



UNIVERSITI TEKNIKAL MALAYSIA MELAKA

**INCORPERATING LEVY FLIGHT METHOD ON THE BEES
ALGORITHM WITH PSEUDO-GRADIENT TOWARDS
NUMERICAL BENCHMARK TEST FUNCTIONS**

This report submitted in accordance with requirement of the Universiti Teknikal
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(Robotics & Automations) (Hons.)

by

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APPROVAL

This report is submitted to the Faculty of Manufacturing Engineering of UTeM as a partial fulfillment of the requirements for the degree of Bachelor of Manufacturing Engineering (Robotics & Automation) (Hons.). The member of the supervisory is as follow:

.....

(Silah Hayati Binti Kamsani)

ABSTRAK

“Bees Algorithm” (BA) adalah kecerdikan berasaskan populasi berkelompok baru yang diilhamkan oleh tingkah laku lebah dalam mencari makanan di alam semula jadi. BA telah diiktiraf oleh ramai penyelidik sebagai alat pengoptimuman yang kukuh dan cekap dalam kombinasi dan berfungsi dalam bidang pengoptimuman. Walau bagaimanapun, kadar penumpuan bagi BA untuk penyelesaian optimum masih memerlukan pembangunan dan memerlukan satu mekanisme untuk mengelakkan daripada terperangkap dalam optima tempatan. Oleh itu, kajian ini menumpukan kepada peningkatan prestasi BA dalam aspek kadar kelajuan penumpuan untuk menyelesaikan fungsi penanda aras berangka. Penambahan itu dicapai dengan menggabungkan pengagihan penerbangan Levy dalam carian kejitiran di BA dengan kaedah pseudo-kecerunan. Kaedah pseudo-kecerunan dilaksanakan sebagai strategi bimbingan untuk lebah pengakap. Sementara itu, penerbangan Levy itu dicadangkan untuk mempercepat proses pencarian algoritma. Algoritma yang lebih baik adalah tertakluk kepada beberapa fungsi penanda aras berangka dimensi yang tinggi. Hasil daripada eksperimen mengesahkan bahawa algoritma yang dicadangkan itu telah berjaya mengatasi prestasi optimisers lain dan versi standard BA dengan purata peningkatan peratusan kepada 71.42% dalam aspek kadar kelajuan penumpuan kepada penyelesaian yang optimum.

ABSTRACT

The Bees Algorithm (BA) is a new population-based swarm intelligence inspired by foraging behaviour of honey in nature. BA has recognised by many researcher as a robust and efficient optimisation tool in combinatorial and functional in optimisation fields. Nevertheless, the convergence rate of BA to the optimal solution still requires further development and need a mechanism to avoid from getting trapped in local optima. Therefore, this study concentrates on the improvement of BA performance in term of convergence speed to solve numerical benchmark function. The enhancement is accomplished by incorporating the Levy flight distribution in the neighbourhood search on BA with pseudo-gradient method. The pseudo-gradient method is implemented as a guidance strategy for the scout bees. Meanwhile, the Levy flight is proposed to speed-up the searching process of algorithm. The improved algorithm is subjected to several high dimensional numerical benchmark functions. The result of the experiments confirmed that the proposed algorithm is significantly outperformed the other population-based optimisers and the standard version of BA with an average percentage improvement of 71.42% in the term of speed-up the convergence rate to optimum solution.

DEDICATION

To my beloved father, Zakaria Bin Hamid, my mother, Norhayati Binti Mat Isa, my siblings and friends. Your prayer and hope encourage me to conduct this research.

To my supervisor, Silah Hayati Binti Kamsani and all staff in UTeM.

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TABLE OF CONTENT

Abstrak	i
Abstract	ii
Dedication	iii
Acknowledgement	iv
Table of Content	v
List of Tables	vii
List of Figures	viii
List Abbreviations, Symbols and Nomenclatures	x
CHAPTER 1: INTRODUCTION	1
1.1 Project Background	1
1.2 Problem Statement	2
1.3 Objectives	3
1.4 Scope of the Project	4
1.5 Report Structure	4
CHAPTER 2: LITERATURE REVIEW	5
2.1 Optimisation	5
2.1.1 Problem in Optimisation	7
2.1.2 Optimisation Techniques using Artificial Intelligence	9
2.2 Swarm Intelligence	12
2.2.1 Ant Colony Optimisation	13
2.2.2 Particle Swarm Optimisation	14
2.3 Foraging Bee-based Algorithms	15
2.3.1 Bees in Nature	15
2.3.2 Artificial Bee Colony	18
2.3.3 The Bees Algorithm	19
2.4 Levy Flight	26
2.5 Summary	28

CHAPTER 3: METHODOLOGY	29
3.1 Research Processes	29
3.2 Software	32
3.3 Proposed Algorithm	33
3.4 Experiment Set-up	38
3.5 Summary	47
CHAPTER 4: RESULTS AND DISCUSSIONS	48
4.1 Comparing Success Rate of Proposed Algorithm with Other Optimisers	48
4.2 Comparing Convergence Rate of Proposed Algorithm with Other Optimisers	50
4.3 Comparing Stability of Proposed Algorithm with Other Optimisers	61
4.4 Percentage Improvement of Proposed Algorithm with Standard BA	66
4.5 Statistical T-test Analysis	68
4.6 Summary	70
CHAPTER 6: CONCLUSIONS AND FUTURE WORKS	71
5.1 Conclusions	71
5.2 Future Works	72
5.3 Sustainable Elements	72
REFERENCES	74

LIST OF TABLES

2.1	Parameters of Standard Bees Algorithm	20
2.2	Applications of BA in engineering	25
3.1	Sample of comparison table	31
3.2	Common parameters setting	38
3.3	Parameter Setting for ABC and SPSO2011	39
3.4	Benchmark function	41
4.1	Success rate over 30 run time	49
4.2	Percentage improvement of LevyPGBA compared with Standard Bees Algorithm	67
4.3	T-test performance comparison between LevyPGBA with SPSO2011, ABC and Standard BA	69

LIST OF FIGURES

2.1	The Optimisation Process	6
2.2	Overview of Stochastic Search of Optimisation Technique	10
2.3	Honey Bees Foraging Process	17
2.4	Flowchart of The Basic Bees Algorithm	21
2.5	Graphical Illustration of The Basic Bees Algorithm	22
2.6	Flowchart of improved Bees Algorithm	24
2.7	Comparison Between Random Walk and Levy Flight Motion	27
3.1	Research Flow Chart	30
3.2	Flow Chart of Bees Algorithm with Levy Flight Pattern	36
3.3	Sphere Function in 2D	42
3.4	Schwefel 2.22 Function in 2D	43
3.5	Schwefel 2.21 Function in 2D	43
3.6	Step Function in 2D	44
3.7	Rastrigin Function in 2D	44
3.8	NCRastrigin Function in 2D	45
3.9	Rosenbrock Function in 2D	45
3.10	Griewank Function in 2D	46
3.11	Ackley Function in 2D	46
3.12	Weiersrass Function in 2D	47
4.1	Convergence curve between LevyPGBA, SPSO2011, ABC and standard BA for $f1$	51
4.2	Convergence curve between LevyPGBA, SPSO2011, ABC and standard BA for $f2$	52
4.3	Convergence curve between LevyPGBA, SPSO2011, ABC and standard BA for $f3$	53
4.4	Convergence curve between LevyPGBA, SPSO2011, ABC and standard BA for $f4$	54

4.5	Convergence curve between LevyPGBA, SPSO2011, ABC and standard BA for f_5	55
4.6	Convergence curve between LevyPGBA, SPSO2011, ABC and standard BA for f_6	56
4.7	Convergence curve between LevyPGBA, SPSO2011, ABC and standard BA for f_7	57
4.8	Convergence curve between LevyPGBA, SPSO2011, ABC and standard BA for f_8	58
4.9	Convergence curve between LevyPGBA, SPSO2011, ABC and standard BA for f_9	59
4.10	Convergence curve between LevyPGBA, SPSO2011, ABC and standard BA for f_{10}	60
4.11	Stability performance between LevyPGBA, SPSO2011, ABC and standard BA for f_1	61
4.12	Stability performance between LevyPGBA, SPSO2011, ABC and standard BA for f_2	62
4.13	Stability performance between LevyPGBA, SPSO2011, ABC and standard BA for f_3	62
4.14	Stability performance between LevyPGBA, SPSO2011, ABC and standard BA for f_4	63
4.15	Stability performance between LevyPGBA, SPSO2011, ABC and standard BA for f_5	63
4.16	Stability performance between LevyPGBA, SPSO2011, ABC and standard BA for f_6	64
4.17	Stability performance between LevyPGBA, SPSO2011, ABC and standard BA for f_7	64
4.18	Stability performance between LevyPGBA, SPSO2011, ABC and standard BA for f_8	65
4.19	Stability performance between LevyPGBA, SPSO2011, ABC and standard BA for f_9	65
4.20	Stability performance between LevyPGBA, SPSO2011, ABC and standard BA for f_{10}	66

LIST OF ABBREVIATIONS, SYMBOLS AND NOMENCLATURE

AI	-	Artificial Intelligence
ABC	-	Artificial Bee Colony
ACO	-	Ant Colony Optimisation
ANOVA	-	Analysis of Variance
BA	-	Bees Algorithm
CPU	-	Central Processing Unit
DE	-	Differential Evolution
EAs	-	Evolutionary Algorithms
GA	-	Genetic Algorithm
LevyPGBA	-	Levy with Pseudo-gradient
MATLAB	-	Matrix Laboratory
NS	-	Newton Search
PCB	-	Printed Circuit Board
PG	-	Pseudo-gradient
PSO	-	Particle Swarm Optimisation
SA	-	Simulated Annealing
SD	-	Steepest Descend
SPSO2006	-	Standard Particle Swarm Optimisation 2006
SPSO2007	-	Standard Particle Swarm Optimisation 2007
SPSO2011	-	Standard Particle Swarm Optimisation 2011

CHAPTER 1

INTRODUCTION

This chapter discusses the project background, problem statement, objective of the project and scope of the project.

1.1 Project Background

Optimisation is a process of finding an alternative with the best possible solution or highest achievable performance to solve a problem. Nowadays, there are many real world engineering problems need the manipulation of a number of system variables in order to optimize a given quality parameter such as the reliability or accuracy of a process and the value or performance of a product produced (Pham and Castellani, 2009). Therefore, Artificial Intelligence (AI) is applied in order to ease the engineers in solving engineering problems. In simple terms, AI is a program which develops by engineers to enable the computers to do things which are normally done by human. This AI program adds the machine with the capability to imitate intelligent human behaviour for solving problem.

Recently, nature-inspired metaheuristic have become increasingly popular among researchers as a computational problem-solving methods in the AI area. Swarm-based optimisation is one of population-based approaches typically inspired by natural phenomenon such as insect behaviour that mimics insect's problem solving abilities. Particle Swarm Optimisation (PSO), Ant Colony Optimisation (ACO), Artificial Bee

Colony (ABC) and the Bees Algorithm (BA) are the examples of these types of method. The advantage of this feature is the ability to prevent getting trap from local optimum, unlike the traditional approaches for example single-point scheme where the single solution is generated at each time-step (Binitha and Sathya, 2012).

Developed in 2005, BA is a rather current member of the swarm-based optimisation metaheuristics that mimics the food foraging behaviour of honeybees (Pham *et al.* 2007a; Ozbakir *et al.* 2010). The algorithm performs a kind of exploitative neighbourhood search combined with random explorative search. Compared to other swarm algorithms, BA is proved to be highly competitive in terms of learning accuracy and speed (Pham and Castellani, 2009).

In order to boost the algorithm performance especially in term of its search direction, several researchers have combined BA with the local gradient-based techniques. Among them are the works of Anantasate *et al.* (2010) that combined BA with Newton Search (NS) in electrical application, while Alfi and Khosravi (2012) hybridised BA with Steepest Descend (SD) to solve non-linear numerical optimisation problems.

1.2 Problem Statement

Nevertheless, the gradient-based scheme requires the differentiation of the problem's objective function. Without prior knowledge, derivative information in many real world optimisation problems are difficult to obtain.

In addition, BA uses a uniform random distribution in its initialisation phase where the randomness helps the system to sample new solutions especially in complex problems. Unfortunately, this has cause BA to have a slow convergence rate to the optimum solution just like other stochastic algorithms (Alfi and Khosravi, 2012; Hussein *et al.* 2013).

To overcome this problem, a pseudo-gradient Bees Algorithm shall be used in this project in place of the standard version of the Bees Algorithm to avoid the necessity of having a differentiable objective function. Additionally, instead of using a uniform random distribution for the local scout bees' initialisation, this project proposes the use of the Levy Flight method. Levy Flight is a heavy-tailed probability distribution that has been attested by Reynolds *et al.* (2009) as the natural movement made by honeybees during food foraging process. It has been used by other researchers in swarm-based optimiser for example Gang *et al.* (2011) for PSO algorithm as well as Sharma *et al.* (2012) in ABC algorithm. Hence, the analysis and comparison of the outcomes of the proposed algorithm shall be done against the other swarm based algorithm such as ABC and PSO.

1.3 Objectives

The objectives of this research are:

- i. To demonstrate the use of Levy Flight distribution in BA with pseudo-gradient in improving its convergence speed.
- ii. To compare the proposed algorithm with the standard BA and other swarm-based algorithms.

1.4 Scope of the Project

This research focuses on the performance of the Bees Algorithm by using Levy Flight approach. The proposed algorithm shall be applied to ten numerical benchmark test functions to determine its convergence speed for each function. Apart from that, this research also studies the previous works including the developments of Levy Flight in other algorithms. The proposed algorithm shall be implemented by using a 64-bit computer system consist of an Intel Core i5 processor 2.40GHz with a MATLAB software installed on it. Then, the outcomes of the proposed algorithm is analysed and compared with other well-known population based optimiser.

1.5 Report Structure

The remainder of the report is organised as follows:

Chapter 1 is the introduction of the research. This chapter consists of background, problem statement, objectives of the report, scope and chapter review of the report.

Chapter 2 is the literature review. This chapter presents the literatures that relevant to particular topic of this research, demonstrating the information of any previous work and awareness of related theories and discussions.

Chapter 3 is the methodology of the report. This chapter discusses the review of the methodology carried out in order to produce the desired result or outcome of the project.

Chapter 4 is the conclusion and future work . This chapter consists of expected results, conclusion for PSM 1 and future work that need to be done later in PSM 2.

CHAPTER 2

LITERATURE REVIEW

This chapter provides a review of the findings and methodology from the previous related studies in the fields of swarm based optimisation techniques.

2.1 Optimisation

Optimisation techniques are utilized in assorted fields such as engineering, manufacturing, finance, medicine, computing art and music, chemistry, physics and economics (Sholedolu, 2009). Optimisation is a process of finding an alternative with the best possible solution or highest achievable performance to solve a problem. According to Pham and Castellani (2009), there are numerous real world engineering problems that need the manipulation of a number of system variables in order to optimize a given quality parameter such as the accuracy or reliability of a process and the value or performance of a product produced. This is the reasons why optimisation is frequently needed in applications. In an optimisation process, usually one's begins with a real life problem, full of details and complexities which there are some relevant and some not (Sinebe *et al.* 2014). Therefore, due to this, essential elements are extracted then a solution or an algorithm is apply to it.

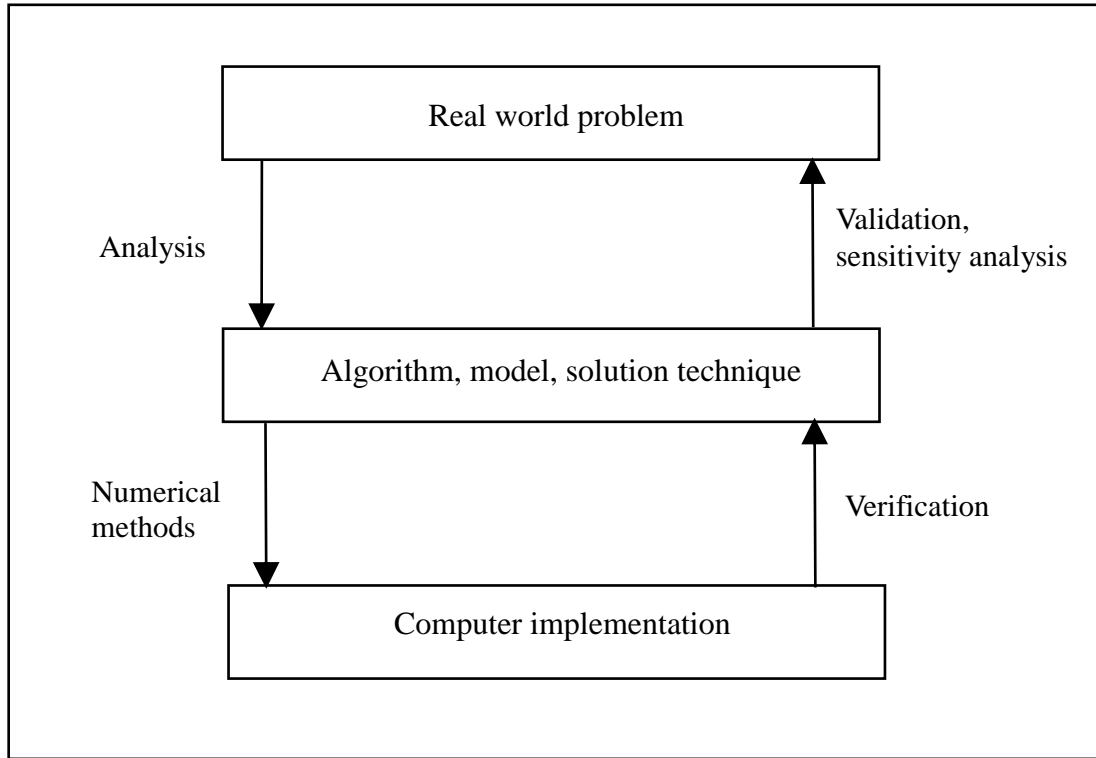


Figure 2.1: The optimisation process

According to Chinneck (2000), there is an unavoidable loss of realism as it moves down to the schematic diagram shown in Figure 2.1 from real world problem stage to algorithm, model or solution technique stage and finally to computer implementation stage. The arrows indicate the normal process of the optimisation cycles. Verification takes place after computer implementation. Verification refers to the process of confirming the simulation model which is correctly translated into a computer program (Okonkwo, 2009). The process of testing and improving a model to increase its validity is commonly referred to as validation. Hence, validation is done to ensure that the model is a true representation to what is obtainable in real system. Essentially, sensitivity analysis is used to determine how sensitive the model parameters can be verified.

2.1.1 Problem in Optimisation

As stated earlier, the systems optimisation is very important to the efficiency and economics of numerous science and engineering field nowadays. Therefore, as indicated by Chai-ead *et al.* (2011) the optimisation problems are solved by using approximate or rigorous mathematical search techniques. The rigorous techniques have utilised linear programming, integer programming, dynamic programming or branch-and-bound procedures to approach the optimal solution for moderate-size problems.

One of the most well-known issues that may be experienced by optimisation algorithm is premature convergence because of the search space boundary constraint (Rajarithnam, 2015). According to Ursem (2003), the process of an optimisation has prematurely converged to a local optimum if it is no longer able to explore the other parts of search space area than the currently being explore region which may contains a superior solution. Premature convergence can happen when the optimisation algorithm cruises by several local optima in the search space before a good solution is achieved. As a result, it may likely get stuck on such an intermediate solution and unable to proceed in other search area in the solution space (Sholedolu, 2009).

Furthermore, the other related problem in optimisation algorithm is ruggedness of the objective function. Most of the optimisation algorithms rely on some type of gradient in the fitness or objective space. According to Sholedulu (2009), a continuous objective function exhibits low total variation to enable the optimiser to easily descent the gradient in the fitness space. Conversely, when the objective function is fluctuates up and down, it will make the optimiser more difficult to find the right direction to proceed. In other words, the more rugged a function is, the harder it is to be optimised. However, this does not mean that it is impossible to find a good solution, but it may take a longer time to do so (Weise, 2009).

Additionally, deceptiveness is one of the upsetting features of the fitness space. As indicated by Sholedulu (2009), the deceptive of objective function gradient lead optimiser far from the global optima. At the point when an optimisation algorithm has found the region with better average fitness, legitimately it concentrate on exploring this area with sureness to converge on true optimum. Intuitively, the deceptiveness happens at whenever a good path leads to bad point or the other way around (Kauffman, 1993). Then, according Liepins and Vose (1991), different objective functions are said to be deceptive.

Next, the issue in optimisation is robustness of the algorithm. In global optimisation, the researchers always find the global optima for the objective functions from the theoretical perspective but not from the practical view. The reason for this is that the solutions of practical issues often depend on parameters which can be identified if certain degree of imprecision is determined as there is no process in the world that 100% accurate (Sholedulu, 2009). The local optima of the search space with strong causality are once in a while superior than global optima with weak causality while the level of acceptability is rely on applications.

Lastly, noise disturbance is also one of optimisation problems. There are two types of noise in optimisation (Sholedulu, 2009), there are:

- i. In the training data, there is a noise that is used as the basis for learning which cause over-fitting. The noise always exists when trying to fit a model to the data being measured as there is no measurement 100% accurate.
- ii. The second type of noise subsumes the annoyances that are expected to happen in the subsequent process.

2.1.2 Optimisation Techniques using Artificial Intelligence

According to Venter (2010), the optimisation techniques are classified as either local (neighbourhood) or global algorithms. Most of the local optimisation algorithms are gradient based. The gradient based techniques are broadly used for solving the optimisation problems in engineering field as it were efficient in terms of the number of function evaluations required to find the optimum. However, these techniques also have several limitations such as they can only locate a local optimum and have difficulty in solving discrete optimisation problems. On the other hand, the global optimisation algorithms typically non-gradient based give a better possibility of finding the global or near global optimum compared to the local algorithms.

In the past few decades, the field of optimisation has grown rapidly. In order to solve various problems in engineering and management, there are many algorithmic and computational contributions of optimisation have been introduced. According to Lin *et al.* (2012); Binitha and Sathya (2012), optimisation technique can be divided into either deterministic or stochastic. Deterministic methods also known as direct search algorithms are the traditional methods that take advantage of the analytical properties of the problem to generate a sequence of points that converge to a global solution. Deterministic methods such as linear programming, non-linear programming and mixed-integer non-linear programming can give general tools for solving optimisation problems to obtain a global optimum (Lin *et al.* 2012). The overview of the stochastic method classification is shown in Figure 2.2.

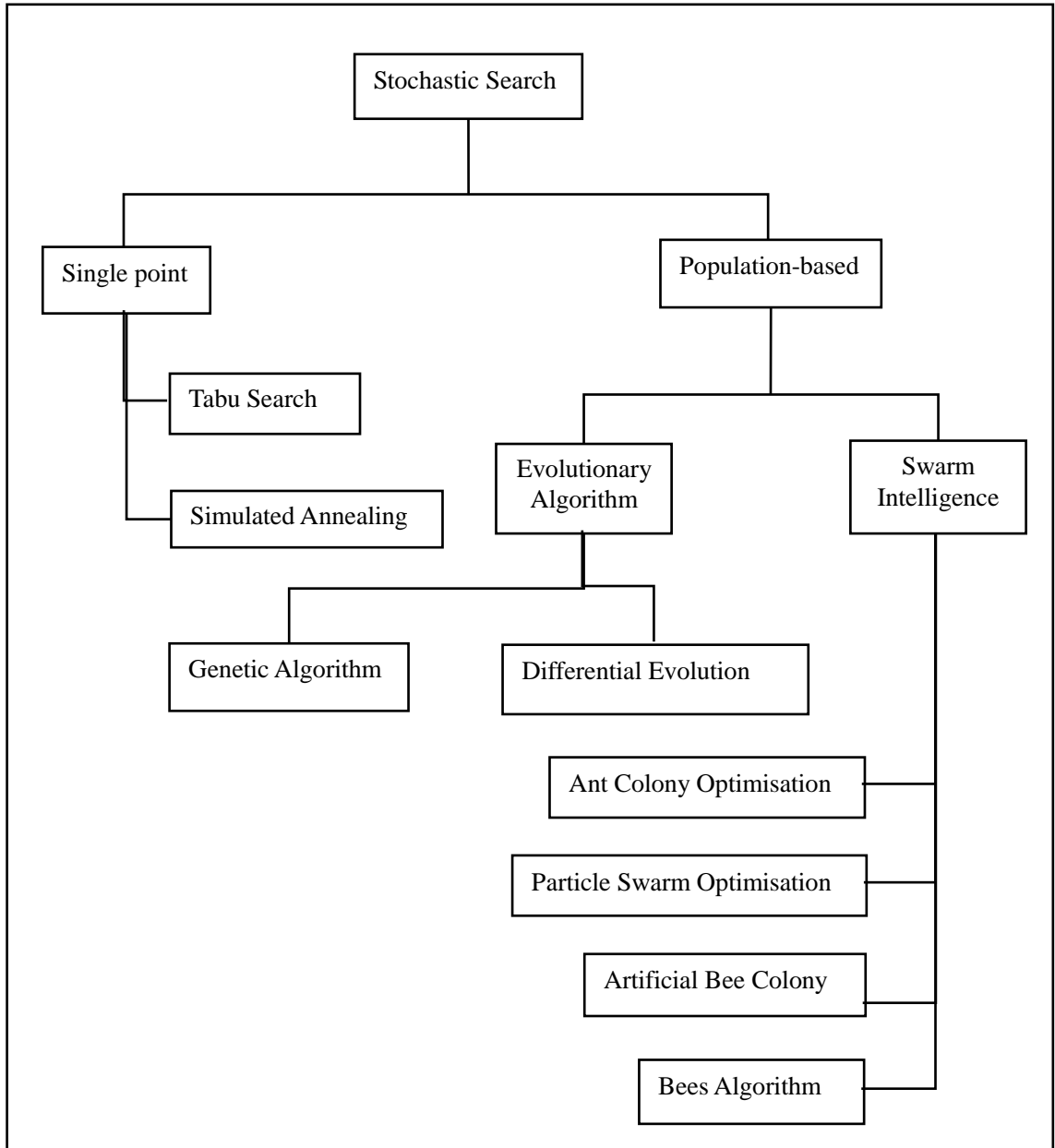


Figure 2.2: Overview of stochastic search of optimisation technique