A SELF-SELECTING FRAMEWORK FOR CONTROL PARAMETERS AND MUTATION STRATEGIES IN DIFFERENTIAL EVOLUTION

HALDI BUDIMAN

SULTAN IDRIS EDUCATION UNIVERSITY

2025

A SELF-SELECTING FRAMEWORK FOR CONTROL PARAMETERS AND MUTATION STRATEGIES IN DIFFERENTIAL EVOLUTION

HALDI BUDIMAN

THESIS PRESENTED TO QUALIFY FOR DOCTOR OF PHILOSOPHY

FACULTY OF COMPUTNG AND META-TECHNOLOGY
SULTAN IDRIS EDUCATION UNIVERSITY

2025

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ACKNOWLEDGEMENT

All praise is due to Allah SWT for His blessings and guidance throughout this endeavor. I extend my deepest gratitude to Associate Professor Dr. Shur Li Wan, Theam Foo Ng, and Farid Morsidi. Our sincere appreciation goes to the Dean of the Faculty of Computing and Meta-Technology for his exceptional administrative support, ensuring UPSI provides outstanding facilities, and for his remarkable hospitality. We are also incredibly thankful to the Deputy Dean of the Faculty of Computing and Meta-Technology for their continuous motivation and for fostering a collaborative environment in Computer education. Special thanks are due to the lecturer from the Faculty of Computing and Meta-Technology for imparting profound knowledge and offering insightful explanations on Data Structure and Algorithms. We are grateful to all the experts who generously assisted in data collection and provided invaluable field-specific information. Furthermore, we acknowledge the unwavering support from all the Faculty of Computing and Meta-Technology Staff for their problem-solving assistance, thoughtful contributions, attentive guidance, and steadfast encouragement throughout the thesis preparation. To everyone else who contributed and cannot be individually named, we pray for their double reward from Allah. The author acknowledges the limitations of this research and welcomes constructive criticism, suggestions, and input to enhance future studies, with the hope that this research significantly contributes to the advancement of science.

ABSTRACT

This study aims to identify optimal parameter configurations in Differential Evolution (DE) by considering population diversity and dimension size. The goal is to select control parameters that balance exploitation rate and algorithm performance. The proposed approach introduces two adaptation stages - microadaptation and macroadaptation - to influence offspring generation and maintain population diversity. An adaptive population sizing scheme called Self-Adaptive Ensemble-based DE with Enhanced Population Sizing (SAEDE-EP) further enhances diversity. Microadaptation and macroadaptation are triggered based on individual fitness and solution stagnation. SAEDE-EP was evaluated on 26 benchmark functions, the CEC 2019 challenge suite, and 57 constrained optimization benchmarks from CEC 2020. Findings showed SAEDE-EP achieved efficient optimization across unimodal, multimodal, hybrid, and composition problems without exhaustive parameter tuning. Comparative analysis indicated that SAEDE-EP performed well in single-objective unconstrained optimization problems, demonstrating faster computation times within the CEC evaluation limit for optimal solutions than jDE100, despite the latter achieving a lower ratio in DC02 and DC03, requiring approximately 5 and 15 times more function evaluations than the specified CEC limit. Given these promising findings, the proposed techniques pave the way for more capable and autonomous DE optimization. Future work should explore alternative adaptation schemes, analyze parameter impacts, and incorporate additional mutation strategies to further advance DE.

KERANGKA PEMILIHAN KENDIRI UNTUK PARAMETER KAWALAN DAN STRATEGI MUTASI DALAM EVOLUSI PEMBEZAAN

ABSTRAK

Kajian ini bertujuan untuk mengenal pasti konfigurasi parameter yang optimum dalam Evolusi Pembezaan (DE) dengan mempertimbangkan kepelbagaian populasi dan saiz dimensi. Matlamatnya adalah untuk memilih parameter kawalan yang mengimbangi kadar eksploitasi dan prestasi algoritma. Pendekatan yang dicadangkan memperkenalkan dua peringkat penyesuaian iaitu makro-mikro penyesuaian untuk mempengaruhi penjanaan individual dan mengekalkan kepelbagaian populasi. Satu skim penentuan saiz populasi adaptif yang dikenali sebagai DE Berensemble Penyesuaian-Kendiri dengan Penentuan Saiz Populasi Dipertingkat (SAEDE-EP) seterusnya meningkatkan kepelbagaian. Makro-mikro penyesuaian dilancarkan berdasarkan kecergasan individu dan genangan penyelesaian. SAEDE-EP dinilai menggunakan 26 fungsi penanda aras, suit cabaran CEC 2019, dan 57 penanda aras pengoptimuman terkongsi dari CEC 2020. Dapatan menunjukkan SAEDE-EP mencapai pengoptimuman yang baik merentasi masalah unimodal, multimodal, hibrid, dan komposisi tanpa penalaan parameter yang meletihkan. Analisis perbandingan menunjukkan bahawa SAEDE-EP berprestasi baik dalam masalah pengoptimuman tanpa kekangan objektif tunggal, dengan menunjukkan masa pengiraan yang lebih pantas dalam had penilaian CEC untuk penyelesaian optimum berbanding jDE100, walaupun yang terkemudian mencapai nisbah yang lebih rendah dalam DC02 dan DC03 yang memerlukan lebih kurang 5 dan 15 kali ganda lebih banyak penilaian fungsi daripada had CEC yang ditetapkan. Berdasarkan penemuan yang menggalakkan ini, teknik yang dicadangkan membuka laluan kepada pengoptimuman DE yang lebih berkeupayaan dan autonomi. Kajian masa depan perlu meneroka skim penyesuaian alternatif, menganalisis impak parameter, dan menggunakan strategi mutasi tambahan untuk memajukan DE selanjutnya.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

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LIST OF ABBREVIATION

c	A performance measure called vector c
Cm	Convergence measure
CR	Crossover rate
DE	Differential Evolution
EAs	Evolutionary Algorithm
ECDF	Emperical cumulative probability distribution function
ECDF	Empirical cumulative probability distribution function
EFDE	An efficient framework of the DE
EP	Evolutionary Programming
EPSDE	Ensemble of mutation strategies and control parameters with the DE
ESs	Evolution Strategies
F	Scale Factor
favarage	average fitness
fbest	Best fitness
fmean	Mean fitness
FR	The feasibility rate
GA	Genetic Algorithm
GP	Genetic Programming
MPDE	Multi-population Ensemble DE
NP	Population size
NSE	Normalized solution error
NSE	The normalized solution Error

Pc	Probality convergence
Qm	A measurement parameter
RMSE	Root mean square error
SADE	Self-adaptive Differential Evolution
SADE-Abs	Self-adapting DE-Abs
SADE-Rel	Self-adapting DE-Rel
SAEDE	Self Adaptive Ensemble-based differential evolution
SAEDE-EP`	Self-adaptive ensemble-based DE with enhanced population sizing
SR	Success rate
TAM	Theory of Acceptance Model

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter provides a brief explanation of the research. Following the introduction, section 1.2 presents the background of the study and research issues, while section 1.3 specifies the problem statement. Further, section 1.4 describes the research objectives, 1.5 outlines the research questions. Section 1.6 significance of the study, section 1.7 scope, and limitation of the study. Section 1.8 provides the thesis organization and 1.19 summary.

1.2 Background of the Study and Research Issues

Evolution algorithms (EAs) for solving difficult non-linear optimization problems were inspired by Darwin's theory of evolution. Encoding schemes have an impact on EA performance. Operators used in evolution and values used for parameter setting. Genetic algorithms are among the algorithms used in EAs (Schwefel., 1977a), Evolutionary Programming (Fogel et al., 1966a). Evolutionary Strategies (J. H. Holland., 1975), Genetic Engineering (J. R. Koza., 1992), and Differential Evolution (Rainer Storn & Price., 1995). Since the introduction of evolutionary computing more than ten years ago, DE has maintained its popularity and competitiveness.

Evolutionary algorithms are widely utilized to accommodate the problems of discovering global and local optima of a function. This provides a better knowledge inquisition on various optima solutions within the search space. The solution steps were also dynamic in motion. The current solution could be altered to another appropriate one while remaining within the confinements of the optimal system performance. Evolutionary algorithms are known to possess the capability of detecting multiple solutions for a particular population. An advantage is exhibited over the contemporary optimization techniques that require various experimentations to locate the perfect solution.

Evolutionary algorithms were devised in the early 1970s to indicate various optimal points. Be it local or global. Evolutionary algorithms consist of stochastic optimization algorithms motivated mainly by biology. Were the processes involved in the growth of organism populations to blend in their environments. This incurs genetic inheritance and survival of the fittest to accommodate the optimal solution for internal domain functions. EAs contain characteristics that surpass other numerical methods. In the sense of only requiring a priori knowledge for the objective function itself, whether explicit or implicit. Usage for EA requires the user to specify the number of candidate solutions to be modified to generate new solutions. Selection of the appropriate parameter values is the primary plague that must be addressed when using EA.

Due to its ease of use, differential evolution, one of the evolutionary algorithms, is frequently used in optimization issues. Another benefit of DE over other EAs is that it has fewer control parameters that affect speed convergence and solution quality. However. The performance of DE in solving optimization problems is influenced by the control parameter settings. Population size (*NP*), also known as control parameters, is mentioned. Scale factor and crossover rate. In recent years, interest in the usage DE algorithm has increased. Along with having understandable fundamental stages, it has also been used in real-world situations because of its capacity to generate reasonable convergence rates.

Storn and Price are the ones who first put forward DE (Rainer Storn & Price., 1995). It is an easy method that works well for many different optimization issues. Forecasting, engineering, pattern recognition, system for power and optics, and signal processing have all been successful areas for DE. DE is highly susceptible to crossover and mutation strategies in a variety of settings, such as *NP* and *CR*, and *F*. Most research improve DE, such as Self-adaptive DE (A. K. Qin et al., 2009), and an ensemble of mutation strategies and control parameters with the DE (Rammohan

Mallipeddi & Suganthan., 2010a). There is also to change the classical structure and to add a new parameter like Multi-Population ensemble DE (G. Wu et al., 2016a).

DE has weaknesses in deciding on parameters, despite being very effective in solving a particular problem. Trial and error is used for parameters in DE due to the expensive computation. As a result, numerous researchers investigated how to improve DE using different methods. Categorized parameter adaptation techniques are deterministically adaptive and self-adaptive (Smith & Fogarty., 1997), as explained in the following.

1. Deterministic parameter control occurs when some deterministic rules change the value of a parameter.
2. Adaptive parameter control is used when feedback from the search is used to assign the direction and magnitude of the transformation to the parameters.

The concept of "evolution of the evolution" as a means of performing self-adaptation of parameters is known as self-adaptive parameter control. In this case, the adaptable parameters are encoded in the chromosome (individuals) and go through genetic operators. Better parameter values result in better individuals who are more likely to survive, procreate, and disperse these better parameter values.

The self-adaptive DE framework proposed in this thesis includes the control parameters as chromosomal components. Each chromosome is made up of the solutions to the optimization problems and the control parameters, which are changed and can adapt depending on the solution in order to determine the control parameters for the following generation. Additionally proposed in the works is an ensemble for the solution pool.

The ensemble consists of common techniques that address issues like average solutions for global optimization problems. likewise the answer chosen at random. The earlier research was being discussed by the author. The best method produced excellent outcomes when the control parameters were self-determined. As a result, the current work demonstrates an interest in learning more about the application of ensemble-based DE in various contexts. The proposed method is tested on 43 functions benchmark and 57 functions benchmark on CEC 2022 problems and evaluated based on multi-criteria measurements. Additionally, the study will examine how control parameters dynamically change as optimization problems evolve through various stages.

Due to their ease of implementation and capacity to find adequate solutions with a reasonable computational effort, Differential Evolution (DE) and its variants have become increasingly popular in the field of optimization. However. identical to any evolutionary algorithm. The characteristics of the targeted problems and the parameter settings of DE have a significant impact on its performance. *F*, *CR*, Mutation strategy (*M*), and *NP* make up DE's primary input and output parameters. The four parameter sets demand that users have a background in and experience with each of these parameters. Investigations have paid a lot of attention to *F* and *CR* but not to *M* and *NP*. But there are extensive investigations into *F* and *CR*. They still lack clarity and are difficult to understand. Therefore, the difficulty of setting parameters by users has been reduced through the use of numerous adaptation techniques. The majority of the work is concentrated on *F* and *CR*. In the parameter settings of DE, adaptation is categorized in a number of different ways. The categorization depends on the number of adaptive parameters (Das et al., 2016c; S. L. Wang et al., 2020), ability to adapt (Al-Dabbagh et al., 2018b), , as well as the involvement of other elements (Neri & Tirronen., 2010). By dividing it into micro-transformation and macro-adaptation, the author provides another perspective on how parameter settings in DE are adjusted. The size of interactions affects both micro and macro adaptation.

1.3 Problems Statement

The DE algorithm's performance is dependent on the mutation strategy and associated control parameters like *CR*, *NP*, and *F* (J. Liu & Lampinen., 2002). For the same functions and different optimization problems with varying time and accuracy requirements, the best control parameter settings may differ. Consequently, to successfully resolve a particular optimization problem. In most cases, finding the best strategy and fine-tuning its associated parameter value requires a time-consuming trial-and-error process. Different search space regions and search tactics may lead to changes in the DE population (A. K. Qin et al., 2009a) with various parameter settings might work better than others. Although numerous partial adaptation schemes have been put forth (Brest et al., 2006) to avoid the lengthy trial-and-error process. With self-adjusting of all parameters and mutation strategies, the researchers show the superior performance of the suggested ensemble strategy.

The classical DE is used in solving sensitive mutation and control parameters. The researchers do not change the structure of D. The parameters are altered via by trial and error (Storn., 1996b) randomly selected based on self-adaptive and ensemble approach (Rammohan Mallipeddi & Suganthan. 2010). The parameter settings for self-adaptive and ensemble are defined as *CR* ε [0.1, 0.9]. *F* ε [0.4, 0.9] and *NP* = 50. Another researcher who used self-adaptive based on an ensemble and changed all the control parameters by using them randomly is SADE-Abs and SADE-Rel (S. L. Wang et al.. 2016) parameters that they used *CR* ε [0.1], *F* ε [0.1]. *NP* ε [10D, 1000D] and *NR* [-0.9, 0.9]. Additionally, changing the structure of classical DE by adding new parameters has been done (Iacocca. et al. 2015) with the following parameters $\tau 1 = \tau 2$ = 0.1. Fl = 0.1, $F\mu$ =0.9, *NP*= 50.

DE is one of the evolutionary algorithms known to have the quality of the solution, rapid convergence, and simple algorithm. However, DE also has deficiencies in terms of trial and error practice for parameter control. Moreover, the problem statements are how to ensure optimal performance of Differential Evolution in various issues.

1.4 Research Questions

Thus, the question is how to develop a framework self-selecting differential evolution algorithm accordingly. This research deals with three major questions, which are:

[1] What frameworks are available for selecting control parameters and mutation strategies in the differential evolution?

[2] Which effective mechanism is employed in DE to self-select control parameters and mutation tactics?

[3] How well does the suggested self-selecting framework perform in DE?

1.5 Research Objectives

The goals of this study are:

[1] To investigate the frameworks for selecting control parameters, mutation strategies, and ensemble in differential evolution.

[2] To suggest a mechanism for DE's self-selection of control parameters, mutational tactics, and ensemble

[3] To evaluate and validate the performances of the proposed framework based on multi-criteria evaluation and on a real-world application.

1.6 Significance of Study

This research has some benefits as follows:

1. Proposed novel self-adjusting DE on an ensemble.
2. The proposed algorithm is evaluated with multi-criteria and real-world benchmark functions.

1.7 Scope and Limitation of the Study

This section underlines the essential part that the research undertakes from the perspective of combining the beneficial traits of differential evolution.

1.7.1 Differential Evolution

Differential Evolution (DE) operates through a series of fundamental steps: Initialization, Selection, Mutation, and Crossover. These foundational steps define the basic DE algorithm, with subsequent iterations involving the latter three. The convergence speed directly impacts DE's performance (Price, Storn, & Lampinen, 2005). Its accuracy and robustness have made it a favored approach for addressing practical problems. DE generates offspring by comparing differences in randomly chosen pairs of individual vectors from the population (Das, Suganthan, & Lim, 2016). The four initial steps continue in a cycle throughout the optimization process. In subsequent generations, offspring compete with parents and other individuals, with superior individuals continuing as parents for the next generation.

1.7.2 Control Parameters

Differential Evolution (DE) operates through a series of fundamental steps: Initialization, Selection, Mutation, and Crossover. These foundational steps define the basic DE algorithm, with subsequent iterations involving the latter three. The convergence speed directly impacts DE's performance(K Price et al., 2006). Its accuracy and robustness have made it a favored approach for addressing practical problems. DE generates offspring by comparing differences in randomly chosen pairs of individual vectors from the populati (S Das et al., 2010). The four initial steps continue in a cycle throughout the optimization process. In subsequent generations, offspring compete with parents and other individuals, with superior individuals continuing as parents for the next generation.

Control parameters significantly influence the efficacy of DE algorithms (Janez Brest et al., 2012). While deterministic engineering relies on a limited number of control parameters, specific objectives necessitate consideration of additional factors. These parameters play a pivotal role in determining the effectiveness of DE algorithms, often requiring a time-consuming experimentation process to find optimal values. Researchers aim to optimize this process, seeking more efficient methods. Given the complexity of optimizing parameter settings across diverse domains, conducting extensive trials may not be practical. In situations where a user lacks the expertise to carefully fine-tune parameters or when automated global optimization is essential, the challenge becomes more pronounced. The optimal setting for control parameters may vary based on accuracy and time constraints.

i. Scale factor (F): Larger values are suitable for global search, while smaller values promote faster convergence.

ii. Crossover rate (CR): A significant CR increases population diversity as trial vectors inherit more information from mutant vectors. Conversely, a low CR emphasizes local exploitation, with trial vectors learning more from target vectors.

iii. Population size (NP): Identifying the ideal population size presents challenges during crossover stages. The choice between binominal (uniform) and exponential (modular two-point) crossover depends on population size. The performance of the exponential crossover operator is often superior in high-dimensional problems.

iv. Dimension (D): DE is effective in both low- and high-dimensional problems, with population size and dimensionality constraints influencing solution quality. While DE seeks quick solutions, dimensionality tends to increase over generations. Addressing this issue involves adapting DE variants, such as self-adaptive and ensemble-based algorithms.

1.7.3 Ensemble

Ensemble-based mutation strategies and control parameters in DE involve a diverse pool of mutation strategies combined with various control parameter values (G. Wu et al., 2018). This process produces offspring subjected to iterative cycles until optimal convergence is achieved through selection. Suitable dynamic parameter values and fitness traits are problem-specific. Identifying optimal control parameter settings varies across optimization problems and necessitates rigorous trial methods. Additionally, this approach is suited for comparing similar functions with varying execution times and accuracy requirements. Ensemble mutation strategies enhance the self-adaptive approach, allowing adaptive responses in line with evolutionary stages to address specific challenges.

1.8 Thesis Organization

This section outlines the organization of the remaining portions of the thesis. The six chapters of this investigation are listed below. Chapter 1 introduces the research's basic ideas and discusses the problems surrounding the topic of study. The literature on parameter choice and mutation strategy in relation to self-adaptive, ensemble, and macro-micro population methods is thoroughly reviewed in Chapter 2. The Differential Evolution Algorithm is specifically discussed in Chapter 3 when discussing the methods for optimization research. Chapter 4 discusses the analysis and conclusions of the proposed experimental framework. Designing desktop user interfaces is covered in Chapter 5. The study's key findings are enumerated in Chapter 6, along with its limitations, ramifications, recommendations for additional research, and conclusions. A comprehensive list of the publications resulting from the thesis work can be found in Appendix A.

1.9 Summary

Differential evolution is a viable branch of evolutionary algorithms that address global optimization problems, apart from its robust and straightforward manner in tackling the issues of premature convergence from evolution stages. Researchers have explored inline traits from mutation and crossover phases to overcome the computational cost and domain exploration. The weak points highlighted by DE could be conquered using combinational efforts from other closely associating algorithms. Especially in terms of fixed variables and limited expansion of population space.

The following chapter will exemplify some of the positive characteristics of DE and the benefits of using ensemble and self-adaptive methods to confront the limitations of convergence limits and obtain an optimal parameter value. Several impacts of DE in autonomous processes brought for real-world assimilation will also be illustrated to correlate the importance of DE with routine operations.

This chapter discusses the subject's issues and describes the research's fundamental concepts. This chapter summarizes studies on parameter control, mutation strategy, and self-adaptive and ensemble systems. Then, this chapter discusses the issues that characterize the research topic, the goals to be accomplished, and the anticipated contribution. The next chapter reviews the literature and provides a comprehensive explanation of the theory, research framework, and suggested Differential Evolution Algorithm.