UNIVERSITI PUTRA MALAYSIA

STANDARDIZING AND WEIGHTING THE EVALUATION CRITERIA OF MANY-OBJECTIVE OPTIMIZATION COMPETITION ALGORITHMS BASED ON FUZZY DELPHI AND FUZZY-WEIGHTED ZERO-INCONSISTENCY METHODS

RAWIA TAHRIR SALIH

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By

RAWIA TAHRIR SALIH

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

July 2021

DEDICATION

This thesis is dedicated to

My beloved father who always believed in me, support me until my research was fully finished, has encouraged me attentively with his fullest and truest attention to accomplish my work with truthful self-confidence, and to my beloved mother who has surrounded me with her love and prayers. Also, I dedicate it to my beloved younger brother Mahir who has supported and cared about me all the time.

With love, respect, and a bunch of memories

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

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Chairman : Associate Professor Razali bin Yaakob, PhD
Faculty : Computer Science and Information Technology

Along with the developments of numerous MaOO algorithms in the last decades, comparing the performance of MaOO algorithms with one another is highly needed. The evaluation criteria of Many Objective Optimization algorithm (MaOO) play a critical role in evaluating the competition MaOO algorithms. Although these criteria have been criticised in literature, they are employed in the evaluation randomly, and the process of selecting them remains unclear. In addition, the weight of importance is critical for evaluating the performance of MaOO algorithms. All evaluation studies for MaOO algorithms have ignored to assign such weight for the target criteria during evaluation process. Thus, the need for standardizing the criteria set became inevitable. Not to mention the role of weight of importance in assessing the performance of MaOO.

These challenges (a) the multiple evaluation criteria and (b) criteria importance considered an intricate multi-criteria decision making (MCDM) problem; in such problem, the MCDM methods are recommended. Several studies in MCDM have proposed competitive weighting methods. However, these methods suffer from inconsistency issues arising from the high subjectivity of pairwise comparison. (c) The inconsistency rate increases in an exorbitant manner when the number of criteria increases which considered an issue in the existing superior weighting methods such as AHP and BWM, and the results are affected accordingly. Thus, this research aims to standardize and weigh the evaluation criteria of MaOO competitive algorithms base on fuzzy Delphi and new fuzzy-weighted zero-inconsistency (FWZIC) methods.

The proposal exhaustive evaluation methodology has three phases: *The first phase,* standardizing the MaOO evaluation criteria, Fuzzy Delphi method utilized to analyse the expert consensus on the best set of evaluation criteria and its indicators. *In the second*

phase, the FWZIC method is proposed to compute the unified criteria set's weight coefficients with zero consistency. *Lastly*, the exhaustive evaluation methodology evaluated to test its validity and efficiency accordingly.

The results show that 31 out of 49 got the expert consensus as the most suitable criteria set; and their importance weight results computed accordingly, the main criterion (called Pareto_based) got the higher weight (0.538) in compared to others.

Lastly, the proposed unified model of the most suitable criteria set validated by the experts from the field of study and the efficiency of the FWZIC method proved in comparison to F-AHP and F-BWM superior methods those show high inconsistency results which overall exceeded the maximum consistent ratio (i.e., 0.1). On the other hand, FWZIC effectively computes the important weight of the criteria with zero inconsistency. The implications of this study bring benefits to the optimization community, industrial and researchers by providing exhaustive evaluation methodology for evaluating MaOO algorithms, which can be generalized to solve such problem effectively.

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

PIAWAIAN DAN PEMBERAT KRITERIA PENILAIAN BAGI ALGORITMA PERSAINGAN PENGOPTIMUMAN BANYAK-OBJEKTIF BERDASARKAN KAEDAH FUZZY DELPHI DAN KABUR BERPEMBERAT TIDAK KONSISTEN SIFAR

Oleh

RAWIA TAHRIR SALIH MOHAMMED

Julai 2021

Pengerusi : Profesor Madya Razali bin Yaakob, PhD
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Seiring dengan perkembangan banyak algoritma MaOO dalam beberapa dekad yang lalu, membandingkan prestasi algoritma MaOO antara satu sama lain sangat diperlukan. Kriteria penilaian algoritma Banyak Objektif Pengoptimuman (MaOO) memainkan peranan penting dalam menilai algoritma MaOO persaingan. Walaupun kriteria ini telah dikritik dalam literatur, kriteria ini digunakan dalam penilaian secara rawak, dan proses pemilihannya tetap tidak jelas. Di samping itu, berat kepentingan sangat penting untuk menilai prestasi algoritma MaOO. Semua kajian penilaian untuk algoritma MaOO telah mengabaikan untuk menetapkan bobot tersebut untuk kriteria sasaran semasa proses penilaian. Oleh itu, keperluan untuk menyatukan kriteria yang ditetapkan menjadi tidak dapat dielakkan. Tidak ketinggalan peranan pentingnya dalam menilai prestasi MaOO.

Cabaran ini (a) kriteria penilaian pelbagai dan (b) kepentingan kriteria dianggap sebagai masalah membuat keputusan pelbagai kriteria (MCDM) yang rumit; dalam masalah seperti itu, kaedah MCDM disyorkan. Beberapa kajian di MCDM telah mencadangkan kaedah pemberat daya saing. Walau bagaimanapun, kaedah ini mengalami masalah ketidakkonsistenan yang timbul dari subjektiviti perbandingan berpasangan yang tinggi. (c) Kadar ketidakkonsistenan meningkat dengan cara yang terlalu tinggi apabila bilangan kriteria meningkat yang dianggap sebagai isu dalam kaedah pemberat unggul sedia ada seperti AHP dan BWM, dan hasilnya dipengaruhi dengan sewajarnya. Oleh itu, penyelidikan ini bertujuan untuk menyatukan dan menimbang kriteria penilaian algoritma kompetitif MaOO berdasarkan kaedah fuzzy Delphi dan kaedah fuzzy-weighted zero-inconsistency (FWZIC) baru.

Metodologi penilaian lengkap cadangan mempunyai tiga fasa: Fasa pertama, menyatukan kriteria penilaian MaOO, kaedah Fuzzy Delphi digunakan untuk

menganalisis konsensus pakar mengenai set kriteria penilaian terbaik dan indikatornya. Pada fasa kedua, kaedah FWZIC dicadangkan untuk menghitung pekali berat set kriteria bersatu dengan konsistensi sifar. Terakhir, metodologi penilaian menyeluruh dinilai untuk menguji kesahan dan kecekapannya.

Hasilnya menunjukkan bahawa 31 dari 49 mendapat konsensus pakar sebagai kriteria yang paling sesuai ditetapkan; dan pentingnya hasil berat dikira dengan sewajarnya, kriteria utama (disebut Pareto_based) mendapat berat yang lebih tinggi (0.538) berbanding yang lain.

Terakhir, model bersatu yang dicadangkan dari kriteria yang paling sesuai yang disahkan oleh pakar dari bidang kajian dan kecekapan kaedah FWZIC terbukti dibandingkan dengan kaedah unggul F-AHP dan F-BWM yang menunjukkan hasil ketidakkonsistenan yang tinggi yang secara keseluruhan melebihi nisbah konsisten maksimum (iaitu 0.1). Sebaliknya, FWZIC dengan berkesan menghitung berat kriteria penting dengan tidak konsisten. Implikasi kajian ini membawa manfaat kepada komuniti, industri dan penyelidik pengoptimuman dengan memberikan metodologi penilaian yang menyeluruh untuk menilai algoritma MaOO, yang dapat digeneralisasikan untuk menyelesaikan masalah tersebut dengan berkesan.

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With the name of Allah, the Most Compassionate and Most Merciful

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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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Date: 14 October 2021

Declaration by graduate student

I hereby confirm that:

- this thesis is my original work;
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- this thesis has not been submitted previously or concurrently for any other degree at any institutions;
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Declaration by Members of Supervisory Committee

This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
- supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) were adhered to.

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LIST OF ABBREVIATIONS

F-AHP	Fuzzy analytic hierarchy process
F-BWM	Fuzzy Best–Worst Method
FWZIC	Fuzzy-Weighted Zero-Inconsistency Method
MaOO	Many-Objective Optimisation Algorithm
MaOPs	Many-Objective Problems
MCDM	Multi Criteria Decision Making
MOEAs	Multi-objective evolutionary algorithms
MOO	Multi-Objective Optimisation

CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter introduces the research topic, the statement of the problem, and research objectives. This chapter also presents the scope of this research where the experimental and technical scopes are explained. A brief background of the research components is presented in Section 1.2. The statement of the problem, on which the direction of the research is based, is identified, and introduced in Section 1.3. Research questions are listed in Section 1.4. This is followed by the objectives of the research, which are described in Section 1.5. The connections amongst research objectives, research questions, the specific and general problem is presented in Section 1.6. Moreover, the scope of the study is discussed in Section 1.7. The research contribution significant of the study is presented in Section 1.8. The main structure of the thesis is briefly outlined in Section 1.9. Finally, a summary of the chapter is presented in Section 1.10.

1.2 Research Background

Optimisation is a method or process of finding the best solution to a problem under a specific circumstance (set of constraints). In handling or optimising a single objective, such as improving performance or reducing cost, the aim is to find the best solution amongst all possible alternatives or the closest one to the ideal solution, i.e., the global optimum solution. Optimising a problem for a single objective is uncommon. Optimisation models are often designed to address problems with more than one objective.

In the optimisation field, cases with conflicting objectives are common. For example, producing a new mobile phone that is lightweight might conflict with providing an affordable phone. When the objective problem has two or three functions such as in this case, it is referred to as multi-objective optimisation (MOO). In this case, the algorithmic and mathematical models used for a single objective are unsuitable, and even the principle of optimality changes from a single global optimum to a set of ideal solutions.

According to (Jin et al., 2018), in the past 20 years, single- and multi-objective problems (problems with less than three objectives) have been addressed effectively by using evolutionary algorithms. Multi-objective evolutionary algorithms (MOEAs) exhibit better performance in a single run compared with traditional mathematical programming techniques in finding a set of non-dominated solutions. However, the performance of these algorithms in term of the convergence and diversity of the solution results towards the Pareto Front (PF) dramatically declines when the number of objectives exceeds four, (i.e. many-objective problems (MaOPs)) (de Campos Jr et al., 2010; Zheng et al., 2016).

Therefore, an efficient solving method is required to resolve this type of problem that represents the most common real-world problems. Real-world problems are often complicated because of their multiple conflicting objectives and are referred to as multi-objective problems (MOPs). Previous studies have not reached a consensus regarding the definition of Many Objective Problems (MaOPs). Several scholars define MaOPs as MOPs with more than two objectives (Wang et al., 2013). However, when MOPs have four or more objectives, they are called MaOPs to distinguish them from MOPs (Li et al., 2015a). MaOPs have many applications in the real world; for example, they are used when the number of objective problems reaches or exceeds 100, such as electric vehicle control (Cheng et al., 2017c), socio-environmental field (Al-Jawad et al., 2019b), design of optical networks (Figueiredo et al., 2016a), water resource management (Al-Jawad et al., 2019a), QoS-aware web services (Ramírez et al., 2017), energy consumption (Fan et al., 2019) and multi-city robustness (Trindade et al., 2017). Many challenges are encountered in solving MaOPs because of the curse of high dimensionality in MaOPs. Such difficulties are evident in maintaining balance between good diversity and decent convergence over the Pareto front (set of ideal solutions), in the unclear relation between articulate preferences and objectives that are difficult for a decision maker to differentiate and in the unaffordable computational complexity. **The current scenario for** evaluating and benchmarking the many-objective optimisation (MaOO) algorithms using existing performance indicators are difficult regardless of the capability of these indicators to assess optimisation algorithms for MaOPs. Thus, comparing and evaluating optimisation algorithms of MaOPs are difficult and present a challenging issue in visualizing the MaOO solution (Maltese et al., 2016).

Although MaOO problems have received much research attention, but MaOO evaluation is indisputably difficult in the context of continuous improvement and development in the optimisation community. MaOO evaluation requires further inspection. Moreover, the methodological aspects of performance assessment in MaOO must be emphasised to ensure that the evaluation and comparison of MaOO algorithms are efficient and sufficient.

1.3 Problem Statement

The problem statement of this research driven from the research gap and theoretical gap as will present in the following sections:

1.3.1 Research Gap

Comparing and evaluation processes consider the challenges and limitations of MaOO. In MaOO approaches, the evaluation process proceeds via a random selection of one or two evaluation metrics. The benchmarking process is an essential step in the comparison of algorithm performance under similar conditions, parameter settings and applied criteria to evaluate the quality of proposed algorithms. (Coello et al., 2020; He et al., 2016b; Jin et al., 2018; Pal et al., 2016a; Wang et al., 2017b; Wang et al., 2020; Wang et al., 2018; Yu et al., 2018a).

Problem 1: Lack of identifying the MaOO evaluation criteria and unified model is one reason for the MaOO evaluation problem.

The main challenge in the development of MaOO is that many metrics have been proposed to compare the performance of different evolutionary approaches in MaOO. This situation leads to difficulties when comparisons of the outputs of different algorithms are needed, and the appropriate metrics must be selected to perform such comparisons. Hence, the process of choosing appropriate metrics remains unclear. Accordingly, this conflict reflects the evaluation of algorithms in the benchmarking process (Yu et al., 2018). Studies often encounter conflicts amongst various criteria during the benchmarking process and result in a major challenge because measuring these criteria creates different values representing the different criteria's metrics; criteria with an unknown importance create another problem because developers cannot compare a new approach with other existing approaches (He et al., 2016b; Riquelme et al., 2015). The performance metrics for MaOO, especially convergence, diversity, and cardinality criteria, have received several criticisms. The misleading results obtained from these convergence criterion metrics due to the curse of high dimensionality in MaOO cause evaluation results that rely on one or two metrics to become inaccurate. The sensitivity of certain diversity criterion metrics to the reference point set specification creates confusion in the selection of the best diversity criterion metrics and the differentiation between diversity and uniformity criteria because these two criteria often give rise to confusion (Ishibuchi et al., 2016e). In addition, the number of nondominated solution results increases remarkably with the increase in the number of objectives, thereby making the cardinality criterion an issue during evaluation. Although these metrics have been criticised in literature, they are still randomly selected and applied in the evaluation of the performance of MaOO algorithms. Moreover, the process of selecting any of these metrics remains unclear (Coello et al., 2020; Ishibuchi et al., 2016e; Pal et al., 2016a; Wang et al., 2017b; Wang et al., 2020)

Problem 2: Limitation in determining the significant contribution (weigh of importance) for each of this MaOO criterion and its indicators

In MaOO approaches, performance criteria are considered a critical challenge because the high-dimensional objective space increases the conflict between convergence and diversity; this conflict remains a challenge for evaluation because of the imbalance in the results (Cai et al., 2015b). Many performance metrics have been proposed in the last decades. Several of them have gradually disappeared, whereas others continue to dominate. In addition, the extent to which these metrics affect evaluation performance is still unclear and requires additional effort because of the lack of agreement on which metric to apply in evaluating the performance of MaOO algorithms (He et al., 2016b; Riquelme et al., 2015; Yu et al., 2018a). The evaluation of the work focuses on assisting and comparing the performance quality indicators or the functionality of state-of-the-art optimisation algorithms for MaOPs. A comparison of the performance of MaOO algorithms is the main procedure in performance evaluation. Many studies have attempted to manipulate such comparison to analyse the performance quality of MaOO. Several of them have conducted investigations on the basis of an existing approach, such as in (Chebli et al., 2016), (Ishibuchi et al., 2016c), (Santos et al., 2018) and (Li et al., 2019). However, (Yu et al., 2018a) proposed a new way for evaluating MaOO algorithms. Yet, the role of evaluation criteria is totally ignored. In such cases, the weight of importance is critical for evaluating the performance of MaOO algorithms. Many indicators have been developed in recent decades to compare the quality performance of various evolutionary approaches in MaOO. Although all of these criteria and their indicators show high efficient results in evaluating and comparing the MaOO, the degree of importance for each of them in implementing the evaluation is ambiguous and subject to further study and investigation (He et al., 2016b; Riquelme et al., 2015; Yu et al., 2018a). Furthermore, in a particular evaluation scenario based on a set of selected criteria, some criteria should have more importance than others according to the relevant needs and changes in the scenario. However, relevant studies with an evaluation of MaOO have not provided any weighting mechanisms for the criteria that have been used during the evaluation process. Thus, assigning weights for the evaluation criteria of MaOO needs further study.

1.3.2 Theoretical Gap

A decision support system is proposed on the basis of the MCDM method to solve multiple criteria attributes that may increase the quality of decision making. In the real world, beneficial methods that address MCDM issues are introduced as the recommended solutions to support decision-makers in solving problems and performing weight determination and evaluation (Brugha, 1998; Kaya et al., 2018; Serrai et al., 2017; Yu et al., 2018b).

The mathematical criteria weighting method assigns weights to attributes that are characterised by the relative importance of criteria (Brugha, 1998). These weights indicate the condition and impact within each attribute in the assessment and decision-making process (Hwang et al., 2011). Overall, two approaches can be used to identify criteria weight, namely, objective and subjective assessments (Wang et al., 2009b).

To evaluate the weights of criteria, the objective evaluation approach uses the information on each criterion with certain techniques, including the Criteria Importance through Intercriteria Correlation (CRITIC) and Entropy (Lin et al., 2017; Mohammed et al., 2020; Petković et al., 2017). Such strategies do not rely on the subjective judgment of decision-makers on weight assignment. Weights are assigned by a mathematical method to the criteria (attributes) (Zavadskas et al., 2016). These methods are commonly used in the previous study, while inconsistency issues cannot be produced; however, the subjective weights of the findings are the most important factors to determine, as they reflect the opinions of highly qualified experts with extensive experience (Vinogradova et al., 2018). If the raw data change, the precision of the weights obtained for the evaluation criteria can be changed. Therefore, in these techniques, the mechanism for specifying weights is not perfect. For example, suppose the criteria must be subjectively weighted. In that case, such methods cannot add the expertise and subjective value of decision-makers to a decision, which takes the drawbacks of such techniques into consideration (Khatari, 2020).

Subjective evaluation gives importance to attributes dependent on the experience of decision-makers and subjective value. Subjective weights represent the cumulative experience and subjective judgment of decision-makers (Nigim et al., 2004; Salih et al., 2020). Examples for these techniques are the analytic hierarchy process (AHP) and the best worst method (BWM) (Rezaei, 2015a). AHP is a very popular tool in MCDM, which depends on human preferences (Leung et al., 2000). This method was developed by Thomas L. Saaty (Saaty, 1990). Despite the success of AHP, the weighting procedure has a significant drawback—the inconsistency issue (Tung et al., 1998). In AHP, the measured priorities are only feasible when the consistency check has been passed to the pairwise comparison. In addition, many decision problems cannot be hierarchically ordered if consideration should be given to the relationship and dependency of high-level elements with low-level elements.

In addition, the weights of the criteria are also generated in BWM on the basis of pairwise comparison among the set of criteria (Rezaei, 2015a). BWM is one of the most relevant and most modern MCDM approaches, which requires fewer comparisons than AHP, resulting in high consistency in the determination of weight criteria (Rezaei, 2016). In 2015, BWM suggested that the weights of criteria can be calculated by comparing them with a reduced number of pairwise comparisons (i.e. 2n-3, where n represents the number of criteria). In the meantime, Fuzzy BWM is better compared with Fuzzy AHP in terms of consistency (Guo et al., 2017b; Sofuoğlu et al., 2017). BWM performs reference comparisons, meaning that only the preference for the best criteria and the preference of all the criteria over the worst criterion have to be determined (Guo et al., 2017b). The strengths of fewer comparisons are not fractional, and they facilitate the understanding of decision-makers (experts) compared with most MCDM approaches. BWM utilises a 1-9 scale to perform pairwise comparisons (Rezaei, 2015a). As mentioned above, BWM effectively decreased the number of the pairwise comparisons from $\mathrm{n}(\mathrm{n}-1)/2$ in AHP to $2\mathrm{n}-3$ in BWM (Yang et al., 2016).

Similar to AHP, the first problem in the BWM is the difficulty in deciding the best and worst criteria and the significant value of all criteria against the worst criterion and the best criteria over certain criteria (Rezaei, 2015a). The decision-maker specifies the number of times a certain criterion is compared with other criteria when the measure takes a scale, which ranges from 1 to 9. Given uncommon subjective comparisons, this comparison requires a large cognitive capacity. In other words, it is not a normal method, and it is hard to compare the two uncorrelated criteria. Furthermore, the original and the extended versions of the BWM propose several measurements for consistency; however, certain weaknesses exist, including: (i) deficiency of a procedure to offer the decision-maker instant feedback on the consistency of pairwise comparisons, (ii) absence of accounting for ordinary consistency and (iii) shortage of consistency threshold value to evaluate the reliability of results (Liang et al., 2019). Defining the significant level for MaOO criteria is considered a challenging task. As mentioned, MCDM weighting methods can tackle such issue. However, superior weighting methods, such as AHP and BWM, suffer from inconsistency issues. On the basis of the inconsistency issues of the existing MCDM weighting methods, using any of the existing methods is impractical because of the highlighted drawbacks. Furthermore, one theoretical gap is that no method that provides a practical weighting paradigm without inconsistency has been proposed yet.

In conclusion, the proposed evaluation criteria model that aims to standardize the most suitable criteria and propose a new weighting method to weigh them based on their importance without inconsistency will provide an exhaustive evaluation methodology for assessing the MaOO algorithms. The configuration of the problem statement is demonstrated in Figure 1.1.

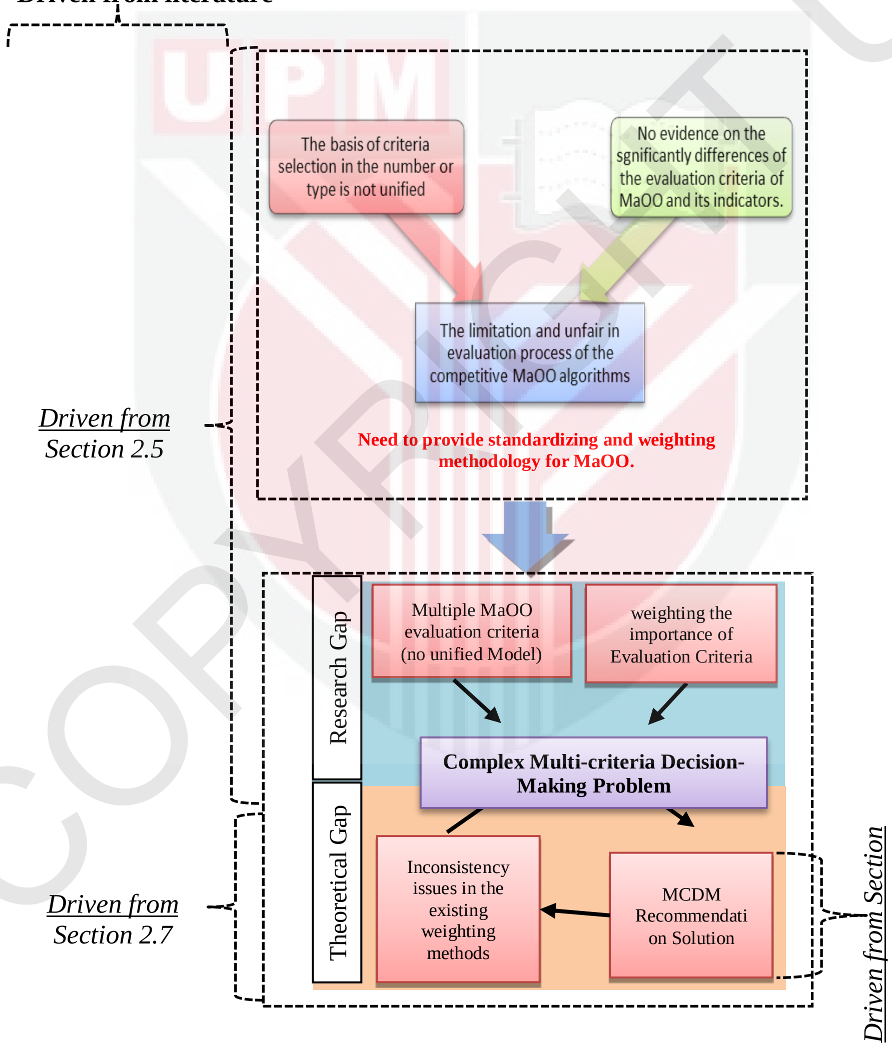

Figure 1.1 : Problem Statement Configurations

1.4 Research Questions

- **RQ-1**: What are the available techniques for evaluation the performance of many objective optimization (MaOO) algorithms? And how are they employed to evaluate the competitive MaOO algorithms?
- **RQ-2**: Which evaluation criteria are addressed for many objective optimization algorithms?
- **RQ-3**: To what extend these criteria significantly affect the evaluating of the competitive MaOO algorithms?
- **RQ-**4: How can overwhelming the inconsistency of pairwise and reference comparisons in the existing weighting methods in determining the importance of each evaluation criterion?
- **RQ-**5: What are the suitable methods for developing an exhaustive evaluation methodology to evaluate the MaOO algorithms?
- **RQ-**6: To what extent are the results of the proposed method valid and efficient?

1.5 Research Objectives

This study aims to develop standardizing and weighting methodology for the evaluation criteria of many-objective optimization competitive algorithms based on fuzzy Delphi and fuzzy-weighted zero-inconsistency methods. Therefore, the objectives of this study are presented as follows:

- To investigate the existing technologies on many-objective optimization algorithms evaluation and highlight the weakness.
- To propose a unified criteria model for the evaluation process in the context of MaOO based on fuzzy Delphi Method.
- To develop a new weighted method with zero inconsistency.
- To determine the weight of criteria based on exhaustive evaluation methodology of the unified model and the new proposed method**.**
- To evaluate the Fuzzy weighted method with zero inconsistency (FWZIC), based on subjectively and comparison analysis.

1.6 The Connectivity amongst Research Objectives, Questions and Research problem

The specific and general research problems that have derived from the proposed research questions and its relationship with the research objectives are demonstrated in Table 1.1. This research questions are used to guide and focus on the research, whereas the research objectives have provided the necessary answered to solve the discussed research problem.

Table 1.1 : The Connectivity amongst Research Objectives, Questions and Research problem

		Research Problem mapping	
Research Questions	**Research Objectives**	**Specific Problem**	**General Problem**
RQ-1: What are the available techniques for evaluation the performance of many objective optimization (MaOO) algorithms? And how are they employed to evaluate the competitive MaOO algorithms?	• To investigate the existing technologies on many objective optimization algorithms evaluation and highlight the weakness.		Standardizing and weighting problem
RQ-2: Which evaluation criteria are addressed for many objective optimization algorithms?	• To propose a standardized criteria model for the evaluation process in the context of MaOO based on fuzzy Delphi Method.	• Lack of defining the MaOO evaluation criteria. • Lack of a unified model is one reason for the MaOO evaluation problem.	
RQ-3: To what extend these criteria significantly affect the evaluating of the competitive MaOO algorithms? **RQ-5: What are the suitable methods for developing an exhaustive evaluation methodology to evaluate the MaOO algorithms?**	• To develop new weighted method with zero inconsistency	• Inconsistency in criteria weighted values.	
RQ-4: How can overwhelm the inconsistency of pairwise and reference comparisons in determining the importance of each evaluation criterion?	• To determine the weight of criteria based on exhaustive evaluation methodology of the unified model and the newly developed method.	• Multi-criteria evaluation • Importance of criteria.	
RQ-6: To what extent are the results of the proposed exhaustive evaluation methodology valid and efficient?	• To evaluate the Fuzzy weighted method with zero inconsistency (FWZIC), based on subjectively and comparison analysis.		

1.7 Scope of the study

This research investigates the existing methods in evaluating the performance of MaOO algorithms. The research was designed to solve the problem of randomize selection of the criteria and the ignorance of its significant in evaluating the MaOO. Thus, this research focusses on developing a standardizing and weighting methodology for evaluation criteria of MaOO. However, this research does not claim that the evaluation criteria are only limited to the criteria in the proposed unified model.

The research focuses on proposing a new weighing method that can compute the importance of evaluation criteria without any inconsistency. The unified evaluation criteria of MaOO are used in the experimental to compute the importance weight for each criterion and its indicators as proof of concept of our proposed methodology.

1.8 Research Contribution and significant

The main contribution of this research is to create a standardizing and weighting methodology for the evaluation criteria of many-objective optimization competitive algorithms based on fuzzy Delphi and fuzzy-weighted zero-inconsistency methods. This methodology can solve the evaluation process in optimization field. Furthermore, it can provide and assist the optimization community and industrial (researchers and developers) by provide exhaustive evaluation methodology for evaluating MaOO algorithms, which can be generalized to solve such problem effectively. Figure 1.2 demonstrates the contribution diagram.

Standardizing and Weighting Methodology for the Evaluation Criteria of Many-Objective Optimization Competitive Algorithms Based on Fuzzy Delphi and Fuzzy-Weighted Zero-Inconsistency Methods

Problem 1:

The basis of criteria selection in the number or type is not clear.

- Evaluation process for Optimization algorithms (MaOO) is challenging job and are problematic due to multiple criteria that need to be considered (Ma, Yang, Wu, Ji, & Zhu, 2016), (Ishibuchi, Imada, Setoguchi, & Nojima, 2016) (Ishibuchi, Masuda, & Nojima, 2015).
- There is no agreement on which of those criteria are the most suitable for evaluation of MaOO, (Yu & Lu, 2018).

Objective

To standardize the criteria model for exhaustive evaluation process in the context of MaOO.

How to solve the problem 1:

Identify the most important evaluation criteria using Fuzzy Delphi method (FDM)

Contribution 1:

A standardized model for evaluation criteria of MaOO

Problem 2:

There is no study considered or computed the importance of the evaluation criteria of MaOO and its indicators.

- Some of the studies considered only few criteria metrics with no evidence of its performance overwhelming in compared to others, such as Hypervolume, IGD, and GD (Wang, Jin, & Yao, 2017). Defining the significant level for MaOO criteria is considered a challenging task.
- In AHP the number of comparisons increase progressively when the number of criteria is increased. As a result, pairwise comparisons introduce a particular amount of inconsistency (Destercke, 2018; Koczkodaj & Urban, 2018; Morgan, 2017) BWM **shows difficulty to determine** the best and worst criteria and importance level of the best criterion overall criteria as well as the importance of all criteria over the worst criterion (Salih et al., 2020)

Objectives

To formulate and develop a new weighted method with zero inconsistency.

How to solve the problem 2:

Based on proposed criteria model and the proposed new weighting method without consistency (FWZIC)

Contribution 2:

A new method for weighing the MaOO criteria importance with zero inconsistency.

Figure 1.2 : Contribution diagram

1.9 Structure of Thesis

This research is composed of six chapters. Figure 1.2 demonstrates the structure of the study These chapters are briefly reviewed as follow:

Chapter 1 – Introduction: this chapter introduce the research background, problem statement. In addition to illustrate the research questions, objectives and connectivity among research objectives, research questions, specific problem, and general problem. Moreover, this chapter presents the research scoup and contribution to the body of knowledge and the significant of the study.

Chapter 2 - Literature Review: a systematic review analysis for the Many-objective optimization algorithms presents in this chapter, an overview on optimization and the differences between single-, multi- and many objective optimizations discussed in this chapter. In addition, to exam, analysis and criticize the literature work on Many objective optimization algorithms. Moreover, analyse the existing evaluation criteria weighting methods and highlight its issues. End with the open issues of evaluating the MaOO and the recommended solutions.

Chapter 3 – Research Methodology: describe the research methodology in detail which consists of in four main phases, namely, investigation phase, proposed unified MaOO evaluation criteria model phase, development of new weighting method phase, and evaluation and comparison study phase. Through the phases, this chapter will show in precisely how the five research objectives will be achieved.

Chapter 4 - Unifying the Evaluation Criteria of Many-Objective Optimization Competitive Algorithms: This chapter presents and discusses the result model of the most suitable evaluation criteria set for MaOO. Further, this chapter explains how the proposed model solve the problems outlined in the problem statements. The validation process of the proposed model also presented.

Chapter 5 - Application of The Fuzzy-Weighted Zero-Inconsistency Method: This chapter presents and discusses the results of the proposed weighting methods FWZIC. Further, this chapter explains how the proposed exhaustive evaluation methodology's results solve the problems outlined in the problem statements. The results of the comparison studies are also discussed.

Chapter 6: Conclusion and Future Work. This chapter provides the study's conclusion and is followed by the highlights, the summary of research contributions, the limitations, and a discussion of future work.

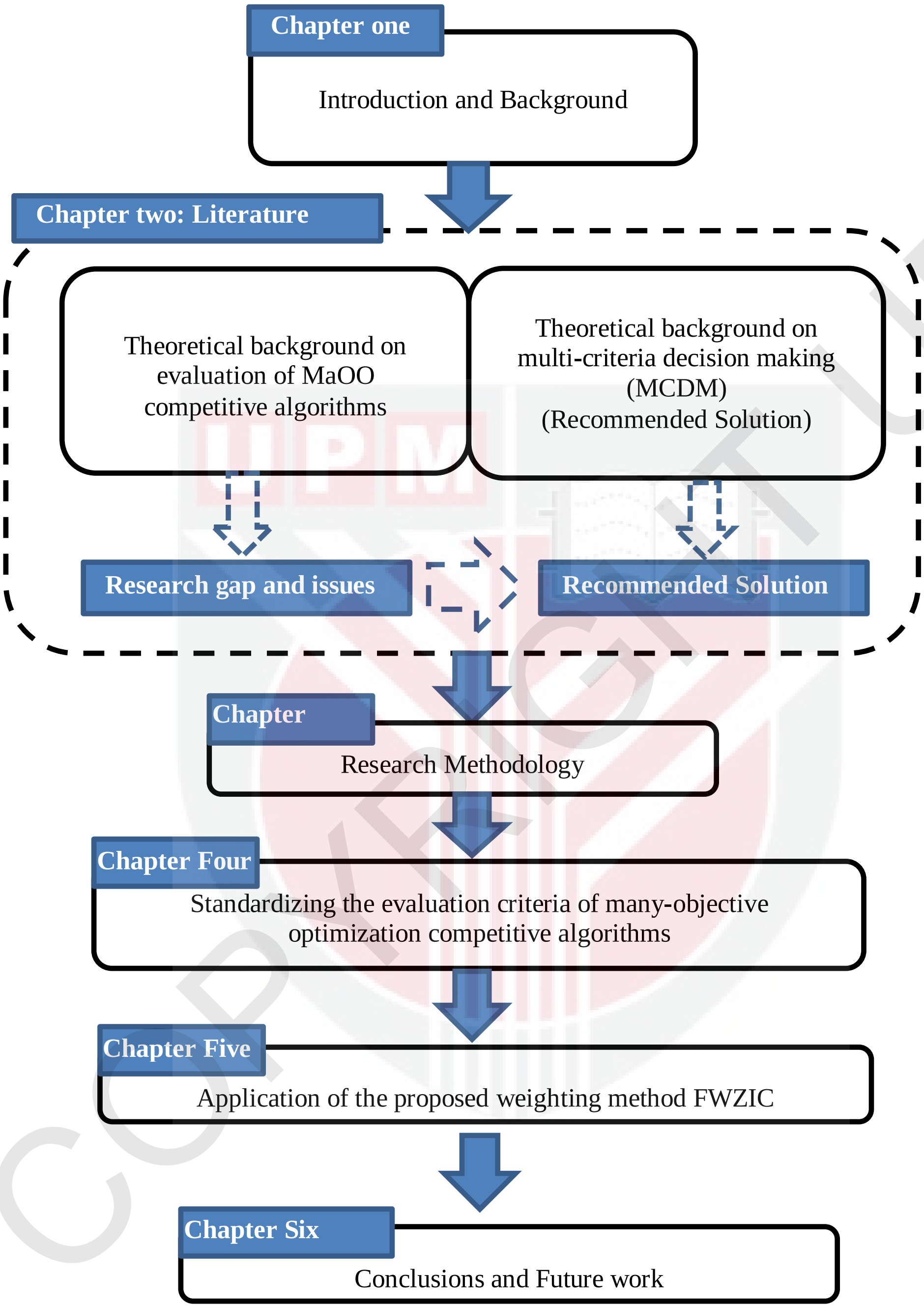

Figure 1.3 : Structure of the thesis

1.10 Chapter Summary

This chapter presents the background of the study. Specifically, it describes the concept of optimization and evaluation many objective optimization algorithms, as well as the criteria that use in evaluation process. The most vital point of this study's background is that evaluation criteria which is indicate the quality of MaOO performance. As such, different criteria might measure the same MaOO and show comparison results in a different way. This chapter also illustrates the inappropriate and random selection of evaluation criteria and how it can adversely affect the results and decision making in developing of comparing the MaOO algorithms and might be financially cost for the industry and optimization community if it is failed to meet their expectations. Following this are detailed explanations of the problem statement, the research objectives and scope, and the study's significance.

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Rawia Tahrir Salih Mohammed (R. T. Mohammed) was born in Dec. 1982 in Baghdad – Iraq. She studied her bachelor in computer science at the University of Baghdad from 2000 to 2004, and she graduated as the first rank among the 144 students with a CGPA of 8.86/100. In 2005 the good academic record granted her the opportunity to be hired as a lecturer at the University of Baghdad and pursue her master study in computer science at the university of technology – Baghdad to be graduated in 2007 with the second rank. In 2010, she was invited as a scholar visitor for one year at Smith College – the USA under the Iraq women fellowship foundation program. In 2011, she was invited to attend the International Forum on Women in Science &Technology held in Kuala Lumpur. Furthermore, she is IEEE student member and IEEE WIE member since 2012. In addition to her volunteer work as a member of Peer Support Group under School of Graduated - Universiti Putra Malaysia. In February 2018, she enrolled as a full-time student at Universiti Putra Malaysia, Malaysia where she is pursuing a Ph.D. degree in Intelligent Systems.

LIST OF PUBLICATIONS

Journals

Mohammed, R. T., Yaakob, R., Zaidan, A. A., Sharef, N. M., Abdullah, R. H., Zaidan, B. B., & Dawood, K. A. (2020). Review of the Research Landscape of Multi-Criteria Evaluation and Benchmarking Processes for Many-Objective Optimization Methods: Coherent Taxonomy, Challenges and Recommended Solution. *International Journal of Information Technology & Decision Making (IJITDM), 19*(06), 1619-1693. (published)

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