FORECASTING MODEL FOR THE CHANGE OF RESERVOIR WATER LEVEL STAGE BASED ON TEMPORAL PATTERN OF RESERVOIR WATER LEVEL

Nur Athirah Ashaary, Wan Hussain Wan Ishak, and Ku Ruhana Ku-Mahamud

Universiti Utara Malaysia, Malaysia,
athirah_2501@yahoo.com;hussain@uum.edu.my;ruhana@uum.edu.my

ABSTRACT. Reservoir water level forecasting is vital in reservoir operation and management. The output of the forecasting model can be used in reservoir decision support systems. This study demonstrates the application of Artificial Neural Network (ANN) in developing the forecasting model for the change of reservoir water level stage. In this study, sliding window technique has been used to extract the temporal pattern that represents time delays in the reservoir water level. The patterns are used as input to the ANN model. The results show that a model with 4 days of time delay has produced the acceptable performance with both low error rate and high accuracy.

Keywords: reservoir operation, reservoir water level, forecasting model, temporal data mining, artificial neural network

INTRODUCTION

Reservoir system plays a key role in the successful management of fresh water resources (Valizadeh & El-Shafie, 2013). A reservoir is a natural or artificial lake or large tank, which is used to impound and regulate the water for irrigation, hydroelectric energy and supplies. Furthermore, it also smoothens out extreme inflows and can be a defense mechanism to mitigate floods or drought situations (Romanescu, Stoleriu, & Romanescu, 2011).

Reservoir can be categorized based on its functions as either single reservoir (for single purpose) or multipurpose reservoir systems. The most complex reservoir system is created for the multipurpose operations such as flood protection, navigation, hydropower generation and recreation. Multipurpose reservoir is more complex than a single purpose reservoir (Gotoh, Maeno, Takezawa, & Ohnishi, 2011).

Flooding is one of the extreme events with a major impact on reservoirs, especially ungauged sites. It can directly or indirectly cause extreme losses to the public such as homes, infrastructures, properties or innocent souls. In preventing the problem of flooding, a few models have been developed by computing the appropriate water releasing condition beforehand (Abdul Mokhtar, Wan Ishak, & Md Norwawi, 2014; Seckin, Cobaner, Yurtal, & Haktanir, 2013). Another extreme event that is related with reservoirs is drought. It cannot be viewed solely as a physical phenomenon, but the impacts on society and surrounding area must also be considered.

The forecasting model for the change of reservoir water level stage using neural network is the focus of this paper. The next section presents related studies on ANN and studies on forecasting of reservoir water level. The development of the forecasting model is then discussed followed by the results of the experiment. The conclusion and future work are provided in the last section.

ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) is a highly simplified mathematical model of biological neural networks. ANN has the ability to learn, give solutions to the problems with high level complexity and nonlinearity. Basically, ANN modeling is to establish a mapping between the input and output data targets. The multilayer perceptron is usually trained using the error backpropagation algorithm. The objective of a backpropagation is to find the weight that approximates target values of output with a desired accuracy. In this algorithm, each input pattern of the training dataset is passed into the network through the input layer, hidden layer and output layer, where results for given inputs are produced (Junsawang & Asavanant, 2007).

The advantage of ANN is better compared to its conventional techniques, robust in noisy environments and can solve a wide range of problems. Due to its advantages, ANN has been used in numerous real-time applications. ANN has been deployed in many fields such as finance, business, medical and many more. ANN has been successfully applied in water resources planning and management. The application of ANN in hydrology started in the early 1990s where it was applied as an alternative technique in rainfall forecasting model (Hung, Babel, Weesakul, & Tripathi, 2009), stream-flow forecasting (Edossa & Babel, 2011), river water level forecasting (Adnan, Ruslan, Samad, & Md Zain, 2012), reservoir operation (Sharifi, Haddad, Naderi, & Alimohammadi, 2005) and reservoir water release decision (Abdul Mokhtar et al., 2014).

Rani and Parekh (2014) highlighted that ANN is one of the most accurate forecasting models with the ability to map an input-output pattern without the prior knowledge of the criteria that influence the forecast procedure. Furthermore, ANN can model, map and demonstrate the complex nonlinear relationship of phenomena (Othman & Naseri, 2011). Therefore, ANN is a highly potential tool to be applied in reservoir system application.

FORECASTING OF RESERVOIR WATER LEVEL

The prediction of reservoirs water levels was based on previous operators experiences, rule curves and mathematical models that mostly relied on linear relationships (Tokar & Markus, 2000). However, due to the nonlinearity relationship that exists in reservoir operation advanced techniques such as ANN, Adaptive neuro fuzzy interface system (ANFIS), Support Vector Machine (SVM) and Autoregression Integrated Moving Average (ARIMA), they have been employed in reservoir water level forecasting.

Rani and Parekh (2014), for example, employed three different ANN models; Cascade, Elman and Feedforward backpropagation (FBP) to investigate the best forecasting model for real-time water level forecasting of Sukhi Reservoir. The findings show that FBP yields a better performance compared to the other techniques. Hipni et al. (2013) compared the performances between SVM and ANFIS techniques. The statistical evolution shows that SVM's performance is superior compared to ANFIS. Nwobi-Okoye and Igboanugo (2013) used ANN and ARIMA to forecast reservoir water level. The findings shows that ANN produces better prediction accuracy compared to ARIMA. Wan Ishak et al. (2011) employed ANN in reservoir water level forecasting model and reservoir water release decision model. The findings show that ANN has achieved an acceptable performance in both forecasting and decision model.

DEVELOPMENT OF THE FORECASTING MODEL

The Timah Tasoh reservoir has been used as the case. The reservoir is one of the largest multipurpose reservoirs in Northern Peninsular Malaysia. Timah Tasoh reservoir is 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 water supply and recreation. Water from Timah Tasoh is used for domestic, industrial and irrigation purposes. In this study, the data on reservoir water level and release from 1999 to 2013 have been obtained from the Perlis Department of Irrigation and Drainage (DID). The data have been pre-processed and segmented into several datasets using sliding window technique.

Data Normalization

Data normalization is one of the steps of data pre-processing. This process aims to scale the data within a small specified range. In this study, the data is normalized in a range between 1 and -1 using min-max method (Jain & Bhandare, 2011) as follows:

$$New\ (x) = (D - C) * \frac{x - \min(x)}{\max(x) - \min(x)} + C \quad (1)$$

where x is the actual data and min(x) is the minimum value of attribute and max(x) is the maximum value of attribute. C is the new minimum and D is the new maximum of [-1, 1]. Table 1 shows the representation of the Timah Tasoh reservoir water level. The flood stage is defined based on the common practice at DID. Each flood stage is associated with a nominal value which is normalized within the range of [-1, 1] before feeding into ANN model.

Table 1. Water Level Stage Representation and Nominal value

Water Level (m)	Flood Stage	Nominal Value	Normalized Value
< 29.0	Normal	1	1
< 29.4	Alert	2	0.33333
< 29.6	Warning	3	-0.33333
>29.6	Danger	4	-1

Standard backpropagation neural network with bias, learning rate and momentum are used to develop the model. The models used the temporal pattern based on the normalized data (Table 2). The temporal pattern of the reservoir water level data is obtained from sliding window (Wan Ishak, Ku-Mahamud, & Norwawi, 2011). This process is called segmentation process. The temporal patterns are used as the input patterns instead of the actual data. The output is the change of the stage reservoir water level at t which either has changes (1) or no changes (-1). Each dataset represents the different window sizes and each window size represents the time duration of the delay.

Table 2. Example of temporal pattern using nominal value (*w*=3)

SWL_{t-2}	SWL_{t-1}	SWL_t	ΔSWL_{t+1}
-1	-0.33333	0.33333	1
-0.33333	0.333333	1	1
0.33333	1	0.333333	1
1	1	-0.33333	1
-0.33333	0.333333	-0.33333	-1
0.333333	0.333333	-0.33333	-1
-1	-0.33333	1	-1

Table 3 shows the original dataset of each window size for the water level model. The data are divided randomly into three datasets: training (80%), validation (10%), and testing (10%). 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 (Sarle, 1995).

Table 3. Original data and experiment dataset of each window size

Dataset	Window Size	# Input	
		Original	Unique Record / No Redundancy
1	2	5779	14
2	3	5778	35
3	4	5777	64
4	5	5776	104
5	6	5775	142
6	7	5774	182

Performance Evaluation

The performance of the forecasting model is evaluated using mean square error (MSE) and prediction correctness (*Equation 2*). The model predictions are optimum if MSE (*Equation 3)* are found to be close to zero, and acceptable if the percentage of correctness is close to 100% (Wali, Baqir, & Naghmash, 2014).

$$\%Correct = \frac{\sum_{i=1}^{N}[number\ of\ correct\ for\ Class\ i]}{total\ number\ of\ samples} \times 100\% \tag{2}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2 \tag{3}$$

where n is the number of classes and *i* is the time or place. X_{obs} is the observed values or forecast value and $X_{model\,=}$ modelled values.

RESULT

The results produced by ANN after training, validation and testing are shown in Table 4. Overall, the minimum training, validation and testing errors are small which shows that neural network has learned quite well. Referring to the relative performance of ANN methods, it can be observed that the lowest MSE between the observed and simulated results is achieved by dataset 3, where the window size is 4. Window size 4 indicates that 4 days of observed changes in the reservoir stage will trigger the change of reservoir water level stage on the 5th day. The highlighted color in Table 4 shows the best model with the lowest MSE of training, validation and testing.

Table 4. Results of Training, Validation and Testing

Dataset	Training		Validation		Testing	
	MSE	%	MSE	%	MSE	%
1	0.166666208	91.67	0.010554764	100	0.0000000222	100
2	0.518519083	74.07	0.500000001	75	0.0000000002	100
3	0.153913659	92.31	0.006453737	100	0.019636617	100
4	0.489835559	71.43	0.589901874	70	0.684932503	70
5	0.560240315	71.93	0.428165889	78.57	0.571530997	71.43
6	0.425798538	78.08	0.403071357	77.78	0.592914878	72.22

Table 5 shows ANN parameters that were obtained after training and testing. The backpropagation neural network architecture is 4-21-1 with the learning rate of 0.9 and momentum of 0.3, which were obtained from the minimum MSE and maximum value of percentage correctness with the best time duration.

Table 5. Neural Network Parameters

Dataset	Input	Hidden Unit	Output	Learning Rate	Momentum
1	2	17	1	0.7	0.17
2	3	13	1	0.9	0.8
3	4	21	1	0.9	0.3
4	5	3	1	0.9	0.5
5	6	5	1	0.6	0.7
6	7	7	1	0.2	0.8

CONCLUSION AND FUTURE WORK

The reservoir water level is one of the measurements for reservoir water release decision. The sliding window technique has been successfully applied on reservoir water level data to extract and segment the data to preserve based on the reservoir water level stage. The large number of temporal patterns can be used for neural network modeling and are vital as the performance of neural network model, which is highly influenced by the size of the dataset. In this study, 4 days have been found to be the significant time delay for the change of reservoir water level. Findings from this study can be used as a guideline in flood and drought control. For future studies, other variables such as volume of reservoir water release, upstream rainfall, and spatial relationship can be investigated to improve the forecasting model of the change of reservoir water level stage.

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