The Impact of Artificial Intelligence and Machine Learning on Reservoir Characterization: A Review of Recent Advances

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ABSTRACT

Effective reservoir characterization has been one of the major challenges encountered in the oil and gas industry. Several tools and models have been created to analyze a reservoir accurately to tackle this challenge. This paper reviewed using artificial intelligence and machine learning for reservoir characterization, which has proven an efficient method. With a good understanding of porosity and permeability, reservoir engineers can carefully create a sustainable reservoir development plan, create an effective production system for naturally unproductive reservoirs, determine the drilling optimization, estimate hydraulic flow units, choose the pressure-volume-temperature of reservoirs and reservoir rock properties such as porosity and permeability using well-log data. Support Vector Machines and Artificial Neural Networks from the studies have shown to be vital for a comprehensive reservoir analysis in the future, but there is a need to improve the algorithms for better optimization of new datasets.

Keywords: Reservoir Characterization, Machine Learning, Artificial Intelligence, Artificial Neural Network, Genetics Algorithm.

INTRODUCTION

Reservoir Characterization is a process that uses the field data that is currently available to identify reservoir parameters in spatial variability quantitatively. It presents essential details on the distribution and development of reservoir heterogeneity and petrophysical parameters [1], [2], [3]. This would help in making reliable predictions about the reservoirs and increase the accuracy of reservoir projections by correlating the petrophysical parameters identified by multiple methods (core analysis, well logging, and well-production data) to geologic fabrics [4]. The ultimate goal is a realistic reservoir model that can withstand uncertainty and imprecision. Porosity and permeability are two essential characteristics of a reservoir's capacity to hold fluids and its tendency to flow. The impacts of these characteristics can be seen significantly in reservoir management and petroleum field operations [5], [6], [7], [8].

The challenge of developing computers that learn automatically is addressed by machine learning. The interplay of computer science and statistics, as well as the foundation of artificial intelligence and data science, makes it one of the technical domains with the fastest growth rates today [9]. Machine learning alternatives are getting increasingly popular in the oil and gas sector; however, most of these solutions are still extremely nascent in conceptualization and implementation. Data-driven techniques may be used by machine learning-based proxies to map intricate correlations between input parameters and reservoir responses [10], [2]. Moreover, they may also act as "black box" predictors, which depend on inputs like well rates and locations, bottom hole pressures, etc. to generate outputs like cumulative oil produced or net present value [11].

The application of artificial intelligence techniques in the oil and gas sector has the benefit of improving the use of existing infrastructure. It offers improved potential results, making it a crucial technology for the sector's operations. The use of artificial intelligence approaches for effective planning, identifying the features of reservoir rock, drilling optimization, and production facilities is examined. Reservoir engineers can create solid reservoir development plans and manage hydrocarbon recovery efficiently with an exact understanding of permeability and porosity [10]. Wire-line log data seismic features are employed in artificial intelligence-based algorithms for porosity prediction [12].

However, the quality of findings obtained from the classical reservoir characterization approaches [13], [14], [15], petrophysics [1], [2], [8], [14], and monitoring practices in the petroleum industry has significantly improved by the addition of artificial intelligence and machine learning; optimization of production performance of a field's life depends on accurate reservoir characterization. Using machine learning frameworks to tackle complicated reservoir challenges requires the development of physics-based data models [16], [10].

The impacts and advancements in machine learning and artificial intelligence shown by numerous scholarly studies are carefully analyzed in this study.

Overview of Artificial Intelligence and Machine Learning

Artificial Intelligence (AI) is the study of how to solve exceedingly complex, highly non-linear problems by combining human intelligence and computing power. Science in artificial intelligence enables computers to reason and make decisions on their own. A branch of artificial intelligence called machine learning (ML) offers statistical tools for exploring and analyzing large amounts of data. Machine learning is divided into several categories including supervised, unsupervised, and reinforcement learning. When some labelled or historical data is available for function approximation predictions, supervised learning is the data learning approach used [17].

A growing number of people are becoming interested in artificial intelligence technologies because of their quick response times and powerful generalization skills. Across a wide range of reservoir engineering issues, artificial intelligence technology shows remarkable potential to support and enhance traditional reservoir engineering methodologies [18], [19], [20], [21]. Several studies use sophisticated machine learning algorithms as tools for regression and classification, including fuzzy logic (FL), artificial neural networks (ANN), support vector machines (SVM), and response surface models (RSM) [6], [22], [23], [24]. However, supervised learning is a machine learning technique employed in reservoir engineering applications, often using evolutionary protocols such as the genetic algorithm (GA) and particle swarm optimization (PSO) [25], [26], [27].

[28] , in his study, presented that, artificial neural networks (ANNs) are one of the oldest and most significant methods utilized in reservoir characterization. Having devices that can simulate the brain was originally the motivation behind the neural network (NN) algorithm. In the late 1980s and early 1990s, ANNs initially were used for reservoir characterization. These networks proved to be incredibly effective when used to simulate and forecast reservoir characteristics like porosity and permeability.

Deep learning became a viable artificial intelligence tool for reservoir characterization in the late 2000s. In deep learning, a subset of machine learning, complex patterns in data are learned and represented using neural networks with several layers. The processing of enormous volumes of data from many sources, including well logs, seismic data, and production data, has transformed reservoir characterization thanks to deep learning algorithms. They have also augmented the creation of models that can precisely forecast reservoir behaviour and features, such as the rates at which oil and gas are produced. Additionally, surrogate reservoir models (SRMs), a sort of data- driven model used in reservoirs, are a relatively recent development and were first used in 2006. SRMs are three-dimensional numerical reservoir models that approximate the full field models and can closely resemble their behavior [29].

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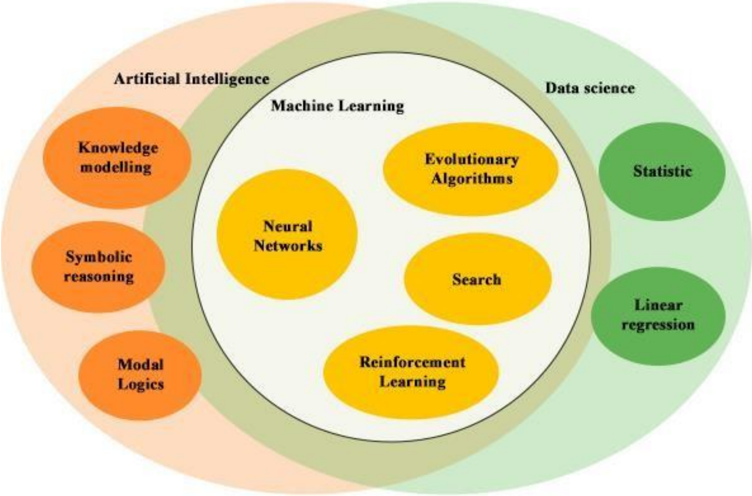

Fig. 1. Venn's diagram showing the relationship between Artificial Intelligence, Machine Learning and Deep Learning [30], [31].

METHODOLOGY

To comprehensively review the impact of Artificial Intelligence (AI) and Machine Learning (ML) on reservoir characterization, we conducted a systematic literature search using multiple databases, including Google Scholar, IEEE Xplore, ScienceDirect, and the Society of Petroleum Engineers (SPE) Digital Library. The search was limited to articles published between January 2000 and December 2023 to capture recent advances. Keywords used in the search included "Artificial Intelligence," "Machine Learning," "Reservoir Characterization," "Petroleum Exploration," "Seismic Interpretation," and "Geostatistics."

We applied the following inclusion criteria to select relevant studies:

1. Articles published in peer-reviewed journals and conference proceedings.
2. Studies that specifically discuss the application of AI and ML in reservoir characterization.
3. Articles written in English.

Exclusion criteria included:

1. Studies not directly related to reservoir characterization.
2. Non-peer-reviewed articles, editorials, and opinion pieces.
3. Duplicate studies across different databases.

Each article was reviewed, and relevant data were extracted, including:

1. Study objectives and scope.
2. Types of AI and ML techniques applied.
3. Data types and sources used in the studies (e.g., seismic data, well logs, production data).
4. Key findings and contributions to the field of reservoir characterization.

Limitations and future research directions are highlighted by the authors.

The extracted data were then synthesized to identify common themes, trends, and gaps in the current research.

We categorized the studies based on the AI and ML techniques used (e.g., neural networks, support vector machines, decision trees) and their specific applications in reservoir characterization (e.g., lithology prediction, porosity estimation, fluid distribution).

We conducted a critical analysis of the selected studies to evaluate the effectiveness and limitations of different AI and ML approaches in reservoir characterization. This involved:

1. Comparing the performance metrics reported in the studies (e.g., accuracy, precision, recall, F1 score).
2. Assessing the robustness and generalizability of the proposed models.
3. Analyzing the interpretability of the AI and ML models in the context of geological and reservoir engineering principles.

DISCUSSIONS

Artificial Intelligence and Machine Learning Techniques in Reservoir Characterization

Reservoir characterization is an essential part of the oil and gas industry, which involves understanding the geological properties and fluid behaviour of a subsurface reservoir. Artificial intelligence and machine learning are increasingly becoming popular in reservoir characterization due to their ability to process large amounts of data and extract valuable insights. This part of our studies gives the state-of-the-art of artificial intelligence and machine learning techniques in reservoir characterization.

Machine Learning and Reservoir Exploration

[32], defined machine learning as the study of making computers learn and behave like people and improve their learning behavior over time in an independent manner, by providing them with data and knowledge in the form of observations and interactions with people in the real world. This branch of artificial intelligence known as machine learning includes creating statistical models and algorithms that allow computers to discover patterns and insights from massive amounts of data without having to be explicitly programmed. The application of machine learning has completely changed the oil and gas sector in recent years, enabling more precise and efficient exploration of various reservoir types.

Going further to the last 20 years, regression, function approximation, and classification issues have experienced an increase in the application of machine learning in engineering publications. As a result of big data technology and intelligent oilfield growth, the application of machine learning techniques in the analysis of issues about oilfield development has regained relevance. The development of these computational methods has led to the appearance of numerous machine learning-based correlations in several domains, most notably reservoir engineering [33], [34], [35], reservoir geomechanics [36], and reservoir characterization [[28], [37] and in other applications within the petroleum engineering domain.

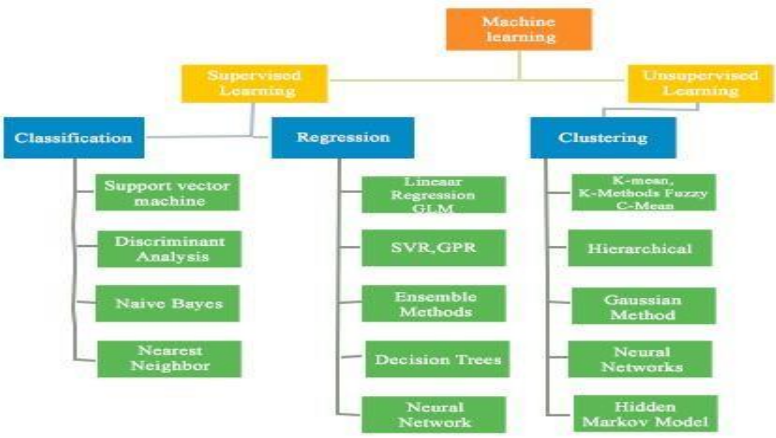

Fig. 2 Steps in Machine Learning Problems, [31].

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However, reservoir properties such as porosity, permeability, and water saturation can significantly impact the production and recovery of oil and gas resources. By more precisely anticipating these features, machine learning has been increasingly employed to enhance reservoir characterization. In a recent review paper, [38] reported that machine learning has been used to characterize reservoirs in a variety of ways, including forecasting porosity and permeability from well logs and seismic data, classifying fluid types and lithology, and calculating reserves and production rates. To locate the oil-water contact and estimate the amount of recoverable oil, machine-learning models have also been created to forecast water saturation.

[38] , also noted that the application of machine learning to reservoir characterization has several advantages over the conventional methods. Machine learning models can handle large, complex datasets, identify non-linear relationships between variables, and generate more accurate predictions. Machine learning can also incorporate various types of data, such as geological, geophysical, and production data, into a single model to provide a more comprehensive view of the reservoir.

For instance, [39] used ML to predict porosity and permeability in a carbonate reservoir in Saudi Arabia. The authors compared various ML algorithms and found that random forest regression provided the most accurate predictions. The ML models also revealed the spatial distribution of porosity and permeability, which helped to identify areas with high production potential.

Artificial Intelligence comprises Machine Learning as one of its subsets. The oil and gas industries collect diverse types of data from both surface and subsurface to comprehend the hydrocarbon potential. Sensors are the most prominent tools to collect this data in large numbers. Technical analysis and intervention are necessary to plot and analyze this data. Machine learning methods establish a relationship between input variables and predict the output without interfering with the physical behavior of the system. The data associated with the oil and gas industries are massive, and the process of data correlations is highly complex [40].

ANN models associate several input and output signals with synaptic weights. The model sums the product of inputs and their corresponding weights and then passes it through a transfer function to obtain the layer's output. The number of hidden layers determines the model’s convolution and non-linearity. Two calculations compute hidden and output nodes: summation and transformation through active functions, which can be linear or non-linear [41].

The ANN model's general relationship between input and output is expressed as follows:

$yk = fo\,(\Sigma j(wkj * fh(\Sigma i(wji * xi + bj) + bk)))$

Where:

x = Input vector

Wji = Connection layer in the ith neuron to jth neuron in the hidden layer

bj = Threshold value or bias of the jth hidden neuron

wkJ = Connection weight from the jth neuron in the hidden layer to the kth neuron in the output layer.

Artificial Neural Network (The Nerd Brainy Network)

Artificial neural networks (ANNs) are a subset of machine learning algorithms modelled after the human brain's structure and function. ANNs have been extensively studied in recent years due to their ability to learn and recognize complex patterns in data.

Recent studies by [42] provide a comprehensive overview of ANNs, including their history, architecture, and applications. The authors describe how ANNs are composed of layers of interconnected nodes, or neurons, trained on input data to learn the underlying patterns and relationships in the data. The authors also discuss the different types of ANNs, including feedforward neural networks, recurrent neural networks, and convolutional neural networks, and how they are used for tasks such as image recognition, natural language processing, and prediction.

However, research has shown that ANNs can be effective in various applications. For example, [43] used ANNs to predict the severity of Parkinson's disease based on patients' speech patterns, achieving high accuracy in their predictions. The figure below shows the structure of the artificial neural network.

In another study, [44] used ANNs to predict the growth of microorganisms in food products, which could help to improve food safety and prevent foodborne illnesses.

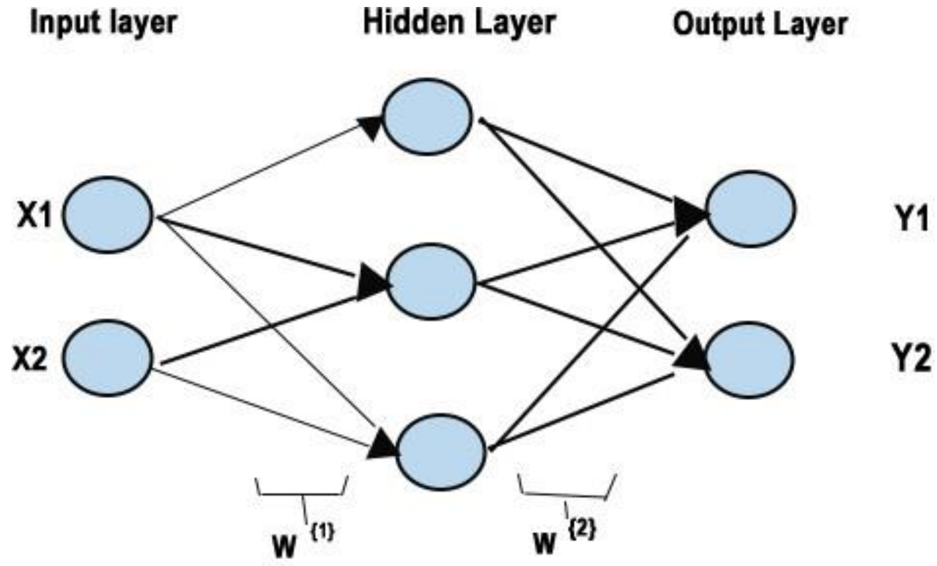

Fig. 3 Multilayer Perceptron Architecture X=[X1, X2] = Input Vector, Y = [Y1, Y2] = Output Vector, W =[W1, W2] =Vector of Weight matrices for layer 1 and layer 2 [45].

While ANNs have shown great promise in many areas, there are still challenges to be addressed in their development and implementation. For example, ANNs can require large amounts of training data and computing power and can be prone to overfitting or underfitting the data. Nonetheless, ANNs are a powerful tool for data analysis and decision-making and will likely play an increasingly important role in many fields in the coming years.

The most basic and straightforward ANN model is the multilayer perceptron, also known as the feed-forward neural network (FFNN). It consists of one hidden layer, one input layer, and one output layer with no loops. In contrast, other neural networks contain loops or feedback, such as recurrent neural networks [46]. Nodes in the multilayer perceptron are interconnected such that information can only flow in the forward direction, with each successive layer receiving information from the previous one. The activation function in the hidden layer transforms the input features into a more representable feature that is more relevant in determining the target.

ANN is a popular machine learning technique because of its ability to model complex nonlinear functions. A one-hidden-layer neural network can approximate any continuous function with an appropriate number of hidden neurons with nonlinear functions [47]. Increasing the number of hidden layers may provide efficient modelling capability for more complex problems, such as time series, computer vision, and speech recognition [48]. When the number of hidden layers exceeds one, the ANN model becomes deep. Deep models can learn multiple levels of representation and hence better able to model real-world complex data.

Artificial Neural Network in Reservoir Characterization

Artificial neural networks (ANNs) have been widely used in reservoir characterization to model the complex relationships between geological and engineering parameters. To predict reservoir properties such as lithology, porosity, and permeability, ANNs can be trained using various data types, such as logs, seismic data, and production data.

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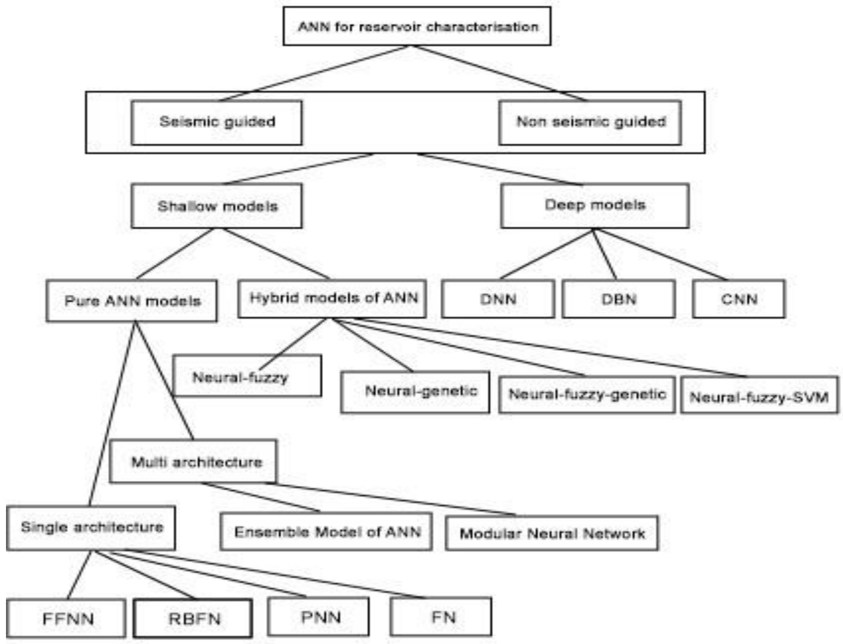

Fig. 4 ANN model in reservoir characterization [45].

Recent research has shown the effectiveness of ANNs in reservoir characterization. For example, in a study by [49]. ANNs were used to predict reservoir permeability using well-log data. The study found that ANNs outperformed traditional regression models and provided more accurate permeability predictions.

Another study by [50] used ANNs to predict lithology and porosity from well-log data. The study found that the ANNs were able to predict lithology and porosity accurately, and could be used to improve reservoir characterization in heterogeneous reservoirs. In another study by [51], ANNs were used to predict the amount of oil recovery from a reservoir based on production data. The study found that the ANNs were able to predict oil recovery accurately and could be used to optimize production strategies. The figure below shows the Artificial Neural Network model used in reservoir characterization.

Artificial neural networks (ANNs) have been increasingly used in the oil and gas industry to improve reservoir characterization and management. Here are some examples of recent research studies and review papers that highlight the ways ANN has been applied and improved reservoir characteristics:

- Reservoir Characterization: ANNs have been used to predict reservoir properties based on well-log data, a critical aspect of reservoir characterization. For example, a study by [43] used ANNs to predict reservoir permeability and porosity accurately. ANNs can also identify potential hydrocarbon-bearing zones within a reservoir [52].

- Production Optimization: ANNs have been applied to optimize production strategies, such as well placement and artificial lift optimization. For instance, a study by [45] used ANNs to optimize gas-lifted oil production, leading to a 10% increase in the oil production rate. ANNs have also been used to optimize hydraulic fracturing design parameters for unconventional reservoirs [53].

- Reservoir Simulation: ANNs have been applied to improve the accuracy of reservoir simulations. A study by [54] used ANNs to predict reservoir pressure and temperature, and the results were more accurate than traditional methods. ANNs have also been used to optimize history matching, which is matching a reservoir simulation model to historical production data [53].

- Seismic Interpretation: ANNs have been applied to improve the accuracy of seismic interpretation, which is the process of identifying subsurface structures based on seismic data. For example, a study by [53] used ANNs to classify seismic facies and identify potential hydrocarbon reservoirs with high accuracy.

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Limitations of Artificial Neural Network

While artificial neural networks (ANNs) have shown great potential in improving reservoir characterization and management, their use also has some limitations. Here are some of the limitations of ANN in reservoir characteristics:

1. Data Availability: One of the major limitations of ANNs is the availability of data. ANNs require large amounts of high-quality data for training, and in some cases, such data may not be available. Moreover, the data used to train ANNs may not always be representative of the actual reservoir conditions, which can affect the accuracy of predictions [54].

2. Overfitting: ANNs can be prone to overfitting, which occurs when the model is too complex and is trained to fit the noise in the data rather than the underlying pattern. This can lead to inaccurate predictions when the model is applied to new data. Overfitting can be reduced by using regularization techniques and ensuring that the model is not too complex [53].

3. Interpretability: ANNs are often referred to as "black box" models because it can be difficult to interpret how they arrive at their predictions. This can be a limitation in reservoir characterization, where engineers may need to understand the underlying geology and physics to make informed decisions [52].

4. Computing Resources: ANNs can require significant computing resources, especially for large datasets and complex models. This can be a limitation for companies that do not have access to such resources [43].

Overall, ANNs have limitations that should be considered when applying them to reservoir characterization and management. However, many of these limitations can be addressed through careful data selection, model design, and interpretation of results.

Support Vector Machines

The supervised learning method known as Support Vector Machines (SVMs) may be applied to classification, regression, and outlier identification applications. Vapnik and his associates originally presented SVMs in the 1990s [55], and they have subsequently gained popularity as a tool in numerous domains, including reservoir characterisation.

Finding the optimum hyperplane that divides data points into distinct groups or forecasts the results of a regression job is the fundamental tenet of SVMs. The distance between the hyperplane and the closest data points for each class of data is selected so that it optimizes the margin between the various classes of data. Although SVMs are often thought of as binary classifiers, there are approaches to adapt them to multi-class issues.

SVMs can handle both linear and non-linearly separable data using a technique called kernel methods. A kernel function transforms the input data into a higher-dimensional feature space where the data points may become linearly separable. Common kernel functions include linear, polynomial, radial basis function (RBF), and sigmoid.

Recent research has focused on improving the performance of SVMs and extending their applications. One area of research is the development of new kernel functions that can handle more complex data structures. For example, [56] proposed a new kernel function based on wavelet transform that improved the accuracy of SVMs in predicting reservoir permeability.

Another area of research is the development of hybrid models that combine SVMs with other machine-learning techniques to improve their performance. For example, [54] combined SVMs with convolutional neural networks (CNNs) to predict reservoir facies from seismic data, and achieved better performance than using SVMs or CNNs alone. SVMs also have some limitations, such as their sensitivity to the choice of hyperparameters, computational complexity, and difficulty in handling imbalanced datasets. Research is ongoing to address these limitations and improve the scalability and robustness of SVMs.

Support Vector Machines in Reservoir Characterization

Support Vector Machines (SVMs) have found widespread application in reservoir characterization due to their ability to extract valuable information from different types of data, such as seismic attributes, well logs, and production data. The SVM algorithm can be used for classification, regression, and optimization tasks, and has been applied to a wide range of reservoir characterization problems. Here are some common applications of SVM in reservoir characterization:

Facies Classification:

One of the most common applications of SVM in reservoir characterization is facies classification. SVMs have been used to classify geological facies based on various data sources, including well logs, seismic data, and core samples. SVM algorithms can be trained to classify facies based on a combination of different input variables, such as acoustic impedance, density, and neutron porosity. SVM-based facies classification has been shown to provide high accuracy and can improve reservoir characterization and modelling. For instance, a recent study by [56] applied SVM to classify sandstone and shale facies based on well-log data. The authors used a modified SVM algorithm called the Geologic Object-Based SVM (GOB-SVM) to classify the facies and achieved high classification accuracy.

Petrophysical Property Prediction:

Another application of SVM in reservoir characterization is petrophysical property prediction. SVM algorithms have been used to predict a wide range of petrophysical properties, such as porosity, permeability, and water saturation based on well-log data. SVMs can be trained on multiple well-log data types to improve prediction accuracy. For instance, in a study by [54], [56], SVM was used to predict porosity and permeability based on well-log data. The authors proposed a new SVM algorithm called the Multiple-Feature Combination SVM (MFC-SVM) to combine different well-log data types and achieve better prediction accuracy compared to other machine learning algorithms.

Production Forecasting:

SVM has also been applied to production forecasting in reservoir characterization. SVM algorithms can be trained on production data and reservoir properties, such as pressure and permeability, to predict future production rates.

For instance, in a study by [56], SVM was used to forecast production from unconventional reservoirs based on production data and reservoir properties. The authors proposed a new SVM algorithm called the Reservoir Characteristics-Based SVM (RCB-SVM) to integrate reservoir properties with production data and achieve better forecasting accuracy compared to traditional methods such as decline curve analysis and neural networks.

Challenges in Exploration Solved by Support Vector Machine

A recent review paper by Yu *et al*. (2021) highlighted how SVM has been used to address some of the challenges faced in reservoir exploration, such as data heterogeneity, noise, and limited data availability. The authors discussed how SVM has been applied to various reservoir exploration problems and demonstrated its effectiveness in providing accurate and reliable solutions.

One of the main challenges in reservoir exploration is dealing with heterogeneous data sources, which can include well logs, seismic data, and production data. SVM is effective in integrating these data sources and extracting valuable information for reservoir characterization. For example, in a study by [53], [54], SVM was used to combine well-log data and seismic attributes to classify sandstone and shale facies. The authors showed that SVM-based classification outperformed traditional methods such as fuzzy logic and decision trees.

Another challenge in reservoir exploration is dealing with noisy data, which measurement errors, environmental factors, and other sources of interference can cause. SVM is robust to noise and can provide reliable predictions even with noisy data. For example, in a study by [57], SVM was used to predict permeability based on noisy well-log data. The authors showed that SVM-based prediction outperformed other machine learning algorithms such as random forest and artificial neural networks.

SVM is effective in dealing with limited data availability, which is a common problem in reservoir exploration due to the high cost and complexity of data acquisition. SVM can be trained on limited data samples and can provide accurate predictions even with small datasets. For example, in a study by [58], SVM was used to predict reservoir permeability based on a small number of well logs. The authors showed that SVM-based prediction was more accurate than traditional methods such as linear regression and principal component analysis.

Reservoir Characterization Using Artificial Intelligence.

According to [59], one of the major objectives of the petroleum industry is to obtain an accurate estimate of the initial hydrocarbon in place before investing in development and production. Due to the heterogeneous nature of the reservoir, classical characterization methods often fail to detect the orientation and location of the fracture. This led to the application of Artificial Intelligence in the area of Reservoir Characterization and has made the problems or challenges a possible practice [60].

According to [61], machine learning demonstrates good potential for assisting and enhancing traditional reservoir engineering approaches in a wide range of reservoir engineering issues.

In oil field technology, the application of AI tools such as fuzzy logic and neural networks is evolving rapidly [60]. In various studies, advanced machine-learning algorithms e.g. fuzzy logic, artificial neural network, supporting vector machine (SVM), and response surface model (RSM) as classification and regression problem tools [24].

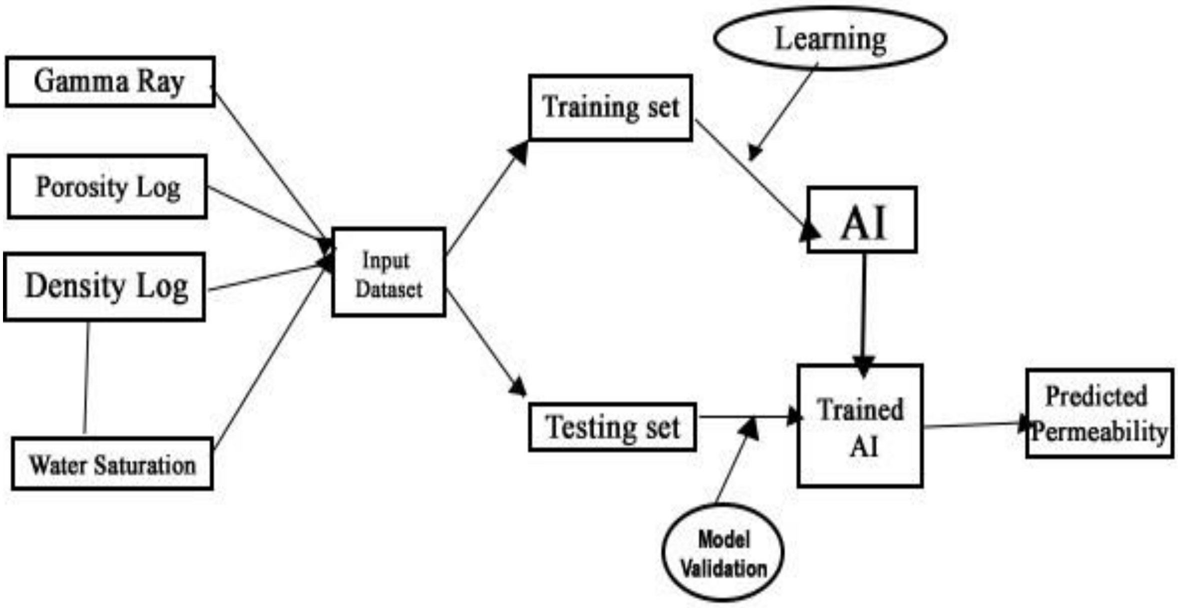

Fig. 5 Framework for Artificial Intelligence Application, [61].

Successful Applications in Reservoirs and Their Impacts Permeability

[62], applied the artificial intelligence technique for three wells using artificial neural network, fuzzy logic, and genetics algorithm approaches, which targeted the Permeability of SDR, which are obtained in boreholes. In the artificial neural network technique, well 1 was the training, while well 2 and 3 were the blind test. Comparing the estimates, permeability obtained with the SDR permeability using MSE and R^2 as an indication of the quality of each technique. Artificial neural networks obtained better results than fuzzy logic, but the results were better with the genetics algorithm.

The two hybrids of functional network, fuzzy logic and support vector machine were applied to predict the porosity and permeability of some Pacific and Middle Eastern oil and gas reservoirs. According to the results, hybrids performed better than individual techniques [63].

[64] applied a fuzzy model for permeability estimation in heterogeneous sandstone oil reservoirs using core porosity and gamma ray log. The result showed that the fuzzy model prediction was accurate and in perfect agreement with the measured core.

Estimation of Pressure-Volume-Temperature Property

The artificial neural network technique is applied to determine PVT parameters and estimate the bubble point pressure of a reservoir. A comparative study between the performance of ANN and other published correlations showed an excellent response with smaller absolute relative average errors and higher correlation coefficients for the designed networks among all correlations [65].

In their study, [66] presented an implementation of ANN, Support Vector Regression and Functional Networks used to predict crude oil's Pressure-Volume-Temperature (PVT) properties. Instead of the usual single or multi-data point prediction that is described by a curve, the approach predicted PVT over a specified range of required reservoir pressures. The shapes of the predicted curves were smooth and consistent with the experimental curves.

Drilling Problems Detection

According to [67], their studies showed an artificial neural network model with Multi-Layer Perceptron (ANN-MLP) and Support Vector Machines (SVM) for classifying drill cuttings using image processing technology to detect stuck pipe problems. The results identified ANN-MLP and SVM as promising techniques for further study.

[68] presented two different types of artificial neural network models: Multi-Layer Perceptron (MLP) and Radial Basis Functions (RBF). These models provided solutions for problems associated with differential pipe sticking using a stuck pipe database of 64 side-tracked and horizontal wells drilled in a reservoir section.

Estimation of Hydraulic Flow Units

Using a hybrid neuro-fuzzy approach, [69], the hydraulic flow units and well log responses were estimated using Porosity-Permeability relationships to characterize heterogeneous reservoir rocks in the mixed carbonate-clastic Asmari Formation of the Ahwaz oilfield in Southern Iran. The study's results showed that the Fuzzy logic model successfully modelled flow units from well logs at well locations for which no core data was available.

The application of AI in this field is still very new in the estimation of hydraulic flow units, and as such there are limited research studies in this area.

Advancements, Challenges, and Limitations of Artificial Intelligence on Reservoir Characterization Advancements

[70] , summarize how application advancements have improved conventional reservoir engineering approaches in their studies. Big data gathered from the field and processed by artificial intelligence models is possible. Compared to the classic data processing method, artificial intelligence models are more successful in correlating different field data that cannot be articulated using physical or mathematical models and extracting information. However, the development of intelligent models better addresses the non-unique nature of solutions to inverse reservoir engineering problems.

Artificial intelligence models have significantly reduced the computational overhead of reservoir engineering problems that require large volumes of simulation runs, such as history matching, sensitivity analysis, uncertainty characterization etc.

Finally, its application enables some of the traditional reservoir engineering procedures, which are normally handled in an automated and quantitative manner by reading charts and tables (for example, screening of EOR technologies).

According to [71], [72], [73], and [74], the benefits of AI techniques are:

i. The leverage artificial intelligence techniques have over other modelling techniques is their ability to model complex, non-linear processes without any form of relationship assumption between input and output variables.

ii. Artificial intelligence has gained enormous popularity as a developing and promising technology for prediction, diagnosis, monitoring, selection, forecasting, inspection, and identification in various fields.

iii. It has a great potential for generating accurate results from large historical databases. Most engineers may not deem the type of data meaningful or important in standard modelling and analysis methods.

iv. Artificial intelligence models are more accurate than other empirical models When making predictions using linear or non-linear multiple regression or graphical methods.

v. Artificial intelligence tools can analyze large quantities of data to establish patterns and characteristics in situations where rules are unknown and sometimes make sense of incomplete or noisy data in many cases. It can implicitly detect complex nonlinear relationships between independent and dependent variables.

vi. Artificial intelligence tools can be developed using multiple different training algorithms and they can carry out boring tasks and complete them faster with fewer errors and defects, unlike humans.

Challenges

Just like every other technology, there are limitations and challenges attached to the use of AI in reservoir characterization.

1. ANN is often tagged as black boxes that merely attempt to map a relationship between output and input variables based on a training data set. This raises some concern regarding the ability of the tool to generalize to situations that were not well represented in the data set [75].

2. [76] in their study presented that one proposed solution in addressing the black box problem is the combination of multiple AI paradigms into a hybrid solution (e.g., combining neural networks and fuzzy sets into neuro-fuzzy systems) or integrating AI tools with more traditional solution techniques.

3. According to [76], another limitation of using AI such as genetic algorithm (GA) is the lack of ability to reach the “optimal” solution. Also, when using AI-based search methods to solve a problem, it is often hard to gain true insight into the problem and the nature of the solution, as is possible, for example, when using mathematical programming methods.

The difficulty of doing sensitivity analysis fast is a significant illustration of the restriction of optimization. A “solution” is preferable to a “no solution” for difficult optimization problems that defy solutions using conventional optimization and mathematical programming methods. Artificial intelligence-based search algorithms provide “excellent” results, according to a substantial body of empirical evidence, but the model may need to be run numerous times to analyze the sensitivity of the solution to the various assumptions and parameters of the issue.

Limitations

Several studies have been carried out on the limitations of artificial intelligence and machine learning and have also given possible solutions. The table below gives an overview of the limitations of various authors:

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Table 1: A summary of the limitations of AI and ML, models [17]

Limitations	Reason	Solution	References
Overfitting	Lack of appropriate amount to be used for training.	Using the ratio of input data points to the total number of network weights used by the connections ($ʄ$).	[77], [78]
Coincidence	Getting a good match by coincidence for a specific dataset.	Using discriminant analysis.	[78]
Overtraining	When the error keeps decreasing by updating the model structure the model can be more complex to fit a specific dataset.	A training methodology that is named “early stopping” can be used. Reinforcement learning with in-stream supervision, for example, the generative adversarial networks.	[79]
Data vailability	Sometimes the gathered data is limited	Single-shot learning in which the AI model is pre-trained on a similar dataset and then is enhanced with experience.	[80]
Interpretability	The single connections in the models do not affect alone but the whole model connections combined affect results.	Local interpretable model and its agnostic explanations. The generalized additive model’s method.	[81], [82]
Generalization	Model failure in the circumstances different from the set of circumstances, which were used in building the original model.	Additional resources are to be utilized for training new datasets.	[83], [84]
Bias	The nature of black-box models makes it to be prone to biases.	Using model-independent perturbations.	[85]

CASE STUDIES

Case Study 1: ANNs for Reservoir Characterization with Limited Data

[86] demonstrated the application of artificial intelligence in characterising oil reservoirs in West Virginia using limited data. Their study used ANNs to identify flow units, predict their distribution, and estimate permeability throughout the reservoir.

Methodology

Flow Unit Identification: A self-organising (Kohonen) ANN was used to cluster core and log data, identifying two main flow units and a transition zone.

Flow Unit Prediction: Development of a back-propagation ANN to predict flow units in wells without core data using only log data.

Permeability Prediction: Another back-propagation ANN was created to estimate permeability within each flow unit.

Reservoir Characterization: Applied the trained ANNs to characterise flow units and permeability throughout the field (Fig. 6).

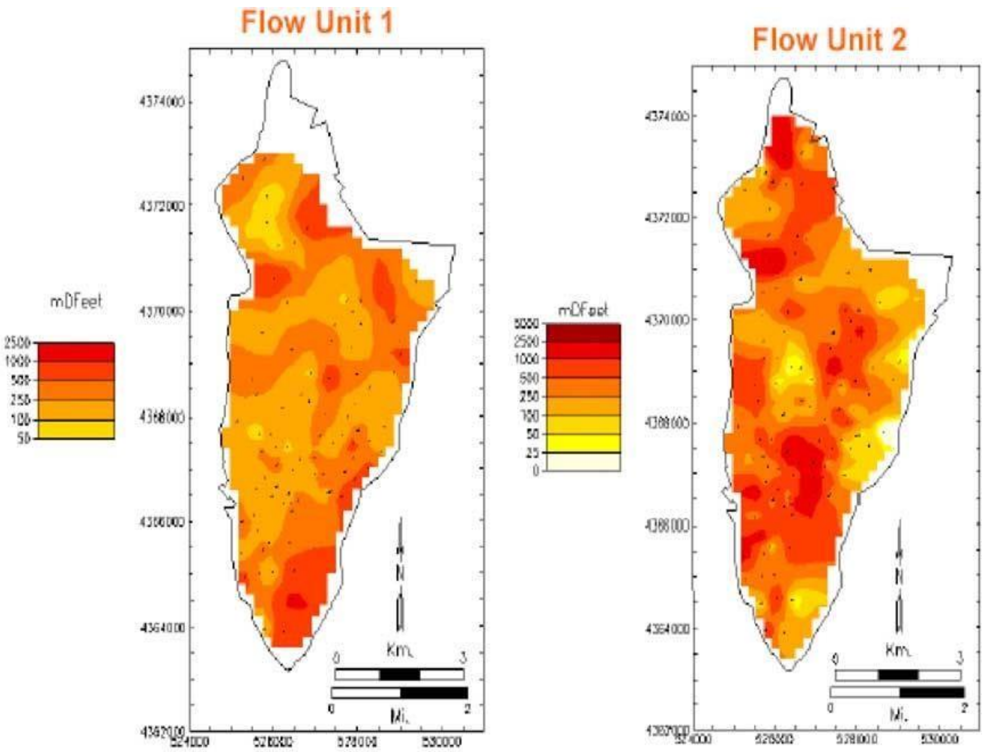

Fig. 6: Shows the distribution of the flow capacity of flow units in the reservoir [86].

Case Study 2: Artificial Neural Networks for Reservoir Inflow Forecasting

Investigation conducted by [87] on the application of Artificial Neural Networks ANNs for long-term reservoir inflow forecasting using monthly historical data: a case study of Sultan Mahmud hydro-power reservoir in Malaysia

Methodology

Levenberg-Marquardt Back Propagation (LMBP) algorithm was used to develop ANN models. The author first tested six input patterns for the ANN models, using one hidden layer in all networks. They employed Mean Squared Error (MSE) and Correlation Coefficient (CC) as performance criteria and early stopping approach to avoid overfitting (Table 2).

Results:

After the evaluation of multiple network configurations, the optimal ANN model was found to have 4 inputs, 5 neurons in the hidden layer, and 1 output (4-5-1 structure), achieving the performance of:

Training: MSE = 0.0188, CC = 0.7282

Testing: MSE = 0.0283, CC = 0.7228

Table 2: Performance of Training and Testing for the selected ANN Model [87]

Model	Training MSE	Training CC	Testing MSE	Testing CC
4-5-1	0.0188	0.7282	0.0283	0.7228

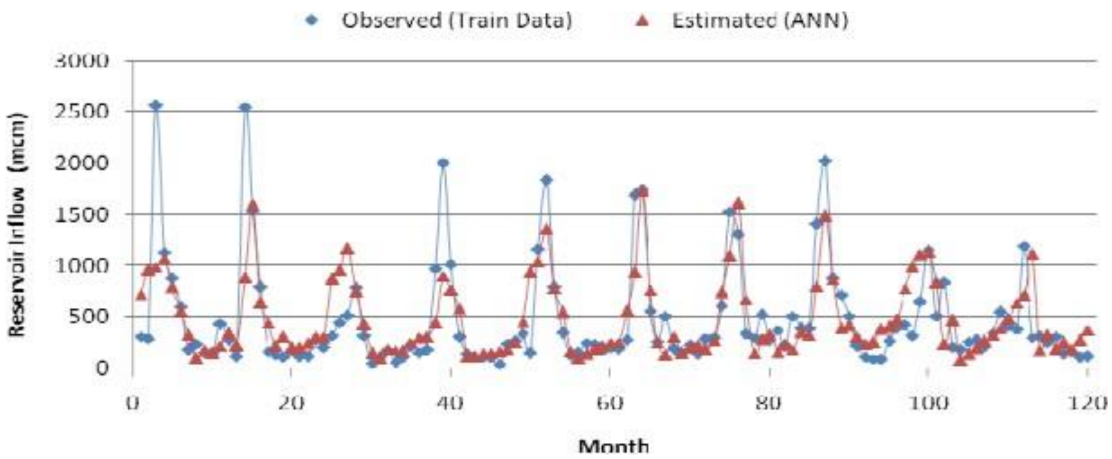

Fig. 7: Showing the comparison between observed and forecasted inflows for training and testing datasets respectively [87]

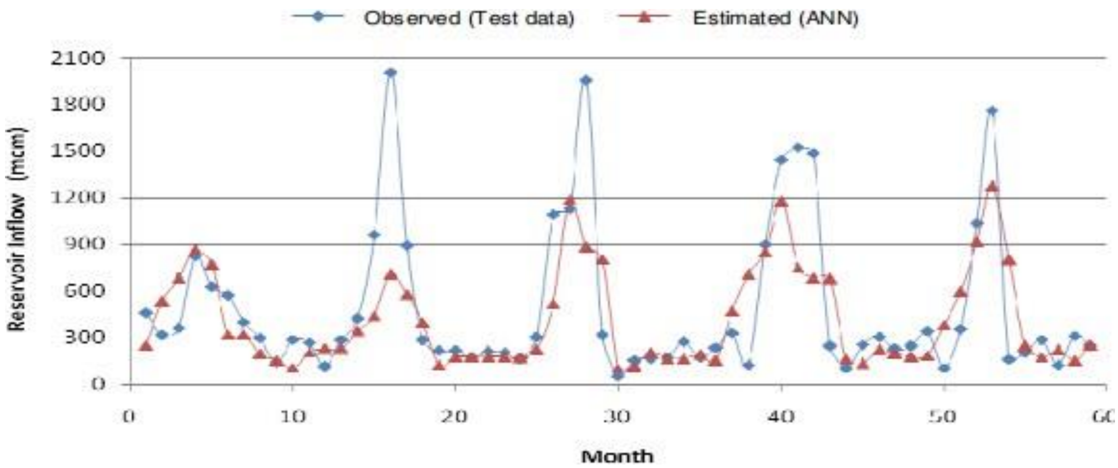

Fig. 8: Showing the comparison between observed and forecasted inflows for training and testing datasets respectively [87] [87] noted that the model showed good agreement between observed and estimated inflows, except for a few high flow events (Fig. 7 and Fig. 8). This means that ANNs can effectively forecast long-term reservoir inflows, outperforming traditional time series methods. The authors concluded that their ANN model provided relatively accurate predictions, as evidenced by the low MSE and reasonably high CC values for both training and testing datasets.

Case Study 3: ANN-Based Production Forecasting for a Water-flooding Reservoir

A recent study by [88] demonstrated the application of artificial neural networks (ANNs) for production forecasting in a water-flooding reservoir. The researchers used 14 years of historical production data from a reservoir in the Malay basin to develop and validate their models.

Methodology:

1. Data preparation: The researchers used 90% of the available data for training and validation, reserving 10% for blind testing.
2. Feature extraction: They developed physics-based features combining various input parameters to improve model performance. For example, they created features representing pressure differences along wellbores and ratios of surface-to-bottom hole pressures.
3. Model architecture: The team tested various ANN architectures, ultimately selecting a nonlinear

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autoregressive network with external inputs (NARX) structure.

4. Training algorithm: After comparing different algorithms, they found that Bayesian regularisation provided the best generalisation for the noisy production data.

5. Model evaluation: The researchers assessed model performance using mean square error (MSE), R-squared values, and error distribution histograms.

RESULTS

The ANN models developed in this study achieved impressive results in predicting oil, gas, and water production rates:

Oil production: R-squared value of 0.947 for the test dataset

Gas production: R-squared value of 0.971 for the test dataset

Water production: R-squared value of 0.971 for the test dataset

Figure 12 demonstrates the close agreement between the ANN-predicted oil production rates and the actual field data. Similar results were obtained for gas and water production forecasts.

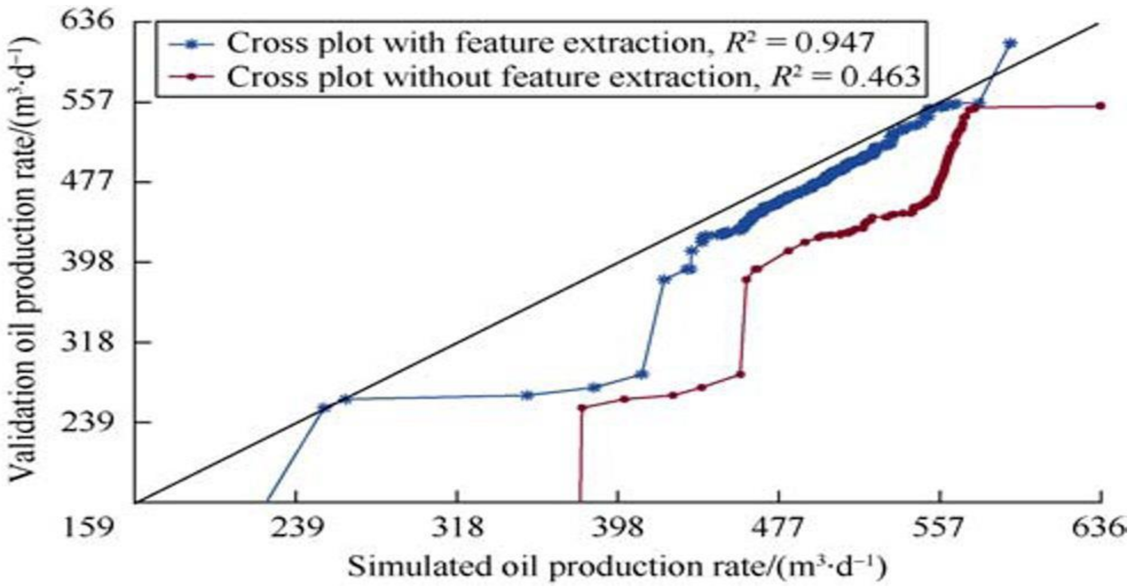

Fig. 12. Cross-plot of simulated oil production rate and validation data [88].

Physics-based feature extraction significantly improved model performance compared to basic models using only raw input data. Error distribution histograms suggested that the remaining discrepancies between predicted and actual production rates were primarily due to measurement errors in the field data. The ANN models demonstrated the ability to provide accurate production forecasts using readily available field data.

This case study highlights the potential of ANN models to provide accurate production forecasts using readily available field data when combined with appropriate feature engineering and model optimisation techniques. Such approaches could complement traditional reservoir simulation methods, offering rapid forecasting capabilities with minimal data requirements.

CONCLUSION

This paper has reviewed the application of artificial intelligence (AI) and machine learning (ML) in reservoir characterisation. It highlights their efficiency and potential in addressing one of the significant oil and gas industry challenges. AI and ML techniques, particularly Support Vector Machines (SVM) and Artificial Neural Networks

(ANN) have shown significant promise in enhancing the understanding of critical reservoir properties such as porosity and permeability. These advancements enable reservoir engineers to develop sustainable development plans, optimise drilling operations, estimate hydraulic flow units, and accurately determine pressure-volume-temperature (PVT) properties and other reservoir rock characteristics using well-log data.

The review demonstrates that AI and ML improve the accuracy and comprehensiveness of reservoir analyses and provide innovative solutions for managing naturally unproductive reservoirs. However, to fully realise the potential of these technologies, there is a need for continued improvement of algorithms to optimise new datasets and adapt to the evolving complexities of reservoir characterisation. By addressing these challenges, AI and ML can play an increasingly vital role in the future of reservoir engineering, driving more efficient and effective exploration and production strategies.

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Conflicts of Interest

The authors declare that they have no conflicts of interest.

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