# IMPROVED FLOWER POLLINATION OPTIMIZATION ALGORITHM BASED ON SWAP OPERATOR AND DYNAMIC SWITCH PROBABILITY SELECTION

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## DEDICATION

With Love and Trillion Thanks,



To my beloved mother and father who never stopped encouraging me to study further and my success is their only dream

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#### ABSTRACT

Meta-heuristic algorithms have become popular in finding optimal solutions for nonlinear complex problems. These algorithms belong to stochastic and nondeterministic classes, have some problems with exploration or exploitation. The researchers used different strategies to tackle these issues. The flower pollination algorithm (FPA) is one of the more popular nature-inspired search algorithms. It has powerful global searchability to find the best optimal solution of real-world problems by using levy flight to explore the search space. Moreover, its single tuning parameter and simple mathematical model make it easier to implement. However, the flower pollination algorithm has a few drawbacks which are partially addressed by the practitioners. The first issue is regarding the balance between global pollination and local pollination, which may negatively affect the optimality of solution. Secondly, the FPA has a diversification problem which may leads to premature convergence of the optimal solution. This research proposed an algorithm which is based on dynamic switch probability to control the balance between exploration and exploitation which increases its searchability. The swap operator has been added in local pollination to enhance the exploitation behavior of pollens during the pollination process. Furthermore, it is hybridized with the Pattern Search algorithm to ensure the optimality of the solution. The performance of the proposed algorithm (IFPDSO-PS) has been evaluated on seventeen standard test functions and compared with the stated metaheuristic algorithms. The statistical tools (Absolute Mean Error & Fried Man) are used to rank the performance of all algorithms. The proposed algorithm is ranked first among the stated algorithms with respect to its performance in getting the optimal solution.



#### ABSTRAK

Algoritma meta-heuristik telah menjadi popular dalam mencari penyelesaian optimum untuk masalah kompleks bukan linear. Algoritma ini tergolong dalam kelas stokastik dan bukan deterministik, mempunyai beberapa masalah dengan penerokaan atau eksploitasi. Para penyelidik menggunakan strategi yang berbeza untuk menangani isu ini. Algoritma pendebungaan bunga (FPA) ialah salah satu daripada algoritma carian yang diilhamkan oleh alam semula jadi yang lebih popular. Ia mempunyai kebolehcarian global yang berkuasa untuk mencari penyelesaian optimum terbaik bagi masalah dunia sebenar dengan menggunakan penerbangan levi untuk meneroka ruang carian. Lebih-lebih lagi, parameter penalaan tunggal dan model matematik mudah menjadikannya lebih mudah untuk dilaksanakan. Walau bagaimanapun, algoritma pendebungaan bunga mempunyai beberapa kelemahan yang sebahagiannya ditangani oleh pengamal. Isu pertama adalah mengenai keseimbangan antara pendebungaan global dan pendebungaan tempatan, yang mungkin menjejaskan optimum penyelesaian secara negatif. Kedua, FPA mempunyai masalah kepelbagaian yang boleh membawa kepada penumpuan pramatang bagi penyelesaian optimum. Penyelidikan ini mencadangkan satu algoritma yang berasaskan kebarangkalian suis dinamik untuk mengawal keseimbangan antara penerokaan dan eksploitasi yang meningkatkan kebolehcariannya. Operator swap telah ditambah dalam pendebungaan tempatan untuk meningkatkan tingkah laku eksploitasi debunga semasa proses pendebungaan. Tambahan pula, ia dihibridkan dengan algoritma Carian Corak untuk memastikan penyelesaian yang optimum. Prestasi algoritma yang dicadangkan (IFPDSO-PS) telah dinilai pada tujuh belas fungsi ujian standard dan dibandingkan dengan algoritma meta-heuristik yang dinyatakan. Alat statistik (Absolute Mean Error & Fried Man) digunakan untuk menilai prestasi semua algoritma. Algoritma yang dicadangkan berada di kedudukan pertama antara algoritma yang dinyatakan berkenaan dengan prestasinya dalam mendapatkan penyelesaian yang optimum.

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## LIST OF SYMBOLS AND ABBREVIATIONS

SUMT	-	Sequential Unconstrained Minimization Techniques
ККТ	-	Kuhn- Tucker
ACO	-	Ant Colony Optimization
WSNs	-	Wireless Sensor Networks
PSO	-	Particle Swarm Optimization
VC	-	Velocity Clamping
FA	-	Fire Fly Algorithm
HBA	-	Honey Bee Algorithm
ABC	-	Artificial Bee Colony
PS	-	Pattern Search
SA	-	Simulating Annealing
FPA	-	Flower Pollination Algorithm
LSGS	- 1	Local Self Adaptive Greedy Strategy
GEOL	-	Global Elite Opposition based Learning Strategy
GA	-	Generic Algorithm
FCM	-	Fuzzy C-mean
IFPDSO	-	Improved Flower Pollination with Dynamic Switch
		Probability and Swap Operator
IFPDSO-PS	-	Hybrid Improved Flower pollination and Pattern Search
WOA	-	Whale Optimization Algorithm
GWO	-	Grey Wolf Optimizer
KNN	-	K-Nearest Neighbour
ED	-	Economic Dispatch
MAE	-	Mean Absolute Error



### LIST OF PUBLICATIONS

- i. M. Iqbal, Nazri Mohd Nawi, Azizul Azhar Ramli, and Fanni Sukma. (2021) An Improved Flower Pollination Algorithm for Global and Local Optimization. JOIV: 5, no. 4: 461-468
- Iqbal, Muhammad, Nazri Mohd Nawi, and Radiah Bt Mohamad. (2021). ii. An improved flower pollination solution for economic dispatch with valve point effect. IJEEC, 22, no. 2): 629-637



#### **CHAPTER 1**

#### INTRODUCTION

#### 1.1 Research background

In computer science particularly in operations research and mathematics, optimization is the procedure to find the optimal solution by comparing number of solutions iteratively. In other words, optimization is a technique of making something (a design, system, or decision) as perfect, functional and effective as possible. In optimization, mathematical procedures are involved in finding the maximum or minimum value of the function with a given set of inputs. Optimization provides an elegant mixture of theory and applications where the theory uses some elements of basic calculus and elementary linear algebra and continues with functional and complex analysis. Optimization has been applied in many industries such as in the information technology industry, Medical Science, Bio-informatics, medical images, Engineering and Economics. In this era, optimization has become one of the growing research fields for researchers, practitioners, and students to study, apply, and conduct research.

The Optimization algorithms have been divided into two distinct types, gradient base or (dependent) techniques and gradient free or (independent) techniques. The gradient base techniques use specific rules in getting an optimum solution as compare to other promising solutions while the gradient free techniques use random process to get the optimum solution. This research focus on nature inspired metaheuristic (gradient free) non deterministic techniques. These techniques can be further divided into main three subtypes: Bio inspired, Swarm intelligence inspired, physics-based and chemistry-based. Swarm intelligence is one of the popular field of artificial intelligence (AI) over the last three decades (Hussain *et al.*, 2019; Komsiyah *et al.*, 2016) which has been used in many applications in solving complex



optimization problems. Swarm intelligence is inspired by the collective behaviors of social swarms of the ant colony, school of fish, bees, worms, termites, and a flock of birds, in achieving their goals. The bio-inspired techniques are based on biological evolutionary process. These new approaches use biological mechanism like immune system, genetic evolution and clonal selection for survival of the fittest.

In the meta-heuristic approaches, exploration (diversification) is the process of finding the different solutions in the search space. Whereas, the exploitation (intensification) is the process of focusing the search process in the neighborhood for good solutions by exploiting the information obtained (Diab and El-Sharkawy, 2016). In each meta-heuristic algorithm, the process of searching the best global solution depends on the balancing between exploration and exploitation (Nabil, 2016).

In the nature-inspired algorithms, the Flower Pollination Algorithm (FPA) is one of the meta-heuristic algorithms which has single tunning parameter and simple mathematical model. It is easy to understand the mathematical processes of FPA as compare to other metaheuristic algorithms which attracts the practitioners to apply it, in various domains of research. It has been applied in the domains of engineering, education and medical to get near optimal solution. The flower pollination algorithm was developed by Xin-She Yang (2012), inspired by the pollination behaviors of flower to pollinate for reproduction according to the principles of survival of the fittest (Yang, 2014, Karamanoglu & He, 2014, Emary *et al.*,2016). The consistency of flower in reducing the costs of investigation has helped the pollinators to increase the transferring time of pollen, which maximizes the process of production. The limited memory of pollinators helps flower consistency to eliminate its learning and investigation which represents the incremental steps that depend on the difference or similarity of two flowers.



The flower pollination algorithm (FPA) has some advantages over other metaheuristic algorithms due to having single controlling parameter to select exploration (global search) or exploitation (local search) (He *et al.*, 2018). In the literature studies, Markov theory has proved the FPA as the global best algorithm (He *et al.*, 2017a). However, the flower pollination algorithm also faces some issues for solving different complex multimodal optimization problems. First one is the high switch probability value 0.8 has been used in basic FPA which causes an imbalance between exploration and exploitation (Liu *et al.*, 2019). The balance between exploration and exploitation means to control its searchability according to the nature

of the problem. In optimization problems search space varies which required more exploration as compare to exploitation to get global best solution in the whole search space. The flower pollination algorithm also face the problem of premature convergence in exploitation when the problem is multimodal (Zhou and Wang, 2016, Sreenivasa Rao *et al.*, 2018).

In addressing the problem of balancing between the exploration and exploitation, numbers of researchers introduced modifications in the standard FPA to enhance its efficiency. There are some modified versions of FPA that have been introduced by the authors (Lazim *et al.*, 2017, Alyasseri *et al.*, 2018, Mishra and Deb, 2019). All those authors have addressed a single modification in some parts of the FPA e.g. some authors have modified levy's flight with random walk in standard FPA to enhance its searchability, few of the authors brought some changes in switch probability by fuzzy inference system and some replace it with exponential dynamic switch probability (Valenzuela *et al.*, 2017) (Wong & Ming, 2019).Whereas other authors modified in the step size of the levy's flight and uniform distribution parameter (He *et al.*, 2017). Some authors have addressed the issue mentioned earlier by using mutation and crossover operator in basic FPA but failed to handle all those problems that have been identified (Abdel-baset & Hezam, 2015).



Furthermore, many researchers have hybridized the FPA with other metaheuristic and dynamic algorithms to balance the exploration and exploitation of the FPA. The Flower Pollination Algorithm has been used for exploration to hybridize with other meta-heuristic algorithms (Kherfane *et al.*, 2014, Alyasseri *et al.*, 2018, Sidhu and Mehta, 2017, Abdel-Fattah *et al.*, 2016, Lazim *et al.*, 2017). In this research an improved Flower Pollination algorithm has been proposed for exploration and Pattern Search (local search) optimization algorithm for exploitation to tackle the issues of diversification and premature convergence appropriately.

#### **1.2** Motivation for research

In the last three decades a number of metaheuristic algorithms have been developed to handle the enormous complexity and high computational cost of real-world problems. In the literature studies, it has been identified that these algorithms work well in practice but most of them do not have theoretical analysis. Therefore, it was rarely known how to improve their working mechanism. The standard Flower Pollination Algorithm (FPA) has been analyzed theoretically to identify its strengths and weaknesses which are associated with it in solving complex optimization problems. This information helps in this research to understand the strength of FPA and its drawbacks. The basic flower pollination algorithm belongs to the class of global search algorithms. Therefore, this research has improved the basic FPA and hybrid it with local search algorithm (PS) to address the issues of searchability and premature convergence to enhance its performance.

#### **1.3 Problem statement**

The standard Flower Pollination Algorithm (FPA) has become popular among researchers; however, some drawbacks have been associated with it in solving complex optimization problems. These drawbacks have been listed below:

- a) The premature convergence of algorithm in multi-modal optimization problems being trapped in local optima may affect the optimality of the solution.
- b) The fixed switch probability creates imbalance between global pollination and local pollination which affects the searchability and performance in getting the optimum solution.
- c) If the best solution is obtained in maximum number of iterations in FPA, there is still need for further exploring and exploiting to get the universal best optimal solution.

#### 1.4 Research objectives

The main task of this research is to develop an improved flower pollination algorithm by handling the local optimum with swap operator, dynamic switch probability for balancing the exploration and exploitation, and hybridizing it with pattern search for improving the performance. The following main objectives have been proposed for this research:

- a) To propose an improved flower pollination algorithm by introducing swap operator within local pollination for diversification of promising solutions to avoid the premature convergence for improving the optimality of solution.
- b) To further enhance the proposed method in (a) by modifying the fixed switch probability to dynamic switch probability for balancing the exploration and exploitation to enhance the searchability of the flower pollination algorithm to improve the performance of FPA.
- c) To enhance the quality of solution hybridized the pattern search approach and to evaluate the performance of the proposed method by comparing with prevailing meta-heuristic algorithms, standard flower pollination algorithm on some selected benchmark functions and real-life power generation (electrical engineering) problems.

#### 1.5 Scope of research



The proposed version of the hybrid flower pollination algorithm (IFPDSO-PS) has been evaluated on single and multi-objective optimization problems (Economic load dispatch to minimize the cost of production, Valve point Loading effect, Transmission loses minimization and Minimizing the emissions, Distributed Generation to minimize loses, wireless sensor network (Sidhu and Mehta, 2017, Abdelaziz et al., 2016, Hajjej et al., 2016; Sakthivel et al., 2016). The proposed algorithm has been evaluated on standard benchmark functions (Khursheed et al., 2020, Kamboh et al., 2021) and real-world optimization problems (Yang, 2015). The performance of the proposed algorithm has been compared and analyzed with the standard flower pollination algorithm, different improved flower pollination algorithms, hybrid flower pollination algorithms, simulated annealing algorithm, artificial bee colony algorithm, Whale optimization algorithm, genetic algorithm, grey wolf optimizer and some other optimization techniques. The criteria of assessment for the proposed algorithm are based on mean and standard deviation (SD) as well as Mean A b s o l ute Error and Friedman statistical tool have been used to rank the algorithms to measure its performance. All the results and simulations have been discussed in Chapter 4 to justify the robustness (in the sense of quality of solution) of the improved hybrid flower

pollination algorithm (IFPDSO-PS) with dynamic switch probability and swap operator.

#### **1.6 Outlines of the thesis**

The thesis consists of five chapters including the introduction and the conclusion. Following is the brief outline of each chapter. First chapter consists of brief introduction of historical background of study, motivation for research, problem statement, scope of research, aims and objective of study. The second chapter describes the concept of optimization and detailed review of Meta-heuristic algorithms and the advancements in Flower Pollination algorithm have been discussed in detail. After deep review of flower pollination algorithm, gaps are identified and further improvements have been identified. In Chapter 3, the research methodology of the proposed algorithm has been explained thoroughly. The identified gaps in FPA are adjusted to improve the searchability and convergence of the basic algorithm. The pattern search algorithm has been discussed to hybridize with the improved flower pollination algorithm. In Chapter 4, the proposed hybrid algorithm is tested on standard benchmark test functions, and its performance is compared with other stated metaheuristic algorithms. The algorithm is also tested on economic dispatch problem. The last chapter summarizes the research contributions and recommendations for future work. PERP



#### **CHAPTER 2**

#### LITERATURE REVIEW

#### 2.1 Introduction

The theory about nature-inspired algorithms explains the main process (natural selection, reproduction, and survival) of living creatures on earth which try its best to adapt the demands of the environment. If an organism has succeeded in adapting to such an environment, then it has the most chance to survive. This also shows that these entities are able to adapt the fluctuations of the environment. This is why these entities have more chance to survive longer and to spread their genotype (Yusoff *et al.*, 2011, Xue *et al.*, 2016).



In the last three decades a number of optimization algorithms have been developed metaheuristic to handle the enormous complexity and high computational cost of real-world problems. The deterministic algorithms produce same output against any particular input but the non-deterministic algorithms can produce different output for same input in every run. However, hard optimization problems are those problems that cannot be solved by deterministic (exact) method within the limits of time. These problems can be divided into many categories such as continuous or discrete, mono or multi-objective, constrained or unconstrained, and static or dynamic. Among those optimization methods, the nature-inspired meta-heuristic techniques are more applicable to get possible solution. The nature-inspired meta-heuristic methods are divided into four categories: Evolutionary algorithms (EA),Swarm intelligence, Physics rule base algorithms and Human behavior base algorithms (Wierstra *et al.*, 2008, Sun *et al.*, 2019). Most of the optimization methods are showing the common problems related to comprehensive coverage of change in the behavior of algorithms with respect to its performance (Sun *et al.*, 2020).

This chapter explains on previous literatures that show the classification of optimization and global overview of meta-heuristic optimization techniques. The main focus of this chapter is to identify the gaps and limitations of the meta-heuristic methods. Finally, the research related to the topic has been reviewed to find future research promising paths. This chapter does not only target on a single problem but focuses on more practical problems.

#### 2.2 **Optimization**

The main aim of optimization is searching for optimality which involves a large number of problems. Optimization problems can be named and classified in different ways. Because of these optimization techniques vary significantly from problem to problem. The use of same approach is not possible for different problems because the UN AMINAI complexity of optimization problems mostly depends on the form of the objective function and its constraints.

The generic mathematical form of most optimization problems: Minimize/Maximize: f(x)

Subject to: $g_j(x) \le 0$	$j = 1,2,3 \dots \dots \dots \dots m$	
$h_k = 0$	$k = 1,2,3 \dots \dots p$	
$x_i l \leq x_i \leq x_i u$	$i = 1,2,3 \dots \dots \dots \dots \dots n$	(2.1)

Where, f(x) represents the fitness (or goal) function,  $g_i(x)$  inequality constraints and  $h_k$  (x) equality constraints of objective function are represented in equation 2.1. Where, 'j' and 'k' are the number of constraints with limits 'm' and 'p' respectively. The vector 'x' represents the 'n' design variables to find the optimum. The searchable design space is represented by the upper and lower bounds  $x_i u$  and  $x_i l$ , of the design variables respectively (Yar et al., 2016).

In general case, the objective functions and constraints can be linear or nonlinear and can be explicit or implicit functions. Implicit functions normally appear, when a numerical simulation (e.g., a finite element simulation) is used to evaluate a fitness function (e.g., a stress value). Also, the design variables should not to be continuous. Optimization problems referred to some or all of the design variables restricted to integer or discrete values (Ratniyomchai et al., 2016).

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