub>, **W**<sub>2</sub>, **W**<sub>3</sub> are expressed in matrix form as follows:  $\begin{array}{l} b_1 \ \in \ R^{10x1} & ; \ b_2 \ \in \ R^{20x1} & ; \ b_3 \ \in \ R^{1x1} \\ W_1 \ \in \ R^{10x4} & ; \ W_2 \ \in \ R^{20x10} & ; \ W_3 \ \in \ R^{1x20} \end{array}$ 

#### **Training of Artificial Neural Network**

Prediction process with ANN method was started with training process to observational data. The first step is to normalize the data used as input, from the value of -1 to 1. Training algorithm process was as shown in Fig. 4.

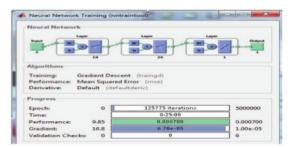


FIGURE 4. Training Process of ANN

#### Validation of ANN Models

Training algorithm process was conducted to obtain daily Kapuas river flow data from 2002 to 2011. Training process was used as a model with Mean Square Error (MSE) of 0.0007. The validation charts on the training process are presented in Fig. 5. The prediction results of training process for 2002-2011 data and the observational data in 1982-2015 are presented in Fig. 6.

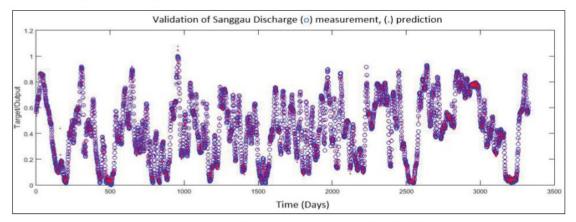


FIGURE 5. Validation of ANN Prediction Results of River Flow Data in 2002-2011

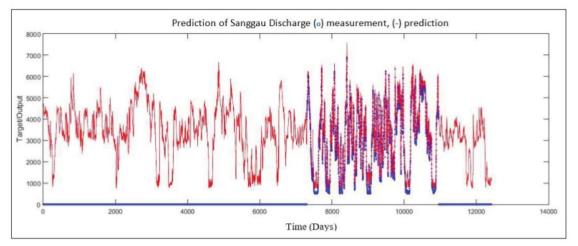


FIGURE 6. Results of River Flow Predictions and Observational Data of River Flow in 1982-2015

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#### **RESULTS AND DISCUSSION**

Kapuas River flow comes from the rainfall which occurs around Kapuas Watershed. In addition to rainfall, river flow is also affected by evaporation process occurs in Kapuas Watershed. From the observation in Sanggau telemetry station (Fig. 7), river flow data of Kapuas River in 2002-2011 were obtained. To obtain the river flow data in 1982-2015, predicting Kapuas river flow needs to be done. Prediction of Kapuas river flow was done by using river flow modeling with ANN method. Data used as input of the model are data of rainfall, evaporation and catchment area.



FIGURE 7. Sanggau Telemetry Station, Field Documentation on March 14, 2015

After conducting training and validation process of ANN model, the most optimal architectural structure, where the results are the closest to river flow data from observational data in the field, was chosen. Based on available rainfall data, river flow data of Kapuas River in 1982-2001 and 2012-2015 were obtained.

The modeling of Kapuas river flow in Sanggau with the best estimation using Artificial Neural Network (ANN) method was constructed with 1 input layer (4 input data), 2 hidden layers, and 1 output layer. The first hidden layer consists of 10 neurons, the second hidden layer consists of 20 neurons, and the output layer has 1 neuron. To obtain the output value, input value was inserted into first hidden layer, then the output of first hidden was passed to second hidden layer (output of hidden layer 1 was used as the input of hidden layer 2), then output of hidden layer 2 was passed to output layer (the output of hidden layer 2 was used as the input of output layer).

From the rainfall data in Kapuas Watershed, data of water discharge in Kapuas River were obtained. The results showed that during the last 34 years, there has been a decrease of river flow in Kapuas River (Fig. 8). The results of research are very useful to identify the condition of water availability in Kapuas River as well as to identify the condition of water resistance in Kapuas River in the future.

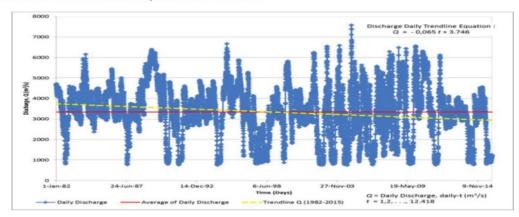


FIGURE 8. Trend line of Daily Water Discharge of Kapuas River from 1982 to 2015 at Sanggau Observation Point

#### CONCLUSION AND RECOMMENDATION

Artificial Neural Network approach can predict an event according to data used as input. Implementation of back propagation method for river flow modeling gives relatively good result on training process and validation process. From existing data as the input, outputs in the form of daily Kapuas river flow data are obtained.

Results of this research show that ANN approach can be used to obtain Kapuas river flow data prediction, with results close to observational data. This can happen with the best ANN architectural structure, which consists of 1 input layer with 4 neuron nodes, 2 hidden layers with 10 and 20 neuron nodes each and 1 output layer which is the daily water discharge of Kapuas River. ANN architecture used in this calculation provide the most optimum data generation in testing process.

From the prediction and estimation result of Kapuas river flow for 34 years, it is known that there has been a decrease of water flow in Kapuas River. Further research regarding the evaluation of model resulted by real conditions in the field needs to be done.

#### ACKNOWLEDGEMENTS

This study was conducted with financial support from the Directorate General of Higher Education, Ministry of Research, Technology and Higher Education of Indonesia. The authors would like to express gratitude to the reviewer who provides valuable comments and suggestions in order to improve the quality of this paper.

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