A Brief Comparison of Particle Swarm Optimization Algorithm and Firefly Algorithm

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Abstract— In this article, we try to present some optimization algorithms that are often used by researchers. Through the information contained in this article, the reader can know and understand the development and mechanism of optimization algorithms. The algorithms presented in this article include particle swarm optimization algorithm and firefly algorithm. We chose the swarm particles optimization algorithm and the firefly algorithm to discuss because both of these algorithms are widely used for various optimization problems. Both algorithms, particle optimization algorithms as well as the newer firefly algorithms, are well known today among researchers Furthermore, after knowing the mechanism and the difference of each optimization algorithm, it is expected the reader can choose the algorithm to be used as needed.

Keywords— Particle swarm optimization, PSO, firefly algorithm

I. INTRODUCTION

There are many optimization algorithms to improve the results of a study. We can choose the algorithm according to the needs, as some researchers have done [1]-[6]. The problems studied ranging from the simplest to complex problems. Such as search problem, traveling salesman problem, image processing, health, disease detection and others. Each algorithm has its own weaknesses and advantages. There are several optimization algorithms to this article published like lightning search algorithm, swarm optimization paint, swarm optimization algorithm, sine cosine algorithm, wind driven optimization, amoeba optimization method, chaotic biogeography-based optimization, evolutionary optimization, firefly algorithm, hill climbing and multi-verse optimizer. But in this article, will only discuss the 2 most frequently used algorithms are particle swarm optimization and firefly algorithm. Some researchers have discussed optimization algorithms, [7]-[12]. Then [13] has also passed the Particle Swarm Optimization algorithm Based on Run-Length Distribution, it is necessary to know the advantages of each optimization algorithm and the algorithm's understanding that it is the most suitable for the optimization problem. This article consists of four parts: introduction, literature study, discussion of algorithms and conclusions.

II. METHODS

The methodology or systematic steps that researchers use in this article are as follows:

1. Conducting study literatures

At this stage we look for and study related research or that have been done by previous researchers. The learning process is done by reading a paper or manuscript that discusses particle swarm optimization and firefly algorithm algorithm.

2. Understand how each algorithm works

We try to understand step by step systematically the optimization algorithms discussed.

3. Conduct analysis

The analysis is done on the workings, parameters and characteristics of the optimization algorithm

4. Do the discussion

The discussion is based on the previous stage, understanding the key factors that distinguish between the two optimization algorithms.

5. Conclusions

After finding the key factor, we tried to infer the characteristics, advantages and differences of the two optimization algorithms.

Based on the steps outlined above, we summarize the procedures to be used in discussing or comparing the particle swarm optimization and firefly algorithms as follows (dashed lines describe a dynamic process, not binding means a process can be resumed to previous step if it necessary):

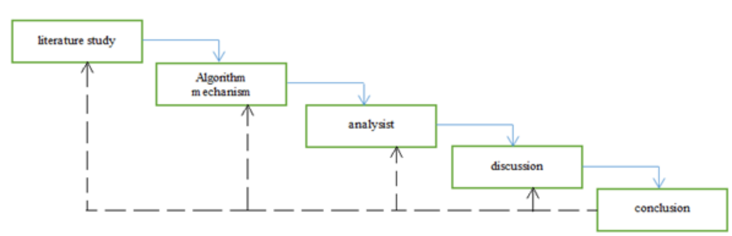

Figure 1. Procedures for Algorithm Comparison

The litera will begin from particle swarm optimization algorithm and then firefly algorithm. After that, will proceed with the results, discussion, and conclusions.

A. Particle swarm optimization

The Particle Swarm Optimization (PSO) algorithm [14] is an artificial intelligence based algorithm used to solve optimization problems [15]-[18]. This algorithm is inspired by the social behavior of the intelligence of animal colonies, such as birds and fish. This social behavior takes the form of individual action and the influence of other individuals in a group. Each individual or particle behaves in a distributed manner using its own intelligence and also influenced by the behavior of its collective group. If one particle or a bird finds the right or short way to the food source, the rest of the other group will also be able to follow the path immediately even if their location is far away in the group. Here is an illustration of how the PSO algorithm works:

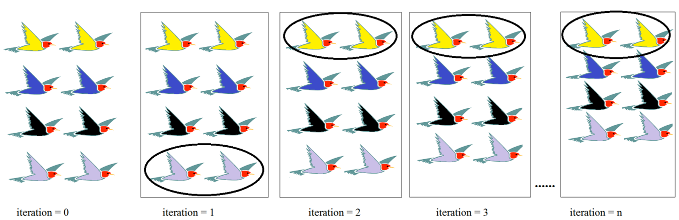

Figure 2. The Illustration of Particle Swarm Optimization

For example, there are 4 populations (swarm) and each population has 2 birds (particles to be optimized). When the first flight (*iteration-1*), all groups of birds will get the best food (*Pbest*) in their respective positions. Of the four positions, there must be the best group food (*Gbest*) from other groups. In this example, for example, the best group food (*Gbest*) for the first flight is the fourth bird group. So when the second flight (*iteration-2*), another group of birds will move closer to the fourth bird group. Apparently, on the second flight (the second iteration), the best group food (*Gbest*) is owned by the first bird group. Thus, on the third flight (the third iteration), another group of birds will move closer to the first bird group. If the best food group food on the next flight (iteration-n) continues to be owned by the first bird group, then other bird groups will continue to approach the position of the first bird group and eventually one day will gather in one position (convergent).

From the above analogy, a mathematical equation for the PSO algorithm is formulated, the formula for updating speed:

$$Vir+1 = w * Vir + c1.rand * (Pbestir - Xir) + c2.rand * (Gbestir - Xir) \quad (1)$$

The formula for updating position:

$$Xir+1 = Xir + Vir+1 \quad (2)$$

The formula for weight calculation:

$$Wit = Wmax - ((Wmax - Wmin) * It) / Itmax \quad (3)$$

Information:

Vir : The current particle velocity
Xir : Current particle velocity position
Vir + 1 : The position and velocity of the next iteration particle
Xir + 1 : The position of the next iteration particle
c1 : The cognitive of constant
c2 : The constant of social acceleration
rand : Random values distributed between *0* & *1*
Pbestir : The best position of the particle itself
Gbestir : The best position of the entire population
Wmax : The maximum inertial weight coefficient
Wmin : The minimal inertial weight coefficient
It : The ever-changing iteration of 1,2, ... *Itmax*
Tmax : Maximum value of the iteration used

A. Firefly algorithm

Firefly Algorithm is one of the algorithms in the field of Artificial Intelligence. In the field of Artificial Intelligence, there is a term of swarm intelligence which is defined as the design of algorithms or distributed problem-solving tools that are inspired by the collective social behavior of insect colonies and animal colonies. Firefly Algorithm is one of the swarm intelligence. Firefly Algorithm is a metaheuristic algorithm that is inspired by the flashing behavior of fireflies.

The algorithm developed by Xin-She Yang. The general formulation of this algorithm is presented together with mathematical modeling to solve problems with the purpose of function equivalent. The results were compared with those obtained with other alternative techniques to show that this method was able to produce an optimum solution [19]. In particular, the firefly algorithm has many similarities with other algorithms based on colony intelligence, such as particle swarm optimization (PSO), artificial bee colony optimization (ABC), and bacterial foraging (BFA) algorithms. But firefly algorithm is simpler both in concept and implementation. Furthermore, this algorithm is very efficient and can outperform other conventional algorithms, such as genetic algorithms, to solve many optimization problems.

Dr. Xin-She formulates the firefly algorithm as follows:

1. All fireflies are unisex, so a firefly will be attracted to other fireflies.
2. The attraction is proportional to the brightness of the fireflies, fireflies with lower brightness levels will be attracted and move to fireflies with higher brightness, brightness may decrease with increasing distance and the absorption of light due to air factor.
3. The brightness or intensity of the firefly of the fireflies is determined by the value of the objective function of the given problem. For optimization problems, the intensity of the light is proportional to the value of the objective function.

There are two things that are related and very important in the firefly algorithm namely light intensity and attractiveness function. In this case, many of us assume that attractiveness is affected by the degree of light intensity.

For the simplest case, for example, the problem of maximum optimization, the degree of light intensity on a firefly x can be seen as,

$$I(x) = f(x) \tag{4}$$

With the value, I is the level of light intensity on x fireflies that is proportional to the solution of the objective function of the problem to be sought $f(x)$. The β-relative magnitudes are of relative importance, because of the light intensity that must be seen and judged by other fireflies. Thus, the results of the assessment will be different depending on the distance between fireflies with one another (rij). In addition, the light intensity will decrease from the source because it is absorbed by the media eg air γ.

The function of attractiveness is as follows:

$$\beta(r) = \beta 0 * e(-\gamma rm), \ \ (m \geq 1) \tag{5}$$

1. The distance between firefly

The distance between fireflies i and j at the locations x, xi and xj can be determined when they are placed at the point where the firefly is randomly distributed in the cartesian diagram by the formula.

$$Rij = \sqrt{}\ (xi - xj)2 + (yi - yj)2 \tag{6}$$

Where the difference from the coordinates of the location of firefly i to firefly j is the distance between the two (rij).

The firefly movement

The movement of fireflies that move towards the best level of light intensity can be seen from the following equation:

$$xi = xi + \beta 0 * exp(-\gamma r2ij) * (xj - xi) + \alpha * (rand - ½) \tag{7}$$

Where the initial variable xi indicates the initial position of fireflies located at location x, then the second equation consisting of the variable $\beta 0$ = 1.0 is the initial attractiveness value of firefly, exponential variable, the variable γ = 1.0 is the value for the level Absorption in the environment around firefly ie air and last rij is variable difference of initial distance between firefly i and j. All variables in the second equation are given from the firefly attractiveness function which determines the brightness level. Furthermore, the third equation consists of the difference in the value of the solution on firefly i against firefly j. Then the function of firefly movement equations (rand) shows random numbers that range between [0,1]. A variables that have a range between [0,1] commonly determined with values of 0.2. All the variables formed on the firefly movement equation ensure the fast algorithmic work toward the optimal solution [20].

The standard procedure for using firefly algorithm is as follows:

1. Initialize firefly populations, the number of iterations and firefly algorithm parameters.
2. Evaluate the fitness function on each firefly.
3. Initialize the initial fitness function as a determination of the level of early light intensity.
4. Update the movement of each firefly using the equation of movement.
5. Compare each of the best firefly candidates from the value of the fitness function to get the best firefly value.
6. Do iteration to the limit or to get firefly with a pretty good fitness function.

III. RESULTS AND DISCUSSION

Based on the learning outcomes that have been done in the previous stage, a comparison of the two algorithms is produced; particle optimization and firefly algorithms are as follows:

TABLE I

The Comparison of Optimization Algorithms

No	Key Factors	PSO	Firefly algorithm
1	metaheuristic	√	√
2	flexibility	√	√
3	genetic operators		√
4	low time complexity	√	√
5	easy to modify	√	
6	use of randomness		√
7	certain of the most optimal solutions		√
8	convergence	√	√

The results in Table I, is a temporary result, there can still be errors and inaccuracies, so research and further measurements are needed.

Based on the literature studies that have been done before, we will give an opinion on the use of optimization algorithms. PSO is one of the metaheuristic methods, this is because PSO does not have principles about the problem to be optimized and can provide many alternatives. Metaheuristic methods such as PSO are uncertain of the most optimal solutions. Specifically, the PSO does not require gradient problems as optimized, as it does in the form of classical optimization methods such as quasi-newton and the derived gradient.

Broadly speaking, the PSO method has much in common with the EC (Evolutionary Computation) method. Both techniques start from a group of randomly generated populations and use fitness values to evaluate the population as a whole. However, the main difference between PSO and other optimization methods PSO does not have genetic operators such as mutation or crossover. Particles in the PSO method update values using internal speed, the update process is repeated as many times as needed. In the last iteration only the best particles will be taken and made the optimal solution.

The absence of genetic operators, such as crossover PSO clarity methods is easy to implement. This becomes a vocational method. Time complexity with PSO method is very efficient, because the parameters used are very minimal, it can be said the PSO method is a simple method.

There are many metaheuristic methods, each method has its own advantages and limitations. Some researchers try to make improvements, with ups and downs, so was born variants PSO, variant GA and others. Variants that are produced on one side more time-saving, low complexity but with a less optimal solution and vice versa. The PSO method is highly dependent on severe problems, such as the convergence of loss of population diversity. There are many more common uses for global optimization solutions. Other problems that can be solved easily.

Another metaheuristic method is the firefly algorithm. The clarity method makes use of randomness to find problem solutions. Not all problems can be found in the same solution, even with the same parameters. The firefly method is inspired from the natural life that can be observed directly. In this normal method comdition can find the optimal solution, where the method of masculinity can not be effective.

IV. CONCLUSIONS

From the discussion that has been done in the previous section, we can know the mechanism of the use of each optimization algorithm. Researchers must be careful in choosing the algorithm to be used, adjust to the data and difficulty level encountered. Another thing to note is the purpose of the research undertaken, namely how high the desired optimization value and how the impact of optimization conducted on the final results of the study. The following are some of the advantages obtained using the optimization algorithm discussed in the previous chapter:

TABLE II

The Advantages of Each Algorithms

No	Algorithm	The advantages
1	Particle swarm optimization	1. Easy to implement and requires only a few parameters 2. There is no evolution or mutation in the operator 3. PSO requires less computing so it is more efficient 4. In several cases PSO is more flexible in maintaining a balance between global and local searches for its search space
2	Firefly Algorithm	1. Highly efficient to solve complex problems 2. Low time complexity 3. Can be used for various optimization problems, because its flexibility

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