ARTIFICIAL NEURAL NETWORKS
FOR RAINFALL RUNOFF MODELLING
WITH SPECIAL REFERENCE TO
SG. BEDUP CATCHMENT AREA

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DECLARATION

No portion of the work referred to in this report has been submitted in support of an application for another degree or qualification of this or any other university or institution of higher learning.

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ABSTRACT

The rainfall-runoff relationships are among the most complex hydrologic phenomena to comprehend due to the tremendous spatial and temporal variability of watershed characteristics, precipitation patterns as well as a number of variables involved in modeling the physical processes. Hydrologists have developed conceptual models to provide daily, monthly and seasonal runoff. These are composed of a large number of parameters and the interaction of these is highly complicated.

Artificial Neural Network (ANN) is an information-processing system composed of many nonlinear and densely interconnected processing elements or neurons. ANN is able to extract the relation between the inputs and outputs of a process, without the physics being explicitly provided to them. The natural behavior of hydrological processes is appropriate for the application ANN in hydrology. In the last few years ANNs were used to build rainfall runoff models, estimate pier scour, predict sediment transport, and setup rating curves.

A rainfall runoff model for Sungai Bedup Basin in Sarawak was built using three different ANN architectures namely Multilayer perceptron (MLP), Recurrent (REC) and Radial Basis function (RBF). These networks were used to simulate daily runoff and generate storm hydrograph for a given rainfall event. Antecedent rainfall, antecedent runoff and rainfall for actual event were used as input. The runoff for the actual event was the output. The ANNs were trained using different training algorithms, different learning rates, different length of data and different number of
hidden neurons. All the relevant data was collected from the Department of Irrigation and Drainage, Sarawak. The ANNs were designed to simulate daily runoff and hourly runoff. It was also attempted to simulate runoff for few days ahead, and few hours ahead in the case of hourly simulation. The results were evaluated using the coefficient of correlation $R$ and the Nash-Sutcliffe Coefficient $E^2$.

The ANNs trained during this investigation have been able to simulate daily runoff with high accuracy of up to $R=0.97$. The storm hydrograph simulated were very close to the observed hydrograph. It was also shown that ANN can simulate runoff with few days ahead or few hours ahead. This makes them useful for flood warning systems. Comparing the three ANNs investigated, it was found that REC performs slightly better than MLP but RBF performance is below expectation.
Hubungan antara kadarair dan hujan adalah antara fenomena hidrologi yang paling kompleks disebabkan sifat watershed yang berubah-ubah, pattern hujan serta bilangan input yang terlibat untuk memodelkan proses fisikal. Pakar-pakar hidrologi telah membina model secara Konseptual untuk medapatkan kadarair pada setiap jam, harian seta semusim. Namun, ia melibatkan parameter yang banyak dan interaksinya adalah amat merumitkan.

Artificial Neural Network (ANN) merupakan sistem yang memproseskan informasi yang mengandungi elemen atau neurons yang banyak, tidak linear dan berhubung-kait antara satu sama lain. ANN berupaya untuk mewujudkan hubungan antara input dan output tanpa diberi sifat-sifat fizik kepadanya. Sifat-sifat semulajadi hidrologi adalah amat bersesuaian untuk menggunakan ANN. Masa kini, ANNs telah digunakan untuk membina model kadarair-hujan, menganggar pier scour dan pemindahan sedimen serta membentuk rating curves.

Model kadarair-hujan di Sungai Bedup, Sarawak telah dibina dengan menggunakan tiga jenis network architectures iaitu Multilayer perceptron (MLP), Recurrent (REC) dan Radial Basis Function (RBF). Ketiga-tiga jenis network architectures telah digunakan untuk simulasi kadarair harian dan menjanakan hidrograf. Hujan antecedent, Kadarair antecedent serta hujan semasa digunakan sebagai input Manakala, outputnya adalah kadarair semasa. ANNs telah dilatih dengan menggunakan pelbagai training algorithms, pelbagai learning rates, panjang data yang berlainan dan bilangan hidden neurons yang berlainan. Semua data yang digunakan diperolehi daripada Jabatan Pengairan
dan Saliran (JPS), Sarawak. ANNs yang direkabentuk untuk simulasi kadaralir harian dan kadaralir sejam. ANNs juga turut mengimulasi kadalir harian pada beberapa hari ke hadapan dan kadaralir sejam pada beberapa jam ke hadapan. Ketepatanya diukur dengan menggunakan coefficient of correlation $R$ dan Nash-Sutcliffe coefficient $E^2$.

Keputusan ujikaji menunjukkan ANNs berupaya untuk mempamerkan ketepatan yang tinggi untuk kadaralir harian, $R=0.97$. Pada masa yang sama, hidrograf yang disimulasikan hampir serupa dengan hidrograf sebenar. Ini menunjukkan bahawa ANNs berupaya untuk simulasi kadaralir pada beberapa hari ke hadapan dan beberapa jam ke hadapan. Ini amat berguna sebagai flood warning system. Dengan membandingkan ketiga-tiga ANNs yang dikaji, didapati bahawa REC mempersembahkan keputusan yang lebih baik daripada MLP tetapi RBF mempamerkan keputusan di bawah jangkaan.
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LIST OF SYMBOLS

P  Rainfall
Q  Runoff
$u_k$  Linear combiner output
$x_j$  Input signals
$w_{kj}$  Synaptic weights
$\theta_k$  Threshold
$\phi_k$  Activation function
$y_k$  Output signal of a neuron
$\nu_k$  Activation potential
$n_i$  Neurons
$t_i$  Target value
$\eta$  Learning rate
$\alpha$  Decreasing learning rate
$s$  State of neuron
$\tau$  Time constant
$f$  Nonlinear activation function
$R$  Coefficient of Correlation
$E^2$  Nash-Sutcliffe Coefficient

MLPD1  MLP network for daily runoff simulation with 1 antecedent day
MLPD2  MLP network for daily runoff simulation with 2 antecedent days
MLPD3  MLP network for daily runoff simulation with 3 antecedent days
MLPD4  MLP network for daily runoff simulation with 4 antecedent days
MLPD5  MLP network for daily runoff simulation with 5 antecedent days
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RECH5  REC network for hourly runoff simulation with 5 antecedent hours
RECH10  REC network for hourly runoff simulation with 10 antecedent hours
RECH15  REC network for hourly runoff simulation with 15 antecedent hours
RECH24  REC network for hourly runoff simulation with 24 antecedent hours
RECH36  REC network for hourly runoff simulation with 36 antecedent hours
CHAPTER 1

INTRODUCTION

1.1 Introduction

From early times, human civilization has always been developed along rivers because of the need of irrigation for crops, water supply for communities and latter power generation. For example Bandar Kapit, Bandar Sarikei, Bandar Sibu and Bandar Bintangor along Rejang River, Sarawak. These advantages have been counterbalanced by the danger of floods which will destroy our properties, crops and sometimes even our lives. For civil engineers who are responsible for designing flood protection measures, they are required to plan engineering structures such as storage reservoirs, barrage and tidal control gates. Further as the flood wave passes through a river it is necessary to know how the stage varies with respect to time and distance for the design of river engineering works as well as for establishment and operation of flood warning systems by the civil authorities. For this purpose, predicting flood discharge magnitude accurately is very important.

For the past, conceptual models had provided daily, monthly and seasonal estimates of streamflow for short and long term forecasting in continuous basis. The entire physical process in the hydrologic cycle is mathematically formulated in the conceptual models. Thus, they are composed of a large number of parameters for example the Sacramento soil moisture accounting (SAC-SMA) model is defined by 22 parameters in addition to 12 parameters required by the potential evaporation, the number of water balance