Multi-Objective Optimization of Oilfield Development Planning Based on Shuffled Frog Leaping Algorithm

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***Abstract*—Oilfield development planning is a complex task that involves multiple optimization objectives and constraints. Therefore, a study proposes an improved shuffled frog leaping algorithm to achieve multi-objective optimization tasks. In multi-objective problems, the fitness value of the algorithm is not adaptive to the memetic evolution, resulting in local search failures. Research is conducted on improving the shuffled frog leaping algorithm through non-dominated sorting genetic algorithm-II, memetic evolution, and traversal methods, and then verifying the effectiveness of the algorithm. The outcomes denoted that when the population was 30 and the grouping was 5, the algorithm proposed in the study had the fastest search speed and better optimization effect. The improved shuffled frog leaping algorithm had advantages in both construction period and cost compared to the shuffled frog leaping algorithm, with a construction period difference of 19 days and a cost difference of $13871. In comparative experiments with other algorithms, the average optimal solution and running time of the proposed algorithm were 0.324 and 7.2 seconds, respectively, which can quickly find the optimal solution in a short time. The algorithm proposed in the study can effectively optimize the complex objectives and constraints in oilfield development planning problems.**

Keywords*—*Shuffled frog leaping algorithm; oilfield development; multi-objective; optimization; improve

I. Introduction

Oilfield development planning indicates the corresponding measures taken to maintain relative production and reduce cost expenditures after the decline period of oilfield development. As the intensity of oilfield development increases, its development form becomes increasingly severe. Due to its non-renewability and limited reserves, it is particularly important to design effective development plans and improve oil recovery in oil fields. The goal of oilfield development planning is to achieve maximum profit, but the problem of oilfield development planning is extremely complex, involving multiple conflicting goals and various constraints, such as maximizing recovery rate, minimizing costs, maximizing production efficiency, etc. [2-3]. Meanwhile, it is necessary to consider the constraints and impacts of geological conditions, environmental policies, etc. on oilfield development. Therefore, oilfield development planning problems are often a typical multi-objective optimization (MOO) problem, and the difficulty of project development is also increasing. In the past, there were still significant limitations in oilfield development planning, which regarded oilfield development work as a deterministic planning problem and ignored the impact of various uncertain factors in the oilfield development process, such as the uncertainty of measures to increase oil production, the uncertainty of geological conditions in oil reservoirs, and the uncertainty in production management. The management of oilfield engineering projects involves multiple hierarchical dimensions, and different management objectives are interdependent and constrained. Therefore, it faces significant challenges in multi-planning and design [4-5]. On the basis of analyzing the uncertainty and multi-objective of oilfield development, this study considers analyzing the scope of resource evaluation, economic benefit evaluation, and scheduling planning design, and establishes an uncertainty planning optimization model. At the same time, the study introduces MOO technology into oilfield development planning, designs sustainable oilfield development plans while considering economic benefits, environmental protection, and social responsibility, improves the shuffled frog leaping algorithm (SFLA), provides technical support for oilfield development planning and decision-making, and provides suggestions for the development of the energy industry. Analyzing the entire process of offshore oil engineering project construction through research can reduce costs, improve resource utilization and economic benefits of oil and gas fields by optimizing development planning.

The analysis of the raised algorithm contains five sections. Related works is given in Section II. Section III is to build and analyze the proposed algorithm, and introduce the improved methods. Section IV is to verify the algorithm performance through comparative experiments. Section V is to summarize the experiment findings, point out the deficiencies in the research, and propose future research directions.

II. Related Works

Han Y et al. [6] focused on optimizing preventive maintenance intervals for safety critical equipment, integrating the dynamic characteristics of risks, conflict effects, and maintenance related costs, and proposed a systematic MOO framework. The results indicate that these two dynamic risk models can achieve MOO of the three objective function and have good application effects. Chen H et al. [7] developed a nonlinear multi-objective binary program (NMBP) to optimize investment portfolios under three competitive objectives in response to the problem of single objectives in existing overseas oil investment models. The non-dominated sorting genetic algorithm-II (NSGA-II) was combined with the ideal solution similarity sorting technique (TOPSIS), and the outcomes denoted that this improved method can determine the best compromise solution based on investor preferences, [1] with high feasibility and effectiveness. Xidonas P et al. [8] incorporated energy and environmental corporate responsibility (EECR) into the decision-making process and introduced a multi-objective programming model to provide a Pareto optimal investment portfolio (Pareto set) with the net present value of the project and the EECR score of the enterprise. The results indicate that the decision-making approach of the multi-objective planning system can effectively evaluate the investment portfolio results. Rinaldi G et al. [9] investigated the optimization of operations using genetic algorithms and the maintenance assets of offshore wind farms, taking into account both the reliability characteristics of offshore wind turbines and the composition of maintenance fleets. This method can minimize the operating costs of offshore farms.

Many scholars have achieved numerous research results in MOO. Scholars such as Zheng S [10] put forward a parallel series magnetic path multi-permanent magnet motor for MOO of permanent magnet machines. The motor used two types of permanent magnets as common magnets. This study provided a detailed explanation of the design method for parallel series multi permanent magnet motors using the equivalent magnetic circuit method. Then, an MOO method was proposed, which comprehensively considered the effects of changes in magnet characteristics and the anti-demagnetization ability. The results showed that the studied motor and design method were effective. Scholars such as Song Y [11] have proposed an MOO scheme that combines photovoltaic, hydrogen, and natural gas in the field of comprehensive energy utilization. This scheme established a multi-objective hierarchical optimization configuration model to analyze the economy, environment, and energy efficiency, and it was compared with other MOO schemes. The findings illustrated that the proposed scheme in the study could increase the cost of leveling electricity by 25% and energy utilization efficiency by 8.51%, indicating its feasibility. Nakashima R N [12] proposed an MOO scheme with the NSGA-II algorithm to address the revenue and efficiency issues in solid oxide fuel cells. This scheme combined mixed integer linear optimization programs to ensure efficient operation of the heat recovery system. The experiment outcomes expressed that the proposed scheme could achieve high power generation efficiency and significantly reduce costs. Although there has been an increase in equipment, the proposed solution in the study has strong competitiveness. Scholars such as Soltani M [13] proposed an MOO scheme for the lateral stability strength of laminated composite beams with different cross-sectional lateral loads. Then, the optimal arrangement of the layer sequence was obtained through a Non-dominated Sorting Genetic Algorithm (NSGA). The study determined and discussed the optimal layer arrangement for the web and flanges, and the outcomes showed that the proposed scheme increased the bearing capacity by about 52%.

The geological structure of oil fields is complex, and there are many factors that affect the effectiveness of oil field development, including geological conditions, reservoir characteristics, and extraction technology. Due to the limitations of computing resources, the optimization problem of oilfield development planning often cannot be fully solved. Previous studies have not explicitly considered these diverse constraints. And existing optimization models may not fully consider the long-term impact and risks of oilfield development planning on the ecological environment. Unlike previous design ideas, this study utilized the principle of application simulation to establish a correlation relationship between system development indicators, and built a MOO model with total construction period, total cost, quality level, and resource balance index as optimization objectives. At the same time, the study set logical relationships, resource requirements, and other constraints, innovatively combining classical model ideas with engineering practice conditions. The selection of dimensions for multi-objective planning considerations and the selection of quantitative indicators for environmental impact can provide reference ideas for oilfield development planning.

III. Multi-Objective Optimization Based on SFLA

The oilfield development planning project is analyzed in this study, and combining the optimization objectives and constraints, an SFLA is proposed and improved.

A. *SFLA Combined with Multi-Objectives*

In oilfield development planning projects, research selects the total construction period, total cost, quality level, and resource balance index as optimization objectives. Simultaneously, logical relationships, resource requirements, and others are set as constraints [14]. Each task is assigned three attributes, namely start time, duration, and end time, and the duration of each task is determined by its execution mode. The total duration of oilfield development planning is determined by the longest working path, which is the critical path. Therefore, the total construction period can be expressed as the end time of the last task, as shown in Formula (1).

$$TD = \max f_j \tag{1}$$

In Formula (1), TD represents the total duration, and f_j means the end time of the j th task. The total project cost consists of direct and indirect costs, expressed as formula (2).

$$TC = DC + IC \tag{2}$$

In Formula (2), TC represents total cost, DC represents direct cost, and IC represents indirect cost. The direct cost can be expressed as Formula (3).

$$DC = \sum_j \sum_{m \in M_j} (x_{jm} \times c_{jm}) \tag{3}$$

In Formula (3), x_{jm} means the execution mode of each task, and c_{jm} means the direct cost of each task. The direct cost is expressed as the total direct cost of each task, which is only related to the execution mode adopted for each task. The indirect cost is expressed as Formula (4).

$$IC = TD \times c_{\mathrm{in}\,d} = \max f_i \times c_{ind} \tag{4}$$

In Formula (4), c_{ind} represents the unit indirect cost. Assuming that the cost per unit time is fixed and unchanging, indirect costs are only related to the project duration. In actual project planning, it will be constrained by the contract duration. If the project is not completed within the specified time, a penalty function needs to be added, as denoted in Formula (5).

$$p = y \times c_p \times (\max f_j - T_{con}) \tag{5}$$

In Formula (5), T_{con} represents the agreed duration in the contract, and c_p represents the penalty value for delay, depending on the agreement in the contract. y is a variable with values of 0 and 1, as shown in Formula (6).

$$y = \begin{cases} 1, & \max f_j > T_{con} \\ 0, & \max f_j \le T_{con} \end{cases} \tag{6}$$

In Formula (6), when the actual construction period is greater than the contract period, y is taken as 1, and vice versa is taken as 0. Therefore, the final cost objective function is expressed as Formula (7).

$$TC = \sum_j \sum_{m \in M_j} (x_{jm} \times c_{jm}) + \max f_i \times c_{ind} + y \times c_p \times (\max f_j - T_{con}) \tag{7}$$

In oilfield development planning projects, each task may correspond to multiple different execution modes and have corresponding execution times. Cost and resource allocation is an MOO approach. The study considers quality level as a parameter corresponding to different modes of work, and sets weights based on the impact of different work on quality, which changes according to the different modes. A comprehensive evaluation of the project is conducted, with the objective function as denoted in Formula (8).

$$Q = \sum w_{ij} \sum w_{ij,r} \times Q_{j,r}^m \tag{8}$$

In Formula (8), w_{ij} represents the weight of the j work that affects the overall quality, $\sum w_{ij} = 1$. The quality level is judged by the indicator r. $w_{ij,r}$ represents the weight of quality indicator r in j project work, $\sum w_{ij,r} = 1$. $Q_{j,r}^m$ represents the quality standard achieved by j work in execution mode m under the quality indicator r. In MOO, indicators for measuring resource balance include variance, imbalance coefficient, resource volatility, and resource balance objective function. Due to the fact that resource demand units in actual engineering are in days, the variance expression is shown in Formula (9).

$$\sigma^2 = \sum_{k=1}^{K} \sum_{t=1}^{T} (r_k(t) - \overline{r_k})^2 \tag{9}$$

In Formula (9), σ represents the equation for the r th resource equilibrium demand. $r_k(t)$ represents the usage of k resources at t time. $\overline{r_k}$ means the average usage of k resources. The petroleum engineering project is an engineering activity with huge investment, complex technology, and high management requirements. Its resource types include a variety of resources, such as human resources, mechanical equipment, materials, finance, etc. The effective allocation of resources can ensure that project funds are not wasted and ensure economic benefits and costs. And through demand balancing, it can avoid excessive purchase and backlog of resources, improve resource utilization efficiency, reduce idle time caused by waiting for resources, and raise the overall work efficiency of the project. Each stage and process in the project requires different resource support. A balanced resource demand can ensure the timely completion of work tasks in each stage of the project, and ensure that the project progress meets the plan. The smaller the variance of resource equilibrium, the better the balance of resources. The calculation method for the imbalance coefficient is shown in Formula (10).

$$u = \frac{r_k^{\max}}{\overline{r_k}} \tag{10}$$

In Formula (10), u represents the imbalance coefficient of k resources. $r_k^{\max}$ represents the maximum demand for the k th resource in the plan, and $\overline{r_k}$ denotes the average usage of the k resource. The smaller the u, the better the overall resource balance level of the project. The calculation method for resource fluctuations is shown in Formula (11) [15].

$$\begin{cases} RRH = H - MRD = \frac{1}{2} \times HR - MRD \\ HR = \left[r_1 + \sum_{t=1}^{T-1} |r_1 - r_{t+1}| + r_T \right] \end{cases} \tag{11}$$

In Formula (11), RRH represents the overall resource fluctuation level of the project, and MRD represents the highest resource demand in the project. HR represents the sum of daily resource fluctuations in the planned project. r_t represents the resource demand on day t. The smaller the RRH, the better the overall resource balance level of the plan. The objective function of resource balance is expressed as Formula (12) [16].

$$\begin{cases} RLI = \sum_{k=1}^{K} \sum_{t=1}^{TD} (r_k(t) - \overline{r_k})^2 \\ \overline{r_k} = \frac{1}{TD} \sum_{t=1}^{TD} r_k(t) \end{cases} \tag{12}$$

In Formula (12), RLI represents the resource objective function, and $r_k(t)$ represents the k th resource usage at time t. The research will standardize the proposed objective function and constraint conditions. Using the SFLA for oilfield project development planning [17-18]. The SFLA is a metaheuristic search algorithm based on individual meme evolution and population information exchange. SFLA uses metaheuristic search, based on meme algorithm and PSO algorithm, to find the optimal solution of the problem while achieving local search and global information exchange. In the SFLA, individuals are divided into different particle populations, each carrying different ideas and information.

Under the leadership of elite individuals, independent searches are carried out to achieve local optimization and information exchange. After the subpopulation evolves to a certain extent, the isolation between subpopulations is broken, allowing information to be transmitted throughout the entire population until convergence conditions are reached and terminated. Global search effectively prevents extreme thoughts in one subpopulation, causing the entire population to jump in the correct direction. In the solution space, it randomly generate an initial population $U=\{U_1,U_2,...,U_F\}$ containing F individuals, and the i th individual in the d dimensional solution space is indicated as $U=\{U_i^1,U_i^2,...,U_i^d\}$. Individuals and memes are assigned using Formula (13).

$$Y^k=\{U_{k+m(l-1)}\in F\,|1\le l\le n\},1\le k\le m \tag{13}$$

In Formula (13), Y^k represents the K th meme group. All individuals in the initial population are divided into m meme groups, each containing n individuals. The fitness values of all individuals are calculated and they are sorted based on their fitness values. The person with the best fitness is placed in meme group 1, the second individual is placed in meme group 2, the m-th individual is placed in meme group m, and the m+1st individual is placed in meme group 1, and they are assigned in sequence. After the division of meme groups is completed, the step size is calculated using the Formula (14).

$$D=r\times(P_b-P_w) \tag{14}$$

In Formula (14), r means a random number with a value between 0 and 1. P_b represents the individual with the worst fitness, and P_w denotes the individual with the best fitness. D represents the step size. Through evolution, if a new individual has a better fitness value than the original individual, the original individual is replaced by a new individual. If there is no progress, the individual with the best fitness is used to improve again. The improvement method is as shown in Formula (15).

$$P_w{}'=P_w+D,|D|\le D_{\max} \tag{15}$$

In Formula (15), $D_{\max}$ represents the maximum value at which an individual can change position. If there are no individuals with better fitness values, it will randomly generate new individuals to replace P_w. When the local search reaches the termination condition, all individuals are re broken into meme groups based on their fitness values, and the local search continues until the convergence condition is reached. The basic process of the SFLA is indicated in Fig. 1.

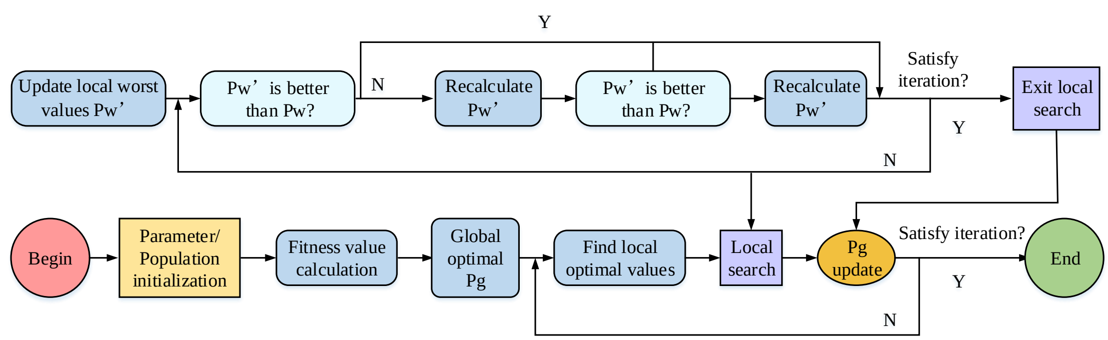


Fig. 1. Basic flow of SFLA.

Fig. 1 showcases the basic process of the SFLA. The SFLA, like other heuristic algorithms, has important parameters that directly affect the implementation of algorithm performance. The important parameters that affect the SFLA include population scale, amount of meme groups, amount of meme group individuals, max amount of evolutions per meme group, and maximum step size that individuals can jump.

B. Improvement of SFLA

The NSGA, based on traditional genetic algorithms, utilizes non dominated Pareto stratification and uses virtual fitness values as sorting conditions for MOO to adjust the virtual fitness values through niche technology. With NSGA, the NSGA-II algorithm is proposed, and Fig. 2 denotes the basic flow of NSGA-II.

Fig. 2 shows the basic process of NSGA-II. NSGA-II is a non-dominated genetic algorithm with elite strategy, which has been improved in three aspects based on NSGA. Firstly, fast non dominant sorting is used to evaluate the optimal solution, and then sorting, the complexity is reduced. Secondly, by using crowding comparison operators for fitness sharing, parameter simplification can be achieved while maintaining population diversity. Finally, an elite retention strategy is introduced to mix parental and offspring individuals and the next generation population is selected based on their strengths and weaknesses, which is beneficial for improving the overall level of the population. Although the traditional SFLA has advantages such as strong search ability, it is not adaptive in terms of fitness calculation and meme evolution in multi-objective discrete problems [19-20]. In the traditional SFLA, the evaluation and ranking of individuals are based on fitness values, and the calculation is simple in a single objective. However, in a multi-objective approach, it may lead to significant individual differences between meme groups. In the traditional SFLA, intra-group iteration is achieved through individual meme group evolution operations, using step size to iterate individual positions. In MOO studies, using step size for optimization may affect the direction of individual evolution, leading to local search failures. Therefore, the study sorted candidate solutions using NSGA-II, selected all individuals in the population to form a non-dominated hierarchy, and traversed all individuals in the non-dominated hierarchy until all individuals were assigned. The memetic evolution method uses cross genetic operators, as shown in Fig. 3.

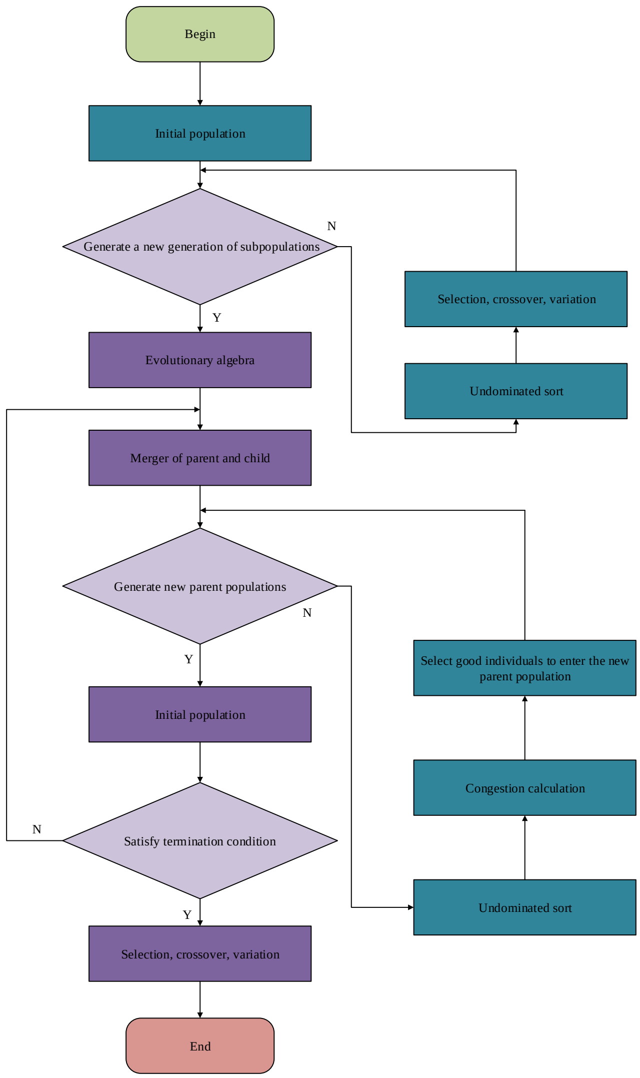


Fig. 2. NSGA-II basic process.

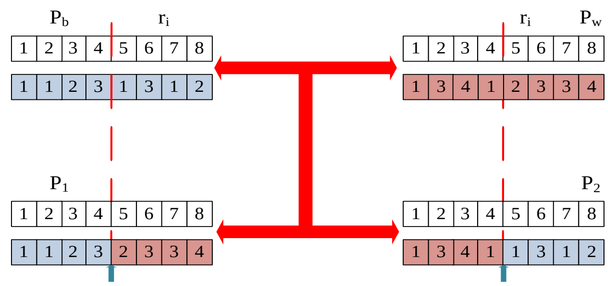


Fig. 3. Single point crossing process.

Fig. 3 shows the single point crossover mechanism of the improved SFLA. Firstly, the optimal and worst individuals in the meme selected, and based on the random integer of the breakpoint position, the optimal and worst individuals are crossed to obtain new two individuals. If the improved new individual is still dominated by the worst individual, it will replace the worst individual with the new individual and repeat the crossover process. If the generated individual is still dominated by the new individual, a new solution is randomly created to replace the worst individual. In the multi-objective model proposed in the study, the feasibility of candidate solutions is tested through traversal method, and the constraint traversal mechanism is shown in Fig. 4.

Fig. 4 showcases the traversal mechanism of constraint conditions. When using the traversal mechanism, for work that does not meet the constraint conditions, the start time is postponed until the constraint conditions are met. The improved algorithm process is indicated in Fig. 5.

Fig. 5 illustrates the improved SFLA process. Through improvements in candidate solution sorting, meme evolution, and constraint mechanism, the algorithm has a faster computational speed, a wider range of Pareto solution sets, and stronger algorithm effectiveness.

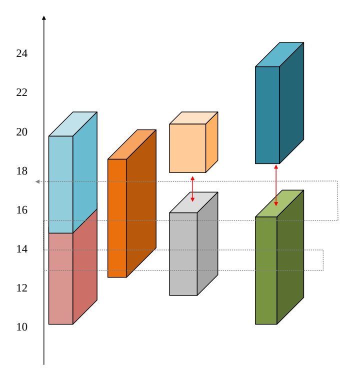


Fig. 4. Single point crossing process.

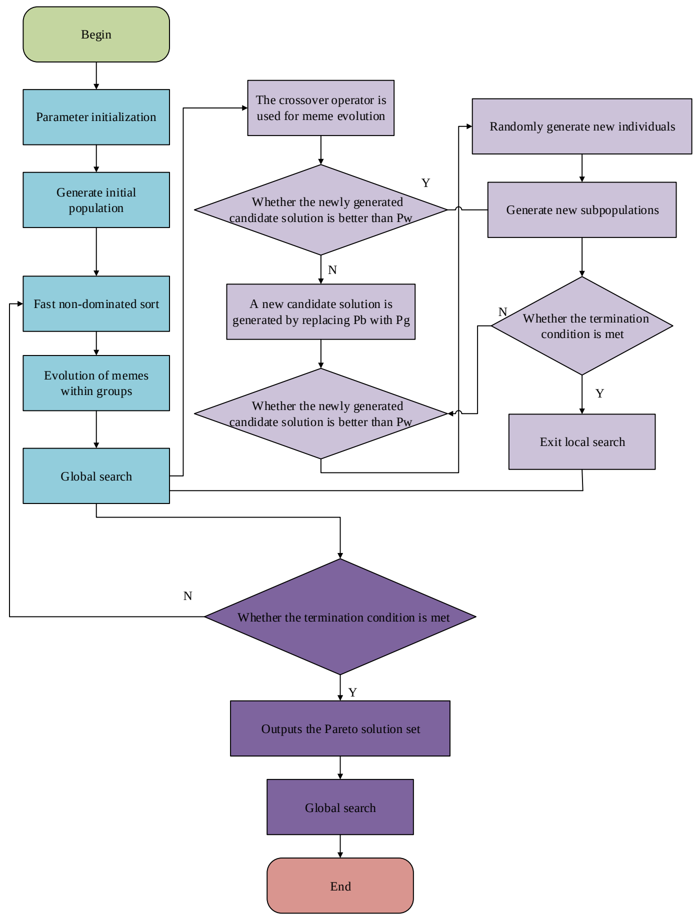


Fig. 5. Improved SFLA flow.

IV. Performance Analysis of Improved SFLAs

The important parameters for improving the SFLA were studied, and then the effectiveness and superiority of the algorithm were verified through comparative experiments.

C. Analysis of Important Parameters for Improved SFLA

The study analyzed important parameters in an improved SFLA that combines multi- objectives, with a dataset from 50 simulation cases in the VBP test set. The laboratory environment settings are denoted in Table I.

Table I shows the laboratory environment settings. The important parameter selection was the initial population size F and grouping method M, and different parameters had different effects on the performance of the improved SFLA. The initial population F was set as 10, 20, 30, 40, 50, 60, 70, 80, and 90, and the total amount of iterations was set to 100. The outcomes are expressed in Fig. 6.

TABLE I. Laboratory Environment Settings

Hardware and software configuration	Version model
CPU	Intel(R)Core i7-7700@3.6GHz
Operating system	Ubuntu 18.04 LTS
CUDA	9.1
Deep learning frameworks	Pytorch1.10
Python version	3.9

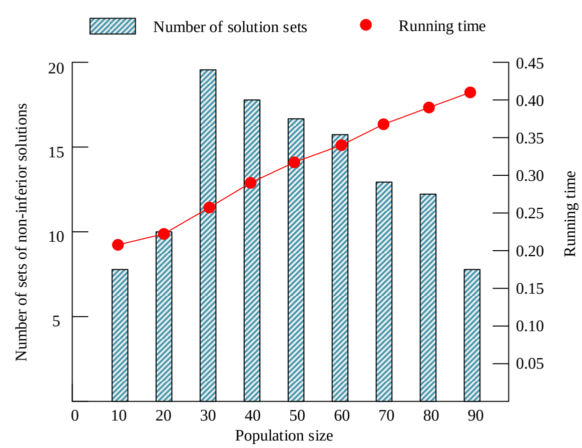
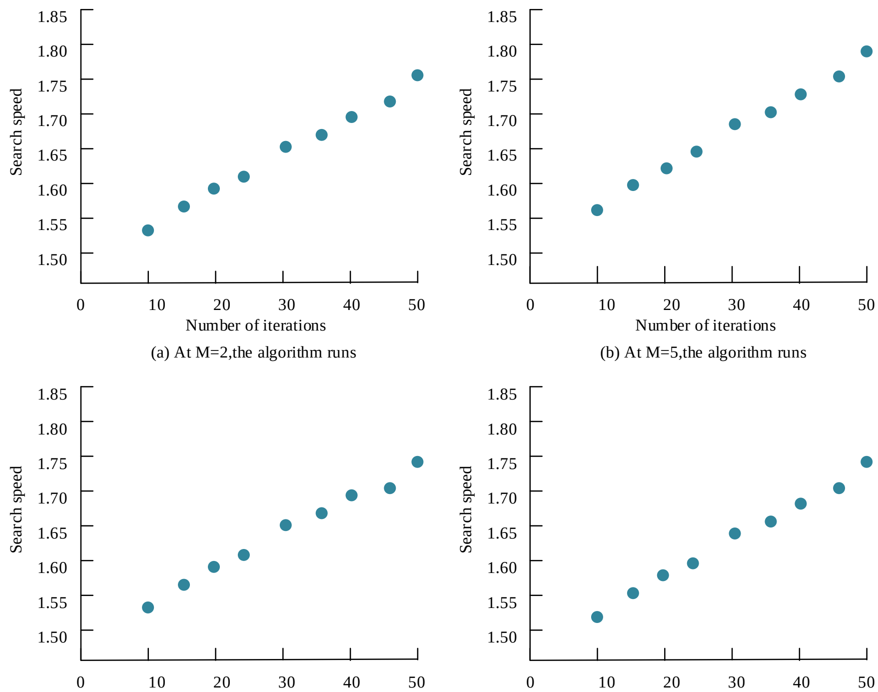


Fig. 6. The results of algorithm operation under different population numbers.

Fig. 6 showcases the running outcomes of algorithms with different population sizes. From the graph, when the population size was 30, the proposed algorithm had the highest number of non-inferior solution sets, with 19 non-inferior solution sets. When the population size was 10 and 20, the non-inferior solution sets of the proposed algorithm were 7 and 10, respectively. When the population size was 60 and 90, the proposed algorithm had a non-inferior solution set of 16 and 7, respectively, which was lower than the result when the population size was 30. From the perspective of running time, as the population size increased, the algorithm's running time continued to grow. When the population size was 10, 30, 60, and 90, the algorithm proposed in the study had running times of 0.21s, 0.25s, 0.34s, and 0.41s, respectively. Therefore, a small population size will influence the search ability of the algorithm, while a large population size will lead to a long running time of the algorithm. The initial population F was set to 30, and the grouping methods M were set to 2, 5, 10, and 15, respectively. The total amount of iterations of the algorithm was set to 50, and the running result is shown in Fig. 7.

D. Analysis of The Effectiveness of Improving The SFLA

A comparative experiment was conducted between the improved SFLA proposed in the study and the original SFLA. The population size was set to 30, group M was set to 5, and the global max iteration was set to 100. The Pareto solution set results are denoted in Fig. 8.



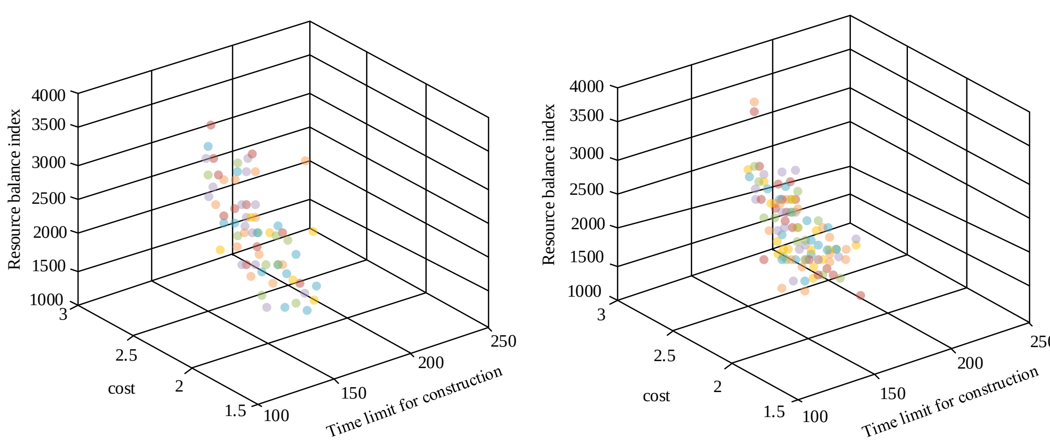
(a) At M=2,the algorithm runs

(b) At M=5,the algorithm runs

(c) At M=10,the algorithm runs

(d) At M=15,the algorithm runs

Fig. 7. Results of algorithms in different grouping modes.



(a) SLFA Pareto solution set

(b) Improved SLFA Pareto solution set

Fig. 8. Pareto solution set of two algorithms.

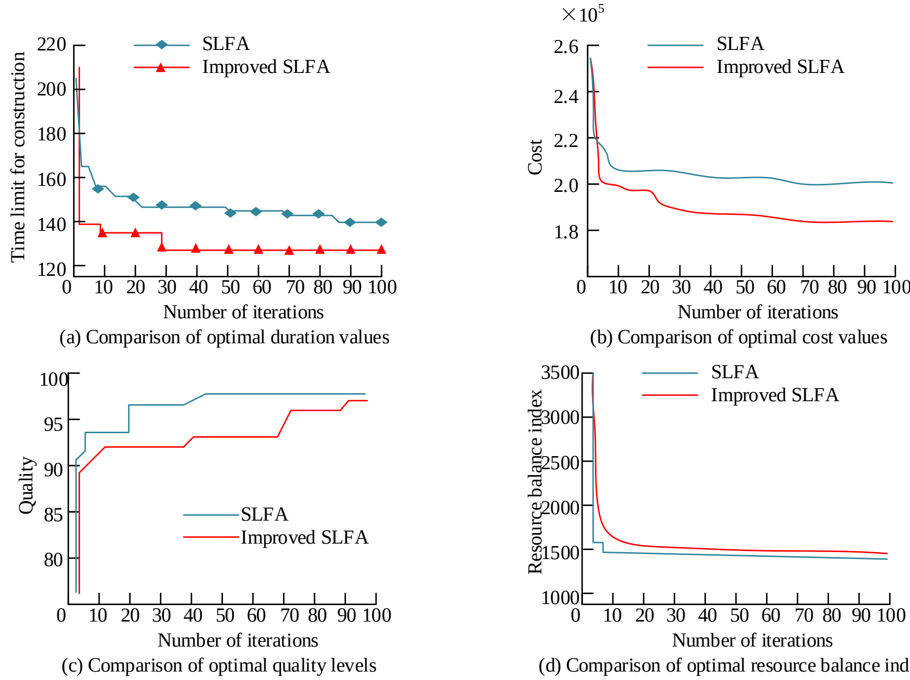


Fig. 9. The change trend of the optimal target value of the two algorithms.

Fig. 8 showcases the Pareto solution set results of two algorithms. Fig. 8(a) showcases the Pareto solution set of the SFLA. After 100 iterations, a total of 61 Pareto solution sets were generated globally. Fig. 8(b) showcases the Pareto solution set of the improved SFLA. After 100 iterations, a total of 89 Pareto solution sets were generated globally. From the comparison of the Pareto solution sets obtained by the two algorithms, the optimal solution obtained by the improved SFLA was superior to the SFLA in terms of duration and cost. The difference in duration was 19 days, and the difference in cost was 13871 US dollars. In terms of resource balance index comparison, the SFLA was superior to the improved SFLA, with a difference of 15 in resource balance index, which was a small difference at the same level. The changes in the optimal objectives of the Pareto solution set obtained by the two algorithms are denoted in Fig. 9.

E. Analysis of the Superiority of Improving the SFLA

The improved SFLA was compared with Genetic Algorithm (GA), PSO algorithm, Ant Colony Optimization (ACO), Simulated Annealing (SA) algorithm and Tabu Search (TS) algorithm. Among them, GA is a search heuristic algorithm, which reflects the natural selection, where individuals who are most suitable for the environment are chosen for reproduction to produce the next generation of offspring. PSO is a population-based stochastic optimization algorithm. PSO simulates the movement of individuals in search space. Individuals communicate and cooperate with each other to find the best solution. ACO is an algorithm for finding the best path. ACO is inspired by the foraging behavior of ants, which use pheromones to communicate and find the shortest path to the source of food. SA is a probabilistic optimization algorithm utilized to find the global optimal solution for problems with a large search space. TS is a metaheuristic optimization algorithm applied to solve combinatorial optimization issues, which can be utilized to address combinatorial optimization issues. The amount of iterations was 100, the initial population was 30, and the grouping was 5. Multiple algorithms were run independently 20 times, and the comparison results are indicated in Fig. 10.

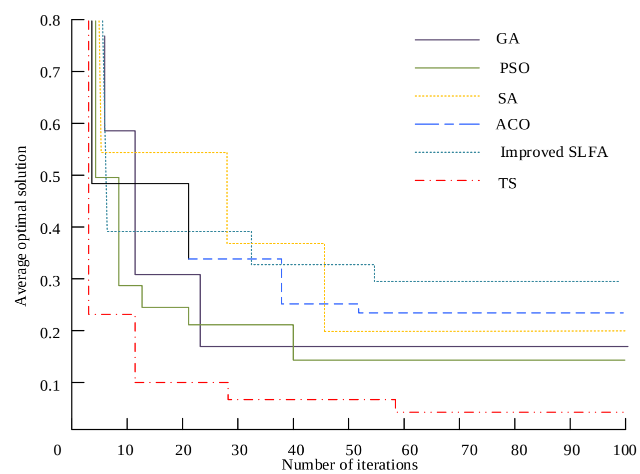


Fig. 10. Comparison of average optimal solutions of multiple algorithms.

Fig. 10 shows a comparison of the average optimal solutions of multiple algorithms. From the graph, it can be seen that the average optimal solution curve of the algorithm shows a decreasing trend with the number of iterations, and then tends to flatten out. Specifically, when the number of iterations is in the range of 10-30, the average optimal solution from small to large is: SA<ACO<Improved SLFA<GA<PSO<TS. As the amount of iterations increases, in the later stage, the SA,ACO, improved SLFA, GA, PSO algorithms tend to stabilize with 0.253, 0.247, 0.286, 0.176,

0.168 iterations, respectively. The algorithm proposed in the study converged quickly in 40 iterations, with a relatively small number of overall changing nodes, and gradually stabilized at an average optimal solution of 0.324 in 50-60 iterations. The other comparison outcomes of multiple algorithms are denoted in Table II.

Table II shows the comparison results of the optimal solutions, running time, and average optimal solutions of various algorithms. From the perspective of optimal solution, the algorithm proposed in the study had a higher optimal solution than other algorithms, with an optimal solution of around 0.051. The optimal solution of SA algorithm was the lowest, around 0.17. From the perspective of running time, the proposed algorithm had a shorter running time compared to the PSO algorithm, maintaining at 7.2s and 6.8s. The TS algorithm and ACO algorithm took longer and more time to run. In summary, the proposed algorithm has a high optimization rate and can quickly find the optimal solution in a short period of time.

TABLE II. COMPARISON OF OPTIMAL SOLUTION, RUNNING TIME AND AVERAGE OPTIMAL SOLUTION OF MULTIPLE ALGORITHMS

Algorithm	Optimal solution	Running time(s)	Average optimal solution
Improved SFLA	0.051±0.000003	7.2	0.324
GA	0.012±0.000004	8.7	0.178
SA	0.017±0.000003	7.6	0.209
ACO	0.024±0.000005	10.0	0.239
TS	0.036±0.000004	9.3	0.051
PSO	0.042±0.000005	6.8	0.143

V. CONCLUSION

Research used an improved SFLA for MOO of oilfield development planning. Research selected total construction period, total cost, quality level, and resource balance index as optimization objectives. Research utilized the SFLA to address multi-objective issues, but in multi-objective discrete problems, fitness calculation and memetic evolution were not adaptive. Therefore, this study aimed to improve the SFLA through NSGA-II, memetic evolution, and traversal methods. The study analyzed the effectiveness of the proposed improved SFLA, investigated the influence of population size and grouping methods on the algorithm, and then compared it with the SFLA to verify its effectiveness. Finally, its superiority was verified by comparing it with other algorithms. The experiment findings indicated that when the population was 30 and the grouping was 5, the algorithm proposed in the study had the fastest search speed and better optimization effect. The optimal solution obtained by improving the SFLA was superior to the SFLA in terms of duration and cost, with a duration difference of 19 days and a cost difference of $13871. In comparison with other algorithms, the proposed algorithm had a shorter running time and the highest optimal solution, which was 7.2s and 0.051, respectively, and could quickly find the optimal solution in a shorter time. Based on the model solving approach and MOO problem analysis, the SFLA was improved. The results showed that the improved approach can effectively improve the uncertainty problem of the target and demonstrate good project application effects. However, it is worth noting that the proposed equilibrium model is based on the assumption that cost, resource allocation, and other factors are only determined by the work execution mode. Its content does not take into account the uncertainty factors and parameter changes of actual projects too much in the selection, which needs further discussion in future research. Meanwhile, in the future design of engineering project models, it is necessary to better consider the impact factors of labor consumption, material and equipment consumption on multi-objective planning problems, and further expand the application scenario conditions of the SFLA.

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