IDENTIFICATION OF NON-LINEAR DYNAMIC SYSTEMS USING FUZZY SYSTEM WITH CONSTRAINED MEMBERSHIP FUNCTIONS

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Dedicated to Aya, Sara, Yan, and Iman.

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ABSTRACT

This study deals with the use of the rule-based fuzzy system for the identification of non-linear dynamic systems. Main research directions in this field include the complexity reduction of fuzzy models, structure identification of fuzzy system, and application of new or improved training algorithms. In this study, a constrained fuzzy system (CFS), which is a simplified form of the standard fuzzy system (SFS), was proposed as an alternative identifier of non-linear dynamic systems in order to indirectly reduce the rule explosion problems inherent in fuzzy systems. In addition, the use of two alternative training algorithms, namely the recursive prediction error (RPE) and Levenberg-Marquardt (LM) algorithms, were proposed. In this study, the identification performance of the SFS trained by the back-propagation (BP) algorithm forms the basis of comparison when evaluations were made on the performance of the newly proposed CFS models. It was found that, in most cases, the CFS performs better than the SFS with similar number of adjustable parameters. It was also found that the convergence properties of the RPE algorithm are better than those of the BP algorithm, and the performance of the LM algorithm is comparable to that of the RPE algorithm. Furthermore, this study has shown that the CFS is capable of producing adequate models that can satisfy the 95% confidence requirement of the correlation tests. In addition, in a case study, it has been shown that the CFS has some potential to be an alternative tool for aircraft parameter estimation from flight data. It was also found that the CFS could be used as substitutes for the rainfall-runoff models in cases where the autoregressive with exogenous inputs (ARX) and the autoregressive moving average with exogenous inputs (ARMAX) models need further improvements.

ABSTRAK

Kajian ini adalah berkaitan dengan penggunaan sistem fuzi berasaskan petua untuk pengenalpastian sistem dinamik tak lelurus. Arah utama kajian dalam bidang ini termasuk pengurangan kekompleksan model fuzi, pengenalpastian struktur sistem fuzi dan aplikasi algoritma baru atau yang diperbaiki. Dalam kajian ini, satu bentuk sistem fuzi terkekang (CFS) berasaskan sistem fuzi piawai (SFS) yang dipermudahkan telah dicadangkan untuk digunakan sebagai pengenalpasti alternatif sistem dinamik tak lelurus supaya secara tidak langsung mengurangkan masalah ledakan petua yang diwarisi oleh sistem fuzi. Sebagai tambahan, pengunaan dua lagi algoritma latihan yang dinamai algoritma ralat ramalan jadi semula (RPE) dan algoritma Levenberg-Marquardt (LM) telah dicadangkan. Dalam kajian ini, prestasi pengenalpastian sistem dinamik tak lelurus menggunakan model SFS yang dilatih oleh algoritma rambatan balik (BP) adalah menjadi asas perbandingan apabila penilaian dibuat terhadap prestasi model CFS yang dicadangkan. Kajian ini mendapati bahawa, dalam kebanyakan kes, prestasi pengenalpastian model CFS adalah lebih baik daripada model SFS yang mengandungi bilangan parameter yang setara. Kajian ini juga mendapati penumpuan algoritma RPE adalah lebih baik daripada algoritma BP dan prestasi algoritma LM adalah setara dengan algoritma RPE. Di samping itu, kajian ini telah menujukkan bahawa CFS mampu menghasilkan model yang memenuhi syarat 95% keyakinan yang diperlukan oleh ujian sekaitan. Kajian ini turut mendapati bahawa model CFS mempunyai keupayaan sebagai alat alternatif untuk menganggar parameter pesawat terbang daripada data penerbangan. Ia juga boleh menggantikan model auto mundur dengan masukan luar (ARX) dan model purata bergerak auto mundur dengan masukan luar (ARMAX) dalam permodelan air hujan-air larian jika prestasi model perlu diperbaiki.

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LIST OF SYMBOLS

A	-	Input fuzzy set
a_i	-	Parameters in the ARX or ARMAX models
a_i^l	-	Half-width of the base of the triangular type membership function
B	-	Output fuzzy set
b	-	Notation for simplification of an expression
b_i	-	Parameters in the ARX or ARMAX models
c_i	-	Parameters in the ARMAX model or functional fuzzy system
D	-	Number of input space partitions
d	-	Number of adjustable parameters in fuzzy model
E	-	Expectation operator
e	-	Number of prediction error terms in the ARMAX model
e^j	-	The j^{th} time step model error
F_X	-	Force in the *X*-axis
$\hat{F}_X$	-	Predicted force in the *X*-axis
F_Z	-	Force in the *Z*-axis
$\hat{F}_Z$	-	Predicted force in the *Z*-axis
$\overline{F}_Z$	-	Modified force in the *Z*-axis
f	-	Function or functional form of fuzzy system
G	-	Fuzzy rule
g	-	Function
$\hat{g}$	-	Prediction of g
$\mathbf{H}$	-	Hessian matrix
$\mathbf{I}$	-	Identity matrix
I_Y	-	Moment of inertia about *Y*-axis

i	-	General integer index
J	-	Mean square error
$\bar{J}$	-	Normalized root mean square
j	-	General integer index
k	-	Iteration step
L	-	Total number of fuzzy rules
l	-	Rule number
M	-	Pitching moment
$\hat{M}$	-	Predicted pitching moment
m	-	Mass of an aircraft
N	-	Total number of data pairs in the estimation data set
n	-	Number of input variables
$\mathbf{P}$	-	Covariance matrix for RPE algorithm
$\mathbf{P}_0$	-	Initial covariance matrix
$P(t)$	-	Precipitation (rainfall)
p	-	Input lag
$\mathbf{Q}$	-	Measure of fit
$Q(t)$	-	Observed runoff
$\hat{Q}(t)$	-	Predicted runoff
$\bar{Q}(t)$	-	Mean observed runoff
q	-	Pitch rate
R	-	Set of real numbers or fuzzy relation
R^2	-	Nash and Sutcliffe criterion for rainfall-runoff modeling
r	-	Output lag
$\mathbf{S}$	-	Matrix in the RPE algorithm
$\bar{\mathbf{S}}$	-	Matrix in the LM algorithm
$\bar{\mathbf{S}}_0$	-	Initial value of matrix $\bar{\mathbf{S}}$
s	-	Positive integer
s_0	-	Small diagonal elements of initial matrix $\bar{\mathbf{S}}_0$
T	-	Period of oscillation
t	-	Time step
u	-	General system input or aircraft forward velocity in the X-axis

u_0	-	Nominal speed of an aircraft
$\overline{u}$	-	Mean value of sequence u
V_N	-	Least squares cost function
$\mathbf{V}$	-	Criterion function
v	-	Absolute velocity of an aircraft
w	-	Downward aircraft velocity in the Z-axis
w^l	-	Weight or truth value of the premise of fuzzy rule
X	-	Input space universe of discourse
x	-	Input variable
$\mathbf{x}$	-	Input vector
$\tilde{x}$	-	Linguistic input variable
$\overline{x}$	-	Center of input membership function
Y	-	Output space universe of discourse
$Y(t)$	-	Translated output of $y(t)$
y	-	System output or output variable
$\tilde{y}$	-	Linguistic output variable
$\overline{y}$	-	Center of output membership function
$\hat{y}$	-	Prediction of y
z	-	Notation for simplification of an expression
α	-	Angle of attack or learning rate for BP algorithm
$\tilde{\alpha}$	-	Variation of angle of attack
α_0	-	Nominal angle of attack
β	-	Momentum gain
Δ	-	Integer increment
δ	-	Elevator deflection
δ_0	-	Nominal elevator position
$\boldsymbol{\delta}$	-	Small correction vector
$\hat{\boldsymbol{\delta}}$	-	Estimate of correction vector $\boldsymbol{\delta}$
$\delta(\tau)$	-	Delta function
ε	-	Prediction error or small positive real number
$\boldsymbol{\epsilon}$	-	Prediction error vector
$\overline{\varepsilon}$	-	Mean value of error sequence ε

ϕ	-	Correlation function
$\hat{\phi}$	-	Normalized correlation function
γ	-	Positive scalar of flight path angle
η	-	Positive multiplier for LM algorithm
λ	-	Forgetting factor
$\mathbf{\Lambda}$	-	Positive definite matrix
μ	-	Membership function
ν	-	Resolution factor of the spread of the membership function
$\mathbf{\Theta}$	-	Parameter vector
$\hat{\mathbf{\Theta}}$	-	Estimate of $\mathbf{\Theta}$
$\mathbf{\Theta}^0$	-	Nominal parameter vector
θ	-	Pitch angle
θ_i	-	Elements in the parameter vector $\mathbf{\Theta}$
σ	-	Spread of input membership function
τ	-	General time lag
$\mathbf{\Psi}$	-	Gradient vector of $\hat{y}$ with respect to parameter vector $\mathbf{\Theta}$
ψ	-	General sequence

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CHAPTER 1

INTRODUCTION

1.1 Introduction

An essential step toward the solution of many scientific problems is to accomplish modeling and identification of some objects or systems under investigation. In loose terms, a system is an object in which variables of different kinds interact and produce observable signals. The observable signals are usually called outputs and the external signals that can be manipulated by the observer to affect the system are called inputs. System identification is defined as the process of deriving mathematical models of dynamical systems based on observed data, sometimes called input-output data, in accordance with some predetermined criterion (Johansson, 1993). The resultant of the identification process is called a mathematical model. Mathematical models can also be obtained by splitting up the system under investigation into subsystems whose properties are well understood from previous experiences. These subsystems are then integrated mathematically or in a form of block diagram to produce a model of the whole system. This practice is known as modeling and does not necessarily involve any experimentation on the actual system (Ljung, 1999). Historically, modeling and identification as a methodology dates back to Galileo (1564-1642), who was first to establish the law of falling bodies (Johansson, 1993). Nowadays, since dynamical systems are abundant in our environment, the techniques of system identification have many areas of application such as in the field of control engineering, electrical engineering, economics, biomedicine, and computer science (Johansson, 1993; Ljung, 1999). The main purposes for system identification include prediction or forecasting, control systems analysis and design, signal processing, data compression, and simulation (Ljung and Soderstrom, 1983; Johansson, 1993).

The main problem in system identification is to find a suitable model structure within which a good model is to be found. Parameter estimation within a given structure is in most cases a lesser problem (Sjoberg *et al.*, 1995). In general, classifications of model structure have been color-coded based on the level of prior knowledge as white-box models, gray-box models, and black-box models (Sjoberg *et al.*, 1995; Babuska and Verbruggen, 1996). The model is called white-box when it is perfectly known and it has been possible to construct the model entirely from prior knowledge and physical insight. When only some physical insight is available but several parameters remain to be determined from observed data, then the model is called gray-box. The model is called black-box when no physical insight is available or used, but the chosen model structure belongs to families that have been successful in the past. Many types of black-box model structure have been developed to fulfill the demands imposed by advances in scientific and technological areas. Some of the black-box model structures include finite impulse response (FIR) model, state-space model, output-error model, autoregressive moving average with exogenous inputs (ARMAX) model, non-linear autoregressive moving average with exogenous inputs (NARMAX) model, basis function expansions model, feedforward and recurrent neural networks, and fuzzy model (Sjoberg *et al.*, 1995). Basically, the construction of a model from data involves three entities, namely the data record, the set of models or model structure, and the identification method for determining the 'best' model in the set guided by the data. After a particular model has been identified, model validation tests are conducted to evaluate whether the identified model is acceptable or valid for its purpose. It is quite likely that the model first obtained will not pass the model validation tests. If the model is found to be deficient, then it is necessary to revise the various steps in the identification procedures. It should be noted that a model can never be accepted as a final and true description of the system, rather, it can at best be regarded as a good enough description of certain aspects that are of particular interest (Ljung, 1999).

The main theme of this thesis is the use of rule-based fuzzy system, which is a form of non-linear black-box model structure, for identification of non-linear dynamic systems. In this study, major identification properties of the standard fuzzy system (SFS) trained by the popular back-propagation (BP) algorithm for identification of non-linear dynamic systems were established. Advantages and shortcomings of the BP algorithm were highlighted, and the needs to explore other training algorithms were established. In this study, a form of simplified structure of rule-based fuzzy system was proposed to be use as an alternative identifier of non-linear dynamic systems. In this thesis, this simplified fuzzy system is called the constrained fuzzy system (CFS) due to the nature of the spreads of its membership functions that are constrained to be fixed and uniform. The motivation behind this proposal is to indirectly reduce the rule explosion problems inherent in all fuzzy systems. Major identification properties of the CFS trained by BP algorithm for identification of non-linear dynamic systems were established in this thesis. Direct comparisons between the performances of the SFS and CFS models were conducted. Besides the use of BP algorithm, the use of two alternative algorithms, namely the recursive prediction error (RPE) algorithm and Levenberg-Marquardt (LM) algorithm, were proposed for training the CFS models. It has been shown that, in the field of feedforward neural networks, the RPE and LM algorithms often yield better model predictions and superior convergence properties than the BP algorithm but at the expense of increased computational load (Gawthrop and Sbarbaro, 1990; Billings *et al.*, 1991 and 1992; Fun and Hagan, 1996; Jang and Mizutani, 1996; Mashor, 2000). In this study, direct comparisons were made on the convergence properties of the BP, RPE, and LM algorithms when they were used as training algorithms for the CFS models. Furthermore, model validation tests were conducted on the identified CFS models to show that, despite using a more rigid structure, the CFS is capable of producing adequate and acceptable models. In addition, practical applications of the CFS for identification of non-linear systems in two case studies were explored. One of the case studies involves the use of CFS for estimating the flight parameters of an aircraft for the longitudinal flight motion. The other case study involves the use of CFS for modeling the transformation of the rainfall to runoff for selected river systems in Malaysia.

1.2 Statement of the problem

The basic problem in fuzzy model identification is how to construct a fuzzy system from numerical data. Fuzzy model identification can be formally stated as given some function $g : X \subset R^n \rightarrow Y \subset R,$ where X is compact, a function $f : X \subset R^n \rightarrow Y \subset R$ that approximates the function g is to be constructed such that the function f is in some form of fuzzy logic system. Here R is a set of real numbers. Determining the structure of the respective fuzzy system and its parameters is basically a system identification problem.

1.3 Background of research

It is generally recognized that fuzzy systems can be regarded as model-free estimator that can approximate any real non-linear function to any arbitrary degree of accuracy if enough fuzzy rules are used (Wang and Mendel, 1992a; Kosko, 1997). Generally, three main types of fuzzy structure have been presented in the literature, namely rule-based fuzzy systems, fuzzy relational systems, and fuzzy functional systems which sometimes referred to as Takagi-Sugeno fuzzy systems (Branco and Dente, 2000; Babuska, 1999). There are two important advantages of using fuzzy system as an identifier. First, the parameters of the fuzzy systems have clear physical meaning, i.e. the centers and spreads of the membership functions, and it is therefore possible to choose good initial parameters. The second advantage of fuzzy system is that it provides a framework in which human linguistic descriptions about the unknown non-linear system can be incorporated (Wang, 1994). However, it has been reported in the literature that all fuzzy system suffer from the rule explosion problem (Kosko, 1997). All fuzzy systems face exponential rule growth in high dimension. In general, the identification of fuzzy models consists of three basic subproblems: structure identification, parameter estimation, and model validation (Yen, 1999). Structure identification involves finding the important input variables from all possible input variables, specifying membership functions, partitioning input space, and determining the number of fuzzy rules in the underlying model.

Parameter estimation involves the determination of unknown parameters in the model using some optimization method based on both linguistic information and numerical data obtained from the actual physical system. Structure identification and parameter estimation are interdependent, and either of them cannot be independently identified without resort to another (Takagi and Sugeno, 1985; Sugeno and Yasukawa, 1993: Yen, 1999). Finally, model validation involves testing the identified model based on some performance criterion.

In the early days, the development of fuzzy systems required manual tuning of the system parameters based on observing the system performance. However, it is sometimes too difficult or impossible for human beings to give the desired fuzzy rules or membership functions due to the complexity of the system to be identified. Therefore, it is natural and necessary to generate or tune fuzzy rules by some learning techniques. Using the fuzzy relational system, Pedrycz (1984) proposed a new composition rule and the corresponding identification algorithm with the aid of clustering techniques. Takagi and Sugeno (1985) took an important step by developing the first approach for constructing (not tuning manually) fuzzy rules using training data. Their approach utilized the fuzzy functional system that learned fuzzy rules for controlling a water cleaning process by observing how a human operator controlled the process. For tuning the rule-based fuzzy system, the back-propagation (BP) algorithm, sometimes referred to as the gradient descent method, has been proposed by Nomura *et al.* (1992) and Wang and Mendel (1992a) independently. These pioneer works laid the foundation for further research in fuzzy model identification. In recent years, a plethora of related works on fuzzy model identification have been published in literatures (Dubois *et al.*, 2002a and 2002b).

This current study represents part of the continuous efforts in the search for improved performance of fuzzy models and new practical application of fuzzy identification. The subjects addressed in this study include identification of non-linear dynamic systems using standard fuzzy system (SFS) and the newly proposed constrained fuzzy system (CFS). The CFS was proposed in this study to simplify the standard rule-based fuzzy system and indirectly reduce the rule explosion problem. The use of alternative algorithms for the training of fuzzy systems was also explored. As an integral part of this thesis, comprehensive discussions are given on the description of the rule-based fuzzy systems, the training algorithms, the inherent problem of rule explosion in fuzzy systems, the use of fuzzy systems for identification, and the method for model validation. Practical applications of fuzzy system identification investigated in this study are in the field of aircraft parameters estimation and the rainfall-runoff modeling.

1.4 Objectives and scope of the study

The primary objective of this study is to explore the use of more powerful algorithms for training the rule-based fuzzy systems. The alternative training algorithms proposed in this study were selected based on their proven capabilities in the field of feedforward neural networks where they have been shown to possess superior convergence properties than the back-propagation algorithm but receive little attention in the training of rule-based fuzzy systems. The second objective of this study is to provide a more attractive form of rule-based fuzzy structure with similar or better identification properties compared with those of the standard rule-based fuzzy system. The motivation behind this objective is to indirectly reduce the rule explosion problem inherent in all forms of fuzzy systems. Finally, it is also the objective of this study to evaluate the performance of the proposed fuzzy structure and the respective training algorithms when they are used for system identification in practical applications.

The scope of this study is defined such that the model structure for system identification is the rule-based fuzzy logic system and the selected training algorithms are recursive in nature. The adaptations of the models are conducted off-line and the applications are limited to the identification of discrete non-linear dynamic systems. Although fuzzy model identification consists of structure and parameter identifications, this study focuses only on the parameter estimation procedures. Furthermore, the model validity tests conducted on the identified fuzzy systems are statistical in nature. For practical applications, this study explores the use of the rule-based fuzzy system for the identification of longitudinal aircraft parameters and the modeling of rainfall-runoff processes.

1.5 Methodology

As a preliminary study, this study begins with an investigation about identification properties of the standard fuzzy system (SFS) trained by BP algorithm used as an identifier of dynamic systems. This preliminary work is necessary since, in this thesis, the performance of the SFS trained by BP algorithm forms the basis of comparison when evaluations were made on the identification properties of the newly proposed constrained fuzzy system (CFS). Computer simulations for identification of dynamic plants were conducted using six data sets. Three of these examples used data sets collected from real experiments or observations of real events. Meanwhile, the remaining three examples used synthetic data sets generated using known mathematical expressions. Attentions were given mainly to the study of the effects of user-selected conditions on the training of the SFS by the BP algorithm. These user-selected conditions include the choice of learning rate, momentum gain, initial parameters, number of fuzzy rules, and type of membership functions. Four methods of defining the initial parameters were investigated, namely the on-line initial parameters, off-line initial parameters, extrema initial parameters, and random initial parameters. In addition, the use of two types of fuzzy membership functions was explored, namely the Gaussian type membership functions and triangular type membership functions.

Once the identification properties of the SFS trained by BP algorithm have been established, this study proceeds with investigations about the identification properties of the newly proposed CFS trained by BP algorithm. Special attentions were given to the effects of the resolution factor of the fixed spreads of the membership functions on the identification performance of the CFS. Guidelines for designing the resolution factor of the spreads of the membership functions for the CFS were established. Furthermore, with respect to the number of adjustable parameters in the models, direct comparisons were made between the identification performances of the SFS and CFS models when they were trained under the same training conditions using the BP algorithm. Direct comparisons were also made between the performances of the SFS and CFS for on-line identification.

Besides the use of BP algorithm, two alternative training algorithms were proposed for the training of CFS models, namely the recursive prediction error (RPE) algorithm and the Levenberg-Marquardt (LM) algorithm. Through simulations, using the previously selected six data sets, the properties of the CFS trained by the RPE and LM algorithms were established. Attentions were given mainly to the effects of user-selected conditions on the training of the CFS using these two alternative algorithms. These user-selected conditions include the choice of the initial covariance matrix $\mathbf{P}_0$ for the RPE algorithm, and the initial matrix $\overline{\mathbf{S}}_0$ and multiplier η for the LM algorithm. Guidelines for selecting these designed parameters for the respective training algorithms were established. Furthermore, direct comparisons on the identification performances were made between the CFS models trained by RPE and BP algorithms respectively and between the CFS models trained by RPE and LM algorithms respectively. Further comparisons were also made between the identification performances of the SFS and CFS models when they were trained under the same training conditions using these two alternative training algorithms. The correlation based model validity tests were also conducted on the identified models using CFS as the model structure.

Practical applications of the proposed CFS are demonstrated through case studies. The first case study involves the use of the CFS models for estimating the flight parameters of an aircraft for the longitudinal flight motion. The flight parameters identified in this case study are estimated from flight data as conventionally defined in terms of stability and control derivatives. These identified stability and control derivatives occur in the equations of motion of an aircraft, which represent the partial derivatives of the aerodynamic forces or moments with respect to the corresponding motion or control variables. The stability and control derivatives were estimated as the change in the aerodynamic force or moment due to small variation in one of the motion or control variables about its nominal value when the rest of the variables were held constant at their respective nominal values. In the estimation procedures, the changes in the aerodynamic force and moment were predicted using the CFS. In this case study, the capabilities of the CFS models in estimating the aircraft parameters for both the short-period and the phugoid mode of motions were explored. The flight data used were generated using the three non-linear longitudinal equations of motion for a small remotely piloted vehicle. All the aerodynamic coefficients for this aircraft were obtained from wind-tunnel tests. The flight data sets were obtained from maneuvers made through the deflection of the aircraft elevator when all other control variables such as throttle, ailerons, and rudder were held at fixed positions. Two methods of perturbation of the aircraft elevator for data collection were investigated, namely the pulse and doublet elevator input signals. In order to have an approximately balance number of data pairs about the nominal values of the variables, two complementary sets of flight data obtained from maneuvers made by positive and negative elevator input signals were used simultaneously for the training of CFS model. In this study, both the BP and RPE algorithms were used separately as training algorithms of the CFS. The numerical values of the identified stability and control derivatives are compared with the values obtained using aerodynamic coefficients from wind-tunnel tests, where the wind-tunnel values are regarded as the 'true' values of the stability and control derivatives.

The second case study involves the modeling of the transformation of the rainfall to runoff for selected river systems in Malaysia using CFS. The modeling of the rainfall-runoff process was done on a daily basis as well as on an hourly basis. For the daily rainfall-runoff modeling, the use of one-day-ahead prediction model for forecasting the daily streamflow discharge of three river systems in Malaysia was proposed. These three selected catchments are Sungai Lenggor, Sungai Lui, and Sungai Bernam. In addition to the development of the daily rainfall-runoff models, the application of CFS model for forecasting the hourly rainfall-runoff was also explored. The hourly rainfall-runoff records for Sungai Klang catchment were selected for the purpose of the hourly rainfall-runoff modeling. Although this is not a comprehensive study of a rainfall-runoff modeling for a particular river system, the use of standard performance criteria normally used in the field of rainfall-runoff modeling provides some insight on the accuracy of the CFS models. Comparisons between the performances of the CFS models, the autoregressive moving average with exogenous inputs (ARMAX) models, and the autoregressive with exogenous inputs (ARX) models for modeling the rainfall-runoff processes were also conducted.

Finally, it should be noted that all numerical computations and computer simulations were conducted using the MATLAB programming software version 5.3 developed by the MathWorks, Inc.

1.6 Summary of research contributions

This study deals with the use of the rule-based fuzzy system for identification of non-linear dynamic systems. The outcome of this study can be summarized into four major contributions. Firstly, a more attractive form of rule-based fuzzy structure with better identification properties compared with those of the standard rule-based fuzzy system has been successfully developed. This simplified fuzzy system is called the constrained fuzzy system (CFS) due to the nature of the spreads of its membership functions that are constrained to be fixed and uniform. The use of this simplified form of fuzzy structure can indirectly reduce the rule explosion problem inherent fuzzy systems. Secondly, this study has successfully implemented the use of the recursive prediction error (RPE) algorithm and the Levenberg-Marquardt (LM) algorithm for training both the standard fuzzy system and the constrained fuzzy system. These two algorithms have been shown in this study to possess superior convergence properties than the back-propagation algorithm in the training of the rule-based fuzzy systems. Thirdly, new method for estimating the flight parameters of an aircraft for the longitudinal flight motion has been successfully developed. It has been demonstrated in this thesis that the flight parameters as conventionally defined in terms of stability and control derivatives for the longitudinal flight motion can be estimated from flight data using the CFS model structure. Fourthly, this study has shown that the CFS models could be use as substitutes for rainfall-runoff models in cases where the ARX and ARMAX models need further improvement. For the rainfall-runoff modeling, it was found that the CFS models performed their designed task of modeling the estimation data sets better than the ARX or ARMAX models.

1.7 Thesis outline

This thesis consists of seven chapters. Chapter 1 is the introduction chapter. This chapter presents the research background, objectives of the study, methodology of research, summary of research contributions, and the overall outline of this thesis.

Chapter 2 presents the literature reviews on related subjects concerning this thesis. In this second introductory chapter, the historical development of fuzzy systems, the concept of fuzzy set, relevant notions in fuzzy set theory, and the classification of fuzzy systems are reviewed. As an integral part of this thesis, comprehensive discussions are given on the description of the rule-based fuzzy systems, the training algorithms, the inherent problem of rule explosion in fuzzy systems, the use of fuzzy systems for identification, and the method for model validation. Finally, reviews on recently published articles related to fuzzy modeling which has become an attractive and powerful modeling environment are presented.

Chapter 3 presents the findings of this study concerning the properties of the back-propagation (BP) algorithm when it was used as training algorithm for tuning the standard fuzzy system (SFS) and the newly proposed constrained fuzzy system (CFS). The advantages and the shortcomings of the BP algorithm were highlighted, and the needs to further explore other training algorithms were established. This chapter also discusses the properties of the CFS with respect to the resolution of the spreads of its membership functions. Comparative study between the identification performances of the SFS and CFS for both off-line or batch identification and on-line identification are also presented.

Chapter 4 presents the findings of this study concerning the properties of recursive prediction error (RPE) algorithm and Levenberg-Marquardt (LM) algorithm when they were used for training the SFS and CFS models. Direct comparisons were made between the performances of the RPE and BP algorithms and between the RPE and LM algorithms. Further comparisons were made between the identification performances of the SFS and CFS models when they were trained by RPE algorithm under the same training conditions. This chapter also presents the correlation based model validity tests of the identified models using CFS as model structure.

Chapter 5 presents the findings of this study concerning the estimation of longitudinal aircraft parameters using CFS. This chapter presents the overview of aircraft parameter estimation procedures, the longitudinal modes of flight motion, and the method of flight data collection. The implementation steps for aircraft parameter estimation using CFS are also highlighted. This chapter demonstrates the capabilities of the CFS in estimating the aircraft parameters for both the short-period and the phugoid mode of motions where the identified aircraft parameters were compared with the values obtained using aerodynamic coefficients from wind-tunnel tests.

Chapter 6 presents the findings of this study concerning the modeling of rainfall-runoff processes using SFS and CFS. This chapter discusses the overview of rainfall-runoff modeling procedures, the design of test experiments, the daily rainfall-runoff modeling, and the hourly rainfall-runoff modeling. The use of standard performance criteria normally used in the field of rainfall-runoff modeling provides some insight on the accuracy of the SFS and CFS models. Comparisons between the performances of the CFS models, the autoregressive moving average with exogenous inputs (ARMAX) models, and the autoregressive with exogenous inputs (ARX) models for modeling the rainfall-runoff processes were presented in this chapter.

Finally, Chapter 7 is the concluding chapter. This chapter summarizes the works done in this entire study, infers conclusions that can be drawn, and provides recommendations for future work.