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

KUOK KING KUOK

UNIVERSITI TEKNOLOGI MALAYSIA

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

KUOK KING KUOK

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Civil Engineering)

Faculty of Civil Engineering
Universiti Teknologi Malaysia

AUGUST 2010

ACKNOWLEGEMENT

I wish to express my sincere appreciation to my main thesis supervisor, Associate Professor Dr. Sobri Harun from Faculty of Civil Engineering, UTM, for all the invaluable excellent guidance, technical support, encouragement, concern, critics, advices and friendship. I am also very thankful to my co-supervisors, Professor Dr. Siti Mariyam Shamsuddin from Faculty of Computer System and Information System, UTM for her technical support, guidance, advices and motivation. Certainly, this thesis would not have been the same as presented here without their continued support, guidance and interest. My sincere appreciation also extends to Professor Van Thanh Van Nguyen from McGill University, Canada for his technical support, supplying relevant literatures and information at the beginning of this project. Last but not least, I am deeply grateful to my lovely family members for their unconditional supports and encouragements from the beginning of this project until the end. Thanks.

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 network*s 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.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

Q	-	discharge in m^3/s
H	-	stage discharge in m
N	-	size of a chromosome population
Pc	-	crossover probability
Pm	-	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
presLocation	-	present location of the particle
prevLocation	-	previous location of the particle
rand()	-	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
$\sum$	-	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
TRAINSCG	-	Scaled Conjugate Gradient
TRAINGDX	-	Variable Learning Rate Backpropagation
TRAINCGB	-	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
PSONN	-	Particle Swarm Optimization Feedforward Neural Network

LIST OF APPENDICES

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 algorithmn (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 catachment 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.

REFERENCES

Abbaspour, M., Rahmani, A.M. and Teshnehlab, M. (2005). Carbon Monoxide Prediction using Novel Intelligent Network. *International Journal of Environmental Science and Technology, IJEST.* Volume 1, Number 4, Winter 2005, Article 2.

Abbott, M. B., Bathurst, J. C., Cunge, J. A., O'Connell, P. E. and Rasmussen, J. (1986a). An Introduction to the European Hydrologic System-Systeme Hydrologique Europeen, SHE, 1: History and Philosophy of a Physically-Based, Distributed Modeling System. *J. Hydrol.* 87, 45–59.

Abbott, M. B., Bathurst, J. C., Cunge, J. A., O'Connell, P. E. and Rasmussen, J. (1986b). An Introduction to the European Hydrologic System-Systeme Hydrologique Europeen, SHE, 2: Structure of a Physically-Based, Distributed Modeling System. *J. Hydrol,* 87, 61–77.

Alexandre, M. B. and Darrell, G. F. (2006). A Generalized Multiobjective Particle Swarm Optimization Solver for Spreadsheet Models: Application to Water Quality. *Hydrology Days 2006*, 1-12

Al-kazemi, B. and Mohan, C.K. (2002). Training Feedforward Neural Network Using Multi-phase Particle Swarm Optimization. *Proceedings of the 9th International Conference on Neural Information Processing*, New York.

Ashlock, D. (2006). *The Evolutionary Computation for Modeling and Optimization*. Springer.

Baldi, P. and Hornik, K. (1989). Neural Networks and Principal Component Analysis: Learning from Examples without Local Minima. *Neural Networks.* 2, 53-58.

Bandyopadhyay, G. and Chattopadhyay,S. (2007). Single Hidden Layer Artificial Neural Network Models versus Multiple Linear Regression Model in Forecasting the Time Series of Total Ozone. *International Journal of Environmental Science and Technology, IJEST.* Volume 4, Number 1, Winter 2007, Article 18.

Barnes, B. S. (1940). Discussion on Analysis of Runoff Characteristics by O. H. Meyer. *Trans. Am. Soc. Civ. Eng.* 105, 104–106.

Bathurst, J. C., Wicks, J. M., and O'Connell, P. E. (1995). Chapter 16: The SHE/SHESED Basin Scale Water Flow and Sediment Transport Modeling System. *Computer Models of Watershed Hydrology*, V. P. Singh, ed., Water Resources Publications, Littleton, Colo. 563–594.

Becker, R.W., and Lago, G.V. (1970). A Global Optimization Algorithm. *Proceedings of the 8th Allerton Conference on Circuits and System Theory,* Monticello, Illinois, pp. 3-12.

Beven, K. J., and Kirkby, M. J. (1979). A Physically-Based Variable Contributing Area Model of Basin Hydrology. *Hydrol. Sci. Bull.* 24(1), 43–69.

Bishop,C.M. (1995). *Neural Networks for Pattern Recognition*. Chapter 7, pp.253-294. Oxford University Press.

Bong, S. J. and Bryan, W. K. (2006). Hydraulic Optimization of Transient Protection Devices Using GA and PSO Approaches. *Journal of Water Resources Planning and Management © ASCE* / January/February 2006:44-54

Brazil, L. E., and Krajewski, W. F. (1987). Optimization of Complex Hydrologic Models using Random Search Methods. *Proc., ASCE Conf. on Engineering Hydrology*, Williamsburg, New York, 726–731.

Brazil, L. E. (1988). Multilevel Calibration Strategy for Complex Hydrologic Simulation Models. *PhD dissertation Colorado State Univ*., Fort Collins, Colo.

Burnash, R. J. C., Ferral, R. L., and McGuire, R. A. (1973). *A Generalized Streamflow Simulation System - Conceptual Modeling for Digital Computers*. U.S. Dept. of Commerce, National Weather Service, Silver Springs, Md., and State of California, Dept. of Water Resources, Sacramento, Calif.

Chen, J.Y., and Barry, J. A. (2006). Semidistributed Form of the Tank Model Coupled with Artificial Neural Networks. *Journal of Hydrologic Engineering*, Vol. 11, No. 5, September 1, 2006. ©ASCE: 408-417

Chen, R.S., Pi, L.C., and Hsieh, C.C. (2005). A Study on Automatic Calibration of Parameters in Tank Model. *Journal of the American Water Resources Association (JAWRA)*, April, 2005: 389-402.

Cheok, H.S. (2005). *Development of a PC-Based Tank Model Real-Time Flood Forecasting System*. MEng. Thesis, Universiti Teknologi Malaysia.

Clarke, R. T. (1973). A Review of Some Mathematical Models used in Hydrology, with Observations on their Calibration and Use. *J. Hydrol.,*19, 1–20.

Cooper, V.A., Nguyen, V-T-V. and J.A. Nicell (1997). Evaluation of Global Optimization Methods for Conceptual Rainfall-Runoff Model Calibration. *Water Sci. Technol*. 36(5):53-60.

Cooper, V**.,** Nguyen, V-T-V. and Nicell, J. (2007). Calibration of Conceptual Rainfall-Runoff Models using Global Optimization Methods with Hydrologic Process-based Parameter Constraints. *Journal of Hydrologic*, Vol. 334, No. 3-4, pp. 455-466.

Coulibaly, P., Anctil, F., and Bobee, B. (2000). Daily Reservoir Inflow Forecasting Using Artificial Neural Networks with Stopped Training Approach. *Journal of Hydrology*, 230: 244-257.

Crawford, N. H., and Linsley, R. K. (1966). Digital Simulation in Hydrology: Stanford Watershed Model IV. *Tech. Rep. No. 39*, Stanford Univ., Palo Alto, Calif.

Cummings, N. W. (1935). Evaporation from Water Surfaces: Status of Present Knowledge and Need for Further Investigations. *Trans., Am. Geophys. Union,* 16(2), 507–510.

Cybenko, G. (1989). Approximation by Superposition of a Sigmoidal Function. *Math. Control Systems Signals*, 2(4):303{314, 1989.

Dastorani, M.T., and Wright, N.G. (2001). River Flood Prediction Using Artificial Neural Networks (ANN) and Hydraulic Models (HM). http://www.civeng.nottingham.ac.uk/efm/project/dastorani.htm.

Dawdy, D. R., and O'Donnell, T. (1965). Mathematical Models of Catchment Behavior. *J. Hydraul. Div., Am. Soc. Civ. Eng.,* 91(HY4), 123–127.

Dawson, C. W., and Wilby, R. (1998). An Artificial Neural Network Approach to Rainfall–Runoff Modeling. *Hydrol. Sci. J.* 43 (1), 47–66.

Demuth, H., and Beale, M. (2004). *Neural Network Toolbox - For Use With MATLAB*. The Math Works, Inc.

Dibike, Y.B, and Solomatine, D.P. (1999). River Flow Forecasting Using Artificial Neural Networks. *EGS Journal of Physics and Chemistry of the Earth*.

DID (2004). *Hydrological Year Book Year 2004.* Department of Drainage and Irrigation Sarawak, Malaysia.

Diskin, M. H., and Simon, E. (1977). A Procedure for the Selection of Objective Functions for Hydrologic Simulation Models. *J. Hydrol,* 34, 129–149.

Dixon, L.C.W., and Szego, G.P. (1978). *The Global Optimization Problem: An Introduction, Toward Global Optimization 2*. Edited by L.C.W. Dixon and G.P. Szego, North Holland, Amsterdam, Holland, pp. 1-15.

DOA (1975). *Jabatan Pertanian Malaysia*. Scale 1:50,000

Dooge, J. C. I. (1959). A General Theory of the Unit Hydrograph. *J. Geophys. Res.,* 64(2), 241–256.

Duan, Q., Gupta, V. K., and Sorooshian, S. (1992). Effective and Efficient Global Optimization for Conceptual Rainfall-Runoff Models. *Water Resour. Res.* 28, 1014–1015.

Duan, Q., Gupta, V. K., and Sorooshian, S. (1993). A Shuffled Complex Evolution Approach for Effective and Efficient Global Minimization. *J.Optim. Theory Appl.* 76, 501–521.

Eberhart, R. and Hu, X. (1999). Human Tremor Analysis using Particle Swarm Optimization. *Proceedings of IEEE Congress on Evolutionary Computation, CEC*. Washington.

Eberhart, R. and Shi, Y. (2001). Particle Swarm Optimization: Developments, Application and Resources. *IEEE*: 81-86.57

Eckhardt, K. and J.G. Arnold. 2001. Automatic calibration of a distributed catchment model. *J. Hydrol.* (251)1-2 (2001): 103-109.

Elshorbagy, A., Simonovic , S.P., and Panu, U.S. (2000). Performance Evaluation of Artificial Neural Networks for Runoff Prediction. *Journal of Hydrologic Engineering*, 5(4): 424-427.

Fair, G. M., and Hatch, L. P. (1933). Fundamental Factors Governing the Streamline Flow of Water through Sand. *J. Am. Water Works Assoc.* 25, 1551–1565.

Ferguson, D. (2004). *Particle Swarm*. University of Victoria, Canada.

Gan, T. Y., and Biftu, G. F. (1996). Automatic Calibration of Conceptual Rainfall-Runoff Models: Optimization Algorithms, Catchment Conditions, and Model Structure. *Water Resour. Res.* 32, 3513–3524.

Garcia-Bartual, R (2002). Short Term River Flood Forecasting with Neural Networks. *Universidad Politecnica de Valencia, Spain,* 160-165.

Gautam, M.R., Watanabe, K., and Saegusa, H., (2000). Runoff Analysis in Humid Forest Catchment with Artificial Neural Networks. *Journal of Hydrology*. 235: 117-136.

Gen, M.S. and Cheng, R.W. (1997). *Genetic Algorithm And Engineering Design*. John Willey and sons, inc.

Green, W. H., and Ampt, C. A. (1911). Studies on Soil Physics: 1. Flow of Water and Air through Soils. *J. Agric. Sci.* 4, 1–24.

Gupta, H. V., Sorooshian, S., and Yapo, P. O. (1998). Toward Improved Calibration of Hydrologic Models: Multiple and Noncommensurable Measures of Information. *Water Resour. Res.* 34(4), 751–763.

Hagan, M. T., Demuth, H. B., and Beale, M. (1996). *Neural Network Design.* PWS/Kent Publishing Co., Boston.

Halff, A.H., Halff, H.M., and Azmoodeh, M. (1993). Predicting Runoff from Rainfall using Neural Network. *Proc., Engrg, Hydrol., ASCE*, New York, 760-765.

Hamby, D.M. (1994). A Review of Techniques for Parameter Sensitivity Analysis of Environmental Models. *Journal of Environmental Monitoring*. 32(2). 135-154

Harun, S., Kassim, A.H., and Nguyen, V.T.N. (1996). Inflow Estimation with Neural Networks.*10th Congress of The Asia and Pacific Division of the International Association for Hydraulic Research.*150-155.

Harun, S. (1999). *Forecasting and Simulation of Net Inflows for Reservoir Operation and Management*. Ph.D dissertation, Universiti Teknologi Malaysia.

Harun, S., Kassim, A.H., and Nor Ahmat, N.I. (2002). Rainfall-Runoff Modelling Using Artificial Neural Network. *2nd World Engineering Congress*, 19-23.

Haykin, S. (1994). *Neural Networks – A Comprehensive Foundation.* Macmillan College Publishing Company, Inc. United States of America.

Haza, N. (2006). *Particle Swarm Optimization for Neural Network Learning Enhancement*. MSc. Thesis, Universiti Teknologi Malaysia.

Hewlett, J. D. (1961a). Some Ideas about Storm Runoff and Base Flow. *Southeast Forest Experiment Station Annual Rep.*, USDA Forest Service, Athens, Ga., 62–66.

Hewlett, J. D. (1961b). Soil Moisture as a Source of Base Flow from Steep Mountain Watersheds. *Southeast Forest Experimental Station Paper No. 132*, USDA Forest Service, Athens, Ga.

Hjelmfelt, A.T., and Wang, M. (1993). Runoff Hydrograph Estimation using Artificial Neural Networks. *Proc., ASAE Conference, American Society of Agricultural Engineers*, St. Joseph, Mich.

Holland, J.H. (1975). *Adaptation in Natural and Artificial Systems*. University of Michigan Press, Ann Arbor.

Hoover, M. D., and Hursh, C. R. (1943). Influence of Topography and Soil-Depth on Runoff from Forest Land. *Trans., Am. Geophys. Union,* 24, 693–697.

Hornik, K., Stinchcombe, M. and White, H., (1989). Multilayer Feedforward Networks are Universal Approximators. *Neural Networks, 2*, 395-403, 1989.

Horton, R. E. (1919). Rainfall Interception. *Monthly Weather Rev.,*147, 603–623.

Horton, R. E. (1933). The Role of Infiltration in the Hydrologic Cycle. *Trans., Am. Geophys. Union,* 145, 446–460.

Horton, R. E. (1935). Surface Runoff Phenomena, Part 1—Analysis of Hydrograph.'' *Horton Hydrology Laboratory Publication No. 101*, Voorheesville, N.Y.

Horton, R. E. (1939). Analysis of Runoff Plot Experiments with Varying Infiltration Capacities. *Trans., Am. Geophys. Union* 20(IV), 683–694.

Horton, R. E. (1940). An Approach toward a Physical Interpretation of Infiltration Capacity. *Soil Sci. Soc. Am. Proc.,* 5, 399–417.

Horton, R. E. (1945). Erosional Development of Streams and their Drainage Basins: Hydrophysical approach to Quantitative Geomporphology. *Bull. Geol. Soc. Am.,* 56, 275–370.

Hsu, K. L., Gupta, H. V., and Sorooshian, S. (1995). Artificial Neural Network Modeling of the Rainfall-Runoff Process. *Water Resour. Res.,* 31(10), 2517–2531.

Huang, M.C., Xie, J.C., Cai, Y., Wang, N. and Zhang, Y.J. (2006). Application of Middleware Technique in Web of Flood Forecasting System with Multiple Models. *2006 International Conference on Hybrid Information Technology (ICHIT'06), IEEE Computer Society*.

Hursh, C. R. (1936). Storm Water and Absorption. *Trans., Am. Geophys. Union,* 17(II), 301–302.

Hursh, C. R. (1944). Appendix B - Report of the Subcommittee on Subsurface Flow. *Trans., Am. Geophys. Union,* 25, 743–746.

Hursh, C. R., and Brater, E. F. (1944). Separating Hydrographs into Surface- and Subsurface-Flow. *Trans., Am. Geophys. Union,* 25, 863–867.

Hydrologic Engineering Center (HEC). (1968). HEC-1 Flood Hydrograph Package, User's Manual. *U.S. Army Corps of Engineers*, Davis, Calif.

Imrie, C.E., Durucan, S. and Korre, A. (2000). River Flow Prediction Using Artificial Neural Networks: Generalization Beyond the Calibration Range. *Journal of Hydrology*, 233: 138-153.

Irwan, A. N., Harun, S., and Kassim A.H. (2007). Radial Basis Function Modeling of Hourly Streamflow Hydrograph. *Journal of Hydrologic Engineering* © *ASCE* / Vol. 12, No. 1, January 1, 2007: 113-123

Jacob, C. E. (1943). Correlation of Groundwater Levels and Precipitation on Long Island, New York: 1. Theory. *Trans., Am. Geophys. Union* 24, 564–573.

Jacob, C. E. (1944). Correlation of Groundwater Levels and Precipitation on Long Island, New York: 2. Correlation of data. *Trans., Am. Geophys. Union,* 24, 321–386.

Janga, M. R. and Nagesh, D. K. (2007). Multi-Objective Particle Swarm Optimization for Generating Optimal Trade-Offs in Reservoir Operation. *Hydrological Processes.* 21: 2897–2909. Published online 10 January 2007 in Wiley InterScience.

John, D.H. and Wade, L.N. (1969). *Outline of Forest Hydrology*. School of Forest Resources, University of Georgia, Athens, Georgia.

Jones M.T (2005). *AI Application Programming*. 2nd Ed. Hingham, Massachusetts.

JUPEM (1975). *Jabatan Ukur dan Pemetaan Malaysia*. Scale 1:50,000

Kawasaki, R. (2003). Application of Synthetic Tank Model Simulation on the Area with Poor Basic Hydrological Data Availability. *Japan Society of Shimanto Policy and Integrated River Management*, Vol 2-2, pp 18-19.

Kennedy, J. and Eberhart, R. (1995). Particle Swarm Optimization. *Proceedings IEEE Int'l Conf. on Neural Networks (Perth, Australia), IEEE Service Center,* Piscataway, NJ, IV: 1942-1948.

Keulegan, G. H. (1944). Spatially Variable Discharge over a Sloping Plane. *Trans., Am. Geophys. Union,* 25(VI), 959–965.

Kostiakov, A. M. (1932). On the Dynamics of the Coefficient of Water Percolation in Soils and of the Necessity of Studying it from a Dynamic Point of View for Purposes of Amelioration. *Trans. 6th Communic., Int. Soil Science Society*, Part 1, 17–29. (Russia)

Kuczera, G. (1983a). Improved Parameter Inference in Catchment Models. 1: Evaluating parameter uncertainty. *Water Resour. Res.* 19, 1151–1162.

Kuczera, G. (1983b). Improved Parameter Inference in Catchment Models. 2: Combining Different Kinds of Hydrologic Data and Testing their Compatibility. *Water Resour. Res.* 19, 1163–1172.

Kuczera, G. (1997). Efficient Subspace Probabilistic Parameter Optimization for Catchment Models. *Water Resour. Res.* 19, 1163–1172.

Lauzon, N., Rousselle, J., Birikundavyi, S., and Trung, H.T. (2000). Real-time Daily Flow Forecasting Using Black-box Models, Diffusion Processes and Neural Networks. *Can. J. Civ. Eng*. 27: 671-682.

Leavesley, G. H., Lichty, R. W., Troutman, B. M., and Saindon, L. G. (1983). Precipitation-Runoff Modeling System User's Manual. *USGS Water Resources Investigations Rep. No. 83-4238*, Denver.

Lee, J. S., Lee, S., Chang, S. and Ahn, B. H. (2005). A Comparison of GA and PSO for Excess Return Evaluation in Stock Markets. *Springer-Verlag*: 221-230.

Lenhart, T., Eckhardt, K., Fohrer, N., and Frede, H.G. (2002). Comparison of Two Different Approaches of Sensitivity Analysis. *Journal of Physics and Chemistry of Earth*, 27(9-10), 645-654.

Lighthill, M. J., and Whitham, G. B. (1955). On Kinematic Waves: 1. Flood Movement in Long Rivers. *Proc. R. Soc. London, Ser. A,* 229, 281–316.

Liong, S.Y., Cheu R.L., and Chan W.T. (1996). An Excellent Flow Forecasting Tool: Neural Network. *10th Congress of The Asia and Pacific Division of the International Association for Hydraulic Research,*156-163.

Lowdermilk, W. C. (1934). Forests and Streamflow: A Discussion of Hoyt-Trozell Report. *J. Forestry,* 21, 296–307.

Luce, C. H., and Cundy, T. W. (1994). Parameter Identification for a Runoff Model for Forest Roads. *Water Resour. Res.,* 30, 1057–1069.

Markus, M. (1997). *Application of Neural Networks in Streamflow Forecasting*. PhD dissertation, Colorado State University, Fort Collins, Colo.

McCarthy, J. (1956). Artificial Intelligence. *Workshop on Dartmouth Summer Research Conference on Artificial Intelligence, USA.*

Metcalf and Eddy, Inc., Univ. of Florida, and Water Resources Engineers, Inc. (1971). *Storm Water Management Model, Vol. 1—Final Report.* EPA Rep. No.11024DOC07/71 (NITS PB-203289), EPA, Washington, D.C.

Minns, A. W., and Hall, M. J. (1996). Artificial Neural Networks as Rainfall-Runoff Models. *Hydrol. Sci. J.,* 41(3), 399–417.

Mitchell, M. (1998). An Introduction to Genetic Algorithms, *MIT Press*, Cambridge, Massachusetts. 1998.

Morris, E. M. (1980). Forecasting Flood Flows in Grassy and Forested Basins using a Deterministic Distributed Mathematical Model. *IAHS Publication No. 129 (Hydrological Forecasting), International Association of Hydrological Sciences,* Wallingford, U.K., 247–255.

Mulenbein, H. (1990). Limitations of Multi-Layer Perceptron Networks-Steps towards Genetic Neural Networks. *Parallel Computing* 14, 249-260.

Nash, J. E. (1957). The Form of the Instantaneous Unit Hydrograph. *Hydrol. Sci. Bull.* 3, 114–121.

Negnevitsky M. (2002). *Artificial Intelligence*. Addison Wesley, Pearson Education Limited, England.

Nelder, J.A., and Mead, R. (1965). A Simplex Method for Function Minimization. *Computer Journal*, Vol. 7, pp. 308-313.

Nielsen, D. R., Kirkham, D., and van Wijk, W. K. (1959). Measuring Water Stored Temporarily above the Field Moisture Capacity. *Soil Sci.Soc. Am. Proc.,* 23, 408–412.

Nishimura, S. and Kojiri, T. (1996). Real-time Rainfall Prediction Using Neural Network and Genetic Algorithm with Weather Radar Data, *10th Congress of the Asia and Pacific Division of the International Association for Hydraulic Research*, 204-211.

Paik, K., Kim, J.H., and Lee, D.R. (2005). A Conceptual Rainfall-runoff Model Considering Seasonal Variation. *Wiley InterScience* 19:3837-3850.

Penman, H. L. (1948). Natural Evaporation from Open Water, Bare Soil and Grass. *Proc. R. Soc. London, Ser. A,* 193, 120–145.

Poff, L.N., Tokar, A.S., and Johnson, P.A. (1996). Streamflow Hydrological and Ecological Responses to Climate Change Assessed with an Artificial Neural Network. *Limnol. and Oceanorg*., 41(5), 857-863.

Price, W.L. (1983). Global Optimization by Controlled Random Search. *Journal of Optimization, Theory and Applications.* Vol. 40, pp. 333-328.

Price, W.L. (1987). Global Optimization Algorithms for a CAD Workstation. *Journal of Optimization, Theory and Applications.* Vol. 55, pp. 133-146.

Puls, L. G., (1928). Flood Regulation of the Tennessee River. *Proc., 70th Congress, 1st Session*, H. D. 185, Part 2, Appendix B.

Rao, A. R., and Han, J. (1987). Analysis of Objective Functions used in Urban Runoff Models. *Adv. Water Resour.* 10, 205–211.

Remson, I., Randolf, J. R., and Barksdale, H. C. (1960). The Zone of Aeration and Groundwater Recharge in Sandy Sediments at Seabrook, New Jersey. *Soil Sci,* 89, 145–156.

Rene,E.R., Kim,J.H.and Park, H.S. (2008). An Intelligent Neural Network Model for Evaluating Performance of Immobilized Cell Biofilter Treating Hydrogen Sulphide Vapors. *International Journal of Environmental Science and Technology, IJEST.* Volume 5, Number 3, Summer 2008, Article 1.

Richardson, B. (1931). Evaporation as a Function of Insolation. *Trans. Am. Soc. Civ. Eng.,* 95, 996–1011.

Rockwood, D. M. (1982). Theory and Practice of the SSARR Model as Related to Analyzing and Forecasting the Response of Hydrologic Systems. *Applied Modeling in Catchment Hydrology*, V. P. Singh, ed., Water Resources Publications, Littleton, Colo., 87–106.

Roessel, B. W. P. (1950). Hydrologic Problems Concerning the Runoff in Headwater Regions. *Trans., Am. Geophys. Union,* 31, 431–442.

Roger, L. L., and Dowla, F. U. (1994). Optimization of Groundwater Remediation using Artificial Neural Networks with Parallel Solute Transport Modeling. *Water Resour. Res.*, 30(2), 457–481.

Rosenbrock, H. H. (1960). An Automatic Method for Finding the Greatest or Least Value of a Function. *Comput. J.*, 3, 175–184.

Rzempoluck E.J. (1998). *Neural Network Data Analysis Using Simulnet.* Springer; 1st edition (January 15, 1998).

Servat, E., and Dezetter, A. (1991). Selection of Calibration Objective Functions in the Context of Rainfall-Runoff Modeling in a Sudanese Savannah Area. *Hydrol. Sci. J.,* 36(4/8), 307–330.

Setiawan, B.I., Fukuda, T., and Nakano. Y. (2003). Developing Procedures for Optimization of Tank Model's Parameters. *CIGR Journal of Scientific Research and Development*. June:1-13.

Shamseldin, A.Y. (1997). Application of a Neural Network Technique to Rainfall-Runoff Modelling". *Journal of Hydrology*. 199, 272-294.

Sherman, L. K. (1932). Stream Flow from Rainfall by the Unit Graph Method. *Eng. News-Rec.,* 108, 501–505.

Shi, Y. and Eberhart, R. (1998). A Modified Particle Swarm Optimizer. *Proceedings of the 105 IEEE Congress on Evolutionary Computation*, p. 69–73, May 1998.

Sima, S. (1989). Back-Propagation is not Efficient. *Neural Networks*. 9(6), 1017-1023.

Song, M.P. and Gu, G.H. (2004). Research on Particle Swarm Optimization: A Review. *Proceedings of the Third International Conference on Machine Learning and Cybernectics.* Shanghai, China.

Sorooshian, S., and Dracup, J. A. (1980). Stochastic Parameter Estimation Procedures for Hydrologic Rainfall-Runoff Models: Correlated and Heteroscedastic Error Cases. *Water Resour. Res.,* 16, 430–442.

Sorooshian, S. (1981). Parameter Estimation of Rainfall-Runoff Models with Heteroscedastic Streamflow Errors: The Noninformative Data Case. *J. Hydrol.* 52, 127–138.

Sorooshian, S., Duan, Q., and Gupta, V. K. (1993a). Calibration of Rainfall-Runoff Models: Application of Global Optimization to the Sacramento Soil Moisture Accounting Model. *Water Resour. Res.,* 29, 1185–1194.

Sorooshian, S., Gupta V. K., and Fulton, J.L. (1993b). Evaluation of Maximum-Likelihood Parameter Estimation Techniques for Conceptual Rainfall-runoff Models: Influence of Calibration Data Variability and Length on Model Credibility. *Water Resources Research*, Vol. 19, pp. 251-259.

Sorooshian, S., and Gupta V. K. (1995). Chapter 2: Model Calibration. *Computer models of watershed hydrology*, V. P. Singh, ed., Water Resources Publications, Littleton, Colo., 23–68.

Sothea. K., Goto, A. and Mizutani, M. (2006). A hydrologic Analysis on Inundation in the Flooding Area of the Mekong Delta, Cambodia-The Combined Deterministic and Stochastic Models for Flood Forecasting. *World Environmental and Water Resources Congress 2006*, ASCE: 1-10

Spendy, W., Hext, G. R., and Himsworth, F. R. (1962). Sequential Application of Simplex Design in Optimisation and Evolutionary Design. *Technometrics*, 4, 441–461.

Sugawara M, Funiyuki M. (1956). A Method of Revision of the River Discharge by Means of a Rainfall Model. *Collection of Research Papers about Forecasting Hydrologic variable*s: 14-18.

Sugawara, M. (1957). On the Analysis of Runoff Structure About Several Japanese Rivers. *Research memoir of the Ins. of statistical math*: 1-76.

Sugawara, M. (1967). The Flood Forecasting by a Series Storage Type Model. *Int. Symposium Floods and their Computation*, International Association of Hydrologic Sciences, 1–6.

Sugawara, M. (1974). Tank model and Its Application to Bird Creek, Wollombi Brook, Bikin River, Kitsu River, Sanga River and Nam Mune. Research Note, *National Research Center for Disaster Prevention, No. 11*, Kyoto, Japan, 1–64.

Sugawara, M. (1979). Automatic Calibration of the Tank Model. *Hydrological Sciences-Bulletin*. 24. No.3.

Sugawara, M. (1984). Tank Model with Snow Component. *Research Note of the National Research Center for Disaster Prevention,* No. 65, 1–293.

Sugawara, M. (1995). Chapter 6: Tank model. *Computer models of watershed hydrology*, V. P. Singh, ed., Water Resources Publications, Littleton, Colo.

Tanakamaru, H. (1995). Parameter Estimation for the Tank Model using Global Optimization. *Trans. Jpn. Soc. Irrig., Drain. Reclam.,* 178, 103–112.

Tanakamaru, H., and Burges, S. J. (1996). Application of Global Optimization to Parameter Estimation of the Tank Model. *Proc., Int. Conf. on Water Resources and Environmental Research: Towards the 21st Century*, Kyoto, Japan.

Theis, C. V. (1935). The Relation between the Lowering of the Piezometric Surface and the Rate and Duration of Discharge of a Well using Groundwater Storage. *Trans., Am. Geophys. Union,* 16, 519–524.

Thirumalaiah, K. and Deo, M.C. (2000). Hydrologic Forecasting Using Neural Network. *Journal of Hydrologic Engineering*, 5(2): 180-189.

Thornthwaite, C. W. (1948). An Approach toward a Rational Classification of Climate. *Geogr. Rev.,* 38, 55–94.

Timmer, G.T. (1987). Stochastic Global Optimization Methods, Part I: Clustering Methods. *Mathematical Programming*. Vol. 39, pp-27-56, 1987.

Tokar, A.S. (1996). *Rainfall Runoff Modeling in an Uncertain Environment.* PhD dissertation, University of Maryland, College Park, Md.

Tokar, A.S. & Johnson, P.A. (1999). Rainfall-Runoff Modeling Using Artificial Neural Networks. *Journal of Hydrologic Engineering*, 4(3): 223-239.

Tokar, A.S., and Markus, M. (2000). Precipitation-Runoff Modelling Using Artificial Neural Networks and Conceptual Models. *Journal of Hydraulic Engineering*, 5(2): 156-161.

Torn, A. (1978). *A Search Clustering Approach to Global Optimization, Toward Global Optimization 2*. Edited by L.C.W. Dixon and G.P. Szego, North Holland, Amsterdam, Holland.

Torn, A., and Zilinskas, A. (1989). *Global Optimization.* Springer-Verlag, Berlin, Germany.

Van den Bergh, F. and Engelbrecht, A. P. (1999). Particle Swarm Weight Initialization In Multi-Layer Perceptron Artificial Neural Networks. *ICAI*. Durban, South Africa.

Van den Bergh, F. and Engelbrecht, A. P. (2000). Cooperative Learning in Neural Networks using Particle Swarm Optimizers. *South African Computer Journal*, (26):84-90.

Van den Bergh, F. (2001). *An Analysis of Particle Swarm Optimizers*. Ph.D dissertation,University of Pretoria, South Africa.

Vijay, P. S. and David A. W. (2002). Mathematical Modeling of Watershed Hydrology. *Journal of Hydrologic Engineering*/ July/August 2002: 270-292

Wang, Q. J. (1991). The Genetic Algorithm and its Application to Calibrating Conceptual Rainfall-Runoff Models. *Water Resour. Res.,* 27(9), 2467–2471.

Warren, V. Jr., Gary, L L. and John, W. K. (1989). *Introduction to Hydrology*. Harper & Row publisher, Singapore.

Wright, N.G., and Dastorani, M.T. (2001). Effects of River Basin Classification on Artificial Neural Networks Based Ungauged Catchment Flood Prediction. *Proceeding of the 2001 International Symposium on Environmental Hydraulics*.

Yokoo, Y., Kazama, S., Sawamoto, M. and, Nishimura, H. (2001). Regionalization of Lumped Water Balance Model Parameters Based on Multiple Regression. *Journal of Hydrology*. 246 (2001), 209-222.

Zhang, C., Shao, H. and Li, Y. (2000). Particle Swarm Optimization for Evolving Artificial Neural Network. *IEEE*: 2487-2490.

Zweiri, Y.H., Whidborne, J.F. and Sceviratne, L.D. (2003). A Three-term Backpropagation Algorithm. *Neurocomputing*. 50: 305-318.