MULTI-OBJECTIVE OPTIMIZATION OF MIMO CONTROL SYSTEM USING SURROGATE MODELING

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To the people who are crazy enough to think they can change the world.

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Mohd Fauzi bin Nor Shah, Jasin

ABSTRACT

A multi-objective optimization approach using surrogate modeling is applied to a nonlinear Multi Input Multi Outputs (MIMO) control system model to predict Pareto-front of objective functions which is defined using Integral Square Error (ISE). Typically, practical multi-objective optimization was highly expensive even in computer simulation. To address such a challenge, approximation or surrogate based techniques are adopted to reduce the computational cost. The surrogate modeling developed as surrogates of the expensive simulation process in order to improve the overall computation efficiency in multi-objective optimization problem. By using surrogate modeling, the location of the actual Pareto-front is predicted by Radial Basis Function Neural Network (RBFNN) using only a small fraction of the design space. Some case studies show that the surrogate modeling manages to predict most of the Pareto-front of the design space. The best compromise of ISE obtained from predicted Pareto-front produces optimum response for MIMO control system. The result indicates that the procedure to construct the 'model of the model' totally compensates the computational expense. This thesis also demonstrates that there are a number of techniques which can be used to tackle difficult multi-objective problems.

ABSTRAK

Sebuah pendekatan pengoptimasi multi-objektif menggunakan pemodelan pengganti diaplikasikan kepada sebuah sistem kawalan Multi Masukan Multi Keluaran (MMMK) tidak linear untuk menganggar fungsi objektif Pareto-hadapan di mana ianya didefinisikan menggunakan Ralat Integral Persegi (RIP). Kebiasaanya, pengoptimasi multi-objektif yang praktikal adalah sangat mahal walaupun dalam simulasi komputer. Untuk mengatasi cabaran ini, penganggaran atau teknik berasaskan pengganti diadaptasi untuk mengurangkan kos pengiraan. Pemodelan pengganti dibangunkan sebagai pengganti kepada proses simulasi yang membebankan demi meningkatkan keefisienan pegiraan secara keseluruhan dalam permasalahan pengoptimasi multi-objektif. Dengan menggunakan pemodelan pengganti lokasi Pareto-hadapan sebenar diramal oleh Fungsi Saraf Rangkaian Asas Jejarian menggunakan hanya sedikit pecahan dari ruang reka bentuk. Kes-kes kajian menunjukkan pemodelan pengganti berupaya menganggar kebanyakan Pareto-hadapan dari ruang reka bentuk. Kompromi RIP terbaik diperolehi dari Pareto-hadapan yang dianggar menghasilkan respons optimum untuk sistem kawalan MMMK. Hasil keputusan menunjukkan prosedur membangunkan ‘model kepada model’ secara keseluruhan mengkompensasikan pengiraan berkomputer. Tesis ini juga mendemonstrasikan dimana terdapat pelbagai teknik yang boleh diguna bagi menyelesaikan masalah multi-objektif yang sukar.

TABLE OF CONTENTS

CHAPTER		TITLE	PAGE
	DECLARATION		ii
	DEDICATION		iii
	ACKNOWLEDGEMENT		iv
	ABSTRACT		v
	ABSTRAK		vi
	TABLE OF CONTENTS		vii
	LIST OF TABLES		xi
	LIST OF FIGURES		xii
	LIST OF ABBREVIATIONS		xiv
	LIST OF SYMBOLS		xv
	LIST OF APPENDICES		xvi
1	**INTRODUCTION**		1
	1.1	Problem Statement	2
	1.2	Objective of Research	2
	1.3	Scope of Research	3
	1.4	Thesis Outline	4
2	**LITERATURE REVIEW**		5
	2.1	Introduction	5
	2.2	Multi-objective Optimization	5
	2.3	Terminology of Surrogate Modeling	8
	2.4	Surrogate Modeling in Engineering Design Optimization	9
	2.5	Surrogate Modeling Technique	11
	2.6	Surrogate Modeling in Control System	12
	2.7	Surrogate Modeling Design Optimization Strategies	13
	2.8	Multi-objective Optimization Using Surrogate Modeling	14

	2.9	Summary	15
3		**MULTI-OBJECTIVE SURROGATE MODELING OPTIMIZATION ALGORITHM**	16
	3.1	Introduction	16
	3.2	General Algorithm	16
	3.3	Input Design Space	18
	3.4	Design of Experiment - Latin Hypercube	20
	3.5	Radial Basis Function Neural Network (RBFNN)	21
	3.6	Objective Function - Integral Square Error (ISE)	24
		3.6.1 Best Compromise	25
	3.7	Summary	25
4		**CASE STUDY 1: FORCED CIRCULATION EVAPORATOR**	26
	4.1	Introduction	26
	4.2	Force Circular Evaporator	26
	4.3	Experimental and Simulation Setup	31
	4.4	Optimization Setup	32
		4.4.1 Artificial Neural Network Setting	33
		4.4.1.1 Radial Basis Function Neural Network Setting	34
		4.4.1.2 Feed Forward Neural Network Setting	34
	4.5	Results	35
		4.5.1 Surrogate modeling versus Brute-force search	35
		4.5.2 Comparison with different approximation model	37
		4.5.3 Comparison with Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Strength Pareto Evolutionary Algorithm 2 (SPEA2)	39
	4.6	Summary	43
5		**CASE STUDY 2: REMOTELY OPERATED VEHICLE**	45
	5.1	Introduction	45

	5.2	Case Study - Nonlinear Model of the Underactuate ROV		45
		5.2.1	Body-Fixed Model of the Underactuated ROV	46
		5.2.2	An Earth-Fixed Model of the Under-actuated ROV	47
		5.2.3	Thruster Model	48
	5.3	Optimization Setup		48
	5.4	Results		51
		5.4.1	Surrogate versus brute force search	51
		5.4.2	Comparison with different approximation model	53
		5.4.3	Comparison with Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Strength Pareto Evolutionary Algorithm 2 (SPEA2)	54
	5.5	Overall Comparison of the Controllers Performance based On Best Compromise		56
	5.6	Summary		60
6	**THE MOSMO TOOLBOX**			61
	6.1	Introduction		61
	6.2	Development goals		61
	6.3	Toolbox Overview		62
		6.3.1	Toolbox Limitation	64
	6.4	Toolbox Algorithm and Organization		64
	6.5	Toolbox Overview		67
		6.5.1	Files	67
		6.5.2	Installation	68
		6.5.3	Setting up Simulink® File for MOSMO Toolbox	69
	6.6	Using Surrogate Modeling Optimization Toolbox		70
		6.6.1	Defining the Problem	71
		6.6.2	Defining the Design Space	73
		6.6.3	Running the algorithm	73
		6.6.4	Sampling Strategy	75
		6.6.5	Surrogate Model	75
		6.6.6	Plot and Display	76
	6.7	Summary		78

7	**CONCLUSIONS AND FUTURE WORKS**		79
	7.1	Conclusions	80
	7.2	Suggestion for Future Works	81
REFERENCES			82
Appendices A – B			89 – 90

LIST OF TABLES

TABLE NO.	TITLE	PAGE
3.1	Example of design space using a grid sequence	19
4.1	Constant value and description	28
4.2	Variables and steady state values	29
4.3	Variable constrain	31
4.4	Design space configuration for evaporator control system	32
4.5	Design space for evaporator optimization	33
4.6	Summary of PID evaporator optimization simulation result	39
4.7	NSGA-II and SPEA2 basic parameters setting	40
4.8	Comparison MOSMO with NSGA-II and SPEA2	41
5.1	Design space configuration for ROV control system	49
5.2	Parameters gains of PD input	50
5.3	Surrogate models setting	51
5.4	Summary of ROV optimization simulation result	54
5.5	NSGA-II and SPEA2 basic parameters setting	54
5.6	ROV comparison summary	56
5.7	Comparison of surge (x) response's characteristics	57
5.8	Comparison of sway (y) response's characteristics	58
5.9	Comparison of heave (z) response's characteristics	59
6.1	MOSMO Toolbox sampling options	65

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
2.1	Illustration of non-dominated solutions	6
2.2	Close-up view non-dominated solutions	7
2.3	Metamodeling hierarchy	8
2.4	Surrogate modeling design optimization strategies	14
3.1	Flowchart of multi-objective surrogate modeling optimization	17
3.2	Difference between random and grid design space	18
3.3	Example of Latin Hypercube sampling and filling	21
3.4	An RBF Neural Network	21
4.1	Force Circulation Evaporator.	27
4.2	Simulink® block diagram of force circular evaporator of PID controller	27
4.3	Pareto-front of objective functions obtained by MOSMO and actual simulation using Brute-force search	36
4.4	Pareto-fronts of MOSMO-RBFNN and MOSMO-FFNN with actual Pareto-front of Brute-force search	38
4.5	Comparison MOSMO. NSGA-II and SPEA2.	40
4.6	Close-up view of best compromise MOSMO, NSGA-II and SPEA2.	41
4.7	Respond of an evaporator using parameter gains obtained from MOSMO, NSGA-II and SPEA2	43
5.1	Advance two coordinates frame of the ROV.	46
5.2	Simulink® block diagram of ROV PD controller.	49
5.3	Pareto-front of objective functions obtained by MOSMO and actual simulation using Brute-force search	52
5.4	Pareto-fronts of different approximation model compare with actual Pareto-front of from Brute force search	53
5.5	Comparison MOSMO. NSGA-II and SPEA2.	55
5.6	Best compromise MOSMO. NSGA-II and SPEA2.	56
5.7	Respond of surge (x) position using parameter gains obtained from MOSMO, NSGA-II and SPEA2	57

5.8	Respond of sway (y) position using parameter gains obtained from MOSMO, NSGA-II and SPEA2	58
5.9	Respond of heave (z) position using parameter gains obtained from MOSMO, NSGA-II and SPEA2	59
6.1	MOSMO Toolbox interface	62
6.2	Flowchart MOSMO operation	63
6.3	Flowchart for loop inside MOSMO Toolbox	65
6.4	Sequence diagram of MOSMO Toolbox	67
6.5	List of files for MOSMO Toolbox	68
6.6	Setting up objective function from block parameter to workspace in Matlab Simulink®	69
6.7	Simulink® model properties setup	70
6.8	MOSMO Toolbox user interface	71
6.9	Define problem using GUI	71
6.10	Define problem using file function	72
6.11	Example of design space	73
6.12	Run the MOSMO Toolbox	73
6.13	Status of design space	74
6.14	Termination of MOSMO algorithm	74
6.15	Sampling option	75
6.16	Surrogate model option	76
6.17	Plot and Display	76
6.18	Training plot	77
6.19	Testing plot	77
6.20	Pareto-front and best compromise plot	77

LIST OF ABBREVIATIONS

DoE	–	Design of Experiment
FFNN	–	Feed Forward Neural Network
GUI	–	Graphic User Interface
GUIDE	–	Graphic User Interface Development Environment
ISE	–	Integral Square Error
LH	–	Latin Hypercube
LHD	–	Latin Hypercube Design
LHS	–	Latin Hypercube Sampling
MIMO	–	Multi Input Multi Outputs
MOSMO	–	multi-objective optimization using surrogate modeling
NSGA-II	–	Non-dominated Sorting Genetic Algorithm II
PD	–	Proportional Derivative
PID	–	Proportional Integral Derivative
RBFNN	–	Radial Basis Function Neural Network
ROV	–	Remote Underwater Vehicle
SPEA2	–	Strength Pareto Evolutionary Algorithm 2

LIST OF SYMBOLS

D	–	Input parameter
D_E	–	Euclidean distance
E_x	–	Error
$\bar{E}_x$	–	Estimated error
l_x	–	Lower bound
u_x	–	Upper bound
$\|\cdot\|$	–	Euclidean Norm
ϕ_k	–	Basis function
$x \in \Re^{R \times 1}$	–	Input vector
ϕ	–	Pseudo
Wij	–	Weight for network from neuron i to j
wlk	–	Weight in the output layer
K_p	–	PID proportional gain
K_i	–	PID integral gain
K_d	–	PID derivative gain

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
A	LIST OF PUBLICATIONS	89
B	MAIN CODING	90

CHAPTER 1

INTRODUCTION

In the world of control engineering design, there are often multi-input multi-output (MIMO) non-linear systems with complicated mathematical model. The system usually consists of controlled variables and manipulated variables and in practice, it is normally desired to find the controlled values that would give optimal responds of the system. For example, a MIMO control system for a fluid mixing system which consists of a mixing tank and two auxiliary tanks. The first auxiliary tank contains colored water, while the second one contains clear water. The input flow to the mixing tank is controlled by two valves, which regulate the output flows from the auxiliary tanks.

The control system is used to control the level of the liquid in mixing tank and the coloration of the resulting mix at the desired set point. Common practice usually needs to find the optimum controller parameter values that minimize both liquid level and coloration. However there are certain cases engineer emphasis to find the optimal value by selecting one of the controllers. To increase the responsiveness for coloration of the mixing result, the respond on liquid level need to be decreased or vice versa. The process of finding parameters of different respond in MIMO control system is known as a multi-objective problem.

There are mainly two ways to optimize multiple variables in MIMO system. First by aggregating the objectives to a single objective and second by solving a multi-objective optimization problem. Multi-objective optimization is a tool that aids engineers in choosing the best design in a world where many targets need to be satisfied. Unlike conventional optimization, multi-objective optimization will not produce single solution, but rather a set of solutions, commonly referred to as Pareto-front [1]. By definition it will contain only non-dominated solutions. It is up to engineers to select the final design by examining this front. Hence the main purpose of multi-objective problem is to find this Pareto-front points.

1.1 Problem Statement

In MIMO control system problem user usually find an optimum respond for all controller. The optimum response can be obtained by aggregating the objective functions to a single objective function. However in real world not every objective function weight the of same of each other. By aggregating the objective function, only one solution can be achieve in a simulation. User need to re-simulate the problem when the weight in one of the objective function changed. This is why multi-objective optimization is needed to let engineer to have a set of solution or Pareto-front using only a single simulation.

The simulations needed when applying multi-objective optimization for non-linear MIMO control system might be very expensive computationally due to the complexity of the actual model. Despite the continuous advances in computer technology, the long simulation time is still unavoidable. This is due to the fact that the control system to be simulated also keeps getting more complex everyday. Thus it becomes impractical to rely exclusively on simulation for the purpose of multi-objective control system optimization. Here, surrogate modeling is proposed to adopt with multi-objective optimization to produce the Pareto-front. Surrogate modeling requires simple computational algorithm to provide multi set of controller parameters.

This thesis is concerned with how this simulation problem is often tackled in engineering design: simpler approximation models are created to predict the Pareto-front by developing a relationship between the system inputs and outputs. When properly constructed, these approximated Pareto-front models mimic the behavior of the simulation code while being computationally cheap(er) to evaluate.

1.2 Objective of Research

1. To develop the **M**ulti-objective **O**ptimization using **S**urrogate **Mo**deling (MOSMO) algorithm for optimizing Multi Input Multi Output (MIMO) controller system.

2. To apply the MOSMO algorithm on different model of the PID controller system as a case study to verify the effectiveness of MOSMO.
3. To compare the performance of MOSMO with brute force search approach and other type of multi-objective optimization approach.
4. To compare the effectiveness of RBF with other approximation approach in searching actual Pareto-front.
5. To develop and integrated a user friendly MOSMO tool using MATLAB® Graphical User Interface Development Environment (GUIDE).

1.3 Scope of Research

The emphasis of this project will be on the aspect of developing the MOSMO algorithm model for the MIMO control system which can perform exactly as the Simulink® performs. This algorithm then will be used to find the parameters of the controller that gives non-dominated error.

MOSMO is then applied to different type of controllers and MIMO model as a case study to verify the effectiveness of MOSMO in tuning the Pareto-front parameters. Two case studies presented, forced circulation evaporator and remotely operated vehicle using PID controller.

The most common characterizations to be compared are Pareto-front point obtained by surrogate modeling and actual Pareto-front obtained by using brute force search approach. The MOSMO use RBF to approximate the actual Pareto-front of input design space. The performance of RBF also will be evaluated by comparing with Feed Forward (FF) back propagation neural network.

Two other well known types of optimization approach: Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Strength Pareto Evolutionary Algorithm 2 (SPEA2) are used to compare MOSMO as an optimization algorithm. The performance evaluated based on Pareto-front performance and best compromise value.

The final scope is to develop an integrated and user friendly MOSMO tool using MATLAB® Graphical User Interface Development Environment (GUIDE) to aid designer in producing an accurate model of the original system for the control system optimization purpose. The software package is intended for use with any Simulink® model. User will also enter the parameters to be optimized through GUI.

1.4 Thesis Outline

This thesis consists of six chapters. This chapter gives a brief description of the objectives and scopes of the project. Chapter 2 consists of a literature review of surrogate modeling, multi-objective optimization and related works on multi-objective optimization using surrogate modeling. Chapter 3 presents the methodology and details of the MOSMO algorithm development process. In Chapter 4 and 5, the MOSMO is demonstrated to an evaporator and a ROV. Chapter 6 describes the development, user interface and usage of the MOSMO GUI Toolbox. Chapter 7 concludes this research.

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