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Study on Optimization of Chemical Process Based on Intelligent Computing

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In order to solve the problem that the traditional optimization algorithm cannot calculate the optimal solution, this paper proposes an improved intelligent algorithm to get the optimal solution. Artificial fish swarm algorithm (AFSA) is a new research direction of intelligent optimization algorithm, which provides a new theory and new idea for the optimization of complex chemical process. This subject is based on the basic artificial fish swarm algorithm (AFSA). First, the parameters and disadvantages of the algorithm are analyzed, and an improved artificial fish swarm algorithm (IAFSA) that automatically acquires visual perception ranges and steps is proposed. Then, on the basis of several classic test functions, IAFSA's practicality and stability are proven. Finally, IAFSA is applied to the process optimization of the heat transfer pipe network and the optimization of the T alkylation process to verify the practicability of the algorithm in the actual chemical process.

1. Introduction

Chemical process is a very typical complex large system, its characteristics include variable, large-scale, complex structure and so on (Ali et al., 2016). After the process is optimized, you can get good results. Therefore, it has gradually become the focus of research over the years (Kunde et al., 2016). The optimization method is based on the math, which can solve a wide variety of engineering optimization problems (Asaithambi et al., 2016). In addition, its birth and development provide powerful tools for optimization of complex large systems (Thirugnanasambandham et al., 2016). At the same time, the proposed new algorithm and the improvement of various algorithms have shown a strong effect in the solution of complex large-scale system problems (Liu et al., 2016). In general, chemical process optimization refers to the availability of appropriate process variables or operating parameters under certain conditions (Nezungai and Majozi, 2016). It not only can get the objective function of the system to be optimized, but also can get the minimum or maximum performance index.
Process optimization is expressed in the following aspects (Rio-Chanona et al., 2016). Optimization of process input variables or operating parameters, optimization of process conditions for chemical processes, optimization of process dynamic systems, optimization of plant production plans, and optimization of parameters in mathematical models (Sim, 2016). Modern chemical process systems are a typical complex system. Its process contains a lot of general material, these materials affect each other (Ozturk et al., 2016). In addition, the system structure is complex, large scale (Psaltis et al., 2016). Moreover, the variables have a lot of constraints, the model is also very complex (Franke, 2016). In view of the above reasons, the traditional optimization method is difficult to be applied (Shi et al., 2016). The existing optimization method will usher in a huge challenge (Giuliano et al., 2016). Therefore, this paper studies the artificial fish swarm algorithm, analysis algorithm improvement program (Liu et al., 2016). The algorithm is applied to the actual background of the chemical process, in order to achieve its optimization (Wang et al., 2016).

2. Basic artificial fish swarm algorithm

2.1 Artificial fish swarm algorithm description

In a natural water, the higher concentrations of water will gather more fish. According to this feature, artificial fish is used to mimic the basic behaviour of the fish, in order to achieve the overall optimization. This formed

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the basic idea of AFSA. When the virtual artificial fish is initialized, the initial position of the virtual artificial fish can be arbitrarily generated or can be set in advance (Rouhani and Ravasan, 2016). In addition, the basic behaviour of the fish is simulated, the behaviour of the virtual artificial fish is evaluated. Finally, the current optimal behaviour is selected to find the location where the food concentration is greatest. The algorithm encapsulates the virtual artificial fish into two parts: variable parameter and function (Moein et al., 2016). On the basis of object-oriented technology, the model of virtual artificial fish is reconstructed (Sadhasivam and Thangaraj, 2016). The steps of the AFSA algorithm are as follows (Huang et al., 2016).

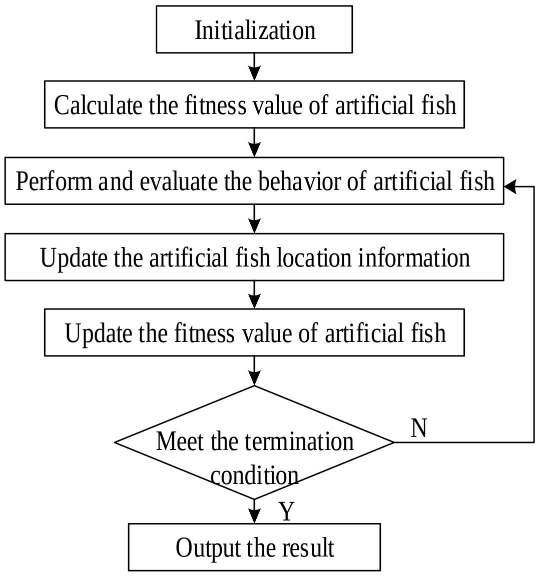

Figure 1: The flow chart of AFSA

The steps for the AFSA algorithm are as follows:
Step 1: The parameters of the algorithm are set. The parameters include the total number of virtual artificial fish, the number of attempts, the maximum forward step, the visual perception range of the virtual artificial fish, and the crowding factor.
Step 2: The fitness value of each virtual artificial fish is calculated, that is, the size of the virtual artificial fish is currently the size of the food is calculated.
Step 3: The behaviour of each virtual artificial fish is evaluated and the basic behaviour is selected.
Step 4: Virtual artificial fish action is obtained, and all virtual artificial fish information is changed, and then the fitness value of the virtual artificial fish is changed.
Step 5: If the algorithm meets the termination condition, then the experimental results are output, otherwise continue to evaluate the behaviour of artificial fish.

2.2 Basic behavior description

Foraging behaviour: Under the aid of the sensory organs, the virtual artificial fish can perceive the size of the surrounding food and determine the direction of its own action.
Clustering behaviour: Fish in the waters are often swim in groups. This approach not only avoids danger, but also facilitates the survival of the entire fish. Like the birds flying in the sky, the flock of fish does not require a leading fish. However, each individual in the fish needs to follow certain rules. In the AFSA, it is assumed that each fish will swim to nearby fish and avoid excessive congestion.
Rear-end behaviour: When a fish to find food, the surrounding fish will follow the fish, and thus swim to the location of fish food. This is the fish rear-end behavior. In this case, the fish in the AFSA algorithm will swim and chase the artificial fish with higher fitness value. The algorithm can be regarded as the process of advancing to the nearest fish.
Random behaviour: The location of the fish in the water is a random phenomenon from the surface, in fact they are in order to be able to find food in a larger range. In AFSA, random behaviour is a default foraging behaviour. The fish randomly selects a state within the perceived range and then moves in that direction.

3. Analysis and improvement of artificial fish swarm algorithm

3.1 Reason for the algorithm improvement

Although the AFSA algorithm has many advantages, but there are still the following questions:
Virtual artificial fish visual perception range is random, forward direction and behaviour are also random. Therefore, the accuracy of the algorithm is not very high.
When the change of the algorithm is not obvious, the convergence rate the global optimal solution will be reduced, thus reducing the search speed.
In the early stage of optimization, the algorithm has a faster convergence. At the later stage, the convergence rate becomes slower.
If you increase the number of artificial fish to get more accurate results, it will increase the amount of computer computing, thus slowing the optimization speed.
Thus, the basic artificial fish swarm algorithm is improved. This approach can increase the convergence rate of the algorithm, improve the accuracy of computing and other issues. This approach can improve the search efficiency of the algorithm, which is of great significance.

3.2 Improved Artificial Fish Swarm Algorithm

IAFSA has the following characteristics:
Simplified parameter design: The basic AFSA needs to consider the total number of virtual artificial fish, the number of attempts, the maximum forward step, the field of view, and the crowding factor. IAFSA algorithm can automatically obtain the visual perception range of artificial fish, and then by setting the step size field of view to get the maximum forward step, thus simplifying the design of the parameters.
The disappearance of local optimal solution: At the beginning, the virtual artificial fish and the optimal artificial fish has a large interval. Therefore, the range of visual perception is wide and the forward step is larger, so as to avoid the local optimal solution. When the optimization is progressively carried out, the virtual artificial fish will gradually approach the optimal artificial fish. The perceived range is also narrowed, the forward step is also reduced, and the accuracy of the algorithm is improved.
Fast convergence rate: If the state of the bulletin board is stabilized within the error range, the optimal solution of the system can be obtained. So the convergence rate of the algorithm will be faster.
The algorithm complexity is slightly increased: As the distance between the virtual artificial fish and the optimal artificial fish and the nearest artificial fish is increased, the complexity of the improved algorithm is slightly increased.

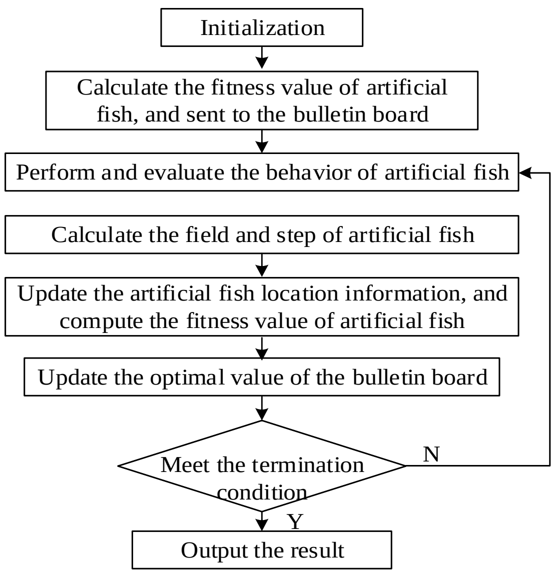

Figure 2: The flowchart of IAFSA

IAFSA simplifies parameter design and automatically acquires the perceived visual range of virtual artificial fish. In addition, the step-by-step field ratio and the maximum advance step can also be obtained.

3.3 Analysis of IAFSA algorithm

IAFSA can automatically obtain the visual perception range of virtual artificial fish, and adjust its advance step. At the beginning of the algorithm, virtual artificial fish and the optimal artificial fish are far apart, and their visual perception range is relatively wide. In addition, the forward step is relatively large, which can successfully avoid the algorithm caught in the local extreme. When the virtual artificial fish gradually approached the optimal artificial fish, the visual perception range was narrowed. At the same time, after joining the bulletin board, the convergence speed of the algorithm is greatly accelerated. If the state of the bulletin board can be stabilized within the error range, then the optimal solution of the system can be obtained, so the convergence rate of the algorithm will be faster.

3.4 The optimization principle of artificial fish swarm algorithm

Foraging behaviour is based on the perception of organs, it can analyse the surrounding environment, and thus swim to the location of large food. The AFSA algorithm is an iterative approach that targets the optimal result. This behaviour lays the foundation for the convergence of the algorithm.
Agglomeration behaviour is virtual artificial fish to the vicinity of similar activities to swim. In this case, the surrounding environment needs to remain open, thus avoiding congestion. This behaviour makes the artificial fish swarm algorithm more stable.
The rear-end behaviour is the behaviour of the virtual artificial fish to chase the surrounding fish. In the optimization algorithm, it is a process to advance to the optimal value. This behaviour not only increases the convergence speed of the algorithm, but also enhances the global nature of the algorithm.
The most important feature of the AFSA algorithm is that the initial value of the algorithm is not required, that is, the initial value can be arbitrarily generated, and the range of the parameters is relatively loose.

4. Application of improved algorithm in chemical process optimization

4.1 Optimization of Heat Exchange Pipe Network Process

The IAFSA is used to solve the heat exchanger network optimization model. First, the total number of artificial fish is 20, the number of attempts is 5, the crowding factor is 0.600. Second, the forward distance field of view is 0.8, the number of iterations is 100 times. Finally, 10 experiments were performed to obtain the following data. The abscissa is the number of iterations, and the ordinate is the optimal value of the function, that is, the minimum value of the heat transfer area. The experimental results show that the improved artificial fish swarm algorithm is still very fast on the basis of no given initial value. When the number of iterations is less than 10, the algorithm can converge and the search algorithm is very stable. We compare the results of the improved artificial fish swarm algorithm with the results of simple and simulated annealing algorithms. The results are shown in the following Table 1 and Figure 3.

Table 1: Experimental result of HEN with three algorithms

Algorithm	t1	t2	Min f
Simple algorithm	181.0000	296.0000	7049.4191
Simulated annealing	182.9802	295.5493	7049.2500
IAFSA	182.0176	295.6011	7049.2493

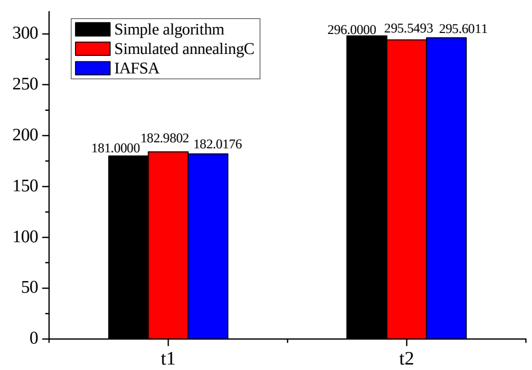

Figure 3: The comparison of three algorithms

The results show that the improved artificial fish swarm algorithm is more accurate than the experimental results of simple algorithm and simulated annealing algorithm. The design of the heat transfer pipe network area smaller, so as to effectively reduce energy waste. At the same time, it also illustrates its effectiveness and practicality in solving this type of chemical process optimization problem.

4.2 Butene alkylation process optimization

IAFSA was used to solve the above-mentioned Butene Alkylation process optimization model. The total number of virtual artificial fish is 20, the number of attempts is 5, the fish crowding factor is 0.600, and the forward step distance is 0.8.

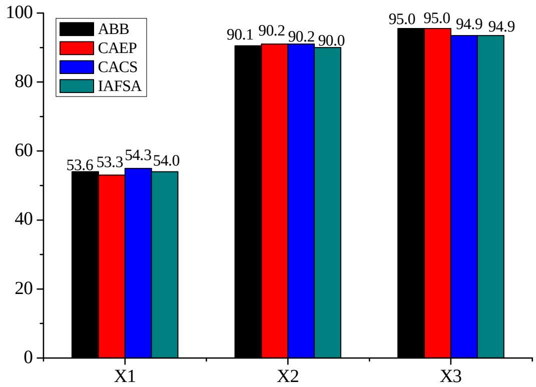

Figure 4: The optimization graph of BA process

We compare the results of IAFSA with the A Branch Bounding method (ABB), culture algorithm combined with evolutionary programming algorithm (CAEP) and improved ant colony algorithm (CACS). The results are shown in Table 2 and Figure 4.

Table 6: Experimental result of BA process with four algorithms

Algorithm	X1	X2	X3	Profit
ABB	53.6	90.1	95.0	1772.8
CACS	54.3	90.2	94.9	1776.6
IAFSA	54.0	90.0	94.9	1780.2

Therefore, the results of the improved artificial fish swarm algorithm are better than those of the other three optimization algorithms. This algorithm has a good feasibility in solving the chemical process optimization problem with complex constraints.

5. Conclusion

Chemical process is a very typical large system, if the chemical process is optimized, the good effect will be generated. Therefore, it has gradually become the focus of research over the years. In this study, the artificial fish swarm algorithm was studied and improved. At the same time, the optimized algorithm is applied to the actual background of the chemical process, in order to achieve its optimization. At the same time, on the basis of the shortcomings of the algorithm, an improved artificial fish swarm algorithm (IAFSA) which can automatically obtain the visual perception range and advance step of virtual artificial fish is proposed. In addition, the bulletin board is introduced into the algorithm, thus speeding up the algorithm optimization speed. The external penalty function method is used in the constraint condition. Finally, six classic test functions are experimented to verify the feasibility and practicability of the improved algorithm.

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