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Review Article

Oil Reservoir Simulation via Deep Learning: Mini Review

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Abstract *- Reservoir engineers are faced with constitutive reservoir estimation due to monumental data. In some cases, these datasets are difficult to analyze and extrapolate. Geological uncertainties can also affect the way reservoir data are managed. This intricacy has, in one way or the other, created many discrepancies in data utilization, determining how this reservoir data are incorporated into production forecasting. For this reason, data generated from these reservoir operations are used to obtain surrogate models via smart systems (Deep learning). This review aims to evaluate the systemic application of deep learning models to oil reservoir processes by considering various models, such as the Time series models. We first looked at the current trend of technological innovation in the oil and gas sector. We reviewed work done by several authors in different areas of reservoir modelling and simulation and how their works impact the global production of oil and gas by implementing smart technology. With the tremendous applicability of smart systems, oil reservoir management has become less complex due to automation. Artificial Neural Networks have been shown to improve the production efficiency of oil reservoirs even though geological uncertainties are inherent.*

Keywords *- Artificial Neural Networks, Data Driven Modelling, Enhanced Oil Recovery, Reservoir Simulation.*

1. Introduction

Reservoir engineers are faced with constitutive reservoir estimation due to monumental data. In some cases, these datasets are difficult to analyze and extrapolate. Geological uncertainties can also affect how reservoir data are managed [1]. This intricacy has, in one way or another, created many discrepancies in data utilization, determining how this reservoir data are incorporated into production forecasting. For this reason, data generated from these reservoir operations are used to obtain surrogate models via smart systems (Deep learning). Deep learning is a branch of data science that involves interconnected networks that function like the human brain. These networks receive and process information to produce an unseen outcome.

There are scenarios where oil resources are degraded over time due to undetermined reservoir properties and inappropriate recovery mechanisms. For example, in waterflooding recovery, one of the challenges encountered is early water breakthrough which depletes sweep efficiency even though integrating inflow control valves ICVs is appropriate. ICVs are control valves used to regulate oil flow in an oil well. Oil wells that incorporate ICVs are known as intelligent wells [2]. It gives rise to the implementation of intelligent systems for both local and international oil exploration and development [3]. To facilitate reservoir estimations, the choice of network architecture is very important [4]. Machine learning applied to oil reservoir estimation can be determined depending on the nature and quality of data. However, for some cases, like the stratified reservoirs, simple neural network models will not suffice [5]. Complex networks like the Recurrent Neural Network (RNN) and Nonlinear Autoregressive with Exogenous Input (NARx) might suffice, depending on the nature and amount of data. One major advantage is that the sophisticated network with appropriate parameter specification will give good predictability. Although, With the advent of optimization, petroleum exploration has become efficiently realized in the presence of geological uncertainties. Most oil reservoirs can potentially produce about 60% of the original oil volume in a reservoir by employing the basic enhanced oil recovery technique [6]. It necessitates the need to employ optimal design strategies to improve recovery. Studies have shown that the rate of demand for energy increases intermittently [7]. Still, major oil and gas companies have recently initialized the idea of increasing production efficiency through automated systems. Conventional enhanced recovery could still be insufficient and needed to be digitalized, and this is why innovation in the technological fields has become increasingly prevalent [8].

1.1. Artificial Neural Networks (ANN)

Artificial Intelligence has been described as the branch of data science that deals with the ability of machines to simulate the functionalities of the brain [9]. However, these models are known to be limited to cognitive abilities, such as the ability to extrapolate knowledge from unprocessed data.

AI in engineering has gained much traction over the years through the applications of several paradigms. Among the most used AI paradigms in Engineering are knowledge-based systems, neural networks, genetic algorithms, fuzzy logic, and intelligent agent [10]. AI has been categorized into usability forms. One of these forms is the machine learning technique. This technique simulates the brain exclusively. Machine learning techniques are subdivided into other classes, such as K-means, KNN, and Deep Learning. Deep learning is an intrinsic kind of learning that applies the concept of brain neurons. The interconnection of several neurons forms these neurons to form a network called the neural network. It brings us to the concept of the neural network, which forms the bases for all Artificial Intelligent systems. Our review of the production prediction of oil reservoir systems will be investigated for neural network systems.

Several neural networks architecture has been widely employed depending on the nature of the problem needed to be solved. Although with the recent implementations of the use of this technology, more advanced and optimal neural network models are being developed. For example, recently, a new kind of architecture called the graph neural network (GNN) has emerged as a major tool for predicting the structures of graph domains. Some of the intrinsic functions of the GNNs are in performing complex tasks like clustering, link prediction, and node classification [11]. This work will briefly describe some concepts of neural networks used to identify oil reservoirs.

The Artificial neural network is a complex system of interconnecting units called neurons. The neurons are usually divided into layers (input, hidden, output). The input values $\boldsymbol{x}$ are combined with some so-called transient parameter called the weights w and a constant parameter called bias b to give an output which is further combined to an activation function f to produce some certain output y (Figure 2). The weight's value determines the error rate the neural network model can generate. So, in other to mitigate these errors, a technique called training or learning is used to optimize the network by observing the values of the weights that minimize the error. A neural network in which the weights are fixed is referred to as a fixed network such that $\frac{dW}{dt} \neq 0$. Networks in which the weights can change are called adaptive networks, such that $\frac{dW}{dt} = 0$.

Furthermore, adaptive networks are categorized into three learning classes: supervised learning, unsupervised learning, and reinforcement learning. A target set is given for supervised learning and then compared with the computed output. Example of supervised learning is the regression, Time series forecasting, etc. Unsupervised learning is called self-organizing learning, whereby the neural network can understand patterns and properties from a given data set.

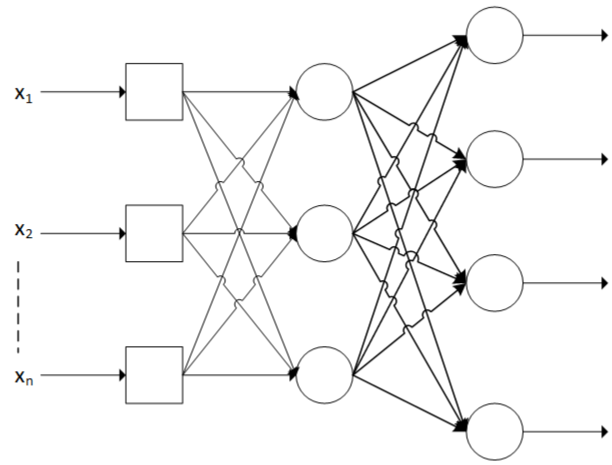

Fig. 1 ANN schematics for Multi-layered Network.

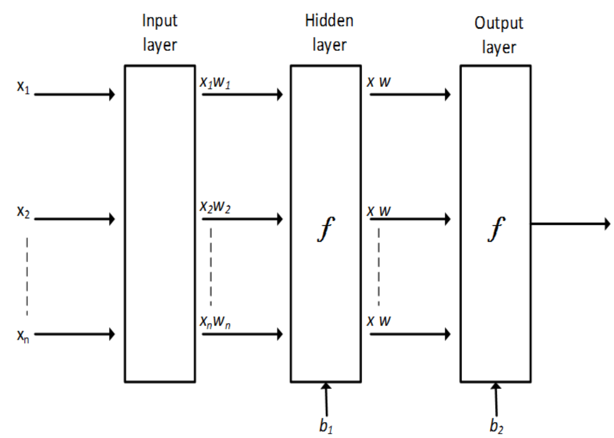

Fig. 2 Vectorized form of multi-layered Neural Networks.

An example of unsupervised learning is clustering and classification analysis. Reinforcement learning is mostly concerned with how intelligent systems can derive knowledge by exclusively studying the environment they dwell in. In essence, Reinforcement learning was designed to give a more advanced study than the supervised and unsupervised learning methods [12]. However, this learning has not been able to describe its environmental inductions efficiently. The basic flowchart for basic neural network training is shown in figure 3.

1.2. Mathematical Background of ANN

In training a multilayer network system, a method called backpropagation is used. It is the most common method for obtaining the optimal weights of many interconnected neurons.

Mathematically, backpropagation is written in the form:

$$w_{updated} = w_{old} - \eta \nabla E \tag{1}$$

Where w is the weight, η is the learning rate, and E is the function used to estimate the trained network's overall performance.

Minimizing error through the backpropagation method is implemented by the gradient descent method. Although one major drawback of backpropagation is that it requires a longer time for the change of weight to be initialized, and it is invariably impossible to estimate new weight values for a large number of neurons.

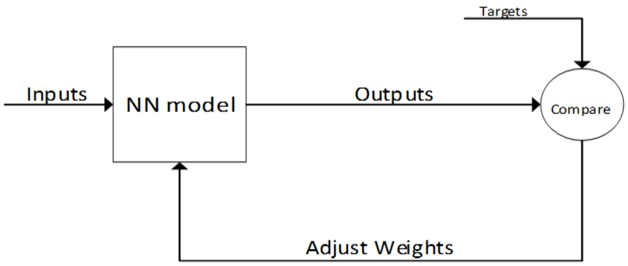

Fig. 3 Backpropagation Scheme.

The error is considered as the difference between the true value and the neural network computed value. Hence, if the true value is given as t_0 and the computed value is y_0, then the error function can be given as [13]:

$$E = \frac{1}{2}\sum_{output}(t_0-y_0)^2 \quad (2)$$

The error derivative can be written as described by I. Mackie [14];

$$\frac{dE}{dy_0} = -\left(t_0-y_0\right) \quad (3)$$

Reformulating the error derivative to Z_0 by applying the chain rule function;

$$\frac{\partial E}{\partial z_0} = \frac{\partial y_0}{\partial Z_0}\frac{\partial E}{\partial y_0} = y_0\left(1-y_0\right)\frac{\partial E}{\partial y_0} \quad (4)$$

Calculating the error derivative to y_0;

$$\frac{\partial E}{\partial y_h} = \sum_0 \frac{\partial z_0}{\partial y_0}\frac{\partial E}{\partial z_0} = \sum_0 w_{h0}\frac{\partial E}{\partial z_0} \quad (5)$$

Equation (5) describes the general concepts of the backpropagation scheme for multi-layered networks.

Several training algorithms are employed based on the simple and sophisticated network's data structure and prediction ability. Such algorithm is the Levenberg-Marqudt (LMA), Gradient descent, Bayesian regularization, scaled conjugate gradient, and gauss newton. In most complex network training like oil reservoir identification, Bayesian regularization is commonly used to eliminate data overfitting. Regularization is a term used to describe the prevention of data fitting problems [15]. It is used to describe the addition of a variable term in the error function, as shown in equation (6). The variable term can be denoted as $L_2(x)$ or $\|w\|_2$

$$E_{updated} = E_{initial} + \|w\|_2 \quad (6)$$

There are two regularization techniques used: the L_2 regularization, which is known as the weight decay, ridge regression, or Tikhonov regularization (since it was formulated by a Russian mathematician called Andrey Tikhonov). The L_2 regularization uses a Euclidean norm having a vector function $x = (x_1, x_2.. x_n)$, and it can be written as;

$$\|w\|_2 = \sqrt{x_1^2 + x_2^2 + \dots x_n^2} \quad (7)$$

For simplicity, equation (7) can be written as;

$$\|w\|_2^2 = x_1^2 + x_2^2 + \dots x_n^2 \quad (8)$$

The modified form of equation (6) can be written as;

$$E_{updated} = E_{initial} + \frac{\gamma}{n}\sum_{i=1} w_i^2 \quad (9)$$

Where γ is the so-called hyper-parameter known as the regularization rate, and it is divided by the size of the batch used. Hyper-parameters are constant numbers used to define the learning process of an artificial neural network [16]. This number does not change during the learning process and can only be adjusted manually. Taking the partial derivative of equation (9) for the changing weights, we get;

$$\frac{\partial E_{updated}}{\partial w} = \frac{\partial E_{initial}}{\partial w} + \frac{\gamma}{n} w \quad (10)$$

Another regularization technique is the L_1 regularization, also known as 'lasso' or 'basis pursuit denoising.' In contrast to the L_2 regularization, which uses the squares of the variable term, the L_1 regularization uses the absolute values. L_2 regularization is better suited for classification and prediction problems. However, in a situation where there is disintegration and inconsistent data, L_1 regularization is used.

1.3. Time Series Proxy Neural Networks Models

A time series neural network is important in which past observations are analyzed to help predict future occurrences by developing a systematic model based on the pre-specified data. It is important to note that the problems associated with oil reservoir systems are, in all cases, time-dependent. Simulation of a basic and complex oil reservoir is carried out by observing dynamic changes over a stipulated period. These changes, in some cases, can span up to a period of 2 to 7 years, depending on the nature and complexity of the oil reservoir. The geometry of oil reservoirs is usually produced from seismic data, and this data are time-based. It is, however, important to fix an elementary time scale for this production data.

In a broad sense, time series neural networks are networks that exhibit time lags. These time lags have shown to be effective in predicting the future occurrence of the computed observations. Time series predictions are usually classified into linear and non-linear predictions. In the linear times series network, the preceding investigation is related to the previous observations in a linear manner. An example of a linear time series network is the Autoregressive Integrated Moving Average (ARIMA) model. For the non-linear time series network, the next and past observations are related nonlinearly. It can be described in equation (11):

$$y_t = f\left(y_{t-1}, y_{t-2}, \ldots.. y_{t-p}\right) + \varepsilon_t \tag{11}$$

An example of a non-linear time series network is the Nonlinear Autoregressive with exogenous inputs (NARx) model and the non-linear autoregressive moving average with exogenous input (NARIMAx). The major difference between the two is that, in the NARx, there is the feedback of the network output as the new input, while in the NARIMAx, both the network output and error are simultaneously fed back as new inputs. Linear and non-linear neural networks are generally called recurrent neural networks (RNNs).

2. Review Methodology

In this review, we first looked at the current trend of technological innovation in the oil and gas sector. The basic concept of artificial neural networks was discussed. We reviewed work done by several authors in different areas of reservoir modelling and simulation and how their work impacts the global production of oil and gas by implementing smart technology such as Deep learning. Figure 4 gives a detailed overview of the review carried out.

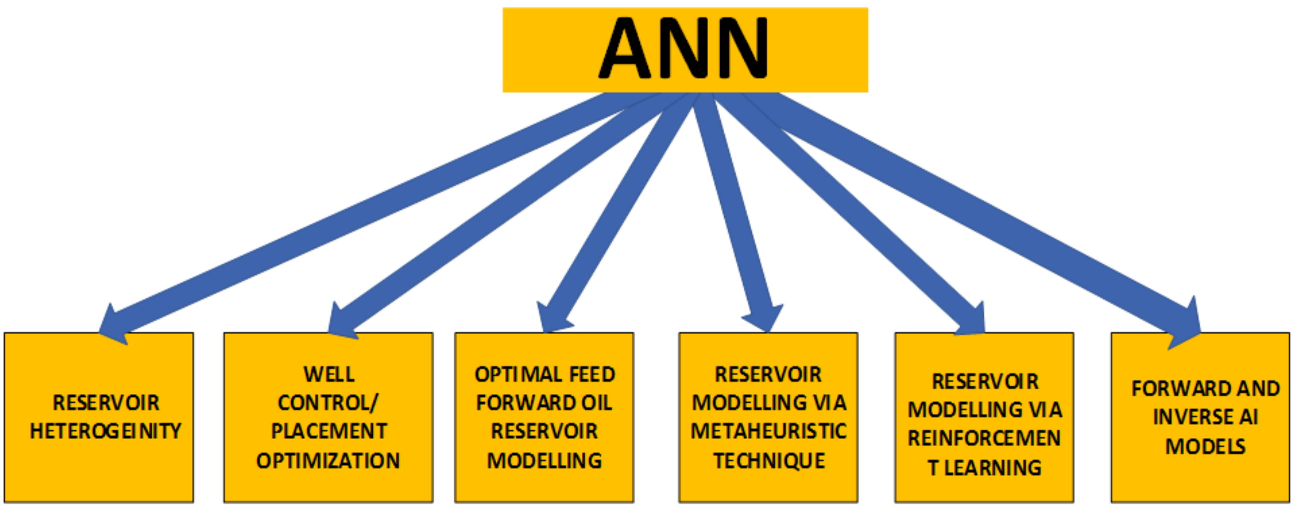

Fig. 4 Methodology of review.

3. Discussion of Review

Literature gave progressive facts and application of intelligent systems to oil reservoir prediction. It can be seen in figure 6, which shows reservoir property estimation based on intelligent history matching. Effective contributions using automated systems have been applied to geophysical exploration, logging curve reconstruction, well logging, drilling and completion methods, surface facility engineering, etc. [17] predicted the performance of a vertical heterogeneous reservoir by implementing three neural network structures which include the backpropagation (BP), convolutional neural network (CNN) and long short-term memory (LSTM). The performance evaluation of the deep network was characterized based on their training time and how well they captured precision on their respective predictabilities. The input dataset for the model is the oil production rate, water cut, and injection pressure, while the output dataset is the vertical permeability. However, it is important to note that the prediction characteristics were done on dynamic data generated from the prototyped model. A statistical test strategy was carried out to investigate the model's performance. Some statistical tests include average relative deviation (ARD) and average absolute relative deviation (AARD). The relevant formula is shown as follows [17]:

$$\text{ARD\%} = \frac{100}{N}\sum_{i=1}^{N}\left(\frac{X_i^{data}-X_i^{model}}{X_i^{data}}\right) \tag{12}$$

$$\text{AARD\%} = \frac{100}{N}\sum_{i=1}^{N}\left(\left|\frac{X_i^{data}-X_i^{model}}{X_i^{data}}\right|\right) \tag{13}$$

Where N is the total number of datasets, X_i^{data} is the unprocessed data values, X_i^{model} is the processed data value generated by the neural network model. The study's results showed that a high accuracy characterized the predictive performance of the CNN model compared to BP and LSTM. The statistical result, such as the average absolute relative deviation (AARD) for the CNN model, was recorded at 11.51%.

3.1. ANN for Reservoir Heterogeneity and Well Control Optimization

J. Zhou et al. [11] implemented a neural network based on a forward-looking and inverse model to predict the production performance of steam-flooded reservoirs by considering reservoir heterogeneity and its corresponding time lag datasets. Production uncertainties were also analyzed using forward-looking ANN models. This study used steam injection rate, bottom hole pressure (BHP), steam quality, well distance, and permeability distribution as the ANN model input data. In contrast, cumulative oil production was used as the ANN model output data. This data characterization is exclusively applied to the forward-looking ANN model, whereas cumulative oil production and permeability distribution were used as the input dataset for the inverse design model. The relative error was investigated using equation (12) to validate the model. The kriging interpolation generated the permeability distribution for the basic reservoir model. From the analysis, it was shown that the forward-looking model produced more accurate results. In contrast, the inverse model was shown to have the ability to retrieve production parameters for the heterogeneous reservoir. However, no investigation was done to obtain the optimal production efficiency of the model by considering the number of layers and hidden neurons.

A well-control optimization was carried out on an L-shaped reservoir [19]. This study used a deep learning strategy involving a multi-input system. Data from the reservoir production history was used as the primary input set, while the saturation field was used as the second input set. Afterward, a good control optimization was carried out on the actual reservoir model.

The study showed that the production dynamics for multiple input has better accuracy than a single-input prediction model. Also, the recovery factor for the optimized reservoir was shown to be 2.76% better than the basic reservoir. [20] implemented a hybrid intelligent system for predicting the good productivity of horizontal wells in drainage areas. The exclusive model used was the least square support vector machine (LSSVM) integrated with a stochastic-based optimization algorithm known as the particle swarm optimization for the effective production performance of the reservoir model. The productivity of the horizontal well performance was estimated by the equation [21];

$$J_h = \frac{q_o}{P_R - P_{wf}} = \frac{kh}{141.2\beta_o \mu_o}\left(\frac{1}{\ln\left(\frac{r_e'}{r_w}\right) - A' + S_f + S_m + S_{CAh} - C' + D_{qo}}\right) \quad (14)$$

Where;

$$r_e' = \sqrt{\frac{A}{\pi}} \quad (15)$$

$$S_f = -\ln\left[\frac{L}{4r_w}\right] \quad (16)$$

The basic logic behind integrating a PSO algorithm was to improve the productivity of the horizontal wells by optimizing the adjustable parameters of the LSSVM model. It was shown that the LSSVM-PSO model increased the oil well productivity with high accuracy. The predictive model was also asserted to have high predictive efficiency for situations where real data may not be available.

[22] applied multiple systems involving multivariate partial least squares (PLS), response surface methodology (RSM), and neural networks (ANN) to evaluate the predictive performance on heavy and medium waterflooded oil reservoirs. The PLS was used to reduce the complexities of the neural network input parameters. This study was done on an oil reservoir in western Canada, including about 120 reservoir parameters in 177 waterfloods. The RSM was used to increase the quality of the database for 38 reservoir parameters. A feedforward neural network was used for the production prediction. However, this study has not investigated stratified oil reservoirs. This study shows that heavy water floods are more sensitive to operational parameters than reservoir properties.

3.2. Optimal Feed-Forward ANN

An optimal feedforward artificial neural network was applied to predict the performance of an oil field flooded with a surfactant polymer [23]. The network input data consists of the surfactant slug size, polymer slug size, surfactant concentration, rock wettability, gravity, optimal salinity in the three-phase region, waterflood residual saturations, capillary pressure, relative permeability, reservoir heterogeneity, interfacial tension, surfactant, and polymer adsorption, polymer/surfactant mobility ratio, surfactant/oil bank mobility ratio. The network model was trained on 499 simulation datasets generated by a chemical flood simulator. This study also gave an account of the very effect of the network layer and neuron number on the predictive ability of the model. However, for dynamic datasets, the feedforward model will not suffice.

The validation of the ANN model was investigated using blind test data, which consists of 125 rows of the input parameters. However, the ANN model could not give a reliable substitute for estimating the breakthrough time. The selection of the optimal number of the hidden layer was investigated, such that more precision was confirmed with a substantial increase in the hidden layer. The ANN model also performed better than the non-linear multivariate model, which was used in estimating the recoveries.

[24] illustrated the characteristic effect of data-driven models for evaluating the performance of heterogeneous reservoirs with a difference in porosity and permeability

values. In this case, the ANN model was considered a proxy model for the heterogeneous reservoir. The ANN model was constructed for a single output (cumulative production rate) and multiple inputs, which includes the mean porosity values for each well, the mean permeability values for each well, dykstra-parsons coefficient (VDP), residual oil saturation (Sro) and residual water saturation (Srw). The dykstra-parsons coefficient is a technique used to measure the rate of heterogeneity for permeability datasets, and it is estimated using equation (12) [25]. The coefficient varies between 0 for homogeneous reservoirs and 1 for heterogeneous reservoirs. A sensitivity analysis was done to map out the discrepancies between the predicted and actual values of the output datasets. It was shown that increasing the number of hidden layers for a mini-scale dataset will advertently overfit the model, making it less accurate to approximate.

$$\mathrm{DP} = \frac{K_{50}-K_{16}}{K_{50}} = \frac{K_{84}-K_{50}}{K_{84}} \tag{17}$$

[26] presented a systematic approach to estimating the average pressure of reservoir injection wells using partial data recorded from fall-off tests. This technique was shown to help map the pressure of a reservoir having monumental injection wells. This systematic approach involves the use of artificial neural networks. The study was initially carried out on a simulation dataset by considering property cases for homogenous and heterogeneous reservoirs. Early-time data were used for the prediction due to their ability to mitigate fall-off durations in an oil field. Fall-off curves can be plotted for well bottom hole pressure over time.

In the utilization of ANN, the fall of curves was normalized for clustering. The essence of normalization was to unify the data to an acceptable range. Furthermore, the data clusters were formed through a histogram-based algorithm. Even though there were predefined clustering methods, such as the k-means, the author observed that employing other clustering methods (primarily the k-means) will lead to a fall of curve disintegration. The ANN model was used to improve the prediction accuracy of the clustering results. The methodology, however, was implemented to improve the fall-off test predictability, thereby reducing time duration.

[27] provided a machine learning-based method to describe the proximal operability between injection and production wells that are controlled by the interlayer. This method used feedforward backpropagation (FFBP) in conjunction with the convolutional neural network (CNNs). The input data files were used as the oil production rate, water cut, and injection volume. The CCN comprises five distinct parts: the input layer, the convolutional layer, the pooling layer, the fully connected layer, and the output layer. The convolutional layer functioned as a feature extractor, while the pooling layer was used to decrease the dimension of the extracted data feature.

Another basic observation the author deduced was the connectivity factor between the injection and producer wells. The mathematical model of the connectivity coefficient was established on the bases of the production and pressure data of the injection and producer wells. Also, the effect of the interlayer at about a certain angle of connectivity for both the injection and producer wells was studied. The training datasets were the dynamic data of the average permeability and the interlayer angle. The dynamic data were used to calculate the average permeability and interlayer angle. The author deduced the equation of connectivity as given in equations (18) and (19), respectively;

$$f_k = \frac{\text{Trained-k}}{\sum \text{Trained-k}} \tag{18}$$

$$f_\theta = \frac{\text{Trained-}\theta}{\sum \text{Trained-}\theta} \tag{19}$$

Were f_k and f_θ are the training factor, while Trained-k and Trained-θ are the training datasets, respectively. The author concluded that the CCN had better performance in connectivity, and an average absolute relative deviation (AARD) below 10.01% was obtained.

The numerical approximation has effectively described reservoir uncertainties [28]. These uncertainties usually arise from extrapolating the entire rock's properties. However, despite being able to approximate this reservoir model parameter, computational complexities may arise when the reservoir description exhibits more parameters for the simulation.

3.3. Metaheuristic Technique for ANN Prediction

[29] implemented a data-driven proxy model based on a metaheuristic algorithm to maximize a waterflooded reservoir's net present value (NPV) by controlling its well injection rate. Net present value is the difference between the present value of cash inflow and the present value of cash outflow over time. It is used in planning and determining capital budgeting and investment profitability. An investment with a positive NPV depicts that the project is profitable and vice versa. The net present value is given in equation (20) [30]:

$$J^k = \left\{ \frac{\sum_{j=1}^{N_{prod}} \left[r_0 (y_{0,j})^k - r_{wp} \left(y_{w,j} \right)^k \right] - \sum_{i=1}^{N_{inj}} r_{wi} (u_{wi,i})^k}{(1+b)^{\frac{t^k}{r}}} \right\} \Delta t^k \tag{20}$$

Were r_{wi} stands for the Water injection cost, r_{wp} stands for the Water production cost, r_0 stands for the Oil price per barrel, $u_{wi,i}$ stands for Water injection rate, y_w stands for Water production rate, $y_{0,j}$ stands for Oil production rate, N_{prod} stands for the number of production wells, N_{inj} is the number of injection wells, b is the Discount factor, Δt^k is the Time step size, t^k is the evolution time, τ is the time unit. In some modelling cases, the water injection rates are commonly used as the decision variables [31]. Two synthetic reservoir model was used (2D-model and the Egg model). The optimization task was performed using particle swarm optimization and the grey-wolf optimization algorithm. It was shown from the results that the optimization errors investigated using the proxy model were within 5% when compared with the reservoir simulator.

3.4. Reinforcement Learning for Oil Reservoir Estimation

Reinforcement learning is an unsupervised kind of learning that is inspired by environmental conditions. It describes the autonomy of machines to learn from their surrounding without prior data accumulation. In reinforcement learning, an agent is exposed to environmental factors which it derives information from. As a result, the learner or agent is left to decide and extrapolate decisions on its own from the environment and then come up with a solution. However, cognitive abilities in this kind of system are limited.

Reinforcement learning has recently been used to describe waterflooding optimizations [32]. Here, the framework of this learning process was used to optimize a reservoir waterflooded process through a method of derivative-free and model-free optimization and then implemented on a well-studied egg model. The reinforcement learning strategy effectively appropriates reservoir learning challenges and variables, determining the optimal solution.

3.5. Forward and Inverse AI Models

In oil reservoir simulation, three possible categories of problems may arise. It includes the project design parameters, reservoir properties, and field response data. Forward-looking models implement the reservoir properties and project design parameters to predict the field response, thereby developing efficient approaches for better assessment. The inverse model uses field data to predict the reservoir properties and project design parameters [33]. Studies show that the forward-looking model efficiently serves as a proxy for numerical reservoir models involving optimization [34] and reservoir uncertainty study [35]. Figure 7 gives an extensive workflow that implements the forward and inverse AI model for the reservoir simulation study.

Forward AI models have seen significant improvement in incorporating genetic algorithm (GA) and particle swarm optimization (PSO) to carry out a multi-objective optimization for CO_2 water-alternating-gas (WAG). The objective functions were the net present value, CO_2 storage rate, and oil recovery rate [36, 37].

Owing to the fact that ANN models are inherently able to handle complex approximations by reproducing continuous functions, [38] developed an ANN proxy model under reservoir uncertainties to optimize some set of performance indices for different well production configurations. The solutions were examined with the Sharpe ratios and the frontier plot.

3.6. ANN-Based Well Placement Optimization

Conventional and nonconventional oil fields are described by optimal well placement. In this description of well placement, possible simulation is done in drilling locations, commonly known as the exhaustive simulation method. Optimization techniques have been developed to minimize the simulation period of the reservoir model. One of these techniques is gradient-based optimization, which investigates optimum well placement for a given production trajectory [39-43]. Gradient-based optimization is known for obtaining optimum solutions rapidly. However, the limitation of the gradient-based optimization lies in obtaining a local solution that strongly relies on initial guesses. Another optimization technique implemented to overcome these limitations is the stochastic technique, which involves a global search around the optimum. Such techniques include the Genetic algorithm (GA), Particle Swarm optimization (PSO), differential evolution, etc. Placements based on ANN-based genetic algorithms were recently reported by [44] and [45]. Again, stochastic-based optimization requires that the simulation runs of the reservoir be reduced to obtain a global solution. Oil reservoir data generation from a reservoir model, such as sensitivity analysis, history matching, and uncertainty evaluation, will also require higher simulation runs [46]. Hence, to do this, ANN models are used to perform these given conditions. Some of the earliest instances of good optimizations using ANN were reported by [47], [48]. [49] computed the production rate using a production-potential map. [50] developed a new algorithm based on a sequential ANN model to compute the global solution of optimal drilling sites of oil and gas fields. The method was implemented on horizontal wells in a coalbed methane oilfield. [51] predicted fluid production as a good placement function via a data-driven ANN approach. Data-driven models require that the data are first generated via process identification. Moreover, artificial neural networks are inherently data-driven.

4. Conclusion

Reservoir modelling and simulation have greatly impacted production efficiency; however, with today's technology, complexities associated with these reservoirs can be simplified. Artificial neural networks have been shown to improve the production efficiency of oil reservoirs even though geological uncertainties are inherent. However, for such efficiency to be achieved, Artificial Neural Network architecture must be critically selected because different ANN model architecture has different use and functionality based on the prevailing problem. Optimizing these ANN architectures has found great importance, especially using nature-based optimizers, which are more effective and powerful than traditional trial-and-error techniques [52]. It was also noted that time lags must be considered for a neural network to identify a reservoir efficiently. It implies that complex reservoir models built for production and economic predictions must include output feedback. These models are sometimes incorporated with optimization algorithms for better performance[53].

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