MULTIOBJECTIVE MODEL STRUTURE OPTIMIZATION USING HYBRID DIFFERENTIAL EVOLUTION FOR MULTIVARIABLE DYNAMIC SYSTEM MODELING

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DEDICATION

This thesis is dedicated to my beloved

wife & daughter,

late mother & father,

and family

who taught me that even the largest task can be accomplished if it is done one step at a time, and who also taught me that the best kind of knowledge to have been that which is learned for its own sake

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ABSTRACT

Most real engineering systems are multivariable systems and multiobjectives in nature, especially in a complex dynamic system. The ultimate objective of dynamic system modeling is to obtain parsimonious and adequate model, where the predictive error and model complexity need to be optimized and satisfied simultaneously. This study attempts to establish the needs of a multiobjective optimization algorithm by comparing it with a single-objective of the multivariable optimization algorithm. Two different types of optimization techniques are used: (1) elitist the non-dominated sorting genetic algorithm (NSGA-II) for multiobjective optimization and (2) the modified genetic algorithm (MGA) for single-objective optimization. The results showed that advantage of the multiobjective optimization algorithm compared with the single objective optimization algorithm in developing an adequate and parsimonious model for a discrete-time multivariable dynamics system. A new algorithm based on a multiobjective optimization algorithm for model structure selection is proposed namely multivariable multiobjective optimization using hybrid differential evolution (MOHDE). The proposed algorithm was compared with NSGA-II for model selection in dynamic system modeling of multivariable optimization. The study involved simulated and real systems data for comparison in terms of model predictive accuracy and model complexity. The case studies for real systems were considered in this study for investigating the effectiveness of the multivariable proposed algorithm namely Reference Evapotranspiration (ETo) for MISO systems, offshore structure response for SIMO systems and CD-player arm for MIMO systems. The results showed that the proposed algorithm is capable to produce a good and adequate model with a minimal number of terms and a good predictive accuracy with lower error (less than 1%) on average for all study cases where the result shows that MOHDE outperformed NSGA-II.

ABSTRAK

Kini kebanyakan sistem kejuruteraan adalah sistem pembolehubah-pelbagai dan objektif-pelbagai, terutamanya dalam sistem dinamik yang kompleks. Objektif utama pemodelan sistem dinamik ini adalah untuk mendapatkan model yang parsimoni dan mencukupi, dimana ralat ramalan dan kerumitan model perlu dioptimumkan dan dipenuhi dengan serentak. Kajian ini dibuat untuk menunjukkan keperluan algoritma pengoptimuman objektif-pelbagai dengan membandingkannya dengan algoritma pengoptimuman objektif-tuggal dalam aplikasi pembolehubah-pelbagai. Dua teknik pengoptimuman yang digunapakai adalah: (1) algoritma genetik elitist tersusun tak-terdominasi II (NSGA-II) untuk pengoptimuman objektif-pelbagai dan (2) algoritma genetic terubahsuai (MGA) untuk pengoptimuman objektif-tunggal. Hasil menunjukkan kelebihan algoritma pengoptimuman objektif-pelbagai berbanding dengan algoritma pengoptimuman objektif-tunggal dalam membangunkan model yang mencukupi dan parsimoni untuk sistem dinamik pembolehubah-pelbagai masa diskret. Algoritma baru berdasarkan algoritma pengoptimuman objektif-pelbagai bagi pemilihan struktur model dicadangkan iaitu pengoptimuman objektif-pelbagai menggunakan evolusi pembezaan hibrid (MOHDE). Algoritma cadangan telah dibandingkan dengan NSGA-II dalam pemilihan pemodelan sistem dinamik pengoptimuman pembolehubah-pelbagai. Kajian ini melibatkan data sistem simulasi dan sistem sebenar untuk perbandingan dari segi kejituan ramalan dan kerumitan model. Untuk menyelidiki keberkesanan algoritma pembolehubah-pelbagai yang dicadangkan, kajian kes sistem sebenar dipertimbangkan dalam kajian ini adalah Evapotranspirasi Rujukan (ETo) untuk sistem MISO, Respon Struktur Luar persisir untuk sistem SIMO dan lengan pemain careka (CD) untuk sistem MIMO. Keputusan menunjukkan bahawa algoritma yang dicadangkan mampu untuk menghasilkan model yang baik dan mencukupi dengan bilangan terma yang minimum dan kejituan ramalan yang baik dengan ralat yang rendah (kurang dari 1%) secara purata untuk kesemua kajian kes dimana hasilnya menunjukkan bahawa MOHDE mengatasi prestasi NSGA-II.

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LIST OF ABBREVIATIONS

ACO	-	Ant Colony Optimization
ANN	-	Artificial Neural Network
ARX	-	Autoregressive with Exogenous Inputs
BCO	-	Bee Colony Optimization
BS	-	Quasi-static Base Shear
BW	-	Best Worst Method
CR	-	Crossover rate
CO_2	-	Carbon Dioxide
DE	-	Differential Evolution
DSA	-	Differential Search Algorithm
EA	-	Evolutionary Algorithm
EP	-	Evolutionary programming
ET_O	-	Reference Evapotranspiration
FAO	-	Food and Agricultural Organization of United Nations
FFT	-	Fast Fourier Transform
FIR	-	Finite Impulse Response
GA	-	Genetic Algorithm
GRA	-	Grey Relational Analysis
IA	-	Immune Algorithm
ICID	-	International Commission for Irrigation and Drainage
LRWT	-	Linear Random Wave Theory
MC	-	Monte Carlo
MMD	-	Malaysian Meteorological Department
MOABC	-	Multi-objective Artificial Bee Colony
MOO	-	Multiobjective Optimisation
MPO	-	Model Predicted Output
MGA	-	Modified Genetic Algorithm
MOGP	-	Multiobjective Genetic Programming
MOHDE	-	Multiobjective Optimisation Hybrid Differential Evolution
MR	-	Mutation rate
MSE	-	Mean Square Error
M-BGV	-	Combination of MOABC, BW, GRA and VIKOR
NARX	-	Non-linear Autoregressive with Exogenous Inputs

NARMAX	-	Non-linear Auto-Regressive Moving Average with eXogenous Inputs
NLS	-	Non-Linear System
NN	-	Neural Network
NSDE	-	Non-Dominated sorting DE
NSGA	-	Non-dominated Sorting GA
NSGA-II	-	Elitist Non-dominated Sorting Genetic Algorithm
ODE-NN	-	combined Opposition-based DE Neural Network
OLS	-	Orthogonal Least-Square
OLS-ERR	-	Orthogonal Least-Squares Estimator with Structure Detection
OSA	-	One Step Ahead
OTM	-	Overturning Moment
PAES	-	Pareto Archived Evolution Strategy
PDE	-	Pareto DE
PESA	-	Pareto Envelope-based Selection
PMU	-	Phasor Measurement Unit
PRBS	-	PseudoRandom Binary Sequence
PSO	-	Particle Swarm Optimization
RD	-	Real Data
RPM	-	Revolutions Per Minute
SI	-	System Identification
SGA	-	Simple Genetic Algorithm
SISO	-	Single-Input-Single-Output
SOO	-	Single Objective Optimization
SPEA	-	Strength Pareto EA
SPEA2	-	Strength Pareto EA2
SS	-	Simulated System
SSE	-	Sum of Square Error
TDGA	-	Thermodynamical GA
VIKOR	-	Visekriteri- Jumsko Kompromisno Rangiranje

LIST OF SYMBOLS

$a_1 \ldots a_{n_y}$	-	coefficients of the output model
$b_1 \ldots b_{n_u}$	-	coefficients of the input model
C_k	-	value of insignificant terms
c	-	Constant
CR	-	crossover rate
D	-	size of vector or called dimensional vector
d	-	local crowding distance
$e(t)$	-	random white noise
$E[.]$	-	expectation operator
$f(.)$	-	nonlinear function
$F^l(.)$	-	polynomial nonlinear function
F	-	constant rate
$\hat{F}$	-	estimate of the nonlinear function $f(.)$
F_i	-	Morison load per unit length
Gen	-	maximum generation
H	-	upper boundary
i	-	elevation of node
L	-	lower boundary
l	-	degree of nonlinearity
L_t	-	maximum number of possible terms
$Maxgen$	-	maximum generation
M	-	maximum number of terms
MR	-	mutation rate
N	-	size of data
n_a	-	output number/s
n_b	-	input number/s
n_u	-	input lags
n_y	-	output lags
NP	-	size of population
NS	-	number of nodal loads
$newvar_i$	-	new variable
OFn_1	-	model predictive error (objective function 1)
OFn_2	-	model predictive error (objective function 2)

P_0	-	initial population
P_t	-	parent population
P_{t+1}	-	next generation of parent population
Q_t	-	offspring population
Q_{t+1}	-	next generation of offspring population
r	-	number of runs
r_i	-	Non-dominated rank
SV	-	positive scaling value
$u_{ji,G+1}$	-	trial vector
$u(t)$	-	system input
$y(t)$	-	system output
$\hat{y}(t)$	-	predicted system output
$\varepsilon(t)$	-	residual sequence
$\delta(t)$	-	impulse function
τ	-	general time lag
$v_{i,G+1}$	-	mutant vector for the next generation
$x_{r1,G}$	-	target vector for the current generation
z_i	-	elevation of node i from the seabed
Δli	-	length of the element associated with node i,
θi	-	unknown coefficients
$\phi(t)$	-	regressors
$\phi_{\varepsilon\varepsilon}(t)$	-	auto correlation test
$\phi_{u\varepsilon}(t)$	-	cross correlation test

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CHAPTER 1

INTRODUCTION

1.1 Background Study

In most practical applications, control processes or systems need the knowledge of the mathematical equations of those processes or systems. Most application in control systems are complex, time-varying or nonlinear. It is crucial to model a system, especially in engineering and science since they are both mostly involved with designing systems based on mathematical models. This can be done by developing a mathematical model based on the information of input and output variables, known as System Identification (SI). SI uses statistical methods to build mathematical models of dynamical systems from measured data. It is mainly used for two purposes, namely model estimation and controller design, to develop mathematical models in some SI applications. Additionally, it is important to recognize the behaviour of the system in order to improve the accuracy and efficiency of the system. Four procedures are involved in system identification: the acquisition of data, the choice of model presentation, parameter estimation, and model validation (Ljung, 1999). The previous researcher chose this method as it can easily be implemented with the current advanced digital technology and allows for simple modeling.

The identification of unknown system has been studied and developed as mathematical models where mostly of these models are based on parameterized nonlinear models such as difference equation models, artificial neural networks (Billings et al., 1989; Z. Chen et al., 1993), Volterra series (Hélie & Roze, 2008), wavelet networks (Aadaleesan et al., 2008) and Wiener and Hammerstein models (Xu et al., 2008; Zhai et al., 2006). By minimize the errors, the parameters are estimated between the outputs of proposed model with the measured output of the system which to be modelled. According to Nowak (2002), there are some issues regarding approaching nonlinear system identification; these are test for nonlinearity of the system, selection of the model class either parametric or nonparametric, selection of the optimality criterion of the system and consideration of the input signal of the system., Liu et al. (2017) proposed a novel many-objective evolutionary algorithm using a one-by-one selection strategy to solve the inefficacy of attempts to balance convergence and diversity in a high-dimensional objective space.

Parsimonious model is required in modelling process, where the simplest model that adequately representing the measured input-output data of the process. The model structure that represents the nonlinear system should be optimized and adequate. The importance of selecting model structure in modeling dynamic systems can be summarized by Ahmad et al. (2004):

i. It is important to find parsimonious model in order to complete polynomial model in modelling the dynamic systems.
ii. The selection of an optimal model structure will drive to the development of an adequate model.
iii. The calculation matrix of the complete parameters of the model is always ill conditioned by simply increasing the dynamic terms of the model in order to achieve the desired predictive accuracy.

Over the past decades, optimization algorithms have received increasing attention by the research community as well as the industry. The optimization problem in system identification is an important issue in order to develop an adequate and parsimony model. Ahmad (2004) has mentioned the issue in system identification by using single objective optimization algorithm or also called as Modified Genetic Algorithm (MGA). Mean Square Error (MSE) is defined as an objective function in optimizing the model structure in system identification. Even though models with good predictive accuracy can be found successfully, however the optimal complexity of the model is not guaranteed especially for processes of high order of nonlinearity. Hence, in this research study, solving the problem of optimizing two objective functions in the nonlinear system identification will be focused. The two objective functions that will be considered are; minimizing the error of predicted and measured and minimizing the complexity of the model. To provide an optimal model structure, these two conflicting objectives must be satisfied simultaneously that will lead to solve multiobjective optimization problem.

According to Coello et al. (2007), multiobjective optimization problem can be defined as finding the best solution which can satisfies all the objective functions simultaneously. Although multiobjective optimization problem is difficult to solve, various proposed algorithms have been studied. Stochastic optimization is one of the categories beside deterministic and enumerative methods. This method comprises of random search, simulated annealing, Monte Carlo, Tabu search, differential evolution and evolutionary computation. Random search is the simplest stochastic optimization. It simply evaluates a given number of randomly selected solutions. This method is not suitable for many multiobjective optimization problems because of its failure to incorporate problem domain knowledge (Goldberg, 1989). Simulated annealing is an analogy of annealing process (physical cooling phenomenon) that is an analogy from natural evolution system. Simulated Annealing usually starts from a high temperature, which decreases exponentially. The slower the cooling process, a better solution can be obtained. This method is slow to achieve the global optimum (Russell & Norvig, 2010).

The most popular method that is used in multiobjective optimization problems is Evolutionary Computation (EC). This method embodies the techniques of genetic algorithms, evolution strategies, genetic programming and evolutionary programming, collectively known as Evolutionary Algorithms (EA). In general, this method consists of a population of solutions that will go through genetic operations for evaluation and produce a new generation. It is important to involve multiobjective optimization in selecting model structure for nonlinear system identification, including getting adequate and parsimony model (McLeod, 1993).

Zitzler et al. (2000) state that evolutionary algorithms is established method for solving multiobjective optimization because they deal simultaneously with a set of feasible solutions. The following is an incomplete historical list of EA for solving multiobjective optimization problem are: Multiple Objective GA, MOGA (Fonseca & Fleming, 1996), Non-dominated Sorting GA, NSGA (Srinivas & Deb, 1994), Thermodynamical GA, TDGA (Kita et al., 1996), Pareto Archived Evolution Strategy, PAES (Knowles & Corne, 1999), Strength Pareto EA, SPEA (Zitzler, 1999), Multi-Objective Messy GA, MOMGA (Van Veldhuizen, 1999), Pareto Envelope-based Selection, PESA Corne (Corne et al., 2000), Strength Pareto EA2, SPEA2 (Zitzler et al., 2001), Elitist Non-dominated Sorting Genetic Algorithm, NSGA-II (Deb et al., 2002), and Multi-Objective Differential Evolution, MODE (Babu et al., 2005). All the proposed methods are used in different multiobjective optimization problems. Basically, these methods generate solutions in the Pareto front that need trade-off between model objective functions that are usually conflicting.

To solve the multiobjective optimization problems, a researcher Deb (2002) performed an elitist multiobjective genetic algorithm (NSGA-II). They used elitism approach in order to avoid the best solution being deleted during the optimization process. For the diversity mechanism, they applied the crowding distance estimation procedure to maintain the diversity of the trade-off of the solutions. This method has been applied in several applications of multiobjective optimization such as mechanical component design, truss-structure design and microwave absorber design (Deb, 2001).

For several problems a simple evolutionary algorithm might be good enough to find the desired solution. As reported, there are several types of problems where a direct evolutionary algorithm could fail to obtain a convenient (optimal) solution (Kuroda et al., 2015; Li et al., 1997; Lo & Chang, 2000; Qiao et al., 2019; Tseng & Liang, 2005; Y. Wang et al., 2007). This clearly paves way to the need for hybridization of evolutionary algorithms with other optimization algorithms, machine learning techniques, heuristics etc. Some of the possible reasons for adapt or implement hybrid are as follows:

i. To improve the quality of the solutions obtained by the evolutionary algorithm

ii. To improve the performance of the evolutionary algorithm (i.e. speed of convergence).

iii. To incorporate the evolutionary algorithm as part of a larger system especially for complex system that involve multivariable parameter.

Hence, if first algorithm outperforms second algorithm in some cost functions, it should be roughly as many as any other function in which second outperforms first. Therefore, from a problem-solving perspective, it is difficult to formulate a universal optimization algorithm that solves all problems and hybridization can be the key to solving real problems. Nowadays, differential evolution (DE) has been applied to multiobjective optimization (MOO) problems. DE is suitable for solving huge and complex problems with just a simple algorithm (Feoktistov, 2006). Thus, many works have implemented DE to MOO problems (Adeyemo & Otieno, 2009; Babu et al., 2005; Basu, 2011; Fan et al., 2006; Peng et al., 2010). This research proposes a new MOO algorithm based on DE namely MOHDE to determine optimum model structure for dynamic systems and studied its effectiveness using the simulated and real multivariable data systems.

1.2 Problem Statement

Model structure selection in identification problems conventionally is selected based on its model representation consisting of full expansion of the equation. Most real engineering system optimization problems are multivariable and as well as multiple objectives in nature since they have several problems to be solve and objectives need to be satisfied simultaneously. Therefore, the needs of multiobjective optimization in system identification must be consider for the problem which has more than one objective function i.e., model predictive error and model complexity. An adequate model must fulfil two requirements; these are predictive accuracy and parsimony model. However, in most reported works in system identification, the model is developed by optimizing the prediction error and model parsimony is obtained through trial and error, i.e., single objective optimization (SOO) algorithms.

SOO signifies all algorithms that use only one objective function in the development of dynamic models. These algorithms have been successfully applied to linear parametric modelling but have some disadvantages. The disadvantages are:

i. Only suitable for one objective function in modeling dynamic system;

ii. Several procedures need to be added to find an optimal model structure that will affect computational time.

iii. High order of nonlinearity or complexity for modeling dynamic system will not guarantee getting a parsimonious model structure.

Hence, alternative algorithms based on more than one objective function need to be investigated to optimize the developed dynamic system. Furthermore, this study will elaborate and propose a suitable method of multiobjective optimization algorithm that suitable for dynamic system modeling. In addition, since it took advantage of integrated methods, incorporated with hybrid evolutionary algorithm as part of a larger system, especially for complex multivariable systems that can be solved simultaneously in MOO.

1.3 Objectives

The main objectives of this research are:

i. To evaluate the needs for multiobjective optimization and multivariable in system identification (SI) on model structure by comparing study between single objective optimization and multiobjective optimization algorithms that is suitable for dynamic system modeling.

ii. To propose an efficient hybrid differential evolution based algorithm for multiobjective optimization.

iii. To validate the proposed algorithm using simulated systems and published real plant data for nonlinear multivariable system.

Multi-objective optimization methods will be further investigated to obtain good results for model structure selection in nonlinear system identification. The multiobjective optimization algorithms will be improvised to make effective modeling dynamic systems in consequential of the parsimony and adequate models.

1.4 Scopes and Limitation

The research is subjected to several scopes and limitation due to wide area of research in system identification and multiobjective optimization algorithms. The scopes and limitations are listed as:

i. Only Nonlinear Auto-Regressive with eXogeneous input (NARX) models will be used with and without additional of white noise and only least square estimation (LSE) is considered in the simulation studies for fitting the regression.

ii. Input-output data is reliable and available from simulated systems and experimental data.

iii. Multivariable system application including Multi input single output (MISO), Single input multi output (SIMO), and Multi input multi output (MIMO) are considered.

iv. All simulation and implementation of the algorithms are using Matrix Laboratory (MATLAB) software and Off-line system identification is considered.

1.5 Importance of the Research

Choosing a model structure is one of the main processes of system identification. This process can be tedious if the model representation used to represent the system has a large number of candidate terms especially in multivariable system. If the number of input and output lags and the nonlinearity order used are large, the number of candidate terms, M will basically increase. Therefore, searching for an adequate and parsimonious model requires a high computational cost. Most model structure selection algorithms show that it is not practical to select a significant term from all candidate terms if the number of possible models is very huge. In particular, the NARX model is used, which is especially possible in multivariable systems.

An alternative approach for identifying parsimonious model especially for nonlinear structures is needed, and therefore being proposed. Most modeling problems need to consider minimizing two objective functions i.e. model predictive error and model complexity. Hence, this study proposed an alternative algorithm using MOO approach for resolving these objective functions. This algorithm is based on evolutionary algorithms where DE is chosen to be combined with MOO procedures in model structure selection in an identification problem. By taking the advantages of global characteristic in genetic algorithm, the algorithm will simplify the model structure selecting to search for optimal solution without comprehensively testing every possible solution. The results of the study provide an alternative approach for choosing model structures, especially for nonlinear and multivariable systems.

1.6 Research Methodology

The initial stage of the methodology for the study is based on system identification procedures: i. Acquisition of either simulated or real data, ii. Selection of a model structure, iii. Estimation of parameters, and iv. Validation of the identified models. This research focuses on the development of a suitable multiobjective optimization method in modeling multivariable dynamic system. Next, the study continue with coded NSGA-II and MOODE in MATLAB software that was proposed by Loghmanian (2010) and Zakaria (2013), respectively to familiarise with multiobjective optimization method that is applied to system identification problem.

This multiobjective optimization algorithm is investigated to capture its effectiveness and shortcomings.

The purpose of this study is to incorporate and improve the NSGAII and MOODE algorithms for selecting model structures since the execution time is too long. The modifications of this coding will reduce the computational time and make it suitable for modeling dynamic systems. The modified encoded MOO based on the NSGAII algorithm is then compared to the MGA-based SOO algorithm in dynamic system modeling to justify the use of the MOO advantages. A new MOO algorithm based on the DE algorithm is being developed. This proposed algorithm will be investigated and identify its strengths and weaknesses. The effects of various genetic parameters of DE also will be investigated to find the correct combination of these parameters for model structure selection.

Comparative study between NSGA-II and the proposed algorithm (MOHDE) is investigated for multiobjective optimization problem. Both simulated and real experimental data are also used for the comparative studies. The proposed algorithm is applied to the identification of real experimental data obtained from multivariable systems. Three case studies are considered namely ocean wave offshore response, reference evapotransporation and CD-player arm system to verify the effectiveness of proposed algorithm. The validity of the proposed algorithm is studied using simulated systems with known model structures at initial stage of investigated case studies. Finally, for real process data, the model validity tests such as one step ahead prediction (OSA), model predicted output (MPO) and correlation tests are used for validation of the identified models produced by the proposed algorithm. The summaries of the methodology of the research study are illustrated in Figure 1.1.

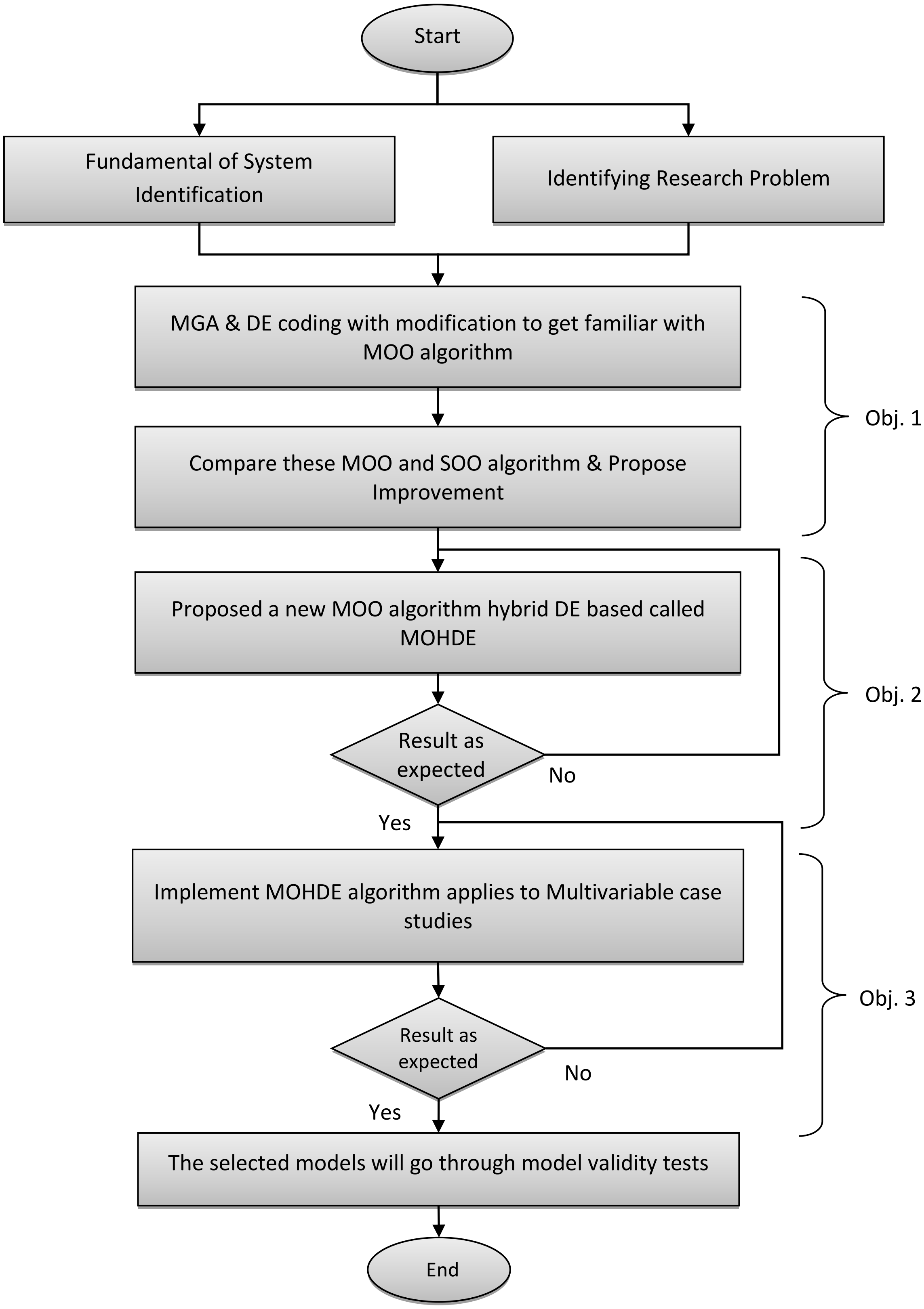

Figure 1.1 Flowchart of research methodology

1.7 Research Contributions

The contributions of the research can be summarized as follows:

i. The justification of MOO algorithm through comparative study between MOO and SOO algorithms in optimizing model structure for system identification. The improved NSGA-II algorithm is investigated in order to identify their strengths and weaknesses.

ii. The proposed algorithm consists of Hybrid Differential Evolution where the model structure selection use DE as framework combined with Nondominated selection operator namely MOHDE. This proposed algorithm will help researcher to choose a suitable model structure from a set of possible model structures.

iii. The implementation of the proposed algorithm (ii) in real case study data for all components of complex multivariable (SIMO, MISO, and MIMO) application systems to identify and prove the effectiveness of the proposed algorithm that will contribute to a better algorithm for system identification dynamic systems modeling.

1.8 Outline of the Thesis

In overall this thesis composes of six chapters. Chapter 1 presents the introduction and background of the research. Further, the other chapters are outlined in the following paragraphs.

Chapter 2 reviews the interest of this research which is system identification where the critical problem is model structure selection. Different approaches developed in model structure selection algorithm in order to get the optimal model to represent the behaviour of dynamic system are presented. SOO and MOO algorithms for model structure selection tools are reviewed. Since this study involve with multivariable application, hence the needs of MOO and proper selection of suitable algorithm also being studied and reviewed to resolve the complex multivariable dynamic system. DE algorithm for MOO problem as well as for model structure selection is discussed and reviewed.

Chapter 3 discusses the comparison between SOO and MOO algorithms in finding the optimal model structure of the dynamic systems. This chapter is presented to show the merit of MOO in solving system identification problem. Initially, the description of model representation used in this study is elaborated to provide overview for model structure selection. Two algorithms are considered which MGA for SOO algorithm while NSGA-II for MOO algorithm. These algorithms are compared in modeling simulated systems and real data available in the literature.

Chapter 4 presents the development proposed algorithm for multiobjective optimization using hybrid differential evolution (MOHDE). The proposed algorithm is based on DE algorithm. Thus, the structure of DE algorithm is elaborated to provide the basis for the development of the proposed algorithm. Details implementation of MOHDE in model structure selection is described. The effect of varying genetic parameters of MOHDE studied and the right combination of those parameters is presented. To show the capability of the proposed algorithm, comparative studies between MOHDE and NSGA-II are conducted and discussed. These comparative studies show that the identification performance of the proposed algorithm is better than NSGA-II and can be employed as an alternative for model structure selection.

Chapter 5 studies the identification of multivariable dynamic nonlinear system using proposed algorithm. Initially, the effectiveness of the proposed algorithm is tested through modeling simulated systems. Next, three case studies were considered in this chapter. These are modeling of offshore structure response, reference evapotranspiration and CD-player arm. Nevertheless, initial stage of these investigated case studies needs to be investigated using simulated systems with known model structures to the effectiveness of the proposed algorithm. The identified models are validated through several model validity tests which are correlation tests, one step ahead prediction (OSA), and model predicted output (MPO). All the model validity results are presented and discussed.

Finally, Chapter 6 concludes the finding of the research. Further, the final chapter provides possible extension works and recommendations for future work.

REFERENCES

Aadaleesan, P., Miglan, N., Sharma, R., & Saha, P. (2008). Nonlinear system identification using Wiener type Laguerre-Wavelet network model. *Chemical Engineering Science*. https://doi.org/10.1016/j.ces.2008.04.043

Abbass, H. A., & Sarker, R. (2002). the Pareto Differential Evolution Algorithm. *International Journal on Artificial Intelligence Tools*, *11*(04), 531–552. https://doi.org/10.1142/s0218213002001039

Abd Samad, M. F., & Mohd Nasir, A. R. (2017). Parameter magnitude-based information criterion in identification of discrete-time dynamic system. *Journal of Mechanical Engineering*, *SI 4*(1), 119–128.

Abdelghani, M., Basseville, M., & Benveniste, A. (1997). In-operation damage monitoring and diagnostics of vibrating structures, with applications to offshore structures and rotating machinery. *Proceedings of the International Modal Analysis Conference - IMAC*, *2*, 1815–1821.

Abdelghani, M., Verhaegen, M., Van Overschee, P., & De Moor, B. (1998). Comparison study of subspace identification methods applied to flexible structures. *Mechanical Systems and Signal Processing*, *12*(5), 679–692. https://doi.org/10.1006/mssp.1998.0169

Abraham, A., Lakhmi Jain, & Robert Goldberg. (2005). Evolutionary Multiobjective Optimization: Theoretical Advances and Applications. In *Advanced Information and Knowledge Processing*. London: Springer-Verlag London Limited. https://doi.org/10.1007/1-84628-137-7

Abu Husain, M. K., Mohd Zaki, N. I., M.B., J., & G., N. (2016). Extreme Response Prediction for Fixed Offshore Structures by Monte Carlo Time Simulation Technique. *Proceedings of the ASME 2016 35th International Conference on Ocean, Offshore and Arctic Engineering OMAE2016*, 1–7.

Abu Husain, M. K., & Najafian, G. (2010). An efficient Monte Carlo simulation technique for derivation of the probability distribution of the extreme values of offshore structural response. *Proceedings of the International Conference on Offshore Mechanics and Arctic Engineering - OMAE*, *2*(November), 369–375. https://doi.org/10.1115/OMAE2010-20506

Abu Husain, M. K., & Najafian, G. (2011). Efficient derivation of the probability distribution of the extreme values of offshore structural response taking advantage of its correlation with extreme values of linear response. *Proceedings of the International Conference on Offshore Mechanics and Arctic Engineering - OMAE*, *2*(January 2011), 335–346. https://doi.org/10.1115/OMAE2011-49458

Adeli, H., & Kumar, S. (1999). *Distributed computer-aided engineering: For analysis, design, and visualization*. Florida: CRC Press.

Adeyemo, J., & Otieno, F. (2009). MODE for solving engineering problems. *Journal of Applied Sciences*, *9*(20), 3652–3661.

Adeyemo, J., & Otieno, F. (2010). Differential evolution algorithm for solving multi-objective crop planning model. *Agricultural Water Management*, *97*(6), 848–856. https://doi.org/10.1016/j.agwat.2010.01.013

Aguirre, L. A. (1997). On the structure of nonlinear polynomial models: higher order correlation functions, spectra, and term clusters. *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications*, *44*(5), 450–453. https://doi.org/10.1109/81.572342

Ahmad, R. (2004). *Identification of Discrete-Time Dynamic Systems Using Modified Genetic Algorithm*. PhD. Thesis, Universiti Tekonologi Malaysia, Skudai.

Ahmad, R., Jamaluddin, H., & Hussain, M. A. (2004). Model structure selection for a discrete-time non-linear system using a genetic algorithm. *Proceedings of the Institution of Mechanical Engineers. Part I: Journal of Systems and Control Engineering*, *218*(2), 85–98. https://doi.org/10.1243/095965104322892258

Ahmad, R., Jamaluddin, H., & Hussain, M. A. (2008). Application of memetic algorithm in modelling discrete-time multivariable dynamics systems. *Mechanical Systems and Signal Processing*, *22*(7), 1595–1609. https://doi.org/10.1016/j.ymssp.2008.01.006

Ahmad, R., Lazin, N., & Samsuri, S. F. M. (2014). Parametric and Non-parametric Identification of Naturally Ventilation Tropical Greenhouse Climates 3 Parametric Modeling and Simulation of NVTG. *Proceedings of the 14th International Conference on Robotics, Control and Manufacturing Technology (ROCOM '14)*. https://doi.org/http://www.wseas.org/multimedia/journals/control/2014/a045703-276.pdf

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration: Guidelines for computing crop water requirements. In *FAO* (p. 300). https://doi.org/10.1016/j.eja.2010.12.001

Allen, R. G., Smith, M., Perrier, A., & Pereira, L. S. (1994). An Update for the Definition of Reference Evapotranspiration. *ICID Bulletin*.

Altay, E. V., & Alatas, B. (2021). Differential evolution and sine cosine algorithm based novel hybrid multi-objective approaches for numerical association rule mining. *Information Sciences*, *554*, 198–221. https://doi.org/10.1016/J.INS.2020.12.055

Amiri, B., Hossain, L., Crawford, J. W., & Wigand, R. T. (2013). Community Detection in Complex Networks: Multi–objective Enhanced Firefly Algorithm. *Knowledge-Based Systems*, *46*, 1–11. https://doi.org/10.1016/J.KNOSYS.2013.01.004

Amrane, Y., Boudour, M., & Belazzoug, M. (2015). A new Optimal reactive power planning based on Differential Search Algorithm. *International Journal of Electrical Power and Energy Systems*, *64*, 551–561. https://doi.org/10.1016/J.IJEPES.2014.07.060

Arora, S., & Singh, S. (2017). An improved butterfly optimization algorithm with chaos. *Journal of Intelligent and Fuzzy Systems*, *32*(1), 1079–1088. https://doi.org/10.3233/JIFS-16798

Arora, S., & Singh, S. (2019). Butterfly optimization algorithm: a novel approach for global optimization. *Soft Computing*, *23*(3), 715–734. https://doi.org/10.1007/S00500-018-3102-4

Azuwir, M. N., Abdulmuin, M. Z., & Adom, A. H. (2011). Modelling and Validation of Automotive Engine Fuelled with Palm Oil Biodiesel. *International Journal of Engineering and Technology*, *3*(6), 582–586. https://doi.org/10.7763/ijet.2011.v3.289

Babu, B. V., Chakole, P. G., & Syed Mubeen, J. H. (2005). Multiobjective differential evolution (MODE) for optimization of adiabatic styrene reactor. *Chemical Engineering Science*, *60*(17), 4822–4837. https://doi.org/10.1016/j.ces.2005.02.073

Bäck, T., Fogel, D. B., & Michalewicz, Z. (2000). *Evolutionary computation. Vol. 1, Basic algorithms and operators*. 384.

Basu, M. (2011). Economic environmental dispatch using multi-objective differential evolution. *Applied Soft Computing Journal*. https://doi.org/10.1016/j.asoc.2010.11.014

Billings, S. A., Chen, S., & Korenberg, M. J. (1989). Identification of MIMO non-linear systems using a forward-regression orthogonal estimator. *International Journal of Control*, *49*(6), 2157–2189. https://doi.org/10.1080/00207178908961377

Billings, S. A., & Tao, Q. H. (1991). Model validity tests for non-linear signal processing applications. *International Journal of Control*, *54*(1), 157–194. https://doi.org/10.1080/00207179108934155

Billings, S. A., & Voon, W. S. F. (1986). Correlation based model validity tests for non-linear models. *International Journal of Control*, *44*(1), 235–244. https://doi.org/10.1080/00207178608933593

Billings, S. A., & Wei, H. L. (2008). An adaptive orthogonal search algorithm for model subset selection and non-linear system identification. *International Journal of Control*, *81*(5), 714–724. https://doi.org/10.1080/00207170701216311

Billings, S. A., & Zhu, Q. M. (1991). Rational model identification using an extended least-squares algorithm. *International Journal of Control*, *54*(3), 529–546. https://doi.org/10.1080/00207179108934174

Björkqvist, J.-V., Pettersson, H., & Kahma, K. (2019). The wave spectrum in archipelagos. *Ocean Science Discussions*, 1–30. https://doi.org/10.5194/os-2019-59

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2016). *Time series analysis : forecasting and control* (5th ed.). John Willey & Sons, Inc.

Camasca, C., Swain, A. K., & Patel, N. D. (2006). *Intelligent Structure Selection of Polynomial Nonlinear Systems using Evolutionary Programming*. *December*, 5–8.

Chandrasekaran, G., Sreebalaji, V. S., Saravanan, R., & Maniraj, J. (2019). Multiobjective optimisation of bevel gear pair design using NSGA-II. *Materials Today: Proceedings*, *16*, 351–360. https://doi.org/10.1016/j.matpr.2019.05.101

Chang, W.-D. (2007). Nonlinear system identification and control using a real-coded genetic algorithm. *Applied Mathematical Modelling*, *31*(3), 541–550. https://doi.org/10.1016/j.apm.2005.11.024

Chen, B., Zhu, Y., Hu, J., & Príncipe, J. C. (2011). Δ-Entropy: Definition, properties and applications in system identification with quantized data. *Information Sciences*, *181*(7), 1384–1402. https://doi.org/10.1016/j.ins.2010.11.037

Chen, S., & Billings, S. A. (1989). Representations of non-linear systems: The narmax model. *International Journal of Control*, *49*(3), 1013–1032. https://doi.org/10.1080/00207178908559683

Chen, S., Billings, S. A., & Luo, W. (1989). Orthogonal least squares methods and their application to non-linear system identification. *International Journal of Control*, *50*(5), 1873–1896. https://doi.org/10.1080/00207178908953472

Chen, Z., Kavvas, M. L., & Govindaraju, R. S. (1993). Upscaling of Richards equation for soil moisture dynamics to be utilized in mesoscale atmospheric models. *Exchange Processes at the IMnd Surface for a Range of Space and Time Scales*, *212*, 125–132.

Coello, C. A. C., Lamont, G. B., Veldhuizen, D. A. Van, Goldberg, D. E., & Koza, J. R. (2007). *Evolutionary Algorithms for Solving Multi-Objective Problems* (Second Edi). Springer New York. https://doi.org/10.1046/j.1365-2672.2000.00969.x

Cook, D. F., Ragsdale, C. T., & Major, R. L. (2000). Combining a neural network with a genetic algorithm for process parameter optimization. *Engineering Applications of Artificial Intelligence*, *13*(4), 391–396. https://doi.org/10.1016/S0952-1976(00)00021-X

Corne, D., Knowles, J., & Oates, M. (2000). The pareto envelope-based selection algorithm for multiobjective optimization. *Parallel Problem Solving from Nature – PPSN VI, Vol. 1917 of Lecture Notes in Computer Science*, *Mcdm*, 839–848.

D’Errico, G., Cerri, T., & Pertusi, G. (2011). Multi-objective optimization of internal combustion engine by means of 1D fluid-dynamic models. *Applied Energy*, *88*(3), 767–777. https://doi.org/10.1016/j.apenergy.2010.09.001

de Callafon, R. A., den Hof, P. M. J. V., & Steinbuch, M. (1993). Control relevant identification of a compact disc pick-up mechanism. *Proceedings of the IEEE*

Conference on Decision and Control, *3*(January), 2050–2055. https://doi.org/10.1109/cdc.1993.325558

De Moor, B. L. R. (2004). *DaISy (Database for the Identification of Systems) Department of Electrical Engineering, ESAT/SISTA, K. U. Leuven, Belgium*. https://homes.esat.kuleuven.be/~smc/daisy/%0Ahttps://ftp.esat.kuleuven.be/pub/SISTA/data/mechanical/robot_arm.txt

Deb, K. (2001). *Multiobjective Optimization Using Evolutionary Algorithms*. Wiley, New York.

Deb, K., Pratab, S., Agarwal, S., & Meyarivan, T. (2002). A Fast and Elitist Multiobjective Genetic Algorithm: NGSA-II. *IEEE Transactions on Evolutionary Computing*, *6*(2), 182–197. https://doi.org/10.1109/4235.996017

Debnath, S., Baishya, S., Sen, D., & Arif, W. (2021). A hybrid memory-based dragonfly algorithm with differential evolution for engineering application. *Engineering with Computers*, *37*(4), 2775–2802. https://doi.org/10.1007/S00366-020-00958-4

Desrochers, A. A., & Mohseni, S. (1984). Quadratic Optimization via Conjugate Directions and Projection Matrices | IEEE Conference Publication | IEEE Xplore. *1985 American Control Conference*. https://doi.org/10.23919/ACC.1985.4788884

Ding, J., Ding, F., & Zhang, S. (2008). Parameter identification of multi-input, single-output systems based on FIR models and least squares principle. *Applied Mathematics and Computation*, *197*(1), 297–305. https://doi.org/10.1016/J.AMC.2007.07.076

Dutta, S., Paul, S., & Roy, P. K. (2018). Optimal allocation of SVC and TCSC using quasi-oppositional chemical reaction optimization for solving multi-objective ORPD problem. *Journal of Electrical Systems and Information Technology*, *5*(1), 83–98. https://doi.org/10.1016/J.JESIT.2016.12.007

Eiben, A. E., & Smit, S. K. (2011). Parameter tuning for configuring and analyzing evolutionary algorithms. *Swarm and Evolutionary Computation*, *1*(1), 19–31. https://doi.org/10.1016/J.SWEVO.2011.02.001

Eiben, A. E., & Smith, J. E. (2003). *Introduction to Evolutionary Computing*. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-05094-1

Fan, H.-Y., Lampinen, J., & Levy, Y. (2006). An easy-to-implement differential evolution approach for multi-objective optimizations. *Engineering Computations*, *23*(2), 124–138. https://doi.org/10.1108/02644400610644504

Feoktistov, V. (2006). Differential Evolution. In *Differential Evolution*. Springer US. https://doi.org/10.1007/978-0-387-36896-2

Ferariu, L., & Patelli, a. (2009). Migration-based multiobjective genetic programming for nonlinear system identification. *2009 5th International Symposium on Applied Computational Intelligence and Informatics*, 475–480. https://doi.org/10.1109/SACI.2009.5136295

Fonseca, C. M., & Fleming, P. J. (1996). Non-Linear System Identification with Multiobjective Genetic Algorithms. *IFAC Proceedings Volumes*, *29*(1), 1169–1174. https://doi.org/10.1016/s1474-6670(17)57823-4

Gao, Y., Zhou, J., & Jia, S. (2010). A new multi-objective differential evolution algorithm. *Proceedings - 2010 International Conference on Computational Intelligence and Security, CIS 2010*, 170–173. https://doi.org/10.1109/CIS.2010.44

Garduno-Ramirez, R., & Lee, K. Y. (2016). A multiobjective-optimal neuro-fuzzy extension to power plant co-ordinated control: *Http://Dx.Doi.Org/10.1191/0142331202tm056oa*, *24*(2), 129–152. https://doi.org/10.1191/0142331202TM056OA

Geurts, M., Box, G. E. P., & Jenkins, G. M. (1977). Time Series Analysis: Forecasting and Control. *Journal of Marketing Research*, *14*(2), 269. https://doi.org/10.2307/3150485

Goldberg, D. E. (1989). Genetic algorithms in search, optimization, and machine learning. *Information Technology Journal*, *3*(1), 301–302. https://doi.org/10.5860/choice.27-0936

Grefenstette, J. (1986). Optimization of Control Parameters for Genetic Algorithms. *IEEE Transactions on Systems, Man, and Cybernetics*, *16*(1), 122–128. https://doi.org/10.1109/TSMC.1986.289288

Gu, F., Li, K., & Liu, Y. (2017). *A Hybrid Evolutionary Algorithm for Solving Function Optimization Problems*. 526–529. https://doi.org/10.1109/CIS.2016.0128

Gu, Y., & Wei, H. L. (2018). A robust model structure selection method for small sample size and multiple datasets problems. *Information Sciences*, *451–452*, 195–209. https://doi.org/10.1016/J.INS.2018.04.007

Guerra, F. A., Ayala, H. V. H., Lazzaretti, A. E., Sans, M. R., Coelho, L. S., & Tacla, C. A. (2010). Multivariable nonlinear boiler power plant identification through neural networks and particle swarm Optimization approaches. *2010 9th IEEE/IAS International Conference on Industry Applications, INDUSCON 2010*. https://doi.org/10.1109/INDUSCON.2010.5739862

Guo, X., Sun, X., & Ma, J. (2010). Estimating Reference crop evapotranspiration using HGA-LSSVM. *Proceedings - 2010 6th International Conference on Natural Computation, ICNC 2010*, *4*(Icnc), 1654–1658. https://doi.org/10.1109/ICNC.2010.5584576

Hélie, T., & Roze, D. (2008). Sound synthesis of a nonlinear string using Volterra series. *Journal of Sound and Vibration*. https://doi.org/10.1016/j.jsv.2008.01.038

Holland, J. H. (1975). Adaptation in Natural and Artificial Systems. *Ann Arbor MI University of Michigan Press*. https://doi.org/10.1137/1018105

Huang, Y., Gao, L., Yi, Z., Tai, K., Kalita, P., Prapainainar, P., & Garg, A. (2018). An application of evolutionary system identification algorithm in modelling of energy production system. *Measurement*, *114*, 122–131. https://doi.org/10.1016/J.MEASUREMENT.2017.09.009

Ibrahim, A. O., Shamsuddin, S. M., Abraham, A., & Qasem, S. N. (2019). Adaptive memetic method of multi-objective genetic evolutionary algorithm for backpropagation neural network. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-018-03990-0

Jamaluddin, H., Samad, M. F. A., Ahmad, R., & Yaacob, M. S. (2007). Optimum grouping in a modified genetic algorithm for discrete-time, non-linear system identification. *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, *221*(7), 975–989. https://doi.org/10.1243/09596518JSCE362

Jeyadevi, S., Baskar, S., Babulal, C. K., & Willjuice Iruthayarajan, M. (2011). Solving multiobjective optimal reactive power dispatch using modified NSGA-II. *International Journal of Electrical Power and Energy Systems*, *33*(2), 219–228. https://doi.org/10.1016/j.ijepes.2010.08.017

Kasprzyk, J. (2009). Model Structure Selection in LTI MISO System Identification. *IFAC Proceedings Volumes*, *42*(13), 278–283. https://doi.org/10.3182/20090819-3-PL-3002.00049

Kita, H., Yabumoto, Y., Mori, N., & Nishikawa, Y. (1996). Multi-objective optimization by means of the thermodynamical genetic algorithm. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. https://doi.org/10.1007/3-540-61723-X_1014

Knowles, J., & Corne, D. (1999). The Pareto archived evolution strategy: A new baseline algorithm for Pareto multiobjective optimisation. *Proceedings of the 1999 Congress on Evolutionary Computation, CEC 1999*. https://doi.org/10.1109/CEC.1999.781913

Kondo, N., Hatanaka, T., & Uosaki, K. (2007). Nonlinear dynamic system identification based on multiobjectively selected RBF networks. *Proceedings of the 2007 IEEE Symposium on Computational Intelligence in Multicriteria Decision Making, MCDM 2007*, *Mcdm*, 122–127. https://doi.org/10.1109/MCDM.2007.369426

Krink, T., & Paterlini, S. (2011). Multiobjective optimization using differential evolution for real-world portfolio optimization. *Computational Management Science*, *8*(1–2), 157–179. https://doi.org/10.1007/s10287-009-0107-6

Kristinsson, K., & Dumont, G. A. (1992). System identification and control using genetic algorithms. *IEEE Transactions on Systems, Man, and Cybernetics*, *22*(5), 1033–1046. https://doi.org/10.1109/21.179842

Kubalčík, M., & Bobál, V. (2014). Continuous-time and discrete multivariable decoupling controllers. *WSEAS Transactions on Systems and Control*, *9*(1), 327–335.

Kuroda, K., Magori, H., Ichimura, T., & Yokoyama, R. (2015). A hybrid multi-objective optimization method considering optimization problems in power distribution systems. *Journal of Modern Power Systems and Clean Energy*, *3*(1), 41–50. https://doi.org/10.1007/S40565-015-0096-0

Leontaritis, I. J. ., & Billings, S. A. (1985). Input-Output Parametric Models for Nonlinear Systems . Part 2. *International Journal of Control*, *41*(2), 303–328.

Li, F., Morgan, R., & Williams, D. (1997). Hybrid genetic approaches to ramping rate constrained dynamic economic dispatch. *Electric Power Systems Research*, *43*(2), 97–103. https://doi.org/10.1016/S0378-7796(97)01165-6

Liang, J., Xu, W., Yue, C., Yu, K., Song, H., Crisalle, O. D., & Qu, B. (2019). Multimodal multiobjective optimization with differential evolution. *Swarm and Evolutionary Computation*, *44*(October 2017), 1028–1059. https://doi.org/10.1016/j.swevo.2018.10.016

Liao, T. W. (2010). Two hybrid differential evolution algorithms for engineering design optimization. *Applied Soft Computing Journal*, *10*(4), 1188–1199. https://doi.org/10.1016/j.asoc.2010.05.007

Lind, I., & Ljung, L. (2008). Regressor and structure selection in NARX models using a structured ANOVA approach. *Automatica*, *44*(2), 383–395. https://doi.org/10.1016/j.automatica.2007.06.010

Liu, Y., Dai, J., Sisi, Z., Wang, J., Shang, W., Li, T., Zheng, Y., Lan, T., & Wang, Z. (2020). Optimization of five-parameter BRDF model based on hybrid GA-PSO algorithm. *Optik*, *219*, 164978. https://doi.org/10.1016/J.IJLEO.2020.164978

Liu, Y., Gong, D., Sun, J., & Jin, Y. (2017). A Many-Objective Evolutionary Algorithm Using A One-by-One Selection Strategy. *IEEE Transactions on Cybernetics*, *47*(9), 2689–2702. https://doi.org/10.1109/TCYB.2016.2638902

Liu, Z., Du, W., & Sun, D. (2017). Energy and spectral efficiency tradeoff for massive MIMO systems with transmit antenna selection. In *IEEE Transactions on Vehicular Technology*. https://doi.org/10.1109/TVT.2016.2598842

Ljung, L. (1999). *System Identification: Theory for User*. New Jersey: Prentice-Hall Inc.

Ljung, L. (2010). Perspectives on system identification. *Annual Reviews in Control*, *34*(1), 1–12. https://doi.org/10.1016/j.arcontrol.2009.12.001

Lo, C. C., & Chang, W. H. (2000). A multiobjective hybrid genetic algorithm for the capacitated multipoint network design problem. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, *30*(3), 461–470. https://doi.org/10.1109/3477.846234

Loghmanian, S. M. R. (2010). *Structure optimization of dynamic system model using multi-objective genetic algorithm*. PhD. Thesis, Universiti Teknologi Malaysia, Skudai.

Loghmanian, S. M. R., Jamaluddin, H., Ahmad, R., Yusof, R., & Khalid, M. (2012). Structure optimization of neural network for dynamic system modeling using multi-objective genetic algorithm. *Neural Computing and Applications*, *21*(6), 1281–1295. https://doi.org/10.1007/s00521-011-0560-3

Ludvig, D., & Perreault, E. J. (2012). System identification of physiological systems using short data segments. *IEEE Transactions on Biomedical Engineering*, *59*(12), 3541–3549. https://doi.org/10.1109/TBME.2012.2220767

Luh, G.-C., & Wu, C.-Y. (1999). Non-linear system identification using genetic algorithms: *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, *213*(2), 105–118. https://doi.org/10.1243/0959651991540421

Ma, Q., Ohsaki, M., Chen, Z., & Yan, X. (2019). Multi-objective optimization for prestress design of cable-strut structures. *International Journal of Solids and Structures, 165*, 137–147. https://doi.org/10.1016/J.IJSOLSTR.2019.01.035

Mao, K. Z., & Billings, S. A. (1997). Algorithms for minimal model structure detection in nonlinear dynamic system identification. *International Journal of Control*, *68*(2), 311–330. https://doi.org/10.1080/002071797223631

McLeod, A. I. (1993). Parsimony, Model Adequacy and Periodic Correlation in Time Series Forecasting. *International Statistical Review / Revue Internationale de Statistique, 61*(3), 387. https://doi.org/10.2307/1403750

Mendes, E. M. A. M., & Billings, S. A. (2001). An alternative solution to the model structure selection problem. *Systems, Man and Cybernetics, Part A:*, *31*(6), 597–608. https://doi.org/10.1109/3468.983416

Mohammadi, B., Guan, Y., Moazenzadeh, R., & Safari, M. J. S. (2021). Implementation of hybrid particle swarm optimization-differential evolution algorithms coupled with multi-layer perceptron for suspended sediment load estimation. *CATENA, 198*, 105024. https://doi.org/10.1016/J.CATENA.2020.105024

Mohd Zain, M. Z. bin, Kanesan, J., Chuah, J. H., Dhanapal, S., & Kendall, G. (2018). A multi-objective particle swarm optimization algorithm based on dynamic boundary search for constrained optimization. *Applied Soft Computing*, *70*, 680–700. https://doi.org/10.1016/J.ASOC.2018.06.022

Muhammad, Y., Khan, R., Raja, M. A. Z., Ullah, F., Chaudhary, N. I., & He, Y. (2020). Solution of optimal reactive power dispatch with FACTS devices: A survey. *Energy Reports*, *6*, 2211–2229. https://doi.org/10.1016/J.EGYR.2020.07.030

Naitali, A., Giri, F., Elayan, E., & Haloua, M. (2008). Biosocial Culture Inspired Hierarchical Algorithm for MISO Block Oriented Nonlinear System Identification: Application to Ozone Modelling. *IFAC Proceedings Volumes*, *41*(2), 7433–7438. https://doi.org/10.3182/20080706-5-KR-1001.01256

Naserbegi, A., & Aghaie, M. (2020). Multi-objective optimization of hybrid nuclear power plant coupled with multiple effect distillation using gravitational search algorithm based on artificial neural network. *Thermal Science and Engineering Progress*, *19*, 100645. https://doi.org/10.1016/J.TSEP.2020.100645

Nehmzow, U., Akanyeti, O., & Billings, S. A. (2010). Towards modelling complex robot training tasks through system identification. *Robotics and Autonomous Systems*, *58*(3), 265–275. https://doi.org/10.1016/j.robot.2009.11.002

Nowak, R. D. (2002). Nonlinear system identification. *Circuits, Systems, and Signal Processing*, *21*(1), 109–122. https://doi.org/10.1007/BF01211655

Oh, S. R., Sun, J., Li, Z., Celkis, E. A., & Parsons, D. (2010). System identification of a model ship using a mechatronic system. *IEEE/ASME Transactions on Mechatronics*, *15*(2), 316–320. https://doi.org/10.1109/TMECH.2009.2024308

Osyczka, A., & Kundu, S. (1995). A new method to solve generalized multicriteria optimization problems using the simple genetic algorithm. *Structural Optimization*, *10*(Goldberg 1989), 94–99.

Peng, C., Sun, H., & Guo, J. (2010). Multi-objective optimal PMU placement using a non-dominated sorting differential evolution algorithm. *International Journal of Electrical Power & Energy Systems*, *32*(8), 886–892. https://doi.org/10.1016/j.ijepes.2010.01.024

Petković, D., Gocic, M., Trajkovic, S., Shamshirband, S., Motamedi, S., Hashim, R., & Bonakdari, H. (2015). Determination of the most influential weather parameters on reference evapotranspiration by adaptive neuro-fuzzy methodology. *Computers and Electronics in Agriculture*, *114*, 277–284. https://doi.org/10.1016/J.COMPAG.2015.04.012

Qiao, J., Li, F., Yang, S., Yang, C., Li, W., & Gu, K. (2020). An adaptive hybrid evolutionary immune multi-objective algorithm based on uniform distribution selection. *Information Sciences*, *512*, 446–470. https://doi.org/10.1016/j.ins.2019.08.032

Qiao, J., Zhou, H., Yang, C., & Yang, S. (2019). A decomposition-based multiobjective evolutionary algorithm with angle-based adaptive penalty. *Applied Soft Computing Journal*, *74*, 190–205. https://doi.org/10.1016/j.asoc.2018.10.028

Qiu, W., Sales Junior, J., Lee, D., Lie, H., Magarovskii, V., Mikami, T., Rousset, J. M., Sphaier, S., Tao, L., & Wang, X. (2014). Uncertainties related to predictions of loads and responses for ocean and offshore structures. *Ocean Engineering*, *86*, 58–67. https://doi.org/10.1016/J.OCEANENG.2014.02.031

Rao, R. M. A., & Shyju, P. P. (2010). A meta-heuristic algorithm for multi-objective optimal design of hybrid laminate composite structures. *Computer-Aided Civil and Infrastructure Engineering*, *25*(3), 149–170. https://doi.org/10.1111/J.1467-8667.2009.00610.X

Rodríguez-Vázquez, K., Fonseca, C. M., & Fleming, P. J. (1997). Multiobjective Genetic Programming: A Nonlinear System Identification Application. *Genetic Programming Conference*, 207–212.

Rodríguez-Vázquez, K., Fonseca, C. M., & Fleming, P. J. (2004). Identifying the Structure of NonLinear Dynamic Systems Using Multiobjective Genetic Programming. *IEEE Transactions on Systems, Man, and Cybernetics---Part A: Systems and Humans*, *34*(4), 531–545.

Rollins, D. K., & Bhandari, N. (2004). Constrained MIMO dynamic discrete-time modeling exploiting optimal experimental design. *Journal of Process Control*, *14*(6), 671–683. https://doi.org/10.1016/j.jprocont.2003.10.004

Russell, S., & Norvig, P. (2010). *Artificial Intelligence: A Modern Approach* (3rd ed.). Prentice Hall. https://doi.org/10.1017/S0269888900007724

Samsuri, S. F. M., Ahmad, R., & Zakaria, M. Z. (2018). Comparison of Evolutionary Computation and Empirical Penman-Monteith Equation for Daily and Monthly Reference Evapotranspiration Estimation in Tropical Region.

International Journal of Integrated Engineering, *10*(7), 117–129. https://doi.org/10.30880/ijie.2018.10.07.011

Saravanan, R., Ramabalan, S., Ebenezer, N. G. R., & Dharmaraja, C. (2009). Evolutionary multi criteria design optimization of robot grippers. *Applied Soft Computing Journal*, *9*(1), 159–172. https://doi.org/10.1016/j.asoc.2008.04.001

Sarma, K. C., & Adeli, H. (2001). Bilevel parallel genetic algorithms for optimization of large steel structures. *Computer-Aided Civil and Infrastructure Engineering*, *16*(5), 295–304. https://doi.org/10.1111/0885-9507.00234

Schaffer, J. D. (1985). Multiple objective optimization with vector evaluated genetic algorithms. *The 1st International Conference on Genetic Algorithms*.

Schetzen, M. (1980). *The Volterra and Wiener Theories of Nonlinear Systems*. Wiley, New York.

Schetzen, M. (1981). Nonlinear System Modeling Based on the Wiener Theory. *Proceedings of the IEEE*, *69*(12), 1557–1573. https://doi.org/10.1109/PROC.1981.12201

Schoukens, M. (2015). *Identification of Parallel Block-Oriented Models starting from the Best Linear Approximation Maarten Schoukens* [Vrije Universiteit Brussel]. www.universitypress.be

Shafik, M. B., Chen, H., Rashed, G. I., & El-Sehiemy, R. A. (2019). Adaptive multi objective parallel seeker optimization algorithm for incorporating TCSC devices into optimal power flow framework. *IEEE Access*, *7*, 36934–36947. https://doi.org/10.1109/ACCESS.2019.2905266

Sim, S. H., Carbonell-Mrquez, J. F., Spencer, B. F., & Jo, H. (2011). Decentralized random decrement technique for efficient data aggregation and system identification in wireless smart sensor networks. *Probabilistic Engineering Mechanics*, *26*(1), 81–91. https://doi.org/10.1016/j.probengmech.2010.07.002

Simon, V. V. (2020). Multi-objective optimization of hypoid gears to improve operating characteristics. *Mechanism and Machine Theory*, *146*. https://doi.org/10.1016/j.mechmachtheory.2019.103727

Sivanandam, S. N., & Deepa, S. N. (2008). Introduction to genetic algorithms. In *Introduction to Genetic Algorithms*. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-73190-0

Srinivas, N., & Deb, K. (1994). Muiltiobjective Optimization Using Nondominated Sorting in Genetic Algorithms. *Journal of Evolutionary Computation*, *2*(3), 221–248. https://doi.org/10.1162/evco.1994.2.3.221

Storn, R. (1996). On the usage of differential evolution for function optimization. *Proceedings of North American Fuzzy Information Processing NAFIPS'96*, 519–523. https://doi.org/10.1109/NAFIPS.1996.534789

Storn, R., & Price, K. (1997). Differential Evolution - A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces. *Journal of Global Optimization*. https://doi.org/10.1023/A:1008202821328

Sun, H. J., Peng, C. H., Guo, J. F., & Li, H. S. (2009). Non-dominated sorting differential evolution algorithm for multi-objective optimal integrated generation bidding and scheduling. *Proceedings - 2009 IEEE International Conference on Intelligent Computing and Intelligent Systems, ICIS 2009*, *1*, 372–376. https://doi.org/10.1109/ICICISYS.2009.5357823

Tan, K. C., & Li, Y. (1997). Evolutionary system identification in the time domain. *Proceedings of the Institution of Mechanical Engineers. Part I: Journal of Systems and Control Engineering*, *211*(5), 319–323. https://doi.org/10.1243/0959651971539849

Tian, G., Ren, Y., & Zhou, M. (2016). Dual-Objective Scheduling of Rescue Vehicles to Distinguish Forest Fires via Differential Evolution and Particle Swarm Optimization Combined Algorithm. *IEEE Transactions on Intelligent Transportation Systems*, *17*(11). https://ieeexplore.ieee.org/document/7378948/

Tian, L., Li, Z., & Yan, X. (2019). Differential evolution algorithm directed by individual difference information between generations and current individual information. *Applied Intelligence*, *49*(2), 628–649. https://doi.org/10.1007/S10489-018-1255-6

Tseng, L. Y., & Liang, S. C. (2005). A Hybrid Metaheuristic for the Quadratic Assignment Problem. *Computational Optimization and Applications 2006 34:1*, *34*(1), 85–113. https://doi.org/10.1007/S10589-005-3069-9

Van Veldhuizen, D. a. (1999). Multiobjective Evolutionary Algorithms: Classifications, Analyses and New Innovations. *IRE Transactions on Education*. https://doi.org/10.1109/TE.1962.4322266

Wang, D., & Ding, F. (2016). Parameter estimation algorithms for multivariable Hammerstein CARMA systems. *Information Sciences*, *355–356*, 237–248. https://doi.org/10.1016/j.ins.2016.03.037

Wang, L., Zou, F., Hei, X., Yang, D., Chen, D., Jiang, Q., & Cao, Z. (2014). A hybridization of teaching–learning-based optimization and differential evolution for chaotic time series prediction. *Neural Computing and Applications*, *25*(6), 1407–1422. https://doi.org/10.1007/S00521-014-1627-8

Wang, Y., Cai, Z., Guo, G., & Zhou, Y. (2007). Multiobjective optimization and hybrid evolutionary algorithm to solve constrained optimization problems. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, *37*(3), 560–575. https://doi.org/10.1109/TSMCB.2006.886164

Xiong, G., Zhang, J., Shi, D., Zhu, L., & Yuan, X. (2021). Optimal identification of solid oxide fuel cell parameters using a competitive hybrid differential evolution and Jaya algorithm. *International Journal of Hydrogen Energy*, *46*(9), 6720–6733. https://doi.org/10.1016/J.IJHYDENE.2020.11.119

Xu, K.-J., Zhang, J., Wang, X.-F., Teng, Q., Tan, J., & Zhang, Y.-Y. (2008). Improvements of nonlinear dynamic modeling of hot-film MAF sensor. *Sensors and Actuators A: Physical*, *147*(1), 34–40. https://doi.org/10.1016/J.SNA.2008.03.003

Yadav, J. S., Patidar, N. P., & Singhai, J. (2009). *Differential Evolution Algorithm for Model Reduction of SISO Discrete Systems*. *0*, 1053–1058.

Yagmahan, B., & Yenisey, M. M. (2008). Ant colony optimization for multi-objective flow shop scheduling problem. *Computers and Industrial Engineering*, *54*(3), 411–420. https://doi.org/10.1016/j.cie.2007.08.003

Zadeh, L. A. (1962). From Circuit Theory System Theory. *Proceedings of the IRE*, *50*, 856–865. https://doi.org/10.1109/JRPROC.1962.288302

Zaharie, D. (2009). Influence of crossover on the behavior of Differential Evolution Algorithms. *Applied Soft Computing Journal*, *9*(3), 1126–1138. https://doi.org/10.1016/j.asoc.2009.02.012

Zakaria, M. Z. (2013). *Multiobjective Model Structure Optimization Using Differential Evolution For Dynamic Systems Modelling*. PhD. Thesis, Universiti Teknologi Malaysia, Skudai.

Zakaria, M. Z., Jamaluddin, H., Ahmad, R., Harun, A., Hussin, R., Khalil, A. N. M., Naim, M. K. M., & Annuar, A. F. (2015). Perturbation parameters tuning of multi-objective optimization differential evolution and its application to dynamic system modeling. *Jurnal Teknologi*. https://doi.org/10.11113/jt.v75.5335

Zakaria, M. Z., Jamaluddin, H., Ahmad, R., & Muhaimin, A. H. (2011). Effects of genetic algorithm parameters on multiobjective optimization algorithm applied to system identification problem. *2011 4th International Conference on Modeling, Simulation and Applied Optimization, ICMSAO 2011*, 1–5. https://doi.org/10.1109/ICMSAO.2011.5775624

Zhai, D., Rollins, D. K., Bhandari, N., & Wu, H. (2006). Continuous-time Hammerstein and Wiener modeling under second-order static nonlinearity for periodic process signals. *Computers and Chemical Engineering*, *31*(1), 1–12. https://doi.org/10.1016/j.compchemeng.2006.04.003

Zhang, C., & Bitmead, R. R. (2008). MIMO equalization with state-space channel models. *IEEE Transactions on Signal Processing*, *56*(10 II), 5222–5231. https://doi.org/10.1109/TSP.2008.929126

Zhang, F., Deb, C., Lee, S. E., Yang, J., & Shah, K. W. (2016). Time series forecasting for building energy consumption using weighted Support Vector Regression with differential evolution optimization technique. *Energy and Buildings*, *126*, 94–103. https://doi.org/10.1016/J.ENBUILD.2016.05.028

Zhang, H., Peng, Y., Hou, L., Tian, G., & Li, Z. (2019). A hybrid multi-objective optimization approach for energy-absorbing structures in train collisions. *Information Sciences*, *481*, 491–506. https://doi.org/10.1016/J.INS.2018.12.071

Zhang, S., Wang, H., Yang, D., & Huang, M. (2015). Hybrid multi-objective genetic algorithm for multi-objective optimization problems. *Proceedings of the 2015 27th Chinese Control and Decision Conference, CCDC 2015*, 1970–1974. https://doi.org/10.1109/CCDC.2015.7162243

Zibo, Z., & Naghdy, F. (1995). Application of genetic algorithms to system identification. *Proceedings of the IEEE Conference on Evolutionary Computation*, *2*, 777–782. https://doi.org/10.1109/icec.1995.487484

Zitzler, E. (1999). *Evolutionary Algorithms for Multiobjective Optimization: Methods and Applications*. PhD. Thesis, Swiss Federal Institute of Technology Zurich.

Zitzler, E., Deb, K., & Thiele, L. (2000). Comparison of multiobjective evolutionary algorithms: empirical results. *Evolutionary Computation*, *8*(2), 173–195. https://doi.org/10.1162/106365600568202

Zitzler, E., Laumanns, M., & Thiele, L. (2001). SPEA2: Improving the Strength Pareto Evolutionary Algorithm. *Evolutionary Methods for Design Optimization and Control with Applications to Industrial Problems*, 95–100. https://doi.org/10.1.1.28.7571

Zou, F., Wang, L., Hei, X., Chen, D., & Wang, B. (2013). Multi-objective optimization using teaching-learning-based optimization algorithm. *Engineering Applications of Artificial Intelligence*, *26*(4), 1291–1300. https://doi.org/10.1016/J.ENGAPPAI.2012.11.006

LIST OF PUBLICATIONS

Indexed Journals

M. Samsuri, S. F., Ahmad, R. and Zakaria, M. Z. (2018) 'Comparison of Evolutionary Computation and Empirical Penman-Monteith Equation for Daily and Monthly Reference Evapotranspiration Estimation in Tropical Region', *The International Journal of Integrated Engineering,* 7(Int. J. of Integrated Engineering), pp. 117–129. doi: https://doi.org/10.30880/ijie.2018.10.07.011.

Ahmad, R., Lazin, M. N. M. and Samsuri, S. F. M. (2014) 'Neural network modeling and identification of naturally ventilated tropical greenhouse climates', *WSEAS Transactions on Systems and Control*, 9(1), pp. 445–453.

Indexed Conference proceeding

Samsuri, S. F. M., Ahmad, R., Zakaria, M. Z and Zain, Z. M. (2019) 'Parameter Tuning For Comparing Multi-Objective Evolutionary Algorithms Applied To System Identification Problems', in *2019 IEEE 6th International Conference On Smart Instrumentation, Measurement And Applications (Icsima2019)*. Kuala Lumpur, Malaysia.

Samsuri, S. F. M., Ahmad, R. and Zakaria, M. Z. (2018) 'Reference Evapotranspiration Estimation in Tropical Region using Penman-Monteith Equation and Evolutionary Computation', in *2nd International Conference on Smart Sensors and Applications (ICSSA2018)*. Kuching, Malaysia.

Ahmad, R. Lazin, M. N. M. and Samsuri, S. F. M. (2014) 'Parametric and Non-parametric Identification of Naturally Ventilation Tropical Greenhouse Climates 3 Parametric Modeling and Simulation of NVTG', in *Proceedings of the 14th International Conference on Robotics, Control and Manufacturing Technology (ROCOM '14)*. Kuala Lumpur, Malaysia.

Ahmad, R., Samsuri, S. F. M. and Zakaria, M. Z. (2012) 'Evapotranspiration prediction using system identification and genetic algorithm', in *Proceedings of the 2nd IASTED Asian Conference on Modeling, Identification, and Control, AsiaMIC 2012*. doi: 10.2316/P.2012.769-053.

Zakaria, M. Z., Jamaluddin H.,Ahmad, R., and Samsuri, S. F. M. (2012) 'Hourly reference evapotranspiration modeling by using system identification and differential evolution approach in southern peninsular of malaysia', in *The 2nd International Malaysia-Ireland Joint Symposium on Engineering, Science and Business 2012 (IMiEJS2012)*. Kuala Lumpur, Malaysia.