



Forecasting the Change of Reservoir Water Level Stage Using Neural Network

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Abstract: The reservoir is one of the structural defenses that function to reduce the negative effect of flood and drought. The decision of water release is very critical in both situations where it is influenced by changes of reservoir water level. In this study, the potential of neural network model for forecasting the change of reservoir water level stage is studied. Six neural network models have been developed and tested. Sliding windows have been used to segment the data into various ranges. The finding shows that 2 days of delay have affected the change in stage of the reservoir water level. The finding was achieved through 4-17-1 neural network architecture.

Keywords: Model Forecasting, Reservoir Water Level, Neural Network.

1. Introduction

Reservoir system is one of the significant components and a part of water resource management. A reservoir is a natural or artificial lake or large tank, where it functions to impound and regulate the water for supplies and irrigation. Moreover, the reservoir can also act as a defense mechanism for flood and drought situations [15; 17; 33].

Reservoir can be classified into two types, which are single reservoir and multipurpose reservoir systems. A multireservoir system is more complex compared to a single reservoir system. The reservoir can also be classified based on its purposes and functions. A reservoir with one purpose or function is called a single purpose reservoir, while a reservoir with more than one purpose is a multipurpose reservoir. According to [16], a single purpose single unit reservoir is the simplest system and a multipurpose multiunit reservoir system is the most complex system. The simplest system is developed for the single purpose operation such as hydropower generation or flood protection. The most complex reservoir system is created for the multiple purpose operation such as flood protection, navigation, hydropower generation and recreation [20].

Reservoir system can be separated into four parts, which are upstream, reservoir, spillway gate and downstream. Upstream is the water source or inflow of the reservoir. The spillway gate is a structure which functions to control the release of the reservoir water. Some reservoirs are equipped with an ungated spillway and some others have both types of spillways. The gated spillway requires several numbers of decisions such as the number of gates to be opened, the duration and size of the opening.

Flood is one of the natural disasters that could strike repeatedly. It can indirectly or directly cause extreme losses to the public such as properties, homes and innocent souls.

Flood is directly associated with the reservoir as the latter is one of the flood mitigation mechanisms. According to [31], a flood situation usually occurs in the lowland areas which are much more fertile and crowded with human activities, especially in the agriculture sector. This area is typically the downstream area of the reservoir. It usually occurs in areas which are dry and obviously interferes and disrupts social activities and human. An early decision on the reservoir water release can help to reduce and prevent losses to the flood affected areas as the water flow can be controlled in accordance to the river capacity. Another natural disaster that is related with reservoirs is water shortage (drought). It cannot be viewed solely as a physical phenomenon, but the impacts on society and surrounding area must be considered. Drought is a critical situation causing more deaths compared to other natural disasters [28].

This paper discusses the findings of the forecasting model for the change of reservoir water level stage using neural network. The next section presents some related literature on Artificial Neural Network (ANN) and studies on forecasting of water level. This is followed by the methodology and findings of this study.

2. Literature Review

Reservoir operating policy is important in reservoir operation as the impact of the reservoir operation of society and economy is huge [32]. Reservoir operators and planners are required to plan a strategy that can be used to determine the decision [1]. The operating policies for reservoirs are usually developed based upon previous meteorological and hydrological data [9]. In certain conditions, operating policies, also known as operating rules, are commonly used in the early or planning level of the proposed reservoir. Moreover, reservoir water release decisions are guided by the reservoir operating policy [2; 24].

In the reservoir operation, decision making is one of the vital procedures that needs to be implemented wisely in order to balance the demand and supply of water for optimal social, economic and environmental benefits. The problems in early decision making of reservoir water release usually occur in unpredicted weather conditions. Therefore, several decision making procedures such as simulation and optimization techniques have been developed to identify optimal operating rules in reservoir systems. As referred to [17], there are four optimization strategies for the multiple reservoir system that have multiple objectives, namely, implicit stochastic optimization, explicit stochastic



optimization, real-time optimal control with forecasting and heuristic programming methods.

The reservoir operator uses the information on the delay and current reservoir water level to make an early water release decision. Changes of the water level are monitored and referred to the superior officer before taking any action. Early water release is crucial to reserve space for incoming upstream inflow. Furthermore, the capacity of the downstream river will be controlled by the quantity of water being released. Thus, it can avoid the risk of flooding in downstream rivers, which is caused by the massive water release from the reservoir.

The availability of historical data such as water level, rainfall and current outflow had been considered for the prediction of reservoir water level. The daily rainfall and water level data had been used in the multipurpose reservoir forecasting model [1; 22; 23; 32]. Rale et al [4] used daily water level of the Kainji Dam in their prediction model. However, Rafiei et al [11] used the hourly water level and the current outflow data to develop a forecasting model upon the reservoir water level for the next three hours during a flood event.

There are several techniques that have been used in forecasting reservoir water level such as an Artificial Neural Network (ANN), Adaptive Neuro fuzzy interface system (ANFIS), Support Vector Machine (SVM) and Autoregressive Integrated Moving Average (ARIMA). Rittima [1] compared the performances between SVM and ANFIS techniques. The SVM performance is superior and much better than ANFIS based on statistical evaluation. Meanwhile, Rale et al [4] used ANN in forecasting water level and the findings are compared with ARIMA. The findings suggest that ANN produces better prediction models, however simpler mathematical formulation is needed to build a good model.

ANN model was a useful tool for modeling complex nonlinear systems and making predictions [10]. ANN is an algorithm that dynamically inherits human neuron information processing capability [8]. The ANN can be categorized into single and multi-layer network. The single layer network is a model that consists of input and output where multi-layer network consist at least one hidden layer between input and output layer.

ANN has been deployed in many forecasting applications such as in finance [12], business [6], medical [3] and much more. In the hydrological forecasting, ANN has been successfully deployed in rainfall forecasting [21], stream-flow forecasting [5], river water level forecasting [20; 26], groundwater modeling [29; 35] and reservoir operation [13]. The multilayer feed forward neural networks were extensively used and trained by standard backpropagation (BP) algorithm [7; 13].

3. Methodology

In this study, the Timah Tasoh reservoir was used as a case study. The Timah Tasoh reservoir is one of the largest multipurpose reservoirs in Northern Peninsular Malaysia. Timah Tasoh, located on Sungai Korok in the state of Perlis, about 2.5km below the confluence of Sungai Timah and Sungai Tasoh. The Timah Tasoh reservoir serves as a flood

mitigation in conjunction to other purposes: water supply and recreation. Water from Timah Tasoh is used for domestic, industrial and irrigation. In this study, a total of 5779 daily reservoir water level (WL) data from 1999-2013 are used. The data is preprocessed and normalized into the range of -1 and 1. The changes of reservoir water level, which refer to the increase or decrease of water level, affect the stage of water level. Table 1 shows the representation of the water level at Timah Tasoh Dam, according to expert classification and nominal value.

Table 1. Water Level Stage Representation and Nominal value

Water Level (m)	Flood Stage	Nominal Value
< 29.0	Normal	1
< 29.4	Alert	2
< 29.6	Warning	3
>29.6	Danger	4

Standard backpropagation neural network with bias, learning rate and momentum are used to develop the model. The model used the temporal pattern based on the changes of the reservoir water level stage. The changes of the reservoir water level and stage of water level were used as the input patterns instead of the actual reservoir water level. These changes of reservoir water level will be calculated using Equation 1, where ΔWL_t = the change of reservoir water level at t , WL_t = reservoir water level at t and WL_{t-1} = reservoir water level at $t-1$.

$$\Delta WL_t = WL_t - WL_{t-1} \quad (1)$$

Each dataset consists of N number of input columns and 1 output column. The N is equal to the window size that represent the reservoir water level at different time $t, t-1, t-2, t-w$, where t represent the time and w is the window size. The input is then normalized using Min-Max method (Equation 2) to transform a value x to fit in the range [C, D]. Where, C is the new minimum and D is the new range of [-1, 1]. The output is the change of the stage reservoir water level at t which either has a change (1) or no changes (-1).

$$New(x) = \left[\frac{x - \min(x)}{\max(x) - \min(x)} \right] * (D - C) + C \quad (2)$$

The temporal information of the reservoir water level data is preserved by using a sliding window technique [33]. This process is called segmentation process. In this study, six datasets have been formed. Each dataset represents the different window sizes. Each window size represents time duration of the delays. For example, window size (w) 3 represents three days of delays. An example of the data is shown in Table 2. Table 3 shows the number of instances extracted for each dataset. Redundant and conflicting instances are removed from the dataset.



Table 2. Example of Data for Window Size 3

ΔWL_{t-2}	SWL_{t-2}	ΔWL_{t-1}	SWL_{t-1}	ΔWL_t	SWL_t	ΔSWL_{t+1}
1	1	-1	1	-1	0.33333	1
-1	-1	-1	-1	1	1	1
0	-1	-1	-1	1	-1	1
1	-1	-1	-1	-1	-1	-1
0	-1	0	-1	-1	-1	-1

Table 3. The number of instances

Dataset	Window Size	Number of instances	
		Original	Used
1	2	5779	50
2	3	5628	150
3	4	5426	350
4	5	5070	709
5	6	4562	1213
6	7	3963	1811

Each dataset is then divided randomly into three datasets: training set (80%), validation (10%), and testing set (10%). The training set is used in the training phase of NN, while validation set is used to validate the NN performance during the training. The testing set is used to test the performance of NN after the training has completed.

In this study, six neural network models were developed. Each neural network model is trained with one dataset. Each model is trained with different combinations of hidden unit, learning rate and momentum. The training is controlled by three conditions: (1) maximum epoch, (2) minimum error, and (3) early stopping condition. Early stopping is executed when the validation error continues to arise for several epochs [34]. Figure 1 shows the procedure for the neural network training. The aim of this procedure is to get the combination that gives the best result.

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for each hidden unit (HU)
  where HU = {3,5,7,9,11,13,15,17,19,21,23,25}
  for each learning rate (LR)
    where LR = {0.1, 0.2,
0.3,0.4,0.5,0.6,0.7,0.8,0.9}
    for each momentum (Miu)
      where Miu =
{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9}
      Training:
        Feedforward()
        Backpropagation of error()
        Weight update()
      Validation()

      end loop (Miu)
    end loop (LR)
  end loop (HU)
    
```

Figure 1. Pseudo Code for Neural Network Training.

4. Result and Discussion

The results of neural network training, validation and testing are shown in Table 4. Overall, the lowest error achieved for training was 0.136307, and for validation and testing was 0. The best result for training was 92.62%, and for both validation and training was 100%. There is a small difference between the highest and lowest results achieved from training, validation and testing. Thus, the difference shows that neural network has learned the data quite well. Based on the results, dataset 1 is chosen as the best dataset for the change of reservoir water level stage forecasting model. The result for training is 92.5%, whereas validation and testing results are both 100%, and the error for each was 0.150001, 0 and 0. Dataset 1 was formed with window size 2 with 50 instances.

Table 4. Results of Training, Validation and Testing

Data Set	Training		Validation		Testing	
	MSE	%	MSE	%	MSE	%
1	0.150001	92.5	0	100	0	100
2	0.432851	73.33	0.605506	66.67	0.497327	73.33
3	0.448399	77.58	0.457142	77.14	0.318824	82.86
4	0.246922	87.65	0.273057	85.92	0.294699	84.51
5	0.207943	88.26	0.18908	89.26	0.216076	87.6
6	0.136307	92.62	0.163824	91.16	0.187749	90.06

Values for the network parameters that were achieved for the training phase are shown in the Table 5. As for dataset 1, the best result achieved was with learning rate 0.7 and momentum 0.7. The best network architecture achieved is 4-17-1. The finding of this study has shown that neural network architecture 4-17-1 has produced the acceptable



performance during training (92.5%), validation (100%) and testing (100%). The finding also suggests that 2 days are the best time duration for the delay. This also suggests for 2 days of observation of the changes in reservoir water level and stage of reservoir water level.

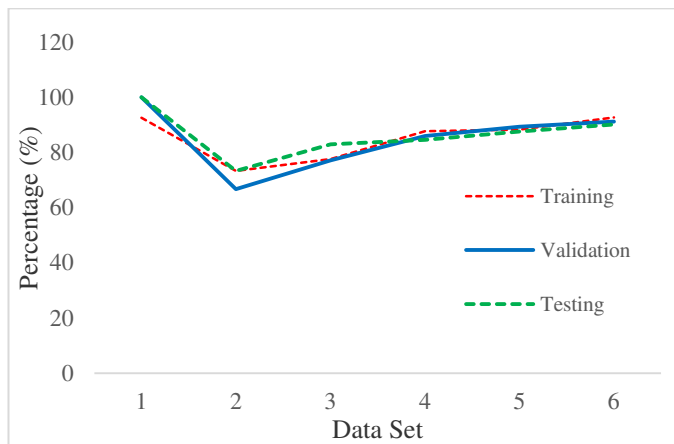


Figure 2. The Results of Training, Validation and Testing.

Table 5. Neural Network parameters

Dataset	Input	Hidden Unit	Output	Learning Rate	Momentum
1	4	17	1	0.7	0.7
2	6	3	1	0.6	0.6
3	8	25	1	0.4	0.6
4	10	11	1	0.3	0.6
5	12	3	1	0.6	0.4
6	14	3	1	0.8	0.4

5. Conclusion

The reservoir water level had been one of the measurements for reservoir water release decision. The small valuable information is the changes of the reservoir water level which provides insights on the increase or decrease of observed reservoir water level. Early water release is crucial to reserve space for incoming upstream inflow. Furthermore, the capacity of the downstream river will be controlled by the quantity of water being released. Thus, it can avoid the risk of flooding at downstream rivers which is caused by the massive water release from the reservoir. This study will help in flood and drought control as it predicts the changes of reservoir water level and stage of reservoir water level.

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