

Reservoir Water Level Forecasting Model Using Neural Network

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Abstract— Reservoir is one of the structural defense mechanism for flood. During heavy rainfall, reservoir hold excessive amount of water to reduce flood risk at downstream area. During less rainfall, reservoir maintains the water supply for major uses such as domestic and commercial usage. In both situations, the water release decision is very critical. The decision is typically influence by the reservoir storage capacity that is the reservoir water level. Early decision regarding the water release can be made if the future water level can be forecasted. In this paper, the potential of neural network model for forecasting the reservoir water level is experimented. The time delay of upstream flow to increase the water level is also experimented. Sliding windows have been used to segment the data into a various range. The findings show that 8 days for delay has significantly affected the reservoir water level. The best neural network model obtain from the experiment is 24-15-3.

Keywords- Forecasting Model; Neural Network; Reservoir Operation and Management; Reservoir Water Level

I. INTRODUCTION

The reservoir is a physical structure such as pond or lake either natural or artificially developed to impound and regulate the water. It has been used as one of the structural approaches for flood defence and water storage. Flood defence is a mechanism use to modify the hydrodynamic characteristics of river flows in order to reduce the flood risk downstream [1]. Water storage is to maintain water supply for usage such as in agriculture, domestic and industry.

The term “reservoir” is often used in conjunction with “dam” which refers to a structure typically made from concrete material constructed across a waterway to confine and control the water flow [2]. The dam will eventually raise the level of water in the river to form a reservoir [3]. The dam outflow can either with uncontrolled spillways or gated spillways [4]. Uncontrolled spillways would come to its function once the reservoir exceeded its full supply level (FSL). FSL is the maximum capacity of the reservoir storage. Gated spillways function under a sequence of rule triggered by specific reservoir water levels which typically above the FSL.

Reservoir dam is built using materials such as concrete, steel, soil and sand is prone to damage due to aging, environmental effect, human and technological error.

Reference [5] has compiled some of the dam failure cases from 1828 to 2006. The typical factors identified are heavy rainfall, geological, and poor maintenance. Heavy rainfall increases the reservoir water level up to the maximum water level cause overflow and reduces the integrity of the reservoir dam wall. The geological factor such as earthquake causes crack and leakage to the dam structure. In a period of time, the structure might burst or collapse. Poor maintenance of the reservoir dam especially old dams could affect the dams operation which resulted malfunction or failure to the dam’s components.

Dam failure will not only affect its purposes, but the major effect is flooding. Flood is one of the severe emergencies that are associated with the reservoir operation. This is a fact as most of dams’ failure that resulted collapse or burst will discharge large magnitude of water to the downstream. The impact is devastating; major flood, heavy flow wash away anything on its path, leaving the ruins of the infrastructures, the dead and injured. These impacts are evident by Situ Gintung Dam incident located at south-west edge of Jakarta, Indonesia [6].

Another emergency that is associated with the reservoir is water shortage (drought). Drought is a critical situation causing more death compare to other natural disasters [7]. The reservoir operation during less intense rainfall is aim to impounded water and the water release is constraint to its major usage that is water supply. During this period, the flood-control reservoir has to establish operating policies for water allocation so that the supply can be optimized [8]. Similar to other hazards, drought can be described by its magnitude, duration, location, and timing [7].

Reservoir water release decision during heavy or less rain season can be assisted if the reservoir water level is forecasted. In particular, during heavy rain forecasted water level may allow reservoir operator to release water earlier so that reservoir can be ready for incoming water. During less rainfall season, water release for less priority usage can be suspended until the operator certifies that the reservoir storage is adequate for its main purposes.

Intelligent techniques such as fuzzy logic, neural network and genetic algorithm have been shown to be promising to support reservoir water release decision [9-13]. In this study, the efficacy of neural network in reservoir decision modelling is explored. In this paper, reservoir water level forecasting model using neural network is proposed. This model utilizes upstream rainfall measures by taking its temporal association.

II. NEURAL NETWORK MODEL

Neural Network is an algorithm that dynamically inherits human neuron information processing capability [14]. This capability enables Neural Network to perform a brain like function such as forecasting, classification, and pattern matching. The neural network model is used to predict the consequence of the given action. Neural network can be categorized into single and multi layer network. Single layer network is a model that consists of input and output layers. Whereas, multi-layer network consists of at least one hidden layer between input and output layer.

Fig. 1 shows a simple neural network model. The input layer represents the action which is feed into the next layer until the output layer.

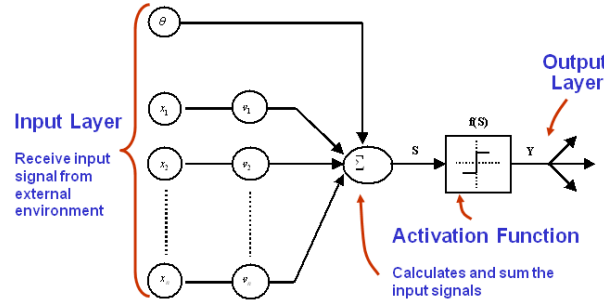


Fig. 1 Simple Neural Network Model

In this study, a typical feedforward neural network called backpropagation neural network model is implemented. This neural network model is train to minimize the error between the actual and predicted output. The learning is achieve when the model produce the minimum error. The error is calculated using square error formula (Equation 1).

$$SE = \frac{1}{2} \sum_{k=1}^m (t_k - y_k)^2 \quad (1)$$

III. METHOD

Theoretically, backpropagation neural network model was not meant for solving dynamic problem such as temporal and time series problems. In order to adapt with these kinds of problems a modified version of backpropagation neural network has been introduced such as temporal backpropagation algorithm [15] and backpropagation through time (BTT) [16]. However, these algorithms amend certain equations specifically to handle the time delays in the data. This approach increases the complexity of backpropagation neural network.

In this study, standard backpropagation neural network with bias, learning rate and momentum are used to train the reservoir water level data. The temporal information of the rainfall and water level data are preserve by using

sliding window technique. Once data has been prepared, the training was conducted base on the standard training procedure.

A. Data Preparation

Reservoir water level is influence by a number of factors such as upstream rainfall, water flow, heat and temperature, and evaporation rate. However, technological and political constraints have limited the availability of the data. In this study, a total of 3041 data from Jan 1999 – April 2007 were gathered from Timah Tasoh reservoir located in the state of Perlis, the smallest state of Malaysia. This reservoir was influenced by upstream rainfall which was recorded through 5 upstream gauging stations. Rainfall data from these stations and the current reservoir water level (t) are used as the input data and the reservoir water level at time $t+1$ is used as the target.

Sliding window technique is used to capture the time delay within the data set. Sliding window technique was proven able to detect patterns from temporal data [17]. This process is called segmentation process. In this process, nine data sets have been formed. Each data set represents different sliding size. Each sliding size represent time duration of the delays. For example, sliding size 2 represents two days of delays. Table 1 summarizes the number of instances extracted for each data set.

TABLE 1
DATA SET AND THE NUMBER OF INSTANCES

Data Set	Sliding Size	Number of Instances
1	2	2075
2	3	2408
3	4	2571
4	5	2668
5	6	2732
6	7	2774
7	8	2805
8	9	2826
9	10	2844

Each data set consists of N number of input columns and 1 output column. The output consists of 4 classes. 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 maximum values. In this study the new value is set in range of $[-1,1]$. The output is encoded based on Binary-Coded-Decimal (BCD) scheme. BCD is preferably as the total number of output nodes can be reduced to the integer of $\log_2 M$, where M is the number of classes [18]. Table 2 shows BCD representation of each output class.

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

TABLE 2
OUTPUT CODING USING BCD

Output Class	BCD Representation
0	-1,-1
1	-1, 1
2	1,-1
3	1, 1

Each data set is then divided randomly into three data sets: training set, validation set and testing set. Training set is used in the training phase of neural network, while validation set is used to validate the neural network performance during the training. Testing set is used to test the performance of neural network after the training has completed. These data sets are shown in Table 3.

TABLE 3
DATA DIVISION FOR EACH DATA SET

Data Set	Training	Validation	Testing
1	1659	208	208
2	1926	241	241
3	2057	257	257
4	2134	267	267
5	2186	273	273
6	2220	277	277
7	2243	281	281
8	2260	283	283
9	2276	284	284

B. Neural Network Modelling

The aim of neural network modelling is to create a mapping between the input data and the target output. This mapping was established by training the neural network to minimize the error between the network output and the target (Equation 1).

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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)

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Fig. 2 Pseudo Code for Neural Network Training

In this study, nine neural network 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. The training is control by three conditions (1) maximum epoch (2)

minimum error, and (3) early stopping condition. Early stopping is executed when the validation error continue to arises for several epochs [19].

Fig. 2 shows the procedure for the neural network training. The aim of this procedure is get the combination that gives the best result.

IV. RESULTS AND DISCUSSION

Table 4 shows the results for each data set after training and testing. Overall the minimum training, validation and testing error are 0.461878, 0.41825 and 0.416571 respectively. The best result achieved for training, validation and testing are 89.99%, 91.34% and 91.52% respectively. There is a small difference between the highest and lowest results achieve from training, validation and testing. Thu difference shows that neural network has learned the data quite well. Based on the results, data set 7 is chosen as the best data set for reservoir water level forecasting model. The result for training, validation and testing are 89.61, 91.34 and 90.75. Data set 7 was formed using sliding size 8 which contains 2805 instances.

TABLE 4
RESULTS OF TRAINING, VALIDATION AND TESTING

Data Set	Training		Validation		Testing	
	(%)	Error	(%)	Error	(%)	Error
1	87.48	0.785791	86.22	0.860958	89.26	0.667375
2	87.92	0.58714	87.00	0.573727	87.56	0.586856
3	87.65	0.599483	89.75	0.457907	89.36	0.490453
4	89.45	0.492463	88.52	0.502691	90.76	0.444052
5	89.50	0.483055	89.87	0.50378	90.36	0.503575
6	89.43	0.480323	90.74	0.421007	89.05	0.534949
7	89.61	0.474844	91.34	0.41825	90.75	0.443816
8	89.99	0.461878	89.52	0.474101	91.52	0.416571
9	89.77	0.467551	90.85	0.430233	90.73	0.4428
Min	87.48	0.461878	86.22	0.41825	87.56	0.416571
Max	89.99	0.785791	91.34	0.860958	91.52	0.667375

Values for the network parameters that were achieved from the training phase are shown in Table 5. As for data set 7, the total epoch is 21 and the best result achieved was with both learning rate (LR) and momentum (Mom) equal to 0.2. The best network architecture achieved is 24-15-3.

The finding of this study has shown that neural network architecture 24-15-3 has produced the acceptable performance during training (89.61%), validation (91.34%) and testing (90.75%). Fig. 3 shows the diagram of the neural network model. In addition, training the network is less time consuming where the total epoch is only 21 epochs. The finding also suggests that 8 days are the best time duration for the delay. This suggests that 8 days observation of the upstream rainfall will significantly increase the reservoir water level. This information is vital for reservoir management to plan for the water release.

TABLE 5
NEURAL NETWORK PARAMETERS

Data Set	Epoch	#Input	#hidden unit	#output unit	LR	Mom
1	88	6	31	3	0.7	0.5
2	91	9	35	3	0.4	0.4
3	39	12	21	3	0.5	0.2
4	21	15	7	3	0.3	0.1
5	46	18	3	3	0.3	0.1
6	21	21	5	3	0.3	0.1
7	21	24	15	3	0.2	0.2
8	21	27	23	3	0.1	0.3
9	21	30	21	3	0.2	0.1

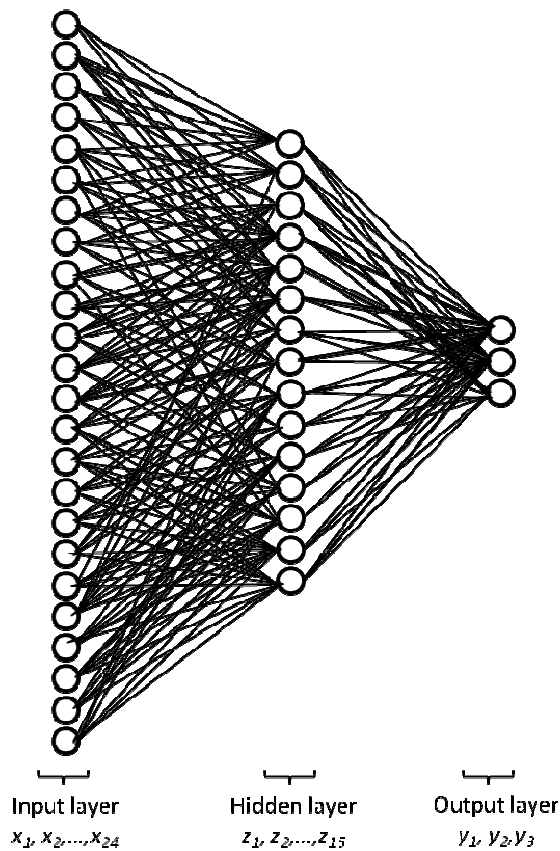


Fig. 3 Neural Network Model (24-15-3) for Reservoir Water Level Forecasting

V. CONCLUSION

The reservoir water level forecasting model proposed in this study can be used in water release decision making. Reservoir operator can use the model to forecast the future water level and decide early water release so that reservoir can have enough space for incoming inflow. In addition, the water release can be controlled within the safe carrying capacity of downstream river. Thus flood risk downstream

due to extreme water release from the reservoir can be reduced.

Similarly during less rainfall season, water release can be controlled to ensure that major need of water such as domestic and commercial used are sufficient.

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