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Research paper

A Literature Survey on Artificial Swarm Intelligence based Optimization Techniques

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Abstract

From few decades' optimizations techniques plays a key role in engineering and technological field applications. They are known for their behaviour pattern for solving modern engineering problems. Among various optimization techniques, heuristic and meta-heuristic algorithms proved to be efficient. In this paper, an effort is made to address techniques that are commonly used in engineering applications. This paper presents a basic overview of such optimization algorithms namely Artificial Bee Colony (ABC) Algorithm, Ant Colony Optimization (ACO) Algorithm, Fire-fly Algorithm (FFA) and Particle Swarm Optimization (PSO) is presented and also the most suitable fitness functions and its numerical expressions have discussed.

Keywords: *Optimizations Techniques (OT), Artificial Intelligence, Artificial Bee Colony (ABC) Algorithm, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Firefly Algorithm (FFA), Fitness functions.*

1. Introduction

The term optimization can be defined as, "the selection of a best element with regard to some criterion from some set of available alternatives". In general, an optimization problem consists of maximizing or minimizing a real function by systematically choosing input values from within an allowed set and computing the value of the function [1],[2].

In engineering applications existence of multiple solutions lead to ambiguity in decision making. To overcome this choosing of best solution with respect to constraints is required. This can be done by either minimizing or maximizing the objective function, which leads to the optimized solution.

Optimizations techniques find a broad range of applications in the field of science and engineering applications, such as robotics [3]-[5], artificial intelligence, machine learning, power systems[6], [7], navigation systems [8], communication systems [9], [10], state estimation, image processing [11]-[15], computer graphics, battery based energy systems, renewable energy based systems, mathematical modelling of systems, etc.

Optimization techniques can be classified in many ways. In a broad scope, they can be classified as standard optimization, heuristics and meta-heuristics. In engineering applications heuristics and meta-heuristic techniques play a major role in problem solving due to randomness in their nature. Mainly swarm intelligence techniques are considered in this work for their simplicity. Among them most widely used algorithms are Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Artificial Bee Colony Optimization (ABC) and Fire-fly Algorithm (FFA) and these algorithms are discussed in the section. II

2. Optimization Techniques

This section deals with the most popular swarm intelligence optimization techniques which are used for the most of the engineering applications have been discussed.

2.1. Ant Colony Optimization

Ant Colony Optimization (ACO) or Ant System is a meta-heuristic algorithm developed by Marco Dorigo in 1991 by studying the behaviour of ants and their colonial nature [16]-[18]. The method by which ants find the best route from source to target is studied and developed an algorithm as shown in Fig.1. Various variants are proposed based on objective function and search criteria used. Variants include elitist ant system, max – min ant system, rank based ant system, etc [19]-[23]. Applications include travelling sales man problem, image processing, finding shortest route, economic load dispatch, etc [24], [25].

2.2. Particle Swarm Optimization

Particle swarm optimization (PSO) is a meta-heuristic algorithm developed by Dr. Eberhart, Dr. Kennedy in 1995 by studying the social behaviour of bird flocking or fish schooling [26], [27]. The method by which the bird flock find their way based on both individual and group's best direction is modelled and developed an algorithm shown in figure 2.

Various variants such as GA-PSO, EPSO, QPSO, BPSO, etc are proposed [29]. PSO can be applied for wide range of engineering problems such as industrial optimization, power system optimization, robotics, image processing, biometrics, weather forecasting, load forecasting, etc [28], [29].

2.3. Artificial Bee Colony Optimization

Artificial Bee Colony (ABC) is a meta-heuristic algorithm developed by Karabogain 2005 by carefully studying the foraging behaviour of honey bees [30]. The algorithm of ABC is shown as flowchart in Fig.3. The ABC algorithm has variants such as enhanced bee's algorithm, modified bee's algorithm, grouped bee's algorithm, etc [31], [32]. ABC has wide range of applications in neural networks, industrial engineering, mechanical engineering, electrical engineering, electronics engineering, control engineering, civil engineering, image processing, data mining, etc [33].

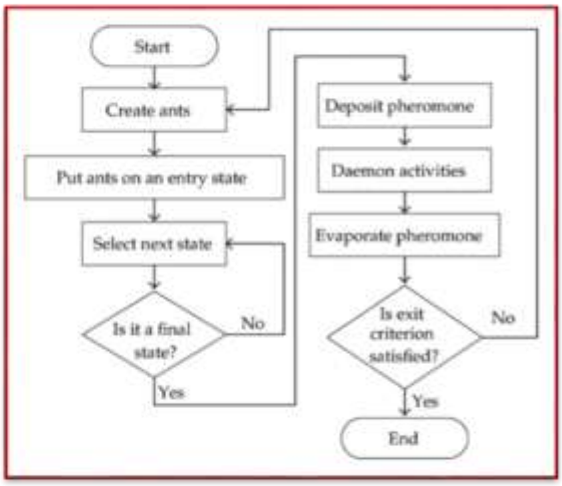

Fig.1:. Ant Colony Optimization Flowchart

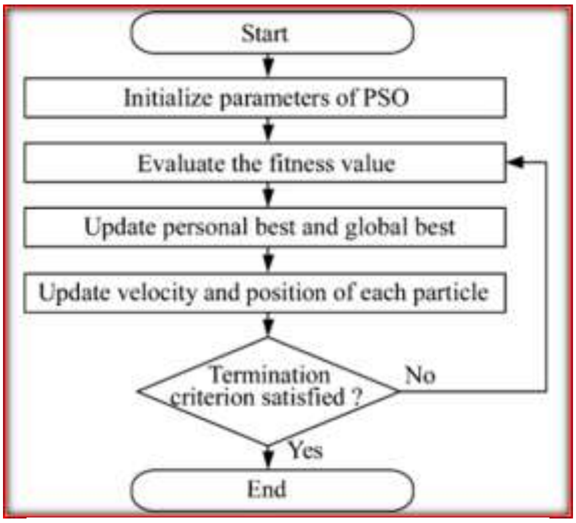

Fig.2:. Particle Swarm Optimization Optimization Flowchart

2.3. Fire Fly Algorithm

Fire-fly algorithm (FFA) is a meta-heuristic algorithm developed by Xin She Yang in 2008 by studying the flashing patterns and behaviour of fire-flies [34]. The algorithm is modelled as a flowchart shown in Fig.4. Firefly algorithm has various modified and hybrid variants such as elitist firefly algorithm, binary represented firefly algorithm, gaussian randomized firefly algorithm, levy flight randomized firefly algorithm, chaos randomized firefly algorithm, parallel firefly algorithm, etc [35]-[42]. Firefly algorithms are applied in every aspect of engineering to solve problems such as industrial optimization, image processing, antenna design, power system optimization, robotics etc [43]-[52].

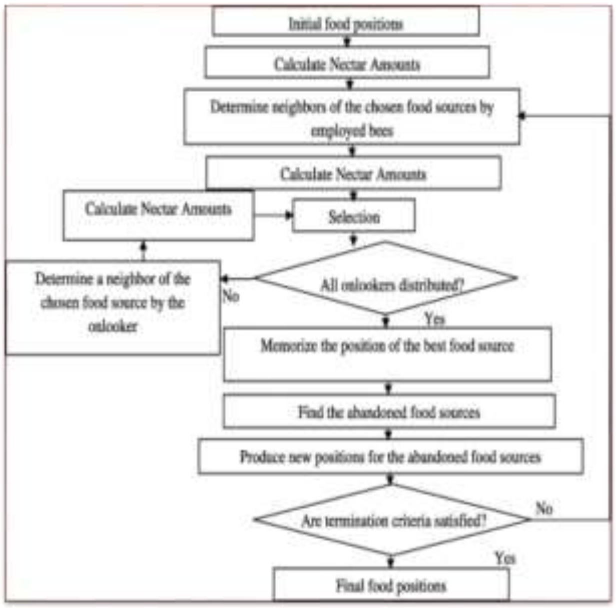

Fig.3:. Artificial Bee Colony Flowchart

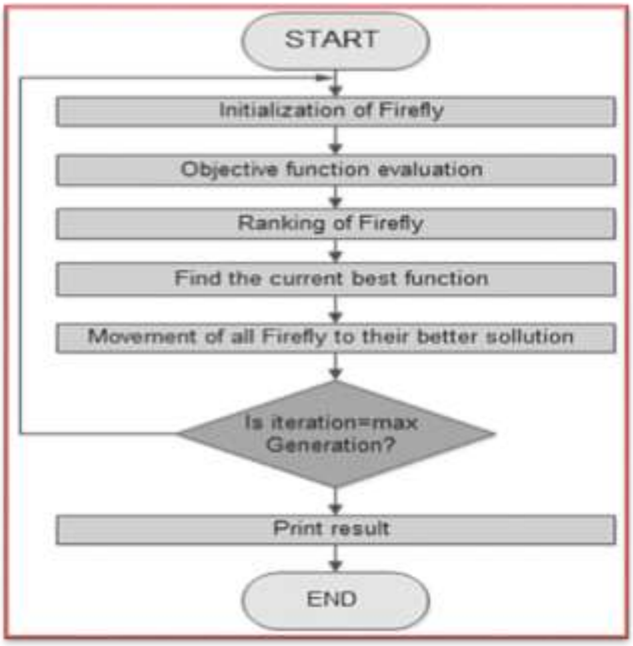

Fig.4:. Flowchart of Fire-fly Algorithm

3. Test Functions of Optimization Techniques

This section converses the various test functions which are used to find the best results in optimization techniques.

Beale: This function is defined as follows

$$f(x) = (1.5 - x_1 + x_1x_2)^2 + (2.25 - x_1 + x_1x_2^2)^2 + (2.625 - x_1 + x_1x_2^3)^2$$

$$f(x) = (1.5 - x_1 + x_1x_2)^2 + (2.25 - x_1 + x_1x_2^2)^2 + (2.625 - x_1 + x_1x_2^3)^2$$

Search domain of this function is x_i ε [-4.5, 4.5] □i = 1,2.

Booth: This function is defined as follows

$$f(x) = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2$$

$$f(x) = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2$$

This function is a plate shaped function. Search domain of this function is x_i ε [-10, 10] □ i = 1,2.

Bukin: The sixth Bukin function can be defined as follows

$$f(x) = 100\sqrt{|x_2 - 0.01x_1^2|} + 0.01|x_1 + 10|$$

This function has many local minima. The function is usually evaluated on the rectangle x_1 ε [-15, -5], x_2 ε [-3, 3].

Three-Hump Camel: This function can be defined as follows

$$f(x) = 2x_1^2 - 1.05x_1^4 + \frac{x_1^6}{6} + x_1x_2 + x_2^2$$

This function is a valley shaped function. The function is usually evaluated on the square x_i ε [-5, 5] □ i = 1, 2.

Cross-in-Tray: This function can be defined as follows

$$f(x) = -0.0001\left(\left|\sin(x_1)\sin(x_2)e^{\left|100-\frac{\sqrt{x_1^2+x_2^2}}{\pi}\right|}\right|+1\right)^{0.1}$$

It has multiple global minima. The function is usually evaluated on the square x_i ε [-10, 10] □ i = 1, 2.

Easom: This function can be defined as follows

$$f(x) = -\cos(x_1)\cos(x_2)e^{-((x_1-\pi)^2+(x_2-\pi)^2)}$$

It has multiple local minima. It is unimodal and the global minimum has a small area relative to search space. The function is usually evaluated on the square x_i ε [-100, 100] □ i = 1, 2.

Egg holder: This function can be defined as follows

$$f(x) = -(x_2+47)\sin\left(\sqrt{\left|x_2+\frac{x_1}{2}+47\right|}\right) - x_1\sin\left(\sqrt{|x_1-(x_2+47)|}\right)$$

This function is a difficult function to optimize as it has multiple local minima. The function is usually evaluated on the square x_i ε [-512, 512] □ i = 1, 2.

Griewank: This function can be defined as follows

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

Where, d – No. of dimensions

This function has multiple widespread local minima that are regularly distributed. The function is usually evaluated on the hypercube x_i ε [-600, 600] □ i = 1 to d.

Levy: This function can be defined as follows

$$f(x) = \sin^2(\pi\omega_1) + \sum_{i=1}^{d-1}(\omega_i-1)^2[1+10\sin^2(\pi\omega_i+1)] + (\omega_d-1)^2[1+\sin^2(2\pi\omega_d)]$$

Where,

$\omega_i = 1 + \frac{x_i-1}{4}$, □ i = 1 to d

d – No. of dimensions

This function is usually evaluated on the hypercube x_i ε [-10, 10] □ i = 1 to d.

Matya: This function can be defined as follows

$$f(x) = 0.26(x_1^2 + x_2^2) - 0.48x_1x_2$$

This is a plate shaped function and hence, this function has only global minima but no local minima. It is usually evaluated on the square x_i ε [-10, 10] □ i = 1, 2.

Mccormick: This function can be defined as follows

$$f(x) = \sin(x_1+x_2) + (x_1-x_2)^2 - 1.5x_1 + 2.5x_2 + 1$$

This is a plate shaped function and hence, this function has only global minima but no local minima. This function is usually evaluated on the rectangle x_1 ε [-1.5, 4], x_2 ε [-3, 4].

Rastrigin: This function can be defined as follows

$$f(x) = 10d + \sum_{i=1}^{d}[x_i^2 - 10\cos(2\pi x_i)]$$

Where, d – No. of dimensions

This function has multiple widespread local minima that are regularly distributed. The function is usually evaluated on the hypercube x_i ε [-5.12, 5.12] □ i = 1 to d.

Rosenbrock: This function can be defined as follows

$$f(x) = \sum_{i=1}^{d-1}\left[100\left(x_{i+1}-x_i^2\right)^2 + (x_i-1)^2\right]$$

Where, d – No. of dimensions

The Rosennrock function is also called as valley or banana function. It is unimodal and the global minimum lies in a narrow parabolic valley. The function is usually evaluated on the hypercube x_i ε [-5, 10] □ i = 1 to d.

Schaffer2: This function can be defined as follows

$$f(x) = 0.5 + \frac{\sin^2(x_1^2 - x_2^2) - 0.5}{[1 + 0.01(x_1^2 + x_2^2)]^2}$$

The second Schaffer function has multiple local minima. The function is usually evaluated on the square x_i ε [-100, 100] □ i = 1, 2.

Schaffer4: This function can be defined as follows

$$f(x) = 0.5 + \frac{\cos(\sin|x_1^2 - x_2^2|) - 0.5}{[1 + 0.01(x_1^2 + x_2^2)]^2}$$

The fourth Schaffer function has multiple local minima. The function is usually evaluated on the square x_i ε [-100, 100] □ i = 1, 2.

Sphere: This function can be defined as follows

$$f(x) = \sum_{i=1}^{d} x_i^2$$

Where, d – No. of dimensions

The sphere function is a bowl shaped function. It is continuous, convex and unimodal. The function is usually evaluated on the square x_i ε [-5.12, 5.12] □ i = 1 to d.

Results:

The above mentioned test functions are supplied as fitness functions for the optimization algorithms and tested for best fit values.

4. Conclusion

This paper presents a basic flat form to work on swarm intelligence algorithms i.e., PSO, ACO, ABC and FFA. The behaviour and basic understandings of fitness functions have been discussed in this paper.

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