Performance Comparison of Different Swarm Intelligence Methods towards Benchmark Functions

BY

SONG WEN HUAN

A REPORT

SUBMITTED TO

Universiti Tunku Abdul Rahman

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JANUARY 2020

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(Author's signature) (Supervisor's signature)

Address:

17, LORONG 5, TAMAN

PATANI JAYA, 08000, Ts. Dr. Lim Seng Poh

SUNGAI PETANI, KEDAH Supervisor's name

Date: 23/4/2020 **Date**: 23/4/2020

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DECLARATION OF ORIGINALITY

I declare that this report entitled "**PERFORMANCE COMPARISON OF DIFFERENT SWARM INTELLIGENCE METHODS TOWARDS BENCHMARK FUNCTIONS**" is my own work except as cited in the references. The report has not been accepted for any degree and is not being submitted concurrently in candidature for any degree or other award.

Signature : ____________________

Name : SONG WEN HUAN

Date : 23/4/2020

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ABSTRACT

Optimization problems are associated with different kinds of complicated and constraints which make optimization still being so important until today. This is because optimization is able to help researchers and organisations reached an optimal solution on different research works or applications using limited resources. In the past 20 years, Swarm Intelligence (SI) methods have been trendy in solving different kinds of complex problems. However, researchers or organisations still did not consider on the performance of the SI methods as there are various SI methods and not everyone contains the knowledge on the methods. Hence, the objective of this research is to analyse different Particle Swarm Optimization (PSO) models and to identify the best method in SI. The original version of PSO, Inertia Weight PSO (IW-PSO), Linearly Decrease Inertia Weight PSO (LDIW-PSO), Random Inertia Weight PSO (RIW-PSO), Constriction Factor PSO (CF-PSO) along with and without velocity clamping (VC) are analyzed and compared with Grey Wolf Optimizer (GWO) and Bat Algorithm (BA). The performance of SI method is tested using ten benchmark functions. The results in Experiment 1 show that CF-PSO with VC is performed more significant compared to the other PSO models. Hence, it is considered as the best PSO model in Experiment 1. Therefore, Experiment 2 is conducted and compared with GWO and BA using CF-PSO with VC. The results in Experiment 2 also reveal that CF-PSO with VC is the best SI method when it is compared towards the other SI methods. The result produced can help researchers to acknowledge and have better understanding on the SI methods so that better performance SI method with good accuracy can be applied on their research.

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LIST OF SYMBOLS

v_{id}^{t+1}	Velocity of next iteration
v_{id}^{t}	Velocity of current iteration
c1 and c2	Constant acceleration for PSO
rand	Random number between 0 and 1
p_{id}^{t}	Personal best position of PSO
x_{id}^{t}	Current Position of particles
x_{id}^{t+1}	Next iteration position of particles
p_{gd}^{t}	Global best position of PSO
w	Inertia weight
K	Constriction factor
f_i	Frequency of current iteration for BA
f_{min}	Minimum frequency
f_{min}	Maximum frequency
β	Beta
x_*, x_{old}	Global best value for BA
x_{new}	New local position for BA
ε	Random value between -1 and 1 for BA
A^t	Loudness of current iteration for BA
$\overrightarrow{D_\alpha}, \overrightarrow{D_\beta}, \overrightarrow{D_\delta}$	D coefficient vector for alpha, beta and delta wolf for GWO
$\overrightarrow{C_1}, \overrightarrow{C_2}, \overrightarrow{C_3}$	C random coefficient vector for GWO
$\vec{X}$	Current position of wolf in GWO
$\overrightarrow{X_\alpha}, \overrightarrow{X_\beta}, \overrightarrow{X_\delta}$	Position of alpha, beta and delta wolf in GWO
$\vec{X}(t+1)$	New position of wolf for next iteration in GWO
$\vec{a}$	Linearly decreasing value from 2 to 0 for GWO

$\vec{A}$	Random coefficient vector A for GWO
x_i	*Ith* dimension of particles
n	Number of dimension
π	Pi number

LIST OF ABBREVIATIONS

EC	Evolutionary Computing
EA	Evolutional Algorithm
GA	Genetic Algorithm
DE	Differential Evolution
SI	Swarm Intelligence
PSO	Particle Swarm Optimization
GWO	Grey Wolf Optimiser
AI	Artificial Intelligence
BA	Bat Algorithm
PSO01	PSO without inertia weight without velocity clamping
PSO02	PSO without inertia weight with velocity clamping
PSO03	PSO with inertia weight without velocity clamping
PSO04	PSO with inertia weight with velocity clamping
PSO05	PSO with linearly decreasing inertia weight without velocity clamping
PSO06	PSO with linearly decreasing inertia weight with velocity clamping
PSO07	PSO with random inertia weight without velocity clamping
PSO08	PSO with random inertia weight with velocity clamping
PSO09	PSO with constriction factor without velocity clamping
PSO10	PSO with constriction factor with velocity clamping

Chapter 1 Introduction

1.1 Research Background

According to James Blondin (2009) optimization often refer as finding the maximization and minimization value of a certain function. Wright (2016) mentioned that optimization problem involves 3 types of basic elements. First is objective function to maximize or minimize, second is the collection of variables which by controlling the quantities in order to achieve the optimization and third elements is variables can only take in certain range of values, which is also called constraints. Optimization is able to choose an input based on the limits and constraints on available resources involved to produce a best possible output. It also means the effective on allocation and use of resources available. Optimization is still important until today is because it helps organizations, scientist and others to achieve optimal solution by minimizing the cost and waste as well as maximizing the profit and speed depends on the problems given.

According to Zhou (2017), Artificial Intelligence has been becoming more popular and being learned and applied by many. In this fast development on the Artificial Intelligence in modern science and technology and the problem solved by using it are usually optimization problem. Optimization problem were associated with complicated constraints nowadays in variety of applications as stated by (Yang and He, 2015). Evolutionary Computing and Swarm Intelligence are the subfield of Artificial Intelligence which is inspired by nature which used it as an example as a strategy to find optimization on a given problems. Evolutionary Computing (EC) includes Evolutional Algorithms (EA) which can be further sub-divided to Genetic Algorithm (GA) and also Differential Evolution (DE) whereas Swarm Intelligence (SI) such as Particle Swarm Algorithm (PSO), Ant Colony Optimization (ACO) and more. Lim & Haron (2013) mentioned that Genetic Algorithm (GA), Differential Evolution (DE) and Particle Swarm Intelligence (PSO) were consistently implemented by others to solve different kind of complex optimization problems.

1.2 Problem Statement

Optimization problems are often referred as given a limitation on the resources to obtain the best possible solution. Based on Mavrovouniotis et al. (2017), difference swarm intelligence methods like PSO, ACO, Firefly Algorithms(FA) and other swarm methods have already been proven to be great methods on sophisticated optimization methods. However, most of the previous works uses different Swarm Intelligence methods on real-world applications in industrial and also science field, and various methods are suitable for different applications. For example, ACO is ideal for optimization problems like scheduling, and vehicle routing whereas Artificial Bee Colony is proper on numerical optimization problems. Performance of different methods in Swarm Intelligence and parameters settings are not considered by most of the authors. According to Lim and Haron in 2013, the most optimum value will be obtained for GA, PSO and also DE by adjusting the parameter settings and also the criteria for termination can also be achieved sooner. Besides, (Russell C. Eberhart and Shi, 2001) said that a suitable range value of inertia weight in PSO would give a balance on the global and local search. (Lim and Haron, 2013) also mentioned that other Soft Computing(SC) methods like ABC can be implemented and compared on the performance and the result obtained may be improved and obtained. Therefore, the performance of different techniques in Swarm Intelligence, along with various parameters will be analyse and investigate in this research.

1.3 Research Objectives

This research aims to determine performance comparison of different Swarm Intelligence methods towards benchmark functions. The objectives of this research are intended:

1. To analyse different models of Particle Swarm Optimization.
2. To identify the best method in Swarm Intelligence.

1.4 Research Scope

The scopes of this research are stated as follows:

1. Ten different models of Particle Swarm Optimization(PSO), Grey Wolf Optimizer(GWO) and Bat Algorithm(BA) are being focused.
2. Same parameter settings applied on ten PSO models, GWO and also BA are considered in this research(population size and are considered in this research)
3. Different PSO models, GWO and BA of parameter settings are also discussed in this research.
4. Maximum generation is being applied in this research as the termination criterion.
5. Ten benchmark functions are used as the objective functions in this research
6. C++ programming language is used for the coding part of this research.

1.5 Impact, Significance and Contribution

Most of the Swarm Intelligence techniques are applied in different application and performance is not being considered in most of the previous work on different Swarm Intelligence methods which stated in the problem statement. In real-time problems, the potential solutions for particular issues often to be a lot and time to find an optimal solution within a constraint or limit is crucial, so the performance of different Swarm Intelligence method is vital and should be examined to reduce the time usage and get an optimal solution.

In this research, various Swarm Intelligence methods are being studied and being determined using benchmark functions, and the best performance of Swarm Intelligence method is being obtained. Therefore, the contribution of this research is other authors can use the result obtained in the future for reference. Moreover, they can also improve different Swarm Intelligence methods to get better performance for their research.

1.6 Research Organization

The research organization for this research is organised as follows. Chapter Two introduces the background of Swarm Intelligence. Furthermore, different methods in the category of Swarm Intelligence are also discussed. Moreover, different benchmark functions are listed and some of the previous works on different Swarm Intelligence methods are discussed in this chapter.

Chapter Three describes on the research methodology for this research whereas Chapter Four elaborates on the analysis and discussion on the results based on the experiment conducted. Conclusion and future work are discussed at the end of this research.

Chapter 2 Literature Review

2.1 Overview

This chapter will discuss the Swarm Intelligence, followed by the introduction of benchmark function and lastly the previous work for different SI methods is discussed.

2.2 Swarm Intelligence

SI is the subfield of Artificial Intelligence (AI) (Blum et al., 2015). According to Beni (2014), he defined Swarm Intelligence as a "swarm" of either biological or artificial agents working together to solving tasks usually needed of some structure of "intelligence". Rosenberg (2017) also mentioned that swarm intelligence is like a system of the brain that deeply bridged and thought together as a system that is super intelligence. According to Blum et al. (2015), Swarm Intelligence was first being mentioned in the article proposed by Beni and Wang (1988), which is about the cellular robot system.

Nowadays, Swarm Intelligence method are based on the nature of biological inspired which acquire the collective behaviour of grouped animals like flock of birds, school of fish, swarm of bats or grouped insects like ants, bees, firefly and others as they will strive to survive under different constraint of environment (Chakraborty et al., 2017 and Blum et al., 2008). Nowadays, there are more and more complex problems arise and many fields like science field and engineering applications needed better optimization method to solve their optimization problem. Gireesha (2018) mentioned that optimization methods from SI are better than the older or usual optimization method in optimizing different field system operation and application in terms of accuracy and also reliability.

As mentioned above, an optimization method is vital to solving different complex problems. SI and optimization are interconnected, and optimization is the most critical component and most significant research area inside the SI (Beni, 2014).

However, SI method is based on different natural inspired behaviour, and different grouped animals and insects have a kind of operation strategies in handling a different type of problems like different SI methods possible in solving different domain of applications area (Chakraborty et al., 2017). Each SI method usually starts by initializing a set of variables and then evolving the variables to obtain the local or global maximum or minimum result based on the objective function (Rajabioun, 2011). Then, benchmark function is used to calculate the performance of SI methods, and then a further comparison of production is made with different SI method. Lim & Haron (2013) proved that using the same parameter settings and benchmark function will also get different performance results between the Particle Swarm Optimization (PSO), Differential Evolution (DE) and Genetic Algorithm(GA). Gireesha (2018) also used the same parameters for the fitness function and compared the best fitness values between four different SI methods. Next, the flow of the different SI methods will be explored in the next section.

2.3 Particle Swarm Optimization

PSO is first proposed by Kennedy and Eberhart (1995) and is an optimization method based on the flocking behaviour of birds and also school behaviour of fishes. There are particles which is a possible solution inside the search space, and each particle keeps moving in the search space finding the global minimum or maximum based on the objective function as stated by Blondin (2009). Each individual will have positions and the velocity, and they will track their own personal best fitness value which is their best position, *pbest* and also the overall best fitness value among all the particles which is *gbest*. Each particle's velocity is updated based on the previous speed, the *pbest* and also *gbest* of the particles and the position of the particle updated by adding the updated current velocity. The velocity and position of the particles are updated using the equation (1) and (2).

$$v_{id}^{t+1} = v_{id}^{t} + c_1 \cdot rand(0,1) \cdot (p_{id}^{t} - x_{id}^{t}) + c_2 \cdot rand(0,1) \cdot \left(p_{gd}^{t} - x_{id}^{t}\right) \quad (1)$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \tag{2}$$

As shown in the equation (1) and (2), v_{id}^{t} is the previous velocity and v_{id}^{t+1} is the current velocity that being updated. The *i* and *d* in *id* means the *i*th particles and also d-dimensions in the search space. The $rand(0,1)$ is the random value between 0 to 1 which include both values. The second part of the equation (1) which is $c_1 \cdot rand(0,1) \cdot (p_{id}^{t} - x_{id}^{t})$ is called cognitive component which help particles on local exploration as the particles as value were updated based on *pbest* of the particles. The third part of equation (1) which is $c_2 \cdot rand(0,1) \cdot \left(p_{gd}^{t} - x_{id}^{t}\right)$ called the social component which helps particles on the global exploration because value is updated based on *gbest*. While c1 and c2 is the constant acceleration which is also consider as the learning rate in equation. The equation (2) is to update the position of the particles by adding the previous position, x_{id}^{t} with the current velocity, v_{id}^{t+1}. This is the original version that proposed by Kennedy and Eberhart (1995). Then Shi and Eberhart, 1998 introduced a new parameter which is inertia weight, w adding into the equation (1) which is shown in equation (3). By adding inertia weight, it limits the value of the previous velocity and also contains a greater control on the local and global search.

$$v_{id}^{t+1} = w * v_{id}^{t} + c_1 \cdot rand(0,1) \cdot (p_{id}^{t} - x_{id}^{t}) + c_2 \cdot rand(0,1) \cdot \left(p_{gd}^{t} - x_{id}^{t}\right) \tag{3}$$

In the same year, Shi and Eberhart again proposed a decrease linearly inertia weight which improved the performance and has a better result which is more lesser iteration to find the global optimum compared to fixed inertia weight.

$$v_{id}^{t+1} = K * [v_{id}^{t} + c_1 \cdot rand(0,1) \cdot (p_{id}^{t} - x_{id}^{t}) + c_2 \cdot rand(0,1) \cdot \left(p_{gd}^{t} - x_{id}^{t}\right)] \tag{4}$$

Clerc (1999) introduced a K function which depends of the value of social or confidence coefficient, ϕ where ϕ needed to be more than 4 which shows in equation (5). The constant K is then multiply the equation (1) which shown in equation (4). The details of parameter of different models of PSO are further discussed in Chapter 4.

$$K = \frac{2}{2 - \phi - \sqrt{\phi^2 - 4\phi}} \quad , where\ \phi = c_1 + c_2 \ , \quad \phi > 4 \tag{5}$$

Furthermore, Shi and Eberhart (2000) introduced velocity clamping by which limit the maximum velocity, V_{max} which prevents the particles to fly away from the optimal solution as big velocity indicates bigger step taken. In 2001, Shi and Eberhart again introduced random inertia weight which generates the random number between 0.5 and 1.0 using Equation (6). This is also an improvement from the previous Equation(4) linearly decreasing inertia weight method as sometimes it converge to quickly and get stuck inside local optimum. Random Inertia Weight will generate large and also small values in the early iteration and also late iteration, so it can jump out the fast convergence into local optimum when gets trap. It can also balance the global and also local search exploration ability as stated by M. Lin, Z. Wang and F. Wang (2019).

$$Random\ Inertia\ Weight = [0.5 + \left(\frac{Rnd}{0.2}\right)] \tag{6}$$

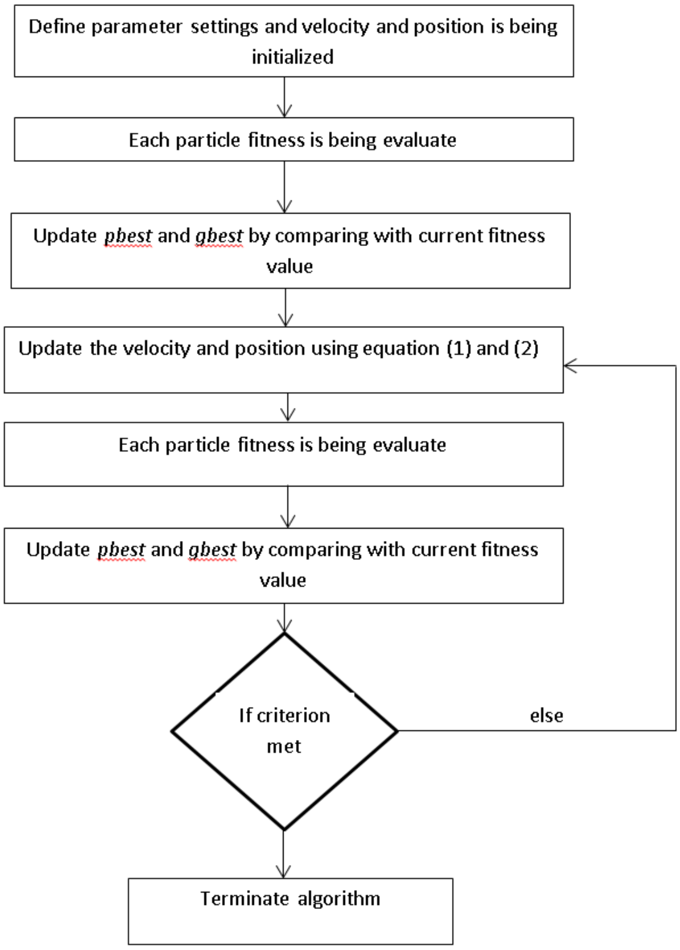

Figure 2.3.1

1. First, the parameter settings are being defined, and the velocity and position of the particles are being initialized.
2. Then, each of the particle's position is being evaluated using benchmark function.
3. The individual particles current fitness value is being compared with their *pbest* and also towards *gbest* and being updated.
4. The velocity and the position of the particles are then updated using equation (1) and equation (2).
5. The current position is then being evaluated using benchmark function.

2.4 Bat Algorithm

Bat Algorithm was originally being introduced by Yang in 2010. The bat algorithm are based on the sound waves and also echo produced by microbats which is called echolation to navigate their way, locate and dodge obstacles and also find prey in the dark. Yang (2010) also mentioned that microbats produce loud sound pulse to detect the surrounding object by listen to the echo that reflect back from the surrounding object. Different rate of pulses may means that different kind of strategies in hunting prey and also different species. Furthermore, according to Ryckegham(1998), bats produce low frequency sounds to detect further and high frequency sounds to received more detailed information such as the range, speed and also direction of the prey.

BA is quite similar to PSO as BA also start with velocity, v_i^t and position, x_i^t. Each microbats position is randomly generated inside the d – dimensional search space with starting velocity, v_i^t of zero. Each microbats' position are the candidate solution and n population of the candidate solution moving in the search space searching for the global best solution in t iteration and update their velocity, v_i^t and position, x_i^t based on the global best position and also frequency, f_i. The equation (7) is for frequency, f_i of each individual microbats and equation (8) and (9) for updating the velocity, v_i^t and position, x_i^t of the microbats are based on the original paper of Yang in 2010.

$$f_i = f_{min} + (f_{max} - f_{min})\beta \tag{7}$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_*)f_i \tag{8}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{9}$$

where β is a random vector between 0 and 1. f_{min} is the minimum frequency and f_{max} is the maximum frequency. For Equation (8), v_i^t is the current velocity and v_i^{t-1} is the previous velocity of the *ith* microbats. x_* is the global best position among all the population and x_i^t is the current position of ith microbats. Moreover, Equation (10) is used to improve the global best position by randomly searching around the global position and generate a local solution.

$$x_{new} = x_{old} + \varepsilon A^t \tag{10}$$

where ε is random number between -1 and 1, x_{old} is the value of global best position and x_{new} is the new local position generated, A^t is the loudness emitted by the individual microbats. Equation (10) will be used under the condition where the random number between 0 and 1 is bigger than pulse rate which is 0.5.

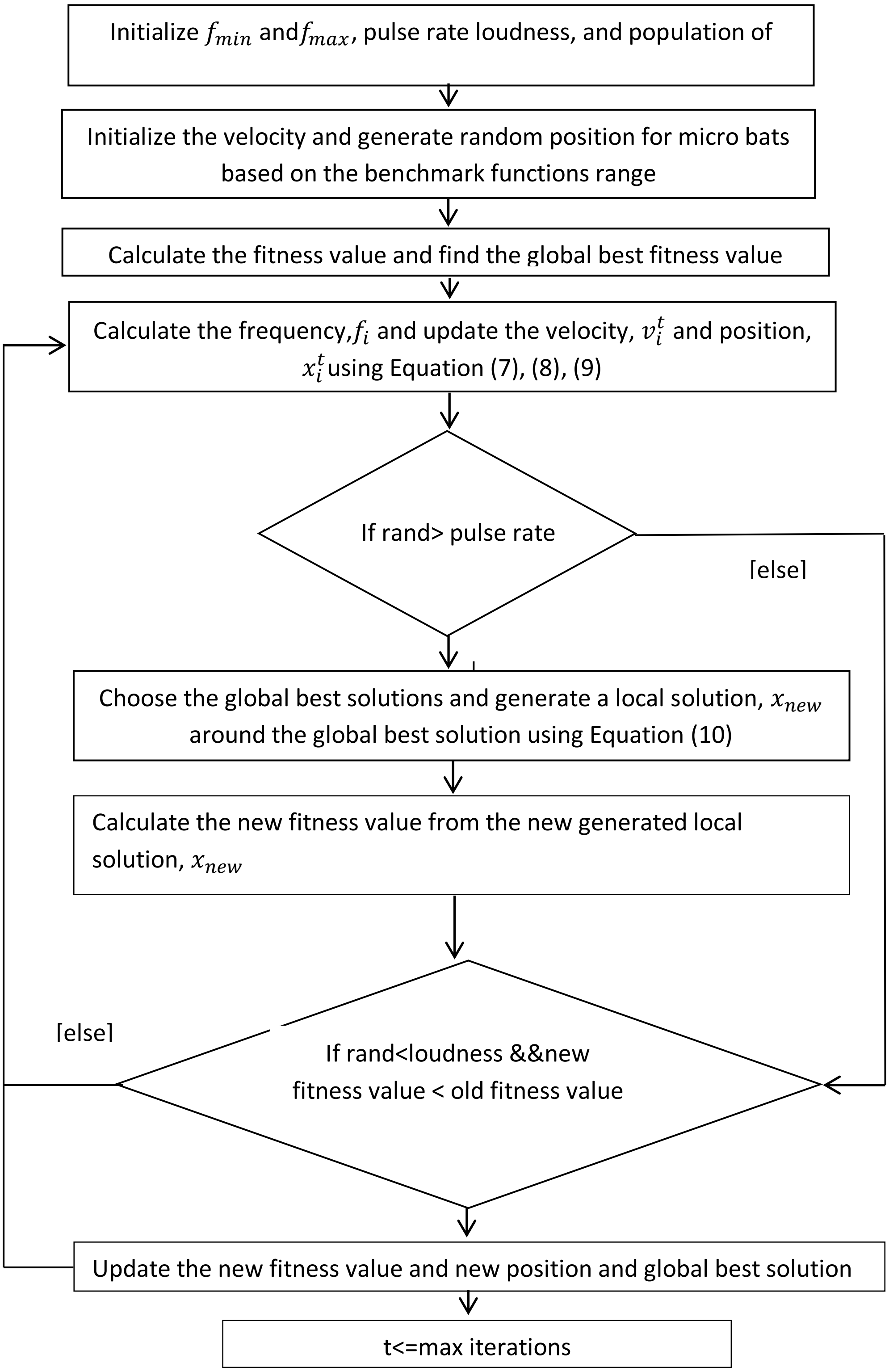

Figure 2.4.1 Flow Chart of BA

1. The f_{max} , f_{min}, pulse rate, loudness and population of micro bats are being initialized.
2. Then initialize the velocity of each individual to zero and generate random position for the micro bats based on the benchmark functions range.
3. Next, calculate the fitness value and find the global best fitness value among all the population.
4. Calculate the frequency, f_i and update the velocity, v_i^t and position, x_i^t using Equation (6), (7), (8) in the main loop.
5. After updating, random value between 0 to 1 is being compared with pulse rate
6. If random values are bigger, a local solution is being generated using Equation (9) around global best solution else jump to step 8.
7. The new fitness value is being generated from the local solution.
8. The random value is then compare again with loudness value and the new fitness value is compared with old fitness value.
9. If new fitness value and random value are smaller, replace the new fitness value and new local position to the old fitness value and old position for ith micro bats.
10. Do step 4 to 9 until max iterations is reached.

2.5 Grey Wolf Optimizer

Grey Wolf Optimizer was introduced by Mirjalilil et al in 2014. This method is based on the nature behavior on grey wolf on their leading hierarchy and also the hunting skills. There were four types of wolf which is alpha, beta, delta and also omega and have different level of strict dominance to the wolf pack. The hierarchy below shows the dominance of wolf by which the alpha is the highest dominance in wolf pack followed by beta, delta and lowest is omega. First, alphas is the most dominance wolf the wolf pack and thus other wolf will follow the alpha's order and also respect the alphas. Alpha wolf are great in managing the pack and it doesn't need to be the strongest in the pack. It also responsible for different situation decision making like hunting, sleeping and others. Below the alpha is beta. Beta is more of a guide role to alpha by helping the alpha in terms of making decision, activities of pack, reinforce the command of alpha and also provide feedback to the alpha. When the alpha dies, the beta is the best candidate to become the next alpha. Next, the third one on the hierarchy is delta also also called subordinate and belongs to category of scouts, elders, sentinels, hunters and also the caretakers. Where sentinels protects the wolf pack and elders are once a alpha or beta which are experienced. The lowest one is the omega which are the weakest dominance in the pack and are the last that allowed to eat. Other than the social hierarchy of dominance level of wolves, the hunting skills of the wolves also being focus as they track, chase and approach their prey and encircling, pursuing the prey to make it stops to move and then attack the prey.

As shown that alpha is the most dominancce wolves in a pack so alpha is the most fittest solution, followed by beta and delta and lastly the omega in the GWO algorithm. In GWO, alpha, beta and delta will guide the omega wolf.

$$\vec{D} = \left| \vec{C} \cdot \overrightarrow{X_p}(t) - \vec{X}(t) \right| \quad (11)$$

$$\vec{X}(t+1) = \left| \overrightarrow{X_p}(t) - \vec{A} \cdot \overrightarrow{|D|} \right| \quad (12)$$

Equation (11) and (12) calculate on how the grey wolves encircling the prey on a hunt. t is the current iteration and A and C are coefficient vector, $\overrightarrow{X_p}$ is the position of the prey which also means that $\overrightarrow{X_p}$ is the global best position and $\vec{X}$ is the position of the current ith wolf.

$$\vec{A} = 2\vec{a} \cdot \overrightarrow{r_1} - \vec{a} \quad (13)$$

$$C = 2 \cdot \overrightarrow{r_2} \quad (14)$$

The equation (13) and (14) is the calculation for A and C random vector where $\vec{a}$ will be linearly decrease from 2 till 0. r_1 and $\overrightarrow{r_2}$ and random values between 0 and 1. A current wolf position is being updated based on Equation (11) and (12) by which the

$\overrightarrow{X_p}$ is being replaced with position of alpha, $\overrightarrow{X_\alpha}$, beta, $\overrightarrow{X_\beta}$, and delta, $\overrightarrow{X_\delta}$ and formed the Equation (15) by which calculate the coefficient $\overrightarrow{D_\alpha}$, $\overrightarrow{D_\beta}$ and $\overrightarrow{D_\delta}$. Then $\overrightarrow{D_\alpha}$, $\overrightarrow{D_\beta}$ and $\overrightarrow{D_\delta}$ were used for Equation (12) to calculate 3 position value which is $\overrightarrow{X_1}$, $\overrightarrow{X_2}$ and $\overrightarrow{X_3}$ for current wolf which then generate like the Equation (16). Then the 3 position values are then calculated using Equation (17) to form the final updated position for current *ith* wolf.

$$\overrightarrow{D_\alpha} = \left| \overrightarrow{C_1} \cdot \overrightarrow{X_\alpha} - \vec{X} \right|, \overrightarrow{D_\beta} = \left| \overrightarrow{C_2} \cdot \overrightarrow{X_\beta} - \vec{X} \right|, \overrightarrow{D_\delta} = \left| \overrightarrow{C_3} \cdot \overrightarrow{X_\delta} - \vec{X} \right| \tag{15}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1} \cdot \left(\overrightarrow{D_\alpha} \right), \overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2} \cdot \left(\overrightarrow{D_\beta} \right), \quad \overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3} \cdot \left(\overrightarrow{D_\delta} \right) \tag{16}$$

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \tag{17}$$

In the problem search space, we did not know the optimal solution(prey) location and the alphas will always guide on the hunt first so the alpha, beta and also delta have a better knowledge on where the optimal solution which is prey because we already consider alpha, beta and delta as the better candidate solution. So the other wolves like omega will update their position based on the current best three solutions with the equation (15), (16) and (17).

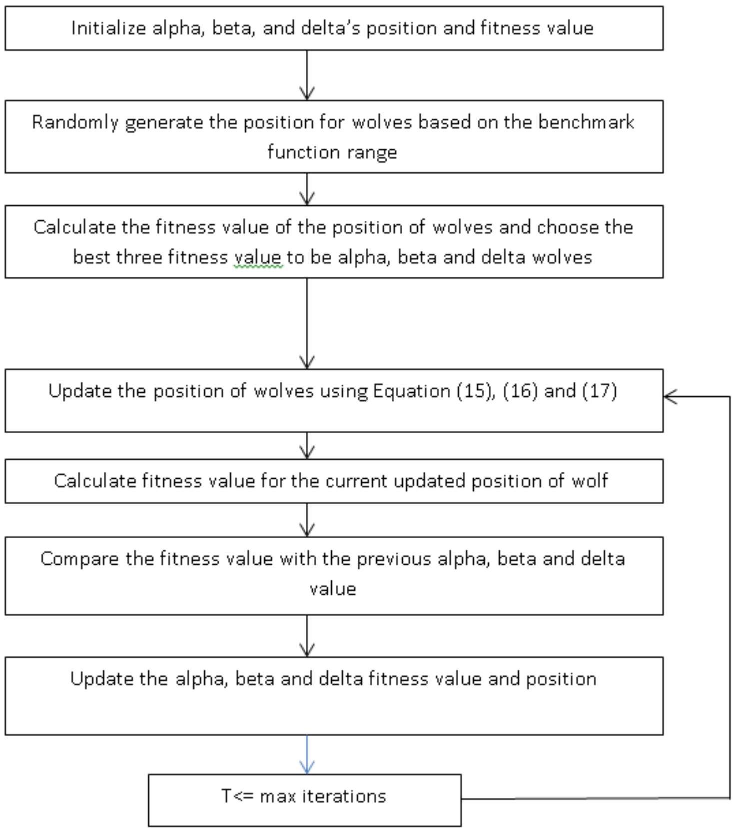

Figure 2.5.1 Flow Chart of GWO

1. Initialize the alpha, beta and delta's position to zero and their fitness value to infinity for later comparison.
2. The position of wolves are randomly generated based on the benchmark function range.
3. The fitness value is being calculated using the wolf's position
4. The best 3 fitness value is being chosen as alpha, beta and delta wolves.
5. Update the position of wolves using Equation (15), (16) and (17) in the main loop.
6. Calculate the fitness value of the current updated position of wolf.
7. Compare the fitness value with the fitness value of alpha, beta and delta.
8. Update the fitness value and position of alpha, beta and alpha after compared .
9. Do from step 5 till 8 until maximum iterations is reached.

2.6 Benchmark Functions

In this research, the ten benchmark function is being as an objective function or a optimization problem to test the performance of the different SI method analyzed in this research. This ten benchmark functions are referred from the work done by Lim and Haron(2013) and also Lim, Hoon and Ong(2018). Benchmark functions are stated down below:

1. Sphere function

$$f(x) = \sum_{i}^{n} x_i^2 \tag{18}$$

$-5.12 \leq x_i \leq 5.12, i = 1, \ldots, n$

Global minimum, $f(x) = 0\ for\ x_i = 0, i = 1, \ldots, n$

n is the number of dimension

2. Axis parallel hyper ellipsoid function

$$f(x) = \sum_{i=1}^{n} i x_i^2 \tag{19}$$

$-5.12 \leq x_i \leq 5.12, i = 1, \ldots, n$

Global minimum, $f(x) = 0\ for\ x_i = 0, i = 1, \ldots, n$

n is the number of dimension

3. Rastrigin function

$$f(x) = 10n + \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i)) \tag{20}$$

$-5.12 \leq x_i \leq 5.12, i = 1, \ldots, n$

Global minimum, $f(x) = 0\ for\ x_i = 0, i = 1, \ldots, n$

4. Ackley function

$$f(x) = 20 + \exp(1) - 20\exp(-0.2\sqrt{1/n\sum_{i=1}^{n} x_i^2}\text{-}\exp(1/n\sum_{i=1}^{n}\cos(2\pi x_i)) \quad (21)$$

$-30 \le x_i \le 30, i = 1, \ldots, n$

Global minimum, $f(x) = 0\ for\ x_i = 0, i = 1, \ldots, n$

n is the number of dimension

5. Sum of different powers function

$$f(x) = \sum_{i=1}^{n} |x_i|^{i+1} \quad (22)$$

$-1 \le x_i \le 1, i = 1, \ldots, n$

Global minimum, $f(x) = 0\ for\ x_i = 0, i = 1, \ldots, n$

n is the number of dimension

6. Schwefel22 function

$$f(x) = \sum_{i=1}^{n} |x_i| + \prod_{i=1}^{n} |x_i| \quad (23)$$

$-10 \le x_i \le 10, i = 1, \ldots, n$

Global minimum, $f(x) = 0\ for\ x_i = 0, i = 1, \ldots, n$

n is the number of dimension

7. Quartic with noise function

$$f(x) = \sum_{i=1}^{n} ix_i^4 + random[0,1) \quad (24)$$

$-1.28 \le x_i \le 1, i = 1.28, i = 1, \ldots, n$

Global minimum, $f(x) = 0 \; for \; x_i \; = 0, i = 1, \dots, n$

n is the number of dimension

8. Rotated hyper-ellipsoid function

$$f(x) = \sum_{i=1}^{n} \sum_{j=1}^{i} x_j^2 \tag{25}$$

$-65.536 \; \leq \; x_i \; \leq 65.536, i = 1, \dots, n$

Global minimum, $f(x) = 0 \; for \; x_i \; = 0, i = 1, \dots, n$

n is the number of dimension

9. Zakharov function

$$f(x) = \sum_{i=1}^{n} x_i^2 + (\sum_{i=1}^{n} 0.5x_i)^2 + (\sum_{i=1}^{n} 0.5x_i)^4 \tag{26}$$

$-5 \; \leq \; x_i \; \leq 10, i = 1, \dots, n$

Global minimum, $f(x) = 0 \; for \; x_i \; = 0, i = 1, \dots, n$

n is the number of dimension

10. Griewank function

$$f(x) = \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod_{i=1}^{d} \cos(\frac{x^i}{\sqrt{i}}) + 1 \tag{27}$$

$-600 \; \leq \; x_i \; \leq 600, i = 1, \dots, n$

Global minimum, $f(x) = 0 \; for \; x_i \; = 0, i = 1, \dots, n$

n is the number of dimension

2.7 Previous works

Karaboga et al. (2007) test the performance of the ABC algorithm with DE, PSO and also EA for multi-dimensional numeric problems towards five benchmark functions. The results show that ACO and DE obtain better performance, and both find the optimum. However, different parameter settings are used in this experiment for different methods so different result will be produced, so same parameter settings should be applied to make sure a more accurate results on which four methods the better performance.

Next, Bansal et al. (2011) carried out an experiment by comparing 15 different inertia weight in PSO towards 5 benchmark functions by considering 3 criterion which is the average error, average number of iterations and also minimum error obtained and results show that chaotic inertia weight is a better strategy in terms of accuracy and random inertia weight is better in terms of efficiency. However, this work only justifies the performance of the PSO with different inertia weight strategies.

Lim and Haron (2013) compared the performance between the Genetic Algorithm(GA), Differential Evolution(DE) and PSO towards the benchmark functions. They used the same parameter settings towards the three different methods, which are GA, DE, and PSO and results show that although the same parameters applied still different performance on a different method. Again, the paper is comparing the performance of PSO with other methods and not the SI method.

Another previous work proposed by Sama et al. in 2006 which by using the ACO to solve the real-time train routing selection problem. This work aims to address the subproblem of the real-time Railway Traffic Management Problem(rtRTMP) which is the real-time Train Routing Selection Problem(rtRTSP) were to select the best subset of routing for the train among the alternatives railway infrastructure based on the ACO algorithm. This is because ACO performs well on the subset selection problem. The result improved the efficiency of the train by 22 per cent on the case study railway line of Rouen and 56 per cent for the Lille railway line. However, the result only shows that the ACO algorithm is great on solving a complex real-world problem and maybe other SI methods are better on solving the routing problem than ACO, so comparison of performance on different SI method is essential.

Chakraborty et al. (2017) review different methods of SI. In this work, they discussed different SI method, which is ACO, ABC, FA, Glowworm algorithm, Lion Algorithm, Grey Wolf Optimizer, Bat Algorithm and also Monkey Algorithm. Furthermore, this work also shows the potential domain of application areas for the eight different SI method. However, it only provided an initial understanding of the eight different methods and didn't compare their performance.

Another work from Obaiahnahatti in 2018 which compare and evaluate the performance of SI method which contains PSO, ACO, ABC, and FA towards 16 types of fitness functions. Best fitness values of these four methods and the time taken for evaluation being tested and the result justify that the fitness value of four methods is almost similar, but for the time taken for evaluation, PSO has a lesser time, so the result shows that PSO is better among the four methods. However, there are only four comparisons of SI method, the performance of the different SI method will be more accurate if adding a more different SI method for comparing performance.

Most of the previous works are improving a particular SI method or using the SI method into the different domains of real-world applications. Some of the previous works considered the performance of the different SI method, but different parameter settings are applied, or less SI method is being compared. Therefore, this research focuses on the performance of varying SI methods towards the ten benchmark functions.

2.8 Summary

This chapter discusses the introduction of SI, BA, GWO and also the benchmark functions. Different SI methods and previous works on the SI methods are being discussed. Therefore, different SI methods are being tested towards ten benchmark functions.

Chapter 3 Research Methodology

3.1 Overview

This chapter discusses about the methodology of this research which contains the research framework of the research methodology.

3.2 Research Framework

The research framework shown in Figure 3.2.1 which is applied in this research.

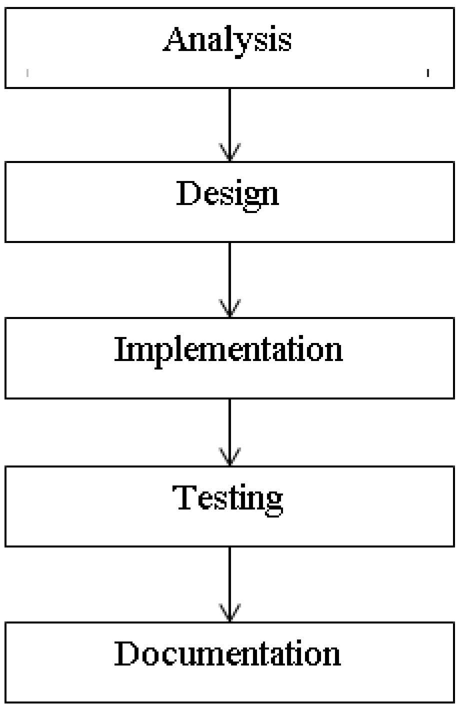

Figure 3.2.1.1 Research Framework

The main outcome of this research is to propose the best Swarm Intelligence method by comparing the performance of different Swarm Intelligence method towards the benchmark function.

3.2.1 Analysis Phase

In the analysis phase, the different SI methods, various models of PSO, parameters of different PSO models and also benchmark functions are being studied. For example, different parameters settings for the different model of PSO are being studied. Furthermore, previous works on the solution are also being referred, the strength and weakness are being determined, the review in prior works was carried out for this research. The research scopes, objectives and the problem statement are also defined in this research.

3.2.2 Design Phase

In the design phase, developing and designing of code is carried out for this research. Furthermore, the parameters settings of different SI method are being further explored. For example, the value of the population of particle in a search space and also the termination criteria are defined. In addition, software and hardware specifications are also determined in this research. Microsoft Visual Studio 2015 is used to perform the experiment of the SI method by using C++ programming language in this research.

In this research, ten different models of PSO, Grey Wolf Optimizer and Bat Algorithm are tested towards the benchmark functions and 3 same parameter settings is used for all ten PSO models which refer to the parameter settings adapted by Lim and Haron (2013), GWO from Mirjalilil et al (2014) and BA from Yang (2010). Table 3.2.2.1 shows the parameter settings of PSO, BA and also GWO for the experiment. Below listed different PSO models, GWO and also BA.

PSO01 – Original PSO

PSO02 – Original PSO with velocity clamping

PSO03 – PSO with constant inertia weight, *w*

PSO04 – PSO with constant inertia weight, *w* and velocity clamping

PSO05 – PSO with linearly decreasing inertia weight, *w*

PSO06 – PSO with linearly decreasing inertia weight, *w* and velocity clamping

PSO07 – PSO with random inertia weight

PSO08 – PSO with random inertia weight and velocity clamping

PSO09 – PSO with constriction factor, *K*

PSO10 – PSO with constriction factor, *K and* velocity clamping

GWO – Original Grey Wolf Optimizer

BA – Original Bat Algorithm

No.	Parameter		Value
1.	Population Size		40
2.	Number of Generation		2000
3.	Dimensions		30
4.	Inertia Weight for PSO03 and PSO04		0.7
5.	Linearly decrease inertia weight for PSO05 and PSO06	Maximum inertia weight	0.9
		Minimum inertia weight	0.4
6.	Random Inertia Weight for PSO07 and PSO08		[0.5+(Rand/0.2)]
7.	Constant acceleration for PSO01, PSO02, PSO03,PSO04, PSO05 and PSO06	*c1* and *c2*	2.0
8.	Constant acceleration for PSO07 and PSO08	*c1* and *c2*	1.494
9.	Constant acceleration for PSO09 and PSO10	*c1* and *c2*	2.05
10.	Constriction factor, *K*		0.729
11.	Linearly decreasing coefficient vector $\vec{a}$ for GWO		2 to 0

12.	Loudness, A of BA		0.5
13.	Pulse Rate of BA		0.5
14.	Frequency, f_i for BA	f_{min}	0
		f_{max}	2

Table 3.2.2.1Parameter settings of ten different PSO models, GWO and BA

Next, tools, software and hardware are used in this research to conduct the experiment. The details of tools are listed down below, details of the hardware is shown in Table 3.2.2.2 and details of the software is shown in Table 3.2.2.3.

Microsoft Visual Studio

- an integrated development environment(IDE) released by Microsoft. It is used to code computer programs in C++, which is the programming language we used in this research.

Notepad

- Notepad is a basic text-editing program and our output produced from the program is stored in notebook.

Microsoft Excel 2010

- Excel is a spreadsheet released by Microsoft, and it is quite easy to use, which has some great features like calculation, graphic tools and pivot tables.

Hardware Specification

Hardware	Description
Processor	Intel® Core™ i5 6200U Processor 2.30GHz
RAM	8.00 GB RAM DDR3

Table 3.2.2.2 Hardware Specification for this research

Software Specification

Software	Description
Operating System	Windows 10 Home
Development Tool	Microsoft Visual Studio 2015
Documentation Tool	Notepad, Excel

Table 3.2.2.3 Software application for this research

3.2.3 Implementation Phase

For the implementation phase, the coding of ten different PSO models, GWO and BA towards benchmark functions is being conducted. This phase also need to evaluate the coding and prove the correctness of the coding.

3.2.4 Testing Phase

After implementation, the program can perform ten different PSO models, GWO, BA using ten benchmark functions. Then the performance comparison among the SI methods are tested in this phased by using the program. The performance of the SI methods is obtained by running the coding 30 times so that the result is more accurate results. Then the best PSO models is determined by comparing the performances among the 10 PSO models and it is used to compare with GWO and BA to determined which is the better SI methods.

3.2.5 Documentation Phase

The result produce from the previous phase are documented in this phase. The details of documentation include the description of ten different PSO models, GWO, BA and benchmark functions that applied, the parameter settings which used in this research. Furthermore, the thirty results that have been run for each of the PSO models towards benchmark functions also being documented in excel to perform calculation. The performance evaluation and analysis of different SI methods are also done in this phase.

3.3 Implementation and Challenges

The most challenging part about this research is to understand, implement and develop the algorithm into coding as there are many small details needed to be a note or the evaluated fitness value of particles and the overall performance will be affected. Furthermore, ten different models applied of PSO, GWO and BA is assessed by ten benchmark functions, so there will be 120 different results can be obtained, so 30 experiments are needed to do for each of the 120 different PSO models towards benchmark functions. Hence, this research requires a lot of running and testing; thus, it is quite a time consuming as well.

Other than that, the parameter setting is also an essential thing to realise as slightly different parameter values will affect the whole performance and result.

3.4 Timeline

As FYP 1 is in short semester, literature review and understanding on the algorithm of the PSO is quite important as writing background and coding require the knowledge. Moreover, some of the coding is conducted in FYP1.

In FYP2, literature review of two new algorithms GWO and BA are being analyzed and understand so further steps like coding and experiment can be taken. Furthermore, 6 more different model of PSO also being analyzed and compared with previous 4 models of PSO done in FYP1. Coding and experiment will also be conducted to find the best SI method.

3.4.1 FYP 1 Gantt chart

Figure3.4.1.1 shows the task and the duration of task of FYP1 and FYP2.

Task Name	Start	End	Duration(days)
Analysis	12/10/2019	18/10/2019	7.00
Study concept	12/10/2019	18/10/2019	7.00
Previous work Review	15/10/2019	18/10/2019	3.00
Define project objectives	19/10/2019	20/10/2019	1.00
Define project scope	19/10/2019	20/10/2019	1.00
Design	21/10/2019	27/11/2019	7.00
Identify software and tools	21/10/2019	23/10/2019	3.00
Explore and understand algorithm	22/10/2019	26/10/2019	5.00
Define parameter setting	25/10/2019	27/10/2019	3.00
Develop algorithms	25/10/2019	27/10/2019	3.00
Implementation of Coding	28/10/2019	12/11/2019	15.00
Running Experiment	13/11/2019	18/11/2019	6.00

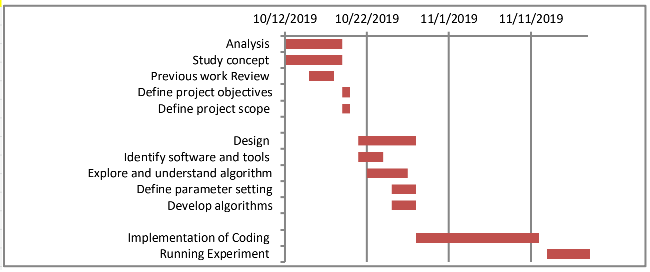

Figure 3.4.1.1Gantt chart of FYP1

Task Name	Start	End	Duration(days)
Analyse new parameters for PSO	23/1/2020	5/2/2020	14
Analyze new SI method, GWO	7/2/2020	22/2/2020	16
Aanlyze new SI method, BA	23/2/2020	7/3/2020	15
Literature Review for GWO and BA	8/3/2020	15/3/2020	7
Flow Chart for GWO and BA methods	15/3/2020	16/3/2020	1
Implementation and Coding	17/3/2020	14/4/2020	28
Experiment and Report	15/4/2020	20/4/2020	5

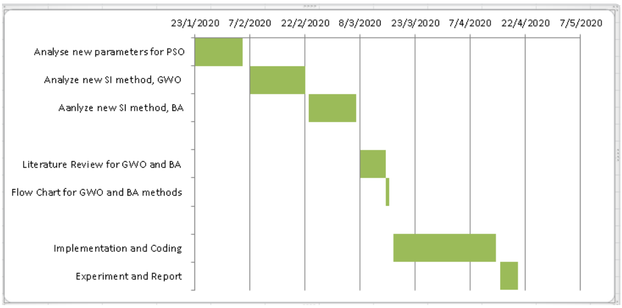

Figure 3.4.1.2Gantt chart of FYP2

3.5 Summary

This research is divided into 5 different phases which is analysis phase, design phase, implementation phase, testing phase and also documentation phase. Furthermore, in this research, Microsoft Visual Studio and C++ language are used to develop the coding for the ten different PSO models, GWO, BA and also the benchmark functions.

Chapter 4 Analysis and Discussion

4.1 Overview

In this research, analysis is needed to identify the best models of Particle Swarm Optimization and best Swarm Intelligence method. Each of the models of PSO, GWO and also BA are tested towards different benchmark functions and result obtained then collected and analyzed. Hence, this chapter included the analysis of different models of PSO, original Grey Wolf Optimizer and original Bat Algorithm towards different benchmark functions. Then the performance is being compared and the best SI method is being chosen. In the testing, coding that had been done was executed, and results of different models of PSO, GWO and BA towards benchmark functions are obtained.

4.2 Experimental Results

In this section, the result obtained in experiment will be shown. The result of Experiment consists of thirty experiment result with global best fitness value of each iteration. In addition, maximum and minimum global best fitness value of each Experiment and the time taken for the code to execute in each Experiment and also the average time taken for the thirty experiments are also recorded. In the Table 4.2.1 shows the global best minimum fitness value, best maximum fitness value, average fitness value and the average CPU time of ten PSO models which is Experiment 1 towards different benchmark functions in Experiment. Table 4.2.2 shows the global best minimum fitness value, best maximum fitness value, average fitness value and the average CPU of the best model from PSO achieved from Experiment 1, GWO and also BA towards different benchmark functions in Experiment 2.

There are ten models of PSO, which is PSO01, PSO02, PSO03, PSO04, PSO05, PSO06, PSO07, PSO08, PSO09, PSO10 and two other SI methods which are GWO and BA. In the Table 4.2.1, Table 4.2.2 B1 to B10 are referred as Benchmark Function 1 to 10 in Section 2.7 and PSO01 to PSO10, GWO and BA are referred from 3.2.2 Design Phase.

In Experiment 1, the results of ten different models of PSO are being compared and analyzed. Furthermore, ten sequences of different PSO models for each of the benchmark functions in Experiment 1 is being examined and discussed. While in Experiment 2, the best PSO models obtained will then compare its performance with GWO and also BA by listing out three sequences to further compare and analyze to determine the best SI method. Full results of Experiment 1 and 2 can refer Appendix A-1 and A-2. Table 4.2.1 and Table 4.2.2 that shows yellow highlighted values are the best values compared to other SI methods or PSO models. Green Highlighted are the best PSO models and best SI methods.

Experiment 1 Results

PSO Model	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
PSO01	150.1626	2095.9377	409.4344	19.9260	0.6898	1.2939E+11	98.1739	348313.0000	475.1437	532.2616
PSO02	44.1916	615.9123	266.1829	16.8941	0.0062	60.7765	9.7986	101871.0400	268.9846	157.4548
PSO03	6.2485	159.7828	173.1357	7.8344	7.7103E-08	46.1557	2.3200	34700.0295	174.1345	1.4934
PSO04	0.0177	0.2079	67.7240	1.6440	4.1712E-15	0.3330	0.0585	29.5128	114.2583	1.0585
PSO05	6.6749E-09	230.7093	137.2219	3.3406	4.6692E-19	46.3333	5.7691	38941.0257	232.5425	30.1110
PSO06	6.1805E-10	7.7781E-09	50.0437	2.0264E-04	1.4861E-29	6.6432E-06	0.0232	1.5939E-06	153.1204	0.0200
PSO07	1.1232E-09	36.7001	107.4490	1.3706	3.2830E-28	16.0001	0.4628	8017.2690	114.7159	3.0497
PSO08	5.4746E-11	2.3469E-09	48.8003	0.0002	8.2191E-32	3.1018E-05	0.0114	1.8195E-07	117.0116	0.0167
PSO09	2.0734E-14	5.2653	107.2751	1.1812	4.2733E-44	14.6667	0.9928	7301.5020	129.1092	3.0264
PSO10	3.9368E-15	1.0830E-14	48.6558	8.2109E-07	1.3878E-48	1.0360E-06	0.0088	2.4946E-11	99.9735	0.0044

Table 4.2.1 Results of average fitness value of ten PSO models towards ten benchmark functions

Experiment 2 Results

SI method	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
BA	1.1567	18.0287	290.5506	19.0032	0.0053	80.2787	2.0015	20.9862	2.1574	0.0760
GWO	0.1244	1.4851	14.2806	1.2419	2.8216E-07	0.7587	0.0126	320.2221	1.7210	1.0487
PSO10	3.9368E-15	1.0830E-14	48.65576	8.2109E-07	1.3878E-48	1.0360E-06	0.0088	2.4946E-11	99.9735	0.0044

Table 4.2.2 Results of average fitness value of PSO10, GWO and BA towards ten benchmark functions

The results in Table 4.2.1 and Table 4.2.2 will be discussed in the next section.

4.3 Analysis and Discussion on Different PSO Models

This section involves the analysis and also discussion for Experiment 1. Based on the average results from Table 4.2.1, the sequence of different PSO models on each of the benchmark functions in Experiment 1 is being identified. The sequence is based on the average global best fitness value of the ten models of PSO in each of the ten different benchmark functions. The closer the fitness value of PSO models to the global minimum of the benchmark functions, the higher the sequence of the PSO models in each of the benchmark functions. Based on the sequence that has been identified in Table 4.3.1, PSO10 models achieved first sequence in 10 out of 10 of different benchmark functions, and PSO08 performed the best on second sequence which achieved 4 out of 10 for second sequence. Furthermore, PSO08 and PSO06 achieved same 4 out of 10 each for the third sequence followed by PSO04 as the best on forth sequence and PSO09 as the best for fifth sequence. This shows that the global best fitness value of PSO10 models are the most closer to achieve global minimum in most of the benchmark functions compared to the other three PSO models. PSO02 and PSO01 has the worst and second worst fitness values which place in the ninth and tenth sequence on 10 out of 10 benchmark functions. Table 4.3.1 shows the sequence of 10 PSO model in Experiment 1 where BF is referred as the Benchmark Functions.

BF	PSO Models sequence in Experiment 1									
	1	2	3	4	5	6	7	8	9	10
B1	PSO10	PSO09	PSO08	PSO06	PSO07	PSO05	PSO04	PSO03	PSO02	PSO01
B2	PSO10	PSO08	PSO06	PSO04	PSO09	PSO07	PSO03	PSO05	PSO02	PSO01
B3	PSO10	PSO08	PSO06	PSO04	PSO09	PSO07	PSO05	PSO03	PSO02	PSO01
B4	PSO10	PSO06	PSO08	PSO09	PSO04	PSO07	PSO05	PSO03	PSO02	PSO01
B5	PSO10	PSO09	PSO08	PSO06	PSO07	PSO05	PSO04	PSO03	PSO02	PSO01
B6	PSO10	PSO06	PSO08	PSO04	PSO09	PSO07	PSO03	PSO05	PSO02	PSO01
B7	PSO10	PSO04	PSO07	PSO08	PSO09	PSO06	PSO03	PSO05	PSO02	PSO01
B8	PSO10	PSO08	PSO06	PSO04	PSO09	PSO07	PSO03	PSO05	PSO02	PSO01
B9	PSO10	PSO04	PSO07	PSO03	PSO08	PSO09	PSO06	PSO05	PSO02	PSO01
B10	PSO10	PSO08	PSO06	PSO04	PSO03	PSO09	PSO06	PSO05	PSO02	PSO01

Table 4.3.1 10 PSO Models sequence in the Experiment 1

As referred from the 3.2.2 Design Phase, PSO01, PSO03, PSO05, PSO07 and PSO09 are almost the same with PSO02, PSO04, PSO06, PSO08 and PSO10 except that the velocity clamping is not being included. According to the Table 4.3.1, the sequence of PSO models with velocity clamping are always higher than the same PSO models that do not have velocity clamping. This is because without velocity clamping, the velocity value will sometimes become relatively large causing the particles to take a larger step to move which may cause the particles to miss the great solution. Furthermore, bigger velocity value will cause the particles keep in a state of exploration search and without exploitation search which even the global optimal solution is found, it will jump out the global optimal solution as if the velocity explore with large values again.

Out of the ten PSO models, PSO01 and PSO02 have the worst second worst global best fitness value on ten benchmark functions. PSO01 and PSO02 model is the original models which the equation is to update the velocity and position of the particles. PSO01 and PSO02 does not have any new parameter adding into the equation compared to other PSO models as other PSO models have added a new settings to the original equation which can improve the performance of their PSO models. The particles in the search space can fly faster towards an optimum position.

PSO04 is on forth sequence for 5 out of 10 benchmark functions while PSO03 has 4 out of 10 benchmark functions in seventh and eighth sequence which are better than PSO01 as PSO02 has a new parameter added into the original version of the equation which is called inertia weight. The inertia weight parameter was set to 0.7, which referred from Lim and Haron, 2013. By adding inertia weight, it will affect the impact of the value of the previous velocity of the particles on the value of current velocity (Shi and Eberhart, 1998). Thus, this will help the particles to fly faster towards the global optimum in lesser iterations. As also mentioned by Shi and Eberhart, 1995, which more significant inertia weight helps global search to explore more new areas and smaller inertia weight helps particles on local search. Still, in PSO03 and PSO04, the inertia weight is 0.7, which the value does not change throughout the whole iterations, so inertia weight does not maximize the usage of both global search and also local search.

PSO05 and PSO06 have the parameter of linearly decreasing inertia weight. The value of the linearly falling inertia weights is in the range of [0.4, 0.9] which starts from maximum 0.9 to minimum of 0.4 and reduces steadily based on a maximum iteration by dividing the value of subtraction of maximum inertia weight with minimum inertia weight to the maximum iteration. The parameter value range [0.4, 0.9] is referred from Shi and Eberhart, 2001. The decreasing of inertia weight in each iteration can help maximize the global search at the start of the iteration and more on local search at the end of the iteration. (Shi and Eberhart, 1999). The performance of PSO06 is better than PSO04 which as maximum higher inertia weight in the start make the particle fly towards the global optimum faster and when reaching around the global optimum, while smaller inertia slows down the particles to perform a local search so that the particles will not fly towards the global optimum. While for PSO05 which does not perform that well compared to PSO03 because the update velocity equation contains random variables which the velocity may not be large all the time, so PSO05 and PSO03 achieve around seventh and eighth sequence.

PSO08 has the second best sequence with 4 out of 10 benchmark functions and PSO07 has the sixth sequence with 5 out of 10 benchmark functions. As PSO08 has smaller fitness value compared to most of the PSO06 is because when high inertia weight decreases to smaller inertia weight over iteration, PSO06 converge fast towards the optimal. However, sometimes the fast convergence will also easily get the particles stuck inside the local optimal and as the inertia weight already decreased to a smaller value, so the particles cannot jump out the local optimal. PSO08 has random inertia weight which can generate big and small inertia weights randomly in the early iteration and also later iteration which can solve the fast convergence towards the local optimal by getting a large inertia weights and jumping out the local optimal.

PSO09 and PSO10 have the parameter of *K*, which is a function for *c1* and *c2* that affect the whole original equation by multiplying the entire original equation. The *c1* and *c2* in this experiment for PSO04 models were using 2.05 as ϕ needed to be more than 4. The results in the constant *K* value to be 0.729, which referred to the equation (5). PSO10 model has global best fitness value in 10 out of 10 benchmark functions and PSO09 achieved fifth sequence with 5 out of 10 benchmark functions. PSO10 is able to achieve the minimum fitness value compared to other PSO models because constant *K* not only effect on previous velocity value but also affect the impact of the value behind which is the cognitive component and the social component. Hence, PSO10 model is considered as the best PSO model based on the result shown in Table 4.3.1. Therefore, it is used to compare with other SI methods in the next section.

4.4 Analysis and Discussion on Different SI Methods

This section involves the analysis and discussion for Experiment 2. Table 4.4.1 shows the Sequence result of best PSO models, GWO and BA.

Benchmark Functions	Best PSO model, GWO and BA sequence in Experiment 2		
	1st sequence	2nd sequence	3rd sequence
B1	PSO10	GWO	BA
B2	PSO10	GWO	BA
B3	GWO	PSO10	BA
B4	PSO10	GWO	BA
B5	PSO10	GWO	BA
B6	PSO10	GWO	BA
B7	PSO10	GWO	BA
B8	PSO10	GWO	BA
B9	GWO	PSO10	BA
B10	PSO10	GWO	BA

Table 4.4.1 Sequence result of Best PSO model, GWO and BA in Experiment 2

As shown in Table 4.4.1 which is the sequence result of comparison of average fitness value towards 10 benchmark functions, PSO10 still achieve the best result which achieved 8 out of 10 of benchmark functions in the first sequence. GWO placed on second sequence with also 8 out of 10 benchmark functions while BA has the worst result among the 3 SI methods which achieved 10 out of 10 benchmark functions on third sequence. PSO10 still achieved the best fitness value as the *K* constant not only affect previous velocity but also the distance between the particles with its personal best and the global best which enhance a better exploration search and also avoid convergence towards local optimal.

Next, GWO performed better than BA but worse than PSO10. Each candidate solution which is wolf in the search space update their position based on two random vectors. One affect the equation where calculate the distance between current wolves position and the three best position of wolves which and one affects the new position calculated based on three best position of wolf. Furthermore, these candidate solution wolves searching for the global optimal solution based on the three best solutions which can decrease the probability of other candidate solutions to reach the premature convergence and fall into local optimum. However, as the movement is being restricted by three best solutions, further exploration search are hard to achieve so some better optimal solutions may be miss, so the result didn't as good as PSO10.

BA has the worst fitness value among other 3 SI methods as BA is quite similar to PSO04 which have one linearly decreasing frequency parameter affecting the distance between global best and current position in the velocity update equation. BA also consists of pulse rate and also loudness to local search around the global best position to find some better solution. But in early velocity update, as only the parameter frequency affecting the distance between global best and current position, and the parameter frequency linearly decrease over time to achieve exploration in early stage and exploitation search in later stage. The minimum parameter frequency is zero so premature may be likely to happen as if candidate solution stuck in local optimal in early stage, the low parameter frequency in later stage can't get the candidate solution out of the local optimal. Therefore, PSO10 model from PSO considered as the best SI method compared with the other SI methods based on the results as shown in Table 4.4.1.

4.5 Findings in Research

Based on the results of the Experiment 1, PSO10 has the best fitness value, followed by PSO08, PSO06, PSO04, PSO09, PSO07, PSO03, PSO05, PSO02 and PSO01 which has the worst fitness value. For the Experiment 2, PSO10 still has the best fitness value follow by GWO and BA.

PSO01, PSO03, PSO05, PSO07 and PSO09 have their fitness value worse than its same PSO model which is PSO02, PSO04, PSO06, PSO08, PSO10 is because their velocity didn't clamped which may cause their velocity to be large sometimes and missing the better optimal solution.

PSO02 has the worst fitness value than other models because there is no parameter to limit or control the velocity in equation (1) and particles will easily trap inside the local optimum. PSO04 contains better results than PSO02 because a new parameter inertia weight has been added to control the velocity and balance the global and local exploration and exploitation.

While PSO06 is the improved methods of PSO04 contains better fitness value than PSO04 because PSO04 has a fixed inertia weights which let the particles to fly in a constant speed towards *gbest*. When a particle is flying in the different direction from the *gbest* and due to the velocity is affected by fixed inertia weight, hence the particle will not fly directly towards the *gbest* location. However, it will still move in the same direction, which indirectly makes the particle even further than *gbest*.

Furthermore, PSO06 contains linearly decrease inertia weight in each iteration which the particles will roam around the search space by finding more local optimums when the inertia value is high. It will slow down the velocity when the inertia weight is low, it can change the direction of particle moving towards *gbest* more easily.

PS10 has the best results compared to other PSO models as the PSO04 and PSO06 only affect the previous velocity. These two models and PSO02 have premature convergence which fast convergence towards the local optimal. PS10 got a parameter of constriction factor, K, which affects three parts of the Equation (1) that achieve balance on the convergence and also avoid premature convergence.

For Experiment 2, PSO10 still achieved the best fitness value followed by GWO and BA. PSO10 has the constant, *K* which affect the whole velocity update equation which makes finding a best global optimal solution easier compared to GWO and BA. GWO is better than BA as the candidate solution in GWO are leaded by three best solutions according to Wang and Li (2019). BA has the worst fitness value because fast convergence in the early stage may lead to stuck inside the local optimal. Yang et al (2014) stated that convergence behaviour is based on the parameters of BA and BA converge quickly in early iteration but slows down in later iteration. Hence, PSO10 is the best SI method in this research.

4.6 Summary

In this Chapter, 2 experiments have been conducted and the results are being obtained, compared and analyzed. Experiment 1 compared between 10 different PSO models towards benchmark functions and the best PSO models are being obtained which is PSO10. Next, a further comparison is being done in Experiment 2 which takes the best PSO model which is PSO10 and compare to 2 other SI methods which are GWO and BA. The result shows that PSO10 still the best SI method compared to GWO and BA.

Chapter 5 Conclusion

5.1 Conclusion

The optimization is still very significant in the current trend is because there are more and more complex and complicated constraints associated with different problems and applications. The optimization can help organisation, scientist and others to achieve an optimal solution by minimising or maximising the objective function depending on the problems given. There are a lot of ways in solving optimization problems, and different kind of Swarm Intelligence methods are quite popular in solving a different type of complex optimization problems. But most of the previous works of Swarm Intelligence methods do not consider on the performance of different Swarm Intelligence methods and only focus on applying them in various real-world applications. Thus, most researchers did not know which SI method can help achieve a better optimal solution. So the performance of different SI methods is essential as it helps other researchers to improve the accuracy of their research.

This research focuses in analysing the different models of PSO and also different SI methods. Furthermore, various models of PSO performance in solving the optimization problems are being tested. In the current experiment, different parameters applied will affect the performance of different PSO models. The best PSO models are chosen based on the PSO models that can achieve a better global optimum value of different benchmark functions. Based on the result in this experiment 1, the best PSO models is PSO10 which has the best global best fitness value on 10 out of 10 benchmark functions. A further comparison in Experiment 2 between the best PSO model which is PSO10 in Experiment 1, GWO and BA shows that PSO10 still has the best fitness value with 8 out of 10 benchmark functions in first sequence. Hence, PSO10 is considered as the better model in optimising the benchmark functions.

5.2 Future Work

In the future works, more various parameter settings will be tested and compared GWO and BA to further analyse their performance as only the original GWO and BA model are being used in this research. Furthermore, different SI methods like Ant Colony Optimization, Artificial Bee Colony, and Cuckoo Search can be analyse, apply towards benchmark functions and compared with SI methods used in this research to further expand the comparison of different SI methods.

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Appendix A

A.1

	B1				B2			
	Minimum	Maximum	Average	CPU Time	Minimum	Maximum	Average	CPU Time
PSO01	113.6630	200.7060	150.1626	0.7229	1361.9400	2538.4500	2095.9377	0.8301
PSO02	36.7442	53.4964	44.19158	0.9071	440.1210	772.6200	615.9122667	0.8350
PSO03	0.0499	26.3906	6.2485	0.7170	0.6740	602.9590	159.7828	0.7412
PSO04	0.0047	0.0523	0.01766	0.8517	0.0352	0.8724	0.2079	0.9023
PSO05	1.3271E-10	3.7442E-08	6.6749E-09	0.7785	3.5428E-08	760.2180	230.7093	0.7570
PSO06	7.8634E-12	4.7287E-09	6.1805E-10	0.7452	8.2534E-11	8.2372E-08	7.7781E-09	0.7776
PSO07	7.5488E-13	1.5268E-08	1.1232E-09	0.9986	5.4686E-11	288.3600	36.7001	1.0628
PSO08	5.4023E-13	3.0128E-10	5.4746E-11	1.0808	2.2511E-11	1.5082E-08	2.3469E-09	1.1365
PSO09	7.3155E-19	6.1388E-13	2.0734E-14	0.7883	6.4141E-18	52.4288	5.2653	0.7485
PSO10	1.3025E-20	9.8743E-14	3.9368E-15	0.8015	7.0952E-18	1.4063E-13	1.0830E-14	0.7605
	B3				B4			
	Minimum	Maximum	Average	CPU Time	Minimum	Maximum	Average	CPU Time
PSO01	353.7190	464.8290	409.4344	0.9421	19.5233	20.2128	19.9260	0.8494
PSO02	229.8690	289.2590	266.1828667	0.8683	15.7792	17.6690	16.8941	1.2257
PSO03	128.6130	231.6380	173.1357	0.8512	2.8925	17.2755	7.8344	0.8434
PSO04	43.4155	107.1930	67.7240	0.9070	0.4922	2.6140	1.6440	0.9908
PSO05	59.7685	196.4350	137.2219	0.8668	0.0001	16.1256	3.3406	0.8336
PSO06	13.9455	88.7023	50.0437	1.2379	1.3884E-05	8.7237E-04	2.0264E-04	0.8549
PSO07	56.7835	185.2750	107.4490	1.1204	1.2597E-05	13.8732	1.3706	1.1722
PSO08	25.8689	90.5409	48.8003	1.1908	7.5460E-06	0.0016	0.0002	1.1707
PSO09	52.7327	187.2640	107.2751	0.8494	7.9721E-09	6.1569	1.1812	0.8650
PSO10	27.8588	66.6621	48.65576	1.0833	1.8357E-08	6.3679E-06	8.2109E-07	0.9185
	B5				B6			
	Minimum	Maximum	Average	CPU Time	Minimum	Maximum	Average	CPU Time
PSO01	0.1477	1.1070	0.6898	0.9420	1818.7900	3.1075E+12	1.2939E+11	0.8723
PSO02	0.0005	0.0125	0.0062	1.2000	50.5610	70.7706	60.7765	1.1058
PSO03	6.5521E-11	1.0775E-06	7.7103E-08	0.9363	1.0720	70.4290	46.1557	0.8710
PSO04	3.0417E-18	6.4847E-14	4.1712E-15	1.2194	0.0971	0.7937	0.3330	1.1291
PSO05	6.9010E-25	9.1539E-18	4.6692E-19	0.9368	10.0000	90.0000	46.3333	0.8668
PSO06	3.3415E-33	2.2868E-28	1.4861E-29	1.2665	6.5006E-07	2.1742E-05	6.6432E-06	1.1635
PSO07	1.0186E-36	6.3678E-27	3.2830E-28	1.2933	2.9808E-05	50.0000	16.0001	1.1708
PSO08	1.2746E-38	1.0360E-30	8.2191E-32	1.3035	6.6680E-07	1.8166E-04	3.1018E-05	1.1892
PSO09	5.6153E-56	1.2383E-42	4.2733E-44	0.9440	9.5582E-07	40.0000	14.6667	0.8611
PSO10	1.8171E-57	2.7452E-47	1.3878E-48	1.2867	2.7489E-08	1.6112E-05	1.0360E-06	1.2851
	B7				B8			
	Minimum	Maximum	Average	CPU Time	Minimum	Maximum	Average	CPU Time
PSO01	51.3067	141.6520	98.1739	0.9575	245286	444553	348313	1.7980
PSO02	6.2112	14.4967	9.798585	0.9984	66357.6	126413	101871.04	2.6019
PSO03	0.0921	16.2470	2.3200	0.9533	138.1570	77507.2000	34700.0295	1.8246
PSO04	0.0287	0.0921	0.0585	1.0120	8.4722	110.9800	29.5128	2.8015
PSO05	0.0251	24.2131	5.7691	0.9730	1.2693E-06	111669	38941.0257	1.7895

PSO06	0.0088	0.0486	0.0232	1.0467	3.1465E-09	2.5210E-05	1.5939E-06	2.7314
PSO07	0.0056	10.7506	0.4628	1.1826	5.0342E-09	47255.6000	8017.2690	2.2364
PSO08	0.0057	0.0202	0.0114	1.3017	3.7876E-09	1.1598E-06	1.8195E-07	2.1912
PSO09	00028	10.7420	0.9928	0.9524	2.8681E-14	38654.7000	7301.5020	1.7764
PSO10	0.0046	0.0160	0.0088	0.9893	2.9938E-14	4.0290E-10	2.4946E-11	3.1042
	B9				B10			
	Minimum	Maximum	Average	CPU Time	Minimum	Maximum	Average	CPU Time
PSO01	298.0880	734.2850	475.1437	0.7864	375.4730	612.4620	532.2616	0.9641
PSO02	107.0660	513.6540	268.9846	0.9494	120.5930	185.4570	157.4548	1.2632
PSO03	34.4103	454.8210	174.1345	0.7930	0.9503	3.0978	1.4934	0.9577
PSO04	25.7771	325.9420	114.2583	1.1102	0.8611	1.2632	1.0585	1.2586
PSO05	25.7641	536.7070	232.5425	0.7790	2.4163E-06	90.9255	30.1110	0.9688
PSO06	25.7641	353.9930	153.1204	1.0820	1.0503E-07	0.0931	0.0200	1.1653
PSO07	1.5895E-05	233.4210	114.7159	1.0936	9.3058E-09	90.9803	3.0497	1.2494
PSO08	7.5242E-12	325.9390	117.0116	1.1292	6.1168E-09	0.10	0.0167	1.3003
PSO09	1.1580E-12	381.4380	129.1092	0.7884	5.5511E-15	90.2055	3.0264	1.0543
PSO10	7.0650E-13	265.7590	99.9735	1.1038	3.3307E-15	0.0197	0.0044	1.1548

Results of Experiment 1

A.2

	B1				B2			
	Minimum	Maximum	Average	CPU Time	Minimum	Maximum	Average	CPU Time
BA	0.9119	1.3829	1.1567	0.3706	13.9010	27.4310	18.0287	0.3796
GWO	0.0015	0.4950	0.1244	2.1224	0.0116	4.3192	1.4851	2.1062
PSO10	1.3025E-20	9.8743E-14	3.9368E-15	0.8015	7.0952E-18	1.4063E-13	1.0830E-14	0.7605
	B3				B4			
	Minimum	Maximum	Average	CPU Time	Minimum	Maximum	Average	CPU Time
BA	192.7240	401.5260	290.5506	0.4909	17.1966	20.0301	19.0032	0.4951
GWO	10.1416	26.2756	14.2806	2.1052	0.2414	2.8294	1.2419	2.1428
PSO10	27.8588	66.6621	48.65576	1.0833	1.8357E-08	6.3679E-06	8.2109E-07	0.9185
	B5				B6			
	Minimum	Maximum	Average	CPU Time	Minimum	Maximum	Average	CPU Time
BA	0.0004	0.0110	0.0053	0.5782	4.3836	584.3070	80.2787	0.4834
GWO	13386E-09	1.6594E-06	2.8216E-07	2.2644	0.1539	2.4589	0.7587	2.2984
PSO10	1.8171E-57	2.7452E-47	1.3878E-48	1.2867	2.7489E-08	1.6112E-05	1.0360E-06	1.2851
	B7				B8			
	Minimum	Maximum	Average	CPU Time	Minimum	Maximum	Average	CPU Time
BA	1.1851	2.8645	2.0015	0.5618	13.9688	28.5749	20.9862	1.5248
GWO	0.0011	0.0400	0.0126	2.3358	2.9451	1232.9800	320.2221	3.0865
PSO10	0.0046	0.0160	0.0088	0.9893	2.9938E-14	4.0290E-10	2.4946E-11	3.1042
	B9				B10			
	Minimum	Maximum	Average	CPU Time	Minimum	Maximum	Average	CPU Time
BA	1.3131	2.7334	2.1574	0.4228	0.0443	0.1030	0.0760	0.5476
GWO	0.0271	8.7399	1.7210	2.0870	0.4551	1.9238	1.0487	2.3427
PSO10	7.0650E-13	265.7590	99.9735	1.1038	3.3307E-15	0.0197	0.0044	1.1548

Results of Experiment 2

Poster

Performance Comparison of Different Swarm Intelligence Methods towards Benchmark Functions

Song Wen Huan 1602672

Faculty of Information and Communication Technology(FICT) University TUnku Abdul Rahman

Project supervisor: Dr. Lim Seng Poh

1 Abstract

Optimisation problems are associated with different kinds of complicated and constraints which make optimisation still being so important until today. This is because optimisation is able to help researchers and organisations reached an optimal solution on different research works or applications using limited resources. In the past 20 years, Swarm Intelligence (SI) methods have been trendy in solving different kinds of complex problems. However, researchers or organisations still did not consider on the performance of the SI methods as there are various SI methods and not everyone contains the knowledge on the methods. Hence, the objective of this research is to analyse different Particle Swarm Optimization (PSO) models and to identify the best method in SI. The original version of PSO, Inertia Weight PSO (IW-PSO), Linearly Decrease Inertia Weight PSO (LDIW-PSO), Random Inertia Weight PSO (RIW-PSO), Constriction Factor PSO (CF-PSO) along with and without velocity clamping (VC) are analysed and compared with Grey Wolf Optimizer (GWO) and Bat Algorithm (BA). The performance of SI method is tested using ten benchmark functions. The results in Experiment 1 show that CF-PSO with VC is performed more significant compared to the other PSO models. Hence, it is considered as the best PSO model in Experiment 1. Therefore, Experiment 2 is conducted and compared with GWO and BA using CF-PSO with VC. The results in Experiment 2 also reveal that CF-PSO with VC is the best SI method when it is compared towards the other SI methods. The result produced can help researchers to acknowledge and have better understanding on the SI methods so that better performance SI method with good accuracy can be applied on their research.

2 Problem Statement

i. Performance of different methods in Swarm Intelligence and parameters settings didn't consider by most of the authors.

ii. Performance of different SI method will be affected with different parameter settings being applied

3 Project Objectives

i. To analyse different models of Particle Swarm Optimization

ii. To identify the best method in Swarm Intelligence

4 Project Scope

i. Ten different models of Particle Swarm Optimization(PSO), Grey Wolf v Optimizer(GWO) and Bat Algorithm(BA) are being focused.

ii. Same parameter settings applied on ten PSO models, GWO and also BA are considered in this research(population size and are considered in this research)

iii. Different PSO models, GWO and BA of parameter settings are also discussed in this research.

iv. Maximum generation is being applied in this research as the termination criterion.

v. Ten benchmark function are used as the objective functions in this research

vi. C++ programming language is used for the coding part of this research.

5 Experimental Result

Experiment 1 is taken which ten different models of PSO is tested towards different benchmark functions and result obtained then collected. The best PSO model is PSO10 which is PSO with constriction factor and velocity clamping shows in Experiment 1 Result Table and PSO models sequence table. Then a further experiment 2 is taken which compare the best PSO models which is PSO10 model with two SI methods which are GWO and BA. The results obtained shows that PSO10 still the best SI method which show in Experiment 2 Results Table and PSO10, GWO and BA sequence table.

Experiment 1 Results

PSO Model	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
PSO1	150.1626	2095.9377	409.4344	19.9260	0.6898	1.2939E+11	98.1739	348313.0000	475.1437	532.2616
PSO2	44.1916	615.9123	266.1829	16.8941	0.0062	60.7765	9.7986	101871.0400	268.9846	157.4548
PSO3	6.2485	159.7828	173.1357	7.8344	7.7103E-08	46.1557	2.3200	34700.0295	174.1345	1.4934
PSO4	0.0177	0.2079	67.7240	1.6440	4.1712E-15	0.3330	0.0585	29.5128	114.2583	1.0585
PSO5	6.6749E-09	230.7093	137.2219	3.3406	4.6692E-19	46.3333	5.7691	38941.0257	232.5425	30.1110
PSO6	6.1805E-10	7.7781E-09	50.0437	2.0264E-04	1.4861E-29	6.6432E-06	0.0232	1.5939E-06	153.1204	0.0200
PSO7	1.1232E-09	36.7001	107.4490	1.3706	3.2830E-28	16.0001	0.4628	8017.2690	114.7159	3.0497
PSO8	5.4746E-11	2.3469E-09	48.8003	0.0002	8.2191E-32	3.1018E-05	0.0114	1.8195E-07	117.0116	0.0167
PSO9	2.0734E-14	5.2653	107.2751	1.1812	4.2733E-44	14.6667	0.9928	7301.5020	129.1092	3.0264
PSO10	3.9368E-15	1.0830E-14	48.6558	8.2109E-07	1.3878E-48	1.0360E-06	0.0088	2.4946E-11	99.9735	0.0044

Aver k functions

Experiment 2 Results

SI method	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
BA	1.1567	18.0287	290.5506	19.0032	0.0053	80.2787	2.0015	20.9862	2.1574	0.0760
GWO	0.1244	1.4851	14.2806	1.2419	2.8216E-07	0.7587	0.0126	320.2221	1.7210	1.0487
PSO10	3.9368E-15	1.0830E-14	48.65576	8.2109E-07	1.3878E-48	1.0360E-06	0.0088	2.4946E-11	99.9735	0.0044

A

BF	PSO Models sequence in Experiment 1									
	1	2	3	4	5	6	7	8	9	10
B1	PSO10	PSO09	PSO08	PSO06	PSO07	PSO05	PSO04	PSO03	PSO02	PSO01
B2	PSO10	PSO08	PSO06	PSO04	PSO09	PSO07	PSO03	PSO05	PSO02	PSO01
B3	PSO10	PSO08	PSO06	PSO04	PSO09	PSO07	PSO05	PSO03	PSO02	PSO01
B4	PSO10	PSO06	PSO08	PSO09	PSO04	PSO07	PSO05	PSO03	PSO02	PSO01
B5	PSO10	PSO09	PSO08	PSO06	PSO07	PSO05	PSO04	PSO03	PSO02	PSO01
B6	PSO10	PSO06	PSO08	PSO04	PSO09	PSO07	PSO03	PSO05	PSO02	PSO01
B7	PSO10	PSO04	PSO07	PSO08	PSO09	PSO06	PSO03	PSO05	PSO02	PSO01
B8	PSO10	PSO08	PSO06	PSO04	PSO09	PSO07	PSO03	PSO05	PSO02	PSO01
B9	PSO10	PSO04	PSO07	PSO03	PSO08	PSO09	PSO06	PSO05	PSO02	PSO01
B10	PSO10	PSO08	PSO06	PSO04	PSO03	PSO09	PSO06	PSO05	PSO02	PSO01

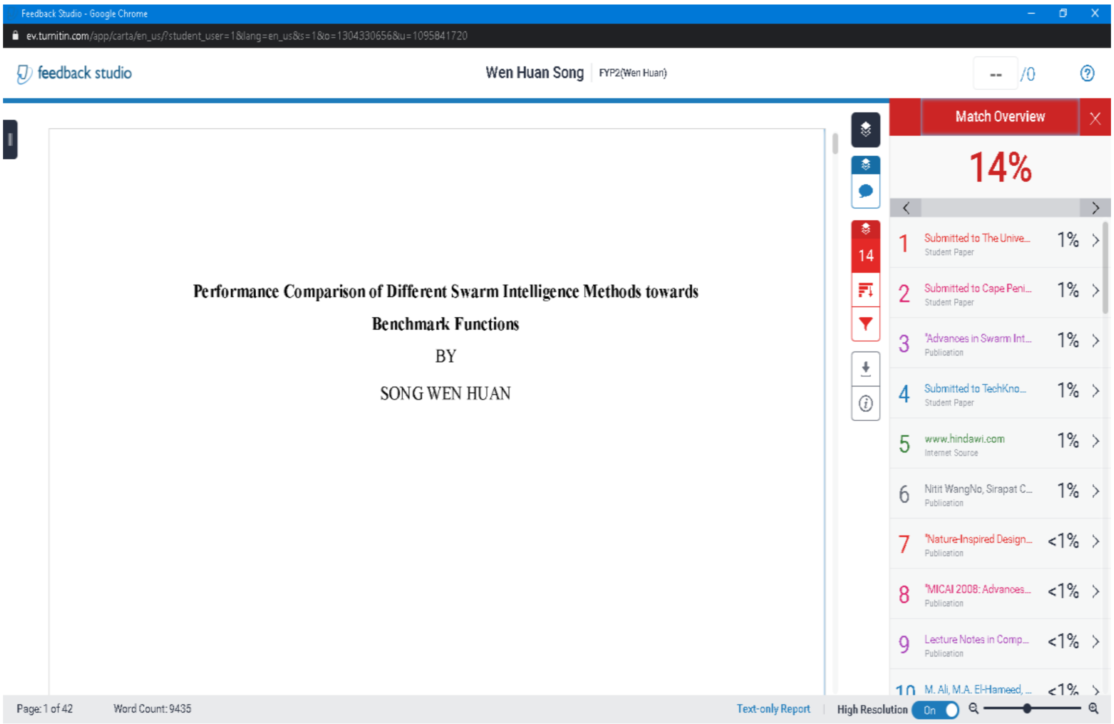
Benchmark Functions	Best PSO model, GWO and BA sequence in Experiment 2		
	1st sequence	2nd sequence	3rd sequence
B1	PSO10	GWO	BA
B2	PSO10	GWO	BA
B3	GWO	PSO10	BA
B4	PSO10	GWO	BA
B5	PSO10	GWO	BA
B6	PSO10	GWO	BA
B7	PSO10	GWO	BA
B8	PSO10	GWO	BA
B9	GWO	PSO10	BA
B10	PSO10	GWO	BA

PSO10, GWO and BA comparison sequence

6 Conclusion

This project focuses in analysing the different models of PSO and also different SI methods. The best PSO models are chosen based on the PSO models that can achieve a better global optimum value of different benchmark functions. Based on the result in this experiment, the best PSO models is PSO4 which has the best global best fitness value on 9 out of 10 benchmark functions, and PSO1 has the worst fitness value for 10 of the benchmark functions. Hence, PSO4 is considered as the better model in optimising the benchmark functions.

Plagiarism Check result



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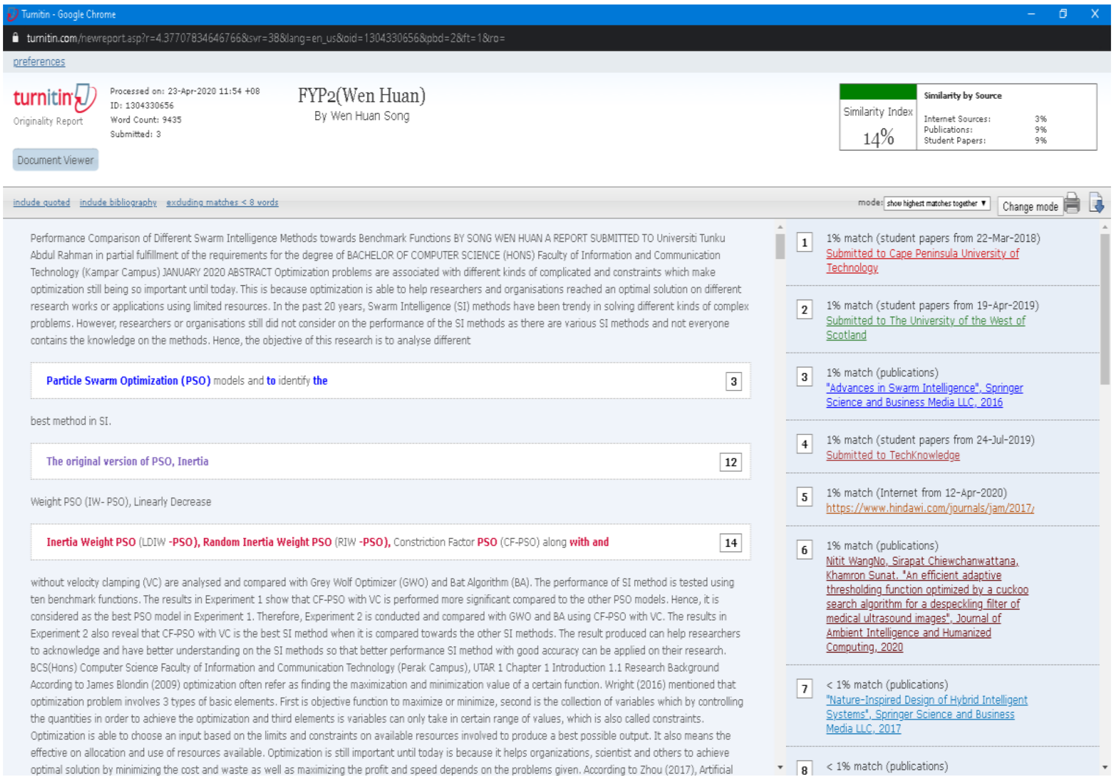

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FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY

Full Name(s) of	SONG WEN HUAN
ID Number(s)	16ACB02672
Programme / Course	CS
Title of Final Year Project	Project Title: Performance Comparison of Different Swarm Intelligence Method towards Benchmark Functions

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Based on the above results, I hereby declare that I am satisfied with the originality of the Final Year Project Report submitted by my student(s) as named above.

Signature of Supervisor	Signature of Co-Supervisor
Name: Ts. Dr. Lim Seng Poh	Name: ____________
Date: 23/4/2020	Date: ____________

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FINAL YEAR PROJECT WEEKLY REPORT

(Project I / <u>Project II</u>)

Trimester, Year: 3,3	Study week no.:1
Student Name & ID: Song Wen Huan 1602672	
Supervisor: Dr. Lim Seng Poh	
Project Title: Performance Comparison of Different Swarm Intelligence Method towards Benchmark Functions	

1. WORK DONE [Please write the details of the work done in the last fortnight.] 4 different PSO models
2. WORK TO BE DONE Study and Analyse about more parameter settings for PSO model
3. PROBLEMS ENCOUNTERED -
4. SELF EVALUATION OF THE PROGRESS Analyse more parameters for PSO

Supervisor's signature

Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project I / <u>Project II</u>)

Trimester, Year: 3,3	**Study week no.:2**
Student Name & ID: Song Wen Huan 1602672	
Supervisor: Dr. Lim Seng Poh	
Project Title: Performance Comparison of Different Swarm Intelligence Method towards Benchmark Functions	

1. WORK DONE
[Please write the details of the work done in the last fortnight.] Decided to choose parameters of PSO which is random inertia weights and settings for no velocity clamping
2. WORK TO BE DONE
Look for how to implement random inertia weights and velocity clamping
3. PROBLEMS ENCOUNTERED
-
4. SELF EVALUATION OF THE PROGRESS
-

Supervisor's signature

Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project I / <u>Project II</u>)

Trimester, Year: 3,3	**Study week no. 4**
Student Name & ID: Song Wen Huan 1602672	
Supervisor: Dr. Lim Seng Poh	
Project Title: Performance Comparison of Different Swarm Intelligence Method towards Benchmark Functions	

1. WORK DONE

[Please write the details of the work done in the last fortnight.]

Understand how to implement random inertia weight and without velocity clamping

2. WORK TO BE DONE

Learn for other SI method

3. PROBLEMS ENCOUNTERED

-

4. SELF EVALUATION OF THE PROGRESS

Understand more about the performance of different PSO models

Supervisor's signature

Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project I / Project II)

Trimester, Year: 3,3	**Study week no. 5**
Student Name & ID: Song Wen Huan 1602672	
Supervisor: Dr. Lim Seng Poh	
Project Title: Performance Comparison of Different Swarm Intelligence Method towards Benchmark Functions	

1. WORK DONE [Please write the details of the work done in the last fortnight.] Decide on doing GWO and BA
2. WORK TO BE DONE Understanding on the literature review of GWO and BA
3. PROBLEMS ENCOUNTERED **-**
4. SELF EVALUATION OF THE PROGRESS - Understanding more on GWO and BA methods

Supervisor's signature

Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project I / Project II)

Trimester, Year: 3,3	**Study week no. 6**
Student Name & ID: Song Wen Huan 1602672	
Supervisor: Dr. Lim Seng Poh	
Project Title: Performance Comparison of Different Swarm Intelligence Method towards Benchmark Functions	

1. WORK DONE [Please write the details of the work done in the last fortnight.] Finish doing literature review of GWO and BA
2. WORK TO BE DONE Finish understanding and done the flow chart of GWO and BA
3. PROBLEMS ENCOUNTERED **-**
4. SELF EVALUATION OF THE PROGRESS - Understand the flow, equation and algorithm of GWO

Supervisor's signature

Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project I / <u>Project II</u>)

Trimester, Year: 3,3	**Study week no. 6**
Student Name & ID: Song Wen Huan 1602672	
Supervisor: Dr. Lim Seng Poh	
Project Title: Performance Comparison of Different Swarm Intelligence Method towards Benchmark Functions	

1. WORK DONE [Please write the details of the work done in the last fortnight.] Finish doing flow chart for GWO and BA
2. WORK TO BE DONE - Implement the coding for different PSO models, GWO and BA
3. PROBLEMS ENCOUNTERED -
4. SELF EVALUATION OF THE PROGRESS - Understand the flow, equation and algorithm of BA

Supervisor's signature

Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project I / Project II)

Trimester, Year: 3,3	**Study week no. 7**
Student Name & ID: Song Wen Huan 1602672	
Supervisor: Dr. Lim Seng Poh	
Project Title: Performance Comparison of Different Swarm Intelligence Method towards Benchmark Functions	

1. WORK DONE [Please write the details of the work done in the last fortnight.] Finish random inertia weight implementation
2. WORK TO BE DONE - Finish implementation without velocity clamping and bat algorithm
3. PROBLEMS ENCOUNTERED **-**
4. SELF EVALUATION OF THE PROGRESS - Understand more about the algorithm steps of PSO for coding

Supervisor's signature

Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project I / Project II)

Trimester, Year: 3,3	**Study week no. 8**
Student Name & ID: Song Wen Huan 1602672	
Supervisor: Dr. Lim Seng Poh	
Project Title: Performance Comparison of Different Swarm Intelligence Method towards Benchmark Functions	

1. WORK DONE

[Please write the details of the work done in the last fortnight.]

Finish implementation of without velocity clamping and some BA coding

2. WORK TO BE DONE

- Finish implementation of BA and GWO, and experiment testing

3. PROBLEMS ENCOUNTERED

-

4. SELF EVALUATION OF THE PROGRESS

- Analyzed of different PSO models and choose the best models

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