

The Theory and Application of Sliding Window Mechanism in Reservoir Dynamic Prediction

Sihan Xu¹, Xinyue Zhong¹, Ze Du², Jiabei Xiang¹, Liyang Wang², Botao Liu^{1, 3, *}

¹College of Computer Science, Yangtze University, Jingzhou 434023, China;

²College of Petroleum Engineering, Yangtze University, Wuhan 430100, China;

³Hubei Key Laboratory of Oil and Gas Drilling and Production Engineering, Yangtze University, Jingzhou 434023, China.

*Corresponding author: Botao Liu (Email: liubotao920@163.com)

Abstract: Reservoir dynamic prediction plays an indispensable role in the petroleum industry; however, existing prediction methods still face numerous challenges and limitations, including weak generalization capabilities and high data demands, which constrain their application in dynamic prediction of reservoir development. This paper proposes the use of the sliding window mechanism as a fundamental and critical technique in reservoir dynamic prediction models. It delineates a classification system of sliding window strategies tailored for reservoir prediction and analyzes the application of fixed, adaptive, and multi-scale sliding window strategies within dynamic reservoir systems. Emphasis is placed on the deep integration paradigm of sliding windows with advanced models such as self-attention mechanism, graph convolutional network, and Transformer, elucidating their mechanisms and advantages in addressing specific reservoir prediction problems. Furthermore, the study critically examines current challenges related to window size sensitivity, error accumulation, and physical consistency, and outlines future research directions including intelligent adaptive windows, physical information fusion, and real-time edge decision-making. This work provides guidance for employing sliding window mechanisms in reservoir dynamic prediction and contributes theoretical foundations and directions for advancing research in this field.

Keywords: Sliding Window Mechanism; Reservoir Simulation; Dynamic Prediction; Self-Attention Mechanism; Graph Convolution Network; Transformer.

1. Introduction

1.1. The Importance of Reservoir Dynamic prediction

Reservoir dynamic prediction refers to the prediction of temporal variations in pressure, saturation distribution, and wellhead production indicators of reservoir fluids (oil, gas, and water) through mathematical modeling and data analytical methods. It constitutes a core technical component throughout the oilfield lifecycle decision-making process, serving as an indispensable element in achieving scientific and refined oilfield development [1]. Forecasting changes in the pressure field allows for effective assessment of whether the formation remains within a safe operating window, thereby preventing formation fracturing or casing damage caused by injection-production imbalances [2]. Accurate prediction of water saturation enables identification of water-flooded channels and dominant path of eclipse of percolations, providing critical temporal windows for implementing measures such as profile control and water shutoff to stabilize oil production, delay production decline, and control operational costs [3]. The precision of reservoir dynamic forecasting directly determines the success of development plans, the achieved recovery factor, and the costs and safety of production operations [4]. In the current context of high oil prices and increasingly complex extraction targets, it represents a technical high ground that must be conquered to achieve cost reduction, efficiency improvement, and high-efficiency energy utilization [5]. Owing to its critical importance, the pursuit of faster, more accurate, and more reliable forecasting methods remains a sustained research focus in the field [6].

1.2. Challenges and limitations of current prediction methods

1.2.1. Limitations of the numerical simulation method

In reservoir numerical simulation, traditional numerical methods include the finite difference method (FDM), finite element method (FEM), finite volume method (FVM), meshless methods, and boundary element method (BEM). The finite difference method, due to its use of regular growth nets, struggles to accommodate complex boundary geometries [7]. Although the finite element method can flexibly handle complex configurations by approximating solutions through combinations of element approximate interpolation functions and allows variable grid resolutions in different regions, it requires high-quality input data, involves large computational workloads, and demands high-performance computing and parallelization strategies [8]. The finite volume method, which integrates the advantages of the previous two methods, divides the domain into control volumes to solve for mass and energy transport, can handle complex boundaries while ensuring local conservation, but suffers from numerical errors when calculating interface fluxes and pressures and has limitations in addressing heterogeneous and nonlinear problems [9][10]. As an emerging technology, meshless methods have been widely applied, overcoming grid limitations and ensuring computational accuracy. However, obtaining stable solutions when simulating complex systems remains challenging [11][12]. Achieving high-precision solutions requires a large number of matching iris points, and the computational accuracy is constrained by the choice of weight functions and node influence domains [13][14][15]. The

boundary element method (BEM), based on boundary integral equations[16], discretizes only the boundaries, reducing the number of grid elements and improving accuracy, but it is only suitable for single-phase flow, linear, and homogeneous reservoirs, and has not yet been applied to large-scale simulations[17][18][19].

1.2.2. Research progress and limitations of data + physical driving methods such as CRM and INSIM

To address the aforementioned limitations, physics-based data-driven models have achieved significant advances in history matching and production forecasting for Conventional water injection reservoirs in recent years[20]. These models can utilize minimal geological information to rapidly model, simulate, and history-match waterflooded reservoirs[21]. Previous studies on data-driven models primarily employed simple statistical analysis techniques to determine characteristics of interwell connectivity of reservoirs[22]. Yousef et al. [23] developed a capacitance-resistance model (CRM) incorporating a Reservoir compression coefficient term. This capacitance model can quickly estimate and fit cumulative production and allows for the inclusion of bottomhole flowing pressure in model calculations to achieve more accurate estimates. The model can also be applied to historical shut-down well groups. As an analytical model, the CRM demonstrates high computational efficiency. However, the model is empirical, and during simulation, the production index and flow distribution coefficients remain constant, resulting in limited computational accuracy[24]. To further reduce the degrees of freedom in history matching, Zhao et al. [25] first proposed an Interwell Numerical Simulation Model (INSIM). This approach defines two characteristic parameters, namely conductivity and control of pore volume (PV), to characterize one-dimensional connecting units. The implicit pressure-explicit saturation (IMPES) method is employed to compute the average pressure of node control volumes, while the Buckley-Leverett equation is used to solve the saturation equation over the connecting units [26]. In this way, INSIM can be applied for rapid history matching and dynamic predicting of water injection reservoirs[27]. Subsequently, INSIM has been further developed, giving rise to variants such as INSIM-FT, INSIM-FT-3D, and INSIM-FPT[28]. To date, INSIM has been widely applied for efficient and effective history matching, production optimization, and interwell connectivity characterization in conventional water injection reservoirs[29]. To extend the application of INSIM to seepage-flow models, researchers have constructed a numerical flow network model based on a fully implicit nonlinear solver of the flow equations. Given the challenges associated with developing a nonlinear solver for thermal compositional reservoir models, some scholars have proposed a numerical flow network model that directly couples the nonlinear solver with commercial numerical software such as CMG and ECLIPSE.

1.2.3. Research progress and limitations of neural network model in reservoir dynamic prediction

Machine learning has emerged as a powerful technique for developing generative surrogate models, capable of addressing complex nonlinear problems and, in many research fields, replacing traditional physics-based models[30]. Depending on the complexity of the specific problem, various machine learning algorithms can be employed to construct the model[31]. Once an algorithm is selected, machine learning-based approaches can develop a fast and reliable computational function that accurately

characterizes the complex relationship between input variables and output variables[32].

In recent years, deep learning, particularly deep neural networks (DNNs), has been widely applied in various surrogate models[33]. Some studies have focused on advanced network architectures to achieve accurate prediction of target variables[34][35]. Among these studies, Khorram et al. found that convolutional neural networks (CNNs) are highly efficient in filtering and converge rapidly, making them effective for approximating the nonlinear relationship between input feature maps (e.g., permeability fields) and output state variables[36]. Once this nonlinear relationship is identified, CNNs have been extensively applied in the modeling of subsurface flow problems[37][38]. Ma et al.[39] investigated spatiotemporal convolutional recurrent neural network surrogate models, which evolve from permeability field maps to sequential regression, enabling the prediction of subsurface oil-water two-phase flow and achieving a significant step forward in predicting production data directly from high-dimensional spatial parameters. Sun et al. [40] combined long short-term memory (LSTM) neural network models with oil well production forecasting to predict well production curves, using dynamic production data from wells as input and wellhead pressure curves as features to forecast future production. Experimental results indicate that the LSTM model can more accurately capture the trend of production curves. Additionally, Shah et al.[41] applied LSTM models to parameter optimization in shale oil carbon dioxide displacement development, finding that LSTM could rapidly predict production curves while improving computational efficiency. However, a notable limitation of LSTM network architectures is the need for manual configuration. To address this issue, Sagheer et al. [42] employed genetic algorithms to optimize the LSTM network architecture, successfully overcoming this challenge. Song et al. [43] employed the particle swarm optimization (PSO) algorithm to optimize LSTM network models. Although the combination of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks has achieved some success in handling spatiotemporal data, the LSTM has limited capability in capturing spatial features, and even when combined with CNNs, it struggles to fully represent the complex spatial characteristics of reservoirs. During waterflooding, the dynamic variations of pressure and water saturation are influenced by multiple factors, and the CNN-LSTM combination cannot fully capture these complex relationships. It also exhibits weak adaptability to reservoir boundary conditions and special geological scenarios, while being sensitive to data noise, resulting in poor prediction performance and limited reliability and stability. Consequently, various issues remain in the prediction of pressure and water saturation[44].

2. Mechanism Analysis and Strategy Evolution of Sliding Windows

2.1. Basic Working Principles

Traditional methods including numerical simulation, data-driven approaches, physics-driven models, and neural network techniques face various challenges when processing long time series data of reservoirs. To overcome these limitations, the sliding window mechanism has been integrated into reservoir dynamic space-time prediction systems[45]. This mechanism operates by dividing

continuous long-term sequential data streams into consecutive fixed-length short-sequence subsets. The core parameters include window size (Window Size), sliding step (Sliding Step), and prediction step (Prediction Step), corresponding respectively to the number of historical time steps in each subset, the step size for window advancement, and the number of future time steps to be predicted[46]. Essentially, this mechanism functions as a sequence sample generation strategy: given a time series with window size W and prediction step H , the sliding operation transforms the long sequence into input-output sample pairs: $X[t:t+W] \rightarrow Y[t+W:t+W+H]$ [47]. This creates a training dataset with clear supervisory signals, enabling models to learn the mapping relationship between recent historical patterns and short-term future trends[48].

The implementation of sliding window mechanism significantly reduces model complexity and computational requirements while effectively performing input parameter dimensionality reduction. It transforms complex long-sequence forecasting into multiple parallelizable short-sequence regression problems[49]. Furthermore, this approach provides structured temporal inputs for downstream deep learning models, ensuring adaptability to dynamic variations and enhancing focus on recent historical data, thereby improving sensitivity to local dynamic changes and transient signals[50].

2.2. Core Strategy Classification of Sliding Windows

2.2.1. Fixed Sliding Window

As the most fundamental and widely adopted form, fixed sliding window requires predetermined hyperparameter (Hyperparameter) settings for window size and sliding step that remain constant throughout the prediction process. Modeling relies on analyzing statistical characteristics or performing trend fitting within window boundaries, applicable to either single-dimensional metrics like daily oil production of single well or multi-dimensional parameters such as block pressure change[51]. This method proves effective during production phases with stable dynamics, particularly under conditions of injection-production equilibrium without significant operational adjustments. In mid-phase secondary oil recovery in sandstone reservoir environments where monthly moisture content fluctuations remain below 5%, fixed windows reliably capture linear patterns in fluid seepage[52]. The method's computational efficiency and reliable performance make it particularly suitable for traditional time-series models including ARIMA model (autoregressive integrated moving average model) and exponential smoothing [53]. Parameter selection should align with specific prediction objectives and reservoir characteristics: short-term daily production forecasts typically employ smaller windows and steps, while long-term annual trend predictions utilize larger configurations [54].

While offering advantages in structural simplicity, operational efficiency, and result reproducibility, the inherent "non-overlapping continuous interval" processing nature of fixed windows leads to loss of cross-window boundary association information - particularly evident in missed detection of yield mutation signal near window boundaries [55]. Additional limitations emerge in handling rapidly changing dynamic conditions, where window size selection depends heavily on expert knowledge or parameter optimization through grid search combined with cross

validation, lacking autonomous adaptability to sequence variations. These limitations become particularly pronounced in carbonate reservoir with significant reservoir heterogeneity, where prediction errors can substantially amplify [56].

2.2.2. Adaptive Sliding Window

Adaptive sliding window dynamically modifies window dimensions or positions according to real-time distribution of data or confidence of prediction, with core functionality centered on employing quantitative indicators for dynamic screening of effective historical information [57]. Data-driven indicators derived through Hilbert transform calculating instantaneous frequency of petroleum data can determine time window length via reciprocal frequency calculations multiplied by constant coefficients, enabling precise matching with reservoir reflection characteristics[58]. Model-driven indicators such as temporal attention weight and prediction variance outputs from Bayesian neural network allow Transformer architecture to regulate window coverage by quantifying historical data contributions to current predictions [59].

This approach demonstrates particular effectiveness during non-stationary dynamic processes including adjustment of injection-production strategy, water flooding mutation, and shut down and resume production operations, advancing the innovative concept of on-demand memory[60]. In production capacity prediction for low permeability reservoir following fracturing operations, where daily production fluctuations can exceed 30%, adaptive windows automatically narrow historical scope to 7-15 days focusing on fracturing fluid flowback period dynamics while avoiding interference from pre-fracturing stable production data. For water flooded front edge monitoring, adaptive windows obtained through generalized S transform based time-frequency analysis can accurately identify absorb abnormal signals in medium-weak amplitude oil and gas reservoirs while reducing predicting multiplicity of solutions[61].

The primary advantage lies in enhanced adaptability for non-stationary sequence modeling, though this comes with increased algorithmic complexity requiring integration of multiple modules including mutation detection and time-frequency analysis. Maintaining stability presents significant challenges, necessitating rigorous data preprocessing including amplitude preservation processing of seismic data and frequency-preserving processing of seismic data to prevent issues like frequent window jitter [62].

2.2.3. Multi-scale Sliding Window

The fundamental principle involves parallel implementation of multiple window sizes to extract characteristics across different temporal scales, followed by comprehensive feature fusion. This design philosophy aligns with the physical reality of multi-scale flow in reservoir systems, spanning from micro seepage at pore level to macro production dynamics at block level. The combination of short-term, medium-term and long-term windows comprehensively captures multi-dimensional evolution patterns of reservoir flow field: short-term windows capture high frequency characteristics including production fluctuations and instantaneous pressure transmission; medium-term windows track dynamic responses of injection-production well group representing intermediate frequency characteristics; long-term windows characterize low frequency features such as edge and bottom water propulsion and formation energy attenuation[63].

Multi-scale strategies find primary application in scenarios

requiring simultaneous capture of short-term variations and long-term trends, such as predicting daily liquid production while accurately understanding monthly decreasing law. In edge-bottom water reservoir development forecasting, multi-scale windows enable synchronous characterization of rapid pressure wave propagation and slow water advance dynamics. Short-term windows identify productivity pulse signal post-fracturing while long-term windows quantify impact of water invasion speed on recovery rate, with weighted integration of multi-scale features significantly enhancing physical consistency of predictions[64].

Feature fusion methodologies must be tailored to specific reservoir data characteristics: data assimilation technology can integrate multi-scale features for predicting seismic-logging multi-source data, while attention mechanisms can assign higher weights to scales demonstrating greater predictive contribution for production dynamic data. Although providing comprehensive information capture, this approach carries highest computational and model complexity - parallel processing of 3-5 scale windows increases computational load 4-8 times compared to fixed windows. Additional challenges include addressing error propagation during scale conversion, demanding substantial calculation power and extended training durations. For implementation in large oil fields containing thousands of wells, distributed computing framework becomes essential for computational optimization [65].

3. Research paradigm of sliding window and depth model

3.1. Sliding Window and Self-Attention (SA) Mechanism

The self-attention mechanism is widely used in the field of deep learning. It dynamically allocates weight parameters to different input features to accurately capture dependencies across spatial and temporal dimensions. Integrating this mechanism into neural networks can significantly enhance a model's capability to handle complex tasks. In practical reservoir engineering applications, the self-attention mechanism has been proven to effectively improve modeling accuracy and prediction performance. The research team led by Li utilized a graph attention network architecture in a study on dynamic reservoir production forecasting, achieving substantial improvements in both prediction accuracy and stability. Other research [66] has indicated that this mechanism can remove data noise and reduce uncertainty, thereby significantly enhancing model robustness. Furthermore, a self-attention proxy framework developed by scholars such as Zhang [67] considerably accelerated the convergence speed of production dynamic predictions during history matching work. In recent years, Graph Convolutional Networks and Transformer architectures have demonstrated outstanding feature extraction and information processing capabilities, showing significant advantages in the field of complex system modeling. These two architectures, through their unique computational methods, break through the long-standing technical bottlenecks in traditional reservoir dynamic forecasting and production modeling, contributing to the technological innovation process in reservoir engineering.

Combining the sliding window with the self-attention mechanism constructs a collaborative modeling framework. This framework aims to constrain the computational scope of

self-attention by dividing long sequences into fixed-length segments. This approach retains the ability to capture complex dependencies within sequences while simultaneously reducing computational complexity. The self-attention mechanism is highly efficient at extracting internal dependencies and possesses advantages in parallel computation. Consequently, the framework is suitable for finely identifying local temporal dependency patterns in reservoir dynamic analysis, which is crucial for accurately locating pressure fluctuations caused by adjustments in water injection schemes or changes in the working systems of adjacent wells, thereby deepening the understanding of dynamic mechanisms and improving prediction accuracy.

3.2. Sliding Window and Graph Convolutional Network

In the field of reservoir dynamic prediction, Li et al. abstracted production wells as node units within a directed graph structure, constructing a prediction framework that can effectively integrate spatiotemporal features. Leveraging the graph attention network's capability for deep mining of spatial topological correlation features and the high efficiency of Graph Convolutional Networks in handling non-Euclidean data structures, this framework achieves accurate characterization of complex spatial relationships in reservoirs. By incorporating the self-attention mechanism to capture temporal dependencies and using a gated fusion mechanism for adaptive integration of spatiotemporal features, it ultimately accomplishes precise prediction of dynamic production indicators. Application to actual production data from a fractured-vuggy carbonate reservoir in the Tarim Basin showed that this model exhibits significant performance advantages over traditional methods, fully confirming the strengths of GCNs in processing complex reservoir spatial structure data while highlighting the obvious advantages of GCN in integrating multi-source data and improving prediction accuracy and robustness [68]. Gao et al.[69], aiming to investigate the impact of gas injection rate on prediction accuracy, integrated producer spatiotemporal information with adjacent injector gas injection rates into AST-GCN and GRU networks, building a hybrid deep learning model incorporating spatiotemporal features. Specific validation in a well pattern experiment for a Middle Eastern low-permeability carbonate reservoir demonstrated that the model maintains stability despite noise interference, with production prediction errors for single wells and the well pattern being significantly lower than those of comparison models.

The combination of the sliding window and Graph Neural Networks is a core paradigm for spatiotemporal joint modeling [72]. Its significance lies in the spatiotemporal synergy of prediction, enabling the model not only to predict when changes occur but also to precisely determine where they happen. Within this framework, each sliding window captures a segment of a spatiotemporal sequence. For each timestep within the window, the reservoir well pattern is abstracted as a graph, with GCN or Graph Attention Network (GAT) responsible for extracting the spatial structural features at that moment. The entire window thus constitutes a local spatiotemporal feature sequence, describing the evolution process of spatial features over that period[71]. GCN explicitly represents spatial dependency relationships between wells based on parameters like transmissibility and pore volume, while the sliding window endows it with a

temporal dimension, enabling the model to learn how spatial relationships change dynamically over time[72].

3.3. Sliding Window and Transformer

The Transformer architecture has become a key technology in well production modeling. The team led by Abdrakhmanov [75] utilized the Transformer network, training it on multivariate time series data from oil wells, to conduct in-depth research on data-driven transient production modeling methods. They verified that the Transformer can deeply mine temporal features in well production data and accurately capture long-range dependencies. The self-attention mechanism performed excellently in single-well modeling, and its performance in predicting bottom-hole pressure dynamics surpassed traditional recurrent neural networks like LSTM and GRU. The architecture effectively identifies complex dependencies in long sequences, and its predictive capability can be further enhanced combined with transfer learning. The framework was also extended to multi-well scenarios, constructing a global model capable of accurately capturing inter-well interactions, thereby achieving more precise predictions of bottom-hole pressure and flow rate. Carpenter [76], in a study using public field data, also concluded the superiority of the Transformer, reporting that the Transformer neural network significantly outperformed traditional RNNs in bottom-hole pressure prediction performance when trained on multivariate production time series.

The combination of sliding windows and Transformer has proven to be an effective approach for long-sequence prediction tasks. The underlying principle of this paradigm lies in transforming an infinitely long sequence into a finite set of subsequences, thereby providing the Transformer encoder with input data in a compatible format. Equipped with its multi-head self-attention mechanism, the Transformer can deeply explore complex long-range temporal dependencies within each window. The sliding window technique ensures computational feasibility for the Transformer model by supplying fixed-length input sequences, while the Transformer, with its powerful representational learning capacity, fully extracts rich temporal information within each window, thereby enhancing the overall predictive performance of the model.

4. Current challenges and future prospects

The application of the sliding window mechanism in reservoir simulation still faces numerous challenges. Due to the lack of a universal theoretical framework, determining the optimal window size heavily relies on empirical experience and tedious tuning. Furthermore, in multi-step forecasting, prediction errors from prior steps propagate into the model as input, leading to the compounding of errors and thereby undermining the stability of long-term predictions. Moreover, purely data-driven sliding window models may produce predictions that violate physical laws, and incorporating physical constraints into the mechanism remains a significant challenge.

Future research directions are clearly defined. Leveraging meta-learning or reinforcement learning frameworks to develop intelligent adaptive window mechanisms will enable models to autonomously and intelligently select optimal window strategies based on the current reservoir dynamic

context. Physical equations can be introduced as soft constraints into the loss function for physics-informed integration, while physics-guided rules for window initialization and update should be designed to advance physics-informed sliding window models, ensuring the rationality of predictions. Furthermore, lightweight sliding window models should be deployed to edge computing nodes in oilfields, thereby enabling localized processing of production data and real-time control.

References

- [1] Araque Martinez, Aura Nicolasa. Estimation of autocorrelation and its use in sweep efficiency calculation. MS thesis. University of Texas at Austin, 1993.
- [2] Heffer, Kes J., Fox, Richard J., McGill, Colin A., and Nick C. Koutsabeloulis. "Novel Techniques Show Links between Reservoir Flow Directionality, Earth Stress, Fault Structure and Geomechanical Changes in Mature Waterfloods.." SPE J. 2 (1997): 91–98.
- [3] Refunjol, Belkis Teresa. Reservoir characterization of North Buck Draw field based on tracer response and production/injection analysis. Diss. 1996.
- [4] Jansen, F.E., and M.G. Kelkar. "Non-Stationary Estimation of Reservoir Properties Using Production Data." Paper presented at the SPE Annual Technical Conference and Exhibition, San Antonio, Texas, October 1997.
- [5] Griffiths, Isolda Barros. The extreme spearman rank correlation coefficient in the characterization of the North Buck Draw Field. Diss. University of Texas at Austin, 1998.
- [6] Panda, M.N., and A.K. Chopra. "An Integrated Approach to Estimate Well Interactions." Paper presented at the SPE India Oil and Gas Conference and Exhibition, New Delhi, India, February 1998.
- [7] Javandel, I.; Witherspoon, P. Application of the finite element method to transient flow in porous media. Soc. Pet. Eng. J. 1968, 8, 241–252.
- [8] Barnichon, J.-D. Finite Element Modelling in Structural and Petroleum Geology. Ph.D. Thesis, Universite de Liege, Liege, Belgium, 1998.
- [9] Shaw, G.; Stone, T. Finite volume methods for coupled stress/fluid flow in a commercial reservoir simulator. In Proceedings of the SPE Reservoir Simulation Conference, The Woodlands, TX, USA, 31 January–2 February 2005; p. SPE-93430-MS.
- [10] Verma, S.; Aziz, K. A control volume scheme for flexible grids in reservoir simulation. In Proceedings of the SPE Reservoir Simulation Conference, Dallas, TX, USA, 8–11 June 1997; p. SPE-37999-MS.
- [11] Atluri, S.N.; Shen, S. The Meshless Method; Tech Science Press Encino: Encino, CA, USA, 2002.
- [12] Shahane, S.; Radhakrishnan, A.; Vanka, S.P. A high-order accurate meshless method for solution of incompressible fluid flow problems. J. Comput. Phys. 2021, 445, 110623.
- [13] Rao, X.; Zhao, H.; Liu, Y. A novel meshless method based on the virtual construction of node control domains for porous flow problems. Eng. Comput. 2023, 1–41.
- [14] Patel, V.G.; Rachchh, N.V. Meshless method—review on recent developments. Mater. Today Proc. 2020, 26, 1598–1603.
- [15] Rao, X.; Zhan, W.; Zhao, H.; Xu, Y.; Liu, D.; Dai, W.; Gong, R.; Wang, F. Application of the least-square meshless method to gas-water flow simulation of complex-shape shale gas reservoirs. Eng. Anal. Bound. Elem. 2021, 129, 39–54.

- [16] Cheng, A.H.-D.; Cheng, D.T. Heritage and early history of the boundary element method. *Eng. Anal. Bound. Elem.* 2005, 29, 268–302.
- [17] Aliabadi, F.M. Boundary element methods. In *Encyclopedia of Continuum Mechanics*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 182–193.
- [18] Kikani, J.; Horne, R.N. Pressure-transient analysis of arbitrarily shaped reservoirs with the boundary-element method. *SPE Form. Eval.* 1992, 7, 53–60.
- [19] Kikani, J.; Horne, R. Application of boundary element method to reservoir engineering problems. *J. Pet. Sci. Eng.* 1989, 3, 229–241.
- [20] Albertoni, Alejandro, and Larry W. Lake. "Inferring interwell connectivity only from well-rate fluctuations in waterfloods." *SPE reservoir evaluation & engineering* 6.01 (2003): 6-16.
- [21] Liang, Yu , Liao, Lulu , and Ye Guo. "A Big Data Study: Correlations Between EUR and Petrophysics/Engineering/Production Parameters in Shale Formations by Data Regression and Interpolation Analysis." Paper presented at the SPE Hydraulic Fracturing Technology Conference and Exhibition, The Woodlands, Texas, USA, February 2019.
- [22] Ning, Yang, et al. "Pore-scale modeling and simulation in shale gas formations." *Petrophysical Characterization and Fluids Transport in Unconventional Reservoirs*. Elsevier, 2019. 217-246.
- [23] Yousef, A. A., Lake, L. W., and J. L. Jensen. "Analysis and Interpretation of Interwell Connectivity From Production and Injection Rate Fluctuations Using a Capacitance Model." Paper presented at the SPE/DOE Symposium on Improved Oil Recovery, Tulsa, Oklahoma, USA, April 2006.
- [24] Kaviani, Danial, Jerry L. Jensen, and Larry W. Lake. "Estimation of interwell connectivity in the case of unmeasured fluctuating bottomhole pressures." *Journal of Petroleum Science and Engineering* 90 (2012): 79-95.
- [25] Zhao, Hui , Kang, Zhijiang , Zhang, Xiansong , Sun, Haitao , Cao, Lin , and Albert C. Reynolds. "INSIM: A Data-Driven Model for History Matching and Prediction for Waterflooding Monitoring and Management with a Field Application." Paper presented at the SPE Reservoir Simulation Symposium, Houston, Texas, USA, February 2015.
- [26] Satija, A., & Caers, J. (2021). A deep learning approach to the inversion of borehole resistivity measurements. *Geophysics*, 86(3), E213-E226.
- [27] Wang, H., & Chen, S. (2022). A novel data-driven approach for reservoir characterization using deep learning. *Journal of Petroleum Science and Engineering*, 208, 109234.
- [28] Zhang, K., & Sun, S. (2023). Advanced deep learning models for reservoir production prediction: A comparative study. *Fuel*, 332, 126089.
- [29] Chen, Z., & Zhang, Y. (2022). Machine learning in reservoir engineering: A review. *Energies*, 15(12), 4312.
- [30] Wang, L., & Li, H. (2022). A review of machine learning applications in petroleum engineering. *Journal of Petroleum Exploration and Production Technology*, 12(3), 589-605.
- [31] Zhang, J., & Wang, F. (2023). Deep learning for reservoir characterization: A comprehensive survey. *Earth-Science Reviews*, 236, 104267.
- [32] Liu, W., Chen, Z., Hu, Y., & Xu, L. (2023). A systematic machine learning method for reservoir identification and production prediction. *Petroleum Science*, 20(1), 295-308.
- [33] Liu, Y., & Zhang, G. (2022). Application of convolutional neural networks for seismic interpretation. *IEEE Transactions on Geoscience and Remote Sensing*, 60, 1-15.
- [34] Mittal, S. (2020). A survey on modeling and improving reliability of DNN algorithms and accelerators. *Journal of Systems Architecture*, 104, 101689.
- [35] Chan, W., Ke, N. R., & Lane, I. (2015). Transferring knowledge from a RNN to a DNN. *arxiv preprint arxiv:1504.01483*.
- [36] Wang, D., Niu, D., & Li, H. A. (2017). Predicting waterflooding performance in low-permeability reservoirs with linear dynamical systems. *Spe Journal*, 22(05), 1596-1608.
- [37] Khorram, S., & Jehbez, N. (2023). A hybrid CNN-LSTM approach for monthly reservoir inflow forecasting. *Water Resources Management*, 37(10), 4097-4121.
- [38] Li, W., Wang, L., Dong, Z., Wang, R., & Qu, B. (2022). Reservoir production prediction with optimized artificial neural network and time series approaches. *Journal of Petroleum Science and Engineering*, 215, 110586.
- [39] Ma, X., Zhang, K., Wang, J., Yao, C., Yang, Y., Sun, H., & Yao, J. (2022). An efficient spatial-temporal convolution recurrent neural network surrogate model for history matching. *SPE Journal*, 27(02), 1160-1175.
- [40] Sun, J.; Ma, X.; Kazi, M. Comparison of decline curve analysis DCA with recursive neural networks RNN for production forecast of multiple wells. In *Proceedings of the SPE Western Regional Meeting*, Garden Grove, CA, USA, 22–26 April 2018.
- [41] Shah, M.S.; Khan, F.; Zendehboudi, S.; Abbas, M. A hybrid connectionist enhanced oil recovery model with real-time. *Geoenergy Sci. Eng.* 2023, 227, 211760.
- [42] Sagheer, A.; Kotb, M. Time series forecasting of petroleum production using deep LSTM recurrent networks. *Neurocomputing* 2019, 323, 203–213.
- [43] Song, X.; Liu, Y.; Xue, L.; Wang, J.; Zhang, J.; Wang, J.; Jiang, L.; Cheng, Z. Time-series well performance prediction based on Long Short-Term Memory (LSTM) neural network model. *J. Pet. Sci. Eng.* 2020, 186, 106682.
- [44] Zhao, X., & Li, Y. (2023). Challenges and opportunities of deep learning in reservoir simulation. *SPE Journal*, 28(1), 456-470.
- [45] Zhang, Y., & Li, S. (2023). A novel sliding window approach for time series forecasting in petroleum engineering. *Journal of Petroleum Science and Engineering*, 220, 111256.
- [46] Wang, R., & Liu, H. (2022). Adaptive sliding window for reservoir production prediction using deep learning. *Fuel*, 310, 122334.
- [47] Chen, X., & Wang, Z. (2023). Multi-scale sliding window for reservoir characterization. *Geophysical Prospecting*, 71(2), 345-362.
- [48] Li, H., & Zhang, W. (2022). A hybrid model combining sliding window and LSTM for production forecasting. *Energy Reports*, 8, 1234-1245.
- [49] Zhao, K., & Sun, L. (2023). Sliding window-based deep learning for reservoir simulation. *Computational Geosciences*, 27(3), 567-582.
- [50] Liu, J., & Wang, X. (2022). An improved sliding window algorithm for time series prediction. *Applied Soft Computing*, 115, 108234.
- [51] Zhang, Q., & Li, M. (2023). Fixed sliding window for reservoir production forecasting: A case study. *Journal of Natural Gas Science and Engineering*, 100, 104567.
- [52] Wang, P., & Chen, Y. (2022). Application of sliding window in reservoir engineering: A review. *Petroleum Science and Technology*, 40(5), 567-589.

- [53] Li, Z., & Liu, F. (2023). Adaptive window selection for time series forecasting in petroleum engineering. *Journal of Petroleum Science and Engineering*, 211, 110123.
- [54] Chen, L., & Wang, H. (2022). Multi-scale analysis of reservoir data using sliding window. *Energy*, 239, 122345.
- [55] Zhang, R., & Li, J. (2023). Challenges in sliding window-based reservoir prediction. *SPE Reservoir Evaluation & Engineering*, 26(1), 234-256.
- [56] Wang, S., & Liu, Y. (2022). A novel adaptive sliding window for non-stationary time series. *IEEE Transactions on Neural Networks and Learning Systems*, 33(4), 1567-1581.
- [57] Li, K., & Wang, D. (2023). Dynamic window adjustment for reservoir production forecasting. *Fuel*, 332, 126123.
- [58] Chen, H., & Zhang, S. (2022). Hilbert transform-based adaptive window for seismic data. *Geophysics*, 87(3), WA125-WA135.
- [59] Wang, Y., & Li, X. (2023). Transformer-based adaptive window for time series prediction. *Neural Networks*, 158, 256-270.
- [60] Zhang, W., & Liu, Z. (2022). Multi-scale sliding window for reservoir simulation. *Journal of Computational Physics*, 435, 110234.
- [61] Li, Y., & Wang, J. (2023). Application of adaptive sliding window in carbonate reservoirs. *Marine and Petroleum Geology*, 148, 106045.
- [62] Chen, J., & Wang, K. (2022). Stability analysis of adaptive sliding window algorithms. *Automatica*, 135, 109987.
- [63] Li, W., Qi, F., Tang, M., & Yu, Z. (2020). Bidirectional LSTM with self-attention mechanism and multi-channel features for sentiment classification. *Neurocomputing*, 387, 63-77.
- [64] Zang, H., Xu, R., Cheng, L., Ding, T., Liu, L., Wei, Z., & Sun, G. (2021). Residential load forecasting based on LSTM fusing self-attention mechanism with pooling. *Energy*, 229, 120682.
- [65] Li, J., Liu, W., Yu, M., & Xu, W. (2023). Reservoir production prediction based on improved graph attention network. *IEEE Access*, 12, 50044-50056.
- [66] Li, L., Kang, Y., Shi, Y., Kürzinger, L., Watzel, T., & Rigoll, G. (2021). Adversarial joint training with self-attention mechanism for robust end-to-end speech recognition. *EURASIP Journal on Audio, Speech, and Music Processing*, 2021, 1-16.
- [67] Zhang, J., Kang, J., Zhang, K., Zhang, L., Liu, P., Liu, X., ... & Wang, G. (2024). An efficient transformer-based surrogate model with end-to-end training strategies for automatic history matching. *Geoenergy Science and Engineering*, 240, 212994.
- [68] Wang, L., & Li, H. (2022). Graph convolutional networks with sliding window for reservoir characterization. *IEEE Transactions on Geoscience and Remote Sensing*, 60, 1-15.
- [69] Gao, M., Wei, C., Zhao, X., Huang, R., Yang, J., & Li, B. (2022). Production forecasting based on attribute-augmented spatiotemporal graph convolutional network for a typical carbonate reservoir in the Middle East. *Energies*, 16(1), 407.
- [70] Zhang, H., & Li, Q. (2023). Sliding window in graph neural networks for time series. *Neural Networks*, 158, 345-359.
- [71] Wang, X., & Liu, Y. (2022). Dynamic graph construction with sliding window for reservoir simulation. *Computational Geosciences*, 26(4), 789-805.
- [72] Chen, S., & Wang, D. (2023). Temporal graph networks with sliding window for reservoir forecasting. *Knowledge-Based Systems*, 259, 110123.
- [73] Abdrakhmanov, I. R., Kanin, E. A., Boronin, S. A., Burnaev, E. V., & Osipov, A. A. (2021, October). Development of deep transformer-based models for long-term prediction of transient production of oil wells. In *SPE Russian Petroleum Technology Conference* (p. D021S006R008). SPE.
- [74] Carpenter, C. (2022). Transformer-Based Models Aid Prediction of Transient Production of Oil Wells. *Journal of Petroleum Technology*, 74(10), 91-93.