Modelling of Reservoir Water Release Decision Using Neural Network and Temporal Pattern of Reservoir Water Level

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***Abstract*—The reservoir is one of flood mitigation methods that aim to reduce the effect of flood at downstream flood prone areas. At the same time the reservoir also serves other purposes. Through modelling, how the reservoir operator made decisions in the past can be revealed. Consequently, the information can be used to guide reservoir operator making present decision especially during emergency situations such as flood and drought. This paper discussed modelling of reservoir water release decision using Neural Network (NN) and the temporal pattern of reservoir water level. Temporal pattern is used to represent the time delay as the rainfall upstream may not directly raise the reservoir water level. The flow of water may take some time to reach the reservoir due to the location. Seven NN models have been developed and tested. The findings show that the NN model with 5-25-1 architecture demonstrate the best performance compare to the other models.**

Keywords-Reservoir Modelling; Reservoir Water Level; Reservoir Water Release Decision; Temporal Data Mining; Neural Network

I. INTRODUCTION

The reservoir is one of the structural flood mitigation approaches that aim to store water during heavy rainfall in order to maintain safe discharges at the downstream areas [1]. Previous research such as [2] defined reservoir as a natural or artificial lake, or pond where water is collected and stored that are used for multipurpose operation such as water supply, flood control, hydropower generation and other purposes like agricultural and recreation. Reservoir water release decision is one of the challenging tasks for reservoir operator in order to determine the quantities of water to be stored and to be released from a reservoir [3]. The reservoir water release must be adequate, especially during flood to ensure that the reservoir capacity is at a safe level and water to be released will not trigger a flood downstream. During drought, the reservoir will store water and minimum water discharge policy is applied to maintain its operational needs. During both situations, the gate opening decision is crucial as a late decision might cause overflow at the downstream river and might affect the dam's structure.

Reservoir water release decision is a critical action that needs to be undertaken by experienced reservoir operator due to extreme events or emergency situation. The reservoir capacity needs to be maintained in order to prevent flood downstream and reduce water shortage problem in the future. In both flood and drought situations, decisions regarding water release is made in accordance with the available water, inflows, demands, time, previous release and etc. [4]. However, different reservoir has different objectives and purposes, thus required different operation rule [5]. Reservoir operation rule or also known as operation policy can be defined as guideline or strategies generated that provide guidance for reservoir operations especially to determine release decisions [6].

Traditionally, the reservoir was operated based on the standard operating procedure (SOP) which was devised by the reservoir engineer when it was built. The SOP provides reservoir engineer the guideline on how the reservoir should be operated. Reservoir hedging rules were also established at the planning stage of the reservoir and these rules provide guidelines for reservoir releases to meet planned demand [7]. However, the reservoir operation is also influenced by several factors such as sediment [8,9], water usage, climate change [10,11], and urbanization at reservoir upstream [12]. These factors reduce the efficacy of SOP and the operation rule. Eventually, reservoir operator has to apply heuristic procedures by embracing rule curves and subjective judgements [13]. Hence, the reservoir hedging rule needs to be periodically re-evaluated and updated to improve reservoir operation.

This study is aimed to modelled the reservoir water release decision using Neural Network (NN) and temporal pattern of reservoir water level. The next section presents some related literature on NN and its application on reservoir operation and modelling. Following are the methodology and findings.

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II. LITERATURE REVIEW

NN is one among the intelligence methods that has ability to handle dynamic, non-linear and noisy data effectively especially when the physical relationships are not fully understand. It represents a computational mechanism based on a simplified mathematical model of the neurons. NN has been widely used for reservoir operation and decisions especially in deriving operating policies [5,14,15,16,17,18].

Raman and Chandramouli [14] proposed reservoir operating policies using NN for improving management of the reservoir operation. The performance of Dynamic Programming (DP) model, Stochastic Dynamic Programming (SDP) model, Standard Operating Policy (SOP) model and Multiple Linear Regression Procedure (DPR) model are compared and NN based on dynamic programming algorithm yield better performance compare to the other models.

According to [15], simulation-optimization model based on NN has been developed for water supply reservoir system. This study involves three stages of general framework for developing simulation-optimization model. The results of this study show NN-based simulation-optimization model perform satisfactorily compared to the conventional simulation-optimization model. In other hands, [17] proposed model based on NN with four different multi-layer feedforward NN (MLFFNN) modes for dam operation and control by representing the training set to the network in following four different data forms which are historical data without optimization given as monthly (HANN), classical method of optimized results given as monthly (ANN), implicit method with optimized results given as yearly (IANN), and explicit method with optimized results given as monthly (EANN). The findings show that data representation based on the explicit method of using optimized values (EANN) yield better performance compared to the other representation. This study recommends that NN should be used with data mining rather than optimization alone.

Cancelliere et al. [16] apply NN with dynamic programming techniques to derive irrigation reservoir operating rules. The results of their study show that the operating rules improve performances of system operation in both normal and drought periods. Another study by [2,5] used NN to model reservoir water release decision. Temporal data mining technique has been successfully applied to extract temporal patterns of reservoir operational data. NN model was developed to classify the reservoir data for reservoir water release decision. The findings indicate that NN depicted acceptable performance.

III. 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 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 daily reservoir water level (WL) from 1999-2006 are used. The data is preprocessed and normalized into the range 0 and 1. The reservoir water release decision which refers to the gate opening (G) is represented as 0 for gate close and 1 for gate open.

Standard backpropagation neural network with bias, learning rate and momentum is used to develop the model. The modeling is based on the temporal pattern of reservoir water level. The temporal information of the reservoir water level data is preserved by using a sliding window technique [18]. This process is called segmentation process. In this study seven data sets have been formed. Each data set represents the different window size. Each window size represents time duration of the delays. For example, window size (*w*) 3 represents three days of delays. Example of data is shown in Table I.

Each data set 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 output is the reservoir gate condition at *t* that is either open (1) or close (0).

TABLE I. EXAMPLE OF DATA FOR WINDOW SIZE 3

WL_{t-2}	WL_{t-1}	WL_t	G
0.9695	0.97	0.970833	0
0.97	0.970833	0.970833	0
0.970833	0.970833	0.971333	1
0.970833	0.971333	0.970167	1

Table II summarizes the number of instances extracted for each data set. Redundant and conflicting instances are then removed.

TABLE II. DATASET AND THE NUMBER OF INSTANCES

Data Set	Window Size	Number of Instances		
		Generated	Redundant	Used
1	3	2889	257	2632
2	5	2887	18	2869
3	7	2885	0	2885
4	9	2883	0	2883
5	11	2881	0	2881
6	13	2879	0	2879
7	15	2877	0	2877

Each data set is then divided randomly into three data sets: training set (80%), validation set (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. Testing set is used to test the performance of NN after the training has completed.

In this study, seven NN models were developed. Each neural network model is trained with one data set. Each model is trained with different combination of hidden unit, learning rate and momentum [19]. 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 [20]. Fig. 1 shows the procedure for the neural network training. The aim of this procedure is get the neural network model that gives the best result.

```
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.

IV. Findings

The results of neural network training, validation, and testing are shown in Table III. Overall, the lowest error achieves for training, validation and testing was 0.056626, 0.046832, and 0.038756 respectively. The best results of training, validation, and testing was 100%. These results show that the neural network classifier has performed very well on temporal data set. Based on the results in Table II, data set 2 is chosen to be the best data set. Neural network training with data set 2 achieves 100% of training performance and 100% of validation and testing performance. The error was 0.062426, 0.046832, and 0.038756 respectively. Data set 2 was formed with window size 5 with 2869 instances.

TABLE III. Result of Training, Validation and Testing

Data Set	Training		Validation		Testing	
	%	Error	%	Error	%	Error
1	100	0.064226	100	0.063591	100	0.056552
2	100	0.062426	100	0.046832	100	0.038756
3	100	0.059284	100	0.060005	100	0.051464
4	100	0.056626	100	0.051977	100	0.07694
5	100	0.058775	100	0.049386	100	0.064815
6	99.74	0.060066	100	0.052911	100	0.067451
7	100	0.058619	100	0.060399	100	0.057133

Values for the network parameters that were achieved from the training phase are shown in Table IV. As for data set 2, the best result achieved was with learning rate 0.1 and momentum 0.8. The best network architecture achieved is 5-25-1.

TABLE IV. Neural Network Parameters

Data Set	Input	Hidden Unit	Output	Learning Rate	Momentum
1	3	5	1	0.1	0.4
2	5	25	1	0.1	0.8
3	7	25	1	0.1	0.1
4	9	25	1	0.1	0.1
5	11	23	1	0.1	0.1
6	13	5	1	0.1	0.9
7	15	25	1	0.1	0.1

V. Discussion

The sliding window technique has been successfully applied on reservoir water level data to extract and segment the data to preserve the temporal relationship of the data. It was shown in Table II that the size of the window has influenced the number of generated instances. The bigger the window size the smaller the generated instances. However the small window size contains a large number of redundant instances, therefore reduce the usability of the data. The number of redundant instances reduced when the window size increases.

The large number of usable instances contains a large number of temporal patterns that can be used for NN modeling. The large size of data is vital as the performance of neural network model is highly influenced by the size of data set. However, as the data size increases the number of input also increase. The large number of input unit will increase the complexity of the NN modeling.

In this study seven NN models have been developed and each model has been simulated with different combination of hidden unit, learning rate and momentum. The combination that gives the best results (lowest error rate for training, validation and testing) is selected. Based on the findings, almost all models produces 100% accuracy for training, validation and testing. This shows that NN has learnt the entire pattern very well. The overfitting has been handled through early stopping procedure.

The finding of this study also suggests that 5 days are the best time duration for the delay. This suggests that 5 days of observed reservoir water level are significant for the reservoir water release decision. This information is vital for reservoir management to plan an early water release.

VI. Conclusion

The reservoir water level has been one of the indicators for reservoir water release decision. Typically, the reservoir operator seriously monitored the rise of the reservoir water level. Upon reaching certain level standard operating procedure (SOP) will be applied to release the water for a certain period of time. Occasionally, reservoir water will be released as a preparation of incoming heavy rainfall. For this purpose the reservoir operator has to estimate the magnitude of incoming rainfall and at the same time maintaining the reservoir storage for other usages.

Naturally, reservoir water level will rise when rainfalls occurred upstream. However, as rainfalls occurred at distant location the rainfall may not immediately affected reservoir water level. This phenomenon is called time delay. Due to this phenomenon reservoir water release decision is complex and can be executed by the experience reservoir operator. Modelling this experience will reveal how reservoir operator made a decision in the past. This information can be used by the present reservoir operator to deal with emergency situations such as flood and drought.

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