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• Review •

Review of Reservoir Closed-Loop Optimization Control Methods

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Abstract: This paper presents a review of reservoir closed-loop optimization management technology, with a particular focus on its core software component—reservoir closed-loop optimization control technology. This technology constitutes a closed-loop process encompassing two fundamental steps: automatic history matching and production optimization. History matching involves refining model parameters to align numerical models with actual production dynamics. Subsequently, production optimization is performed based on the updated model. The goal is to maximize economic benefits or cumulative oil production by automatically identifying the optimal injection-production scheme.

The mainstream methods in both areas can be categorized into gradient-based and gradient-free algorithms. Gradient-based algorithms offer fast convergence but are complex to implement and difficult to integrate with commercial simulators. In contrast, gradient-free algorithms provide greater versatility but may face challenges in computational efficiency or convergence accuracy. In recent years, to overcome the high computational cost associated with traditional numerical simulations, surrogate modeling techniques have emerged as a significant research focus. These techniques accelerate the optimization cycle by approximating the simulation process.

Keywords: Meshless method; Reservoir numerical simulation; Generalized finite difference method; Fluid-solid coupling; Numerical algorithm

1 Introduction

Petroleum, widely regarded as the lifeblood of industry, has long served as a strategic resource vital to the national economy. In recent years, the rapid advancement of various modern intelligent technologies has driven traditional industries to continuously pursue intelligent and digital transformation based on information technologies. As a pillar of the energy sector, domestic oilfields have extensively deployed intelligent oilfield infrastructure. Consequently, oilfield development is gradually transitioning from reliance on on-site human experience, judgment, and manual operation to computer-aided remote decision-making and automated control. Currently, oilfields are undergoing further modernization and intelligent upgrades utilizing big data [1-3].

In recent years, stemming from the concept of the intelligent oilfield, scholars both domestically and internationally have proposed the reservoir closed-loop optimization management technology to enhance the efficiency of modern reservoir development and the application of information technology. This technology primarily encompasses reservoir dynamic monitoring and real-time control techniques, which facilitate the real-time updating of reservoir development data, optimization of development strategies, and adjustment of production equipment. The process begins with monitoring reservoir formation production status and output dynamics to obtain production data. These data are then transmitted to surface software platforms for comprehensive computer analysis to rapidly formulate an optimal reservoir development plan. Finally, the plan is fed back to the field via a control system to regulate downhole indicators such as fluid flow and flow pressure [4-5].

The reservoir closed-loop optimization management technology takes the reservoir system (numerical model/reservoir model) as the primary research object, combining reservoir numerical simulation to accurately reproduce the entire oilfield development process and assist in formulating development plans. This technology mainly comprises two key steps: automatic reservoir history matching and reservoir development production optimization. First, actual reservoir production data are used for history matching to automatically correct reservoir model parameters, thereby improving the model's prediction accuracy. Then, based on the history-matched reservoir model, reservoir production is treated as an optimization problem. Targeting oilfield development benefits or cumulative oil production and combining reservoir numerical simulation with intelligent optimization algorithms, the system automatically optimizes injection-production schemes for oil and water wells. This process ultimately determines the optimal future reservoir development policy. After new development policies are adjusted and implemented, the newly acquired production data are used to continue history matching, further refining the reservoir model. Once the model's predictive capability is enhanced, a new round of production optimization is initiated. Through continuous iterations of history matching and production optimization, this technology can significantly improve oilfield recovery rates [6-7].

In recent years, this technology has become a prominent research focus in intelligent reservoir development management. Its advantages include accurately reproducing the reservoir production process, utilizing production dynamic data in real-time to analyze reservoir development status, reducing reservoir development risks, and further improving development outcomes. However, the reservoir closed-loop optimization process still largely relies on manual experimental design. Actual reservoir production optimization constitutes a complex, large-scale optimization problem. Traditional methods often suffer from long implementation cycles, and the resulting optimized schemes frequently fail to meet expected targets. Benefiting from the rapid development of computer technology, automatic history matching and production optimization technologies—based on reservoir numerical simulation and optimization theory—can now automatically adjust reservoir geological parameters and derive optimal development plans through optimization algorithms. While these methods can more accurately characterize reservoir geological features and perform effective production optimization, they typically require repeated calls to numerical simulation. Consequently, closed-loop optimization methods based on traditional numerical simulation exhibit low computational efficiency, are time-consuming, and struggle to achieve efficient computation. Therefore, it is necessary to explore novel approaches to studying reservoir closed-loop optimization control methods from the perspectives of both history matching and production optimization. In the context of developing intelligent reservoirs, this research holds significant theoretical importance and practical value for improving reservoir production management, enhancing development efficiency, and advancing the field [8].

2 Research Status

Automatic reservoir history matching and production optimization represent two core aspects of reservoir numerical simulation research and are important topics within intelligent reservoir studies. Traditional history matching is based on a reservoir geological model, framing the improvement of the match between reservoir model predictions and observed data as an optimization problem. Combined with optimization algorithms, it automatically determines optimal reservoir model parameters through repeated numerical simulation processes. In contrast, reservoir production optimization technology aims to maximize reservoir development economic benefits or oil production. Based on a history-matched reservoir model, it treats the operational parameters of oil and water wells as independent variables. By invoking numerical simulation coupled with optimization algorithms, it solves for the optimal reservoir development plan. Concerning the specific issues involved in history matching and production optimization, numerous scholars have conducted extensive research. This paper primarily examines the mainstream methods in both areas [9-10].

2.1 Methods for Automatic Reservoir History Matching

After nearly five decades of development, mainstream history matching algorithms are now divided into gradient-based and gradient-free categories. Among gradient-based methods, the adjoint gradient method combined with the Limited Memory Broyden-Fletcher-Goldfarb-Shanno (LBFGS) method is notably efficient and widely applied. Among gradient-free algorithms, stochastic perturbation optimization algorithms, ensemble-based algorithms, and other stochastic optimization algorithms ensure high computational stability and efficiency. Additionally, to address large-scale reservoir history matching problems more conveniently, parameterization and dimensionality reduction algorithms have been proposed. These methods transform the original high-dimensional computational problem into a lower-dimensional space for solution.

In optimization algorithms, gradient-based approaches require calculating the Jacobian or Hessian matrix (second-order derivatives) to swiftly determine the optimization direction. In 1991, Tan et al. employed a Quasi-Newton scheme to study a three-dimensional, three-phase fully implicit numerical simulator, successfully demonstrating simple applications of history matching [11]. In 2002, Zhang and Reynolds utilized the LBFGS algorithm to solve automatic reservoir history matching problems. Their method required only a few iteration steps to approximate the Jacobian matrix using the objective function gradient, thereby reducing computational costs [12]. Although gradient-based algorithms exhibit faster convergence rates, they necessitate using the adjoint method to compute gradients. However, due to the high dimensionality of reservoir parameters, obtaining analytical gradients via the adjoint method is challenging, and the solution process is exceptionally complex, making integration with commercial simulators difficult.

Since the number of model grid characteristic parameters requiring inversion in automatic history matching can reach millions, direct computation under current conditions is extremely challenging. Therefore, many researchers have not only improved and innovated optimization algorithms but also proposed reservoir model re-parameterization methods to reduce the number of history matching parameters. In 1976, Gavalas et al. employed a simple approach, coarsening and partitioning a large number of reservoir geological parameters before adjusting uncertain parameters within each region as a whole. Although this method improved computational efficiency, it could not guarantee accuracy [13]. In 2004, Gao and Reynolds first parameterized production data to reduce the solution dimensionality, combining this with the LBFGS algorithm to correct model parameters [14]. In 2010, Tavakoli and Reynolds proposed initially reducing the covariance matrix dimensionality based on singular value decomposition before combining it with LBFGS to obtain reservoir models with higher prediction accuracy [15]. In 2012, Sarma et al., drawing on principal component analysis, decomposed the covariance between inverted geological parameters to reduce computational dimensionality [16]. In 2008, Jafarpour et al. utilized the Discrete Cosine Transform (DCT) to treat reservoir geological parameters related to production performance as inversion targets for history matching [17]. Jin [18] and Benjamin et al. [19] applied the gradual deformation method. Based on a set of reservoir models satisfying a Gaussian distribution, they used a perturbation mechanism to gradually modify deformation parameters, ensuring the updated models retained spatial correlations.

Compared to gradient-based algorithms, gradient-free algorithms operate by constructing approximate gradients, offering strong portability and ease of integration with commercial simulators. Gradient-free optimization algorithms are further divided into global and local categories. Local algorithms construct stochastic gradients, allowing the optimization direction to navigate among multiple local minima and eventually converge to a superior local or even global extremum. These algorithms share similar convergence properties with global gradient algorithms but exhibit slower convergence speeds. Among local optimization algorithms, the Simultaneous Perturbation Stochastic Approximation (SPSA) is widely applied[20] . However, because it did not account for correlations between reservoir model parameters, the computational results showed significant deviations from actual geological parameters. In 2011, Li and Reynolds incorporated correlations between reservoir model parameters into the SPSA algorithm to correct gradient search directions. They also changed the perturbation vector from a symmetric Bernoulli distribution to a Gaussian distribution, making the inversion results more consistent with geological understanding [21]. Compared to local optimization algorithms, global optimization algorithms search for the optimal solution across the entire feasible domain of the independent variables. Typical global algorithms, such as simulated annealing [22] and genetic algorithms [23-25], are often applied to reservoir history matching problems. However, these algorithms typically require a large number of numerical simulations, incurring high computational costs.

Reservoir systems are subject to significant uncertainties, primarily stemming from the reservoir model itself and production observation data. Quantifying this uncertainty and improving model prediction accuracy are major challenges in automatic history matching. To address reservoir model uncertainty, ensemble-based algorithms generate a series of randomly perturbed models based on an initial model and production dynamic data. They use the average gradient computed from this ensemble of reservoir models to approximate the true gradient. Through multiple data assimilation steps, they obtain multiple reservoir models and production predictions, thereby characterizing reservoir system uncertainty. The Ensemble Kalman Filter (ENKF), the Ensemble Smoother with Multiple Data Assimilation (ESMDA), and their derivative algorithms are typical ensemble-based approaches. Since their computational cost relates primarily to the number of reservoir models and does not require direct inversion of model geological parameters, they achieve higher computational efficiency compared to many gradient-free algorithms [26-28]. Currently, these algorithms represent the main next-stage development in automatic history matching, following gradient-based and gradient-free methods. Concerning reservoir system uncertainty, in 1999 Reynolds introduced the Randomized Maximum Likelihood (RML) method from statistics. This technique involves randomly sampling the initial model and corresponding observation vectors. By using production dynamic data from multiple initial models to fit their corresponding perturbed production observation data, it yields posterior production dynamic predictions that conform to a Gaussian distribution. This method assumes a linear relationship between reservoir predictions and model parameters. When the model ensemble is sufficiently large, the posterior estimates from the ENKF and RML methods become approximately equal [29]. Additionally, Markov Chain Monte Carlo (MCMC) methods and Rejection Sampling (RS) methods sample the posterior model to further improve model quality [30-31]. However, these methods still require a substantial number of prior model computations, leading to considerable computational expense.

The model updating process necessitates numerous repeated numerical simulations, which is time-consuming. Consequently, many scholars worldwide have turned to machine learning methods to build proxy models. These models approximate the computationally intensive reservoir numerical simulation process, thereby improving overall computational efficiency. In 2018, Guo et al. employed a support vector machine model as a proxy. Using a set of reservoir numerical simulation results under different operational regimes as a training sample set, they utilized the trained model as a forward model for production prediction [32]. Artificial neural networks have been used to simulate and predict the relationships between reservoir production rates, pressure, and injection-production data. By employing specially designed features for network training, these models achieve high matching accuracy between simulation results and actual data [33]. To enhance the generalization ability of machine learning proxy models, a reservoir production forecasting model based on conditional generative adversarial networks has been developed. This model utilizes Bayesian optimization algorithms to automatically optimize the model architecture through extensive adversarial network training. Compared to fully connected neural networks and random forest models, it reduces the percentage error on test set validation, thereby improving both generalization ability and prediction accuracy [34]. In 2021, Zhou et al. leveraged the high nonlinear global effects, strong adaptability, and self-learning capabilities of artificial neural networks to establish a model for steam-flooding reservoirs. This enables fast and effective prediction of crude oil production and aids in designing production parameters [35]. While machine learning algorithms can achieve effective reservoir production predictions through extensive data training, a significant limitation persists. Due to their lack of inherent physical meaning, the extrapolation results of such models may show substantial deviations when reservoir development and production conditions change. Furthermore, their complex training processes can hinder practical application in actual reservoir development.

The history matching methods described above primarily treat reservoir model parameters as the inversion target. Solving this optimization problem still requires numerous repeated numerical simulations. To address this issue, Sun et al. [36-37] proposed a novel data assimilation-like method called Data-Space Inversion (DSI). This approach directly performs history matching calculations using reservoir production prediction data as the inversion target. The method involves using numerical simulation results from a large set of initial reservoir models to construct a data space. A proxy-like model is then established by parameterizing this data space. This proxy model is subsequently used for production prediction through history matching, with the entire fitting calculation process involving only mathematical computations. Unlike typical machine learning models, this proxy model quantifies the weight relationship of the true model relative to each prior model. In DSI-based history matching calculations, an objective function is established based on Bayesian principles. Following the randomized maximum likelihood principle, the method computes credible production predictions and quantifies reservoir system uncertainty—all without inverting reservoir model parameters, thus avoiding repeated numerical simulation. To date, the DSI method has been primarily applied to predicting reservoir production dynamics, as well as formation CO2 concentration, oil saturation, and pressure fields [38-39].

2.2 Methods for Reservoir Development Production Optimization

In reservoir development and production, the operational parameters of oil and water wells significantly influence the migration of underground fluids, thereby altering the internal distribution of oil saturation and pressure. Conventional injection-production parameter design often relies on subjective human experience and limited enumeration methods to formulate development plans. This approach proves inadequate for reservoirs with complex well connectivity and irregular well patterns. Reservoir development production optimization technology addresses this by building upon a history-matched reservoir model. It frames the optimal control of the reservoir production system as an optimization problem. By combining with algorithms, it automatically determines optimal production adjustment plans for oil and water wells across various development stages, aiming to improve overall reservoir development outcomes. In 2002, Brouwer et al. conducted pioneering production optimization research using a three-dimensional, three-phase implicit reservoir numerical simulator and proposed a gradient-based solution algorithm employing the adjoint method [40]. Similar to the evolution of automatic history matching technology, the primary algorithms for production optimization can be classified into gradient-based and gradient-free categories.

In production optimization calculations, obtaining gradients directly is often very difficult. The adjoint gradient method, developed based on variational principles, is currently the mainstream gradient algorithm for solving production optimization problems. In 2021, Ibiam combined the adjoint method with the discrete maximum principle to solve a polymer flooding production parameter control model. By optimizing polymer injection concentration and injection rate, an optimal injection scheme was derived, leading to improved outcomes for polymer flooding reservoir development [41]. Similarly, Zhang Kai et al., based on a fully implicit black-oil simulation model and the maximum principle solution method, employed the adjoint gradient method to solve an optimal control mathematical model, thereby enhancing reservoir development benefits [42]. While this class of algorithms can accurately determine the objective function gradient, their implementation is complex. They require embedding the adjoint matrix into the numerical simulation code, and each iteration necessitates both forward and backward gradient calculations under fully implicit conditions. This significantly increases program complexity and poses challenges for direct commercialization. For more complex real-world reservoir development problems, such as those involving secondary and tertiary recovery, the adjoint gradient method may struggle to compute the true gradient accurately. Consequently, its comprehensive application to actual reservoir production optimization remains limited.

Gradient-free algorithms, which obtain approximate gradients, offer simpler calculations and broader applicability. The stochastic perturbation approximate gradient algorithm, a member of the gradient-free optimization family, has also been applied to production optimization. This algorithm performs random perturbations on each control variable and then computes an average perturbation gradient. This ensures the search direction consistently moves uphill, guaranteeing algorithm convergence [43]. In 2009, Chen et al. proposed an ensemble-based gradient-free optimization algorithm (EnOpt). This method generates multiple realizations of control variables to compute a sensitivity matrix between each realization and the optimization objective, thereby determining the search direction [44]. In practical applications, gradient-free algorithms generally demonstrate better applicability, though their computational efficiency is often lower than that of gradient-based methods. Considering the inherent uncertainty in reservoir systems, the concept of robust optimization has been introduced into production optimization calculations. By generating a large ensemble of reservoir model realizations and performing unified optimization across them, more robust optimization schemes can be obtained [45]. Additionally, heuristic algorithms such as ant colony optimization and simulated annealing—recognized for their strong global search capabilities—have found practical application in oilfield development [46-50].

Machine learning proxy model-assisted production optimization represents a current research hotspot in intelligent reservoir development. These methods significantly improve optimization computational efficiency by establishing proxy models to replace the traditional, complex, and time-consuming reservoir numerical simulation process. In 2015, Golzari et al. used production dynamics to train and update an artificial neural network, which was then combined with a genetic algorithm to perform production optimization calculations [51]. In 2020, Chen et al. approximated the numerical simulation process by establishing a combined global and local proxy modeling framework [52]. The Data-Space Inversion (DSI) method also facilitates optimization by establishing a specialized proxy model. In 2019, Jiang et al. pioneered the extension of the DSI method to reservoir production optimization. They incorporated operational parameters (well controls) into the data space. Optimization calculations within this framework yielded production predictions that satisfied historical observation data under the corresponding oil and water well production controls, ultimately leading to an optimal production control scheme [53-54]. In 2022, Kim et al., building upon the DSI method, utilized a history-matched proxy model to extrapolate production predictions conforming to different operational regimes (well controls), thereby conducting reservoir production optimization [55]. A key distinction from standard machine learning models is that this proxy model quantifies the weight of the true model relative to each prior model in the ensemble. This allows it to effectively extrapolate future production trends when reservoir production conditions change.

3 Conclusion

This paper provides a systematic review of the literature and current research status concerning the reservoir closed-loop optimization management technology within the context of intelligent oilfield development. Regarding automatic reservoir history matching, it offers a comprehensive overview of mainstream methods, categorizing them into gradient-based and gradient-free algorithms. It introduces the development, advantages, and disadvantages of representative techniques, such as the adjoint gradient method, SPSA, and the Ensemble Kalman Filter. Simultaneously, it reviews parameterization/dimensionality reduction methods and proxy model approaches—including machine learning models and Data-Space Inversion—developed to mitigate computational costs. The paper similarly categorizes and examines the application and evolution of gradient-based algorithms (e.g., the adjoint method) and gradient-free algorithms (e.g., EnOpt, heuristic algorithms). It highlights the current research emphasis on employing proxy models to assist optimization, thereby circumventing the limitations of time-consuming traditional numerical simulation. In summary, exploring novel approaches—particularly from the dual perspectives of efficient history matching and production optimization—is essential for advancing the study of reservoir closed-loop optimization control methods. Such endeavors are crucial for improving reservoir management efficiency and propelling the intelligentization of oilfield operations.

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Author Contributions

The author confirms sole responsibility for the following: study conception and design, data-collection, analysis and interpretation of results, and manuscript preparation.

Availability of Data and Materials

None.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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