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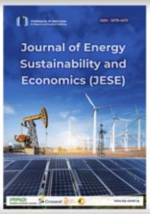

Oil Well Productivity Prediction by Machine Learning: A Case Study of an Iraqi Oil Field

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Keywords:

Oil Productivity Prediction; Machine Learning; Temporal Convolutional Network; Trichoderma reesei ; Decline Curve Analysis ; Root Mean Square Error**;**

Abstract

Accurate prediction of oil well productivity is essential for reservoir management, production optimization, and field development planning. This study evaluates the applicability of machine learning techniques for forecasting oil production and compares their performance with conventional Decline Curve Analysis (DCA) using production data from an Iraqi oil field. Historical production data from three representative wells covering the period 1976–2020 were collected and preprocessed through filtering and outlier removal. A Temporal Convolutional Network (TCN) model was developed using lookback windows of 3, 4, and 5 time steps to capture temporal dependencies in production behavior. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2), and the results were compared with those obtained from conventional DCA forecasting. The TCN model demonstrated strong predictive capability, achieving R^2 values ranging from 0.885 to 0.956 and RMSE values between 96 and 204 across the studied wells. In contrast, the DCA model produced an R^2 value of 0.55 and an RMSE of 665, indicating significantly lower predictive accuracy. The results confirm that the TCN model outperforms conventional forecasting methods by effectively capturing nonlinear production trends and long-term temporal dependencies. This study demonstrates the potential of deep learning approaches, particularly Temporal Convolutional Networks, to enhance production forecasting accuracy and support decision-making in complex reservoir environments using long-term production data.

Introduction

Forecasting oil well productivity is one of the most important tasks in reservoir engineering because it directly influences reservoir management, production optimization, reserve estimation, and field development planning. Reliable production forecasts assist engineers in making critical decisions related to drilling programs, artificial lift installation, stimulation treatments, workover operations, and long-term reservoir management[1,7].

Traditional techniques for predicting oil well productivity have been widely used in the petroleum industry for decades. These techniques include Decline Curve Analysis (DCA), well testing, Inflow Performance Relationships (IPR), and nodal analysis. Although these methods remain valuable because of their simplicity and relatively low data requirements, they rely on several assumptions such as homogeneous reservoir properties, stable operating conditions, and predictable flow behavior. These assumptions are often violated in modern reservoirs characterized by geological heterogeneity, pressure depletion, multiphase flow, and complex completion designs [1,8,16]. Recent studies have demonstrated the importance of integrating conventional reservoir engineering approaches such as IPR and nodal analysis with production optimization strategies. For example, Asad et al[26]. successfully applied gas-lift optimization combined with IPR and nodal analysis in the Asmari Formation, Iraq, showing the effectiveness of these techniques in improving production performance and recovery efficiency.

The increasing availability of production and reservoir data has encouraged the application of data-driven techniques in petroleum engineering. Machine learning (ML) methods have demonstrated significant potential for modeling complex and nonlinear relationships that cannot be adequately represented by conventional analytical and empirical approaches. Previous studies have successfully applied Artificial Neural Networks (ANN), Random Forests, Gradient Boosting, Long Short-Term Memory (LSTM), and other deep learning architectures to production forecasting problems, frequently achieving superior prediction accuracy compared with traditional methods[2,6,12,22]. Machine learning has also been applied to reservoir characterization, well test interpretation, bottom-hole pressure estimation, water-cut prediction, and enhanced oil recovery analysis. Its ability to learn hidden patterns from large datasetsenables more accurate forecasting under complex reservoir conditions[11,17,19,24].Despite these advances, there remains a need to evaluate advanced deep learning architectures capable of capturing long-term temporal dependencies in production data. Temporal Convolutional Networks (TCNs) have recently emerged as an effective alternative to recurrent neural networks for time-series forecasting due to their ability to model sequential data efficiently while maintaining stable training performance. Furthermore, advanced deep learning models have demonstrated promising forecasting capabilities in complex oil production systems, highlighting the potential of TCN-based approaches for production prediction tasks [6,12,14].
Therefore, the objective of this study is to investigate the applicability of a Temporal Convolutional Network (TCN) model for oil production forecasting and compare its predictive performance with conventional Decline Curve Analysis using long-term production data. The figure (1) will provide a simplified illustration of the main differences between traditional and modern methods.

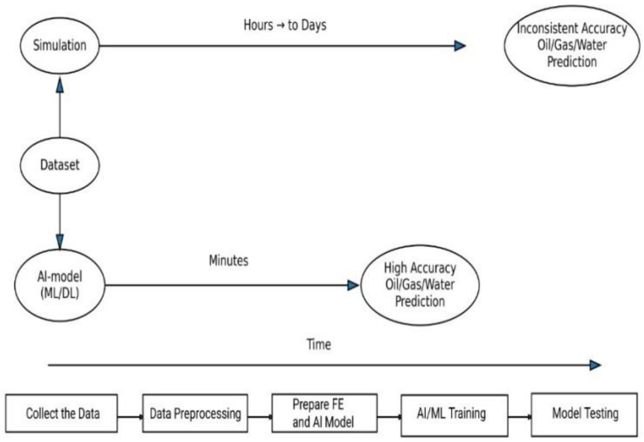

Figure 1 The difference in terms of time and accuracy between traditional method and ML model

Geological Setting

The study was conducted using production data obtained from a major oil field located in southern Iraq. The field contains several hydrocarbon-bearing reservoirs, including the Mishrif, Yamama, Zubair, and Nahr Umr formations (fig 2) .

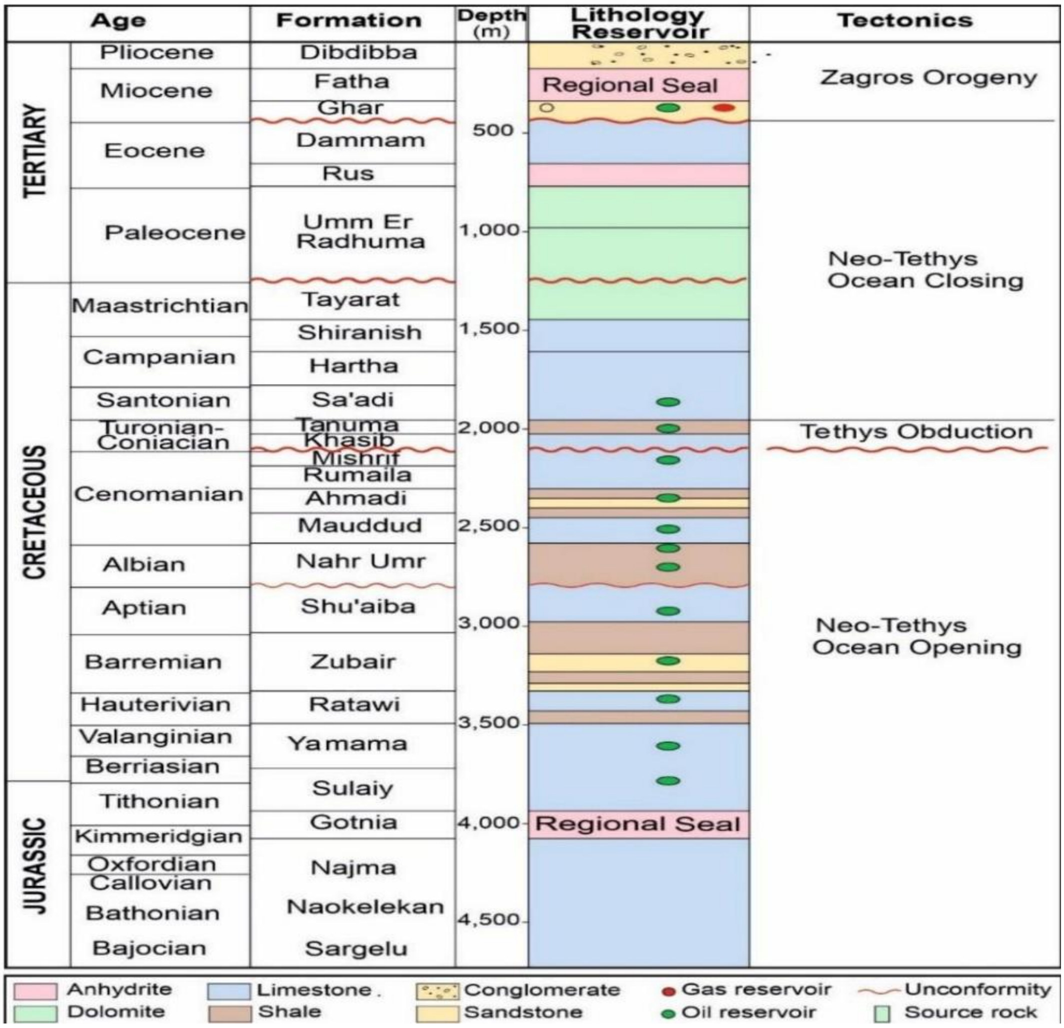

Figure 2 The generalized stratigraphic column of southern Iraq.

Among these reservoirs, the Mishrif Formation represents the principal producing reservoir and was selected as the primary source of data for this study. Previous studies conducted on the Mishrif Formation in southern Iraq have highlighted the importance of productivity indicators and reservoir characterization in evaluating well performance and forecasting production behavior. Khashman et al. [27] demonstrated that productivity indicators can provide valuable insights into reservoir performance and well deliverability in Iraqi carbonate reservoirs. These findings support the selection of Mishrif reservoir data as a representative case for assessing advanced forecasting techniques in carbonate reservoirs.The field is characterized by a long production history and mature reservoir behavior. Due to confidentiality agreements, the field name is not disclosed. The selected wells represent different production trends and reservoir conditions, making them suitable for evaluating and comparing forecasting techniques.

Data and Methods

The prediction of oil and gas production is primarily based on fluid flow through porous media, which is described by Darcy's Law. According to this law, production rate increases with permeability and pressure differential and decreases with fluid viscosity. This principle forms the basis of most reservoir engineering flow models and highlights the influence of rock properties, fluid properties, and operating conditions on well productivity and reservoir performance. [1].

Production Equations

Transient Flow (Oil)

$$q = \frac{K\,h\,(pi - pwf)}{162.6\,Bo\,\mu o\,(\log t + \log(\frac{k}{\emptyset\,\mu o\,ct\,rw^2}) - 3.23 + 0.87S)} \quad (1)$$

The transient flow model describes the early production period before reservoir boundaries influence fluid flow. Derived from Darcy's law, it shows that production rate increases with permeability, reservoir thickness, and pressure differential, and decreases with oil viscosity and formation volume factor. The model also considers time-dependent pressure diffusion through parameters such as porosity, total compressibility, and wellbore radius, while the skin factor accounts for near-wellbore damage or stimulation effects. [1,17].

Steady State Flow

$$q_o = \frac{Kh(p_e - p_{wf})}{141.2 B_o \mu_o (\ln\left(\frac{r_e}{r_w}\right) + s)} \quad (2)$$

The steady-state flow equation describes conditions where reservoir pressure remains constant over time due to continuous pressure support, such as water drive or fluid injection. Under these conditions, the production rate depends on the pressure difference between the reservoir boundary pressure and the flowing bottom-hole pressure. The equation also considers the drainage radius, wellbore radius, and radial flow geometry, while the skin factor accounts for near-wellbore damage or stimulation effects that influence well productivity [16,1].

Pseudo–Steady-State Flow(oil)

$$q = \frac{Kh(p - p_{wf})}{141.2 B_o \mu_o (\frac{1}{2} \ln\left(\frac{4A}{\gamma C_A r_w{}^2}\right) + s)} \quad (3)$$

The pseudo–steady-state flow model describes reservoir behavior after reservoir boundaries begin affecting pressure distribution. At this stage, pressure declines uniformly throughout the reservoir, so the average reservoir pressure is used instead of the initial pressure. The equation also considers reservoir area and shape factors, which account for the effects of reservoir geometry and boundary conditions on fluid flow and well productivity[7].

IPR Equation

$$\mathrm{q} = \mathrm{j}\ (p_r{}^2 - p_{wf}{}^2 \quad (4)$$

The Inflow Performance Relationship (IPR) equation describes the relationship between production rate and flowing bottom-hole pressure and is commonly used to evaluate well productivity. Recent work by Khashman et al. [27] demonstrated the effectiveness of IPR analysis as a key productivity indicator for carbonate reservoirs and highlighted its practical application in evaluating well performance within Iraqi oil fields.

Vogel Equation

$$q_g = q_{max}[1 - 0.2(\frac{p_{wf}}{p}) - 0.8\left(\frac{p_{wf}}{p}\right)^2] \qquad (5)$$

The Vogel equation was developed by John Vogel in 1968 to describe the performance of oil wells producing from solution-gas drive reservoirs. This empirical correlation relates the production rate to the flowing bottomhole pressure by expressing the production rate as a fraction of the maximum production rate (qmax). The equation captures the nonlinear relationship between pressure and production rate due to the presence of two-phase flow (oil and gas) in the reservoir[10].

Two-Phase Flow (Oil)

$$q = \left(J^* \frac{p}{1.8}\right)\left[1 - 0.2\left(\frac{p_{wf}}{p}\right) - 0.8\left(\frac{p_{wf}}{p}\right)^2\right] \qquad (6)$$

This equation describes two-phase flow conditions in which both oil and gas move simultaneously through the porous reservoir rock toward the wellbore. The production rate depends on the modified productivity index (J) and the ratio of flowing bottom-hole pressure to average reservoir pressure. The equation accounts for nonlinear flow behavior resulting from the interaction between the two flowing phases[8]

Exponential Decline Curve Analysis:

q (t)=qie-Dit (7)

8) Linear formula [1]:

$\ln q(t) = \ln q_i - D_i t$ (8)

9) Cumulative Production[1]:

$$N_p(t) = \frac{(q_i - q_t)}{D_i} \qquad (9)$$

10) Harmonic Decline Curve Analysis[1]:

$$qt = \frac{q_i}{(1 + D_i t)} \qquad (10)$$

11) Linear formula used in estimation[7]:

$$\frac{1}{q(t)} = \frac{1}{q_i} + \left(\frac{D_i}{q_i}\right) t \qquad (11)$$

12) Cumulative production[7]:

$$Np(t) = \left(\frac{q_i}{D_i}\right) In\left(\frac{q_i}{qt}\right) \qquad (12)$$

Hyperbolic Decline Curve Analysis:

13) General average equation[7]:

$$q(t) = \frac{q_i}{(1 + bD_i t)^{1/b}} \qquad (13)$$

Where: $0 < b < 1 \rightarrow$ Hyperbolic, $b = 1 \rightarrow$ Harmonic, $b \rightarrow 0 \rightarrow$

Exponential

14) Linear formula used in estimation[7] :

$$q(t)^{(-b)} = qi^{(-b)} (1 + b\,Di\,t) \qquad (14)$$

15) Linear form ($b \neq 1$)[7]:

$$q(t)^{(-b)} = A + B\,t \qquad (15)$$

Factors Effecting Flow Equations

Most reservoir engineering flow equations are based on Darcy's law, which describes fluid flow through porous media. In this framework, production rate is directly proportional to permeability and pressure differential, and inversely proportional to fluid viscosity. High permeability enhances fluid flow and increases productivity, while low permeability restricts flow and reduces production. Pressure drawdown provides the driving force for flow; however, excessive drawdown may lead to operational issues such as water or gas coning and sand production.

Fluid viscosity also strongly affects productivity, as higher viscosity increases flow resistance, leading to lower production rates, particularly in heavy oil reservoirs. The skin factor further influences near-wellbore flow conditions, where positive values indicate formation damage and reduced productivity, while negative values reflect improved performance due to stimulation.

Additional reservoir properties such as porosity, thickness, compressibility, and reservoir geometry also control production behavior by affecting storage capacity, flow area, and pressure depletion. Although these parameters may not appear explicitly in empirical methods such as Decline Curve Analysis, their effects are implicitly reflected in production trends and model calibration [1].

Data Collection and Filtration

Production data were obtained from an Iraqi oil field, from which three representative wells were selected for detailed analysis. The dataset spans a long-term production period from 1976 to 2020, providing a comprehensive basis for evaluating reservoir performance and decline behavior. Due to strict confidentiality agreements and data sharing policies, the name of the field cannot be disclosed. The overall research workflow adopted in this study, which compares conventional decline curve analysis with machine learning approaches. Following data acquisition, the dataset underwent rigorous preprocessing to ensure accuracy and consistency. This included data filtration and smoothing by removing outliers, such as zero-production days resulting from well shut-ins or measurement (gauge) errors. These steps were essential to establish a reliable and continuous production trend, enabling accurate decline curve modeling and subsequent analysis. And a sample of the data is shown in (table 1,2,3)

ML Model (TCN)

The Temporal Convolutional Network (TCN) is a deep learning architecture designed for sequential and time-series data. Unlike recurrent neural networks such as LSTM and GRU, which process data sequentially, TCN uses convolutional operations that enable parallel computation and more efficient training. It is based on causal convolutions, which ensure that predictions at any time step depend only on past inputs, preserving temporal causality. In addition, dilated convolutions are used to expand the receptive field without increasing computational cost, allowing the model to capture long-term dependencies in oil production data. Residual connections are also incorporated to improve gradient flow and support deeper network structures.The selection of TCN in this study is motivated by its ability to capture long-term temporal patterns in oil production data, its stable training behavior compared to recurrent models, and its reduced training time due to parallel processing. Previous studies have also demonstrated its strong performance in time-series forecasting, supporting its suitab ility for this application.

The proposed model was implemented in Python using NumPy and Pandas for data preprocessing, TensorFlow and Keras for building and training the TCN, Matplotlib for visualization, and Scikit-learn for performance evaluation. The workflow included data collection, cleaning, normalization, and sequence preparation, followed by model development, training, evaluation, and visualization As shown in figure (3) .The code was organized in a modular structure to ensure clarity, maintainability, and ease of future improvement.

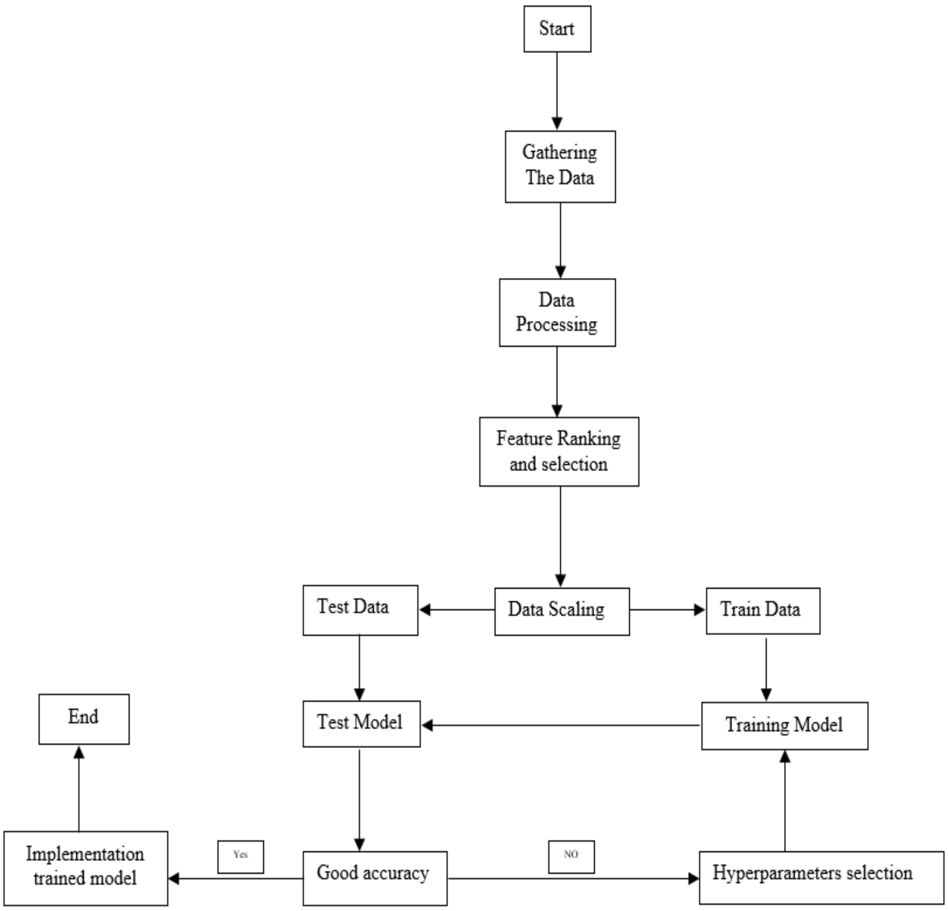

Figure 3 A simple visualization for the cod stracture and how it works

Table 1 A data samples for well 1

Well -1	
Date	**Oil prod /D**
1/3/2015	332
2/3/2015	360
3/3/2015	301
4/3/2015	328
5/3/2015	343
6/3/2015	342
7/3/2015	334
8/3/2015	318
9/3/2015	322
10/3/2015	337
11/3/2015	335
12/3/2015	318
13/03/2015	279
14/03/2015	374
15/03/2015	389
16/03/2015	335
17/03/2015	319
18/03/2015	368
19/03/2015	368
20/03/2015	366
21/03/2015	377
22/03/2015	358
23/03/2015	349
24/03/2015	304
25/03/2015	314
26/03/2015	191
27/03/2015	276
28/03/2015	293
29/03/2015	294
30/03/2015	338
31/03/2015	366
1/4/2015	305
2/4/2015	342
3/4/2015	337
4/4/2015	324

Table 2 A data samples for well 2

Well -2	
Date	**Oil prod /D**
14/07/2019	2255
15/07/2019	2260
16/07/2019	2290
17/07/2019	2324
18/07/2019	2350
19/07/2019	2374
20/07/2019	2397
21/07/2019	2399
22/07/2019	2401
23/07/2019	2436
24/07/2019	2490
25/07/2019	2511
26/07/2019	2514
27/07/2019	2540
28/07/2019	2495
29/07/2019	2490
30/07/2019	2465
31/07/2019	2390
1/8/2019	2340
2/8/2019	2330
3/8/2019	2332
4/8/2019	2332
5/8/2019	2370
6/8/2019	2377
7/8/2019	2399
8/8/2019	2444
9/8/2019	2459
10/8/2019	2450
11/8/2019	2437
12/8/2019	2410
13/08/2019	2392
14/08/2019	2396
15/08/2019	2420
16/08/2019	2425
17/08/2019	2430

Table 3 A data samples for well 3

Well -3	
Date	**Oil prod /D**
1/1/2020	1250
2/1/2020	1236
2/1/2020	1230
3/1/2020	1222
4/1/2020	1222
5/1/2020	1194
6/1/2020	1194
7/1/2020	1208
8/1/2020	1194
9/1/2020	1194
10/1/2020	1194
11/1/2020	1153
12/1/2020	1181
13/01/2020	1222
14/01/2020	1236
15/01/2020	1222
16/01/2020	1222
17/01/2020	1194
18/01/2020	1250
19/01/2020	1250
20/01/2020	1208
21/01/2020	1181
22/01/2020	1181
23/01/2020	1167
24/01/2020	1167
25/01/2020	1167
26/01/2020	1194
27/01/2020	1194
28/01/2020	1222
29/01/2020	1222
1/2/2020	1194
2/2/2020	1153
3/2/2020	1139
4/2/2020	1181
5/2/2020	1208

5/4/2015	303
6/4/2015	314
7/4/2015	342
8/4/2015	313

18/08/2019	2445
19/08/2019	2420
20/08/2019	2435
21/08/2019	2450

6/2/2020	1181
7/2/2020	1181
8/2/2020	1181

Results and Discussion

TCN Model Performance

Three wells were analyzed with the TCN model and with three different lookback windows of 3, 4, and 5 time steps. We found that model results varied based on the look-back size used; performance varies significantly from one time-frame to another.

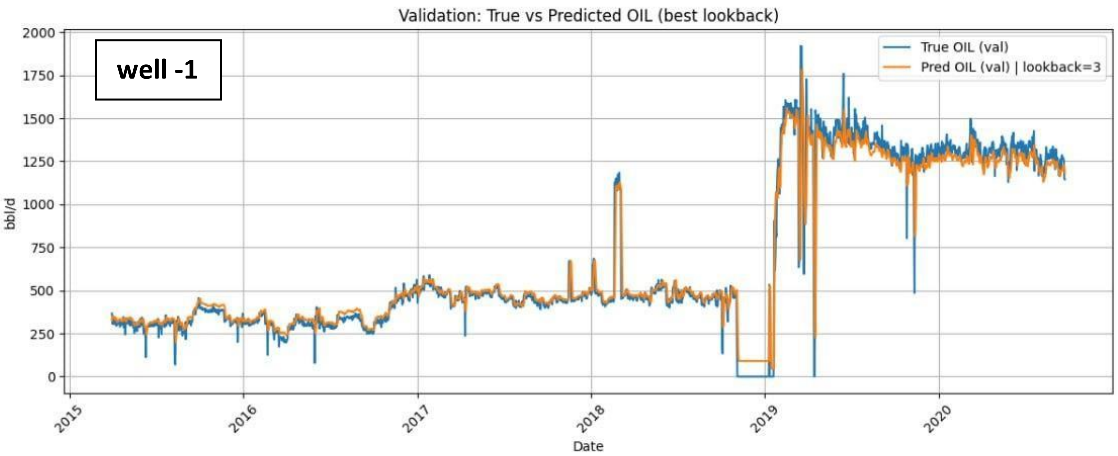

Figure 4 comparison between actual and Credicted oil production with time for well 1

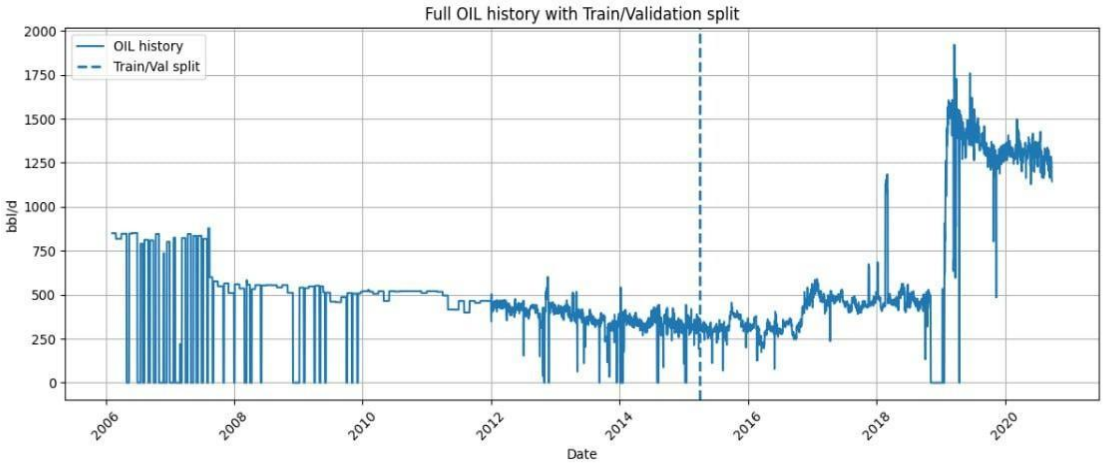

Figure 5 visualizing the Train/Validation aplite in production history chart for well 1

Table 4 The value of R*2 MAE RMSE of the three lookback for the well 1

LOOKBACK	MAE	RMSE	R2
3	46.640789	96.770019	0.955511
4	54.749096	104.577339	0.948042
5	58.276749	115.281534	0.936862

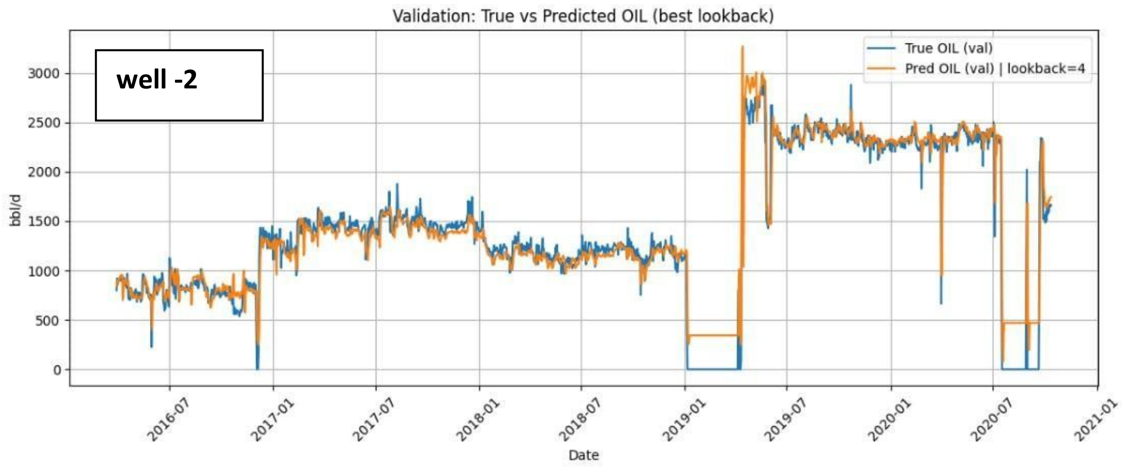

Figure 6 Comparison between actual and predicted oil production with time for well 2

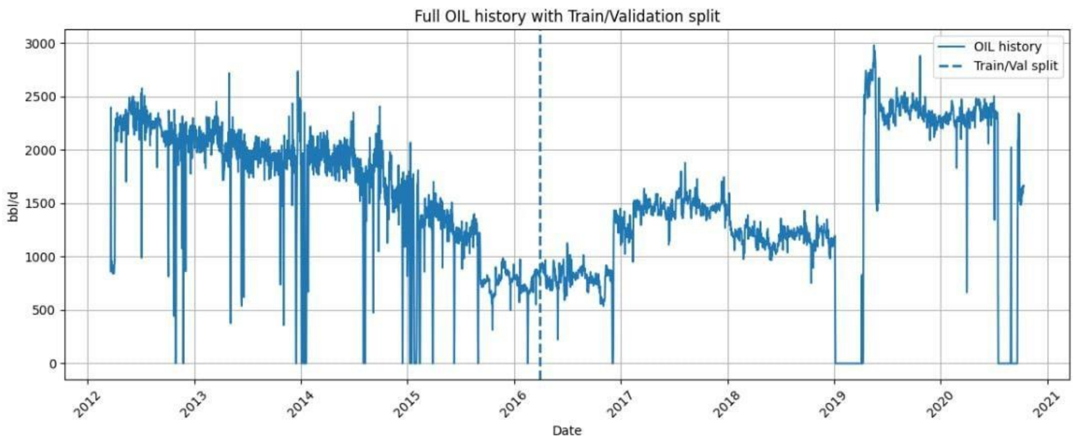

Figure 7 visualizing the Train/Validation aplite in production history chart for well 2

Table 5 The value of R*2 MAE RMSE of the three lookback for the well 2

LOOKBACK	MAE	RMSE	R2
4	117.729919	197.971599	0.925725
5	124.665855	207.578214	0.918342
3	173.059265	224.209384	0.904733

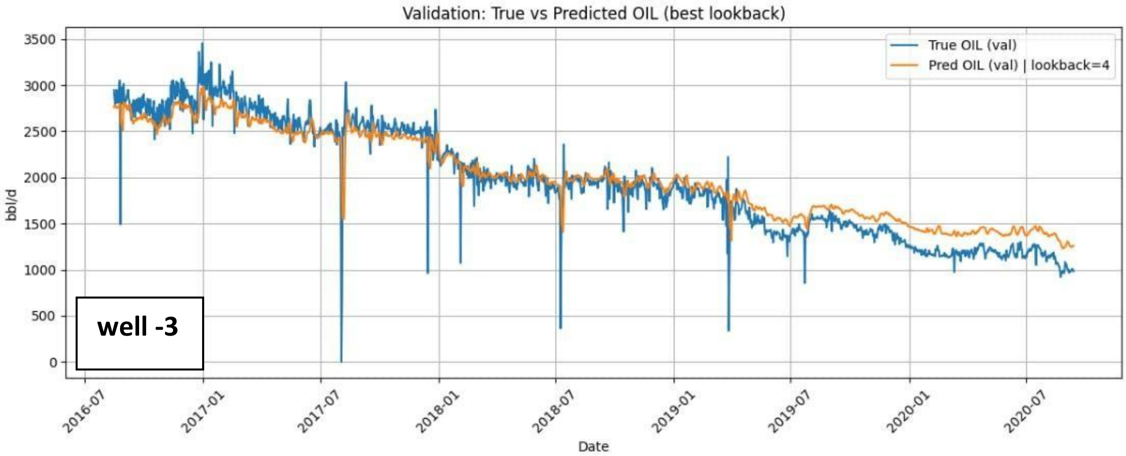

Figure 8 comparison between actual and predicted oil production with time for well 3

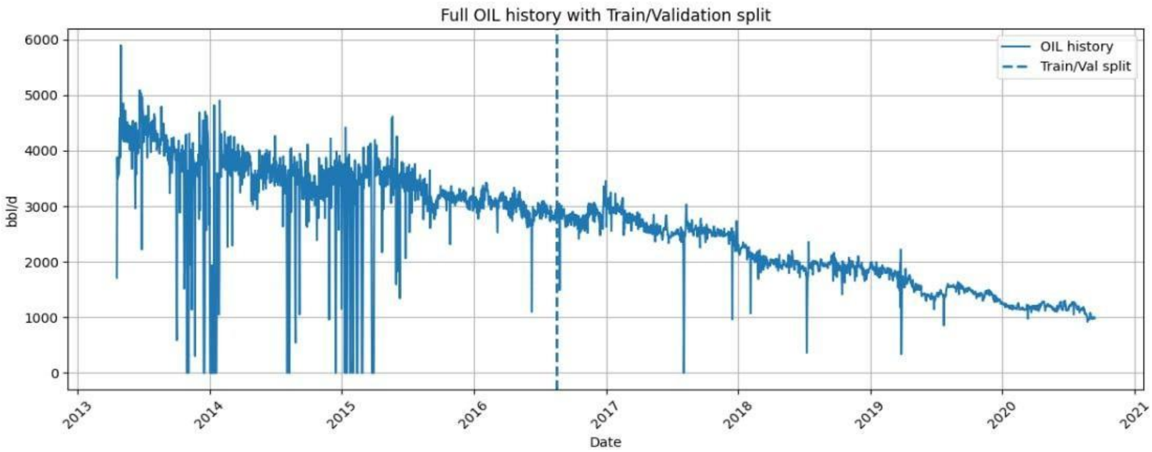

Figure 9 visualizing the Train/Validation aplite in production history chart for well 3

Table 6 The value of R*2 MAE RMSE of the three lookback for the well 3

LOOKBACK	MAE	RMSE	R2
4	147.313370	203.941168	0.885342
3	151.736221	206.923191	0.881965
5	193.835632	248.745312	0.82943

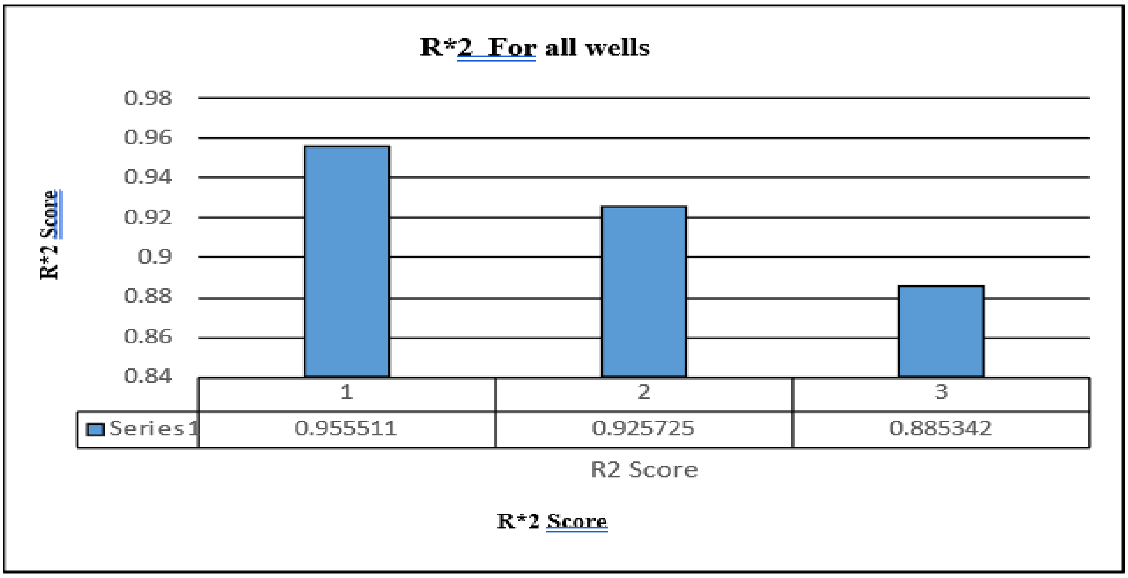

Figure 10 comparison between the value of R*2 for all wells

Table 7 each well and their best value of R*2 MAE RMSE of the three lookback

WELL NO.	LOCKBACK	MAE	RMSE	R2
Well -1	3	46.640789	96.770019	0.955511
Well -2	4	117.729919	197.971599	0.925725
Well -3	4	147.313370	203.941168	0.885342

Declin Curve Analysis

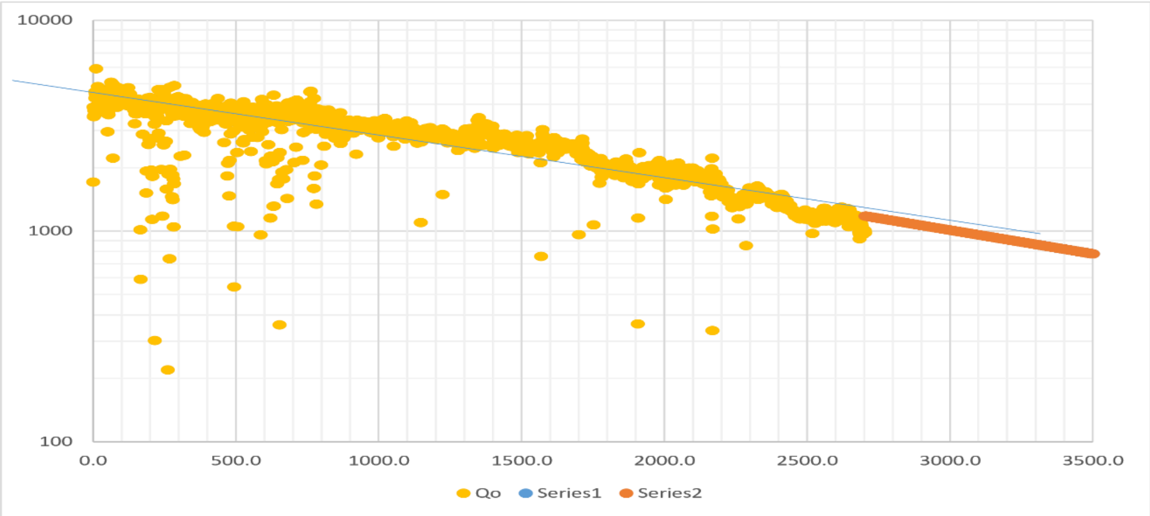

Figure 11 The actual and predicted oil production with time using exponential method for well 3

The **Decline Curve** Analysis model yielded the following results:

- **R^2 = 0.55 • RMSE = 665**

These results indicate relatively poor predictive performance compared to the TCN model.

Comparison of Results

The previous two approaches show a very large difference in performance, with the TCN model achieving R^2's >0.88 across all three wells and DCA only achieving 0.55 indicating that TCN provides a much larger explanation for variance in production data. Also, TCN's RMSE's range from 96 to 248 are well below DCA estimate of 665 and demonstrate TCN's superior prediction accuracy.

The variations in the production forecast (as measured by the derivative of the forecast) can be attributed to the following:

1. The Capability of the Model
DCA uses simplified empirical equations with a predictable decline of production per well, and therefore cannot accurately model complex reservoir behavior. TCN is a deep learning technology and can learn non-linear, dynamic extraction of production data over time.

2. How Temporal Relationships Are Handled
TCN explicitly models time order by having convolutional layers, and TCN has look-back windows for identifying past production behavior. DCA, on the other hand, does not appropriately use time history when developing a production forecast.

3. TCN is More Adaptable

TCN has the ability to adapt to multiple patterns of production by well and DCA has generalized decline assumptions.This study contributes to the existing body of knowledge by demonstrating the applicability of Temporal Convolutional Networks (TCN) for long-term oil production forecasting using historical production data from an Iraqi oil field. While previous regional studies have focused on production optimization and productivity assessment using conventional engineering methods such as gas-lift optimization, nodal analysis, and IPR evaluation [26,27], the present work highlights the capability of deep learning techniques to capture nonlinear production behavior and improve forecasting accuracy. The findings provide additional evidence supporting the adoption of advanced machine-learning approaches for reservoir management and production planning in Iraqi petroleum fields.

Conclusion

1. This study demonstrates that machine learning is an effective tool for predicting oil well production, achieving high predictive performance as indicated by strong R^2 values and acceptable error metrics.
2. Compared with traditional forecasting methods such as Arps decline curve analysis, machine learning models provided predictions that were closer to actual production data. This improvement is mainly due to their ability to capture complex non-linear relationships and dynamic reservoir behavior.
3. The results also showed that the lookback parameter significantly affects model performance. Selecting an appropriate lookback window improves the model's ability to capture temporal dependencies and enhances prediction accuracy.
4. Despite these advantages, machine learning models remain sensitive to data quality, outliers, and variations between wells. Their successful application requires sufficient, well-organized historical data, and model interpretation can be more challenging than with conventional methods.
5. This study contributes to the existing knowledge by demonstrating the applicability of machine learning techniques for oil production forecasting under the conditions of the selected field. The findings provide a practical framework for improving production prediction accuracy, supporting reservoir management decisions, and encouraging the adoption of data-driven approaches in the region's petroleum industry.

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