

The Water Level and Outflow Prediction Using the Artificial Neural Network (ANN) for the Management of the Reservoir Flooding

Hari Nugroho, Suripin, Iwan K. Hadihardaja

The aim of operation reservoir during flood is to prevent overflow that endangers the dams. It is also to prevent flooding in the downstream of the dam, which leads to loss of life and property. This aim can be achieved with optimal reservoir management which is influenced by the reservoir's condition during flooding such as: rain, reservoir storage, inflow, water level, and discharge of reservoir water released to the downstream. The successfully of the reservoir management depends on the accuracy of the estimated a). water level (due to the inflow of the reservoir) and b). outflow from the reservoir.

One of the models which can be used to predict the water level and reservoir water released during flooding is the Artificial Neural Network (ANN). ANN can simulates flood events that are similar in fact to the previous occurrence In this study a backpropagation ANN model was applied to the Wonogiri Reservoir in Central Java, Indonesia.

The optimal ANN architecture produced in this study are the Input Pattern of 5-3-4 (which has a rain input recorded 1 – 5 hours earlier, a water level input recorded 1 – 3 hours earlier and a release input recorded 1 – 4 hours earlier). 27 pieces hidden layer, total epoch which is 200 and the learning rate of 0.01. The output is predicting the water level, the Outflow and Gate Opening of Reservoir. The current flood data was applied to the above model and it was concluded that the network can follow the flood management pattern adequately. In addition, the network is extra flexible with a lower flood discharge rate; and has the final elevation of the reservoir slightly lower than the normal operation.

Index Terms : Artificial Neural Network, optimal model, reservoir operation during flood

I. INTRODUCTION

Throughout history, people have always wished to live in the riverbank area. This is due to the area being fertile and providing various benefits, which improves their living

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standards. Although the area is prone to flood, the community intend on dwelling there regardless, because the benefits obtained from the area outweigh the risks that may occur. For instance, the FEMA (Federal Emergency Management Agency), an institution that handle floods in the United States, recorded that more than 10 million Americans live in flood-prone areas [13]. This makes consequences in the planning and management of water resources management, is how to develop a strategy to prevent or reduce flood damage and losses in inundated areas that are inhabited either by local flooding, or due to runoff from reservoirs during floods.

Management of reservoirs in flood control structure aims to manage and prevent damages caused by floods in the downstream of the reservoirs. The channel size of the dam's downstream should be considered when deciding the release of water. The prevention of an overflow on the body of the dam is a top priority and it should be considered when planning because if it overflows it can be extremely dangerous.

The development strategies of prevention and management of floods in the lowlands with the optimization of reservoir flood was started in 1970 [21]. The management of reservoirs as flood control are: 1). able to anticipate the increase of inflow or flooding into the reservoir and store water in accordance with the planned storage capacity. 2). able to regulate the amount of water so as not to endanger the release of downstream reservoir. Although the reservoir storage capacity can always be known, the uncertainty of inflow makes reservoir management is challenge, especially if it is associated with limited storage capacity.

The operations of the flood control reservoirs are specific to a type of operation rule, which states that the decision to release the water is highly dependent on the hydraulic conditions, hydrology and the size of the reservoir storage capacity. The characteristics of the reservoir flooding, is that

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it occurs very quickly and with a high discharge. During flood, the release of the reservoir water is carried out in a very short period and in real-time operation by the flood control components. The operations of flood control components are carried out in a short time (in hour or every 15 minutes) and based on the following data: the reservoir storage and elevation, rainfall, the position of flood control gates, and discharge of reservoir inflow and outflow.

This study therefore aims to predict the water level and the outflow of the reservoir during flooding, by using the ANN. The forecast results are used as a reference in the management of reservoirs during flood. Furthermore, it reduces the losses caused by flood in the downstream of the reservoir.

II. LITERATURE STUDY

Several models have been developed for the analysis of water resources, and these models can be classified as optimization or simulation, statics, dynamics, deterministic and stochastic [22,23]. The optimization models are useful for identifying, evaluating and solving problems relating to complex water resource systems [22]. Notwithstanding, the model may not be applicable unless they imitate the uncertain conditions that affect the system [9]. Studies about techniques used to determine the patterns of reservoir operations are directed towards the modeling of real-time, realistic and representative reservoir operations [21].

In optimizing water resources, several optimization techniques are used to determine the policy of reservoir operation patterns. In principle, there are five methods used to determine the patterns [18], namely: 1) Distribution of allocation-zone and by rule-curve method, 2) Standard Operating Policy (SOP), 3) Linear programming, 4) Dynamic deterministic program or implicit stochastic and 5). Dynamic stochastic program. In addition to the methods above, the optimization of the dynamic stochastic program is currently developing with the use of fuzzy set theory [17] and ANN application [4,5].

The reservoir operations are carried out by prediction, especially when the factors that influence the reservoir are known (certain), such as information about inflow and water requirements. In fact, the data on the inflow and actual water needs are not certainly known, especially in the decision of the volume of water needed to be released (release). The planning steps for operating the reservoir need to consider the two factors as uncertain numbers, because they are inherently high in the level of uncertainty. Suharyanto [16] shows the limitations of operating with a deterministic model. It implied that the operations would produce greater costs, especially in extreme conditions in reservoirs with a limited capacity.

To overcome its shortcoming, a stochastic management model is proposed. Several suggestions for modeling the hydrological time series, are Auto-regressive (AR). Several researchers have carried out various reservoir managements with dynamic stochastic models. Venkatesh [20] concludes that:

1. Stochastic Dynamic programming can be used to optimize reservoirs. However, the level of difficulty depends on the number of state variables.
2. The operations of reservoirs, which generally form some of these methods, are only applicable to be used as the function of a single reservoir (single purpose). For

example, it is used only for irrigation, hydropower, drinking water, and so on, however, for multi-purpose reservoirs, it is considered less applicable.

3. Fuzzy logic and neural network application used for optimization of the reservoirs develops rapidly. The results obtained from several studies indicate that they produce better outcome when compared to the conventional optimization method.
4. Fuzzy Systems and neural network will be used as the mainstay methods in future to simulate the complex behavior of reservoir systems.

For two decades, the heuristic algorithms have been developed to solve problems relating to reservoir optimization. It uses a set of pieces point simultaneously to obtain the optimum solution. Chen [3] succeeded in developing a Fuzzy Neural Network that predicts the discharge of the optimization of reservoirs in its systems in Taiwan. The results show that the simulation model used produces a better management and the technique can be used for a better rule-curve optimization, which is not limited to one objective function.

One of the alternative models, which can be developed, is the ANN. The model optimization is trained to replace the reservoir simulation model [11], employed this application to improve the reservoir operation performance and it resulted in a better quality than the conventional simulation-optimization models. Solomatine and Torres [14] also used ANN for river optimization models with MIKE 11 for the optimization of reservoirs.

A. The Definition of Reservoir Flooding

Reservoir flooding is when the increased water level is higher than the normal water level (NWL) which causes an overflow in the reservoir. It continues to increase to the control water level (CWL) and flood water level (FWL). At this stage, the water level needs to be lowered immediately, to anticipate the runoff from the body of the dam, which can be very dangerous. In reservoirs, the water storage starts from the bottom to the maximum level, according to the design [19].

In a case where the elevation at the control water level (CWL) and inflow is still large, the operator should become alert to the operations of the flood structure through the spillway (*uncontrolled*) and the flood control gates (*controlled reservoir*). The flood control procedures will be applied once the height of the reservoir starts to exceed the NWL. The water level rises during the flood and downs when the flood is over. Firstly, the flood /inflow (I) fills the control storage and then water discharge fills the reservoir when the elevation increases due to the amount of inflow that exceeds the outflow capacity (O). The storage equation is developed from the continuity equation [19], where the storage changes (dS) are the result of the difference in inflow and outflow of the reservoir: $\frac{dS(t)}{dt} = I(t) - O(t)$, where; $I(t)$ is the inflow, $O(t)$ is the outflow. It is a non-linear function of depth (Hb) and storage (S). For details, see the Figure 1.

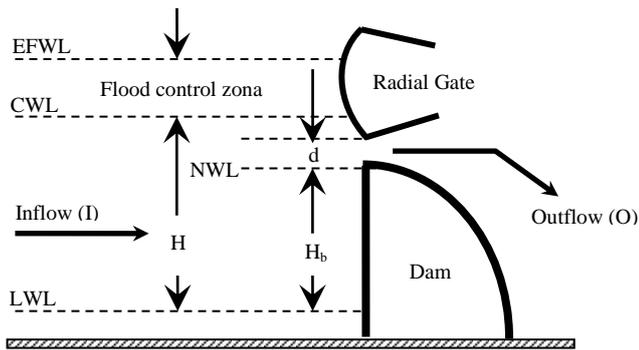


Figure 1. The Sketch of Flood Water in Reservoir [2]

In general, reservoir flooding has the characteristics of occurring for a very short time with a large volume of water and a rise in the water level over a short period. A reservoir flooding is categorized into two, namely:

1. **Normal (Ordinary) flood** follows the Q design and it is equivalent to a certain return of flood period. It is used as the maximum flood standard, which safely controls the downstream of the dam (Standard Highest Flood Discharge/SHFD).
2. **Abnormal (Extraordinary) Flood** is above the Q design and it is equivalent to floods caused by Probable Maximum Flood (PMF).

The normal flood is managed by the flood control structure in reservoirs and their magnitude can be reduced in order for the discharge flowing out to be safely contained in the downstream of the reservoirs, while abnormal flood can only be controlled in the reservoirs. However, it contributes to flooding of the downstream channel.

Reservoir management during flood is carried out with the aim of minimizing the impact of damages in the downstream and maximizing the availability of water when the flood ends [10]. Conventionally, the operating pattern of the existing reservoir is established for operations that are below the normal conditions, where the reservoir water level is between the minimum (Low Water Level-LWL) and normal water level (Normal Water Level-NWL) [15]. If the reservoir water level increases above the maximum normal level, the release of the reservoir water will be carried out to maintain water level elevation. The goal is to ensure that any time a flood occurs, the control zone will be prepared to suppress the outcome. Furthermore, in the field, the limits of the minimum and maximum normal water levels are not a fine line [18]. When the reservoir water rises and is approaching the maximum normal water level, the operator begins to use his intuition, perception, and experience to enlarge the release (excess release) in flood control situations. Here the operator's ability greatly determines the success of the reservoir management in controlling floods.

B. Artificial Neural Network Method

Artificial Neural Network (ANN) is a black-box model, it is a theory designed to represent the way the brain works in

solving a problem and it is often called an adaptive function [6]. One of the applications of the ANN is for forecasting. A method that is often used during the forecasting process is a back propagation algorithm with a multilayer perceptron architecture and a hidden layer, such as forecasting the flow of discharge of the Nile in Egypt [1], Mae Kong [12]. and prediction of the discharge of the Cikapundung with ANN [8].

ANN is developed and applied in various fields to predict the random natural phenomena including in the field of water resources. The ANN technique is intensively developed and applied in various fields for reservoir operations. It is used to find the optimum solution for the release of the water to the downstream and to maintain the maximum reservoir storage with a least amount of damage during the climax of the downstream flood. The ANN technique commonly used is the multilayer perceptron network and back propagation learning.

The reservoir operation pattern is extremely dependent on the characteristics of the reservoir for a particular purpose and the limit (constraint) of the related reservoir. The operation of a system principle is the application of the theory of mass balance or the law of conservation of mass, the theory is often called the hydrologic budget. it states that the amount of water deposited at the beginning of the month (t+1), is equal to the initial water deposits of the month (t) along with the amount of water entered during the month (t), excluding the amount of water flowing out and evaporating during the month (t) [22].

The ANN modeling procedure consists of three steps, which are the selection of network architecture through a trial process until the training is successful, the learning and the testing. The number of hidden layers determines the architecture and nerves in each layer. A multilayer (with two or more hidden layers) examines every continuous mapping at a certain level of accuracy, and by using more than one hidden layer can be beneficial for several applications, nevertheless using just one, is sufficient. Therefore, to be more efficient, using only one hidden layer is adequate.

The determination of the number of nerves (nodes) in the input layer is based on the parameters associated with the operating patterns of the reservoir during the flood. Those parameters are: Rainfall (R), inflow (I), reservoir volume (V), water level (WL), size of gate openings (G) and so on.

The number of the nodes in the hidden layer is obtained from study or papers on ANN modeling written by several researchers with experience. The smaller number usually lacks a satisfactory performance, while the larger number does not add a large amount to the performance of the model, and it can be detrimental because it requires a longer learning time.

The number of the nodes in the output layer is selected based on the parameters, which are intended to be discovered, for instance, the water level and release of the reservoir. Generally, the calculation is obtained by applying the water balance equation (mass balance) to the reservoir.

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III. DATA DAN METHODOLOGY

A. Data

The Wonogiri Reservoir was built on the Bengawan Solo River, in Wonogiri District, Central Java, Indonesia. This multi-functional dam has its main function as a flood controller. Furthermore, it also provides irrigation water, power plants, fishery, and tourism. For the power plants, the two Kaplan type turbines have a capacity of 6,500 KVA each, and a maximum discharge of 36.30 m³/sec. The electricity production of the Wonogiri Reservoir is 12.4 MW with an annual energy supply of 55,000 MWh.

The downstream of the dam has been irrigating the agricultural areas of 30,000 ha through the Colo Weir (located at ± 13 km) and its irrigation system. In addition, the implementation of a technical farming system with three planting times in a year is supported through the irrigation system. Figure 2. shows the location of the Wonogiri Reservoir in the Map of the Bengawan Solo Watershed and Figure 3. shows the storage of the Wonogiri Reservoir.



Figure 2. The Location of the Wonogiri Reservoir in the Bengawan Solo Watershed (JICA, 2007a)

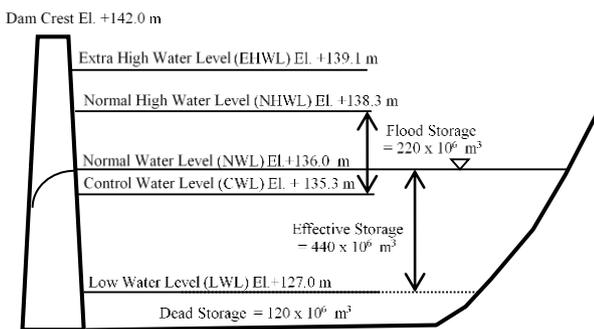


Figure 3. The Wonogiri Reservoir Storage (JICA, 2007a)

To carry out the function of the reservoir in flood control, storage size of +135.3 m to +138.3 m is provided and the allocation of storage is 220 million m³. The flood control uses four spillway gates, which are radial gates that measure 7.5 m x 7.8 m. With those flood control infrastructures in place, the largest inflow that amounts to 4,000 m³/sec and 400 m³/sec outflow can be set. The river capacity in the downstream of the reservoir can safely contain an outflow of 400 m³/sec. The spillway gates are not operated when the water level is below an elevation of +135.30 m, however, if the water level is

between +135.30 m and +138.30 m, the spillway gates will be partially operated with a maximum outflow of 400 m³/sec. The spillway gates will be opened fully when the water level is above El +138.30 m, with an outflow between 400 – 1,360 m³/sec.

In the Wonogiri Watershed there are 4 rain gauge stations Automatic Rainfall Recorder (ARR), namely: ARR Pracimantoro (1), ARR Jatisrono (2), ARR Batuwarno (3) and ARR Tirtomoyo (4) and 1 Automatic Water Level Recorder (AWLR) in Wonogiri Dam. The ARR and AWLR locations are shown in Figure 4.

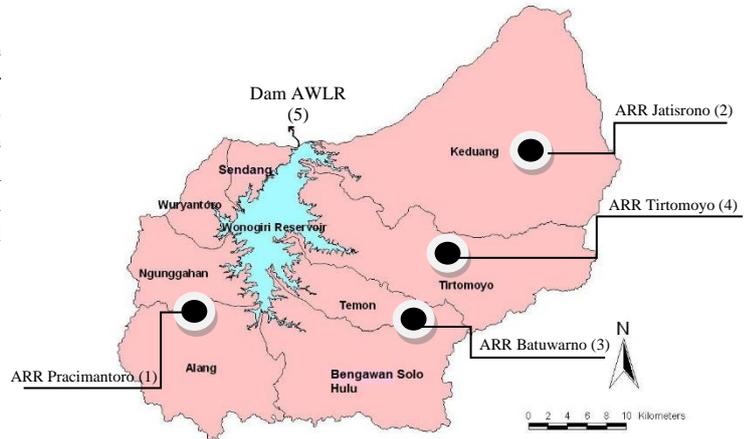


Figure 4. Wonogiri Reservoir Watershed, 4 ARR Stations and 1 AWLR Station (JICA, 2007a)

Data used for predicting water level and outflow are presented in Table 1.

Table 1. The data set and statistics

Data	Training, Validation, Verification (68 %)			Trial (32 %)		
	Data of Rainfall (mm)	Data of Elevation (m)	Data of Outflow (m ³ /sec)	Data of Rainfall (mm)	Data of Elevation (m)	Data of Outflow (m ³ /sec)
Total of data	5,316	5,316	5,316	3,273	3,273	3,273
Total of set	39	39	39	18	18	18
Min	0	134.21	0	0	133.64	0
Max	75.00	137.10	279.50	78.00	137.29	350.00
Average	0.42	135.83	158.06	0.44	135.85	136.03
Std	2.81	0.54	55.69	2.42	0.52	68.88

B. The Application of ANN Method to Predict Outflow and Water Level of Reservoir

In broad outlines, the steps in modeling the ANN in the prediction of water level and outflow, are further transformed into predictions for reservoir gate openings. The steps are as follows:

- Rainfall data of four stations with an hourly observation is the input obtained from the ARR. The hourly water level of the Wonogiri Reservoir obtained from AWLR data for 1995 – 2012 (18 years).
- Training/validation/verification data for the ANN is the rainfall data of four stations with an hourly observation. The water level of the reservoir obtained from AWLR data is for

- 1995 – 2012 (18 years), and the discharge for 39 flood events (68%).
- Testing data by using flood data of 18 flood events between 2007 – 2010 (32%)
 - The architecture of ANN chosen to produce the most optimal form, then the result of the prediction is compared to the target (real data) which has the least error.
 - From the data of rainfall level, reservoir water level and outflow data from the previous hours are the input and the output is the next hour Water Level and Outflow so that the data is the training data of ANN.
 - The input data is divided into several models, by considering the flood response from each of the existing rain stations. The ANN data for rainfall is carried out for 1-5 hours earlier with hourly rainfall data and the water level data is taken 3 hours earlier with hourly water level data. In addition, the outflow data is 4 hours earlier; this means that the water level in the next 1 hour is affected by rainfall in data taken 1-5 hours earlier, the water level of 3 hours earlier and outflow of 4 hours earlier.
 - The learning parameters include the epoch, rate of learning, and the number of neurons.
 - The ANN used is a multilayer perceptron. It provides better results in handling non-linear data compared to other networks. The chosen architecture consists of three layers of processing elements, which are one input, hidden and output layer as shown in Figure 5.

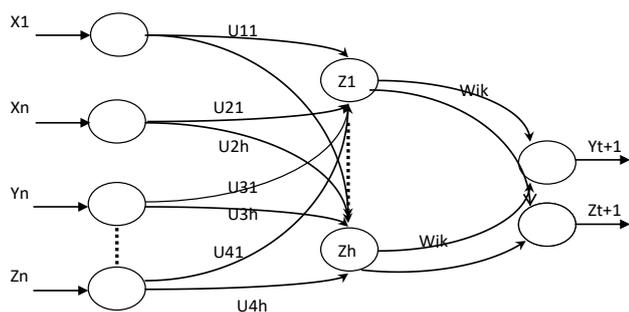


Figure 5. The architecture of the ANN used

Where :

- X_1, \dots, X_n = The rainfall data at hour t, at Sta 1, 2, 3, etc.
- Y_1, \dots, Y_n = The water level data at hour t, t-1, t-2, etc.
- Z_n = The outflow data at hour t, t-1, t-2, etc.
- Y_{t+1} = The reservoir water level in the next 1 hour
- Z_{t+1} = The reservoir outflow in the next 1 hour

From Figure 5., X_i is the rainfall data at hour t, which is at sta 1, 2, etc. and X_{t-1} is the rainfall data at hour t-1, which is at Station 1, 2, etc., while Y_{t+1} is the prediction of water level in the next hour. From these data, it can be observed that the forecast for the water level and outflow for the next hour is influenced by the backward rainfall data of the earlier 1-5 hours, water level, and 1-hour backward outflow as shown in Figure 6.

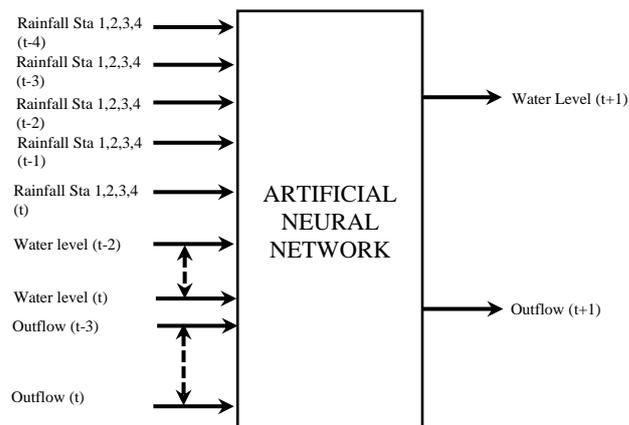


Figure 6. Example of data input (rainfall and water level) and Output (Water level and Outflow) on the ANN Network

Network training is used to prepare the data set that has been created. The training is carried out with various network parameters such as network architecture, number of neurons, epoch and the rate of learning. Each variation of the parameters is obtained by calculating the Mean Square Error (MSE) with the formula:

$$MSE = \frac{1}{n} \sum_{i=1}^n (WL \text{ target } i - WL \text{ prediction } i)^2$$

The trained network needs to be tested in order to discover its ability to learn the given training. The testing is done by observing the target data, actual output, errors and MSE, where the lowest MSE value obtained is the best prediction result. Furthermore, the R^2 calculation, which is the correlation coefficient, is calculated. Correlation is calculated by the formula:

$$R^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2 \sum_{i=1}^n (Y_i - \bar{Y})^2}}$$

Where:

- R^2 = Correlation coefficient
- n = total of the data
- x_i = calculation data i
- y_i = observation data i

IV. RESULT AND DISCUSSION

A. The Results of the ANN Architecture

The optimal network architecture is obtained by trial and error. The experiment was carried out by determining the epoch from 10 to 500 and seeing the performance of R^2 .

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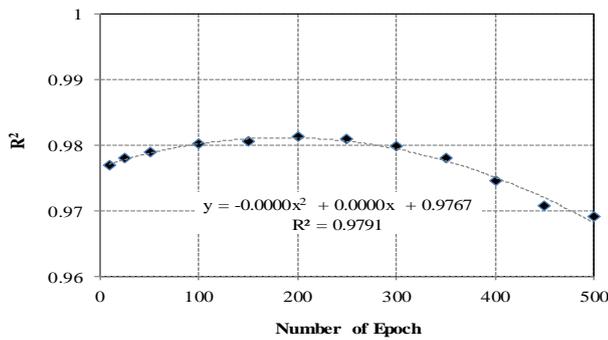


Figure 7. The Influence of the Number of Epoch on R² Value

As Shown Figure 7. the optimum number of epoch obtained was 200. The increase in the number of epoch ($n > 200$) significantly decrease the R² and MSE performance.

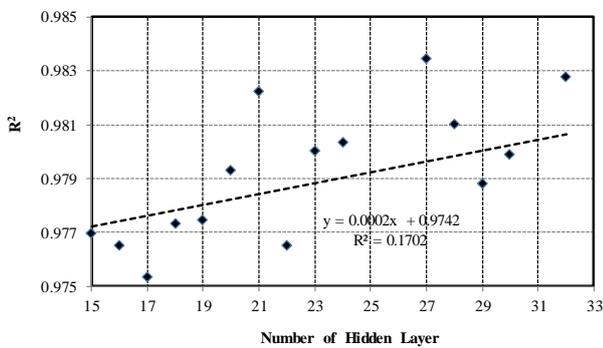


Figure 8. The Influence of Number of Hidden Layer on R² Value

From Figure 8. the optimum number of hidden layers obtained was 27 with the largest R² performance. The optimum hidden layer is on the 27 totals of neurons.

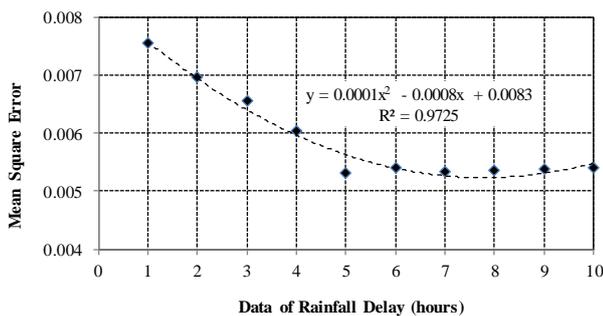


Figure 9. The Influence of the Input Layer (Data of Rainfall Delay) on the MSE Network

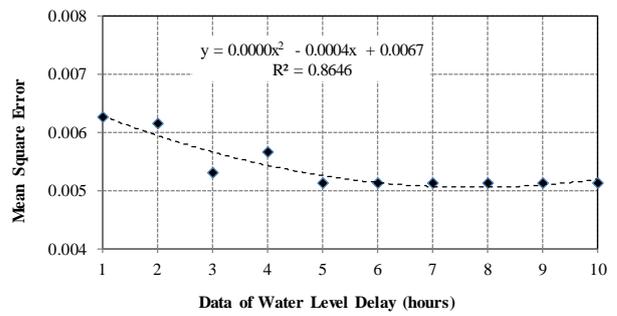


Figure 10. The Influence of the Input Layer (Data of Water Level Delay) on the MSE Network

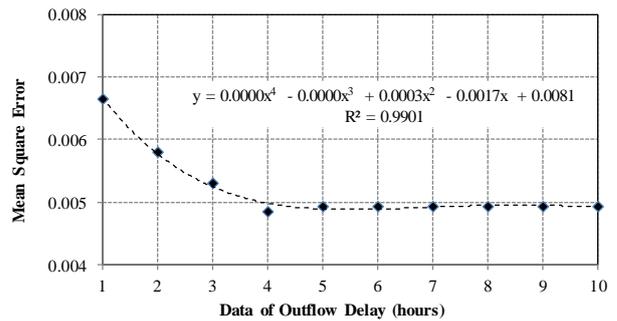


Figure 11. The Influence of the Input Layer (Data of Outflow Delay) on the MSE Network

From the Figure 9., Figure 10. and Figure 11., the optimum amount of the rain delay was 5 hours, the water level was taken at a delay of 3 hours and the outflow was at 4 hours, with the smallest MSE performance. Thus, the chosen network architecture was in the input pattern of 5-3-4 (rain delay was 5 hours earlier, water level delay was 3 hours earlier, and outflow delay was 4 hours earlier)

B. The Operation for Wonogiri Reservoir

The optimum results were applied to the Wonogiri Reservoir flood control operation with interface as shown as Figure 12.

The Simulation Program of Wonogiri Reservoir Operation With Artificial Neural Network						
DATA ENTRY :						
Rainfall (mm)				WL (m)	Out (m ³ /sec)	
ARR1	ARR2	ARR3	ARR4	Dam AWLR	Dam Outflow	
t 10	t 11	t 12	t 1	t 135.07	t 150.00	
t-1 0	t-1 0	t-1 21	t-1 1	t-1 135.00	t-1 100.00	
t-2 8	t-2 1	t-2 25	t-2 1	t-2 135.00	t-2 100.00	
t-3 2	t-3 1	t-3 2	t-3 1		t-3 50.00	
t-4 3	t-4 1	t-4 0	t-4 10			
PROCESS						
PREDICTION :				THE GATE OPENING :		
Prediction of WL at t+1				135.07 m	Gate 1 and 4	
Prediction of Outflow at t+1				149.96 m ³ /sec	Gate 2 and 3	
					0.69 m	
					0.69 m	
CLOSE						

Figure 12. Example of The Operation to Predict the Water Level, Outflow and Gate Openings

In which :

1. Data Entry :
 - a. ARR1: ARR Pracimantoro
 - b. ARR2: ARR Jatisrono
 - c. ARR3: ARR Batuwarno
 - d. ARR4: ARR Tirtomoyo
 - e. WL : Water Level of Reservoir
 - f. Out: The amount of water that flows out of the spillway and turbine
2. Time :
 - t = time of the occurrence
 - t-1 = 1 hour earlier
 - t-2 = 2 hours earlier
 - t-3 = 3 hours earlier
 - t-4 = 4 hours earlier
3. Prediction Results:
 - a. The reservoir water level at (t+1), is the prediction of the water level after 1 hour
 - b. The reservoir outflow at (t+1), is the prediction of the outflow after 1 hour
4. Prediction of the Gates Opening:
 - a. The prediction of Gate 1 and 4 openings, which is the prediction of the gate openings after 1 hour (**Gate 1 and 4 are opened together**)
 - b. The prediction of Gate 2 and 3 openings, is the prediction of the gate openings after 1 hour (**Gate 2 and 3 are opened together**)

C. Network Performances

To measure the network performance, the inflow and outflow between the human-based and the ANN control in the management of reservoirs during flood were compared and presented in the following Figure.

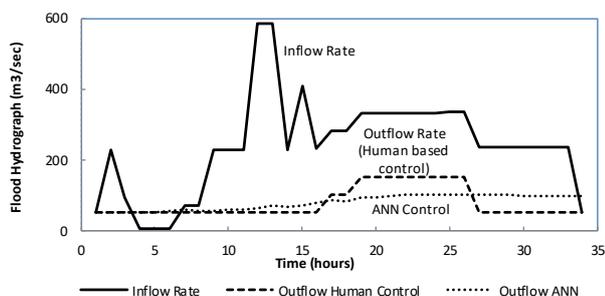


Figure 13. The Comparison of the Outflow between the Human-based control and the ANN Control at Flood event -11

From Figure 13, it is observed that the peak discharge of the ANN control graph is under the outflow rate human-based control. This indicates that the possibility of a magnitude amount of flood in the downstream can be reduced due to its limited channel.

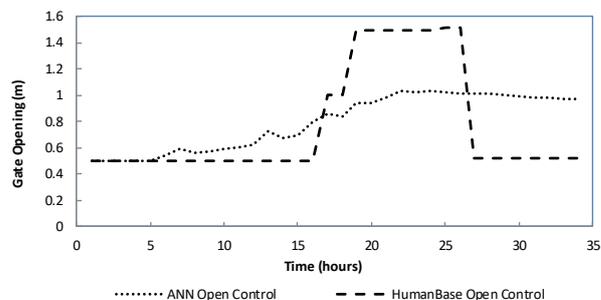


Figure 14. The Comparison of Water Level Between Human-based Control and ANN Control at Flood event -11

From Figure 14, it can be observed that the peak discharge in the ANN control graph was under the outflow rate in the human-based control, this implies that the operation with ANN is easier and more flexible due to the gate openings not being extremely high.

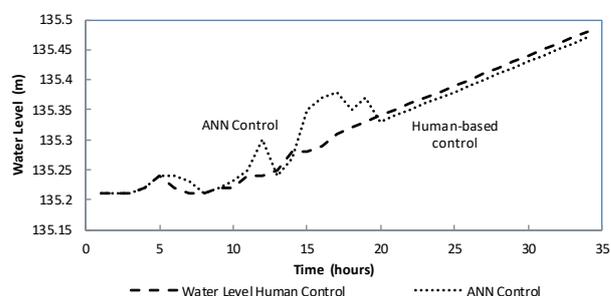


Figure 15. The Comparison Of The Gate Opening Between Human-based Control and ANN Control at Flood event -11

From Figure 15, it is observed that the elevation in the ANN control graph followed the pattern of the human-based control with the final elevation of the reservoir slightly below the average elevation.

V. CONCLUSION AND IMPLICATION

From the result and discussion, it can be conclude that the network follows the pattern perfectly. This can be proven by the small value of the RMSE parameter and R^2 , which has close to 1. Network architecture was in the input pattern of 5-3-4 (rain delay was 5 hours earlier, water level delay was 3 hours earlier, and outflow delay was 4 hours earlier), while the number of the hidden layer was 27 pieces, the epoch was 200, and the learning rate was 0.01. The network follows the outflow pattern, which previously occurred in 18 flood events, and have taken place with a large coefficient of determination. The operations using the ANN are more flexible, less prone to flood, and have the final elevation of the reservoir is slightly less than the normal operation.

Along with technological advancement in the area of computing, the implementation of Neural Networks in the domain of water resources can be optional. If the data of other reservoir optimization problems can be acquired, then the program used as a model in this study can be applied to assist in the training process, as long as the new data consists of relatively the same characters as the data in this study.

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