Mining Temporal Reservoir Data Using Sliding Window Technique

Wan Hussain Wan Ishak, Ku-Ruhana Ku-Mahamud and Norita Md Norwawi

***Abstract*---**Decision on reservoir water release is crucial during both intense and less intense rainfall seasons. Even though reservoir water release is guided by the procedures, decision usually made based on the past experiences. Past experiences are recorded either hourly, daily, or weekly in the reservoir operation log book. In a few years this log book will become knowledge-rich repository, but very difficult and time consuming to be referred. In addition, the temporal relationship between the data cannot be easily identified. In this study window sliding technique is applied to extract information from the reservoir operational database: a digital version of the reservoir operation log book. Several data sets were constructed based on different sliding window size. Artificial neural network was used as modelling tool. The findings indicate that eight days is the significant time lags between upstream rainfall and reservoir water level. The best artificial neural network model is 24-15-3.

***Keywords*---**Neural Network, Sliding Window, Reservoir Management, Reservoir Water Level, Temporal Data Mining

I. Introduction

To date, decision making involve not only static data but also a series of data. These series of data tells more information compare to those static data. For example, in video previewing continuous images tells more story (more meaning) compare to still (snapshot) images. These series of event and action are time series data in which not recorded in databases. In business for example, the company growth can be forecasted based on three quarters of performances first, second and third quarters. The second quarter may be forecasted based on the first quarter performance and the third quarter may be forecasted based on the second performance. While, the third quarter performance may be used to forecast the next year performance.

As these illustration is concern, collecting data is not just retrieving data from the database, yet required a special data mining (DM) techniques namely, temporal mining. This technique is crucial as databases traditionally do not contain temporal data [1]. According to [2] temporal data mining is concerned with data mining of large sequential data sets (data that is ordered with respect to some index). Lin et al. [3] defined temporal data mining as follows:

“Temporal Data Mining is a single step in the process of Knowledge Discovery in Temporal Databases that enumerates structures (temporal patterns or models) over the temporal data, and any algorithm that enumerates temporal patterns from, or fits models to, temporal data is a Temporal Data Mining Algorithm.”

The ultimate goal of temporal DM is to discover hidden relations between sequences and subsequences of events [4]. The discovery of relations between sequences of events involves mainly three steps: the representation and modelling of the data sequence in a suitable form; the definition of similarity measures between sequences; and the application of models and representations to the actual mining problems.

In decision making, retrieving temporal information is very important to tell a story about the certain event due to other events that had occurred. Flood emergency planning for example can be planned earlier if the temporal information of the water basin level and rain are known and predicted. We have discussed this proposition in [5] and a conceptual model of intelligent decision support system is proposed. In this paper, we focus on the application of temporal data mining using sliding window technique to extract data from reservoir operation database. The impact of different size of sliding window to the performance of neural network forecasting model is also presented.

II. Reservoir Operation: A Case of Timah Tasoh Reservoir

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 [6]. Water storage is to contain water in order to maintain water supply for it use such as in agriculture, domestic and industry.

Reservoir operation is a real-time multitude decision making process which range from determining optimum reservoir storage or water level to selecting the optimal release policies [7;8]. The optimum control of reservoir storage or water level is based on three general principal segments namely, the flood control storage, active storage, and dead storage [7]. Flood control storage is used to access water during flood. The active storage is the main water usage where water is supply for various purposes. Dead storage is used for sediment control and recreation. The active storage of the reservoir is the most important segment, where the deficit of its capacity will affect the supply.

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Timah Tasoh reservoir is one of the largest multipurpose reservoirs in Peninsular Malaysia. Timah Tasoh located on Sungai Korok in the state of Perlis, about 2.5 km below the confluence of Sungai Timah and Sungai Tasoh. Timah Tasoh reservoir covered the area of 13.33 km^2 with the catchment area 191.0 km^2. Its maximum capacity is 40.0 mm^3. 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.

Timah Tasoh is also influenced by the seasonal changes such as period of intense rainfall and less intense rainfall. Intense rainfall will increase river and reservoir water level causing flood in prone areas. During less intense rainfall, water shortage will become a major problem. These two different situations cause two conflicting challenges in maintaining the supply during drought and provide storage during flood but at the same time maintaining reservoir dam safety from the high pressure and overload. This conflict also cause uncertainty as the seasons do not have exact begin and end date every year [8].

III. Temporal Data Mining

Some literature cited that temporal data mining is still a new area for exploration. Despite this claims, many literatures have been published and report the application of temporal data mining (including time series) in many domains such as financial, web mining, business, and criminology. Some of these applications are summarized in Table 1.

TABLE 1
SUMMARY OF APPLICATIONS OF TEMPORAL DATA MINING

Application	Modelling Technique/Method	Reference
Estimating future sales of products	Neural Network (NN)	Shanmugasundaram et al [9]
Daily Financial Time Series Events	Time Series Data Mining (TSDM) framework	Povinelli [10]
Predict stock market	Neural Network (NN)	Moisao and Pires [11]
Weekly Financial Time Series	Time Series Data Mining (TSDM) framework	Diggs and Povinelli [12]
Web Mining	Temporal Web Mining (TWM)	Samia [13]
Modelling user behavior in an e-commerce website	Neural Network (NN)	Zehraoui and Bennani [14]
Computational Criminology	Abstract State Machine and Multi-Agent Modelling	Brantingham et al. [15]

Based on [1] there are at least two main related concepts in temporal data mining i.e. time series and sequence. A time series is a set of attribute values over a period of time. While, a sequence is an ordered list of item sets. The typical applications for time series include time series analysis, trend analysis, transformation, similarities measurement, and prediction. Roddick and Spiliopoulou [16] has determined four broad categories of temporality within data, i.e. static, sequences, timestamped, and fully temporal. Static data contains no temporal information, but the temporal inference can be made through reference to transaction-time such as referring to audit trails or transaction logs. Sequence data is an ordered list of events. The temporal information can be extracted based on the sequences. Compare to sequences, timestamped contains more temporal information as it is a timed sequence of static data taken at certain intervals. Total temporal information can be found in fully temporal category as each tuple in a time-varying relation in the database may have one or more dimensions of time.

Modeling the temporal events can be performed using artificial intelligence techniques or non artificial intelligence techniques. Artificial intelligence techniques include neural network [11;9;14] and genetic algorithm [17]. Non artificial intelligence techniques are Markov models (MM) and hidden Markov models (HMM). One example of the usage of HMM in temporal data mining is by [18]. In addition, [4] classified four main methods of temporal data representations namely, time-domain continuous representations, transformation based representations, discretization based methods, and generative methods. Another method is transactional databases with timing information. This representation method is rarely use, yet serves as useful alternative especially when dealing with time information contained in the database.

Based on the previous study many algorithms or approaches have been proposed both for temporal and time series data mining, such as Genetic Algorithm and Pattern Wavelet Transform [17], modified priori algorithm [19], Dynamic Fuzzy Network (DyFN) [20], ∆STP-Solver [21], Time Series Data Mining (TSDM) [22], Gaussian Mixture Models [23], Unsupervised Learning [24], TSETMAX [25], Moving Approximation (MAP) [26], discovering the frequent temporal patterns from interval-based data [27] and window sliding [28;29].

IV. Method

In this study, standard backpropagation neural network with bias, learning rate and momentum are used to model the temporal event of 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 [28]. 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 1) 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 Log2 M, where M is the number of classes [30]. Table 2 shows BCD representation of each output class.

TABLE 2
OUTPUT CODING USING BCD

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

$$New(x) = \left[\frac{x - \min(x)}{\max(x) - \min(x)}\right] * (D - C) + C \qquad (1)$$

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 2).

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

where *m* is the total number of output units

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 [31]. Fig. 2 shows the procedure for the neural network training. The aim of this procedure is get the combination 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)
```

Fig. 2 Pseudo Code for Neural Network Training

V. RESULTS

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. The 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.

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 (Figure 3).

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

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

VI. SOME COMMON MISTAKES

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 1 that the size of window has influence the number of usable instances. The bigger the window size the larger the usable instances. The large number of usable instances will contains large number of temporal patterns that can be used for neural network 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 increase the number of input also increase. The large number of input unit will increase the complexity of the neural network modeling.

The finding of this study 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 water level at the reservoir. This information is vital for reservoir management to plan early water release.

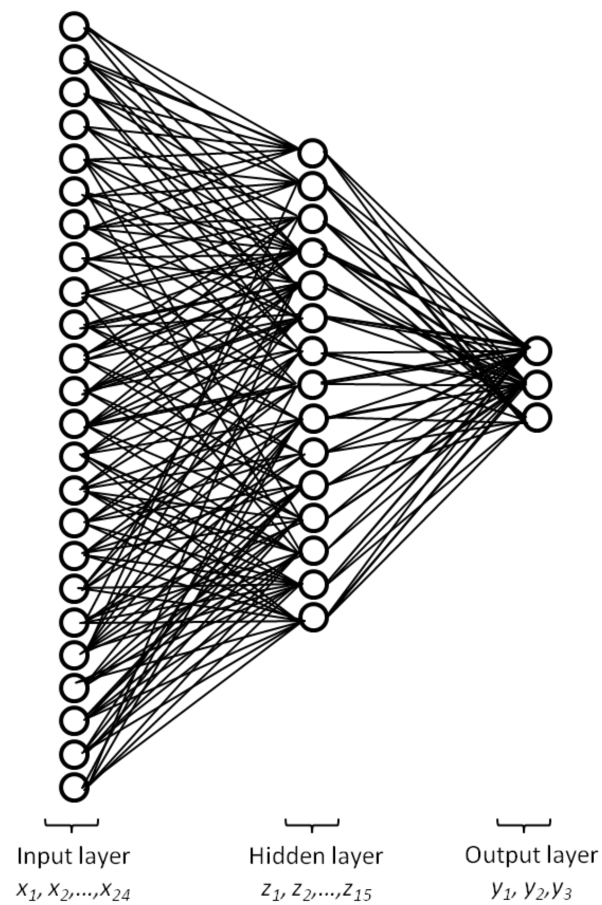

Figure 3 Neural Network Model (24-15-3) for Reservoir Water Level Forecasting

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%). In addition, training the network is less time consuming where the total epoch is only 21 epochs.

VII. CONCLUSION

The findings of this study can be used to aid reservoir water release decision. Typically, reservoir water release decision was influenced by the upstream rainfall. Since upstream rainfall was recorded through upstream gauging stations which are located quite far from the reservoir and river water might be lost due to environmental factors, the time delay is expected before the rain water can give effect to the reservoir water level. In this study, window sliding has been shown to be a successful approach to model the time delays, while neural network was shown as a promising modelling technique.

Information on the delay and the forecasted reservoir water level can be used by reservoir operator to decide early water release so that reservoir can have enough space for incoming inflow. In addition, the water release can be controlled within the capacity of the downstream river. Thus flood risk downstream due to extreme water release from the reservoir can be reduced

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