KPI Achievement
4 scopus ·
Status ✓

Universiti Malaysia PAHANG

RESEARCH REPORT UMP GRANT

Laporan Prestasi Skim Geran UMP

Final	/	Progress		*Progress Period : 24.12.2018*	*√ Please tick*

PROJECT DETAILS *(Keterangan Projek)*

Grant No	RDU1603138
Faculty/CoE	FKEE
Project Title	DEVELOPMENT OF IMPROVED METAHEURISTIC ALGORITHMS FOR MODELLING AND CONTROL OF A FLEXIBLE MANIPULATOR SYSTEM
Project Leader	AHMAD NOR KASRUDDIN BIN NASIR
Project Member	1.MOHD ASHRAF BIN AHMAD 2.RAJA MOHD TAUFIKA BIN RAJA ISMAIL 3. MUHAMMAD HAMKA BIN EMBONG

PROJECT ACHIEVEMENT *(Pencapaian Projek)*

B

ACHIEVEMENT PERCENTAGE				
Project progress according to milestones achieved up to this period	**0 - 25%**	**26 - 50%**	**51 - 75%**	**76 - 100%**
Percentage (please state %)				100

EXPENDITURE *(Perbelanjaan)*

C

Budget Approved *Peruntukan diluluskan*	**Amount Spent** *Jumlah Perbelanjaan*	**Balance** *Baki*	**% of Amount Spent** *Peratusan Belanja*
RM31,800.00	**RM25,492.60**	**RM6307.40**	**80.17%**

RESEARCH OUTPUT *(Output Penyelidikan)*

KPI 1 ISI 2
2 scopus
1 index
1 master

D

NO OF PUBLICATION

KPI FOR NO OF PUBLICATION

	ISI	Scopus	Index Proceedings	Others
KPI	1	4 2	1	
Achievement		1		

The contribution of funder (UMP, MOHE, MOSTI, Industry etc.) as the fund provider must be acknowledged at all times in all forms of publications. Please state the grant number (RDU/UIC) and grant name.

	ISI	**Scopus**
		1. Journal of Telecommunication, Electronic and Computer Engineering (JTEC)- A Hybrid Spiral-Genetic Algorithm for Global Optimization.
	International	**National**

Page of Publication)	2. A multiobjective Spiral Dynamic Algorithm and Its Application for PD Design. Proceedings of IEEE 8th Control and Systems Graduate Research Colloquium ICSGRC2017, 4-5 August 2017, Shah Alam Malaysia. 3. Adaptive Sine-Cosine Algorithms for Global Optimization. Proceedings of IEEE International Control on Automatic Control and Intelligent Systems (I2CACIS2018), 20 October 2018, Shah Alam Malaysia. 4. A Multiobjective Simulated Kalman Filter Optimization Algorithm. Proceedings of IEEE International Control on Applied Systems Innovation 2018.	1. 2.

HUMAN CAPITAL DEVELOPMENT

KPI FOR HUMAN CAPITAL DEVELOPMENT

	PhD Student	Master Student
KPI		
Achievement		

	Number			
	On-going		**Graduated**	
Citizen	Malaysian	Non Malaysian	Malaysian	Non Malaysian
PhD Student				
Masters Student				
Undergraduate Student				
Total				

Name of Student: **ID Matric No:** **Faculty:** **Thesis title:** **Graduation Year:** **Name of Student:** **ID Matric No:** **Faculty:** **Thesis title:** **Graduation Year:** *** enter for more space*	Comments: Allocation of vote 11000 with an amount RM5000 for student is not used yet. At this time we understood that PnI policy only allows the allocation to pay undergraduate students only. Although we had several postgraduate students, we did not spend the vote due to the restriction mentioned above.

INTELECTUAL PROPERTIES

KPI FOR INTELECTUAL PROPERTIES

Patent, Copyright, Trademark,Industrial Design: ____________

Patent, Copyright, Trademark, Industrial Design ect	NONE

OTHERS

KPI FOR OTHERS

Prototype, Technology,Collaborations etc: ____________

Prototype, Technology, Collaborations etc	None

ASSET ***(Aset)***

E	Bil	Peralatan *(Equipment)*	Model	No Daftar Aset *(Asset Tagging No)*	Amount (RM)	Lokasi *(Location)*
	1	myRIO-1900. Incl Wifi, MSP Connector And Accesories	MyRIO-1900	1. FTK1000-PB101(R)-1710-0002-0001 2. FTK1000-PB101(R)-1710-0002-0002 3. FTK1000-PB101(R)-1710-0002-0003	10,504.80	FKEE

PRODUCT DESCRIPTION FOR UMP R&D DIRECTORY (SHORT & BRIEF) *Only for Final Report*

F

The purchased products were used for signal conditioning circuit and data acqusition module for communication between a robot with controller unit.

PRODUCT PICTURE FOR UMP R&D DIRECTORY *Only for Final Report*

G

SUMMARY OF RESEARCH FINDINGS *(Ringkasan Penemuan Projek Penyelidikan)*

H

This research focuses on developing metaheuristic algorithm for application in controller design. 4 differents algorithms have been developed as follows.

1. Hybrid Spiral-GA algorithm. – has better performance compared to Spiral dynamic algorithm.
2. Multiobjective Spiral Dynamic algorithm. – Has comparable performance compared to well-known NSGA2 algorithm. This is the first multiobjective SDA introduced. No one has introduced before.
3. Mulltiobjective Simulated Kalman Filter algorithm.- Has comparable performance compared to well-known NSGA2 algorithm. This is the first multiobjective SKF introduced. No one has introduced before.
4. Adaptive Sine-Cosine Algorithms for Global Optimization. It is an improved version of Sine –Cosine Algorithm.

All the algorithms have been tested with benchmark functions and some were applied to optimize PD controller for a robotic system. They successfully optimized, functioned properly, and achieved a comparable performance compared to other well-known algorithms in their group.

Although all the algorithms mentioned above have achieved a comparable performance compared to other well-known existing algorithms, there are more chances for them to be developed further.

PROBLEMS / CONSTRAINTS IF ANY *(Masalah/ Kekangan sekiranya ada)*

I

Problem in getting research assistance from undergraduate students. The budget should be allowed ~~tp~~ to spend on postgraduate students in the future.

Date : 2.8.2019 *Tarikh*	**Project Leader's Signature:** *Tandatangan Ketua Projek* DR. AHMAD NOR KASRUDDIN NASIR, CENG, MIET (UK) SENIOR LECTURER FACULTY OF ELECTRICAL & ELECTRONICS ENGINEERING UNIVERSITI MALAYSIA PAHANG 26600 PEKAN PAHANG DARUL MAKMUR TEL: 09-424 6153 FAX: 09-424 6111

COMMENTS, IF ANY/ ENDORSEMENT BY FACULTY (*Komen, sekiranya ada / Pengesahan oleh Fakulti*)

J Recommend / ~~Not Recommend / KIV / Need Ammendment~~

Progress 100% complete.

KPI publication achieved.

Name: IR. DR. MUHAMAD ZAHIM BIN SUJOD, DEPUTY DEAN (RESEARCH & POSTGRADUATE STUDIES), FACULTY OF ELECTRICAL & ELECTRONICS ENGINEERING, UNIVERSITI MALAYSIA PAHANG, 26600 PEKAN, PAHANG DARUL MAKMUR, TEL: 09-424 6131 FAX: 09-424 6111
Nama:

Date: 9/8/19
Tarikh:

Signature:
Tandatangan:

IR. DR. MUHAMAD ZAHIM BIN SUJOD
DEPUTY DEAN (RESEARCH & POSTGRADUATE STUDIES)
FACULTY OF ELECTRICAL & ELECTRONICS ENGINEERING
UNIVERSITI MALAYSIA PAHANG
26600 PEKAN
PAHANG DARUL MAKMUR
TEL: 09-424 6131 FAX: 09-424 6111

** Dean/TDR/Director/Deputy Director

COMMENTS, IF ANY/ ENDORSEMENT BY RMC PNI (*Komen, sekiranya ada / Pengesahan oleh RMC PNI*)

K Recommend / Not Recommend / KIV / Need Ammendment

Recommended

Name:
Nama:

Date: 29/11/19
Tarikh:

Signature:
Tandatangan:

PROFESOR Ts. DR. MD. MUSTAFIZUR RAHMAN
Dekan Penyelidikan
Jabatan Penyelidikan dan Inovasi
Universiti Malaysia Pahang

JOURNAL OF TELECOMMUNICATION, ELECTRONIC and COMPUTER ENGINEERING
UTeM UNIVERSITI TEKNIKAL MALAYSIA MELAKA

A Hybrid Spiral-Genetic Algorithm for Global Optimization

Ahmad N.K. Nasir, Ahmad A. A. Razak, Raja M. T. R. Ismail, Mohd A. Ahmad

Abstract

Genetic algorithm (GA) is a well-known population-based optimization algorithm. GA utilizes a random approach in its strategy which inspired from a biological process of a chromosome alteration. Chromosomes which consists of several genes are randomly self-altered their own structure and also randomly combined their structure with other chromosomes. The unique biological process has inspired many researchers to develop an optimization algorithm. Yet, the algorithm still popular and is adopted as a tool to solve many complex problems. On the other hand, Spiral Dynamic Algorithm (SDA) is a relatively new population-based algorithm inspired by a natural spiral phenomenon. It utilizes a deterministic approach in its strategy. Movement of a search point from one location to another in a form of a spiral trajectory and relies on pre-defined parameters. However, both algorithms suffer a pre-matured convergence and tend to trap into a local optima solution. This paper presents an improved algorithm called a Hybrid Spiral-Genetic Algorithm. The algorithm is developed based on a combination of the wellknown GA and the SDA. The spiral equation of the SDA is adopted into the GA to enhance both exploration and exploitation of the original GA. The algorithm is tested with several benchmark functions of a single-objective algorithm and compared with the original SDA and GA. The result of the test shows that the proposed algorithm outperformed its predecessor algorithms significantly.

Keywords

Spiral Dynamic Algorithm; Genetic Algorithm;

Full Text:

PDF

References

James K., Particle Swarm Optimization, Encyclopedia of Machine Learning, Springer US, pp. 760-766.

David E. G., 1989, Genetic Algorithms in Search, Optimization, and Machine Learning. Addison Wesley, Reading MA.

Xin S.Y. Firefly algorithms for multimodal optimization. International Symposium on stochastic algorithms, 26th October 2009, Springer, Berlin, Heidelberg, pp.169-178.

Zong W.G., Joong H.K., G V. L. (2001). A new heuristic optimization algorithm: harmony search. Simulation 76 (2), pp. 60-68.

B. Alatas (2011) ACROA: artificial chemical reaction optimization algorithm for global optimization. Expert Systems with Applications 38 (10), pp. 13170-13180.

Tamura K. and Yasuda K. (2011). Primary study of spiral dynamics inspired optimization. IEEJ Transactions on Electrical and Electronic Engineering, 6 (S1), pp. S98–S100.

Mahmoodabadi M. J. and Nemati A. R. 2016. A novel adaptive genetic algorithm for global optimization of mathematical test functions and real-world problems. Engineering Science and Technology, an International Journal, 19 (2016) pp. 2002–2021.

Ahmed Z. H. 2015. An improved genetic algorithm using adaptive mutation operator for the quadratic assignment problem. 2015 38th International Conference on Telecommunications and Signal Processing (TSP), Prague, Czech Republic, 9-11 July 2015, pp. 1-6.

Mashwani W. K., Salhi A., Yeniay O., Hussian H., Jan M.A. 2017. Hybrid non-dominated sorting genetic algorithm with adaptive operators selection. Applied Soft Computing 56 (2017) pp. 1–18.

Maheshwari A., Garg R. and Sharma E. N. 2016. A Review Paper on Brief Introduction of Genetic Algorithm. International Journal of Emerging Research in Management &Technology, 5 (2), pp. 87-89.

Eroglu D. Y. and Kilic K. 2017. A novel Hybrid Genetic Local Search Algorithm for feature selection and weighting with an application in strategic decision making in innovation management. Information Sciences, Volume 405, September 2017, pp. 18-32.

Rahmani A. and MirHassani S.A. 2014. A hybrid Firefly-Genetic Algorithm for the capacitated facility location problem. Information Sciences, Volume 283, 1 November 2014, pp. 70-78

Alsaeedan W., Menai M. E. B., Al-Ahmadi S. 2017. A hybrid geneticant colony optimization algorithm for the word sense disambiguation problem. Information Sciences, Volume 417, November 2017, pp. 20- 38.

Garai G. and Chaudhurii B. B. 2013. A novel hybrid genetic algorithm with Tabu search for optimizing multi-dimensional functions and point pattern recognition. Information Sciences, Volume 221, 1 February 2013, pp. 28-48.

Nasir A. N. K., Tokhi, M. O., Sayidmarie, O. and Ismail, R.M.T.R. (2013), A novel adaptive spiral dynamic algorithm for global optimization. 2013 13th UK Workshop on Computational Intelligence (UKCI), pp. 334-341.

Nasir, A.N.K., Tokhi, M.O., Ghani, N.M.A. Novel hybrid bacterial foraging and spiral dynamics algorithms. 2013 13th UK Workshop on Computational Intelligence (UKCI), Surrey, pp. 199-205.

Nasir, A.N.K., Tokhi, M.O., Ghani, N.M.A. and Ahmad, M.A. A novel hybrid spiral dynamics bacterial chemotaxis algorithm for global optimization with application to controller design. 2012 UKACC International Conference on Control (CONTROL), pp. 753-758.

Hashim M. R. and Tokhi M. O. 2016. Enhanced chaotic spiral dynamic algorithm with application to controller design. 2016 IEEE International Conference on Power and Energy (PECon), Melaka, Malaysia. 28-29 Nov. 2016, pp. 752-756.

Hashim M. R. and Tokhi M. O. 2016. Greedy spiral dynamic algorithm with application to controller design. 2016 IEEE Conference on Systems, Process and Control (ICSPC), Melaka, Malaysia. 16-18 Dec. 2016, pp. 29-32.

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A multi-objective Spiral Dynamic algorithm and its application for PD design

Publisher: IEEE

4 Author(s) Ahmad N. K. Nasir ; A. R. A. Azwan ; A. M. Ashraf ; M. J. M. Falfazli **View All Authors**

Abstract

Document Sections

Abstract: This paper presents a novel multi-objective Spiral Dynamic Optimization (MOSDA) algorithm. It is an extended version of a single objective type SDA. A Non-dominated sorti...**View more**

Metadata

Abstract:

This paper presents a novel multi-objective Spiral Dynamic Optimization (MOSDA) algorithm. It is an extended version of a single objective type SDA. A Non-dominated sorting (NS) approach from Non-dominated Sorting Genetic Algorithm II (NSGAII) is adopted into SDA to develop its multi-objective (MO) type algorithm. SDA has a good elitism strategy and a simple structure. On the other hand, NS is a fast strategy to develop good Pareto Front (PF) characteristics for MO type algorithm. The proposed algorithm is tested with various benchmark functions used to test a newly developed MO algorithm. A PF graph is presented as a result of the test. Moreover, it is adopted to optimize parameters of Proportional-Derivative (PD) controller for an Inverted Pendulum (IP) system. Time-domain response of the IP is presented to show performance of the optimized controller. Result presented in this paper shows that MOSDA has a better performance in terms of finding PF and solution spread when tested with benchmark functions compared to NSGAII. In terms of its application in solving a real problem, both algorithms successfully optimize the PD and control the system very well. IP controlled by MOSDA-based PD shows better rise time.

Published in: 2017 IEEE 8th Control and System Graduate Research Colloquium (ICSGRC)

Date of Conference: 4-5 Aug. 2017

INSPEC Accession Number: 17262324

DOI: 10.1109/ICSGRC.2017.8070557

Adaptive Sine-Cosine Algorithms for Global Optimization

Publisher: IEEE

5 Author (s) Mohd Falfazli Mat Jusof ; Shuhairie Mohammad ; Ahmad Azwan Abd Razak ;... **View All Authors**

Abstract

Abstract: This paper introduces improved versions of a Sine-Cosine algorithm called Adaptive Sine-Cosine algorithms. It is made adaptive through incorporation of a linear and an ex...**View more**

Metadata

Abstract:

This paper introduces improved versions of a Sine-Cosine algorithm called Adaptive Sine-Cosine algorithms. It is made adaptive through incorporation of a linear and an exponential term with respect to an individual agent's fitness. Based on the newly introduced formulas, an individual agent moves with a dynamic and different step sizes compared to other agents through the whole searching process. It also introduces a balance exploration and exploitation strategies. The proposed algorithms in comparison to the original algorithm are then tested with several test functions that have different properties and landscapes. The algorithms performance in terms of their achievement of finding a near optimal solution is analyzed and discussed. Numerical result of the test shows that the proposed algorithms have achieved a better accuracy. The finding also shows that the proposed algorithms have attained a faster convergence toward the near optimal solution.

Published in: 2018 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS)

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INSPEC Accession Number: 18373537

DOI: 10.1109/I2CACIS.2018.8603684

Publisher: IEEE

Conference Location: Shah Alam, Malaysia

A multiobjective simulated Kalman filter optimization algorithm

Publisher: IEEE

5 Author(s) A. Azwan ; A. Razak ; M. F. M. Jusof ; A. N. K. Nasir ; M. A. Ahmad **View All Authors**

Abstract: This paper presents a new multiobjective type optimization algorithm known as a Multiobjective Optimization Simulated Kalman Filter (MOSKF). It is a further enhancement o...**View more**

Metadata

Abstract:

This paper presents a new multiobjective type optimization algorithm known as a Multiobjective Optimization Simulated Kalman Filter (MOSKF). It is a further enhancement of a single-objective Simulated Kalman Filter (SKF) optimization algorithm. A synergy between SKF and Non-dominated Solution (NS) approach is introduced to formulate the multiobjective type algorithm. SKF is a random based optimization algorithm inspired from Kalman Filter theory. A Kalman gain is formulated following the prediction, measurement and estimation steps of the Kalman filter design. The Kalman gain is utilized to introduce a dynamic step size of a search agent in the SKF algorithm. A Non-dominated Solution (NS) approach is utilized in the formulation of the multiobjective strategy. Cost function value and diversity spacing parameters are taken into consideration in the strategy. Every single agent carries those two parameters in which will be used to compare with other solutions from other agents in order to determine its domination. A solution that has a lower cost function value and higher diversity spacing is considered as a solution that dominates other solutions and thus is ranked in a higher ranking. The algorithm is tested with various multiobjective benchmark functions and compared with Non-Dominated Sorting Genetic Algorithm 2 (NSGA2) multiobjective algorithm. Result of the analysis on the accuracy tested on the benchmark functions is tabulated in a table form and shows that the proposed algorithm outperforms NSGA2 significantly. The result also is presented in a graphical form to compare the generated Pareto solution based on proposed MOSKF and original NSGA2 with the theoretical Pareto solution.

Published in: 2018 IEEE International Conference on Applied System Invention (ICASI)

RDU 1603138

DEVELOPMENT OF IMPROVED METAHEURISTIC ALGORITHMS FOR MODELLING AND CONTROL OF A FLEXIBLE MANIPULATOR SYSTEM

(PENGHASILAN ALGORITMA METAHEURISTIC YANG DITAMBAH BAIK UNTUK APPLIKASI MENDAPATKAN MODEL DAN SISTEM PENGAWALAN ROBOT YANG FLEKSIBEL)

AHMAD NOR KASRUDDIN NASIR

MOHD ASHRAF AHMAD

RAJA MOHD TAUFIKA RAJA ISMAIL

MOHAMMAD HAMKA EMBONG

RESEARCH VOTE NO: RDU1603138

Faculty of Electrical & Electronics Engineering,

Universiti Malaysia Pahang,

26600 Pekan Pahang Malaysia.

2019

ACKNOWLEDGEMENT

First of all, Praise to Almighty God for making this project a success. All the objectives of the project are successfully achieved. Result obtained from the work gives a meaningful contribution of this research. From this project, four papers are successfully published in four different Scopus-index proceedings.

At this point, as a representative to all project members, I would like to express sincere appreciation to the Research and Innovation Department, Universiti Malaysia Pahang for awarding financial support to fund this research work. Also to all management team and members of the Research and Innovation Department for giving their full cooperation and assistance in handling all the administrative matters, documentation and grant management. Appreciation also to the management team and members of the Faculty of Electrical & Electronics Engineering who directly and indirectly involved in all the administrative processes from the beginning until the end of the project period.

I also would like to extend my appreciation to the members of research team for their dedication and hard work that makes this project successfully achieved its objectives and outcomes. Appreciation also goes to all postgraduate PhD and MSc students who have involved and supported their technical expertise in this project.

RDU 1603138

ABSTRACT

This project develops two variants of single-objective type optimization algorithm and two variants of multi-objective type optimization algorithm. The developed algorithms are formulated based on a spiral model approach and a sine model approach. The aim of the single type algorithms is to improve the algorithms capability to find an optimal solution. The algorithm is considered as more effective if the solution found has a higher accuracy. On the other hand, the aim for the multiobjective type algorithm is to find an optimal pareto front solution. A good pareto front should have a higher accuracy and a diverse solution along the pareto front. The performance of the developed algorithms are tested on various benchmark functions for both single and multiobjective type problems. It is found that all the developed algorithms have competitive accuracy performance compared to other state of the art algorithms i.e NSGA2, SCA, Sine-Cosine algorithms. In this work the algorithms are developed on a Matlab and Simulink software.

The developed algorithms have been applied to optimize Proportional Integral Derivative (PID) controller parameters for a flexible manipulator system and an inverted pendulum system. The inverted pendulum system has almost the same control problem like the flexible manipulator system. It has a single input and multi output. In actual application, the output of interest are the position of a cart and angle of pendulum rod. Both angle and position must be controlled simultaneously to ensure the stability of the system during operation. The experiment has been performed on Matlab and Simulink software and verified on the actual inverted pendulum system. Actual application of these two system in industry include safe operation of an overhead crane to transfer object from one location to another location. Another application is the precise position control of surgery robot that widely used in hospital to help surgeon conduct various operations. The surgery robot has a flexible structure which is different to conventional industrial robot which has solid link.

The project has been successfully implemented and a good result has been achieved. The research on controlling the crane and surgery robot should be carried on further. This is due to its advanced technology and complex system hence it requires lots of funds and a good research collaboration with industries is needed

Key researchers : Dr. Ahmad Nor Kasruddin Nasir, Dr. Mohd Ashraf Ahmad, Dr. Mohd Raja Taufika Raja Ismail, Mohd Hamka Embong.

E-mail : kasruddin@ump.edu.my
Tel. No. : 094246153
Vote No. : RDU 1603138

Abstrak

Projek ini membangunkan dua variasi satu-objektif algoritma optimum serta dua variasi dua-objektif algoritma optimum. Semua algoritma yang telah dibangunkan telah difomulasi berdasarkan model spiral dan model sine. Tujuan utama mebangunkan satu objeltif algoritma adalah untuk meningkatkan kebolehan algoritma dalam mencari solusi yang optimal. Algoritma ini dianggap sebagai effektif sekiranya solusi yang dijumpai mempunyai ketepatan yang tinggi. Sebaliknya, tujuan utama membangunkan dua-objektif algoritma adalah untuk mencari jawapan hadapan pareto yang optimal. Hadapan pareto yang baik seharusnya mempunyai ketepatan yang tinggi dan jawapan yang menyeluruh serta sekata sepanjang garisan Pareto. Pencapaian algoritma yang telah dibangunkan diuji keatas pelbagai persamaan matematik bagi kedua-dua masalah satu-objektif dan dua-objektif. Didapati semua algoritma yang telah dibangunkan mempunyai pencapaian ketepatan yang kompetitif jika dibandingkan dengan algorithma yang lain-lain seperti algoritma NSGA2, SCA dan Sine-Cosine. Dalam projek ini, semua algoritma telah dibangunkan menggunakan perisian Matlab dan Simulink.

Algoritma yang telah dibangunkan telah digunakan untuk mencari nilai pengawal PID yang optimum bagi mengawal tangan robot yang fleksibal and sistem pendulum. Sistem pendulum mempunyai hamper sama masalah kawalan seperti tangan robot yang fleksibal. Ia mempunyai satu kemasukan respon dan dua keluaran respon. Dalam applikasi sebenar, keluaran respon yang dikawal adalah kedudukan badan pendulum serta sudut pendulum. Kedua-dua sudut dan kedudukan mesti dikawal secara serentak untuk memastikan kestabilan system pendulum semasa beroperasi. Exsperimen ini telah dijalankan dengan menggunakan perisian Matlab dan Simulink serta telah diuji bersama prototype system pendulum.Applikasi sebenar kedua-dua system pendulum serta tangan robot yang fleksibal di industry merangkumi operasi selamat kren overhead untuk memindahkan objek dari satu lokasi ke lokasi yang lain. Applikasi yang lain adalah kawalan kedudukan robot bedah secara tepat yang digunakan dengan meluas di hospital untuk membantu doctor bedah melakukan pelbagai pembedahan. Robot bedah mempunyai struktur yang fleksibal yang mana ia berbexa dengan robot indutri ysng mempunyai badan yang keras.

Projek ini telah berjaya dilaksanakan dan keputusan yang baik telah dicapai. Penyelidikan terhadap kawalan kren dan robot bedah seharusnya diteruskan lagi. Ini adalah disebabkan teknologi yang sangat maju serta system yang begitu komplek seterusnya menyebabkan penyelidikan ini memerlukan kepada dana yang banyak serta memerlukan kolaborasi penyelidikan yang baik dengan industry.

Table of Contents

CHAPTER 1 INTRODUCTION

1.1 Problem statement

Spiral dynamic algorithm (SDA) and sine-cosine algorithm (SCA) are two recent optimization algorithms that received attentions from researchers. Both algorithms have a good elitism approach in its formulation but with different strategy. SDA uses a deterministic spiral trajectory while the SCA uses a random based technique. Due to the deterministic feature, exploration of SDA is not at optimal and hence it unable to give a highly accurate solution for many problems. However due to the spiral strategy, the algorithm has a faster convergence. On the other hand, a linear adaptive strategy in the SCA formulation has limited search agents to dynamically move within a predefined range of a search space. It creates unbalanced exploration and exploitation and hence resulted in low accurate solution.

1.2 Objective

1. To developed spiral and sine based optimization algorithms.
2. To develop multi-objective algorithms based on spiral and sine cosine strategy.
3. To apply the developed algorithm to optimize PID controller for the flexible manipulator system.

1.3 Scope

The project can be divided into two parts. The first part is the development of improved spiral and sine based optimization algorithms. It focuses on the strategy on solving problems faced by spiral and sine cosine algorithms. The performance measure of the improved algorithm is mainly on the accuracy attainment of the improved algorithm to find optimal solution. The proposed algorithms in comparison with the original spiral and sine-cosine algorithms are tested on various benchmark functions. Then a statistical analysis are conducted on the acquired result from the benchmark test. Here, Wilcoxon sign rank test and Friedman test are considered for the analysis.

The second part of the work is the application of the developed algorithms to optimize controller parameters for a flexible manipulator robot. A simple but practical proportional integral and derivative (PID) controller is selected as the controller of interest. An inverted pendulum system and a flexible manipulator robot are two system that has almost the same concept. Both of them have a single input i.e applied torque and two outputs i.e position and vibration. Therefore in this work, an inverted pendulum system is considered as the engineering problem to be solved. At the end of the project, it is expected that the developed algorithms should be successfully determined a set of optimal value for the PID controller to control the inverted pendulum system.

CHAPTER 2 TECHNICAL PAPER 1

2.1 Title

A Hybrid Spiral-Genetic Algorithm for Global Optimization

2.2 Abstract

Genetic algorithm (GA) is a well-known population-based optimization algorithm. GA utilizes a random approach in its strategy which inspired from a biological process of a chromosome alteration. Chromosomes which consists of several genes are randomly self-altered their own structure and also randomly combined their structure with other chromosomes. The unique biological process has inspired many researchers to develop an optimization algorithm. Yet, the algorithm still popular and is adopted as a tool to solve many complex problems. On the other hand, Spiral Dynamic Algorithm (SDA) is a relatively new population-based algorithm inspired from a natural spiral phenomena. It utilizes a deterministic approach in its strategy. Movement of a search point from one location to another in a form of a spiral trajectory and is relied on pre-defined parameters. However, both algorithms suffer a pre-matured convergence and tend to trap into a local optima solution. This paper presents an improved algorithm called a Hybrid Spiral-Genetic Algorithm. The algorithm is developed based on a combination of the well-known GA and the SDA. Spiral equation of the SDA is adopted into the GA to enhance both exploration and exploitation of the original GA. The algorithm is tested with several benchmark functions of a single-objective algorithm and compared with the original SDA and GA. Result of the test shows that the proposed algorithm outperformed its predecessor algorithms significantly.

2.3 Introduction

Nowadays, an optimization algorithm plays an important role in solving many complex problems in real world. It has been widely applied in various fields including science and non-science as a tool to get many optimal parameters. With the application of the algorithm, an optimum result or decision can be easily achieved. Moreover, with a growing of fast computing technologies, the adoption of the optimization algorithm is increasing. Yet, fast computing machines with affordable price can be easily found in the current world market.

Research on developing and improving optimization algorithms has started since many years back. Most of the developed algorithms are inspired from biological or natural phenomena. Algorithms inspired from living creature are known as biological-inspired algorithms while algorithms inspired from other than living creature are known as natural-inspired algorithms. Some of the well-known biological-based optimization algorithms include Particle swarm optimization [1], Genetic algorithm (GA) [2] and Firefly algorithm [3]. Examples of natural-inspired optimization algorithms include Harmony search algorithm [4], Chemical reaction algorithm [5] and Spiral dynamic algorithm (SDA) [6]. All these algorithms free from derivative operation and thus suitable for solving simple and complex problems.

GA is one of the earliest introduced optimization algorithm among the population-based category. Research on GA has reached a matured-phase. Various adaptive and hybrid types GA-based algorithms have been developed since the introduction of the original GA. Adaptive types GA include formulation to adjust mutation and crossover operators [7], [8] and operators selection [9]. Several types of selection have been applied in GA. Some of the commonly found in literature are roulette wheel, elitism, rank and tournament selections. There are also different types of crossover and mutations have been proposed by researchers [10]. These variants of adaptive types GA open new perspectives to researchers on the strategy to improve the algorithm performance.

Hybrid type GA can also be extensively found in literature. Eroglu and Kilic [11] proposed a Hybrid GA-Local search method. Random selection, single-point mutation and crossover were applied as the basic GA operations. Local search method was adopted as a further step to include additional mutation operation based on feature selection. Rahmani and Mirhassani [12] proposed GA-Firefly algorithm. Crossover operation of GA was applied to the first two best fitness of ranked fireflies. It was followed by a mutation operation on a randomly selected firefly to increase diversity of the algorithm. Alsaeedan et al. proposed a GA-Ant colony algorithm [13]. Single-point crossover and mutation or uniform crossover and mutation operations were adopted into Ant colony algorithm based on crossover rate or mutation rate respectively. Value of the mutation and crossover rates in the proposed algorithm was adaptively varied with respect to fitness of the ant agent. Garai and Chaudhurii proposed a GA- Tabu algorithm [14]. Local tabu search method was applied into GA to avoid the GA from being trapped into local optima solution. Tabu search was invoked whenever the best fitness of GA was not changed after several GA iterations. The rest of GA operations will continue once the Tabu algorithm has completed its cycle.

SDA is a relatively new population based algorithm. Various adaptive and hybrid type SDA have been introduced. The adaptive type SDA includes ASDA where a linear-based equation was adopted into spiral equation of SDA [15]. Unlike the original SDA, the equation defined spiral radius and angle within a specified range for each search point. Throughout the search process, different search points can have different motion trajectories. Examples of hybrid SDA include hybrid spiral-bacterial foraging algorithm [16] and hybrid spiral dynamic-bacteria chemotaxis algorithm [17]. In both algorithms, chemo taxis strategy of a bacterial foraging algorithm (BFA) was combined with the spiral equation of SDA. The strategy combined random approach of a bacterium with a deterministic approach of SDA. The proposed algorithm improved accuracy of both original BFA and SDA algorithms. Most recent work of SDA development was an enhanced chaotic SDA [18]. SDA was combined with bio-logical inspired artificial bee colony (ABC) algorithm and chaos function. A logistic chaotic map was applied into the spiral equation to replace a constant radius of SDA. Meanwhile, the local search strategy of ABC was adopted as an additional step into SDA to tackle exploitation strategy in a local region. In another work, the authors adopted greedy selection strategy into SDA to determine the best search point in every iteration [19].

This paper proposes a new hybrid GA type named Hybrid Spiral-Genetic algorithm (HSGA). The strategy integrates a spiral equation of the SDA into the original GA. It improves accuracy of both SDA and GA algorithms.

2.4 Methodology

In HSGA, a deterministic spiral motion of SDA and a random approach of GA is synergized. GA is viewed as a good algorithm in terms of its diversity and thus able to search a feasible search space thoroughly. On the contrary, the spiral trajectory of SDA is considered as a good algorithm to search at a more confined space. The concept of elitism of SDA is also adopted into GA. All of agents in SDA are formulated such that they move towards the best agent in the population. Moreover, movement of the agents from outer layer of the spiral form towards the center of the spiral form creates dynamic step size. A step-by-step HSGA algorithm is explained as follows.

A. A step-by-step HSGA algorithm.

1. **Initialize chromosome populations.**

   a) Randomly generate chromosome population.
   b) Evaluate fitness value of each chromosome.

2. **Apply crossover operation.**

   a) Randomly select two parent chromosomes.
   b) Apply a random-based crossover.
   c) Evaluate fitness value of the crossovered chromosome offsprings.

3. **Apply mutation operation.**

   a) Randomly select two parent chromosomes.
   b) Apply a random-based mutation.

c) Evaluate fitness value of the mutated chromosome offsprings.

4. **Apply SDA**.

    a) Move chromosomes spirally by applying the spiral equation as shown in Eqn. (1).
    b) Evaluate fitness value of the new generated chromosomes.

5. **Rank** the chromosomes and retain some of the fittest chromosomes in the population.

6. **Repeat** the process until termination criterion is reached.

In HSGA, the selection, crossover and mutation operations for GA as shown in steps 2 and 3 utilize a random approach. The operations are the same as other basic GAs found in literature. The integration of SDA strategy into GA is shown in step 4. A spiral equation of SDA is adopted and thus moves all the chromosomes in a spiral form. This ensures combination of random and deterministic spiral strategies are applied.

2.5 Result & Discussion

Results of the performance test are presented in terms of both graphical and numerical representations. Graphical result shows convergence trend while numerical result presents the accuracy achieved by both GA and HSGA. Figures 1- 6 show graphical results of both GA and HSGA convergence to a near optimal accuracy. The red dotted-line and the blue smoothed-line represent GA and HSGA graphs respectively. The x-axis represents number of iteration while the y-axis represents cost function result.

Notice that, for function 1, the GA trapped into local optima solution starting at about the first 100 iterations until the rest of iterations. Graph 2 shows both GA and HSGA present almost the same performance. HSGA presents a little bit better performance starting from iteration 500 towards the end. In graph 3, HSGA performed slightly better than GA in terms of speed and accuracy. HSGA presents a little bit better performance starting from iteration 600 towards the end. Graph 4 shows that HSGA trapped into a local optima. It unable to converge further starting from iteration 100. GA performed significantly better than HSGA. In terms of convergence speed, HSGA shows a faster convergence speed for the 100 iterations. Graph 5 shows both algorithms have reached almost the same accuracy at iteration 800. However, GA was not able to further converge and trapped into a local optima for the last 200 iterations. Graph 6 shows that HSGA significantly outperformed GA in term of searching for an optimal solution and thus has a better accuracy. It also presents slightly faster convergence speed.

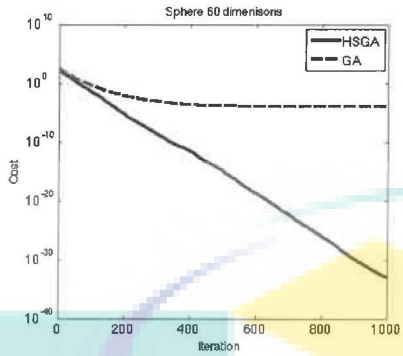


Figure 1: 60 dim. of a Sphere function.

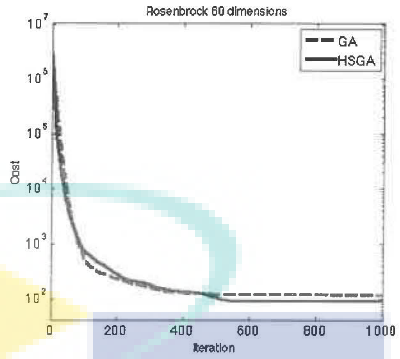


Figure-2: 60 dim. of a Rosenbrock function.

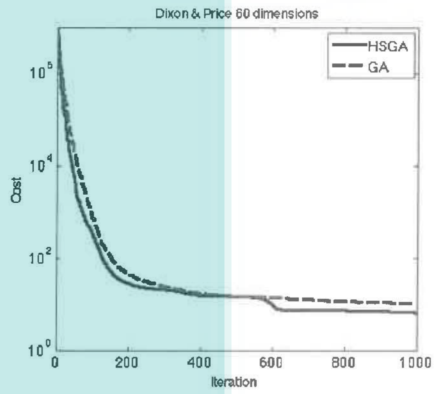


Figure 3: 60 dim. of a Dixon & Price function.

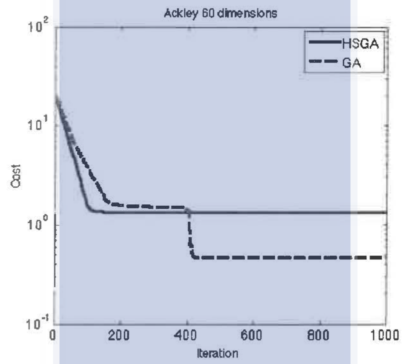


Figure 4: 60 dim. of an Ackley function.

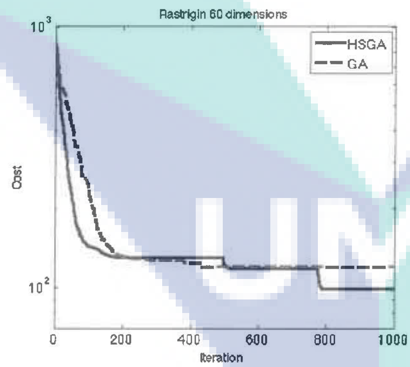


Figure 5: 60 dim. of a Rastrigin function.

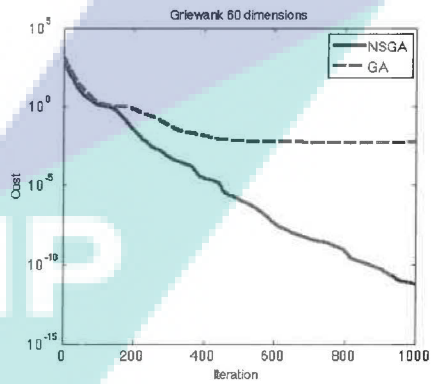


Figure-6: 60 dim. of a Griewank function.

Numerical result of the acquired optimal solutions for the benchmark functions optimized by GA and HSGA is shown in Table-1. The best result is highlighted in bold font. Notice that out of 6 functions, GA outperformed the HSGA only for function 4, Ackley. Table-2 shows numerical result of the total computation time in second for both GA and HSGA. Since the proposed approach has additional steps in its strategy, therefore it has a higher computational time for all test functions. HSGA has about double total computation time of the original GA.

Table 1
Acquired optimal solution for the test functions.

Func. No.	Function name	GA	HSGA
1	Sphere	1.23×10^{-4}	**1.75×10^{-33}**
2	Rosenbrock	116.50	**89.88**
3	Dixon & Price	10.67	**6.43**
4	Ackley	**4.65×10^{-1}**	1.34
5	Rastrigin	120.40	**98.59**
6	Griewank	5.80×10^{-3}	**6.60×10^{-12}**

Table 2
Total computation time in seconds.

Func. No.	Function name	GA	HSGA
1	Sphere	**14.61**	31.34
2	Rosenbrock	**15.59**	31.29
3	Dixon & Price	**15.63**	33.30
4	Ackley	**16.95**	34.12
5	Rastrigin	**15.58**	32.25
6	Griewank	**17.73**	31.54

2.6 Conclusion

A new algorithm namely a Hybrid Spiral-Genetic Algorithm (HSGA) has been presented. It has been developed based on mainly from a Genetic algorithm (GA) and partly from a Spiral dynamic algorithm (SDA). A spiral equation of SDA has been adopted into GA. It introduces a deterministic approach into the GA strategy. A concept of an elitism and a dynamic step size have been incorporated into GA. Result has shown that the proposed HSGA significantly improves the accuracy of GA in most of the benchmark functions. It also has shown that including the spiral equation into GA has introduced a little bit faster response. However, the equation has introduced an additional step into GA strategy. Therefore, it increases a total computation time for the proposed algorithm to complete a full cycle. The proposed algorithm will be further tested with other state-of-the-art benchmark functions with various dimensions and parameter setting. The algorithm is seen as a good algorithm to be applied to solve various real world problems.

CHAPTER 3 TECHNICAL PAPER 2

3.1 Title

A Multi-objective Spiral Dynamic Algorithm and Its Application for PD Design

3.2 Abstract

This paper presents a novel multi-objective Spiral Dynamic Optimization (MOSDA) algorithm. It is an extended version of a single objective type SDA. A Non-dominated sorting (NS) approach from Non-dominated Sorting Genetic Algorithm II (NSGAII) is adopted into SDA to develop its multi-objective (MO) type algorithm. SDA has a good elitism strategy and a simple structure. On the other hand, NS is a fast strategy to develop good Pareto Front (PF) characteristics for MO type algorithm. The proposed algorithm is tested with various benchmark functions used to test a newly developed MO algorithm. A PF graph is presented as a result of the test. Moreover, it is adopted to optimize parameters of Proportional-Derivative (PD) controller for an Inverted Pendulum (IP) system. Time-domain response of the IP is presented to show performance of the optimized controller. Result presented in this paper shows that MOSDA has a better performance in terms of finding PF and solution spread when tested with benchmark functions compared to NSGAII. In terms of its application in solving a real problem, both algorithms successfully optimize the PD and control the system very well. IP controlled by MOSDA-based PD shows better rise time.

3.3 Introduction

Optimization algorithm is a common tool used to solve a complex real world problem in science, engineering and social science studies. Applying the optimization algorithm can introduce a more accurate and promising result. Optimization algorithm can be categorized into single-objective (SO) and multi-objective (MO) types algorithm. A SO algorithm is normally applied to solve a problem with a single objective while the MO is normally used to solve a problem with more than one objective. Apart from that, a MO algorithm is also applied to solve a problem with two or more conflict objectives. A MO algorithm is normally an extended version of a SO type algorithm with more complex structure and strategy.

Particle Swarm Optimization (PSO) [20], [21], Genetic Algorithm (GA) [22], [23], and Differential Evolutionary (DE) [24], [25] are some of the well-known SO type algorithms while Spiral Dynamic Algorithm (SDA) [26] is a relatively new SO algorithm. SDA has a relatively simple structure and thus low computation cost to complete the whole searching process. Moreover, it has an elitism strategy that can offer a promising performance. Therefore, it is seen as a good and a potential algorithm to be developed further either to improve its performance within SO context such convergence speed and accuracy or introduce a new MO.

In literature, there exist at least one MO type algorithm for those three well-known SO type algorithms mentioned before, such as MOPSO [27], [28], Non-dominated Sorting GA 2 (NSGAII) [29], [30] and MODE [31], [32]. Those three algorithms were developed based on different strategies and thus have different performances. MOPSO implemented external memory, which is called 'repository' in its strategy to store the global best agent. It also used a Grid Index strategy to offer a good distribution of PF solution. NSGAII implemented a Non-dominated (NS) approach utilizing cost of objective functions and crowding distance (CD) mechanism. Combination of those two strategies introduced a good Pareto Front (PF) diversity. MODE algorithm utilized Pareto-based rank assignment and crowd parameter as a strategy to get a set of Pareto optimal solution. All the well-known MO algorithms have been widely applied to solve numerous real world problems. Research of SDA however, still at infant level. Therefore, the performance of MO type of SDA and its application to solve problem with many objectives is hardly found in literature.

This paper proposed a new MO algorithm, which is an extended version of SO type SDA called MOSDA. This study compares the performance of MO version of SDA and GA in which both utilizing the well-known NS approach. On top of that, the paper demonstrates the capability of MOSDA and NSGAII in dealing with a control design for an IP system.

3.4 Methodology

MOSDA is an extended version of SO type SDA. The application of SDA alone to develop MO type algorithm is not sufficient to give a good performance. This is due to the solely adoption of a deterministic approach in a spiral equation of SDA. In this work, the SDA is hybridized with four main components of NSGAII. It is clear that NS and CD are two good strategies to produce a good PF solution. Therefore, those 2 strategies are adopted into SDA. Both NS and CD in SDA have the same function like in GA. Beside that, they are also considered as a strategy to find the spiral centre, x^*. Instead of solely selecting the best agent based on objective function value like in SO type SDA, in MOSDA, the best agent is determined based on the output of NS and CD. On top of that, Mutation and Crossover strategies are also adopted into SDA to introduce more randomness. The first 3 and the last 3 agents of the populations are mutated and crossovered respectively. Unlike NSGAII, TS strategy is excluded and not used in MOSDA. Figure 3 shows the proposed MOSDA algorithm.

Step 0: Preparation

Select the number of search points $m \geq 2$, number of variable, n parameters $0 \leq \theta < 2\pi$, $0 < r < 1$ of $S_n(r,\theta)$, and maximum number of iterations, $k_{\max}$. Set $k = 0$.

Step 1: Initialization

(i) Set initial points $x_i(0) \in R^n, i = 1,2,...m$ in the feasible region at random.

(ii) Apply Non-dominated Sorting and Crowding Distance.

(iii) Sort population

Step 2: Define Spiral centre

The best agent of the population is defined as Spiral centre, x^*

Step 3: Apply spiral equation

(a)Update x_i

$$x_i(k+1) = S_n(r_{tumble}, \theta_{tumble})x_i(k) - (S_n(r_{tumble}, \theta_{swim}) - I_n)x^* \quad i = 1,2,...,m.$$

(b) Check fitness cost

If $f_n(x_i(k+1))$, $i = 1,2,...,m$

Step 4: Apply Mutation

Apply Mutation for the first 3 agents in the population.

Step 5: Apply Crossover

Apply Crossover for the last three agents in the population.

Step 6: Apply non-dominated sorting and crowding distance strategies.

Step 7: Sort population, *m* and display Pareto Front.

Step 8: Checking termination criterion

If $k = k_{\max}$ then terminate. Otherwise return to Step 2.

Fig. 1. MOSDA algorithm.

PD controller is a well-known linear type controller that has been widely used in industry as well as academia. It consists of two gains known as a proportional gain, K_p and a derivative gain, K_d as shown in Equation (1). In the equation, K_p and K_d are multiplied with an error and derivative of an error respectively.

$$PID = e \times K_p + \frac{de}{dt} K_d \qquad (1)$$

In this study, 2 PDs will be used to control the IP system. PD_1 is used to control an angle inverted pendulum rode, θ while PD_2 is used to control the position of the cart, x. MOSDA is applied to simultaneously optimize Kp_1 and Kd_1 for PD_1 and Kp_2 and Kd_2 for PD_2. Block diagram of the application of MOSDA and NSGAII to optimize PD to control the IP system is shown in Figure 4. r is considered as a desired input to the system. Difference between the cart position, x and the desired input, r is considered as an error of the cart position. It is used as an input to PD_1. The input for PD_2 is the angular position, θ of the rode. Since, the desired θ must be 0 (zero), then no desired angle should be defined in the block diagram.

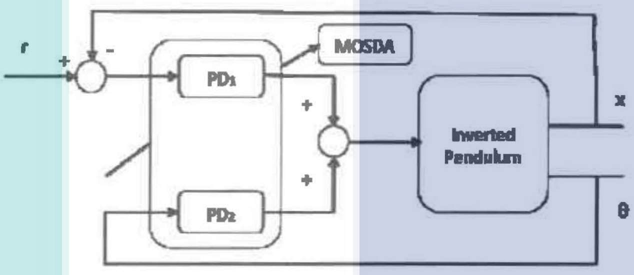
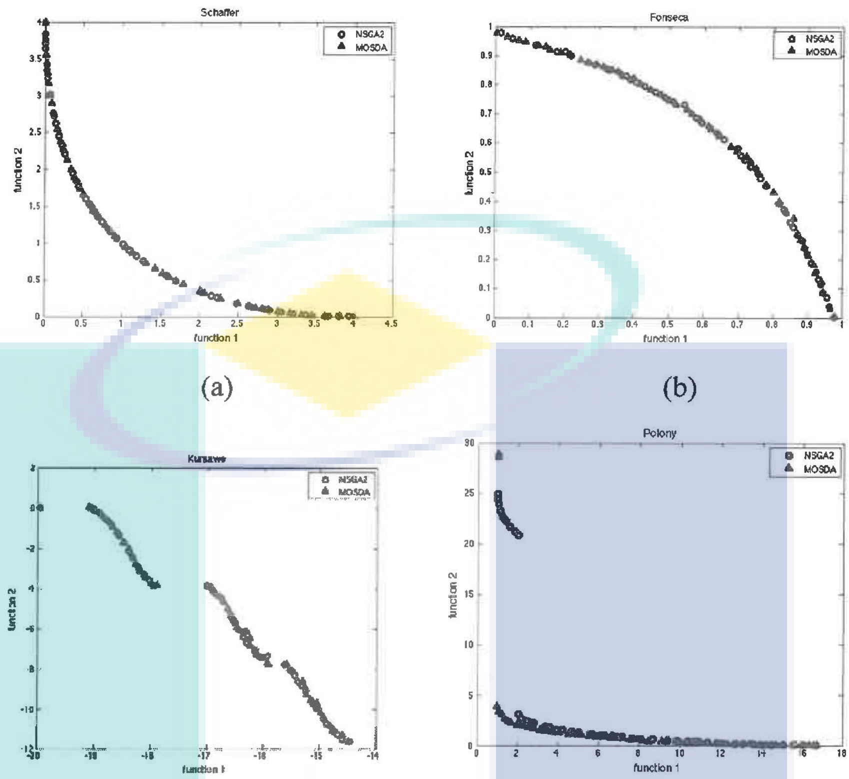


Fig. 2. Application of MOSDA to optimize PDs for IP system [33].

3.5 Result and discussion

This section presents result of the performance test of the proposed MOSDA with the benchmark functions and result of the proposed MOSDA to optimize PD controller for the IP system. Three criteria will be assessed to analyze the performance of the proposed MOSDA to solve benchmark functions [34]. First is the ability of the algorithm to find PF solution. Second is the diversity of the solution along the PF and third is the total computation time of the algorithm to complete the whole searching process.

Figure 5 presents PF solution of the proposed MOSDA tested with all the benchmark functions in comparison to NSGAII. The result shows that the proposed MOSDA and NSGAII have successfully found the optimal solution of the PF for all functions. In terms of diversity, solution tested based on MOSDA and NSGAII are distributed almost even on the PF for all benchmark functions. Total computation time recorded in the unit of seconds for the algorithms is presented in Table IV. The result shows that for all benchmark functions, MOSDA has the shortest total computation time. Notice that, after the integration of Mutation and Crossover strategies into the proposed algorithm, the total computation time is still better compared to NSGAII.

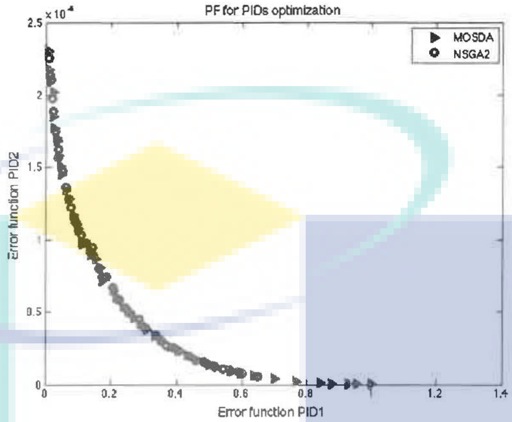


(a) (b)

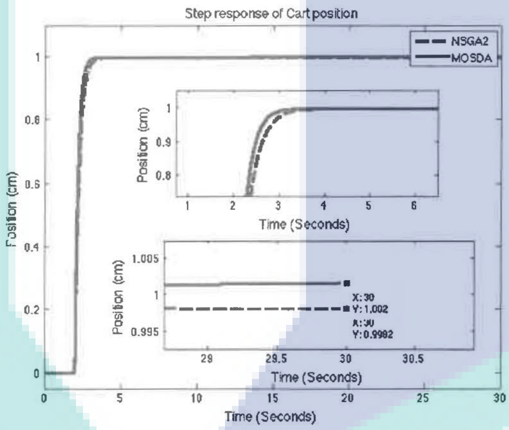
(c) (d)

Fig. 3. Pareto Front solutions based on MOSDA and NSGAII algorithms, (a) Schaffer's function, (b) Fonseca's function, (c) Kursawe's function and (d) Poloni's function.

PF graph for the application of the MO algorithms to optimize PD controllers for the IP system is shown in Figure 6. Noted that both algorithms have successfully found the solution very well. However, in term of diversity, the proposed MOSDA has shown a better distribution compared to NSGAII. The solution presented by NSGAII for PD_1 is restricted between [0, 0.62] while the solution based on MOSDA lies between [0, 1]. The total computation time required to complete the whole searching process when it is applied to optimize PDs is presented in Table IV. Notice that, NSGAII required a longer time that is 2706.0 seconds to complete the whole searching process compared to MOSDA which required 2699.7 seconds. Time domain response of the IP for the cart position is shown in Figure 6 while its performance is presented in Table V. It shows that the performances are the same for the settling time, percentage overshoot and steady state error which has the value of 0 second, 0% and 0.02 respectively. However, for the rise time, the output response based on MOSDA has shown better performance that is 4.5 seconds faster than the output response based on NSGAII.



(a)



(b)

Fig. 4. Result application of MOSDA and NSGAII to control IP, (a) Pareto Front solution to optimize PD controllers and (b) Time-domain response of the cart position.

TABLE I. TOTAL COMPUTATION TIME OF NSGAII AND MOSDA

Function	NSGAII (Sec)	MOSDA (Sec)
Schaffer	251.9706	236.2158
Fonseca	268.1247	234.9538
Kursawe	253.5653	234.8718
Poloni	250.9644	232.9863
PD optimization	2706.0	2699.7

TABLE II. PERFORMANCE OF THE IP BASED ON TIME DOMAIN RESPONSE

Function	NSGA2	MOSDA
Setting time, t_s, (Sec)	0	0
Percentage Overshoot, OS (%)	0	0
Steady-state error, e_{ss},	0.02	0.02
Rise time, t_r, (Sec)	0.59	0.45

3.6 Conclusion

A multiobjective SDA (MOSDA) based on Non-dominated Sorting and Crowding Distance approaches has been developed. It has been tested with various MO benchmark functions. Result of the test has shown that the strategy has successfully found Pareto Front (PF) solutions for all benchmark functions and they were distributed well. The accuracy and diversity solution of MOSDA is almost similar to the result presented by NSGAII. Moreover, total computation cost for MOSDA is significantly shorter compared to NSGAII. The proposed algorithm has also been applied to optimize PD control parameter for an Inverted Pendulum (IP) system. The result is presented in time-domain response for a performance analysis. It has shown that the PD based on both MO algorithms has successfully controlled the IP system very well. The output response based on MOSDA has faster response compared to output response based on NSGAII. Inline with the benchmark functions test result, the total computation cost for MOSDA also shorter. In the future, MOSDA will be applied to solve nonlinear and complex system such as fuzzy or neural network.

CHAPTER 4 TECHNICAL PAPER 3

4.1 Title

Adaptive Sine-Cosine Algorithms for global optimization

4.2 Abstract

This paper introduces improved versions of a Sine-Cosine algorithm called Adaptive Sine-Cosine algorithms. It is made adaptive through incorporation of a linear and an exponential term with respect to an individual agent's fitness. Based on the newly introduced formulas, an individual agent moves with a dynamic and different step sizes compared to other agents through the whole searching process. It also introduces a balance exploration and exploitation strategies. The proposed algorithms in comparison to the original algorithm are then tested with several test functions that have different properties and landscapes. The algorithms performance in terms of their achievement of finding a near optimal solution is analyzed and discussed. Numerical result of the test shows that the proposed algorithms have achieved a better accuracy. The finding also shows that the proposed algorithms have attained a faster convergence toward the near optimal solution

4.3 Introduction

Sine-Cosine optimization algorithm is a relatively new population based metaheuristic algorithm [35]. It is formulated inspired from mathematical sine and cosine terms. The algorithm has received a great attention from researchers worldwide due to its accuracy performance as compared to other state-of-the-art algorithms and also other advantages that it offers.

Many researchers have applied the algorithms as a tool to solve various real life problems in various fields. Mostafa et al. (2018) [36] applied the SCA for optimal design of a grid-connected hybrid power generation system. The SCA was applied to minimize annual cost of the power plant operation and annual pollution affected on the environment due to a natural gas usage. The study compared Firefly, Cuckoo search and Whale algorithms. Result presented showed that the SCA outperformed all other algorithms. Hamdan et al. (2017) [37] adopted the SCA to train artificial neural network model for electricity load forecasting. The SCA performance was compared with Genetic Algorithm (GA). Result of the work showed that GA outperformed SCA. Majid and Rao (2017) [38] used the SCA to optimize a circuit design for CMOS differential and operational amplifiers. The performance of SCA was compared with a Particle Swarm Optimization (PSO) and a hybrid Gravitational Search algorithm-PSO. The authors concluded that SCA had a better performance compared to other tested algorithms. Ismael et al. (2017) [39] applied SCA to optimize a selection of various types of conductors for radial distribution networks. The authors revealed that the SCA was an effective algorithm in reducing network losses and at the same able to maintain some constraints.

Apart from the applications, a lot of modifications have been made to improve the algorithm's performance further. This is to solve some drawbacks of the Sine-Cosine algorithm. Although the algorithm has shown a relatively good accuracy, it is still unable to find the best solution for some problems with certain features, complexity and fitness landscape. Therefore, to solve a certain real life problem that has a great complexity and unknown features, modification and improvement of the original algorithm is necessary. Issa et al. (2018) [40] proposed a hybrid Particle Swarm Optimization (PSO) and adaptive sine-cosine algorithm. The algorithm was known as ASCA-PSO. The authors incorporated velocity and position update equations of PSO into the original SCA. The proposed algorithm was tested on various benchmark functions and successfully improved the accuracy performance. ElAziz et al. (2017) [41] proposed a hybrid SCA and Differential Evolution (DE) algorithms. DE operator was adopted into SCA to function more effectively within a local search area. Crossover operator was also applied to increase diversity of the search agents. Singh (2017) [42] proposed a hybrid Grey Wolf Optimizer (GWO) and SCA algorithm. The proposed algorithm was formulated such that GWO operator acted to handle exploitation phase while the SCA acted to handle the exploration phase. The presented result showed the algorithm improved the accuracy performance. ElAziz and Xiong (2017) [43] proposed a hybrid Opposition-based SCA algorithm. Opposition strategy was incorporated into SCA to improve the exploration phase of the SCA. With the opposition strategy, the opposite location to the current agent's position was taken into consideration in the search process. The strategy resulted the algorithm achieved faster and more accurate solution.

This paper proposes a Linear-Adaptive and an Exponential-Adaptive Sine-cosine Algorithms. These two algorithms improve accuracy performance of the original algorithm.

4.4 Methodology

B. Sine-Cosine Algorithm

The fundamental of the Sine-Cosine algorithm is the mathematical Sine and Cosine terms. These two terms have almost similar behaviour. They introduce a repetitive oscillation behaviour when plotting on a time-domain response. The most crucial part of the terms is that they are able to produce a circular shape through a simple modification. With the incorporation of a random strategy, those terms seem to be good formulas to randomize various search agents on a feasible searching area. Equations of the sine and cosine for the application of the optimization algorithm are presented as (1) and (2). The function of the equations is mainly to update position for every single search agent as the agent moves from one location to another.

$$X_i^{t+1} = X_i^t + r_1 \times \sin(r_2) \times r_3 \left| P_i^t - X_i^t \right| \qquad (1)$$

$$X_i^{t+1} = X_i^t + r_1 \times \cos(r_2) \times r_3 \left| P_i^t - X_i^t \right| \qquad (2)$$

where r_1 , r_2 and r_3 are adaptive equation of the agent's step, random equation for the sine and cosine terms and a random parameter for the agent's position relative to the population best position. The r_1 is defined as (3).

$$r_1(t) = a - t\frac{a}{T} \tag{3}$$

where a is a constant, t is an iteration at a current time, and T is the maximum iteration defined for the algorithm. The equation r_1 is formulated such that it is decreased as the current iteration is getting higher. The equation r_2 is defined as (4).

$$r_2 = 2 \times \pi \times rand \tag{4}$$

where *rand* is a random number. It portrays a stochastic behaviour of the algorithm in determining agent's motion. The parameter r_3 is simply a random number applied to every single agent's position.

Description of the Sine-Cosine algorithm is described as follows.

Step1: Initialize i^{th} agents' position, X_i and maximum iteration, T.

Step2: Update cost function, $f(X_i)$ value of every single agent, i.

Step3: Determine the best agent X_{fmin}. Agent with lowest cost function value, f_{min} is considered as the best agent.

Step4: Update every single individual i_{th} agent's position using equations (1) and (2).

Step5: Update cost function, $f(X_i)$ value of every single agent, i.

Step6: Determine the best agent X_{fmin}. Agent with lowest cost function value, f_{min} is considered as the best agent.

Step7: Check if the iteration has reached the maximum value. If it is true, stop the algorithm. If it is not true, repeat Step4 until Step7.

C. Adaptive Sine-Cosine Algorithms

Adaptive Sine-Cosine algorithms have almost the same structure as compared to their predecessor algorithm. They are different in the adaptive formulations of the agent's motion. Instead of defining the equation in terms of iteration, the proposed equations are defined with respect to an individual agent's fitness. With the strategy, motion of an agent is more dynamic and different to each other throughout the searching process. The Linear-Adaptive and Exponential-Adaptive equations are defined as (5) and (6) respectively.

$$r_1(t) = \frac{m}{1 + \dfrac{1}{j \times \left| f(t)_{best} - f_i(t) \right|}} \tag{5}$$

$$r_1(t) = \frac{m}{1 + \frac{1}{\exp\left(j \times \left|f(t)_{best} - f_i(t)\right|\right)}} \quad (6)$$

where the j is a tunable constant and m is a maximum initial value. These equations represent a proportional relationship between distance of an individual agent's position to the best agent's position and the agent's step. The step is maximum when the distance between the agent's position and the best agent's position is far, and it is small when the distance is closer. Equation (5) is a linear adaptive while the equation (6) represent the exponential adaptive. Adoption of exponential term into the linear adaptive formula tend to make the whole agents to move faster. Lesser steps will be taken to reach the best global position and this leads to higher accuracy and reduce computational time.

4.5 Result and discussion

Result of the performance test for both SCA, Linear-Adaptive SCA (LASCA) and Exponential-Adaptive SCA (EASCA) algorithms was recorded based on 30 repeated runs for each benchmark function. The best, worst and average value of the runs are recorded in Tables I, II and III for the SCA, LASCA and EASCA respectively. All the readings represent the cost function value attained by the algorithms. Lowest value indicates highest accuracy attainment. Average value of the 30 repeated runs which is represented as a mean value in the tables is taken as the basis of performance comparison for SCA and all adaptive SCA algorithms.

The best of the mean result, the worst and the best result of the data presented in tables I-III are highlighted in bold font. Noted that SCA achieved the worst result for all functions. This is followed by the LASCA and EASCA. In terms of the attainment of the best accuracy and attainment of the best mean value, EASCA achieved the first for functions f_1-f_4, followed by the LASCA and SCA. However for function f_5, LASCA achieved the first, followed by the EASCA and SCA. From the results shown in the tables, EASCA achieved the best overall accuracy performance followed by the LASCA and SCA. Noted also, the difference between the two proposed adaptive algorithms and the original SCA for the mean value is obvious and significant. The LASCA and EASCA have shown competitive result compared to each other.

TABLE I. ACCURACY ATTAINMENT OF THE SCA

Func. No	Accuracy attainment result		
	Best	*Worst*	*Mean*
f_1	$4.63\text{x}10^{-6}$	**0.10**	$1.27\text{x}10^{-2}$
f_2	$1.55\text{x}10^{-6}$	**$6.20\text{x}10^{-3}$**	$3.71\text{x}10^{-4}$
f_3	6.13	**$2.15\text{x}10^{3}$**	576.87

Func. No	Accuracy attainment result		
	Best	*Worst*	*Mean*
f_4	0.53	**23.11**	6.19
f_5	17.99	**513.09**	82.10

Based on result presented in Tables I-III, a statistical analysis was then conducted. Wilcoxon Sign Rank test was selected as the method of analysis. It is to check significant difference between any two algorithms. This can be done by calculating and observing the p-value acquired from the statistical test.

TABLE II. ACCURACY ATTAINMENT OF THE LASCA

Func. No	Accuracy attainment result		
	Best	*Worst*	*Mean*
f_1	9.34×10^{-203}	1.10×10^{-92}	3.70×10^{-94}
f_2	2.14×10^{-95}	3.45×10^{-50}	1.17×10^{-51}
f_3	3.33×10^{-96}	9.34×10^{-65}	3.11×10^{-66}
f_4	1.58×10^{-99}	5.66×10^{-43}	1.89×10^{-44}
f_5	**8.00×10^{-3}**	18.95	**18.24**

TABLE III. ACCURACY ATTAINMENT OF THE EASCA

Func. No	Accuracy attainment result		
	Best	*Worst*	*Mean*
f_1	**7.70×10^{-207}**	2.60×10^{-105}	**8.71×10^{-107}**
f_2	**8.17×10^{-109}**	1.90×10^{-55}	**6.39×10^{-57}**
f_3	**1.05×10^{-136}**	1.96×10^{-74}	**8.81×10^{-76}**
f_4	**2.78×10^{-113}**	4.91×10^{-51}	**1.75×10^{-52}**
f_5	4.13	18.95	18.38

If the calculated p-value is lower than 5% or 0.05, the compared results are considered as significantly different to each other. Results of the Wilcoxon test between SCA and LASCA and between SCA and EASCA are shown in Table IV. Noted that for all functions f_1-f_5, the p-value has achieved smaller than 5%. It indicates that all the results have shown significant difference. That is all the adaptive algorithms have significantly improved the accuracy performance of the original SCA algorithm. It is also noted that, the sum of positive rank, sum of negative rank and z-value are 465, zero and -4.7821 respectively. The result are the same for all functions.

TABLE IV. WILCOXON SIGN RANK TEST

Func. No	Wilcoxon test result between SCA and LASCA and between SCA and EASCA			
	Sum of +ve rank	***Sum of -ve rank***	***z-value***	***p-value***
f_1 *to* f_5	465	0	-4.7821	<0.05

Analysis on the accuracy performance for the SCA, LASCA and EASCA is conducted through a Nonparametric Friedman test. The test is to rank the three algorithms based on the accuracy performance taken from the result presented in tables I-III. Lowest rank indicates that the algorithm has the best accuracy attainment. Result of the Friedman test is shown in Table V. Noted that for functions f_1 to f_4, EASCA has shown the first rank, followed by the LASCA and SCA. However for function f_5, LASCA has achieved the first rank followed by the EASCA and SCA.

TABLE V. FRIEDMAN TEST RESULT

Func. No.	Rank		
	SCA	***LASCA***	***EASCA***
f_1	8	4.3	**2.7**
f_2	8	4.1	**2.8**
f_3	8	4.3	**2.6**
f_4	8	4.3	**2.6**
f_5	7.6	**3.4**	3.8

Graphical representation of the searching operation for the 500 iterations is plotted to see convergence trend of the algorithms. Figures 1-5 represent the convergence plot for the functions f_1-f_5 respectively. Noted that for function f_1, the graph for the SCA has converged to almost zero at iterations 200 while the proposed adaptive SCAs has converged at approximately iterations 5. For function f_2, all the algorithms under test achieved about the same convergence speed. For function f_3, the SCA graph has shown slower convergence speed. It achieved at almost zero cost value at approximately iterations 350. The SCA has shown the worst performance on function f_4. It unable to achieve zero cost solution. The speed of convergence also is slower than other algorithms. For function f_5, all algorithms successfully achieved zero cost value, however, the SCA has shown the slowest speed where it achieved the zero cost value at approximately iterations 240.

From all the plotted graphs, it can be deduced that, the speed of convergence towards the global optima solution of the proposed adaptive algorithms is significantly better than the original SCA algorithm. Both graphical and numerical results of the work are also tally to each other. Adopting the adaptive equations improves both convergence speed and accuracy performance.

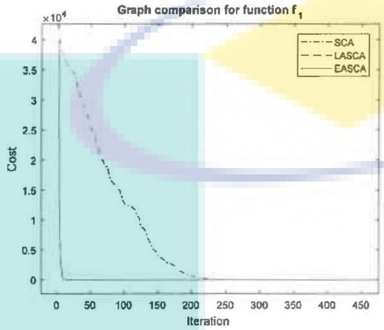


Fig. 1 Function f_1

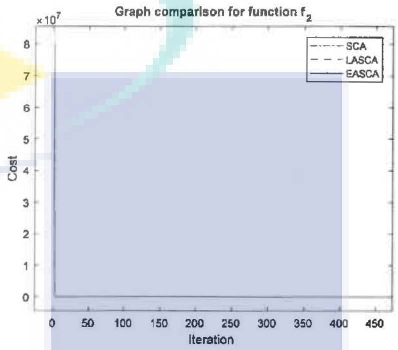


Fig. 2 Function f_2

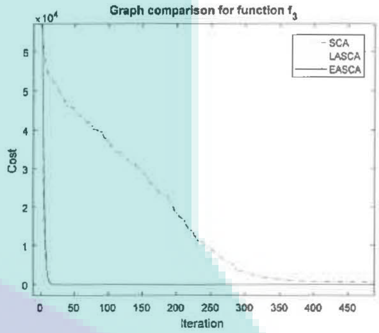


Fig. 3 Function f_3

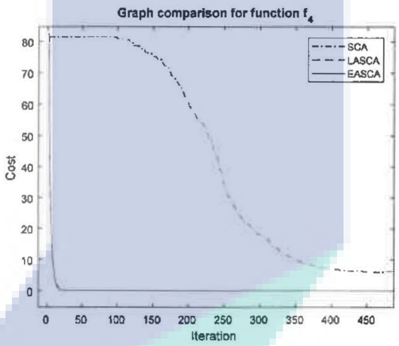


Fig. 4 Function f_4

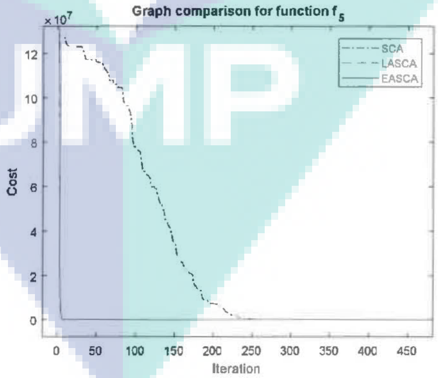


Fig. 5 Function f_5

4.6 Conclusion

An Exponential-Adaptive and a Linear-Adaptive Sine-Cosine optimization algorithms have been introduced in this paper. Search agents have been formulated such that they exponentially and linearly move toward a better solution as the searching operation progress forward. The adaptive formulas have been developed based on an individual agent's fitness. The algorithms have been tested with several benchmark functions from various fitness landscapes in comparison to their predecessor algorithm. Analysis on the accuracy achievement has been conducted and discussed. Result of the test shows that the proposed adaptive versions outperformed original sine-cosine algorithm significantly. The algorithms will be applied to optimize a neural network model for a robotic system and a more complex problem in the future.

CHAPTER 5 TECHNICAL PAPER 4

5.1 Title

A Multiobjective Simulated Kalman Filter Optimization Algorithm

5.2 Abstract

This paper presents a new multiobjective type optimization algorithm known as a Multiobjective Optimization Simulated Kalman Filter (MOSKF). It is a further enhancement of a single-objective Simulated Kalman Filter (SKF) optimization algorithm. A synergy between SKF and Non-dominated Solution (NS) approach is introduced to formulate the multiobjective type algorithm. SKF is a random based optimization algorithm inspired from Kalman Filter theory. A Kalman gain is formulated following the prediction, measurement and estimation steps of the Kalman filter design. The Kalman gain is utilized to introduce a dynamic step size of a search agent in the SKF algorithm. A Non-dominated Solution (NS) approach is utilized in the formulation of the multiobjective strategy. Cost function value and diversity spacing parameters are taken into consideration in the strategy. Every single agent carries those two parameters in which will be used to compare with other solutions from other agents in order to determine its domination. A solution that has a lower cost function value and higher diversity spacing is considered as a solution that dominates other solutions and thus is ranked in a higher ranking. The algorithm is tested with various multiobjective benchmark functions and compared with Non-Dominated Sorting Genetic Algorithm 2 (NSGA2) multiobjective algorithm. Result of the analysis on the accuracy tested on the benchmark functions is tabulated in a table form and shows that the proposed algorithm outperforms NSGA2 significantly. The result also is presented in a graphical form to compare the generated Pareto solution based on proposed MOSKF and original NSGA2 with the theoretical Pareto solution.

5.3 Introduction

Multiobjective optimization (MOO) algorithm is a class of optimization algorithms that deals with a problem that consists of two or more objectives. In some cases, the objectives have a proportional relationship to each other. Increasing a value of one objective may cause a value of another objective to increase or vice versa. On the contrary, in some other cases, the objectives are conflicting to each other. They have an inverse relationship to each other. Increasing a value of one function may reduce a value of another function. For a problem that consists of two objectives, a Pareto Front (PF) is introduced. It contains definite number of solutions that provide a trade-off between the two objectives. Some of the solutions may favour to the first objective while some other solutions may incline to the second objective. The PF also provides a solution with a balanced, a trade-off between the objectives. However, to find a PF that provides an accurate solution with a good diversity satisfying those objectives is challenging.

Due to the challenges, research on MOO algorithm is gaining attentions from researchers worldwide. Different strategies of multiobjective type algorithms have been introduced. Okabe et. al (2004) [44] proposed a Voronoi-based estimation MOO algorithm where a Voronoi mesh was utilized to generate various new offspring of search agents. Guzman et al (2010) [45] proposed a MOO that utilized a chemotaxis strategy of Escherichia Coli bacteria. Alvarez et al (2011) [46] developed a Multiobjective Gravitational search Algorithm (MOGSA). It is formulated based on the well-known theory of gravity and interaction of masses. Savsani and Tawhid (2017) [47] proposed a Nondominated sorting Moth Flame Optimization (NS-MFO) that inspired from a strategy of a moth to move in a spiral way around a light source. Nasir et. al (2017) [48] and Azwan et al. (2018) [49] proposed a Multiobjective Spiral Dynamic Algorithm (MOSDA) that was formulated inspired from a spiral phenomena in nature. All the algorithms mentioned earlier adopted nondominated sorting (NS) approach that was introduced by Deb et. al (2002) [50] to determine nondominating solutions as a way to develop MOO type algorithm. It is noted that all these MOO algorithms introduced after the NSGAII have a better performance compared to NSGAII. It implies that the application of NS with the help of a single-objective optimization algorithm can produce a good performance of MOO algorithm.

This paper proposes another MOO type algorithm namely Multiobjective Simulated Kalman Filter (MOSKF) algorithm. It is developed through a synergy of a single–objective Simulated Kalman Filter (SKF) algorithm that was introduced by Zuwairie et. al (2016) [51] with Mutation and Crossover operators, NS and Crowding Distance (CD) approaches that were introduced by Deb et al. (2002).

5.4 Methodology

A. Kalman Filter

Two main stages in KF are known as prediction and measurement stages. Prediction stage is a process to predict state variables of a system of interest based on prior information of the state variables at previous time and their corresponding prediction noise. It also involves the calculation of a variance associated with the prediction of the state variables. On the other hand, the measurement stage is a process to read information about the state variables at current time with consideration of measurement noise. Combination of the information from the prediction and measurement stages is then used to estimate the next state variable of the system of interest. It also involves the calculation of a variance associated with the measurement of the state variables. The process is recursively occurred.

B. Simulated Kalman Filter Optimization

SKF algorithm is developed inspired from a theory of a KF. There are three main stages of the SKF algorithm, which is known as prediction, measurement and estimation. Prediction and measurement of SKF and KF are the same. However, the combination of prediction and measurement data in KF is known as an estimation stage in SKF.

In developing an optimization algorithm, a KF is considered as an individual agent in which acts to search theoretical global optima solution. Every agent carries information about a system's state variable. It reflects the position of an individual agent in search space. This is shown in equation (1):

$$X_i(t-1) = \{x_i^1(t-1), x_i^2(t-1), .x_i^3(t-1) ... \; x_i^D(t-1)\} \quad (1)$$

where $x_i^D(t-1)$ is a position of an agent, i is a number of an agent, D is a search space dimension and t is a number of iteration. In the prediction stage, the equations (2) and (3) take place.

$$\hat{X}_i(t) = X_i(t-1) \quad (2)$$

$$\hat{P}(t) = \hat{P}(t-1) + \hat{Q} \quad (3)$$

where $\hat{X}_i(t)$ is a predicted position of an agent. $\hat{P}(t)$, $\hat{P}(t-1)$ and $\hat{Q}$ are a current variance associated with the prediction, a previous variance associated with the prediction and prediction noise covariance which is defined as a constant respectively. In the measurement stage, the search agents are set to move in a random manner through the utilization of the predicted position and it is implemented by using equation (4).

$$z_i(t) = \hat{X}_i(t) + \sin(rand \times 2\pi) \times (1 - \exp(|\hat{X}_i(t)|)) \quad (4)$$

where $\sin(rand \times 2\pi) \times (1 - \exp(|X_i(t)|))$ is to introduce random behavior in the agents movement. Equation (4) also measures a new position of the search agents. Information from equations (2) – (4) is then used in the final stage of SKF algorithm to estimate and update the agents' position. Equations (5), (6) and (7) are applied and thus complete the algorithm's cycle.

$$X_i(t) = \hat{X}_i(t) + K \times (z_i(t) - (|\hat{X}_i(t)|)) \quad (5)$$

where $X_i(t)$ is the i agent's current position and K is a Kalman gain and is defined as (6).

$$K(t) = \frac{\hat{P}(t)}{\hat{P}(t) + R} \quad (6)$$

where R is an estimation noise covariance which is defined as a constant.

$$P(t) = (1 - K(t)) \times \hat{P}(t) \qquad (7)$$

where $P(t)$ is the a current variance associated with the estimation.

C. MultiObjective Simulated Kalman Filter Algorithm

The SKF is converted to MOSKF by applying NS approach of NSGAII. NS is a technique used to classify and sort a potential solution in comparison to other solutions based on its accuracy and distance of the solution to the others along a Pareto Front (PF). A solution that has relatively a better accuracy and a distance away from the other solution is known as a nondominated solution and thus is ranked in higher ranking. On top of that, Mutation and Crossover operators of Genetic Algorithm (GA) [52] are also adopted into the MOSKF. The first three agents that have good fitness and the last three agents with worst fitness are selected to undergo the Mutation and Crossover operations. Limited agents are selected in the strategy is to avoid a more complex algorithm while the adoption of both operators is to introduce more randomness. Flowchart of the MOSKF algorithm is shown in Figure 1.

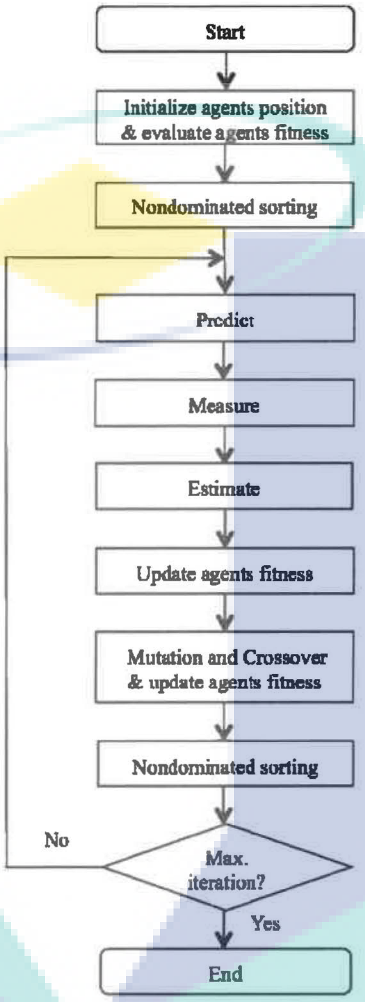


Fig. 1 Flowchart of MOSKF algorithm.

5.5 Result and discussion

Assessment of the performance is done in terms of the accuracy of the solution to reach the PF as well as its corresponding diversity along the PF line. Figures 2-4 show PF graph of MOSKF and NSGAII algorithms tested on Fonseca-Fleming, Kursawe and Schaffer functions. The round-dotted or blue color graph represents MOSKF acquired PF while the star-dotted or red color graph represents NSGAII acquired PF. Graphically, it is noted that for all three functions, PF solution set for both MOSKF and NSGAII algorithms have achieved a good and comparable accuracy. However, MOSKF presents a PF solution set that is more uniformly distributed.

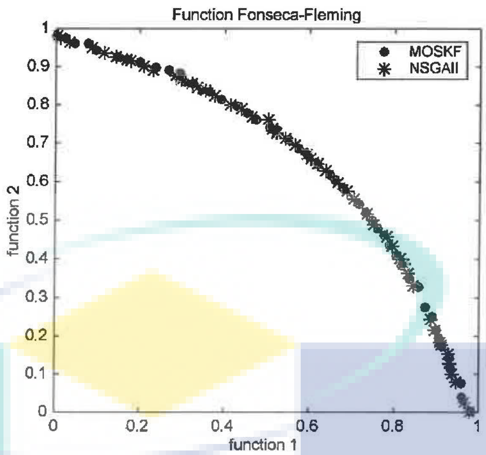


Fig. 2 Pareto Front of Fonseca-Fleming function.

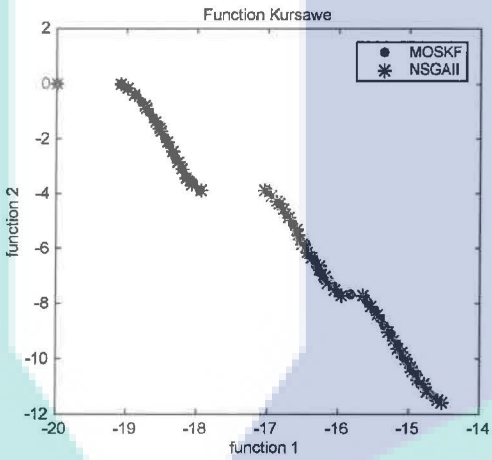


Fig. 3 Pareto Front of Kursawe function.

A solution set is considered to have the best performance if it exactly lies co-inside and at the same time is distributed uniformly along the theoretical PF line. A more accurate analysis is presented in terms of numerical value. On the accuracy assessment, a parameter that is called Generalizational Distance (GD) is evaluated, while on the diversity, parameters that are named as Spacing (S) and Maximum Spread (MS) are measured. Smaller value for GD and S indicates better accuracy and diversity respectively. A larger value of MS indicates a better spread along the theoretical PF solution. In other words, it has covered a longer line along the PF solution. Tables II and III show result of the three performance parameters. The best result between the two algorithms is highlighted in bold font. It is noted that NSGAII outperformed MOSKF for the accuracy of the Kursawe and Fonseca functions. MOSKF achieved better performance for the rest of the functions for both accuracy and diversity assessments.

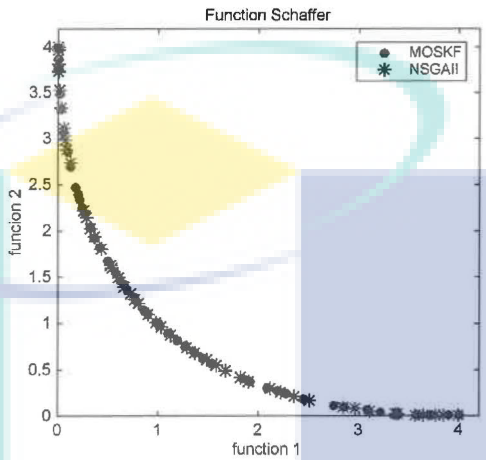


Fig. 4 Pareto Front of Schaffer function.

TABLE I

PERFORMANCE INDEX OF MOSKF

Function	Performance parameter		
	Generalization Distance (GD)	Spacing (S)	Max. Spread (MS)
Schaffer	**1.2900 x 10^{-35}**	**6.3635 x 10^{-01}**	**5.6569**
Fonseca	3.9327 x 10^{-4}	**9.0534 x 10^{-2}**	**1.3875**
Kursawe	1.8095 x 10^{-3}	**2.2155**	12.5845

TABLE II

PERFORMANCE INDEX OF NSGAII

Function	Performance parameter		
	Generalization Distance (GD)	Spacing (S)	Max. Spread (MS)
Schaffer	1.1446 x 10^{-5}	7.8127 x 10^{-1}	5.6558
Fonseca	**6.3356 x 10^{-5}**	9.2941 x 10^{-2}	1.3805
Kursawe	**1.6311 x 10^{-3}**	2.2478	**12.8186**

5.6 Conclusion

A new multiobjective optimization algorithm which is known as MOSKF has been proposed in this paper. It is developed based on Simulated Kalman Filter optimization that is inspired from a Kalman Filter theory. A fast elitism Nondominated Sorting approach has been incorporated to solve the multiobjective domain. The proposed MOSKF has been tested with several standard benchmark functions and compared with NSGAII. The accuracy and diversity performances of the algorithms have been analyzed and discussed. Results of the test have shown that the MOSKF has outperformed the NSGAII for most of the functions. In the future, the algorithm will be used to solve a real world application and more complex problem.

CHAPTER 6 CONCLUSION & RECOMMENDATION

6.1 Conclusion

Four variants of improved algorithms formulated based on a spiral equation and a sine equation has been presented in this report. Two of the variants are single type optimization algorithm while the other two algorithms are multi-objective type algorithm. The first single type algorithm combined strategy of a deterministic spiral and a random based of a genetic algorithm. Combination of both deterministic and random strategies complements each other and thus increased the performance. The second single objective type algorithm presents adaptive variants of SCA algorithm. Linear and Exponential adaptive equations have been developed and replaced the original adaptive equation of SCA. The two proposed equations forced search agents of SCA to move dynamically within a predefined search space. An agent's fitness feature has been introduced into the adaptive equation. Both algorithms have been tested on various benchmark functions. Result of the test has shown that the proposed algorithm achieved better accuracy.

On the other hand, the first multiobjective type algorithm has been developed mainly based on a deterministic spiral strategy. The spiral strategy alone hardly find pareto front solution of many multiobjective problems. Therefore, a random sine approach has been adopted into the algorithm to help the agents explore thoroughly. The second type multiojective algorithm has been developed based on a synergy between sine-cosine equation and kalman filter approach. The kalman filter strategy has been adopted to update a parameter of adaptive equation of the SCA. In both multiobjective type algorithms, a nondominated sorting approach and a matric diversity technique have been applied to generate the pareto front solution. Both algorithms have been tested on multiobjective benchmark functions. The result of the test has shown that both algorithms have competitive performance compared to other state of the art multiobjective algorithms. The proposed algorithms also has been applied to determine a set of optimal value for the PID controller that has been used to control a flexible manipulator robot.

6.2 Recommendation

This work has contributions firstly on developing new algorithms and secondly on solving control problem. The following points can be considered as recommendation for future work.

Combination of the deterministic and random approaches to acquire a higher accuracy result has been presented. There are lot more algorithms that applied solely on random based approach but still suffers from local optima problem. These algorithms can be synergized with other algorithms that used a deterministic approach. Adaptive equation is the key to the improvement of the SCA performance. Introducing another adaptive equation that incorporate another feature of agents can be another possibility to improve the algorithm performance.

The developed algorithm can be applied to acquire a dynamic model for the flexible manipulator through system identification approach. A neural network model or a fuzzy logic system can be used as the nonparametric model for the robot system. They have nonlinear structure and more challenging problems. The models have been applied in many other problems efficiently. The algorithms also can be applied to a multi-link flexible robot system.

References

[1] James K., Particle Swarm Optimization, Encyclopedia of Machine Learning, Springer US, pp. 760-766.

[2] David E. G., 1989, Genetic Algorithms in Search, Optimization, and Machine Learning. Addison Wesley, Reading MA.

[3] Xin S.Y. Firefly algorithms for multimodal optimization. International symposium on stochastic algorithms, 26th October 2009, Springer, Berlin, Heidelberg, pp.169-178.

[4] Zong W.G., Joong H.K., G V. L. (2001). A new heuristic optimization algorithm: harmony search. Simulation 76 (2), pp. 60-68.

[5] B. Alatas (2011) ACROA: artificial chemical reaction optimization algorithm for global optimization. Expert Systems with Applications 38 (10), pp. 13170-13180.

[6] Tamura K. and Yasuda K. (2011). Primary study of spiral dynamics inspired optimization. IEEJ Transactions on Electrical and Electronic Engineering, 6 (S1), pp. S98–S100.

[7] Mahmoodabadi M. J. and Nemati A. R. 2016. A novel adaptive genetic algorithm for global optimization of mathematical test functions and real-world problems. Engineering Science and Technology, an International Journal, 19 (2016) pp. 2002–2021.

[8] Ahmed Z. H. 2015. An improved genetic algorithm using adaptive mutation operator for the quadratic assignment problem. 2015 38th International Conference on Telecommunications and Signal Processing (TSP), Prague, Czech Republic, 9-11 July 2015, pp. 1-6.

[9] Mashwani W. K., Salhi A., Yeniay O., Hussian H., Jan M.A. 2017. Hybrid non-dominated sorting genetic algorithm with adaptive operators selection. Applied Soft Computing 56 (2017) pp. 1–18.

[10] Maheshwari A., Garg R. and Sharma E. N. 2016. A Review Paper on Brief Introduction of Genetic Algorithm. International Journal of Emerging Research in Management &Technology, 5 (2), pp. 87-89.

[11] Eroglu D. Y. and Kilic K. 2017. A novel Hybrid Genetic Local Search Algorithm for feature selection and weighting with an application in strategic decision making in innovation management. Information Sciences, Volume 405, September 2017, pp. 18-32.

[12] Rahmani A. and MirHassani S.A. 2014. A hybrid Firefly-Genetic Algorithm for the capacitated facility location problem. Information Sciences, Volume 283, 1 November 2014, pp. 70-78

[13] Alsaeedan W., Menai M. E. B., Al-Ahmadi S. 2017. A hybrid genetic-ant colony optimization algorithm for the word sense disambiguation problem. Information Sciences, Volume 417, November 2017, pp. 20-38.

[14] Garai G. and Chaudhurii B. B. 2013. A novel hybrid genetic algorithm with Tabu search for optimizing multi-dimensional functions and point pattern recognition. Information Sciences, Volume 221, 1 February 2013, pp. 28-48.

[15] Nasir A. N. K., Tokhi, M. O., Sayidmarie, O. and Ismail, R.M.T.R. (2013), A novel adaptive spiral dynamic algorithm for global optimization. 2013 13th UK Workshop on Computational Intelligence (UKCI), pp. 334-341.

[16] Nasir, A.N.K., Tokhi, M.O., Ghani, N.M.A. Novel hybrid bacterial foraging and spiral dynamics algorithms. 2013 13th UK Workshop on Computational Intelligence (UKCI), Surrey, pp. 199-205.

[17] Nasir, A.N.K., Tokhi, M.O., Ghani, N.M.A. and Ahmad, M.A. A novel hybrid spiral dynamics bacterial chemotaxis algorithm for global optimization with application to controller design. 2012 UKACC International Conference on Control (CONTROL), pp. 753-758.

[18] Hashim M. R. and Tokhi M. O. 2016. Enhanced chaotic spiral dynamic algorithm with application to controller design. 2016 IEEE International Conference on Power and Energy (PECon), Melaka, Malaysia. 28-29 Nov. 2016, pp. 752-756.

[19] Hashim M. R. and Tokhi M. O. 2016. Greedy spiral dynamic algorithm with application to controller design. 2016 IEEE Conference on Systems, Process and Control (ICSPC), Melaka, Malaysia. 16-18 Dec. 2016, pp. 29-32

[20] M. Clerc and J. Kennedy (2002). "The particle swarm-explosion, stability, and convergence in a multidimensional complex space," IEEE Transactions on Evolutionary Computation, vol. 6, no. 1, pp. 58–73.

[21] Agarwal, Aashna, and N. Nanavati (2016). "Association rule mining using hybrid GA-PSO for multi-objective optimisation." 2016 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), 15-17 Dec. 2016, Chennai, India. pp 1-6.

[22] D.E.Goldberg, Genetic Algorithms in Search, Optimization, and Machine, Addison-Wesley, Reading, MA, 1989.

[23] Lai, Chunyan, et al. (2017). "Genetic algorithm based current optimization for torque ripple reduction of interior PMSMs." IEEE Transactions on Industry Applications (99), pp. 1-10.

[24] R. Storn and K. Price, (1997). "Differential evolution: A simple and efficient heuristic for global optimization over continuous spaces," J. Global Optimization, vol. 11, no. 4, pp. 341–359.

[25] Chin, V. Jack, Z. Salam, and K. Ishaque (2016). "An accurate modelling of the two-diode model of PV module using a hybrid solution based on differential evolution." Energy Conversion and Management 124, pp. 42-50.

[26] Tamura K, Yasuda K. (2011). Spiral optimization-A new multi-point search method. IEEE International Conference on Systems, Man and Cybernetics, Anchorage, AK. 2011. pp. 1759–1764.

[27] C. A. Coello Coello and M. S. Lechuga (2002). "MOPSO: A proposal for multiple objective particle swarm optimization," Proc. Congr. Evolutionary Computation (CEC'2002), vol. 1, Honolulu, HI, May2002, pp. 1051–1056.

[28] S. Soheyli, M. H. S. Mayam, and M. Mehrjoo (2016). Modeling a novel CCHP system including solar and wind renewable energy resources and sizing by a CC-MOPSO algorithm. Applied Energy (184), pp. 375-395.

[29] Deb, K., S. Agrawal, A. Pratap, and T. Meyarivan (2000). A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. In M. S. et al. (Ed.), Parallel Problem Solving from Nature – PPSN VI, Berlin, pp. 849–858. Springer.

[30] S. M. Mousavi, J. Sadeghi, S. T. A. Niaki, and M. Tavana (2016). A bi-objective inventory optimization model under inflation and discount using tuned Pareto-based algorithms: NSGA-II, NRGA, and MOPSO. Applied Soft Computing (43), pp. 57-72.

[31] R. J. G. Feng Xue, Arthur C. Sanderson (2003). Pareto-based multi-objective Differential Evolution. In Proceedings of the 2003 Congress on Evolutionary Computation, Canberra, Australia, 2003. pp 862–869.

[32] Xia, Bin, et al. (2016). "Utilizing adaptive dynamic taylor kriging assisted multi-objective DE algorithm for optimization design of electromagnetic device." 2016 IEEE Conference on Electromagnetic Field Computation,13-16 Nov. 2016, Miami, FL, USA, pp. 1-6.

[33] Pendulum designer 03 manual, Real Gain Company, 2008.

[34] S. Huband, P. Hingston, L. Barone and L. While (2006). A review of Multiobjective test problems and a scalable test problem toolkit. IEEE Transactions on Evolutionary Computation, 10 (5), pp. 477- 506.

[35] Seyedali Mirjalili (2016). SCA: A Sine Cosine Algorithm for solving optimization problems. Knowledge-BasedSystems 000 (2016) pp. 1–14.

[36] Mostafa A. Algabalawy, Almoataz Y. Abdelaziz, Said F. Mekhamer, Shady H.E. Abdel Aleem (2018). Considerations on optimal design of hybrid power generation systems using whale and sine cosine optimization algorithms. Journal of Electrical Systems and Information Technology, Article in Press, 201, pp. 1-14.

[37] Sadeque Hamdan, Shaikha Binkhatim, Anwar Jarndal and Imad Alsyouf (2017). On the Performance of Artificial Neural Network with Sine-Cosine Algorithm in Forecasting Electricity Load Demand. IEEE proceeding of 2017 International Conference on Electrical and Computing Technologies and Applications (ICECA), Ras Al Khaimah, United Arab Emirates, 21-23 Nov. 2017, pp 1-5.

[38] M A Mushahhid Majeed; Patri Srihari Rao (2017). Optimization of CMOS analog circuits using sine cosine algorithm. 8th IEEE International Conference on Computing, Communication and Networking Technologies (ICCCNT), Delhi, India, 3-5 July 2017, pp. 1 – 6.

[39] Sherif M. Ismael, Shady H. E. Abdel Aleem and Almoataz Y. Abdelaziz (2017). Optimal selection of conductors in Egyptian radial distribution systems using sine-cosine optimization algorithm. Proceeding of 2017 Nineteenth International Middle East Power Systems Conference (MEPCON), Cairo, Egypt, 19-21 Dec. 2017, pp. 1-6

[40] Mohamed Issa, Aboul Ella Hassanien, Diego Oliva, Ahmed Helmi, Ibrahim Ziedan, Ahmed ALzohairy (2018). ASCA-PSO: Adaptive sine cosine optimization algorithm integrated with particle swarm for pairwise local sequence alignment, Expert Systems With Applications 99 (2018), pp. 56–70.

[41] Mohamed E. Abd Elaziz, Ahmed A. Ewees, Diego Oliva, Pengfei Duan and Shengwu Xiong (2017). A Hybrid Method of Sine Cosine Algorithm and Differential Evolution for Feature Selection, ICONIP 2017, Part V, LNCS 10638, pp. 145–155.

[42] N. Singh, S.B. Singh, A novel hybrid GWO-SCA approach for optimization problems, Engineering Science and Technology, an International Journal 20 (2017) pp. 1586–1601.

[43] Mohamed Abd Elaziz, Diego Oliva, Shengwu Xiong (2017). An improve Opposition-Based Sine Cosine Algorithm for global optimization, Expert Systems With Applications 90 (2017) pp. 484–500.

[44] T. Okabe, Y. Jin, B. Sendoff and M. Olhofer, "Voronoi-based estimation of distribution algorithm for multi-objective optimization," Proceedings of the 2004 Congress on Evolutionary Computation, Portland OR USA, 19-23 June 2004, pp. 1-8.

[45] M. A. Guzman, A. Delgado, J. D. Carvalho (2010), "A novel multiobjective optimization algorithm based on bacterial chemotaxis," Engineering Applications of Artificial Intelligence, 23 (2010), pp. 292–301.

[46] G. Alvarez, D.L., V. Rodrıguez, M.A., G. Pulido, J.A., S. Perez, J.M. (2011). "Applying a multiobjective gravitational search algorithm (MO-GSA) to discover motifs". International Work Conference on Artificial Neural Networks (IWANN'11), Lecture Notes in Computer Science, vol. 6692/2011, pp. 372–379.

[47] V. Savsani and M. A. Tawhid (2017), "Non-dominated sorting moth flame optimization (NS-MFO) for multi-objective problems," Engineering Applications of Artificial Intelligence, 63 (2017), pp. 20–32

[48] A. N. K. Nasir, A. R. A. Azwan, A. M. Ashraf ; M. J. M. Falfazli, (2017). "A multi-objective Spiral Dynamic algorithm and its application for PD design," IEEE 8th Control and System Graduate Research Colloquium (ICSGRC), 4-5 Aug. 2017, Shah Alam, Malaysia, pp. 1-6.

[49] A. Azwan A.R, A.N.K. Nasir, Sha'akmal S., M. Sawal A.R (2018). MOSDA: A Proposal for Multiple Objective Spiral Dynamics Algorithm, Journal of Telecommunication, Electronic and Computer Engineering (JTEC), 10, (1-3), pp. 15-19.

[50] Deb, K., Pratap, A., Agarwal, S. and Meyarivan,T. (2002), "A Fast And Elitist Multiobjective Genetic Algorithm: NSGA-II," IEEE Transactions on Evolutionary Computation, 6(2), pp 182–197.

[51] Z. Ibrahim, N. H. A. Aziz, N. A. A. Aziz, S. Razali, M. S. Mohamad (2016). "Simulated Kalman Filter: A Novel Estimation-Based Metaheuristic Optimization Algorithm", Advance Science Letters, Vol. 22, pp. 2941-2946.

[52] Mitchell, M. (1996). An Introduction to Genetic Algorithms. Cambridge, MA: MIT Press.