



Faculty of Engineering

**WATER LEVEL PREDICTION FOR LIMBANG BASIN USING
MULTILAYER PERCEPTRON (MLP) AND RADIAL BASIS
FUNCTION (RBF) NEURAL NETWORK**

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(RBF) NEURAL NETWORK

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To my beloved family and Noorhana binti Mohd Sapawi.

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ABBREVIATION

ANN	Artificial Neural Network
R ²	Correlation coefficient
DID	Department of Irrigation and Drainage
EMF	Estimated Maximum Flood
<i>traincgf</i>	Fletcher-Reeves Update
LTF	Linear transfer function
LMS	Least mean squared error
MT	Model trees
BPANN	Multilayer Backpropagation Artificial Neural Network
MLP	Multilayer Perceptron
PERSIANN	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks
PoP	Probability of Precipitation
QPF	Quantitative Precipitation Forecast
RBF	Radial Basis Function
<i>newrb</i>	RBF model
<i>trainrp</i>	Resilient backpropagation
RMSE	Root Mean Squared Error
<i>trainscg</i>	Scale conjugate
SSE	Sum Squared Error
USGS	U.S. Geological Survey

ABSTRACT

This study proposes the application of Artificial Neural Network (ANN) in the prediction of water level under tidal influence for Sungai Limbang. ANN is undoubtedly a robust tool for forecasting various non-linear hydrologic processes, including the water level prediction. It is a flexible mathematical structure which is capable to generalize patterns in imprecise or noisy and ambiguous input and output data sets. In this study, the ANN is developed specifically to forecast the daily water level for Limbang Station. Distinctive networks were trained and tested using daily data obtained from the Department of Irrigation and Drainage (DID), Samarahan. Various training parameters are considered in order to gain the best prediction possible. The performances of the ANN is evaluated based on the coefficient of efficiency, E^2 and the coefficient of correlation, R . Multilayer Perceptron (MLP) and Radial Basis Function (RBF) were adopted in this study. MLP is trained with conjugate gradient algorithms, *trainscg* and RBF with *newrb*. The optimal model found in this study is the MLP which is using four days of antecedent data with combination of learning rate and number of neurons in the hidden layer of 0.6 and 60. This model generated the highest E^2 and R Testing of 0.950 compared to RBF which gives the highest value of 0.276 for E^2 and for R Test is 0.390. It is found that the ANN has the potential to solve the problems of water level prediction. After appropriate simulations, ANN generates satisfactory results for MLP during both of the training and testing phases but not for RBF. Further, strength and limitations of the ANN are discussed, based on the results attained in this study.

ABSTRAK

Kajian ini mengcadangkan aplikasi Rangkaian Neural Buatan dalam meramal paras air akibat kesan paras pasang surut untuk Sungai Limbang. Rangkaian Neural Buatan merupakan satu alternatif yang efektif dalam meramalkan pelbagai proses hidrologi tidak linear, termasuk ramalan paras air di sungai-sungai. Ia merupakan struktur matematik yang fleksibel yang berupaya membuat kesimpulan secara menyeluruh terhadap sesuatu bentuk keadaan yang kurang jelas, dengan set data input dan output yang kurang tepat. Dalam kajian ini, Rangkaian Neural Buatan dibangunkan secara spesifik untuk meramal paras air setiap hari untuk Stesen Limbang. Rangkaian yang berbeza dilatih dan diuji menggunakan data setiap hari yang diperolehi daripada Jabatan Pengairan dan Saliran, Samarahan. Pelbagai parameter latihan diambil kira untuk mencapai keputusan ramalan terbaik. Prestasi Rangkain Neural Buatan dinilai berdasarkan Pekali Kecekapan, E^2 dan Pekali Perkaitan, R. Algoritma '*Multilayer Perceptron (MLP)*' dan '*Radial Basis Function (RBF)*' telah diaplikasikan dalam kajian ini. Rangkaian *MLP* telah dilatih dengan '*conjugate gradient algorithms*', *trainscg* dan *RBF, newrb*. *MLP* adalah model optimum dengan menggunakan '*learning rate*' 0.6 dan bilangan neuron 60 dan mengecapi nilai tertinggi E^2 dan R untuk fasa ujian dengan nilai 0.950 jika dibandingkan dengan *RBF* yang hanya mencapai nilai sebanyak 0.276 untuk E^2 manakala 0.390 untuk R. Oleh yang sedemikian, Rangkaian Neural Buatan berpotensi untuk menyelesaikan masalah meramal paras air. Setelah melaksanakan latihan yang sesuai, keputusan yang optimum ditunjukkan oleh *MLP* manakala keputusan yang tidak memuaskan untuk *RBF*. Selain itu, kekuatan dan kelemahan rangkaian ini turut dibincangkan, berdasarkan keputusan yang telah diperolehi dalam kajian ini.

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION TO THE STUDY

Sarawak, situated at north of the Equator between latitude $0^{\circ} 50'$ and 5°N and longitude $109^{\circ} 36'$ and $115^{\circ} 40'$ E is located in the western region of the Borneo island. Covering an area of $124, 449.51 \text{ km}^2$, Sarawak is the largest country in Malaysia. Sarawak stretches 800 km along north-west coast of the island of Borneo and is separated from Peninsular Malaysia by a distance of 600 km by the South China Sea. Sarawak shares its boundaries with Sabah in the north, Brunei and Kalimantan (Indonesia) in the south.

Sarawak is divided into three zones, consist of coastal lowlands comprising of peat swamps and narrow deltaic and alluvial plains, a large region of undulating hills ranging to about 300 m and mountain highlands extending to Kalimantan border.

Located near the equator with a tropical climate, Sarawak is warm and sunny all year round. Daily temperature ranges from 33°C in the afternoon to 22°C during the night. Its mean annual rainfall is very high, about 3800 mm yearly which makes it effortless to flood (Bustami *et al.* 2007).

Some of the local communities are still depending on river for food, water and as a way of transportation from villages to town. Rivers also provide recreational interaction and numerous agricultural activities. Hence, an accurate forecasting of water level is important to warn local of potential increasing in water level and take necessary safety measures.

There are some available methods in forecasting water level. One of it is conventional method. Via conventional method, an accurate estimation of water level needs accurate estimation of runoff from the past rainfall event and accurate hydraulic model for a given discharge. Runoff depends on catchment topography, river network, soil characteristic, antecedent moisture and for hydraulic model, accurate cross sections at a particular river are needed. These parameters are hard to obtain and not available at all time, which makes it complicated to estimate the water level (Bustami *et al.* 2007).

Artificial Neural Network (ANN) is becoming acceptable for its ability to solve complex, mathematically or stochastic problems by using a simple computational operations. These properties are suitable to forecast water level and which the relationship are not recognized (Graupe, 1997).

1.2 SELECTION OF ARTIFICIAL NEURAL NETWORK

According to Professor Dr. Eduardo Gasca A. (n.d.), ANN is an abstract simulation of real nervous system and its study corresponds to a growing interdisciplinary field which considers the system as adaptive, distributed and mostly nonlinear.

ANN is composed of large number of highly interconnected processing elements analogous to neurons and tied together with weighted connections analogous to synapses. This will enable it to solve complex and nonlinear problems (Saad, 2004). ANN has been proven to provide better solution when applied to complex system. ANN was chosen based on its ability to generalized patterns and overcome difficulties due to the selection of a model form such as linear, power and polynomial. Within the last decade, ANNs has been successfully applied in hydrology related areas such as water level predictions, rainfall-runoff modeling, stream flow forecasting, groundwater modeling, precipitation forecasting and reservoir operation (ASCE, 2000).

On the other hands, conventional method requires numerous of detailed data. Topographical maps, river networks and characteristic, soil characteristic, accurate rainfall and runoff data is needed if using this method. The parameters are hardly to obtain as it is not available at all time. This will makes it complicated to forecast the water level. Additionally, a sufficient time is needed for forecasting to take the flood measures.

By referring to hydrology field, problems are usually not clear understood and are too complex for analysis by conventional method. Even such model are available, they have to rely on assumptions that make ANN more attractive. The presents of noise in the inputs and outputs is handled by an ANN without severe loss of accuracy because of the distributed processing within the network. Along the nonlinear nature of activation function, generalizing capabilities of ANN makes them desirable for a large class of problems in hydrology. Thus, application of ANN in hydrology for predicting water level is great alternative in order to achieve the best solution.

1.3 PROBLEM STATEMENT

Over the last 50 years, there have been a number of significant hydrologic events, all of which caused extensive flooding throughout Limbang River. In December 1956, flood occurred at Limbang Division which affects the shop houses where the water level is about 4 feet. In January 1965, Limbang was severely flooded

and the flood level even passed the 1963 marks of water level. Major flood occurred in Limbang in December 1993. Flood levels are estimated to be as high as 8 feet.

Knowing that Sarawak economic development takes place by the river, accurate forecasting of water level is therefore essential to warn public of potential rise in water level and call for necessary precautions.

1.4 OBJECTIVE OF THE STUDY

The objective of the study is to estimate water level for Limbang basin by using Multilayer Perceptron (MLP) and Radial Basis Function (RBF). Besides estimating water level, this study can compare the accuracy of MLP and RBF.

1.5 OUTLINE OF THE FOLLOWING CHAPTER

This Final Year Project's Report was organized into 5 chapters. The brief information of each chapter is described as the following:

Chapter 1 provides introduction to the project and a brief description of ANN. This chapter also contains problem statement and project objective.

Chapter 2 elaborates on literature review regarding ANN and the previous study on ANN and its application in hydrology.

Chapter 3 presents the research methodology and approach used for this study consisting of model development, network training, transfer function, evaluation of network performance and software used.

Chapter 4 evaluates the performance, result and analysis based on the project. The results are based on the model that has been done using the selected algorithm. Discussion for this project based on analysis and result also included.

Lastly, chapter 5 contains conclusion based on the analysis, results and discussions from the previous chapters. In addition, further research and recommendation for this project is also being discussed in this chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

ANN has been found to have the ability to learn and generalized knowledge from sufficient data pairs which makes it possible to solve large scale complex problems such as pattern recognition, non linear modeling, classification, association, control, and others, all which find application in hydrology today (ASCE, 2000).

Various studies all around the world have been done on the application of ANN in this field. This literature review is written by summarizing and reviewing the

related information and sources, generally collected from books, journals and related websites in hydrology. The earlier part of this chapter defines the ANN, while the latter part of this chapter reviews the previous, including precipitation estimations, rainfall-runoff modeling, stream flows and runoff prediction.

2.2 ARTIFICIAL NEURAL NETWORK

ANN is based on the understanding of the problem solving process of the human brain. The structure of an ANN works like the human brain, which applies knowledge gained from experience to solve new problems (Kurtulus and Razack, 2007).

A network consist of a few number of nodes, called neurons which are the processing element of a network. A layer is a group of neurons with the same pattern of connections. A MLP consists of an input layer, one or more hidden layers and an output layer as illustrated in Figure 2.1. Input neuron in the input layer receives an external input data and relays the elements to neurons of the next layer. Each hidden neurons receives input data then transform the input into a single output which will be transferred to output neurons. All the output of this layer constitutes the response of the network to the external inputs.