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Perspective

Artificial intelligence methods for oil and gas reservoir development: Current progresses and perspectives

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Abstract:
Artificial neural networks have been widely applied in reservoir engineering. As a powerful tool, it changes the way to find solutions in reservoir simulation profoundly. Deep learning networks exhibit robust learning capabilities, enabling them not only to detect patterns in data, but also uncover underlying physical principles, incorporate prior knowledge of physics, and solve complex partial differential equations. This work presents the latest research advancements in the field of petroleum reservoir engineering, covering three key research directions based on artificial neural networks: data-driven methods, physics driven artificial neural network partial differential equation solver, and data and physics jointly driven methods. In addition, a wide range of neural network architectures are reviewed, including fully connected neural networks, convolutional neural networks, recurrent neural networks, and so on. The basic principles of these methods and their limitations in practical applications are also outlined. The future trends of artificial intelligence methods for oil and gas reservoir development are further discussed. The large language models are the most advanced neural networks so far, it is expected to be applied in reservoir simulation to predict the development performance.

1. Introduction

Dynamic prediction is the foundation of research in oil and gas field development, including scheme design, dynamic analysis, production allocation, and scheme adjustment. Accurate dynamic prediction is an important issue for rational development of oil and gas reservoirs and a key basis for decision-making. It requires the construction of quantitative mathematical models to obtain the quantitative prediction. Essentially, the prediction model represents the mapping relationship between control parameters and system states. There are usually two basic approaches to model establishment: physics-driven and data-driven modeling approaches. The physics-driven modeling approach is based on the quantitative mapping relationship of the flow control equations. It involves solving the governing equations using analytical methods or numerical simulation methods to predict production capability. Analytical methods provide explicit mathematical expressions and are typically based on point source function theory (Gringarten and Ramey, 1973; Cui et al., 2023), elliptical flow theory (Zhang et al., 2017), and linear flow theory (Brown et al., 2011). Numerical simulation methods discretize the governing equations of oil and gas flow to obtain numerical solutions. The physics-driven approach is subject to significant influences from the flow physics assumptions, geological model construction, and computational power. In recent years, the data-driven methods have catalyzed technological advances in a variety of fields, including computer vision, biomedicine, and petroleum engineering. The data-driven modeling approaches use observed or numerically generated data as training sets to explore the quantitative mapping relationship between inputs and outputs through artificial intelligence algorithms.

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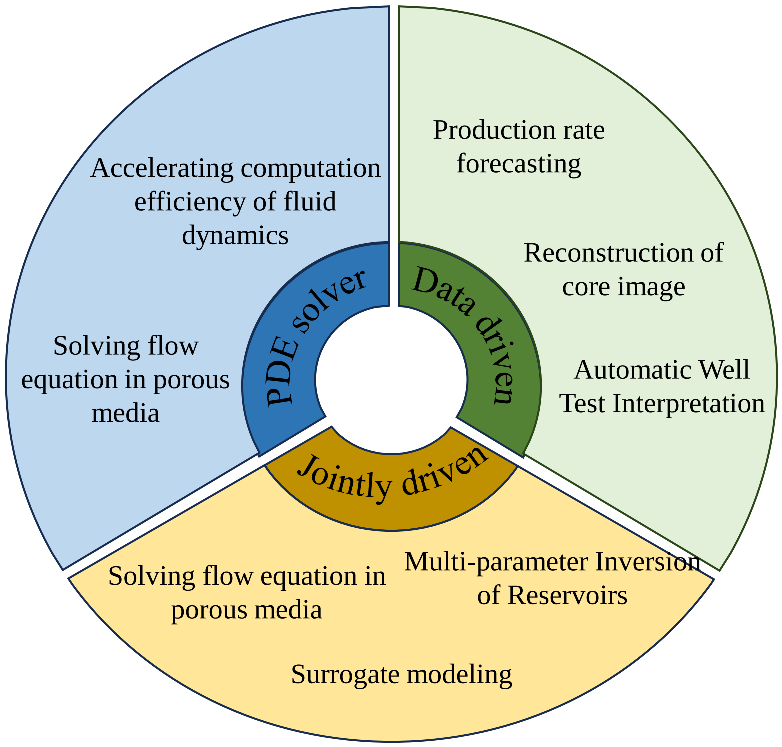

Fig. 1. Research paradigms in oil and gas reservoir development for artificial intelligence.

In reservoir engineering, these algorithms have been widely used to address key challenges of complex problems. Deep learning, the cornerstone of the development of artificial intelligence, has shown exceptional performance. This has led to a burgeoning wave of research in the field of oil and gas development, with artificial intelligence, especially deep learning. At present, its applications in oil and gas reservoir development consist primarily of three key directions: the data-driven methods, the physics driven artificial neural network partial differential equation solver, and the data and physics jointly driven methods, as shown in Fig. 1.

2. Data driven method

Data-driven methodologies rely on the observed data or numerically generated data to train artificial neural network models, subsequently utilized for predictive tasks. A classical artificial neural network is shown in Fig. 2. This widely employed approach has found extensive applications in the realm of oil and gas development, facilitating diverse functions, such as production rate forecasting, core image reconstruction, automated well-test interpretation, and flow dynamics prediction. The data-driven modeling approach encompasses various models, such as random forest, fully connected neural networks, convolutional neural networks, long and short term memory neural networks, graph convolutional neural networks, generative adversarial neural networks. Random forest is an ensemble learning method that combines multiple decision trees (Breiman, 2001). It can be employed for regression prediction of dynamic shale gas production data from multi-stage hydraulic fracturing horizontal wells (Xue et al., 2021) and the water drive gas reservoir well test data analysis problems (Xue et al., 2022). Furthermore, the integration of conventional screening guidelines and the random forest algorithm can establish a hybrid scoring system for enhanced oil recovery processes (Zhang et al., 2019). Fully connected neural networks are basic neural network structures where each neuron is connected to every neuron in the subsequent layer and is widely used for regression tasks in petroleum field. Zhang et al. (2022) identified and predicted the gas-bearing strata using a Deep Neural Network. Additionally, they assessed the proposed method in terms of the structure and fracture characteristics and predict favorable exploration areas for identifying gas reservoirs. Due to the high water content and rapid decline characteristics of unconventional oil and gas reservoir production, conventional methods such as material balance (Mattar and McNeil, 1998) and decline curve analysis (Arps, 1945) are difficult to predict future production changes. Long and short term memory neural networks (LSTM) can automatically capture and learn long-term dependencies from data and it can be used to process and predict production rate time series data of unconventional reservoir. Yang et al. (2022) proposed a LSTM model combining exponential smoothing method and autoregressive integrated moving average to provide robust support for the production behaviors of shale gas. To address the limitations of the LSTM model, Zha et al. (2022) proposed the CNN-LSTM model integrating static geological parameters and dynamic production rate data simultaneously. Furthermore, the use of graph neural networks (GNN) for production forecasting has been explored to identify the relationships between injector-

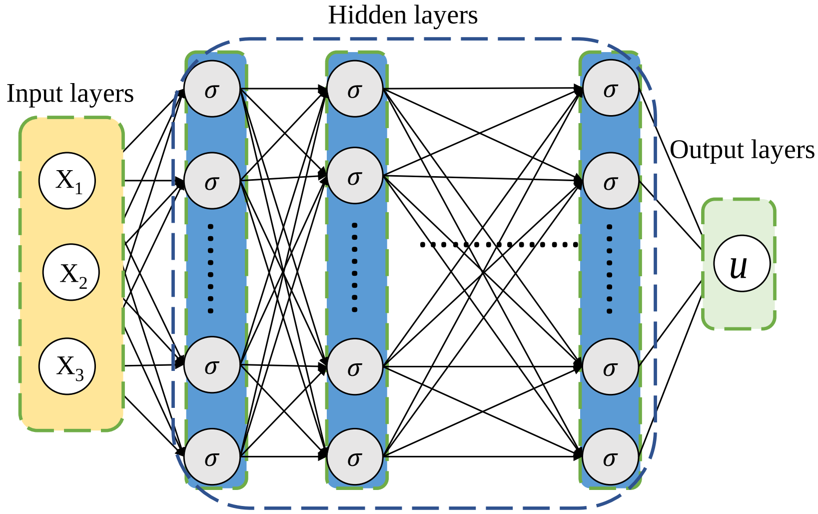

Fig. 2. The structure of classic artificial neural networks.

producer pairs and producer-producer pairs. This enables a clearer characterization of connectivity patterns. GNN are particularly suitable for processing graph-structured data (Du et al., 2022a, 2022b; Huang et al., 2023). However, the majority of production forecasting methods currently used are point forecasting methods developed in the setting of individual well forecasting. Han and Xue (2023) developed a method utilizing deep autoregressive recurrent neural networks to enable global modeling and probabilistic forecasting for numerous related production time series. Generative adversarial neural networks (GAN) (Goodfellow et al., 2014) is a method of unsupervised learning, where two neural networks play against each other. As important generation models, have cast light on the reconstruction of digital cores. Traditional high-resolution reconstruction methods of digital cores are often quite CPU-intensive and cannot reuse the previously extracted statistical information (Zhang et al., 2021). Although the simulated images by generative adversarial neural network are relatively clear, sometimes it is prone to gradient disappearance and model collapse, making the training process quite unstable (Mosser et al., 2017; Feng et al., 2019; Zha et al., 2020). Furthermore, Zhang et al. (2021) propose a VAE-GAN model for the reconstruction of digital cores by combining GAN with VAE together to foster strengths and circumvent weaknesses of both GAN and VAE in the reconstruction process. Finally, convolutional neural networks (CNNs) (LeCun and Bengio, 1995) is great for extracting features from data and has been shown to be very effective at finding patterns that are difficult to detect. Consequently, specifically tailored CNNs can be employed for automated well-testing analyses as an alternative to manually selecting and extracting feature from the pressure and derivative data (Liu et al., 2023).

The classical development of data-driven neural networks has primarily focused on learning mappings between finite-dimensional Euclidean spaces. Recently, this has been generalized to neural operators that learn mappings between function spaces. For partial differential equations (PDEs), neural operators directly learn the mapping from any functional parametric dependence to the solution. Thus, they learn an entire family of PDEs, in contrast to the classical methods which solve one instance of the equation. Li et al. (2021a) utilized a CNNs-based framework to implement neural operators that learn mappings between function spaces. The Fourier neural operator successfully models turbulent flows with zero-shot super-resolution, and demonstrated in experiments on Burgers' equation, Darcy flow, and the Navier-Stokes equation. Furthermore, in reservoir multiphase flow in porous media field, Yan et al. (2021b) developed a FNO-based deep learning workflow to predict the pressure evolution as fluid flows in large-scale 3D heterogeneous geologic CO_2 storage reservoir. Wen et al. (2022) introduced U-FNO, an optimized Fourier neural operator, for addressing multiphase flow challenges. The research shows that U-FNO generates notably precise flow results for intricate CO_2-water multiphase flow difficulties concerning CO_2 geological storage.

3. Data and physics jointly driven methods

The conventional data-driven approach has remarkable advancements, but it inevitably faces several challenges. Firstly, the data-driven model is perceived as a "black box," since it lacks the incorporation of physical meaning of the dataset, leading to predictions that may be physically inconsistent or implausible (Karniadakis et al., 2021). Secondly, the robustness of the data-driven model may be poor, and its long-term prediction capabilities are weak. To address this change and reduce the demand of labeled data, Raissi et al. (2019) proposed physics-informed neural network (PINN), and utilized the nonlinear partial differential equations residuals to guide the training of networks based on automatic differentiation, and extended it to solve forward and inverse problems, as shown in Fig. 3. In reservoir engineering field, Wang and Lin (2020) proposed a theory-guided convolutional neural network frame for efficient uncertainty quantification and data assimilation of reservoir single-flow with uncertain model

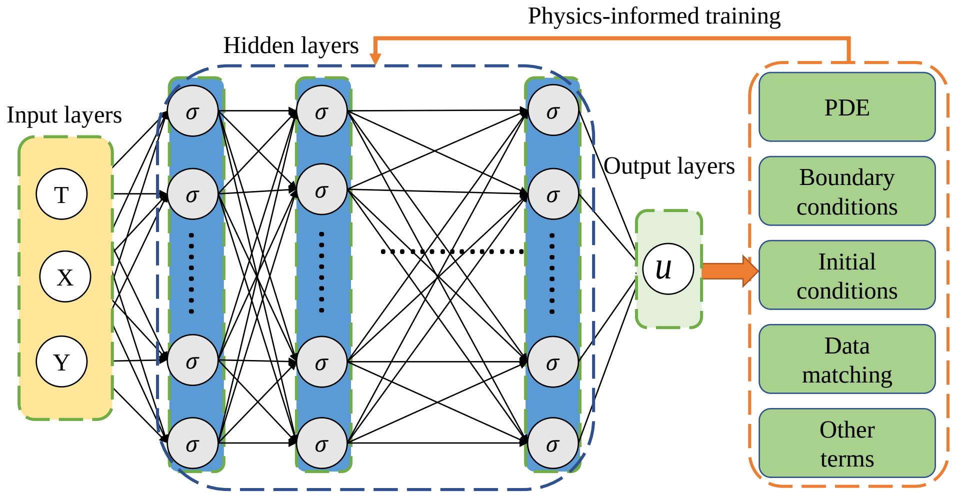

Fig. 3. The structure of physics-informed neural network (Raissi et al., 2019).

parameters. Almajid and Abu-Al-Saud (2022) used the PINNs to simulate the classical problem of drainage of gas into a water-filled porous medium. And, several cases are tested that signify the importance of the coupling between observed data and physics-informed neural networks for different parameter space. For multiphase flow problem, Li et al. (2022) proposed a theory-guided neural network framework as a prediction model for oil/water phase flow. Yan et al. (2021b) developed a gradient-based deep neural network constrained by the physics related to multiphase flow in porous media and applied it to construct a predictive model for pressure management at geologic CO_2 storage sites. For unconventional resources, Xue et al. (2023) proposed a deep learning model driven jointly by the decline curve analysis model and production data for the production performance prediction of tight gas wells. Park et al. (2021) developed a hybrid model by combining physics and data-driven approach for optimum unconventional field development. The existing methods typically require labeled data, particularly the precise solution of PDEs. The scarcity of actual reservoir data for training poses a challenge, often restricted to production rates and bottomhole flow pressures. Aiming at this problem, a new network structure called signpost neural network is proposed, in which the spatial distribution feature information such as signposts is added in the hidden layer. Li et al. (2021b) proposed an improved physics-constrained PDE solution method that incorporates potential features of the PDE in the loss functions to solve seepage equations with source and sink terms with only sparse wellbore pressure label data. Kashefi and Mukerji (2023) predicted steady-state Stokes flow of fluids within porous media at pore scales using sparse point observations and a novel class of physics-informed neural networks, called "physics-informed PointNet".

4. Physics driven artificial neural network PDE solver

Despite of their great potentials to make accuracy predictions, the deep learning-based methods reliant on a limited amount of labeled data continue to exhibit notable limitations in comparison to traditional numerical-solving methods. The dependence on labeled data constrains the practical application of deep learning techniques in petroleum engineering contexts, necessitating a concerted effort to resolve this challenge. Addressing or accelerating the complex task without relying on labeled data assumes paramount significance (Silva et al., 2021), holding the potential to revolutionize solution methodologies within the field (Kochkov et al., 2021). While some endeavors have been undertaken to leverage deep learning for solving PDEs in the absence of labeled data, this remains a formidable undertaking, especially in the case of non-stationary and highly nonlinear PDE systems. Zhu et al. (2019) proposed an innovative approach that integrates the fundamental equations of the physical model into the loss/likelihood functions for surrogate modeling and uncertainty assessment, eliminating the need for labeled data. The study highlights the success of surrogate models based on convolutional encoder-decoder networks, showcasing their ability to accurately predict high-dimensional stochastic input fields in porous media flow problems. Zhang (2022) developed a physics-informed deep convolutional neural network architecture for simulating and predicting transient Darcy flows in heterogeneous reservoirs without labeled data. However, the current exploration of neural network-based solving methods (without labeled data) has not proven to be effective in solving the problem of non-stationary states and source-sinks. The unsupervised solving methods are still in an early development stage, and there is still a big gap to play the same role as the mature numerical methods.

5. Future trends

Currently, significant breakthroughs have been achieved in key aspects of oilfield production and development, leveraging artificial intelligence technology. Despite of these advancements, the current research primarily centers on refining existing methodologies, and a comprehensive groundbreaking framework is yet to be established, with progress remaining in its preliminary stages.

It is imperative to address several key issues to propel the frontier of intelligent oilfield development theories and methodologies. These include constructing a comprehensive, deep cross-fusion model that integrates data, artificial intelligence models, and physical laws, aiming to establish an optimization theory system that accelerates intelligent algorithms through the fusion of dynamic and static data-driven approaches with pertinent physical information. When it comes to handling time series and spatio-temporal data, as well as performing complex simulations, optimizations, and decision-making, the recent research suggests the necessity of constructing a large language model (Jin et al., 2023). Additionally, Kumar and Kathuria (2023) leverage the emerging capabilities of large language models with over 100 billion parameters to extract actionable insights from raw drilling data. Abijith et al. (2023) explore the potential of a domain-specific large language model for oil and gas industries.

Based on the current research findings, the future development trends in the large language model are promising, even though there is a need for further exploration and enhancement of large language model's capabilities in handling time series and spatio-temporal data, as well as complex simulations and optimizations. The application of large language models is expected to provide more precise solutions for information extraction and decision support in the development of the oil and gas reservoir.

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Conflict of interest

The authors declare no competing interest.

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