

DYNAMIC NEURO-FUZZY SYSTEMS FOR RAINFALL-RUNOFF MODELING

NADEEM NAWAZ

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

Faculty of Civil Engineering
Universiti Teknologi Malaysia

JULY 2017

ACKNOWLEDGEMENT

On the very outset of this achievement, I would like to extend my sincere and heartfelt gratitude towards Almighty Allah followed by all the personages who have helped me in this endeavor. I wouldn't have been able to accomplish this dissertation without their valuable guidance and cooperation. I'm overwhelmingly indebted to Professor Dr. Sobri Harun and Dr. Amin Talei for their diligent supervision and directives during the entire research process. They have provided supreme mentorship with rounded experience towards completion of this dissertation and provided autonomy during my exertion and verdict. They have encouraged me to rise as an independent thinker and a mentor too.

I would profusely thankful to all my family members and friends for their precious encouragement and continuous support during the period of my study. I would also like to express my gratitude towards the financial support provided by the Lasbela University of Agriculture, Water and Marine Sciences, Uthal, Pakistan without which I never had come up to complete my studies at Malaysia.

ABSTRACT

Urbanization has significant impact on the hydrological processes that have caused an increase in magnitude and frequency of floods; therefore, a reliable rainfall-runoff model will be helpful to estimate discharge for any watershed management plans. Beside physically-based models, the data driven approaches have been also used frequently to model the rainfall-runoff processes. Neuro-fuzzy systems (NFS) as one of the main category of data-driven models are common in hydrological time series modeling. Among the different algorithms, Adaptive network-based fuzzy inference system (ANFIS) is well-practiced in hydrological modeling. ANFIS is an offline model and needs to be retrained periodically to be updated. Therefore, an NFS model that can employ different learning process to overcome such problem is needed. This study developed dynamic evolving neuro fuzzy inference system (DENFIS) model for event based and continuous rainfall-runoff modeling and the results were compared with the existing models to check model capabilities. DENFIS evolves through incremental learning in which the rule-base is evolved after accommodating each individual new input data and benefitted from local learning implemented through the clustering method, Evolving Clustering Method (ECM). In this study, extreme events were extracted from the historical hourly data of selected tropical catchments of Malaysia. The DENFIS model performances were compared with ANFIS, the hydrologic modeling system (HEC-HMS) and autoregressive model with exogenous inputs (ARX) for event based rainfall-runoff modeling. DENFIS model was also evaluated against ANFIS for continuous rainfall-runoff modeling on a daily and hourly basis, multi-step ahead runoff forecasting and simulation of the river stage. The average coefficients of efficiency (CE) obtained from DENFIS model for the events in testing phase were 0.81, 0.79 and 0.65 for Lui, Semenyih and Klang catchments respectively which were comparable with ANFIS and HEC-HMS and were better than ARX. The CEs obtained from DENFIS model for hourly continuous were 0.93, 0.92 and 0.62 and for daily continuous were 0.73, 0.67 and 0.54 for Lui, Semenyih and Klang catchments respectively which were comparable to the ones obtained from ANFIS. The performances of DENFIS and ANFIS were also comparable for multistep ahead prediction and river stage simulation. This study concluded that less training time and flexibility of the rule-base in DENFIS is an advantage compared to an offline model such as ANFIS despite the fact that the results of the two models are generally comparable. However, the learning algorithm in DENFIS was found to be potentially useful to develop adaptable runoff forecasting tools..

ABSTRAK

Perbandaran mempunyai kesan yang besar ke atas proses hidrologi yang menyebabkan peningkatan ke atas magnitud dan kekerapan banjir; oleh itu, sebuah model hujan-air larian yang tepat dan boleh dipercayai amat berguna untuk menganggar sebarang pelan pengurusan kawasan tadahan air. Selain model berasaskan fizikal, pendekatan data didorong juga kerap digunakan untuk memodelkan proses hujan-air larian. *Neuro-fuzzy systems* (NFS) merupakan salah satu kategori utama model biasa dalam model hidrologi siri masa. Antara algoritma yang berbeza, *Adaptive network-based fuzzy inference system* (ANFIS) merupakan sesuatu yang diamalkan dalam pemodelan hidrologi. ANFIS adalah satu model luar talian dan perlu dilatih semula secara berkala untuk dikemas kini. Oleh itu, model NFS yang boleh menggunakan proses pembelajaran yang berbeza untuk mengatasi masalah berkenaan adalah diperlukan. Kajian ini membangunkan *dynamic evolving neuro fuzzy inference system* (DENFIS) bagi pemodelan hujan dan pemodelan hujan yang berterusan dan hasilnya dibandingkan dengan model sedia ada untuk memeriksa keupayaan model. DENFIS menyesuaikan melalui pembelajaran tambahan di mana peraturan-asas menyesuaikan selepas mengisi setiap individu dengan data input baru dan mendapat manfaat daripada pembelajaran tempatan yang telah dilaksanakan melalui kaedah kelompok; *evolving clustering method* (ECM). Dalam kajian ini, peristiwa yang melampau diambil daripada data dalam sela jam daripada kawasan tadahan tropika Malaysia yang terpilih. Prestasi model DENFIS dibandingkan dengan ANFIS, the *hydrologic modeling system* (HEC-HMS) dan *autoregressive model with exogenous inputs* (ARX) untuk model hujan-air larian berdasarkan peristiwa. Model DENFIS juga dinilai terhadap ANFIS bagi model hujan-air larian berterusan pada setiap hari dan setiap jam, ramalan air larian pelbagai langkah di hadapan dan simulasi aras sungai. Pekali purata kecekapan (CE) yang diperolehi daripada model DENFIS untuk peristiwa dalam fasa ujian adalah 0.81, 0.79 dan 0.65 untuk kawasan tadahan Lui, Semenyih dan Klang yang mana setanding dengan ANFIS dan HEC-HMS dan adalah lebih baik daripada ARX. CE yang didapati dari model DENFIS untuk setiap jam berterusan adalah 0.93, 0.92 dan 0.62 dan untuk setiap hari yang berterusan adalah 0.73, 0.67 dan 0.54 masing-masing bagi kawasan tadahan Lui, Semenyih dan Klang yang mana setanding dengan yang diambil dari ANFIS. Prestasi DENFIS dan ANFIS juga setanding untuk ramalan pelbagai langkah ke hadapan dan simulasi aras sungai. Kajian ini menyimpulkan bahawa masa latihan yang kurang dan fleksibiliti peraturan asas dalam DENFIS adalah satu kelebihan berbanding dengan model tanpa talian seperti ANFIS walaupun pada hakikatnya keputusan kedua-dua model amnya setanding. Walau bagaimanapun, algoritma pembelajaran di DENFIS didapati berpotensi untuk membangunkan adaptasi alat peramalan air.

TABLE OF CONTENTS

CHAPTER	TITLE	PAGE
	DECLARATION	ii
	DEDICATION	iii
	ACKNOWLEDGEMENT	iv
	ABSTRACT	v
	ABSTRAK	vi
	TABLE OF CONTENTS	vii
	LIST OF TABLES	xi
	LIST OF FIGURES	xiii
	LIST OF ABBREVIATION	xvii
	LIST OF SYMBOLS	xx
	LIST OF APPENDICES	xxii
1	INTRODUCTION	1
	1.1 Background of Study	1
	1.2 Problem Statement	2
	1.3 Objectives	4
	1.4 Scope of Study	5
	1.5 Significance of Study	5
	1.6 Thesis Outline	6
2	LITERATURE REVIEW	8
	2.1 Introduction	8

2.2	Rainfall-Runoff Mechanism	9
2.3	Brief History of Rainfall-Runoff Models	12
2.4	Characterization of Rainfall-Runoff models	13
2.4.1	Physically Based Rainfall-Runoff models	13
2.4.2	Conceptual Models	14
2.4.3	Empirical Models	15
2.5	Rainfall-Runoff Modeling in Malaysia	17
2.6	Applications of artificial neural networks	19
2.7	Neuro-Fuzzy Systems	26
2.7.1	Cooperative neuro-fuzzy systems	28
2.7.2	Concurrent neuro-fuzzy systems	28
2.7.3	Hybrid neuro-fuzzy systems	29
2.8	Neuro-fuzzy systems for rainfall-runoff modeling	30
2.9	Training events selection	40
2.10	Input Selection	43
2.11	HEC-HMS	45
2.12	ARX model	48
2.13	Summary	48
3	METHODOLOGY	50
3.1	Introduction	50
3.2	Study Area	51
3.2.1	Lui River Catchment	52
3.2.2	Semenyih River Catchment	54
3.2.3	Klang River Catchment	55
3.2.4	Bekok River Catchment	57
3.3	Homogeneity Tests	58
3.4	Fuzzy Sets and Fuzzy Logic	58
3.4.1	Fuzzy Implication (If-Then Rules)	61
3.4.2	Fuzzy Inference System	62
3.5	ANFIS	65
3.6	DENFIS	68

3.6.1	Evolving clustering method (ECM)	68
3.6.2	Learning Process in DENFIS	72
3.7	ARX Model	74
3.8	HEC-HMS	74
3.8.1	Loss Method	74
3.8.2	Transformation Method	75
3.8.3	Base-Flow Method	76
3.8.4	Routing Method	77
3.8.5	HEC-GeoHMS	79
3.8.6	Mean Areal Rainfall	80
3.9	Data Standardization	80
3.10	Input Selection Criteria	81
3.11	Performance Evaluation	82
4	RESULTS AND DISCUSSION	86
4.1	Overview	86
4.2	Infilling Missing Data	87
4.3	Models Calibration	88
4.3.1	ANFIS Model Calibration	88
4.3.2	DENFIS Model Calibration	89
4.3.3	HEC-HMS Model Calibration	90
4.3.4	ARX Model Calibration	92
4.4	Event-Based Rainfall-Runoff Modeling	93
4.4.1	Lui River Catchment	93
4.4.2	Semenyih River catchment	101
4.4.3	Klang River catchment	107
4.5	Continuous Rainfall-Runoff Modeling	114
4.5.1	Lui River catchement (Hourly)	114
4.5.2	Semenyih River catchment (Hourly)	118
4.5.3	Klang River catchment (Hourly)	122
4.5.4	Lui River Catchment (Daily)	127
4.5.5	Semenyih River catchment (Daily)	131

4.5.6	Klang River Catchment (Daily)	135
4.6	Multistep Ahead Runoff Forecasting	139
4.6.1	Lui River Catchment	139
4.6.2	Semenyih River catchment	143
4.6.3	Klang River catchment	148
4.7	River Stage Simulation	152
4.8	Summary	155
5	CONCLUSIONS	158
5.1	Introduction	158
5.1.1	Event Based Rainfall-Runoff Modeling	158
5.1.2	Continuous Rainfall-Runoff Modeling	159
5.1.3	Multistep Ahead Runoff Forecasting	160
5.1.4	River Stage Simulation	160
5.2	Recommendations for Future Research	161
	REFERENCES	162
	Appendices A-C	188 - 196

LIST OF TABLES

TABLE NO.	TITLE	PAGE
3.1	Statistical summary of the hourly rainfall and runoff datasets for Lui River catcment	53
3.2	Statistical summary of the hourly rainfall and runoff datasets for Semenyih River catchmen	55
3.3	Statistical summary of the hourly rainfall and runoff datasets for Klang River catchment	56
3.4	Detail of missing data record of Klang rainfall Station	57
3.5	Statistical summary of the daily rainfall and river stage datasets for Bekok River catchment	58
4.1	Station used as input for training the ANFIS model	87
4.2	Selection of training and testing events	94
4.3	Input combinations of 2, 3, and 4, inputs chosen by MICCA method and their corresponding average ANFIS performance on testing events	95
4.4	Input combinations of 2, 3, and 4, inputs chosen by MICCA method and their corresponding average DENFIS performance on testing events	96
4.5	Time Shift Error resulted by different models in estimating the peak discharges for the 25 testing events in Lui River catchment	100
4.6	Training time taken by the neuro fuzzy models during training the model	101
4.7	Selection of training and testing events	101

4.8	Input combinations of 2, 3, and 4, inputs chosen by MICCA method and their corresponding average ANFIS performance on testing events	102
4.9	Input combinations of 2, 3, and 4, inputs chosen by MICCA method and their corresponding average DENFIS performance on testing events	103
4.10	Time Shift Error resulted by different models in estimating the peak discharges for the 20 testing events in Semenyih River catchment	107
4.11	Selection of training and testing events	108
4.12	Input combinations of 2, 3, and 4, inputs chosen by MICCA method and their corresponding average ANFIS performance on testing events	109
4.13	Input combinations of 2, 3, and 4, inputs chosen by MICCA method and their corresponding average DENFIS performance on testing events	110
4.14	Time Shift Error resulted by different models in estimating the peak discharges for the 15 testing events in Klang River catchment	113
4.15	Model performances obtained in testing phase for Lui River Catchment	115
4.16	Model performances obtained in testing phase for Semenyih River Catchment	119
4.17	Model performances obtained in testing phase for Klang River Catchment	126
4.18	Model performances obtained in testing phase for Lui River Catchment	130
4.19	Model performances obtained in testing phase for semenyih River Catchment	134
4.20	Model performances obtained in testing phase for Klang River Catchment	138
4.21	Comparison of model performances for river stage simulation of Bekok catchment	154

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
2.1	Schematic representation of the hydrological cycle (USGS 1994)	9
2.2	Example hydrograph including a catchment response to a rainfall event	11
2.3	Schematic representation of cross-sectional hill slope flow (Scanlon, et al. 2000)	11
2.4	Example of lumped, semi-distributed and distributed approach	14
3.1	General approach adopted in this study.	51
3.2	Lui River Catchment	53
3.3	Semenyih River catchment	54
3.4	Klang River catchment	55
3.5	Bekok River catchment	57
3.6	Typical membership functions for a fuzzy set. (Left: a smooth curve function. Right: a piecewise linear function)	59
3.7	Complement (NOT) of a fuzzy set.	60
3.8	Union (OR) of two fuzzy sets	60
3.9	Intersection (AND) of two fuzzy sets.	61
3.10	Basic structure of a fuzzy inference system (Jang, 1993)	63
3.11	Mamdani's fuzzy inference system (Mamdani and Assilian 1975).	64
3.12	Takagi-Sugeno fuzzy inference system (Takagi and Sugeno 1985).	65
3.13	Adapted Network-based Fuzzy Inference System (Jang 1993)	66
3.14	Schematic of ECM clustering procedure (Figure adapted from Kasabov and Song, 2002)	70

3.15	Schematic illustration of ECM algorithm (Figure adapted from Kasabov and Song, 2002)	71
4.1	Observed and simulated hydrograph: (a) ANFIS: best CE; (b) ANFIS: median CE; (c) DENFIS: best CE; and (d) DENFIS: median CE; (e) ANFIS: least CE; (c) DENFIS: least CE	97
4.2	Comparison between different models' performance in simulating the 25 testing events in Lui River Catchment: (a) CE; (b) R ² ; (c) RMSE; (d) MAE; and (e) RPE	98
4.3	Observed and simulated hydrograph: (a) ANFIS: best CE; (b) ANFIS: median CE; (c) DENFIS: best CE; and (d) DENFIS: median CE; (e) ANFIS: least CE; (c) DENFIS: least CE	104
4.4	Comparison between different models' performance in simulating the 20 testing events in Semenyih River Catchment: (a) CE; (b) R ² ; (c) RMSE; (d) MAE; and (e) RPE	105
4.5	Observed and simulated hydrograph: (a) ANFIS: best CE; (b) ANFIS: median CE; (c) DENFIS: best CE; and (d) DENFIS: median CE; (b) ANFIS: least CE; (c) DENFIS: least CE	111
4.6	Comparison between different models' performance in simulating the 15 testing events in Klang River Catchment: (a) CE; (b) R ² ; (c) RMSE; (d) MAE; and (e) RPE	112
4.7	Observed and simulated hydrograph by ANFIS model for Lui River catchment	116
4.8	Observed and simulated hydrograph by DENFIS model for Lui River catchment	117
4.9	Comparison of RPE values for peak discharges > 10m ³ /s for Lui River catchment	118
4.10	Observed and simulated hydrograph by ANFIS model for Semenyih River catchment	120
4.11	Observed and simulated hydrograph by DENFIS model for Semenyih River catchment	121
4.12	Comparison of RPE values for peak discharges > 20m ³ /s for Semenyih River catchment	122
4.13	Observed and simulated hydrograph by ANFIS model for Klang River catchment	124

4.14	Observed and simulated hydrograph by DENFIS model for Klang River catchment	125
4.15	Comparison of RPE values for peak discharges $> 100 \text{ m}^3/\text{s}$ for Klang River catchment	126
4.16	Observed and simulated hydrograph by ANFIS model for Lui River catchment	128
4.17	Observed and simulated hydrograph by DENFIS model for Lui River catchment	129
4.18	Comparison of RPE values for peak discharges $> 10 \text{ m}^3/\text{s}$ for Lui River catchment	130
4.19	Observed and simulated hydrograph by ANFIS model for Semenyih River catchment	132
4.20	Observed and simulated hydrograph by DENFIS model for Semenyih River catchment	133
4.21	Comparison of RPE values for peak discharges $> 20 \text{ m}^3/\text{s}$ for Semenyih River catchment	134
4.22	Observed and simulated hydrograph by ANFIS model for Klang River catchment	136
4.23	Observed and simulated hydrograph by DENFIS model for Klang River catchment	137
4.24	Comparison of RPE values for peak discharges $> 100 \text{ m}^3/\text{s}$ for Klang River catchment	138
4.25	Comparison of model performances for (1-h, 2-h and 3-h) ahead forecasting for Lui River catchment	140
4.26	Comparison of RPE values for forecasted peak discharges $> 10 \text{ m}^3/\text{s}$ for Lui River catchment	141
4.27	Comparison of model performances for (3-h, 6-h and 9-h) ahead forecasting for Lui River catchment	142
4.28	Comparison of RPE values for forecasted peak discharges $> 10 \text{ m}^3/\text{s}$ for Lui River catchment	143
4.29	Comparison of model performances for (1-h, 2-h and 3-h) ahead forecasting for Semenyih River catchment	144
4.30	Comparison of RPE values for forecasted peak discharges $> 20 \text{ m}^3/\text{s}$ for Semenyih River catchment	145

4.31	Comparison of model performances for (3-h, 6-h and 9-h) ahead forecasting for Semenyih River catchment	146
4.32	Comparison of RPE values for forecasted peak discharges > 20m ³ /s for Semenyih River catchment	147
4.33	Comparison of model performances for (1-h, 2-h and 3-h) ahead forecasting for Klang River catchment	148
4.34	Comparison of RPE values for forecasted peak discharges > 100m ³ /s for Klang River catchment	149
4.35	Comparison of model performances for (3-h, 6-h and 9-h) ahead forecasting for Klang River catchment	150
4.36	Comparison of RPE values for forecasted peak discharges > 100m ³ /s for Klang River catchment	151
4.37	Observed and simulated hydrograph for Bekok River Catchment: (a) ANFIS; (b) DENFIS	153
4.38	Comparison of RPE values for river stage > 100mm for Bekok River catchment	154

LIST OF ABBREVIATIONS

ANFIS	-	Adaptive Network-based Fuzzy Inference System
ANGIS	-	Adaptive Neuro Genetic Algorithm Integrated System
ANN	-	Artificial Neural Network
API	-	Antecedent Precipitation Index
AR	-	Auto-Regressive
ARMA	-	Auto Regressive Moving Average
ARMAX	-	Auto-Regressive Moving Average with Exogenous variables
ARX	-	Autoregressive model with exogenous inputs
BPNN	-	Back Propagation Neural Network
CG	-	Conjugate Gradient
CE	-	Nash–Sutcliffe Coefficient of Efficiency
CLS	-	Constrained Linear System
DBP	-	Division-based Back Propagation
DENFIS	-	Dynamic Evolving Neural Fuzzy Inference System
DID	-	Department of Irrigation and Drainage
DNFLMS	-	Dynamic Neuro-Fuzzy Local Modelling system
ECM	-	Evolving Clustering Method
ET_p	-	Time Shift Error
FALCON	-	Fuzzy Adaptive learning Control Network
FFNN	-	Feed Forward Neural Networks
FHMUA	-	Flood Hazard Mapping for Urban Area
FINEST	-	Fuzzy Inference Software
FIS	-	Fuzzy Inference System
FL	-	Fuzzy Logic
FUN	-	Fuzzy Net

GARIC	-	Generalized Approximate Reasoning based Intelligent Control
GenSoFNN	-	Generic Self-organizing Fuzzy Neural Network
GRNN	-	Generalized Regression Neural Networks
GUI	-	Graphical User Interface
HBV	-	Hydrologiska Byråns Vattenbalansavdelning
HEC-HMS	-	Hydrologic Engineering Centre-Hydrologic Modelling System
IWCS	-	Info-Works Collection System
IWRS	-	Info-Works River Simulation
KWA	-	Kinematic Wave Approximation
KWM	-	Kinematic Wave Model
LLSSIM	-	Linear Least Square Simplex
LSE	-	Linear Square Estimator
LTF	-	Linear Transformation Function
MAE	-	Mean Absolute Error
MAYA	-	Most Advanced Yet Acceptable
MLP	-	Multi-layer Perceptron
MLR	-	Multiple Linear Regressions
MR	-	Multi-Regression
MMD	-	Malaysian Meteorological Department
MSMA	-	Manual Saliran Mesra Alam Malaysia
NEFCLASS	-	Neuro-Fuzzy Classification
NEFCON	-	Neuro-Fuzzy Control
NFS	-	Neuro Fuzzy Systems
NNARX	-	Neural Network Auto Regressive with Exogenous Input
POPFNN	-	Pseudo Outer-Product based Fuzzy Neural Network
R^2	-	Coefficient of Determination
RMSE	-	Root Mean Square Error
RPE	-	Relative Peak Error
RTRL	-	Real Time Recurrent Learning
SDSS	-	Spatial Decision Support System
SHE	-	Système Hydrologique Européen
SOFNIN	-	Self Constructing Neural Fuzzy Inference Network

SOM	-	Self Organizing Map
SNHT	-	Standard Normal Homogeneity Test
SWMM	-	Storm Water Management Model
TREX	-	Terrain-induced Rotor Experiment
TSK	-	Takagi-Sugeno-Kang
UBC	-	University of British Columbia
USGS	-	United States Geological Survey

LIST OF SYMBOLS

A'	-	Fuzzy set
β_0	-	Parameters to be optimised
$\mu_A(x)$	-	Membership function
OP_i^l	-	Node out put
C_1^0	-	First cluster
Cc_1^0	-	Cluster centre
Ra	-	Radius
D_{thr}	-	Threshold (clustering parameter)
m	-	Smallest number of initial rules to be created in DENFIS
n_0	-	Number of first group of data pairs used to initialize DENFIS
n	-	Manning's roughness coefficient
p_i	-	Most nearest data point
$R(t-i)$	-	Inputs (rainfall)
$Q(t-i)$	-	Past outputs
n_a	-	Number of past outputs in ARX model
n_b	-	Number of past inputs in ARX model
nk	-	Delay associated with each input in ARX model
f_t	-	Loss period at time
F_t	-	Cumulative loss at time
k	-	Saturated hydraulic conductivity
S_f	-	Wetting from suction
x_n	-	Standardized data
x_{min}	-	Minimum and Maximum of observed data
x_{max}	-	Maximum of observed data
\bar{Q}	-	Average observed discharge
\hat{Q}_i	-	Simulated low rate

Q_p	-	Observed peak discharge
\widehat{Q}_p	-	Simulated peak discharge
\widehat{T}_p	-	Simulated time to peak
T_p	-	Observed time to peak

LIST OF APPENDIX

APPENDIX	TITLE	PAGE
A	Detail of 75 events of Lui River catchment	188
B	Detail of 70 events of Semenyih River catchment	191
C	Detail of 60 events of Klang River cathement	196

CHAPTER 1

INTRODUCTION

1.1 Background of Study

The hydrologists are always dealing with the problem of determining the non-linear relationship between the rainfall and runoff processes. A good understanding of rainfall-runoff relationship is required for hydrologic design, planning and management of a watershed. This relationship depends on many factors such as land use, soil moisture, evapotranspiration, infiltration, distribution and duration of rainfall and so on. Therefore, any effort to model the rainfall and runoff processes would be confronted with difficulties since hydrological processes have a greater degree of spatio-temporal variability, and are further played by the issues of non-linearity of physical process, confliction in spatio-temporal scales, uncertainties involved in parameter estimation, and stochastic. In addition, deficiencies in data due to the unavailability of data, poor quality of data, etc. present a major problem in rainfall–runoff modeling. These are the reasons that make hydrologist’s understanding of hydrologic processes far from the perfect and then empiricism plays a vital role in hydrologic modeling studies (Vemuri and Vemuri, 1970). Hydrologists often strive to give the rational responses to the issues; those arise in designing and management of water resources projects. The desire of reliable modeling tool to model the rainfall–runoff transformation process has been one of the major hydrological research activities for decades (Shoaib et al. 2014).

Since early 1930’s there have been various attempts to develop or to modify the rainfall-runoff models to forecast accurate streamflow. Such techniques can be

characterized into two main groups: physically-based models and system theoretic models. The design of Physically-based models is based on approximation of the internal sub-processes and physical mechanisms which are involved in rainfall-runoff transformation process. These models generally incorporate basic physical laws and are generally non-linear, time-varying, and deterministic, with the parameters that are representative of watershed characteristics. Although the physically-based models are designed to present a clear understanding of the physics involved in hydrological processes but, require sophisticated mathematical tools, and usually require significant user expertise. On the other hand, system theoretic or black-box models apply a different approach to identify a direct mapping between rainfall and runoff, without the need for a detailed understanding of the physical processes. These models include linear and nonlinear regression models, artificial intelligence tools like artificial neural networks (ANNs), neuro fuzzy systems (NFS).

These models do not provide any information about the physical characteristics of the watershed. These models are fast and their results are comparable to those obtained from physical models. Besides their successive applications in rainfall-runoff modeling the researchers are focusing to develop new algorithms, new software and procedures for designing future developments. Adaptive Network based Fuzzy Inference System (ANFIS) developed by Jang (1993) is so far the most popular NFS model and has been widely used in different hydrologic time series simulations. ANFIS is an off-line model which needs to be retrained for any happenings in the catchment for simulation of rainfall-runoff processes. This study focuses on the advancement of NFS modeling techniques for simulation of rainfall-runoff dynamics for the tropical catchments.

1.2 Problem Statement

Rapid population growth, urbanization, and industrialization in many parts of the world have increased the demand of water. The increase in water demand resulted in altered watersheds and river systems and it became critical to plan and manage water resources systems intelligently. In recent years, concern has grown

worldwide that floods and droughts may be increasing in frequency, severity, and duration given changing climatic conditions (Sivakumar, 2012; Peterson et al., 2013). The problem had been worse due to the malfunctioning of the early warning systems at the flood plains. Although these floods have caused massive damage, they also provided valuable information which can help researchers and authorities to develop new algorithms, Software and procedures to prevent these damages.

The reliable hydrological modeling is in need to overcome the growing concern at watershed levels. The reason for modeling the relation between precipitation on a catchment and the runoff from it is that runoff information is needed for hydrologic engineering design and management purposes (Govindaraju, 2000). However, as Tokar and Johnson (1999) state, the relationship between rainfall and runoff is one of the most complex hydrologic phenomena to comprehend. This is due to the tremendous spatial and temporal variability of watershed characteristics and precipitation patterns, and the number of variables involved in the modeling of the physical processes. In the past, prediction of river flow was mainly performed using conceptual and deterministic models (Bazartseren et al., 2003).

In the cases with high rate of uncertainty and complexity where it is difficult to consider every effective physical parameter, it is not a surprising fact that black box models which convert inputs to output values in ways that have nothing to do with what happens in reality, may produce more accurate results than physical based models (Nourani et al., 2011). Recently, intelligence system approaches such as ANNs have been used successfully for time series modelling. In most instances for ANNs, multilayer perceptron (MLP) that are trained with the back-propagation algorithm has been used. The major shortcoming of this approach is that the knowledge contained in the trained networks is difficult to interpret. Using NFS approaches, which enable the information that is stored in trained networks to be expressed in the form of a fuzzy rule base, had overcome this issue. Presently the most popular neuro fuzzy model ANFIS is an offline model and needs to retrain periodically to be updated for any temporal and spatial changes of the catchment. The incremental learning is still an issue in existing neuro-fuzzy models. A real-time

neuro fuzzy rainfall-runoff model having capability of online learning and the ability to update itself without the need of being retrained offline can overcome the issue.

1.3 Objectives

The overall goal of this study is to simulate rainfall- runoff processes for the extreme events using Neuro-Fuzzy Systems approaches and comparisons with the other methods to address their capabilities for the tropical catchments. The specific objectives of this study were as follow:

1. To evaluate the capability of DENFIS in simulating rainfall-runoff processes for the extreme events in three tropical catchments and compare the model performance with benchmark models such as HEC-HMS and autoregressive model with exogenous inputs (ARX).
2. To evaluate the capability of DENFIS in simulating continuous (daily and hourly) rainfall-runoff time series and compare it with offline NFS model, ANFIS.
3. To evaluate the capabilities of DENFIS in forecasting runoff for multistep ahead and compare it with offline NFS model, ANFIS.
4. To explore the capability of DENFIS for other hydrological application such as simulation of river stage.

1.4 Scope of Study

The study mainly focuses on development of dynamic evolving neuro fuzzy inference system (DENFIS) model for rainfall-runoff modeling. The developed model was applied to several tropical catchments of Malaysia. The catchments were selected on the data availability and after quality assessment of data. The study was performed for event based and continuous rainfall-runoff modeling for the selected catchments. The study also highlighted DENFIS application for multi-step ahead prediction and river stage simulation.

To simulate event based rainfall-runoff modeling using DENFIS model, the extreme historical events were selected from the available rainfall and runoff dataset. The event based rainfall-runoff modeling was performed for Semenyih River catchment, Lui River catchment and Klang River catchment. The evaluation of DENFIS model for event based rainfall-runoff modeling was performed by comparing its performances against ANFIS model, HEC-HMS and ARX model. The continuous modeling was performed using DENFIS model on hourly and daily dataset for Lui, Semenyih and Klang River catchments. To assess the model performances DENFIS model was compared with ANFIS model.

DENFIS and ANFIS models were developed for 1 hour, 2 hour and 3 hour ahead forecasting. The hourly data was re-organized to 3 hourly data to simulate 3 hour, 6 hour and 9 hour ahead forecasting for Lui, Semenyih and Klang River catchments. The River stage simulation using DENFIS and ANFIS was only performed for Bekok River catchment, because of the data availability. .

1.5 Significance of Study

Rainfall-Runoff modeling is essential measure in water resources planning and development. Physically based rainfall-runoff models give proper insight of the catchment behavior however, they require significant number of parameters which could be difficult to be measured or estimated. On the other hand the data driven

approaches are able to identify a direct mapping between input and output with less number of physical parameters. This study is important from hydrologic point of view as it aimed to develop rainfall-runoff model using NFS approach known as DENFIS. The DENFIS model uses evolving clustering method (ECM), which is an online and distance based clustering method. DENFIS model can be used as a batch model and also can be employed with incremental learning. The incremental learning allows the model to update its rule base fuzzy inference system automatically with the input of new data. This makes it superior to other data driven modeling techniques. Generally, this research is a 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.

1.6 Thesis Outline

This thesis is divided into five chapters. Descriptions of the chapters are given below in brief.

Chapter 1 presents the general introduction of this study and comprising of the background of study, problem statement, objectives of the study, scope of study and significance of study.

Chapter 2 provides a review of relevant literature. The review covers importance of rainfall-runoff modeling, characterizing of the models, history of models and their use in Malaysia, applications of ANNs and NFS, a general briefing on physically based and regression models used as bench mark, and some relevant issues.

Chapter 3 presents the details of the models used in this study, detailed information of the study sites, data used, data preprocessing, events selection, performance evaluation matrices and input selections used in this study.

REFERENCES

- Abbott, M.B., Bathurst, J.C., Cunge, J.A., O'Connell, P.E. and Rasmussen, J. (1986) An introduction to the European Hydrological System—Systeme Hydrologique Europeen,“SHE”, 1: History and philosophy of a physically-based, distributed modelling system. *Journal of Hydrology* **87(1)**: 45-59.
- Abdullah, J. (2007) *Distributed runoff simulation of extreme monsoon rainstorms in Malaysia using TREX*
- Agarwal, A. and Singh, R. (2004) Runoff modelling through back propagation artificial neural network with variable rainfall-runoff data. *Water Resources Management* **18(3)**: 285-300.
- Agrawal, A. (2005) *PrePro2004: a data model with pre and post-processor for HEC-HMS. Texas A&M University.*
- Alexandersson, H. (1986) A homogeneity test applied to precipitation data. *Journal of climatology* **6(6)**: 661-675.
- Ali, A., Nasrizal, A. and Ariffin, J. (2011) Model reliability assessment: A hydrodynamic modeling approach for flood simulation in Damansara catchment using InfoWorks RS, pp. 3769-3775, *Trans Tech Publ.*
- Alizadeh, M. J., Kavianpour, M. R., Kisi, O., & Nourani, V. (2017). A new approach for simulating and forecasting the rainfall-runoff process within the next two months. *Journal of Hydrology*, **548**: 588-597.
- Anctil, F., Perrin, C. and Andréassian, V. (2004) Impact of the length of observed records on the performance of ANN and of conceptual parsimonious rainfall-runoff forecasting models. *Environmental Modelling & Software* **19(4)**: 357-368.

- Anderson, M., Chen, Z.-Q., Kavvas, M. and Feldman, A. (2002) Coupling HEC-HMS with atmospheric models for prediction of watershed runoff. *Journal of Hydrologic Engineering* **7(4)**: 312-318.
- Ang, K.K. and Quek, C. (2005) RSPOP: Rough Set-Based Pseudo Outer-Product Fuzzy Rule Identification Algorithm. *Neural Computation* **17(1)**: 205-243.
- Antar, M.A., Ellassiouti, I. and Allam, M.N. (2006) Rainfall-runoff modelling using artificial neural networks technique: a Blue Nile catchment case study. *Hydrological Processes* **20(5)**: 1201-1216.
- Aqil, M., Kita, I., Yano, A. and Nishiyama, S. (2007a) A comparative study of artificial neural networks and neuro-fuzzy in continuous modeling of the daily and hourly behaviour of runoff. *Journal of Hydrology* **337(1-2)**: 22-34.
- Aqil, M., Kita, I., Yano, A. and Nishiyama, S. (2007b) Analysis and prediction of flow from local source in a river basin using a Neuro-fuzzy modeling tool. *Journal of Environmental Management* **85(1)**: 215-223.
- Asadi, S., Shahrabi, J., Abbaszadeh, P., & Tabanmehr, S. (2013). A new hybrid artificial neural networks for rainfall-runoff process modeling. *Neurocomputing* **121**: 470-480.
- Ashrafi, M., Chua, L. H. C., Quek, C., & Qin, X. (2017). A fully-online Neuro-Fuzzy model for flow forecasting in basins with limited data. *Journal of Hydrology* **545**: 424-435.
- Bajwa, H. and Tim, U. (2002) Toward immersive virtual environments for GIS-based Floodplain modeling and Visualization.
- Banitt, A. (2010) Simulating a century of hydrographs e Mark Twain reservoir.
- Bazartseren, B., Hildebrandt, G., & Holz, K. P. (2003). Short-term water level prediction using neural networks and neuro-fuzzy approach. *Neurocomputing* **55(3)**: 439-450.

- Berenji, H.R. and Khedkar, P. (1992) Learning and tuning fuzzy logic controllers through reinforcements. *Neural Networks, IEEE Transactions on* **3(5)**: 724-740.
- Bergstrom, S. (1979) Spring flood forecasting by conceptual models in Sweden, pp. 397-405.
- Bergström, S. and Forsman, A. (1973) Development of a conceptual deterministic rainfall-runoff model. *Hydrology Research* **4(3)**: 147-170.
- Beven, K. and Freer, J. (2001) Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *Journal of Hydrology* **249(1)**: 11-29.
- Beven, K. and Kirkby, M.J. (1979) A physically based, variable contributing area model of basin hydrology/Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant. *Hydrological Sciences Journal* **24(1)**: 43-69.
- Billa, L., Mansor, S. and Rodzi Mahmud, A. (2004) Spatial information technology in flood early warning systems: an overview of theory, application and latest developments in Malaysia. *Disaster Prevention and Management: An International Journal* **13(5)**: 356-363.
- Billa, L., Mansor, S., Mahmud, A. and Ghazali, A. (2006) Hydro-meteorological modeling and GIS for operational flood forecasting and mapping, pp. 1-16.
- Bowden, G.J., Dandy, G.C. and Maier, H.R. (2005) Input determination for neural network models in water resources applications. Part 1—background and methodology. *Journal of Hydrology* **301(1)**: 75-92.
- Camoens, A. and Wong, P. M. (2012). “Serdang, Kajang hit by floods.” The Star, Sept. 5, 2012 <<http://thestar.com.my/news/story.asp?file=/2012/9/5/nation/11970180 &sec=nation>> [Accessed on Nov. 28, 2015]

- Carriere, P., Mohaghegh, S. and Gaskari, R. (1996) Performance of a virtual runoff hydrograph system. *Journal of Water Resources Planning and Management* **122(6)**: 421-427.
- Castellano-Méndez, M.a., González-Manteiga, W., Febrero-Bande, M., Prada-Sánchez, J.M. and Lozano-Calderón, R. (2004) Modelling of the monthly and daily behaviour of the runoff of the Xallas river using Box–Jenkins and neural networks methods. *Journal of Hydrology* **296(1)**: 38-58.
- Chang, F. J., & Tsai, M. J. (2016). A nonlinear spatio-temporal lumping of radar rainfall for modeling multi-step-ahead inflow forecasts by data-driven techniques. *Journal of Hydrology* **535**: 256-269.
- Chang, F.-J., Chang, K.-Y. and Chang, L.-C. (2008) Counterpropagation fuzzy-neural network for city flood control system. *Journal of Hydrology* **358(1–2)**: 24-34.
- Chang, F.J., Chiang, Y.M. and Ho, Y.H. (2015) Multistep-ahead flood forecasts by neuro-fuzzy networks with effective rainfall-run-off patterns. *Journal of Flood Risk Management* **8(3)**: 224-236.
- Chang, T. K., Talei, A., Alaghmand, S., & Ooi, M. P. L. (2017). Choice of rainfall inputs for event-based rainfall-runoff modeling in a catchment with multiple rainfall stations using data-driven techniques. *Journal of Hydrology* **545**: 100-108.
- Che-Ani, A., Shaari, N., Sairi, A., Zain, M. and Tahir, M. (2009) Rainwater harvesting as an alternative water supply in the future. *European Journal of Scientific Research* **34(1)**: 132-140.
- Chen, S.H., Lin, Y.H., Chang, L.C. and Chang, F.J. (2006) The strategy of building a flood forecast model by neuro-fuzzy network. *Hydrological Processes* **20(7)**: 1525-1540.
- Cheng, X. and Noguchi, M. (1996) Rainfall-runoff modelling by neural network approach, pp. 29-31.

- Chiang, Y.-M., Chang, L.-C. and Chang, F.-J. (2004) Comparison of static-feedforward and dynamic-feedback neural networks for rainfall–runoff modeling. *Journal of Hydrology* **290(3)**: 297-311.
- Cho, S.-Y., Quek, C., Seah, S.-X. and Chong, C.-H. (2009) HebbR2-Taffic: A novel application of neuro-fuzzy network for visual based traffic monitoring system. *Expert Systems with Applications* **36(3, Part 2)**: 6343-6356.
- Chow, V.T.; Maidment, D.R.; Mays, L.W. (1988). Applied Hydrology. McGraw-Hill Series in Water Resources and Environmental Engineering. McGraw-Hill: New York.
- Chua, L.H., Wong, T.S. and Sriramula, L. (2008) Comparison between kinematic wave and artificial neural network models in event-based runoff simulation for an overland plane. *Journal of Hydrology* **357(3)**: 337-348.
- Clarke, R. (1973) A review of some mathematical models used in hydrology, with observations on their calibration and use. *Journal of Hydrology* **19(1)**: 1-20.
- Committee, A.T. (1993) The ASCE task committee on definition of criteria for evaluation of watershed models of the watershed management committee Irrigation and Drainage Division, Criteria for evaluation of watershed models. *J. Irri. Drain. Engng, ASCE* **119(3)**: 429-442.
- Cunderlik, J.M. and Simonovic, S.P. (2007) Hydrologic models for inverse climate change impact modeling.
- da Costa Couto, M.P. (2009) Review of input determination techniques for neural network models based on mutual information and genetic algorithms. *Neural Computing and Applications* **18(8)**: 891-901.
- Damant, C., Austin, G., Bellon, A. and Broughton, R. (1983) Errors in the Thiessen technique for estimating areal rain amounts using weather radar data. *Journal of Hydrology* **62(1)**: 81-94.
- Damousis, I.G., Alexiadis, M.C., Theocharis, J.B. and Dokopoulos, P.S. (2004) A fuzzy model for wind speed prediction and power generation in wind parks

using spatial correlation. *Energy Conversion, IEEE Transactions on* **19(2)**: 352-361.

Dawson, C. and Wilby, R. (2001) Hydrological modelling using artificial neural networks. *Progress in physical Geography* **25(1)**: 80-108.

Dawson, C.W. and Wilby, R. (1998) An artificial neural network approach to rainfall-runoff modelling. *Hydrological Sciences Journal* **43(1)**: 47-66.

Dawson, C.W. and Wilby, R.L. (1999) A comparison of artificial neural networks used for river forecasting. *Hydrology and Earth System Sciences Discussions* **3(4)**: 529-540.

de Vos, N. and Rientjes, T. (2009) *Practical Hydroinformatics*. pp. 101-112, Springer.

Dibike, Y.B., Velickov, S. and Solomatine, D. (2000) Support vector machines: Review and applications in civil engineering, pp. 215-218, Citeseer.

Dixon, B. (2005) Applicability of neuro-fuzzy techniques in predicting ground-water vulnerability: a GIS-based sensitivity analysis. *Journal of hydrology* **309(1)**: 17-38.

Dorum, A., Yazar, A., Faik Sevimli, M. and Onüçyildiz, M. (2010) Modelling the rainfall-runoff data of susurluk basin. *Expert Systems with Applications* **37(9)**: 6587-6593.

El-Shafie, A., Taha, M.R. and Noureldin, A. (2007) A neuro-fuzzy model for inflow forecasting of the Nile river at Aswan high dam. *Water Resources Management* **21(3)**: 533-556.

Esfahanipour, A. and Aghamiri, W. (2010) Adapted neuro-fuzzy inference system on indirect approach TSK fuzzy rule base for stock market analysis. *Expert Systems with Applications* **37(7)**: 4742-4748.

Fang, X. (2005) Literature review on timing parameters for hydrographs, Lamar University.

- Feldman, A.D. (2000) Hydrologic modeling system HEC-HMS: technical reference manual, US Army Corps of Engineers, Hydrologic Engineering Center.
- Fernando, D.A.K. and Jayawardena, A. (1998) Runoff forecasting using RBF networks with OLS algorithm. *Journal of Hydrologic Engineering* **3(3)**: 203-209.
- Firat, M. (2008) Comparison of Artificial Intelligence Techniques for river flow forecasting. *Hydrology and Earth System Sciences* **12(1)**: 123-139.
- Firat, M. and Güngör, M. (2008) Hydrological time-series modelling using an adaptive neuro-fuzzy inference system. *Hydrological Processes* **22(13)**: 2122-2132.
- Fraser, A.M. and Swinney, H.L. (1986) Independent coordinates for strange attractors from mutual information. *Physical review A* **33(2)**: 1134.
- Fullér, R. (1995) Neural fuzzy systems.
- Furundzic, D. (1998) Application example of neural networks for time series analysis:: Rainfall–runoff modeling. *Signal Processing* **64(3)**: 383-396.
- Galavi, H., Mirzaei, M., Shui, L.T. and Valizadeh, N. (2013) Klang River–level forecasting using ARIMA and ANFIS models. *American Water Works Association (AWWA)* 105(9).
- Ghafari, G. and Vafakhah, M. (2012) Rainfall-runoff modeling using artificial neural networks and adaptive neuro-fuzzy inference system models. *Uncertainty Modeling in Knowledge Engineering and Decision Making* **7**: 951-956.
- Ghazali, J.N. and Kamsin, A. (2008) A real time simulation of flood hazard, pp. 393-397, IEEE.
- Glenn, E.P., Jed Brown, J. and O'Leary, J.W. (1998) Irrigating crops with seawater. *Scientific American-American Edition-* **279**: 76-81.
- Goodwin, G. and Sin, K.S. (1984) Adaptive prediction, filtering and control, Prentice hall.

- Govindaraju, R. (2000a) Artificial neural networks in hydrology: ii, hydrologic applications.
- Govindaraju, R.S. (2000b) Artificial neural networks in hydrology. I: Preliminary concepts. *Journal of Hydrologic Engineering* **5(2)**: 115-123.
- Govindaraju, V., Young, K., & Maudsley, A. A. (2000). Proton NMR chemical shifts and coupling constants for brain metabolites. *NMR in Biomedicine* **13(3)**: 129-153.
- Gupta, H.V., Hsu, K.-l. and Sorooshian, S. (1997) Superior training of artificial neural networks using weight-space partitioning, pp. 1919-1923, IEEE.
- Gupta, H.V., Sorooshian, S. and Yapo, P.O. (1999) Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. *Journal of Hydrologic Engineering* **4(2)**: 135-143.
- Halff, A.H., Halff, H.M. and Azmoodeh, M. (1993) Predicting runoff from rainfall using neural networks, pp. 760-765, ASCE.
- Halwatura, D. and Najim, M. (2013) Application of the HEC-HMS model for runoff simulation in a tropical catchment. *Environmental Modelling & Software* **46**: 155-162.
- Harun, S., Nor, N.I.A. and Kassim, A.H.M. (2012) Artificial neural network model for rainfall–runoff relationship. *Jurnal Teknologi* **37(1)**: 1–12.
- Haugh, L.D. and Box, G.E. (1977) Identification of dynamic regression (distributed lag) models connecting two time series. *Journal of the American Statistical Association* **72(357)**: 121-130.
- Haykin, S. (1994) Neural networks: A comprehensive approach. IEEE Computer Society Press.
- He, J., Valeo, C., Chu, A. and Neumann, N.F. (2011) Prediction of event-based stormwater runoff quantity and quality by ANNs developed using PMI-based input selection. *Journal of Hydrology* **400(1)**: 10-23.

- Hjelmfelt, A.T. and Wang, M. (1993) Artificial neural networks as unit hydrograph applications, pp. 754-759, ASCE.
- Hong, Y.-S.T. (2012) Dynamic nonlinear state-space model with a neural network via improved sequential learning algorithm for an online real-time hydrological modeling. *Journal of Hydrology* **468**: 11-21.
- Hong, Y.-S.T. and White, P.A. (2009) Hydrological modeling using a dynamic neuro-fuzzy system with on-line and local learning algorithm. *Advances in Water Resources* **32(1)**: 110-119.
- Hopfield, J.J. and Tank, D.W. (1985) "Neural" computation of decisions in optimization problems. *Biological cybernetics* **52(3)**: 141-152.
- Horton, R.E. (1933) The role of infiltration in the hydrologic cycle. *Eos, Transactions American Geophysical Union* **14(1)**: 446-460.
- Hosseini, S. M., & Mahjouri, N. (2016). Integrating support vector regression and a geomorphologic artificial neural network for daily rainfall-runoff modeling. *Applied Soft Computing* **38**: 329-345.
- Hsia, T.C. (1977) System identification: Least-squares methods(Book). Lexington, Mass., D. C. Heath and Co., 1977. 177 p.
- Hsu, K.I., Gupta, H.V. and Sorooshian, S. (1995) Artificial Neural Network Modeling of the Rainfall-Runoff Process. *Water Resources Research* **31(10)**: 2517-2530.
- Hughes, D. (1984) An isolated event model based upon direct runoff calculations using an implicit source area concept. *Hydrological Sciences Journal* **29(3)**: 311-325.
- Hunukumbura, P., Weerakoon, S. and Herath, S. (2008) Runoff modeling in the upper Kotmale Basin. Traversing No Man's Land, Interdisciplinary Essays in Honor of Professor Madduma Bandara. University of Peradeniya, Sri Lanka, 169-184.

- Izham, M.Y., Uznir, U., Alias, A. and Ayob, K. (2010) Georeference, rainfall-runoff modeling and 3D dynamic simulation: physical influence, integration and approaches, p. 21, ACM.
- Jacquín, A.P. and Shamseldin, A.Y. (2006) Development of rainfall-runoff models using Takagi-Sugeno fuzzy inference systems. *Journal of Hydrology* **329(1-2)**: 154-173.
- Jain, A. and Prasad Indurthy, S. (2004) Closure to “Comparative Analysis of Event-based Rainfall-runoff Modeling Techniques-Deterministic, Statistical, and Artificial Neural Networks” by Ashu Jain and SKV Prasad Indurthy. *Journal of Hydrologic Engineering* **9(6)**: 551-553.
- Jain, A., Sudheer, K. and Srinivasulu, S. (2004) Identification of physical processes inherent in artificial neural network rainfall runoff models. *Hydrological Processes* **18(3)**: 571-581.
- Jamaludin, S. and Jemain, A.A. (2012) Fitting the statistical distributions to the daily rainfall amount in peninsular Malaysia. *Jurnal Teknologi* **46(1)**: 33-48.
- Jang, J.S.R. (1993a) ANFIS: adaptive-network-based fuzzy inference system. *Systems, Man and Cybernetics, IEEE Transactions on* **23(3)**: 665-685.
- Jang, J.-S.R. (1993b) ANFIS: adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man and Cybernetics* **23(3)**: 665-685.
- Ju, Q., Yu, Z., Hao, Z., Ou, G., Zhao, J. and Liu, D. (2009) Division-based rainfall-runoff simulations with BP neural networks and Xinanjiang model. *Neurocomputing* **72(13-15)**: 2873-2883.
- Juang, C.-F. and Lin, C.-T. (1998) An online self-constructing neural fuzzy inference network and its applications. *Fuzzy Systems, IEEE Transactions on* **6(1)**: 12-32.
- Kalita, D.N. (2008) A study of basin response using HEC-HMS and subzone reports of CWC.

- Karimi-Googhari, S. and Lee, T. (2011) Applicability of adaptive neuro-fuzzy inference systems in daily reservoir inflow forecasting. *International Journal of Soft Computing* **6(3)**: 75-84.
- Karray, F.O. and De Silva, C.W. (2004) Soft computing and intelligent systems design: theory, tools and applications, Addison Wesley Longman.
- Kasabov, N. K., & Song, Q. (2002). DENFIS: dynamic evolving neural-fuzzy inference system and its application for time-series prediction. *IEEE transactions on Fuzzy Systems*. *10(2)*, 144-154.
- Kashani, M. H., Ghorbani, M. A., Dinpashoh, Y., & Shahmorad, S. (2016). Integration of Volterra model with artificial neural networks for rainfall-runoff simulation in forested catchment of northern Iran. *Journal of Hydrology* **540**: 340-354.
- Kavvas, M. and Chen, Z. (1998) Meteorologic Model Interface for HEC-HMS: NCEP Eta Atmospheric Model and HEC Hydrologic Modeling System. Report to the United States Army Corps of Engineers Hydrologic Engineering Center.
- Kholghi, M. and Hosseini, S. (2009) Comparison of groundwater level estimation using neuro-fuzzy and ordinary kriging. *Environmental Modeling & Assessment* **14(6)**: 729-737.
- Khoshnevisan, B., Rafiee, S., Omid, M. and Mousazadeh, H. (2014) Prediction of potato yield based on energy inputs using multi-layer adaptive neuro-fuzzy inference system. *Measurement* **47**: 521-530.
- Kişi, Ö. (2006) Daily pan evaporation modelling using a neuro-fuzzy computing technique. *Journal of Hydrology* **329(3-4)**: 636-646.
- Kisi, O., Shiri, J. and Tombul, M. (2013) Modeling rainfall-runoff process using soft computing techniques. *Computers & geosciences* **51(0)**: 108-117.
- Klaassen, W., Bosveld, F. and De Water, E. (1998) Water storage and evaporation as constituents of rainfall interception. *Journal of Hydrology* **212**: 36-50.

- Kohler, M.A. (1951) Predicting the runoff from storm rainfall.
- Kuok, K.K., Harun, S. and Shamsuddin, S.M. (2010) Particle swarm optimization feedforward neural network for modeling runoff. *International Journal of Environmental Science and Technology* **7(1)**: 67-78.
- Kwin, C. T., Talei, A., Alaghmand, S., & Chua, L. H. (2016). Rainfall-runoff Modeling Using Dynamic Evolving Neural Fuzzy Inference System with Online Learning. *Procedia Engineering* **154**: 1103-1109.
- Leavesley, G.H., Lichty, R., Thoutman, B. and Saindon, L. (1983) Precipitation-runoff modeling system: User's manual, USGS Washington, DC.
- Legates, D.R. and McCabe, G.J. (1999) Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model validation. *Water Resources Research* **35(1)**: 233-241.
- Lekkas, S. and Mikhailov, L. (2010) Evolving fuzzy medical diagnosis of Pima Indians diabetes and of dermatological diseases. *Artificial Intelligence in Medicine* **50(2)**: 117-126.
- Lim, S. and Cheok, H. (2009) Two-dimensional flood modelling of the Damansara River, pp. 13-24, Thomas Telford Ltd.
- Lin, C.-T. and Lee, C.S.G. (1991) Neural-network-based fuzzy logic control and decision system. *Computers, IEEE Transactions on* **40(12)**: 1320-1336.
- Lin, C.T. and Lee, C.S.G. (1996) Neural fuzzy systems: a neuro-fuzzy synergism to intelligent systems, Prentice-Hall, Inc. Upper Saddle River, NJ, USA.
- Lin, G.-F. and Chen, L.-H. (2004) A non-linear rainfall-runoff model using radial basis function network. *Journal of Hydrology* **289(1)**: 1-8.
- Lohani, A.K., Goel, N.K. and Bhatia, K.K.S. (2006) Takagi–Sugeno fuzzy inference system for modeling stage–discharge relationship. *Journal of Hydrology* **331(1–2)**: 146-160.

- Lohani, A.K., Goel, N.K. and Bhatia, K.K.S. (2011) Comparative study of neural network, fuzzy logic and linear transfer function techniques in daily rainfall-runoff modelling under different input domains. *Hydrological Processes* **25(2)**: 175-193.
- Lohani, A.K., Goel, N.K. and Bhatia, K.K.S. (2014) Improving real time flood forecasting using fuzzy inference system. *Journal of Hydrology* **509(0)**: 25-41.
- Luna, I., Soares, S. and Ballini, R. (2007) An adaptive hybrid model for monthly streamflow forecasting, pp. 1-6, IEEE.
- M. A. Kohler, 'The Use of Crest Stage Relations in Forecasting the Rise and Fall of the Flood Hydrograph', U.S. Weather Bureau, 1944 (mimeo).
- Maguire, E.A., Burgess, N., Donnett, J.G., Frackowiak, R.S., Frith, C.D. and O'Keefe, J. (1998) Knowing where and getting there: a human navigation network. *Science* **280(5365)**: 921-924.
- Mah, D.Y.S., Hii, C.P., Putuhena, F.J. and Lai, S.H. (2011) Technical note: River modelling to infer flood management framework. *Water SA* 37(1).
- Mah, Y.S., Lai, S.H., Chan, R. and Putuhena, F.J. (2012) Investigative modelling of the flood bypass channel in Kuching, Sarawak, by assessing its impact on the inundations of Kuching-Batu Kawa-Bau Expressway. *Structure and Infrastructure Engineering* **8(7)**: 705-714.
- Mahabir, C., Hicks, F.E. and Fayek, A.R. (2003) Application of fuzzy logic to forecast seasonal runoff. *Hydrological Processes* **17(18)**: 3749-3762.
- Maier, H.R. and Dandy, G.C. (1997) Determining inputs for neural network models of multivariate time series. *Computer-Aided Civil and Infrastructure Engineering* **12(5)**: 353-368.
- Mamdani, E.H. (1974) Application of fuzzy algorithms for control of simple dynamic plant. *Electrical Engineers, Proceedings of the Institution of* **121(12)**: 1585-1588.

- Mamdani, E.H. and Assilian, S. (1975) EXPERIMENT IN LINGUISTIC SYNTHESIS WITH A FUZZY LOGIC CONTROLLER. *International Journal of Man-Machine Studies* **7(1)**: 1-13.
- Mariño, P., Pastoriza, V., Santamaría, M. and Martínez, E. (2005) *Fuzzy Systems and Knowledge Discovery*. pp. 950-960, Springer.
- Mazion Jr, E. and Yen, B.C. (1994) Computational discretization effect on rainfall-runoff simulation. *Journal of Water Resources Planning and Management* **120(5)**: 715-734.
- McCulloch, W.S. and Pitts, W. (1943) A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics* **5(4)**: 115-133.
- Minns, A. and Hall, M. (1996) Artificial neural networks as rainfall-runoff models. *Hydrological Sciences Journal* **41(3)**: 399-417.
- Mitra, S. and Hayashi, Y. (2000) Neuro-fuzzy rule generation: survey in soft computing framework. *Neural Networks, IEEE Transactions on* **11(3)**: 748-768.
- Moghaddamnia, A., Ghafari Gousheh, M., Piri, J., Amin, S. and Han, D. (2009) Evaporation estimation using artificial neural networks and adaptive neuro-fuzzy inference system techniques. *Advances in Water Resources* **32(1)**: 88-97.
- Mohammed, T.A., Said, S., Bardaie, M.Z. and Basri, S.N. (2011) Numerical simulation of flood levels for tropical rivers, p. 012040, IOP Publishing.
- Moon, Y.I., Rajagopalan, B. and Lall, U. (1995) Estimation of mutual information using kernel density estimators. *Physical Review E* **52(3)**: 2318.
- Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D. and Veith, T.L. (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE* **50(3)**: 885-900.

- Mukerji, A., Chatterjee, C. and Raghuwanshi, N. (2009) Flood Forecasting Using ANN, Neuro-Fuzzy, and Neuro-GA Models. *Journal of Hydrologic Engineering* **14(6)**: 647-652.
- Mukerji, A., Chatterjee, C. and Raghuwanshi, N.S. (2009) Flood forecasting using ANN, neuro-fuzzy, and neuro-GA models. *Journal of Hydrologic Engineering* **14(6)**: 647-652.
- Mutlu, E., Chaubey, I., Hexmoor, H. and Bajwa, S. (2008) Comparison of artificial neural network models for hydrologic predictions at multiple gauging stations in an agricultural watershed. *Hydrological Processes* **22(26)**: 5097-5106.
- Nash, J. (1957) The form of the instantaneous unit hydrograph. *International Association of Scientific Hydrology Publ 3*: 114-121.
- Nash, J. E., and Sutcliffe, J. V. (1970). "River flow forecasting through conceptual models, Part 1 - A discussion of principles." *Journal of Hydrology* **10(3)**: 282-290
- Nauck, D. and Kruse, R. (1995) NEFCLASS; a neuro-fuzzy approach for the classification of data, pp. 461-465, ACM.
- Nauck, D., Klawonn, F. and Kruse, R. (1997) Foundations of neuro-fuzzy systems, John Wiley & Sons, Inc.
- Nayak, P. (2010) Explaining Internal Behavior in a Fuzzy If-Then Rule-Based Flood-Forecasting Model. *Journal of Hydrologic Engineering* **15(1)**: 20-28.
- Nayak, P.C., Sudheer, K.P. and Jain, S.K. (2007) Rainfall-runoff modeling through hybrid intelligent system. *Water Resources Research* **43(7)**: 17.
- Nayak, P.C., Sudheer, K.P. and Ramasastri, K.S. (2005b) Fuzzy computing based rainfall-runoff model for real time flood forecasting. *Hydrological Processes* **19(4)**: 955-968.
- Nayak, P.C., Sudheer, K.P., Rangan, D.M. and Ramasastri, K.S. (2004) A neuro-fuzzy computing technique for modeling hydrological time series. *Journal of Hydrology* **291(1-2)**: 52-66.

- Nayak, P.C., Sudheer, K.P., Rangan, D.M. and Ramasastri, K.S. (2005a) Short-term flood forecasting with a neurofuzzy model. *Water Resources Research* **41(4)**: W04004.
- Nguyen, P. K. T., Chua, L. H. C., & Son, L. H. (2014). Flood forecasting in large rivers with data-driven models. *Natural hazards* **71(1)**: 767-784.
- Noori, R., Karbassi, A., Moghaddamnia, A., Han, D., Zokaei-Ashtiani, M., Farokhnia, A. and Gousheh, M.G. (2011) Assessment of input variables determination on the SVM model performance using PCA, Gamma test, and forward selection techniques for monthly stream flow prediction. *Journal of Hydrology* **401(3)**: 177-189.
- Noori, R., Safavi, S. and Nateghi Shahrokni, S.A. (2013) A reduced-order adaptive neuro-fuzzy inference system model as a software sensor for rapid estimation of five-day biochemical oxygen demand. *Journal of Hydrology* **495**: 175-185.
- Nor, N., Harun, S. and Kassim, A. (2007) Radial Basis Function Modeling of Hourly Streamflow Hydrograph. *Journal of Hydrologic Engineering* **12(1)**: 113-123.
- Nourani, V. (2017). An Emotional ANN (EANN) approach to modeling rainfall-runoff process. *Journal of Hydrology* **544**: 267-277.
- Nourani, V. and Komasi, M. (2013) A geomorphology-based ANFIS model for multi-station modeling of rainfall-runoff process. *Journal of Hydrology* **490**: 41-55.
- Nourani, V., Baghanam, A.H., Adamowski, J. and Gebremichael, M. (2013) Using self-organizing maps and wavelet transforms for space-time pre-processing of satellite precipitation and runoff data in neural network based rainfall-runoff modeling. *Journal of Hydrology* **476(0)**: 228-243.
- Nourani, V., Kisi, Ö., & Komasi, M. (2011). Two hybrid artificial intelligence approaches for modeling rainfall-runoff process. *Journal of Hydrology* **402(1)**: 41-59.

- Ouyang, H. T. (2017). Optimization of autoregressive, exogenous inputs-based typhoon inundation forecasting models using a multi-objective genetic algorithm. *Engineering Optimization* **49(7)**: 1211-1225.
- Oki, T., & Kanae, S. (2006). Global hydrological cycles and world water resources. *science*, 313(5790), 1068-1072.
- Peterson, T. C., Stott, P. A., & Herring, S. (2012). Explaining extreme events of 2011 from a climate perspective. *Bulletin of the American Meteorological Society* **93(7)**: 1041-1067.
- Pettitt, A. (1979) A non-parametric approach to the change-point problem. *Applied statistics* 126-135.
- Pingan, Z. and Xiaohong, G. (2000) Fuzzy modeling for electrical market price forecasting, pp. 2262-2266, IEEE.
- Purnomo, M.R.A., Wahab, D.A., Hassan, A. and Rahmat, R.A.A.O. (2009) A parallel genetic algorithm-based TSK-Fuzzy system for dynamic car-following modeling. *European Journal of Scientific Research* **28(4)**: 628-642.
- Quah, K.H. and Quek, C. (2006) FITSK: online local learning with generic fuzzy input Takagi-Sugeno-Kang fuzzy framework for nonlinear system estimation. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on* **36(1)**: 166-178.
- Quick, M. and Pipes, A. (1972) Daily and seasonal runoff forecasting with a water budget model, pp. 1017-1034.
- Rajurkar, M., Kothiyari, U. and Chaube, U. (2002) Artificial neural networks for daily rainfall—runoff modelling. *Hydrological Sciences Journal* **47(6)**: 865-877.
- Rath, S., Nayak, P. C., & Chatterjee, C. (2013). Hierarchical neurofuzzy model for real-time flood forecasting. *International journal of river basin management* **11(3)**: 253-268.

- Razi, M., Ariffin, J., Tahir, W. and Arish, N. (2010) Flood estimation studies using hydrologic modeling system (HEC-HMS) for Johor River, Malaysia. *Journal of Applied Sciences* **10(11)**: 930-939.
- Regina Siqueira Ortega, N., Cesar Sallum, P. and Massad, E. (2000) Fuzzy dynamical systems in epidemic modelling. *Kybernetes* **29(2)**: 201-218.
- Remesan, R., Shamim, M.A., Han, D. and Mathew, J. (2009) Runoff prediction using an integrated hybrid modelling scheme. *Journal of Hydrology* **372(1)**: 48-60.
- Riad, S., Mania, J., Bouchaou, L. and Najjar, Y. (2004) Rainfall-runoff model using an artificial neural network approach. *Mathematical and Computer Modelling* **40(7-8)**: 839-846.
- Rumelhart, D.E., McClelland, J.L. and Group, P.R. (1986) Parallel distributed processing, Vols 1 and 2. Cambridge, MA: The MIT Press.
- Sajikumar, N. and Thandaveswara, B. (1999) A non-linear rainfall-runoff model using an artificial neural network. *Journal of Hydrology* **216(1)**: 32-55.
- Sargent, D. (1981) Investigation into the Effects of Storm Movement on the Design of Urban Drainage Systems: Part 1. *Public Health Eng.* **9(4)**: 201-207.
- Sargent, D. (1982) An investigation into the effects of storm movement on the design of urban drainage systems: Part 2. Probability analysis. *Public Health Engineer* **10(2)**: 111-117.
- Scanlon, T. M., Raffensperger, J. P., Hornberger, G. M., & Clapp, R. B. (2000). Shallow subsurface storm flow in a forested headwater catchment: Observations and modeling using a modified TOPMODEL. *Water resources research* **36(9)**: 2575-2586.
- Servat, E. and Dezetter, A. (1991) Selection of calibration objective functions in the context of rainfall-runoff modelling in a Sudanese savannah area. *Hydrological Sciences Journal* **36(4)**: 307-330.

- Shafie, A. (2009). "Extreme flood event: A case study on floods of 2006 and 2007 in Johor, Malaysia." Technical report, Department of Civil and Environmental Engineering, Colorado State University, Fort Collins, Colorado.
- Shamseldin, A.Y. (1997) Application of a neural network technique to rainfall-runoff modelling. *Journal of Hydrology* **199(3)**: 272-294.
- Shamseldin, A.Y. (2010) Artificial neural network model for river flow forecasting in a developing country. *Journal of Hydroinformatics* **12(1)**: 22-35.
- Shamseldin, A.Y., Nasr, A.E. and O'Connor, K.M. (2002) Comparison of different forms of the multi-layer feed-forward neural network method used for river flow forecasting. *Hydrology and Earth System Sciences Discussions* **6(4)**: 671-684.
- Sherman, L.K. (1932) Streamflow from rainfall by the unit-graph method. *Eng. News Record* **108**: 501-505.
- Shim, K.-C., Fontane, D.G. and Labadie, J.W. (2002) Spatial decision support system for integrated river basin flood control. *Journal of Water Resources Planning and Management* **128(3)**: 190-201.
- Shoaib, M., Shamseldin, A. Y., & Melville, B. W. (2014). Comparative study of different wavelet based neural network models for rainfall–runoff modeling. *Journal of Hydrology* **515**: 47-58.
- Shoaib, M., Shamseldin, A.Y. and Melville, B.W. (2014) Comparative study of different wavelet based neural network models for rainfall–runoff modeling. *Journal of Hydrology* **515(0)**: 47-58.
- Siang, I.C., Abdullah, R., Zakaria, N.A., Ghani, A.A. and kiat, C.C. (2007) Modelling urban river catchment: A case study of Berop River, Tanjong Malim, Perak. *Education* **5**, 1.
- Singh, A., Quek, C. and Cho, S.-Y. (2008) DCT-Yager FNN: A novel Yager-based fuzzy neural network with the discrete clustering technique. *Neural Networks, IEEE Transactions on* **19(4)**: 625-644.

- Singh, V. (1998) Effect of the direction of storm movement on planar flow. *Hydrological Processes* **12(1)**: 147-170.
- Singh, V.P. (1988) Hydrologic systems. Volume I: Rainfall-runoff modeling. Prentice Hall, Englewood Cliffs New Jersey. 1988. 480.
- Singh, V.P. and Woolhiser, D.A. (2002) Mathematical modeling of watershed hydrology. *Journal of Hydrologic Engineering* **7(4)**: 270-292.
- Sivakumar, M. V. K., Wilhite, D. A., Pulwarty, R. S., & Stefanski, R. (2014). The high-level meeting on national drought policy. *Bulletin of the American Meteorological Society* **95(4)**: ES85-ES88
- Snead, D.B. (2000) Development and application of unsteady flood models using geographic information systems, Citeseer.
- Snyder, F.F. (1938) Synthetic unit-graphs. *Eos, Transactions American Geophysical Union* **19(1)**: 447-454.
- Sohail, A., Watanabe, K. and Takeuchi, S. (2008) Runoff analysis for a small watershed of Tono Area Japan by back propagation artificial neural network with seasonal data. *Water Resources Management* **22(1)**: 1-22.
- Solomatine, D.P. and Wagener, T. (2011) Treatise on Water Science. Wilderer, P. (ed), pp. 435-457, Elsevier, Oxford.
- Song, N.K.a.Q. (1999) Dynamic Evolving Fuzzy Neural Networks with 'm-out-of-n' Activation Nodes for On-line Adaptive Systems. Technical Report TR99/04, Department of information science, University of Otago.
- Srinivasulu, S. and Jain, A. (2006) A comparative analysis of training methods for artificial neural network rainfall-runoff models. *Applied Soft Computing* **6(3)**: 295-306.
- Straub, T.D., Melching, C.S. and Kocher, K.E. (2000) Equations for estimating Clark unit-hydrograph parameters for small rural watersheds in Illinois, US Dept. of the Interior, US Geological Survey; Branch of Information Services.

- Subasi, A. (2007) Application of adaptive neuro-fuzzy inference system for epileptic seizure detection using wavelet feature extraction. *Computers in Biology and Medicine* **37(2)**: 227-244.
- Sudheer, K. (2005) Knowledge extraction from trained neural network river flow models. *Journal of Hydrologic Engineering* **10(4)**: 264-269.
- Sudheer, K. and Jain, A. (2004) Explaining the internal behaviour of artificial neural network river flow models. *Hydrological Processes* **18(4)**: 833-844.
- Sudheer, K.P., Gosain, A.K. and Ramasastri, K.S. (2002) A data-driven algorithm for constructing artificial neural network rainfall-runoff models. *Hydrological Processes* **16(6)**: 1325-1330.
- Suhaila, J. and Jemain, A. (2008) Fitting the statistical distribution for daily rainfall in Peninsular Malaysia based on AIC criterion. *J. Appl. Sci. Res* **4(12)**: 1846-1857.
- Sulaiman, M., El-Shafie, A., Karim, O. and Basri, H. (2011) Improved water level forecasting performance by using optimal steepness coefficients in an artificial neural network. *Water Resources Management* **25(10)**: 2525-2541.
- Sulzberger, S.M., Tschichold-Gurman, N. and Vestli, S.J. (1993) FUN: optimization of fuzzy rule based systems using neural networks, pp. 312-316 vol.311.
- Surkan, A. (1974) Simulation of storm velocity effects on flow from distributed channel networks. *Water Resources Research* **10(6)**: 1149-1160.
- Takagi, T. and Sugeno, M. (1984) Derivation of fuzzy control rules from human operator's control actions, pp. 55-60, IFAC by Pergamon Press, Marseille, Fr.
- Takagi, T. and Sugeno, M. (1985) Fuzzy identification of systems and its applications to modeling and control. *Systems, Man and Cybernetics, IEEE Transactions on SMC* **15(1)**: 116-132.
- Talei, A. and Chua, L.H.C. (2012) Influence of lag time on event-based rainfall-runoff modeling using the data driven approach. *Journal of Hydrology* **438-439(0)**: 223-233.

- Talei, A., Chua, L.H.C. and Quek, C. (2010a) A novel application of a neuro-fuzzy computational technique in event-based rainfall–runoff modeling. *Expert Systems with Applications* **37(12)**: 7456-7468.
- Talei, A., Chua, L.H.C. and Wong, T.S.W. (2010b) Evaluation of rainfall and discharge inputs used by Adaptive Network-based Fuzzy Inference Systems (ANFIS) in rainfall–runoff modeling. *Journal of Hydrology* **391(3–4)**: 248-262.
- Talei, A., Chua, L.H.C., Quek, C. and Jansson, P.-E. (2013) Runoff forecasting using a Takagi–Sugeno neuro-fuzzy model with online learning. *Journal of Hydrology* **488(0)**: 17-32.
- Tallaksen, L. (1995) A review of baseflow recession analysis. *Journal of Hydrology* **165(1)**: 349-370.
- Tan, S.B., Chua, L.H., Shuy, E.B., Lo, E.Y.-M. and Lim, L.W. (2008) Performances of rainfall-runoff models calibrated over single and continuous storm flow events. *Journal of Hydrologic Engineering* **13(7)**: 597-607.
- Tano, S.i., Oyama, T. and Arnould, T. (1996) Deep combination of fuzzy inference and neural network in fuzzy inference software — FINEST. *Fuzzy Sets and Systems* **82(2)**: 151-160.
- Tayfur, G. and Singh, V. (2006) ANN and Fuzzy Logic Models for Simulating Event-Based Rainfall-Runoff. *Journal of Hydraulic Engineering* **132(12)**: 1321-1330.
- Teo, F., Falconer, R. and Lin, B. (2009) Modelling effects of mangroves on tsunamis, pp. 3-12, Thomas Telford Ltd.
- Thevaril, J. and Kwan, H. (2005) Speech enhancement using adaptive neuro-fuzzy filtering, pp. 753-756, IEEE.
- Todini, E. and Wallis, J. (1978) A real-time rainfall-runoff model for an on-line flood warning system. Application of Kalman filter to hydrology, hydraulics and water resources, edited by: Chaolin, C, 355-368.

- Todini, E. and Wallis, J.R. (1977) Using CLS for daily or longer period rainfall-runoff modelling. *Mathematical models for surface water hydrology* **100**: 149-168.
- Tokar, A. S., & Johnson, P. A. (1999). Rainfall-runoff modeling using artificial neural networks. *Journal of Hydrologic Engineering* **4(3)**: 232-239.
- Tokar, A.S. and Johnson, P.A. (1999) Rainfall-runoff modeling using artificial neural networks. *Journal of Hydrologic Engineering* **4(3)**: 232-239.
- Tokar, A.S. and Markus, M. (2000) Precipitation-runoff modeling using artificial neural networks and conceptual models. *Journal of Hydrologic Engineering* **5(2)**: 156-161.
- Toriman, M.E., Hassan, A.J., Gazim, M.B., Mokhtar, M., Mastura, S.S., Jaafar, O., Karim, O. and Aziz, N.A.A. (2009) Integration of 1-d hydrodynamic model and GIS approach in flood management study in Malaysia. *Research Journal of Earth Sciences* **1(1)**: 22-27.
- Tung, W.L. and Quek, C. (2002) GenSoFNN: a generic self-organizing fuzzy neural network. *Neural Networks, IEEE Transactions on* **13(5)**: 1075-1086.
- Tutmez, B., Hatipoglu, Z. and Kaymak, U. (2006) Modelling electrical conductivity of groundwater using an adaptive neuro-fuzzy inference system. *Computers & geosciences* **32(4)**: 421-433.
- Uhrig, R.E. and Tsoukalas, L.H. (1999) Soft computing technologies in nuclear engineering applications. *Progress in Nuclear Energy* **34(1)**: 13-75.
- Valizadeh, N., El-Shafie, A., Mirzaei, M., Galavi, H., Mukhlisin, M. and Jaafar, O. (2014) Accuracy enhancement for forecasting water levels of reservoirs and river streams using a multiple-input-pattern fuzzification approach. *The Scientific World Journal* 2014.
- Van Dijk, M., Boekelman, R. and Rientjes, T. (1999) Modelling of hydrological processes. by H.-P. BÃ¶hr and T. VÃ¶gtle. Stuttgart, Schweizerbart, 283-292.

- Van Ooyen, A. and Nienhuis, B. (1992) Improving the convergence of the back-propagation algorithm. *Neural Networks* **5(3)**: 465-471.
- VEMURI, V., & VEMURI, N. (1970). On the systems approach in hydrology. *Hydrological Sciences Journal* **15(2)**: 17-38.
- Vernieuwe, H., Georgieva, O., De Baets, B., Pauwels, V.R., Verhoest, N.E. and De Troch, F.P. (2005) Comparison of data-driven Takagi–Sugeno models of rainfall–discharge dynamics. *Journal of Hydrology* **302(1)**: 173-186.
- Von Neumann, J. (1941) Distribution of the ratio of the mean square successive difference to the variance. *The Annals of Mathematical Statistics* **12(4)**: 367-395.
- Wang, D., Quek, C. and Ng, G.S. (2004) Novel self-organizing Takagi Sugeno Kang fuzzy neural networks based on ART-like clustering. *Neural Processing Letters* **20(1)**: 39-51.
- Wardah, T., Bakar, S.A., Bardossy, A. and Maznorizan, M. (2008) Use of geostationary meteorological satellite images in convective rain estimation for flash-flood forecasting. *Journal of Hydrology* **356(3)**: 283-298.
- Wijngaard, J., Klein Tank, A. and Können, G. (2003) Homogeneity of 20th century European daily temperature and precipitation series. *International Journal of Climatology* **23(6)**: 679-692.
- Wilby, R., Abrahart, R. and Dawson, C. (2003) Detection of conceptual model rainfall—runoff processes inside an artificial neural network. *Hydrological Sciences Journal* **48(2)**: 163-181.
- Wilcox, B.P., Rawls, W., Brakensiek, D. and Wight, J.R. (1990) Predicting runoff from rangeland catchments: a comparison of two models. *Water Resources Research* **26(10)**: 2401-2410.
- Woolhiser, D. and Goodrich, D. (1988) Effect of storm rainfall intensity patterns on surface runoff. *Journal of Hydrology* **102(1-4)**: 335-354.

- Wu, J.S., Han, J., Annambhotla, S. and Bryant, S. (2005) Artificial neural networks for forecasting watershed runoff and stream flows. *Journal of Hydrologic Engineering*.
- Wu, Y.-H., Woolhiser, D. and Yevjevich, V. (1982) Effects of spatial variability of hydraulic resistance of runoff hydrographs. *Journal of Hydrology* **59(3)**: 231-248.
- Yakubu, M.L., Yusop, Z. and Fulazzaky, M.A. (2014) The Influence of Rain Intensity on Raindrop Diameter and the Kinetics of Tropical Rainfall: A Case study of Skudai, Malaysia. *Hydrological Sciences Journal*.
- Yan, H., Zou, Z. and Wang, H. (2010) Adaptive neuro fuzzy inference system for classification of water quality status. *Journal of Environmental Sciences* **22(12)**: 1891-1896.
- Yen, J. and Langari, R. (1999) Fuzzy logic. Intelligence, Control, and Information.
- Yilma, H. and Moges, S.A. (2007) Application of semi-distributed conceptual hydrological model for flow forecasting on upland catchments of Blue Nile River Basin, a case study of Gilgel Abbay catchment. *Catchment and Lake Research* 200.
- Yusop, Z., Chan, C. and Katimon, A. (2007) Runoff characteristics and application of HEC-HMS for modelling stormflow hydrograph in an oil palm catchment. *Water Science and Technology* **56(8)**: 41-48.
- Zadeh, L.A. (1965) Fuzzy sets. *Information and Control* **8(3)**: 338-353.
- Zakhrouf, M., Chettih, M. and Mesbah, M. (2013) Adaptive neural fuzzy inference systems for the daily flow forecast in Algerian coastal basins. *Desalination and Water Treatment* **52(10-12)**: 2131-2138.
- Zhang, C., Wang, Y.L., Zhang, L.L. and Zhou, H.C. (2012) A fuzzy inference method based on association rule analysis with application to river flood forecasting. *Water Science and Technology* **66(10)**: 2090-2098.

- Zhou, R.W. and Quek, C. (1996) POPFNN: A pseudo outer-product based fuzzy neural network. *Neural Networks* **9(9)**: 1569-1581.
- Zhu, M.-L., Fujita, M. and Hashimoto, N. (1994) *Stochastic and statistical methods in hydrology and environmental engineering*. pp. 205-216, Springer.
- Zin, W.Z.W., Ibrahim, W., Jemain, A.A., Ibrahim, K., Suhaila, J. and Sayang, M.D. (2009a) A comparative study of extreme rainfall in peninsular malaysia. *Sains Malaysiana* **38(5)**: 751-760.
- Zin, W.Z.W., Jemain, A.A. and Ibrahim, K. (2009b) The best fitting distribution of annual maximum rainfall in Peninsular Malaysia based on methods of L-moment and LQ-moment. *Theoretical and applied climatology* **96(3-4)**: 337-344.
- Zounemat-Kermani, M. and Teshnehlab, M. (2008) Using adaptive neuro-fuzzy inference system for hydrological time series prediction. *Applied Soft Computing* **8(2)**:928-936.