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A Review of Intelligent Optimization Algorithms for Oilfield Development

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ABSTRACT

To identify the most suitable oilfield development strategy for maximizing energy supply or economic returns, optimization of oilfield development remains one of the most critical challenges in closed-loop reservoir management. In recent decades, with the advancement of artificial intelligence technologies, intelligent optimization algorithms have been increasingly applied to improve the efficiency and accuracy of optimization outcomes in oilfield development. This paper provides a comprehensive review of intelligent optimization algorithms applied to oilfield development optimization problems. It covers several key topics within this domain, ranging from the fundamental components of such problems—decision variables, objective functions, and constraints—to various algorithmic approaches developed from different perspectives and for different types of optimization problems.

KEYWORDS

Oilfield development; Optimization problems; Intelligent optimization algorithms

1. INTRODUCTION

Oilfield development is a complex process that requires continuous optimization and dynamic adjustment. In the early stages, the primary tasks include evaluating reservoir geological characteristics, designing well patterns, and selecting appropriate development strategies. In contrast, the later stages of development design place greater emphasis on the ongoing optimization and dynamic adjustment of existing plans to address various challenges arising during actual production. To maximize both economic and social benefits, oilfield development optimization should adhere to a systematic principle of "minimizing costs, maximizing production, and meeting national energy strategy demands to the greatest extent". In essence, oilfield development optimization involves formulating a scientific, feasible, and operational development plan that enhances the overall efficiency, economic performance, and environmental sustainability of the production process. Under the constraints of controlled production costs and reasonable workload investment, the core objectives are to slow the rate of production decline, extend the plateau production period, and ultimately achieve desirable economic returns.

To this end, it is necessary to systematically address various optimization challenges encountered in oilfield development by employing a range of scientific methods and theoretical tools to improve development quality and management efficiency. These approaches include goal programming, systems engineering theory, optimal control strategies, fuzzy mathematical analysis, modern decision-making methods, and grey system theory. They not only provide a macroscopic, holistic perspective but also enable hierarchical and structured analyses, fully accounting for the impacts of geological structures, production technologies, environmental conditions, and other key parameters on development strategies. Through comprehensive research and optimization of development mechanisms, management models, and technical pathways, a more efficient and sustainable oilfield development paradigm can ultimately be established.

2. OPTIMIZATION OF OILFIELD DEVELOPMENT PLANS

2.1. Model Construction for Oilfield Development Optimization

Oilfield development is a technology, capital, and risk-intensive engineering activity involving non-renewable resources. Therefore, scientific planning and efficient resource allocation are essential for improving development performance and enhancing recovery rates. Current research hotspots include production allocation optimization, well placement, production process management, and enhanced oil recovery (EOR) regulation.

Ge et al. divided a gas field into multiple independent units and constructed a nonlinear mixed-integer programming model to maximize overall economic benefits, while employing sensitivity analysis to evaluate the impact of key parameter variations on optimization results [11]. Antonio C et al systematically reviewed key stages in oilfield development, including drilling, completion, artificial lift, and production stimulation. For each stage, optimization control strategies were proposed, and a hybrid intelligent optimization model integrating genetic algorithms with the complex method was developed [2]. Yang proposed an optimized well pattern design strategy for low-permeability reservoirs [35]. Wu et al. applied an iterative optimization framework combined with artificial intelligence techniques to optimize the concentration, timing, and placement of chemical flooding agents, thereby enhancing oil recovery while enabling automated production management and predictive maintenance [33]. Li et al (2021) integrated wellhead production data, geological information, and pressure variables to construct a neural network model for predicting well productivity. Based on these predictions, a genetic algorithm was employed to optimize production allocation, improving overall output while ensuring that individual well production remains within engineering constraints [15].

2.2. Application of Intelligent Optimization Algorithms in Oilfield Development

To achieve scientific planning and effective management of oil and gas production activities, a variety of strategic tools and methodologies can be employed. These techniques enable comprehensive analysis and trade-off evaluation of multiple objectives and, when integrated with specific development conditions, support the formulation of targeted and practical development plans. Within the overall design of oilfield development, optimization of development schemes is an essential and indispensable component. This is because it involves not only technical and economic considerations, but also requires coordinated assessment of environmental impacts and social benefits, thereby exhibiting the characteristics of a typical multi-criteria decision-making problem. At present, commonly used optimization approaches include fuzzy mathematical methods, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and mathematical programming methods.

2.2.1. Fuzzy Mathematical Optimization Methods

In response to the difficulty of precisely quantifying many parameters in oilfield development, fuzzy mathematical theory has been widely applied to improve the scientific rigor and accuracy of evaluations.

(1) Single fuzzy comprehensive evaluation methods.

These methods integrate complex information and assist decision-makers in balancing multiple objectives. Sun et al. introduced the Analytic Hierarchy Process (AHP) to construct an evaluation system encompassing reservoir geology, technical parameters, and economic benefits, and combined it with fuzzy mathematics to rank and select optimal development schemes [25]. Zhang et al proposed a fuzzy matter-element optimization model based on the TOPSIS principle, which alleviates the excessive dependence on weight assignment in traditional methods [39].

(2) Integrated optimization methods combining fuzzy evaluation with other approaches.

To enhance decision-making adaptability, researchers have integrated fuzzy methods with grey system theory, neural networks, and other techniques. For example, Lin et al. (2006) quantitatively evaluated key indicators based on grey relational analysis and combined it with fuzzy evaluation to construct a practical assessment framework [17]. Chen Z et al employed a combination of fuzzy AHP and fuzzy grey relational analysis to conduct multidimensional quantitative evaluation of tight oilfield development schemes [6].

(3) Extended fuzzy mathematical approaches.

To address uncertainties such as reserve estimation and parameter fluctuations, Guo incorporated risk factors and probability distributions into a fuzzy optimization model, thereby enhancing risk identification in decision-making [12]. Zhang et al established an evaluation system using a fuzzy consistent matrix in conjunction with an improved AHP method, improving the objectivity of weight determination and the overall evaluation capability [37].

2.2.2. TOPSIS Method

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is based on the concepts of a positive ideal solution and a negative ideal solution in a multi-objective decision space. The relative performance of each alternative is evaluated by calculating its distance from these two reference points.

Chen et al. constructed a multidimensional indicator system encompassing production efficiency, economic benefits, and environmental impacts, and applied a multi-objective decision-making approach based on the ideal point method to select optimal development schemes [5]. Chen et al. applied the TOPSIS method to optimize oilfield production management plans by comprehensively considering multiple criteria, including production efficiency, cost control, and environmental protection, ultimately identifying the optimal solution [4].

2.2.3. Mathematical Programming Method

As oilfield development progresses, constraints related to resources, technology, and costs become increasingly significant. Achieving effective cost control while maintaining development performance has become a central concern in planning, with production optimization serving as a key component. This requires analyzing the operational status of production units and making refined arrangements for production allocation and enhanced recovery measures to improve overall economic efficiency.

As a complex engineering system, oilfield development exhibits four notable characteristics. First, it is inherently a multi-objective optimization problem that must balance technical, economic, and policy-related factors. Second, reservoirs are deeply buried underground, leading to uncertainty and ambiguity in parameter acquisition. Third, such projects involve high investment and high risk, requiring dynamic adjustment of strategies. Fourth, there is strong coupling among multiple domains, including reservoir engineering and surface engineering systems.

In response to these complexities, researchers have extensively applied mathematical programming methods such as dynamic programming, goal programming, optimal control theory, and intelligent optimization algorithms. These approaches focus on multi-objective optimization problems in production management, resource allocation, and development strategy design, seeking global optimal solutions under multidimensional constraints. The introduction of mathematical programming techniques has driven oilfield development from experience-based practices toward quantitative modeling and, ultimately, to a new stage of simulation-based scientific decision-making.

3. MULTI-OBJECTIVE OPTIMIZATION IN OILFIELD DEVELOPMENT

3.1. Current Status of Intelligent Algorithms in Multi-Objective Optimization

The concept of multi-objective optimization was first proposed by Edgeworth in 1881 and applied to economic decision-making problems. In 1906, Pareto introduced the theory of Pareto optimality, defining a state of resource allocation in which any further improvement in one objective would lead to deterioration in at least one other objective. In 1951, Koopmans introduced the concept of the production possibility set and developed linear programming tools to achieve efficiency maximization under multiple constraints [14]. From the 1950s to the 1990s, researchers such as Zadeh proposed methods including the weighted sum approach, constraint handling methods, and goal programming, thereby enriching the methodology of multi-objective optimization [36]. Since the 21st century, advances in computer technology and swarm intelligence theory have driven rapid progress in multi-objective optimization methods, significantly enhancing their applicability in scientific research and engineering practice.

Multi-objective optimization algorithms can generally be classified into two categories: traditional optimization algorithms and intelligent optimization algorithms. The key distinction lies in their solution characteristics: traditional methods typically yield a single solution per run, whereas intelligent algorithms can perform parallel searches and generate multiple non-dominated solutions, forming a Pareto-optimal solution set.

(1) Traditional optimization algorithms.

These methods transform multi-objective problems into single-objective ones through techniques such as linear weighting, max–min approaches, and goal constraints. They are computationally efficient and easy to implement, and thus widely used in engineering applications. However, they exhibit several limitations: (i) each run produces only one solution, and solution quality is highly sensitive to parameter settings; obtaining a representative solution set requires repeated tuning, which is time-consuming and labor-intensive ; (ii) they perform poorly when dealing with non-convex Pareto fronts, particularly the weighted sum method; and (iii) weight assignment relies heavily on decision-maker experience, introducing subjectivity and limiting the objectivity of optimization results.

(2) Intelligent optimization algorithms.

Over the past two decades, multi-objective intelligent algorithms inspired by biological behaviors have developed rapidly. Representative approaches include Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO). These algorithms simulate cooperative evolution and collective intelligence observed in natural ecosystems, enabling efficient global search in the solution space and making them particularly suitable for nonlinear, multimodal, and highly constrained problems that are difficult to solve using traditional methods. Compared with conventional approaches, intelligent algorithms offer significant advantages: (i) they support parallel computation, generating multiple non-dominated solutions in a single run and constructing a Pareto-optimal solution set; (ii) they exhibit strong adaptability and robustness when handling convex, non-convex, and discontinuous Pareto fronts; and (iii) through heuristic search and global optimization capabilities, their performance continues to improve, making them a major focus in multi-objective optimization research.

3.1.1. Multi-Objective Genetic Algorithm

Multi-objective genetic algorithms emerged in the 1960s. These algorithms select superior individuals based on fitness evaluation and generate new individuals through genetic operations such as crossover and mutation. Through iterative evolution, a set of optimized solutions is eventually obtained. Each run can produce multiple solutions that collectively form the Pareto front—on which any improvement in one objective inevitably leads to deterioration in at least one other objective. Solutions on this front are referred to as Pareto-optimal (or non-dominated) solutions. Their defining characteristic is that each solution is superior in at least one objective while potentially inferior in others.

To address multi-objective optimization problems, Srinivas and Deb (1994) pioneered the Non-dominated Sorting Genetic Algorithm (NSGA), which ranks and classifies individuals based on dominance relationships [24]. However, NSGA suffers from high computational complexity and the potential loss of elite individuals. To overcome these limitations, Deb et al. introduced an improved version, NSGA-II , which integrates fast non-dominated sorting, an elitism preservation mechanism, and a crowding-distance-based diversity maintenance method. This significantly reduces computational complexity while maintaining population diversity, enabling more efficient generation of the Pareto-optimal solution set [8].

Early research primarily focused on constructing mathematically realistic models. With the advancement of computer technology, the emphasis has shifted toward efficient solution techniques. As one of the earliest intelligent optimization methods, genetic algorithms have been widely applied across various fields due to their strong robustness.

To address these limitations, researchers have focused on improving genetic algorithms through enhancements in encoding mechanisms, operator design, adaptability, and local search capabilities. Shi et al designed a genetic algorithm based on process-constraint chain encoding, reconstructing chromosome representation and incorporating adjacency matrix techniques to effectively address chromosome feasibility issues, demonstrating strong performance in complex product scheduling [23]. Zhu et al optimized traditional mutation operators and proposed an improved interactive genetic algorithm that divides individuals into subunits and integrates user preferences, alleviating user fatigue and enhancing adaptability in product configuration design [41]. Wu et al introduced an adaptive adjustment mechanism, proposing a strategy based on dynamic crossover probability adjustment to strengthen search capability and stability in logistics distribution path optimization [32].

To overcome premature convergence and slow convergence speed in recommendation systems using traditional genetic algorithms, Zhang et al incorporated an extreme-point mechanism within the standard framework, effectively avoiding local optima and enhancing global search capability and solution stability [40]. Additionally, Alshamasin et al developed a selection operator based on an adaptive control mechanism, dynamically adjusting survival selection thresholds to improve population diversity and convergence, thereby preventing entrapment in local optima [1].

Common types of multi-objective genetic algorithms currently include: Vector Evaluated Genetic Algorithms (VEGA), Weighted Genetic Algorithms, Dictionary-Based Sorting Methods, Niching Pareto Genetic Algorithms, Multi-Objective Matter-Element Optimization Models, and Adaptive Genetic Algorithms (AGA), among others.

3.1.2. Multi-Objective Particle Swarm Optimization

In 2004, Carlos proposed the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm [3]. Unlike single-objective optimization, which seeks a single optimal solution, multi-objective optimization aims to obtain a Pareto-optimal solution set that effectively balances trade-offs among multiple objectives. When applied to multi-objective problems, particle swarm optimization guides the population toward the Pareto front by leveraging each particle’s personal best position and the global best position of the swarm. Compared with other algorithms, MOPSO offers advantages such as simple design, high search efficiency, and strong generality.

Coello et al. proposed an improved MOPSO algorithm, incorporating a priority-based mechanism to select optimal objective functions, establish overall objective ranking, and maintain an external elite archive to ensure efficient particle search and dynamic updates. The algorithm also employs a Pareto-adaptive grid strategy to accurately collect and store high-quality solutions during the search process, enhancing optimization performance and solution diversity [7]. Tripathi et al introduced two variants—Time-Varying MOPSO (TV-MOPSO) and Fuzzy MOPSO (FMOPSO)—to improve adaptability and the ability to handle objectives with fuzzy boundaries [28]. Wang et al applied MOPSO to power dispatch problems, optimizing schedules under dual objectives of economic efficiency and environmental impact[30]. Omkar et al developed a general framework for multi-objective design optimization of laminated composite components based on Vector Evaluated PSO (VEPSO) [18]. Durillo et al systematically evaluated six mainstream MOPSO algorithms—including NSPSO, SigmaMOPSO, and OMOPSO—using ZDT, DTLZ, and WFG benchmark functions, assessing global search performance and Pareto set quality, and validating their performance differences and suitability across problems of varying complexity [9].

3.1.3. Multi-Objective Ant Colony Optimization

Ant Colony Optimization (ACO), proposed by Marco Dorigo and Thomas Stützle in 1991, is an evolutionary algorithm inspired by the pheromone-based foraging behavior of ants. It has demonstrated strong performance in combinatorial optimization problems such as the Traveling Salesman Problem (TSP) and quadratic assignment problems. The algorithm is inspired by the way ants deposit pheromones along paths, guiding subsequent ants to select routes based on pheromone concentration and distance. Since its inception, ACO has evolved into numerous variants. Tzle et al explored strategies for implementing ACO in parallel computing environments to improve computational efficiency [29].

Beyond ACO, various nature-inspired multi-objective optimization algorithms have been proposed. In 1967, Rosenberg first suggested using evolutionary algorithms to solve multi-objective optimization problems [21]. In the same year, Toffolo et al. introduced the Genetic Diversity Evaluation Method (GeDEM), incorporating inter-individual distances into fitness assignment to improve population distribution quality and solution diversity [27]. Reddy et al developed a Multi-Objective Evolutionary Algorithm (MOEA) for reservoir operation strategy optimization [20]. Piroozfard et al applied multi-objective optimization to job shop scheduling, minimizing carbon emissions and task delays to support green manufacturing [19]. Wu et al addressed the tendency of the Sparrow Search Algorithm to fall into local optima by integrating multiple adaptive strategies, applying the improved algorithm to wireless sensor node deployment to enhance system coverage and energy efficiency [34].

Overall, the development of multi-objective intelligent optimization algorithms can be divided into two stages: early research focused on modeling and describing problems within intelligent algorithm frameworks, while later work emphasized improving convergence efficiency and computational performance. Current research concentrates on three main directions: (i) designing mechanisms to guide populations toward the Pareto-optimal solution set efficiently; (ii) ensuring a well-distributed solution set along the Pareto front; and (iii) developing efficient constraint-handling methods to enhance algorithm adaptability.

Despite continuous progress, several challenges remain: the theoretical foundation is still incomplete, computational processes are not fully mature, optimization accuracy is limited, and pseudo-optimal solutions may arise; there is a lack of standardized tools for evaluating solution set quality and user satisfaction; mathematical proofs of convergence require strengthening; numerical precision limitations can introduce errors; and selection bias in evolutionary algorithms may lead to premature convergence and biased solution sets. Future work should advance both theoretical frameworks and algorithm implementation simultaneously, further improving computational efficiency, solution set quality, and algorithm speed, while exploring high-dimensional multi-objective optimization problems in depth.

3.2. Current Applications of Intelligent Algorithms for Multi-Objective Optimization in the Petroleum Industry

Multi-objective optimization is a critical tool in decision-making research. Because multiple objectives often conflict, improving the performance of one objective frequently leads to the deterioration of others. Consequently, there is generally no single global optimum, but rather a set of Pareto-efficient solutions.

Oilfield development planning is inherently a typical multi-objective optimization problem. In practical development, multi-objective planning models are widely applied to key areas such as well placement, wellbore trajectory design, and production parameter optimization. Li et al applied multi-objective planning to model emergency base site selection based on Bohai oil spill data, and solved the problem using genetic algorithms [16]. Khishvand et al employed particle swarm optimization to construct an integrated model of downhole tubing and surface equipment, optimizing tubing size, choke specifications, and wellhead flow pressures to extend the production system lifecycle [13]. Zhang et al proposed a multi-objective integrated adjustment model focused on maximizing economic benefits while considering multiple constraints, solved using the Quantum-Behaved Frog Leaping Algorithm [38]. Sharifi et al developed a robust multi-objective optimization model that accounts for reservoir characteristics, production capacity, and development costs, solving it with particle swarm optimization to consistently obtain high-quality solution sets [22]. Sun et al constructed a conventional oilfield development model with multiple objectives—recovery factor, waterflood efficiency, construction difficulty, and economic performance—and solved it using NSGA-II to obtain representative Pareto front solutions [26].

Since the beginning of the 21st century, energy shortages and environmental concerns have become increasingly prominent. China’s rising energy demand, the gradual depletion of fossil fuels, and the ecological damage caused by large-scale oil and gas development have drawn national attention. In 2020, China announced its carbon neutrality goals: peak carbon emissions by 2030 and carbon neutrality by 2060. Against this backdrop, integrating environmental benefits into multi-objective decision-making has become a research hotspot. Feng et al used the Delphi method to select evaluation indicators and conducted a comprehensive analysis of investment project economic, environmental, and social performance [10]. Furthermore, Wang et al developed a multi-objective planning model for oilfield development focused on ecological protection, resource conservation, and social performance, providing feasible development recommendations [31].

4. CONCLUSION

This paper provides a systematic review of the current research on intelligent algorithms for oilfield development optimization, with a focus on the typical applications of genetic algorithms, particle swarm optimization, ant colony optimization, fuzzy mathematical methods, TOPSIS, and mathematical programming. The applicability, strengths, and limitations of each approach are analyzed. The review shows that intelligent optimization algorithms, due to their strong global search capabilities and adaptive parameter features, demonstrate superior performance in key areas such as well pattern design, production parameter configuration, and enhanced recovery. In particular, when addressing complex problems characterized by nonlinearity, multiple objectives, and strong coupling, these algorithms offer higher solution-space exploration efficiency and broader applicability compared with traditional modeling approaches.

The integrated application of multi-objective optimization models in oilfield development has deepened, enabling the coordinated optimization of economic performance, environmental outcomes, and technical feasibility, and has become a crucial technical support for promoting green oil and gas development. Despite the significant achievements of intelligent optimization methods, challenges remain, including unstable convergence rates, uneven solution set distribution, and limited capability in handling high-dimensional problems. Furthermore, the integration of optimization models with dynamic oilfield management systems still requires improvement, particularly regarding large-scale data-driven decision-making, multi-scenario coupling, and interpretability of results.

Future research should focus on enhancing the theoretical foundations of algorithm convergence, developing hybrid algorithm integration mechanisms, and achieving deeper coupling between intelligent optimization, reservoir numerical models, and artificial intelligence techniques. Emphasis should also be placed on diversifying optimization objectives, ensuring the engineering feasibility of algorithm outputs, and constructing optimization frameworks guided by green and sustainable indicators. These efforts will provide both theoretical support and practical pathways for advancing intelligent, low-carbon, and highly efficient oilfield development.

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