



DISCRETE-TIME SYSTEM IDENTIFICATION USING GENETIC ALGORITHM WITH SINGLE PARENT-BASED MATING



FARAH AYIESYA BINTI ZAINUDDIN

DOCTOR OF PHILOSOPHY

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Faculty of Mechanical Technology and Engineering

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ALGORITHM WITH SINGLE PARENT-BASED MATING
TECHNIQUE**

Farah Ayiesya binti Zainuddin

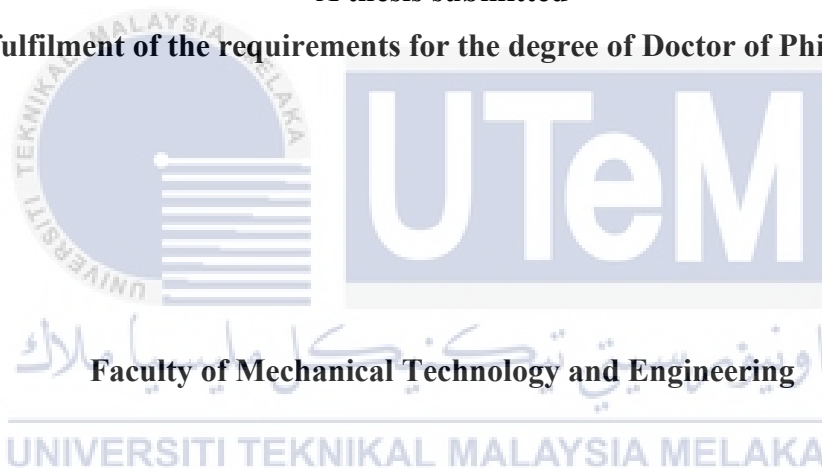
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**DISCRETE-TIME SYSTEM IDENTIFICATION USING GENETIC
ALGORITHM WITH SINGLE PARENT-BASED MATING TECHNIQUE**

FARAH AYIESYA ZAINUDDIN

**A thesis submitted
in fulfilment of the requirements for the degree of Doctor of Philosophy**



UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2024

DECLARATION

I declare that this thesis entitled “Discrete-Time System Identification using Genetic Algorithm with Single Parent-Based Mating Technique” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Doctor of Philosophy.

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Date	:	18 October 2024

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DEDICATION

In the name of Allah, the Most Gracious and the Most Merciful

I dedicate this work to:

My parents,

Zainuddin bin Mohd Noh and Maznah binti Md Yusoff

My husband and my daughter,

Muhammad Amir Asyraf bin Abd Kadir and Nur Rania Tihani binti Muhammad Amir

Asyraf,

My siblings,

Mentor who always give support and encouragement,

Assoc. Prof. Ir. Dr. Md Fahmi Bin Abd Samad @ Mahmood

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ABSTRACT

System identification (SI) is a methodology for developing mathematical models of dynamic systems using measurements of input and output signals. This research focuses on improving Genetic Algorithms (GA) for SI, specifically addressing inefficiencies in common crossover operators that limit search space exploration and lead to premature convergence. The study aims to enhance the performance of GA by introducing a novel Single Parent Mating (SPM) technique. The objectives are to enhance the performance of crossover operator for GA, simulate SI using GA with the SPM technique, and compare the performance of the modified GA to traditional GA in terms of prediction accuracy, convergence to global optimum, and model parsimony. The methodology encompasses data acquisition, GA program development, SPM technique implementation, and simulation using MATLAB. The study simulated single-input-single-output (SISO) models: ARX and NARX. Performance indicators included the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Parameter Magnitude-based Information Criterion 2 (PMIC2). The findings showed that incorporating SPM with single-point crossover resulted in lower objective function (OF) values and improved error indices (EI) compared to traditional GA methods. This enhanced the GA's ability to avoid premature convergence and maintained a diverse solution set, leading to more optimal model selection. The study's results were validated using real-world data from industrial systems, including a hair dryer, an air compression system, and a flexible robot arm. In these cases, the SPM technique consistently outperformed traditional GA, demonstrating improved model fit and predictive accuracy. Rigorous validation tests, including autocorrelation and cross-correlation functions, confirmed the reliability and robustness of these models. These practical applications underscore the versatility and effectiveness of the SPM technique in enhancing GA for SI, proving its utility across different fields such as engineering, finance, and healthcare. The successful validation in real-world systems marks a significant milestone, showing that the SPM technique can significantly improve model optimization in diverse and practical contexts. This research makes several important contributions to the field of GA and SI. The introduction of the SPM technique represents a significant enhancement in the performance of GA, particularly in terms of improving genetic diversity and search optimization. The findings provide a robust framework for applying GAs to complex modeling problems, emphasizing the importance of effective crossover strategies and genetic diversity. The SPM technique offers researchers and practitioners a powerful tool for achieving faster convergence, better optimization, and more accurate models. This study not only advances the theoretical understanding of GA but also provides practical methodologies that can be applied to real-world problems, making it a valuable contribution to both academic research and practical applications.

PENGENALPASTIAN SISTEM DISKRET-MASA MENGGUNAKAN ALGORITMA GENETIK DENGAN TEKNIK PENGAWANAN BERASASKAN INDUK TUNGGAL

ABSTRAK

Pengenalpastian sistem (SI) adalah metodologi untuk membangunkan model matematik sistem dinamik menggunakan pengukuran isyarat masukan dan keluaran. Penyelidikan ini memberi tumpuan kepada memperbaiki Algoritma Genetik (GA) untuk SI, dengan menangani ketidakcekapan dalam operator penyilang biasa yang mengehadkan penerokaan ruang carian dan membawa kepada penumpuan awal. Kajian ini bertujuan untuk meningkatkan prestasi GA dengan memperkenalkan teknik Pengawanan Induk Tunggal (SPM) yang baru. Objektif kajian ini adalah untuk meningkatkan prestasi operator penyilang yang lebih baik untuk GA, mensimulasikan SI menggunakan GA dengan teknik SPM, dan membandingkan prestasi GA yang diubah suai dengan GA tradisional dari segi ketepatan ramalan, penumpuan kepada optimum global, dan kesederhanaan model. Metodologi kajian merangkumi pemerolehan data, pembangunan program GA, pelaksanaan teknik SPM, dan simulasi menggunakan MATLAB. Kajian ini mensimulasikan model masukan-tunggal-keluaran-tunggal (SISO): ARX dan NARX. Penunjuk prestasi termasuk Kriteria Maklumat Akaike (AIC), Kriteria Maklumat Bayesian (BIC), dan Kriteria Maklumat berasaskan Magnitud Parameter 2 (PMIC2). Hasil kajian menunjukkan bahawa penggabungan SPM dengan penyilang titik tunggal menghasilkan nilai fungsi objektif (OF) yang lebih rendah dan indeks ralat (EI) yang lebih baik berbanding dengan kaedah GA tradisional. Ini meningkatkan keupayaan GA untuk mengelakkan penumpuan awal dan mengekalkan set penyelesaian yang pelbagai, yang membawa kepada pemilihan model yang lebih optimum. Keputusan kajian ini disahkan menggunakan data dunia sebenar dari sistem industri, termasuk pengering rambut, sistem pemampatan udara, dan lengan robot fleksibel. Dalam kes ini, teknik SPM secara konsisten mengatasi GA tradisional, menunjukkan kesesuaian model dan ketepatan ramalan yang lebih baik. Ujian pengesahan yang ketat, termasuk fungsi autokorelasi dan silang-korelasi, mengesahkan kebolehpercayaan dan ketahanan model ini. Aplikasi praktikal ini menekankan kepelbagaian dan keberkesanan teknik SPM dalam meningkatkan GA untuk SI, membuktikan kegunaannya dalam pelbagai bidang seperti kejuruteraan, kewangan, dan penjagaan kesihatan. Pengesahan berjaya dalam sistem dunia sebenar menandakan pencapaian penting, menunjukkan bahawa teknik SPM boleh meningkatkan pengoptimuman model dalam pelbagai konteks praktikal. Penyelidikan ini memberikan beberapa sumbangan penting kepada bidang GA dan SI. Pengenalan teknik SPM mewakili peningkatan yang ketara dalam prestasi GA, terutamanya dari segi peningkatan kepelbagaian genetik dan pengoptimuman carian. Penemuan ini menyediakan rangka kerja yang kukuh untuk menerapkan GA kepada masalah pemodelan yang kompleks, menekankan kepentingan strategi penyilangan yang berkesan dan kepelbagaian genetik. Teknik SPM menawarkan alat yang kuat kepada penyelidik dan pengamal untuk mencapai penumpuan yang lebih cepat, pengoptimuman yang lebih baik, dan model yang lebih tepat. Kajian ini bukan sahaja memajukan pemahaman teori tentang GA tetapi juga menyediakan metodologi praktikal yang boleh diterapkan kepada masalah

dunia sebenar, menjadikannya sumbangan berharga kepada penyelidikan akademik dan aplikasi praktikal.



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LIST OF ABBREVIATIONS

<i>ACF</i>	-	Autocorrelation function
<i>AI</i>	-	Artificial intelligence
<i>AIC</i>	-	Akaike information criterion
<i>ANN</i>	-	Artificial neural network
<i>ARX</i>	-	AutoRegressive with eXogenous input
<i>ARMAX</i>	-	AutoRegressive Moving Average with eXogenous input
<i>ASS</i>	-	Assembly sequence scheduling
<i>BIC</i>	-	Bayesian information criterion
<i>BJ</i>	-	Box-Jenkins
<i>CDA</i>	-	Compressed dry air
<i>CCF</i>	-	Cross-correlation function
<i>DC</i>	-	Direct current (constant value in mathematical model)
<i>EA</i>	-	Evolutionary algorithms
<i>EC</i>	-	Evolutionary computation
<i>EI</i>	-	Error index
<i>ES</i>	-	Evolutionary strategies
<i>ESS</i>	-	Explained sum of squares
<i>FF</i>	-	Fitness function
<i>GA</i>	-	Genetic algorithm
<i>HLCMGA</i>	-	Crossover with human-like constrained mating
<i>HW</i>	-	Hammerstein-Wiener
<i>IBAX</i>	-	Inversed Bi-segmented average crossover
<i>LSS</i>	-	Linear state-space
<i>ML</i>	-	Machine learning
<i>MSE</i>	-	Mean square error
<i>MWh</i>	-	Megawatt-hour
<i>NARX</i>	-	Nonlinear AutoRegressive with eXogenous input
<i>NARMAX</i>	-	Nonlinear AutoRegressive Moving Average with eXogenous inputs

<i>NLSS</i>	-	Nonlinear state-space
<i>OE</i>	-	Output error
<i>OF</i>	-	Objective function
<i>OLS</i>	-	Ordinary least squares
<i>PF</i>	-	Penalty function
<i>PMIC2</i>	-	Parameter magnitude based information criterion 2
<i>PSO</i>	-	Particle swarm optimization
<i>RSS</i>	-	Residual sum of square
<i>SCADA</i>	-	Supervisory control and data acquisition
<i>SI</i>	-	System identification
<i>SISO</i>	-	Single-input-single-output
<i>SPM</i>	-	Single parent mating
<i>TF</i>	-	Transfer function
<i>TSP</i>	-	Traveling salesman problem
<i>TSS</i>	-	Total sum of squares



LIST OF SYMBOLS

a_i, b_i and c_i	-	Parameter values of regressor i
C	-	Constant
d	-	Time delay
$e(t)$	-	Noise value at time t
$E(P)$	-	Entropy (population)
$F_*^1[.]$	-	Nonlinear function
$fitness_i$	-	Fitness value for chromosome i
k (in k -point)	-	Number of crossover point
k (in k -step ahead)	-	Smallest lag order of predicted output in a difference equation model
L	-	Number of regressors
l	-	Degree of nonlinearity
$lchrom$	-	Length of bit string chromosome
M	-	Number of independent variables
n	-	Number of individuals in the population
n_y	-	Output lag order
n_u	-	Input lag order
n_k	-	System delay
N	-	Total number of data
N (in N -point)	-	Number of crossover point
P	-	Partition according to fitness value
$popsiz$	-	Population size
p_c	-	Crossover probability or rate
p_i	-	Selection probability of individual i

p_m	-	Mutation probability or rate
p_k	-	partition k
R^2	-	Squared multiple correlation coefficient
t	-	Time; Target output
$u(t)$	-	Input signal
x	-	Rate of electricity; Data sets of input
$X \triangleq (x_1, x_2, \dots, x_n)$	-	Sample vector
χ^2	-	Chi-squared test
$y(t)$	-	Output value at time t
$\hat{y}(t)$	-	Predicted output value at time t
$Y \triangleq (y_1, y_2, \dots, y_n)$	-	Corresponding label of vector X on n dimensional space
Z^N	-	Function of parameter vector
$\varepsilon(t)$	-	Residual or prediction error at time t
$\emptyset$	-	Regressor vector
$\phi_{\varepsilon\varepsilon}$	-	Autocorrelation function
$\phi_{u\varepsilon}$	-	Cross-correlation function
$\phi_{u^2\varepsilon}$	-	Correlation square of the input and residuals
$\phi_{u^2\varepsilon^2}$	-	Correlation square of the input and square of the residuals
$\phi_{\varepsilon\varepsilon u}$	-	Correlation residuals and product of the residuals and input
θ	-	True parameter vector

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