IMPROVED MICRO GENETIC ALGORITHM FOR MULTIOBJECTIVE KURSAWE FUNCTION AND LOW PASS FILTER CIRCUIT OPTIMIZATION

by

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LIST OF ABBREVIATIONS

Cmizer	Circuit Optimizer
CMOS	Complementary Metal Oxide Semiconductor
ComPop	Composite population
EA	Evolutionary Algorithm
EC	Evolutionary Computation
EP	Evolution Programming
ES	Evolution Strategies
FPGA	Fast Pareto Genetic Algorithm
FPTA	Field Programmable Transistor Array
GA	Genetic Algorithm
GD	Generational Distance
GP	Genetic Programming
GUI	Graphic User Interface
HMGA	Hybrid Micro Genetic Algorithm
IGA	Interactive Genetic Algorithm
IMGA	Improved Micro Genetic Algorithm
maxPOPsize	Maximum population size
MMGA	Modified Micro Genetic Algorithm
MMIC	Monolithic Microwave Integrated Circuit
MO	Multiobjective optimization
MOEA	Multi-Objective Evolutionary Algorithm
MOGA	Multi-Objective Genetic Algorithm
MOO	Multi-objective optimization

MOP	Multi Objective Optimization
NPGA	Niched-Pareto Genetic Algorithm
NSGA	Nondominated Sorting Genetic Algorithm
NSGA-II	Nondominated Sorting Genetic Algorithm II
numObjs	Number of objectives
numVar	Number of variables
OLPSO	Orthogonal Learning Particle Swarm Optimization
PAES	Pareto Archived Evolution Strategy
PP	Initial population
PPN	New population
PPR	Pareto production ratio
PSO	Particle Swarm Optimization
SM	Space Mapping
SME	Small medium enterprise
SOP	Single Objective Optimization
SP	Spacing
SPEA	Strength Pareto Evolutionary Algorithm
SPEA2	Strength Pareto Evolutionary Algorithm 2
ZDT	Zitzler-Deb-Thiele
SBX	Simulated Binary Crossover

LIST OF SYMBOLS

dB	Decibel
Hz	Frequency in hertz
anom	Output Gain
fc	Cutoff frequency
arip	Passband ripple
t	Current generation
$t+1$	Next generation
β	Spread factor
δ	Mutation distribution index
nc	distribution index for SBX
$\boldsymbol{\Omega}$	Feasible region
PF	Pareto Front
$\mathfrak{T}$	Solution set
$\mathbb{P}_t$	Population set
$\mathbb{Z}_t$	Archive set
$R(i)$	Raw fitness
$D(i)$	Distance value
$\boldsymbol{a_t}$	Constant with positive integer variable
$\boldsymbol{b_t}$	Constant with positive real variable
$\boldsymbol{c_t}$	Constant with positive integer variable
$\boldsymbol{d_t}$	Constant with positive real variable
NP_t	Number of non-dominated solutoins

Mikro Genetik Algoritma Diperbaiki untuk Fungsi Berbilang Objektif Kursawe dan ZDT dan Pengoptimuman Litar Penapis Pas Rendah

ABSTRAK

Walaupun Algoritma Evolusi (EAs) telah dilaksanakan untuk menyelesaikan Masalah Berbilang Matlamat (MOPs), penumpuan EAs kepada Pareto optimum depan masih merupakan salah satu isu yang membimbangkan. Demi meningkatkan kemantapan EAs, hibrid algoritma diwujudkan untuk mencari penyelesaian yang lebih baik untuk MOPs. Fokus utama pada penyelidikan terletak pada integrasi elitisme yang baru dalam Mikro Genetik Algoritma (MGA). Elitisme yang dicadangkan dalam penyelidikan ini untuk mewujudkan Mikro Genetik Algoritma Diperbaiki (IMGA). Dalam penyelidikan ini, Kursawe dan ZDT fungsi telah dipilih sebagai penanda aras untuk penaksiran pada IMGA. Kejituan dan keberkesanan IMGA dinilai berdasarkan beberapa penunjuk kualiti seperti generasi jarak dan non-dominated optimum jarak. IMGA yang dicadangkan dibandingkan dengan Non-dominated Sorting Genetik Algoritma II (NSGA-II), Strength Pareto Evolusi Algoritma 2 (SPEA2), MGA and Fast Pareto Genetik Algoritma (FPGA). Keputusan taksiran daripada IMGA membukti bahawa IMGA mempunyai kelebihan daripada MGA dalam Kursawe fungsi dengan mencapai 3.571E-4 untuk generasi jarak dan 2.026E-2 untuk non-dominated optimum jarak, manakala IMGA masih mempunyai ruang peningkatan semasa berurusan dengan ZDT fungsi. Selepas penilaian pada ujian fungsi, IMGA yang dicadangkan digunakan untuk kajian kes praktikal pada pengoptimuman reka bentuk litar. Dua litar aktif penapis pas rendah yang berlainan bilangan masukan parameter telah dikaji. Litar dioptimumkan untuk mencapai objektif pada gandaan keluaran, frekuensi potongan dan riak passband dimana semua objektif ini adalah tidak selaras untuk pengoptimum serentak kerana prestasi salah satu objektif akan dikurangkan pada masa yang sama objektif lain dioptimasikan. Penilaian pada pengoptimum litar dijalankan bersama jurutera dari industri dimana masa dan pencapaian pada objektif digunakan untuk perbandingan dengan IMGA dan juga algoritma yang lain. Pemerhatian daripada analisis keputusan menunjukkan IMGA menggunakan masa yang lebih singkat berbanding jurutera iaitu 17.12 minit untuk perintah kelima aktif penapis pas rendah dan 35.54 minit untuk perintah kesembilan pelbagai maklum balas chebyshev penapis pas rendah. IMGA juga mengoptimumkan objektif litar perintah kelima aktif penapis pas rendah yang diingini iaitu 0.967 V/V untuk gandaan 106.796Hz for frekuensi potongan dan 0.073dB for riak passband. IMGA juga mengoptimakan penyelesaian untuk perintah kesembilan pelbagai maklum balas chebyshev penapis pas rendah dengan nilai 26.24dB, 1017.73Hz dan 0.0858dB untuk gandaan, frekuensi potongan dan riak passband. Secare keseluruhan, penyelidikan ini membuktikan IMGA merupakan salah satu alternative dalam menyelesaikan MOPs.

IMPROVED MICRO GENETIC ALGORITHM FOR MULTIOBJECTIVE KURSAWE FUNCTION AND LOW PASS FILTER CIRCUIT OPTIMIZATION

ABSTRACT

Although Evolutionary Algorithms (EAs) have been widely implemented for solving Multiobjective Optimization Problems (MOPs), the convergence of EAs towards Pareto optimal front is still an issue of concern. In order to enhance the robustness of EAs, hybrid algorithms are commonly developed to identify better solutions for MOPs. The prime focus of this research is placed on the integration of new proposed elitism in conventional Micro Genetic Algorithm (MGA). The proposed elitism has been studied in this research to develop Improved Micro Genetic Algorithm (IMGA). In this research, Kursawe and ZDT test functions are chosen as the benchmark studies for the assessment on IMGA. The accuracy and effectiveness of IMGA are evaluated based a number of quality indicators such as generational distance and non-dominated optimal spacing. The proposed IMGA is compared with Non-dominated Sorting Genetic Algorithm II (NSGA-II), Strength Pareto Evolutionary Algorithm 2 (SPEA2), MGA and Fast Pareto Genetic Algorithm (FPGA). The assessment results show that IMGA can surpass the MGA in Kursawe test function by achieved 3.571E-4 for generational distance and 2.026E-2 for spacing. Meanwhile for ZDT benchmark, IMGA solved and suggested the optimal Pareto front for all the ZDT test functions. After having the benchmark evaluation, the proposed IMGA is applied to a practical case study on circuit design optimization. Two different circuit designs of active low pass filter that comprise of different number of input parameters are studied. The circuits are optimized to achieve objectives on output gain, cutoff frequency and passband ripple which are incommensurable for simultaneous optimization such that the performance of one objective decreases while optimizing another. Evaluation on circuit optimization has been conducted with a group of industrial engineers whereby the time and achievement of the objectives are compared with the proposed IMGA and a few existing algorithms. Observation from the result analysis shows that IMGA consumed lesser time compared to engineers result where 17.120 minutes for fifth order active low pass filter and 35.540 minutes for ninth order multiple feedback chebysheve low pass filter, while engineer used upto 35 minutes and 101 minutes for both circuits. IMGA also optimized the circuit output parameters to desired values especially for fifth order active low pass filter, 0.967 V/V for gain 106.796Hz for cutoff frequency and 0.073dB for passband ripple. IMGA also find the optimized solution for the ninth order multiple feedback chebyshev low pass filter with values 26.240dB, 1017.730Hz and 0.085dB for gain, cutoff frequency and passband ripple corresponding. Overall, this research shows that IMGA is a potential alternative for solving MOPs.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Multiobjective optimization is closely related to all engineering disciplines. It is a challenging task especially when dealing with real-world applications. The work presented in this thesis concerns the development of a novel multiobjective evolutionary algorithm for solving benchmark as well as practical circuit design optimization problem. This chapter gives an overview on evolutionary computation (EC) and reveals problem statement that motivates our research. Our research objectives, scopes, and contribution are explained in separated sections following the problem statement.

1.2 Overview of Evolutionary Computation

Since year 1960's, an algorithm imitating living beings has been created for solving complicated optimization problems and this technique is known as EC (Gen et al., 2000). The goal of evolutionary computation is to create an effective computing system for problem solving by using natural behavioral selection and learning process. Thus, the EC has led to the development of evolutionary algorithms (EAs). The four best known algorithms in this class include genetic algorithms (Holland, 1975), evolution strategies (Beyer, 2001), evolutional programming (Fogel, 1992), and genetic programming (Koza, 1991). Together, these algorithms form the backbone of the field of evolutionary algorithm.

i. Genetic algorithm (GA) is the original form of evolutionary computation that employs evolutionary operators to change and improve a population of possible solutions to a problem (Holland, 1975)

ii. Evolution strategies (ES) is similar to the genetic algorithm, but it differs in the method of selection and mutation activity (Beyer, 2001)

iii. Evolution programming (EP) does not rely on the complex macromutations for successful optimization. (Fogel, 1992)

iv. Genetic programming (GP) is similar to the genetic algorithm, but with the extension of genetic forms using trees and graphs expression (Iba et al., 2012).

In general, optimization refers to seek the solution over a set of possible choices to optimize certain criteria. Single objective optimization problem (SOP) always consider only one criterion whereas multiobjective optimization problem (MOP) always appear to have more than one criterion that must be treated simultaneously (Coello et al., 2007). Optimum results in MOP are referred as Pareto optimal set which consists of nondominated solutions found in the search space corresponding to the objectives considered. There are various types of EAs that have been proposed and examined in MOPs. MOPs often involve incommensurable or conflicting objectives which will decrease the performance of one objective while optimizing the other objective. In this case, EAs will guide the search toward the true Pareto front in the MOPs.

Multiobjective Evolutionary Algorithms (MOEAs) can generally be divided into two generations. Niched-Pareto Genetic Algorithm (NPGA), Multi-Objective Genetic Algorithm (MOGA), and Nondominated Sorting Genetic Algorithm (NSGA) are some of the first generation MOEAs.

i) NSGA proposed by Srivinas et al (1994) uses a layered-based classification suggested by Goldberg et al. (1988), sharing dummy fitness values among the layer of nondominated individuals to keep the diversity of the population. The population is ranked before the selection is performed. However, repetitive Pareto ranking decreases the efficiency of NSGA.

ii) NPGA (Horn et al., 1994) used Pareto dominance scheme in the tournament selection. The comparison is performed on two randomly chosen individuals where the nondominated individuals are always selected in the tournament and fitness sharing is used to decide the result of tournament if there is a tie in comparison.

iii) MOGA (Fonseca et al., 1993), a rank-based fitness assignment method is implemented in which the selection procedure is guided by rank values in the population.

The second generation MOEAs consist of Strength Pareto Evolutionary Algorithm (SPEA), Pareto Archived Evolution Strategy (PAES), Nondominated Sorting Genetic Algorithm II (NSGA-II), and Strength Pareto Evolutionary Algorithm 2 (SPEA2).

i) SPEA (Zitzler et al., 1999) introduces an external population and preserves population diversity using Pareto dominance relationship. The drawback of external population is the search process is time consuming with the growing size of the external population. Thus a pruning technique applied to external nondominated population to sustain the size below certain threshold.

ii) SPEA2 (Zitzler et al., 2001), is an enhanced version of SPEA with three important aspects: 1) Individual domination using fine-grained fitness assignment. 2) More precise guidance in the search by using nearest neighbor density estimation. 3) New archive truncation methods to preserve the boundary of the Pareto optimal set.

iii) PAES which is proposed by Knowles et al. (2000), employs elitism based archive approach that allow single parent to generate single offspring. Crowding procedure is applied to maintain the diversity of the Pareto optimal set. Although there are some similarities between PAES and Micro Genetic Algorithm (MGA), the addition of population in PAES claimed to be computational expensive. Considering such issue, MGA uses replaceable and non-replaceable memory to maintain the population diversity (Coello et al., 2005).

iv) NSGA-II (Deb et al., 2002) is developed as an enhanced version of NSGA which uses elitism in (μ+λ) (where μ denoted archive size and λ the population size) selection and crowd comparison operator. Crowding distance is used to calculate the distance between the individual with its neighbor. NSGA-II prefers to select the nondominated solution. If two solutions are in the same nondominated rank, the less crowded region is preferred.

1.3 Problem Statement and Motivations

Multiobjective optimization (MO) has become popular since year 1980's and has been found to be profoundly useful in handling MOPs (Knowles et al., 2008). A lot of MOEAs have been created and proposed in various fields. Each MOEAs have advantages and disadvantages and there are notably successful MOEAs designed for dealing with many different challenges. As mentioned in Section 1.2, each algorithm has its special features such as crowding distance operation, external memory (archive) to save nondominated solutions, and strength fitness assignment. Researchers believe that a good coverage of the trade-off surface from a Pareto optimal set needs to strike a balance among convergence, diversity and spread (Durillo et al., 2011)

Although multiobjective problems could be solved by at least a type of evolutionary algorithm, there is no individual evolutionary algorithm that could be claimed to be the best in solving all multi-objective problems. Considering different advantages in different algorithms, there are motivations on the development of hybrid evolutionary algorithm to integrate several evolutionary strategies for improvements in optimization performance. As a result, this study investigates several unique features of available evolutionary algorithms and innovates a new model to enhance good coverage of Pareto optimality for multiobjective optimization problem.

ZDT (Zitzler-Deb-Thiele) and Kursawe test function are two well-known benchmark studies used to evaluate multi-objective evolutionary algorithms. Up to now, there are many research conducted to improve the search of Pareto optimality using these test functions as benchmarks testing. For instance, Coello (2001) has proposed a micro evolutionary algorithm to solve Kursawe test function (Coello et al., 2007). Due to the intrinsic mathematical properties, these functions are employed to reveal the challenging issues of MOPs. According to Zitzer et al. (2000), ZDT test function can cause difficulty of Pareto convergence whereas Kursawe test function has a non-connected Pareto front with concave and convex regions. Considering these challenges, both ZDT and Kursawe functions are used as the benchmark evaluations for our research validation.

Besides benchmark studies, practical case study is also important to give more convincing research assessment. In the electronic industries, the rapid change of customer requirement for different electronic applications leads to the requirement of rapid circuit design in order to fulfil the application specifications. Conventionally, circuit design engineers fine tune the circuit parameter to achieve the required specifications by experience and trial-and-error approach. The frequent tuning of circuit parameter can be tedious and time consuming especially for fresh engineers and the situation become worse when complicated circuits that involved many topologies and parameters are dealt. In addition, it is common that a circuit is designed to fulfil a number of objectives such as passband ripples, gain, and cutoff frequency. As a result, a flexible multiobjective circuit optimizer that could assist the tuning of circuit performance is very much required in the circuit industries.

Based on the above mentioned challenges and motivations, we develop a improved evolutionary algorithm, Improved Micro Genetic Algorithm (IMGA), by integrating a number of evolutionary strategies from the previous research considering the strength of different algorithms. Next, our proposed optimization model then applied on ZDT and Kursawe benchmark functions to investigate the capability to obtain better Pareto optimality. Finally, the model is used to develop a multi-objective evolutionary circuit optimizer, so called Cmizer, to assist practical circuit design parameter tuning.

1.4 Objectives of this Study

This research aims to achieve the following objectives:

i. To determine and extract the important search strategies of different evolutionary algorithms and develop a novel hybrid evolutionary optimization model.
ii. To investigate the capability of the proposed model in achieving Pareto optimality.
iii. To develop a multi-objective evolutionary circuit optimizer for practical circuit design assistance with integration of plug-and-play feature and user-friendly interface.
iv. To investigate the performance of the developed circuit optimizer.