Iraqi Journal of Oil & Gas Research, Vol. 04, No. 2 (2024)

Iraqi Journal of Oil & Gas Research

Journal homepage: https://ijogr.uotechnology.edu.iq/

Applications of Artificial Neural Networks in the Petroleum Industry: A Review

[1]*Noor F.Hameed**, [2] *Rwaida K.AbdulMajeed*

[1] Petroleum Department, College of Engineering, University of Baghdad, Baghdad, Iraq

[2] Petroleum Department, College of Engineering, University of Baghdad, Baghdad, Iraq

Article information

Article history:
Received: March, 27, 2024
Revised: July, 24, 2024
Accepted: July, 25, 2024
Available online: October, 04, 2024

Keywords:
Artificial Neural Networks,
Petroleum Industry,
Exploration,

Corresponding Author:
Noor F.Hameed
noor.hameed1608@coeng.uobaghdad.edu.iq

Abstract

One of the most crucial phases in creating an accurate and ideal field development plan for oil and gas projects is evaluating the formation and characterizing the reservoir. Many different types of data are required for reservoir characterization and modeling, including wireline logs, LWD logs, SCAL data, geology and seismic data. Furthermore, sufficient understanding of the underlying physical interactions between each parameter. Recent developments in artificial intelligence and neural network-based petroleum exploration technology have opened up new possibilities for the sector in terms of reservoir characterization, that is more affordable, effective, and precise. Several research works pertaining to the application of artificial neural networks (ANNs) in the petroleum sector were examined, synthesized, and categorized into four main categories: applications in exploration, drilling, production, and reservoir engineering. An overview of applications of artificial neural networks in petroleum engineering was presented. An established process for using ANNs in any petroleum application was performed and displayed through a flowchart that may be used as a useful guide to implement ANNs for any petroleum application.

DOI: http://doi.org/10.55699/ijogr.2024.0402.1068 , Department of Oil and Gas Engineering, University of Technology-Iraq

1. Introduction

One of the most well-known and extensively used machine learning models is the artificial neural network (ANN), which is modeled after the structure and operations of the human brain, which is composed of billions of interconnected neurons. ANN is a type of deep learning model that processes input data and generates output using a layered structure. The layers of the network are made up of nodes, also known as artificial neurons, which receive inputs from one layer, process them using a mathematical function, and then pass them on to the next layer, the result of which is the prediction or classification of the input data. ANN has several advantages over traditional machine learning models, including the ability to learn and generalize from vast amounts of data. The first computational model with neurons as the architecture was developed by Jassim et al., 2022 [1]. Because the findings compared the model parameter values to determine the output, the model was unable to learn because some of the model parameters (weights) were fixed [2]. The adaptive linear element (Adaline) and the perceptron [3-6] were the first artificial neural networks on computers. A two-layer network cannot express or approximate functions outside of a narrow range, as proved by Minsky and Papert in 1969 [7]. The first research on the use of neural networks was eventually published in 1989 [8]. This work used a feedforward neural network, in which the input data moves forward from input to output as it passes across the network. The learning functions or rules are primarily what distinguish the networks from one another. Learning strategies such as back propagation was first introduced in 1974 and were rediscovered in 1986 with a new technique and a clear framework [9-10].

2. Artificial Neural Networks (ANN)

According to Sammut and Webb, 2011 [11] artificial networks are computer models built on the basis of biological neural networks, such as those seen in the human brain. According to Adamowski et al. 2012 [12], The computational model can be thought of as a network of neurons with basic processing abilities that can do simple mathematical calculations. The data-driven approach using artificial neural networks (ANNs) and mathematical algorithms can leverage the relationship between the input and output data to solve complex, non-linear problems [12]. ANNs were first created to simulate the information-processing capabilities of a brain network of neurons.

ANN was originally designed to mimic the information processing functions of a network of neurons in the brain. According to Sammut and Webb, 2011 [11] artificial networks are computer models built on the basis of biological neural networks, such as those seen in the human brain. According to Adamowski et al, 2012 [12] the computational model can be thought of as a network of neurons with basic processing abilities that can do simple mathematical calculations. The data-driven approach using artificial neural networks (ANNs) and mathematical algorithms can leverage the relationship between the input and output data to solve complex, non-linear problems [12]. The computational model can be thought of as a network of neurons with basic processing abilities that can do simple mathematical calculations. ANNs are often adaptive systems that modify their structure in response to internal or external data utilized, throughout the network's training phase [11]. They are employed to identify patterns in data or to simulate intricate interactions between inputs and outputs. An artificial neural network (ANN) gains the ability to associate a vast array of input patterns with a corresponding set of outputs or effects in order to learn how to solve problems. The ANN trains on provided examples to create a solution system. Artificial neural networks (ANNs) are capable of identifying patterns in data, adapting dynamically to changes, deriving general rules from particular situations, and taking in a vast array of input variables [13].

The plasticity of neural nets is another crucial feature. Algorithmic procedures are not used by neural networks. Like people, they react to lessons gained via experience. Thus, in order for the network to learn and modify its interconnections and connections between various neurons, it must be exposed to enough examples. In summary, neural networks estimate sampled functions when the form of the functions is unknown. They can be designed to handle combinatorial optimization issues, filter noise from measurement data, control ill-defined problems, train, store, recognize, and associatively retrieve patterns or database entries [14].

The development of neural networks is predicated on the learning of training algorithms. Although there are many learning algorithms to study, they can be distilled and divided into three primary classes [15].

• Supervised learning: the network is trained using a set of target outputs, and its weights and biases are adjusted to produce an output that approaches the target output.
• Reinforcement learning: the network is evaluated based on how well its algorithm performs; there is no target output specified.
• Unsupervised learning: only clustering procedures are used to modify the weights and biases in accordance with the input's response.

3. Neural Network Structure

An artificial neural network is "an information-processing system that has certain performance characteristics in common with biological neural network". Cells comprise every living thing on Earth. The fundamental units of the nervous system are neurons. As seen in **Fig. 1**, a normal biological neuron is made up of a cell body, an axon, and dendrites. Dendrites allow information from the cell body to enter. The output from the cell body then passes along the axon to reach a different receiving neuron; the output from this neuron then serves as an input for a subsequent neuron.

An artificial network is built up of three fundamental parts: the input layer, hidden layers, and output. A single neural network with one input (x), one hidden layer, and one output (y) is depicted in Figure 2 in its most basic form. Moreover, the connections between the hidden layer and the output layer are represented by layer weights, whereas the connections between the input layer and the hidden layer are represented by input weights. If there are many hidden layers, there are distinct layer weights for the links. The activation or transfer function (y) and bias (b) of the hidden layer are additional components [16].

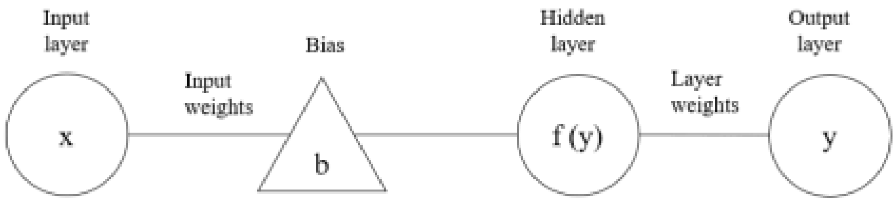

Figure 2: Model of a simple network with one input and one hidden layer where information is forwarded from left to the right [17]

Additionally, it has been demonstrated that a continuous neural network employing a sigmoidal function can closely approximate any continuous function with just one hidden layer [18]. Since it is easier to train with a higher number of neurons, neural networks are frequently huge and trained to relatively small errors. Due to their weak response to patterns outside of the training set, large networks are difficult to train to tiny errors [19]. Depending on the problem, neural networks can have quite different architectures or structures.

4. How to Successfully Apply ANNs to Any Petroleum Applications

Any Petroleum Applications Since supervised training techniques form the foundation of most petroleum applications, the focus will be on supervised ANNs [16]. An overview flowchart of the effective use of ANNs in the petroleum industry is presented in **Fig 3.**

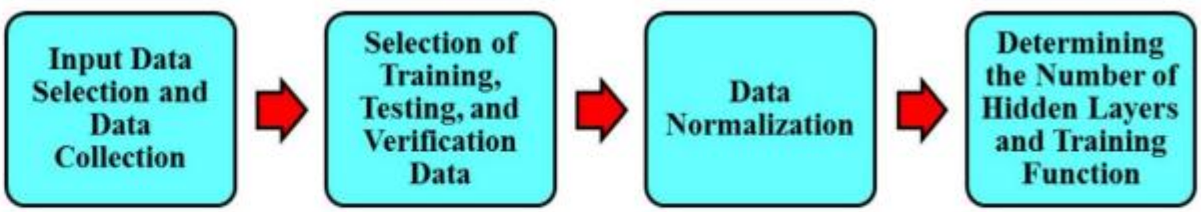

Figure 3: Flowchart for How to Successfully Apply ANNs in the Petroleum Industry [16]

Numerous scholars concur that the size of the network utilized to address the problem affects the quality of the outcome. Choosing a suitable architecture or network size is an essential first step in building a neural network [20]. The quantity of hidden layers, the number of neurons within the hidden layers, and the connectivity between each layer all affect the network's size. Generally speaking, the following are impacted by network size:

- The network's intricacy
- Its learning curve
- Its capacity for generalization

The quantity of unknowns (such as weights and biases) produced by the network is correlated with its complexity. The neural network's capacity to generate precise results outside of the training set is known as its "generalization capabilities." Since the weights and biases in the network are used to fine-tune the model fitting, their correctness affects the model's accuracy. The quantity of training samples in the training set may have an impact on the network's ability to generalize. A neural network's hidden layer count is user-defined. Research indicates that any non-linear function may be approximated for classification issues using a network with two hidden layers [20].

5. Application of Artificial Neural Networks in the Petroleum Industry

5.1. Exploration

There are many examples of ANN applications in exploration, when traditional methods fell short in handling the intricacies of non-homogeneous environments, but the advent of Radial Basis Function (RBF) neural networks brought a ray of hope. These powerful ANNs tackled the problem head-on, accurately calculating point-to-point travel times and paving the way for a complete 3D mapping of the subsurface. On the other hand, processing seismic data involves the use of velocity analysis extensively. Seismic velocity picking has been done using some automated techniques. Hopfield introduced the Hopfield neural network (HNN), a recurrent model, in 1982. It has the potential to resolve optimization issues. When selecting a velocity in the time-velocity semblance image of seismic data, the Hopfield neural network (HNN) is utilized. The optimal velocity picking result can be obtained by using the HNN to tackle the optimization problem. Identifying key parameters is another critical aspect such as Total Organic Content (TOC) and frackability. Recognizing the correlation between gamma ray log responses and these parameters. Through a cascade of correlations, the PNNs bridged the gap between core data, well logs, and 3D seismic data, A comprehensive gamma ray magnitude, Periods-clay content and organic-rich content have been identified and the frackability potential of rocks, empowering economic completion processes. In addition, A subjective and time-consuming technique, seismic facies analysis underwent a revolution through the fusion of seismic textural attributes and probabilistic neural networks. The ANNs seamlessly integrated vast amounts of seismic data, reducing subjectivity and cycle-time. this innovative approach enhanced the predictive power of seismic facies analysis, minimizing uncertainties, and guiding efficient field development. Hydrocarbon prediction was performed using a neural network. The dual neural network, which consists of a fuzzy and a self-organizing neural network, may handle structured knowledge, or rules provided by professionals, increasing the validity of the hydrocarbon prediction result. Furthermore, it utilizes a homotopy learning technique to train fuzzy neural networks, resulting in a global optimum and significantly accelerating network training convergence. The dual neural network can forecast hydrocarbons with high accuracy, as demonstrated by the practical applications, which can improve the chances of well drilling success [21-22].

5.2. Drilling

In the field of drilling engineering, artificial neural networks (ANNs) have emerged as powerful tools for addressing various challenges and optimizing drilling processes. There are some of these applications. One area where ANNs have been successfully employed is in the determination of drill bit grade or state of wear. Conventional methods often struggle to provide accurate estimates, leading to suboptimal drilling performance. researchers have developed neural networks specifically trained to estimate drill-bit grade based on a range of input parameters. This enables drillers to monitor the condition of the drill bit in real-time and make informed decisions regarding maintenance or replacement. The dynamic behavior of the bottom hole assembly (BHA) during drilling is another critical aspect that directly affects drilling efficiency and tool longevity. ANNs have been instrumental in predicting the dynamic response of the BHA, allowing drillers to select appropriate control parameters and optimize drilling conditions. By avoiding detrimental vibrations and maintaining optimum drilling performance, ANNs contribute to improved drilling efficiency and reduced downtime. One of the key challenges in drilling engineering is the prediction of drilling troubles. ANNs, in conjunction with efficient data mining tools, have been employed to develop predictive models that identify potential issues during drilling operations. By analyzing historical data, these models can anticipate trouble scenarios and provide early warnings, allowing drillers to take proactive measures and mitigate risks. Prediction of important drilling parameters is another area where ANNs have demonstrated their effectiveness. For instance, ANNs have been used to improve the prediction capabilities of the rate of penetration. ROP is a crucial factor in well planning and decision-making, as it directly impacts drilling costs and overall project timelines. Neural networks help establish reliable ROP prediction models, enabling engineers to optimize drilling strategies and make informed economic and engineering decisions. Furthermore, ANNs have been leveraged for automatic classification and analysis of drilling reports. By training on large volumes of drilling data, ANNs can automatically categorize sentences written in drilling reports and extract valuable insights. This facilitates the interpretation of measurements from downhole sensors and surface equipment, enabling operation optimization and accident mitigation through real-time analysis of drilling data, ANNs have found application in predicting geomechanical parameters. By training on available data, ANNs can estimate geomechanical properties of the subsurface, even when direct measurements are challenging or time-consuming. This capability aids in geomechanical modeling and enhances the understanding of subsurface conditions, contributing to improved drilling performance and wellbore stability. Finaly A neural network has been proposed to select rotary drilling bits in an oil or gas well. The drilling engineer's choice of bit is a crucial one. A three-layer back propagation architecture was used in the building of several neural networks to choose the bits for the subsequent drilling interval. More neural networks were created to forecast the price of bits. These new models were able to accurately forecast the bit types and cost-per-foot values for multiple fields using the provided data sets [23-28].

5.3. Production

In the vast and dynamic world of petroleum production engineering, the utilization of Artificial Neural Networks (ANNs) has emerged as a powerful tool. the applications of ANNs in this field. Deep offshore fields often encounter phenomenon known as wax formation. This can lead to flow disruptions, blockages, and production delays. To combat these issues, ANNs have been employed to accurately predict the Wax Appearance Temperature (WAT) for different hydrocarbon mixtures. By anticipating the onset conditions for wax formation, engineers can take preventive measures to mitigate wax deposition, ensuring smooth flow and preventing system abandonment. Another significant challenge in petroleum production is optimizing gravel pack performance during well installations. Traditional methods rely on offset well data for predicting grain-size distributions, which may not provide an accurate representation of the entire reservoir. ANNs have proven successful in this regard, enabling engineers to estimate grain-size distributions across the entire reservoir. This improved accuracy leads to enhanced gravel pack performance, saving costs associated with early failures and well interventions. Production rate is a paramount parameter in assessing well performance. However, real-time monitoring of individual well production rates is often lacking, and flow transmitters used in such monitoring can introduce errors during multiphase flow. ANNs come to the rescue by offering real-time fluid rate prediction. By providing accurate and up-to-date information, ANNs empower production engineers to optimize well performance efficiently. The economic importance of forecasting natural gas supply cannot be underestimated, especially considering its increasing value relative to crude oil. ANNs have proven to be valuable tools for predicting natural gas production. These models serve both short-term and long-term forecasts, allowing for quantitative analysis of the physical and economic factors influencing gas production. Decision-makers can rely on these insights to plan and strategize effectively. ANNs have been instrumental in identifying conductive features, such as fractures, which play a critical role in fluid. By leveraging neural network analysis, fractures can be classified based on multiple conditions that correlate with conductivity. This classification technique can be applied to various classification problems and even extrapolate data to unexplored locations. The flexibility and adaptability of ANNs empower engineers to better understand and model fluid flow dynamics, lastly adapting computational intelligence algorithms were used to predict oil flow rate in artificial lift oil wells, which, in combination with artificial neural networks, support vector machines, and artificial neuro fuzzy inference systems which haven't been used before for this subject. According to the results, the ANN performs better than any of the existing empirical correlations. This work presents an industrial understanding of the function of data-driven computational models for the production reconnaissance scheme, serving as a useful instrument to lower production provision concerns in addition to validating the well tests [28-37].

5.4. Reservoir

Indeed, artificial neural networks (ANNs) have found numerous applications in reservoir engineering and management. Here are some of the key applications of ANNs in reservoirs. Evaluating the hydrocarbon potential of shaly sand layers. Conventional methods struggled to accurately determine porosity and convert apparent water saturation to true water saturation in these complex formations. Where artificial neural networks were used and training them to analyze well logging data and replace traditional interpretation techniques. The neural networks offering more precise estimates of porosity and water saturation. With this newfound accuracy. The hydrocarbon potential of the clean sand and clay layers was determined. On the other hand, Nowadays, it is generally accepted that Low Salinity Waterflooding (LSW) offers superior oil recovery than High Salinity Waterflooding (HSW), following over thirty years of research and development. Previous studies have also shown that there are significant advantages to combining LSW with other conventional Enhanced Oil Recovery (EOR) techniques like chemical flooding (polymer and surfactant flooding) or miscible gas flooding in order to capitalize on their synergies and achieve a higher oil recovery factor. These intricate EOR processes were mechanistically modeled using artificial intelligence technology. Viscosity, a critical fluid property. which is considered another application of artificial intelligence. Traditionally, viscosity measurements relied on laboratory equipment. ANNs could develop models to predict viscosity below the bubble point, even in cases where comprehensive PVT information was lacking. By training the neural networks on empirical correlations and considering temperature and pressure inputs, enabling better decision-making in reservoir engineering. Furthermore, the best enhanced oil recovery (EOR) methods for boosting hydrocarbon output, particularly in heavy oil reservoirs, are thermal procedures. Thermal EOR modifies the physical characteristics of subterranean reservoirs by injecting steam or hot fluids to change their viscosity and effective mobility. to develop a reliable model to expect thermal-EOR processes distributions in porous rocks, With an appropriate tolerance, the heat spreads over time and distance from the wellbore. In order to create efficient neural network models, the effects of formation permeability, injection time, and wellbore distance were taken into consideration. A neural network model was also proposed to determine the formation pore. Artificial neural networks can be employed to analyze data for the building of pre-drilling prediction models and the optimization of post-well prediction models. These models can reliably give independent forecasts of pore pressure. There are also many applications for artificial neural networks, such as Feature recognition, Primary reflection identifications, Petro-seismic characterization, Amplitude variation with offset (AVO), Drill bit selection, Bed height for horizontal wells, Bit bounce detection, Drilling hydraulics optimization and prediction, Fracturing restimulation candidates, Casing collapse due to production, Wax disappearance temperature, History matching Built a reservoir simulation model, Re-fracture candidate selection, Reservoir characterization, Rock properties, Reservoir monitoring, Fluid properties and Well testing [38-40].

6.Conclusions

ANNs are very useful tool which can be used to solve problems that are hard to be modeled analytically. ANNs have demonstrated a respectable level of accuracy in numerous petroleum applications. Following a thorough examination of numerous articles regarding ANN applications in the petroleum sector, the following findings were drawn:

• The petroleum business has access to vast amounts of historical data, which may be utilized to forecast future events and aid in decision-making. Due to the significant uncertainties in the future, making predictions about the future is never easy. ANNs can be used to produce accurate predictions in the future or in real time, enabling decision makers to plan ahead and solve problems before they arise.

• Analytical solutions to certain petroleum engineering problems are challenging. As a result, ANNs can be employed to accurately tackle these kinds of issues. This publication included a summary of numerous ANN applications found in the literature. In addition, the applications were separated and classified into four categories: reservoir, production, drilling, and exploration. This paper offers a clear process for using the DTA successfully, which can be used as a guide for any ANN applications in the petroleum industry in the future.

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