Fault Diagnosis of Embedded Pumping Unit Based on Quantum Frog Leaping Algorithm

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Abstract

Oilfield safety production is the basis and prerequisite for oil industry production and development. In China, the monitoring of the operating status and wellhead parameters of the pumping unit mainly adopts the manual routine inspection method. This paper is aiming at the shortcomings of large amount of calculation, time-consuming and high-failure in the traditional man-made arrangement of oilfields; a multi-objective comprehensive adjustment scheme optimization model is established and maintained under the constraint of injection-production balance. A new algorithm based on quantum leapfrogging algorithm pumping unit fault diagnosis, and completes the optimization model to calculate the effect of different workload implementations, which also meets the objectives and constraints of the comprehensive adjustment program as an implementation plan. It can be seen from the comparison that the overall workload of the comprehensive adjustment scheme, which is intelligently arranged by using the model and the algorithm in this paper is basically the same as the actual arrangement, the monthly workload is controlled within the monthly construction capability, and a high input-output ratio is obtained.

Keywords: Oilfield safety, Quantum leapfrogging algorithm, Workload.

1. INTRODUCTION

Petroleum exploitation belongs to the four high-tech industries with high investment, high risk, high technology and high profit. The implementation of any one project involves the input of large resources such as manpower, material resources and financial resources, and how to utilize the limited resources rationally to obtain the best. The development of the oil effect and reservoir management investment is decision-making purposes. At present, Chinese oilfields have entered the middle and late stages of development, and it is more and more difficult to stabilize the production of crude oil. In order to slow down the decline of crude oil production and keep the output relatively stable, a large amount of stimulation measures need to be implemented each year, and the funds are huge (Zhao et al., 2016; Zhao and Gao, 2013). It is of vital importance to maintaining the stability of crude oil production and enhancing the overall efficiency of the oilfield. However, the input of each measure will vary depending on its cost, workload and development dynamics. At present, some scholars have done some researches in this field. In view of the shortcomings of large-scale, time-consuming and inefficient economic work in the traditional artificial arrangement of oilfields, this paper is based on the actual working conditions of an oil recovery plant, annual increase target, and keeps balance of injection as the constraint condition. We propose a quantum frog leaping algorithm to solve the model and achieve a good practical Application effect.

In 2003, American scholar Eusuff and Lansey have proposed a sub-heuristic evolutionary algorithm based on swarm intelligence called Hybrid Frog Leaping Algorithm (SFLA), which has the advantages of high computational speed, strong global searching ability and easy to implement. They have been widely used in many fields. However, there are some shortcomings such as premature convergence, slow convergence speed and poor solution precision, which make it unsatisfactory in solving high-dimensional continuous optimization problems. The main reason leading to this defect is the rapid decline of population diversity in the late evolutionary period and the lack of local refinement of search capabilities (Zhao et al., 2014; Wang et al., 2013). In order to improve the performance of frog leaping algorithm optimization, many scholars do a lot of work, but most of the improvements are based on the original algorithm within the sub-group search strategy to make some amendments and improve the algorithm optimization ability. In this paper, a quantum shuffled frog leaping algorithm (QSFLA) is proposed by combining the quantum search mechanism with the basic hybrid frog leaping algorithm. The algorithm uses the Pauli matrix to set up the rotation axis and uses the qubit to rotate
around the axis of the Bloch sphere. The optimal solution is optimized so that the three optimal solutions represented by each particle are updated at the same time. The Hadamard door is used to realize individual variation to avoid premature, and then effectively expand the search space of the solution space and enhance the ergodicity of the solution space, which can quickly approximate the global optimal solution.

2. SHUFFLED FORG LEAPING ALGORITHM

In the 1990s, inspired by the animals and insects living in the nature, swarm intelligence algorithms represented by the Partial Swarm Optimization (PSO). It is an important branch of artificial intelligence. As a new method of evolutionary computation, it has been paid more and more attention by researchers at home and abroad (Wang et al., 2015). Group intelligence is reflected in the group consisting of a large number of simple individuals, capable of accomplishing the task of a complex individual and having more advantages in performance and relying on the cooperation and competition among individuals to guide the optimization of the search. The behavior of biological communities in nature to construct stochastic optimization algorithm is its basic idea, and its mutual cooperation and function are its important factors.

A new swarm intelligence algorithm called Shuffled Frog Leaping Algorithm (SFLA) was introduced in 2000. It was proposed by two American scholars, and it was originally applied to the design optimization of distributed systems. And it is successfully solved. Its principle is clear, easy to understand, less optimization parameters, superior ability to solve problems. The execution of SFLA simulates the behavior of a group of frogs beating on a wet ground which is shown in Figure 1.

\[ \text{Search space: After each population first performs a local search, each population exchanges information again} \]

Each frog is considered as a carrier or thought in foraging behavior. Each frog can exchange ideas with other frogs and it can improve the information of other frogs by transmitting the information, which can be obtained through behaviors such as imitation Pass in the frog brain. At the beginning of the algorithm, a group of frogs are divided into multiple ethnic groups, and different ethnic groups are considered as a collection of frogs with different ideas. According to certain meta-evolutionary strategy, the frogs in a population adopt the evolutionary method similar to particle swarm optimization to conduct local depth search and exchange of internal thoughts in the solution space (Zhao et al., 2009). This process continues to evolve repeatedly until the predefined convergence condition is satisfied. The internal exchange of ideas makes the algorithm have the ability to avoid premature falling into the local extreme point, and thus we can guide the algorithm search process to search toward the global optimal point.

3. FAULT DIAGNOSIS MODEL

The three elements of building an optimization model are: Determining decision variables, constraints, and goals. In this paper, according to the actual situation of a pumping unit in a certain oil field in our country, the decision variables of the model are determined as follows: measure of well of operation, cost of measures, forecast potential of single well, days of increase in current year and expiration of measures. The balance is between injection and production, and the number of measures for individual measures is the constraints (Xu et
al., 2012); the optimization model is set up with the objective of maximizing the input-output ratio and the cumulative output-input ratio of oil production in the current year.

### 3.1 Leapfrog algorithm principle

The principle of the leapfrog algorithm is that each individual in the population is treated as a frog, and the entire population is divided into subpopulations of a size. For frog individuals in subgroups, a new sub-entity (which can be regarded as a jump of a frog) is generated by using the best and the worst individuals of the subgroup firstly. If the sub-individuals have a better fitness than the parent, they are replaced. Otherwise, the new individual is regenerated using the best individual in the population and the worst individual in the subgroup (as the frog jumps again), and if it is still worse than its parent, a new individual is randomly substituted for the parent. Generation of individuals. Will be a certain number of times after the evolution of the population mixed, so that the best information between the various populations exchange, the formation of a new population of the same size, and then re-divided ethnic groups, so the cycle of operation, to find the overall optimal purpose. This evolutionary strategy of stochastic leapfrog algorithm is just like frogs continually revising the direction to jump towards the optimal solution, which makes the algorithm converge to the optimum gradually.

### 3.2 Quantum leapfrog algorithm steps

In 1996, the quantum derivative genetic algorithm proposed by Narayanan in the United Kingdom. A multi-objective optimization method based on the quantum hybrid frog leaping algorithm developed a new direction for the fusion of quantum computation and evolutionary computation. Based on some concepts and theories of quantum computing, such as quantum bit and quantum superposition state, quantum evolutionary algorithm has better group diversity and global optimization ability than classical evolutionary algorithm. The population size small but does not affect the performance of the algorithm and so on. In QSFLA (quantum shuffled frog leaping algorithm), each individual contains Bloch coordinates of 3 groups (x group, y group, z group), each group of coordinates represents an optimal solution. Since Bloch coordinates are in the interval [-1, 1], a solution space transformation is required.

![Figure 2. Quantum leapfrog algorithm](image)

Here, the steps of the leapfrogging algorithm are divided into a global searching step and a local searching step. The global execution of this algorithm is as follows.

**Step 1:** Initialize the parameters to determine the number of frogs $F$.

**Step 2:** randomly generate initial frogs, calculate the optimal value of each frog.

**Step 3:** Descending the size of the optimal value, and record the best solution $P_g$, and the frogs $F$ are divided into groups $m$, the frogs $n$ are assigned to a group, each group includes a frog. For example, $m = 3$ at the time,
the first, second, and third frogs will be assigned to the first, second and third groups, and the fourth, fifth and sixth frogs will be assigned to the first, second, and third groups.

Step 4: Local search process, that is, evolve in each ethnic group according to the algorithm formula of random frog leaping algorithm. 1) Counter initialization. Set the serial number of the ethnic group \( im=0 \), use it to mark the evolution to which ethnic group and compared with the total number \( m \) of ethnic groups. Let the number of independent evolutions \( in=0 \) be compared with the number of evolutions \( LS \) of local elements \( Y^{im} \) to determine whether the independent evolution is over (Ma et al., 2014). At the same time, find the best individual position and the worst individual position in the current group, denoted as \( P_B \) and \( P_W \) respectively. 2) We can set \( im=im+1 \) to the next ethnic group. 3) We can set \( in=in+1 \) for the next independent evolution. 4) Update the location of the worst frog in the current population by using the update strategy. The update strategy is as follows.

Frog updated step:

\[
STEP = \begin{cases} 
\min(rand()) \times (P_B - P_W), S_{\text{max}} \\
\max(rand()) \times (P_B - P_W), -S_{\text{max}} 
\end{cases} 
\]

(1)

The frog’s new location:

\[
newDw = Pw + STEP 
\]

(2)

Rand () produces a random number in the range of \([0, 1]\), which \( S_{\text{max}} \) is the maximum step in frog leaping. Such as \( S_{\text{max}} = 3 \), \( rand() = 0.5 \), \( P_B = \{2, 1, 5, 3, 4\} \), \( P_W = \{1, 3, 5, 4, 2\} \). So we can get that as follows.

\[
newDw(q1) = 1 + \text{int}(\min(0.5 \times |(2-1)|), 3)) = 1 \\
newDw(q2) = 3 + \text{int}(\min(0.5 \times |(1-3)|), 3)) = 2 \\
newDw(q3) = 5 + \text{int}(\min(0.5 \times |(5-5)|), 3)) = 5 \\
newDw(q4) = 4 + \text{int}(\min(0.5 \times |(4-3)|), 3)) = 4 \\
newDw(q5) = 2 + \text{int}(\min(0.5 \times |(4-2)|), 3)) = 3 
\]

Hence, \( newDw = \{1, 2, 5, 4, 3\} \)

5) If the worst frog position is improved in step (4), replace the worst frog with the newly generated one \( newDw \), otherwise use the global best solution \( P_g \) instead of \( P_B \) in step (1), and update the worst frog position. 6) If step (5) does not improve the position of the worst frog, then randomly generate a frog anywhere in the wetland to replace the worst frog and calculate its fitness. 7) Update population \( P_B \) and \( P_W \). 8) If \( in < LS \), skip to Step (3), otherwise go to Step (9) and let \( in = 0 \). 9) If \( im < m \), skip to step (2); otherwise, exit local search and return to global search.

Step 5: Mix each ethnic group. After a round of meta-evolution in each ethnic group, the frogs in all races are rearranged and ethicized, and the global optimal solution \( P_g \) is recorded.

Step 6: Verify that the stop condition is calculated. If the convergence condition of the algorithm is satisfied, then the execution of the algorithm is stopped; otherwise, go to step 3. Generally speaking, if the optimal
solution has not been significantly improved after several global exchanges of ideas, the algorithm should be stopped. In some cases, the maximum number of evaluation of the function can also be used as the algorithm to stop the criteria.

3.3 Test function

This article chose the following six functions as test functions.

Tablet:

$$f(x) = 10^6 x_1^2 + \sum_{i=2}^{n} x_i^2$$

(3)
Quadric:

\[ f(x) = \sum_{i=1}^{D} \left( \sum_{j=1}^{i} x^j \right)^2 \]  \hspace{1cm} (4)

Rosenbrock:

\[ f(x) = \sum_{i=1}^{D-1} [100(x_{d+i} + x_d^2)^2 + (1-x_d)^2] \]  \hspace{1cm} (5)

Griewank:

\[ f(x) = \frac{1}{4000} \sum_{d=1}^{D} x_d^2 - \prod_{d=1}^{D} \cos \left( \frac{x_d}{\sqrt{d}} \right) + 1 \]  \hspace{1cm} (6)

Rastrigin:

\[ f(x) = \sum_{i=1}^{D} (x_d^2 - 10 \cos(2\pi x_d) + 10) \]  \hspace{1cm} (7)

Schaffer’ s f7:

\[ f(x) = \sum_{i=1}^{D-1} (x_i^2 + x_{i+1}^2) 0.25 \sin(50(x_i^2 + x_{i+1}^2)^{0.5}) + 1.0 \]  \hspace{1cm} (8)

The functions (3), (4) and (5) have a single minimum point, and the functions (6), (7) and (8) have multiple local minimum points. The Tablet function and the Quadric function are variants of the Spherical function (1), commonly used to test the performance of the algorithm.

Figure 4. The result of QSFLA
We can see from Figure 4 (a) that the function has many maxima and minima. Near (0, 0), the maxima are estimated to be around one. If you use the ordinary method, it is difficult to find the exact point of the function. Next, we can use the SFLA algorithm to find the maximum value of this function. As can be seen from (b) and (c), the leapfrog algorithm runs for 300 generations and consumes 14.7 seconds. Finally, the optimal individual fitness value is 1.004737, and the corresponding position is (0.003306, 0.003652). QSFLA optimization value is close to the actual value of the function, which proves that the QSFLA algorithm has a strong ability to search.

For the fault diagnosis detection of embedded pumping unit, we run the algorithm 10 times to find the best result that can be obtained by the comparison algorithm and give the corresponding solution (Ye et al., 2013). The number of iterations of the algorithm is 100, the number of partial evolutions of subgroups is 10, the population size is 100 and the number of subgroups is 20. In the results table also lists the relevant literature test results for comparative verification quantum frog leapfrog algorithm to solve 0-1 knapsack problem correctness.

![QSFLA Convergence curve](image)

**Figure 5. QSFLA Convergence curve**

5. CONCLUSIONS

SFLA is a new swarm intelligence optimization algorithm. This paper introduces fault diagnosis based on quantum leapfrog algorithm and improves the local search strategy of SFLA. Experiments show that the improved algorithm has strong search ability, and it can effectively avoid premature convergence, and the algorithm convergence speed, good stability. Future work, you can also study the SFLA algorithm to improve the overall search strategy. It can also be seen from the comparison that the overall workload of the comprehensive adjustment scheme which is intelligently arranged by using the model and the algorithm in this paper is basically the same as the actual arrangement. The monthly workload is controlled within the monthly construction capability, and a high input-output ratio is obtained. Although many constraints are introduced into the model, the difficulty of solving the model is increased. However, the experimental results show that the proposed QSFLA algorithm can solve the model quickly and effectively, which can make the result more comprehensively reflect the man-made comprehensive adjustment mentality, more in line with the actual situation of oilfield development, thus reducing the workload of manual arrangements, a substantial increase in the comprehensive adjustment program implementation of the economic benefits.

REFERENCES


identification of fault feature phases, Journal of Northeastern University, 34(6), 761-765.