Neural Network Application in Reservoir Water Level Forecasting and Release Decision

Wan Hussain Wan Ishak[1], Ku Ruhana Ku-Mahamud[1], Norita Md Norwawi[2]

[1]College of Arts and Sciences, Universiti Utara Malaysia, UUM Sintok, Kedah, Malaysia
{hussain, ruhana}@uum.edu.my

[2]Faculty of Science and Technology, Universiti Sains Islam Malaysia, Nilai, Ng Sembilan, Malaysia
norita@usim.edu.my

ABSTRACT

Reservoir dam is one of the defense mechanism for both flood and drought disasters. During flood, 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. While, during drought the reservoir needs to impound water and release adequately to fulfil its purposes. Modelling of the reservoir water release is vital to support the reservoir operator to make fast and accurate decision when dealing with both disasters. In this paper, intelligent decision support model based on neural network (NN) is proposed. The proposed model consists of situation assessment, forecasting and decision models. Situation assessment utilized temporal data mining technique to extract relevant data and attribute from the reservoir operation record. The forecasting model utilize NN to perform forecasting of the reservoir water level, while in the decision model, NN is applied to perform classification of the current and changes of reservoir water level. The simulations have shown that the performances of NN for both forecasting and decision models are acceptably good.

KEYWORDS

Emergency Management, Intelligent Decision Support System, Neural Network, Forecasting

1 INTRODUCTION

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 contain water in order to maintain water supply for it use such as in agriculture, domestic and industry.

During both flood and drought situations, decision to open or close water gate is a critical action that need to be undertaken by dam operator as late decision will not only cause flood downstream but also will damage 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 released water will be replaced and use during less intense rainfall. As for multipurpose dam low water in the reservoir will cause conflict on its usage. Researchers (such as [2]) believe that the use of forecasting and warning system might improve the dam operation and decision.

In practice, the water release or the gate opening decision depends on the operating rules [3]. These rules are static and do not consider the dynamic nature of the hydrology systems. Therefore, non-structural approach such as forecasting is vital to support the water release or the gate opening decision. The dynamic of the forecasting system will be able to cope with the event frequency and triggered alert to the authority when the situation is at the severe level. Flood forecasting is significant to cope with the great floods [4].

In this paper neural network is employed in the reservoir water level forecasting and decision models. Both models are the main component of proposed reservoir intelligent decision support system.

2 CONCEPTUAL MODEL OF RESERVOIR SYSTEM

A reservoir system can be divided into four components namely, upstream, reservoir catchment, the spillway gate, and downstream (Figure 1). The upstream consists of one or several rivers that carry the water into the reservoir. The water is stored in the reservoir catchment before releases through the spillway gate to the downstream. This kind of system is designed to ensure that during heavy rainfall, the upstream water flow does not directly flow to the downstream. The reservoir system will control the water flow and the releases within the safe carrying capacity of the downstream river [1], thus minimize the downstream damages [5].

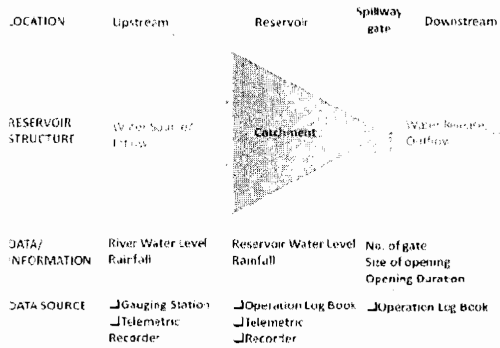

Figure 1. Conceptual Model of Reservoir System

As shown in Figure 1, 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 the telemetric recorder situated at the strategic location of both upstream river and reservoir. Additionally, manual reading of the rainfall also recorded through the gauging stations. At the spillway gate, the typical data are number of gate opened, the size of opening, and the opening duration. These data are recorded manually by the reservoir operator in the operation log book.

3 NEURAL NETWORK APPLICATIONS IN RESERVOIR OPERATION

Neural network (NN) is a mathematical computational model that imitates the biological neuron capability. The theoretical foundation and logic of NN was known to be first introduced by McCulloch and Pitts [6]. McCulloch and Pitts simple NN architecture consists of two layers of input and output layers and one layer of connection weight (Figure 2). As shown in Figure 2, the x_1, x_2, ..., x_n represent the input neuron, the w_1, w_2, ..., 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.

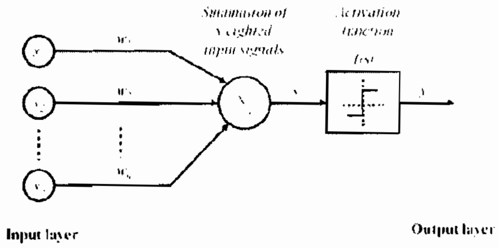

Figure 2: Simple Neural Network Model

One of the main features of neural network is it be able to learn a pattern and apply the "knowledge" to the similar pattern. Through the learning process, NN gain a natural propensity for storing experiential knowledge and making it available for use [7].

The ability of NN has been recognized in various applications domain including unpredictable and changing environments, especially in safety-related applications [8]. According to Kurd et al [8], this recognition is due to the functional benefits offered by NN, which include; the ability to learn, dealing with novel inputs, excellent operational 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., [9]	River Flow Prediction	Range-Dependent NN(RDNN)
Dibike and Solomatine [10]	River Flow Forecasting	Multi-Layer Perceptron Network (MLP) & Radial Basis Function Network (RBF)
Chang and Chen [11]	Streamflow Prediction	Counterpropagation Fuzzy-NN (CFNN)
Kisi [12]	Streamflow Prediction	Backpropagation NN
Coulibaly et al. [13]	Multivariate Reservoir Inflow Forecasting	Temporal NNs
Coulibaly et al. [14]	Daily Reservoir Inflow Forecasting	Multi-layer Feed-Forward NN (FNN)
Chang and Chang [15]	Prediction of Reservoir Water Level	Adaptive Network-Based Fuzzy Inference System (ANFIS)
Lobbrecht and Solomatine [16]	Controlling the Polder Water Levels	ANN and Fuzzy Adaptive Systems (FAS)
Solomatine and Xue [17]	Flood Forecasting	Multilayer Perceptron & Hybrid (M5 & MLP)
Kumar et al. [18]	Flood Control Operation and Conservation Operation	Standard Backpropagation Algorithm
Chaves and Chang [19]	Intelligent Reservoir Operation System	Evolving ANN

4 INTELLIGENT DECISION SUPPORT SYSTEM

Intelligent Decision Support System (IDSS) is an integration of DSS and artificial intelligence (AI) technology combining the basic function of DSS and reasoning capabilities of AI techniques [20]. Figure 3 shows the conceptual of model IDSS for reservoir operation. This model comprises of three main stages: data extraction, water level forecasting and water release decision modules. Detail discussion of this model together with the theoretical foundation has been discussed in Wan-Ishak et al. [21].

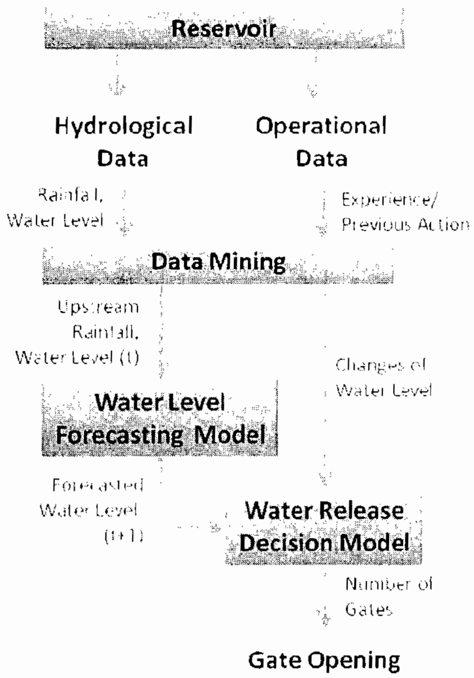

Figure 3. Conceptual Model of IDSS for Reservoir Operation

Data extraction is the capability to extract the useful information from the abundance of information. This information will serve as the input to the IDSS or to be represented to the user in a meaningful format. Data extraction utilize data mining approach will combine both hydrological and operational data and extract the temporal data that maintain the temporal relationship of the data. The extraction process will include data integration, data preprocessing, temporal data mining, and post processing. The extracted data will be feed into water level forecasting model, which will calculate the probability of the rising of reservoir water level using neural network. The result of this model is the forecasted water level at time $t+1$. The forecasted data will be used in the decision model. Finally, the gate opening decision will be produced.

Both forecasting and decision modules implement neural network to learn and mapping the data patterns. These modules are developed independently by utilizing data from the data mining module. Typically, based on the forecasted and the changes of the reservoir water level, the reservoir operator can decide the water release. Therefore, in the IDSS model the forecasting model is developed prior to the water release decision model.

5 METHOD

In this study, standard backpropagation neural network with bias, learning rate and momentum are used in both forecasting and decision model. In forecasting model, neural network is used to train the rainfall data (at t) and to create a mapping with the reservoir water level at $t+1$. In the decision model, neural network is used to train the water level (at t and t+1) and the changes of water level. The output produce by the decision model is the number of gate to be opened. 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.

5.1 Case Study: Timah Tasoh Reservoir

Timah Tasoh, reservoir, one of the largest multipurpose reservoirs in northern Peninsular Malaysia has been used as a case study. The reservoir is 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 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.

5.2 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 management? have limit the availability of the data. In this study, a total of 3041 daily data from Jan 1999 – April 2007 were gathered from the Timah Tasoh reservoir operation record. Timah Tasoh upstream rainfall was manually recorded through 5 upstream gauging stations. Rainfall observed from these stations will eventually increase the reservoir water level.

For the forecasting model, 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. In the decision model 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, while the gate opening/closing at t is used as the target. The constant t and w represent time and days of delays (which later represented as window size). 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 that begins from that point onwards according the specified window size, w.

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 [22;23]. This process is called segmentation process. For both forecasting and decision model, 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 2 summarizes the number of instances extracted for each data set. Segmentation process for decision model will return a total of 124 instances. Redundant and conflicting instances are then removed.

Table 2. Data set and the number of instances

Data Set	Sliding Size	Number of Instances	
		Forecasting Model	Decision Model
1	2	2075	43
2	3	2408	54
3	4	2571	71
4	5	2668	82
5	6	2732	95
6	7	2774	109
7	8	2805	113
8	9	2826	118
9	10	2844	119

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 (-1) and D is the new maximum (1) 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 [24].

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

Each data set is then divided randomly into three data sets: training set (80%), validation set (10%) and testing set (10%). 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.

5.3 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 square error (SE) between the network output (y_k) and the target (t_k) where $k = 1,2,3,\ldots, m$ (Equation 2).

In this study, nine neural network models were developed for both forecasting and decision model. Each neural network model is trained with one data set. This data set is further divided into three sets: training, validation and testing sets. Each model is trained with different combination of hidden unit (3,5,7…, 25), learning rate (0.1,0.2,…,0.9) and momentum (0.1,0.2,…,0.9). 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 [25].

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

6 FINDINGS

6.1 Forecasting Model

Table 3 shows the results for each data set after training and testing for the forecasting model. 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. Figure 4 compare the results for all data sets.

Values for the network parameters that were achieved from the training phase are shown in Table 4. As for data set 7, the total epoch (Ep) is 21 and the best result achieved was with both learning rate (LR) and momentum (Mo) equal to 0.2. The input (I), hidden unit (H) and output (O) are 24, 15, and 3 respectively. The best network architecture achieved is 24-15-3.

Table 3. Results of Training, Validation and Testing

Data Set	Training (%)	Training Error	Validation (%)	Validation Error	Testing (%)	Testing 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

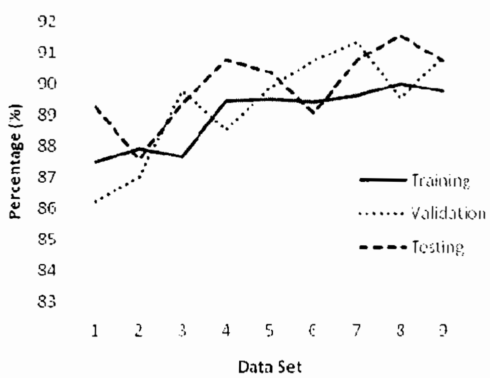

Figure 4. Comparison of the Results for Forecasting Model

Table 4. Neural Network Parameters

Data Set	Ep	I	H	O	LR	Mo
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

6.2 Decision Model

The results of neural network training, validation, and testing for the decision model are shown in Table 5. 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 data set. Based on the results in Table 3, data set 4 is chosen to be the best data set. 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. Figure 5 shows the comparison of results for all data sets.

Table 5. Results of Training, Validation and Testing

Data Set	Training (%)	Training Error	Validation (%)	Validation Error	Testing (%)	Testing Error
1	90.00	0.39996	87.50	0.5	100	9E-10
2	90.91	0.362563	100	0.007216	100	6.13E-05
3	95.62	0.147186	85.72	0.626408	100	0.034537
4	93.94	0.23505	100	0.023383	100	0.007085
5	89.34	32.00295	100	1.59E-07	100	1.4E-07
6	97.70	0.092475	95.46	0.188657	100	0.002146
7	98.35	0.065796	100	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	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

Values for the network parameters that were achieved from the training phase are shown in Table 6. As for data set 4, the total epoch is 86 and the best result achieved was with learning rate (LR) 0.8 and momentum (Mo) 0.2. The input (I), hidden unit (H) and output (O) are 8, 23, and 2 respectively. The best network architecture achieved is 8-23-2.

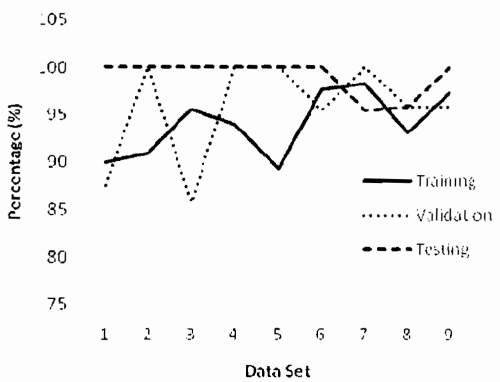

Figure 5. Comparison of the Results for Decision Model

Table 6. Neural Network Parameters

Data Set	Ep	I	H	O	LR	Mo
1	77	5	25	2	0.9	0.4
2	42	6	23	2	0.8	0.4
3	33	7	17	2	0.7	0.3
4	86	8	23	2	0.8	0.2
5	31	9	9	2	0.9	0.8
6	31	10	7	2	0.7	0.5
7	54	11	5	2	0.5	0.5
8	42	12	25	2	0.4	0.8
9	27	13	9	2	0.4	0.6

7 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 can be seen from 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. Large size 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 increases. 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 is 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. Additionally, 5 days of observed water level changes has been found to be significant of the reservoir water release decision. This information is vital for reservoir management to plan early water release.

The 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 $t+1$. As shown in this paper, the water level can be forecasted based hydrological variables. The changes of reservoir water level represent the increase or decrease of reservoir water level. Observing 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.

8 CONCLUSION

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, 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 time delays, while neural network was shown as a promising modelling technique.

Manually, reservoir operator monitors the changes of water level and consults the superior officer before taking the appropriate action. Having unpredicted circumstances of the weather, early decision of the reservoir water release is always a difficult decision. Information on the delay and the forecasted reservoir water level can be used by reservoir operator to decide early water release. 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 downstream due to extreme water release from the reservoir can be reduced.

Acknowledgments. The authors' most appreciation to the Perlis Department of Drainage and Irrigation for permission and supplying Timah Tasoh reservoir operational data.

9 REFERENCES

1. Smith, K., Ward, R.: Floods: Physical Processes and Human Impacts. England: John Wiley (1998)
2. Tucci, C. E. M.: Flood Flow Forecasting. Presented at 54th Session of Executive Council of WMO World Meteorological Organization, Geneva (2002)
3. Wurbs, R. A.: Reservoir-System Simulation and Optimization Models. Journal of Water Resources Planning and Management. 119(4), 455-472 (1993)
4. Calenda, G., Mancini, C. P.: The Role of the Corbara Reservoir on the Tiber River in the Flood Protection of the Town of Rome, Italy. In Peggy A. Brookshier (Ed.), Proceedings of Waterpower Conference. ASCE Research Library (1999)
5. Jain, S. K., Singh, V. P.: 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 (2003)
6. McCulloch, W. S., Pitts, W.: A Logical Calculus of the Ideas Immanent in Nervous Activity, Bulletin of Mathematical Biophysics, 5, 115-133 (1943)
7. Haykin, S.: Neural Networks: A Comprehensive Foundation (2nd), New Jersey: Prentice Hall (1998)
8. Kurd, Z. Kelly, T., Austin, J.: Developing Artificial Neural Networks for Safety Critical Systems, Neural Computation & Application, 16, 11-19 (2007)
9. Hu, T. S., Lam, K. C., Ng, S. T.: River flow time series prediction with a range-dependent neural network, Hydrohgical Sciences. 46(5), 729-745 (2001)
10. Dibike, Y. B., Solomatine, D. P.: River flow forecasting using artificial neural networks. Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere. 26(1), 1-7 (2001)
11. Chang, F-J., Chen, Y-C.: A Counterpropagation Fuzzy-Neural Network Modeling Approach to Real Time Streamflow Prediction. Journal of Hydrology. 245, 153-164 (2001)
12. Kisi, O.: River Flow Modeling Using Artificial Neural Networks. Journal of Hydrologic Engineering. 9(1), 60–63 (2004)
13. Coulibaly, P., Anctil, F., Bobee, B.: Daily reservoir inflow forecasting using artificial neural networks with stopped training approach. Journal of Hydrology. 230, 244–257 (2000)
14. Coulibaly, P., Anctil, F., Bobee, B.: Multivariate Reservoir Inflow Forecasting using Temporal Neural Networks. Journal of Hydrologic Engineering. 6(5), 367-376 (2001)
15. Chang, F-J., Chang, Y-T.; Adaptive Neuro-Fuzzy Inference System for Prediction of Water Level in Reservoir. Advances in Water Resources. 29, 1-10 (2006)
16. Lobbrecht, A.H., Solomatine, D.P.: Control of water levels in polder areas using neural networks and fuzzy adaptive systems. Water Industry Systems: Modelling and Optimization Applications, vol. 1, pp: 509-518 (1999)

17. Solomatine, D. P., and Xue, Y.: 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 (2004)
18. Kumar, A. R. S., Jain, S. K., Agarwal, P. K.: Application of Artificial Neural Networks (ANN) in Reservoir Operation. Technocal Report No. TR/BR-6/1999-2000, National Institute of Hydrology, India (1999)
19. Chaves, P., Chang, F-J.: Intelligent Reservoir Operation System Based on Evolving Artificial Neural Networks. Advances in Water Resources. 31, pp. 926-936 (2008)
20. Zhou, F., Yang, B, Li, L., Chen, Z.: Overview of the New Types of Intelligent Decision Support System. Proceedings of International Conference on Innovative Computing Information and Control. pp:267-267 (2008)
21. Wan-Ishak, W. H., Ku-Mahamud, K. R., Md-Norwawi, N.: Conceptual Model of Intelligent Decision Support System Based on Naturalistic Decision Theory for Reservoir Operation during Emergency Situation. International Journal of Civil & Environmental Engineering, 11(2), pp. 06-11 (2011)
22. Ku-Mahamud, K.R., Zakaria, N., Katuk, N., Shbier, M.: Flood Pattern Detection Using Sliding Window Technique. Third Asia International Conference on Modeling & Simulation, pp. 45-50 (2009)
23. Wan-Ishak, W. H., Ku-Mahamud, K. R., Md-Norwawi, N.: Mining Temporal Reservoir Data Using Sliding Window Technique, CiiT International Journal of Data Mining Knowledge Engineering, 3(8), pp. 473-478 (2011)
24. Chong, C. C., Jia, J.C.: Assessments of neural network output codings for classification of multispectral images using Hamming distance measure. Proceedings of the 12th IAPR International. Conference on Pattern Recognition, vol. 2, pp: 526 – 528, (1994)
25. Sarle, W.: Stopped Training and Other Remedies for Overfitting. Proceedings of the 27th Symposium on the Interface of Computing Science and Statistics, pp. 352-360, (1995)