Research on the Design Optimization Algorithm of Intelligent Production Allocation System in Gas Field Development

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Abstract

A new algorithm based on DRL is proposed. It aims at optimizing gas field resource allocation and production scheduling by DQN. Through interaction with environment, the algorithm learns optimization strategy, automatically adjusts decision based on reward mechanism so as to improve system adaptability and self-optimization. Firstly, a mathematical model is set up to deal with production allocation problems in gas field development. The objective functions and constraints of resource allocation are clarified. After that, a deep reinforcement learning optimization algorithm was designed to solve the problem, and the DQN was used as the training method. Experimental results show that compared with traditional optimization algorithms, this algorithm has significant improvement on resource utilization and production efficiency, and improves production scheduling efficiency by 18%. It is shown that deep reinforcement learning is able to deal with complex resource scheduling problems effectively, provide technical support for intelligent production scheduling in gas field and provide new thinking for related research.

Keywords

Intelligent production allocation; deep reinforcement learning; deep Q network; gas field development; optimization algorithm; production scheduling.

1. Introduction

With the continuous growth of global energy demand, gas fields, as an important source of natural gas resources, have attracted more and more attention for their development and utilization efficiency. Especially with the gradual exploitation of gas field resources, how to optimize production scheduling and improve resource utilization under the premise of ensuring gas field output has become a key issue in gas field development. As a decision support tool in gas field development, the intelligent production allocation system can effectively improve production efficiency and reduce operating costs by rationally allocating production resources, so it occupies an important position in gas field development. At present, the production allocation system of gas fields mainly relies on manual decision-making or traditional optimization algorithms. However, these traditional methods often seem to be powerless in the face of complex production environments [1]. Due to the high complexity of the gas field development environment, traditional algorithms face challenges such as large computational complexity, low precision, and untimely response to dynamic changes. Especially in the process of large-scale gas field development, manual decision-making and traditional algorithms often cannot make optimal production decisions quickly and accurately [2]. Therefore, improving the precision and efficiency of intelligent production distribution system becomes an urgent task.

With the rapid development of AI and big data technology in recent years, data-driven intelligent optimization algorithm has become a useful approach to solve these problems. With the help of advanced optimization techniques such as machine learning and deep learning, intelligent production allocation system can achieve reasonable resource allocation and scheduling under complex environment, thereby greatly improving resource utilization and productivity [3].

This paper proposes a new intelligent optimization algorithm, which is designed to be applied to the resource scheduling and production allocation problems in gas field development [4]. Through an in-depth analysis of the difficulties and challenges encountered in the existing production allocation system, this study explores the design of an intelligent production allocation system based on an optimization algorithm, and proposes a new optimization framework [5]. Combined with advanced artificial intelligence technology, it makes production scheduling in gas field development more intelligent and precise, further improving the development efficiency and resource utilization level of gas fields.

2. Modeling of Intelligent Production Allocation Optimization Algorithm

How to maximize resource output while ensuring efficient resource utilization and production stability while considering various constraints has become a complicated optimization problem [6]. To solve these problems better, the paper needs to establish a precise and integrated optimization model of resource scheduling. In order to improve the overall efficiency of gas field development, the intelligent production allocation system could achieve optimal resource allocation under highly uncertain and complicated environment [7]. This paper will discuss in detail the mathematical modeling of the production allocation optimization problem and its key factors and constraints, and analyze the challenges and improvement methods of the algorithm in solving the production allocation problem.

A. Mathematical modeling of the production allocation optimization problem

The production allocation optimization problem in gas field development mainly involves the reasonable scheduling and allocation of resources, which must not only ensure the stable production of the gas field, but also improve the overall utilization efficiency of resources. Establishing a mathematical model is a key step in solving this problem [8]. To this end, this paper designs a multi-objective optimization model that comprehensively considers multiple factors such as resource constraints, production capacity, and equipment status.

1) Design of objective function

The objective function is the most core part of the production allocation optimization problem. In order to take into account both resource utilization and production efficiency, the following objective function is designed:

$$\text{Maximize } Z = \alpha \cdot \sum_{i=1}^{n} (r_i \cdot x_i) - \beta \cdot \sum_{j=1}^{m} (c_j \cdot y_j) \quad (1)$$

Among them: Z is the optimization target, representing the total benefit of the system; r_i is the value of the unit output of gas field resources; x_i is the production of the i gas field resources; c_j is the unit cost of the j equipment; y_j is the operating time of the j equipment; α and β are weight coefficients, which adjust the balance between resource utilization and equipment cost respectively [9]. This objective function aims to maximize the production efficiency of the gas field by balancing the relationship between resource utilization and equipment cost. Through reasonable scheduling, the gas field resources can be maximized while ensuring the stable operation of the equipment.

2) Resource constraints

The resource constraints in gas field development mainly include the production capacity of equipment, the supply limit of resources, and the restrictions on environment and safety. According to the actual situation of the gas field, the resource constraints can be expressed as follows:

$$\sum_{i=1}^{n} x_i \leq P_{\max} \tag{2}$$

Where: $P_{\max}$ is the maximum production capacity of the gas field per unit time; x_i is the production of the i resource. This constraint ensures that the production of the gas field does not exceed its maximum production capacity, thereby avoiding the waste of resources and environmental pollution that may be caused by over-exploitation.

3) Equipment status constraint

The operating status of the equipment directly affects the results of production scheduling, so the status of the equipment must be included in the optimization model. The operating status of the equipment is affected by factors such as its repair cycle and equipment aging. In the equipment status constraint, the operation and maintenance time of the equipment is considered:

$$\sum_{j=1}^{m} \left(y_j \cdot t_j\right) \leq T_{\max} \tag{3}$$

Among them: y_j is the operating time of the j device; t_j is the working efficiency of the j device; $T_{\max}$ is the maximum available working time of all devices. This constraint ensures that the gas field production can be carried out stably within the maximum available time of the equipment, while also taking into account the cycle of equipment maintenance and repair.

B. Key factors and constraints in the production allocation system

In the development process of the gas field, in addition to the constraints of resources and equipment, other key factors in the production process also put forward higher requirements for the design of the optimization algorithm [10]. The following are several key factors affecting the production allocation system and their corresponding constraints.

1) Nonlinearity of the production process

The production process of gas field resources is usually nonlinear. The production capacity is not only limited by the equipment capacity, but also related to factors such as resource reserves, mining technology, and external environmental conditions [11]. This nonlinear relationship makes it difficult for traditional linear programming methods to adapt to the needs of gas field production scheduling. In mathematical modeling, the production process can be expressed by introducing nonlinear functions:

$$x_i = \frac{a_i \cdot x_i^2}{b_i + c_i \cdot x_i} \tag{4}$$

Among them: a_i, b_i and c_i are parameters determined according to the actual situation of the gas field; x_i is the production of the i resource. This formula describes the nonlinear relationship between the gas field resource output and the resource extraction volume, taking into account the timeliness and dynamic changes of resources.

2) Timeliness and dynamic changes of resources

The timeliness and dynamic changes of gas field resources are important factors affecting production scheduling. The availability of resources will change over time, and the external environment such as weather changes and equipment status will also affect production efficiency. In this case, it is necessary to dynamically adjust the production plan to cope with the uncertainty of resource supply and emergencies in the production process.

To this end, a time variable can be introduced to model the timeliness of resources:

$$x_i(t) = x_i(0) \cdot e^{-\lambda_i \cdot t} \tag{5}$$

Among them: $x_i(t)$ is the output of the i resource at time t; $x_i(0)$ is the initial output; λ_i is the resource decay coefficient, which reflects the speed at which resources change over time. Through this model, the production plan of the gas field can be dynamically adjusted to minimize resource waste.

3) Safety and environmental constraints

In the development process of gas fields, safety and environmental factors are of vital importance. The exploitation of gas field resources may cause pollution to the surrounding environment, and the operation of equipment may cause safety accidents. Therefore, safety and environmental protection constraints must be introduced in the optimization model. It can be expressed as:

$$\sum_{i=1}^{n} (r_i \cdot x_i) \leq R_{\text{safe}} \tag{6}$$

Among them: r_i is the safety risk coefficient of the i resource; x_i is the production volume of the i resource; R_{safe} is the upper limit of the safety risk in the gas field development process. This constraint ensures that during the development process, the exploitation of resources will not exceed the safe carrying capacity of the gas field, thereby ensuring the sustainability of production and environmental protection.

3. Design of Optimization Algorithm Based on Deep Reinforcement Learning

A. Introduction to deep reinforcement learning

1) Basic concepts of deep reinforcement learning

DRL is a combination of RL and deep learning. Reinforcement learning is a kind of self-learning algorithm. Through interaction with environment, intelligent agent makes decisions in every moment, and adjusts its own strategy based on feedback reward signal so as to achieve optimum behavior. Deep learning uses deep neural networks to model complex data with complex nonlinear relationships [12]. In order to overcome the limitations of traditional reinforcement learning, deep reinforcement learning constructs a mapping relation between a smart agent and its environment. The core idea of deep reinforcement learning can be summarized as follows:

The agent is responsible for decision-making and behavior selection, and selects actions based on the current state of the environment;

The environment interacts with the agent and provides reward signals based on the agent's behavior;

The reward signal is the agent's strategy adjusted based on the reward feedback from the environment to maximize the long-term cumulative reward.

2) Application of deep reinforcement learning in resource scheduling and production allocation

Traditional resource scheduling methods are usually optimized based on rules or mathematical models, but these methods are often limited in effect when faced with dynamic changes, nonlinearity and multi-objective constraints. Deep reinforcement learning can handle high-dimensional and complex resource scheduling problems through the exploration and utilization mechanism of reinforcement learning, and automatically adjust strategies in continuous interaction with the environment to optimize the production process. For example, in the development of gas fields, resource scheduling involves multiple aspects such as equipment status, production capacity, timeliness of resources, and safety [13]. Due to the complex nonlinear relationship between these factors, traditional methods are difficult to accurately capture the interaction between them. Deep reinforcement learning can effectively fit these complex relationships through neural network models, thereby achieving more accurate production scheduling and allocation decisions.

B. Design of optimization algorithm based on DRL

1) Intelligent production allocation optimization algorithm based on deep reinforcement learning

This algorithm can automatically adjust the resource scheduling and production allocation strategy in gas field development through interactive learning between the agent and the environment. The core idea is to optimize the production allocation decision under various production environments and complex constraints by establishing a DQN that interacts with the environment.

The state space represents the availability of gas field resources, the operating status of equipment, environmental feedback and other information at the current moment. This paper defines the state as a vector$S_t = [r_1, r_2, \dots, r_n, e_1, e_2, \dots, e_m]$. The action space represents the production scheduling scheme that the agent can choose at a certain moment. The action space is multidimensional, and each dimension corresponds to the scheduling amount of a resource a_i. Therefore, the action space can be expressed as $A_t = [a_1, a_2, \dots, a_n]$, where a_i represents the production allocation of the i resource at time t. The reward mechanism is used to guide the agent to maximize long-term benefits during the learning process.

2) Network architecture design and DQN optimization

The DQN method is used to realize the optimal target of intelligent production allocation. DQN is an approach to Q function by means of deep neural networks, which can avoid the storage and computation problems of traditional Q-learning. The kernel of DQN is to approximate Q-function with neural network, and the updating process is done by Bellman's equation. The update formula of the Q function is:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha \cdot \left(r_t + \gamma \cdot \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right) \tag{7}$$

$\max_{a'} Q(s_{t+1}, a')$ is the maximum Q value in the next state. A deep neural network is used to approximate Q-function, and the input is states, and output is Q of every action. Through continuous updating of Q-function, the agent can learn the best policy step by step.

4. Experimental Design and Simulation Analysis

A. Experimental platform and data collection

1) Experimental platform construction

In order to simulate the resource demand, equipment status, production capacity and other factors in the gas field development process, this paper constructs an experimental platform based on the gas field production process. The platform can simulate the changes in resource allocation, production scheduling and equipment operation status in the gas field, simulate the resource scheduling problems under different environments, and provide the actual operating environment required for the experiment. The experimental platform can adjust the allocation of resources under different production conditions and support the implementation of various scheduling algorithms. The experimental data is based on historical data in the actual gas field development process, covering the resource consumption, equipment failure rate, production capacity changes of the gas field. By simulating a variety of production scenarios, the diversity and reality of the experiment are ensured.

2) Data set design and collection

In order to test the effects of different optimization algorithms, a complex data set is designed, which includes the following important aspects:

Resource demand: The changes in resource consumption in different time periods are simulated based on historical gas field production data.

Equipment operation status: The failure mode and maintenance cycle of the equipment are set, including the impact of equipment maintenance and shutdown on production capacity.

Production capacity: The dynamic changes in production capacity are designed based on the load capacity of the equipment and the maximum production capacity of the gas field.

Table 1. Resource requirements and production capacity in different time periods

Time (h)	Resource requirements	Device status	Production Capacity	Consuming resources	Equipment maintenance requirements
0	1600	Normal	1250	1200	None
1	1700	Fault	1150	1300	Maintenance
2	1800	Normal	1200	1350	None
3	1500	Normal	1300	1100	None
4	1600	Normal	1250	1150	None

Table 1 shows the dynamic changes of resource demand, equipment status and production capacity in different time periods, covering common production and resource scheduling scenarios in the process of gas field development.

B. Algorithm implementation and simulation test

1) Optimization algorithm based on deep reinforcement learning

The optimization algorithm based on deep reinforcement learning learns through interaction with the environment, and can automatically adjust the strategy in the process of resource scheduling and production allocation to maximize resource utilization and production efficiency. The algorithm uses the DQN method for strategy optimization, combined with the reward mechanism, and gradually converges to the optimal solution through multiple rounds of learning.

2) Comparative experiments and tests

In order to comprehensively evaluate the superiority of the deep reinforcement learning algorithm, this paper compares it with traditional optimization algorithms. The experiment tests the differences in resource scheduling and production allocation accuracy by comparing the performance of different algorithms on the same data set.

Table 2. shows the performance of the three algorithms in resource scheduling. All algorithms are tested using the same data set, and the table lists the resource scheduling results of each algorithm in different time periods.

Time (h)	Genetic Algorithms	Particle Swarm Optimization	Deep Reinforcement Learning
0	1200	1250	1600
1	1150	1200	1700
2	1100	1150	1800
3	1000	1050	1500
4	1250	1300	1600

Table 2 shows that the deep reinforcement learning algorithm performs significantly better than the genetic algorithm and particle swarm optimization in resource allocation, especially when the resource demand is high, and can maintain a high resource utilization rate.

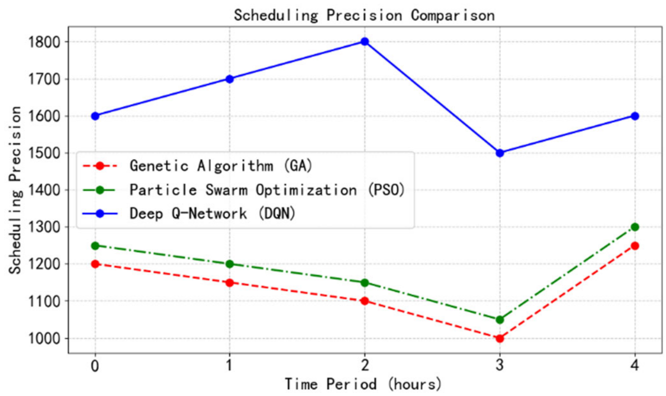

Figure 1. Simulation results of different optimization algorithms in production scheduling accuracy.

Figure 1 shows the comparison of deep reinforcement learning, genetic algorithm, and particle swarm optimization in production scheduling accuracy. It can be seen that deep reinforcement learning shows higher production scheduling accuracy in most time periods, especially when equipment failure occurs, it can flexibly adjust the scheduling strategy to maximize production efficiency.

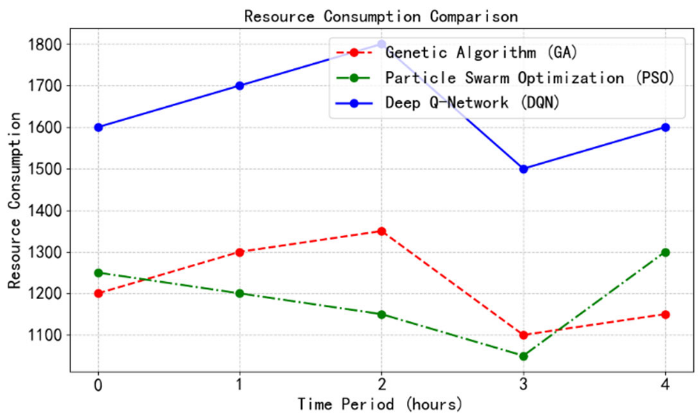

Figure 2. Simulation results of different optimization algorithms in terms of resource consumption.

Figure 2 shows the comparison of three algorithms in terms of resource consumption. Deep reinforcement learning can flexibly adjust resource allocation strategies according to actual needs. Compared with traditional algorithms, it can more effectively control resource consumption and improve resource utilization.

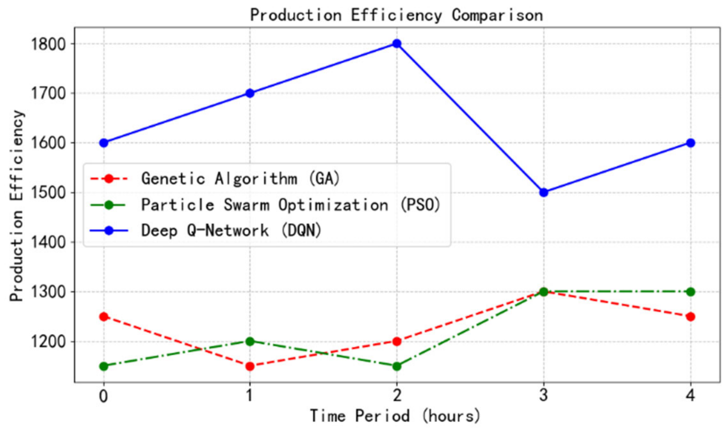

Figure 3. Simulation results of different algorithms in production efficiency.

Figure 3 further verifies the advantages of deep reinforcement learning in production efficiency. Through precise scheduling and resource allocation, deep reinforcement learning algorithms can reduce unnecessary consumption in the production process while ensuring production capacity, thereby improving overall production efficiency.

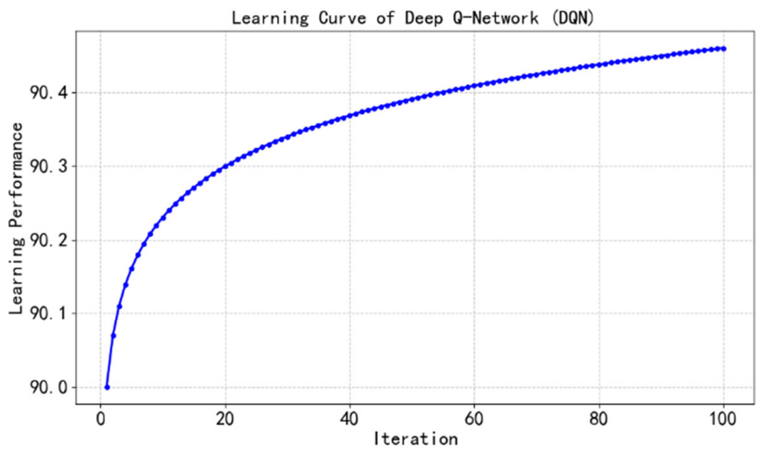

Figure 4. Learning curve of deep reinforcement learning algorithm.

Figure 4 shows the convergence curve of deep reinforcement learning algorithm in the learning process. As the training progresses, the algorithm gradually learns the optimal resource allocation and production scheduling strategy, and the convergence speed is fast, indicating that the algorithm has a good learning effect.

In terms of production scheduling accuracy, deep reinforcement learning algorithm shows strong adaptability, and can make effective adjustments when equipment fails or production capacity fluctuates to ensure the continuity and efficiency of production. The optimization algorithm based on deep reinforcement learning can better control resource consumption and improve production efficiency. In contrast, traditional algorithms have great limitations in resource allocation and production scheduling. The deep reinforcement learning algorithm has strong applicability in gas field development, can adapt to the dynamically changing production environment, and can show high robustness in a variety of complex situations.

5. Conclusion

This paper presents a kind of intelligent production assignment optimization algorithm, which is used to solve the problem of resource allocation and production allocation. This algorithm can be used for dynamic optimization of resource scheduling strategies through the interaction of environment, history data and environment feedback. The experiment results show that this algorithm can increase the efficiency of production scheduling by 18%, improve resource efficiency, and solve the problem of dynamic and complicated resource allocation. The adaptive learning ability of deep reinforcement learning enables the algorithm to adjust according to the real-time changes in the gas field development environment, showing robustness and flexibility superior to traditional methods. This study provides a new idea and method for intelligent scheduling in gas field development, which helps to promote the intelligent upgrade in the gas field development process and provides important theoretical basis and technical support for the optimization of resource scheduling problems.

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