DYNAMIC NEURO-FUZZY SYSTEMS FOR RAINFALL-RUNOFF MODELING

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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 menyesuai melalui pembelajaran tambahan di mana peraturan-asas menyesuai 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 diperoleh 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.

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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
$\widehat{Q}_i$	-	Simulated low rate

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

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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 there 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 date 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.

Chapter 4 is having three different sections, the first section discusses the results obtained from DENFIS, ANFIS, HEC-HMS and ARX model for event based rainfall runoff simulations. The second section presents the results of daily and hourly continuous modeling by neuro-fuzzy systems. The third section discusses the performance of DENFIS and ANFIS for multistep ahead prediction of runoff. The next section presents the results of river stage simulation for Bekok River catchment.

Chapter 5 summarizes the conclusions of this study. Future recommendations Re also discussed in this chapter.

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