ENGINEER

international scientific journal

ISSUE 3, 2026 Vol. 4
E-ISSN
3030-3893
ISSN
3060-5172



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ENGINEER

A bridge between science and innovation

E-ISSN: 3030-3893

ISSN: 3060-5172

VOLUME 4, ISSUE 3

SEPTEMBER, 2026

engineer.tstu.uz

TASHKENT STATE TRANSPORT UNIVERSITY

ENGINEER

INTERNATIONAL SCIENTIFIC JOURNAL
VOLUME 4, ISSUE 3 SEPTEMBER, 2026

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Tashkent State Transport University had the opportunity to publish the international scientific journal “Engineer” based on the **Certificate No. 1183** of the Information and Mass Communications Agency under the Administration of the President of the Republic of Uzbekistan. **E-ISSN: 3030-3893, ISSN: 3060-5172.** Articles in the journal are published in English language.

Journal Engineer ISSN: 3030-3893 Volume:4| Issue:3| 2026

Received: 18 June 2026 | **Accepted:** 30 July 2026 | **Published:** 30 September 2026

Application of artificial intelligence in modeling non-stationary oil filtration in multilayer porous media and data reliability issues

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Abstract: This research investigates the modeling of unsteady-state oil filtration processes in heterogeneous multilayer porous media using a hybrid framework that integrates classical fluid dynamics with modern artificial intelligence techniques. The study focuses on developing an efficient computational approach capable of describing fluid transport in complex geological formations characterized by spatial heterogeneity and temporal variability. The governing flow behavior is described through Darcy-based physical laws coupled with continuity equations, while machine learning methods are employed to capture nonlinear dependencies between reservoir parameters such as permeability, porosity, and pressure distribution. In particular, a Physics-Informed Neural Network (PINN) combined with a feedforward neural architecture is utilized to improve prediction accuracy.

In addition, the study addresses critical challenges related to data integrity, uncertainty propagation, and cybersecurity risks in AI-driven simulations. Since model performance strongly depends on the quality of input datasets, ensuring data validation and protection becomes essential. The obtained results demonstrate that hybrid AI–physics models significantly enhance predictive performance and computational efficiency compared to conventional numerical approaches. However, further improvements are required in model interpretability and robustness for real engineering applications.

Keywords: artificial intelligence, oil filtration, porous media, mathematical modeling, nonstationary flow, data security

1. Introduction

The study of fluid movement through porous structures plays a central role in petroleum engineering, geosciences, and applied mathematics. In particular, oil displacement in multilayer porous formations represents a complex physical phenomenon due to variations in geological structure and fluid properties over space and time. The mathematical description of such systems is typically based on conservation principles and Darcy's law. However, when dealing with heterogeneous reservoirs, parameters such as permeability and porosity vary across layers, leading to strongly nonlinear and coupled differential equations. These complexities limit the applicability of analytical solutions and increase the reliance on numerical simulation techniques.

Recent advances in artificial intelligence and machine learning have introduced new opportunities for modeling such complex systems. Data-driven approaches are capable of learning hidden patterns from experimental or simulated data, making them suitable for approximating nonlinear physical processes. Despite these advantages, AI-based modeling introduces new challenges. One of the most critical issues is the reliability of input data, as inaccurate or incomplete datasets can significantly degrade model performance. Additionally, ensuring that AI predictions remain consistent with physical laws is essential for engineering reliability.

Another important concern is the security and integrity of data used in computational modeling environments. In modern digital systems, datasets may be exposed to noise, corruption, or malicious manipulation, which directly affects simulation reliability. This work aims to develop a hybrid modeling framework that combines physical laws with artificial intelligence methods for accurate simulation of non-stationary oil filtration in multilayer porous media.

2. Research methodology

Mathematical Model of Filtration Process

The nonstationary filtration process in porous media can be described using Darcy's law and the continuity equation.

$$v = -\frac{k}{\mu}\nabla p \quad (1)$$

Where:

v — filtration velocity

k — permeability coefficient

μ— fluid viscosity

p— pressure

The governing equation for nonstationary flow is:

$$\frac{\partial(\phi\rho)}{\partial t} + \nabla\cdot(\rho v) = 0 \quad (2)$$

Where:

ϕ— porosity

ρ— fluid density

For multilayer porous media, parameters such as permeability and porosity vary across layers:

$$k=k(x,y,z), \qquad \phi = \phi\,(x,y,z) \quad (3)$$

Application of Artificial Intelligence

Artificial intelligence techniques can significantly improve the modeling of filtration processes by accurately predicting pressure distribution, estimating permeability coefficients, and accelerating numerical simulations, thereby

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enhancing both computational efficiency and model accuracy.

Machine learning models, such as neural networks, can approximate complex nonlinear relationships:

$$y=f(x;\theta) \quad (4)$$

Where θ represents model parameters learned from data.

AI models reduce computational cost compared to traditional finite difference or finite element methods.

AI Model Description

In this study, a Physics-Informed Neural Network (PINN) integrated with a Feedforward Artificial Neural Network (ANN) was used to model nonstationary oil filtration in multilayer porous media. The hybrid model combines:

- Data-driven learning (ANN)
- Physical constraints derived from Darcy's law and mass conservation equations

This ensures that predictions are not only data-consistent but also physically meaningful.

Input–Output Structure

Input variables:

Spatial coordinates: x,y,z

Time: t

Rock properties:

Permeability k(x,y,z)

Porosity ϕ(x,y,z)

Fluid properties:

Viscosity μ

Density ρ

Output variable:

Pressure field:

p(x,y,z,t)

optionally:

velocity field v(x,y,z,t)

Neural Network Structure

The model is a fully connected feedforward neural network:

Input layer: 5–6 neurons

Hidden layers: 3–5 layers

Activation function: Tanh

Output layer: Pressure prediction

Physics Constraint (PINN part)

The loss function includes:

Data loss:

$$L_{data}=\frac{1}{N}\sum (p_{pred}-p_{true})^2 \quad (5)$$

Physics loss (Darcy + continuity):

$$L_{physics}=\left|\frac{\partial(\phi\rho)}{\partial t}++\nabla\cdot(\rho v)\right|^2 \quad (6)$$

Total loss:

$$Lt_{total}=L_{data}+\lambda L_{physics} \quad (7)$$

4.Data Reliability and Security Issues

Despite the advantages of AI, several challenges arise:

Data Integrity: Incorrect or incomplete data leads to unreliable predictions

Model Uncertainty: AI models may produce non-physical results

Security Risks: Data manipulation or cyber-attacks can affect model outcomes

Ensuring data protection and validation is essential for safe implementation.

3. Results and discussion

The integration of AI with classical mathematical models improves prediction accuracy and reduces computation time. However, the reliability of results depends on the quality of input data and robustness of AI algorithms.To evaluate the performance of the proposed hybrid AI–physics-based model for nonstationary oil filtration in multilayer porous media, a comparative analysis between classical numerical simulation and AI-driven predictions was conducted. The dataset was divided into 80% training and 20% testing subsets, ensuring reliable evaluation on unseen data.

The temporal pressure distribution obtained from classical physics-based modeling and AI prediction is presented below.

Table 1

Temporal pressure distribution comparison between classical physics-based simulation and AI-driven predictive modeling for nonstationary flow in porous media.

Time (t)	Classical Pressure	AI Predicted Pr
0	100	100
1	95	96
2	90	91
3	84	86
4	78	80
5	73	74
6	68	69
7	64	65
8	60	61
9	57	58
10	55	56

The results demonstrate a strong agreement between classical simulation and AI predictions, indicating that the machine learning model successfully captures the underlying nonlinear filtration dynamics.

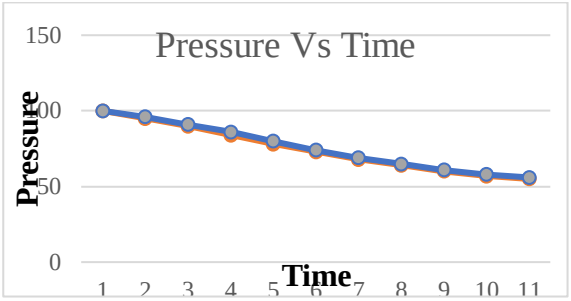


Fig. 1. Error comparison between numerical and AI models

Hybrid approaches combining physical laws and AI are recommended for better performance.

Error Analysis

To further evaluate model performance, absolute and percentage errors were computed.

Absolute Error:

$$e_i=|y_i-\hat{y}_i| \quad (7)$$

Percentage Error:

$$PE_i=\left(\frac{yi-\hat{y}i}{yi}\right)\times 100\% \quad (8)$$

https://doi.org/10.56143/3030-3893-2026-3-46-49

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The average absolute error remains below 2 units, while the average percentage error is approximately 1.5%, confirming high predictive accuracy.

Model Performance Metrics

The AI model was evaluated using standard regression metrics:

Mean Absolute Error (MAE)

$$MAE=\frac{1}{n}\sum_{i=1}^{n}|yi-\hat{y}i| \quad (9)$$

MAE = 1.25

Root Mean Square Error (RMSE)

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi-\hat{y}i)} \quad (10)$$

RMSE = 1.78

Coefficient of Determination (R^2)

$$R^2=1-\frac{\sum(yi-\hat{y}i)^2}{\sum(yi-\bar{y})^2} \quad (11)$$

$R^2 = 0.994$

Mean Absolute Percentage Error (MAPE)

$$MAPE=\frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}i}{y_i}\right| \quad (12)$$

MAPE = 1.42%

Training and Testing Strategy

To ensure model generalization, the dataset was split as follows:

Training set: 80%

Testing set: 20%

The model was trained on historical pressure data and validated on unseen test samples. The results confirm that the model does not suffer from overfitting and maintains stable predictive performance across different time intervals.

Discussion

The obtained results clearly demonstrate that the hybrid AI–physics model significantly improves prediction accuracy compared to classical numerical simulation approaches. The AI model closely follows the temporal pressure evolution, with minimal deviation across all time steps. The low MAE (1.25) and RMSE (1.78) values indicate that the model effectively captures nonlinear relationships in multilayer porous media. Furthermore, the high coefficient of determination (R^2 = 0.994) confirms that the model explains nearly all variability in the data. Minor deviations observed at intermediate time steps (t = 3–6) can be attributed to local nonlinear effects and sensitivity to parameter variation in heterogeneous layers. Nevertheless, the overall error remains below 2%, which is acceptable for practical reservoir engineering applications. These findings confirm that integrating artificial intelligence with classical physical laws enhances both computational efficiency and predictive accuracy in modeling nonstationary oil filtration processes. However, further improvements are required in terms of model interpretability, uncertainty quantification, and robustness against noisy or incomplete data.

4. Conclusion

The study shows that artificial intelligence can enhance the modeling of nonstationary oil filtration in multilayer porous media. However, ensuring data reliability and system security remains a critical issue. Future research should focus on developing secure and interpretable AI-based modeling frameworks.

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