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Estimate oil production in Iraq using an artificial neural network

Zahraa Ghanim Younis [1], **Hudhaifa Hamzah** [2*], **Muhammed Alhasan** [3]
[1] *Department of Petroleum and Refining Engineering, College of Petroleum and Mining, University of Mosul, Mosul, IRAQ*
[2] *Department of Mining Engineering, College of Petroleum and Mining, University of Mosul, Mosul, IRAQ*
[3] *Department of Mechanical Engineering, Faculty of Engineering, Cukurova University, Adana, TÜRKİYE.*

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Correspondence:
Name: **Hudhaifa Hamzah**
Hudhaifahamzah@gmail.com

ABSTRACT

Estimating petroleum production is crucial in strategic planning and decision-making within the petroleum industry. In this study, we propose the use of artificial neural network (ANN) methods, implemented through MATLAB software, to forecast petroleum production in Iraq, a major oil-producing nation with vast reserves and complex geological characteristics. By using 50 years of historical production data (1973–2023) and a range of relevant input factors, including (1) normal conditions, (2) wartime conditions, (3) economic blockade conditions, and (4) epidemic conditions, we used and train ANN models to estimate future petroleum production levels in Iraq over the next five years (2024–2028). The study compares the ANN estimation results with the Iraqi Oil Ministry's official production plan for the same period. According to the Ministry's plan, production is expected to reach 7 million barrels per day (Mb/d) by the end of 2028. The ANN model forecasts indicate that, under normal conditions, the Ministry can achieve its planned production target with a maximum margin of error of 2.7%, corresponding to a shortfall of approximately 0.189 Mb/d. However, in scenarios affected by war, economic blockades, or epidemics, the ANN estimations show that these factors could negatively impact production, hindering the achievement of the planned target by up to 80% in the worst-case scenario.

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تقدير إنتاج النفط في العراق باستخدام الشبكة العصبية الاصطناعية

زهراء غانم العلاف[1]، **حذيفة رعد حمزة**[2*]، **محمد الحسن**[3]

[1] *قسم هندسة النفط والتكرير، كلية هندسة النفط والتعدين، جامعة الموصل، الموصل، العراق*

[2] *قسم هندسة التعدين، كلية هندسة النفط والتعدين، جامعة الموصل، الموصل، العراق*

[3] *قسم الهندسة الميكانيكية، كلية الهندسة، جامعة شوكوروفا، أضنة ، تركيا*

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المراسلة:

الاسم: **حذيفة رعد حمزة**

Hudhaifahamzah@gmail.com

الملخص

يُعد تقدير إنتاج النفط أمرًا بالغ الأهمية في التخطيط الاستراتيجي وصنع القرار ضمن قطاع الطاقة. في هذه الدراسة، نقترح استخدام تقنيات الشبكات العصبية الاصطناعية (ANN) المُنفذة عبر برنامج الماتلاب MATLAB للتنبؤ بإنتاج النفط في العراق، باعتباره أحد أبرز الدول المنتجة للنفط، والتي تتميز باحتياطيات ضخمة وخصائص جيولوجية معقدة. تم استخدام بيانات الإنتاج التاريخية على مدى خمسين عامًا (1973–2023)، إلى جانب مجموعة من العوامل المدخلة، تشمل: (1) الظروف الطبيعية، (2) ظروف الحرب، (3) الحصار الاقتصادي، و(4) الظروف الوبائية. تم تدريب نماذج الشبكات العصبية على هذه البيانات لتقدير مستويات الإنتاج المستقبلية خلال الفترة 2024–2028. تُقارن الدراسة نتائج تقديرات الشبكات العصبية الاصطناعية بخطة الإنتاج الرسمية الصادرة عن وزارة النفط العراقية للفترة نفسها، والتي تستهدف الوصول إلى 7 ملايين برميل يوميًا بحلول نهاية عام 2028. وتشير نتائج نموذج الشبكات العصبية الاصطناعية إلى أن تحقيق هذا الهدف ممكن في ظل الظروف الطبيعية، مع هامش خطأ لا يتجاوز 2.7%، أي ما يعادل عجزًا يُقدَّر بنحو 0.189 مليون برميل يوميًا. ومع ذلك، تُظهر التقديرات أنه في ظل سيناريوهات الحرب أو الحصار أو الأوبئة، قد يتأثر الإنتاج سلبًا بشكل كبير، مما قد يُعيق تحقيق الهدف بنسبة تصل إلى 80% في أسوأ الحالات.

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Introduction

Oil is a vital economic resource for Iraq, which holds the world's second-largest proven oil reserves, estimated at approximately 114 billion barrels—potentially reaching up to 260 billion barrels if probable reserves are included. The early discovery of oil in Iraq made it a focal point for major powers, such as Britain and the United States, while also becoming a critical element in the strategic calculations of neighbouring countries, including Turkey and Iran. Consequently, Iraqi oil has historically been a central factor in regional power struggles and political ambitions. Western companies controlled Iraq's oil until national decisions in 1961 and 1972 allowed Iraq to reclaim a significant portion of its oil revenues, with 95% of the oil fields returned to Iraqi control. Furthermore, decisions made by the Organization of the Petroleum Exporting Countries (OPEC) strengthened Iraq's role in the global oil market, notably after the 1967 decision to cut oil exports to certain countries, thereby asserting greater control over national resources (U.S. EIA, 2022). On the global stage, oil exploitation became more organized with the formation of the so-called "oil cartel" in 1928, involving major companies such as Exxon, Shell, and British Petroleum. These corporations dominated the market until the establishment of OPEC in 1960, which gradually gained influence and today controls about 40% of the world's oil supply. The oil and natural gas industry remains critical to the global economy, with oil projected to account for 36.5% of total energy demand by 2030, according to OPEC. However, the industry faces significant challenges, particularly regarding the optimization of asset and equipment utilization, largely due to the lack of appropriate data analysis tools. Advanced data analysis is vital for enhancing operational efficiency, improving extraction techniques, drilling accuracy, and maintenance management. Leveraging these tools can help bridge a performance gap currently estimated at $200 billion, thereby substantially increasing production efficiency (Oil Companies, 2023; Al Jazeera, 2013). Estimations of future production and the potential recoverable oil reserves of petroleum wells are critical for achieving cost-effective operations in the petroleum industry. However, accurately estimating production is a challenging task due to uncertain and complex underground conditions (Costello, 2018). Traditionally, reservoir engineers rely on time-consuming numerical simulations as the primary basis for estimating oil production outcomes. At the same time, there is a vast amount of underutilized data readily available from internal company records and public databases, which can be leveraged to build estimative models for oil production (Zhou et al., 2024). In this study, historical oil production datasets are analyzed to classify production patterns based on geological variables (Li et al., 2013), aiming to develop more efficient and reliable forecasting models. Previous attempts at data-driven reservoir production estimation have typically employed two main approaches: decline curve fitting and artificial neural networks (ANNs). Most existing decline curve analysis techniques are based on empirical equations, including the exponential, hyperbolic, and harmonic models (Li & Horne, 2003). However, a major limitation of this method is the difficulty in identifying which equation best describes a given reservoir's production behavior. Additionally, a single decline curve often cannot accurately represent the entire lifecycle of a reservoir. The curve-fitting process can become complex, making it prone to unreliable estimations and misinterpretations (El-Banbi & Wattenbarger, 1996). More recent efforts have turned to artificial neural networks (Nguyen et al., 2004; Weiss et al., 2007), which have demonstrated a superior ability to closely fit production data. Nevertheless, these models often suffer from a lack of interpretability, making it difficult for engineers to understand the relationships between inputs and outputs, a crucial aspect in decision-making and operational planning. Decision tree learning (DTL) has emerged as one of the most widely used methods for classification problems in data analysis. In petroleum engineering, DTL has been applied successfully to a variety of tasks. For instance, Perez et al. (Perez et al., 2007) utilized decision trees to classify permeability estimations based on well log data, while Jensen (Jensen, 1998) applied decision tree analysis to estimate the range of uncertainty in reservoir production forecasts. Most DTL algorithms perform univariate attribute testing at each node, but this approach can encounter significant challenges when input attributes are interdependent (Lee et al., 2006; Lee & Yen, 2002). In petroleum production forecasting, some of the core analysis parameters, such as porosity and permeability, have been found to be critical. However, such parameters are usually interdependent. For example, permeability, which measures the level of ease through which oil flows in reservoir rocks, is highly correlated with porosity, which measures the space in such rocks. Such interdependencies introduce distortions to the true underlying relationships between input and output variables, which will lead to poor or biased models. Preprocessing data to remove such interdependencies is not possible, as the special nature of these dependencies is rarely known. The Nonlinear Decision Tree (NDT) model has been devised for this (Lee et al., 2006; Yen & Lee, 2011). The NDT model utilizes artificial neural networks to automatically extract and eliminate underlying attribute dependencies that are not readily observable by human analysts, thereby improving model reliability and estimative accuracy (Yuan et al., 2021). This study focuses on the difficulty in accurately estimating Iraq's future oil production due to complex geological conditions, historical factors such as wars and sanctions, and the lack of effective data-driven analytical tools. Traditional forecasting methods often fail to capture these complexities, resulting in unreliable forecasts. This study aims to develop a robust estimation model using artificial neural networks (ANNs) to provide more accurate and adaptable oil production forecasts under various practical scenarios. The model is intended to support strategic planning and decision-making in Iraq's oil industry. Due to the limited interpretability of artificial neural network models, especially in understanding the complex relationships between reservoir properties such as porosity and permeability, this study adopted a scenario-based approach that relies heavily on historical production sequences. Rather than focusing on the subsurface reservoir characteristics, which are often interdependent and uncertain, the model was trained using 50 years of production data divided into four strategic conditions: normal operations, wartime disruptions, economic blockades, and pandemic impacts. This approach enables the artificial neural network to learn from real responses to major geopolitical and economic events in history, thereby providing more scenario-sensitive future oil production estimates without the need for precise interpretation of reservoir parameters. Therefore, the present research suggests the implementation of Artificial Neural Network (ANN) techniques, executed on MATLAB software, in forecasting Iraqi oil production. Iraq remains one of the world's leading producers of oil due to the enormity of its reserves and complex geology. Applying five decades of production history data (1973–2023) and a selected list of key input parameters such as natural conditions, wartime disturbances, economic sanctions, and pandemic effects, ANN models are built and trained to forecast future levels of oil production during the period 2024–2028. They are compared with the Iraqi Ministry of Oil's 2028 strategy plan, which is to achieve a production level of 7 million barrels per day by the end of 2028. The results of these comparisons give hints on the robustness of Iraq's production plan under various possible future scenarios.

Methodology

This section includes the data preparation and definition of the neural network parameters used. The methodology adopted in this study aims to ensure accurate estimation of oil production under different operating scenarios.

General Description of Artificial Neural Network (ANN)

Artificial neural networks (ANNs) are computational systems inspired by the biological neural networks found in the human brain. They consist of layers of interconnected artificial neurons that transmit and process data through adjustable weighted connections. Each neuron receives inputs, processes them using an activation function, and passes the result to the next layer. In this study, the ANN is employed to establish a mathematical relationship between historical oil production data and influencing factors across different scenarios, rather than to identify specific patterns. This allows the model to estimate future production values based on previously observed outcomes (Lee et al., 2006). A mathematical function represents each of the multiple layers of artificial neurons that make up this computer system. Each neuron is often connected to every other neuron in the neighboring layers, and a network weight or parameter indicates how strong the connections are. The ANN mimics the biological phenomena of neuroplasticity by varying these parameters, which are the fundamental mechanisms of long-term memory in the ANN (Yen & Lee, 2011). An artificial neuron is schematically represented in Figure 1, where φ is the activation function, x_m is the input value from the preceding layer, w_{km} is the weight, and v_k is the summation result (Mursina, 2010).

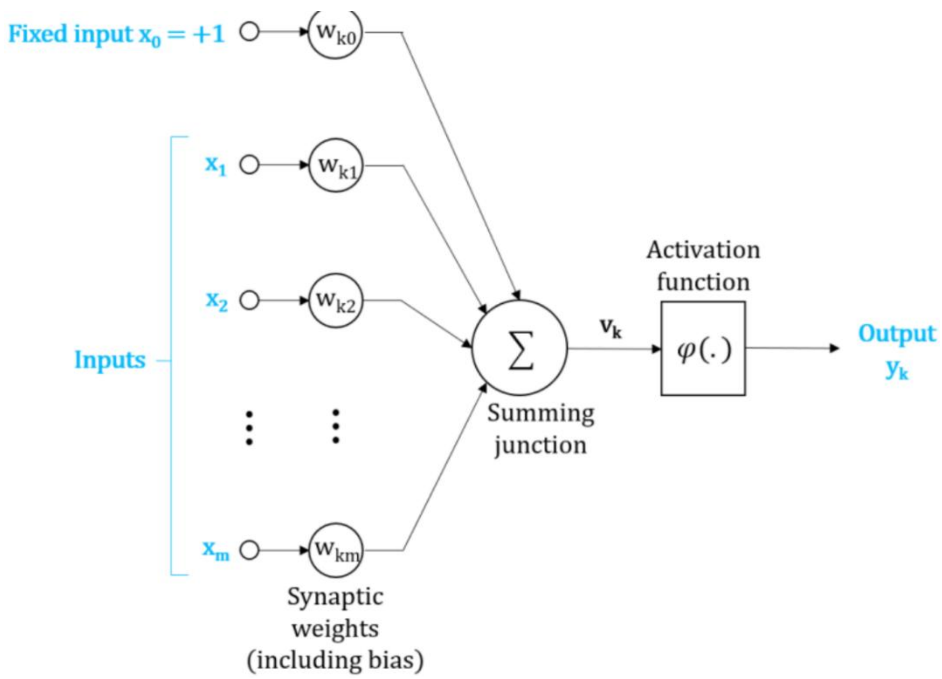

Figure 1. Model of a simple artificial neural network.

In Figure 1, an artificial neuron applies a weighted summation with the synaptic weights as coefficients to input values received from a different layer. The intermediate value v_k, which represents the complete electrical signal received by the neuron, is the outcome of this summation. This value is then passed into the activation function, which produces the neuron's output $\boldsymbol{y_k}$ by simulating the electrical signal's transmission inside a biological neuron. The following formulae reflect the summation and the neuron's activity, respectively (Krenker et al., 2011):

$$\boldsymbol{v_k = \sum_{j=0}^{m} w_{kj} x_j} \qquad (1)$$

$$\boldsymbol{y_k = \varphi\ (v_k)} \qquad (2)$$

Selection of ANN

The concept of neurons, transfer functions and connections is the essential element of ANNs. The similarity between the different structures of ANN can be found in many studies. The majority of the variation stems from the various learning rules, as well as how these rules modify a network's typical topology. Generally, most applications of ANN include the following four categories: estimation, classification, data association and Data association (Haykin, 2008).

Modeling Procedure

The modelling procedure adopted in this article is organized into four distinct phases: data collection and organization, statistical analysis, the estimation model creation and evaluation, and the generation of forecasts based on the related scenarios. A flowchart diagram is presented in Figure 2 to guide the descriptions for each phase, with different colours representing distinct phases.

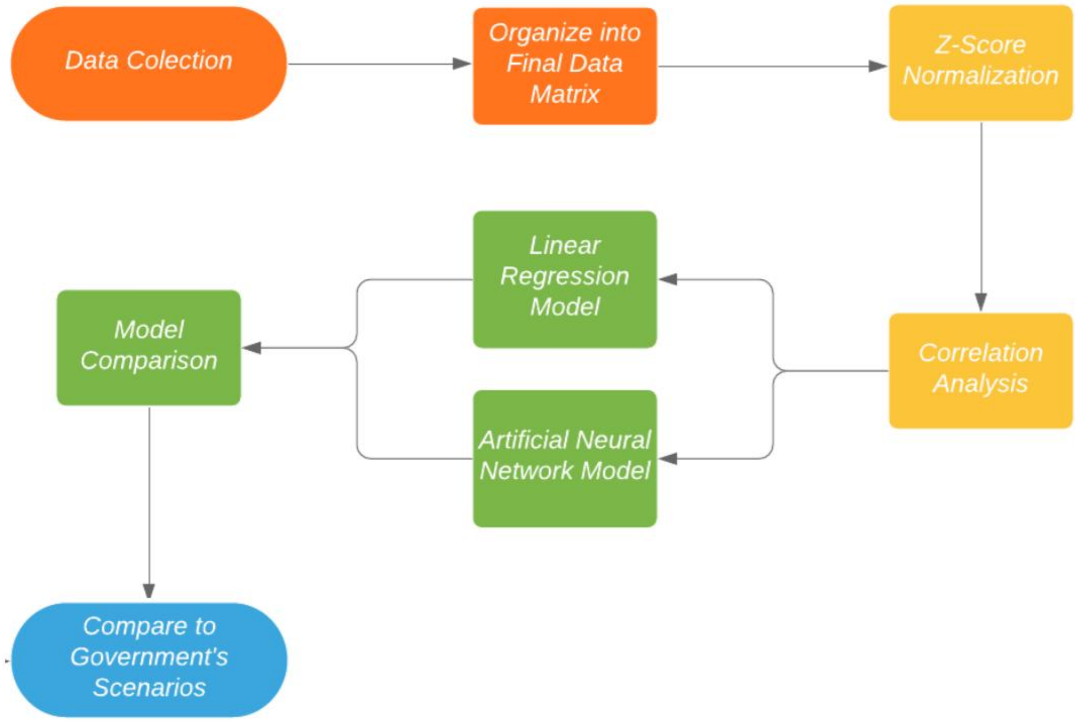

Fig. 2. Process flowchart of the current study.

Data Collection

Iraq's oil ministry plans to lift crude oil production capacity to 7 Mb/d by 2027 and will target several upstream expansion projects from fields in southern Iraq to bolster the country's output (Iraqi Ministry of Oil, 2023). Some of these projects are likely to be delayed because of Iraq's political struggles, regulatory challenges, delays in restoring and expanding the southern export infrastructure, and the international oil companies' uncertainty about the investment climate. Several new projects are planned, along with capacity expansion and upgrades at several existing production industries. Table 1 gives information on crude oil projects in Iraq (U.S. EIA, 2023).

Table 1. Information on crude oil projects in Iraq (U.S. EIA, 2023).

Field name	Operator or project investor	Additional capacity (thousand of barrels per day)	Announced start date
Missan Cluster (Bazergan, Fakka, and Abu Gharb fields)	China's CNOOC	100	November 2022
Majnoon	Basra Oil Company	200	End–2023
Zubair	ENI	50	End–2024

Faihaa crude oil processing facility	**China's United Energy Group**	**100**	**Second half 2024**
Ratawi	**TotalEnergies**	**130**	**2025**
West Qurna-1	**ExxonMobil and Basra Oil Company**	**330**	**2028**
Fields in the Dhi Qar province (Nasariya, Gharaf, and Subba)	**Dhi Qar Oil Company (DQOC)**	**310**	**2028**
Eridu	**Lukoil**	**250**	**2028**
West Qurna-2	**Lukoil**	**330**	**2030**

Database

In the present study, we collected data on oil production in Iraq from 1973 to 2023, sourced from the U.S. Energy Information Administration website (U.S. EIA, 2023). Figure 3 illustrates Iraq's oil production trends over the past fifty years, highlighting significant fluctuations influenced by economic, political, and other factors during this period. The first noticeable decline occurred during the Iran-Iraq War (1980–1988), when oil production was severely affected. Most of Iraq's production fields, located in the southern region, were on the frontlines of the conflict. Following the war, production rebounded slightly between 1988 and 1991. However, this recovery was interrupted by the outbreak of the Gulf War in 1991. The lowest production levels were recorded during the period of economic sanctions imposed on Iraq. This sharp decline resulted from the withdrawal of most international companies and the shutdown of several fields damaged during the Gulf War. During this time, Iraq relied heavily on local companies to maintain production and rehabilitate affected fields. With the lifting of economic sanctions, production gradually increased, reaching nearly 2 million barrels per day. However, another decline occurred in 2003 following the war that led to a regime change in Iraq, once again disrupting oil production.

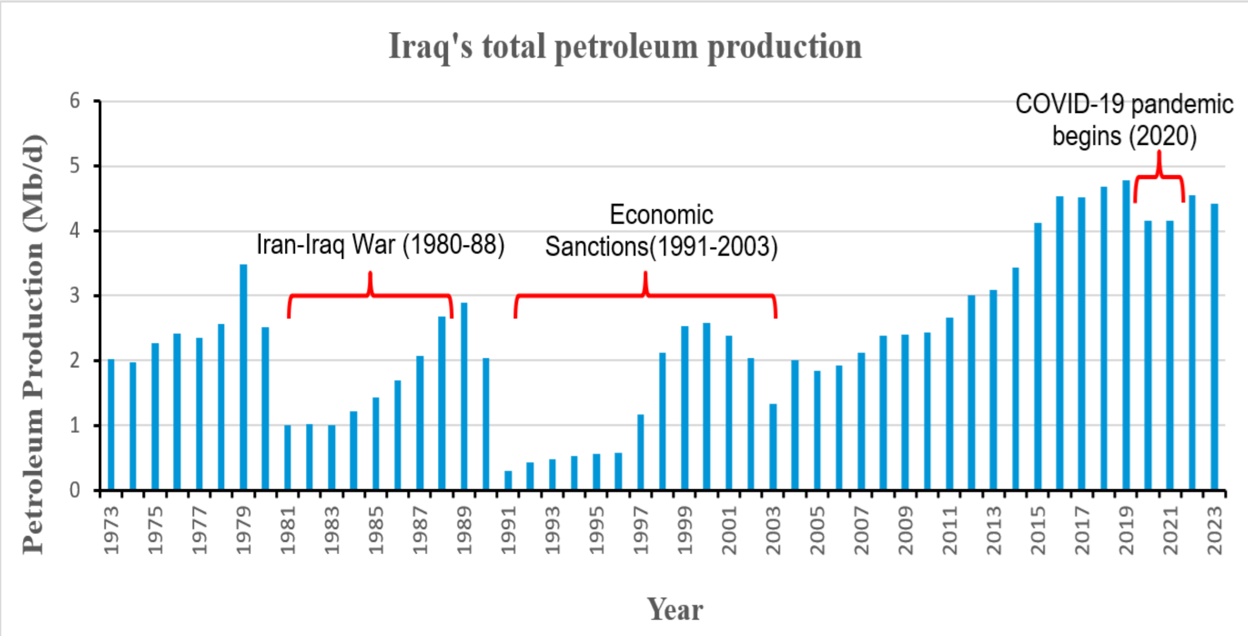

Fig. 3. Petroleum production in Iraq over the last 50 years (1973-2023).

Test and Training

A generalized artificial neural network (ANN) structure was utilized in this study (Hassoun et al., 1996). The ANN architecture was implemented using MATLAB (Anghel et al., 2014). The model employed a multiple-input, single-output dataset, with the inputs representing the petroleum production year and the impact scenario, while the output corresponded to petroleum production in million barrels per day (Mb/d). The parameters and their respective values used in the model are listed in Table 2. The dataset covers 50 years of petroleum production, resulting in 50 input values, each associated with four different parameter cases, resulting in 200 total data points. These inputs were used to train the ANN model. For modeling purposes, the data was divided into two subsets: a training set and a testing set. Specifically, 40 years of data (from 1973 to 2013) were used for training, while the remaining 10 years (from 2014 to 2023) were allocated for testing. For model development, 80% of the data were used for training, and 20% were used for testing. The implemented ANN model consists of 10 hidden layers, as illustrated in Figure 4. The training phase included a validation set split from the training data (typically 15% of the training) to prevent overfitting. The performance was monitored using mean squared error (MSE), and early stopping was applied when the validation error ceased to improve. The mathematical formulation for MSE is:

$$\mathbf{MES} = \frac{1}{2}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (3)$$

Where:

n is the number of samples.

y_i is the actual value for the i^{th} sample.

$\hat{y}_i$ is the estimated value for the i^{th} sample.

The MES is validated through comparison of training and testing datasets, as shown in Figure 5. This figure illustrates the mean squared error (MSE) progression over training epochs for both the training and validation sets. The convergence of the two curves indicates successful model learning with minimal overfitting. The validation set was used to monitor generalization performance, and early stopping was employed to prevent overtraining. The results demonstrate a convergence between the training and testing outputs, indicating that the model is reliable and can be used with confidence. Finally, Figure 6 presents the regression analysis performed on the validation dataset using the trained ANN model, further confirming its estimative capability. This figure presents the regression plot comparing actual petroleum production values with those estimated by the ANN. The proximity of data points to the 45-degree reference line (y = x) and the high correlation coefficient (R-value) demonstrate strong agreement between predicted and actual outputs. This confirms the model's accuracy and reliability in estimating production under varying conditions. After training, the model's accuracy was assessed using the test set. The ANN was adapted for estimation by training on structured input scenarios reflecting real operational influences, allowing it to generalize across diverse future conditions. New data can be fed into the trained model to estimate future production, and if results are unsatisfactory, retraining with more data or tuning the number of neurons, learning rate, or training algorithm is recommended. The percentage errors for both training and testing were computed by comparing predicted and actual values year by year and averaging the differences as a percentage of the actuals.

Table 2. Data sets used for estimation, different parameters, and their values.

Input Parameters			Output
Years	Impact Case		
1973-2023	Normal Case	1	Petroleum Production in Mb/d
	War Case	2	
	Economic Blockade Case	3	
	Epidemic Case	4	

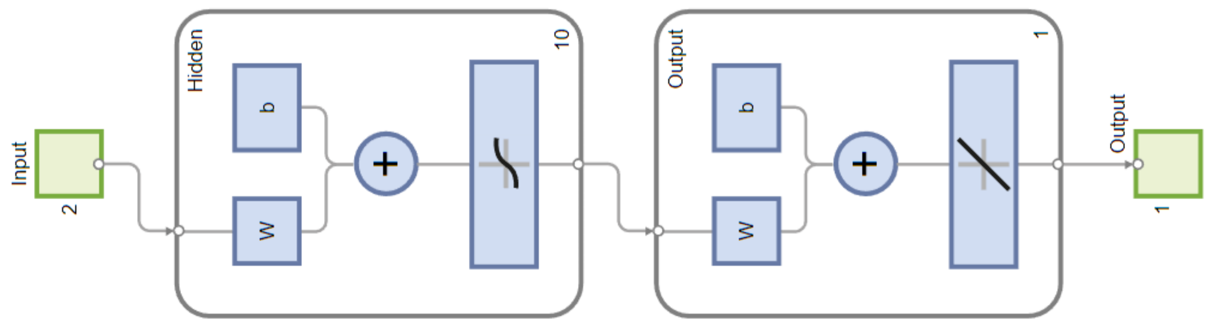

Fig. 4. Implemented a network in this work.

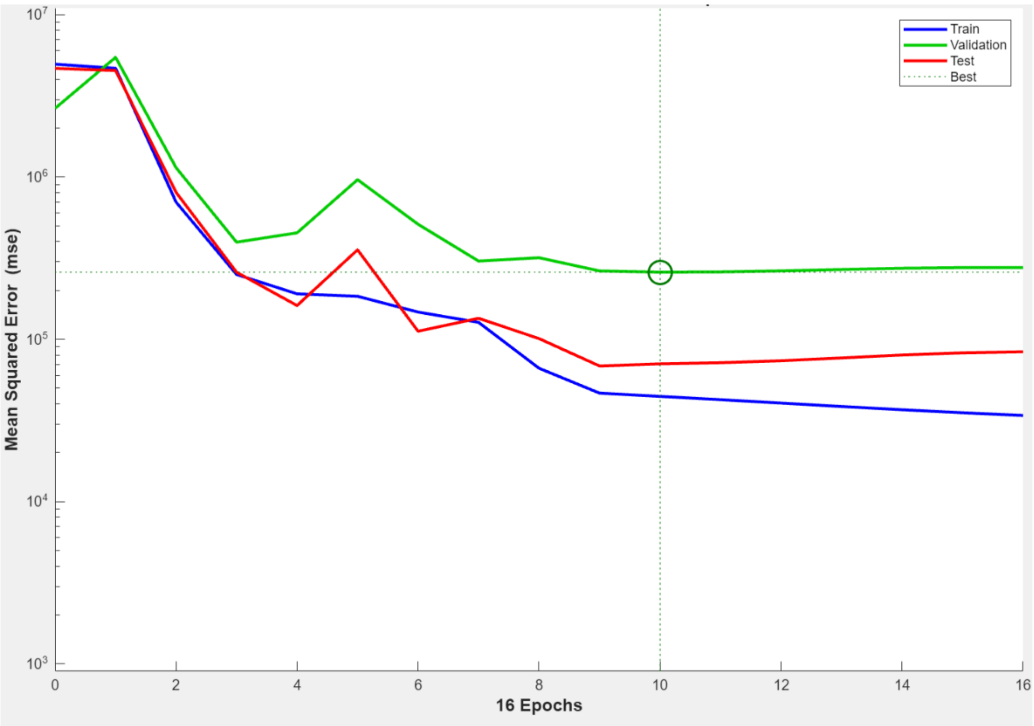
Train
Validation
Test
Best
Mean Squared Error (mse)
16 Epochs

Fig. 5. Mean Squared Error (MSE) performance curve for training and validation sets during the training process of the ANN model for petroleum production estimation.

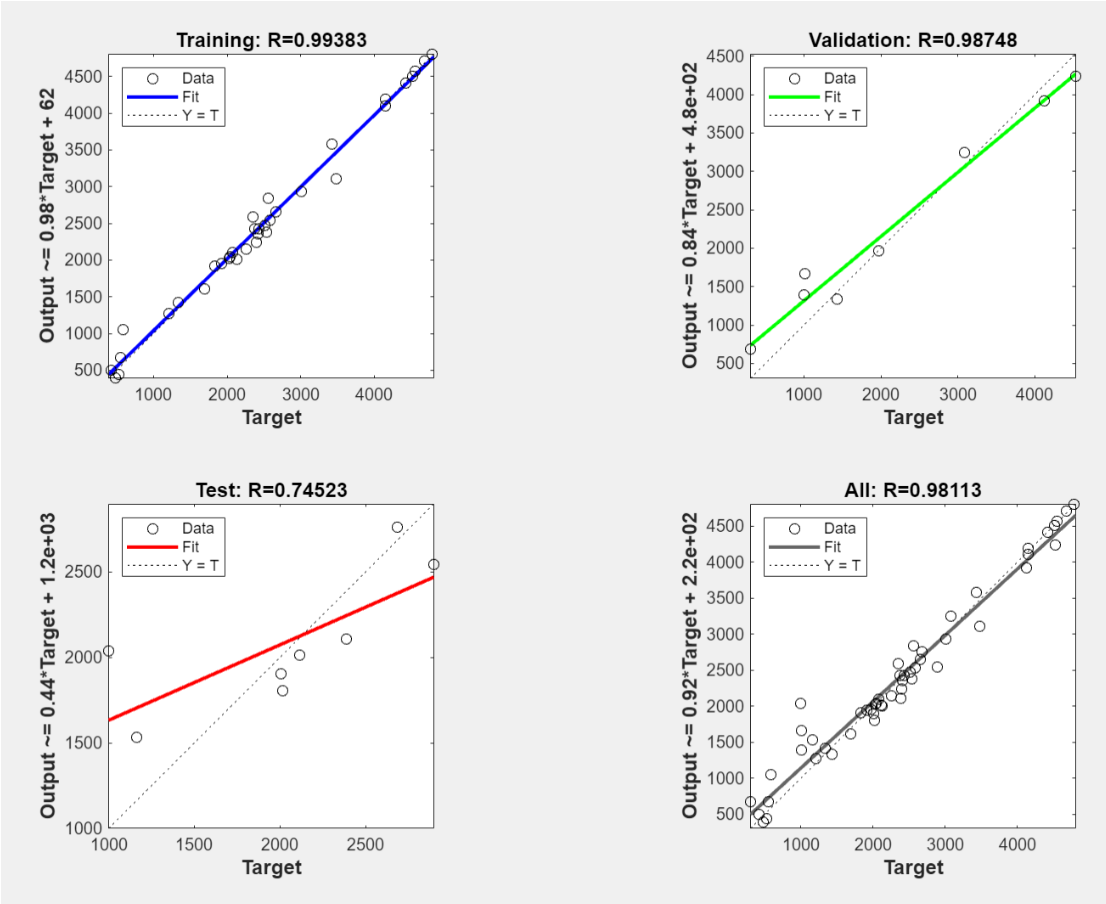

Fig. 6. Regression analysis between actual and estimated petroleum production values using the trained artificial neural network (ANN) model on the validation dataset.

Results and Discussion

This study presents the estimated results obtained using MATLAB based on the artificial neural network (ANN) method. Further, this study compares the results of ANN with the Iraqi Oil Ministry's plan for the next five years (2024-2028). Previous data on Iraqi petroleum production over the past fifty years (1973-2023) showed the presence of four factors that influenced production levels. The factors that affected the production quantity are as follows: (1) the normal situation, (2) the war situation, (3) the economic blockade situation and (4) the epidemic situation. Therefore, the results were shared, represented and compared with the expected results for production levels according to the Iraqi Oil Ministry plan. This section presents the results of each influential case and compares them with the Oil Ministry's plan. These results are presented in figures in the form of five-year curves for each influencing factor. In addition to displaying a data table showing the percentage difference between the plan and the artificial intelligence estimation results, as well as the amount of error between the two values for each year. The percentage of error in Tables 3 through 7 was calculated using the following formula:

$$\textbf{Error}\ \% = \left(\frac{\textbf{Estimated Value} - \textbf{Planned Value}}{\textbf{Planned Value}}\right) \times \mathbf{100} \qquad (4)$$

In this study, negative error percentages indicate that the estimated production is lower than the planned production. This is scientifically reasonable and expected in scenarios where external conditions (e.g., war, economic blockade, epidemics) negatively impact operational capacity.

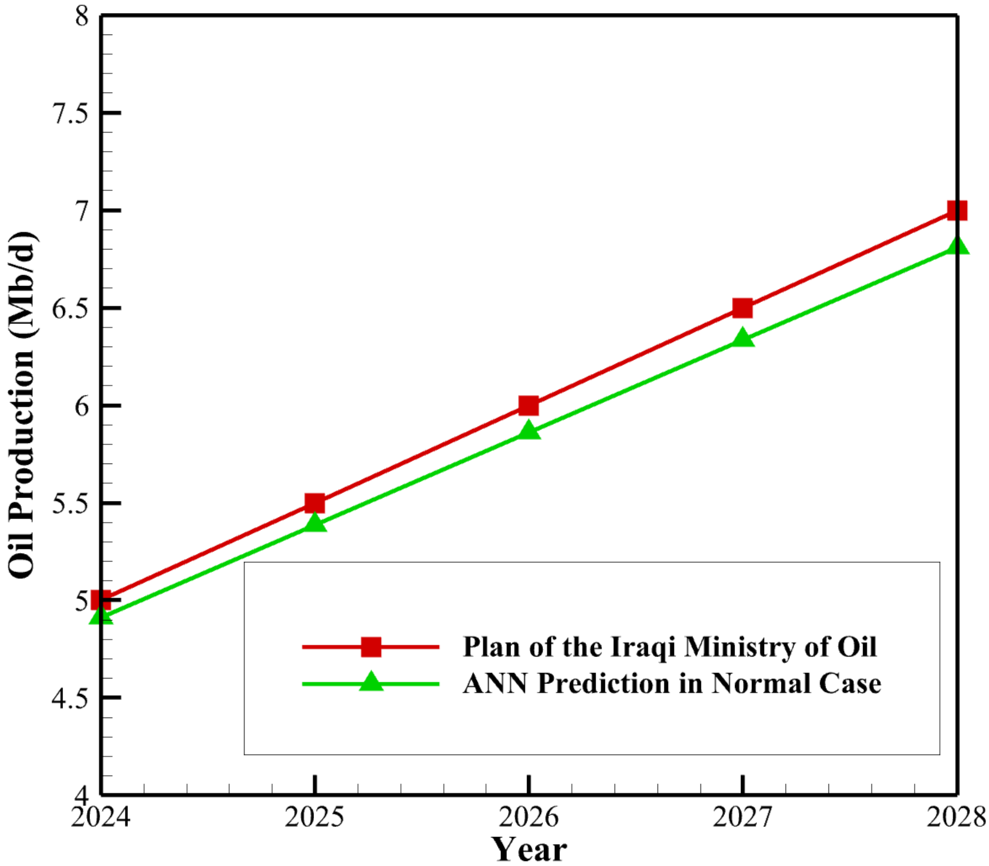

Fig. 7. Comparison of oil production between the Iraqi Oil Ministry plan and the ANN-based forecast data for the next 5 years in the case of a normal situation.

Table 3. Oil production results according to the Iraqi Oil Ministry plan and the ANN-based forecast data for the next 5 years in the case of a normal situation.

Year	Oil Ministry Plan (Mb/d)	Normal Case (Mb/d)	Difference	Error%
2024	**5**	**4.910175**	**-0.08982**	**-1.79649**
2025	**5.5**	**5.385175**	**-0.11482**	**-2.08772**
2026	**6**	**5.860175**	**-0.13982**	**-2.33041**
2027	**6.5**	**6.335175**	**-0.16482**	**-2.53576**
2028	**7**	**6.810175**	**-0.18982**	**-2.71178**

Figure 7 shows the comparison between the Iraqi Oil Ministry's plan and the artificial intelligence estimations under normal conditions without the influence of war, economic crises, or health emergencies. According to this figure, the Ministry's plan consistently estimates higher production levels than those estimated by artificial intelligence. The red line represents the Ministry's plan, while the green line indicates the artificial intelligence estimations. The error margin slightly increases as the forecast progresses. In 2024, the error was relatively small, but by 2028 it had grown. As shown in Table 3, the maximum difference occurred in 2028, reaching 0.189 Mb/d, which corresponds to an error of 2.7% compared to the Ministry's plan. The smallest difference was recorded in 2024 at 0.089 Mb/d, with an error of 1.79%. This discrepancy may be attributed to production challenges, technical errors in data recording systems, or inaccurate and inefficient data entry. Despite this, artificial intelligence demonstrates superior capabilities in performing complex calculations and analyses with speed and accuracy, and can identify issues affecting production estimations. Nevertheless, the overall difference between the Ministry’s plan and the artificial intelligence estimates under normal conditions remains relatively minor.

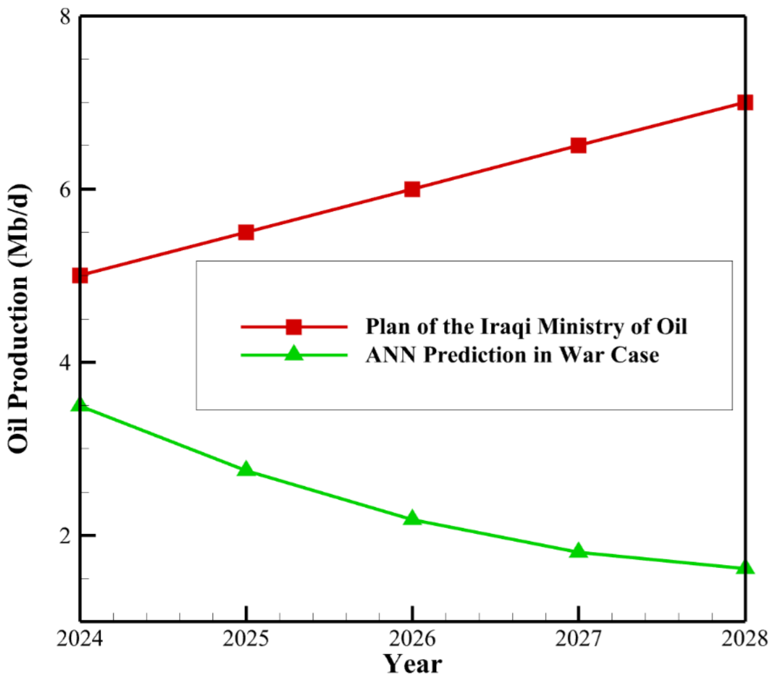

Fig. 8. Comparison of oil production between the Iraqi Oil Ministry plan and the ANN-based forecast data for the next 5 years in the case of a war situation.

Table 4. Oil production results according to the Iraqi Oil Ministry plan and the ANN-based forecast data for the next 5 years in the case of a war situation.

Year	Oil Ministry Plan (Mb/d)	War case (Mb/d)	Difference	Error%
2024	**5**	**3.495175**	**-1.50482**	**-30.0965**
2025	**5.5**	**2.743175**	**-2.75682**	**-50.1241**
2026	**6**	**2.179175**	**-3.82082**	**-63.6804**
2027	**6.5**	**1.803175**	**-4.69682**	**-72.2588**
2028	**7**	**1.615175**	**-5.38482**	**-76.9261**

Figure 8 presents a comparison of petroleum production between the Iraqi Oil Ministry's plan and the ANN-based forecast for the next five years under wartime conditions. The red line represents the Ministry's plan, which assumes normal circumstances free from emerging crises, while the green curve reflects the artificial intelligence estimation considering the war scenario. The figure clearly indicates a significant disparity between the ANN forecast and the Ministry's plan, with the gap widening substantially over time. By 2028, the largest difference between the two projections was recorded. According to Table 4, the maximum difference in 2028 reached 5.38 Mb/d, corresponding to an error of 76.9% relative to the Ministry's plan. The smallest difference occurred in 2024 at 3.49 Mb/d, representing an error of 30.09%. These findings highlight the complex and multifaceted impacts of war on petroleum production, which have far-reaching consequences for global energy markets, geopolitical stability, environmental sustainability, and human welfare. Mitigating such impacts often requires coordinated international efforts, conflict resolution strategies, and sustainable development initiatives.

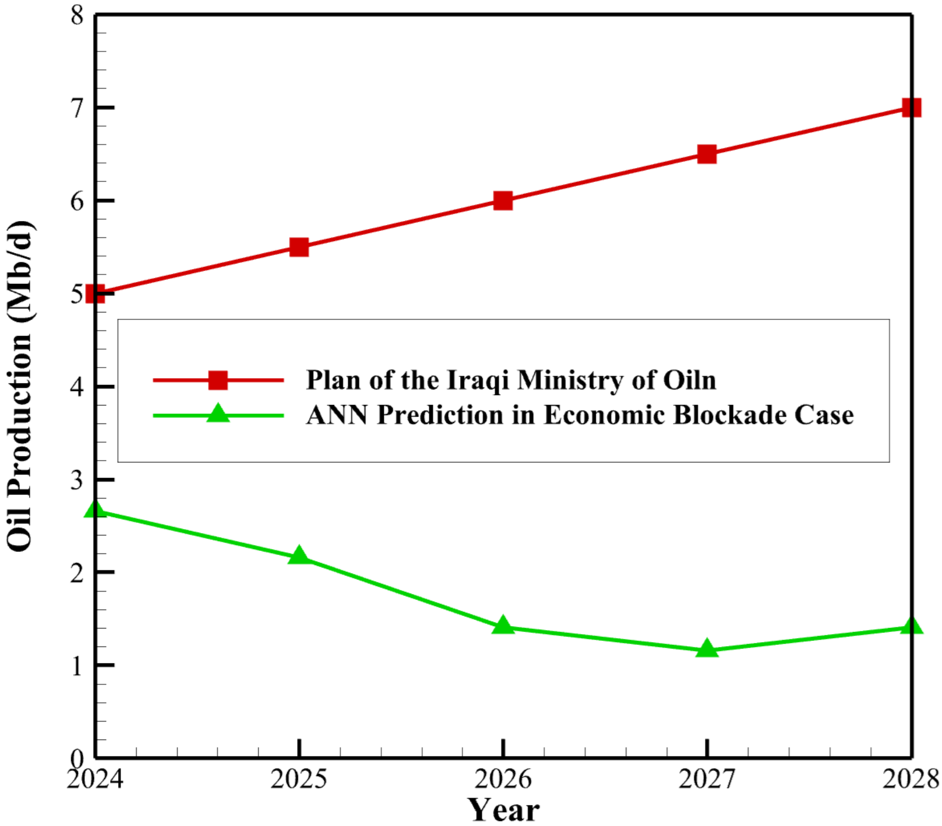

Fig. 9. Comparison of oil production between the Iraqi Oil Ministry plan and the ANN-based forecast data for the next 5 years in the case of an economic blockade situation.

Table 5. Oil production results according to the Iraqi Oil Ministry plan and the ANN-based forecast data for the next 5 years in the case of an economic blockade situation.

Year	Oil Ministry Plan (Mb/d)	Economic case (Mb/d)	Difference	Error%
2024	**5**	**2.65**	**-2.35**	**-47**
2025	**5.5**	**2.2**	**-3.3**	**-60**
2026	**6**	**1.5**	**-4.5**	**-75**

2027	**6.5**	**1.3**	**-5.2**	**-80**
2028	**7**	**1.45**	**-5.55**	**-79.285**

Figure 9 shows the comparison of petroleum production between the Iraqi Oil Ministry's plan and the artificial intelligence forecast for the next five years under the scenario of an economic blockade. The red line represents the Ministry's plan, which projects oil production to increase to 7 million barrels per day by 2028. In contrast, the green line, representing the artificial intelligence estimation, shows a decline in production as it accounts for the impact of the economic blockade. The diagram clearly indicates a substantial difference between the two projections. According to Table 5, the maximum difference occurred in 2027, reaching 5.2 Mb/d, which corresponds to an error of 80% relative to the Ministry's plan. The smallest difference was observed in 2024 at 2.35 Mb/d, representing a 47% error. This discrepancy can be attributed to the significant negative impacts of economic sanctions on petroleum production. Such sanctions restrict access to technology, investment, financing, and export markets, disrupt supply chains, and contribute to infrastructure deterioration and loss of expertise. These effects are especially severe in oil-dependent economies, where petroleum production plays a vital role in national revenue and employment.

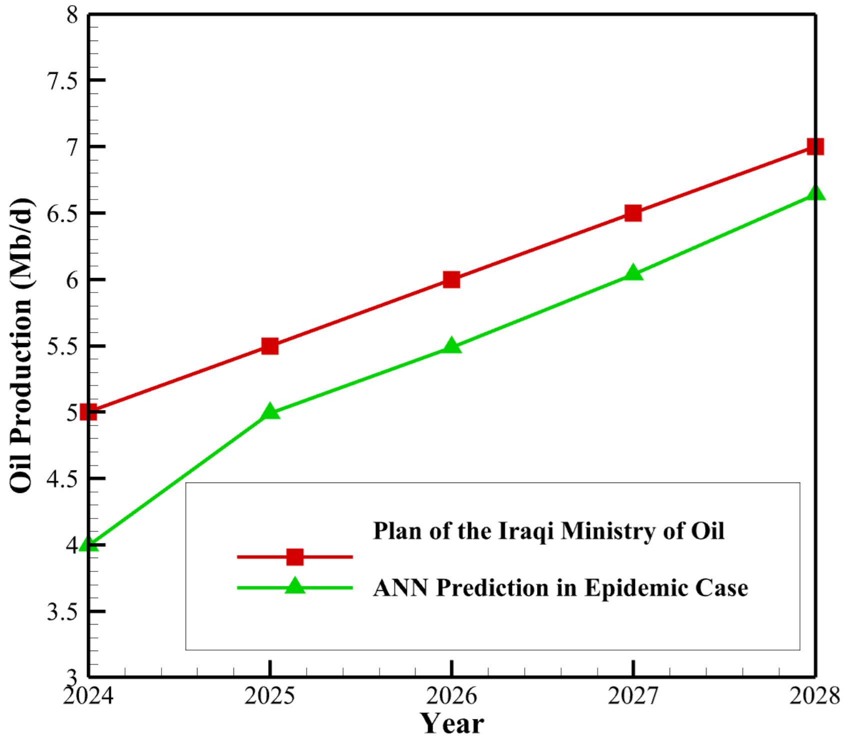

Fig. 10. Comparison of oil production between the Iraqi Oil Ministry plan and the ANN-based forecast data for the next 5 years in the case of an epidemic situation.

Table 6. Oil production results according to the Iraqi Oil Ministry plan and the ANN-based forecast data for the next 5 years in the case of an epidemic situation.

Year	Oil Ministry Plan (Mb/d)	Epidemic case (Mb/d)	Difference	Error%
2024	**5**	**4**	**-1**	**-20**

2025	**5.5**	**4.95**	**-0.55**	**-10**
2026	**6**	**5.5**	**-0.5**	**-8.3333**
2027	**6.5**	**6**	**-0.5**	**-7.6923**
2028	**7**	**6.7**	**-0.3**	**-4.2857**

Figure 10 presents a comparison of oil production between the Iraqi Oil Ministry's plan and the artificial intelligence forecast for the next five years under an epidemic scenario. The red line indicates the Ministry's projection, which anticipates production increasing to 7 million barrels per day by 2028. This is close to the artificial intelligence estimation, shown by the green line, which estimates production will reach 6.5 million barrels per day. The figure demonstrates that the production trend estimated by artificial intelligence generally aligns with the Ministry's plan over time, although the Ministry's projections remain consistently higher. According to Table 6, the maximum difference occurred in 2024 at 1 Mb/d, representing an error of 20% relative to the Ministry's plan. The smallest difference was recorded in 2028 at 0.3 Mb/d, corresponding to an error of 4.2%. This relatively small discrepancy is due to the typical factors that reduce oil production during epidemics, including labor shortages, supply chain disruptions, decreased demand, price volatility, financial constraints, and health and safety concerns. The magnitude of the reduction largely depends on the severity and duration of the epidemic, as well as the countermeasures implemented by governments and oil companies.

Table 7. Comparison of estimated oil production under different scenarios in 2028.

Scenario	Oil Ministry Plan (Mb/d)	Estimated Production (Mb/d)	Difference	Error%
Normal Conditions	**7**	**6.81**	**-0.189**	**-2.71%**
Wartime Scenario	**7**	**1.62**	**-5.38**	**-76.93%**
Economic Blockade	**7**	**1.45**	**-5.55**	**-79.29%**
Epidemic Scenario	**7**	**6.7**	**-0.3**	**-4.29%**

Table 7 presents a comparison of estimated oil production under different scenarios in 2028. This table reveals the different impacts of external factors on Iraq's oil production. Under normal conditions, the ANN model estimates production in 2028 to be 6.81 million b/d, very close to the Ministry of Oil's target of 7 million b/d, with an error margin of only -2.71%. In contrast, war conditions and economic blockades severely disrupt production, with production estimated to fall to 1.62 million b/d and 1.45 million b/d, respectively, with gaps of more than 76% and 79%, respectively. The impact of the epidemic scenario is moderate, with production estimated at 6.7 million b/d, with an error margin of only -4.29%. These results highlight the ability of ANN models to simulate the realistic impact of geopolitical and economic turmoil, providing important insights for strategic planning in resource-dependent industries.

Conclusion

This study compares the petroleum production forecast in Iraq with the Iraqi Oil Ministry plan and artificial neural network data. Four different factors that significantly influenced petroleum production were taken into account. These factors are (1) the normal situation, (2) the war situation, (3) the economic blockade situation and (4) the epidemic situation. The following conclusions are obtained:

1. According to the ANN forecast, the ministry can normally achieve the planned petroleum production plan with a maximum margin of error of 2.7%, which corresponds to production 0.189 barrels lower than expected.

2. According to the ANN estimation, the economic blockade factor was one of the factors that had the most negative impact on oil production expectations, as the deficit ratio reached 80% compared to the ministry's plan.

3. According to the ANN estimation, except for the normal situation, the epidemic situation had the least impact on oil production, with a deficit rate of 4.28% compared to the ministry's plan.

References

Al Jazeera. (2013). The secret of the Seven Sisters [Documentary]. https://www.aljazeera.com/program/featured-documentaries/2013/4/26/the-secret-of-the-seven-sisters/

Anghel, D. C., Ene, A., & Belu, N. (2014). A MATLAB neural network application for the study of working conditions. Advanced Materials Research, 837, 310–315. https://doi.org/10.4028/www.scientific.net/AMR.837.310

Costello, H. C. (2018). Examining uncertainty in reserves estimation for oil and natural gas wells completed with hydraulic fracturing.

El-Banbi, A. H., & Wattenbarger, R. A. (1996). Analysis of commingled tight gas reservoirs. https://doi.org/10.2118/36736-ms

Hassoun, M. H., Intrator, N., McKay, S., & Christian, W. (1996). Fundamentals of artificial neural networks. https://doi.org/10.1063/1.4822376

Haykin, S. (2008). Neural networks and learning machines. https://doi.org/978-0131471399

Jensen, T. B. (1998). Estimation of production forecast uncertainty for a mature production license. SPE Annual Technical Conference and Exhibition, 331–337. https://doi.org/10.2523/49091-ms

Krenker, A., Bester, J., & Kos, A. (2011). Introduction to the artificial neural networks. https://doi.org/10.5772/15751

Lee, Y., Yen, S., & Wu, Y. (2006). Using neural network model to discover attribute dependency for improving the performance of classification. Journal of Informatics and Electronics, 1, 9–19.

Lee, Y. S., & Yen, S. J. (2002). Neural-based approaches for improving the accuracy of decision trees. In Lecture Notes in Computer Science (Vol. 2454, pp. 114–123). https://doi.org/10.1007/3-540-46145-0_12

Li, K., & Horne, R. N. (2003). A decline curve analysis model based on fluid flow mechanisms. https://doi.org/10.2118/83470-ms

Li, X., Chan, C. W., & Nguyen, H. H. (2013). Application of the neural decision tree approach for prediction of petroleum production. Journal of Petroleum Science and Engineering, 104, 11–16. https://doi.org/10.1016/j.petrol.2013.03.018

Mursina, L. (2010). Artificial neural networks.

Nguyen, H. H., Chan, C. W., & Wilson, M. (2004). Prediction of oil well production: A multiple-neural-network approach. Intelligent Data Analysis, 8, 183–196. https://doi.org/10.3233/ida-2004-8206

Iraqi Ministry of Oil. (2023). https://www.oil.gov.iq/

Oil companies cooperate in a cartel covering the Middle East. (2023). EBSCO Research Starters. https://www.ebsco.com/research-starters/law/oil-companies-cooperate-cartel-covering-middle-east

Perez, H., Akhil, D.-G., & Mishra, S. (2007). The role of electrofacies, lithofacies, and hydraulic flow units in permeability predictions from well logs: A comparative analysis using classification trees. https://doi.org/10.2523/84301-ms

U.S. Energy Information Administration. (2022). Country analysis executive summary: Iraq. https://www.eia.gov/petroleum/

Weiss, W., Balch, R., & Stubbs, B. (2007). How artificial intelligence methods can forecast oil production. https://doi.org/10.2523/75143-ms

Yen, S. J., & Lee, Y. S. (2011). A neural network approach to discover attribute dependency for improving the performance of classification. Expert Systems with Applications, 38, 12328–12338. https://doi.org/10.1016/j.eswa.2011.04.011

Yuan, P., Jiang, L., Liu, J., Zhou, D., Li, P., & Gao, Y. (2021). Dual-level attention based on a heterogeneous graph convolution network for aspect-based sentiment classification. Wireless Communications and Mobile Computing, 2021. https://doi.org/10.1155/2021/6625899

Zhou, W., Liu, C., Liu, Y., Zhang, Z., Chen, P., & Jiang, L. (2024). Machine learning in reservoir engineering: A review. Processes, 12(6). https://doi.org/10.3390/pr12061219