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MODELLING OF HUMAN EXPERT DECISION MAKING IN RESERVOIR OPERATION

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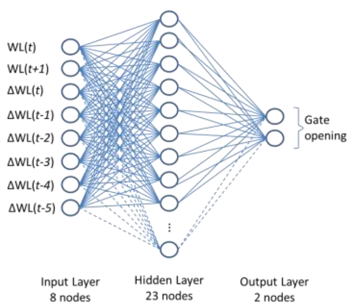
Graphical abstract



Abstract

Reservoir is one of the structural approaches for flood mitigation and water supply. During heavy raining season, reservoir operator has to determine fast and accurate decision in order to maintain both reservoir and downstream river water level. In contrast to less rainfall season, the reservoir needs to impound water for the water supply purposes. This study is aimed to model human expert decision making specifically on reservoir water release decision. Reservoir water release decision is crucial as reservoir serve multi purposes. The reservoir water release decision pattern that comprises of upstream rainfall and current reservoir water level has been form using sliding window technique. The computational intelligence method called artificial neural network was used to model the decision making.

Keywords: Modelling human decision, reservoir operation, computational intelligence, data mining, artificial neural network

1.0 INTRODUCTION

Reservoir management has been one of the potential applications in Intelligent Decision Support System (IDSS) due to the complexity of the operation, expert knowledge requirement and intelligent judgement [1]. Reservoir plays an important function in water resources planning and management. Typically two categories of reservoir have been established around the world that is single and multi-purpose reservoir. In conjunction to these categories, the reservoir operation is influenced by it purposes [2]. The operation problem for a single-purpose reservoir is to decide the adequate release volume so that the benefits for that purpose are maximized. The operation of multi-purpose reservoir inherit the same problem, additionally, the release need to be optimally allocated among purposes. The compatibility of the purposes will affect the coordination effort and thus will increase the complexity of the reservoir operation.

The operation of multi-purpose reservoir with flood control and water supply purposes is one of the complex and dynamic problems in reservoir operation. Flood is one of the natural disasters that can cause damages to the infrastructure and loss of life. The reservoirs that function as flood mitigation mechanism require fast and accurate decision in determining the water release. During heavy rain, reservoir needs to impound water and release them gradually to maintain safe discharges at downstream areas [3] and minimize the downstream damages and to ensure dam safety [2]. Conversely, during less intense rainfall, the reservoir has to impound adequate water to maintain its water level without affecting its release for water supply. Through these major functions, reservoir can be regard as one of the emergency environments that require human expert decision making and monitoring.

The reservoir operations are monitored and managed by qualified and experienced reservoir operator. In practice most of the reservoirs are guided by their intuition and common sense [2] supported by the standard operations rule. The operation rules are obtained from the reservoir operation manual established when it was first operated. Heuristically, the rule was gradually updated to adapt the structural changes that occur to the reservoir such as due to the sedimentation. The actual reservoir operator decision has been recorded in reservoir operation log book.

This paper is aim to discuss the effort to model the reservoir operator decision making based on operator's decision history. In conjunction to previous studies, this study employed Artificial Neural Network (ANN) as the modelling algorithm. The data was presented in a temporal form using window sliding technique. Through this technique, several data sets have been formed and tested using ANN.

2.0 LITERATURE REVIEW

Decision commonly is defined as making a choice from a set of alternatives [4;5]. It involves series of action which resulted from an inference of facts or information. Bohanec [5] stated that DM refers to "the whole process of making the choice" which begins from problem assessment, information gathering, identifying alternatives, anticipating consequences, action and evaluating the decisions. The major activities in DM processes are problem recognition, information search, problem analysis, alternative evaluation, and decision [4;5]. The interrelation among the activities is shown in Figure 1.

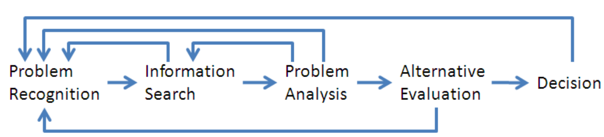


Figure 1 Major Activities in Decision Making Process [4]

Typically, decision making modelling is based on two main approaches: classical and naturalistic decision theory [6]. Classical decision making (CDM) is the oldest theory in decision making. CDM focus on how people make decision based on the choices of alternatives [6]. The essential characteristics of CDM were choice (choosing among concurrently available alternatives), input-output orientation, comprehensiveness and formalism [7].

Naturalistic decision making (NDM) is a study of how people make decision in dynamic, challenging and emergency situations [6;7;8;9]. Typically, NDM describes how decision makers utilized their experience to access the situations to arrive at certain action. The essential characteristics for NDM are process orientation, situation-action matching decision rules, context-bound informal modelling, and empirical-based prescription [7]. The features of NDM are summarizes in Table 1. Table 2 summarizes the different of CDM and NDM.

Table 1 Features of Naturalistic Decision Making [8]

1.	Ill-defined goals and ill-structured tasks
2.	Uncertainty, ambiguity, and missing data
3.	Shifting and competing goals
4.	Dynamic and continually changing conditions
5.	Action-feedback loops (real-time reactions to changed conditions)
6.	Time stress
7.	High stakes
8.	Multiple players
9.	Organizational goals and norms
10.	Experienced decision makers

Table 2 Comparison of CDM and NDM [6;7;9]

	CDM	**NDM**
Type	Normative and Prescriptive	Descriptive
Strategy	Analytical	Intuitive
Human Experience	Ignored	Experience-based
Orientation	Input-output Orientation	Process Orientation
Decision rules/judgement	Based on rational choice or alternative	Situation assessment
Data Criteria	Fixed set	Dynamic
Modelling	Context-free formal modelling	Context-bound informal modelling

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 [10;11]. 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 [10]. 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. Additionally, the change in reservoir water level stage may also affect the storage, thus influence the water release decision [12;13].

The seasonal changes such as period of intense rainfall and less intense rainfall is another factor that influences the reservoir operation. 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 [11].

The complexities of a multipurpose and multiple-reservoir system generally require decisions to be determined by an optimization or simulation model [14]. The optimization model will produce operating rule which will optimize the water release and at the same time maintain the supply during drought. In addition, the actual reservoir operation is a real time problem, where decision making has to be made in a short time period [15]. Delay cannot be negotiated as late decision will give negative impacts. According to Dubrovin et al., 2002 real-time reservoir operation is a continuous decision-making process of determining the water level of a reservoir and release from it [11].

Previous studies have shown that optimization models have been shown to perform well for both planning and real-time operation [14]. However, the real time optimization models are more complex as it involves time series data. Data ranges are either daily, monthly, and annually. The uncertainties, inaccuracies and seasonal variations have also contributed to the complexity of the real time reservoir operation [11]. Naresh and Sharma [16] for example, apply a hybrid of Fuzzy Logic and Neural Network to maximize the annual hydropower generation by finding its optimum water release. The optimum water release decision often in conflict with reservoir water usage. As most of the reservoirs are multi-purpose, finding efficient operating policies so that optimum release can be achieved is vital in reservoir management [17].

3.0 METHODOLOGY

3.1 Conceptualization of Reservoir Operation

In this study, Timah Tasoh reservoir was used as a case study. Timah Tasoh reservoir is one of the largest multipurpose 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. Figure 2 shows the conceptual model of Timah Tasoh reservoir system.

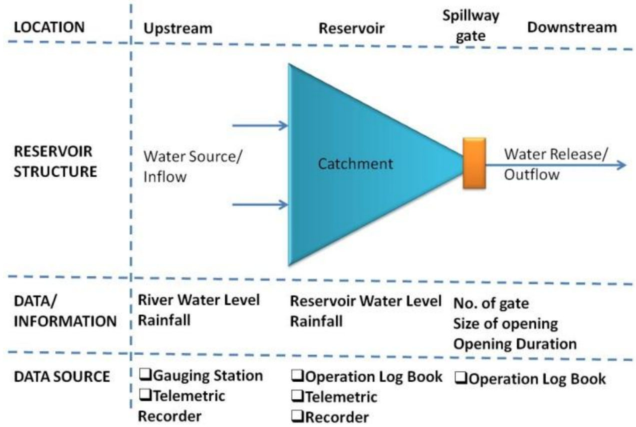


Figure 2 Conceptual model of reservoir system

As shown in Figure 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).

3.2 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 7. Each segmentation process will return a total of 124 instances. Redundant and conflicting instances are then removed. Table 3 shows the usable number of instances and the window size.

Table 3 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

3.3 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.

In this study, six neural network models were developed. Each neural network model is trained with one data set. Inputs of all data sets are normalized into [-1,1] 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. Prior to the training, the each data set is randomly divided into three different sets: training (80%), validation (10%) and testing (10%) sets.

4.0 FINDINGS

The results of neural network training, validation, and testing are shown in Table 4. These results show that neural network classifier has performed very well on temporal data set. Based on the results in Table 4, 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.

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

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

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 as shown in Figure 3.

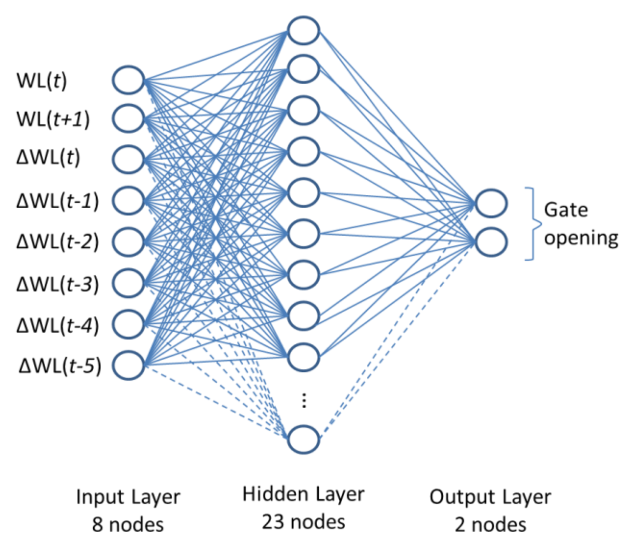


Figure 3 The ANN Model

5.0 DISCUSSION

In this study, reservoir water level data typically the current, the (expected) tomorrow reservoir water level and the changes of water level have been 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 (*t+1*). Theoretically, this water level can be forecasted based hydrological variables (Wan Ishak et al, 2010). 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.

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 finding is inline [18] which found that 5 days of observed reservoir water level is vital to trigger the reservoir water release decision. This information is vital for reservoir management to plan the early water release.

6.0 CONCLUSION

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. This study has successfully modeled the reservoir operator decision making using ANN. Findings of this study can be used as alternative information by the reservoir operator in making early decision of reservoir 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 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.

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