

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

FORMULATION OF METAHEURISTIC ALGORITHMS BASED ON ARTIFICIAL BEE COLONY FOR ENGINEERING PROBLEMS



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Faculty of Electrical Technology and Engineering

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UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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DEDICATION

To the Almighty, my beloved family and friends.



ABSTRACT

The Artificial Bee Colony (ABC) algorithm is a powerful metaheuristic optimization technique inspired by the honeybee foraging behaviour. However, ABC algorithm can struggle to explore new regions effectively, leading to slow convergence and premature convergence on suboptimal solutions. This research addresses these limitations by developing modified ABC algorithms specifically for tackling engineering optimization problems. Recognizing limitations in the employed bee phase, the research applies the modification rate (MR) in the employed bee phase to increase the permutation chances for each dimension within the solution space. The impacts of these modification rates in optimizing the engineering problems are analyzed. Additionally, two new hybrid algorithms called Artificial Bee Rabbit Optimization (ABRO) and Bee Eel Forage Algorithm (BEFA) are proposed by combining ABC with Artificial Rabbits Optimization (ARO) or Electric Eel Foraging Optimization (EEFO). The performances of these hybrid algorithms are evaluated using 25 benchmark functions and applied to the IEEE 26-bus system for power system economic dispatch, emission dispatch, and weighted sum optimization. Results demonstrate that the proposed hybrid algorithms (ABRO and BEFA) improve convergence speed and solution quality compared to predecessor algorithms on most benchmark functions. According to the Friedman test, ABRO outperforms ABC and ARO on 16 out of 25 benchmarks, while BEFA achieves the best performance on all 25 benchmark functions than EEFO and ABC. Moreover, they are also able to minimize generated costs and emissions for the IEEE 26-bus system where they achieve the least average and least standard deviation. Furthermore, a novel multiobjective variant is proposed where it incorporates Pareto concepts with non-dominated sorting, crowding distance, and adaptive grid mechanisms. Its effectiveness is showcased through evaluation using 5 benchmark ZDT functions and application to the IEEE 26-bus system for multiobjective optimization challenges such as economic and emission dispatch. The MOBEFA obtains higher average hypervolume and maximum spread which shows better solution quality and diversity when comparing to Non-Dominated Sorting Genetic Algorithm II (NSGA-II) in all five ZDT functions. This research significantly contributes to the advancement of ABC variants and their hybridizations. The developed algorithms demonstrate promising potential for enhancing optimization performance across both single-objective and multiobjective domains within the field of engineering.

FORMULASI ALGORITMA METAHEURISTIK BERDASARKAN KOLONI LEBAH TIRUAN BAGI MASALAH KEJURUTERAAN

ABSTRAK

Koloni Lebah Tiruan (ABC) adalah teknik pengoptimuman metaheuristik yang berkuasa dan diinspirasikan oleh tingkah laku mencari makan oleh lebah madu. Namun, ia tetap menghadapi masalah seperti penumpuan yang perlahan atau penumpuan awal pada penyelesaian yang tidak optimum. Kajian ini menangani kekangan ini dengan membangunkan algoritma ABC yang diubah suai khusus untuk menangani masalah pengoptimuman kejuruteraan. Kajian ini menggunakan kadar pengubahsuaian (MR) dalam fasa lebah pekerja untuk meningkatkan peluang permutasi bagi setiap dimensi. Impak kadar pengubahsuaian ini dalam mengoptimumkan masalah kejuruteraan dianalisis. Selain itu, dua algoritma hibrid baharu yang dipanggil Pengoptimuman Arnab Lebah Tiruan (ABRO) dan Algoritma Pencarian Makanan Belut Lebah (BEFA) dicadangkan dengan menggabungkan ABC dengan Pengoptimuman Arnab Tiruan (ARO) atau Pengoptimuman Pencarian Makanan Belut Elektrik (EEFO). Prestasi algoritma hibrid ini dinilai menggunakan 25 fungsi penanda aras dan digunakan pada sistem bas 26 IEEE untuk penghantaran ekonomi sistem kuasa, penghantaran emisi, dan pengoptimuman jumlah berwajaran. Hasil kajian menunjukkan bahawa algoritma hibrid yang dicadangkan (ABRO dan BEFA) meningkatkan kelajuan penumpuan dan kualiti penyelesaian berbanding algoritma pendahulunya pada kebanyakan fungsi penanda aras. Menurut ujian Friedman, ABRO mengatasi ABC dan ARO pada 16 daripada 25 penanda aras, manakala BEFA mencapai prestasi terbaik pada semua 25 fungsi penanda aras berbanding EEFO dan ABC. Selain itu, ia juga dapat mengurangkan kos dan pelepasan yang dihasilkan untuk sistem 26bas IEEE di mana ia mencapai purata paling rendah dan sisihan piawai paling rendah. Selain itu, algoritma varian multiobjektif baharu yang menggunakan konsep Pareto juga dicadangkan dengan menggunakan pengkelasan bukan dominan, jarak kesesakan, dan mekanisme grid adaptif. Keberkesanannya dipamerkan melalui penilaian menggunakan 5 fungsi ZDT penanda aras dan aplikasi pada sistem bas 26 IEEE untuk cabaran pengoptimuman multiobjektif, terutamanya dengan mempertimbangkan kedua-dua ekonomi dan pelepasan. MOBEFA memperoleh hipervolume purata dan penyebaran maksimum yang lebih tinggi yang menunjukkan kualiti dan kepelbagaian penyelesaian yang lebih baik apabila dibandingkan dengan Algoritma Genetik Pengisihan Tidak Didominasi II (NSGA-II) dalam semua lima fungsi ZDT. Kajian ini memberi sumbangan yang signifikan ke arah kemajuan varian ABC dan hibridisasinya. Algoritma yang dicadangkan menunjukkan potensi yang menjanjikan untuk meningkatkan prestasi pengoptimuman merentas kedua-dua domain objektif tunggal dan multiobjektif dalam bidang kejuruteraan.

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LIST OF ABBREVIATIONS

UTeM	-	Universiti Teknikal Malaysia Melaka
IEEE	-	Institute of Electrical and Electronics Engineers
ABC	-	Artificial Bee Colony
ARO	-	Artificial Rabbits Optimization
ABRO	-	Artificial Bee Rabbit Optimization
EEFO	-	Electric Eel Foraging Optimization
BEFA	-	Bee Eel Forage Algorithm
EBMR – Al	BC -	Employed Bee with Modification Rate in Artificial Bee Colony
PSO	-14	Particle Swarm Optimization
ACO	1	Ant Colony Optimization
GA	TEX	Genetic Algorithm
DE	FIRE	Differential Evolution
MR	211	Modification Rate
Avg	ملاك	اونيۇم سىتى تيكنىكل مليAverage
Std	UNIVE	Standard Deviation
Min	-	Minimum Value
Max	-	MaximumValue

LIST OF SYMBOLS

D	- Dimension
NP	- Number of Populations
ub	- Upper Bound
lb	- Lower Bound
Pos	- Current Potential Position / Solution
NPos	- Newly Generated Potential Position / Solution
MaxIt	- Maximum Iteration
Arch	- Archive
HV	- Hypervolume
MS	- Maximum Spread
P_G	- Generator's Power
P_{min}	- Minimum Power
P _{max}	- Maximum Power
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LIST OF PUBLICATIONS

The following is the list of publications related to the works of this thesis:

W. W. Lee, M. R. Hashim and C. K. Gan, 2024. Hybrid Optimization Algorithms for Economic and Emission Dispatch Optimization, 2024 20th IEEE International Colloquium on Signal Processing & Its Applications (CSPA), pp. 196-201, 2024. (SCOPUS indexed)

W. W. Lee and M. R. B. Hashim, 2023. A Hybrid Algorithm Based on Artificial Bee Colony and Artificial Rabbits Optimization for Solving Economic Dispatch Problem, *2023 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS)*, pp. 298-303, 2023. (SCOPUS indexed))

W. W. Lee, M. R. Hashim and C. K. Gan, 2024. Artificial Bee Rabbit Optimization Algorithm for Solving Economic Dispatch Problem, *IAES International Journal of Artificial Intelligence (IJ-AI)*. (Submitted for 2nd review)

W. W. Lee, M. R. Hashim and C. K. Gan, 2024. A Hybridized Artificial Bee Colony and Electric Eel Foraging Algorithm for Constrained Engineering Problem, *7th Asia Pacific Conference on Manufacturing System 6th International Manufacturing Engineering Conference*. (Accepted)

CHAPTER 1

INTRODUCTION

1.1 Background

Optimization is the process of finding the best possible solution to a problem (Rao, 2019). In engineering, engineers are responsible for making decisions during design, build and maintain processes that minimize undesired factors and maximize desired ones. A typical engineering design process involves engineers specifying the problem through parameters, objectives, and constraints, followed by evaluating potential designs. However, issues can arise during these stages, such as misspecified problems, suboptimal baseline designs, or improper implementation, leading to less-than-ideal outcomes (Peel and Moon, 2020). This is where optimization algorithms become crucial. An optimization algorithm iteratively searches for the optimal solution to a problem. It starts with a candidate solution and refines it in each step, aiming to generate a superior solution that adheres to any imposed constraints (Peel and Moon, 2020).

Metaheuristic algorithms have gained significant attention from researchers due to their wide applicability (G. Li et al., 2024). The term "metaheuristic" is the combination of two terms where meta means high level while heuristic appears as "to find" or "to discover" (Nassef et al., 2023). These algorithms can be applied to a wide range of optimization problems and involve elements of randomness. Popular examples include the Genetic Algorithm (GA) (Man et al., 1996), Particle Swarm Optimization (PSO) (Kaveh and Kaveh, 2017), Ant Colony Optimization (ACO) (Dorigo et al., 2006), and the Artificial Bee Colony (ABC) algorithm (Karaboga, 2005), which this research focuses on. The ABC algorithm's simplicity, ease of implementation, and minimal control parameters have contributed to its popularity (Soufyane Benyoucef et al., 2015). The ABC algorithm draws inspiration from the foraging behaviour of honey bees. It categorizes bees into three groups: employed bees, onlooker bees, and scout bees. Initially, scout bees randomly search for potential food sources. Employed bees then take over, exploiting specific food sources they have discovered. Onlooker bees, using information shared by employed bees through a waggle dance, join in on exploiting these sources. When a food source is depleted, the employed bee transitions into a scout bee and resumes searching for new ones. In the context of the ABC algorithm, food sources represent potential solutions to the given problem, while the nectar quantity signifies the quality or fitness of that solution.

The "No Free Lunch Theorem" states that no single optimization algorithm is universally superior to others (Wolpert and Macready, 1997). Similarly, the ABC algorithm has limitations, such as limitations in being easily stuck in local optima and converging slowly (P. Li et al., 2024). To address these drawbacks, researchers are actively exploring modifications to the ABC algorithm, including parameter tuning, hybridization with other algorithms, and adaptation strategies. These modification and hybridization techniques will be discussed in detail in Chapter 2.

The economic dispatch problem is a crucial aspect of electrical power system management (Tabassum et al., 2021), aiming to optimize power generation distribution among different units while considering operational constraints and minimizing production costs. The electricity demand has been observed to have increased significantly over the past few decades. An increase in electricity demand can have a cascading effect on gas emissions and generation costs in a power system. This effect is primarily due to the complex interplay between power generation, fuel consumption, and operational constraints within the system. Besides, emission dispatch is also an important aspect of the power system that aims to reduce the generated pollutant emissions. Hence, there is a growing concept called the combined economic and emission dispatch (Dey et al., 2019). The world is transiting towards a more sustainable and efficient energy landscape, hence the need for advanced optimization techniques becomes crucial.

The focus of this research is to investigate and develop modified versions of Artificial Bee Colony (ABC) algorithms for solving the economic dispatch problem, the emission dispatch problem, and the combined economic and emission problem, which are optimization problems in power system planning. Additionally, several engineering problems are included to evaluate the broader applicability of the proposed ABC variant algorithm.

This study aligns with several Sustainable Development Goals (SDGs) established by the United Nations (Nations, 2023) as shown in Figure 1.1, including Affordable and Clean Energy (SDG 7), Industry, Innovation and Infrastructure (SDG 9), Responsible Consumption and Production (SDG 12), and Climate Action (SDG 13). For example, optimization algorithms help by optimizing economic and emission dispatch which ensures efficient use of existing resources and promotes cleaner energy sources (SDG 7 and SDG 13). Besides, optimization contributes to SDG 9 by optimizing logistics networks, resource allocation in manufacturing, and sustainable infrastructure design. Specific examples include the Traveling Salesman Problem (TSP), which can optimize logistics networks and waste collection routes (SDG 9), and the Machine Scheduling Problem, which improves production efficiency and minimizes resource waste (SDG 9 and SDG 12). Furthermore, optimization techniques can minimize material usage and extend equipment lifespan, as seen in spring design and rolling element bearing design (SDG 12).



Figure 1.1 Sustainable Development Goals (United Nations, 2023)

1.2 Problem Statements

The ABC algorithm is well known for its simplicity, requiring minimal control parameters and simple implementation (Karaboga and Akay, 2009). However, ABC suffers from certain limitations, such as slow convergence, premature convergence, and a tendency to get stuck in local optima, particularly when applied to complex optimization problems (A. Sharma et al., 2020). For example, studies have shown that ABC takes a longer time to converge compared to other algorithms on benchmark problems (Chaudhary, 2023). These limitations highlight the need for enhancing the ABC algorithm.

To address these limitations, this research proposes four new ABC variants, which will be evaluated on various benchmark functions. Benchmark functions offer a standardized framework for comparing the performance of different optimization algorithms across various problem landscapes (Hussain et al., 2017). For example, researchers such as Wang et al. (2022) and W. Zhao et al. (2024) have used benchmark problems like the Sphere and Ackley functions when proposing new algorithms. Testing an algorithm on a diverse set of benchmark functions allows researchers to gain insights into its strengths and weaknesses and facilitates performance comparisons with other algorithms (P. Sharma and Raju, 2024).

In addition, it is crucial to apply proposed algorithms to real-world problems to assess their applicability and effectiveness (Alorf, 2023). This research applies the proposed algorithms to ten types of engineering problems such as pressure vessel design, rolling bearing design, tension/compression spring design, cantilever beam design, gear train design, travelling salesman problem, single machine scheduling problem, economic dispatch, emission dispatch, and combined economic and emission dispatch.

A pressure vessel is a container designed to hold gases or liquids at varying pressures. The objective in pressure vessel design is to minimize fabrication costs while ensuring safety and functionality (Khatab et al., 2025). Rolling element bearings are critical components in machinery, from household appliances to spacecraft. The aim of rolling bearing design is to maximize the dynamic load-carrying capacity of the bearing (Zhang and Wang, 2023). Tension/Compression Springs store and release energy, and their design aims to minimize the spring's weight while maintaining its mechanical properties. This is essential for devices such as machinery and automobiles (Khatab et al., 2025). Next, a cantilever beam is a structural element that is fixed at one end and free at the other. The objective in cantilever beam design is to reduce the weight by optimizing its hollow square shape while maintaining structural integrity (Kutlu Onay and Aydemir, 2022). The gear train design problem is a discrete optimization problem that aims to minimize the cost of a complex gear train. The objective is to find the optimal number of teeth for four gears in the train to achieve a desired gear ratio while minimizing errors (Dinkar and Deep, 2017).

The traveling salesman problem is a combinatorial optimization problem where the objective is to find the shortest route that visits each city exactly once and returns to the

starting point (Toaza and Esztergár-Kiss, 2023). The single machine scheduling problem is also a classic combinatorial optimization problem that involves scheduling jobs on a single machine to minimize total tardiness while considering factors like job release dates and sequence-dependent setup times (Costa et al., 2025).

In power systems, the Economic Dispatch problem is a crucial optimization challenge. Its goal is to minimize power generation costs while meeting the demand across a power grid (Visutarrom and Chiang, 2024). Alongside economic dispatch, the growing environmental concerns have made Emission Dispatch increasingly important. Emission dispatch aims to minimize pollutants from power generation while still meeting energy demands (Xu and Yu, 2023). Finally, the combined Economic and Emission Dispatch, also known as Environmental Economic Dispatch, has gained popularity. This multi-objective optimization problem seeks to simultaneously minimize operating costs and emissions, balancing economic efficiency with environmental sustainability (Xu and Yu, 2023).

1.3 Research Questions

Research questions serve as the foundation for the research, providing a clear focus, guiding method selection, and shaping the literature review. The studies presented in this thesis are conducted based on the following research questions:

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- i) What are the limitations of the ABC algorithm?
- ii) What is the importance of enhancing the ABC algorithm?
- iii) Are the proposed ABC variants suitable for practical implementation?
- iv) How to measure the performance of the ABC algorithm and its variants?
- v) How to develop single and multi-objective variants of the ABC algorithm?
- vi) What methods did the previous researcher use to enhance the ABC algorithm?