Extending Dual Porosity Models to Anisotropic Fractured Reservoirs Using Physics Guided Neural Networks

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Abstract

The non-orthogonal fractures in conventional Warren and Root (WR) induce directional permeabilities and anisotropic flow patterns that cannot be captured using simple fracture properties. In this paper, we use the proposed equivalent fracture aperture through a correction coefficient (η), to account for this effect Previous studies used an estimation of this coefficient by calibration to the static field data. The main contribution is to treat this coefficient as a physics-dependent parameter rather than a calibration value to bridge fracture-scale flow with continuum model. A data-driven approach is developed to quantify η as a function of fracture geometry and reservoir-scale properties. A dataset of 2,478 samples of simulations was generated using COMSOL Multiphysics, covering a range of fracture and reservoir properties. An artificial neural network (ANN) was trained and optimized on this dataset to learn the nonlinear relation with the correction coefficient, achieving a predictive accuracy of R^2 = 0.9946. By using the ANN-predicted correction coefficient into the WR approach, a multiscale bridge between fracture-scale physics and dual-porosity models can be achieved. The cubic relationship between permeability and fracture aperture ($k_\theta = \eta^3 k$) highlights the importance of accurate η estimation, as any error in η propagate results into large permeability uncertainties. The numerical results showed the dependency of the correction coefficient η on fracture orientation is much greater than its dependency on either fracture size and matrix shape or system size. Also using this simple correction factor extends the applicability of conventional dual-porosity models to anisotropic fractured reservoirs with non-orthogonal fractures..

Keywords

Naturally Fractured Reservoirs, Anisotropy, Artificial Neural Network , Fracture Aperture Correction Coefficient

1. Introduction

Understanding the behavior of fluid flow in naturally fractured reservoirs is important for designing a suitable reservoir development scenario and increasing hydrocarbon recovery, as fractures act as preferential pathways for fluid flow. Fractured reservoirs consist of two interacting low-permeability matrices, and a high-permeability fracture medium. Fractures introduce significant anisotropy due to their spatial distribution and their directions and consequently provide different permeability values for different directions.

Fractured reservoirs are classified based on the fracture and matrix permeability ratio (Saeedi [1]), the differences in rock properties (Nelson [2]), or the capacity for fluid storage and their interconnection (Allan & Sun [3]). However, these classifications often neglect anisotropy, which plays a key role in designing appropriate reservoir development scenario. The contribution of each fracture or set of fractures depends on parameters such as aperture, size, orientation, density, connectivity, and filling material, all of which affect the flow behavior. Fracture orientation, i.e., dip and strike, control the reservoir anisotropy. Fracture size has an influence on the rock permeability (Narr et al. [4]), and the condition of fracture walls and fracture filling details (i.e., type and amount of sedimentary material) affects the flow behavior at fracture scale. Moreover, fracture density or spacing, which is related to the degree of rock fracturing, is essential for main flow (Dershowitz & Einstein [5]). Fracture aperture—the perpendicular distance between fracture walls—strongly influences both porosity and permeability, and it varies with depth, in-situ stress, lithology, and pore pressure (Aguilera [6]). Fracture permeability depends on the aperture by,

$$k_f = \frac{b^2}{12}\cos^2(\alpha) \qquad \textbf{Eq. 1}$$

where b is fracture aperture and α is the fracture angle relative to the flow direction (Bear [7]). Similarly, fracture porosity, in the case of Warren and Root (WR) model, depends linearly on the aperture by,

$$\phi \approx b\left(\frac{1}{a_1}+\frac{1}{a_2}+\frac{1}{a_3}\right) \qquad \textbf{Eq. 2}$$

Previous studies indicate a cubic relationship between rock porosity and permeability in single-phase flow (Reiss [8]; Lucia [9]; Aguilera [10]). However, for multi-phase flow other complementary functions including relative permeability and capillary pressure are needed (Corey [11]).
Modeling flow through fractured porous media can be performed by using various approaches. The first method is to use discrete fracture network (DFN) by which fractures randomly distributed in the medium are explicitly represented as 2D line segments or 3D shapes (Parsons [12]; Long et al. [13]; Dershowitz & Miller [14]). On the other hand, continuum models such as dual-porosity or multi-porosity models treat fractures and matrix as two overlapping continua with possible flow exchange between them (Barenblatt et al. [15]; Warren & Root [16]). However, to apply this approach in real cases we need appropriate calibration of the parameters to account for anisotropy and local heterogeneity. The continuum approaches have been extended by many researchers, including Kazemi [17], De Swaan [18], and Gerke & van Genuchten [19], focusing on improving numerical methods (e.g., finite difference discretization) or analyzing the gravity and mobility terms. There is also other publication which used coupling terms for flow in fractured porous media to enhance flow exchange (Zimmerman et al. [20]; Dershowitz & Einstein [5]). The continuum models are computationally efficient methods, especially for multiphase flow, but their results will be questionable if fractures are not interconnected (Dershowitz & Miller [14]; Young et al. [21]; Nelson [2]). In some studies, discrete fracture models have been used to evaluate transfer functions between the two mediums in continuum models. As an example, dual-porosity models have been used to assess CO2 storage potential in a fractured reservoir through analysis of the fracture system (Zhang et al. [22]). Another dual-porosity model for geothermal fractured reservoirs considered convective flow faster (Aguilera [6]). In other study, an improved dual-porosity-dual-permeability model was used, which enhances the accuracy in the flow modelling (Geiger & Matthäi [23]).

COMSOL Multiphysics can be utilized for simulating flow through porous media under various displacement mechanisms. For direct pore-scale simulations, it employs the main flow equations (Navier-Stokes) coupled with interface tracking algorithms (Tryggvason et al. [24]). The flow equations are solved using finite element, finite volume, or boundary element methods, along with algorithms like level set or phase field to track the fluid interfaces (Hirt & Nichols [25]; Osher & Sethian [26]; Sussman et al. [27]). Guadala et. al. investigated the relative changes in porosity, permeability, and elastic modulus through single-phase flow in fractured media using coupled hydrodynamic and geomechanical models (Guadala et al. [28]). It is observed that the streamlines are influenced by fracture orientation, well distance, and fracture density. Also, Kumar et. al. conducted COMSOL simulations for analysis of viscous fingering in porous media, using the Brinkman equation for non-Darcy cases (Kumar et al. [29]). Recent advancements have further oriented the analysis of flow in fracture networks. For instance, Patani et al. [30] employed probabilistic assessments of equivalent fracture aperture constrained by real-time drilling mud loss data. Additionally, Zhou et al. [31] developed a phase-field model in COMSOL for fluid-driven dynamic crack propagation in porous media, providing insights into the interaction between fluid flow and fracture development.

Furthermore, machine learning techniques have been applied to enhance fracture characterization and to improve simulation performance. For instance, El Ouahed et al. developed a 2D fracture intensity map and network in the Hassi Messaoud field using artificial neural networks (ANN) and fuzzy logic, showing AI's potential to predict fracture zones from well data (El Ouahed et al. [32]). Similarly, Al-Dhamen et al. proposed an AI-based model for the estimation of acid fracturing performance in naturally fractured reservoirs, which offers a computationally efficient approach compared with traditional simulations (Al-Dhamen et al. [33]). In another study, Peng et al. considered embedded discrete fractures along with AI for history matching purposes in fractured reservoirs (Peng et al. [34]). Furthermore, other approaches, such as support vector machines (SVM), have been coupled with neural networks to identify fractures in shale gas reservoirs (Kumar et al. [35]). AI methods coupling reservoir simulations have also been applied to generate simulation cases for characterizing fracture properties in shale gas reservoirs (Zheng et al. [36]). Lastly, techniques such as random forests and neural networks, have been used to predict complex fluid flow behavior and address fluid losses in fractured reservoirs (Alqahtani et al. [37]). Al-Sulaiman et al. [38] utilized machine learning to study the role of a single fracture in fractured dolomite formations. Recent ANN models in fractured reservoirs emphasize their suitability for capturing complex nonlinearities in fracture flow (Hassan et al. [39]; Zhang et al. [40]).

Fractures as heterogeneous mediums create anisotropic flow patterns. For anisotropy representation in fractured porous media, the idea of using equivalent aperture from a realistic aperture distribution, or stress-aperture relations in the medium have been proposed[21, 22, 41]. For example, Young et al [21] proposed an equivalent fracture aperture to account for the anisotropic flow patterns in terms of permeability tensor. However, their approach focuses only on fracture orientation and ignores the matrix shape. Nick and Bisdom (2018) emphasized highlighted that utilizing a constant aperture for the fracture network may not reproduce the true anisotropy of the permeability. Zhang et al. [22] recently applied this concept to coalbed methane reservoirs, showing improved consistency with field data. They found that incorporating such an anisotropic correction factor into WR models enhances the representation of directional permeability and reservoir behavior more accurately. However, the great deal of uncertainty in the spatial distribution of fractures and scarce of fracture data may influence their estimation of this correction factor. To overcome this effect, we use a combination of COMSOL-based numerical simulation results with an appropriate artificial neural network (ANN) to estimate the fracture aperture correction coefficient for anisotropic fractured reservoirs. By incorporating this coefficient which represents the directional flow behavior, the proposed correction coefficient extends the applicability of dual-porosity WR models for anisotropic reservoirs.

2.Matrials and Methods

2.1. Characterization and Physical Properties of Fractured Rocks

Hydrocarbons in fractured reservoirs primarily exist within matrix pore networks, while fluid transport towards production wells occurs primarily through interconnected fracture systems. Fracture networks possess various attributes, such as aperture dimensions, spatial extent, orientation patterns, distribution density, intensity variations, connectivity characteristics, and spatial correlations (Rutqvist et al. [42]; Wong et al. [43]). Accurate reservoir characterization and performance prediction require a thorough understanding of fracture-influenced rock properties, particularly compressibility, permeability tensors, effective porosity, capillary pressure curves, and wettability alterations. These properties exhibit significant heterogeneity depending on fracture attributes and spatial configurations, leading to complex flow behavior that conventional models often struggle to capture. To investigate these complex interactions, we investigate two distinct flow scenarios: (1) single-phase fluid transport through fractured porous media with fractures oriented at different inclination angles relative to the primary flow direction, and (2) two-phase immiscible water-oil displacement in fractured systems with systematically varied fracture inclinations. This section elucidates the theoretical basis of flow modeling in fractured media, outlines the assumptions of our base model formulation, and describes the numerical simulation methodology used to address these multiscale, coupled phenomena.

2.2. Single-Phase Fluid Flow in a Porous Medium with Fractures

The governing equations for single-phase fluid flow in a fractured porous medium are given by,
For matrix:

$$\frac{\partial(\varphi\rho)}{\partial t} = -\nabla \cdot (\rho u) - q_{mf} \qquad \textbf{Eq. 3}$$

For fractures:

$$\frac{\partial(\varphi_f\rho_f)}{\partial t} = -\nabla \cdot (\rho_f u_f) + q_{mf} + q_{ext} \qquad \textbf{Eq. 4}$$

where the term q_{mf} represents the fluid transfer between matrix and fractures is calculated by:

$$q_{mf} = \alpha_w(p_{matrix} - p_{fracture}) \qquad \textbf{Eq. 5}$$

α_w is the fluid transfer function, the porosity is denoted by ϕ, the fluid density per unit volume by ρ, the Darcy superficial velocity by $u = (u_1, u_2, u_3)$, and external sources and sinks by q, k is the absolute permeability tensor of the porous medium, μ is the fluid viscosity, g is the gravitational acceleration, z is the depth, and ∇ is the gradient operator.

2.3. Two-Phase Fluid Flow in a Porous Medium with Fractures

For immiscible two-phase flow (water and oil), the governing transport equations are:
-for fracture:

$$\varphi_f \frac{\partial(S_{\alpha f})}{\partial t} + \nabla \cdot u_{\alpha f} = +\tau_\alpha = +T_\alpha(\psi_{\alpha m} - \psi_{\alpha f}) \qquad \textbf{Eq. 6}$$

- for matrix:

$$\varphi_m \frac{\partial(S_{\alpha m})}{\partial t} = -\tau_\alpha = -T_\alpha(\psi_{\alpha m} - \psi_{\alpha f}) \qquad \textbf{Eq. 7}$$

where S_α is phase saturation, $\psi_\alpha = p_\alpha - \rho g \Delta z$ is flow potential, and T is the matrix transmissibility coefficient, with the subscript α indicating the water or oil phase.
The transfer function is defined as follows:
For oil:

$$\tau_o = \frac{\alpha K_m K_{ro}}{\mu_o B_o}(\psi_{om} - \psi_{of}) \quad \textbf{Eq. 8}$$

For water:

$$\tau_w = \frac{\alpha K_m K_{rw}}{\mu_w B_w}(\psi_{wm} - \psi_{wf}) \quad \textbf{Eq. 9}$$

2.4. Fracture Aperture, Porosity, and Equivalent Permeability
The classical Warren-Root (WR) model assumes orthogonal fracture networks with uniform apertures, which limit its applicability for fractures inclined relative to the flow direction. To address this limitation, the approach introduced by Yang et al. [44] can be used. This approach incorporates an exponential correction factor η to adjust fracture apertures and account for the anisotropy effects.:

$$b_\theta = \eta b \quad \textbf{Eq. 10}$$

where b is the base fracture aperture, b_θ is the fracture aperture in an anisotropic system with fractures at an angle θ relative to the main flow and η is s coupling parameter between the geometry and flow. Considering non orthogonal fractures with respect to the main flow direction enhances the fracture connectivity and the conductivity of the medium. This improvement in the flowability may be represented by an increase in the fracture aperture; hence, we expect the aperture correction factor η to have some values greater than 1. However, the detail dependency of this parameter on fracture orientation θ is not clear as the size of fracture projection along the main flow is decreased with fracture orientation.
Porosity and permeability can then be adjusted accordingly, with porosity scaling linearly $\eta\varphi$, and permeability scaling cubically;

$$k_\theta = \eta^3 k \quad \textbf{Eq. 11}$$

This correction improves dual-porosity model applications when simulating anisotropic fractured reservoirs (Zhang et al. [22]; Kim & Lee [45]).

2.5. Numerical Model Setup
A comprehensive two-phase (oil-water) flow model was implemented using COMSOL Multiphysics to investigate immiscible fluid displacement mechanisms within heterogeneous fractured porous media. The computational domain consisted of a two-dimensional reservoir section (120 m × 50 m) where fractures were explicitly represented as discrete line segments with systematically varied orientations and spacing to effectively capture the inherent anisotropic flow behavior. The ratio of reservoir size to matrix block sizes of 4 to 28 are considered to represent the fracture-matrix interactions in the medium. Moreover, the fracture orientation distribution covered a wide range from 5 to 90 degree to provide a range of anisotropy in the permeability. The multiphase transport phenomena were simulated through the Multiphase Flow in Porous Media interface, which integrates Darcy's Law with Phase Transport equations to resolve the coupled pressure-saturation dynamics at both fracture and matrix scales.
This investigation specifically focused on the influence of fracture network geometry on displacement efficiency and flow anisotropy. Multiple numerical experiments were conducted with fracture systems

configured at two principal orientations and systematically varied matrix block dimensions to examine scale-dependent behaviors. For each configuration, the spatiotemporal evolution of fluid pressures was monitored at discrete points throughout the fracture network, enabling the calculation of the volume-averaged pressure distribution across the entire fracture system at each time step. Furthermore, we quantitatively assessed the impact of an empirical correction factor on critical performance indicators, including oil saturation profiles within fractures, water saturation distribution within the matrix domain, and fluid velocity distributions along the outflow boundary.

The governing parameters and constitutive relationships utilized in the numerical simulations are comprehensively summarized in **Table 1**. The Brooks-Corey formulation was implemented to characterize the relative permeability functions and capillary pressure-saturation relationships for the two-phase system. This constitutive model provides a robust framework for quantifying the nonlinear dependence of relative permeability on normalized water saturation and establishes the functional relationship between capillary pressure and fluid saturation in heterogeneous porous media. For the compressible storage calculations, a linearized storage model was employed that incorporates both fluid compressibility and rock compressibility coefficients, thus accounting for the total storage capacity of the fractured porous medium under transient pressure conditions.

Discrete fractures were incorporated into the rectangular computational domain as explicit line segments with precisely controlled orientations and spatial distributions to represent the heterogeneous reservoir architecture. The governing equations for fluid transport were implemented by applying the Darcy's Law physics module throughout the entire domain, with fractures systematically integrated as distinct geometric features within this physics interface to capture their unique flow characteristics. Each fracture element was parameterized with specified physical properties, including aperture dimensions, effective porosity, intrinsic permeability tensor, and mechanical compressibility, based on the calibrated values presented in **Table 1**. The hydraulic boundary conditions were carefully defined to reflect realistic reservoir conditions: constant wellbore pressure boundaries were set at designated production/injection locations, while fluid outflow constraints were applied within the Phase Transport physics module at corresponding boundary segments to maintain mathematical consistency.

The computational domain was discretized using an adaptive, physics-controlled finite element mesh consisting of triangular elements with local refinement near fracture interfaces and in regions of anticipated high-pressure gradients to ensure numerical accuracy and stability. Mesh sensitivity analyses were conducted to establish mesh independence, confirming that the selected discretization adequately resolved the multiscale transport phenomena without introducing numerical artifacts. The transient simulations were executed over a 100-day production period using progressive daily time-stepping with automatic time-step adjustment capabilities to capture both early-time rapid dynamics and late-time quasi-steady behavior efficiently. This comprehensive numerical approach enables robust characterization of the complex, coupled processes governing multiphase flow in fractured reservoirs while maintaining computational efficiency.

Table 1. The input parameters for the constructed model

Input Parameter	**Value**	**Unit**	**Input Parameter**	**Value**	**Unit**
Reservoir Dimensions	120 x 50	m^2	Water Viscosity	1	cP

Initial Reservoir Pressure	2	MPa	Water Compressibility	4.00e-10	1/Pa
Initial Oil Saturation	0.7	-	Matrix Porosity	0.15	-
Residual Oil Saturation	0.2	-	Matrix Permeability	2.00e-12	m^2
Residual Water Saturation	0	-	Matrix Compressibility	1.00e-4	1/Pa
Perforated Zone	30	m	Initial Fracture Aperture	0.02	m
Wellbore Pressure	6	atm	Fracture Porosity	1	-
Oil Density	800	kg/m^3	Fracture Permeability	1.00e-7	m^2
Oil Viscosity	1.5	cP	Fracture Compressibility	1.00e-4	1/Pa
Oil Compressibility	4.00e-10	1/Pa			
Water Density	1000	kg/m^3			

2.6. Artificial Intelligence-Based Estimation of Fracture Aperture Correction Coefficient

2.6.1 Data Preparation

A dataset of 2,478 samples was generated by running COMSOL simulations. Different fracture angles, matrix sizes, and other rock/fluid properties were assumed to capture realistic fracture flow behavior. These data are stored in a CSV file. The initial dataset comprises multiple simulation-derived samples, each representing a unique combination of input conditions under controlled settings. Data preprocessing was conducted to address common machine learning challenges, such as overfitting, noise sensitivity, and scale-related biases, in order to ensure data quality, consistency, and compatibility with the machine learning model:

1. **Data Loading and Selection**: The dataset is loaded from the CSV file, with the first three columns designated as input features (X) and the fourth column as the target output (y). The initial size of the dataset is verified to confirm the correct structure and integrity of the data.
2. **Outlier Removal**: Outliers are identified and removed using the Z-score method, with a threshold of 1.7. By removing outliers, the dataset becomes more robust against erroneous simulation outputs. Samples where all features have a Z-score below this threshold are retained, while others are discarded. This step reduces the dataset size but enhances its quality by eliminating anomalous data points that could skew model performance. After outlier removal, a statistical summary is computed, including metrics such as minimum, maximum, mean, median, variance, and standard deviation. This summary provides insights into the data distribution and ensures the dataset remains representative of the underlying physical phenomena.
3. **Normalization**: To improve the neural network's training efficiency and prevent features with larger scales from dominating the model and ensure numerical stability during training, both input features and the target output are normalized to the range [0, 1] using the Min-Max Scaler. This normalization ensures that all features contribute equally to the model's learning process, regardless of their original scales.

4. **Data Splitting**: The normalized dataset is split into training (85%) and testing (15%) sets using the train_test_split function from Scikit-learn, with a fixed random seed (random_state=42) to guarantee that the model is evaluated on a representative subset of the data. The training set is used to fit the neural network, while the testing set evaluates its generalization performance on unseen data.
5. **Statistical Validation**: Post-preprocessing, a detailed statistical analysis was also performed to confirm the dataset's suitability for training. The number of samples in the training and testing sets is reported (approximately 85% and 15% of the filtered dataset, respectively), ensuring sufficient data for robust model training. The statistical summary, including variance and standard deviation, is visualized to verify that the data distribution aligns with expectations for the physical system being modeled.

The resulting preprocessed dataset is therefore suitable for training a neural model aimed at capturing the nonlinear dependency of the fracture aperture correction coefficient on fracture geometry and reservoir-scale parameters. The preprocessing steps collectively ensure that the data is clean, normalized, and appropriately structured, laying a strong foundation for accurate and reliable model predictions.

2.6.2 Artificial Neural Network (ANN) Modeling

Artificial Neural Networks (ANNs) are computational models designed to identify complex patterns and relationships within data (Goodfellow et al. [46]). ANNs consist of interconnected nodes, or neurons, organized into layers: an input layer that accepts data, hidden layers that process it, and an output layer that generates predictions or classifications. Each neuron combines inputs with weights and biases, applies an activation function like ReLU, and produces an output (Goodfellow et al. [46]). Training an ANN involves adjusting weights through backpropagation and optimization algorithms, such as gradient descent, to minimize a loss function(Goodfellow et al. [46]). ANNs handle noisy data, scale with large datasets, and adapt to complex problems (Mohaghegh [47]). However, challenges like overfitting, computational demands, and interpretability issues are common, often addressed through regularization, dropout, or early stopping (Goodfellow et al. [46]). ANNs are widely used for pattern recognition, predictive modeling, and data-driven decision-making in engineering and beyond (Ouenes et al. [48]).

Artificial Neural Networks (ANNs) were selected for this study due to their ability to approximate nonlinear response surfaces in low-dimensional, physics-driven problems. In the present application, the objective is not to replace physical modeling but to capture the implicit relationship between fracture-scale flow behavior and the equivalent aperture correction coefficient derived from numerical simulations. Given the limited number of input parameters and the nature of η, a shallow feedforward ANN architecture was adopted to balance model expressiveness, interpretability, and generalization capability. A feedforward ANN using TensorFlow and Keras for a regression task was constructed with:

- Input layer: 3 nodes corresponding to fracture angle, matrix block size, and reservoir area are used. We use these input parameters as i) the structure of WR models as continuum models assumes full connections among fractures in the medium, ii) the other controlling parameters in WR models such as fracture density, fracture spacings depend on the matrix block size, and iii) other small-scale ingredients such as roughness variations in the fractures are usually ignored in large scale field simulations. i.
- One hidden layer: 25 neurons with ReLU activation (optimized via sensitivity analysis as shown in **Fig. 2**).

- Output layer: 1 node with linear activation function representing the correction coefficient η .The model is compiled with the Adam optimizer (learning rate of 0.01) and Mean Squared Error loss function, which measures the squared differences between predicted and actual values.

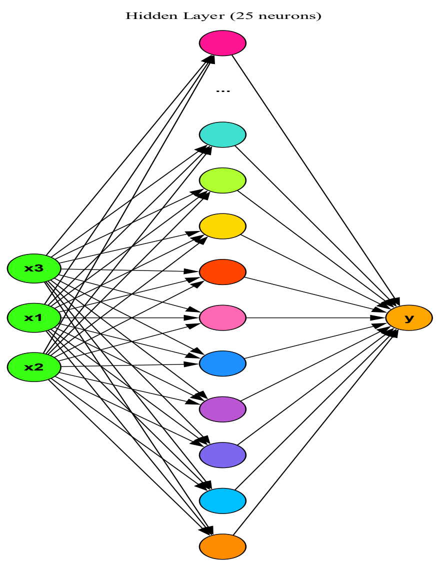

Fig. 1. ANN design and Categorize Data for Prediction

The model was trained for up to 400 epochs with a batch size of 40. A 20% validation split is used to monitor performance on a subset of training data. The Early Stopping callback halts training if validation loss does not improve for 100 consecutive epochs, restoring the weights from the best epoch to prevent overfitting. This ensures the model balances learning and generalization. Predictions are made on both training and test sets in the scaled [0, 1] range. These predictions are clipped to [0, 1] to respect normalization bounds and then inverse-transformed using the scaler to return to the original data scale, making results interpretable.

Model evaluation used metrics such as R^2, MSE, MAE, RMSE, MAPE, and bias, which shows excellent predictive performance ($R^2 = 0.9946$). **Fig. 1** and **Fig. 2** illustrate the ANN architecture and performance analysis. These scatter plots of actual versus predicted values for both training and test sets, with fitted and ideal lines show the prediction accuracy. Additionally, a line graph of absolute errors for test samples highlights prediction inaccuracies, and a histogram with a kernel density estimate (KDE) illustrates the distribution of prediction errors, providing insights into model bias and error patterns. This range of relatively high values of R^2 (0.9946) enables us to use this correction factor in WR dual porosity models to account for geometrically complex fracture system.

3. Results and Discussion

The developed artificial neural network (ANN) was trained on an extensive dataset comprising 2,478 high simulation samples generated through COMSOL Multiphysics, with the fracture aperture coefficient (η) as the target output parameter. This dataset systematically provides a range of reservoir conditions, fracture configurations, and petrophysical properties (**Table 2**), ensuring robust model generalization across varying fracture orientations, matrix block dimensions, and reservoir geometries encountered in naturally fractured reservoirs. Importantly, the relatively narrow range of η values (1–1.317) reflects physically realistic anisotropy effects rather than numerical artifacts, emphasizing the need for a regression model capable of resolving subtle but physically significant variations.

Table 2. Statistical Features of the 2478 Datasets used to Train AI Models for Fracture Aperture correction factor

Parameter	**Minimum**	**Maximum**	**Mean**	**Median**	**Var**	**SD**
Matrix Area (m^2)	9.589	496.4	251.626	248.532	19381.4	139.217
Reservoir Area (m^2)	40.132	13968.201	2570.571	1877.008	5844620	2417.565
Fracture Degree (°)	5.425	89.958	48.953	48.938	585.438	24.196
Frac Aperture Coef	1	1.317	1.105	1.085	0.007	0.081

Evaluation of the trained ANN on an independent test dataset (15% of the whole) yielded a coefficient of determination (R^2) of 0.9946, indicating that the model successfully captures the dominant trends governing η. While high predictive accuracy alone does not guarantee physical validity, further analyses were conducted to assess the physical consistency, robustness, and interpretability of the trained model. The high predictive accuracy (99.5%) was consistent with the training set performance ($R^2 = 0.9959$), confirming the model's ability to extract the complex non-linear mapping between input features and the fracture aperture correction coefficient while effectively mitigating overfitting concerns(**Fig. 3**).

Due to the cubic dependence of permeability on η, even marginal inaccuracies in η propagate into large errors in permeability estimation. For example, a 5% underestimation in η (e.g., predicting 1.05 instead of the true 1.10) can cause a permeability error exceeding 14%, severely affecting flow predictions. The high ANN accuracy mitigates this risk, providing more confident input parameters for simulation models. Moreover, the correction coefficient encapsulates the anisotropic permeability effects caused by fractures inclined at arbitrary angles θ relative to flow direction. This allows for realistic representation of fracture networks, which are seldom orthogonal or uniform in natural reservoirs.

Hence, by providing an accurate correction factor, the anisotropy caused by fracture orientation can be efficiently incorporated into conventional simulators, leading to more realistic predictions of:

- Pressure Transients: Well test analysis using a model with a corrected η will yield more accurate interpretations of fracture and matrix properties.
- Fluid Flow Paths: The flow of water or gas during injection processes will be more accurately modeled, improving predictions of breakthrough times and sweep efficiency.
- Ultimate Recovery: More accurate reservoir models, accounting for fracture orientation effects, provide better forecasts of oil recovery, optimizing field development planning.

The presented approach aligns with and extends previous research efforts. The use of an equivalent aperture to handle anisotropy echoes the work of Zhang et al. [22] in coalbed methane reservoirs and the earlier propositions of Young et al. [21]. However, this study advances the field by moving from a conceptual or analytical solution to a practical, generalized predictive tool using machine learning.
Moreover, this research contributes to the growing application of AI in petroleum engineering, demonstrating that ANNs can go beyond mere pattern recognition to effectively learn underlying physical relationships in complex multiphase flow systems (El Ouahed et al. [32]; Al-Dhamen et al. [33]). The ANN model acts as a surrogate for computationally intensive multiphase flow simulations, enabling:

Integration into real-time decision support: Potential for coupling with dynamic reservoir management tools to optimize production in fractured formations.

- Furthermore, this research contributes to the growing application of AI in petroleum engineering (e.g., El Ouahed et al. [32]; Al-Dhamen et al. [33]). It demonstrates that ANNs can also learn the underlying physics of complex hydrodynamic problems, such as the relationship between fracture geometry and effective properties in multiphase flow systems. The model serves as a highly accurate and computationally efficient proxy for the numerical simulations, enabling rapid sensitivity analysis and uncertainty quantification that would be infeasible with full-physics models alone.

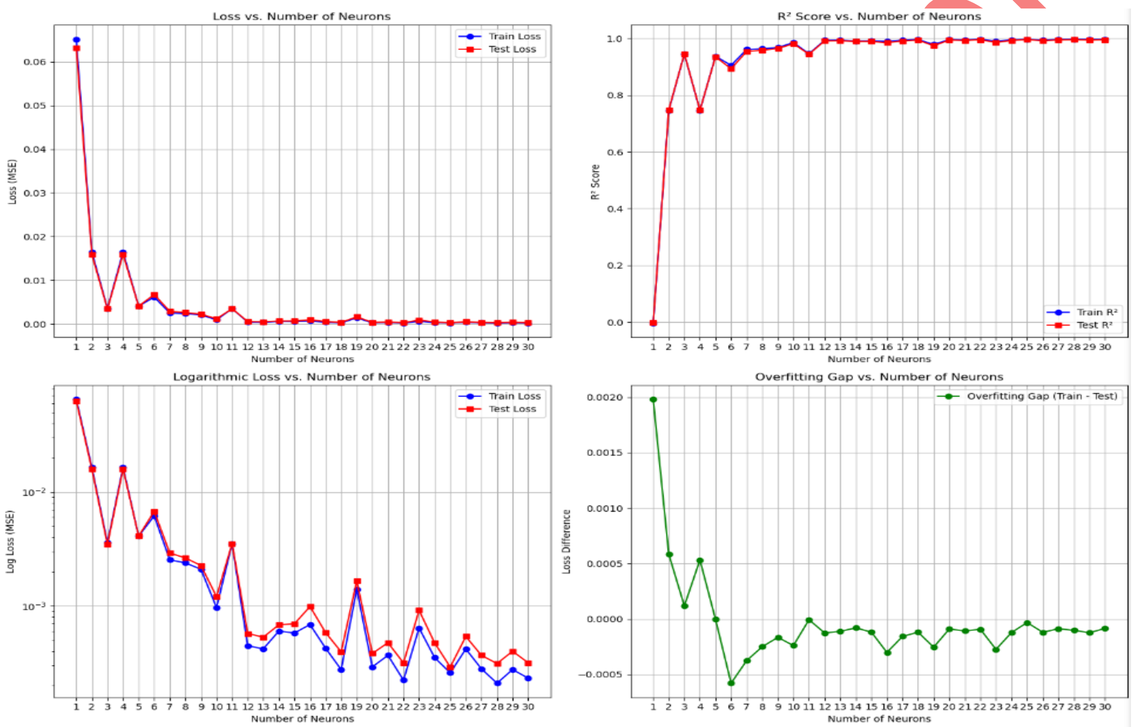

Fig. 2. Performance analysis with different neuron counts. Optimal performance achieved with 25 neurons, balancing model complexity and generalization ability. Shows loss values, R^2 scores, and overfitting gap across 1-30 neuron configuration

To evaluate the robustness of the ANN and mitigate concerns regarding overfitting to synthetic data, an extrapolation test was performed. The model was trained using samples with fracture angles between 10° and 70° and tested on an unseen angular range between 70° and 90°. The low MAPE value (<0.5%) underscores the ANN's practical reliability for industrial implementation, particularly critical in reservoir engineering applications where even marginal prediction errors can propagate into substantial performance deviations during full-field simulations. Visual diagnostic plots reveal tightly clustered predictions around the ideal prediction line (y=x) with minimal scatter (**Fig. 3** and **Fig. 4**), while residual analysis demonstrates a near-normal error distribution centered precisely at zero (**Fig. 5** and **Fig. 6**). This statistical symmetry confirms the absence of systematic bias and highlights the purely stochastic nature of the residual errors, further validating the model's structural integrity.

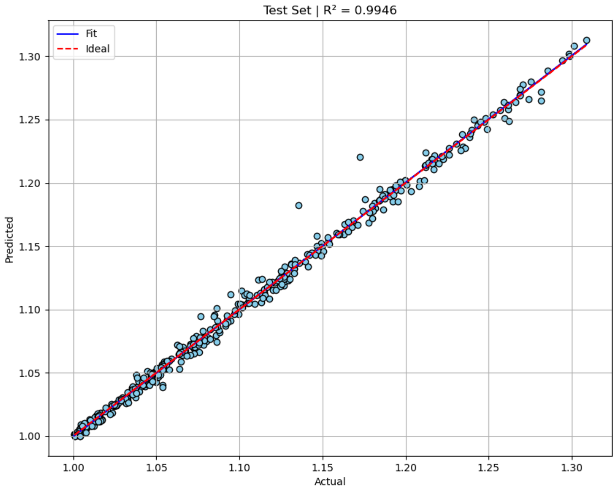

Fig. 3. Actual vs. Predicted Values for the Test Set ($R^2 = 0.9946$)

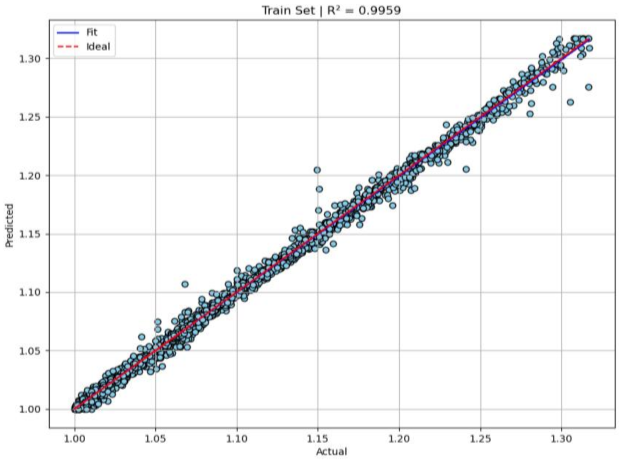

Fig. 4. Actual vs. Predicted Values for the Training Set ($R^2 = 0.9959$)

To assess the relative influence of input parameters on the predicted correction coefficient, a permutation-based feature importance analysis was performed. This analysis quantifies the sensitivity of η to perturbations in each input parameter while preserving the underlying data distribution.

Table 3. Relative Importance of Input Parameters for η Prediction

Input Parameter	**Relative Importance (%)**
Fracture Angle (θ)	61
Matrix Area	25
Reservoir Area	14

The results indicate that fracture orientation is the dominant factor for η, confirming that anisotropy effects are primarily governed by fracture geometry rather than reservoir size. This outcome aligns with physical expectations and supports the validity of the ANN as a physics-consistent model.

The primary scientific contribution of this investigation is the development of a robust, data-driven methodology for accurately quantifying the equivalent fracture aperture correction coefficient (η). This parameter proves instrumental in transcending the limitations inherent in idealized "sugar cube" (Warren-Root) conceptual models by enabling precise representation of reservoirs characterized by non-orthogonal fracture networks.

Due to the cubic relationship between permeability and aperture ($k \propto \eta^3$), even modest inaccuracies in η estimation propagate non-linearly into substantial errors in permeability prediction. For instance, a seemingly negligible 5% underestimation in η (e.g., predicting 1.05 instead of the actual 1.10) manifests as approximately 14.3% error in permeability estimation, potentially leading to significant discrepancies in production forecasts. The exceptional accuracy achieved by our ANN model effectively mitigates this cascading error risk, providing substantially more reliable input parameters for multiphase flow simulation frameworks.

Moreover, the correction coefficient η elegantly encapsulates the complex anisotropic permeability effects induced by fractures inclined at arbitrary angles θ relative to the principal flow direction. This mathematical representation enables realistic characterization of natural fracture networks, which rarely conform to idealized orthogonal or uniform configurations in subsurface formations.

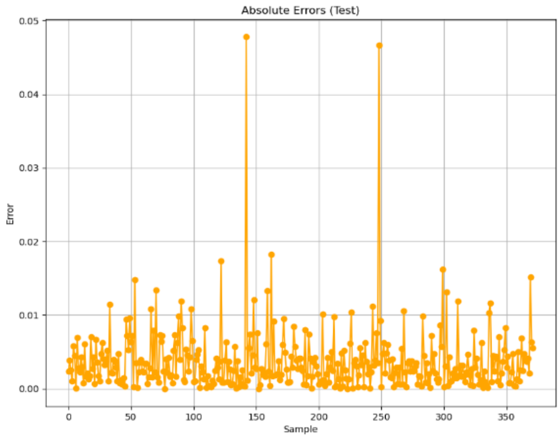

Fig. 5. Absolute Errors Distribution across Test Samples

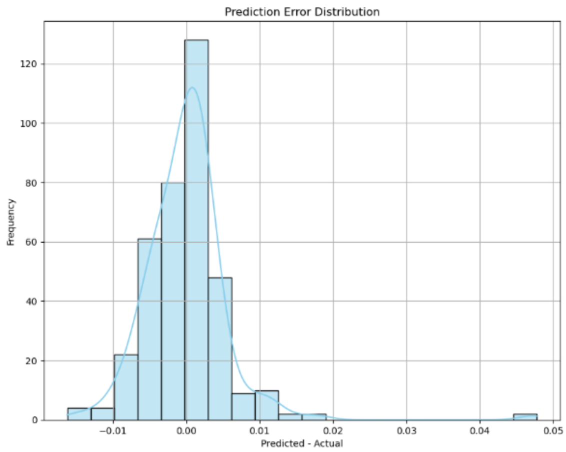

Fig. 6. Prediction Error Distribution Histogram

Hence, by providing an accurate correction factor, the anisotropy resulting from fracture orientation can be effectively incorporated into conventional simulators, leading to more realistic predictions of pressure transients (i.e. well test analysis using a model with a corrected η will yield more accurate interpretations of fracture and matrix properties), fluid flow paths (i.e. flow of water or gas during injection processes will be more accurately modeled, improving predictions of breakthrough times and sweep efficiency) and ultimate recovery (i.e. more accurate reservoir models, accounting for fracture orientation effects, provide better forecasts of oil recovery, optimizing field development planning).

The presented approach both aligns with and substantially extends previous research initiatives in this domain. The utilization of equivalent aperture concepts to address anisotropy resonates with the methodological framework proposed by Zhang et al. [22] for coalbed methane reservoirs and builds upon the foundational theoretical work of Young et al. [21]. However, this investigation advances the scientific frontier by transcending purely conceptual or analytical solutions, instead providing a practical, generalized predictive tool through sophisticated machine learning implementation.

This research makes a significant contribution to the expanding integration of artificial intelligence in petroleum engineering applications (El Ouahed et al. [32]; Al-Dhamen et al. [33]). It convincingly demonstrates that properly designed neural networks can progress beyond pattern recognition to effectively capture the underlying physics of complex hydrodynamic systems, specifically the intricate relationship between fracture geometry and effective flow properties in multiphase transport processes. The developed ANN model functions as a computationally efficient surrogate for resource-intensive numerical simulations, enabling:

- Accelerated Sensitivity Analysis: Rapid exploration of fracture geometry effects on multiphase flow behavior without the computational burden of full-physics simulations.
- Comprehensive Uncertainty Quantification: Systematic assessment of prediction confidence intervals and associated risk mitigation strategies in fractured reservoir management.
- Real-time Decision Support Integration: Potential for seamless coupling with dynamic reservoir management platforms to optimize production strategies in complex naturally fractured formations.

The exceptional predictive accuracy achieved (MAPE < 0.5%) positions this methodology as a valuable addition to the reservoir engineer's analytical toolkit, bridging the persistent gap between idealized conceptual models and the complex reality of naturally fractured reservoir systems.

4 .Conclusions

This study presents an advancement in the characterization and modeling of anisotropic fractured mediums by using by introducing a physics-informed, data-driven framework for quantifying the fracture aperture correction coefficient (η). By treating η as a functional response to fracture orientation, matrix shape and reservoir geometry rather than a constant calibration parameter, the proposed approach bridges fracture-scale flow physics and continuum dual-porosity modeling.

The ANN model designed worked very good with high predictive accuracy ($R^2 = 0.9946$, MAPE = 0.34%) while preserving physical consistency, as confirmed through sensitivity, partial dependence, and extrapolation analyses. The results show that fracture orientation is the dominant control on η and that accurate estimation of this parameter significantly reduces permeability uncertainty arising from the cubic aperture–permeability relationship.

By incorporating this correction factor into the Warren–Root framework, the applicability of conventional dual-porosity models is extended to reservoirs with non-orthogonal fracture networks. The proposed methodology provides a computationally efficient and physically interpretable tool for improving flow prediction, well test analysis, and reservoir management decisions in naturally fractured systems.
In this study, we focused on fracture orientations, and fracture size and system size. Further studies are needed to consider the effects of other factors including stress-aperture relation, aperture variations and roughness within single fractures to propose a more general approach for estimating equivalent aperture in flow simulations to avoid errors in both principal permeabilities and flow patterns.

5 .Nomenclature

η	Fracture aperture correction coefficient	–
ϕ	Porosity	Fraction
k	Permeability	m^2
μ	Fluid viscosity	Pa·s
ρ	Fluid density	kg/m^3
q	Source or sink term	m^3/s
g	Gravitational acceleration	m/s^2
z	Depth	m
∇	Gradient operator	–
θ	Fracture inclination angle	°
T	Transmissibility coefficient	–
$S\alpha$	Phase saturation (α = water, oil)	–
Φ	Flow potential	–
ANN	Artificial Neural Network	–
WR	Warren–Root dual-porosity model	–
DFN	Discrete Fracture Network	–
COMSOL	COMSOL Multiphysics software	–
R^2	Coefficient of determination	–

MAPE	Mean Absolute Percentage Error	%

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