IDENTIFICATION OF DISCRETE-TIME DYNAMIC SYSTEMS USING MODIFIED GENETIC ALGORITHM

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DEDICATION

To Abd. Rahman, Azmi Shafiq, Aisyah Nurhuda, Ariff Mustafa, Anis Fatina and Aiman Hadif

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ABSTRACT

The purpose of this study is to investigate the application of genetic algorithm (GA) in modelling linear and non-linear dynamic systems and develop an alternative model structure selection algorithm based on GA. Orthogonal least square (OLS), a gradient descent method was used as the benchmark for the proposed algorithm. A model structure selection based on modified genetic algorithm (MGA) has been proposed in this study to reduce problems of premature convergence in simple GA (SGA). The effect of different combinations of MGA operators on the performance of the developed model was studied and the effectiveness and shortcomings of MGA were highlighted. Results were compared between SGA, MGA and benchmark OLS method. It was discovered that with similar number of dynamic terms, in most cases, MGA performs better than SGA in terms of exploring potential solution and outperformed the OLS algorithm in terms of selected number of terms and predictive accuracy. In addition, the use of local search with MGA for fine-tuning the algorithm was also proposed and investigated, named as memetic algorithm (MA). Simulation results demonstrated that in most cases, MA is able to produce an adequate and parsimonious model that can satisfy the model validation tests with significant advantages over OLS, SGA and MGA methods. Furthermore, the case studies on identification of multivariable systems based on real experimental data from two systems namely a turbo alternator and a continuous stirred tank reactor showed that the proposed algorithm could be used as an alternative to adequately identify adequate and parsimonious models for those systems.

ABSTRAK

Kajian ini dilakukan bertujuan mengkaji penggunaan algoritma genetik (GA) dalam pemodelan sistem dinamik linear dan tak linear dan membangunkan kaedah alternatif bagi pemilihan struktur model menggunakan GA. Algorithma kuasa dua terkecil ortogon (OLS), satu kaedah penurunan kecerunan digunakan sebagai bandingan bagi kaedah yang dicadangkan. Pemilihan struktur model mengunakan kaedah algoritma genetik yang diubahsuai (MGA) dicadangkan dalam kajian ini bagi mengurangkan masalah konvergens pramatang dalam algoritma genetik mudah (SGA). Kesan penggunaan gabungan operator MGA yang berbeza ke atas prestasi model yang terbentuk dikaji dan keberkesanan serta kekurangan MGA diutarakan. Kajian simulasi dilakukan untuk membanding SGA, MGA dan OLS. Dengan meggunakan bilangan parameter dinamik yang setara kajian ini mendapati, dalam kebanyakan kes, prestasi MGA adalah lebih baik daripada SGA dalam mencari penyelesaian yang berpotensi dan lebih berkebolehan daripada OLS dalam menentukan bilangan sebutan yang dipilih dan ketepatan ramalan. Di samping itu, penggunaan carian tempatan dalam MGA untuk menambah baik algorithma tersebut dicadang dan dikaji, dinamai sebagai algoritma memetic (MA). Hasil simulasi menunjukkan, dalam kebanyakan kes, MA berkeupayaan menghasilkan model yang bersesuaian dan parsimoni dan memenuhi ujian pengsahihan model di samping memperolehi beberapa kelebihan dibandingkan dengan kaedah OLS, SGA dan MGA. Tambahan pula, kajian kes untuk sistem berbilang pembolehubah menggunakan data eksperimental sebenar daripada dua sistem iaitu sistem pengulang-alik turbo dan reaktor teraduk berterusan menunjukkan algoritma ini boleh digunakan sebagai alternatif untuk memperolehi model termudah yang memadai bagi sistem-sistem tersebut.

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LIST OF ABBREVIATIONS

AR	Auto-Regressive
ARMA	Auto-Regressive Moving Average
ARMAX	Auto-Regressive Moving Average with eXogenous input
ARX	Auto-Regressive with exogenous input
BJ	Box-Jenkins
CSTR	Continuous Stirred Tank Reactor
EA	Evolutionary Algorithm
EI	Error Index
EP	Evolutionary Programming
ERR	Error Reduction Ratio
ES	Evolutionary Strategy
FIR	Finite Impulse Response
GA	Genetic Algorithm
GP	Genetic Programming
IV	Instrumental Variable
LMS	Least Mean Square
LSM	Least Square Method
MA	Memetic Algorithm
MA	Moving Average
MGA	Modified Genetic Algorithm
MGA-LS	Modified Genetic Algorithm with Local Search
MIMO	Multi input multi output
ML	Maximum Likelihood
MLP	Multilayered Perceptron
MPO	Model Predicted Output
MSE	Mean Squared Error
NARMAX	Non-linear Auto-Regressive Moving Average with eXogenous input

NARX	Non-linear Auto-Regressive with eXogenous input
NN	Neural Network
OE	Output Error
OLS	Orthogonal Least Square
OSA	One Step Ahead
RBF	Radial Basis Function
RLS	Recursive Least Square
SGA	Simple Genetic Algorithm
SI	System identification
SISO	Single input single output
SSE	Sum Squared Error
VLSI	Very Large-Scale Integration

LIST OF SYMBOLS

$u(t)$	system input
$y(t)$	system output
t	time step
i	general integer index
a_i, b_i, c_i	coefficients of polynomial models
n, m	system orders
n_y, n_u and n_c	output, input and noise lags
M	maximum number of terms
d	time delay
$e(t)$	a random white noise
θ_i	unknown parameters
$h_{xo/ki}$	a homogeneous polynomial degree i
N	data length
k	general integer index
$f(.)$	non-linear function
$\phi_i(t)$	regressors
l	degree of non-linearity
$f^l(.)$	non-linear function of degree l
r	general model orders
$\varepsilon(t)$	error or residual sequence
$\mathbf{W}$	orthogonal matrix
P	covariance matrix
γ	gradient adjustment
ϕ	standard correlation function
$E[.]$	the expectation operator
δ	an impulse function

τ	general time lag
$F^l[.]$	a general non-linear polynomial function
$\hat{y}(t)$	predicted output
$\hat{F}$	estimated non-linear function f
μ	parents
λ	offsprings
p_m	mutation probability
p_c	crossover probability
j	general integer index
p	general integer index
L	maximum degree of non-linearity
c_i	chromosomes
f	general function
$J(\theta)$	mean square error
m_x	multi-point crossover
r_i	random sequence
B_t	total bits in the population
C_k	insignificant terms
J_P	variance contribution
J_B	bias contribution
P	initial population
P'	new population after MGA
P''	new population after MA
na	number of outputs
nb	number of inputs
L_i	polynomial degree of ith subsystem
F	flow rate (m^3/hr)
V	reactor volume (m^3)
C_{af}	Feed concentration (kg.mole/m^3)
C_a	Tank concentration
k_0	Pre-exponential factor(per hr)
$(-\Delta H)$	Heat of reaction (kcal/mole)

UA	Overall heat transfer coefficient (kcal/hour.K)
T	Reactor temperature
T_f	Feed temperature (K)
T_c	Coolant jacket temperature (K)
ρ	Density of water (kg/m^3)
C_p	Specific heat of water (kJ/kg/K)
R	Ideal gas constant (cal/mole.K)
E	Activation energy (kcal/hr)
A	Area for heat exchange

CHAPTER 1

INTRODUCTION

1.1 Background of the research

In practice, most control systems are complex, non-linear or time varying. Controlling such processes or systems need the knowledge of the mathematical equations of those processes or systems. Modelling a system is vital especially in the field of engineering and science since a major part of those fields deal with designing a system based on mathematical model. It is necessary to use model to describe the relationships among the system variables. This can be achieved by developing a mathematical model based on the information of input and output variables available from the process. This method of developing a mathematical model is known as "system identification". The study of system identification is necessary to provide information before further analysis and decision can be made to a particular system. In some application of system identification, a mathematical model is developed for controller design and to simulate the actual system.

The identification of unknown system has been studied and literature on system identification can be found from various sources (Goodwin and Payne, 1977; Johansson, 1993; Ljung and Glad, 1994; and Ljung, 1999). Procedures involve in system identification (SI) are the acquisition of data, definition of model structure, parameter estimation and model validation. Basically a model is constructed based on the observed data. Input and output data from a system is recorded and subject to analysis for modelling. The input-output data used to study system identification technique is usually obtained either using simulated or real experimental data. The simulated data is generated by computer model whereas the real data could come from real process plant. In this study, the input and output data used are both generated from simulated systems examples and data from real process plants.

In system identification, a model representation is defined to emulate the performance of the system to be modelled. The model representations used include continuous model, discrete model, parametric and nonparametric models and others. Once the model representation has been identified, the determination of the model structure is required. Many model structures identification applicable to linear and non-linear systems have been discussed and developed (Korenberg *et al.*, 1988; Miller, 1990; Veres, 1991; and Li and Jeon, 1993; Mao and Billings, 1997). The main task in model structure selection is to determine and select the significant terms to be included in the final model. Two design questions in model structure determination are choosing the right regressors and choosing the right non-linear mapping of the model. The possible choices of regressors include input and output observed data. A larger regression vector sometimes lead to over fitting and therefore an adequate number of regression terms which best describe the system will lower the variance of misfits is desirable.

There are various techniques of the non-linear mapping proposed by several researchers based on traditional approaches (Haber and Kevicsky, 1978; Billings, 1980 and Descrochers and Mohseni, 1984). However, simply expanding the system outputs in terms of its past input and output to non-linear model is impractical because the number of possible terms will be very large especially for complex system. Therefore, it is important to use algorithm that can detect only the significant terms to be included for model representation to ensure that the fitted model is adequate. There are several ways to determine the significant terms to be included in the selected model and various approaches had been proposed (Haber and Unbehauen, 1990). One of the most successful methods is orthogonal least square (OLS) algorithm (Korenberg *et al.*, 1988).

In this algorithm, the significance of the terms selected are measured based on error reduction ratios (*ERR*). However, high computational load is required (Mao and Billings, 1997).

In the last ten years, genetic algorithm (GA) has emerged as practical and robust searching method in optimisation problem. Genetic algorithm has been applied in diverse areas such as pattern recognition, robotics, VLSI technology, manufacturing and also biological applications (Chaiyaratana and Zalzala, 1997). GA is a stochastic search technique that resembles the natural biological evolution. GA is part of the larger class of evolutionary algorithms (EA) that includes evolutionary programming (EP), evolutionary strategies (ES) and genetic programming (GP). EA operates on a population of potential solutions and applies the principle of survival of the fittest, reproduction and mutation to produce a better approximation to a solution. At each generation, a new set of approximation is created by selecting individuals according to their level of fitness in the problem domain. The history of EA can be traced back as follows:

(i) Genetic algorithm (GA) was proposed by John Holland (Holland, 1975) and popularised by David Goldberg (Goldberg, 1989)
(ii) Evolutionary Programming (EP) was proposed by Lawrence Fogel (Fogel, 1963) and further developed by his son David Fogel (Fogel, 1992).
(iii) Evolutionary Strategies (ES) was proposed by Ingo Rechenberg (Rechenberg, 1973) and strongly promoted by Thomas Bäck (Bäck, 1996)
(iv) Genetic Programming (GP) was developed by John Koza (Koza, 1992).

One of EA components, genetic algorithm, is considered in this research as the search mechanism in system identification problems particularly for model structure selection. GA differs from the traditional searching and optimisation methods in four different perspectives (Goldberg, 1989):

- it searches a population of points in parallel and not at single point
- it uses probabilistic transition rules and not deterministic rules
- it requires the objective function and corresponding fitness level and not the derivative information
- it works on an encoding of the parameter set and not the parameter set itself

The study explored the advantages of genetic algorithm in solving model structure selection in identification of dynamical systems. Initially, the study investigated other model structure selection methods and their shortcomings were highlighted. Genetic algorithm properties were studied and problems associated with the algorithm were examined. The study also includes examining the components of GA to improve the convergence performance of the algorithm.

1.2 Statement of the problem

In conventional identification problems, a model structure is selected based on its model representation consisting of full expansion of the equation. The parameters of this model are then estimated. The parameter estimation methods used are normally based on least mean square or maximum likelihood estimate. The parameters are estimated by optimising the objective function based on gradient descent techniques. These methods suffer some drawbacks such as the solution may be trapped in local minima (Jacoby *et al.*, 1972). Orthogonal least square algorithm has successfully been applied as model structure selection tool (Billings *et al.*, 1989; Chen *et al.*, 1989; Mao and Billings, 1997). However, there are some disadvantages associated with this method and therefore, the study presents the need for developing alternative technique to enhance the proposed structure selection method for better identification results.

1.3 Objectives

The main objectives of this research are:

(i) to develop an alternative model structure selection algorithm based on genetic algorithm that selects only the significant terms to be included in a final model and gives adequate and parsimonious model

(ii) to improvise the proposed method for better identification results

(iii) to evaluate the performance of the proposed algorithm for system identification in real data application

The rapid development in computer technology has contributed in the development of system identification techniques. The research will explore the use of genetic algorithm to solve model structure selection problems and to improve model performance. The identified models should have the following features: parsimonious, unbiased and high predictive accuracy.

1.4 Scopes and limitation

The research is subjected to the following scopes and limitations:

(i) all the models considered in this study are linear and non-linear in the regression model.

(ii) for fitting the regression, least square estimation is considered in the simulation studies.

(iii) only systems with white noise are considered.

Throughout the research, few assumptions were adopted:

(i) data is assumed available and reliable

(ii) the application of the proposed algorithm to the jacketed continuous stirred tank reactor (CSTR) process begins when the process is already in a steady state condition

1.5 Importance of the research

The model representation used to represent a particular system under investigation will critically lead to the success of system identification as well as to the controller design procedures. Since the number of all possible candidate terms M is large as the order of input and output lags and the order of non-linearity increases, most model structure selection methods are difficult to handle since they require large computation time. Although some approaches would guarantee finding the model with high accuracy, testing all possible solutions is impractical because the number of possible paths for a model with M candidate terms is equal to $2^M - 1$ which will be extremely large if M is large.

An alternative approach for identifying parsimonious model especially for non-linear structures is needed and therefore being proposed. The algorithm will give simplicity to selecting model structure but uses the power of global characteristic in genetic algorithm to search for optimal solution without exhaustively testing every possible solution. The findings of the research will provide alternative ways to deal with model structure selection especially for non-linear systems as well as multivariable systems. Besides, an improved method for GA searching mechanism is hope to further improve the algorithm so that problems encounter in simple GA will be reduced.

1.6 Research methodology

The initial stage of the methodology for the study is based on system identification procedures:

- acquisition of either simulated or real data
- selection of a model structure
- estimation of parameters
- validation of the identified models

Initially, various model structure selection methods such as orthogonal least square (OLS) and GA are investigated to capture their effectiveness and shortcomings. Data used for case studies are both simulated and real experimental data. Genetic algorithm is adopted as a searching mechanism in finding the model structure. The established simple genetic algorithm (SGA) is investigated and problems associated with it are highlighted and model structure selection algorithm based on modified GA (MGA) is proposed. The identified model structures developed through the algorithm will propose model structures for system identification containing a set of parameters to be estimated. For parametric models, the most commonly used parameter estimation algorithms are based on gradient descent methods such as least square methods, maximum likelihood and others. Least square estimation is the most widely used. Comprehensive analysis, investigation and identification of problems associated with the proposed method are conducted and hybrid method using GA and local search called memetic algorithm (MA) is proposed for fine-tuning the search. To verify the identified models, the final stage in system identification is model validation. The purpose is to ensure that the model adequately represents the true system. The technique used involves statistical analysis between the residuals and the input. Finally, the proposed algorithm is applied to the identification of real experimental data obtained from multivariable systems. Two systems are investigated namely, a turbo alternator and a chemical process. Figure 1.1 summarises the methodology of the research study.

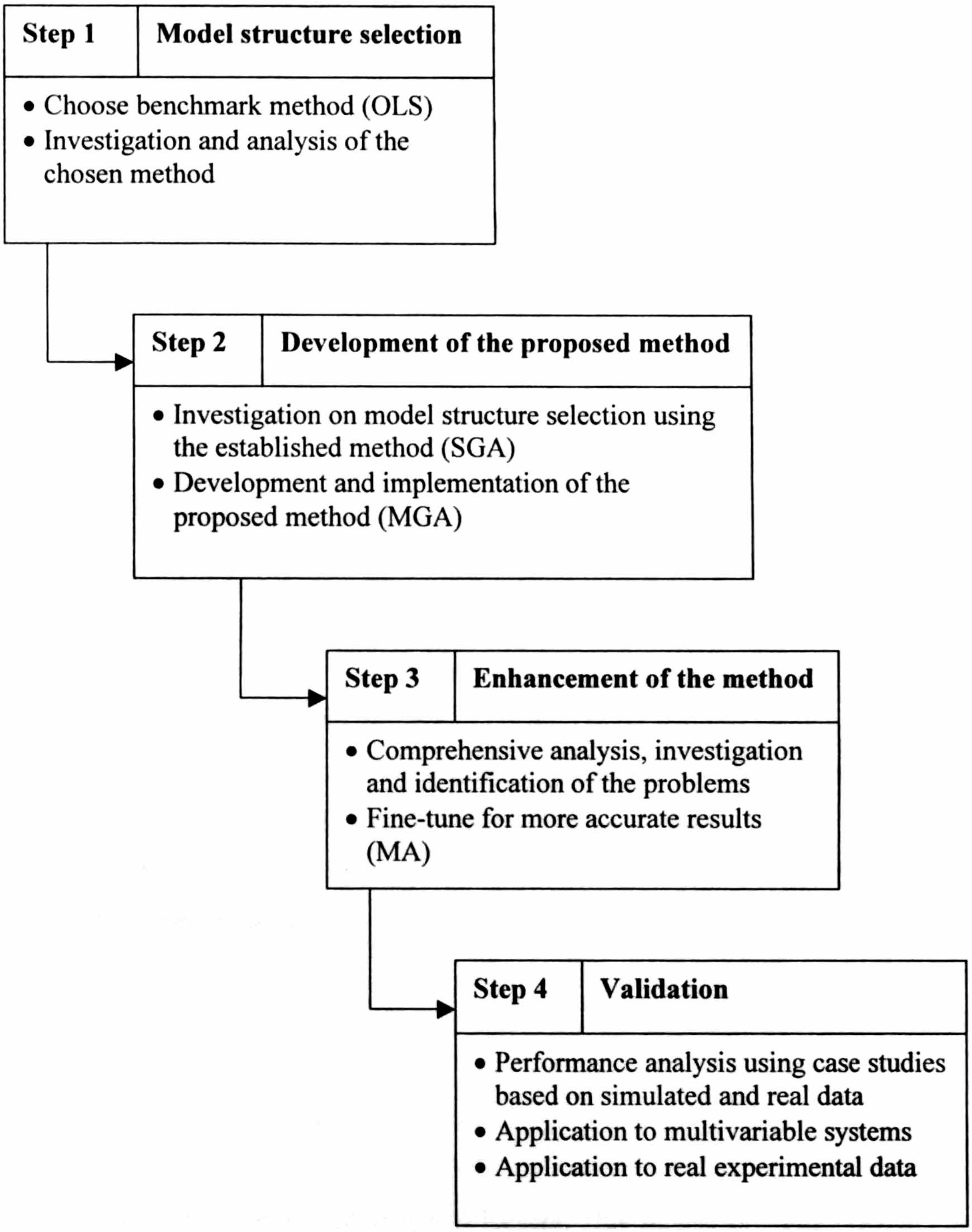

Figure 1.1 Development procedures for the proposed research study

1.7 Research contributions

The main contribution of the research is to provide an alternative approach for model structure selection in system identification. In order to explore the benefit of genetic algorithm in system identification problems, GA is used to optimise the search by automatically selecting the best model among all the possible models. For searching towards highly predictive model, a new selection strategy is proposed in order to find an effective search space in GA and it is called MGA.

Due to the randomness of GA operation, it is sometimes difficult to predict its performances. A new method that combines GA with other techniques is introduced to improve the problem of premature convergence in the algorithm and for better approximations in modelling the systems. The algorithm is hybridised with local search technique in order to fine-tune the genetic algorithm-based search and is called memetic algorithm (MA).

The developed model structure selection based on MA, which was originally derived for single-input single-output (SISO) systems, is extended to the identification of multi-input multi-output (MIMO) dynamic systems. A turbo alternator and a chemical process namely jacketed CSTR were chosen as case studies and real experimental data from these systems was used for validation of the algorithm.

1.8 Outline of the thesis

The thesis is composed of seven chapters. This chapter provides the introduction and background of the thesis while the rest of the chapters are described in the following paragraphs.

Chapter 2 reviews the non-linear system identification and genetic algorithm. The procedure involves in system identification such as the definition of model structure, parameter estimation and model validity tests are reviewed. Different types of model structure used as well as model structure selection tools for system identification problems are discussed and compared. Next, the development of genetic algorithm is also presented and the current researches on GA control parameters as well as the applications of GA in SI problems are also reviewed.

Chapter 3 studies genetic algorithm, its properties and its application in system identification. Initially, the description of polynomial model is presented to provide overview for model structure selection. This chapter also describes the working principle of GA and presents a procedure for model structure selection using GA. Finally, the design and development of the research study is presented and validation of the proposed algorithm is described.

Chapter 4 presents the development of modified genetic algorithm (MGA) and the simulation studies conducted using the proposed algorithm. Initially, issues encountered in simple genetic algorithm (SGA) are discussed to provide basis for the development of the proposed algorithm. Next, it describes the properties of MGA and step-by-step procedure of the algorithm. Three simulation studies were conducted and the results are discussed. First, the effect of different combinations of MGA operators on the performance of the model developed was studied. Secondly, the comparative studies between the identification using SGA and MGA were also conducted. Finally, the performance of the proposed algorithm was also compared to the model developed using orthogonal least square (OLS) algorithm. The adequacy of the developed models was tested using model validation tests to show that the proposed algorithm can be employed as an algorithm for model structure selection.

Chapter 5 introduces the integration of genetic algorithm with local search technique for fine-tuning the search. Memetic algorithm, an evolutionary algorithm incorporating local search technique for selecting model structure, is investigated in this chapter and proposed to further improve the search ability in MGA. Comparative studies between MGA, OLS and MA for the selection of the model structure using a few case studies are also presented.

Chapter 6 studies the identification of multivariable dynamic discrete-time non-linear system using memetic algorithm. Model structure selection based on memetic algorithm, which was originally derived for single-input single-output systems, is extended to multi-input multi-output non-linear systems. The justification of the algorithm is presented using some simulated examples. This chapter also studies the application of the proposed algorithm in identifying adequate model structure of turbo alternator and a continuous stirred tank reactor or CSTR based on their observed data. The identified models are validated using correlation based model validity tests and the simulation results are presented.

Finally, chapter 7 summarises and concludes the work done in this study and discusses the possible extension of the studies for future research work.

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