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Machine Learning and Deep Learning - Enhanced Production Decline Curve Analysis for Improved Oil Recovery Forecasting

Abstract

This study outlines a comprehensive methodological framework aimed at improving the accuracy and predictive power of decline curve analysis (DCA) in hydrocarbon reservoir forecasting. Traditional DCA methods, while widely used, often lack the flexibility to adapt to complex reservoir behaviors, especially in unconventional formations. The enhanced framework integrates statistical, empirical and machine learning techniques to overcome these limitations. Key components include data preprocessing, model selection (e.g., Arps, modified hyperbolic, Duong), hybrid model integration and validation through real field data. The approach also emphasizes uncertainty quantification and sensitivity analysis to ensure robust forecasting. By refining the decline curve modeling process, this framework supports more reliable reserve estimation and production planning, ultimately aiding decision-making in reservoir engineering and asset management.

Keywords: *machine, deep, model, integration, validation, engineering*

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Maşın öyrənməsi və dərin öyrənmə - təkmilləşdirilmiş neft bərpası proqnozu üçün təkmilləşdirilmiş istehsalın azalması əyri analizi

Xülasə

Bu tədqiqat karbohidrogen laylarının proqnozlaşdırılmasında azalma əyrisi analizinin (DCA) dəqiqliyini və proqnozlaşdırıcı gücünü təkmilləşdirməyə yönəlmiş hərtərəfli metodoloji çərçivəni təsvir edir. Ənənəvi DCA metodları geniş istifadə olunsa da, çox vaxt mürəkkəb rezervuar davranışlarına, xüsusən qeyri-ənənəvi birləşmələrdə uyğunlaşmaq üçün çevikliyə malik deyildir. Təkmilləşdirilmiş çərçivə bu məhdudiyyətləri aradan qaldırmaq üçün statistik, empirik və maşın öyrənmə üsullarını birləşdirir. Əsas komponentlərə məlumatların əvvəlcədən işlənməsi, model seçimi (məsələn, Arps, dəyişdirilmiş hiperbolik, Duong), hibrid model inteqrasiyası və real sahə məlumatları vasitəsilə doğrulama daxildir. Bu yanaşma həm də etibarlı proqnozlaşdırmanı təmin etmək üçün qeyri-müəyyənliyin kəmiyyətləşdirilməsini və həssaslığın təhlilini vurğulayır. Azalma əyrisinin modelləşdirilməsi prosesini təkmilləşdirməklə, bu çərçivə daha etibarlı ehtiyatın qiymətləndirilməsini və hasilatın planlaşdırılmasını dəstəkləyir, nəticədə lay mühəndisliyi və aktivlərin idarə edilməsində qərarların qəbuluna kömək edir.

Açar sözlər: *maşın, dərin, model, inteqrasiya, validasiya, mühəndislik*

Introduction

Decline Curve Analysis (DCA) remains a fundamental tool in reservoir engineering for forecasting oil and gas production and estimating recoverable reserves. Traditionally based no empirical equations, DCA has been widely adopted due to its simplicity and minimal data requirements. However, the increasing complexity of modern hydrocarbon reservoirs particularly unconventional resources—has exposed the limitations of classical DCA methods. Challenges such as variable flow regimes, fracture-dominated behaviour and data noise necessitate more advanced modelling approaches to ensure accuracy and reliability (Liu, Liu, Gu, 2020).

In response to these limitations, recent advancements have focused on enhancing the methodological foundations of DCA by integrating statistical methods, machine learning algorithms and hybrid physical-empirical models. This shift aims to improve model adaptability, reduce prediction error and incorporate uncertainty quantification into forecasting workflows. The development of an enhanced methodological framework for DCA not only addresses technical shortcomings but also supports better-informed decision-making in reservoir management, investment planning, and operational strategy (Liu, Liu, & Gu, 2020).

The second component focuses on model selection and customization. Rather than relying solely on traditional Arps models, the framework incorporates a suite of alternative decline models, including the Duong model, stretched exponential decline, and logistic growth models, which are more suitable for complex flow regimes (Cao, & Truong-Khac, 2022). Model performance is evaluated using statistical indicators such as R^2 (coefficient of determination), RMSE (root mean square error), and AIC (Akaike Information Criterion) to identify the most appropriate model for each dataset (Rostami, 2014).

In the third stage, hybrid modelling approaches are employed, integrating empirical decline models with machine learning techniques such as random forests, support vector regression, or deep neural networks. These models are trained on historical production data and used to capture nonlinear relationships that conventional models may miss. Such hybrid systems can adapt dynamically to changes in reservoir behaviour, improving the reliability of both short- and long-term forecasts (Wang, Wang, Zhang, 2020).

Research

Decline Curve Analysis (DCA) has historically served as a cost-effective and straightforward approach for estimating future production performance and reserves in oil and gas reservoirs. Despite its widespread application, traditional DCA models such as exponential, hyperbolic, and harmonic declines are fundamentally empirical and rely heavily on assumptions of reservoir homogeneity and steady-state flow conditions. These assumptions often fail in unconventional and complex reservoirs where transient flow, fracture networks, and pressure depletion introduce nonlinear behaviours (Hong, Bratvold, Lake, Ruiz Maraggi, 2019).

In recent years, the limitations of classical models have prompted the development of enhanced methodologies that incorporate data-driven and hybrid modelling techniques. Statistical methods allow for better fitting of decline trends by minimizing residuals and capturing deviations that arise in real-time production data (Hochreiter, Schmidhuber, 1997). Machine learning models further improve performance by identifying hidden patterns in large datasets, adapting to changing reservoir conditions, and predicting production with greater flexibility (Liu, Pyrcz, 2022). Hybrid approaches, combining physics-based models with algorithmic learning, offer a balanced pathway that respects both empirical evidence and reservoir physics. İncorporating uncertainty quantification through methods such as Monte Carlo simulation or Bayesian inference has become increasingly important to address the inherent variability and risks in forecasting. These methods provide probabilistic outputs rather than single-point estimates, enabling engineers to make more informed operational and financial decisions (Tadjer, Hong, Bratvold, 2021).

Scenario analysis and sensitivity testing are integrated into the workflow to examine how variations in input assumptions (e.g., decline rate, b-factor, economic limit) impact output projections. This provides deeper insight into the range of possible future outcomes and informs risk-based decision-making. As digitalization advances, the integration of real-time data feeds into DCA models has become increasingly feasible. This allows for dynamic updating of forecasts as new production data becomes available, enabling adaptive reservoir management (Tadjer, Hong, Bratvold, 2021). Furthermore, visualization tools and automated dashboards help stakeholders interpret model outputs more intuitively, supporting cross-disciplinary collaboration between engineers, geologists, and financial analysts. The shift toward an enhanced methodological framework in decline curve modelling is driven by the need for greater accuracy, adaptability, and transparency in production forecasting (Roustazadeh, Ghanbarian, Shadmand, Taslimitehrani, Lake, 2022). By leveraging modern computational tools and integrating them with established engineering principles, this approach strengthens the analytical foundation of reservoir performance analysis and aligns with the evolving demands of the energy industry. One of the most transformative developments is the use of artificial intelligence (AI) and deep learning, which allow for high-dimensional modelling of complex reservoir behaviours that are not easily captured by traditional or even hybrid models (Hosseini, Akilan, 2023).

Conclusion

The implementation of an enhanced methodological framework for decline curve modelling offers a significant step forward in overcoming the limitations of traditional empirical approaches. By integrating advanced statistical methods, machine learning algorithms, hybrid modelling and uncertainty quantification, this framework ensures more accurate, adaptable and reliable production forecasts especially in complex and unconventional reservoirs. It improves decision-making in reservoir management, investment planning, and operational strategies by providing deeper insights into reservoir behaviour and production potential. Such a comprehensive approach contributes to more efficient resource utilization and risk-informed development planning in the oil and gas industry.

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