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Modelling Reservoir Water Release Decision Using Temporal Data Mining and Neural Network

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***Abstract*—During emergencies such as flood and drought seasons, reservoir acts as a defence mechanism to reduce the risk of flooding and maintaining water supply. During this period, decision regarding the water release is very crucial. During flood season, early water release decision should be established to prepare the reservoir for incoming in-flow. While during drought season, reservoir water level should be maintained in order to sustain the supply and other usages. Reservoir operation during these two seasons cause conflicting decision as incoming inflow is hardly predicted. Modeling the reservoir water release decision can be one of the solutions to this problem. The modeling is based on reservoir's operator previous experiences when dealing with such situations. These experiences provide valuable information on the decision when the reservoir water should be released. Temporal data mining technique has been applied to extract temporal pattern from the reservoir operational record and neural network has been applied as the modeling tool. The neural network model was developed to classify the data that in turn can be used to aid the reservoir water release decision. In this study neural network model 8-23-2 has produced the acceptable performance during training, validation and testing.**

***Keywords*—Reservoir Operation Water Release, Water Release Modeling, Temporal Data Mining, Neural Network.**

I. INTRODUCTION

Reservoir is one of the defence mechanism during both flood and drought seasons. The use of dam for flood mitigation is aim to impound water in a reservoir during periods of high flow in order to maintain safe downstream discharges [1]. The opening of the dam's spillway gate must be adequate to ensure that the reservoir capacity will not over its limits and the discharges will not cause overflow downstream. During drought, the reservoir needs to impound water and release adequately to fulfil its purposes. During both situations, the decision to open and close the water gate is a critical action need to be undertaken by the dam operator as late decision will not only causing flood downstream but also will damage the dam structure. Releasing the water earlier before the reservoir reaching its full capacity might reduce the flood risk downstream. However, one cannot be sure that the water release will be replaced by the new one to serve it usage during less intense rainfall. As for multi purpose dam, low water in the reservoir will cause conflict on its usage.

In both flood and drought situations, decisions regarding the water releases are made in accordance with the availa-ble water, inflows, demands, time, previous release and etc. [2;3]. However, reservoir operation during these two situations is critical as it involve different objectives and purposes, thus required different operation rule. Moreover, these situations are not static where it changes as the subsequent to the climate changes [3]. The relationship be-tween the water release and the hydrologic information is nonlinear [3;4] and there is a strong tie between them [3].

Typically, in normal and conflicting seasons the reservoir water release decision is guided by the reservoir operation rule. The decision includes determining the quantities of water to be stored and to be released or withdrawn from a reservoir under various conditions [5]. In practice most of the reservoirs are operated based on the operator's intui-tion and common sense enriched with experience [2]. The operation rules are obtained from the reservoir operation manual established when it was first operated. This rule gradually needs to be adapted to structural changes occur-ring to the reservoir such as due to sedimentation. Alternatively, the operation rule can be derived by modelling the reservoir operation [6].

In this paper temporal data mining specifically sliding window technique is proposed to extract temporal data from the reservoir operation record. The backpropagation neural network was then constructed to learn the temporal pattern and perform the classification. The performance of the neural network is measured based on the classification accuracy and the square error.

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In the next section, an overview of temporal data mining is given, followed by an overview of NNs. The methodol-ogy of this study is presented in the Research Design section. The findings are presented in the findings section followed by discussion & conclusion of the study.

II. Page Layout

Data Mining (DM) as an activity that extracts some new nontrivial information contained in large databases [7]. DM basic tasks can be divided into eight categories typically, classification, regression, time series analysis, predic-tion, clustering, summarization, association rules, and sequence discovery [8]. Some studies relate DM with the con-cept of knowledge discovery in databases (KDD). According to Dunham [8], DM is only one part of KDD. Thus, Dunham defined DM as the use of algorithms to extract the information and patterns derived by the KDD process. Even though the definition looks varies and technical, yet, the goal is still the same that is to discover hidden pat-terns from the database.

Temporal data mining is one of the hot topics in DM research. According to Laxman and Sastry [7] 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. [9] 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."*

Based on these definitions, temporal data mining can be considered as mining temporal data from temporal data-base. Temporal data is those which are organized based on time or certain sequence order. Roddick and Spiliopou-lou [10] 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.

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 [11], modified priori algorithm [12], Dy-namic Fuzzy Network (DyFN) [13], ΔSTP-Solver [14], Time Series Data Mining (TSDM) [15], Gaussian Mixture Models [16], Unsupervised Learning [17], TSETMAX [18], Moving Approximation (MAP) [19], discovering the fre-quent temporal patterns from interval-based data [20] and window sliding [21;22;23]. 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 [21;23]. This process is called segmentation process.

Modeling the temporal events can be performed using artificial intelligence techniques or non artificial intelligence techniques. Artificial intelligence techniques include neural network [24;25;26] and genetic algorithm [11]. 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 Oates et al. [27].

III. Neural Network

Artificial neural network (ANN) or usually called neural network (NN) is a computational model that is inspired by the nature of biological neural networks (BNN). Similar to BNN, the information processing in NN is performed through the connection of the processing elements called artificial neurons. The weights that connect the neurons are adjusted until the process is completed. This process is also known as learning. Through the learning process, NN gain a natural propensity for storing experiential knowledge and making it available for use [28]. NN was known to be first introduced by McCulloch and Pitts [29]. They introduce the theoretical foundation and logic of NN. McCulloch and Pitts simple NN architecture consists of two layers of input and output layers and one layer of connection weight (Fig. 1). As shown in Fig. 1, the $x_1, x_2, \ldots, x_n$ represent the input neuron, the $w_1, w_2, \ldots, w_n$ represent the connection weights, s represent the total weighted input signals, and *f(s)* is the activation function and *y* is the output.

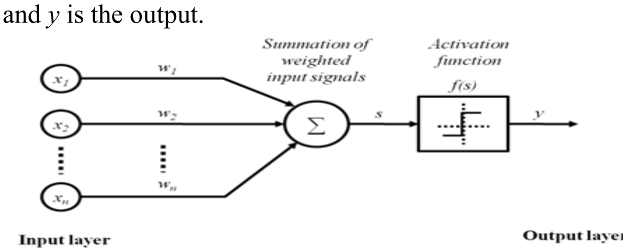

FIG. 1: Simple Neural Network Model

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NN has been used as an alternative to statistical approach to model complex and nonlinear problem. Even though NN and statistics are claim not a competing methodologies for data analysis [30], an empirical study by Hill et al [31] has proven that NN is comparable with their statistical counterparts. This shows that NN is viable and practical approach to be applied in various problem domains. To date many NN models have been established and among the popular models are Backpropagation Neural Network (BPNN), Recurrent Neural Network (RNN) and Kohonen Self-Organizing Maps (SOM).

The ability of NN has been recognized in various applications domain including unpredictable and changing envi-ronments, especially in safety-related applications [32]. According to Kurd et al. [32], this recognition is due to the functional benefits offered by NN, which include; the ability to learn, dealing with novel inputs, excellent operation-al performance, and computational efficiency. In the application of reservoir operation and management, NN has been applied for various simulation and optimization problem. Table 1 summarizes some of the related studies and NN model implemented.

TABLE 1: RELATED STUDIES AND NN APPLICATION IN RESERVOIR OPERATION AND MANAGEMENT

Studies	Application	NN Model
Hu et al., [33]	River Flow Prediction	Range-Dependent NN(RDNN)
Dibike and Solomatine [34]	River Flow Forecasting	Multi-Layer Perceptron Network (MLP) & Radial Basis Function Network (RBF)
Chang and Chen [35]	Streamflow Prediction	Counterpropagation Fuzzy-NN (CFNN)
Kisi [36]	Streamflow Prediction	Backpropagation NN
Coulibaly et al. [37]	Multivariate Reservoir Inflow Forecasting	Temporal NNs
Coulibaly et al. [38]	Daily Reservoir Inflow Forecasting	Multi-layer Feed-Forward NN (FNN)
Chang and Chang [39]	Prediction of Reservoir Water Level	Adaptive Network-Based Fuzzy Inference System (ANFIS)
Lobbrecht and Solomatine [40]	Controlling the Polder Water Levels	ANN and Fuzzy Adaptive Systems (FAS)
Solomatine and Xue [41]	Flood Forecasting	Multilayer Perceptron & Hybrid (M5 & MLP)
Kumar et al. [42]	Flood Control Operation and Conservation Operation	Standard Backpropagation Algorithm
Chaves and Chang [43]	Intelligent Reservoir Operation System	Evolving ANN

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 (a) and predicted output (o). The learning is achieve when the model produce the minimum error. The error is calculated using square error (SE) formula (Equation 1).

$$SE = \frac{1}{2}\sum_{k=1}^{m}(a_k - o_k)^2 \tag{1}$$

where m is the total number of output units.

IV. RESEARCH DESIGN

A. Case Study

In this study, Timah Tasoh reservoir was used as a case study. Timah Tasoh reservoir is one of the largest multipur-pose 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. Timah Tasoh reservoir covered the area of 13.33 Km2 with the catchment area 191.0 Km2. Its maximum capacity is 40.0 Mm3. 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. Fig. 2 shows the conceptual model of Timah Tasoh reservoir system.

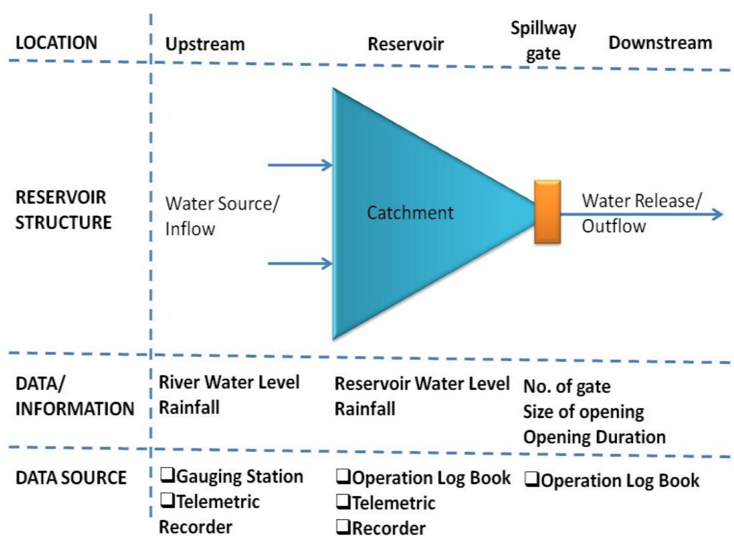

FIG. 2. CONCEPTUAL MODEL OF RESERVOIR SYSTEM

As shown in Fig. 2, each component of the reservoir system is associated with data or information. The water level and rainfall are prevalence in both upstream and the reservoir catchments. These data are recorded hourly using telemetric recorder situated at strategic location of both upstream river and reservoir. Additionally, manual reading of the rainfall are recorded through the gauging stations. At the spillway gate, typical data are number of gate opened, the size of opening, and the opening duration. These data are recorded manually by reservoir operator in the operation log book.

In this study, a total of 3041 daily data from Jan 1999 – April 2007 were retrieved from the Timah Tasoh reservoir operation log book. Operation of Timah Tasoh reservoir was influenced by upstream rainfall which was manually recorded through 5 upstream gauging stations. Rainfall observed from these stations will eventually increase the reservoir water level. In this study the current water level (*t*), tomorrow water level (t+1), and the changes of water level at *t, t-1, …, t-w* were used as the input data or the premises, while the gate opening/closing at t is used as the target or the expected outcome. The constant *t* and *w* represent time and days of delays (which later represented as window size).

B. Data Processing

Data was imported into MS Excel and sorted based on the date. A column that represents gate opening/closing was clean to remove noise. Gate opening/closing value is in range of zero to six. Zero indicates gate is closed and values from one to six indicate the number of gates that are open. The change of this value implies the decision point. At this point window slice will be formed begin from that point and preceding to w days according the window size. In this study, the segmentation processes based on sliding window technique begin with window size 2, that represent 2 days of delay. The maximum window size was set to 10. Each segmentation process will return a total of 124 instances. Redundant and conflicting instances are then removed. Table 2 shows the usable number of instances and the window size.

TABLE 2
DATA SET AND THE NUMBER OF INSTANCES

Data Set	Window Size	Number of Instances
1	2	43
2	3	54
3	4	71
4	5	82
5	6	95
6	7	109
7	8	113
8	9	118
9	10	119

C. Classification Method

In this study, standard backpropagation neural network with bias, learning rate and momentum are used to classify the rules of reservoir water release. The role of neural network is to learn the rule pattern by creating a mapping between the input data (premise) and the target output (consequent). This mapping was established by training the neural network to minimize the error between the network output and the target (Equation 1).

In this study, nine neural network models were developed. Each neural network model is trained with one data set. Inputs of all data sets are normalized using min-max method and the output was represented based on Binary-Coded-Decimal (BCD) scheme. 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 [44]. Fig. 3 shows the procedure for the neural network training. The aim of this procedure is to get the combination that gives the best result. Prior to the training, the each data set is randomly divided into three different sets: training (80%), validation (10%) and testing (10%) sets (Table 3).

```
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. 3. PSEUDO CODE FOR NEURAL NETWORK TRAINING

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TABLE 3:DIVISION OF DATA SETS

Data Set	Number of Instances	Training	Validation	Testing
1	43	35	4	4
2	54	44	5	5
3	71	57	7	7
4	82	66	8	8
5	95	75	10	10
6	109	87	11	11
7	113	91	11	11
8	118	94	12	12
9	119	95	12	12

V. FINDINGS

The results of neural network training, validation, and testing are shown in Table 4. Overall, the lowest error achieve for training, validation and testing was 0.065795, 1.59E-07, and 9E-10 respectively. The best results of training, validation, and testing was 98.35%, 100%, and 100% respectively. These results show that neural network classifier has performed very well on temporal rules. Based on the results in Table 4, data set 4 is chosen to be the best data set. The different between training, testing and validation for all data sets are shown in Fig. 4. Neural network train with data set 4 achieves 93.94% of training performance and 100% of validation and testing performance. The error was 0.23505, 0.023383, and 0.007085 respectively. Data set 4 was formed with window size 5 with 82 instances.

TABLE 4: RESULTS OF TRAINING, VALIDATION AND TESTING

Data Set	Training		Validation		Testing	
	%	Error	%	Error	%	Error
1	90.00	0.39996	87.50	0.5	100.00	9E-10
2	90.91	0.362563	100.00	0.007216	100.00	6.13E-05
3	95.62	0.147186	85.72	0.626408	100.00	0.034537
4	93.94	0.23505	100.00	0.023383	100.00	0.007085
5	89.34	32.00295	100.00	1.59E-07	100.00	1.4E-07
6	97.70	0.092475	95.46	0.188657	100.00	0.002146
7	98.35	0.065796	100.00	0.032103	95.46	0.191186
8	93.09	0.276602	95.84	0.166669	95.84	0.168359
9	97.37	0.104647	95.84	0.171619	100.00	0.003985
Min	**89.34**	**0.065795**	**85.72**	**1.59E-07**	**95.455**	**9E-10**
Max	**98.35**	**32.00295**	**100**	**0.626408**	**100**	**0.191186**

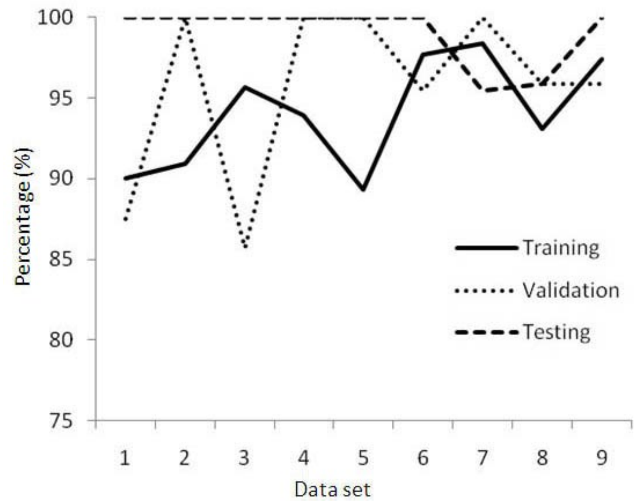

FIG. 4. DIFFERENT BETWEEN TRAINING, TESTING AND VALIDATION FOR ALL DATA SETS

Values for the network parameters that were achieved from the training phase are shown in Table 5. As for data set 4, the total epoch is 86 and the best result achieved was with learning rate (LR) 0.8 and momentum (Mom) 0.2. The best network architecture achieved is 8-23-2.

TABLE 5
NEURAL NETWORK PARAMETERS

Data Set	Epoch	#Hidden Unit	LR	Mom	#Input	#Output Unit
1	77	25	0.9	0.4	5	2
2	42	23	0.8	0.4	6	2
3	33	17	0.7	0.3	7	2
4	86	23	0.8	0.2	8	2
5	31	9	0.9	0.8	9	2
6	31	7	0.7	0.5	10	2
7	54	5	0.5	0.5	11	2
8	42	25	0.4	0.8	12	2
9	27	9	0.4	0.6	13	2

VI. DISCUSSION

In this study, reservoir water level data typically the current, the (expected) tomorrow water level and the changes of water level are extracted from the reservoir operation record. In actual reservoir operation and decision making, the current water level represent the current stage of reservoir water level (t), while the tomorrow water level is water level that is expected for tomorrow at t+1.

Theoretically, this water level can be forecasted based hydrological va-riables [45]. The changes of reservoir water level represent the increase or decrease of reservoir water level. Ob-serving the changes of reservoir water level at time t and the preceding t-1, t-2, …, t-w will give an insight on when to release the reservoir water.

The sliding window technique has been successfully applied on reservoir water release data, to extract the changes of the reservoir water level that lead to the water release decision, which is opening/closing the reservoir's gate. The findings reveal that window size 5, which represent 5 days of observed water level changes contribute to the best classification performance of neural network classifier. This information is vital for reservoir management to plan the early water release.

The finding of this study has also shown that neural network architecture 8-23-2 has produced the acceptable per-formance during training (93.94%), validation (100%) and testing (100%). In addition, training the network takes only 86 epochs.

VII. CONCLUSION

Findings of this study provide and alternative information to the reservoir operator to make early decision of reser-voir water release. Manually, reservoir operator monitors the changes of water level and consults the superior offi-cer before taking the appropriate action. Having unpredicted circumstances of the weather, early decision of the reservoir water release is always a difficult decision.

Early water release of the reservoir will reserve enough space for incoming inflow due to heavy upstream rainfall. In addition, the water release can be controlled within the capacity of the downstream river. Thus flood risk down-stream due to extreme water release from the reservoir can be reduced. 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 modeling technique.

VIII. ACKNOWLEDGEMENT

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REFERENCES

[1] Smith, K. and Ward, R. 1998. Floods: Physical Processes and Human Impacts, England: John Wiley

[2] Jain, S. K. and Singh, V. P. 2003. Chapter 11: Reservoir Operation. In S. K. Jain and V. P. Singh (Eds), Water Resources Systems Planning & Management, Vol. 51, pp. 615-679. Elsevier B. V

[3] Hejazi, M. I. Cai, X. and Ruddell, B. L. 2008. How Reservoirs were Operated-Exploring the Role of Hydrologic Information, In R. W. Babcock and R. Walton, Proceedings of The World Environmental & Water Re-sources Congress, May 12-16, 2008, Honolulu, Hawaii, pp. 1-9, Retrieved from ASCE.org, doi: 10.1061/40976(316)593

[4] Labadie, J. W. 2004. Optimal Operation of Mutireservoir Systems: State-of-the-Art Review, Journal of Water Resources Planning and Management, 130 (2), 93-111

[5] Wurbs, R. A. 1993. Reservoir-System Simulation and Optimization Models, Journal of Water Resources Planning and Management, 119(4), 455-472.

[6] Shrestha, B. P., Duckstein, L., and Stakhiv, E. Z. 1996. Fuzzy Rule-Based Modeling of Reservoir Operation. Journal of Water Resources Planning and Management, 122(4), 262-269.

[7] Laxman, S., and Sastry, P. S. 2006. A Survey of Temporal Data Mining. Sadhana, 31(2), 173-198.

[8] Dunham, M. H. 2002. Data Mining: Introductory and Advance Topics, New Jersey, Pearson Education Inc.

[9] Lin, W., Orgun, M. A., and Williams, G. J. 2002. An Overview of Temporal Data Mining, In Simoff, S. J., Williams, G. J., Hegland, M., Proceedings of the 1st Australian Data Mining Workshop (ADM02), pp: 83-90

[10] Roddick, J. F. and Spiliopoulou, M. 2002. A Survey of Temporal Knowledge Discovery Paradigms and Methods, IEEE Transactions on Knowledge and Data Engineering, 14(4), 750-767.

[11] Povinelli, R. J., and Feng, X. 1998. Temporal Pattern Identification of Time Series Data Using Pattern Wavelets and Genetic Algorithms, Proceedings of Artificial Neural Networks in Engineering, 691-696

[12] Ale, J. M., and Rossi, G. H. 2000. An Approach to Discovering Temporal Association Rules, Proceedings of the 2000 ACM symposium on Applied Computing, Vol. 1, pp. 294-300

[13] Juang, C. 2001. Construction of Dynamic Fuzzy If-Then Rules through Genetic Reinforcement Learning for Temporal Problems Solving, Joint 9th IFSA World Congress and 20th NAFIPS International Conference, Vol. 4, 2341 - 2346

[14] Xu, L., and Choueiry, B. Y. 2003. A New Efficient Algorithm for Solving the Simple Temporal Problem, Proc. of the 10th Int. Sym. on Temporal Representation and Reasoning and Fourth Int. Conf. on Temporal Logic (TIME-ICTL'03), pp: 210 - 220

[15] Povinelli, R. J. 2003. A New Temporal Pattern Identification Method for Characterization and Prediction of Complex Time Series Events, IEEE Transactions on Knowledge and Data Engineering, 15(2), 339-352.

[16] Povinelli, R. J.., Johnson, M. T., Lindgren, A. C., and Ye, J. 2004. Time Series Classification Using Gaussian Mixture Models of Reconstructed Phase Spaces, IEEE Transactions on Knowledge and Data Engineering, 16(6), 779-783.

[17] Lattner, A. D., and Herzog, O. 2004. Unsupervised Learning of Sequential Patterns, Proceedings of Temporal Data Mining: Algorithms, Theory and Applications, Brighton, UK

[18] Guil, F., Bosch, A., and Marin, R. 2004. TSETMAX: An Algorithm for Mining Frequent Maximal Temporal Patterns, Proceedings of Temporal Data Mining: Algorithms, Theory and Applications, Brighton, UK

[19] Batyrshin, I. Herrera-Avelar, R., Seremetov, L., and Panova, A. 2005. Association Networks in Time Series Data Mining, Annual Meeting of the North American Fuzzy Information Processing Society, pp. 754 - 759

[20] Winarko, E., and Roddick, J. F. 2005. Discovering Richer Temporal Association Rules from Interval-Based Data: Extended Report, Technical Report SIE-05-003, School of Informatics and Engineering

[21] Ku-Mahamud, K. R., Zakaria, N., Katuk, N., and Shbier, M. 2009. Flood Pattern Detection Using Sliding Window Technique, Third Asia International Conference on Modeling & Simulation, pp. 45-50.

[22] Li, H. F., and Lee, S. Y. 2009. Mining Frequent Itemsets Over Data Streams using Efficient Window Sliding Techniques, Expert Systems with Applications, 36, 1466–1477

[23] Wan-Ishak, W. H., Ku-Mahamud, K. R., and Md-Norwawi, N. 2011. Mining Temporal Reservoir Data Using Sliding Window Technique, CiiT International Journal of Data Mining Knowledge Engineering, 3(8), 473-478

[24] Moisao, R. L. M., and Pires, F. M. 2001. Prediction Model, Based on Neural Networks, for Time Series with Origin in Chaotic Systems. Proceedings of the Workshop on Artificial Intelligence for Financial Time Series Analysis, Univ. of Porto

[25] Shanmugasundaram, J., Prasad, M. V. N. and Gupta, A. 1997. Temporal Data Mining, Working Paper PROFIT-97-31, Massachusetts Institute of Technology

[26] Zehraoui, F. and Bennani, Y. 2005. New Self-Organizing Maps for Multivariate Sequences Processing, International Journal of Computational Intelligence and Applications, 5(4), 439-456.

[27] Oates, T., Firoiu, L., and Cohen, P. R. 1999. Clustering Time Series with Hidden Markov Models and Dynamic Time Warping. Paper presented at IJCAI-99 Workshop on Sequence Learning, pp: 17-21.

[28] Haykin, S. 1998. Neural Networks: A Comprehensive Foundation (2nd), New Jersey: Prentice Hall

[29] McCulloch, W. S., and Pitts, W. 1943. A Logical Calculus of the Ideas Immanent in Nervous Activity, Bulletin of Mathematical Biophysics, 5, 115-133

[30] Sarle, W. S. 1994. Neural Networks and Statistical Models, Proceedings of the 19th Annual SAS Users Group International Conference, pp: 1538-1550

[31] Hill, T., Marquez, L., O'Connor, M., and Remus, W. 1994. Artificial Neural Network Models for Forecasting and Decision Making, International Journal of Forecasting, 10, pp. 5-15

[32] Kurd, Z., Kelly, T., and Austin, J. 2007. Developing Artificial Neural Networks for Safety Critical Systems, Neural Computation & Application, 16, 11-19

[33] Hu, T. S., Lam, K. C. and Ng, S. T. 2001. River flow time series prediction with a range-dependent neural network, Hydrohgical Sciences. 46(5), 729-745

[34] Dibike, Y. B. and Solomatine, D. P. 2001. River flow forecasting using artificial neural networks, Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere. 26(1), pp. 1-7

[35] Chang, F-J., and Chen, Y-C. 2001. A Counterpropagation Fuzzy-Neural Network Modeling Approach to Real Time Streamflow Prediction, Journal of Hydrology. 245, pp. 153-164

[36] Kisi, O. 2004. River Flow Modeling Using Artificial Neural Networks, Journal of Hydrologic Engineering. 9(1), 60–63

[37] Coulibaly, P., Anctil, F., and Bobee, B. 2000. Daily reservoir inflow forecasting using artificial neural networks with stopped training approach, Journal of Hydrology. 230, 244–257

[38] Coulibaly, P., Anctil, F., and Bobee, B. 2001. Multivariate Reservoir Inflow Forecasting using Temporal Neural Net-works, Journal of Hydrologic Engineering. 6(5), 367-376

[39] Chang F-J, and Chang, Y-T. 2006. Adaptive Neuro-Fuzzy Inference System for Prediction of Water Level in Reservoir. Advances in Water Resources, 29, 1-10

[40] Lobbrecht, A. H. and Solomatine, D. P. 1999. Control of water levels in polder areas using neural networks and fuzzy adaptive systems, Water Industry Systems: Modelling and Optimization Applications, vol. 1, 509-518

[41] Solomatine, D. P. and Xue, Y. 2004. M5 Model Trees and Neural Networks: Application to Flood Forecasting in the Upper Reach of the Huai River in China, Journal of Hydrologic Engineering. 9(6), 1-10

[42] Kumar, A. R. S., Jain, S. K., and Agarwal, P. K. 1999. Application of Artificial Neural Networks (ANN) in Reservoir Operation, Technical Report No. TR/BR-6/1999-2000, National Institute of Hydrology, India

[43] Chaves, P. and Chang, F. J. 2008. Intelligent Reservoir Operation System Based on Evolving Artificial Neural Networks, Advances in Water Resources. 31, 926-936

[44] Sarle, W. 1995. Stopped Training and Other Remedies for Overfitting, Proceedings of the 27th Symposium on the Interface of Computing Science and Statistics, pp. 352-360. Retrieved March 18, 2002 from World Wide Web: ftp://ftp.sas.com/pub/neural/

[45] Wan-Ishak, W. H., Ku-Mahamud, K. R., Md-Norwawi, N. 2010. Reservoir Water Level Forecasting Model Using Neural Network, International Journal of Computational Intelligence Research, 6(4), 947-952.