FORECASTING MODEL FOR THE CHANGE IN STAGE OF RESERVOIR WATER LEVEL

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Abstrak

Takungan merupakan salah satu pendekatan berstruktur utama bagi tebatan banjir. Semasa banjir, pelepasan awal air takungan merupakan salah satu daripada tindakan yang diambil oleh operator takungan bagi menampung hujan lebat yang akan diterima. Pelepasan air lewat mungkin akan memberi kesan negatif kepada struktur takungan dan menyebabkan banjir di kawasan hilir. Walau bagaimanapun, hujan semasa tidak akan mempengaruhi perubahan paras air takungan secara langsung. Kelewatan ini terjadi kerana aliran yang membawa air mungkin akan mengambil sedikit masa untuk sampai ke takungan. Kajian ini bermatlamat untuk membangunkan model peramalan bagi perubahan pada peringkat paras air takungan. Model ini mengambil kira perubahan paras dan peringkat air takungan sebagai input dan perubahan pada peringkat air takungan pada masa hadapan sebagai output. Dalam kajian ini, data pengoperasian takungan Timah Tasoh telah diperolehi dari Jabatan Pengairan dan Saliran Perlis (DID). Paras air takungan telah dikategorikan kepada peringkat tertentu berdasarkan panduan dari DID. Algoritma Sliding Window yang telah diubah suai telah digunakan untuk membahagikan data kepada corak temporal. Berdasarkan corak berkenaan, tiga model telah dibangunkan: model paras air takungan, model perubahan paras air takungan dan peringkat paras air takungan dan model gabungan perubahan paras air takungan dan peringkat paras air takungan. Kesemua model disimulasikan menggunakan rangkaian neural dan prestasinya dibandingkan menggunakan min kuasa dua ralat (MSE) dan peratusan ketepatan. Dapatan kajian menunjukkan model perubahan paras air takungan dan peringkat paras air takungan menghasilkan MSE terendah dan peratusan ketepatan paling tinggi berbanding dua model lain. Dapatan kajian juga menunjukkan bahawa kelewatan dua hari sebelumnya telah memberi kesan terhadap perubahan dalam peringkat paras air takungan. Model ini boleh diaplikasikan bagi menyokong keputusan pelepasan awal air takungan. Oleh itu, mengurangkan kesan banjir di kawasan hilir.

Kata Kunci: Model ramalan, Perkomputeran pintar, Rangkaian neural, Operasi takungan, Paras air takungan.

Abstract

Reservoir is one of major structural approaches for flood mitigation. During floods, early reservoir water release is one of the actions taken by the reservoir operator to accommodate incoming heavy rainfall. Late water release might give negative effect to the reservoir structure and cause flood at downstream area. However, current rainfall may not directly influence the change of reservoir water level. The delay may occur as the streamflow that carries the water might take some time to reach the reservoir. This study is aimed to develop a forecasting model for the change in stage of reservoir water level. The model considers the changes of reservoir water level and its stage as the input and the future change in stage of reservoir water level as the output. In this study, the Timah Tasoh reservoir operational data was obtained from the Perlis Department of Irrigation and Drainage (DID). The reservoir water level was categorised into stages based on DID manual. A modified sliding window algorithm has been deployed to segment the data into temporal patterns. Based on the patterns, three models were developed: the reservoir water level model, the change of reservoir water level and stage of reservoir water level model, and the combination of the change of reservoir water level and stage of reservoir water level model. All models were simulated using neural network and their performances were compared using on mean square error (MSE) and percentage of correctness. The result shows that the change of reservoir water level and stage of reservoir water model produces the lowest MSE and the highest percentage of correctness when compared to the other two models. The findings also show that a delay of two previous days has affected the change in stage of reservoir water level. The model can be applied to support early reservoir water release decision making. Thus, reduce the impact of flood at the downstream area.

Keywords: Forecasting model, Computational intelligence, Neural network, Reservoir operation, Reservoir water level.

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List of Abbreviations

ANN	Artificial Neural Network
MSE	Mean Square Error
BP	Backpropagation
FL	Fuzzy Logic
ARIMA	Autoregression Integrated Moving Average
ANFIS	Adaptive Neural Network Fuzzy Inference System

CHAPTER ONE
INTRODUCTION

1.1 Background of Study

Reservoir is one of the ciritical components in water resources management. Reservoir can be defined as a natural or artificial lake or large tank used to store and control water for various purposes such as supplies and irrigation. It can also serve as a shield during flood and drought situations (Gotoh, Maeno, Takezawa, & Ohnishi, 2011; Romanescu, Stoleriu, & Romanescu, 2011; Wan Ishak, Ku-Mahamud, & Norwawi, 2011b). Typically, reservoir can be clasified into single and multipurpose reservoirs. A single purpose reservoir is constructed to serve only one purpose, such as a hydroeletric reservoir that is to generate electricity. A multipurpose reservoir is aimed to serve more than one purpose, such as flood mitigation, water supply, and recreation. Thus, the water storage has to be divided to fullfil the purposes.

Reservoir systems can be separated into four parts: upstream, reservoir, spillway gate and downstream (Figure 1.1). Upstream is the water source or inflow of the reservoir. The upstream data is recorded through gauging and telemetric stations. The water inflow is compounded at the reservoir before it is released to the downstream water channel. Reservoir is a system that is controlled by human decisions. The decisions are based on their past experience and knowledge and the current hydrological conditions such as precipitation, upstream river water level, etc. The spillway gate is used as the outlet for the reservoir water. Some reservoirs are equipped with an ungated spillway and some others have both types of spillways. A few numbers of decisions are required for the gated spillways, like the numbers of gates and the size and duration of the opening. Typically, this information is recorded in the operation logbook by an authorised reservoir operator (Wan Ishak et al., 2011b).

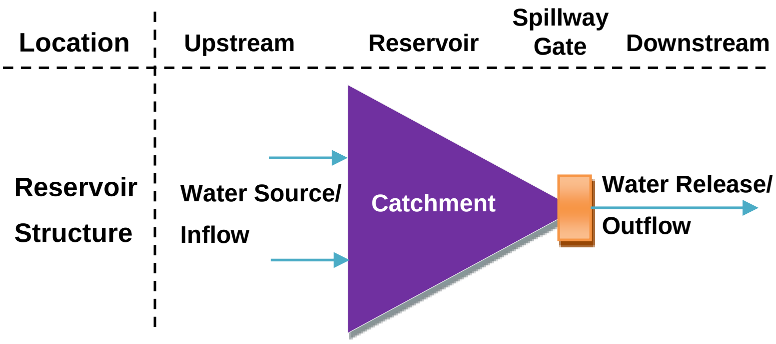


Figure 1.1. Conceptual Model of the Reservoir System (Source: Wan Ishak et al., 2011)

Reservoir release can be expressed as a function to calculate the amount of available water at the current time (i.e., current water level, plus (+) inflows, minus (-) evaporation during the current period). As stated by Wurbs (1993), the water release decision is used to determine the quantity of water to be stored and to be released or withdrawn from a reservoir under various conditions. During unwanted events such as flood and drought situations, the decisions are formulated based on previous releases, water demands, and time and water available (Hejazi, Cai, & Ruddell, 2008; Jain & Singh, 2003) .

Flood is one of the natural disasters that could strike repeatedly. It can indirectly or directly cause extreme losses to the public, such as properties, homes and innocent souls. Flood is directly associated to the reservoir as the latter is one of the flood mitigation mechanisms. According to Jonkman and Kelman (2005), normally the lowland areas are struck with flood and these areas are commonly more populated as the lands are fertile and crowded with human activities, especially in the agriculture sector. This area is typically the downstream area of the reservoir. It usually occurs in areas that obviously impede social interaction. The preventive measure prior to the flood for reservoir water release can assist to control the water flow and the river capacity to reduce and prevent losses.

In a reservoir operation, decision making is one of the vital procedures that need to be implemented wisely in order to balance the demand and supply of water for optimal social, economic and environmental benefits. The problems in early decision making of reservoir water release usually occur in unpredicted weather conditions. Therefore, simulation and optimisation techniques are exploited to be optimised in a reservoir system. According to Labadie (2004), the multiple reservoir systems can utilise the optimisation strategies with multiple objectives, such as implicit stochastic optimisation, explicit stochastic optimisation, real-time optimal control with forecasting, and heuristic programming methods.

In order to make early water release decision, the reservoir operator utilises the information about the delay as well as the current reservoir water level by monitoring the changes of the water level and referring to the superior officer before taking any action. Early water release is crucial to reserve space for incoming upstream inflow. Furthermore, the capacity of the downstream river will be controlled by the quantity of water being released. Moreover, in order to avoid flooding risks at the downstream, the river capacity can be controlled by the appropriate releasing of water quantity.

Many studies have focused on forecasting water level at multipurpose reservoirs (Chang & Chang, 2006; Hipni et al., 2013; Valizadeh, El-Shafie, Mukhlisin, & El-Shafie, 2011; Valizadeh & El-Shafie, 2013). Wan Ishak et al. (2011), for example, applied the Backpropagation Neural Network (BPNN) in forecasting reservoir water level in a multipurpose reservoir. The ability of Artificial Neural Network (ANN) has been accepted by many disciplines and it is suitable for hydrological problems (Piasecki, Jurasz, & Skowron, 2015). Several researches have employed ANN in their water level forecast model. Othman and Naseri (2011), for example, used ANN in forecasting reservoir monthly inflow using the Levenberg-Marquardt BP (LMBP) algorithm. Piasecki et al. (2015) and Young, Liu, and Hsieh (2015) discovered that ANN performs much better in the prediction of water level fluctuation compared to the traditional methods.

There are many factors that could influence the reservoir water level. However, in certain areas, only limited data is available such as rainfall and river water level. Some of the data such as reservoir operation and water release decision can be extracted from the reservoir operation logbook. Timah Tasoh is one of the reservoirs that were developed for flood mitigation purpose in addition to other purposes. Besides the Timah Tasoh Reservoir, there are six other reservoirs in Malaysia developed for the same purpose, such as Padang Saga, Batu, Bekok, Sembrong, Macap and Beris (Table 1.1).

Table 1.1

Data of Dams under the Department of Irrigation and Drainage

Name of Dam (Year Completed)/Size (L/S)	Location	DAM				Reservoir					Hazard Classification	Purpose	Construction Cost (RM)
		Type	Height (m)	Crest Length (m)	Crest Elevation (m)	Catchment Area (sq km)	Capacity (mcm)	Max. Spillway Discharge (cumecs)	Surface Area (sq.km)	Elevation (NPL in m)			
Timah Tasoh (1992)/L	Perlis	Earth	17.30(L)	3455(L)	32.0	191	40.0(L)	436	13.33	29.1	High	I/W/F	24,521,655.60
Padang Saga (1964)/S	Kedah	Earth	8.3	61	23.01	12	0.2	195	0.05	21.18	Significant	I/W/F	243,285.95
Bukit Kwong (1979)/L	Kelantan	Earth	7.62	1524(L)	18.29	11	14.3(L)	42.5	4.04	16.76	High	I/W	NA
Bukit Merah (1906)/L	Perak	Earth	9.1	579.09(L)	11.28	480	74.98(L)	424.7	41.0	8.69	High	I/W	1.6 Juta
Gopeng (1961)/S	Perak	Earth	8.54	85.34	70.71	10.6	0	78	NA	NA	Low	Sr	NA
Old Repas (1925)/S	Pahang	Earth	13.4(L)	210	143.29	10	0	60	NA	NA	Low	Sr	NA
New Repas (1963)/L	Pahang	Earth	20.0(L)	40	128.96	11	0.4	85	0.05	126.22	Significant	Sr	NA
Batu (1987)/L	Selangor	Earth	44.0(L)	550(L)	109.0	50	36.6(L)	228	2.50	102.7	High	W/F	19.7 juta
Pontian (1985)/L	Pahang	Earth	15.5(L)	350	7.5	170	40.0(L)	605	20.0	5.00	Significant	I/W	15,835,664.92
Anak Endau (1985)L	Pahang	Earth	18.0(L)	700(L)	23.0	36	38.0(L)	250	7.20	19.00	High	I/W	9,873,663.50
Labong (1949)/L	Johor	Earth	10.67	259	10.67	16	12.8(L)	84.5	6.05	8.03	Significant	I/W	NA
Bekok (1990)/L	Johor	Earth	20.3(L)	3460(L)	23.00	326	32.0(L)	1152	12.0	13.30	High	W/F	22.0 juta
Sembrong (1984)/L	Johor	Earth	11.0(L)	1770(L)	15.0	130	18.0(L)	640	8.50	8.50	High	W/F	24.0 juta
Macap (1982)/L	Johor	Earth	11.5(L)	550	19.81	77	30.6	306	9.09	15.85	Significant	W/F	15.6 juta
Perting (2003)/L	Pahang	Porous	21.5(L)	138.6	118.0	125	NA	28.3	1.05	NA	High	Sr	NA
Beris (2004)/L	Kedah	CFR	40.0(L)	155	88.0	116	122.4(L)	260	16.1	84.00	High	I/W/F	360 Juta
LEGEND	L-Large Dam/S-Small Dam NPL - Normal Pool Level Mcm - $1x10^6$ m^3 NA - Not Available			F - Flood Mitigation W - Water Supply I - Irrigation Sr - Silt Retention				CFR - Concrete Face Rockfill					

1.2 Problem Statement

Previous studies (Hipni et al., 2013; Nwobi-Okoye & Igboanugo, 2013; Rani & Parekh, 2014; Valizadeh et al., 2011; Valizadeh & El-Shafie, 2013) focused on variables such as rainfall, river water level, reservoir water level, inflow and outflow in their forecasting model. These variables can be considered as typical variables in water resources management. The data is typically measured as density and volume of water, while the aggregation method is usually applied to aggregate the data in groups or categories, such as normal, alert, warning and danger. Through this approach, some of the small valuable information will be lost. Among the information that will be lost is the changes of the reservoir water level, which provides insights on the increase or decrease of reservoir water level (Wan Ishak et al., 2011b). This information is crucial in a reservoir operation as the change of reservoir water level might influence the water release decision. This is evident from the Bertam Valley incident at Cameron Highlands, where the rapid increment of the reservoir water level has triggered the reservoir water release (Tenaga Nasional Berhad, 2013). Prior to the event, the reservoir management decision was relied on the inflow and reservoir water level. Therefore, it is vital to focus the study on the modelling of the change of reservoir water level in forecasting the next day of the reservoir water level. In this study, a modified version of the sliding window algorithm is proposed to extract a temporal pattern from the reservoir water level, particularly the change of reservoir water level pattern.

The modelling of the change of reservoir water level can be established by various computational models that are either based on statistical approaches or computational intelligence (CI) approaches. Statistical approaches are well known to solve linear problems, but have poor performance on nonlinear problems (Tokar & Markus, 2000). CI approaches such as fuzzy logic, neural network, and evolutionary computing (Eberhart & Shi, 2007) are the best approaches to deal with nonlinear problems as these techniques are constructed based on natural intelligence. Among the CI techniques, neural network is advantageous in problems that deal with massive amounts of data and nonlinear mapping of the problems. A study by Litta, Idicula and Mohanty (2013) stated the prediction has worked well using the capability of neural network. However, the neural network model needs to be redeveloped as the combination of parameters varies depending on the nature of the variables.

1.3 Research Questions

The research questions of this study are as follows:

1. How to extract a temporal pattern for the change of reservoir water level that affects the reservoir water level stage?
2. Can a model be formulated to forecast the change in the stage of the reservoir water level?

1.4 Aim and Research Objectives

The aim of this study is to develop a forecasting model for the change in the stage of reservoir water level. The model considers the changes of reservoir water level and the stage of reservoir water level. The modified sliding window algorithm is proposed to segment the data based on the time delay in the change of reservoir water level and to fit the purpose of this study. The study objectives include:

1. To propose a method to extract a temporal pattern for the change of reservoir water level that affects the reservoir water level stage.
2. To formulate a forecasting model for the change in the stage of reservoir water level.
3. To evaluate the performance of the forecasting model.

1.5 Scope of Study

The scope of this study is to forecast the change in the stage of the reservoir water level. The focus of this study is on the reservoir operation and decision making. The computational intelligence technique that has been used in this study is neural network. This research focuses on Timah Tasoh as a case study. The reservoir operation logbook for 1999-2013 has been acquired from the Department of Irrigation and Drainage (DID), Perlis.

Timah Tasoh reservoir is one of the reservoirs under DID that serve multipurpose operations, for instance flood mitigation, and serves water for other purposes such as water supply for house use and irrigation, fishing and recreation. The other reservoirs have different operation procedures from Timah Tasoh, therefore, the model developed from this study is only applicable for Timah Tasoh. Most of the water are automatically released after the reservoir water level exceeds its maximum level. Timah Tasoh is the only flood mitigation reservoir in Malaysia that completely requires human decisions for it to be operational (Ministry of Agriculture Department of Irrigation and Drainage et al., 1993).

The Timah Tasoh reservoir is located around 13 km north of Kangar town, Perlis. It covers an area of 13.33 km^2 with the catchment area of 191.0 km^2 and could hold up until a maximum capacity of 40.0 mm^3. Sungai Korok is located about 2.5 km below the confluence of Sungai Timah and Sungai Tasoh as depicted in Figure 1.2.

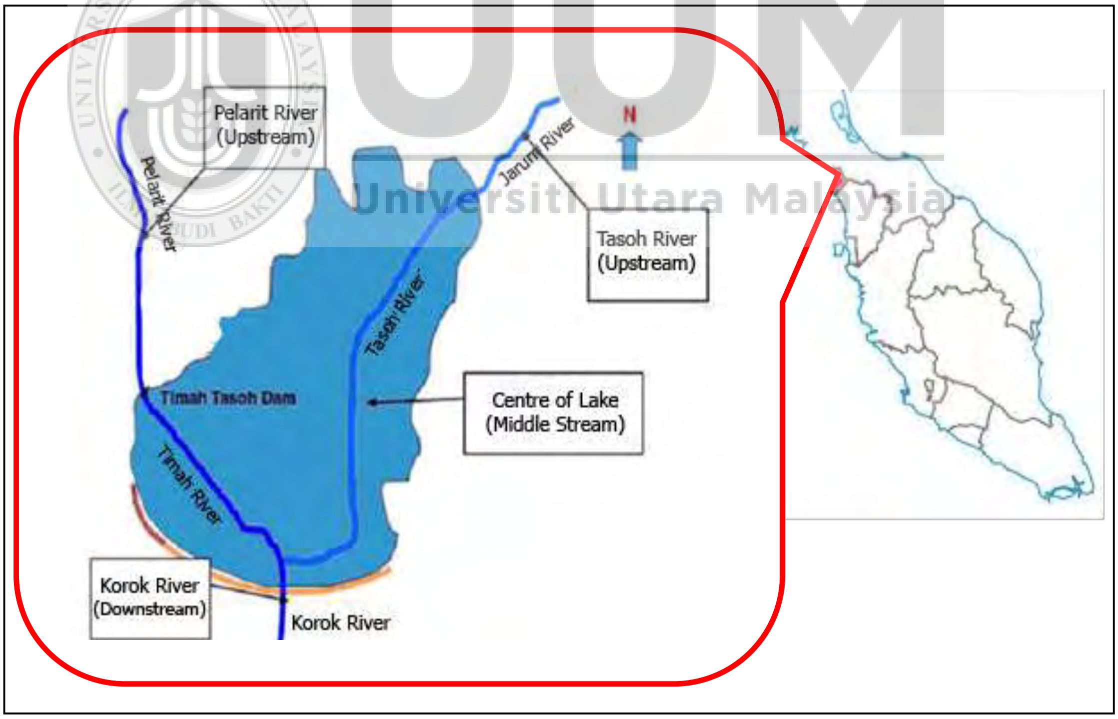


Figure 1.2. A Case Study Area (Source: Kamarudzaman, Feng, Aziz, Faizal, & Jalil, 2011)

Based on the operation and maintenance manual of Timah Tasoh, the flood situation is monitored by DID that reports to the State Security Committee (*Jawatankuasa Keselamatan Negeri*). The assessment of the situation is done by DID at the following stages: alert, warning and danger and the basic action taken for each stage. The reservoir operation rules include operation of spillway, emergency spillway and outlet works.

1.6 Significance of Study

The significance of the study are as follows:

1. The preparation of data using the modification of sliding window where it is based on the changes of reservoir water level stage. For this modification, it can produce the pattern that can be used in forecasting the change of reservoir water level stage for the next day.
2. The proposed model can be useful to help reservoir operators to make early decisions and prepare for the incoming inflow; thus, reducing the impact of flood while maintaining the supply of water for other purposes. It also lowers the risk of property damage, which will consume a lot of costs and time to build back the facilities. Additionally, the authority does not need to spend a large amount of funds to repair and maintain the dam. Hence, it is important to obtain details about the water level to avoid any inappropriate incident while maintaining the dam in a good and safe condition.

1.7 Organization of the Thesis

In this chapter, an overview on reservoir operation has been given. Several concepts such as forecasting, artificial neural network, sliding window, reservoir water level, and temporal data mining have been defined. In Chapter 2, the discussion focuses on the review of the related literature. This section also discusses temporal data mining related to the technique which is involved in developing a forecasting model. In Chapter 3, the step of developing the forecasting model is discussed in detail to achieve the research objectives. It gives an explanation of the five sequential steps in the forecasting model development process. Chapter 4 presents the development of the forecasting model of the reservoir water level stage. During the development, sliding window has been used to produce the temporal pattern and modification of the algorithm based on the changes of the reservoir water level stage. Chapter 5 is devoted to the results of models from the experiments. This chapter is achieved the last research objective, which is phase 4: Model Evaluation, where it evaluates the performance of the forecasting model. Chapter 6 concludes the research summary and contribution. It also provides the limitation of the study and recommendation of future works to improve this study.

CHAPTER TWO
LITERATURE REVIEW

This chapter describes the literature review that has been performed on reservoir operation, reservoir operating policy, reservoir release operation, reservoir water level and reservoir forecasting model. Section 2.1 explains the water resources management and the hydrodynamics characteristics of river, lake and reservoir. In reservoir operating policy, there are several types of operating policy, such as standard operating policy (SOP), rule curve and hedging rule discussed in Section 2.2. The previous studies on reservoir water level with types of reservoir, techniques, data that have been used and findings are elaborated in Section 2.3. Section 2.4 discusses the forecasting techniques in classification and computational intelligence techniques that have been used to forecast, such as neural network, fuzzy logic and hybrid models, which are elaboratively described in the following section. The details of neural network are discussed in Section 2.6.

2.1 Reservoir Operation and Management

Reservoir operation is one of the complex multiobjective and challenging problems in water resources management with an addition of conflicting constraints and objectives. Typically, a reservoir operation is managed by an authorized and experienced reservoir operator. Emergency situations and any uncertainty that occur in the hydrological variables, such as social and economic catastrophies could affect the regulating policy, and also the frequency of the reservoir water release could deviate from the regular reservoir operation (Kim, Heo, Bae, & Kim, 2008; Pinthong, Gupta, Babel, & Weesakul, 2009). According to Duckstein, Bogardi, and Huang (1989), the probability of changes in the operational mode of the reservoir are caused by the needs of certain conditions. Reservoir operating rules are used to determine water yield from a single reservoir system or a multireservoir system under various hydrologic conditions (Wurbs, 1993; Yeh, 1985). In addition, a reservoir operation depends on the purposes and objectives of the reservoir, which require different operation rules (Wan Ishak, Ku-Mahamud, & Norwawi, 2011c).

A reservoir dam is built on a river stream. Typically, only one reservoir is built on one river stream. However, in some cases, more than one reservoir are built on the same river stream or the same river network. This structure is called a multireservoir system. A multireservoir system is more complex compared to a single reservoir system and it can be classified based on its purposes and functions. A reservoir with one purpose or function is called a single purpose reservoir, while a reservoir with more than one purpose is a multipurpose reservoir. As stated by Fischer and Schultz (1991), the simplest system refers to a single purpose single unit reservoir, meanwhile the most complex system refers to a multipurpose multiunit reservoir system. The simplest system is developed for the single purpose operation such as hydropower generation or flood protection. The most complex reservoir system is created for multiple purpose operations such as flood protection, navigation, hydropower generation and recreation (Tu, Hsu, & Yeh, 2003).

In previous studies, the optimization models have been studied and deployed in the operation of complex reservoir systems. Several studies (Chang, Chang, Wang, & Dai, 2010; Mehta & Jain, 2009; Ngoc, Hiramatsu, & Harada, 2014; Pinthong et al., 2009; Shiau, 2009; Tospornsampan, Kita, Ishii, & Kitamura, 2005; Tu, Hsu, Tsai, & Yeh, 2008) have extensively reviewed multipurpose reservoir systems and functions, where various models have been proposed.

Reservoirs have been created by humans to impound water for certain purposes. These artificial water bodies have been created for the specific purposes of water resources management. In the reservoir, runoff will be discharged through the river tributaries. Runoff is a complicated hydrologic process that is influenced by weather, human activities, geomorphology and much more. However, forecasting in reservoir water level and streamflow are totally different because the reservoir is a control system and it is not determined by hydrological effects (Chang, Chen, & Chang, 2005).

The Klang Gates Dam is one of multipurpose reservoirs that operate for flood mitigation, hydropower, and industrial and domestic supplies. The flow of the Klang Gates Dam is influenced by the Klang River, which is joined by 11 major tributaries. The major tributaries include Ampang, Penchala, Kuyoh, Keruh, Damansara, Kerayong, Batu and Gombak Rivers (Akrami, El-Shafie, & Jaafar, 2013). The location of the Klang River is in Peninsular Malaysia and flows through Klang Valley and Kuala Lumpur. Malaysia has a tropical climate that is influenced by a monsoonal climate throughout the year, which receives warm weather and humidity (Hipni et al., 2013).

A river is one of the natural watercourses that link with each other while flowing towards an ocean, or lake, and its water source usually consists of freshwater. The characteristics of a river depend on the climate, rainfall activities and evaporation along the river stream network, which could influence the river features. Typically, the impact of a hydrological cycle on a river can be severe and can cause phenomena such as floods, droughts and low flow effects. The river plays a significant major role in the country's economy development field. In several studies (Bessaih, Rosmina, & Saad, 2004; Bustami, Bessaih, & Muhammad, 2006), it is revealed that the river is one of the main contributors to the economic development in Sarawak. However, over the past 40 years, there have been several hydrological events that caused extensive flooding in the Sarawak River. Heavy rainfall during monsoon seasons between October and March causes flood in certain areas in Terengganu. The Dungun River is one of the longest river in Dungun and one of the rivers that experience flood almost every year (Arbain & Wibowo, 2012a; Gasim, Adam, Toriman, Abd Rahim, & Juahir, 2007). A study by Kar, Winn, Lohani, and Goel (2012) stated that along the river in Myanmar, the areas had been hit with severe flood events in the previous few decades. According to DID, in Malaysia, water level is one of the measurements of flood characteristics (Arbain & Wibowo, 2012a, 2012b). DID introduced the categories of flood stages for the river water level, namely normal, danger and alert levels. The stages of water level are introduced to notify the authority on the rise of the river water level. These stages are currently applied at the Dungun River in Terengganu.

The Yangtze River, China has experienced flood events caused by natural disasters (Hartman, Becker, King, & Jiang, 2008). The inflow of the Yangtze River after the long rainy season in summer also increased flood risks and several studies found that the flood in the Yangtze River is caused by human activities and meteorology events (Becker, Gemmer, & Jiang, 2006; Gemmer, 2004; Wang, Jiang, Bothe, & Fraedrich, 2007). The discharge of the Yangtze River is used as a key variable for the inflow into the Three Gorges Reservoir (Chen, Zong, Zhang, Xu, & Li, 2001).

A lake is entirely different from a stream or river, which have streamflow. There are many other environmental factors that influence the variations in the lake water level, such as direct precipitation, groundwater, inflow and outflow of rivers. In addition, meteorological factors such as water and air temperature, evaporation from the lake surface, and precipitation along the drainage area play important roles in the lake water level fluctuations (Abdüsselam Altunkaynak, 2007). Chini Lake or Tasik Chini is the second largest natural freshwater inland lake in Peninsular Malaysia, which consists of 12 tributaries. The largest tributaries are Laut Gumum, Melai, Serodong, Jembarau and Jerangking (Mohamad & Toriman, 2006). However, it is different from Van Lake, Turkey, where it receives water through precipitation and snow melt inflow (Huguet et al., 2012). Van Lake is the largest lake located in eastern Turkey. Studies by Jaafar et al. (2010) indicated that the water level fluctuation in Chini Lake follows the discharge trend, where the increase of the discharges will be followed by the high water level. The damming of the Chini River is to increase the water level for tourism activities during the drought season; however, it gives a negative impact on ecosystems and water bodies (Mohamad & Toriman, 2006). Table 2.2 summarizes the different characteristics of reservoir, river and lake in terms of water level fluctuations, inflow, outflow and flushing rate. Based on Table 2.2, it is clearly seen that a reservoir is a complex system that involves inflow and outflow. Decision making is required in most of the reservoir outflow channels.

Table 2.2

Hydrodynamic Characteristics of River, Reservoir and Lake

Characteristics	**Rivers**	**Reservoirs**	**Lakes**
Water level fluctuations	Large, rapid, irregular, flooding common	Large, irregular	Small, stable
Inflow	Overland and groundwater runoff; highly irregular and seasonal, less so with large groundwater inflows	Most runoff to reservoir via river tributaries (high stream orders)	Runoff to lake via tributaries (often low stream orders) and diffuse sources
Outflow (withdrawal)	Discharge highly irregular with inflows and precipitation event frequency	Highly irregular with water use; withdrawals from surface layers or from hypolimnion	Relatively stable; usually largely surface water via surface outflow or shallow ground water
Flushing rates	Rapid, unidirectional, horizontal	short, variable (days to several weeks); increase with surface withdrawal	Long, relatively constant (one to many years)

2.2 Reservoir Water Release Decision

Reservoir operating policy is important in reservoir operation as the impact of the reservoir operation on society and economy is huge (Neelakantan & Pundarikanthan, 1999). Reservoir operators and planners are required to plan a strategy that can be used to determine the decision (Rittima, 2009). The operating policies for reservoirs are usually developed based upon previous meteorological and hydrological data (Alemu, Palmer, Polebitski, & Meaker, 2011). In certain conditions, operating policies, also known as operating rules, are commonly used in the early or planning level of the proposed reservoir. Moreover, reservoir water release decisions are guided by the reservoir operating policy (Draper & Lund, 2004; Pinthong et al., 2009).

According to Wurbs (1993), reservoir operating decisions can be categorized into three conditions: 1) during unwanted events: flood, drought (low flow), 2) normal hydrological conditions in terms of maintaining capabilities to face unwanted events at unknown times in time to come: supply water for various purposes; and 3) normal hydrological conditions in terms of optimising the beneficial usability of the reservoir system.

In the past decade, the development of reservoir operating policy has been explored and many improvements on the optimisation and simulation models have been proposed. Techniques such as heuristic algorithm, genetic algorithm and rough set or fuzzy logic have been proposed in developing new reservoir operating rules (Rittima, 2009). These rules are in accordance to the reservoir water demand and operation policies that provide guidelines for the release decision. There are several types of reservoir operating policies such as standard operating policy (SOP), rule curve, and hedging rule.

2.2.1 Standard Operating Policy

SOP is commonly used in reservoir operating. It consists of a set of the most simple rules that guide water release decision to meet the needs and requirements of the operation. However, SOP does not aim to preserve water for future demand. The reservoir might be emptied if the water storage cannot fulfil its operation requirement. On the other hand, if the demand is less than the available water, the excessive water will be spilt out from the reservoir (Vudhivanich & Rittima, 2003). In terms of water supply, it aims to minimise the total deficit along duration (Neelakantan & Pundarikanthan, 1999).

2.2.2 Rule Curve

Rule curve or guide curve is frequently used in reservoir operations. According to previous researches, the best practice of reservoir operation is with a single group of operation rule curves. Traditionally, optimisation techniques of rule curve deal with historical data in order to get the optimum result (Wang, Chen, Tung, & Hsu, 2004). The rule curve is divided into three zones: zone one is for the firm storage curve, while zone two is in the target storage curve, and zone three is the flood control curve. These curves are commonly used in the early planning stage as a guideline for reservoir operation, but they will change and will be updated from year to year.

2.2.3 Hedging Rule

Hedging rules in reservoir operation refer to a policy, where water is stored in the current operation period to reduce the probability of failure to satisfy water demands in the next operation period (Wang & Liu, 2013). Hedging rule is one of the operating policies that is used to minimise the overall damage when drought strikes. In previous studies, hedging rules have been applied to improve the performance of reservoir operation. Since the 1980s, the concept of the hedging rule had been discovered and many future works have been proposed by researchers in this field (Rittima, 2009). Neelakantan and Pundarikanthan (1999) described an improvement in the optimisation and performance for reservoir operation through simulation. Neelakantan and Pundarikanthan (2000) also suggested multiple hedging rules that divide the storage into four zones, in order to reduce the critical water shortage. Tu et al. (2008) proposed new hedging rules for the existing multireservoir system. New hedging rules were developed from the changes of demand characteristics in the reservoir system. The result shows the improvement on the efficiency of the reservoir operation. The common forms of hedging are (Draper & Lund, 2004): Trigger Hedging Value (One-point-hedging), Two-point hedging, Three-point hedging, Continuous hedging and Zone-based-hedging.

2.3 Reservoir Water Level Forecasting Model

The major part of the modelling process in a study is regarding data availability. In previous studies, forecasting reservoir water level using historical data is one of the elements in making a decision operational. The principal inputs which were used for the prediction of reservoir water level were inflow, evoporation, outflow or water release or discharge, rainfall and much more. However, several of the historical information available such as water level, rainfall and current outflow had been utilised for the prediction. The daily rainfall and water level data had been considered in the multipurpose reservoir forecasting model (Hipni et al., 2013; Rani & Parekh, 2014; Valizadeh et al., 2011; Valizadeh & El-Shafie, 2013; Wan Ishak et al., 2011b). Nwobi-Okoye and Igboanugo (2013) used the daily water level of the Kainji Dam in their prediction model. However, Chang and Chang (2006) used the hourly water level and the current outflow data to develop a forecasting model upon the reservoir water level for the next three hours during a flood event.

There are several techniques that have been used in forecasting reservoir water level, such as Artificial Neural Network (ANN), Adaptive Neuro Fuzzy Inference System (ANFIS), Support Vector Machine (SVM), and Autoregressive Integrated Moving Average (ARIMA). Hipni et al. (2013) compared the performances between SVM and ANFIS techniques. The SVM performance is superior and much better than ANFIS based on statistical evaluation. Meanwhile, Nwobi-Okoye and Igboanugo (2013) used ANN in forecasting water level and the findings are compared with ARIMA. The findings suggest that ANN produces better prediction models, however, a simpler mathematical formulation is needed to build a good model. Table 2.3 summarises the related studies on reservoir water level forecasting, type of reservoir, techniques and data used.

Table 2.3

Studies on Forecasting of Reservoir Water Level

Studies	Type	Techniques	Data
Rani and Parekh (2014)	Multipurpose	• Neural Network -Feed Forward Backpropagation (BP) -Cascade -Elman	• Daily water level • Daily inflow • Daily release
Hipni et al. (2013)	Multipurpose	• Support Vector Machine(SVM) • Adaptive Neuro FuzzyInference System (ANFIS)	• Daily rainfall • Daily water level
Nariman Valizadeh and El-Shafie (2013)	Multipurpose	Adaptive Neuro Fuzzy Inference System (ANFIS)	• Daily rainfall • Daily water level
Nwobi-Okoye and Igboanugo (2013)	Single purpose Hydropower	• Neural network • Autoregressive Integrated Moving Average (ARIMA)	• Daily water level
Valizadeh et al. (2011)	Multipurpose	Adaptive Neuro Fuzzy Inference System (ANFIS)	• Daily rainfall • Daily water level
Wan Ishak et al. (2011a)	Multipurpose	• Neural Network -Intelligent decision support model	• Daily rainfall • Daily water level
Chang and Chang (2006)	Multipurpose	Adaptive Neuro Fuzzy Inference System (ANFIS)	• Hourly water level • Current outflow

Based on previous studies, the area of study for the types of reservoir is multipurpose and single purpose for hydropower. ANN and ANFIS received attention as forecasting techniques that had been used by researchers using the ability of both artificial intelligence techniques, i.e neural network and fuzzy logic. The limitation of technology, political issues and human knowledge are used to obtain the data to produce accurate forecasting (Hipni et al., 2013).

Table 2.4 shows the result of previous studies on the forecasting of reservoir water level. There are three previous studies continuous from each other, namely the studies by Valizadeh et al. (2011), Valizadeh and El-Shafie (2013) and Hipni et al. (2013). The study by Valizadeh et al. (2011) showed that the accuracy of Scenario 3 with model R(t-i)L(t-i) gives fitness between the actual and estimated data. In their studies, the different scenarios and various time lags are used as input data. Meanwhile, Valizadeh and El-Shafie (2013) used the historical data of rainfall and water level in two different models for each type of membership function (MF). There are three different time lags that produced the accurate results from Valizadeh et al. (2011), which considered Rt0Lt1, Rt1Lt1 and Rt2Lt2. R and L to represent the rainfall and the reservoir level and t1 and t2 to represent a one- and two-day time lag.

Another study by Hipni et al. (2013) compared the Support Vector Macine (SVM) with the previous study which used ANFIS (Valizadeh and El-Shafie 2013) with the percentage error of 1.64%. A study by Nwobi-Okoye and Igboanugo (2013) used five input neural network architectures to define the best prediction on reservoir water level; however, the result of relative error shows that ARIMA gives a better result with an error of 0.039% compared to neural network with a percentage of 0.062%. According to a study by Wan Ishak et al. (2011a), the aim of their study is to create a forecasting model and decision model, where the forecasting model is for reservoir water level, and the decision model is for the classification of the current and the changes of reservoir water level. Chang and Chang (2006) used a model with and without human decision as input in order to provide a high accuracy and reliability for reservoir water level forecasting. Their study indicated that a model with human decision gives accurate results than without human decision, and it provides accurate results where the correlation coefficients are very close to the higher value (larger than 0.99). Table 2.4 summarises the related studies of reservoir water level from previous studies based on the input, output, methods that have been used and the result of each study.

Table 2.4

Result of Previous Studies on Forecasting of Reservoir Water Level

Studies	Input	Output	Methods	Result
Rani and Parekh (2014)	- Inflow - Water Level - Release	Water level	Neural network • Feed Forward BP • Cascade • Elman	Feed Forword BP RMSE : 0.92 R : 0.97 R^2: 0.95 D: 1.00 Cascade RMSE : 0.73 R : 0.98 R^2: 0.96 D: 1.00 Elman RMSE : 0.81 R : 0.98 R^2: 0.95 D: 1.00
Hipni et al. (2013)	Scenario 1 - rainfall Scenario 2 - rainfall and average dam water level Scenario 3 - rainfall and dam water level	$L(t)$ – Level of dam	SVM	RMSE: 0.0000009 MAE: 0.00000026 MAPE: 0.000009 R: 0.988962 Error: 1.64%
			ANFIS	RMSE: 0.3741 MAE: 0.1359 MAPE: 0.2539 R: 0.9930
Nariman Valizadeh and El-Shafie (2013)	1. Daily rainfall at time(*t*-*i*) 2. Dam level at time(*t*-*j*)	$L(t)$ – Level of dam	ANFIS	Error : 4.00%

Nwobi-Okoye and Igboanugo (2013)	Five input neural network architectures	Level of dam	Neural Network	Four input neural network models: Relative Error : 0.062
			ARIMA	Relative Error : 0.039
Valizadeh et al. (2011)	Model1- R=rainfall R(t-i) Model2 – R=rainfall, average of reservoir's level R(t-i)L7 Model3 - L= level of dam, R=rainfall R(t-i)L(t-i)	*L t* – Level of dam	ANFIS	Model 1: RMSE: 1.5997 MAE: 1.338 MAPE: 2.5939 R: 0.086 Model 2: RMSE: 0.287 MAE: 0.2136 MAPE: 0.403 R: 0.9838 Model 3: RMSE: 0.078 MAE: 0.046 MAPE: 0.085 R: 0.999
Wan Ishak et al. (2011a)	Forecasting model: 1. Current reservoir water level (t)	Forecasting model: *t* + 1 – reservoir water level	Neural Network	Forecasting model: Error : 0.443816%
	Decision model: 1. Current water level (t) 2. Tomorrow water level (t + 1) 3. Changes of water level (t , t – 1,…,t-w)	Decision model: Gate opening/ closing (*t*)		Decision model: Error : 0.032103%

Chang and Chang (2006)	Model 1 – Lm (*t* + *i*) = upstream flow, *O*(*t*) = current outflow Model 2 – Lm (*t* + *i*) = upstream flow	Lm (*t* + *i*) - water level	ANFIS	Gbench : 0.733 MAE : 0.436 RMSE : 0.597 Correlation Coefficients: 0.998

Based on Table 2.4, previous studies focus on the forecasting of reservoir water level using the historical data. The limitation caused by technology and management reduces the availability of the data. As shown in Table 2.3, the data column shows the limitation of data preparation such as data being measured daily, thus an hourly prediction model cannot be performed even though the accuracy of prediction is more precise. In addition, these studies do not consider the change of water level that caused the increase or decrease in the stage of reservoir water level. Therefore, in this study, those inputs are devoted as parameters and input patterns in architecture to define whether they give a minimum error of models. The changes of water level is very important because the rise of water level has been monitored. Then, three models based on the different input pattern and parameter are developed to define the best models as to whether the change of water level gives an impact on the forecasting model.

In terms of water level stage, DID has introduced a guideline to the local authority to alert when the water level rises. The stage of water level has been categorised based on the different ranges of water in the certain areas (river, lake or dam). These categories of water level stage are also known as the flood stages, namely normal, alert, warning and danger levels (refer Table 3.4) for the Timah Tasoh Dam, Perlis.

2.4 Classification of Forecasting Techniques

Forecasting is a prediction of what will occur in the future. It deals with a system in which thousands of inputs interact in a complex nonlinear system and is illustrated as highly "noisy" application (Atiya, El-Shoura, Shaheen, & El-Sherif, 1999). Classification can be a classifying input set into one of two or more groups or categories. There are two types of classification of forecasting techniques that will be discussed, which are statistical and computational intelligence techniques.

There are a variety of well-known statistical methods such as linear regression and general least squares, logistic regression and discrimination, principal component analysis, discriminant analysis, k-nearest neighbour (k-NN) classification, and ARMA and nonlinear ARMA time series forests. Linear regression and general least squares are methods for predicting the value of a dependent variable Y, based on the value of an independent variable X. Logistic regression refers to a simple logistic regression with one nominal variable with two values (female/male) and one measurement variable. These methods have been used in medical fields for the prediction of patients' outcome and identifying the problem by examining the symptoms (Royston & Altman, 2010). The ability of discriminants can identify patients who have (or will have) and those who do not (or will not) have an event of interest. Graphical aids are important in the understanding of a logistic model. Discriminant analysis resulting from an estimated logistic regression is called logistic (Croux, Gentiane, & Joossens, 2008). Principal Component Analysis (PCA) is a method of analysing relationships between sets of data in mathematics and statistical techniques that analyse patterns in datasets of higher dimensions. The standard PCA suffers from the fact that principal components (PCs) are usually linear combinations of original variables.

The k-NN rule is one of the simplest and oldest methods for pattern classification (Cover & Hart, 1967). It has two stages, which are the determination of the nearest neighbours and the determination of the class using those neighbours. A study by Kim, Choi, Moon, and Mun (2011) found that k-NN performs better compared with the other two algorithms, quadratic discriminant and linear discriminant analysis in classifying electromyogram signals based on the wrist-motion direction. The performance through statistical analysis between the three algorithms was not entirely different; however, they declared k-NN is better as a classifier. The disadvantages of k-NN are that it must compute the distance and take all the data which increases the storage space. However, Xiaoyu, Yisheng, and Siyu (2013) improved the efficiency and reduced a lot of the storage space when searching to obtain the best final result.

A time series is a sequence of numbers at regular intervals. The time series data can be found in various applications in wide areas, such as economics, environmental, finance, medicine and much more. During the last few decades, several types of stochastic models have been developed and proposed for modelling hydrological time series (Salas & Smith, 1981). The stochastic models are autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA). The ARIMA and seasonal autoregression integrated moving average (SARIMA) models have been identified to be effective in time series forecasting. The time series seasonal have been successfully used in the application of forecasting economic, foreign exchange, stock problems, social and engineering (Khashei, Bijari, & Hejazi, 2012). The advantage of SARIMA model is that it can deal with data involving trend and seasonality. Traditionally, these techniques are used for building mathematical models to generate hydrologic records in hydrology and water resources (Wang, Chau, Cheng, & Qiu, 2009). However, these techniques are not appropriate because of the complex interaction and poor understanding of the relations between processes (Toro, Gómez Meire, Gálvez, & Fdez-Riverola, 2013). Therefore, nonlinear relationships and a large number of datasets exist in hydrological studies where the traditional methods are not preferable (Valizadeh & El-Shafie, 2013). The comparison between statistical and computational intelligence techniques can be defined in Table 2.5.

Table 2.5

Comparison between Statistical and Computational Intelligence Techniques

Criteria	**Statistical**	**Computational Intelligence**
Pattern	Linear	Nonlinear
Method	Linear regression and general least squares, logistic regression and discrimination, principal component analysis, discriminant analysis, k-nearest neighbour (k-NN) classification and ARMA and nonlinear ARMA time series forests	Neural Network, Fuzzy Logic, Evolutionary computation, hybrid model
Form of data	Time series, seasonal	Spatial, time series, temporal

2.5 Computational Intelligence Techniques

Computational intelligence techniques can be defined in several approaches such as artificial neural network (ANN), fuzzy logic (FL), evolutionary computation, and hybrid models.

FL model, proposed by Zadeh (1968), is another type of artificial intelligence model that deals with the uncertainty of the event (Altunkaynak & Şen, 2007). Due to the uncertainty in the stock markets, the FL approach is combined with the association rule to overcome the difficulty of autoregression integrated moving average (ARIMA) to adapt in a noisy environment (Ho et al., 2012). The limitation of ARIMA had also been improved with the FL approach and other approaches to obtain more accurate results. The proposed model can be used as an alternative tool in the financial market (Khashei, Bijari, & Raissi Ardali, 2009). A research by Tavakkoli, Jamali, and Ebrahimi (2010) proposed a new method using the FL approach to evaluate the financial performance of companies.

FL-based modelling approaches have also received attention in hydrological modelling and reservoir operation (Jacquin & Shamseldin, 2009; Lohani, Goel, & Bhatia, 2011; Moeini, Afshar, & Afshar, 2011; Rani & Moreira, 2010; Zhang, Wang, Zhang, & Zhou, 2012). Moeini et al. (2011) proposed the fuzzy rule-based model for a single purpose (hydropower) reservoir operation, where the knowledge base is obtained from the stochastic dynamic programming (SDP) with the standard policy. The proposed model is based on the actual previous operations, which have been done, and on expert knowledge. The advantages of the proposed model are: the reservoir operator can be involved in constructing, it can be applied, and is easy to be used in rules. The advantages of the FL approach also received the attention of Kar et al. (2012) and Lohani, Goel, and Bhatia (2014) to employ it in flood forecasting. Jacquin and Shamseldin (2009) reviewed the use of the FL approach in river flow forecasting and claimed that this technique is not widely used in river forecasting compared with ANN. However, the uses of the FL approach in river forecasting is commonly used in coupling or hybridising with other approaches (Alvisi & Franchini, 2011).

In meteorological forecasting fields, FL is a clever tool to deal with uncertainty. It can easily cooperate expert knowledge into standard mathematical models in the form of a fuzzy inference system (FIS). Asklany, Elhelow, Youssef, and Abd El-wahab (2011) applied FL with rule based reasoning using five inputs to create the rainfall event prediction model. Monfared, Rastegar, and Kojabadi (2009) proposed the strategy of wind speed using the FL approach, which did not only provide the rule base, it also increased the speed prediction results.

In recent years, there is an increasing number of combination techniques, in which two or more soft computing had been integrated into an individual technique with more advantages. Recently, the potential of both ANN and FL resulted in the proposal of techniques, such as adaptive neural network fuzzy inference system. Monfared et al. (2009) applied both ANN and FL in the wind speed forecasting, where the models not only reduced time process, but also produced a better prediction performance.

The ANFIS model, introduced by Jang (1993), is a universal approximation methodology. It has been applied in numerous studies. ANFIS contains the neural network algorithm and fuzzy reasoning, thus, used to map an input space to the output space. Chang and Chang (2001) employed ANFIS in water resources modelling. Based on their study about reservoir operation, it is stated that ANFIS is more efficient compared to classical models based on the rule curve.

The ANFIS methodology was used in predicting the reservoir water level (Valizadeh & El-Shafie 2013; Hipni et al., 2013; Valizadeh et al., 2011; Chang & Chang 2006). In another study, Chang and Chang (2006) used the hybrid approach to forecast water level using these two ANFIS models based on human decision and vice versa. The result showed that accuracy and reliability in the estimation of level in the reservoir within the next three hours with human decision is more consistent.

The ANFIS techniques are also applied in predicting the changes of water level in a lake (Yarar, Onucyıldız, & Copty, 2009). Yarar et al. (2009) discovered that ANFIS's performance is superior when compared with ANN and SARIMA due to the response towards the climate change in the complex hydrological system at Lake Beysehir, Turkey. ANFIS has also been successfully applied in the modelling of hydrological time events (Firat & Güngör, 2007; Keskin, Taylan, & Terzi, 2006; Zounemat-Kermani & Teshnehlab, 2008). The combination of two methods, ANN and fuzzy system, reduces some disadvantages where ANN becomes transparent and the fuzzy system takes the ability to learn. Based on this knowledge, there are a variety of different backgrounds and fields of experts, and the acquisition process is considered time consuming (Azeez, Ali, Gan, & Saiboon, 2013). Another problem is to find the optimal network architecture and initial weights and the related parameters that influence the performance of ANFIS. However, there are no specific procedures to develop the optimal network, thus a trial and error method is one of the popular practices (Nazari, 2012).

2.6 Artificial Neural Network (ANN)

ANN model, proposed by McCulloch and Pitts, (1943) is a useful tool for modelling complex nonlinear systems and making predictions (Ham & Kostanic, 2000). ANN has been deployed in many forecasting applications, such as in finance (Mokhatab, Manzari, & Bostanian, 2011; Mostafa, 2010), business (Moosmayer, Chong, Liu, & Schuppar, 2013), medical (Rale, Gharpure, & Ravindran, 2009) and much more. In medical, Rale et al. (2009) compared the performance of multilayer perceptron (MLP) between Radial Basis Function (RBF) in the X-Ray images, which is a complex nature and is noisy on the images. In order to capture a nonlinear decision, the advantages of neural network have been used in the business field. Moosmayer et al. (2013) used the neural network to predict the relationship between the factors in predicting price negotiation and discovered that it performs better compared to the regression analysis.

In hydrological forecasting, ANN had been successfully found to be an alternative in rainfall forecasting (Antar, Elassiouti, & Allam, 2006; Hung, Babel, Weesakul, &

Tripathi, 2009), streamflow forecasting (Edossa & Babel, 2011; Singh & Kumar, 2007), river water level forecasting (Adnan, Ruslan, Samad, & Md Zain, 2012; Hartman et al., 2008; Sulaiman, El-Shafie, Karim, & Basri, 2011), groundwater modelling (Affandi, Watanabe, & Tirtomihardjo, 2007; Ghadampour & Rakhshandehroo, 2010; Mohanty, Jha, Kumar, & Sudheer, 2010), reservoir operation (Sharifi, Haddad, Naderi, & Alimohammadi, 2005), and reservoir water release (Abdul Mokhtar, Wan Ishak, & Md Norwawi, 2014) compared to traditional methods. ANN has the ability to be used in several domain areas including unpredictable and changing environments such as safety critical areas (Kurd, Kelly, & Austin, 2007). It also has the capabilities to learn and deal with the input while maintaining a good performance in operational and computational efficiencies. Basically, ANN modelling is to establish the mapping between the input and output data targets. The learning process begins in the data of the input layer of the network. Ondimu and Murase (2007) proposed ANN to predict the lake water level monthly. They focused on features such as water level, rainfall, evaporation, inflow from River Malewa, inflow from River Gilgil and simple time harmonics of the month of the year and also effects on the data compression. Based on the features, they have developed six multilayer perceptron (MLP) models to estimate the accuracy of the lake water level.

Multilayer perceptron (MLP) is a supervised learning procedure to produce an estimation model based on the value of predictor variables for one or more targets. Nwobi-Okoye and Igboanugo (2013) developed MLP for the prediction of the dam water level. The finding showed the accuracy increment, but it started to decline at the four-input model. In hydrological forecasting, the multilayer feed forward neural networks were extensively used and trained by standard BP algorithms (Rumelhart et al., 1986; Sharifi et al., 2005). Even though ANN is well known in accurate forecasting, however, the performance in certain specific situations is still inconsistent (Khashei & Bijari, 2011).

In water resources environment, the nature of data are nonlinear (spatial and temporal) and complex phenomena. Engineers have faced the difficulty in the prediction and estimation of parameters such as rainfall, water level, sediment discharge, streamflow, and runoff. ANN has the ability to deal with that problem and learn the behaviour between input and output, even though with some flaws in the data pattern such as noise, missing value and human error.

2.7 Temporal Data Mining in Reservoir

Data mining is the extraction of some new nontrivial information from large databases to find useful data. The aim is to define hidden patterns, unusual trends or other ambiguous relationships in data using the combination of techniques. Temporal data mining is the data mining of temporal sequence of a set of temporal patterns (Laxman & Sastry, 2006). For example, rainfall temporal patterns represent the variations of rainfall during a typical storm and design storm, which contributes the factors that affect the magnitude, runoff volume and timing of the peak discharge (Rosmina, Rosli, Adam, & Li, 2012).

Temporal pattern is a sequence of events that occurred according to time (Last, Klein, & Kandel, 2001). Shahnawaz, Ranjan and Danish (2011) has assigned different types of temporal data such as static data, sequences, time stamped, time series and fully temporal. Static data does not contain any temporal information, and sequence data is the list of events where the information can be extracted based on sequences. However, time stamped contains more temporal information because it is a timed sequence of static data carried at certain durations. Fully temporal is data that is entirely dependent on time, and time series data is the sequence of data change during a certain time and the events have a distance on the time scale, for example, the behaviour of wind velocity (Vafaeipour, Rahbari, Rosen, Fazelpour, & Ansarirad, 2014), river water level (Arbain & Wibowo, 2012a; Kisi, 2011), time series of river flow (Krishna, Rao, & Nayak, 2011; Toro et al., 2013), and so on.

The problem of data mining usually involves time aspect and time series being frequent forms in representing temporal data. A survey by Keogh, Chu, Hart, and Pazzani (2001) discussed the segmentation techniques that are based on a linear model. In the study, there are three algorithms that have covered a large number of segmentation algorithms based on the Piecewise Linear Representation (PLR), which are as follows: Top-Down, Bottom-Up and Sliding Window Algorithm (SWA).

Top-Down approach works in partitions of time series and splitting it at the best location. The segment of time series is recursively partitioned and it stops when the criteria are reached. The result of this approach is reasonable; however, it does not scale well in the massive time series stream (Alberg & Laslo, 2014). The top-down approach and bottom-up approach are both offline approaches. The accuracy of bottom-up is impractical in the data mining context, it has to deal with the big data (terabytes) or arrives in the continuous stream. The superiority of this approach is it needs to capture the online nature of SWA. The proposed combination of bottom-up and SWA that applies the capabilities of both approaches is called (SWAB) Sliding Window and Bottom-Up (Keogh et al., 2001).

SWA is a well-known time series in the data segmentation method and is an online approach. SWA is especially performed easily using an online algorithm. The goal of using SWA is to find a set of points in partitioning the range into small intervals. SWA has been proven to be able to detect patterns from temporal data, where it captures the time delay within the dataset (Ku-Mahamud, Zakaria, Katuk, & Shbier, 2009; Wan Ishak, Ku-Mahamud, & Norwawi, 2011a). The review on the common segmentation methods in PLA can be found in Keogh, Chu, Hart, & Pazzani (2003). Keogh et al. (2003) claimed that the sliding window algorithm has a poor performance in many real-life datasets based on the test on 10 datasets. However, based on previous studies (Kapoor & Bedi, 2013; Ku Ruhana Ku-Mahamud & Yun, 2009; Malik, 2011; Mozaffari, Mozaffari, & Azad, 2015; Paoli, Voyant, Muselli, & Nivet, 2010; Vafaeipour et al., 2014; Yu, Zhu, Li, & Wan, 2014), the sliding window approach is successful in making predictions in different datasets: forest fire, image, humidity, temperature, rainfall, wind velocity, water level, daily flow, traffic flow, vehicle speed and solar radiation. Studies by Paoli et al. (2010) and Vafaeipour et al. (2014) predicted the solar radiation and wind velocity time series. The combination of the sliding window approach with ANN is developed to predict the values of multilayer perceptron networks, a fixed number *p* of previous data values as the input of the network for training, validation and testing processes, while the output is the future forecast values of time series. The sliding window technique with ANN is illustrated in Figure 2.1.

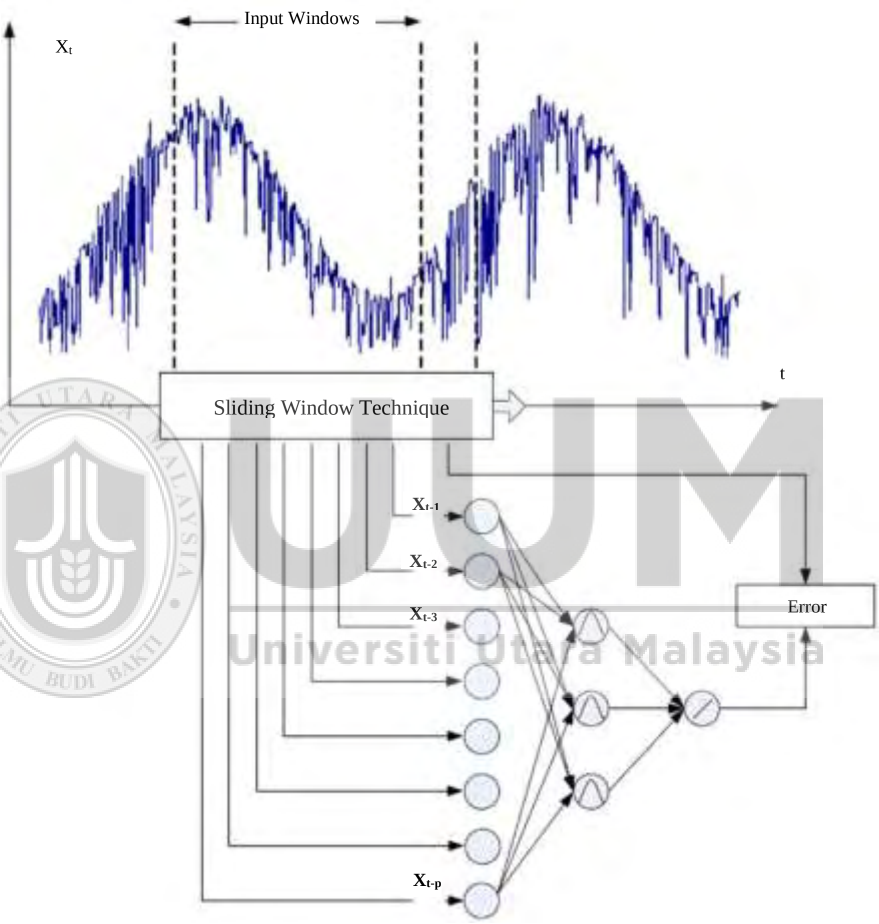


Figure 2.1. Sliding window technique with ANN (Paoli et al., 2010; Vafaeipour et al., 2014)

In forecasting the weather condition on the current days, the selected window for the current years of weekly variations are used (Kapoor & Bedi, 2013). In the study, the weather conditions that occur in a year may not fall on exactly the same day as in previous years. The seven previous days and seven ongoing days in previous years are considered with the parameters of maximum and minimum temperatures, rainfall and humidity. For example, if the weather condition of 20 December 2014 is to be predicted, then consider the conditions from 13 December to 19 December 2014 and the conditions from 13 December to 26 December 2013 for previous years. The concept of sliding window with parameters is illustrated in Figure 2.1. In the figure, W1 represents Window number 1 and W2 represents Window number 2.

S. No.	Max temp.	Min temp.	Humidity	Rainfall	
1					W_1
2					
3					
4					
5					W_2
6					
7					
8					
9					
10					
11					
12					
13					
14					

Figure 2.2. Sliding window concept with the parameters (Kapoor & Bedi, 2013)

Based on the capability of sliding window to capture temporal data with the time delay, the segmentation technique for temporal pattern to classification has been proposed (Nawawi, 2004). Adopted from Nawawi (2004), Hassin, Norwawi, and Aziz (2006) used the steps of sliding window for the temporal case-based reasoning (CBR) engine module. In the study, the event of gate opening in a reservoir depends on the rise of the water level due to rainfall; and the time delay of rainfall has been captured. The segmentation and partition of patterns are used for the proposed temporal CBR engine module. Figure 2.3 shows the steps of sliding window, which is modified based on the purpose of the study.

```
for time t to end of file
    read data at time t
    get data at (t – 1)….(t – n)
    add into window slices set
next
```

Figure 2.3. Steps for Sliding Window (Source : Hassin, Norwawi, & Aziz, 2006)

Figure 2.3 shows the steps of the sliding window technique, where *t* represents the time, and *n* represents the size of the window. This step is to capture the time delay. The first line is to loop time *t* until the end of file and in loop for, the first line is read data at time *t*. The second line is to get data (pattern) from *t-1* until the fixed number of *n* of the prevoius data. The last line in loop for is insert the pattern into the database (window slices set).

2.8 Summary

Reservoir operations have their own functions based on the type of reservoir. Reservoir water release decision model is built to define the precise decisions. In general, the decisions are usually conducted by the reservoir operating policy. The reservoir operating policy is one of the essential elements in reservoir operation and there are several types of reservoir operating policies, such as standard operating policy (SOP), rule curve and hedging rules. Water level or stage information has been studied especially in the context of reservoir, river and lake using a few techniques. The techniques can be divided in two types, which are statistical and computational intelligence techniques. Both of these techniques have their own strengths in forecasting models.

CHAPTER THREE
RESEARCH METHODOLOGY

The previous chapter described the theoretical literature and related areas in the study. This chapter discusses the process conducted in the research framework. In this study, the change of reservoir water level stage model is developed and the sliding window algorithm is modified to construct proper temporal patterns.

3.1 Research Framework

This study consists of four phases that begin with data preparation, temporal pattern formation, forecasting model development, and model evaluation. These phases are as shown in Figure 3.1. The figure shows the phases, methods used during the development, and the expected outcome. The explanations on every phase are discussed in the next section.

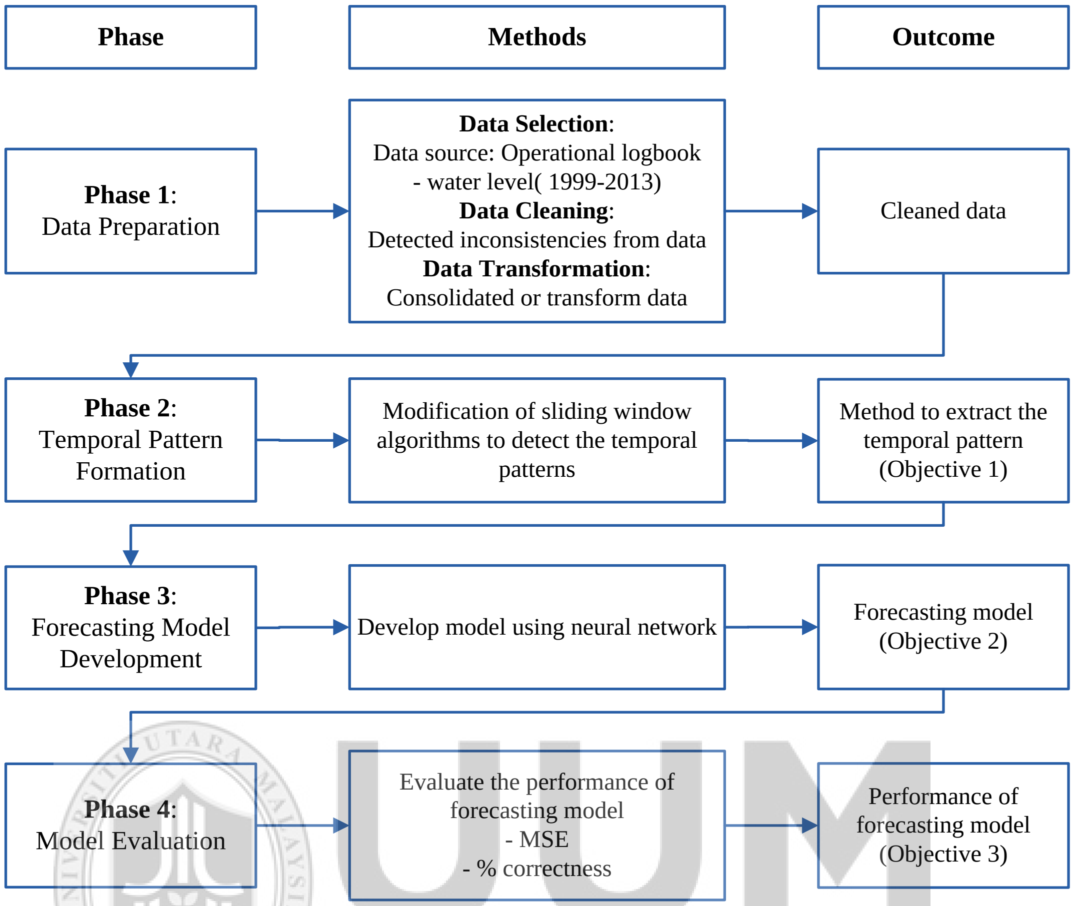


Figure 3.1. Phases in Research Framework

Data preparation describes the step where data is collected and preprocessed. Temporal pattern formation constructs the patterns based on the time using the sliding window technique. In this study, the sliding window algorithm is modified to form patterns for the next phases. The forecasting model development phase is to build the forecasting model. The last phase is model evaluation, where the forecasting model is evaluated.

3.1.1 Data Preparation

Data preprocessing is aimed to prepare the data for this study. The data preparation process (Figure 3.2) consists of three phases, which are data selection, data cleaning and data tranformation. The next section describes the respective steps of data preparation.

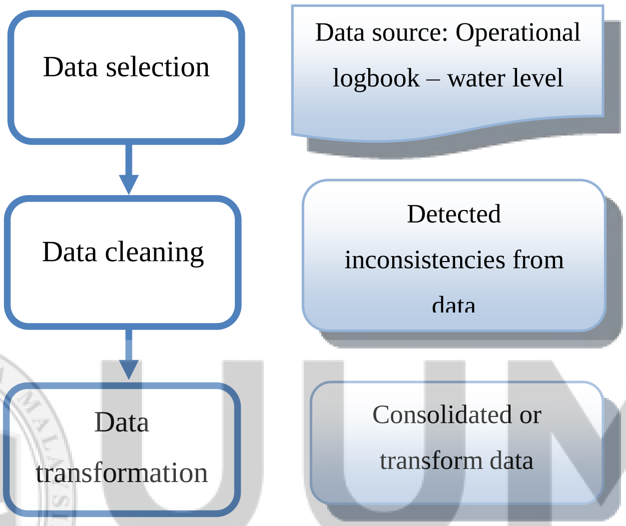


Figure 3.2. Data Preprocessing

Data selection is to identify the targets and relevant datasets. This step is important in order to select the related data to be used in this study. The daily reservoir water level data was obtained from Timah Tasoh reservoir operation. Table 3.1 shows an example of the Timah Tasoh water level data given in meters (m).

Table 3.1

Sample of the Water Level Data

Date	Water Level (m)
1/9/2011	28.930
2/9/2011	28.900
3/9/2011	28.890
4/9/2011	28.890
5/9/2011	28.870
6/9/2011	28.850
7/9/2011	28.810
8/9/2011	28.810
9/9/2011	28.800
10/9/2011	28.830
11/9/2011	29.020
12/9/2011	29.690
13/9/2011	29.840
14/9/2011	29.670
15/9/2011	29.480

In data cleaning, there are a few activities that include data cleaning, such as handling missing values and noise or outliers. In this stage, it deals with detecting and removing errors and inconsistencies from the data in order to improve the quality of the data. Data quality problems are present in single data collections, such as files and databases, e.g., due to misspellings during data entry, missing information or other invalid data.

Table 3.2

Sample Missing, Noise or Outliers Data of the Water Level

Date	Water Level (m)
7/6/2011	27.92
8/6/2011	27.91
9/6/2011	97.9
10/6/2011	27.89
11/6/2011	
12/6/2011	
13/6/2011	27.9
14/6/2011	27.9
15/6/2011	27.9

In Table 3.2, the red colour represents the sample data of noise or outliers and the blue colour represents the missing value in the water level data. The probability of the misspellings during data entry is very high for the red coloured data (97.9), where the range of data is 27.91 – 27.89. The missing value for the blue data and noise or outliers value for the red data have been replaced with the linear interpolation. Linear interpolation is a consecutive missing value between last values before the missing data and the first values after the missing data. The linear interpolation technique connects two data points with a straight line and a linear relationship between consecutive missing values. The equation of the linear interpolation function by Chapra and Canale (1998) has been applied:

$$f_1(x) = a_0 + a_1(x - x_0) \tag{3.1}$$

Where,

x = independent variable,

x_i = known value is independent variable ($i = 0,1,2,..$),

b_i = unknown coefficients,

Table 3.3 shows that the value of missing data and noise or outliers has been filled in using the linear interpolation. Hence, the values in blue or red coloured rows are still in the surrounding range between the missing values.

Table 3.3

Complete Set of Water Level Data

Date	Water Level(m)
7/6/2011	27.92
8/6/2011	27.91
9/6/2011	27.9
10/6/2011	27.89
11/6/2011	27.893
12/6/2011	27.897
13/6/2011	27.9
14/6/2011	27.9
15/6/2011	27.9

In data transformation, the data is transformed or consolidated into forms appropriate for data mining. In this study, normalisation is used where the attribute data is scaled so as to fall within a small specified range, such as from 1 to -1 or from 0 to 1. The normalisation process uses the min-max method (Jain & Bhandare, 2011) to transform a value x to fit in the range $[C, D]$. The min-max values are calculated by the following formula (Equation 3.2):

Before applying the ANN to the data, the training input and output values are normalised using the following equation:

$$New\ (x) = (D - C) * \frac{x - \min(x)}{\max(x) - \min(x)} + C \qquad (3.2)$$

Where,

C = new minimum (-1),

D = new maximum (1),

min(x) = minimum value of attribute,

max(x) = maximum value of attribute.

Data normalisation values are displayed in Table 3.4 using Equation 3.2. data transformation is performed to transform the reservoir water level into its stages. The original data of the changes of reservoir water level and the changes of stage of reservoir water level is discretised for the ease of understanding. Usually, humans are more comfortable with linguistic terms such as normal and alert rather than 29 m and 29.3 m water level measurements (Liu & Jin, 2012). Flood stage is used by Timah Tasoh Dam experts to classify the reservoir water level (Table 3.4).

Table 3.4

Water Level Stage Representation

Water Level (m)	Flood Stage	Nominal Value	Data Normalisation Value
< 29.0	Normal (N)	1	1
> 29.4	Alert (A)	2	0.33333
< 29.6	Warning (W)	3	-0.33333
> 29.6	Danger (D)	4	-1

In this study, the changes of the reservoir water level are used as the input pattern instead of the actual reservoir water level. These changes of reservoir water level are calculated using Equation 3.3.

$$\Delta WL_t = WL_t - WL_{t-1} \tag{3.3}$$

Where

ΔWL_t = the change of reservoir water level at *t*

WL_t = reservoir water level at *t*

WL_{t-1} = reservoir water level at *t-1*.

Table 3.5 shows a sample of reservoir water level data that has been transformed based on Table 3.4 and the changes of reservoir water level data which has been calculated using Equation 3.3. The change of reservoir water level can be either of negative, positive or zero value. A negative value represents the decreasing water level, while a positive value represents the increasing water level. A zero value means that there are no changes in the reservoir water level.

Table 3.5

Sample of the Changes of Reservoir Water Level Data

Date	Water Level (m) (WL)	Flood Stages	Changes of Reservoir Water Level (ΔWL)	Symbolic of ΔWL
1/9/2011	28.930	N	0.125	1
2/9/2011	28.900	N	-0.030	-1
3/9/2011	28.890	N	-0.010	-1
4/9/2011	28.890	N	0.000	0
5/9/2011	28.870	N	-0.020	-1
6/9/2011	28.850	N	-0.020	-1
7/9/2011	28.810	N	-0.040	-1
8/9/2011	28.810	N	0.000	0
9/9/2011	28.800	N	-0.010	-1
10/9/2011	28.830	N	0.030	1
11/9/2011	29.020	A	0.190	1
12/9/2011	29.690	D	0.670	1
13/9/2011	29.840	D	0.150	1
14/9/2011	29.670	D	-0.170	-1
15/9/2011	29.480	W	-0.190	-1

3.1.2 Temporal Pattern Formation

In this phase, the aimed activity is to construct the temporal pattern from the preprocessed data. The sliding window technique will be used to segment the data into temporal patterns continuously (Ku-Mahamud et al., 2009; Wan Ishak et al., 2011a). Sliding window is one of the techniques used in temporal data mining with the aim to capture the time delay within the dataset (Wan Ishak et al., 2011a, 2011b). According to Ku-Mahamud et al. (2009), sliding window can be used to develop a good prediction model with good accuracy. The following parameters: minimum temperature, maximum temperature, humidity and rainfall represent the patterns captured for the seven-day (window size) time delays from Window 1 and Window 2.

In this study, the patterns will be captured based on the changes of water level that affect the stage of water level. After a captured pattern changes, the window size (time delay) is segmented and the next pattern will be captured. The steps of sliding window in Figure 3.3 will be modified in order to segment the data pattern to fit the purpose of study. The purpose of the study using sliding window is to segment the dataset based on the changes of reservoir water level. The changes of reservoir water level for the next day depends on the changes on reservoir water level, whether increase or decrease, which affect the water level stage. The water level is the cause and the time delay between the water level affects the change of water level. In this study, the focus will be on the changes of reservoir water level as input data, while the change of the reservoir water level stage as the predicted output.

3.1.3 Forecasting Model Development

In this phase, a forecasting model for the changes of reservoir water level stage has been developed. The model deployed a supervised ANN algorithm, particularly BP algorithm. ANN is one of the computational intelligence techniques that have been inspired by biological neurons. ANN has been deployed in many forecasting applications, such as in finance (Mokhatab et al., 2011; Mostafa, 2010), business (Moosmayer et al., 2013), medical (Rale et al., 2009), and much more. It is known to yield a better performance compared to statistical approaches in nonlinear problems (Kisi, 2011; Thirumalaiah & Deo, 1998, 2000).

Typically, the ANN model consists of three layers, which are input, hidden and output layers. Figure 3.3 shows the sample diagram of the BP neural network, where the architectures are input layer (n), hidden layer (Z_m), and output layer (1).

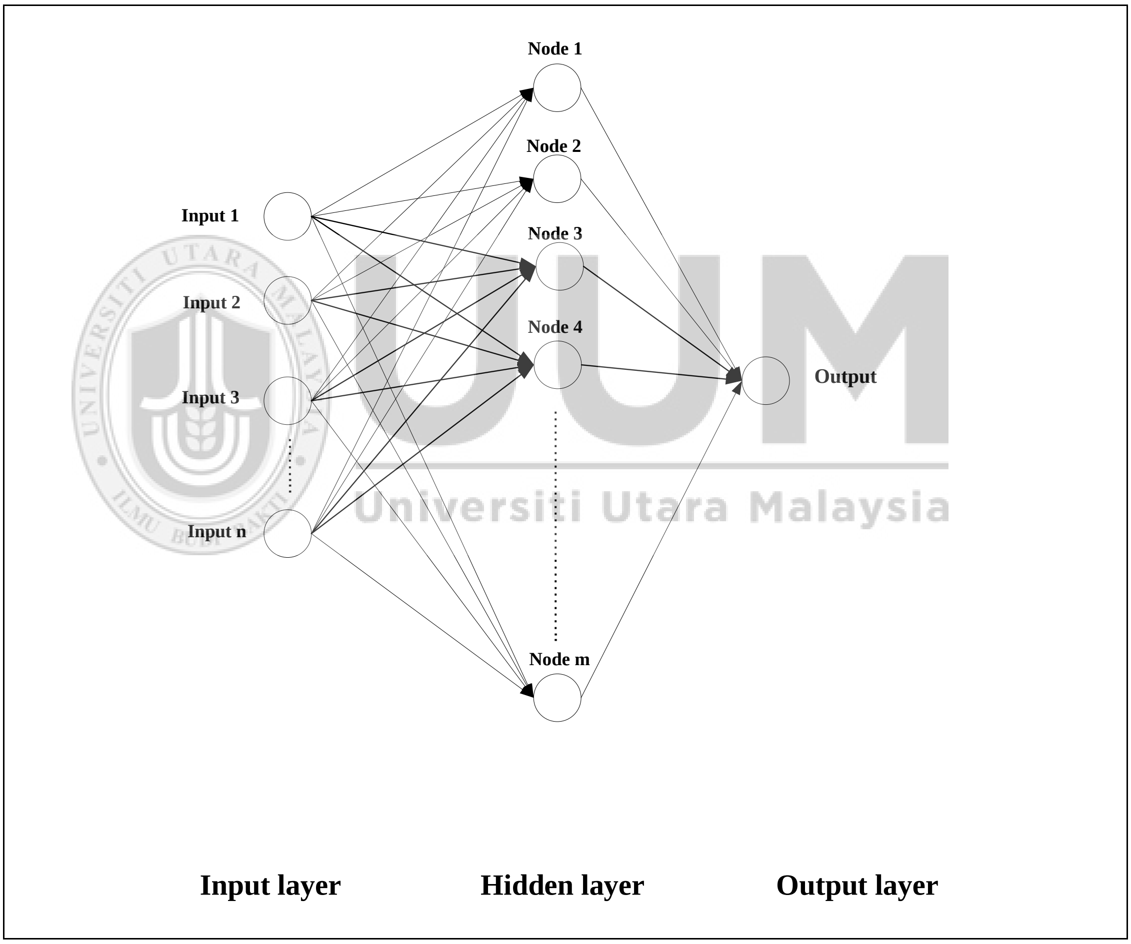


Figure 3.3. Sample of BP Neural Network for Forecasting Model.

Each of these layers have a number of processors called nodes. The BP algorithm trains the network to obtain a balance between the ability to respond correctly to the input patterns that are used for breeding. The BP training algorithm is conducted in three steps: a) feedforward for input pattern, b) calculation and back propagating the error, and c) adjustment of the weight.

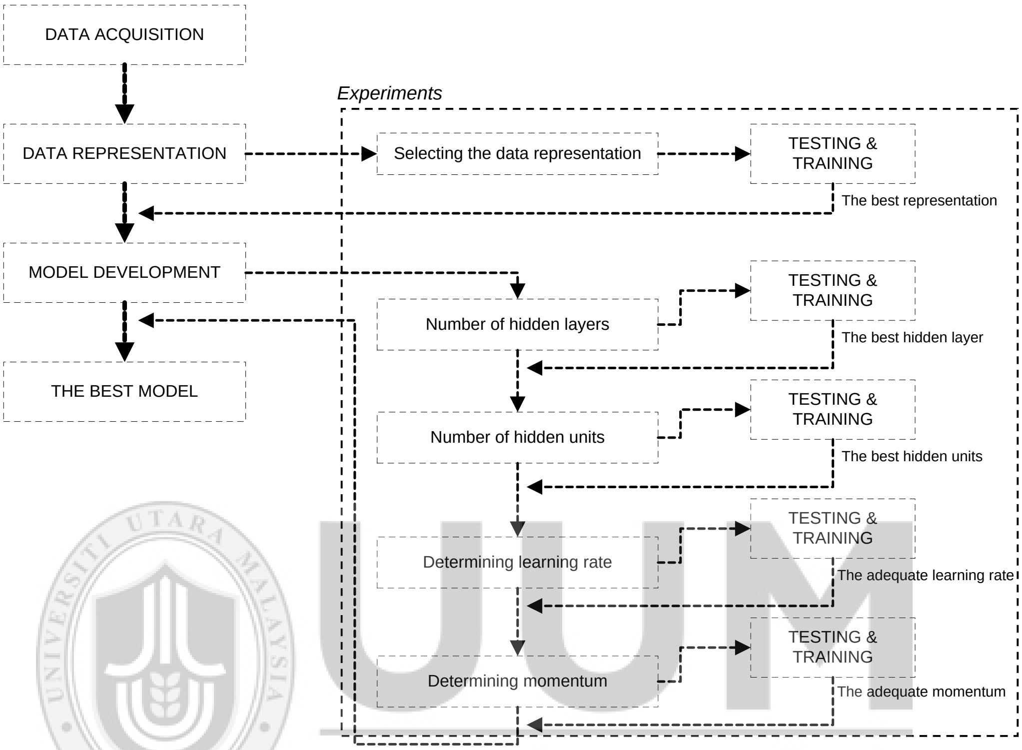


Figure 3.4. Overall Flow in ANN Application (Source: Yamin, Wan Ishak, & Othman, 2006)

Figure 3.4 shows the flow of the ANN experiment. The flow starts with data acquisition, data representation, and model development in order to obtain the best ANN model. The data representation phase needs a series of experiments in order to define the best representation, and the model development phase also requires to repeat the experiments to gain the best hidden layer, the best hidden units, the adequate learning rate and momentum.

3.1.4 Model Evaluation

In this phase, the performance of the forecasting model that has been developed is evaluated using statistical criteria, i.e, root mean square error (MSE) and prediction correctness in conjuction with a confusion matrix by Keally (1999):

$$\%Correct = \frac{\sum_{i=1}^{N}[number\ of\ correct\ for\ Class\ i]}{total\ number\ of\ samples} \times 100\% \quad 3.4$$

Where,

n = number of classes.

MSE is used to evaluate the average of the square of the difference between the actual and forecasted dam levels (Moses & Devadas, 2012). The best fit of MSE is smaller to zero. In Equation 3.5, MSE is defined mathematically as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2 \quad (3.5)$$

where

X_{obs} = observed values or forecast value

X_{model} = modelled values

i = time/place

n = the number of verifying points (grid points or observations) in the verification area

In addition, the model will also be compared with other statistical models such as multivariate multiple nonlinear regression (Sarle, 1995) in order to validate its performance.

3.2 Summary

The method that has been used was able to achieve the objective of the study. Four phases are applied in this study as the flow of process in developing the model of the changes of the reservoir water level stage, namely: data preparation, temporal pattern formation, forecasting model development and model evaluation.

CHAPTER FOUR
PROPOSED FORECASTING MODEL

This chapter describes the forecasting model of the reservoir water level stage. During the development of the model, a technique has been used to produce the temporal pattern. The technique is sliding window and the modification of the algorithm for this technique is based on the changes of the reservoir water level stage. Section 4.1 discusses the data preparation, Section 4.2 explains the modification of the sliding window algorithm and temporal pattern, Section 4.3 describes building the neural network model, and Section 4.4 discusses the result of the experiments.

4.1 Data Preparation

Data preparation is a process to transform the lacking data values, incomplete or missing data into a clean and understandable format to be fit for further processing. This process is to ensure the quality data is selected. For example, Table 4.1 shows an example of normalised data after preprocessing has been performed.

Table 4.1

Example of the Normalised Data

Nominal Value of ΔWL	Nominal Value of SWL	Change of Reservoir Water Level Stage (ΔSWL)
1	-1	-1
-1	-1	-1
-1	-1	-1
0	-1	-1
-1	-1	-1
-1	-1	-1
-1	-1	-1
0	-1	-1
-1	-1	-1
1	-1	-1
1	-0.33333	1
1	1	1
1	1	-1
-1	1	-1
-1	0.333333	1

The nominal value of ΔWL represents the change of water level, where the decrease, increase and no changes are denoted with -1, 1 and 0, respectively. The nominal value of SWL represents the data normalisation value as mentioned in Chapter 3 (Table 3.4), where it refers to the input pattern value. The last column represents the changes of reservoir water level stage (ΔSWL), where one (1) refers to the changes of stage, meanwhile negative one (-1) refers to the same stage from the previous day. The steps in sliding window are modified to detect the changes of the reservoir water level stage and are further discussed in Section 4.2.

4.2 Modified Sliding Window Algorithm

Based on Figure 3.3, the modified sliding window algorithm is proposed to capture the time delay based on the changes of reservoir water level stage. Figure 4.1 illustrates how the modification of sliding window works based on the changes of reservoir water level stage.

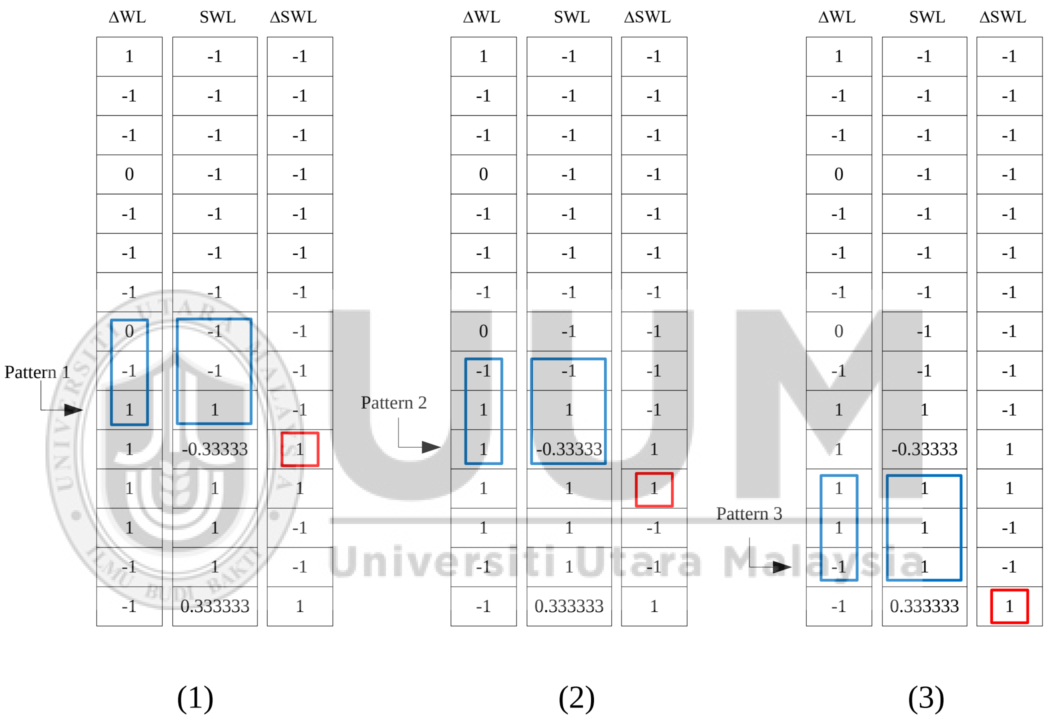


Figure 4.1. Sliding Window with Size 3

The target output is the change of the reservoir water level stage represented by column ΔSWL. Meanwhile, columns ΔWL and SWL represent the input data. The red box in Figure 4.1 (1) indicates that there are changes in the reservoir water level stage. At this point, a window slice will be formed beginning from that point and to the previous *w* days according to the window size. For example, as shown in Figure 4.1, the change of water level has been detected on the previous three days of ∆WL and SWL, which are selected as the following input pattern:

Pattern 1 = {0, -1, -1, -1, 1, 1, 1},

Pattern 2 = {-1, -1, 1, 1, 1, -0.33333, 1},

Pattern 3 = {1, 1, 1, 1, -1, 1, 1}.

In this study, the steps of pseudocode begin with the data being prepared through the data preparation process until cleaned data is obtained. The next process is to define the data containing the event, which is the changes of stage of reservoir water level. If the data does not contain the event, the next process is to read another data and if the data does not exist, it will end the process. If the data contains the event, the next process is to form the window slices and store them in the database. Each window slice captures a set of patterns consisting of input pattern values that depend on the pattern and are recorded in the database. Each time a change of reservoir water level stage is detected at time *t-1*, a window of size w is formed. For example, the segmentation process based on the sliding window technique begins with window size 3, that represents three days of delay and the window slices set is added. Figure 4.2 shows the pseudocode for the modification of the sliding window algorithm and Figure 4.3 represents the flow of the modification of sliding window based on the pseudocode to extract the temporal patterns.

```
repeat
        read clean data at time t
        detect event into data
        if change WL stage detected then
                form window slice at (t-1)…(t-n)
                add pattern to store in database
        else
        if anymore data then
                read next clean data t-1
        end if
until no more data
```

Figure 4.2. Steps in Modification of Sliding Window Algorithm

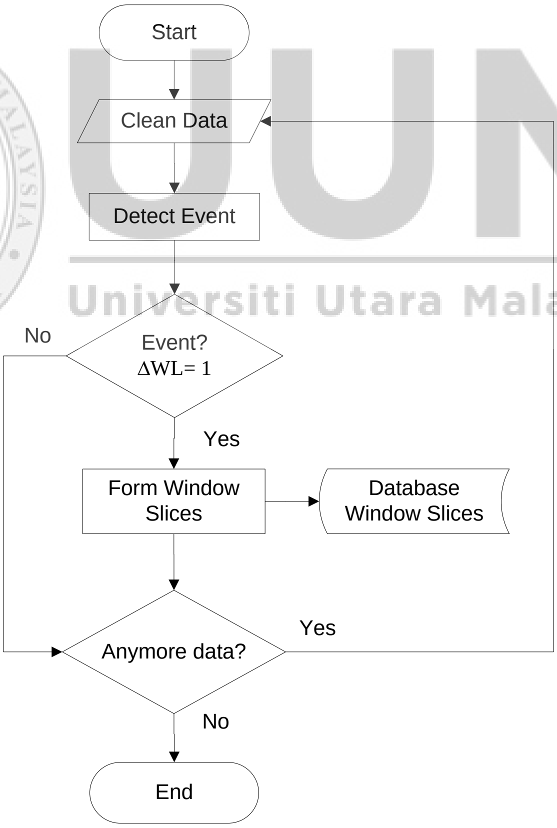


Figure 4.3. Flowchart of Modification of Sliding Window

Then, the temporal pattern is extracted through the steps of the modified sliding window. The extracted temporal patterns are used to develop three models with different architectures in the input pattern. In this study, three models with different architectures are developed as shown in Table 4.2.

Table 4.2

Three models with different architectures

Model	Description
Water Level Model	Reservoir water level (SWL) as input pattern
The Change of Water Level and Stage of Water Level Model	1. The change of reservoir water level (∆WL) as input pattern 2. The stage of reservoir water level (SWL) as input pattern
Combination of The Change of Water Level and Stage of Water Level Model	The changes of reservoir water level and stage of reservoir water level (CSWL) as combination input pattern

4.2.1 Water Level Model

Based on previous studies (Chang & Chang, 2006; Nwobi-Okoye & Igboanugo, 2013; Valizadeh et al., 2011; Valizadeh & El-Shafie, 2013), there have been predictions on water level using actual data of reservoir water level. In this section, the temporal pattern for the water level model deployed by the actual data values are transformed using normalisation as discussed in Section 3.1.1 (Table 3.4). Table. 4.3 shows the temporal pattern for the window size of three days previous with the changes of reservoir water level stage as a target is presented. The temporal patterns (various window sizes) for this model can be referred in Appendix A (pages 111-117). The temporal patterns for this model using nominal values have been normalised from the actual data.

Table 4.3

Example of Temporal Patterns using the Nominal Value (w=3)

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

The general structure of the reservoir water level can be expressed as follows (Equation 4.1):

$$\Delta SWL_{t+1} = f(SWL_{t-1}, SWL_{t-2}, SWL_{t-3} \ldots., SWL_{t-n}) \tag{4.1}$$

Where,

n <= the window size,

t = time,

ΔSWL_{t+1} = the change of reservoir water level stage at time next day,

SWL_{t-n} = reservoir water level stage at time *t-n*,

4.2.2 The Change of Water Level and Stage of Water Level Model

The value of input for the change of reservoir water level (ΔWL_t) has been discussed and calculated using Equation 3.3 in Section 3.1.1. The value of input for the stage of water level (SWL_t) has been represented in Section 3.1.1 (Table 3.4). Both inputs are used in this model, where ΔWL_t represents the changes of water level at current time ($_t$) and SWL_t represents the stage of water level at current time ($_t$). Table 4.4 shows the temporal pattern for the change of water level and stage of water level model that has been extracted from the sliding window algorithm for the previous three days. The temporal pattern (various window sizes) for this model can be referred in Appendix A (pages 118-124).

Table 4.4

Example of Temporal Patterns using the Change of Water Level and Stage of Water Level (w=3)

ΔWL_{t-2}	SWL_{t-2}	ΔWL_{t-1}	SWL_{t-1}	ΔWL_{t}	SWL_{t}	ΔSWL_{t+1}
-1	-0.33333	-1	-0.33333	1	0.333333	1
-1	-0.33333	1	0.333333	1	1	1
1	0.333333	1	1	-1	0.333333	1
1	1	0	1	-1	1	1
0	1	-1	1	-1	-0.33333	1
1	1	-1	1	-1	0.333333	1
-1	-1	-1	-1	1	1	1
0	-1	-1	-1	1	-1	1
1	-1	-1	-1	-1	-1	-1
0	-1	0	-1	-1	-1	-1
0	-1	0	-1	0	-1	-1
0	-1	-1	-1	0	-1	-1
1	-1	0	-1	-1	-1	-1
-1	-1	0	-1	1	-1	-1
1	-1	1	-0.33333	-1	-1	-1

In this study, the target output is the changes of reservoir water level stage for the next days (ΔSWL_{t+1}). The values in column (ΔSWL_{t+1}), which are 1, indicate there are changes, and the values which are -1 imply that there are no changes in the reservoir water level stage. Therefore, once the value changes to a number 1, a window slice will be formed and the previous *w* days according to window size is calculated to capture the time delay. Based on Table 4.4, the total of columns for window size 3 is six columns, where the first column for ΔWL_{t-2} is changes of water level at previous two days and the second column for SWL_{t-2} is water level stage at previous two days until time *t*. The six columns refer to the six input patterns as depicted in Table 4.3. The general structure of the change of reservoir water level and reservoir water level stage model is given in Equation 4.2.

$$\Delta SWL_{t+1} = f(\Delta WL_{t-1},\ SWL_{t-1}, \Delta WL_{t-2}, SWL_{t-2},\ \Delta WL_{t-3}, SWL_{t-3}, \ldots\ldots, \Delta SWL_{t-n}, SWL_{t-n}) \tag{4.2}$$

Where,

n = the window size,

t = time,

ΔSWL_{t+1} = the change of reservoir water level stage at time next day,

ΔWL_{t-n} = the change of reservoir water level at time t-n,

SWL_{t-n} = the reservoir water level stage at t-n,

4.2.3 Combination of the Change of Water Level and Stage of Water Level Model

In this section, the change of reservoir water level and the stage of reservoir water level are combined, where CSWL is determined as an input pattern. The combination produced 12 input pattern values, which used Equation 3.2 (Section 3.1.1). The value of the combination between ΔWL and SWL is represented in the last column, where it is used as an input pattern. ΔWL represents the changes of reservoir water level, where increase (1), decrease (-1) and no changes (0) of the reservoir water level and the nominal value are expressed from Table 3.4. The CSWL pattern values are depicted in Table 4.5. All the combination of 12 input patterns for various window sizes can be referred in Appendix A (pages 125-131).

Table 4.5

Combination of Water Level and Stage of Water Level Representation

Input Pattern	**Changes of Water Level (ΔWL)**	**Stage of Water Level (SWL)**	**Data Normalisation Value**
1	1	1	-1
2	1	2	-0.818181818
3	1	3	-0.636363636
4	1	4	-0.454545455
5	-1	1	-0.272727273
6	-1	2	-0.090909091
7	-1	3	0.090909091
8	-1	4	0.272727273
9	0	1	0.454545455
10	0	2	0.636363636
11	0	3	0.818181818
12	0	4	1

Based on Table 4.5, the values of input patterns are different from the reservoir water level model and the change of reservoir water level and stage of reservoir water level model; however, the target output is still the same, which is the change of stage of reservoir water level. Table 4.6 shows the temporal pattern of the combination with the window size 3 (w=3) and the changes of reservoir water level stage for the next day.

Table 4.6

Example of Temporal Pattern using Combination of Change of Water Level and Stage of Water Level (w=3)

$CSWL_{t-2}$	$CSWL_{t-1}$	$CSWL_t$	ΔSWL_{t+1}
-0.09091	-0.09091	-0.63636	1
-0.09091	-0.63636	-0.45455	1
-0.63636	-0.45455	0.090909	1
-0.45455	1	0.272727	1
1	0.272727	-0.09091	1
-0.45455	0.272727	0.090909	1
-0.27273	-0.27273	-0.45455	1
-1	-0.81818	-0.81818	1
-1	-0.27273	-0.27273	-1
0.454545	0.454545	-0.27273	-1
0.454545	0.454545	0.454545	-1
0.454545	-0.27273	0.454545	-1
-0.27273	0.454545	-1	-1
-1	-0.81818	-0.27273	-1
-0.81818	-0.27273	-0.27273	-1

The first column ($CSWL_{t-2}$) is at two days of delay and the second column ($CSWL_{t-1}$) is for the combination at one day of delay until time *t*. The general structure for CSWL can be expressed as follows (Equation 4.3):

$$\Delta SWL_{t+1} = f(ISWL_{t-1}, ISWL_{t-2}, ISWL_{t-3} \ldots., ISWL_{t-n}) \quad (4.3)$$

Where,

n = the window size,

t = time,

ΔSWL_{t+1} = the change of reservoir water level stage at time next day,

CSWL = combination of changes of reservoir water level and the stage of reservoir water level.

Equations 4.1, 4.2 and 4.3 represent the operations to forecast the changes of reservoir water level stage with 2, 3, 4, 5, 6 and 7 days antecedent data, respectively. The inputs are arranged sequentially as time is one of the important factors in the model.

4.3 Building ANN Forecasting Model

In this study, three models are developed with six different architectures. The six different architectures refer to the data with different window sizes from 2 until 7. The window size alludes to the previous day of time delay. The selection of window sizes (2-7) consider the expert advice from DID, where the large scales can make the prediction itself irrelevant. Table 4.7 shows the parameters of ANN that are used in this study.

Table 4.7

Parameters used in ANN

Parameters	**Values**
No. of input neurons	2 - 14
No. of hidden layers	1
No. of neurons in the hidden layer	3,5,7, 9…, 21, 23, 25
Learning rate	0.1 – 0.9
Momentum	0.1 – 0.9
Comparison function	MSE
Epoch size	1000
Ratio of Training and Validation	10% of each
Ratio of Testing	80% of each

Based on the previous studies (refer Table 2.3) on forecasting reservoir water level, the variables that have been used are water level and rainfall, and several studies considered water release and inflow. In this study, the variables considered are the reservoir water level and the changes of reservoir water level from the manipulation of reservoir water level using Equation 3.3. Three models (refer Table 4.2) with architectures have been developed to determine the ability to deal between the reservoir water level and the changes of reservoir water level and also the combination of both variables.

Each neural network model is trained with one dataset. Each model is trained with a different combination of hidden units, learning rate and momentum. The values for the learning rate and momentum parameters are numbers 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9. The learning parameter plays an important role in the performance of neural network (Hinton, Srivastava, Krizhevsky, Sutskever, & Salakhutdinov, 2012; Matignon, 2005). The performance of a trained neural network depends on its architecture. The learning function used is BP and makes use of two parameters that control the rate at which learning was used. The first parameter is momentum and second parameter is learning rate. The architecture of the network is determined using the trial and error method (Hsu et al., 1995). In this study, the trial and error procedure defines the optimal network for the change of stage of reservoir water level forecasting. The networks are trained for 1000 epochs. For each epoch, the BP learning algorithm builds a different model network with a different set of weights (Carney & Cunningham, 1998). If a neural network is trained to 100 epochs, the learning algorithm process loops through 100 different models. In this study, the epochs are trained until the maximum of 1000 epochs.

Neural network learning can be viewed as a search through a large number of models, for a model that has the set of weights that will provide the best generalisation performance. Hence, the network parameters in this study are given in Table 4.7.

Based on the network parameters (Table 4.7), the architectures are developed. The input layer is the variables of the changes of reservoir water level and reservoir water level stage which are considered as the input, where the total of maximum input node is 14 and the minimum input node is 2.

The data is divided randomly into three groups: training set, validation set and testing set. The training set has three elements: (1) maximum epoch, (2) minimum error, and (3) early stopping condition. The validation error keeps on arising in several epochs, then early stopping is executed (Sarle, 1995). The procedure of the training BP neural network starts from Figure 4.4 until Figure 4.7, where Figure 4.4 is the general nested structures as the main structures to call the other functions (feedforward, BP error and weight update) to find the best result of the training neural network. The process of the experiment using neural network can also be defined in Figure 3.4. After training the network, the results are evaluated using the statistical criteria that are Mean Square Error (MSE) and the percentage of correctness.

```
for Epoch = 1 to Max_Epoch
{
       For pattern = 1 to T_Pattern
       {
        feedforward(Pattern)
        backpropagation_error(Pattern)
        weight_update()
       }
        MSE = calculate_MSE()
        test_stopping_condition(MSE)
}
```

Figure 4.4. General nested structures for the BP Algorithm

```
feedforward(Pattern)
{
        for x=1 to n
        {
                for j = 1 to p
                {
                calculate the output signal of Z
                }
        }
        for j = 1 to p
        {
                for k = 1 to m
                {
                calculate the output signal of Y
                }
        }
}
```

Figure 4.5. Nested structures for feedforward


```
backpropagation_error(Pattern)
{
        for k = 1 to m
        {
                calculate error information term for each output unit y
                calculate Squared Error and Total Squared Error
                for j = 1 to p
                {
                        calculate weight correction term
                }
                calculate bias correction term
        }
        for j = 1 to p
        {
                sums delta input for each hidden unit
                calculate error information term
                for i = 1 to n
                {
                        calculate weight correction term
                }
                calculate weight correction term
        }
}
```

Figure 4.6. Nested structure for BP error

```
weight_update()
{
        for j = 0 to p
        {
                for k = 1 to m
                {
                        update bias and weights for each output unit
                        (at output layer Y)
                }
        }
        for l = 0 to n
        {
                for j = 1 to p
                {
                        update bias and weights for each output unit
                        (at output layer Z)
                }
        }
}
```

Figure 4.7. Nested structure for weight update

4.4 Experimental Design

The actual data is acquired from the reservoir operation logbooks of 1999-2013 from DID, Perlis. The three models with six different architectures are developed based on the manipulation and normalisation of the actual data. The temporal pattern is produced from the modification of the sliding window algorithm with window sizes of 2, 3, 4, 5, 6 and 7. Each temporal pattern is trained using neural network and divided randomly into three datasets: training (80%), validation (10%) and testing (10%). The performance of the models is evaluated using the percentage of correctness and MSE. The comparison of each model is determined based on the best performance with different architectures.

4.5 Summary

This chapter described the proposed forecasting model in detail. Sliding window is a technique that has been used to produce the temporal pattern. The modification of the sliding window technique is discussed and implemented to the three models with different architectures. The models are trained using the trial and error method with different parameters to find the best model with less errors.

CHAPTER FIVE
RESULTS AND DISCUSSION

This chapter discusses the results of the models in forecasting the change in the stage of reservoir water level. The results of each model with different architectures are analysed and compared. Section 5.1 presents the performance result of each model, which explains the original data, sample diagram, result (training, validation and testing) and the neural network parameter. Next, Section 5.2 describes the discussion where a comparison between the models is conducted to define the best model of changes in the stage of reservoir water level. Finally, the summary of the findings are discussed in Section 5.3.

5.1 Performance Results

The performance results are obtained from training the patterns using neural network; six datasets of each model have been formed and a comparison between the three models has been performed. The results are analysed and explained in the next sections.

5.1.1 Result for Water Level Model

The unique record or no redundancy number of input is getting smaller after removing the redundancy compared to other dataset models. Table 5.1 shows the original dataset of each window size for the stage of reservoir water level model.

Table 5.1

Original Data and Experiment Dataset of Each Window Size for the Stage of Reservoir Water Level.

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

The number of unique record is reduced from the original data. Figure 5.1 shows the sample diagram for the BP neural network for water level model architecture. The sample represents the input layer (SWL_t), hidden layer (Z_m) and output layer (ΔSWL_{t+1}) that have been used in training the water level model. The input layer and the output layer have been discussed in Section 4.2.1.

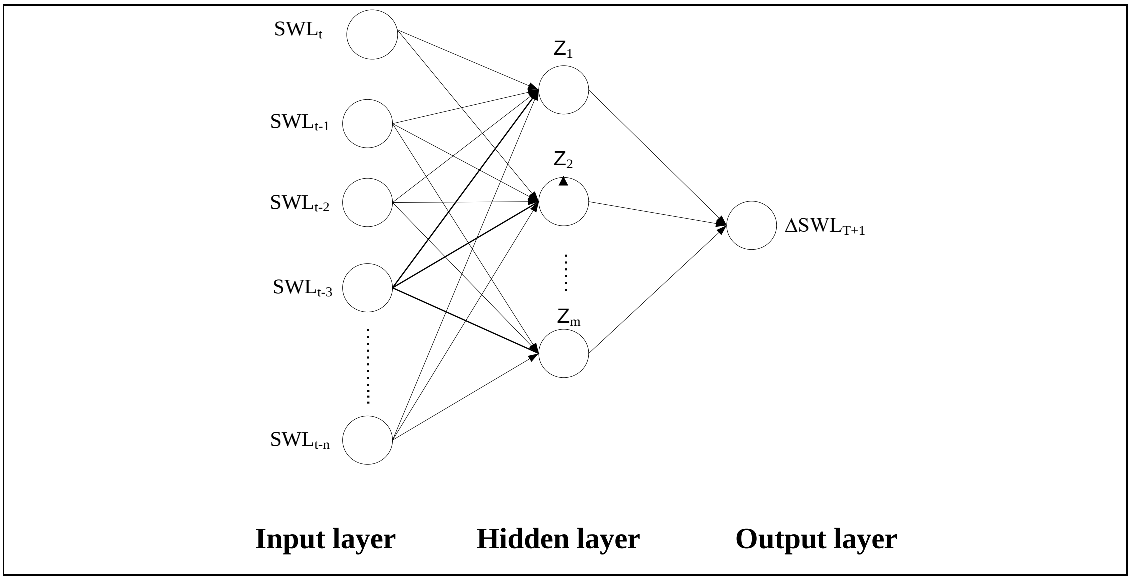


Figure 5.1. Sample Diagram for BP Neural Network for Water Level Model Architecture

Table 5.2 shows that window size 4 (previous four days) gives a better result compared to the other window sizes. Window size 4 with dataset 3 achieves 92.31% of training performance, and validation and testing performance are 100%, which give a better performance than other sizes. The errors of window size 4 are 0.153913659, 0.006453737 and 0.019636617, respectively.

Table 5.2

Results of Training, Validation and Testing

Window Size	Training		Validation		Testing	
	MSE	**%**	**MSE**	**%**	**MSE**	**%**
2	0.166666208	91.67	0.010554764	100	0.0000000222	100
3	0.518519083	74.07	0.500000001	75	0.0000000002	100
4	0.153913659	92.31	0.006453737	100	0.019636617	100
5	0.489835559	71.43	0.589901874	70	0.684932503	70
6	0.560240315	71.93	0.428165889	78.57	0.571530997	71.43
7	0.425798538	78.08	0.403071357	77.78	0.592914878	72.22

Table 5.3 shows the neural network parameters that give the minimum error and maximum percentage correctness in training, validation and testing for the water level model (Table 5.2). The datasets represent the window sizes, where dataset 3 is equal to window size 4 and also equals to 4 input units.

Table 5.3

Neural Network Parameters for Minimum Error and Maximum Percentage of Correctness

Dataset	Input Unit	Hidden Unit	Output Unit	Learning Rate	Momentum
1	2	17	1	0.7	0.7
2	3	13	1	0.9	0.8
3	4	21	1	0.9	0.3
4	5	3	1	0.9	9.5
5	6	5	1	0.6	0.7
6	7	7	1	0.2	0.8

The combination of neural network parameters for dataset 3 was obtained from dataset 3. The architecture for dataset 3 is 4-21-1 (Figure 5.2) with a learning rate of 0.9 and a momentum of 0.3. The combinations of parameters are defined based on the trial and error procedure, in which each combination of parameters had been discussed in Section 4.3 (building ANN forecasting model). Dataset 3 was formed with window size 4 and 64 of number of instances. Figure 5.2 shows the diagram for water level model (4-21-1) architecture, where 4 is the input layer (previous four days), 21 is the hidden layer, and 1 is the target output.

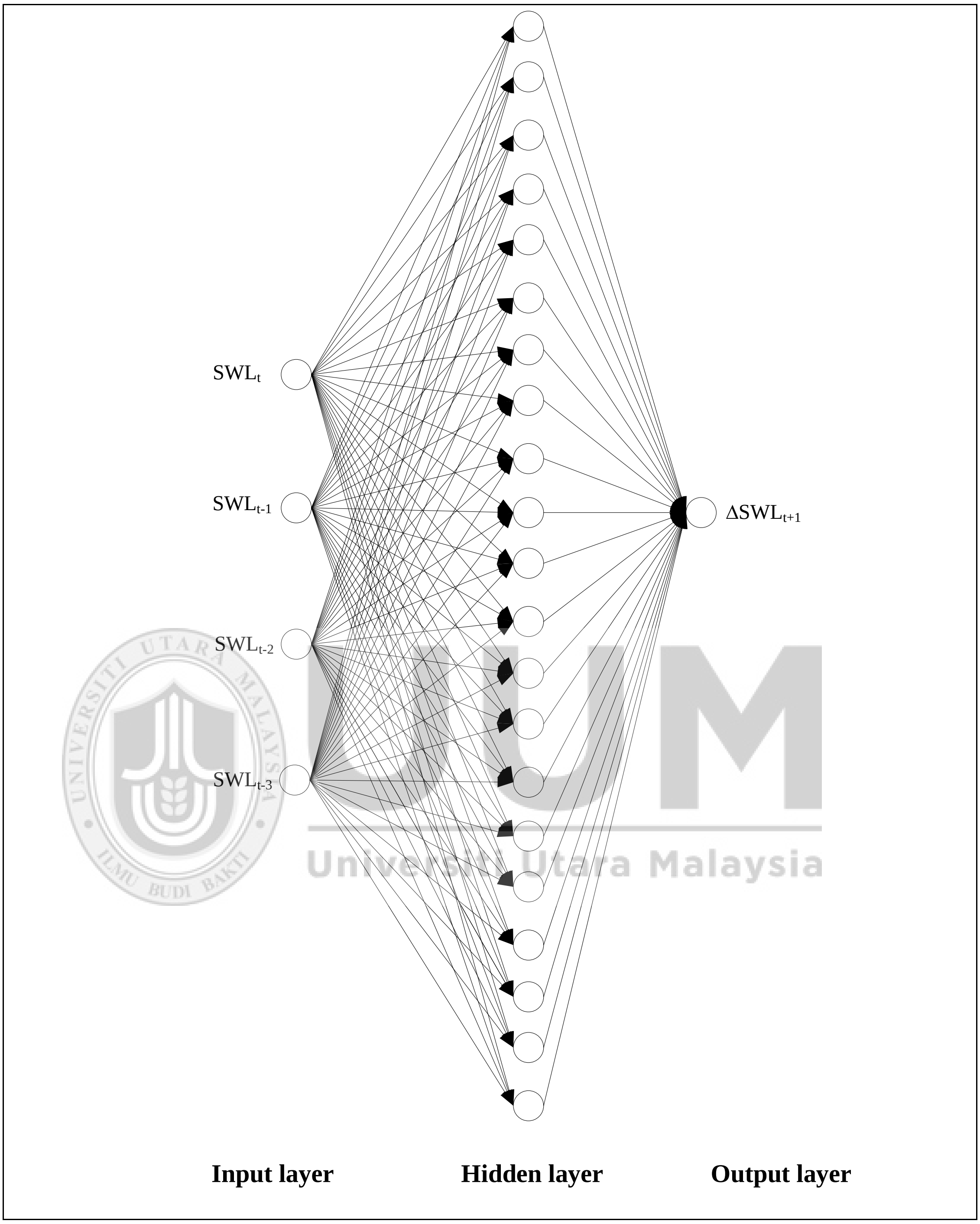


Figure 5.2. BP Neural Network for Water Level Model (4-21-1) Architecture

5.1.2 Result for the Change of Water Level and Stage of Water Level Model

The unique record or no redundancy number of input has been used in the neural network performance and has been divided into three datasets: training, validation and testing. Table 5.4 shows the original dataset of each window size for the changes of reservoir water level and the stage of reservoir water level as the input pattern.

Table 5.4

Original Data and Experiment Dataset of Each Window Size for the Model.

Dataset	Window Size	# Input	
		Original	Unique Record / No Redundancy
1	2	5779	50
2	3	5628	150
3	4	5426	350
4	5	5070	709
5	6	4562	1213
6	7	3963	1811

The numbers of neurons in the hidden units, learning rate and momentum are determined by the trial and error procedure to find the network structure. The target output is 1, which refers to the change of reservoir water level stage. For the remaining datasets, dataset 1 until dataset 6, the input data keeps increasing two inputs depending on the temporal patterns that had been discussed in Section 4.3.1.

Figure 5.3 shows the sample diagram for the BP neural network for water level and stage of water level model architecture. This sample represents the input layer, hidden layer and output layer that had been used in training the model. The input layer and the output layer have been discussed in Section 4.2.2.

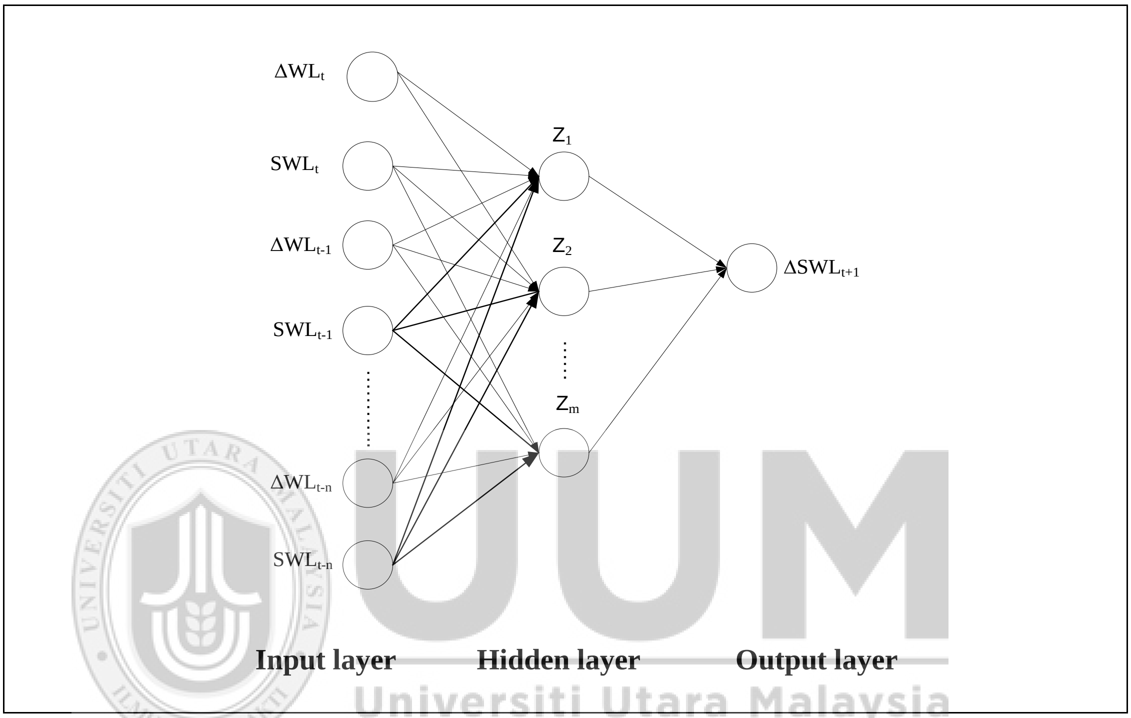


Figure 5.3. Sample Diagram for BP Neural Network for the Change of Water Level and Stage of Water Level Architecture

The results of the model are presented in Table 5.5. From the table, it shows that window size 2 (previous two days) gives a better result compared to the other window sizes. Neural network training with dataset 1 achieves 92.5% of training performance and both validation and testing performance are 0%. The performance of BP ANN models with different combinations of neural network parameters (Table 4.7) is shown in Table 5.5. The different combination of learning rate and momentum, and the number of neurons in the hidden layer are finalised after a trial and error procedure.

Table 5.5

Results of Training, Validation and Testing

Window Size	**Training**		**Validation**		**Testing**	
	MSE	**%**	**MSE**	**%**	**MSE**	**%**
2	0.150000959	92.5	0	100	0	100
3	0.432851051	73.33	0.605505944	66.67	0.497326619	73.33
4	0.448398958	77.58	0.457142574	77.14	0.318823948	82.86
5	0.246922835	87.65	0.273057187	85.92	0.294699054	84.51
6	0.207943	88.26	0.18908	89.26	0.216076	87.6
7	0.136307	92.62	0.163824	91.16	0.187749	90.06

The different numbers of hidden nodes or units from dataset 1 until dataset 6 are selected and obtained from Table 5.5 based on the best results of training, validation and testing. Table 5.6 shows the neural network parameters for the change of reservoir water level and stage of reservoir water level using the parameters in ANN (Table 4.7).

Table 5.6

Neural Network Parameters for Minimum Error and Maximum Percentage of Correctness

Dataset	**Input Unit**	**Hidden Unit**	**Output Unit**	**Learning Rate**	**Momentum**
1	4	17	1	0.7	0.7
2	6	3	1	0.6	0.6
3	8	25	1	0.4	0.6
4	10	11	1	0.3	0.6
5	12	3	1	0.6	0.4
6	14	3	1	0.8	0.4

The architecture found from Table 5.5 is 4-17-1, the learning rate is 0.7 and the momentum is 0.7. Dataset 1 is formed with window size 2 of 50 instances. Figure 5.4

shows the diagram for reservoir water level and stage of reservoir water level (4-17-1) architecture, where 4 is the input layer (previous two days), 17 is the hidden layer, and 1 is the target output.

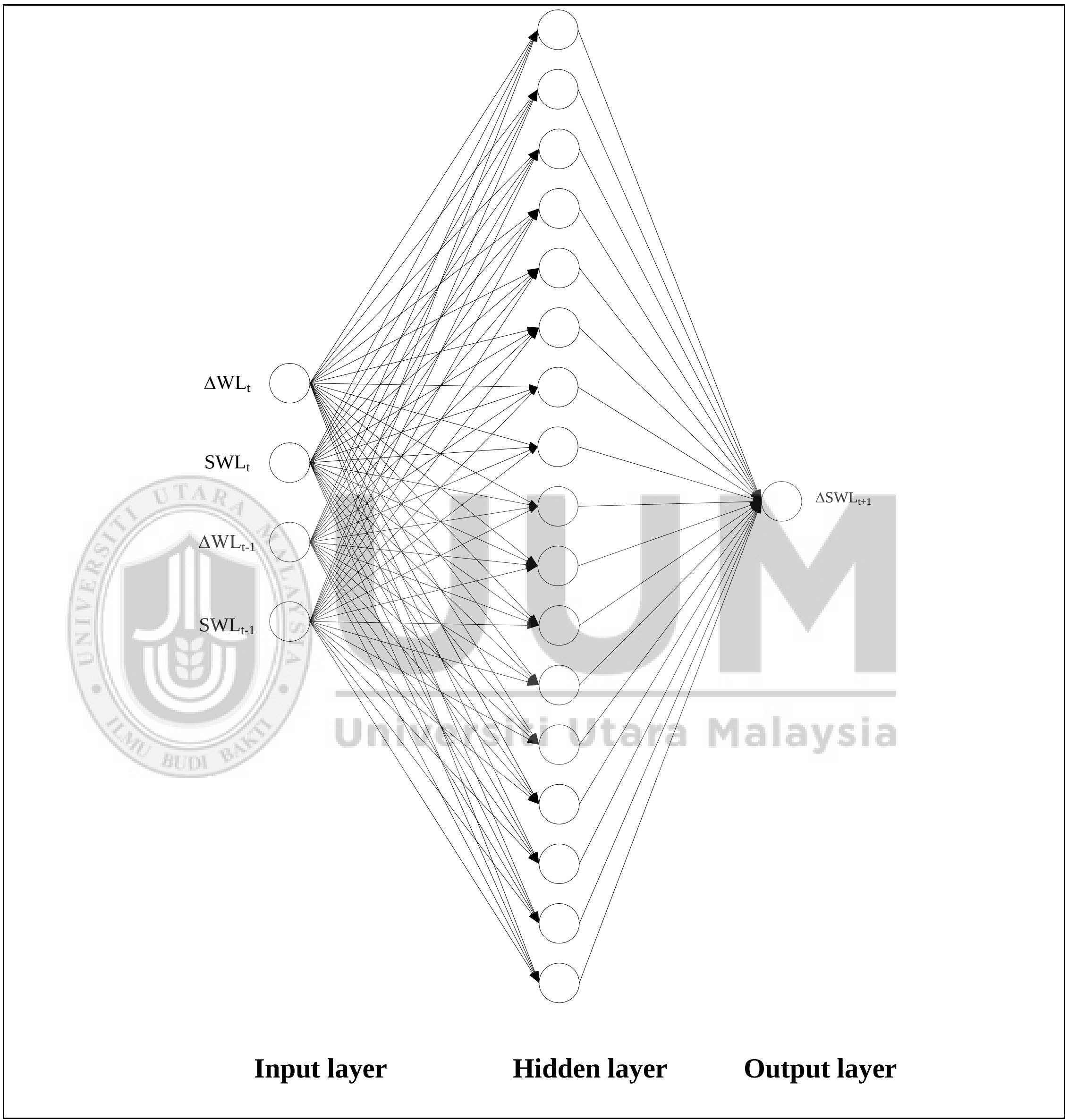


Figure 5.4. BP Neural Network for the Change of Water Level and Stage of Water Level (4-17-1) Architecture

5.1.3 Results for the Combination of the Change of Water Level and Stage of Water Level Model

After removing the redundancy input from the original input, the unique record of the combination of the changes of reservoir water level and stage of reservoir water level is used in training the neural network (Table 5.7). Table 5.7 shows the window size with the unique record for the combination between the changes of reservoir water level and stage of reservoir water level.

Table 5.7

Original Data and Experiment Dataset of Each Window Size for Combination.

Dataset	Window Size	# Input	
		Original	Unique Record / No Redundancy
1	2	5779	49
2	3	5778	144
3	4	5777	348
4	5	5776	707
5	6	5775	1215
6	7	5774	1816

Figure 5.5 shows the sample diagram for the BP neural network for the model architecture. The sample represents the input layer, hidden layer and output layer that have been used in training the model. The input layer and the output layer have been discussed in Section 4.2.3.

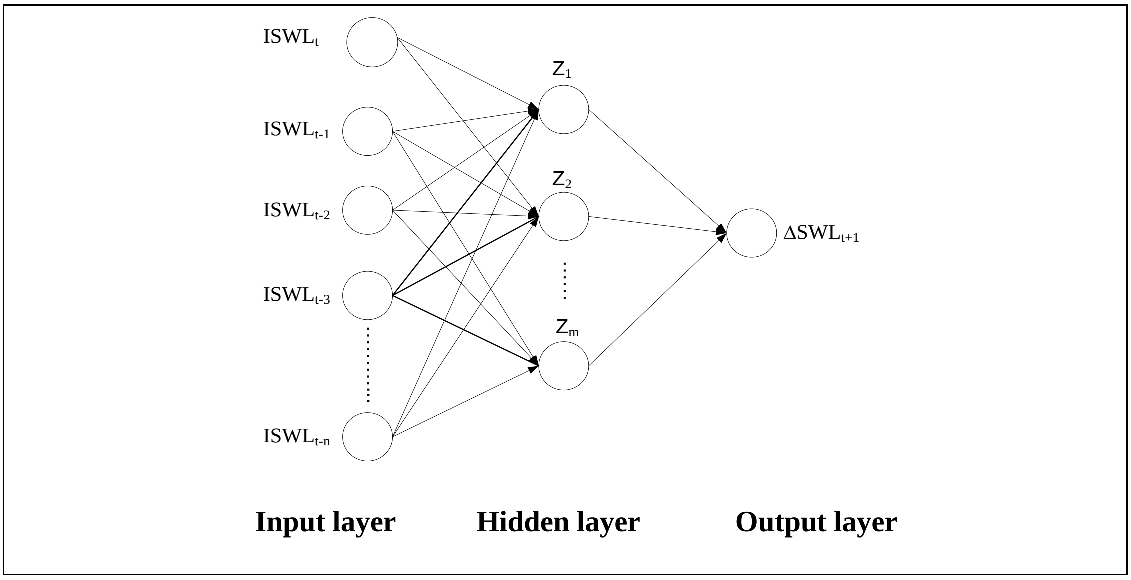


Figure 5.5. Sample Diagram for BP Neural Network for Combination of Water Level and Stage of Water Level Model Architecture

The performance of the model is shown in Table 5.7. The second, third, and fourth columns contain the MSE and percentage correctness for all window sizes in the training, validation and testing datasets. From Table 5.8, it can be seen that window size 7 (previous seven days) gives a better result compared to the other window sizes. Neural network training with dataset 6 achieves 91.46% of training performance, 90.66% of validation and 90.11% of testing performance. The errors are 0.15990066, 0.177182145 and 0.19052576, respectively. The architecture is 7-3-1 with the learning rate of 0.1 and the momentum of 0.1. Dataset 6 is formed with window size 7 of 50 instances.

Table 5.8

Results of Training, Validation and Testing

Window Size	Training		Validation		Testing	
	MSE	%	MSE	%	MSE	%
2	0.168520654	89.74	0.404720598	80	0.401644822	80
3	0.495235126	61.21	0.6552951	57.14	0.623417754	57.14
4	0.421348971	68.71	0.491883337	68.57	0.34632133	68.57
5	0.357993366	78.94	0.456147716	74.65	0.336441073	74.65
6	0.197618269	89.8	0.222921079	88.52	0.215033299	89.34
7	0.15990066	91.46	0.177182145	90.66	0.19052576	90.11

Table 5.9 shows that the neural network parameters are obtained from the minimum MSE and maximum percentage correctness and are used to develop the model for the combination between changes of reservoir water level and the stage of reservoir water level.

Table 5.9

Neural Network Parameters for Minimum Error and Maximum Percentage of Correctness

Dataset	Input	Hidden Unit	Output	Learning Rate	Momentum
1	2	17	1	0.1	0.1
2	3	21	1	0.2	0.7
3	4	23	1	0.1	0.2
4	5	3	1	0.9	0.6
5	6	25	1	0.5	0.2
6	7	3	1	0.1	0.1

The number of hidden nodes is defined after the trial and error procedure, using different combinations of learning rate and momentum terms. In this model, dataset 6 gives the combination of learning rate and momentum as 0.1, while the number of hidden nodes is 3, similar with dataset 1, where the combination of learning rate and momentum is 0.1. However, the number of hidden nodes is high, which is 17. The combination of both datasets also has to refer to the result of the error and percentage of correctness. Every dataset has used the neural network parameters that had been discussed in Section 4.4. The second column contains the input layer, which keeps increasing one input depending on the temporal pattern (Section 4.3.2). The hidden units, learning rate and momentum from dataset 1 until dataset 6 are selected from the best results of training, validation and testing. The parameters of neural network found that the architecture for dataset 6 is 7-3-1, and the learning rate and momentum are 0.1. Figure 5.6 shows the diagram for model 3 (7-3-1) with 7 as the input layer (previous six days), the hidden layer is 3 nodes, and the output layer is 1.

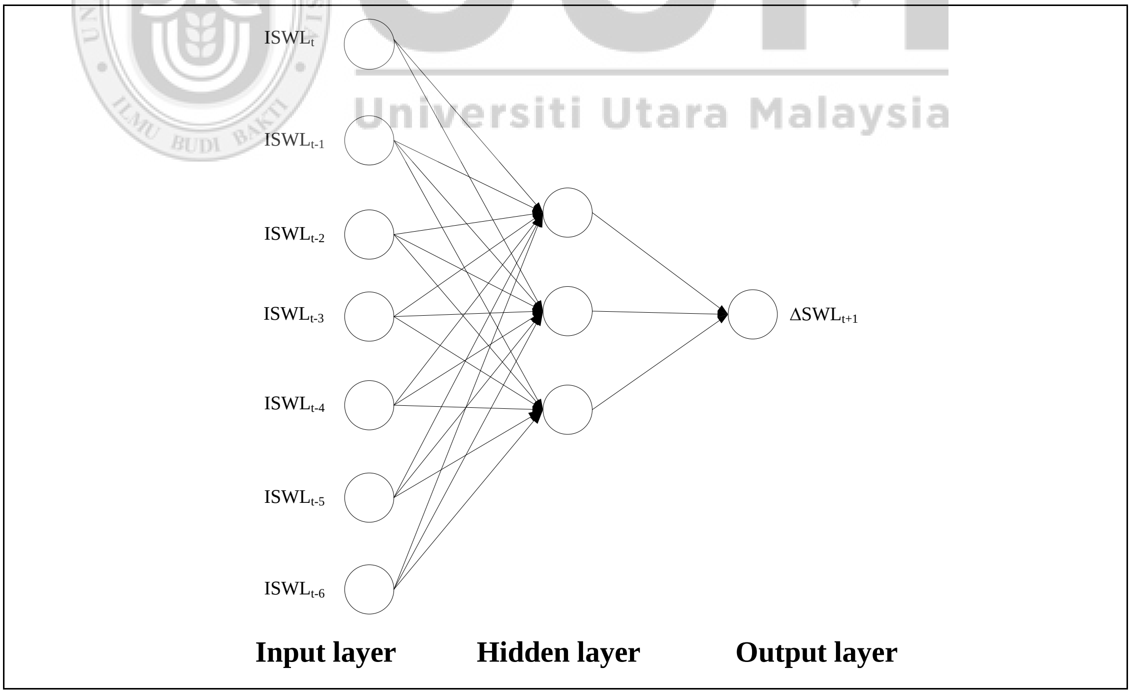


Figure 5.6. BP Neural Network for Combination of the Change of Water Level and Stage of Water Level Model (7-3-1) Architecture

5.2 Discussion

In order to find the best model of the change of reservoir water level stage based on performance, the good performances of the three models with different architectures are defined using MSE. The performance of MSE in testing data demonstrates the differences between actual and observed data with different window sizes as shown in Figure 5.7, Figure 5.8 and Figure 5.9.

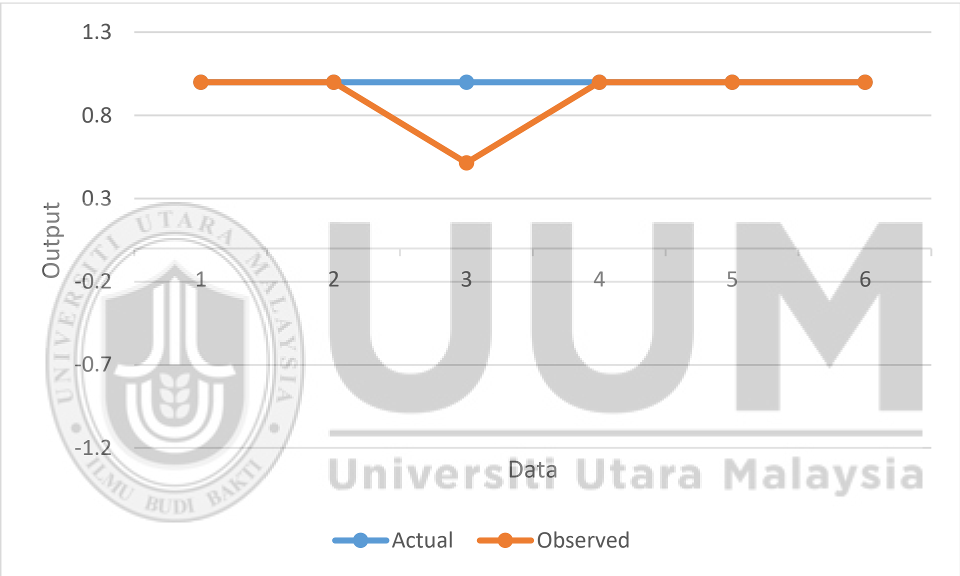


Figure 5.7. The Difference of Actual and Observed Data for Water Level Model (Window Size 4)

Figure 5.8. The Difference of Actual and Observed Data for the Change of Water Level and Stage of Water Level Model (Window Size 2)

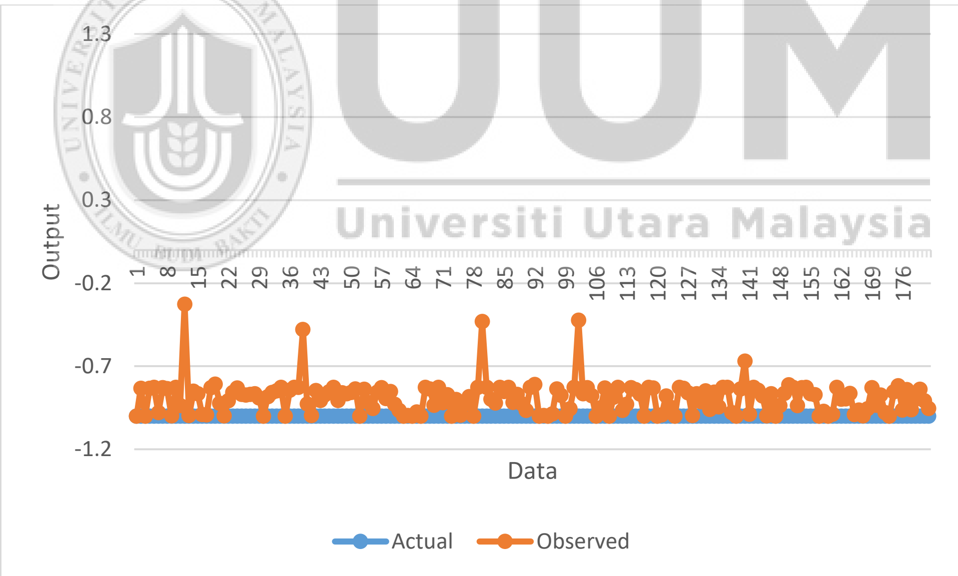
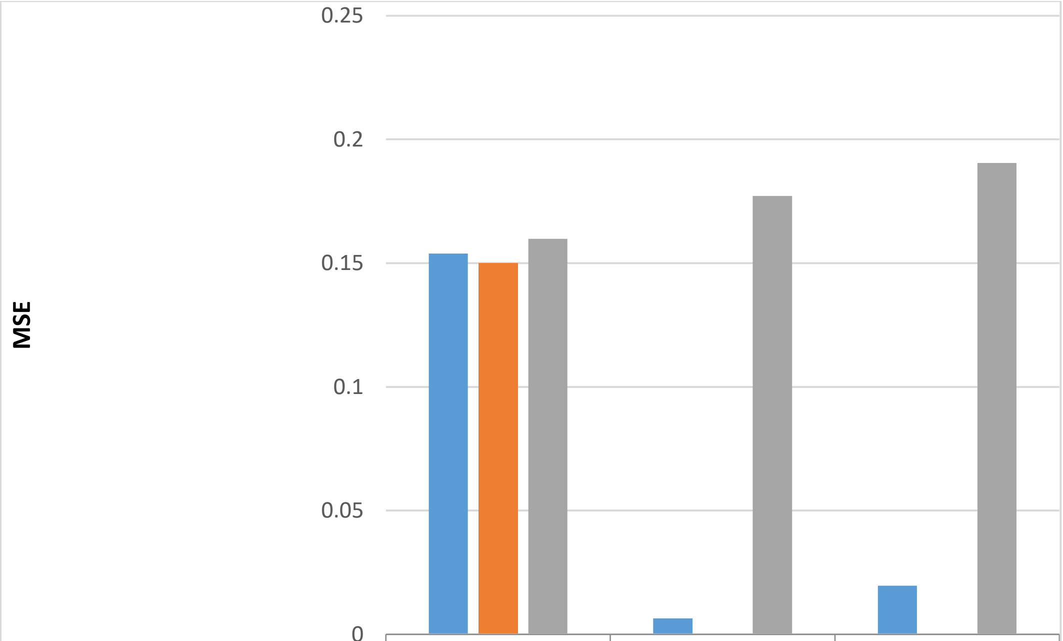


Figure 5.9. The Difference of Actual and Observed Data for the Combination of the Change of Water Level and Stage of Water Level Model (Window Size 7)

From Tables 5.2, 5.5, and 5.8 from the previous section, the best time duration of delay of each model for water level model is window size 4, the change of water level and stage of water level model is window size 2, and the combination of the change of water level and stage of water level model is window size 7. Window sizes 2, 7 and 4 represent the time delay of two days, seven days and four days. The best capture of time delay is the smaller window size of captured two days previous.

Based on Figure 5.10, it shows the comparison of MSE between the models (best time duration). Overall, the change of water level and stage of water level model gives a better result compared with the other models. The smallest error gives a good performance and the highest error gives the worst performance. A study by Arbain and Wibowo (2012b) defined the good performance using MSE to define the accuracy when the smallest MSE value is considered the best model. The error of training has not much difference compared with the other models, where the highest error is 0.15990066 (water level model) and the lowest errors are 0.150000959, and 0.009899701 (the change of water level and stage of water level model). However, the results of validation and testing are obvious different values of errors between each model. The error of the models can be seen in Figure 5.10.



	Training	Validation	Testing
Water Level Model	0.153913659	0.006453737	0.019636617
The Change of Water Level and Stage Water Level Model	0.150000959	0	0
Integration of The Change of Water Level and Stage Water Level Model	0.15990066	0.177118215	0.19052576

Figure 5.10. Comparison of MSE in Training, Validation and Testing between the Models

As seen in Figure 5.11, it shows the percentage of correctness in training, validation and testing among the models. The lowest and highest percentages in training are 91.46% and 92.5%. The lowest and highest percentages in validation are 90.66% and 100%, while for testing, there is not much difference, which are 90.11% and 100%. The different values of training, validation and testing are 1.04%, 9.34% and 9.89%. The percentage of correctness has given a small difference between the lowest and highest results. The neural network has obviously learned the data very well. For the water level model and the change of water level and stage of water level model, the different value of training is very small, which is 0.19%, and the validation and testing give 100%. However, the change of water level and stage of water level model has been chosen as the suitable model to forecast the change of reservoir water level stage, where the result of the change of water level and stage of water level has the lowest error.

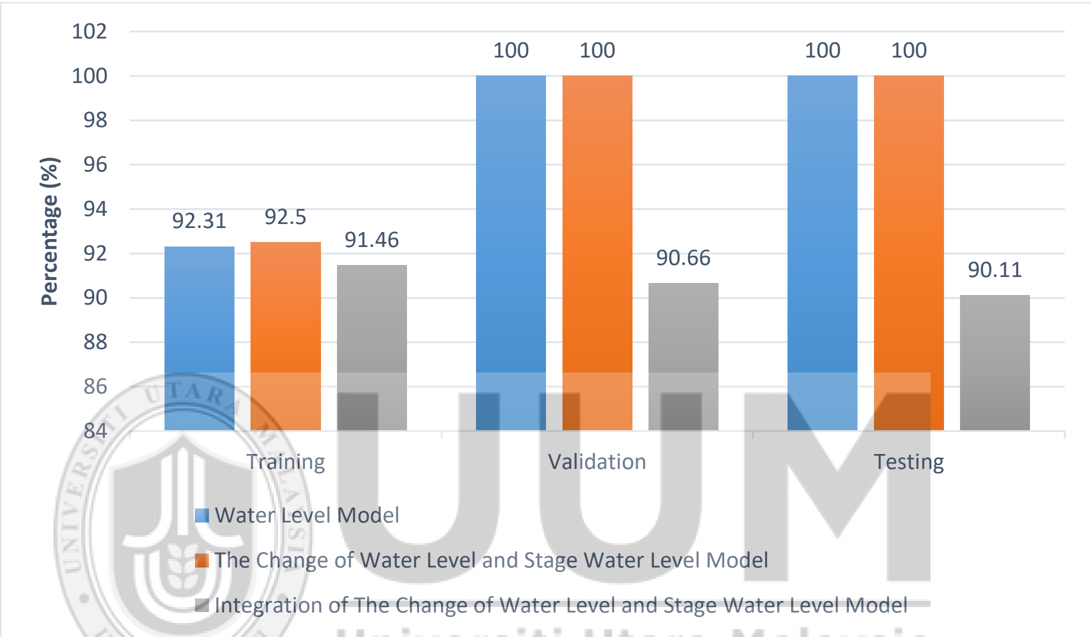


Figure 5.11. Comparison Percentage of Correctness in Training, Validation and Testing between the Models.

The neural network parameters are obtained from the models with the best time duration. The architecture of the BP neural network achieved for the change of water level and stage of water level model is 4-17-1. From Figures 5.10 and 5.11, ANN with 4-17-1 architecture uses the changes of reservoir water level and stage of reservoir water level model, which gives a better result compared to the others. The BP neural network parameters of each model are shown in Table 5.10.

Table 5.10

Comparison of Neural Network Parameters between Models

Model	**Architecture**	**Learning Rate**	**Momentum**
Water Level Model	4-21-1	0.9	0.3
The Change of Water Level and Stage of Water Level Model	4-17-1	0.7	0.7
Combination of the Change of Water Level and Stage of Water Level Model	7-3-1	0.1	0.1

Based on the previous studies (Nwobi-Okoye & Igboanugo, 2013; Rani & Parekh, 2014b) using ANN, the performance of error using the change of water level and stage of water level model is better compared to both of the studies. According to the statistical evaluation, the RMSE was 0.92, in which the mean in the MSE was 0.8464 compared to the change of water level and stage of water level for the testing and validation data, which was zero error. However, in the training data, it was 0.150000959. Furthermore, according to a study by Nwobi-Okoye and Igboanugo (2013), the error in the four input neural network models was 0.062 compared to the change of water level and stage ofwater level, which was zero on the testing data, and it makes the change of water level and stage of water level much better. The input data for both studies are different even though the same techniques have been used. The previous studies can be referred in Table 2.4 in terms of input, output, techniques and result of each studies.

In making the reservoir water release decision, the reservoir water level had been one of the evaluation and measures for the reservoir operator to monitor the changes of water level. The changes of reservoir water level can be divided into two conditions: the increase or decrease of observed reservoir water level. The reservoir operator observes the changes of water level, whether the increase or decrease of water level can cause the changes of flood stage. For example, the data on 10 September 2011 displayed the water level of 28.830 meters, which is in the normal stage, and on the next day, the water level increased 0.19 meters to 29.020 meters and the stage also increased to alert following a day after that date, thus, the trend of data increased. The reservoir operator monitors the trend of data and seeks advice from the superior officer before making any decisions. The decisions are made by the superior officer in terms of the amount of water release, and the opening and closing of gates based on the stage of reservoir water level. However, an early decision of water release can assist the reservoir to reserve space for incoming inflow according to heavy rainfall in the upstream. On the other hand, flood risks in the downstream can be minimised due to the controlled capacity of water release.

5.3 Summary

In this chapter, the developments of modelling and experimental results of forecasting models are performed. The original data of the reservoir water level from Timah Tasoh has been prepared using the modification of the sliding window algorithm. The performances of models are evaluated based on MSE and percentage of correctness results. There are three models with six different architectures developed and trained using the BP neural network.

The first model is developed based on previous studies with actual reservoir water level, the second model is built with the changes of reservoir water level and stage of reservoir water level, and the third model with the changes of reservoir water level and stage of reservoir water level as separate inputs. The finding of this study has shown that the change of reservoir water level and stage of reservoir water level model produced the acceptable performance with training of 92.5%, and both validation and testing are 100%. The result of error with training is 0.150000959 and both validation and testing are 0. The result has shown that dataset 1 is formed with window size 2, where it represents the two days observation of time duration for the delay.

CHAPTER SIX
CONCLUSION

This chapter describes the conclusion of the study by the following sections: Section 5.1 asserts the contribution of the study, Section 5.2 discusses the limitation of the study, and Section 5.3 describes the recommendations for future work.

6.1 Research Summary

This study focused on the forecasting model for the change of stage of reservoir water level on the Timah Tasoh Dam, Perlis as a case study. The reservoir water level data has been collected from DID, Perlis. In this study, there are three models (the reservoir water level model, the change of reservoir water level and stage of reservoir water level model, and the combination of the change of reservoir water level and stage of reservoir water level model) developed with six different architectures, where each model has been trained using a multilayer perceptron BP neural network. The sliding window algorithm has been modified according to the purpose of study, and used to segment the data based on the number of days of delay in the change of reservoir water level. The experiment results show that the change of reservoir water level and stage of reservoir model gives a better performance when the MSE and percentage of correctness are compared with the other two models. The second days previous of time delay to observe the reservoir water level uses the change of reservoir water level and stage of reservoir water level variables.

6.2 Research Contribution

This study focused on a forecasting model for the changes of stage of the reservoir water level. The preparation in the input data for model development is vital to provide the best model. The formation of the temporal pattern has been prepared with the modification of sliding window based on the changes of stage of reservoir water level. In developing the model, the back propagation algorithm is used because of its ability to learn the pattern to obtain the balance response to the input pattern.

The experiments are conducted based on the three models. The experimental results show that the second model with more data input produces better results when compared to less numbers of data input. The models are evaluated based on MSE and percentage of correctness.

As explained in Chapter 1, the aim of this study is to develop a forecasting model for the change in the stage of reservoir water level. The sub-objectives to support the main objective of the study are as follows:

Research Objective 1:

The first objective is to propose a method to extract the temporal pattern for the change of reservoir water level that affects the reservoir water level stage. The availability of data from the first phase (data preparation) is to construct the temporal patterns. Data preparation consists of three phases, such as data selection, data cleaning and data transformation, which are discussed in Chapter 3, Section 3.1.1. The temporal patterns are produced using the modified sliding window technique. The data is segmented based on the changes of stage of reservoir water level.

Research Objective 2:

The second objective is to formulate a forecasting model for the change in the stage of the reservoir water level. The model development deployed the BP Neural Network algorithm to define the parameters: hidden layer, hidden unit, learning rate and momentum rate. The overall process is discussed in Chapter 3 (Section 3.1.3) and the best parameters are discussed in Chapter 4 (Section 4.2).

Research Objective 3:

The third objective is to evaluate the performance of the forecasting model. The performances are evaluated using statistical criteria that are MSE and percentage of correctness. The results of the best model performance are discussed in Chapter 4 (Section 4.3).

6.3 Limitation

The limitations of this study are as follows:

1. This study focuses on the Timah Tasoh reservoir as the case study. The data from other reservoirs cannot be used in this study as those reservoirs have different purposes, characteristics and operational procedures. However, it can be extended and adapted with other reservoir data.

2. The hydrological and operational data recorded at Timah Tasoh is of daily basis. Therefore, the proposed model has been designed for the next day forecasting. Next hour forecasting is not applicable. If the availability of data in hours is obtained, maybe more details and precise information will give better results than in daily data.

6.4 Future Work

The model has been trained using the water level data from the Timah Tasoh Dam, Perlis, Malaysia. Even though this study has achieved the research objectives, however, there are further improvements for the model as explained below:

1. A further study on rainfall forecasting and the forecasting of the total amount of releasing water from the dam and the opening or closing of the spillway gate can be carried out to enhance the changes of stage of reservoir water level prediction model, and then the changes of stage can be predicted much earlier. Hence, it can improve the changes of stage of reservoir water level prediction.

2. The range of daily basis is very long, however, in future, if the availability of data for the water level data includes the scale of rainfall and data telemetry in hourly rates, it will be much easier to predict in a short period.

Finally, the existing model creates a reservoir water level prediction based on the availability of data and techniques as mentioned in Table 2.4. This study is an inspiration of existing models, where it focuses on the changes of flood stage, whether the probability of water increases or decreases, which affects the flood stage.

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