UNIVERSITI PUTRA MALAYSIA

MODIFIED ARCHIVE UPDATE MECHANISM OF MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION IN FUZZY CLASSIFICATION AND CLUSTERING

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By

ALWATBEN BATOUL RASHED A

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

March 2022

DEDICATION

I would like to dedicate this thesis and all my academic achievements to my dearly beloved father, mother, and members of my family.

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

MODIFIED ARCHIVE UPDATE MECHANISM OF MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION IN FUZZY CLASSIFICATION AND CLUSTERING

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March 2022

Chairman : Hazlina binti Hamdan, PhD
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Evolutionary algorithms have been extensively used to resolve problems associated with multiple and often conflicting objectives. The objective of a multi-objective optimization algorithm is to define the collection of best trade-offs between objectives. Among multi-objective evolutionary algorithms proposed in the literature, particle swarm optimization (PSO)-based multi-objective (MOPSO) algorithm has been cited to be the most representative. One characteristic of MOPSO with Pareto optimality scheme is associated with selection mechanism for archive update. However, the PSO algorithm produces a group of non-dominated solutions which makes the choice of a "suitable" Pareto optimal or non-dominated solution more difficult. According to the literature, crowding distance as one of the most efficient algorithms was developed based on density measures to treat the problem of selection mechanism for archive update. Issues arising from these methods are not conducive to balancing diversity and convergence performances. The present study proposed a modified selection mechanism for archive updates in MOPSO (MOPSO-CD). The approach of the proposed mechanism was based on dominance concept and crowding distances to obviate falling in local optima instead of global optima as well as to have a balance between diversity and convergence by using the Pareto dominance concept after calculating the value of the crowding degree for each solution. For optimum results in performance analysis, the optimal value of the MOPSO-CD was evaluated using (ZDT), (WFG), and (DTLZ) with two or three objectives over D2MOPSO, AgMOPSO, MMOPSO, and EMOSO algorithms. Results showed that MOPSO-CD had better performance and a strong superiority in the IGD with the lowest mean of 9.50E-4, while the HV showed the lowest mean of 9.40E-1 compared to other algorithms. Ten datasets sourced from KEEL repository were used to measure the performance of Fuzzy MOPSO-CD with a modified archive update mechanism (FMOPSO-CD). The FMOPSO-CD was compared with multi-objectives evolutionary algorithms (D-MOFARC, GRBCs), and PSO (FMOPSO, FMOPSO-SA). The FMOPSO-CD's accuracy consistently outperformed other algorithms in all datasets

where the best performance accuracy was 99%. Moreover, interpretability also recorded better results on testing problems, where most of the number of rules were fewer than 33. A clustering algorithm based on MOPSO-CD with a modified archive update mechanism (MCPSO-CD) was used to estimate the optimal number of clusters. For optimum results in performance analyses, the technique was evaluated using nine datasets: five datasets were artificially generated, while four were real-world datasets sourced from KEEL over MCPSO and IMCPSO algorithms. The study recorded that the procedure exemplified a state-of-the-art method with significant differences observed in most of the datasets examined. For Shape cluster datasets, the proposed MCPSO-CD method with value of above 7.0 performed better in most datasets in terms of mean ARI. It was superior to the clustering algorithm methods in most real-world datasets with means ARI of over 0.35. MOPSO-CD was proposed as an improvement in multi-objective fuzzy classification in terms of interpretability and accuracy as well as improvement in multi-objective clustering technique in terms of the optimal number of clusters.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

MEKANISMA KEMASKINIAN ARKIB YANG DIUBAHSUAI BAGI *PARTICLE SWARM* UNTUK PENGOPTIMUMAN BERBILANG OBJEKTIF DALAM PENGKELASAN DAN PENGELOMPOKAN FUZZY

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Algoritma evolusi telah diguna pakai dengan meluas bagi menyelesaikan masalah berkaitan dengan kepelbagaian objektif dan yang sering bercanggah. Tujuan pengoptimuman algoritma berbilang objektif adalah untuk menakrifkan koleksi pertukaran yang terbaik antara objektif. Antara algoritma evolusi yang dicadangkan di literatur, pengoptimuman *particle swarm* (PSO) berdasarkan algoritma berbilang objektif (MOPSO) telah dinyatakan sebagai yang paling tipikal. Satu ciri MOPSO dengan skema optimum Pareto adalah berkaitan dengan mekanisma pemilihan untuk kemaskini arkib. Walau bagaimanapun, algoritma PSO menghasilkan sekumpulan penyelesaian tidak dominan yang membuat pemilihan kesesuaian Pareto atau penyelesaian masalah tidak dominan menjadi lebih sukar. Mengikut literatur, jarak kesesakan sebagai algoritma yang paling cekap, telah dibangunkan berdasarkan ukuran ketumpatan bagi mengatasi masalah mekanisma pemilihan dalam kemaskini arkib. Isu-isu yang timbul daripada kaedah ini adalah tidak kondusif bagi mengimbangi kepelbagaian dan prestasi tumpuan. Kajian ini mencadangkan satu mekanisma pemilihan yang diubahsuai bagi kemas kini arkib dalam MOPSO dengan penjarakan kesesakan (MOPSO-CD). Pendekatan yang diambil bagi mekanisma yang dicadangkan adalah berdasarkan konsep dominan dan penjarakan kesesakan untuk mengelak terjatuh ke dalam optima tempatan, tetapi sebaliknya terjatuh ke optima global selain daripada memperolehi keseimbangan antara keberbagaian dan penumpuan dengan menggunakan konsep penguasaan Pareto setelah mengambilkira nilai darjah kesesakan bagi setiap penyelesaian. Bagi mendapatkan keputusan yang optimum dalam analisis prestasi, nilai optimum MOPSA-CD telah diuji dengan menggunakan (ZDT), (WFG), dan (DTLZ) dengan dua atau tiga objektif ke atas algoritma D2MOPSO, AgMOPSO, MMOPSO, dan EMOSO. Keputusan menunjukkan MOPSO-CD mempunyai prestasi yang lebih baik dan keunggulan yang kuat di IGD dengan nilai purata terendah 9.5E-4, sementara HV menunjukkan nilai terendah 9.4E-1 berbanding algoritma lain. Sepuluh set data yang diperolehi daripada repositori KEEL telah digunakan untuk menilai prestasi MOPSA-CD kabur dengan mekanisma arkib algoritma pelbagai kemaskini

(FMOPSO-CD). Perbandingan telah dibuat antara FMOPSO-CD dengan algoritma berbilang objektif (D-MOFARC, GRBCs), dan PSO (FMOPSO, FMOPSO-SA). Ketepatan FMOPSO-CD's didapati mengatasi prestasi algoritma dalam semua set data dimana prestasi tepat yang terbaik adalah 99%. Tafsiran juga merekodkan keputusan yang baik semasa menguji masalah dimana kebanyakan bilangan peraturan adalah kurang daripada 33. Algoritma kelompok berdasarkan MOPSO-CD dengan mekanisma kemaskini arkib yang diubah sesuai (MCPSO-CD) telah digunakan untuk menganggarkan bilangan kelompok yang optimum. Bagi keputusan yang optimum dalam analisis prestasi, kaedah ini telah dinilai dengan menggunakan sembilan set data: lima set data dibangunkan secara tiruan, sementara empat set data diperolehi daripada KEEL keatas algoritma MPSO dan IMCPSO. Kajian mendapati bahawa prosidur ini merupakan kaedah terkini dengan merekodkan perbezaan yang ketara dalam kebanyakan set data yang dikaji. Bagi set data kelompok Shape, kaedah MPSO-CD yang disyorkan adalah lebih baik dalam kebanyakan set data segi purata ARI yang melebihi 0.70. Ia adalah lebih baik daripada purata kaedah kelompok algoritma dalam set data dunia sebenar dengan purata ARI yang melebihi 0.35. MOPSO-CD adalah disyorkan sebagai penambahbaikan dalam klasifikasi fuzzy berbilang objektif dari segi kebolehtafsiran dan ketepatan, dan penambahbaikan dalam teknik pengelompokan pelbagai objektif dari segi bilangan kelompok yang optimum.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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Declaration by graduate student

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LIST OF ABBREVIATIONS

AGMOPSO	An Adaptive Gradient Multi-objective Particle Swarm Optimization
ANFIS	Adaptive Neuron-Fuzzy Inference System
ANN	Artificial Neural Network
ARI	Adjusted Rand Index
BCE-MOEA/D	Bi-Criterion Evolution-Based Multi-Objective Evolutionary Algorithm Based on Decomposition
BIRCH	Balanced Iterative Reducing and Clustering using Hierarchies
CD	Crowding Distance
MOPSOSA	Multi-objective with PSO and simulated annealing
D2MOPSO	Multi-objective particle swarm optimizer
DCBMPSO	A Dynamic Binary PSO-based Multi-objective Clustering approach
D-MOFARC	Discretization Multi-Objective Fuzzy Association Rule-Based Classification
DTLZ	Deb, Thiele, Laumanns & Zitzler
EA	Evolutionary Algorithm
EC	Evolutionary Computation
EM-MOPSO	Elitist-Mutation Multi-Object Particle Swarm Optimization
EMOSO	Efficient Multi-objective Optimization Algorithm Based on level Swarm Optimizer
FMO-PSO	Fuzzy Multi-Objective with PSO
FMOPSO-CD	Fuzzy Multi-objective Particle Swarm Optimization Crowding Distance
FMOPSO-SA	Fuzzy Multi-Objective with PSO and Simulated Annealing
FRBCS	Fuzzy Rule-Based Classification System

GA	Genetic Algorithm
GRBC	Granular Rule-Based Classifier
HV	Hyper Volume
IA	Interpretability-Accuracy
IGA	Improved GA
IGD	Inverted Generational Distance
IMCPSO	Improved Multi-objective Clustering Particle Swarm Optimization
KB	Knowledge-Based
KEEL	Knowledge Extraction based on Evolutionary Learning
MaOP	Many-Objective Problem
MOE	Multi-Objective Evolutionary
MOEA	Multi-Objective Evolutionary Algorithm
MOEOA	Multi-Objective Evolutionary Optimization Algorithm
MOEPSO	Multi-Objective Endocrine Particle Swarm Optimization
MOP	Multi-objective Optimization Problems
MOPSO	Multi-Objective Particle Swarm Optimization
MOPSO/GDR	A Many-Objective Particle Swarm Optimization with Grid Dominance Ranking and Clustering
M-PAES	Modified version of the strength Pareto Evolutionary Algorithm
MPSO/D	Multi-objective Particle Swarm Optimization algorithm based on Decomposition
NGSA	Non-dominated Sorting Genetic Algorithm
PF	Pareto Front
PSO	Particle Swarm Optimization
RB	Rule-Based

RVEA	Reference Vector Evolutionary Algorithm
SI	Swarm intelligence
SPEA2	Strength Pareto Evolutionary Algorithm 2
STD	Standard Deviation
WEKA	Waikato environment for knowledge analysis
WFG	Walking Fish Group
ZDT	Zitzler, Deb &Thiele

CHAPTER 1

INTRODUCTION

1.1 Background

An optimization algorithm can be defined as a procedure of finding the optimal or best solution for a maximum or minimum value of a given function (Yang, 2018) and is executed by comparing various solutions until an optimum or satisfactory solution is found. With the advent of computer technology, Fletcher, (2013) cited that optimization is generally done by choosing a range of values subject to several constraints. Earlier, Deb (2001) reported that multi-objective optimization constitutes a process of optimizing consistently and simultaneously a collection of objective functions to optimize a group of conflicting objectives.

Abbass, Sarker, and Newton (1999) proposed that multi-objective particle swarm optimization (MOPSO) can be considered as the most representative and ideal approach to these conflicting situations. Deb (2001) cited that a solution is being Pareto optimal or non-dominated when there is no other satisfactory solution being found that enhances one objective without compromising another. He labeled multi-objective algorithms that lead to a group of non-denominated solutions as *Pareto optimal* often represented as a vector such that there are two objectives to a concurrent problem.

Generally, a multi-objective optimization problem deals with the situation where multiple objectives need to be optimized concurrently. This suggests that a single solution is analyzed based on different criteria. Evolutionary algorithm (EA), a subset of evolutionary computation, is mostly used to handle this situation. EA is a computational process that involves iteration or repetition of a mathematical or computational procedure when calculating the desired result using repeated cycles of operations (Eckart, Deb & Lothar, 2000). EA generally is characterized by a population of solution candidates. It has a reproduction process that enables the combination of existing solutions in generating new solutions. In a natural selection, EA usually determines which individuals of the current population participate in the new population.

There are several multi-objective evolutionary optimization algorithms (MOEA) that have been commonly used when confronting optimization problems. These include particle swarm optimization (PSO) (Kennedy, & Eberhart, 1995), simulated annealing (SA) (Van Laarhoven, & Aarts, 1987), and genetic algorithm (GA).

Zhang *et al.* (2018) justified why PSO is better than other MOEA in tackling optimization problems. This is because, intuitively, it has a simple representation and a relatively low number of adjustable parameters, which make it the most commonly used PSO for many problems that require approximate solutions. In the present study, PSO was chosen in addressing optimization problems.

1.2 Research Motivation

A fuzzy rule-based classification system (FRBCS) has been acknowledged to have the ability to deduce knowledge from present data that can be understood by a human. FRBCS techniques have been known to be among the most useful machine learning that can be used to produce an interpretable system for users (Gacto, Alcalá & Herrera, 2011). The system may have been improved by an expert in manual form or made automatically based on the set of data that labeled a confident spectacle. Its automation system can be considered as an optimization problem as it focuses more on improving accuracy without considering the rules generated (Fazzolari, Alcalá & Herrera, 2014; Gorzałczany & Rudziński, 2017). The operational procedures of the system have not only considered the accuracy of the system, but also the interpretability that indicates the capability to describe efficiently the operational procedure of a model.

A clustering problem generally involves dividing a set of data into different groups according to their common features. The structure of the data is explored and its objects are grouped into clusters, with each cluster containing similar objects. Therefore, objects of a given cluster are very similar with small distances between clusters members, while objects of different clusters are very distinct based on a similarity measure function. Clustering can therefore be considered as an optimization problem.

MOEAs are generally aimed at optimizing a set of objectives, and at the same time, these objectives conflict with each other. The most suitable solution to fuzzy classification and clustering problems is the application of MOEAs. Zhang *et al.*, (2018) indicated that in optimization problems, PSO is better than MOEA as it has a simple representation and relatively low number of adjustable parameters. For this reason, the multi-objective PSOs are effectively recommended to trade-off accuracy-interpretability and to estimate the optimal number of clusters. However, MOPSO with crowding distance (MOPSO-CD) remains an open problem in terms of selection mechanism for archive update.

1.3 Problem Statement

Scrutinizing the intrinsic characteristics of MOPSO with Pareto optimality scheme, there appeared to be some issues that needed to be addressed about the selection mechanism for archive update (Kuo & Han, 2011; Kuo & Gosumolo, 2019; Toscano-Pulido, Coello & Santana-Quintero, 2007; Pulido, 2005). The issue was associated with the execution of PSO search and the newly generated non-dominated solutions collected into the external archive. As the size of the archive is finite, where the number of non-dominated solutions in incremental particles can crowd in certain regions in the external archive of the objective space, it was necessary to use a proper selection mechanism for archive update, which could help to guide the direction of search toward true Pareto optimal.

Literature has it that crowding distance is one of the most effective algorithms developed to process the problem of selection mechanism for archive update (Al Moubayed, Petrovski & McCall, 2014; Kukkonen & Deb, 2006; Sierra & Coello, 2005). The issues with these methods are that they are not conducive to balancing diversity and convergence performances. To address this issue, Zhu et al., (2017) and Lin et al., (2015) used a selection mechanism for archive updates based on crowding-distance as well as Pareto dominance. The disadvantage of this selection mechanism is the necessity to check dominance to remove dominated solution consequently to apply crowding-distance to remove most crowding, suggesting a drawback of the selection mechanism. Thus, a selection mechanism is needed to obviate falling in local optima instead of global optima and to have a balance between diversity and convergence. Fuzzy classification and clustering can be considered multi-objective optimization problems. However, existing methods have made several improvements in the selection mechanism for archive updates by addressing classification and clustering problems separately.

Multi-objective PSOs with selection mechanisms for archive update based on both Pareto dominance and crowding-distance have been effectively recommended to treat accuracy-interpretability trade-offs and estimate the optimal number of clusters. Several multi-objectives fuzzy classifications have been proposed in the literature (Gorzalczany & Rudziński, 2017; Antonelli et al., 2016; Fazzolari, Alcalá & Herrera, 2014; Jiménez, Sánchez, & Juárez, 2014; Gorzalczany & Rudziński, 2012; Gacto, Alcalá & Herrera, 2008; Gacto, Alcalá & Herrera, 2007).

In other MOEAs, a non-dominated solution has to be found in each generation and computational effort must be done for Pareto optimal solution. This complicated computational effort is due to less theoretical evidence to Pareto optimal solution. Therefore, PSO is better in many situations due to an intuitively simple representation and relatively low number of adjustable parameters. Dinh, Nguyen & Tran, 2013, 2014), used fitness sharing with MOPSO to enhance the interpretability-accuracy trade-off in a fuzzy rule-based system. Their studies achieved acceptable improvement, but the results were considered not good enough due to the computational effort involved in fitness sharing. The studies limited their explanation in the population to certain criteria which resulted in a fall in local optima instead of global optima.

Clustering issues based on multi-objective clustering algorithms have been proposed in the literature (Armano & Farmani, 2016; Abubaker, Baharum & Alrefaei, 2015; Yang, Sun & Zhang, 2009). Gong et al. (2017) proposed a multi-objective clustering framework that uses PSO. Even though the approach provided advancement in the performance as suggested, it showed a setback in clustering distribution solutions that harmed the performance of the selection mechanism, thereby making the optimization models fall into local optima rather than the global optima. In the present study, MOPSO-CD with a modified archive update mechanism was used in both accuracy and interpretability trade-offs for fuzzy classification and to estimate the optimal number of clustering.

1.4 Research Objectives

The main objective of the present research is to propose a new MOPSO-CD for the improvement in accuracy and interpretability in fuzzy classification and to estimate the optimal number of clusters using the clustering technique. To achieve the main objective, the following sub-objectives were established:

- To modify archive update algorithm in MOPSO-CD.
- To apply the modified archive update algorithm into multi-objective fuzzy classification PSO (FMOPSO-CD) for improving fuzzy classification in terms of interpretability and accuracy.
- To apply the modified archive algorithm into multi-objective clustering PSO (MCPSO-CD) in estimating the optimal number of clusters.

1.5 Research Scope

This research can be divided into three parts. Firstly, the research used MOPSO as it is the most commonly used among other multi-objective evolutionary optimizations. secondly, the selection mechanism for archive update was based on crowding distance, as it is the most dominate selection mechanism among others (Zhu et al., 2017; Lin et al., 2015; Al Moubayed, Petrovski, & McCall, 2014; Kukkonen & Deb, 2006; Sierra & Coello, 2005). The third part, MOPSO-CD with an enhanced selection mechanism for archive update was used to solve: fuzzy classification: Contributions of Study

The study presents the following contributions:

i. A new MOPSO-CD based modified selection mechanism for archive update. In this respect, when non-dominated solutions are added to the archive, crowding value is calculated to sort all solutions in descending order based on the value before applying the *CheckDominance* to remove all dominated solutions from the archive;

ii. Enhanced multi-objective fuzzy classification PSO FMOPSO-CD as a trade-off between interpretability and accuracy for fuzzy classification. is enhanced. The procedure is composed of two steps: fuzzy model generation and optimization processes of the candidate systems optimized by MOPSO-

CD. In the first step, the fuzzy model is applied to original data to produce the initial population, subsequently followed by, optimization in MOPSO-CD. The output is Pareto optimal solution which is characterized by various levels of accuracy-interpretability trade-offs;

iii. Enhancement of MCPSO-CD based on modified archive update mechanism for the optimal number of clustering. The procedure consists of an optimization level and a decision-making level designed for clustering purposes. The former provides the optimal solution for a given clustering problem, known as the Pareto solution and each of the solutions is grouped with a different sum of clusters in the embedded form. To this extend, MCPSO-CD uses these solutions to automatically determine the optimal clusters. Lately, the best among the solutions is selected.

1.6 Organization of the Thesis

This thesis is organized as follows:

Chapter 1 is an introductory chapter that discusses the problem statement, objectives, scope, and research contributions;

Chapter 2 is the literature review, which included previous studies on optimization techniques. Existing works on MOPSO and selection mechanisms for archive update were explained to highlight the existing gaps or exploit strengths and weaknesses;

Chapter 3 presents the general methodology of the study to include selection mechanisms for archive updates in MOPSO-CD;

Chapter 4 presents a detailed description of (FMOPSO-CD) framework for a trade-off between interpretability and accuracy;

Chapter 5 presents a detailed description of the MCPSO-CD framework optimal number of clustering;

Chapter 6 presents the implantation of FMSPSO-CD and MCPSO-CD on selected datasets. Results of the comparison are presented.

Chapter 7 presents the conclusions of the study and recommendations for future work.

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