COMPONENT-WISE ANALYSIS OF METAHEURISTIC ALGORITHMS FOR NOVEL FUZZY-META CLASSIFIER

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A thesis submitted in fulfillment of the requirement for the award of the Doctor of Philosophy

Faculty of Computer Science and Information Technology
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In the name of Allah, Most Gracious, Most Compassionate.

I praise and thank Allah.

Special thanks to my spiritual leader Pir Muhammad Saddique Qureshi Naqshbandi,
my beloved father Ashique Hussain and mother Nadra Baloch.

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(Wife, brother, brother, brother, sister, sister, sister, brother-in-law)
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This thesis is dedicated to all of you.
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ABSTRACT

Metaheuristic research has proposed promising results in science, business, and engineering problems. But, mostly high-level analysis is performed on metaheuristic performances. This leaves several critical questions unanswered due to black-box issue that does not reveal why certain metaheuristic algorithms performed better on some problems and not on others. To address the significant gap between theory and practice in metaheuristic research, this study proposed in-depth analysis approach using component-view of metaheuristic algorithms and diversity measurement for determining exploration and exploitation abilities. This research selected three commonly used swarm-based metaheuristic algorithms – Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Cuckoo Search (CS) – to perform component-wise analysis. As a result, the study able to address premature convergence problem in PSO, poor exploitation in ABC, and imbalanced exploration and exploitation issue in CS. The proposed improved PSO (iPSO), improved ABC (iABC), and improved CS (iCS) outperformed standard algorithms and variants from existing literature, as well as, Grey Wolf Optimization (GWO) and Animal Migration Optimization (AMO) on ten numerical optimization problems with varying modalities. The proposed iPSO, iABC, and iCS were then employed on proposed novel Fuzzy-Meta Classifier (FMC) which offered highly reduced model complexity and high accuracy as compared to Adaptive Neuro-Fuzzy Inference System (ANFIS). The proposed three-layer FMC produced efficient rules that generated nearly 100% accuracies on ten different classification datasets, with significantly reduced number of trainable parameters and number of nodes in the network architecture, as compared to ANFIS.
ABSTRAK

Penyelidikan metaheuristik yang terkini telah memberikan hasil kajian yang lebih baik dalam sains, perniagaan, dan masalah kejuruteraan. Namum, banyak analisis tahap tinggi telah dilakukan atas kebolehupayaan kaedah metaheuristik. Persoalan kritikal yang belum diselesaikan adalah masalah ‘kotak hitam’ yang tidak mendedahkan kebolehupayaan algoritma metaheuristik hanya menyelesaikan masalah tertentu dan tidak menyeluruh dalam semua penyelesaian. Bagi menangani jurang yang ketara antara teori dan amalan dalam penyelidikan metaheuristik, kajian ini mencadangkan pendekatan analisis mendalam menggunakan komponen algoritma metaheuristik dan pengukuran kepelbagaian untuk menentukan keupayaan penerokaan dan eksploitasi. Kajian ini memilih tiga algoritma metaheuristik iaitu Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), dan Cuckoo Cuckoo (CS) untuk melaksanakan analisis komponen yang lebih cekap. Hasil kajian yang dicadangkan telah membuktikan kemampuan menangani masalah penumpuan awal PSO, eksploitasi yang lemah ABC, dan isu penerokaan dan eksploitasi yang tidak seimbang CS. Dari kajian sorotan sedia ada, cadangan PSO yang lebih baik (iPSO), penambahbaikan ABC (iABC), dan peningkatan CS (iCS) termasuk Gray Wolf Optimization (GWO) dan Animal Migration Optimization (AMO) telah mengatasi kebolehupayaan algoritma dan variasi piawai berdasarkan masalah modaliti yang berbeza. Implementasi cadangan iPSO, iABC, dan iCS terhadap Fuzzy-Meta Classifier (FMC) yang baru dapat menawarkan penurunan kerumitan model dan meningkatkan ketepatan berbanding kaedah Adaptive Neuro-Fuzzy Inference System (ANFIS). Cadangan tiga lapisan FMC menghasilkan petua yang berkesan dengan ketepatan hampir 100% berdasarkan sepuluh kumpulan data klasifikasi yang terpilih, pengurangan ketara bilangan parameter yang terlatih dan bilangan nod dalam seni bina rangkaian berbanding kaedah ANFIS.
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CHAPTER 1

INTRODUCTION

Computation has been so pervasive in our daily routine that we sometimes do not even realize while using it. From a tiny electronic gadget in our hands to the super systems controlling space shuttles utilize computing so intelligently that we could hardly imagine in past. Today, computational intelligence (CI) keeps airplanes in the air, driver-less cars on the road, and even simply washing clothes. CI plays vital role in computational problem solving that involves large data and enormous computation to make efficient and intelligent decisions. The popular CI techniques include artificial neural network (ANN), fuzzy logic, and evolutionary algorithms, which adhere to the basic requirements of intelligence: comprehend, reason, learn, and make intelligent decision. Such intelligent techniques are aimed at solving ill-defined, complex, nonlinear, and dynamic problems by choosing the best one from the large choice of available solutions to a given problem. Because, the size of solutions is large, these techniques couple with optimization methods, called metaheuristic algorithms, to choose the best solution (Zhang et al., 2015).

In CI techniques, neuro-fuzzy systems have earned more success as compared to neural networks and support vector machines etc., mostly because of accuracy in data approximation and ability to deal with uncertainty (Arshad et al., 2013). Among other neuro-fuzzy systems is adaptive neuro-fuzzy inference system (ANFIS) (Jang, 1993) which has shown significant generalization capability than other neural networks and statistical methods in variety of applications (Bardestani et al., 2017; Faustino et al., 2014; Zamani et al., 2015). However, the applications with large input size halt ANFIS implementation due to curse of dimensionality. To address
This, ANFIS is incorporated with other techniques such as clustering methods (Cai, 2017), support vector machine (Azadeh et al., 2013) to generate smaller number of rules; on the other hand, ANFIS architecture has also been modified to produce accurate results with less computational cost (Peymanfar et al., 2007). Nonetheless, the model complexity still downturns wider applicability of the system. This leads to motivation for developing simple and as efficient classifier based on motivation from fuzzy logic and neural network. This research is aimed at proposing a novel classification model that utilizes effective data interpretability of fuzzy logic, learning capability of neural networks, and efficient optimization ability of the modern metaheuristic algorithms. Since the proposed classification model is simple and efficient, hence it offers opportunities to solve classification problems with large input-size.

The motivation and background of this research is briefed in Section 1.1, followed by Section 1.2 which defines the problem statement. The aims and objectives of the study are presented in Section 1.3 and 1.4, respectively. Section 1.5 determines the scope of the research, while significance is highlighted by Section 1.6. The schedule of this research work is presented in Section 1.7, whereas Section 1.8 provides the outline of the dissertation.

1.1 Research background

It is no exaggeration that optimization is everywhere, be it engineering design, stock market, scheduling, or transportation. Various exact and conventional methods have been used to solve optimization problems, but metaheuristics have earned more popularity; due to efficiency in searching optimal solutions with affordable computational cost (Yang, 2010b). There is established research by metaheuristic community with literature providing outstanding results on wide variety of applications, as compared to traditional statistical and gradient-based optimization methods (Cheng & Prayogo, 2014; Ervural et al., 2017; Manjarres et al., 2013; Zhang et al., 2015). This has overwhelmingly motivated researchers to modify existing metaheuristic algorithms or invent the new methods by inspirations from nature, as well as, man-made processes. Generally, all the metaheuristic algorithms follow same basic principles: stochastic in nature using randomness in search moves,
no gradient information required, problem specific tuning of parameters, and traverse search environment in iterations (Cheng & Prayogo, 2014). That said, Sørensen (2015) argues that the exorbitance in metaheuristic research is often attributed to trivial comprehension of theoretical foundations and practical evidence. Supporting the argument, Yang (2012b) contends that the research in metaheuristics is heuristic and ad-hock. Currently, there exists significant gap between theory and practice, as some of the important questions on metaheuristic performances are yet to be answered. This is detrimental to the development of the field of metaheuristics as there have appeared many “not so important contributions” or even futile metaphore-based methods that are often forgotten quickly (Sørensen et al., 2017).

Despite successful implementations and superiority reported in literature, there are few general issues that need to be addressed in order to utilize metaheuristics to full potential (Boussaïd et al., 2013). This raises immense need of critical and comparative analysis of metaheuristic performance over certain optimization problems. It should be primarily based on theoretical and operational approaches behind mechanisms adopted for search of optimal solutions in large search space (Blum & Roli, 2003). However, it is noteworthy that the field of metaheuristics is still to reach maturity as compared to physics, chemistry, and mathematics; more attention needs to be drawn towards in-depth understanding of metaheuristic algorithms by analysing the issues and try to answer the core question “why certain metaheuristic algorithms perform better on certain problems and not on others?” (Fister Jr et al., 2013; Sörensen, 2015; Sorensen et al., 2017). This is often supported with “no-free-lunch” theorem (Yang, 2012c), although Yang (2012b) nonetheless asserts that inner working of metaheuristic algorithms is still a “blackbox”. Mere high-level analyses of end results may help determine “what” happened, but the important questions of “how” and “why” raised by Sorensen et al. (2017), Yang (2012b), and He et al. (2017) require more in-depth analyses to narrow the gap between theory and practice. According to Sörensen (2015), component-based view of metaheuristic algorithms will lead to focus on specific issues related to algorithm performances.

In metaheuristics, algorithms based on swarm intelligence are gaining more success as compared to other population-based counterparts (Cheng et al., 2016; Yang, 2012a). Thanks to landmark particle swarm optimization (PSO) (Eberhart & Kennedy, 1995) and ant colony optimization (ACO) (Corne et al., 1999) which
derived the addition of adequately increasing number of swarm-based metaheuristic algorithms – not necessarily are all efficient methods hence not achieved generous acceptance in metaheuristic community. This research considers top three swarm-based metaheuristic algorithms for in-depth analyses based on component-view and exploration and exploitation measurements using population diversity.

Data mining is an important research area in soft computing. In data mining and model approximation, several techniques have been developed which employ machine learning approaches to adapt according to the problem under consideration; for example, support vector machine, neural networks, and fuzzy neural networks. Apart from fuzzy neural networks, other models are subjected to inability of explaining the decision. Therefore, scientific models based on these techniques are rather incomprehensible and non-transparent (black-box) (Hussain & Salleh, 2015). Many real-life problems; such as credit risk evaluation and medical diagnosis require evaluators (e.g. financial regulator or auditors, and physicians) to comprehend and reason the decision. Hence, transparency is crucial in such matters. A fuzzy neural network such as adaptive neuro-fuzzy inference system (ANFIS) (Jang, 1993) generates rules that can explain the decision made by the system. ANFIS is highly adaptive and accurate among other fuzzy inference systems (Taylan & Karagözoğlu, 2009), hence applied in wide variety of disciplines including science, engineering, business, and education, etc. (Kar et al., 2014). However, because of high model complexity and computational cost, the applications of ANFIS are often limited to problems with lesser inputs. Even small increase in the number of inputs, makes ANFIS architecture complex due to exponential rise in rules and trainable parameters; resulting in curse of dimensionality (Younes et al., 2015). Many modifications have been proposed by researchers which include incorporating metaheuristic algorithms to replace gradient based learning (Karaboga & Kaya, 2013; Nhu et al., 2013; Pousinho et al., 2012; Rini et al., 2013; Younes et al., 2015), model structure modifications (Faustino et al., 2014; Peymanfar et al., 2007), and rule-base minimization (Eftekhari & Katebi, 2008; Panella, 2012), etc.

Mostly in literature, researchers have embedded feature selection techniques to reduce input-size or clustering algorithms to reduce rule-base. This makes ANFIS applications more complex. The current study proposes a novel classification algorithm to address both the issues of model complexity and computational cost. The proposed classifier utilizes data interpretability of fuzzy logic, rule generation
capability of inference system, and optimization efficiency of metaheuristic algorithms. The core benefit of the proposed classifier lies in optimizing its parameters through metaheuristic algorithms, as these algorithms have proved efficiency in solving optimization problems.

Based on the research motivation discussed earlier, the subsequent section presents the statement of the problem pertaining to current research.

1.2 Problem statement

Today’s complex real-life problems are often solved by techniques coupled with metaheuristic algorithms, to find the best from large number of available solutions (Yang, 2010b). Generally, the success of metaheuristic algorithms over exact methods is attributed to effective search mechanisms adopted from natural or man-made processes. In these approaches are swarm behaviours found in natural organisms demonstrating highly intelligent social interactions, to best survive in a given environment. Swarm-based metaheuristic algorithms have earned more success as compared to other population-based counterparts (Cheng et al., 2016). However, there remain significantly important unanswered questions that develop gap between theory and practice. Metaheuristic research is generally found with high-level analyses of end results – unable to address “black-box” issue of the algorithm performances (Fister Jr. et al., 2013). The in-depth analysis of individual metaheuristic components will lead to address problems in weak components, to effectively modify for performance improvement (He et al., 2017; Sörensen, 2015).

Among the most successful swarm-based metaheuristic algorithms are Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Cuckoo Search (CS). Despite success, each of these algorithms maintains certain shortcomings. PSO suffers from premature convergence due to lack of diversity, ABC has poor exploitation ability because of extraordinary randomness in scout bees, and CS bears imbalanced exploration and exploitation caused by inconsistent swarm behaviour. This research performed in-depth analysis on PSO, ABC, and CS using component-wise approach to address the aforementioned issues. The proposed component-wise approach helped answer the crucial performance related questions pertaining to “why” and “how” instead of just “what” happened. The analyses are
REFERENCES


