

PARAMETER OPTIMIZATION METHODS FOR CALIBRATING TANK MODEL
AND NEURAL NETWORK MODEL FOR RAINFALL-RUNOFF MODELING

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ABSTRAK

Transformasi hujan kepada kadaralir melibatkan banyak komponen hidrologi yang kompleks dan pelbagai data hidrologi serta maklumat topografi. Data-data ini adalah sukar diperolehi dan tidak konsisten. Oleh itu, model tangki hidrologi dan *artificial neural networks* yang hanya memerlukan data hujan dan kadaralir telah dikemukakan. Kawasan kajian terpilih adalah Bedup Basin, Sarawak, Malaysia, satu tadahan luar bandar di dalam kawasan lembap. Kaedah *global optimization* terbaru yang dinamakan *particle swarm optimization* (PSO) telah dicadangkan dan dibandingkan dengan *shuffle complex evolution* dan *genetic algorithm* untuk mengkalibrasi parameter model tangki secara automatik. PSO juga dihibridkan dengan *neural networks* untuk membentuk *particle swarm optimization feedforward neural network* (PSONN) demi mengatasi masalah kadar penumpuan yang lambat dan masalah pemerangkapan pada *local minima*. Prestasi PSONN kemudiannya dibandingkan dengan *multilayer perceptron* dan *recurrent networks* yang menggunakan *backpropagation algorithm*. Prestasi model-model ini diukur dengan pekali korelasi (R) dan pekali *Nash-Sutcliffe* (E^2). Umumnya, prestasi *artificial neural networks* adalah lebih baik daripada model tangki. Keputusan kalibrasi model tangki mencerminkan kaedah PSO adalah yang terbaik berdasarkan keteguhannya, kebolehpercayaan, kecekapan, ketepatan dan kebolehubahan paling kecil dalam *boxplots*. *Shuffle complex evolution* merupakan kedua terbaik dan ketiga terbaik adalah *genetic algorithm* untuk simulasi kadaralir secara harian dan menurut jam. Antara *multilayer perceptron*, *recurrent* dan PSONN, *recurrent network* meramalkan kadaralir secara harian dan menurut jam dengan ketepatan paling tinggi, diikuti kedua terbaik oleh *multilayer perceptron* dan akhirnya PSONN. PSONN telah membuktikan keupayaannya untuk mensimulasikan kadaralir harian dan menurut jam dengan ketepatan yang boleh diterima. Kajian ini membuktikan kaedah kecerdikan buatan terutamanya PSO telah menawarkan satu kaedah yang lebih berkesan, mudah, murah, fleksibel dan sesuai untuk memodelkan proses ramalan banjir.

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LIST OF SYMBOLS

| | |
|---------------------|--|
| Q | - discharge in m ³ /s |
| H | - stage discharge in m |
| N | - size of a chromosome population |
| P_c | - crossover probability |
| P_m | - mutation probability |
| m | - number of points in each complex |
| n | - dimension of the problem |
| q | - number of points |
| α | - number of repeating |
| β | - competitive complex evolution included in the SCE method |
| p | - number of complexes |
| s | - sample size |
| f_i | - function value |
| p_i | - highest probability |
| p_m | - lowest probability |
| V_i | - current velocity |
| Δt | - discrete time interval |
| V_{i-1} | - previous velocity |
| <i>presLocation</i> | - present location of the particle |
| <i>prevLocation</i> | - previous location of the particle |
| <i>rand()</i> | - random number between (0, 1) |
| c_1 | - acceleration constants for “gbest” |
| c_2 | - acceleration constants for “pbest” |
| V_{max} | - maximum velocity allowed |
| ω | - inertia |

| | |
|-------------------|---|
| C1 | - surface runoff coefficient No.1 |
| C2 | - surface runoff coefficient No.2 |
| C3 | - infiltration coefficient from surface tank to intermediate tank |
| C4 | - intermediate runoff coefficient |
| C5 | - infiltration coefficient from intermediate tank to sub-base tank |
| C6 | - sub-base runoff coefficient |
| C7 | - infiltration coefficient from sub-base tank to base tank |
| C8 | - base runoff coefficient |
| X1 | - height of surface runoff No.2 from surface tank |
| X2 | - height of surface runoff No.1 from surface tank |
| OLS | - ordinary least squares |
| D | - number of particles |
| x_j | - signal at the input of synapse j |
| w_{kj} | - synaptic weight for synapse j connected to neuron k |
| Σ | - summing the input signals weighted by the respective synapses of the neuron |
| $IW_{1,1}$ | - input weight matrices |
| a_1 | - hidden neurons's output |
| b_1 | - sum of bias of hidden layer |
| $LW_{2,1}$ | - layer weights |
| a_2 | - neurons's output |
| b_2 | - sum of bias of output layer |
| TRAINS CG | - Scaled Conjugate Gradient |
| TRAIN GDX | - Variable Learning Rate Backpropagation |
| TRAIN CGB | - Powell-Beale Restarts |
| MSE | - Mean Square Error |
| $P(t-1)...P(t-n)$ | - antecedent total precipitation |
| $P(t)$ | - total rainfall of the current day or hour |
| $Q(t-1)...Q(t-n)$ | - antecedent discharges |
| $Q(t)$ | - current runoff |
| R | - Coefficient of Correlation |

| | |
|----------------|--|
| E ² | - Nash-Sutcliffe Coefficient |
| AI | - Artificial Intelligence |
| GOMs | - Global Optimization Methods |
| ANNs | - Artificial Neural Networks |
| PSO | - Particle Swarm Optimization |
| SCE | - Shuffle Complex Evolution |
| GA | - Genetic Algorithm |
| MLP | - Multilayer Perceptron |
| REC | - Recurrent |
| PSO-NN | - Particle Swarm Optimization Feedforward Neural Network |

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CHAPTER 1

INTRODUCTION

1.1 Background of Study

Rainfall-runoff relationships are widely reported by many hydrologists as the most complex hydrologic phenomena to comprehend due to the tremendous spatial and temporal variability of watershed characteristics and rainfall patterns (Tokar and Markus, 2000). The transformation of rainfall to runoff for streamflow forecasting remain important to the hydrologists for the purpose of water supply, flood control, irrigation, drainage, water quality, power generation, recreation, aquatic and wildlife propagation. Such transformation involves many highly complex components including interception, depression storage, infiltration, overland flow, interflow, percolation, evaporation and transpiration.

In general, various types of methods have been used in runoff estimation including conceptual and statistical models. Most of the research studies found that none of these methods can be considered as a single superior model (Irwan *et al.*, 2007). Owing to the complexity of the hydrological process, the accurate runoff is difficult to be predicted using the linear recurrence relations or physically based watershed model. The linear recurrence relation model does not attempt to take into

account the nonlinear dynamic of hydrological process. The physically based watershed model also ignores the stochastic behavior underlying any hydrosystem. Besides, despite the application of deterministic models include all physical and chemical processes, the successful employment is restricted by a need for catchment-specific data and simplifications involved in solving the governing equations. It has been recognized that the application of time series methods may be complicated by non-stationary and non-linearity in the data, requiring experience and expertise from the modeller.

Besides, the conventional models require a great detailed data such as topographical map, river networks and characteristics, soil characteristics, rainfall, runoff, temperature, interception, depression storage, overland flow, interflow, evapotranspiration, infiltration, percolation, antecedent moisture content for simulating runoff accurately (Imrie *et al.*, 2000). Concurrently, runoff also depends on catchment topography, river network, river cross-sections, soil characteristics and antecedent moisture (Gautam *et al.*, 2000). Moreover, the antecedent moisture is changing frequently and depends upon immediate hydrological and meteorological condition of the catchment. Often, these data are hard to obtain and not all the time available. The database may suffer from the problem of missing data due to the failure of gauging equipment. All these non-stationary and non-linearity of meteorological phenomena make the accurate estimation of runoff become very complex and difficult.

Furthermore, the newly developed watershed hydrologic model required various types of data including hydrometeorologic, geomorphologic, agricultural, pedologic, geologic and hydrologic (Vijay and David, 2002). . Some of these data can only obtained through latest technology such as remote sensing and space technology, digital terrain and elevation models, chemical tracers, and it is expensive to obtain these data through the latest technology.

This study is therefore, an attempt to develop rainfall-runoff using only rainfall and runoff data. Two hydrologic models are proposed, named as Hydrologic Tank model and Artificial Neural Networks (ANNs) model.

The proposed hydrologic tank, one of the world famous surface water runoff analysis models, was developed by Sugawara and Funiyuki (1956). Many hydrologists are using this model due to its simplicity of concept and computation while achieving forecasting accuracy comparable with more sophisticated models. Tank model is mainly applied to forecast flood levels (Huang *et al.*, 2006; Sothea *et al.*, 2006).

Meanwhile, the proposed ANNs models are widely used as an efficient tool in different areas of water related activities. The natural behavior of hydrological processes is complex, non-linear and dynamic systems for which there are large amount of noisy data is appropriate for the application of ANNs method. ANNs had successfully applied in hydrologic modeling, such as for modeling of rainfall-runoff relationship (Hsu *et al.*, 1995; Mins and Hall, 1996; Dawson and Wilby, 1998; Harun, 1999); water demand forecasting; rainfall forecasting; assessment of stream's hydrologic and ecologic response to climate change (Roger and Dowla, 1994); sediment transport prediction (Poff *et al.*, 1996); pier scour estimation (Tokar, 1996); groundwater remediation (Markus, 1997) and stage-discharge relationship. The ANNs was also applied for prediction of carbon monoxide as one of primary air pollutants (Abbaspour *et al.*, 2005), forecasting the mean monthly total ozone concentration (Bandyopadhyay and Chattopadhyay, 2007) and evaluating performance of immobilized cell biofilter treating hydrogen sulphide vapors (Rene *et al.*, 2008).

1.2 Statement of the Problem

A major difficulty in the application of tank model is related issue mainly faced by many researchers is the model calibration since most of these models involve a large number of parameters. These parameters usually obtained by calibration, not directly measured in field. The only method for tank model calibration in early days is using manual trial and error method. This method required much time and effort to obtain better results owing to the need of calibrating a large number of parameters in the model. The success of it depends on the expertise of the modeler with prior knowledge of the watershed being modeled. This tedious nonlinear structure calibration process sometime may produce uncertainty results due to the subjective factors involved. Therefore, there is a need to develop an effective and efficient automatic calibration procedure.

Automatic calibration involves the use of a search algorithm to determine best-fit parameters. It is highly desirable as it is faster, less subjective and due to extensive search of parameter possibilities. Two important stages of calibration are parameter specification and parameter estimation. In parameter specification stage, the parameters that need to be adjusted are selected. In the parameter estimation stage, the optimal or near optimal values for the parameters are found (Sorooshian and Gupta, 1995). In this study, a new approach named as Particle Swarm Optimization (PSO) is applied to automatically search for optimal parameters in tank model. The results obtained is then compared with the one calibrated with famous Shuffle Complex Evolution (SCE) and Genetic Algorithm (GA) methods.

Meanwhile, ANNs offer a relatively fast and flexible means of hydrologic modeling. When reviewed the application of ANNs in hydrology over the years, Coulibay *et al.* (2000) reported that 90% of the researches are using multilayer feedforward neural network (MLP) trained by standard backpropagation algorithm (BPNN). However, according to Baldi and Hornik (1989), Mulenbein (1990), Sima

(1989) and Zweiri *et al.* (2003), although BPNN proved to be efficient in some applications, its convergence rate is relatively slow and often trap at local minima.

BPNN learning basically is a hill climbing technique. The weights and biases for BPNN networks are trained using backpropagation technique, which involves performing computations backwards through the network. BPNN networks update weights and biases in the direction of the negative gradient. Therefore, there is a risk of being trapped in local minima, where the network is stuck and another set of synaptic weight were exist for which the cost function is smaller than the local minimum in the weight space. This caused BPNN unable to terminate the learning process at a local minimum.

Thus, neural network was proposed to couple with Particle Swarm Optimization (PSO) to form Particle Swarm Optimization Feedforward Neural Network (PSONN). PSONN was selected since the input pattern is propagated from the network input to the network output through feedforward pass. Weight and bias in PSONN that are represented by particles position, are updated using movement equation and velocity update equation for searching “pbest” and “gbest” values. The ‘gbestparticle’ that represent the best set of weights and biases will be recorded. Thus, the feedforward pass in PSONN will ensure that the network will not stuck at local minima and only global minima will be obtained. The result obtained is then compared with Multilayer Perceptron Network (MLP) and Recurrent Network (REC).

1.3 Study Objectives

The main aim is to explore and establish the methodology of daily and hourly rainfall-runoff modeling in a rural catchment using various artificial intelligence (AI) methods. The probabilistic automatic optimization techniques are applied. The specific objectives are outlined as follows:

- a) To investigate the feasibility and accuracy of the hydrologic tank model and ANNs model using only rainfall and runoff data.
- b) To develop the probabilistic automatic calibration method of the hydrologic tank models based on PSO, SCE and GA algorithms.
- c) To develop a rainfall-runoff model based on hybrid of PSO and ANNs algorithms.
- d) To evaluate and compare the performance of the proposed models applied in a rural catchment in humid region.

1.4 Research Approach and Scope of Work

The scope of this thesis is divided into two parts. The first part is to determine the best number of tanks to simulate runoff accurately for both daily and hourly simulation. Then the parameters for best number of tank determined previously were calibrated automatically using three GOMs named as PSO, SCE and GA techniques. These three GOMs techniques will evaluate the feasibility and accuracy of optimizing the 10 parameters in tank model automatically.

The second part of work is developing the rainfall-runoff model using ANNs methods. Three types of ANNs network architecture were selected namely MLP,

REC and PSONN. The feasibility and accuracy of the proposed MLP, REC and PSONN were tested and compared.

The selected study area that can represent a rural catchment in humid region is Bedup Basin, Sub-basin of Sadong Basin, Sarawak, Malaysia. At the end of the thesis, comparison and conclusion were conducted to determine the most suitable model, between tank model and ANNs model for modeling daily and hourly runoff on a rural catchment in humid region. The models performance are compared in the aspect of robustness, accuracy, complexity, computation time, flexibility, adaptability, efficiency and reliability. The best algorithm for calibrating tank model parameters for both daily and hourly runoff simulation was evaluated and determined. Finally, the capability of three ANNs investigated named as MLP, REC and PSONN to model daily and hourly runoff simulation were analyzed.

1.5 Significance of the Study

This study is important to develop a most suitable and appropriate rainfall-runoff model using only rainfall and runoff data for rural catchment in humid region. It is a study related to prediction of runoff is definitely significant in Malaysia, where floods and droughts have great economic impacts. The data used is only rainfall and runoff as most of the hydrological stations in Sarawak are recording rainfall and water level only. The current numbers of rainfall stations throughout Sarawak are 283, and 58 for water level stations.

The Sarawak government is planning to construct twelve mini hydro dams for supplying electricity power particularly in remote area, apart from the Bakun hydro dam, which is the biggest in Malaysia. The flood event occurs quite frequently

in several areas in Sarawak and it is believed that this is due to rapid development and climate change. Currently, the Hydrology and Water Resources Branch, Department of Irrigation and Drainage (DID), Sarawak is looking for a more accurate and reliable flood forecasting model. Therefore, there is an urgent need to develop a reliable and suitable daily and hourly rainfall-runoff model in Sarawak.

Recognizing the role of DID in meeting its customer's satisfaction in line with the Government's directive, these newly developed rainfall-runoff models are able to forecast the daily and hourly runoff accurately in all the river basins. The accuracy of the hourly forecasting results are very important since it provides an early warning signal to the authorities to take the necessary flood preventive measures before the flood is occurring. Meanwhile, daily runoff simulation is important for designing water resources and reservoir projects.

Generally, this research is part of the pro-active approaches that can be adopted by hydrologists and researchers to model rainfall runoff relationship using only rainfall and runoff data, particularly in humid region.

1.6 Structure of the Thesis

This thesis consists of six chapters. The first chapter presents the background of study, statement of problem, study objectives, research approach and scope of work, significance of study and structure of the thesis. Review of the runoff process for rural catchment, various types of hydrologic component models that developed throughout the years, review of the proposed rainfall-runoff model in this study named as hydrologic tank model and ANNs model, relevant past studies of

automatic calibration of tank model's parameters and calibration of ANNs model are presented in Chapter 2.

Chapter 3 presents the research methodology for this study. The selected study area, methodology for selecting best number of tanks, sensitivity analysis for parameters investigated, model development and validation for optimizing tank model's parameters using PSO, SCE, GA approaches, model development and learning mechanism for MLP, REC and PSONN networks for both daily and hourly runoff simulation are discussed in Chapter 3.

Results and discussion for daily runoff simulation for determining best number of tanks, sensitivity analysis for calibrated parameters, the calibration process and optimal results obtained for PSO, SCE, GA approaches, calibration process and optimal configuration for MLP, REC and PSONN networks for daily runoff simulation are presented in Chapter 4. A similar results and discussion for hourly runoff simulation are presented in Chapter 5. Finally, conclusions from the present study on the proposed models are summarized and recommendations for future studies are outlined in Chapter 6.

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