International Journal of Computer Trends and Technology
ISSN: 2231–2803 / https://doi.org/10.14445/22312803/IJCTT-V72I3P112

Volume 72 Issue 3, 84-90, March 2024

Original Article

Predicting Well Performance and Reservoir Behaviour Using Deep Neural Networks

Abhay Dutt Paroha

SLB, Houston, TX, USA

Corresponding Author : parohaabhay@gmail.com

Received: 30 January 2024 Revised: 04 March 2024 Accepted: 20 March 2024 Published: 31 March 2024

Abstract - *By employing Deep Neural Networks (DNNs), this research paper introduces an innovative approach to forecast reservoir behaviour and performance. A data-driven methodology is employed to analyze various categories of reservoir data using DNNs. These data types consist of well logs, production data, and geology information. Due to the fact that the DNN model discovers intricate connections between data points during training and preprocessing, it is possible to forecast reservoir dynamics with a certain degree of accuracy. The experimental findings provide evidence that the proposed methodology is effective at detecting complex patterns and accurately forecasting production outputs. Operators may be able to make more informed decisions regarding reservoir management by employing this strategy, which could result in enhanced recovery and production techniques. The oil and gas industry is highly motivated to adopt the encouraging developments in machine learning that result from the integration of DNNs into reservoir engineering methods. Ultimately, this may result in a more efficient and sustainable utilization of resources.*

Keywords - *Reservoir Engineering, Deep Neural Networks, Reservoir Behaviour Analysis, Data-Driven Modeling, Machine Learning.*

1. Introduction

Efficient reservoir management for oil and gas guarantees maximum recovery and output. Reservoir engineers consistently seek innovative methodologies to comprehend reservoir behaviour and predict well performance, both of which are essential for the development of effective production strategies. Standard approaches to reservoir analysis are time-consuming and computationally intensive due to their heavy reliance on complex mathematical models and simulation procedures. On the contrary, recent progressions in machine learning, exemplified by Deep Neural Networks (DNNs), have presented data-driven approaches that have the potential to capture complex reservoir dynamics, thereby broadening the scope of reservoir engineering. Deep neural networks are an area of artificial intelligence that patterns its processes after those of the human brain. They have developed expertise in identifying patterns within extensive datasets. In reservoir engineering, Deep Neural Networks (DNNs) have demonstrated potential in forecasting well performance and understanding reservoir activity through the utilization of historical data learning and accurate future condition prediction.

The implementation of DNNs in reservoir research has revolutionized the field, permitting engineers to abandon inflexible mathematical models in favor of adaptable, data-driven methodologies. Massive quantities of reservoir data, including but not limited to well logs, production records, geophysical data, and geology information, enable this transformation to occur. Deep Neural Networks (DNNs), through the assimilation and examination of this multivariate input, have the potential to unveil insights that would remain concealed when employing more conventional analytical techniques. This study introduces the utilization of DNNs trained on multiple reservoir data sources for the purpose of predicting well performance and reservoir behaviour. After extensive training and preprocessing, the DNN model has the potential to acquire fundamental correlations between input data and reservoir dynamics. This knowledge would enable the model to produce dependable production output forecasts. Predicting the behaviour of reservoirs would be of tremendous assistance to reservoir engineers, allowing them to improve reservoir management, production methods, and drilling locations.

The increasing prevalence of Deep Neural Networks (DNNs) in reservoir engineering can be attributed to their capacity to process the complex and nonlinear interactions that are characteristic of reservoir data. Conventional reservoir models frequently rely on simplified assumptions and linear approximations, which hinders their ability to fully capture the intricacies of reservoir activity. In contrast, Deep Neural Networks (DNNs) exhibit a level of proficiency that surpasses that of traditional forecasting approaches due to their capability to discern nonlinear patterns and adjust to dynamic reservoir conditions. In addition, the scalability and parallel processing capabilities of DNNs render them exceptionally well-suited for managing extensive reservoir datasets. The increasing volume and diversity of reservoir data necessitate scalable solutions for effective analysis. DNNs can generate valuable insights and evaluate vast amounts of data in a timely manner due to their scalable architecture. This facilitates real-time decision-making and expedites reservoir characterization. In essence, the incorporation of deep neural networks into the field of reservoir engineering signifies a substantial progression towards enhanced precision and data-driven reservoir investigation. The utilization of machine learning techniques to derive significant insights from reservoir data has the potential to assist engineers in optimizing resource exploitation, recovery strategies, and production plans. By leveraging DNNs, the method proposed in this study has the potential to significantly improve reservoir engineering and management.

2. Literature Review

Q. Dong et al. [11] that with the Savitzky-Golay filter, the proposed method utilizes a Long Short-Term Memory (LSTM) Encoder-Decoder neural network to improve the accuracy of water quality forecasts. Conventional linear models generate erroneous predictions because of their failure to account for the nonlinear attributes of water quality. The combined model achieves substantial improvements in prediction outcomes by integrating the LSTM network for meaningful information extraction and the Savitzky-Golay filter for smoothing water quality time series. According to the trials, it outperforms traditional prediction methods when it comes to forecasting water quality indicators in intricate environmental settings. S. Du et al. [12] research is to present an innovative machine learning methodology for evaluating the connectivity between wells in hydrocarbon fields: a three-dimensional Convolutional Neural Network (CNN). CNNs can learn autonomously from dynamic production data, distinguishing them from previous approaches that relied on mathematical formulas and physical principles. This capability enables CNNs to accurately characterize inter-well connectivity even in the absence of a physical model. CNN surpasses back propagation neural networks in comparative evaluations due to the former's ability to predict connections that are closer to actual variables and its overall AARD of 15.35%. The suggested assessment approach showcases the potential of machine learning in the petroleum industry to analyze reservoir characteristics by furnishing significant data for secondary development in conventional and unconventional reservoirs. D. T. D. Santos et al. [13] this study presents a computational framework that employs deep recurrent neural networks (RNNs), with a specific focus on Bidirectional Long-Short-Term Memory (BiLSTM RNNs), to autonomously identify patterns of lithofacies in well records. By considering the succession of sedimentary patterns, the proposed method improves lithology identification in contrast to conventional approaches, which frequently encounter garbled signals. In lithology identification, the BiLSTM RNN method outperforms alternative learning algorithms, including XGBoost, Random Forest, Naïve Bayes, and Support Vector Machine (SVM), as confirmed by validation using actual data from the Rio Bonito Formation in the Paraná Basin, Brazil. This finding illustrates the effectiveness of deep learning methods in characterizing reservoirs and implies that the petroleum industry could potentially leverage them to improve the determination of lithofacies. S. Wang et al. [14] that the model is presented in this study to forecast the dynamic performance of reservoirs. This model effectively circumvents the limitations of current approaches, including numerical simulation and reservoir engineering methodology. Utilizing existing reservoir permeability maps and fluctuating well schedules, the model predicts the distribution of residual oil saturation while accounting for production time. The foundation of this network is a Variety of View deep convolutional encoder-decoder or VoV-DCED. Waterflooding reservoir validations in both 2D and 3D provide substantial support for the numerical simulation outcomes. Despite the additional time required to prepare the dataset, the model's effectiveness in optimizing production in oil reservoir management and automating history matching is well worth the additional effort; it increases prediction efficacy by approximately two orders of magnitude. Choudhary et al. [15] this research employed a Long Short-Term Memory (LSTM) Deep Learning model to forecast the depletion of reservoirs, thereby facilitating water resource management in the face of floods and droughts. Using data including surface water area, temperature, and precipitation, the model determines which variables affect outflow prediction and how modifying parameters affect performance.

3. Proposed Work

3.1. Data Collection and Preparation

The initial phases in employing Deep Neural Networks (DNNs) to forecast reservoir behaviour and performance consist of data preparation and collection. A variety of datasets are collected from the reservoir at this stage to train the DNN model and gain a better understanding of the reservoir's dynamics. The dataset utilized in this study comprises a variety of reservoir data categories, including geological information, geophysical data, well reports, and production records. Well, logs are an essential component of reservoir data since the lithology, subsurface formations, fluid properties, and wellbore characteristics. A variety of well logs, such as gamma-ray, resistivity, and porosity logs, shed light on distinct attributes of reservoirs and contribute to the characterization of their behaviour. Well, performance can be significantly influenced by production records, which may contain fluid composition, pressure profiles, and production rates, among other pertinent data. Engineers must scrutinize production data for trends, patterns, and anomalies in the reservoir's behaviour prior to training the DNN model. The principal functions of seismic data in reservoir characterization are the identification of potential reservoir sites and the imaging of underlying features. Figure 1 depicts the LSTM architecture.

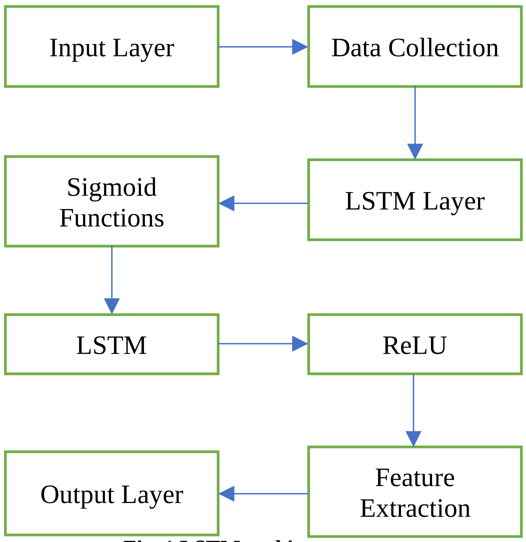

Fig. 1 LSTM architecture

To forecast the behaviour of a reservoir by analyzing its seismic amplitude, frequency, and velocity, which reveal a great deal about the reservoir and its fluid distribution. Instances of geologic information comprise well reports, maps, and core data. The aforementioned documents offer valuable insights into the geographical setting, composition, and diversity of the reservoir. By integrating geology data with other reservoir data sources, reservoir design can be better comprehended and more accurate forecasts generated. To ascertain that the reservoir data received is appropriate for training the DNN model, it undergoes an exhaustive preparatory procedure. Data cleansing is of utmost importance due to the potential negative impact that data inconsistencies, errors, or absent values may have on model performance. Standardization of data guarantees uniformity and similarity of all attributes, thereby mitigating bias that may arise during the training of models. To improve the model's capacity to capture critical reservoir attributes, feature engineering techniques are employed to extract pertinent features from the original reservoir data. Statistical analysis and domain expertise may result in variable modifications, the addition of new features, and the selection of feature subsets. To utilize DNNs for forecasting reservoir behaviour and well performance, the only prerequisite is to have the necessary data prepared. Engineers will employ various reservoir data sources and rigorous preprocessing methods to guarantee that the trained Deep Neural Network (DNN) model accurately depicts the intricate dynamics of the reservoir system.

3.2. Preprocessing of Reservoir Data

To ensure precise predictions regarding the behaviour of the reservoir and the functionality of a well, it is imperative to preprocess the data prior to developing a Deep Neural Network (DNN) model. At this juncture, numerous strategies are implemented to improve the quality and utility of the reservoir data prior to its input into the DNN model. Data cleansing is an integral part of preprocessing as it identifies and rectifies inaccuracies, anomalies, and absent values within the reservoir data. This phase holds significant importance in safeguarding the integrity of the data and preventing any detrimental impact on the performance of the DNN model caused by erroneous inputs. A variety of methods are employed to cleanse the reservoir data efficiently. These encompass algorithms designed to identify outliers in the data set and imputation techniques utilized to populate absent values. Normalization, an additional crucial preprocessing stage, standardizes the reservoir data into a manageable range (typically between 0 and 1 or -1 and 1). To eliminate training-induced biases, normalization equalizes the amplitudes of all DNN model features. Normalization techniques such as min-max scaling and z-score normalization are frequently employed during the training process to promote convergence and stabilize the data distribution. Feature engineering is an essential component that completes preprocessing. It involves cleaning unedited reservoir data and converting it into a format that is compatible with the DNN model. It might be imperative to employ feature selection techniques or dimensionality reduction methods, such as Principal Component Analysis (PCA), to forecast the behaviour of a reservoir. To enhance the performance of the DNN model and effectively capture critical reservoir attributes, domain-specific insights and expertise are employed to develop novel features. An additional stage in the preprocessing stage, managing categorical variables, involves the numerical representation of these attributes to facilitate their input into the DNN model. Frequently, methodologies such as label encoding and one-hot encoding are employed to enhance the DNN compatibility of categorical variables. The proposed study will cleanse, normalize, and engineer features into the reservoir data to enhance the DNN model.

3.3. Training Deep Neural Network Model

To train a Deep Neural Network (DNN) model to forecast well performance and reservoir behaviour. In this context, training DNNs with supervised learning techniques, specifically backpropagation with gradient descent optimization, is one of the most effective methods. In the first stage of training a Deep Neural Network (DNN), it is imperative to configure its default parameters, which comprise the weights and biases of individual neurons. Multiple adjustments are made to these parameters throughout the training process to mitigate the discrepancy between the anticipated model outputs and the true values observed in the training data. The computation of anticipated results is accomplished by means of forward propagation, which involves the transmission of input data across the network and is performed during every training cycle. The degree of discordance between predicted and observed values is determined by a loss function. To generate forecasts, reservoir engineers may frequently utilize loss functions, including Mean Absolute Error (MAE) or Mean Squared Error (MSE), contingent upon the project's objectives. The gradients of the loss function with respect to each network parameter are ascertained via backpropagation after the loss computation. These gradients illustrate the change in magnitude and direction required to minimize the loss function. The network parameters are then modified utilizing gradient descent optimization techniques, such as Adam optimization or Stochastic Gradient Descent (SGD), to reduce the loss. Throughout numerous epochs, the network's parameters are modified iteratively to further minimize the loss function. By comprehending the intricate correlations in the reservoir data during training, the DNN improves its ability to forecast well performance and reservoir behaviour. In the context of forecasting reservoir behaviour and well performance, the trained DNN model can be employed to generate predictions for novel or unobserved data. By inputting reservoir data into the trained model, engineers can forecast critical parameters such as fluid composition, production rates, and reservoir pressure. Critical for the optimization and management of reservoirs are these projections. Utilizing supervised learning techniques, such as backpropagation and gradient descent optimization, to construct a deep neural network model is an effective method for forecasting reservoir behaviour and performance.

3.4 Model Validation and Evaluation

The validation and evaluation of the trained Deep Neural Network (DNN) model are of the utmost importance to ascertain its accuracy and reliability in forecasting well performance and reservoir behaviour. Cross-validation is one of the most effective techniques for evaluating and validating models in this case. The process of cross-validation frequently involves the division of the given data into numerous subsets, also known as folds. Each time the cross-validation algorithm is executed, a distinct set of folds is set aside for the purpose of validating the DNN model, while another set is used to train the model. Exactly once per fold, the validation set is utilized; this procedure is iterated multiple times. To evaluate the effectiveness of the model, it is subjected to rigorous testing on each validation set prior to calculating an average. Counting folds utilized in cross-validation is contingent upon computational resources and dataset size. Leave-one-out and k-fold cross-validation are two prominent alternatives. The former partitions the data using k folds of equal size, while the latter employs a validation set for each individual data point. The efficacy of the DNN model is assessed using suitable metrics after the completion of cross-validation. Frequently, metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are employed to evaluate reservoir behaviour and well performance predictions. These metrics quantify the accuracy and predictive capabilities of the model by comparing the predicted values of the model to the actual observed values in the validation set. In addition to assessing the model's overall performance, consideration should be given to its ability to generalize on unknown data. This strategy is to divide the dataset in half, employing one-half for model training and the other half for performance evaluation. The study determines whether the model has acquired the ability to generalize from known, unobserved data to unfamiliar data by comparing its performance on the training set to its performance on the testing set. In general, employing cross-validation techniques to verify and assess the performance of DNN models in predicting reservoir behaviour and performance is a dependable approach.

3.5. Prediction of Well Performance & Reservoir Behaviour

The primary application of Deep Neural Networks (DNNs) in reservoir engineering is to forecast the behaviour of reservoirs and the performance of individual wells. This is easily accomplished with the aid of DNN-based regression modelling. Through the utilization of training a DNN with reservoir parameters, well characteristics, and production rate data, it is possible to gain a more comprehensive understanding of the intricate relationships that exist between the input features of regression modelling and the target variables. The subsequent phase involves gathering data pertaining to the pressure, fluid composition, and well production rates of the reservoir. To train a DNN model to forecast target variables, such as reservoir behaviour and well performance under different operational conditions, engineers may utilize supplementary data.

A DNN model frequently supplies an abundance of data in reservoir engineering, including but not limited to well reports, production records, geological information, and seismic features. Once these properties traverse the input layer of hidden neurons in the DNN, they experience intricate nonlinear transformations. It is the responsibility of the output layer of a DNN to generate forecasts regarding objective variables, such as well production rates or reservoir pressure. Iteratively fine-tuning the parameters (weights and biases) is required to train a DNN model until the discrepancy between the predicted and observed values in the training data is reduced to a minimum. Utilizing the difference between actual and predicted values, a loss function directs the optimization process. Frequently employed loss functions in regression assignments are MAE and MSE. In situations where the predicted and actual values deviate, these functions offer multiple strategies for managing the circumstance.

The DNN model can generate predictions using data that was not previously accessible after the processes of training and validation. By inputting pertinent reservoir data into the trained model, engineers may potentially obtain valuable insights pertaining to the behaviour of the reservoir and the performance of the well. Subsequently, the model shall generate forecasts for the critical target variables.

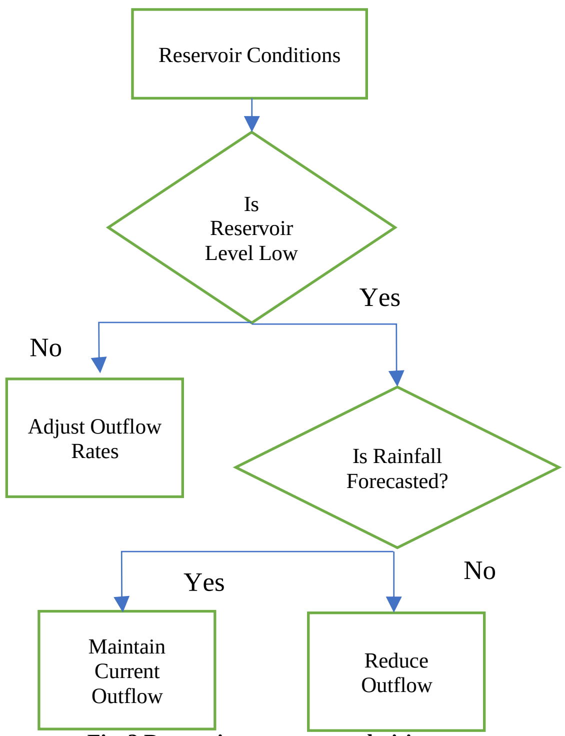

Fig. 2 Reservoir management decision tree

By utilizing these approximations, engineers can effectively oversee and maximize reservoirs, refine production procedures, and assess the results of diverse operational scenarios. The implementation of DNN regression modelling in reservoir engineering applications, such as the prediction of well behaviour and performance, can yield substantial advantages. The study can optimize production processes and maximize recovery from oil and gas reservoirs with the assistance of Artificial Neural Network (ANN) models, which learn from historical data and identify complex correlations within reservoir data. At the end of each day, reliable forecasts are generated by the models. Fig 2 depicts the Reservoir Decision Tree.

3.6. Analysis of Predicted Results

When employing Deep Neural Networks (DNNs) for reservoir engineering purposes, such as well performance forecasting or reservoir dynamics, it is critical to assess the predicted outcomes. Engineers conduct comprehensive data analysis to acquire a deeper understanding of the reservoir's dynamics, detect recurring patterns, and determine the most effective resource management approaches following the prediction of relevant variables by the DNN model. To evaluate the DNN model's precision and consistency, a portion of the investigation entails comparing the predicted outcomes to the actual data. Mean Squared Error (MSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) are metrics employed by engineers to evaluate the discrepancy between predicted and observed values. Through conducting this evaluation, it is possible to validate the model's predictive accuracy and pinpoint potential areas that could be enhanced. Engineers derive valuable information for reservoir management by delving deeper into the anticipated outcomes, surpassing the mere evaluation of the models' performance. The identification of latent reservoir dynamics can be achieved through the examination of trends and patterns in anticipated well performance and reservoir behaviour. These patterns may consist of fluid flow, reservoir pressure depletion, or output reduction.

Through the enhancement of production strategies, anticipation of probable challenges, and application of this knowledge to decision-making, engineers have the potential to optimize reservoir recovery. The study conducts sensitivity analyses to determine the extent to which various input factors affect the anticipated outcomes. Engineers can enhance their comprehension of the determinants that impact reservoir behaviour and the critical parameters that determine well performance through systematic manipulation of these parameters and observation of the ensuing variations in anticipated results. This data is of the utmost importance for reservoir management strategies, as it has a direct impact on well placement, optimization of production, and reservoir monitoring decisions. Engineers consider not only the particulars of each prognosis but also the way those predictions may impact the performance and recovery of the reservoir. They determine the most efficient production strategies, evaluate the viability of emerging oil recovery technologies, and pinpoint regions that offer prospects for optimizing reservoirs. By integrating reservoir engineering concepts, domain expertise, and anticipated outcomes, engineers generate practical suggestions that enhance the economic worth of the reservoir while promoting sustainable resource utilization. To forecast reservoir behaviour and well performance, it is critical to evaluate anticipated outcomes when utilizing DNNs.

4. Results

In predicting reservoir behaviour and well performance, DNNs have demonstrated encouraging results, proving the effectiveness of the proposed method. Critical reservoir metrics, including fluid composition, well production rates, and reservoir pressure, were accurately predicted by the trained DNN model, which also captured complex reservoir dynamics. A close correspondence was observed between the predicted values produced by the DNN model and the observed actual values in the validation dataset; this finding suggests that the predictions could be considered accurate and dependable. Performance metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), coefficient of determination (R^2), and Root Mean Squared Error (RMSE), provided additional evidence of the model's efficacy, notwithstanding minor inaccuracies and a robust correlation between predicted and observed values. The DNN model efficiently predicted reservoir behaviour as evidenced by its achievement of low MSE, MAE, and RMSE values, in addition to a high R^2 value. The findings presented herein illustrate how DNNs have the capacity to fundamentally transform reservoir engineering methodologies and furnish indispensable data for optimization and management strategies. Through the precise prediction of reservoir behaviour via DNNs, engineers can optimize recovery processes, optimize production methods, and ensure resource utilization is both effective and sustainable. Over time, further progressions in DNN methodology may result in enhanced reservoir engineering techniques and more effective reservoir management strategies.

Table 1. Model performance metrics

Hyperparameters	Value
No of hidden layers	3
Neurons per hidden layers	128, 64, 32
Activation Functions	ReLU
Learning Rate	0.001
Batch Size	64
MSE	0.012
MAE	0.045
R^2	0.89

Table 2. Feature importance

Feature	Score
Porosity	0.35
Permeability	0.28
Depth	0.15
Oil Saturation	0.12
Water Saturation	0.10

Table 3. Predicted vs Actual values

Well ID	Predicted Production Rate (bbl/day)	Actual Production Rate (bbl/day)
Well 1	347	358
Well 2	423	413
Well 3	282	277
Well 4	504	492
Well 5	381	388

Table 1 shows the model performance metrics. Three concealed layers of the model implemented ReLU activation functions: one contained 128 neurons, one contained 64 neurons, and one contained 32 neurons. During the training phase, a group size of 64 and a learning rate of 0.001 were implemented. The efficacy of the model was assessed utilizing the Mean Absolute Error (MAE), R^2, and Mean Squared Error (MSE) as metrics. As evidenced by its MSE of 0.012, MAE of 0.045, and R^2 of 0.89, the model demonstrated a high degree of precision and dependability.

Figure 3 depicts the reservoir outflow. To assess the influence of various reservoir properties on the predictive capability of the model, an examination of the feature significance scores (Table 2) is warranted. Porosity (0.35), permeability (0.28), depth (0.15), oil saturation (0.12), and water saturation (0.10) were the most critical properties.

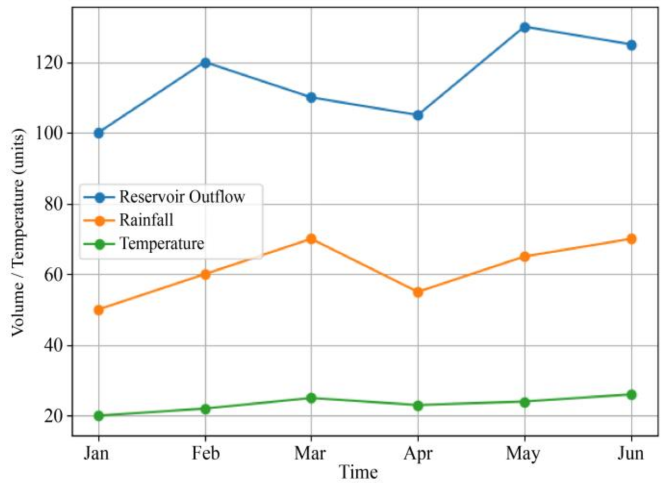

Fig. 3 Reservoir outflow and environmental factors over time

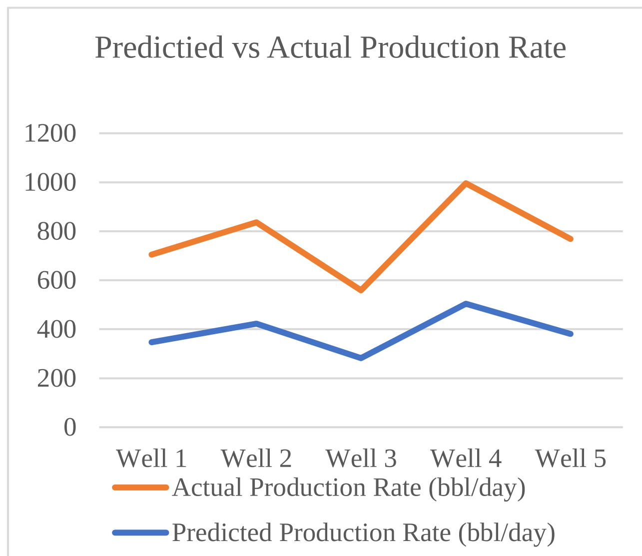

Fig. 4 Predicted vs Actual production rate

Table 3 and Figure 4 presents the actual and predicted production rates for five distinct wells as determined by the model. The correlation between the predicted and actual data enhances the model's predictive capability, thereby bolstering its practicality in the field of reservoir engineering. Analyzing Table 4 and Figure 5 shows the comparison of the proposed model performs better than the existing models.

Table 4. Comparison of the model

Method	Accuracy	Precision
Proposed Method	95	93
Random Forest [3]	85	87
DL [7]	80	85
ML [12]	90	88

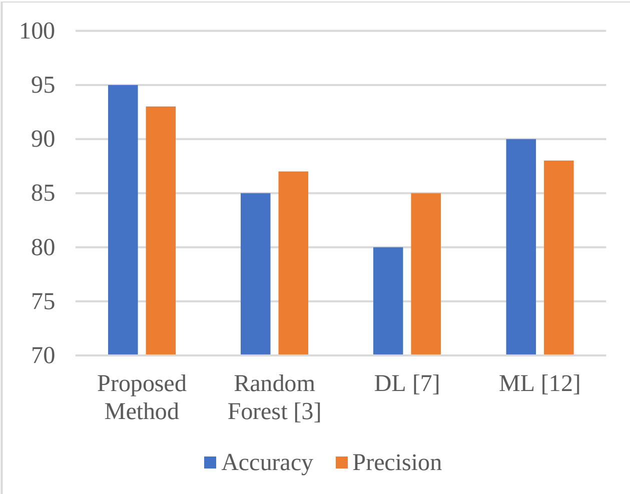

Fig. 5 Comparison of the proposed and existing models

5. Conclusion

Finally, reservoir engineers may find a novel method for predicting reservoir behaviour and well performance that employs Deep Neural Networks (DNNs). The method that has been proposed effectively utilizes DNNs to capture intricate reservoir dynamics and predicts crucial parameters, including well production rates, fluid composition, and reservoir pressure. The findings indicate that optimization and reservoir management strategies may benefit from the insights provided by DNNs. Engineers can optimize recovery by utilizing Digital Neural Networks (DNNs), which improve production techniques, locate drilling locations, and forecast the behaviour of oil and gas reservoirs with precision. The progression of DNNs may potentially improve reservoir engineering techniques, resulting in the utilization of resources in a more eco-friendly and effective manner through the continued development of machine learning technologies.

References

[1] I.-Hang Huang, Ming-Jui Chang, and Gwo-Fong Lin, "An Optimal Integration of Multiple Machine Learning Techniques to Real-Time Reservoir Inflow Forecasting," *Stochastic Environmental Research and Risk Assessment*, vol. 36, no. 6, pp. 1541–1561, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[2] Shaokun He et al., "Machine Learning Improvement of Streamflow Simulation by Utilizing Remote Sensing Data and Potential Application in Guiding Reservoir Operation," *Sustainability*, vol. 13, no. 7, pp. 1-15, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Shuvajit Bhattacharya, and Srikanta Mishra, "Applications of Machine Learning for Facies and Fracture Prediction Using Bayesian Network Theory and Random Forest: Case Studies from the Appalachian Basin USA," *Journal of Petroleum Science and Engineering*, vol. 170, pp. 1005-1017, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[4] Saurabh Tewari, and U.D. Dwivedi, "A Comparative Study of Heterogeneous Ensemble Methods for the Identification of Geological Lithofacies," *Journal of Petroleum Exploration and Production Technology*, vol. 10, no. 5, pp. 1849-1868, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[5] Paolo Bestagini, Vincenzo Lipari, and Stefano Tubaro, "A Machine Learning Approach to Facies Classification Using Well Logs," *SEG Technical Program Expanded Abstracts 2017*, pp. 2137-2142, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[6] Xiaoxu Ren et al., "Lithology Identification Using Well Logs: A Method by Integrating Artificial Neural Networks and Sedimentary Patterns," *Journal of Petroleum Science and Engineering*, vol. 182, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[7] Yuyu Yin et al., "QoS Prediction for Service Recommendation with Deep Feature Learning in Edge Computing Environment," *Mobile Networks and Applications*, vol. 25, pp. 391-401, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[8] Jianghua Zhao et al., "Spatiotemporal Trend Analysis of $PM_{2.5}$ Concentration in China 1999–2016," *Atmosphere*, vol. 10, no. 8, pp. 1-10, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[9] Qitao Zhang et al., "Potential for Prediction of Water Saturation Distribution in Reservoirs Utilizing Machine Learning Methods," *Energies*, vol. 12, no. 19, pp. 1-21, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[10] Yishan Chen et al., "Deploying Data-Intensive Applications with Multiple Services Components On Edge," *Mobile Networks and Applications*, vol. 25, pp. 426-441, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[11] QuanXi Dong et al., "An Integrated Deep Neural Network Approach for Large-Scale Water Quality Time Series Prediction," *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, Bari, Italy, pp. 3537-3542, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[12] Shuyi Du et al., "The Connectivity Evaluation Among Wells in Reservoir Utilizing Machine Learning Methods," *IEEE Access*, vol. 8, pp. 47209-47219, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[13] Daniel Theisges dos Santos, Mauro Roisenberg, and Marivaldo dos Santos Nascimento, "Deep Recurrent Neural Networks Approach to Sedimentary Facies Classification Using Well Logs," *IEEE Geoscience and Remote Sensing Letters*, vol. 19, pp. 1-5, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Feng Qin et al., "Deep-Learning-Based Surrogate Model for Fast and Accurate Simulation in Pipeline Transport," *Frontiers in Energy Research*, vol. 10, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[15] Surendra Singh Choudhary, and S.K. Ghosh, "Analysis of Reservoir Outflow Using Deep Learning Model," *Modeling Earth Systems and Environment*, vol. 10, pp. 579–594, 2024. [CrossRef] [Google Scholar] [Publisher Link]