PREDICTION OF TEMERLOH RIVER WATER LEVEL FOR PREDICTION OF FLOOD USING ARTIFICIAL NEURAL NETWORK (ANN) METHOD

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Thesis submitted in a fulfillment of the requirements for the award of the degree of
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ABSTRACTS

The purpose of this project is to research more about the flood occurrence in Temerloh, Pahang. The data mining approaches using artificial neural network (ANN) techniques will be use to conduct this research for flood estimation. ANN model will be use to estimate river water level by taking present river water level data. The research will be trained using back propagation method to estimate the flood water level at Temerloh River. ANN's trained using backpropagation are also known as "feed forward multi-layered networks" trained using the backpropagation algorithm. 14 years of rainfall data is get from Department of irrigation and drainage (DID). Rainfall data of 10 years(2000-2010) will be training data to predict the others 4 years(2010-2014) river water level using python software with 1000-4000 iteration of data. At the end of the project we can make parameter model that can use as a tools to predict accurately water level data and achieve high accuracy of flood forecasting. From the result we can see that in this research the best prediction for water level data at Temerloh River is 3-hr lead-time with 6 input 1 output in 4000 iteration because it produce the best CE with 0.998.The average RMSE also less than 500 mm with only small difference error in percentage.

ABSTRAK

Tujuan kajian ini dilakukan adalah untuk mengkaji fenomena alam kejadian banjir di Temerloh, Pahang.Ramalan paras tinggi air dilakukan menggunakan kaedah rangkaian neural tiruan atau *artificial neural network (ANN)* dalam kajian ini. Seterusnya, kajian ini dilakukan dengan mengambil data takat paras air sungai di Temerloh Pahang. Kajian ini akan dilatih menggunakan kembali kaedah pembiakan untuk menganggarkan paras air banjir di sungai Temerloh. ANN yang dilatih menggunakan rambatan balik juga dikenali sebagai "*feed forward multi-layered networks*" dilatih menggunakan algoritma rambatan balik itu. 14 tahun data hujan dapat daripada Jabatan Pengairan dan Saliran (JPS). Data hujan 10 tahun (2000-2010) akan melatih data untuk meramalkan empat tahun yang paras air (2010-2014) sungai menggunakan perisian "python" dengan 1000-4000 lelaran data. Pada akhir projek kita boleh membuat model parameter yang boleh digunakan sebagai alat untuk meramalkan dengan tepat data paras air dan mencapai ketepatan yang tinggi daripada ramalan banjir. Dari kajian ini ramalan yang terbaik untuk data paras air di Sungai Temerloh adalah 3-jam mendahului masa dengan enam data masuk satu data keluar dalam 4000 lelaran kerana ia menghasilkan ralat korelasi yang terbaik dengan 0,998. Berdasarkan keputusan purata RMSE juga kurang daripada 500 mm dengan perbezaan hanya kecil dalam peratusan ralat paras air.

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Flood can be described as the occurrence of overflowing or influx of water beyond its normal confines or outpouring of water. When the rain water traps in a particular land area and the water flow rate out from the area is slower than the rain water accumulated, therefore, flood happen. Recently, flooding is one of the most destructive natural disasters that happened in Malaysia. Flood in Malaysia become more serious and dangerous due to deforestation, urbanization and agricultural development.

Since 1660s especially in 1971 Malaysia have face dramatic flood event with dramatic lives and property losses billion of malaysian ringgit. This make Malaysia goverment taken several positive steps and seriously planning to envisage flood mitigation projects in its national plans. The Malaysian Department of Irrigation and Drainage (DID) has estimated that people (22% of the population) are potentially affected by floods annually. The yearly economic damage caused by flooding is estimated at approximately US$300 million approximately 29,000 km2, or 9%, of the total land area and more than 4.82 million (Hazi Mohammad Azamathulla, Aminuddin Ab. Ghani, Cheng Siang Leow, Chun Kiat Chang and Nor Azazi Zakaria, 2011)

The purpose of this project is to research more about the flood occurrence in Pekan, Pahang. Flood overflow are frequently occur at the East Peninsular of Malaysia and the worst is during monsoon season in November until December. In low land area, the flood is more likely to occur compared to high land area. In Pahang, most of the rural areas are located near to the rivers and the rain water can easily trapped and overflow from the rivers itself. For example, the overflow of water from Sungai Lembing and Kampung Panching happened due to the heavy rainfall occurred every year and leads to flooding in the area of Kuantan City.

Structural and non structural measures has adopted in Malaysia to reduce the impact of flood problem that happen since the worst flood in history in 1971. Structural measures include such measures as river deepening , widening and straightening, to reduce the magnitude of the flood, but at the same time this approach often transfers the flooding problem further downstream. Computer models used in non structural measures to quantify the effects of human interference to the river system. This tools already widely used in many countries worldwide, but the application of sophisticated models is still relatively new in Malaysia. Before any structural measure was taken it is important to make analysis and researhe of the flood events with the help of flood models to understand the flood behaviour. Therefore, before any amendments are implemented within a catchment and the flood plain, river engineers must evaluate the potential extent and impact of flood events and advise the implementing agencies as to what steps need to be undertaken to provide further preventative measures to avoid the anticipated flood problems that might occur.

Several methods are introduced to obtain the data about flood occurrence in Pekan. The data mining approaches using artificial neural network (ANN) techniques will be use to conduct this research for flood estimation. ANN model will predict river water level by taking rainfall present river water level data.

1.2 STUDY AREA

The Pahang River basin is located in the eastern part of Peninsular Malaysia between latitude N 2° 48'45" and N 3° 40' 24" and between longitude E 101° 16' 31" and E 103° 29' 34". Sungai Pahang is the longest river in Peninsular Malaysia of about 435 km in figure 1. This river begins to flow in a south east and south direction, passing along several major towns such as Kuala Lipis, at the mouth of the river bearing the same name on Sungai Jelai; Jerantut, the gateway to Taman Negara Sungai Tembeling; Temerloh, midway on the river at its confluence with Sungai Semantan; and finally turning eastward at Mengkarak in the central south of the catchment and flowing through the royal town of Bandar Diraja Pekan near the coast before discharging into the South China Sea. Major towns are located on or near Sungai Pahang and its tributaries: Pekan, the royal town at its mouth; Temerloh midway on the river at its confluence with Semantan; Jerantut, the gateway to Taman Negara on the Tembeling; and Kuala Lipis at the mouth of the river bearing the same name on the Jelai.

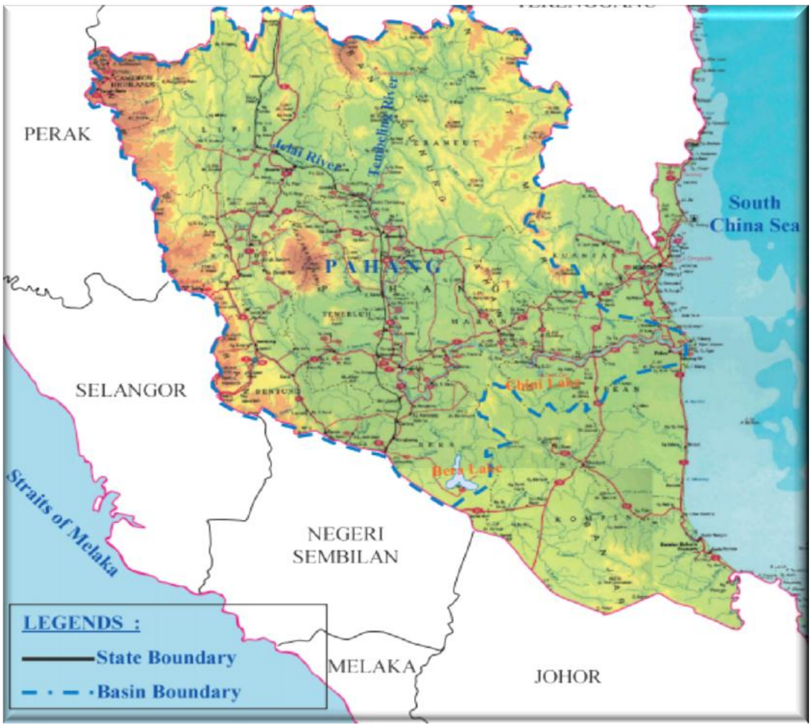


Figure 1.1: List of Pahang River

Temerloh was one of the most effected place during flood disaster in 2007 and cause many distruction interms of economical and enviroment . This research will more focus on Temerloh River that one of the parth flow of Pahang river near the coast before discharging into the South China Sea. Located on the banks of the Pahang River 50 km south of Kuantan and Pekan is the Royal Town of the Malaysian state of Pahang Darul Makmur. Population in district of Pekan is 105,587 people that have three Mukim Ganchong, Kuala Pahang and Bebar. The data set used in this study was obtained from the Malaysian Department of Irrigation and Drainage (DID) . The water level data was taken at Temerloh Pahang station during this research ; figure 1.2.

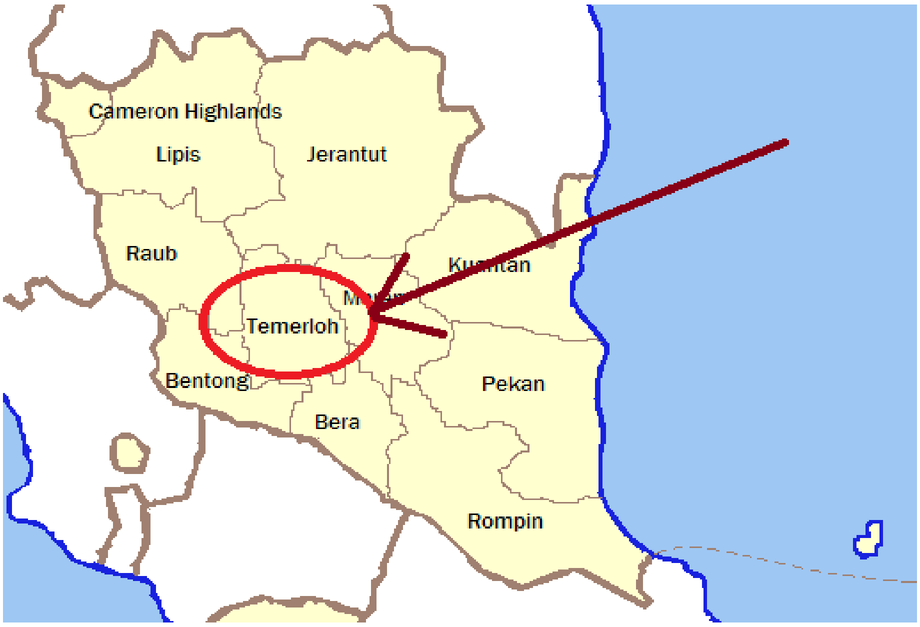


Figure 1.2: Pahang State Mapping

1.3 PROBLEM STATEMENT

Pahang is the largest state in peninsular Malaysia and the 3rd largest state in Malaysia after Sabah and Sarawak. Kuantan is the main capital of Pahang that have population range between 350000-400000 people and known as fast commercial located city at east-coast Malaysia. For the past few years Kuantan had pass through a one of the biggest natural disaster on earth; flood. In December 2013, Kuantan have faced worst flood phenomena that cause much destruction and loses.

Kuantan Municipal Council (MPK) has attributed the floods in this town and nearby areas to the unusually heavy rainfall and denied that the allegedly unmanaged drainage system was the primary cause (Borneo Repost). President of MPK Datuk Zulkifli Yaakob said that the main cause flood in Dec 2013 was the amount of rainfall experience is equivalent the total rainfall for 3 months about 970 mm and because of that the river to burst their banks especially Kuantan river. There was damage estimated at more than RM7 million to schools in Pahang that effected 41 school and 6 districts. Pekan, 3,464 flood victims were placed at 26 relief centers, in Temerloh at 22 relief centers, Jerantut, Maran, Rompin, Bera and Lipis at four relief centers. Due to heavy rainfall up to 1 meters water level on the road several main roads are closed to traffic.

In history show that Pahang River already causes many losses of property and life at Temerloh Pahang. Improper implementations of hydrology practice for river management and follow by deforestation and un-planned land use make prevention of losses was a challenging task during wet season cause by northeast monsoon season.

The critical problem that happens during this disaster was lack of information and warning from authorities on when the flood will happen to make the resident or people in every place to get ready and make earlier preparation to face it. No mechanism can avoid flood but only prediction can be made to save lives and reduce.

Flood estimation can give earlier warning to resident by knowing the river water level that can warn the flood event that will happen. The lack of intelligent tools to produce correct data of water level to estimate the flood event makes the authorities especially weather unit hard to make correct prediction every time flood disaster will happen. Pekan is district of Pahang that experiences the flood event which causes the road and some place electricity had been shutdown to prevent any bad things happen.

1.4 OBJECTIVES OF THE STUDY

In order to achieve a successful study, three objectives as a guideline of outcomes have been determined. The objectives are;

i. To achieve high accuracy of flood forecasting
ii. To make parameter model that can use as a tools to predict accurately water level data.
iii. Ability to predict potential flooding severity.

1.5 SCOPE OF STUDY

The study method used in this research is artificial neural network (ANN) and analyze the result using python software. The data that use was water level data of Pahang River for the past 14 years. Data will be taken from Pahang river in specific at Temerloh area and will be estimate using ANNs method and make comparison with the actual data for the suitability of this method to use for this research. All the data will be research and predict it level at different interval of time such as three hour and six hour.

1.6 SIGNIFICANCE OF STUDY

Prediction of flood using artificial neural network (ANN) model will act as a medium to get relevant information of possible impending floods in populated locations. Using this model as a tool to predict water level at Sungai Pahang will decrease economic loses and human suffering at Pekan, Pahang. The result is important if the ANN model can give accurate or sufficient accurate forecasts, even one day a head, the planning for the subsequent flood emergency measures can be better planned and executed. This can make lower the risk for harm and especially human life loss.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

A simple definition of flooding is water where it is not wanted. Another, more comprehensive definition of a flood is defined as a general and temporary condition of partial or complete inundation of normally dry land areas from overflow of inland or tidal waters from the unusual and rapid accumulation or runoff of surface waters from any source. The Australian Government introduced a standard definition of flood for certain insurance policies In November 2011. This definition is applicable when an insurer offers flood cover for a home building, home contents, small business or strata title insurance policy. For this purpose a flood is defined as the covering of normally dry land by water that has escaped or been released from the normal confines of: any lake, or any river, creek or other natural watercourse, whether or not altered or modified; or any reservoir, canal, or dam. [Bureau of Transport and Regional Economics, 2001].

2.2 CIRCUMSTANCES OF FLOOD

In Malaysia, flood occurrence is very general among Malaysians. According to Leigh, C. and Low, K.S., (1972), "An appraisal of the flood situation in West Malaysia", paper presented at the Symposium on Biological Resources and National Development, Faculty of Agriculture, University of Malaya, Malaysians are historically a riverine people as early settlements grew on the banks of the major rivers in the country.

Coupled with natural factors such as heavy monsoon rainfall, intense convection rain storms, poor drainage and other local factors, floods have become a common feature in the lives of a significant number of Malaysians.

In general, flooding occurs commonly from heavy rainfall when natural watercourses do not have the capacity to convey excess water but not necessary. They can result from other phenomena, particularly in coastal areas where inundation can be caused by a storm surge associated with a tropical cyclone, a tsunami or a high tide coinciding with higher than normal river levels. Dam failure, triggered for example by an earthquake, will result in flooding of the downstream area, even in dry weather conditions. Other factors which may contribute to flooding include:

i. Volume, spatial distribution, intensity and duration of rainfall over a catchment;
ii. The capacity of the watercourse or stream network to convey runoff;
iii. Catchment and weather conditions prior to a rainfall event;
iv. Ground cover;
v. Topography; and Tidal influences.

2.3 FLOOD FORMS

2.3.1 NORMAL FLOOD

Normal floods are seasonal floods which occur annually during the northeast monsoon season between Novembers to March. During these floods the waters do not normally exceed the stilt height of traditional Malay houses. Thus, people living in stilt houses in the rural areas on the east coast are well adapted to normal floods

2.3.2 MAJOR FLOOD

It is the major floods, which are “unusual” or “extreme” events. Major floods also have their origins from seasonal monsoon rains but statistically occur once every few years (but occur in consecutive years in 1970 and 1971 in Pekan). These floods are extensive, severe and unpredictable and result in significant loss of life, damage to crops, livestock, property and public infrastructure. Other classifications such as “flash flood”, “tidal flood”, “river flood” and “monsoon flood” may be grouped as normal or major floods depending on the severity. Flood-prone areas in Malaysia have been mapped by the Drainage and Irrigation Department (DID) on the basis of the extent of past floods. It is evident that most of the extensive flood-prone areas are located along the coastal plains and riverine areas. This statement is clearly mentioned in the journal "Increasing flood risk in Malaysia: causes and solutions", Disaster Prevention and Management: An International Journal, Vol. 6 Iss: 2, pp.72 – 86 (Ngai Weng Chan, 1997).

<u>Flood-prone areas</u>

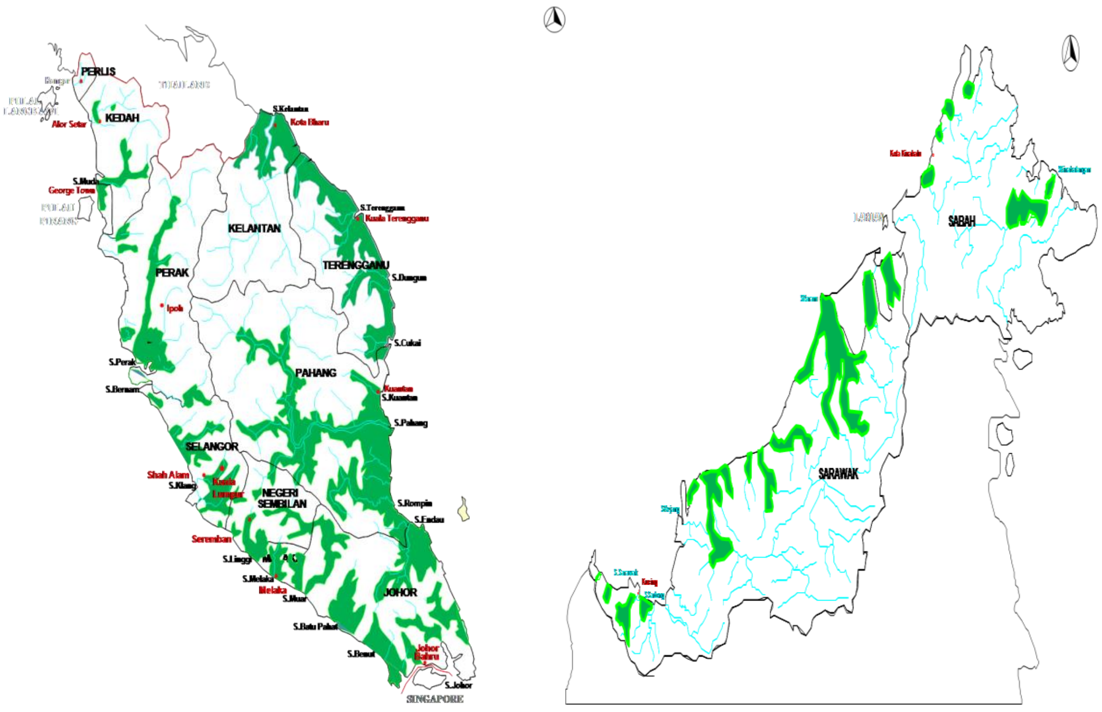


Figure 2.1 : Flood Prone Area in Malaysia

2.4 FLOOD IMPACT

Meanwhile, floods bring negative effects towards the nation, community and nature. Scientifically, floods are the most frequent natural hazards globally [Verdin, 2002], and the hazard of flooding can be divided into primary, secondary and tertiary effects. The primary effects of floods are those due to direct contact with the flood waters, with the water velocities resulting in floods as the discharge velocity increases. Secondary effects, such as disruption of infrastructure and services and health impacts, are secondary effects, while tertiary effects are viewed as the long-term changes that occur, for example changes in the position of river channels [Nelson, 2010].

Based on the objectives of this study, flood forecasting models are a necessity, as they help in planning for flood events, and thus help prevent loss of lives and minimize damage. Flood models are a major tool for mitigating the effects of flooding that provide predictions of flood extent and depth that are used in the development of spatially accurate hazard maps [M. F. Goodchild, 2006].

2.5 NATURE OF FLOOD

Most of the floods happen around us not same and have its own nature depends on the type of flood. There is 5 major type of flood in Malaysia.

2.5.1 River Floods

River flooding is a natural process and part of the hydrological cycle of rainfall, surface and groundwater flow and storage (Madani et al, 2007). Floods occur whenever the capacity of the natural or man-made drainage system is unable to cope with the volume of water generated by rainfall. Floods vary considerably in size and duration. With prolonged rain falling over wide areas, the resultant surface waters flow into a network of ditches, streams and tributaries. The volume increases as it flows downstream and combines with flows from other channels. At the points where the flow is beyond the capacity that can be contained in the river channel, water overflows the river banks and consequently floods the adjacent flood plain.

2.5.2 Regional Floods

Regional floods are also river floods but the events cover a wide area or region. This is typical in large river basins such as that of the Kelantan River, Terengganu River and Pahang River. In large flood plains with extensive river system, flooding can occur over a considerable period after the rainfall stops as it takes time for the large volumes of water to drain out of the catchment. In some cases floods occur in dry weather conditions (no rains) on the downstream section of the river catchment. This is due to heavy rains on the hilly upper catchment away from the points of the flood event and location. River floods in Malaysia usually occur during the monsoon seasons. This is especially so in the East Coast of Peninsular Malaysia during the North-East Monsoon months between October and March every year.

2.5.3 Urban Floods

Urban floods are those in built-up areas such as in cities, townships, commercial and residential areas. Urban floods affect more people and properties per unit area compared to those in agriculture and rural areas. Also the impact on traffic and services extends well beyond the physical location of the flood occurrence itself. The characteristics of urban flood can be more damaging and life threatening with roads becoming swift flowing channels, basements flooded and uncovered drains and bridges and crossings camouflaged by the flood waters.

2.5.4 Localized Floods

These are those occurring in small pockets of low-lying areas and often sensitive to small amount of rains. Being low-lying, natural drainage is difficult. Although some floods last only for a few hours, there are also areas that remain flooded for up to a month or more and well after the floods in the surrounding areas have receded. In this case, the flood water removal is mostly dependent on evaporation. One such area is in Buloh Kasap, Segamat, and Johor led to the colloquial term Banjir Termenong, literally, to “just sit, wait and ponder” whilst the flood takes its time to subside.

2.5.5 Flash Floods

A flood that rises and falls rapidly with little or no advance warning is called flash flood. Flash floods usually result from intense rainfall over a relatively small area. Flooding is usually due to intense local storms. This mostly happen in urban settings. The flood depths can be relatively shallow (100 mm or so) but there are cases of some being up to 2 meters depth but lasting less than 1 hour. In most cases the impact is not as severe as larger floods but, in urban areas, very disruptive to the daily routine of urbanites. As such these floods are also often termed as “nuisance floods”.

2.4 FLOOD WARNING SYSTEM

Flooding is a significant natural hazard that affects 2.7 million people within the 29,000 km2 of flood prone area in Malaysia. Flood forecasting and warning system have proven to reduce loss of lives, trauma of disaster and property damage in effective and economical ways. A timely and accurate flood forecasting and warning system can reduce loss of lives ,properties and disruption to socio-economic development as well as assisting the authority in flood rescue operations [Wardah Tahir and Hafizul Aimme Che Hamid, 2013].

The January 1971 flood that hit Kuala Lumpur and many other states had resulted in a loss of more than RM 200 million then and the death of 61 persons. Moreover, Johor 2006-07 flood due to a couple of “abnormally” heavy rainfall events which caused massive floods, the estimated total cost of these flood disasters is RM 1.5 billion, considered as the most costly flood events in Malaysian history.

After the 1971 Flood Disaster, the Malaysia Government establish two committees:-

i. The Permanent Flood Commission Committee to look into long term solutions to mitigate flood
ii. The National Flood Relief Committee: to reduce losses in the events of impending flood.

Based on the objectives of this study, flood forecasting models are a necessity, as they help in planning for flood events, and thus help prevent loss of lives and minimize damage. Flood models are a major tool for mitigating the effects of flooding that provide predictions of flood extent and depth that are used in the development of spatially accurate hazard maps [M. F. Goodchild, 2006]

CHAPTER 3

METHODOLOGY

3.1 ARTIFICIAL NEURAL NETWORK

Artificial neural network is modelling of mathematical or computational that has similarities of biological neural network (19 Aleksey Gladkov). In a study on the teaching and learning of Artificial Neural Network (Prodipto Das and Abhijit Paul, 2008) state that ANNs was a human perception based on mathematical model that can be used for performing a stated task based on availability of empirical data. Inspiration ANNs models came from motivation desire to produce artificial systems capable of sophisticated, perhaps "intelligent", computations similar to those that the human brain routinely performs, and thereby possibly to enhance our understanding of the human brain (Sucharita Gopal, 1998).

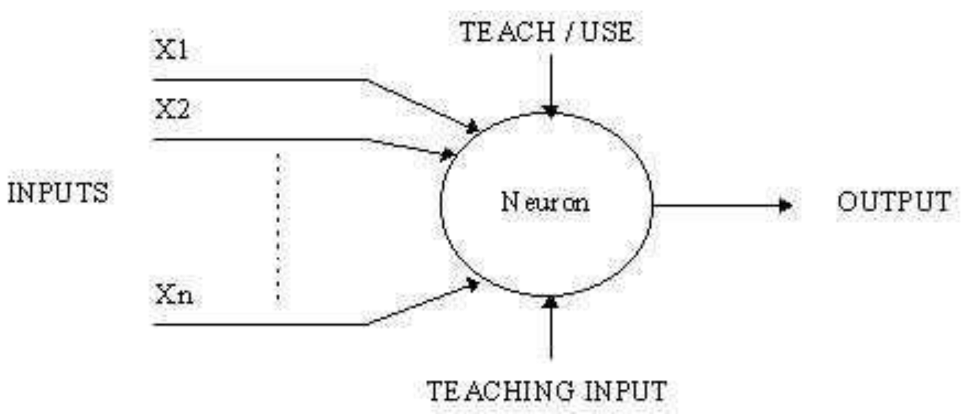


Figure 3.1 : ANN Neuron Model

Generally, ANNs was inspired by natural neuron from a system of interconnected nodes that can give outcome based on the input data such as in figure 1 (Mahmoud Nasr and Hoda Farouk Zahran, 2014).

The input layer receives the data from different sources. Hence, the number of neurons in the input layer depends on the number of input data sources. The neural network will learn through example by data classification and pattern recognition through system and configured for specific function or application. Specialize of neural network are capable to learn complex nonlinear input-output relationship by following the procedure and adapt themselves to the data. (Jayanta Kumar Basu, Debnath Bhattacharyya, Tai-hoon Kim, 2010).

3.2 EFFECT OF ANN

We can say that neural network approaches differ from old statistical techniques in many ways and the differences can be exploited by the application developer. It is a powerful for decision-making tools data are multivariate with a high degree of interdependence between factors data are incomplete, when many hypotheses are to be pursued and high computational rates are required (Irfan Y. Khan, P.H. Zope, S.R. Suralkar, 2013).

3.2.1 Advantages

The advantages in the utilization of a neural network can perform tasks that a linear program cannot and when an element of the neural network fails, it can continue without any problem (Xu Jian-Hao, 2011). The capability of the network to analyzing the data even if the data is incomplete or distorted and would possess the ability to conduct an analysis with data in non-linear fashion was one of the advantages of this method (James Cannady). The only real requirements for the ANN model are for sufficient data for flood modelling events, and the specification of appropriate neural network parameters values to be used.

Neural network models automatically handle variable interactions if they exist and are able to learn any complex non-linear mapping / approximate any continuous function and can handle non linearity’s implicitly (Irfan Y. Khan, P.H. Zope, S.R. Suralkar, 2013).

3.2.2 Disadvantages

The neural network needs training to operate same like biological neural network train. Adjustable parameters to produce desired output by adjust the strength (weight) connection between the neuron needs involvement of training by compared the target and output values (D.J Livingstone, D.T. Manallack and I.V. Tetko, 1996). Unlike expert systems, analyses and estimation of information provides probability the data matches or not with the characteristic that has been trained to recognize. The dependent on accurate training of the systems, training data, and the training methods that are used are critical (James Cannady).Process of training is an important aspect, and the performance of an ANN is crucially dependent on successful training (ASCE Task Committee,2010).

ANNs requires high processing time for large neural networks. The training routine requires a very large amount of data to ensure that the results are statistically accurate (James Cannady). Larger neural networks may require high processing time for training to operate (Ramapulana Nkoana, 2011).

3.3 BACK PROPAGATION

The research will be trained using back propagation method to estimate the flood water level at Pekan River. ANN's trained using backpropagation are also known as "feedforward multi-layered networks trained using the backpropagation algorithm (Haijie Cai, B. Eng, M. ASc, 2010). Generally neural network consist of three layers, input, hidden and output layer. Each layer consists of neurons and the layers are interconnected by sets of correlation weights, which enable the network to process the data (Jorge O. Pierini and Eduardo A.Gómez, 2009). Referring to figures 1, neuron in the previous layer will give signal to each neuron and those signal will be multiplied by random separated weigh value. The input weighed are being totalize and passed through a limiting function which scales the output to a fixed range of values. Each link that applied to connect between layers of neuron has a unique weighting value. There are non-linearly scaled between 0 and +1 and the output value is use on the next layer. Back propagation learning algorithm is use as a method to adjusting the weight between the layers. This method is learning from example.

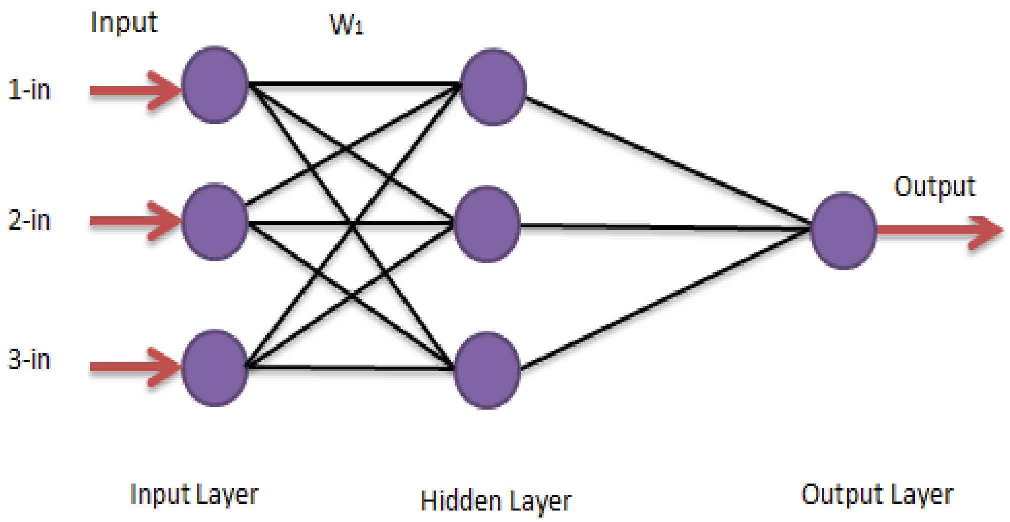


Figure 3.2 : ANN Model with 3 Input 1 Output

For this research 14 years water level data of Temerloh taking from DID Malaysia at Temerloh River from 2000-2014. The data is separated into two for training sets that was 2000-2010 and actual value to predict 4 years after that 2010-2014. This training sets that consists of some input examples and the known-correct output for each case. This output will show the network what type of behavior is expected, and the BP algorithm allows the network to adapt. Mean-squared error (MSE) signal is calculate after compare between known correct-output and training value. The error value is then propagated backwards through the network, and small changes are made to the weights in each layer (Deqiang Zhou, 2012). The errors on the actual and training set usually decrease after many set of training and iteration (i) and as soon as the network begins to over fit the data the training is stop.

The data will pass through 1000- 4000 iteration with different sets of training data sets. Weight (W1) shown in figure 5 will be change in every iteration until the ratio mean square of the data is less or almost equal to one. If this happened it show that this method is suitable to predict water level data. The training data sets will be interval time between 2 input layers are 3 hours and 6 hours. This is because want to check the suitability of this software and method to make correct prediction of water level for different training data sets suite to the objective of this research to make parameter model that can use as a tools to predict accurately water level data.

Phyton software will be used for prediction pattern of water level data and simple programming will be implemented for arrangement of data for every interval time that used as a training sets.

<u>The flow chart for the training process in ANN program</u>

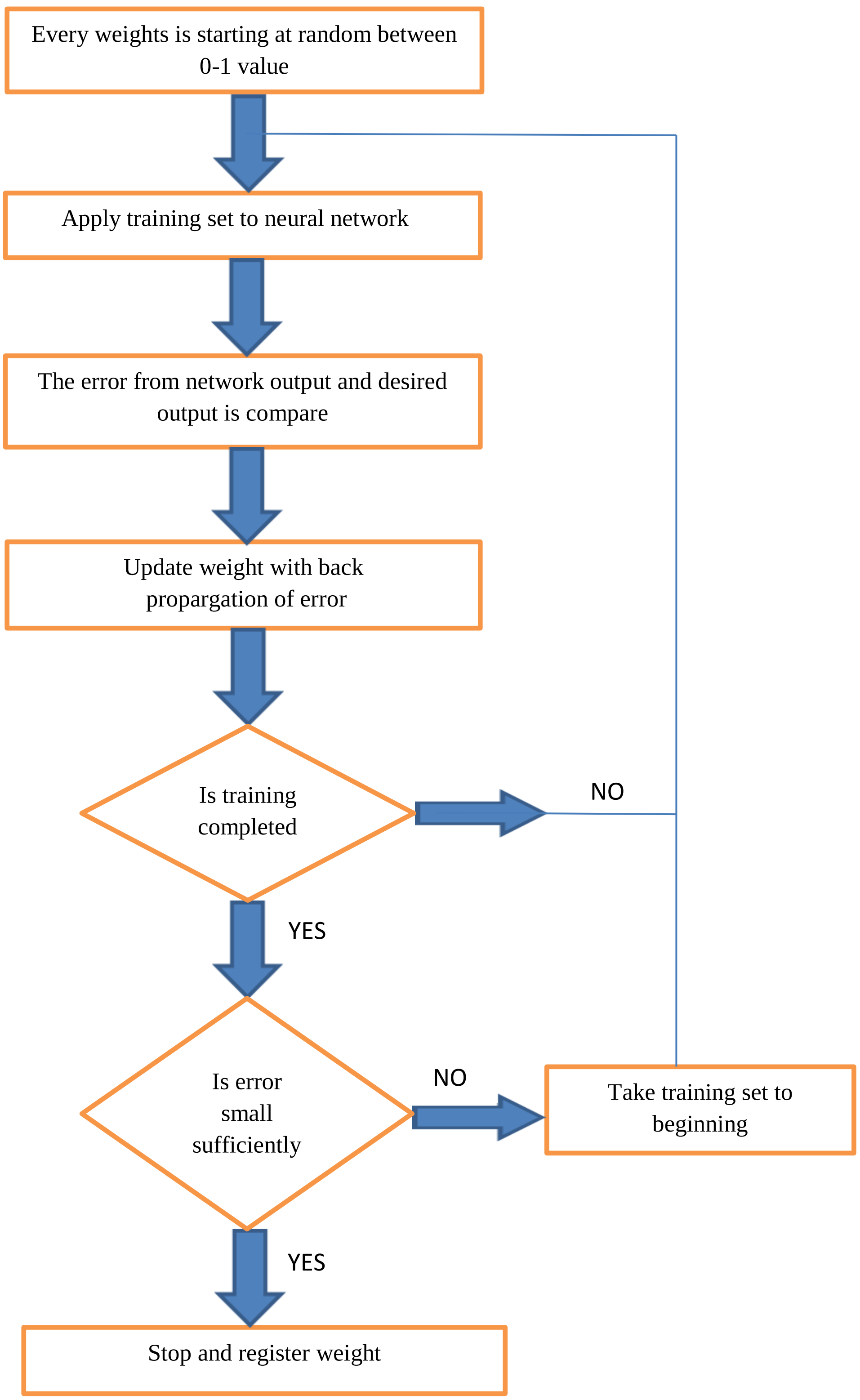


Figure 3.3 : The Flow Chart for the Training Process in ANN Program

<u>The flow chart for the arranging data in ANN program</u>

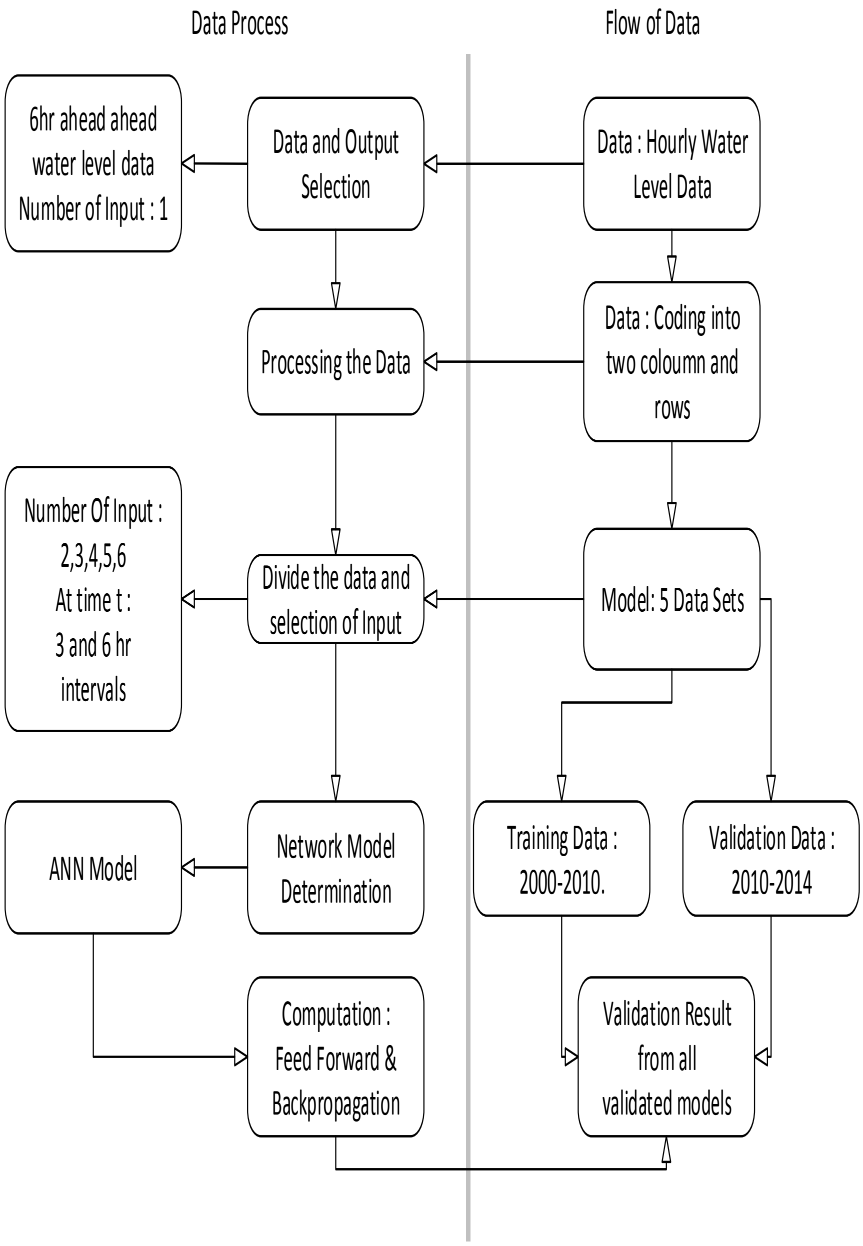


Figure 3.4 : The Flow Chart for the Arranging Data in ANN Program

CHAPTER 4

RESULT AND DISCUSSION

4.1 RESULT ANALYSIS

The data training and validation results for this ANN architectures is trained with five datasets with two different interval of time. All the training and validation data is test with six different iteration for 1000 iteration to 6000 iteration. For this research the comparison will be make for 1000 iteration and 4000 iteration to show the accuracy of the data if we make more iteration for every training and validation data sets. Six different input will be test form two to six input for the different iteration in two interval of time three hours and six hours. The interval of time is the prediction of time before to flood occur, example we predict the next three hours river water level is in the normal state or in danger water level.

The result below show that every different iteration and input will give different consistency in the patern of graph for scattered diagram. Most of the data was very consistent for 3 hour and 6 hour interval. The line graph show the difference or error between forecasted and observed data while the scattered graph show the consistency of the data to reach the optimal forecasting performance for predicted data. From figure 9 the difference for forecasted data and observed data error is slightly small compare to figure 8. This shows when we increase the iteration the result will be more accurate because of the higher repeated training data until approaching desired output. The NSC for figure 9 is 0.934 while figure 8 is 0.80 than show 4000 iteration will give more optimal forecasting result compare to 1000 iteration.

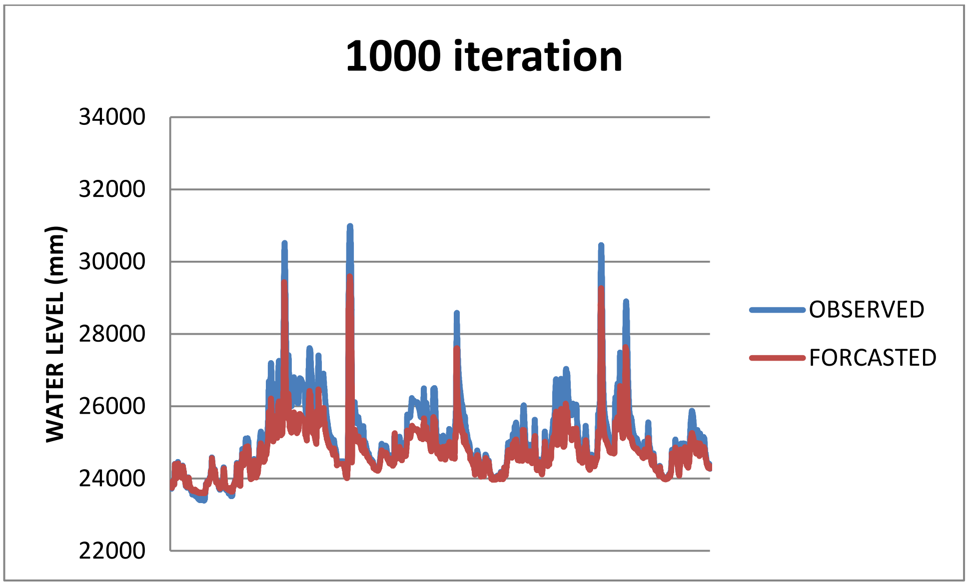
The scatter plot in figure 11 with the NSC value of 0.997 shows the data is more centered among the mid line compare to figure 10 with the NSC value of 0.998 for both forecasted and observed data. Most of the graph shows the predicted data achieve high level of forecasting result because NSC value more than 0.9 while the lower NSC value is less than 0.75. Different number of input also will effect the result for forcasted data such as in figure 13 with 4 number of input data have NSC value of 0.981 while figure 15 with 5 input data have NSC value of 0.984. Although the difference between the value is small but clearly we can see that number of input will effect the optimal result in forcasted water level data in the river.

The interval time that we want to predict also will effect the predicted data result. Based on figure 16 with 3 hour of interval time produce NSC value of 0.997 with the observed and forecasted data in scatter plot is more nearer to mid line compare to figure 26 with NSC value of 0.996. This shows when we increase the interval time that we want to predict for water level data the result will be less accurate. Although with the same iteration the higher interval time of 6 hour will take longer time to shows the result. Most of the NSC value for both 3 hour and 6 hour interval with difference iteration shows result between 0.95 to 0.98 with high achievement of forecasting perfomance of ANN model.

Based on the result achieve after trained the data of Temerloh water level data with ANN model the validated data is already achieve it limit for this for this interval training time because shows consistent result whether with difference iteration. In spite of the fact that the result of the data already achive high level of forecasting severity but the difference between the graph actually to small to make comparison. This type of data can be test with more difference in interval time to show more different in result data to compare such as in 24 hours to 48 hours because the data already show very good result for forcasted data that already test with ANN model.

4.1.1 3 Hours Interval

<u>2 INPUT 1 OUTPUT</u>



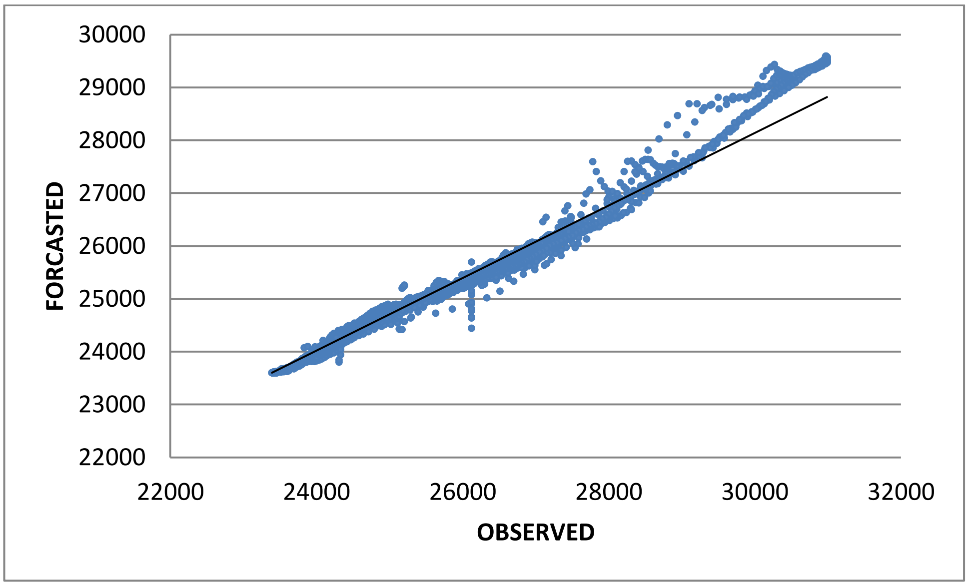
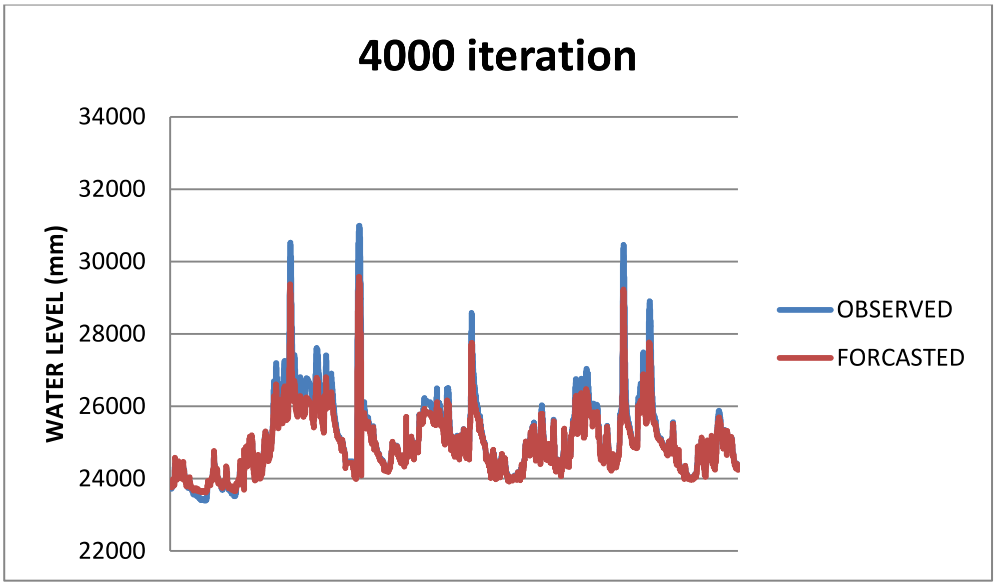


Figure 4.1 : Forecasting performance of ANN model with 2 Data Input



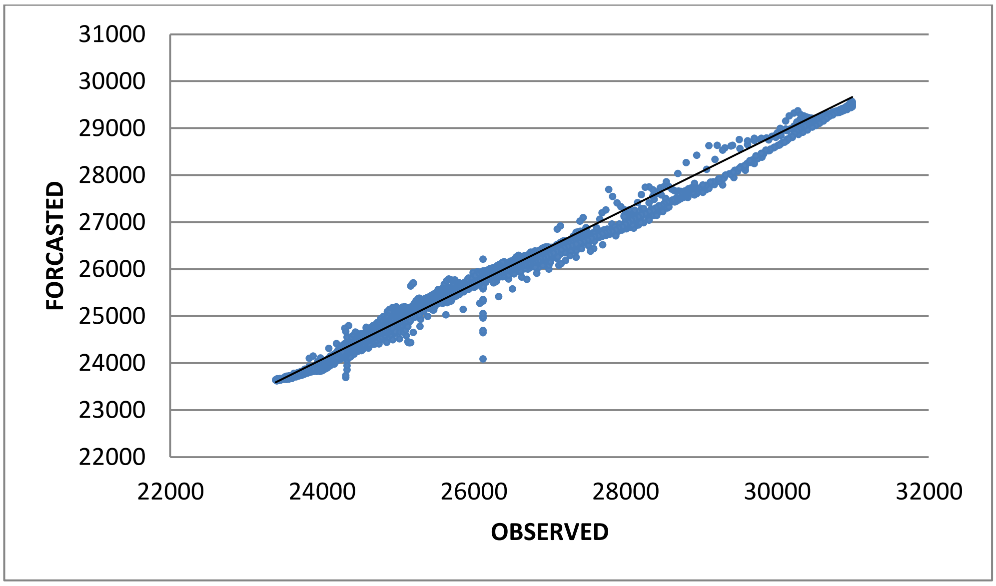
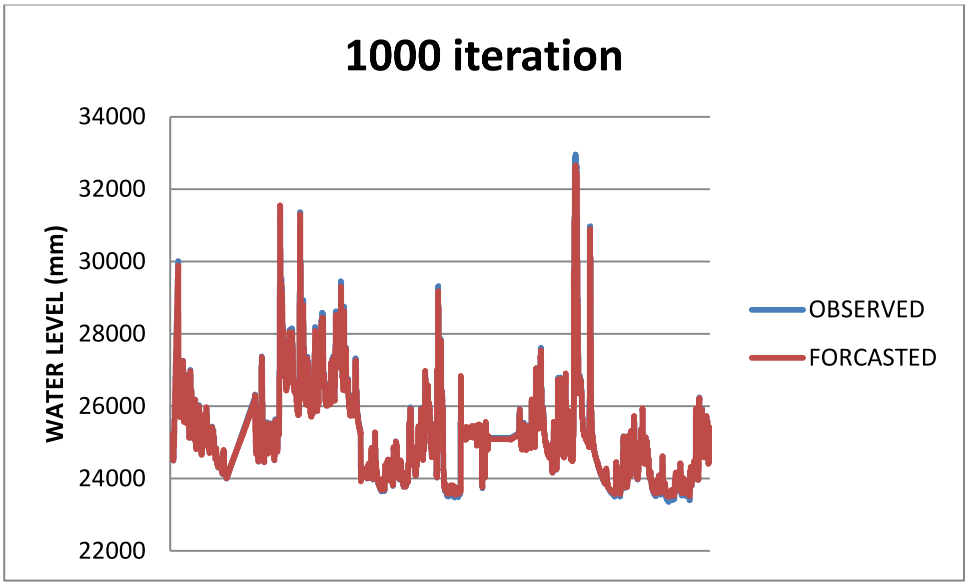


Figure 4.2 : Forecasting performance of ANN model with 2 Data Input

<u>3 INPUT 1 OUTPUT</u>



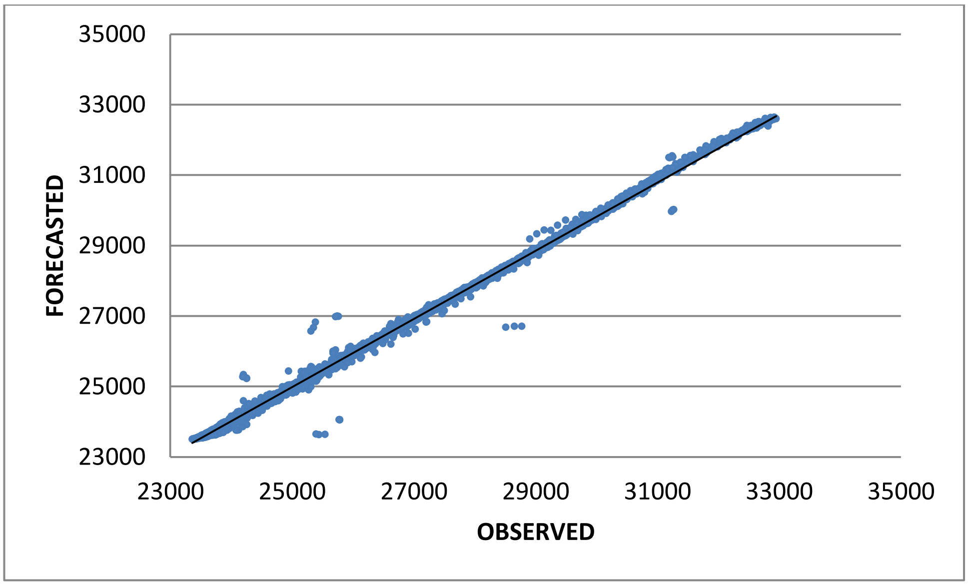
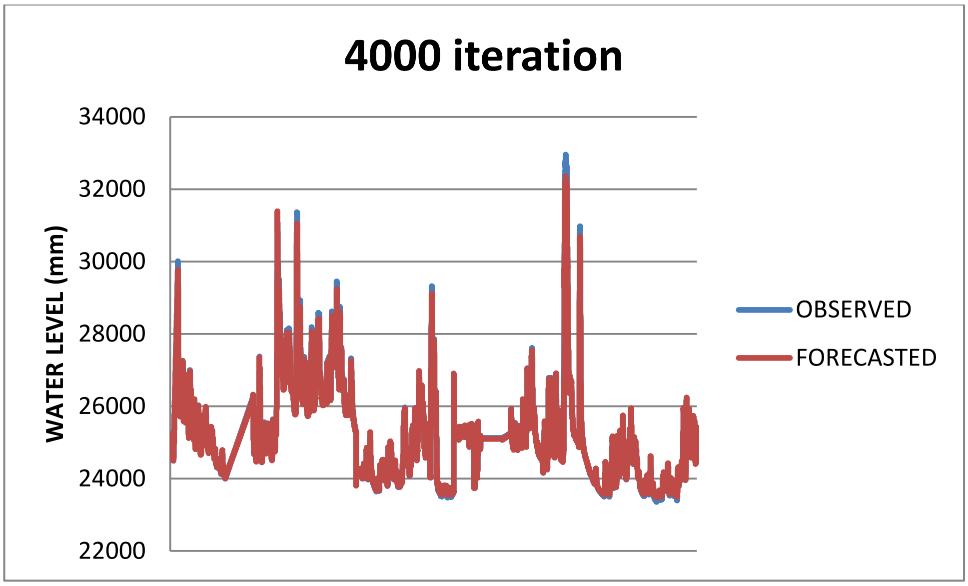


Figure 4.3 : Forecasting performance of ANN model with 3 Data Input



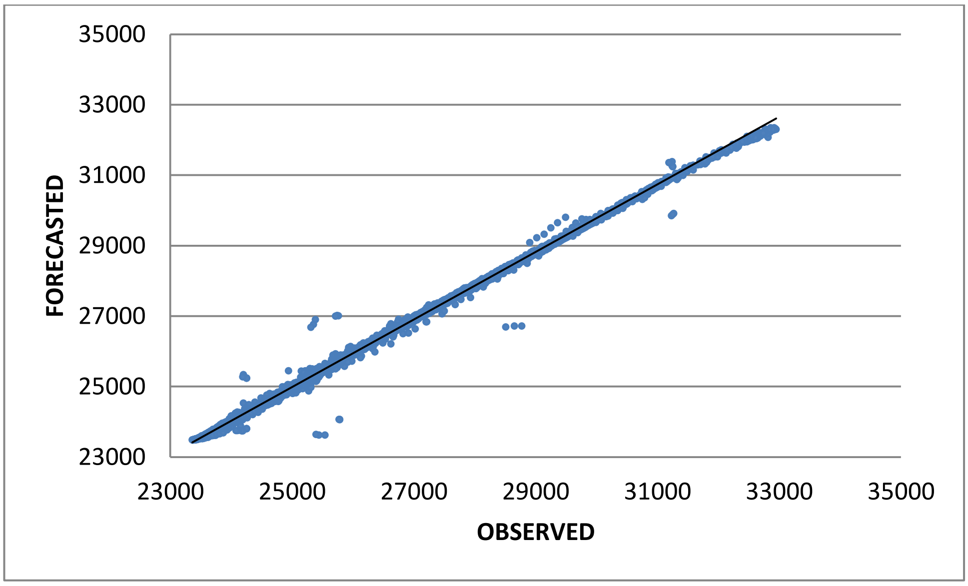
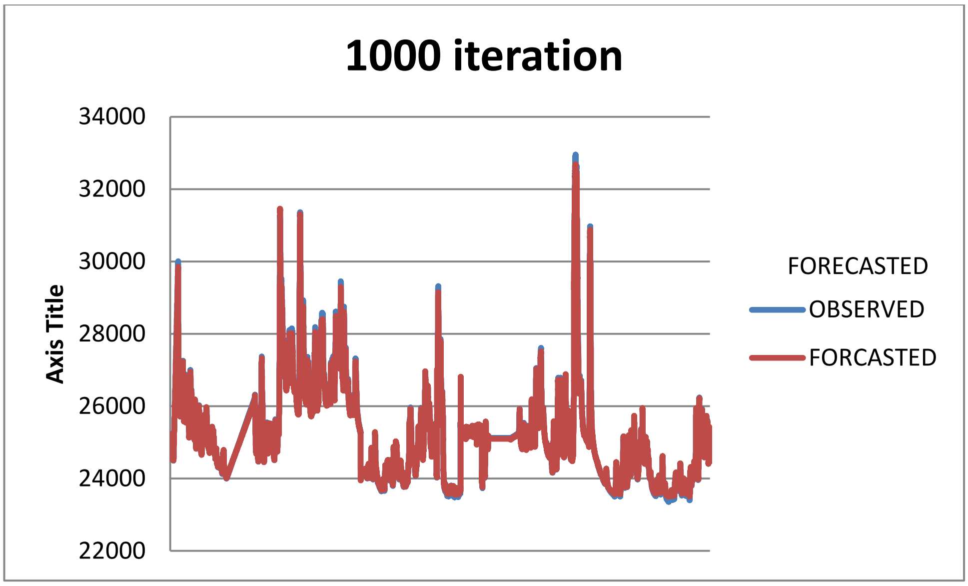


Figure 4.4 : Forecasting performance of ANN model with 3 Data Input

4 INPUT 1 OUTPUT



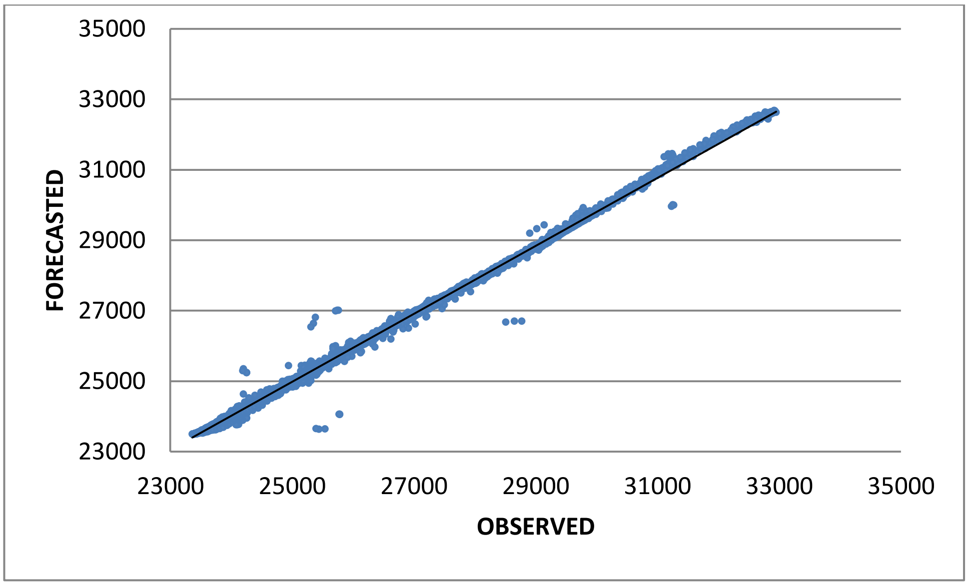
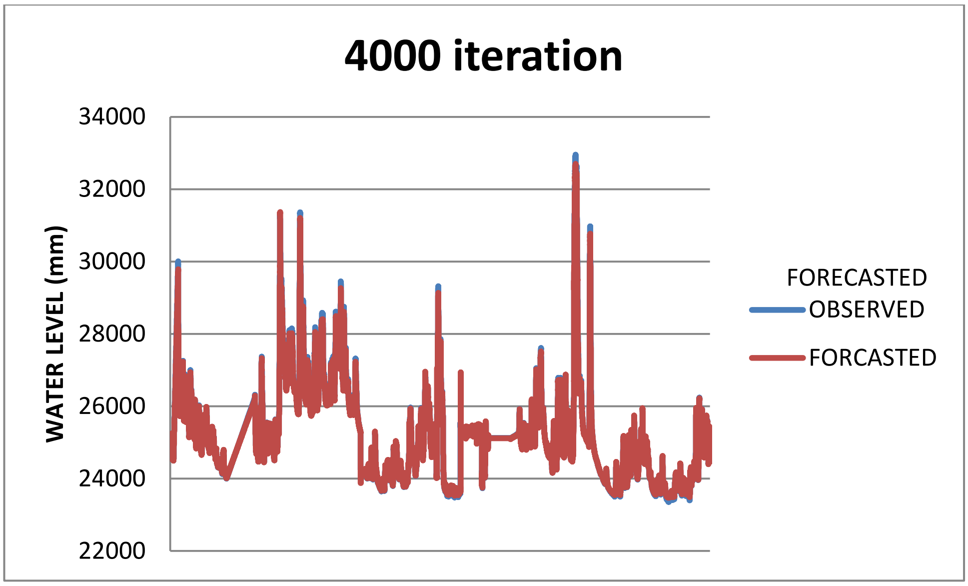


Figure 4.5 : Forecasting performance of ANN model with 4 Data Input



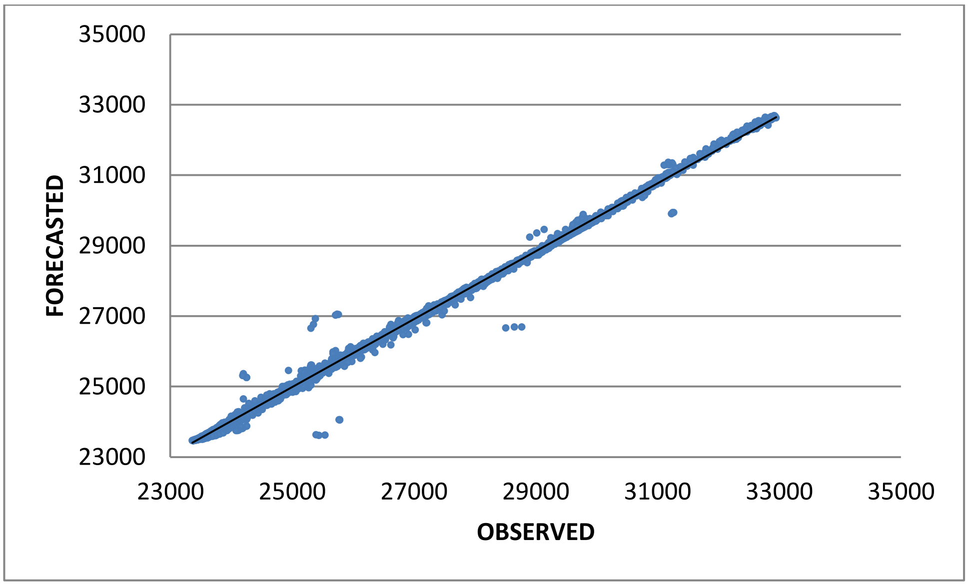
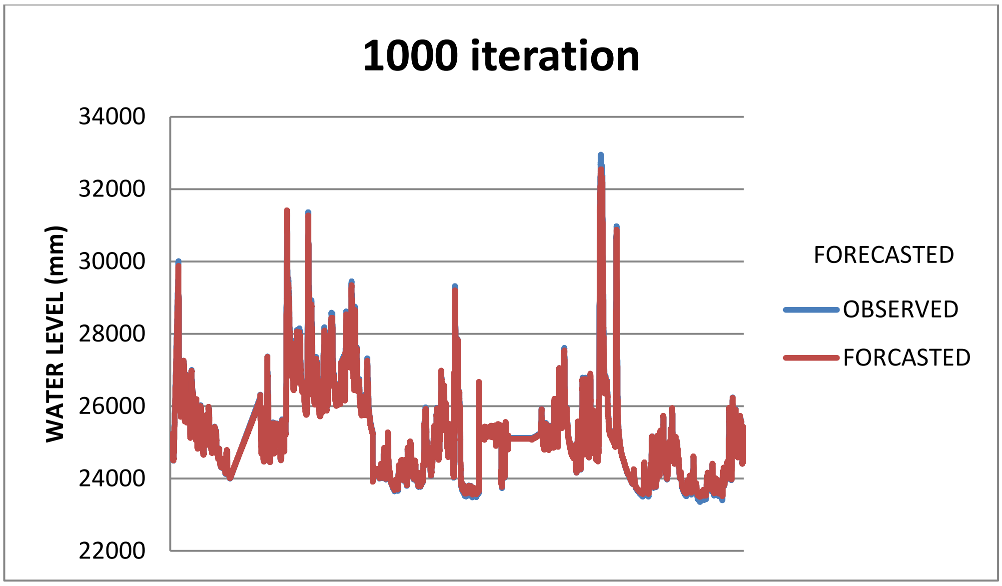


Figure 4.6 : Forecasting performance of ANN model with 4 Data Input

5 INPUT 1 OUTPUT



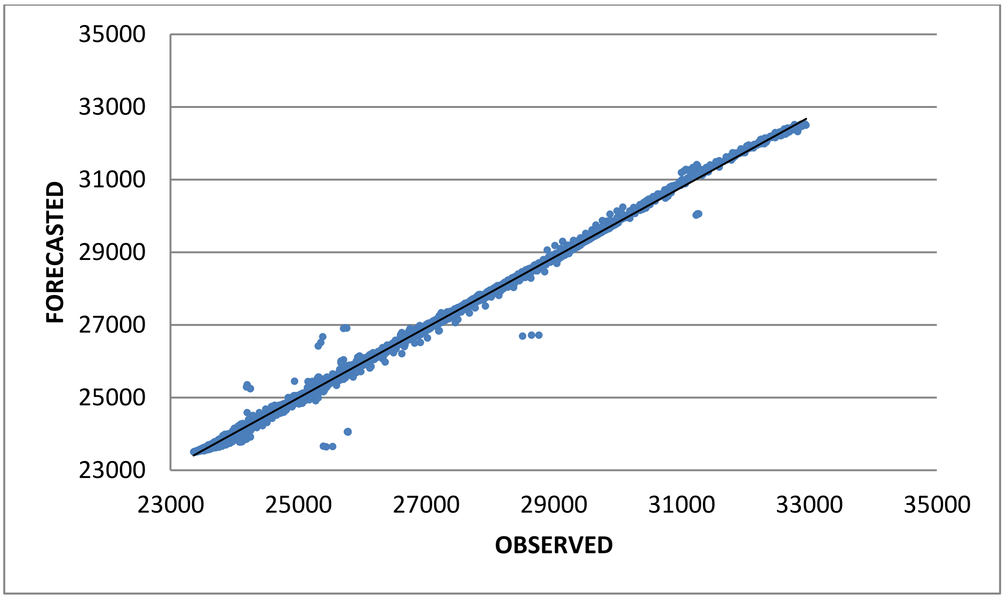
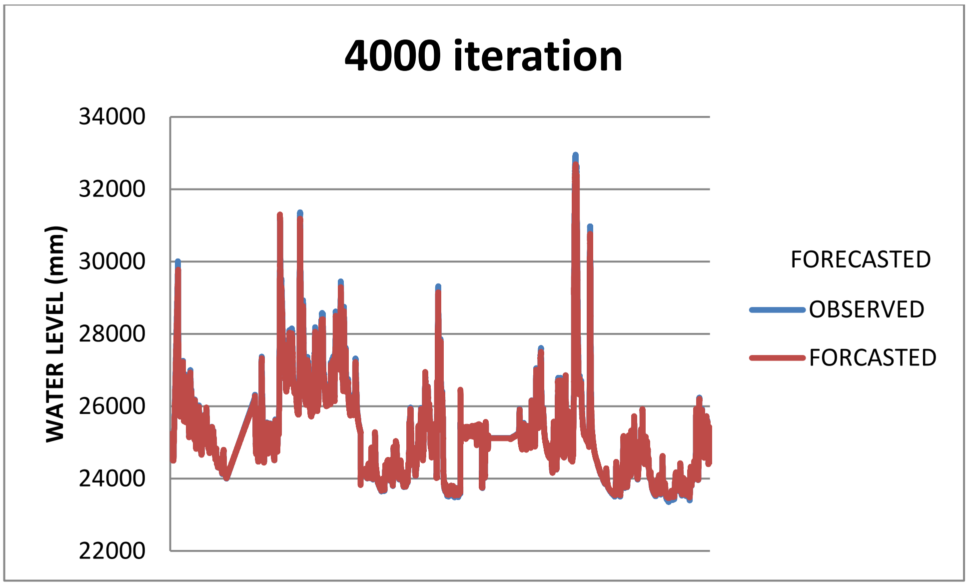


Figure 4.7 : Forecasting performance of ANN model with 5 Data Input



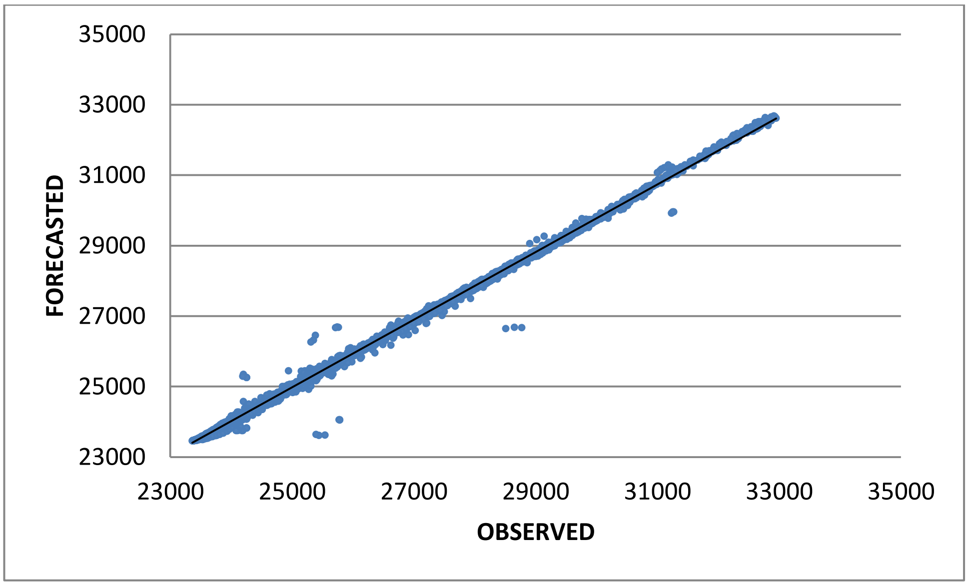
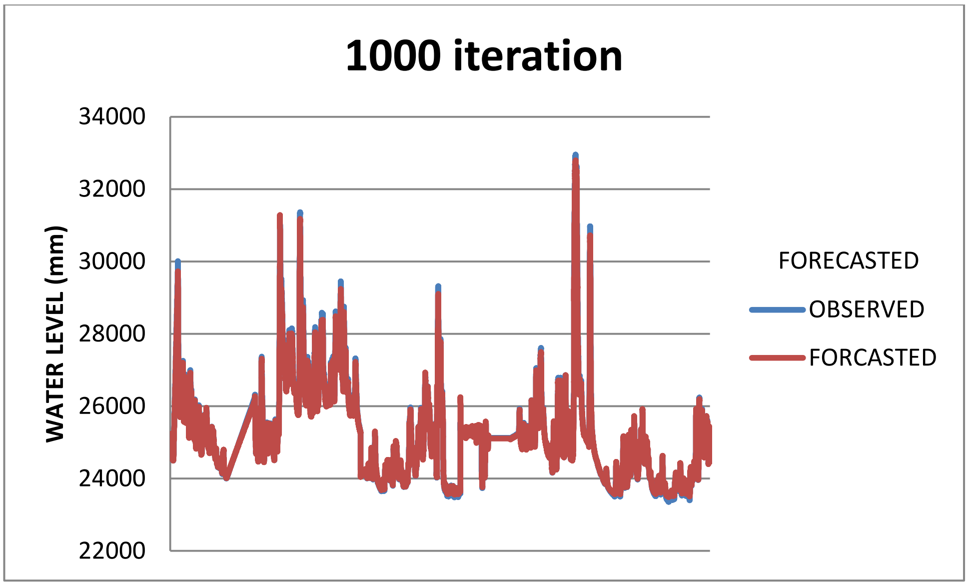


Figure 4.8 : Forecasting performance of ANN model with 5 Data Input

6 INPUT 1 OUTPUT



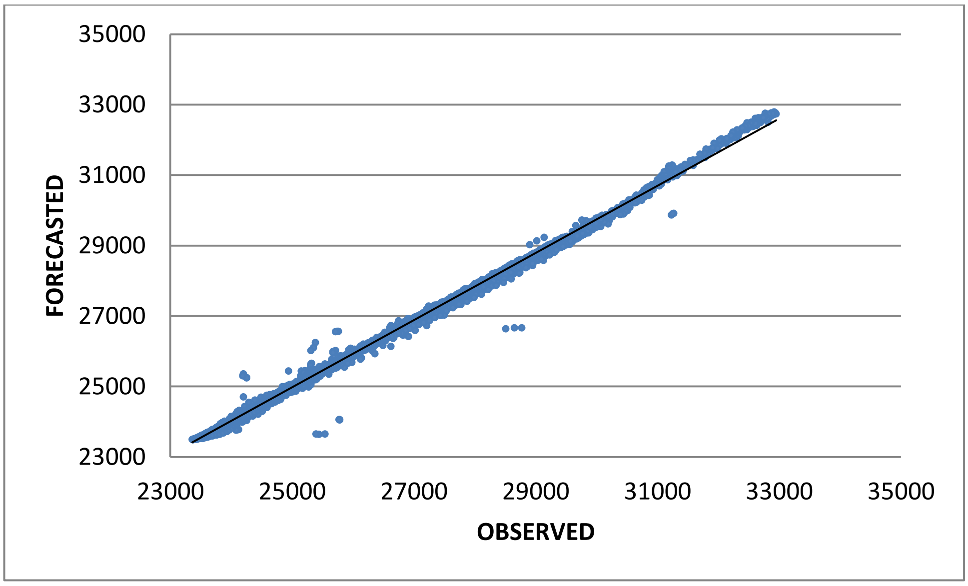
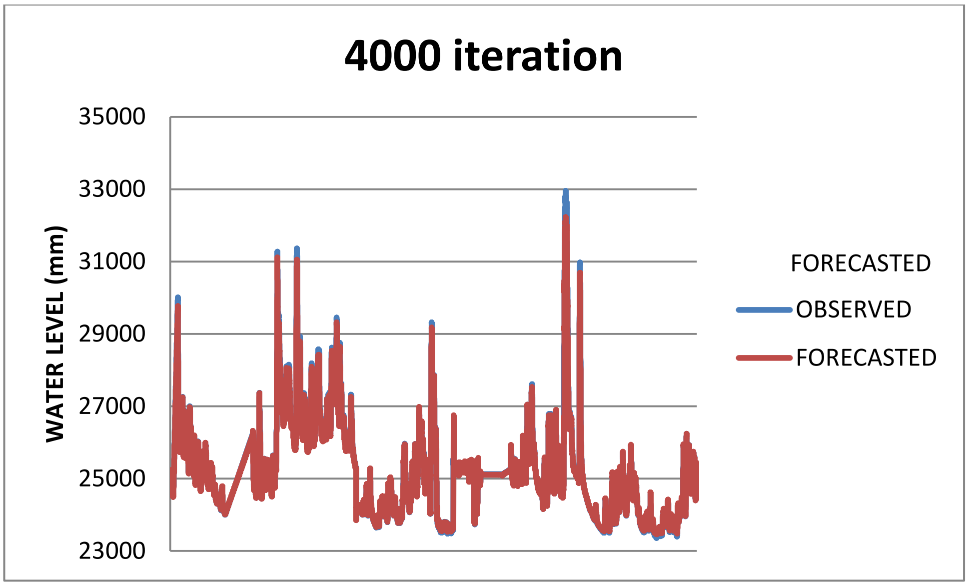


Figure 4.9 : Forecasting performance of ANN model with 6 Data Input



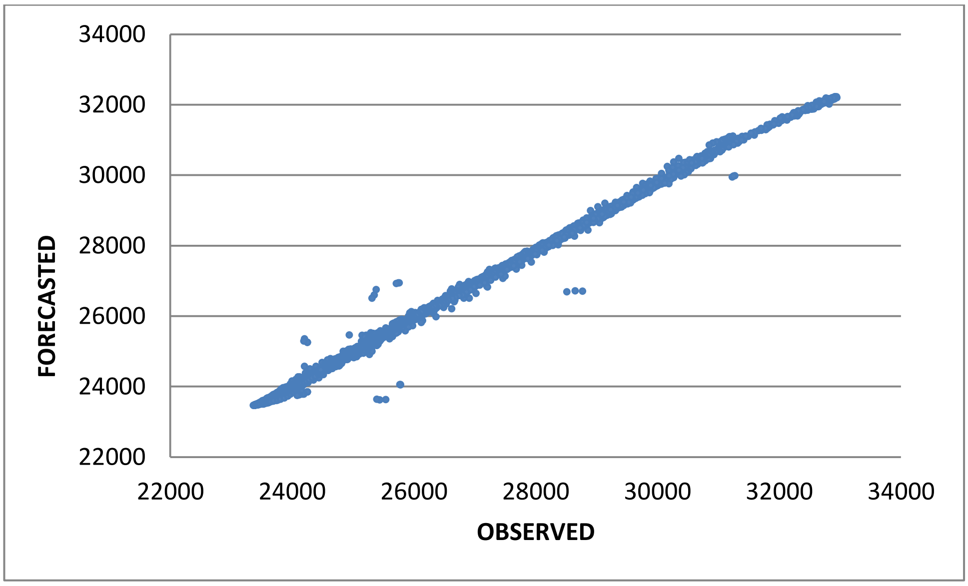
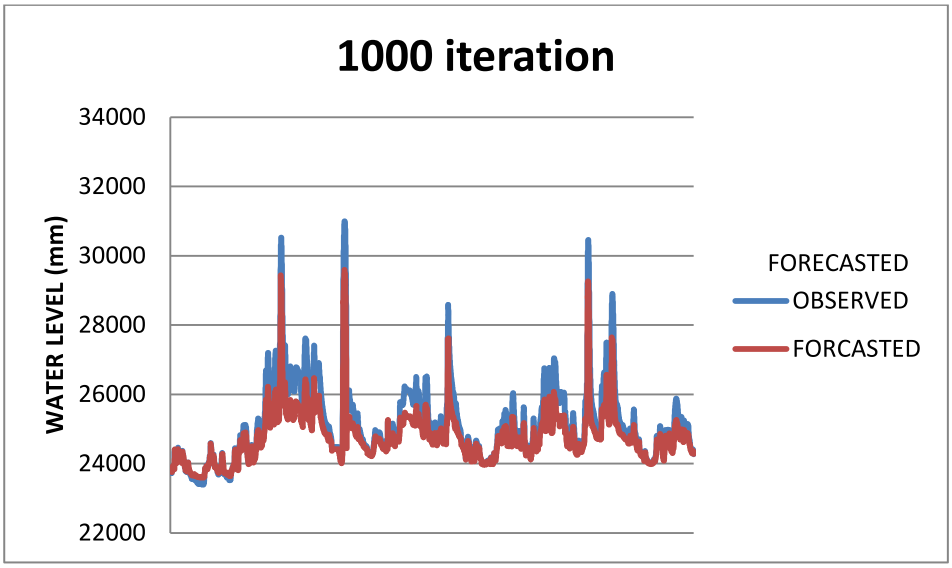


Figure 4.10 : Forecasting performance of ANN model with 6 Data Input

4.1.2 6 Hours Interval

2 INPUT 1 OUTPUT



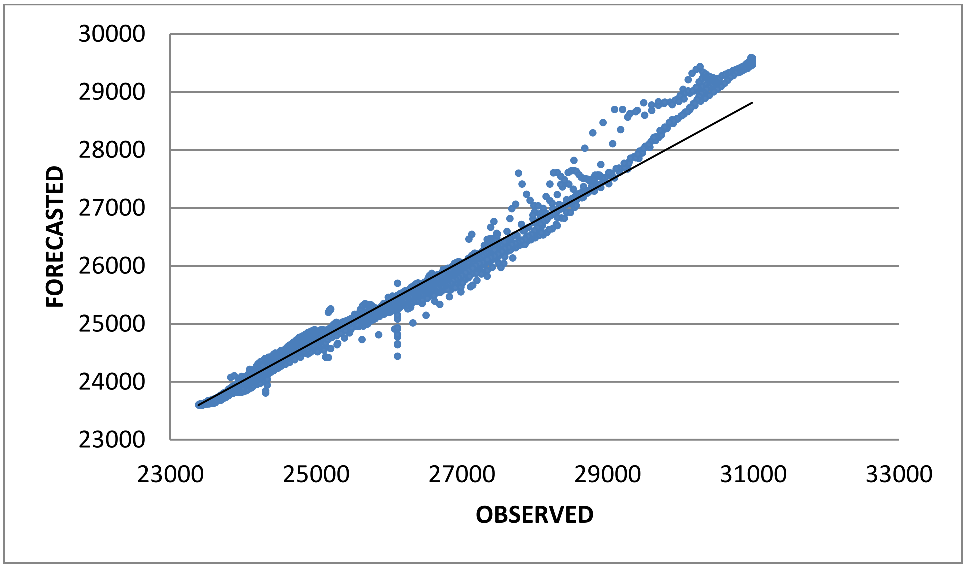
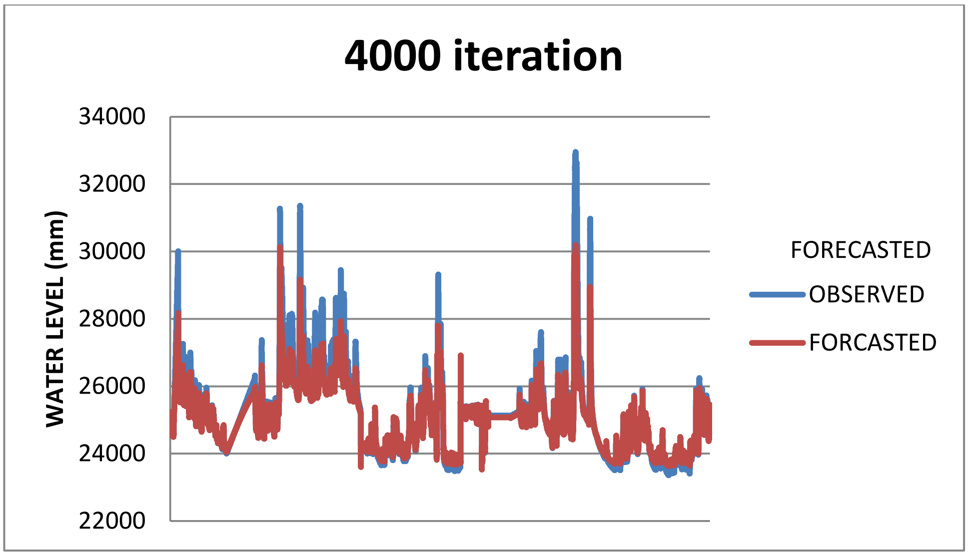


Figure 4.11 : Forecasting performance of ANN model with 2 Data Input

FORECASTED



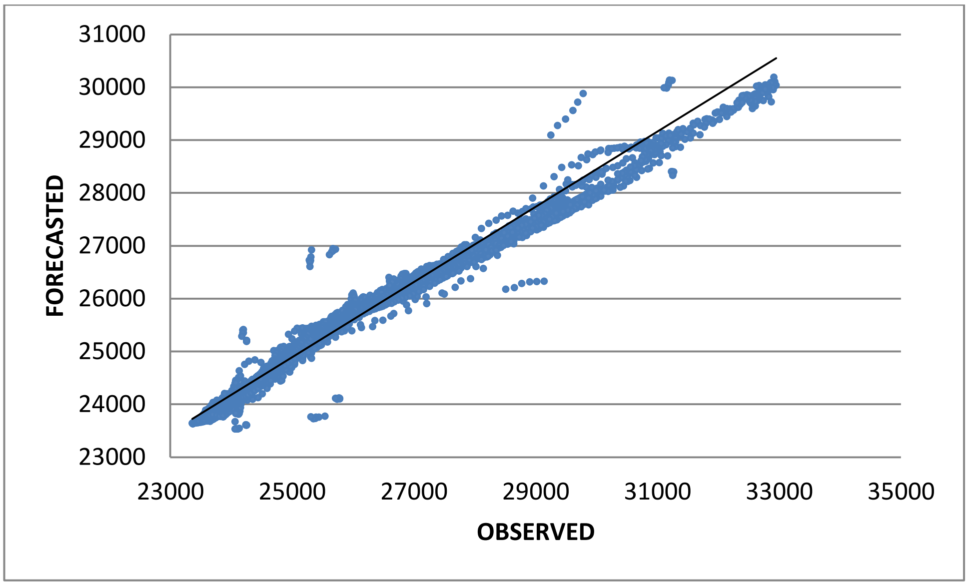
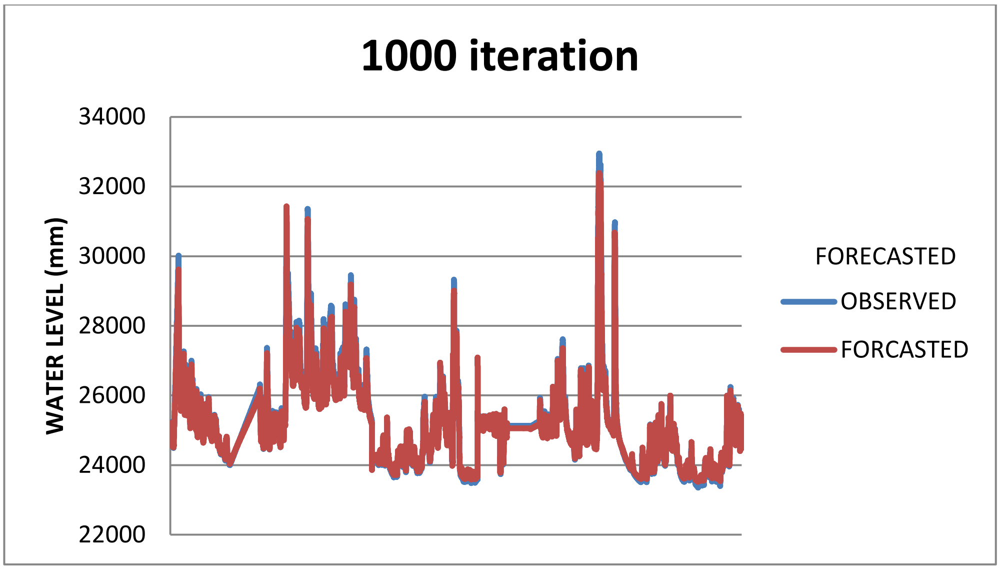


Figure 4.12 : Forecasting performance of ANN model with 2 Data Input

3 INPUT 1 OUTPUT



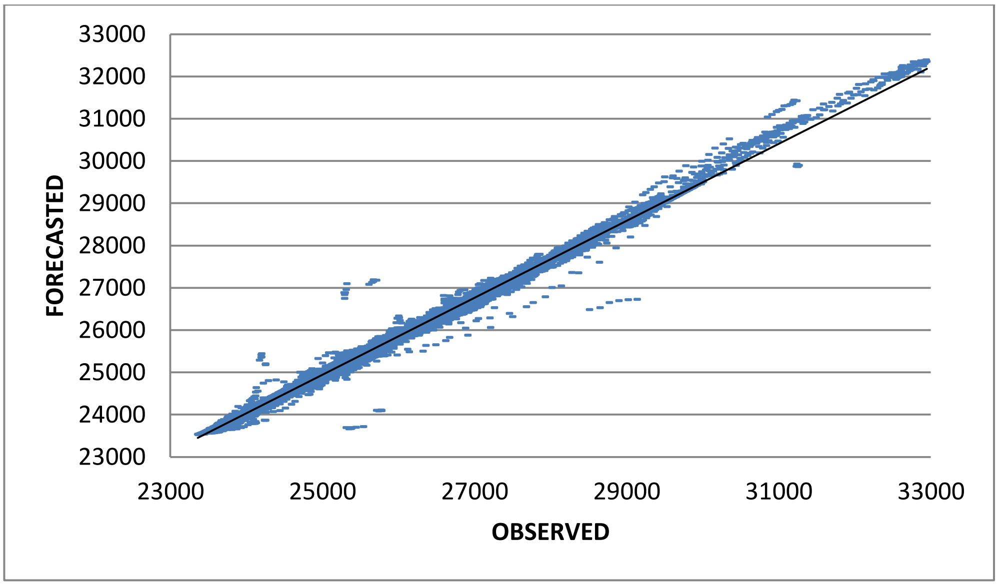
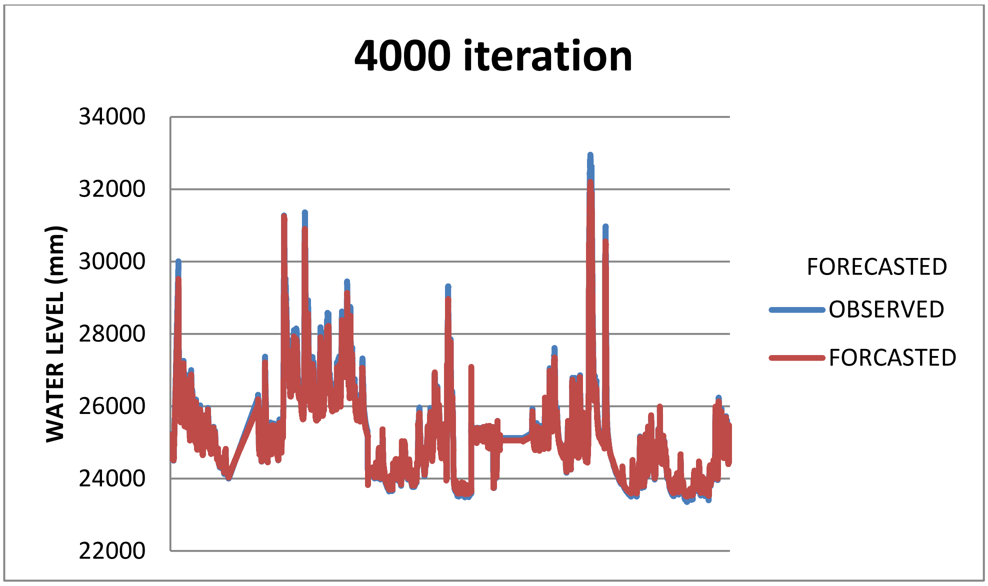


Figure 4.13 : Forecasting performance of ANN model with 3 Data Input



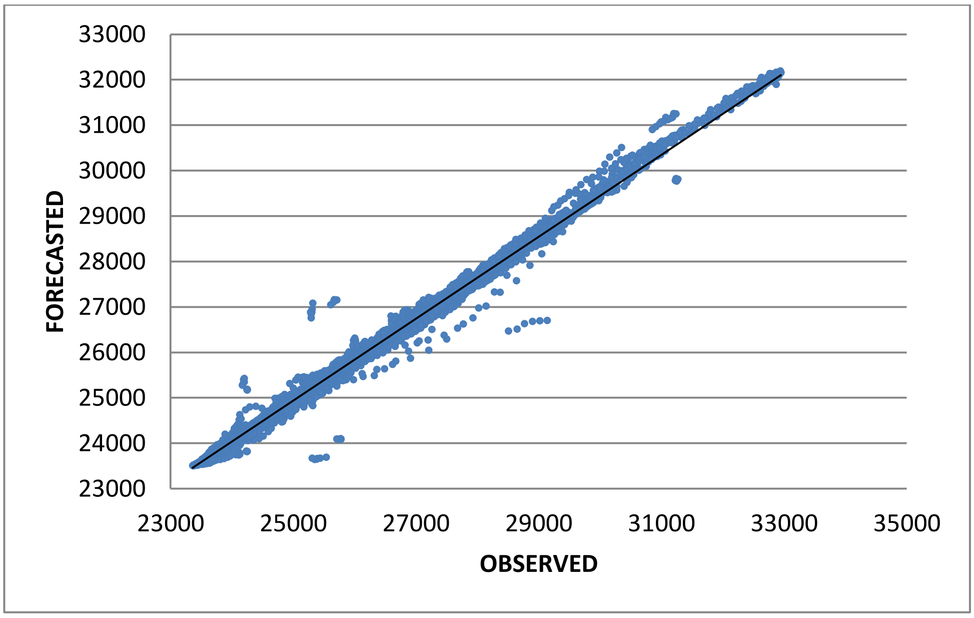
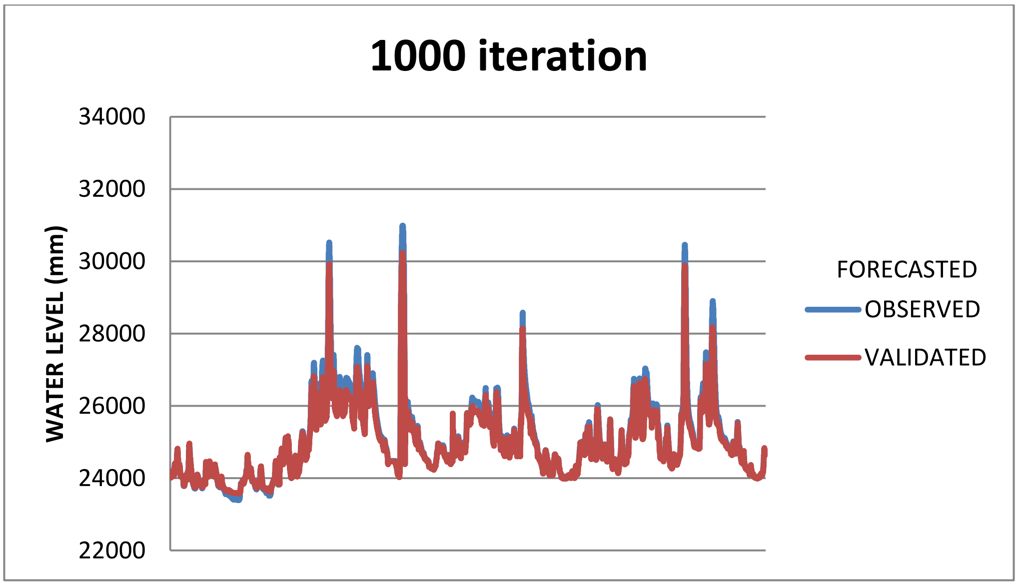


Figure 4.14 : Forecasting performance of ANN model with 3 Data Input

4 INPUT 1 OUTPUT



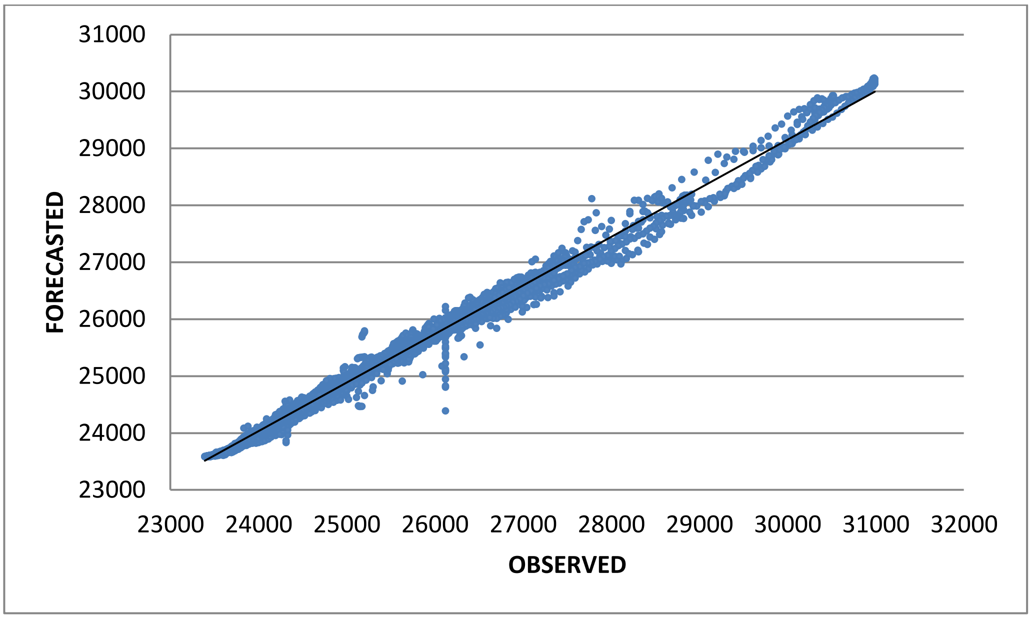
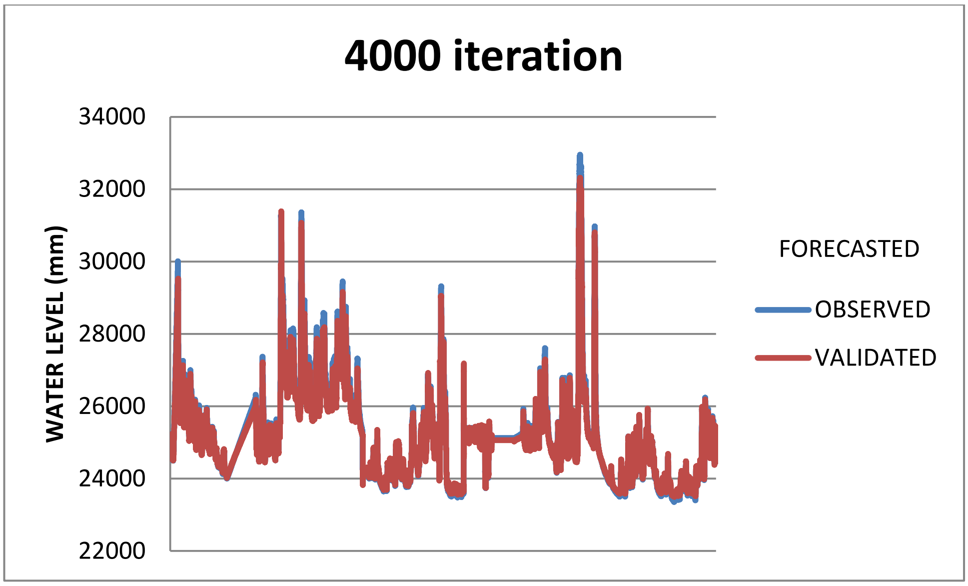


Figure 4.15 : Forecasting performance of ANN model with 4 Data Input



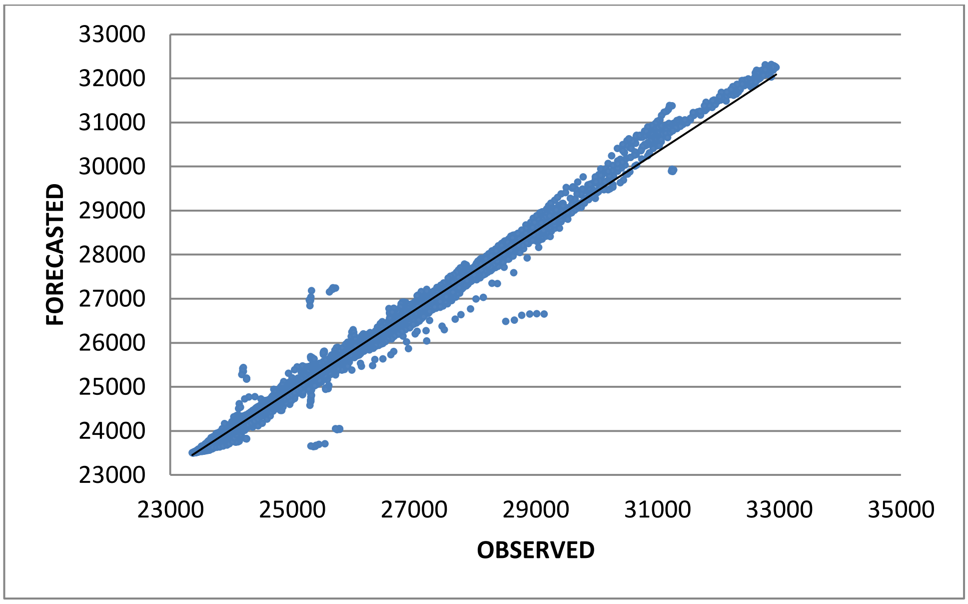
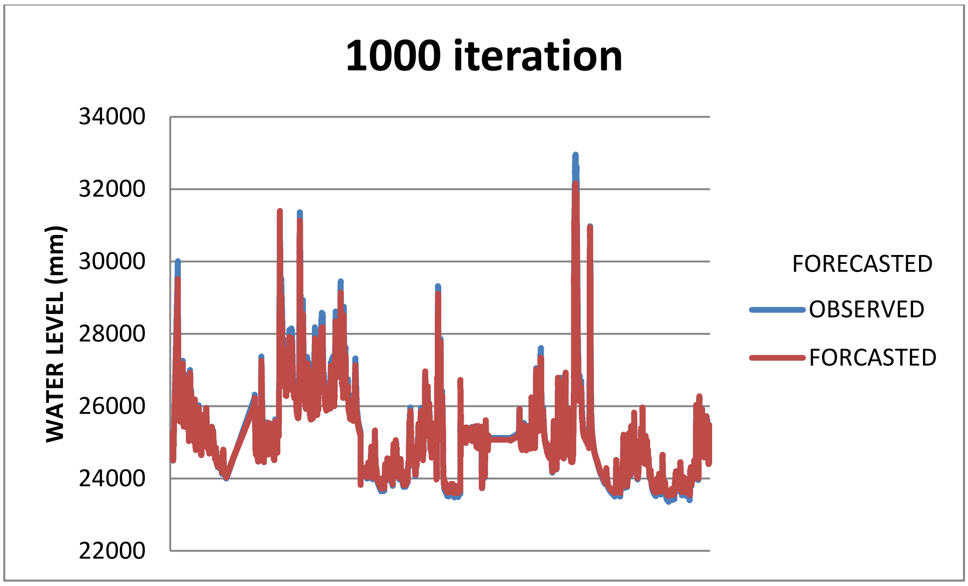


Figure 4.16 : Forecasting performance of ANN model with 4 Data Input

5 INPUT 1 OUTPUT



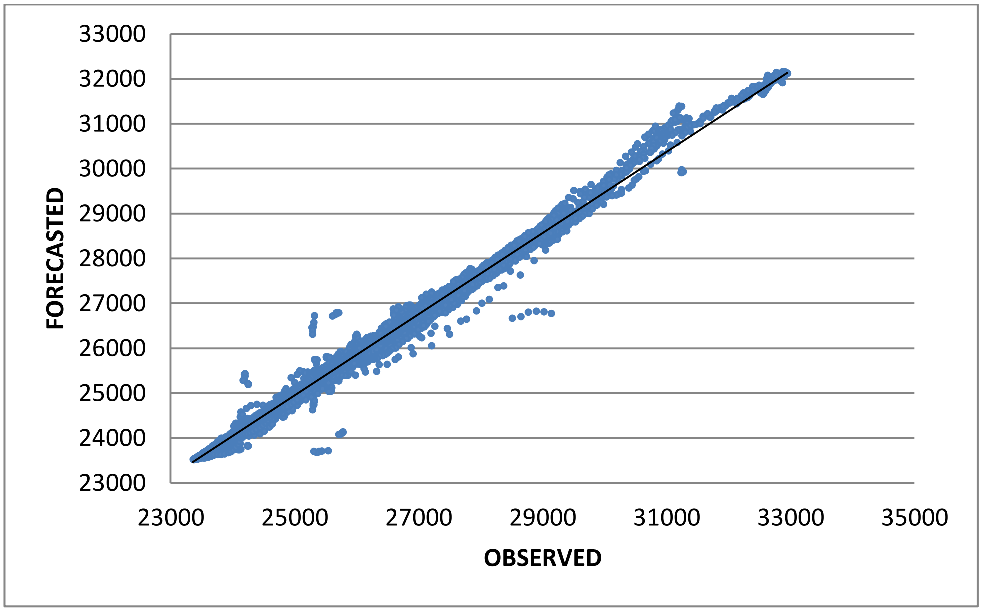
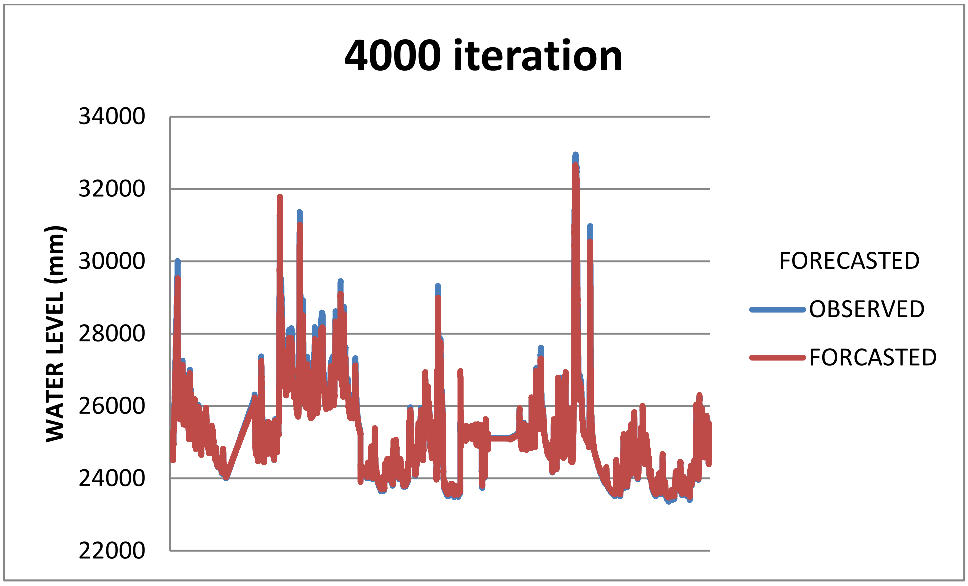


Figure 4.17 : Forecasting performance of ANN model with 5 Data Input



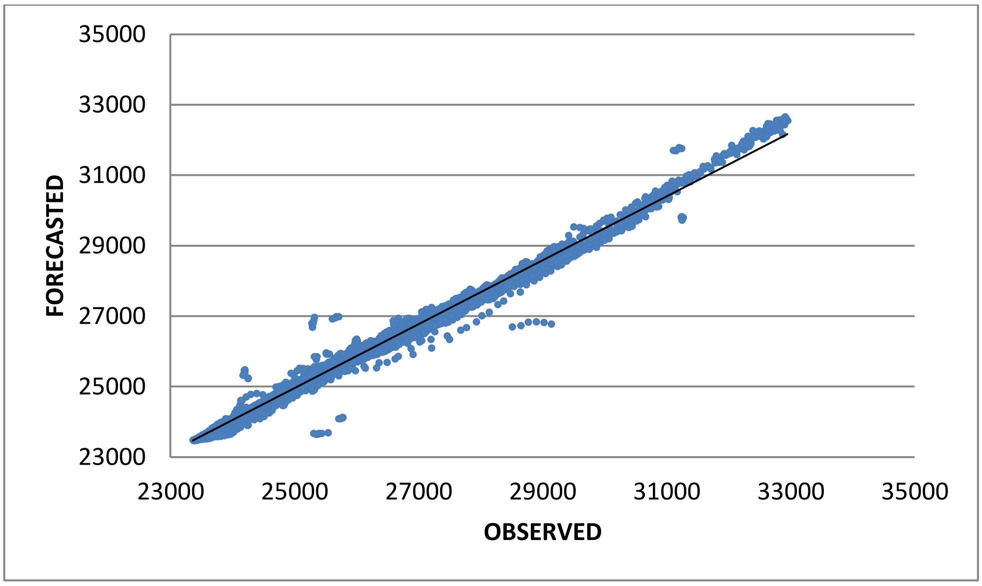
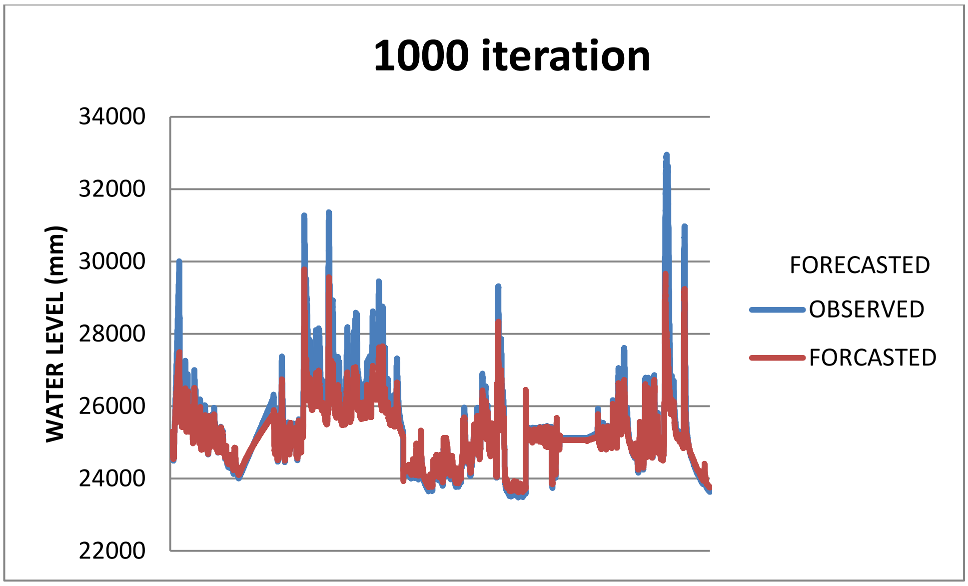


Figure 4.18 : Forecasting performance of ANN model with 5 Data Input

6 INPUT 1 OUTPUT



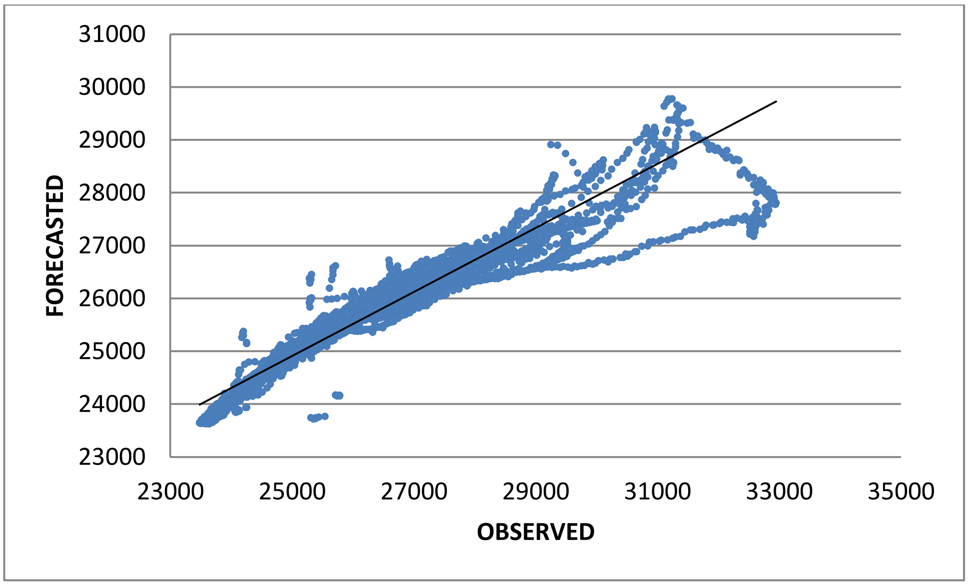
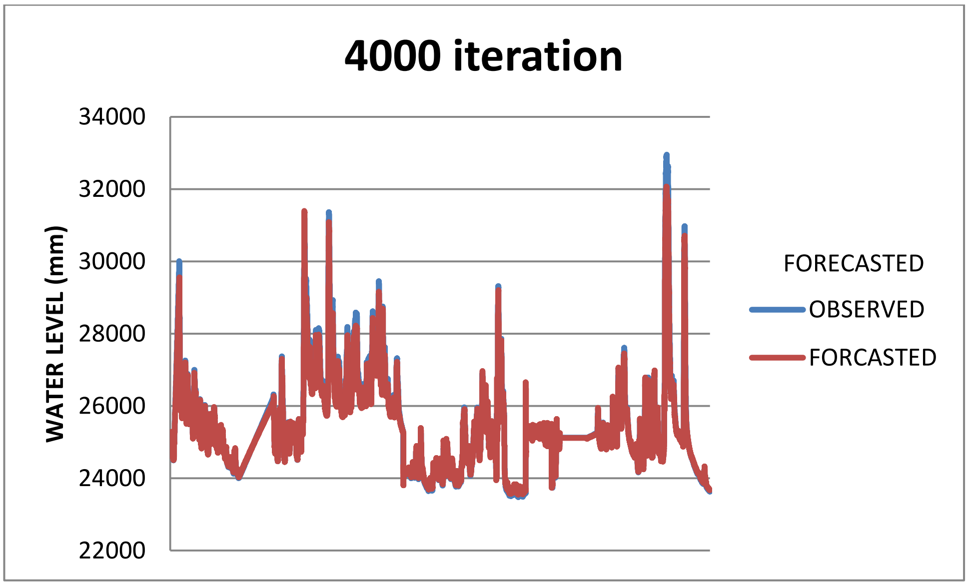


Figure 4.19 : Forecasting performance of ANN model with 6 Data Input



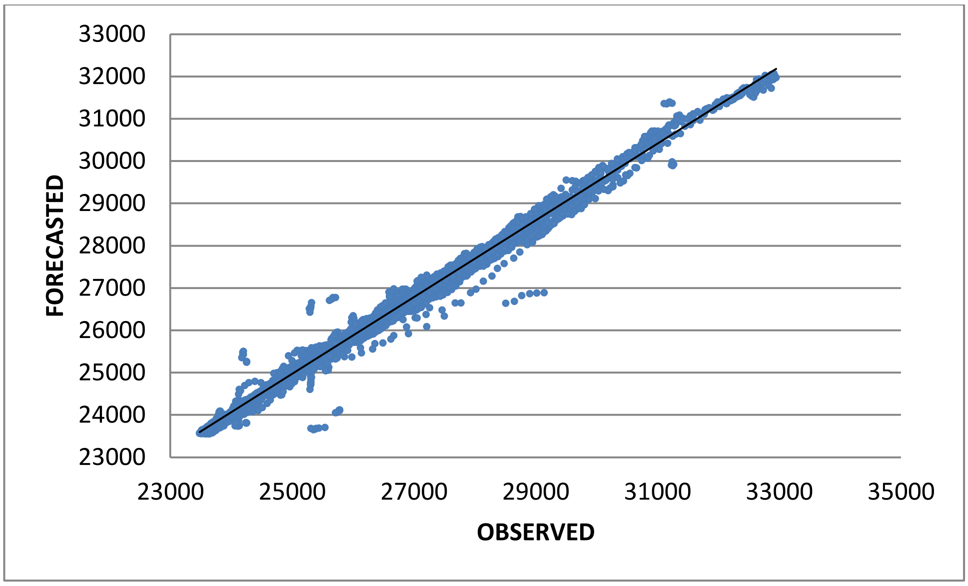


Figure 4.20 : Forecasting performance of ANN model with 6 Data Input

4.2 DATA ANALYSIS

The process is to investigate the performance of ANN model by giving the best forecasting severity at temerloh river. From table 4.1 and table 4.2 we can see that most of the the correlation error (CE) is more than 0.8 that we can conclude that it achieved optimal forecasting water level data.

For 3 hours interval of prediction, refer table 4.1, the RMSE shows that for the 2 input of data is high in RMSE compare to others input with 388.010 for 1000 iteration and 391.78 for 4000 iteration.

The RMSE of 3 data input is 69.198 for both iteration and this prove that when increase the number of input training data will reduce the error in the error produce for forecasted data.

The RMSE for 4 data input is 74.512 for 1000 iteration and 74.018 for 4000 iteration. The data also produce 32119 data error less than 200 mm about 99% for 1000 iteration and 360 data for data less than 500 mm about 1%.

The RMSE for 5 data input is 71.803 for 1000 iteration and 79.123 for 4000 iteration. The data also produce 32556 data less than 200 mm about 99% for 1000 iteration and 268 for data less than 500 mm about 0.9%.

Based on 6 data input of training data the result already increase a bit for RMSE and number of offset error because of the data already achieve it optimal forcasted data at 5 input of data training. The RMSE is 89.561 for 1000 iteration and 80.852 data for 4000 iteration .The data also produce 31480 data less than 200 mm about 96% for 1000 iteration and 1026 for data less than 500 mm about 3%.

The result is different for 6 hours interval of time with almost all the RMSE is more than 100 mm compare to 3 hours interval of time the average is less than 100 mm of error. Based on table 4.2 with 6 hours interval prediction of the forecasted data, the RMSE shows that for the 2 input of data is high in RMSE compare to others input with 493.86 for 1000 iteration and 442.684 for 4000 iteration. The data also produce 8286 error less than 200 mm about 25% for 1000 iteration and 3211 for data less than 500 mm about 10 %.

The RMSE for 3 data input is 168.956 for 1000 iteration and 178.526 for 4000 iteration .The data also produce 26554 error less than 200 mm about 82% for 1000 iteration and 5672 for data less than 500 mm about 17 %.

The RMSE for 4 data input is 221.866 for 1000 iteration and 186.316 for 4000 iteration .The data also produce 11861 error less than 200 mm about 36% for 1000 iteration and 3274 for data less than 500 mm about 10%.

The RMSE for 5 data input is 126.298 for both 1000 and 4000 iteration. The data also produce 30517 error less than 200 mm about 94% and 1783 for data less than 500 mm about 5% for both iteration.

The RMSE for 6 data input is 133.835 for both 1000 and 4000 iteration .The data also produce 24763 error less than 200 mm about 76% and 1560 for data less than 500 mm about 5% for both iteration.

As explained, both the results show the highest RMSE for 2 input of data as compared to the other input. All the RMSE for 3 hours and 6 hours interval are in the range of 60 to 90 and 120 to 220 respectively. The offset errors less than 500 mm show a minimum for ANN performance at 3-hr ahead.

Table 4.1 : Forecasting performance at 3-hr ahead

Number of Input	Number of Itteration	RMSE	CE	Offset Error >200 MM	Offset Error >500MM	Total Data
2	1000	388.0103	0.915	21242	5541	32557
	4000	391.78	0.913	23623	4499	32557
3	1000	69.198	0.997	32145	360	32554
	4000	69.198	0.997	32145	360	32554
4	1000	74.152	0.997	32119	408	32551
	4000	74.018	0.996	31964	563	32551
5	1000	71.803	0.997	32256	268	32548
	4000	79.123	0.996	31740	784	32548
6	1000	89.561	0.995	31480	1026	32545
	4000	80.852	0.998	31871	533	32545

Table 4.2 : Forecasting performance at 6-hr ahead

Number of Input	Number of Itteration	RMSE	CE	Offset Error >200 MM	Offset Error >500MM	Total Data
2	1000	493.86	0.8	8286	3211	32548
	4000	442.684	0.89	5172	21030	32548
3	1000	168.956	0.98	26554	5672	32542
	4000	178.526	0.981	26271	5740	32542
4	1000	221.866	0.98	11861	3274	32536
	4000	186.316	0.981	25563	6293	32536
5	1000	126.298	0.991	30517	1783	32530
	4000	126.298	0.991	30517	1783	32530
6	1000	133.835	0.99	24763	1560	32545
	4000	133.835	0.99	24763	1560	32545

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSION

The using of AAN model for prediction of temerloh river water level have achieve high level of flood forecasting for 3 hours and 6 hours interval of time with different input and iteration. The result show when we increased the iteration the result will becone more accurate but when it increased the head-time of forcaseting data the result will have error a bit. Most of the result show very high accuracy of data from 3-hr lead-time 1000 iteration to 6-hr lead-time 4000 iteration.

From this research the best prediction for water level data at Temerloh River is 3-hr lead-time with 6 input 1 output in 4000 iteration because it produce the best CE with 0.998. Most of the result we can see that the average correlation error for 1000 and 4000 iteration is more than 0.9 that shows the data forecasted is accurate. The difference between observed data and forecasted data also very near from what we can see in the line graph plotted at the result. Based on the result the average RMSE also less than 500 mm with only small difference in percentage of error. In conclusion ANN model can be use as a tools to predict accurately water level data at Temerloh river for 3 hour and 6 hour interval forecasted time.

Lastly, this result show that the prediction of the water level data using ANN method show a high accuracy of forecasting result at the station 3424411 Temerloh River at Pahang.

5.2 RECOMMENDATION

Regarding this research on the prediction of temerloh river water level most of the data show high accuracy forecasting result. This show the data can be use to predict more forecasting data with difference iterval of time that more than 6 hours. The number of iteration also can be increased simultineously with the increased head-time prediction of the water level data. In the next research, can use this data to predict more than one days head time to give the result have better quality interms of give warning about the flood to people because 3 hours and 6 hours was very hard to make anyone to prepare and save anything from disaster of flood.

REFERENCES

Abhijit P. Prodipto D. 2014. Flood Prediction Model using Artificial Neural Network. *International Journal of Computer Applications Technology and Research* (IJCATR). **3**(7): 473 – 478.

Bernama. (undated). *Recent Floods Cause RM7 Million Damage To 41 Pahang Schools*. (online).http://education.bernama.com/index.php?sid=news_content&id=1004308 (27 May 2015)

Borneo Post online. 2013. *Severe floods due to heavy rainfall, says council*. (online). http://www.theborneopost.com/2013/12/11/severe-floods-due-to-heavy-rainfall-says-council/ (31 May 2015)

Cai H. J. 2010. *Flood Forecasting on The Humber River Using An Artificial Neural Network Approach*. Master's Degree Theesis. Memorial University of Newfoundland. Canada.

Christos S. Dimitrios S. (undated). *Neural Networks*. (online). http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/cs11/report.html (5 March 2015)

Ghummana A. R. Ghazawa Y. M. Sohailb A. R. Watanabec K. 2011. Runoff forecasting by artificial neural network and conventional model. Alexandria Engineering Journal. **50**(4): 345–350.

Hao X. J. 2011. *Application of Artificial Neural Network (ANN) for Prediction of Maritime Safety*. **236**: 34-38.

Hazi M. A. Aminuddin A. B. Cheng S. L. Chun K. C. Azazi Z. 2011. *Gene-Expression Programming for the Development of a Stage-Discharge Curve of the Pahang River*. Water Resour Manage. **25**: 2901–2916.

Barzani G. Mazlin M. Salmijah S. Ekhwan T. Sahibin A. R. Pan I. L. 2012. Analysis of Thirty Years Recurrent Floods of the Pahang River, Malaysia. *Asian Journal of Earth Sciences*. **5**: 25-35.

Irfan Y. K. Zope P. H. Suralkar S. R. 2013. Importance of Artificial Neural Network in Medical Diagnosis disease like acute nephritis disease and heart disease. *International Journal of Engineering Science and Innovative Technology (IJESIT).* **2**(2): 210-217.

Jayanta K. B. Debnath B. Kim T. H. 2010. Use of Artificial Neural Network in Pattern Recognition. *International Journal of Software Engineering and I International Journal of Software Engineering and It's Applications It's Applications*. **4**(2): 23-34.

Lekkas D. F. Onof C. Lee M. J. Baltas A. E. 2005. *Application Of Artificial Neural Networks For Flood Forecasting*. Greece. **6**(3): 205-211.

Mahmoud N. Hoda F. Z. 2014. Using of pH as A Tool To Predict Salinity of Groundwater For Irrigation Purpose Using Artificial Neural Network. *The Egyptian Journal of Aquatic Research*. **40**(2): 111–115.

Marina C. Paolo A. Alfredo S. 1999. River Floods Forecasting With a Neural Network Model. *Water Resurces Research*. **34**(4): 1191-1197.

Masoud B. K. Saied P. Biswajeet P. Ahmad R. M. Wan N. A. S. Abbas M. 2011. An Artificial Neural Network Model for Flood Simulation Using GIS: Johor River Basin, Malaysia. *Environmental Earth Sciences.* **67**(1): 251-264.

Noor Y. Z. Ismail A. R. Mahroo E. *Forecasting low-cost housing demand in Pahang, Malaysia using Artificial Neural Networks.*

Omar A. Deli S. Kirubel S. Mehdi M. 1997. *Flood Prediction and Risk Assessment Using Advanced Geo-Visualization and Data Mining Techniques: A Case Study in the Red-Lake Valley*. University Ave., Crookston, USA.

Ramapulana N. 2011. *Artificial Neural Network Modelling Of Flood Prediction And Early Warning*. Master's Degree Thesis. University of The Free State Bloemfontein. USA.

Sucharita G. 1998. *Artificial Neural Networks for Spatial Data Analysis.* NCGIA Core Curriculum in Geographic Information Science. (online). http://www.ncgia.ucsb.edu/giscc/units/u188/u188.html (15 March 2015)

Rao S. G. 2000. Artificial Neural Networks In Hydrology. II: Hydrologic Applications. *Journal of Hydrologic Engineering*. **5**(2): 124-137.

Rosmina A. B. Nabil B. Mohd S. M. 2006. *Artificial Neural Network for Daily Water Level Estimation*. Engineering e-Transaction. **1**(1): 7-12.

Sattar C. B. Wan N. A. S. Latifah A. M. Md N. S. Bahram S. 2010. *Modeling Flood Estimation Using Fuzzy Logic & Artificial Neural Network*. PhD Thesis. Proceedings Of Postgraduate Qolloquium. 278-287.

Sulaiman M. A. Shafie A. E. Karim O. Basri H. 2011. Real-time Flood Forecasting by Employing Artificial Neural Network Based Model with Zoning Matching Approach. *Journal Hydrology and Earth System Sciences (HESS).* **8**: 9357-2011.

The Sun Daily. *2013. 38,099 flood victims at 117 relief centres in Pahang*. (online). http://www.thesundaily.my/news/899489 (3 April 2015)

Wardah T. Hafizul A. C. H. 2013. Flood Forecasting Using Tank Model and Weather Surveillance Radar (WSR) Input for Sg Gombak Catchment. *International Journal of Civil & Environmental Engineering IJCEE-IJENS*. **13**(2): 42-46.

APPENDICES

Approval Letter from UMP for Water Level Data Availability

Universiti Malaysia PAHANG
Engineering • Technology • Creativity

Universiti Malaysia Pahang
Lebuhraya Tun Razak, 26300 Gambang
Kuantan, Pahang Darul Makmur
Tel: +609-549 2999 | Faks/Fax: +609-549 2998
e-Mel/e-Mail : fkasa_admin@ump.edu.my

Fakulti Kejuruteraan Awam & Sumber Alam
Faculty of Civil Engineering & Earth Resources

UMP.13.02/13.11/1/3 Jld 20 (31) 26 Februari 2015

KEPADA SESIAPA YANG BERKENAAN,

Tuan/Puan,

PENGESAHAN PELAJAR MENJALANI PROJEK KURSUS

Dengan segala hormatnya, saya merujuk kepada perkara di atas.

2. Adalah dimaklumkan berdasarkan pengajian kursus, pelajar Fakulti Kejuruteraan Awam & Sumber Alam, Universiti Malaysia Pahang perlu mendapatkan data dan maklumat bagi menjalani projek kursus. Butiran projek dan pelajar adalah seperti berikut:

Tajuk Projek	Flood Estimation By Using Artificial Neural Network
Nama Kursus	BAA4914 – Final Year Project
Nama Penyelia/ Pensyarah	Dr. Muhammad @ S.A. Khusren bin Sulaiman (0199020060)
Nama Pelajar	1) Nurul Qamar Bt Roszaidi (AA11025) 2) Wan Nurul Hafizah Bt Abd Razak (AA11034) 3) Amir Aliff Bin Amri (AA11053) 4) Muhammad Afiq Bin Mustafa (AA11058) 5) Nurul Murshida Bt Mohd Sabri (AA11197)

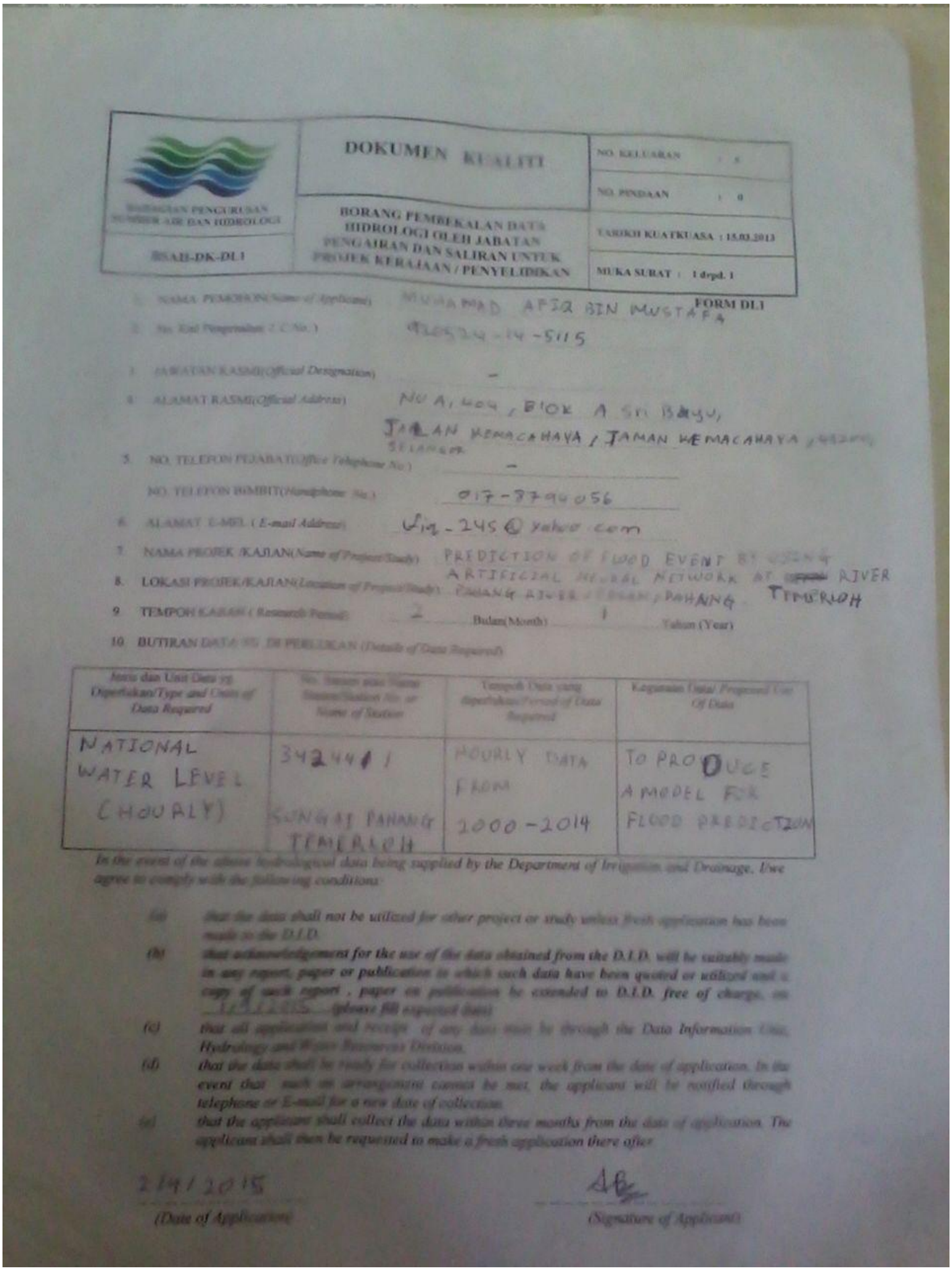
3. Pihak FKASA amat berbesar hati sekiranya pihak tuan/puan dapat membantu dan menyalurkan maklumat dan data yang akan digunakan oleh pelajar bagi tujuan pembelajaran bagi masa hadapan negara amatlah dihargai oleh pihak kami.

Sekian, terima kasih.

"BERKHIDMAT UNTUK NEGARA"
Saya yang menjalankan tugas

ERNIE NURAZLIN BINTI LIZAM
Penolong Pendaftar Kanan
Fakulti Kejuruteraan Awam & Sumber Alam (FKASA)
Universiti Malaysia Pahang (UMP)
Tel : +6095492973/2999
Faks : +6095492998

Water Level Data Application Form for DID



DOKUMEN KUALITI

NO. KELUARAN

NO. PINDAAN : 0

BORANG PEMBEKALAN DATA HIDROLOGI OLEH JABATAN PENGAIRAN DAN SALIRAN UNTUK PROJEK KERAJAAN / PENYELIDIKAN

TARIKH KUATKUASA : 15.03.2013

BSAH-DK-DL1

MUKA SURAT : 1 drpd. 1

FORM DL1

1. NAMA PEMOHON(Name of Applicant) MUHAMAD AFIQ BIN MUSTAFA
2. No. Kad Pengenalan (I.C No.) -14-5115
3. JAWATAN RASMI(Official Designation) -
4. ALAMAT RASMI(Official Address) NO A, 404, BLOK A Sri Bayu, JALAN KEMACAHAYA, TAMAN KEMACAHAYA, SELANGOR
5. NO. TELEFON PEJABAT(Office Telephone No.) -
   NO. TELEFON BIMBIT(Handphone No.) 017-3794056
6. ALAMAT E-MEL (E-mail Address) Vig-245@yahoo.com
7. NAMA PROJEK /KAJIAN(Name of Project/Study) PREDICTION OF FLOOD EVENT BY USING ARTIFICIAL NEURAL NETWORK AT RIVER
8. LOKASI PROJEK/KAJIAN(Location of Project/Study) PAHANG RIVER, PAHANG, TEMERLOH
9. TEMPOH KAJIAN (Research Period) 2 Bulan(Month) 1 Tahun (Year)
10. BUTIRAN DATA YG DI PERLUKAN (Details of Data Required)

Jenis dan Unit Data yg Diperlukan/Type and Units of Data Required	No. Stesen atau Nama Stesen/Station No. or Name of Station	Tempoh Data yang diperlukan/Period of Data Required	Kegunaan Data/ Proposed Use Of Data
NATIONAL WATER LEVEL (HOURLY)	3424411 SUNGAI PAHANG TEMERLOH	HOURLY DATA FROM 2000 - 2014	TO PRODUCE A MODEL FOR FLOOD PREDICTION

In the event of the above hydrological data being supplied by the Department of Irrigation and Drainage, I/we agree to comply with the following conditions:

(a) that the data shall not be utilized for other project or study unless fresh application has been made to the D.I.D.

(b) that acknowledgement for the use of the data obtained from the D.I.D. will be suitably made in any report, paper or publication in which such data have been quoted or utilized and a copy of such report, paper on publication be extended to D.I.D. free of charge, on ______ (please fill expected date)

(c) that all application and receipt of any data must be through the Data Information Unit, Hydrology and Water Resources Division.

(d) that the data shall be ready for collection within one week from the date of application. In the event that such an arrangement cannot be met, the applicant will be notified through telephone or E-mail for a new date of collection.

(e) that the applicant shall collect the data within three months from the date of application. The applicant shall then be requested to make a fresh application there after

2/9/2015
(Date of Application)

(Signature of Applicant)

CODING - ANN PERFORMANCE MEASURE

```
fp=open("VALIDATED_DT.CSV", "r")
fp1=open("result_dt.txt", "w")
C=0
ESS=0
TO=0
SUM=0
diff=0
a=0
b=0
for eachline in fp:
        C=C+1
        dt=eachline.split(",")
        O = eval(dt[2])
        M= eval(dt[3])
        E = abs(O-M)
        ESQ = E**2
        ESS=ESS+ESQ
        TO = TO + O
        AveO= TO/C
        BOTTOM=(O- AveO)
        BSQ=BOTTOM**2
        SUM=SUM+BSQ
        diff=E + 0
        if diff <=200:
            a=a+1
        if diff >200 and diff <=500:
            b=b+1
RMSE=(ESS/C)**0.5
NSC=1-(ESS/SUM)
print("THE SUMMARY OF VALIDATED_DT :", "\n")
print("The RMSE is " +str(RMSE))
```

```
print("The NSC is " +str(NSC))
print("The Error less than 500 is " +str(b) + " and less than 200 is " +str(a))
fp1.write("The Total of Data is " +str(C)+"\n")
fp1.write("SUM(Observed-Model)^2 is " +str(ESS)+"\n")
fp1.write("The Average of observed is " +str(AveO)+"\n")
fp1.write("SUM(Observed- Average of Observed)^2 is " +str(SUM)+"\n")
fp1.write("The RMSE is " +str(RMSE)+"\n")
fp1.write("The NSC is " +str(NSC)+"\n")
fp1.write("The Error less than 500 is " +str(b) + " and less than 200 is " +str(a)+"\n")
print("COMPLETED FOR DT")
fp.close()
fp1.close()
```