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Research Paper

Suitability of Artificial Neural Network Application to Predict Sekayam River Discharge in Indonesia

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ABSTRACT

Data availability of on a river discharge is the key to waterworks planning. Unfortunately, not all rivers have long and complete historical data records to support the planning. Therefore, a hydrological model capable of predicting long-term river discharge is needed. There are many hydrologic models that have been developed, ranging from the simplest ones by using empirical black- box model, to complex ones with physical white-box model. This study used ANN application due to its data requirement that is applicable to be met in study area, Sekayam River, a part of Kapuas Subwatershed, namely Kembayan Watershed. Although the available data is relatively minimal, which is only rainfall and evaporation data, the ANN application can predict river discharge that is close to the measurement in the field, with a mean square error (MSE) of 0.25. The results show that ANN application was able to predict river discharge reasonably with climate and rainfall data as the input. Deviation may occur due the broad scope of the research area, Kembayan Watershed, a Kapuas Subwatershed which amounted to 2,290 km^2.

1. Introduction

In the context of infrastructure planning, especially waterworks, river discharge data is a necessity. Not all river discharge data have sufficiently available discharge data. Thus, prediction and forecasting of river discharge is necessary. Besides as a basis for planning, river discharge is also required for maintaining existing waterworks in the future (Abd and Sammen 2014, Herawati et al. 2018).

Sekayam River is a tributary of Kapuas River, making the Sekayam River is located on a Kapuas Subwatershed namely Kembayan Watershed. Sekayam River did not have sufficient long-term discharge data. Meanwhile, discharge data are needed to determine water availability in Sekayam River. Therefore, the prediction and forecasting of river discharge based on available hydrological data such as rainfall and evaporation data are needed.

With available data taken from Sekayam River surrounding, river discharge forecasting can be done with Artificial Neural Network (ANN) application. The result in the form of complete forecast data can be used strategically for planning and maintaining the watershed in the future.

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Literature Study

Utilization of ANN approach has been applied in the forecasting of hydrological and water resources (Dawson and Wilby 2001; Wang et al. 2008; Nourani 2009; Mustafa et al. 2012; Sarkar and Kumar 2012; Abd and Sammen 2014; Herawati et al. 2017). Forecasting river discharge can be done by using ANN application (Akhtar et al. 2009; Chowdhary and Shrivasta 2010; Bisht and Jangid 2011; Tiwari et al. 2012; Rahsepar and Mahmoodi 2014; Zeroual et al. 2015). Previous studies have succeeded in modeling the river discharge using ANN on several different rivers. But there has been no forecast on the Sekayam River whose catchment area amounted to 2,290 km^2.

Artificial Neural Network (ANN) imitates and represents the human brain which always simulate the learning process of the human brain (Kusumadewi and Hartati 2010). Neural Systems components include:

Neuron

The smallest component of a neural network is a neuron. Neurons will transform the information received through the connections leading to the release of other neurons. In neural network, the connection is known as weighting. The information is stored on a particular value to the weight (Kusumadewi and Hartati 2010). The structure of neurons is presented in Fig. 1.

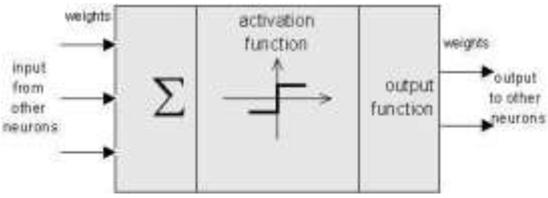

Figure 1 Structure of Neuron (Kusumadewi and Hartati 2010)

Input will be sent to the neurons with a specific weight of arrival. This input will be processed by a propagation function that will add up the values of all weights combined. The result of this sum will be compared to a threshold value given through the activation function which is on each neuron. If the input passed certain threshold, the neuron is activated and vice versa. When a neuron is activated, it will send the output via the output weights to all the connected neurons.

Neural Network Architecture

Single neural network is the simplest type of neural network. This neural network is as shown in Fig. 2. Single neural network has only one layer with weights connected. This system only accepts direct input and it will process them into output without having to go through hidden layer. In other words, neural network architecture with a single layer is only composed of a single layer of input and one output layer, without hidden layers.

Network with multilayer have one or more layers located between the input layer and output layer (having one or more hidden layers). This network is as shown in Fig. 3. Generally, there is a layer where the weights are located between two adjacent layers. Network with multi layers may face more problems during the learning process than the network with a single layer since the learning process is more complicated.

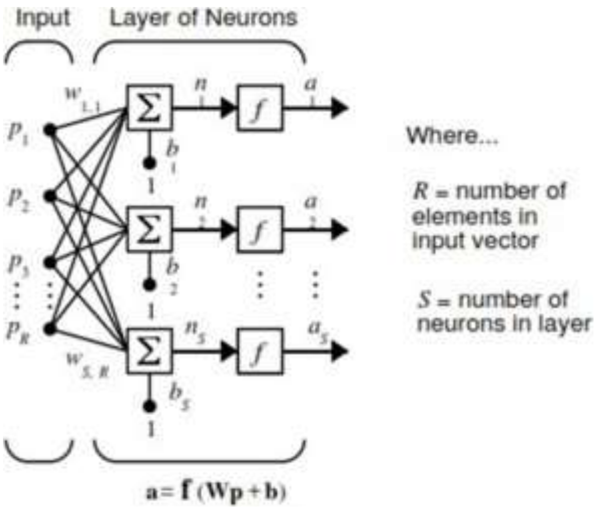

Figure 2 Single Neural Network (Demuth and Beale 1998)

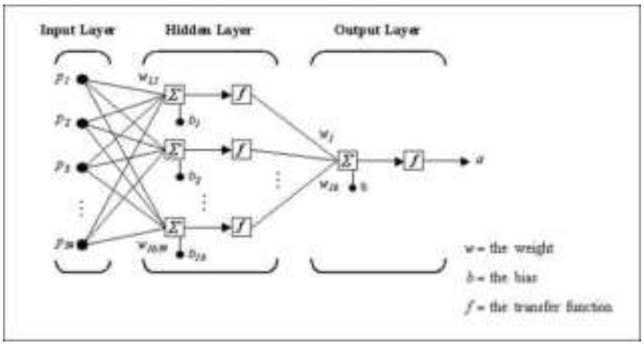

Figure 3 Multilayer Neural Network (Demuth and Beale 1998)

Activation Function

A neural network trained with backpropagation learning algorithm using the sigmoid bipolar or sigmoid binary training function to determine the output value from the input to the hidden layer or the output from the hidden layer 1 to hidden layer 2. Meanwhile, learning process from hidden layer to output layer generally use linear activation function.

a. Sigmoid Binary Function

Binary sigmoid function has output value ranging from 0 to 1.

Therefore, this function is often used for neural network that require an output value which lies between 0 and 1. The binary sigmoid function defined (Demuth and Beale 1998) as follows:

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

With $f'(x) = \sigma f(x)[1 - f(x)]$

b. Sigmoid Bipolar Function

Bipolar sigmoid function is almost the same as binary sigmoid function, except that this function has output value that ranges between 1 and -1. The bipolar sigmoid function defined (Demuth and Beale 1998) as follows:

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

With $f'(x) = \frac{\sigma}{2}[1 + f(x)][1 - f(x)]$,

This function is very close to hyperbolic tangent function. Both have a range between -1 to 1. Hyperbolic tangent function is formulated as follows:

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

With $f'(x) = [1 + f(x)][1 - f(x)]$

c. Linear Function

Linear function has a same output value to the input value. The linear function defined (Demuth and Beale
1998) as follows:

$$y = x$$

Backpropagation Learning Algorithm

Backpropagation algorithm using the error output to change the value of the weights in a backward direction. To get this error, feedforward propagation stage must be done first. At the time of feedforward propagation, neurons activated by using an activation function which can be differentiated, such as binary sigmoid and Bipolar sigmoid. Backpropagation learning algorithm can be seen in Fig. 4.

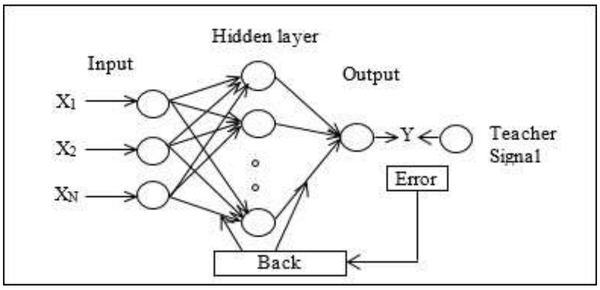

Figure 4 Backpropagation ANN Architecture (Chowdhary and Shrivasta 2010)

Backpropagation training algorithm (Siang 2009):

Phase I : Feedforward

Calculate output of the hidden unit:

$$\boldsymbol{z\_net_j = v_{jo}} + \sum_{i=1}^{n} x_i v_{ji}$$

$$z_j = f(z\_net_j) = \frac{1}{1+e^{-z\_net_j}}$$

Calculate output of the output unit:

$$y\_net_k = w_{ko} + \sum_{j=1}^{p} z_j w_{kj}$$

$$y_k = f(y\_net_k) = \frac{1}{1+e^{-y\_net_k}}$$

Phase II : Backpropagation

Calculate output factor δ unit based on errors in each output units y_k:

$$\delta_k = (t_k - y_k) f'(y\_net_k) = (t_k - y_k) y_k (1 - y_k)$$

calculate the changes of wkj weight with learning rate α

$$\Delta w_{kj} = \alpha \delta_k z_j \qquad (k = 1,2, \dots m \,; j = 0,1, \dots p)$$

Calculate δ hidden factor uni

$$\delta\_net_j = \sum_{k=1}^{m} \delta_k w_{kj}$$

δ hidden factor unit

$$\delta_j = \delta_{net_j} f'(z_{net_j}) = \delta_{net_j}\, z_j (1 - z_j)$$

Phase III: Weight changes

Calculate all the weight changes:

Change of output weight units;

$$w_{kj}(\text{final}) = w_{kj}(\text{initial}) + \Delta w_{kj} \qquad (k = 1,2, \dots m \,; j = 1,2, \dots p)$$

Change of hidden weight units;

$$v_{ji}(\text{final}) = v_{ji}(\text{initial}) + \Delta v_{ji} \qquad (j = 1,2, \dots p \,; i = 1,2, \dots n)$$

2. Methodology of study

The model was built by using rainfall data of 31 years (1982-2012) from Balai Karangan station and Kembayan station, while climate data were obtained from Sanggau station. Modeling was conducted by training, testing and validating by using discharge observational data which are available in 1982 at Kembayan station with a catchment area of 2,290 km^2. Forecasting the discharge is done by modeling the discharge data available in 1982 to obtain complete discharge data from 1982 to 2012. Discharge modeling was done by using Artificial Neural Network (ANN) approach.

In this study, the neural network training method used is the backpropagation algorithm. A neural network trained with backpropagation learning algorithm using sigmoid training function to determine the binary value of the output from input layer to hidden layer or the output from hidden layer 1 to hidden layer 2, while the output from hidden layer to the output layer uses a linear activation function. This research conducted using ANN application with network architecture consisted of a single input, multiple hidden layers and a single output. The basic structure of ANN model used can be seen in Fig. 5. The research conducted some learning processes and tested the prediction results obtained with several MSE values. Based on the results of training, testing and validating the acquired value, the mean square error (MSE) of 0.25 generated the closest and most rational discharge conditions in the field.

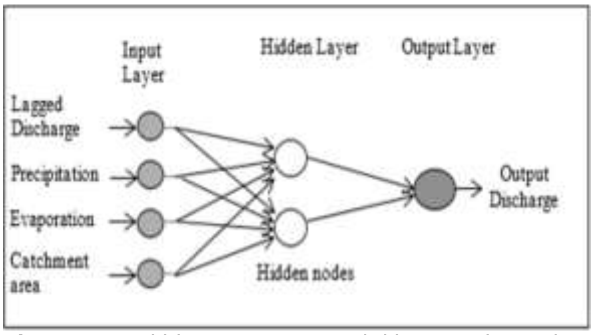

Figure 5 Multi-layer Perceptron (Akhtar *et al.* 2009)

3. Result and Discussion

Discharge modeling was conducted using artificial neural network by training the values of river discharge measurement from the year when the data is available. The modeling was done by following modeling steps, so that the input, process and output obtained the desired river discharge model.

Training process was performed to obtain Sekayam River discharge value in 1982. Training used as a mean square error (MSE) of 0.25. Validation of this training process is presented in Fig. 6. The prediction results of training the 1982 data is presented in Fig. 7.

The research that used rainfall and evaporation data in 1982-2012 as the input obtained Sekayam River discharge data from 1982 to 2012. Testing results from data training processes can be seen in Fig. 8. The forecast for Sekayam River discharge can be seen in Fig. 9. Deviation may occur due the broad scope of the research area, Kembayan Watershed, a Kapuas Subwatershed which amounted to 2,290 km^2.

With the limited data available in the field, the results of this forecast may provide a presentation of Sekayam River discharge.

The research can be used to identify the condition of the water flow in Sekayam River and determine the water availability and resiliency of Sekayam River in the future.

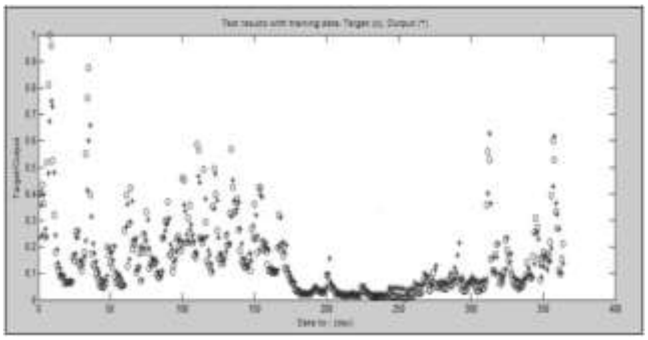

Figure 6 Validation of ANN prediction results of the discharge data in 1982

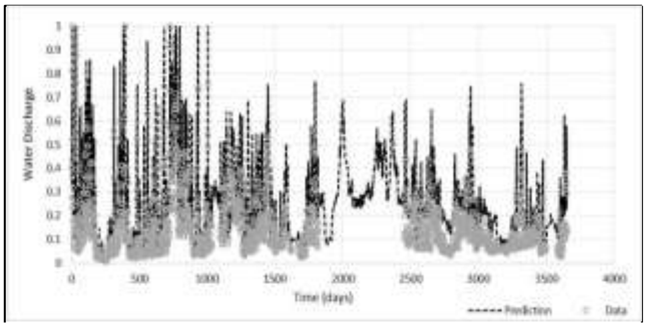

Figure 7 Normalized form of discharge prediction results for the year 1982-1991

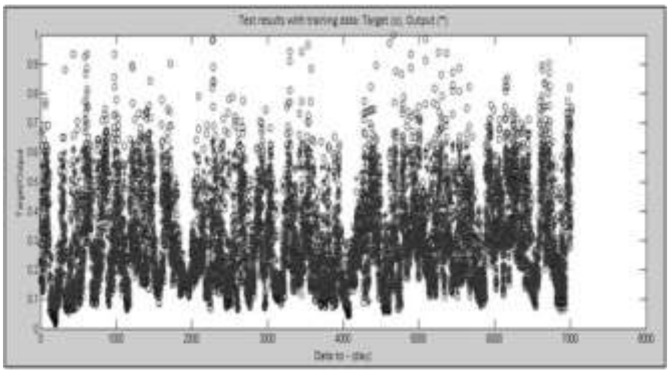

Figure 8 Testing results from training the data

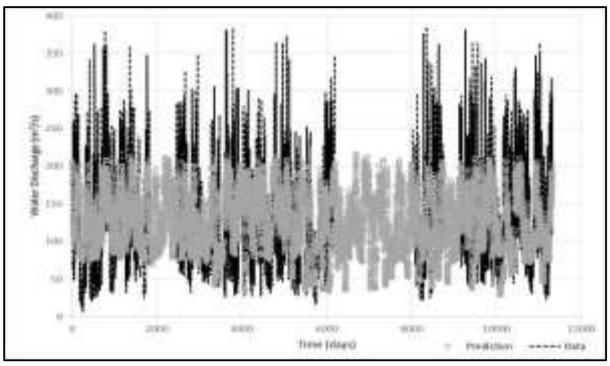

Figure 9 Discharge prediction results and observed discharge data in 1982-2012

4. Conclusion and Recommendation

ANN application is capable and suitable to predict and forecast the condition based on the available data as the input. Results of the research show that ANN application can be used to forecast and predict the Sekayam River discharge although the results showed some deviations. The available data that can be used as the input around Kembayan Watershed, Kapuas Subwatershed were only rain and climate data. Based on the given input, the output in the form of river discharge were obtained.

River discharge is not only determined by the amount of rainfall and climatic conditions. Land cover and soil type also determines the amount of discharge flows in the river. This lack of data is likely the cause of results deviation in a study of this size. Future research result quality may be improved by adding land cover data as the input, so that the forecast.

5. Data Availability Statement

Rainfall and evaporation data used during the study were provided by a third party. Direct requests for these materials may be made to the provider as indicated in the Acknowledgements.

River discharge prediction model that support the findings of this study are available from the corresponding author upon reasonable request.

6. Acknowledgements

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