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Fruit fly optimization algorithm based on differential evolution and its application on gasification process operation optimization

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ABSTRACT

The expression of the smell concentration judgment value is significantly important in the application of the fruit fly optimization algorithm (FOA). The original FOA can only solve problems that have optimal solutions in zero vicinity. To make FOA more universal for the continuous optimization problems, especially for those problems with optimal solutions that are not zero. This paper proposes an improved fruit fly optimization algorithm based on differential evolution (DFOA) by modifying the expression of the smell concentration judgment value and by introducing a differential vector to replace the stochastic search. Through numerical experiments based on 12 benchmark instances, experimental results show that the improved DFOA has a stronger global search ability, faster convergence, and convergence stability in high-dimensional functions than the original FOA and evolutionary algorithms from literature. The DFOA is also applied to optimize the operation of the Texaco gasification process by maximizing the syngas yield using two decision variables, i.e., oxygen–coal ratio and coal concentration. The results show that DFOA can quickly get the optimal output, demonstrating the effectiveness of DFOA.

1. Introduction

In recent years, evolutionary algorithms have been widely used in optimization problems such as scheduling optimization problems [1], the shortest path problems [2], and multidimensional knapsack problems [3]. Evolutionary algorithms not only have the main characteristic of intelligent and parallel search, but also have some basic properties such as incremental optimization, guideline random search, global optimal solution, versatility, robustness, and ease when combined with other algorithms. Initial evolutionary algorithms have only three main branches, namely, genetic algorithm (GA), evolutionary programming (EP), and evolution strategy (ES) [4]. With further research, a variety of intelligent evolutionary algorithms have been proposed and are now used to deal with optimization problems, such as, particle swarm optimization (PSO) [5], differential evolution (DE) [6], GA [7], and Ant Colony Optimization Algorithm (ACO) [8].

Fruit Fly Optimization Algorithm (FOA) [9] is a new evolutionary algorithm proposed by Dr. Pan in June 2011. The algorithm simulates the food-finding behavior of the fruit fly. Compared with other intelligent algorithms, FOA has some advantages such as being easily understandable and having simple calculations. Therefore, the algorithm can be widely used in science and engineering fields, such as in solving the steelmaking casting problem [10], GRNN parameters optimization [11], semiconductor final testing scheduling problem [12], design of the PID controller [13,14], power load forecasting [15], and multidimensional knapsack problem optimization [16].

Compared with other intelligent algorithms, FOA is simple and only requires the adjustment of two parameters, namely, population size and maximum generation number. Meanwhile, other traditional intelligent algorithms require at least three parameters, such as, three parameters of PSO [5], three parameters of GA [7], five parameters of ACO [8], and three parameters of Artificial Fish Swarm Algorithm (AFSA) [17]. The impact of various parameters on the performance of the algorithm is difficult to study clearly, and parameters are usually decided through a large number of experiments. An improper parameter will seriously affect the performance of the algorithm, and cause difficulty in analyzing the complexity of the algorithm.

However, FOA has some disadvantages. The original FOA has two main tricks: the osphresis foraging phase and the vision foraging phase. In the osphresis foraging process, the independent variable is decided by a coordinate position and a smell concentration judgment function, as shown in the formulas $D = \sqrt{x^2 + y^2}$ and $S = 1/D$, where S is the true independent variable of object function and x and y are its coordinates. The two formulas indicate that

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D is at a large scope and S is in a small scope even closing to zero. Therefore, the original FOA is disadvantageous in that it can only solve problems that have optimal solutions in zero vicinity. In addition, the two formulas show that D is a positive number. Therefore, FOA cannot solve problems that have optimal solutions that are negative numbers. The main goal of this study is to achieve an improved FOA that can solve problems that have optimal solutions of any value. To overcome the above-mentioned drawbacks, a great deal of work has been done to improve the FOA. Ref. [14] proposed a modified FOA, which includes an escape parameter that enables the algorithm to escape from the local extreme solution to find the global extreme one. However, the escape parameter is equal to $g \times Dist_i$, where g is a random variable following normal distribution. Therefore, the algorithm goes into random search mode without intelligence. Ref. [16] proposed a novel binary fruit fly optimization algorithm (bFOA) to solve discrete optimization problems. In bFOA, a binary string is used to represent the solution, a global vision mechanism based on differential information is proposed to update the probability vector, and two repair operators are employed to guarantee the feasibility of solutions. Ref. [18] presented an improved fruit fly optimization (IFFO) algorithm for continuous function optimization problems. In IFFO, a new control parameter is introduced to tune the search scope and a new solution-generating method is developed to enhance the performance of the algorithm. On the basis of maintaining the main structure of FOA, and to overcome the disadvantages mentioned, an improved FOA based on differential evolution (DFOA) is introduced. First, in order to make FOA more suitable for continuous optimization problems, especially for those functions with optimal solutions that are not zero, the expression of the smell concentration judgment value is changed by normalization mechanism. Second, the differential vector is introduced to replace the random research at the local optimum, which improves the convergence rate.

The main structure of this article is as follows. Section 1 provides the research motivation and objective of this article is introduced. FOA and DFOA are described in detail in Section 2. Parameter setting, numerical experiments and analysis are given in Section 3. In Section 4, the coal gasification process optimization using DFOA is demonstrated. Section 5 draws the conclusions.

2. An improved fruit fly optimization algorithm based on differential evolution

2.1. Original fruit fly optimization algorithm and its defects

FOA is a swarm optimization algorithm based on the food-finding behavior of fruit flies. Fruit flies mainly use olfaction and vision to find food and can collect different kinds of airborne smells, even when the food source is 40 km away. Fruit flies use olfaction to search for food along the scent concentration path, and then use visual flight to the group gathering place or the food source. The process of using FOA is described as follows [9]:

Step 1. Initial population size and maximum number of iterations. Fruit fly swarm positions are initialized randomly as follow: InitX_axis and InitY_axis.

Step 2. Give an individual fruit fly a random direction and distance for the search for food. In the formula (1), i stands for the ith individual.

$$\begin{aligned} X_i &= X\_axis + RandomValue \\ Y_i &= Y\_axis + RandomValue \end{aligned} \tag{1}$$

Step 3. Since the food location is unknown, the distance to the origin is estimated first (Dist). The smell concentration judgment value (S) is then calculated, which is the inverse of distance.

$$Dist_i = \sqrt{X_i^2 + Y_i^2} \tag{2}$$

$$S_i = 1/Dist_i \tag{3}$$

Step 4. Substitute the smell concentration judgment value (S) into the smell concentration judgment function (Fitness function) to acquire the smell concentration (Smell) of the individual location of the fruit fly.

$$Smell_i = Function(S_i) \tag{4}$$

Step 5. Find the fruit fly with the best smell concentration (the optimal value) among the fruit fly swarm.

$$[bestSmell \quad bestindex] = Opt(Smell_i) \tag{5}$$

Step 6. Keep the best smell concentration value and its x and y coordinates. The fruit fly swarm will then fly toward that location using vision.

$$\begin{cases} Smellbest = bestSmell \\ X\_axis = X(bestindex) \\ Y\_axis = Y(bestindex) \end{cases} \tag{6}$$

Step 7. Execute optimization repeatedly from Steps 2 to 5, then judge if the smell concentration is superior to the previous one, in which case, implement Step 6.

Steps 2 and 3 evidently show that the Dist value is distributed randomly in a large-scale scope, and FOA can only find the solution in the vicinity of the origin, whereas the scope of S is very small. Taking a simple oscillating function, $y = \sin(x-7)/(x-7)$ for example: when x is equal to 7, the function reaches the maximum. FOA cannot find the maximum value to this simple function (the evolution curve is as shown in Fig. 1). To solve this problem and to enhance the optimization capability of the algorithm, this paper makes some improvements and proposes a FOA based on differential evolution (DFOA).

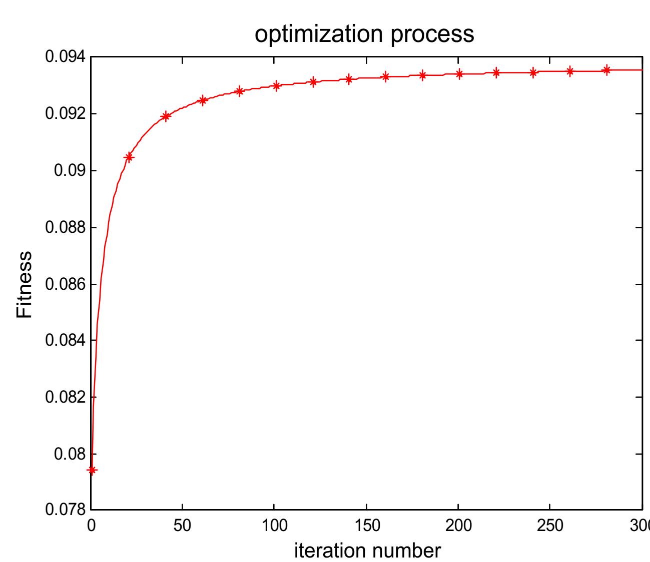

Fig. 1. FOA optimizes the function $y = \sin(x-7)/(x-7)$.