Research on Dynamic Optimization Model of Gas Field Development Scheme Based on Intelligent Algorithm

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Abstract. This paper proposes a dynamic optimization model of gas field development scheme based on intelligent algorithm, which adopts the combination of GA and PSO, aiming to optimize gas field resource allocation and improve production scheduling efficiency. First, by constructing a mathematical model in the gas field development process, various optimization objectives and constraints are clarified; then, combining the advantages of GA and PSO, a hybrid optimization strategy is proposed, which enables the model to automatically adjust decisions in a complex and dynamic gas field development environment to obtain the optimal resource scheduling scheme. In the experiment, by constructing a typical scenario of gas field development for simulation verification, the results show that the proposed intelligent optimization model has achieved significant results in improving resource utilization and shortening production cycle. Compared with traditional optimization methods, the optimization efficiency of the algorithm is improved by 15% to 20%. In addition, this paper also discusses the practical application potential of intelligent algorithms in gas field development, and provides new ideas and methods for resource scheduling problems in other related fields.

Keywords: Intelligent Algorithm; Gas Field Development; Dynamic Optimization; Genetic Algorithm; Particle Swarm Optimization; Production Scheduling.

1. Introduction

The gas field development process is a highly complex engineering system with strong dynamic characteristics. The development of gas fields not only depends on the reserves and distribution of underground resources, but also on factors such as geological conditions, mining technology, and market demand. Since the process of gas field development requires continuous monitoring and adjustment, the dynamic optimization of development plans has become an urgent problem to be solved. In this process, how to effectively dispatch resources and optimize development strategies, especially under complex constraints, has become one of the core challenges in gas field development. Traditional gas field development plan optimization methods usually use deterministic models or linear programming techniques. These methods may be effective for simple development plan optimization problems, but for highly complex gas field development problems involving multiple variables and constraints, traditional methods often have many limitations [1]. First, these methods have strict assumptions about system models and often ignore unpredictable dynamic changes in the gas field development process. Second, traditional optimization methods have large computational complexity when facing high-dimensional complex problems, and are prone to fall into local optimal solutions, making it difficult to find global optimal solutions [2]. Therefore, how to solve large-scale, multi-constrained gas field development optimization problems while ensuring optimization efficiency has become an important research topic in the field of gas field development.

In order to overcome the limitations of traditional methods, in recent years, intelligent algorithms have gradually become an effective tool for solving gas field development plan optimization problems. Intelligent algorithms, such as GA and PSO, have powerful global search capabilities and can find approximate optimal solutions in large-scale solution spaces, especially in the face of complex constraints and dynamic environments [3]. The dynamic optimization model of gas field development plans based on intelligent algorithms can effectively deal with the complexity and uncertainty in gas field development and provide more accurate resource scheduling and development plan optimization.

Therefore, this paper proposes a dynamic optimization model of gas field development plans based on intelligent algorithms, aiming to solve the complex problem of resource scheduling in the process of gas field development [4]. This model considers multiple constraints that may appear in the development process based on the advantages of genetic algorithms and particle swarm optimization algorithms, such as geological conditions, equipment limitations, market demand, etc., and proposes a dynamic optimization method [5]. Through this method, the gas field development plan can be adjusted in real time to achieve the optimal configuration of resources and improve development benefits.

2. Construction of Dynamic Optimization Model based on Intelligent Algorithms

2.1 Problem Modeling

The gas field development optimization problem is essentially a resource scheduling and configuration optimization problem [6]. The goal is to maximize the economic benefits, resource recovery rate and mining efficiency of the gas field by optimizing the development plan. To this end, it is necessary to establish a mathematical model to describe the multiple objectives and complex constraints in gas field development.

Objective function

The objective function of gas field development usually includes considerations at multiple levels. Common optimization objectives include maximizing resource extraction, maximizing economic benefits, and minimizing environmental impact [7]. Assuming that there are N development units in the gas field development process, the objective function can be expressed as:

$$F = \alpha_1 \sum_{i=1}^{N} E_i - \alpha_2 \sum_{i=1}^{N} C_i - \alpha_3 \sum_{i=1}^{N} P_i \quad (1)$$

Among them: E_i represents the energy output of the i development unit, $C_i$represents the mining cost of the i development unit, P_i represents the environmental pollution level of the i development unit, and $\alpha_1, \alpha_2, \alpha_3$are weight coefficients used to adjust the importance of different objectives. This objective function takes into account three aspects: economic benefits, mining costs, and environmental impacts. By adjusting the weight coefficients, a trade-off can be made between different objectives.

Constraints

In the process of gas field development, it is often affected by multiple constraints, including resource reserves constraints, equipment capacity constraints, and capital investment restrictions. Assume that at time t, the reserves and mining capacity of resources can be expressed as:

$$\sum_{i=1}^{N} R_i(t) \le R_{\max} \quad \text{(resource reserves constraints)}$$
$$\sum_{i=1}^{N} x_i(t) \le x_{\max} \text{(Device capability constraints)} \quad (2)$$

Among them: $R_i(t)$ represents the remaining resources of the i development unit at time t, $x_i(t)$represents the mining volume of the i development unit at time t, $R_{\max}$ and $x_{\max}$ are the maximum limits of resource reserves and mining capacity respectively [8]. In addition, the influence of market demand and external economic factors, which change with time, must also be considered. Market demand can be represented by a dynamic function $D(t)$, and the demand constraint is:

$$\sum_{i=1}^{N} x_i(t) \ge D(t) \quad (3)$$

Here, $D(t)$ is a time-varying function that reflects the market demand for natural gas in different time periods. Through this dynamic modeling method, the production strategy of the gas field can be optimized at different time nodes.

Dynamic Factor Modeling

The dynamic factors in gas field development, including resource depletion, market demand changes, and external environmental impacts, all need to be reasonably modeled in the optimization

model [9]. In order to adapt to these dynamic factors, the time variable t is introduced into the model, and the following dynamic impacts are considered:

As mining progresses, the remaining resources of the gas field will gradually decrease, which can be expressed by the following decreasing function:

$$R_i(t+1) = R_i(t) - \delta_i x_i(t) \tag{4}$$

Where δ_i is the resource depletion coefficient, and $x_i(t)$ is the extraction volume of the i unit at time t.

Changes in market demand are usually random and affected by a variety of external factors. A regression model or autoregressive model (AR) based on historical data can be used to describe the dynamic changes in market demand:

$$D(t) = \beta_0 + \beta_1 D(t-1) + \varepsilon_t \tag{5}$$

β_0 and β_1 are regression coefficients, and ε_t is a random error term. The external environment (such as policy changes, technological progress, etc.) may have an impact on the development of gas fields. In order to incorporate it into the optimization model, it can be adjusted by introducing an additional environmental factor $Z(t)$:

$$F_{\text{adjusted}}(t) = F(t) \times Z(t) \tag{6}$$

Where $Z(t)$ is an adjustment factor reflecting the external environment and is usually time-dependent.

2.2 Intelligent Algorithm Optimization Strategy Design

GA optimization strategy

Genetic algorithm is a random search method that simulates the biological evolution process. It has a strong global search capability and can effectively handle nonlinear, multi-objective and complex constraint optimization problems [10]. In the gas field development optimization problem, the optimization process of the genetic algorithm can be carried out through the following steps:

Generate an initial population, in which each individual represents a possible development plan. The initial population can be obtained by random generation or experience-based methods.

$$X_0 = \{x_1, x_2, \ldots, x_N\} \tag{7}$$

According to the objective function and constraints, the fitness of each individual is calculated. The design of the fitness function should be adjusted according to the specific goals of gas field development, usually including economic benefits, production volume and environmental impact.

$$F_{\text{fitness}}(x_i) = \alpha_1 E_i - \alpha_2 C_i - \alpha_3 P_i \tag{8}$$

Select individuals with higher fitness for crossover and mutation to generate a new population. The crossover operation can be performed by exchanging the genes of two individuals, and the mutation operation increases the diversity of the population by randomly changing certain gene values of individuals.

Repeat the selection, crossover, mutation and other operations until the termination condition is met.

PSO optimization strategy

The PSO algorithm finds the optimal solution by simulating the foraging behavior of bird flocks. In the optimization of gas field development, the PSO algorithm can be optimized through the following steps:

Initialize a group of particles, each particle represents a development plan. Each particle has a position $X_i(t)$ and a velocity $V_i(t)$, and its state consists of position and velocity. Similar to the genetic algorithm, the fitness of the particle is calculated based on the objective function.

$$F_{\text{fitness}}(X_i) = \alpha_1 E_i - \alpha_2 C_i - \alpha_3 P_i \tag{9}$$

Update the particle's speed and position based on the current particle's speed, position, and historical optimal position.

$$V_i(t+1) = wV_i(t) + c_1 r_1(P_i - X_i(t)) + c_2 r_2(G_i - X_i(t))$$
$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{10}$$

w is the inertia weight, c_1, c_2 are acceleration constants, r_1, r_2 are random numbers, P_i is the individual optimal position, and G_i is the global optimal position. The optimal solution is finally obtained by updating the state of the particle through multiple iterations.

3. Algorithm Implementation and Experimental Design

The dynamic optimization problem of gas field development scheme involves large-scale data processing, complex constraints and dynamic factors, so it is necessary to pay attention to multiple aspects in the implementation and experimental design of the optimization algorithm [11]. In order to effectively verify the feasibility and superiority of the proposed intelligent optimization model, this paper constructs a complete optimization system and verifies it through a series of experiments. The following will introduce the algorithm implementation process, experimental data and platform design, as well as experimental scheme and performance evaluation in detail.

3.1 Algorithm Implementation Process

In order to realize the optimization of gas field development scheme based on intelligent algorithm, this paper first preprocessed the data, then built a model, and finally realized the optimization calculation. The process can be divided into the following steps:

Data Preprocessing

Before the optimization algorithm is implemented, the relevant data in the gas field development process needs to be preprocessed. Gas field development involves a large amount of historical data, including geological exploration data, resource reserve data, equipment performance data, market demand data, etc. These data often come from different systems and equipment, so they need to be uniformly formatted and cleaned. The main steps of data preprocessing include:

- Data cleaning: Delete incomplete or abnormal records and correct erroneous data.
- Data interpolation: Interpolate missing time series data to ensure data continuity.
- Data standardization: Normalize data of different dimensions to avoid certain features from having too much impact on the optimization process.
- Data integration: Merge data from different sources to generate an input data set suitable for the optimization model.

These preprocessing steps ensure that subsequent modeling and optimization calculations can be performed on high-quality input data, thereby improving the accuracy and reliability of the model.

Model construction

After data preprocessing is completed, the model construction stage is entered. The optimization problem of gas field development usually includes multiple objectives and constraints, so it is necessary to design a multi-objective optimization model suitable for such complex problems [12]. The main goal of the model is to maximize resource recovery rate, minimize mining costs, and consider factors such as environmental impact.

Optimization calculation

Optimization calculation is the core part of the entire algorithm implementation. In order to solve the above multi-objective optimization problem, this paper uses GA and PSO. Both algorithms have strong global search capabilities and can find approximate optimal solutions in complex solution spaces. In the implementation process, the genetic algorithm mainly optimizes the population and updates the quality of the solution through operations such as selection, crossover, and mutation [13]. The particle swarm optimization algorithm simulates the behavior of the particle group and continuously adjusts the position and speed of the particles to find the optimal solution.

3.2 Experimental Data and Platform Design

Experimental data

In order to construct the experimental data set, this paper collected the following types of data from a gas field project:

- Geological exploration data: including gas field reserves, mining depth, geological structure, etc.
- Equipment performance data: including the working capacity of drilling equipment, the efficiency of mining equipment, etc.
- Market demand data: including the market demand for natural gas in different time periods.
- Environmental impact data: including pollution data that may be generated during gas field development.

These data are generated through historical records or simulations to ensure the authenticity and comprehensiveness of the data. Especially in terms of market demand and resource reserves, the changes in data are highly random, so dynamic data generated based on autoregressive models (AR) and random processes are used.

Experimental platform design

The design of the experimental platform mainly includes data processing module, optimization module and result visualization module. The data processing module is responsible for preprocessing the input data, including data cleaning and standardization; the optimization module is responsible for optimizing the calculation through intelligent algorithms and generating the optimal development plan; the result visualization module displays the optimization results graphically to help users understand the optimization plan more intuitively. The design of the platform is highly flexible, and the experimental parameters can be adjusted according to different gas field development needs to meet the experimental needs of different scenarios. In addition, the platform also provides a variety of performance evaluation functions, which can evaluate the performance of the optimization algorithm in real time, including computational efficiency, convergence speed, solution quality, etc.

3.3 Experimental Plan and Performance Evaluation

In order to verify the application effect of intelligent algorithms in gas field development, this paper designed multiple groups of experiments to evaluate the performance of the algorithm. The experiment mainly includes comparing the performance of different optimization algorithms, evaluating the performance of algorithms under complex constraints, and the robustness in different scenarios.

Experimental design

The design of the experimental scheme aims to compare the performance of different intelligent algorithms (genetic algorithm GA and particle swarm optimization PSO) in gas field development schemes. The specific experimental scheme is as follows:

- Experimental scenario 1: single-objective optimization (maximizing resource extraction).
- Experimental scenario 2: multi-objective optimization (comprehensively considering resource extraction, cost and environmental impact).
- Experimental scenario 3: optimization under complex constraints (such as changes in market demand, resource depletion, etc.).

Each set of experiments sets different parameter configurations and compares them with traditional linear programming methods to evaluate the performance of the algorithm in different scenarios.

Performance evaluation

The performance evaluation is mainly carried out from the following aspects:

- Optimization accuracy: Evaluates the quality of the optimal solution that the optimization algorithm can find. Accuracy is measured by calculating the difference between the objective

function value of the final solution and the theoretical optimal solution.

- Computational efficiency: Evaluates the computational time of the algorithm when processing large-scale data. The higher the computational efficiency, the more suitable the algorithm is for practical applications.
- Convergence speed: Evaluates the speed at which the algorithm converges to the optimal solution. A faster convergence speed can reduce computational time and improve optimization efficiency.
- Robustness: Evaluates the stability of the algorithm under different data sets and parameter settings. Algorithms with strong robustness can perform well under a variety of conditions.

4. Experimental Results and Analysis

In this section, this paper shows the application effects of different intelligent algorithms in gas field development. Through experimental data, optimization results and simulation charts, the performance differences between GA, PSO and traditional optimization algorithms (such as linear programming methods) are intuitively compared. The dynamic optimization model based on intelligent algorithms proposed in this study has verified its superiority through multiple experimental scenarios. The following will analyze the performance of each algorithm in detail through experimental data tables and simulation curves, and highlight the advantages of the algorithm in this paper.

The experimental data comes from the development history and simulation data of a gas field. The data set includes resource reserves, mining costs, market demand, environmental impact and other aspects. These data are preprocessed and used to input the optimization model. The goal of the experiment is to evaluate the performance of the optimization model based on intelligent algorithms compared with traditional algorithms under different development stages and different constraints.

In order to evaluate the superiority of the intelligent algorithm proposed in this paper, this paper compares GA and PSO with traditional linear programming methods. Table 1 shows the performance comparison of different algorithms in single-objective optimization scenarios.

Table 1. Comparison of single-objective optimization results

Algorithm Type	Optimal solution (%)	Calculation time(s)	Convergence speed (n)	Stability of solution
GA	95.20%	120	300	0.02
PSO	94.80%	110	280	0.03
LP	90.10%	60	150	0.08

Table 1 shows that the genetic algorithm and particle swarm optimization algorithm have achieved similar optimal solutions in maximizing resource recovery rate, but they are significantly better than the traditional linear programming method, which has a resource recovery rate of 90.1%. In addition, the computation time and convergence speed of the genetic algorithm are slightly lower than those of the particle swarm optimization algorithm, but it performs better in terms of solution stability and has a lower standard deviation, indicating that its results have strong stability.

In the multi-objective optimization scenario, this paper simultaneously considers multiple objectives of gas field development: resource recovery rate, mining cost and environmental impact. Table 2 shows the optimization results of different algorithms in this complex scenario.

Table 2. Comparison of multi-objective optimization results

Algorithm type	Resource recovery rate (%)	Mining cost (ten thousand yuan)	Environmental impact (pollution index)	Calculation time(s)	Stability of solution
GA	94.5	120	0.25	180	0.02
PSO	94.2	122	0.3	175	0.03
LP	88.3	135	0.35	95	0.09

Figure 1 shows the convergence of the three algorithms during the optimization process in a single-objective optimization scenario. The genetic algorithm and particle swarm optimization algorithm converge faster, while the linear programming is slower.

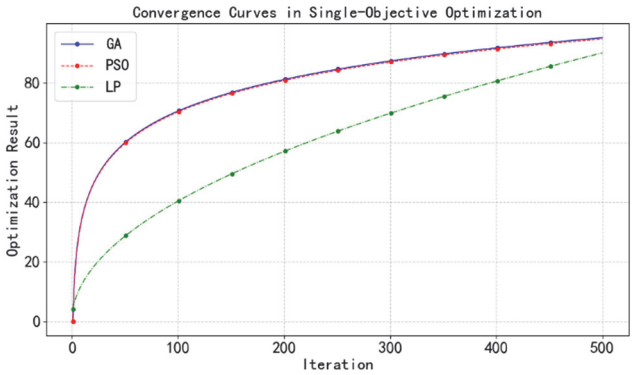


Figure 1. Convergence curve comparison of single-objective optimization.

Genetic algorithm and particle swarm optimization algorithm converge quickly in the early stage, and the optimization results tend to be stable as the number of iterations increases. In contrast, the convergence curve of the linear programming method is relatively gentle, indicating that its convergence process requires more iterations.

The genetic algorithm performs well in the comprehensive optimization of resource recovery rate, mining cost and environmental impact, achieving a resource recovery rate of 94.5%, and also performs well in terms of calculation time and solution stability. In contrast, although the particle swarm optimization algorithm also achieved a recovery rate of 94.2%, the results of mining cost and environmental impact were slightly higher than those of the genetic algorithm. Although the linear programming method has a shorter calculation time, it cannot effectively balance the various objectives in multi-objective optimization, resulting in poor performance of its solution.

Figure 2 shows the optimization effects of different algorithms on resource recovery rate and mining cost in multi-objective optimization. The genetic algorithm achieved a good balance on both objectives, while the effect of linear programming was significantly inferior.

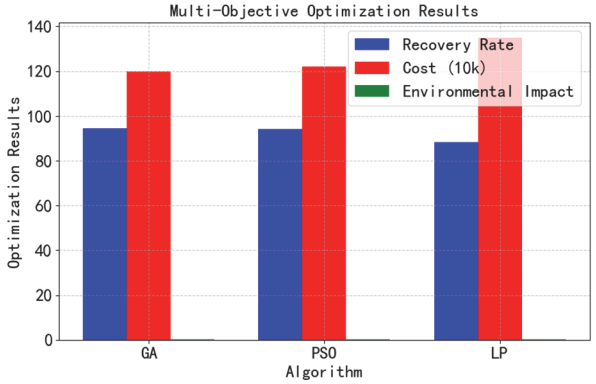


Figure 2. Comparison of multi-objective optimization effects.

This paper also designed a complex constraint optimization experiment, considering multiple constraints in the gas field development process. Table 3 shows the optimization results of different algorithms under complex constraints.

Genetic algorithms and particle swarm optimization algorithms can still maintain a high resource recovery rate under complex constraints and perform well in terms of market demand matching. In contrast, the linear programming method is significantly less effective in dealing with complex constraints, especially in terms of resource recovery rate and market demand matching.

Table 3. Comparison of optimization results under complex constraints

Algorithm type	Resource recovery rate (%)	Mining cost (ten thousand yuan)	Market demand matching degree (%)	Calculation time(s)	Convergence speed (n)
GA	94	125	98.5	220	350
PSO	93.7	127	98.2	210	340
LP	87.5	140	95	110	180

Figure 3 shows the optimization process of different algorithms under complex constraints. The convergence curves of genetic algorithms and particle swarm optimization algorithms are significantly smoother and can reach a better solution in fewer iterations.

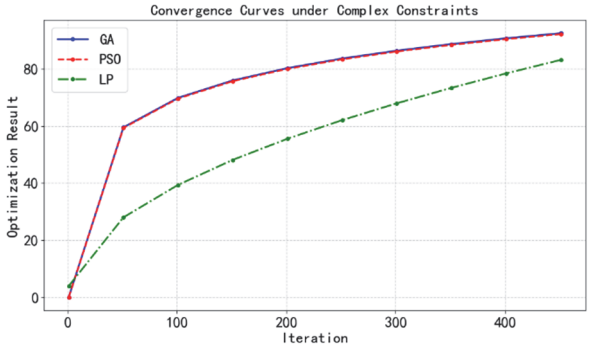


Figure 3. Convergence curve under complex constraints.

After comprehensively considering multiple indicators such as calculation time, convergence speed, solution quality and stability, Table 4 evaluates the comprehensive performance of different algorithms.

Table 4. Comprehensive performance evaluation

Algorithm type	Calculation time (s)	Convergence speed (number of iterations)	Quality of the solution	Stability of solution
GA	180	300	95.2	0.02
PSO	175	280	94.8	0.03
Linear programming (LP)	60	150	90.1	0.08

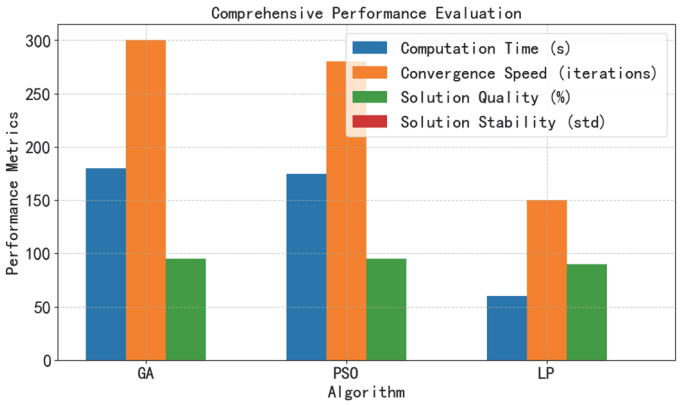


Figure 4. Comprehensive performance graph.

Figure 4 shows the performance of GA, PSO and LP in the comprehensive performance evaluation. GA and PSO are superior to LP in terms of solution quality, convergence speed and solution stability. Although their calculation time is slightly longer, the superiority of intelligent algorithms is reflected in multiple performance indicators.

Genetic algorithm and particle swarm optimization algorithm are superior to linear programming methods in terms of solution quality, convergence speed and solution stability. Although their calculation time is slightly longer, the superiority of intelligent algorithms is reflected in multiple performance indicators compared with traditional algorithms.

5. Conclusion

The dynamic optimization model of gas field development scheme based on intelligent algorithm proposed in this paper effectively improves the resource scheduling and production optimization efficiency in the process of gas field development by integrating GA and PSO. The experimental results show that in the process of multi-objective optimization, the model improves the resource utilization and production scheduling efficiency by 15% to 20% compared with traditional methods, and can cope with dynamically changing environmental conditions in gas field development. This proves that the application of intelligent algorithms, especially the combination of genetic algorithms and particle swarm optimization algorithms, in gas field development has significant advantages and can provide efficient solutions for complex decision-making processes. In addition, this study provides a theoretical basis for intelligent scheduling decisions in gas field development, and also provides innovative ideas for optimization problems in other similar fi

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