Petroleum and Coal

Article Open Access

A Bird's Eye View on the Applications of Neural Networks in Reservoir Characterization

Gulbahar Yazmyradova[1], Maman Hermana[1*], Hassan Soleimani[2], Vinayagam Sivabalan[3]*

[1] *Centre of Seismic Imaging, Department of Geosciences, Universiti Teknologi PETRONAS, Bandar Seri Iskandar, 32610 Perak, Malaysia*
[2] *Department of Fundamental & Applied Sciences, Universiti Teknologi PETRONAS, Bandar Seri Iskandar, 32610 Perak, Malaysia*
[3] *Department of Chemical Engineering, Universiti Teknologi PETRONAS, Bandar Seri Iskandar, 32610 Perak, Malaysia*

Received July 9, 2021; Accepted January 14, 2022

Abstract

This review illustrates the most recent improvements and implementations of ANN in characterizing reservoirs in different regions for faster understanding of young petroleum geoscientists and engineers in the industry. Artificial Neural Networks (ANNs), one of the AI tools, has been effectively employed in several domains and has also gained popularity in reservoir characterization. Reservoir characterization is the act of creating a reservoir model based on its characteristics that are important to its capability to produce and store hydrocarbons with respect to fluid flow. The reservoir characterization domain is tricky because of the high complexity of non-linear data and ambiguity in data and modelling. The major objective of ANN application is to integrate obtained data from various geological, geophysical, petrophysical sources in reservoir characterization by identifying the complex non-linear correlation of input data. This work serves as an insight of the current implementation of ANN in the industry, which encourages more innovative intelligence systems that could accelerate the improvements of reservoir characterization evaluation protocols.

Keywords*: Artificial Neural Network (ANN); Reservoir characterization; Reservoir properties; Seismic data; Well log data.*

1. Introduction

Reservoir characterization is a procedure that combines all the available field data from various data sources to determine different reservoir properties in spatial variability quantitatively [1]. Understanding the reservoirs enables maximum optimization of their lifetime performance, which requires an integrated thorough reservoir study. Seismic, well logs and core data are the most key data sources in this domain. Several studies demonstrated successful implementation of seismic attributes in the estimation of reservoir properties [2]. The primary challenge is to define the relationship between wavelet morphology and lithological changes. Likewise, core data has been efficiently correlated with well log data to evaluate reservoir characteristics [3]. Well log data has a small coverage area with high resolution. In contrast, seismic data has a big coverage area of very low resolution. Core data has the highest resolution and contains the most reliable information; however, it is constrained in availability due to its high cost. The integration of these different data types leads to a more efficient reservoir characterization process. Data integration from multiple sources may necessitate that the sources should be in the same domain (time or depth) [4].

The core data and well logs are recorded in terms of depth, whereas seismic data is recorded in terms of time. They must be put under a common domain before data from different sources is implemented for reservoir characterization. Well-tie is an example process to bring different data in time and depth into the same domain. This method is commonly used by comparing the real seismic trace at a well as precisely as possible with the synthetic trace created in the well [5]. However, geophysical data from numerous sources exhibit various characteristics, including sampling rate, frequency, and information quality variations. To manage such differences, signal processing techniques such as interpolation and regularization are widely used.

Over the years, the application of Artificial Neural Network (ANN) in reservoir characterization was proved to be reliable. ANN can integrate different types of data efficiently, and model complex non-linear functions [6]. The major objective of this approach is to integrate obtained data from various geological, geophysical, petrophysical sources in reservoir characterization by identifying the complex non-linear correlation of this input data [7]. This technique is well-fitting to deal with the data diversity and the associated scales and deliver efficient solutions for various complexity issues [8]. ANN demonstrated better modelling capability and overcame the constraints by integrating with other soft computing methods [9].

This review paper shows a structured brief review of ANN application in the reservoir characterization domain for the last ten years. The key focus of this work is on the broadly adopted approach, ANN, and its changes in terms of learning, architecture, and integration with other soft computational methods.

2. An overview of Artificial Neural Networks (ANNs)

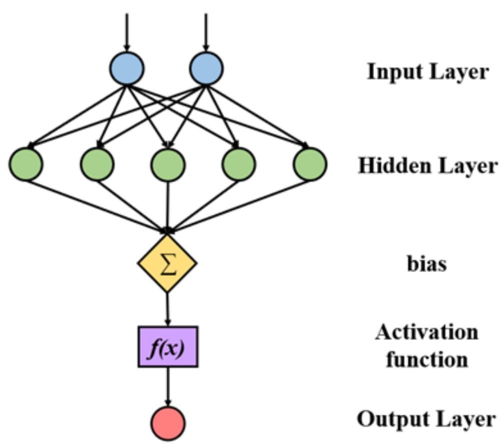

Figure 1. A schematic diagram of a basic ANN model

ANN is inspired by biological learning procedures in human brain [10]. A human brain is a very complex and non-linear system. It can solve many kinds of problems, such as pattern recognition, perception faster than a computer. It consists of neurons that become stronger when they learn something new. Each unit does a relatively easy job: it receives input from its neighbors or external sources and uses it to compute an output signal, which is then propagated to other units [11]. Figure 1 shows the architecture of a basic ANN model. ANN is a buildup of highly connected processing components called neurons like biological neurons.

Firstly, the training step of ANN is performed to identify the pattern between the input and output data. A collection of paired inputs and outputs is fed into the network for ANN training. The input data is routed through nodes connected by links and determine the interconnected weighting factors. Once the training is complete, ANN must be validated to ensure the accuracy of synthetic results before being applied to new data. If the validation outcome is inaccurate, the ANN is trained again [12]. After achieving successful validation performance, the trained network will produce synthetic numerical values for unpaired input data based on the patterns learned through training [13]. The benefit of using ANN is that synthetic outcomes are produced quickly and accurately for big datasets that would otherwise be interpreted manually.

3. Application of ANN network in reservoir characterization

Reservoir characterization implies determining petrophysical properties, like porosity, water saturation, permeability, and sand fractions, of the subsurface, which primarily indicate the presence of hydrocarbon [14]. Because of the heterogeneous nature of the earth's subsurface, estimating these reservoir properties is a challenging task.

The reservoir characterization domain is further tricky by the fact that the methodology must not only deal with high-complexity non-linear data but also with ambiguity in data and modelling [15]. The seismic data is the easy target for background noise [16]. The statistical relationships between the input seismic data and estimated reservoir properties are complicated and differ from location to location. Similarly, the relationships between well logs are highly complex [17]. Therefore, traditional methods such as linear regression may not effectively identify a significant relationship in the problem.

ANN can approximate any complex function using a sufficient number of computing features with the required accuracy [6]. The benefit of using ANN is that synthetic outcomes are produced quickly and accurately for big datasets that would otherwise be interpreted manually [12]. ANN is widely used in reservoir characterization by researchers worldwide to predict different petrophysical properties and well logs, lithofacies classification, seismic data noise attenuation, automatic seismic data interpretation [8].

The overall categorization of the survey is illustrated in Figure 2. A review on the 25 recent studies has been conducted as presented in Table 1.

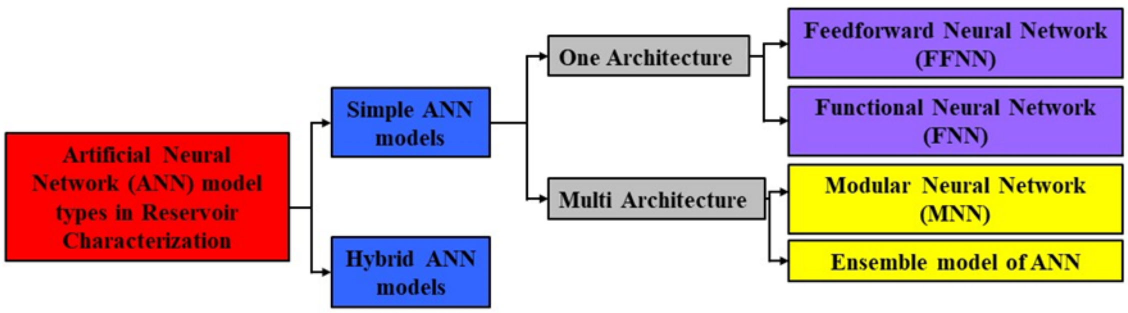

Figure 1. ANN model types in reservoir characterization domain

This table comprises the reviewed articles on ANN application in the reservoir characterization domain for the last ten years. The focus of the summary is on discussing various ANN models, including an overview of the widely used learning algorithms and their application domains.

Table 1. The summary of brief review on ANN models in reservoir characterization

ANN model	No	Authors	Learning algorithm	Application domain
Feedforward Neural Network (FFNN)	1	Moghadam et al., 2011 [11]	Feedforward backpropagation neural network algorithm (FFBPNN)	Porosity and permeability prediction
	2	Parra et al., 2014 [18]	Levenberg-Marquardt	Porosity, permeability, and intrinsic attenuation prediction
	3	Amit et al., 2014 [19]	Bayesian learning	Photoelectric log prediction
	4	Maman et al., 2016 [20]	Probabilistic Neural Network (PNN)	Water saturation, the volume of shale and porosity prediction
	5	Maman et al., 2018 [21]	Probabilistic Neural Network (PNN)	Facies classification
	6	Fadhil et al. 2017 [22]	Gradient descent with momentum & Levenberg-Marquardt	Cementation factor (m) prediction
	7	Mohammad et al. 2017 [23]	Levenberg-Marquardt	Permeability prediction
	8	Lukman et al. 2018 [24]	Levenberg-Marquardt	Geochemical property prediction
	9	Ghasem et al. 2019 [25]	Cuckoo optimization algorithm	Porosity and permeability prediction
	10	Camila et al. 2020 [26]	Differential Evolution (DE) algorithm	Lithology classification
	11	George et al. 2020 [27]	Levenberg–Marquardt	Porosity estimation

ANN model	No	Authors	Learning algorithm	Application domain
Functional Neural Network (FNN)	12	Ahmed et al. 2010 [28]	Group method of data handling (GMHD)	Porosity prediction
	13	Emad et al. 2012 [29]	New FNN with polynomial basis	Permeability prediction
Modular Neural Network (MNN)	14	Tahmasebi et al. 2012 [30]	Levenberg-Marquardt	Permeability prediction
	15	Akhilesh et al. 2013 [31]	Levenberg-Marquardt	Sand fraction prediction
Ensemble model of ANN	16	Anifowose et al. 2013 [32]	Levenberg-Marquardt	Porosity prediction
	17	Anifowose et al. 2015 [33]	Levenberg-Marquardt	Permeability prediction
Hybrid models of ANN	18	Saumen et al. 2010 [34]	ANN + Hybrid Monte Carlo (HMC) algorithm	Lithofacies classification
	19	Anifowose and Abdulraheem, 2011 [35]	Functionl Network + Type-2 Fuzyy Logic System + SVM	Porosity & permeability prediction
	20	Wang et al., 2013 [36]	Fuzzy logic + Levenberg-Marquardt	Porosity
	21	Ahmed et al. 2014 [37]	Fuzzy ranking + Backpropagation ANN	Fracture porosity determination
	22	Morteza et al., 2015 [17]	ANN + Imperialist Competitive Algorithm (ICA)	Water saturation prediction
	23	Soumi et al. 2018 [38]	ANN + Support vector regression (SVR) + Adaptive neuro-fuzzy system (ANFIS)	Prediction of lithological properties
	24	Salaheldin et al. 2018 [39]	ANN + modified self-adaptive differential evolution algorithm (SaDE-ANN)	Prediction of the bubble point pressure (Pb) and gas solubility (Rs) of crude oils
	25	Zhang et al. 2020 [40]	Machine Learning inversion algorithm + SVM inversion algorithm + Sequential Gaussian Simulation + Gaussian Indicator Simulation.	Prediction of acoustic impedance, porosity, lithofacies, and water saturation.

A brief discussion on the application of various ANN types in reservoir characterization domain is made as followed.

3.1. Feedforward neural networks (FFNN)

FFNN, also recognized as a multi-layer perceptron (MLP), is the most common and simplest ANN model [41]. The FFNN nodes are linked so that information can only pass forward. Each subsequent layer obtains information from the previous layer. Hidden layers may or may not exist in the FFNN, but input and output layers are always present [42]. Figure 3 demonstrates the schematic illustration of the structure of the FFNN. This type of neural network is easy to design and maintain; moreover, it is time-effective and responsive to noisy data [43].

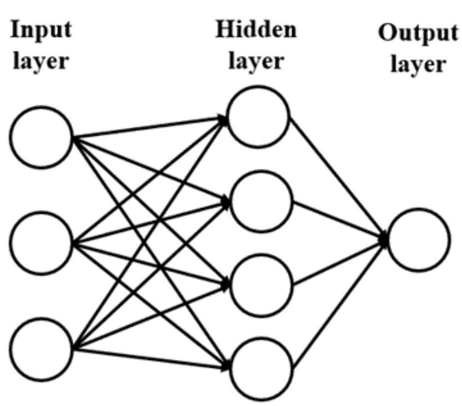

Figure 2. The schematic illustration of FFNN structure

Moghadam *et al.* [11] used the ANN approach to predict porosity and permeability in the Darquvan reservoir, southwest of Iran. Feature selection method, dependency analysis and statistical regression analysis were implemented to select well log set as input for modelling. The results obtained from the ANN approach were compared with multilinear regression and exponential techniques. The results obtained from the multilinear regression showed the correlation coefficients of 0.89 for porosity and 0.53 for permeability. However, this technique overestimated greater values and underestimated smaller values due to the nonlinearity of reservoir properties. Furthermore, the exponential approach's results showed a correlation coefficient of 0.43 for the core permeability estimation. The ANN approach overperformed both techniques and obtained the increased correlation for porosity and permeability to 0.99. This study concluded that the ANN approach is a reliable and effective tool in predicting porosity and permeability.

Parra *et al.* [18] implemented FFNN to determine porosity and permeability. The seismic data was used as the main input in this study. Gamma test was used as an input selection scheme in the area located in southeast Florida. The same technique, except ANN with well log data, was used on a sand-shelf reservoir in northeast Texas. The Gamma test supervised overfitting and established the best practical input-output relationship by determining the appropriate set seismic attributes as input features. The study showed the training correlation coefficient of 0.90 for training data and 0.75 for validation data.

Amit *et al.* [19] utilized the Probabilistic Neural Network (PNN) approach in the prediction of photoelectric log (Pe) log. Furthermore, this log was used to determine the lateral distribution of the dolomitized reservoir in eastern Canada. This log was selected as it provides a sensitive response in the presence of dolomite. Firstly, multi-attribute regression was used to select a suitable input set of attributes for Pe log prediction. The selected seismic attributes were then used to train a PNN. The use of multi-attribute regression for attribute choice improved the correlation of the model from 0.74 to 0.88 in training. The study demonstrated the efficacy of the ANN method in the prediction of photoelectric log.

Maman *et al.* [20] demonstrated the implementation of PNN using new attributes, namely SQp and SQs (Scale of Quality Factor of P and S waves), to predict porosity, the volume of shale and water saturation in the gas sand reservoir of offshore Malaysia. Newly developed attributes, namely SQp and SQs, were developed based on the attenuation concept through rock physics approximation. The log response of SQp attribute is equivalent to the gamma-ray log, and the log response of SQs attribute resembles the resistivity log. These attributes were used as the main input feature for PNN model training. The ANN modelling results were validated using a blind well testing approach. The correlation coefficient in the blind well test proved the effectiveness of SQp & SQs attributes in predicting reservoir properties. A similar approach was implemented by Maman *et al*. [21] for facies classification in offshore Malaysia. The three-dimensional (3D) cubes of SQp & SQs attributes obtained from simultaneous method were used as input for ANN modelling. This approach helped to define and differentiate the gas sand distribution from the brine distribution in the study area.

Fadhil *et al.* [22] predicted the cementation factor in Yamamma carbonate formation using the ANN approach. This methodology provided very efficient performance and excellent prediction of cementation factor value with less than 10^{-4} Mean Square Error (MSE). The results proved that the network could be implemented as a very useful prediction approach, particularly in carbonate formations where nature is complex and highly non-linear, resulting in no close traditional mathematical model explaining this method's behaviour without assumptions.

Mohammad *et al.* [23] proposed a novel Wavenet Neural Network (WNN) model to advance the permeability prediction process. This approach was developed by integrating a FFNN and wavelet theory. The acquired results from WNN were compared with findings from MLP and RBF networks. The results obtained from RBF and MLP networks are similar, with a correlation coefficient of 0.89. However, the novel Wavenet approach achieved results with a correlation coefficient of 0.92. The results demonstrated that the novel WNN approach estimated permeability better than conventional networks. Incorporating a wavelet transfer function, which has perpendicular and strong local properties, led to faster homogeneity than a typical neural network. This suggested method is an additional effective technique for assessing and mitigating risk and ambiguity in oil and gas reservoir discovery.

Lukman *et al.* [24] utilized the Levenberg-Marquardt algorithm for training ANN model to estimate continuous geochemical logs with no or minimal geochemical data from wells. The model was built on existing relationships between traditional well logs and laboratory-measured geochemical data from the Canning Basin, Western Australia. The ANN model gave an accuracy of 75% during the generation of continuous geochemical data at well locations. This data, obtained from the ANN model, was used as input for a subsequent geochemical property model.

Ghasem *et al.* [25] employed ANN optimized by Cuckoo optimization algorithm using well log data to predict NMR log parameters such as porosity and permeability in one of the Iranian super oil fields. The conventional well log dataset, including electrical resistivity, bulk density, sonic wave velocity, and neutron porosity, were used as input for modelling. The correlation coefficient of 0.99 for the training stage and the correlation coefficient of 0.97 were achieved using the optimized ANN approach. The results demonstrated the precision and feasibility of the developed ANN-Cuckoo method in predicting NMR log data. This modelling presents a tremendous opportunity to dramatically reduce costs by eliminating the need for direct reservoir tests.

Camila *et al.* [26] presented the application of ANN trained by an adaptive Differential Evolution (DE) algorithm to categorize lithology using well log data in the Southern Provence Basin. This newly developed approach helped to generate a lithofacies model with high classification accuracy, which provides the opportunity to enhance the knowledge about the reservoir's heterogeneity.

George *et al.* [27] demonstrated a new geologic site characterization workflow using an ANN at the Southeast Regional Carbon Anthropogenic Test in Citronelle, Alabama. The field is covered with hundreds of wells with electrical logs that lack critical porosity measurements. Three new test wells were drilled at the injection site, each paired with a nearby legacy well containing vintage electrical logs. The test wells were logged for density porosity measu-rements and cored over the storage reservoir. ANN was developed at each well pair, trained, and validated by identifying patterns in vintage electrical logs and modern density porosity measurements. The trained neural network was applied to 36 oil wells in the Citronelle Region, creating synthetic porosities of the storage reservoir and overlying stratigraphy. Finally, the storage reservoir's permeability was calculated using a combination of synthetic porosity and an empirically derived relationship between porosity and permeability estimated from the core. The authors mentioned that this workflow could generate synthetic permeability and estimate CO_2 storage capacity in other oil fields.

3.2. Functional Neural Network (FNN)

The FNN is a generalization of the conventional neural network; it operates with generalized functional models rather than sigmoidal forms [35]. The preliminary design of FNN is problem-driven. The FNN's final topology is defined by data domain, information about the neuron's other properties (invariance, commutativity and associativity) and knowledge expertise [44]. In FNNs, the neuron activities associated with each neuron are not set but are learned from input data. Consequently, it is not required to include weights correlated with connections since the influence of weights is included in neuron functions [45]. Furthermore, FNNs enable neurons to be multi-argument, multivariate, and various learnable functions instead of fixed functions. Furthermore, FNNs allow converging neuron outputs, which forces them to coincide. This results in a system of functional equations that necessitates certain compatibility requirements on the neuron functions. The typical architecture of FNNs is illustrated in Figure 4.

Ahmed *et al.* [28] introduced the implementation of abductive network (AN) for porosity prediction in the Ghawar oil field, Saudi Arabia. This type of network uses iterated polynomial regression to construct an optimal non-linear predictor. The model selected the best two to six out of 27 attributes in a computationally efficient manner. The results from the AN were compared with the results from the regularized backpropagation ANN (RNN). The AN achieved a correlation coefficient of 0.9 in porosity prediction. The correlation coefficient obtained with the RNN is 0.45. The AN presented more accurate and efficient outcomes, comparing to the results of the traditional ANN. The study concluded that the AN is an effective and reliable approach in predicting reservoir porosity distribution in heterogeneous reservoirs.

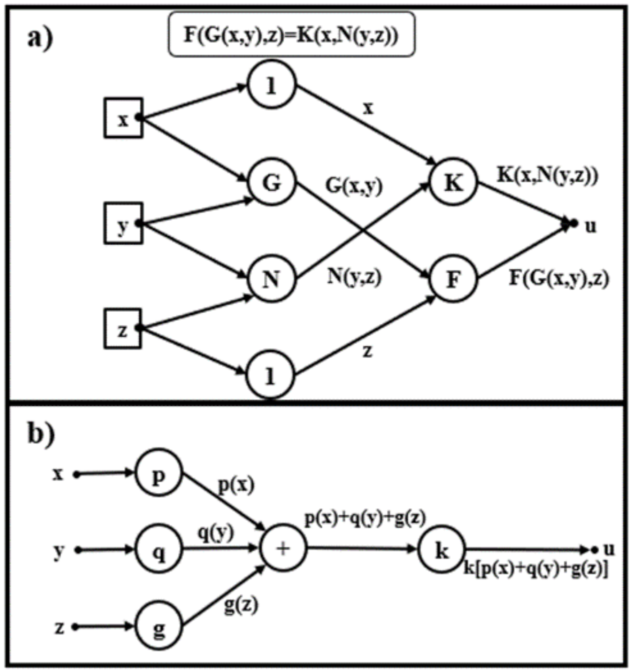

Figure 3. Schematic illustration of typical FNN architecture

Emad *et al.* [29] presented the application of a novel FNN for estimation of permeability in a carbonate reservoir using well logs. The new intelligence approach facilitates delivering the most prevalent shortcomings of current simulation approaches in statistics, machine learning, data processing, and AI. The new approach's output was compared to the most common modelling schemes, such as non-linear regression, neural networks, and fuzzy logic inference systems, using real-life industry wireline logs. The obtained results demonstrated the correlation coefficients of 0.87, 0.93, and 0.95, respectively. However, the FNNs managed to achieve the outcomes with a correlation coefficient of 0.96. The findings demonstrated that FNNs' efficiency (separable and generalized associativity) architecture with a polynomial base is accurate, consistent, and outperforms most current predictive data mining modelling techniques. Furthermore, the established FNNs predictive model was used to predict new unseen wells in real-time. Additionally, due to the strength of the FNN's intelligence structure, the proposed solution is predicted to perform equally with, if not better than, the other empirical and analytical approaches.

3.3. Modular Neural Network (MNN)

An additional ANN approach that gained increasing popularity in reservoir characterization is the MNN. This technique uses the split and conquer strategy. A complicated problem is divided into many, so that each learner can manage a relatively easier problem [30]. The outcome of this method is viewed as an integration of all activities. In other words, MNN can have various structures in itself, and even one can incorporate prior knowledge within it [47]. Also, since the complex task in MNN is decomposed into several smaller and simpler ones, one can anticipate an overall network with a smaller complexity. Each module cannot influence each other's work and uses a smaller part of the data [31]. This network has simpler structures than MLP and can respond to input much faster [30]. The key purpose of MNN is to find the optimal architecture, which will provide time-efficient and successful results [47]. Therefore, MNN is more time-efficient, more reliable in handling very large datasets and can reduce undesirable fluctuations and affect the whole network. Figure 5 shows the schematic representation of MNN architecture.

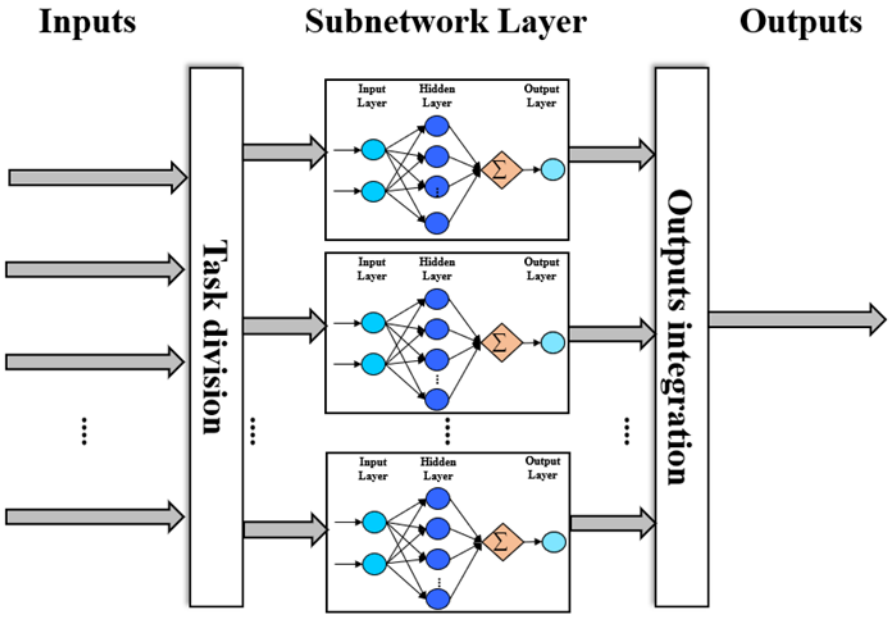

Figure 4. Schematic representation of MNN architecture

In 2012, Tahmasebi *et al.* [30] presented a novel MNN concept to the petroleum industry. This approach was implemented to predict permeability in the field of the Persian Gulf. By splitting the MLP into several simpler networks, the network's complexity was reduced, allowing it to work on smaller and simpler datasets. The obtained result by modularization demonstrated more accuracy and time-efficiency than MLP. The results show that the correlation coefficient was improved from 0.94 to 0.99 for MLP and MNN networks, respectively.

Akhilesh *et al.* [31] implemented a similar technique for determining sand fractions using three seismic attributes, i.e. amplitude, instantaneous frequency, and inverted impedance in the onshore field, western India. The improvement in modelling ability of the model, minimized uncertainty. The average correlation coefficient increased from 0.20 to 0.75 and the average execution time reduced from 239 s to 59 s. The findings showed that MNN outperformed MLP in terms of reliability, time-efficiency and learning capability.

3.4. Ensemble model of ANN

Ensemble learning is an approach that incorporates and intelligently combines diverse multiple expert theories to resolve a problem [9]. This novel learning paradigm has its roots in human sociology, where final choices are made by taking into account the different views of a "committee of experts" to achieve an overall "ensemble" decision [48]. The ensemble learning technique is capable of handling both big data and sparse data situations [33]. This approach can manage and blend multiple expert views, such as different base model architectures, data sampling techniques, and differing examples of improved tuning parameters, to reduce the error associated with the final output [48]. The outcome can be the evaluation metric, the learning algorithm, parameters, et cetera [49]. Figure 6 demonstrates the basic schematic illustration of the Ensemble model of ANN.

The ensemble machine learning idea is particularly valuable in petroleum reservoir characterization due to the highly non-linear nature of the heterogeneity of datasets, reservoir characteristics, and the ambiguities involved in assessing the various reservoir characteristics [50].

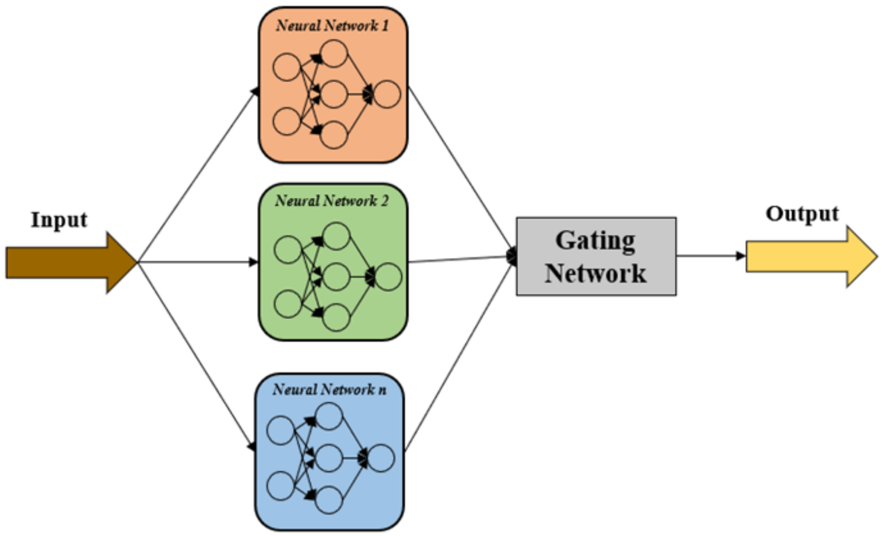

Figure 5. The schematic architecture of the ANN Ensemble model

In 2013, Fatai *et al.* [32] introduced the implementation of the first ensemble model of ANN in reservoir characterization. This model was first used to define the optimal number of hidden neurons in the ANN model to estimate porosity and permeability from well log data in northern Marion, North America. The number of hidden neurons in the individual ensemble models varies, and a combined decision was taken to figure out the best number of hidden neurons to predict the required property. In the presence of noisy and scarce data, the result was stronger in terms of correlation coefficient (higher than 0.86) compared to traditional models and random forest model. In 2015, Fatai *et al.* [33] presented the implementation of an ensemble model for porosity and permeability determination using well log dataset in the Northern Marion Platform of North America and carbonate and sandstone reservoir in the Middle East. The achieved correlation was more than 92%. Moreover, the mean average error was 0.2 for porosity prediction and less than 0.5 for permeability prediction. The ensemble model demonstrated better results than conventional approaches.

3.5. Hybrid ANN models

Hybrid ANN models involve combining two or more soft computing approaches to form a single functional entity for improved performance. The key concept behind hybridization is to overcome the limitations of one technique with the strength of other techniques [35]. A key requirement for integrating technologies is the existence of a "common denominator" to build upon [51]. The hybrid models of ANN are becoming progressively popular. This popularity lies in the extensive success of hybrid systems in many real-world complex problems [52]. Figure 7 illustrates the generalized framework of a hybrid ANN model.

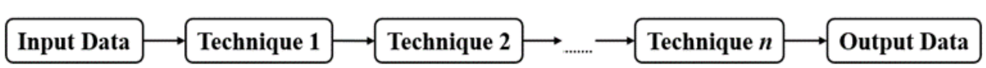

Figure 6. The generalized framework of a hybrid ANN model

Saumen *et al.* [34] developed a novel Bayesian neural network (BNN) using a powerful Hybrid Monte Carlo (HMC) algorithm to discriminate lithofacies from dense well log signals in the presence of various noises. It is a precise algorithm that can be implemented to almost any theory of continuous variables. HMC algorithm is a method of choice when several degrees of freedom are coupled, and single variable updates are impossible. This technique distinguished boundaries of lithofacies with an accuracy of approximately 92% for validation and 93% for test samples. In addition to agreeing well with earlier outcomes, the results from BNN demonstrated the presence of finer bed boundaries missed in previous research. Finer structures seem to have geologic importance for understanding the crustal inhomogeneity and structural discontinuities within the central European crust.

To evaluate permeability and porosity in Northern Marion Plat-form North America, Fatai and Abdulraheem [35] suggested a hybrid ANN approach incorporating type-2 fuzzy logic, SVM and FNN approaches. Every aspect of the complex problem was solved individually. Functional approximation capability of FNN, the ability of type-2 fuzzy logic to handle ambiguity, scalability, and robustness of SVM in handling small and high-dimensional data were utilized in this study. As a result, the hybrid model outperformed other individual approaches with a correlation of 96%. The more flexible and efficient stable model achieved at the expense of time of execution.

Wang *et al.* [36] implemented a SFFNN to estimate porosity in the southwest Alberta region of Canada. A fuzzy ranking method was implemented for the selection suitable input dataset. The implementation of this approach was in two stages. Firstly, the applicable variables were determined by rating the variable using a fuzzy curve. Furthermore, a fuzzy surface was used to exclude highly dependent variables. The best well log set, consisting of 8 well logs were used as input for core porosity prediction. The Levenberg-Marquardt algorithm was implemented for training purposes. A comparative analysis is performed by considering the following function collection methods: crucial component analysis, fuzzy ranking, random selection without selection (considering all the variables), and all well log variables. The fuzzy ranking approach has obtained a balanced and consistent outcome relative to the remaining approaches.

Ahmed *et al*. [37] demonstrated the implementation of fuzzy ranking and ANN integration to define fracture porosity using four conventional log data (including gamma ray, neutron porosity, density and deep resistivity) in Hassi Messaoud oil field. The determination of fracture porosity is challenging due to the heterogeneous distribution of fractures in reservoirs. The laboratory analysis of the core only provides direct measurements of fracture porosity, but it is costly procedure. Fuzzy ranking method defined that gamma ray, neutron porosity, density and deep resistivity logs are critical and relevant well log data and cannot be ignored. The backpropagation algorithm was implemented for ANN training and the correlation coefficient of 0.87 between fracture porosity obtained from ANN and log data was achieved.

Morteza *et al.* [17] determined the distribution of water saturation in one of the fields of the Mesaverde group region, Western US. Backpropagation based ANN integrated with imperialist competitive algorithm (ICA) approach were used for water saturation prediction. This algorithm was developed based on human's socio-political behaviour [53]. Several well logs, including gamma ray (GR), effective density -neutron porosity (PHIDNE), density porosity log (PHID), neutron porosity log (PHIN), were used as input for this approach. Several methods, including Principal Component Analysis (PCA) for data dimensionality reduction, factor analysis for applicable feature selection and outlier removal, were applied to input data to improve the data quality. As a result, ANN-based normal backpropagation provided the correlation coefficient of 0.93 for training data and 0.92 for validation data. However, the optimized model provided a more efficient result, a correlation coefficient of 0.97 for training data and 0.95 for validation data. The optimization methodology assisted in the development of the most practical and improved model performance.

Soumi *et al.* [38] presented various algorithms for signal pre-processing and post-processing in predicting lithological properties. The major algorithms named Adaptive neuro-fuzzy system (ANFIS), Support vector regression (SVR) and ANN, and are extensively discussed for the combined modelling involving seismic and well logs.

Salaheldin *et al.* [39] introduced the integration of ANN with a modified self-adaptive differential evolution algorithm to introduce a hybrid Self-adaptive ANN (SaDE-ANN) model. The novel approach was implemented to predict the bubble point pressure (Pb) and gas solubility (Rs) of crude oils. This technique can be used to predict Rs and Pb with just three input parameters. The developed empirical correlation for Pb predicts the Pb with a correlation coefficient of 0.99 and an average absolute percentage error (AAPE) of 6%. The same results were obtained for Rs using this novel approach with a correlation coefficient of 99% and AAPE of 6%. The developed technique will help reservoir and production engineers to understand better and manage reservoirs.

Zhang *et al.* [40] introduced a novel ANN method based on well logs to determine good reservoir quality regions from seismic inversion and the spatial distribution of key reservoir characteristics in Pakistan's Sawan gas field. To begin, the spatial variations of saturation, porosity, and acoustic impedance were identified using a machine learning (ML) inversion algorithm. Meanwhile, the support vector machine (SVM) inversion method efficiently identified and mapped distinct reservoir characteristics to characterise and quantify fluid-rich areas. Furthermore, the lateral and vertical distributions of porosity and lithofacies from well logs and core data were defined using the Sequential Gaussian Simulation (SGS) and Gaussian Indicator Simulation (GIS) algorithms. This study concluded that integrating SVM and GIS algorithms is an effective approach in predicting reservoir properties' distribution in highly heterogeneous reservoirs.

4. Discussion

This brief survey shows that various advancements in ANN approaches are inspired by the constraints of ANN in solving problems in the reservoir characterization domain. Table 2 demonstrates a general overview of the advantages and disadvantages of previously discussed ANN modelling methods. These methods have similar advantages and limitations in a variety of applications, including reservoir characterization.

Table 2. ANN modelling approaches and their advantages and disadvantages

ANN models	Advantages	Disadvantages
Feedforward neural network (FFNN)	Most basic form of ANN; Not require fundamental knowledge of mechanism of data generation; Has the ability to estimate different types of complex functions; Graceful deterioration;	Proper tuning of hyperparameters is a difficulty. It is typically achieved using the method of trial and error; Computational complexity problem curse;
Functional Neural Network (FNN)	Information on the domain & data can provide greater capacity and time-efficiency for generalization; Learned function is comprehensible; Weight initialization is not required while the activation function is learned during the training stage;	The component change in the network has a great impact on the mathematical equation of the whole training process; Model is problem-driven rather than data-driven;
Modular neural network (MNN)	Complex tasks are divided for easier task management; Shows better performance than general ANN model in the sense of processing time, efficiency and learning ability;	Does not automatically select the range of networks and modelling architecture;
Ensemble ANN	Has the best performance compared to separate individual ANN model; In the sense of selected input attributes, hyperparameter and generalized error, it can provide the improved ANN model;	Decision-making parameters are often hard to determine, on which the performance is dependent;
ANN with Fuzzy Logic	Integrates both ANN's and fuzzy logic's strength; Because of reasoning ability, it can handle inaccuracy and uncertainty; Fuzzy classification can be implemented in the selection of appropriate input elements for ANN modelling;	It is important to pick the membership function properly. It can need experience skills; Demonstrates inefficiency on limited data;

According to the study, FFNN makes reservoir modelling simple; however, proper modelling generally requires a suitable input set, accurate tuning of hyperparameters, and an appropriate dataset. In a heterogeneous reservoir, these requirements become more critical and must be properly considered. Hybrid modelling approaches [35] and ensemble modelling approaches [33] have capability of providing a good set of hypermeters for modelling; however this comes at a high computational expense. Excessive features might affect the modelling abilities, therefore feature selection is critical aspect when looking for efficient modelling. Fuzzy logic based hybrid models [35-37] demonstrated great performance in several studies. Unlike feature selection, feature extraction changes existing features to lower dimensional space rather than explicitly deleting features from the current collection based on feature ranking. It generates new sets of features by combining existing features in a supervised or unsupervised manner.

At present, data is often challenging in the oil & gas industry [54]; therefore, advanced techniques capable of processing high-dimensional and noisy data will offer a major benefit in reservoir characterization. Certain problems include the assumption that traditional ANN is inefficient when the data is extremely non-linear, as well as the risk of being trapped in the local minima [55], gets slow with the rise in the number of hidden layers, taking longer computational time [56], overfitting problem [57], incapable of dealing with ambiguity [58] and etc. However, advances in science have made certain problems, such as the local minima issue, outdated.

ANNs use data-driven methodology. As a result, the output quality is determined not only by the model but also by the quality of input data. Geophysical data is noisy data, and the properties of data from various sources differ greatly. Consequently, appropriate pre-processing tools are necessary. The use of ANN mainly depends on the presumption that the training dataset generated will accurately reflect the relationship between the reservoir property to be projected and the input data. As a result, it is essential to accurately choose a training range that accurately represents the total population [12].

The geological spot has a considerable impact on the collected data too. If the geology varies, so do the features of the gathered data. Since the geology of the earth is dynamic, geophysical data responds differently based on its geology. As a result, we can conclude that the ANN methods for estimating petrophysical characteristics are restricted to a particular area. The simple geological complexity and high data quality can offer a decent accuracy level with fewer data samples and a simpler model. However, enough data is needed to construct the predictive model for high-complexity geological areas, increasing the model's complexity.

5. Conclusion

A survey on application of various ANN models in reservoir characterization domain is presented in this paper. ANN models have been modified over time to overcome the constraints, like the issues of hyperparameter tuning and complex function approximation. ANN delivers better results in various reservoir characterization tasks when integrated with other soft-computational methods. Ensemble and modular ANN models are a very clear example of ANN implementation in a smart way to obtain more optimized architectures, optimal input features and training algorithms. Hybrid ANN models also demonstrated their effectiveness and reliability in this domain. However, dealing with a high volume of data produced by advanced sensors in the petroleum industry needs innovative modelling approaches. The reservoir characterization domain is further tricky by the fact that the methodology must not only deal with high-complexity non-linear data but also with ambiguity in data and modelling.

Finally, the authors believe that the presented review in this study will provide new insights for a deeper understanding of ANN application in the reservoir characterization domain. The existing state-of-art of ANN applications in the reservoir characterization domain indicates promising outcomes. In the future, we expect to see more innovative intelligence systems that could accelerate the enhancements of reservoir characterization evaluation protocols.

Acknowledgments

The authors would like to show gratitude to the Centre for Seismic Imaging (CSI) and Geoscience department at University Technology PETRONAS for valuable resources, facilities, and funding.

Conflicts of interest

The authors declare no conflict of interest.

References

[1] Journel AG. Stochastic Modeling and Geostatistics: Principles, Methods, and Case Studies; Jeffrey M. Yarus and Richard L. Chambers; American Association of Petroleum Geologists, 1995; Chapter 2.
[2] Schultz PS, Ronen S, Hattor, M, Corbett C. Seismic-guided estimation of log properties Part 1: A data-driven interpretation methodology. Lead. Edge 1994; 13(5).
[3] Ahmadi M, Saemi M, Asghari K. Estimation of the reservoir permeability by petrophysical information using intelligent systems. Pet.Sci.Technol., 2008; 26(14): 1656–1667.
[4] Liu D. The Effects of Pre - Stack Seismic Data Conditioning on AVO Analysis. 83rd Annu. Int. Meet. SEG, Expand. Abstr. 2013, 452–456.
[5] Nehaid HA, Ali MY. A case study of porosity prediction from seismic inversion in a carbonate oilfield, Abu Dhabi, UAE. 69th Eur. Assoc. Geosci. Eng. Conf. Exhib. 2007 Secur. Futur. Inc. SPE Eur. 2007; 2353–2357.
[6] Hornik K, Stinchcombe M, White, H. Multilayer feedforward networks are Universal approximators. Neural Networks 1989; 2: 359–366.
[7] Saikia P, Baruah RD, Singh SK, Chaudhuri PK. Artificial Neural Networks in the domain of reservoir characterization: A review from shallow to deep models. Comput. Geosci., 2020; 135: 104357.
[8] Nikravesh M, Aminzadeh F. Past, present and future intelligent reservoir characterization trends. J. Pet. Sci. Eng. 2001; 31(2–4): 67–79.
[9] Anifowose FA, Labadin J, Abdulraheem A. Ensemble machine learning: An untapped modeling paradigm for petroleum reservoir characterization. J. Pet. Sci. Eng. 2017; 151: 480–487.
[10] Barrow H. Chapter 5: connectionism and neural networks. In Artificial Intelligence; 1996; 135–155.
[11] Moghadam JN, Salahshoor K, Kharrat R. Intelligent prediction of porosity and permeability from well logs for an iranian fractured carbonate reservoir. Pet. Sci. Technol. 2011; 29(20): 2095–2112.
[12] Rahmanifard H, Plaksina T. Application of artificial intelligence techniques in the petroleum industry: a review. Artif. Intell. Rev. 2019; 52(4): 2295–2318.
[13] An P. The effect of Random noise in lateral reservoir characterization using feed-forward neural networks. 1994 SEG Annu. Meet. 2018; (6): 787–790.
[14] Lines R, Newrick RT. Fundamentals of Geophysical Interpretation. SEG Geophysical Monograph Series 13. Society of Exploration Geophysicists. 2004; 288.
[15] Mahmoud M, Ghorab M, Shazly T, Shibl A, Abuhagaza AA. Reservoir characterization utilizing the well logging analysis of Abu Madi Formation, Nile Delta, Egypt. Egypt. J. Pet. 2017; 26(3): 649–659.
[16] AlHakeem AA. 3D Seismic Attribute Analysis and Machine Learning for Reservoir Characterization in Taranaki Basin, New Zealand. ProQuest Diss. Theses 2018; 119.
[17] Amiri M, Ghiasi-Freez J, Golkar B, Hatampourd A. Improving water saturation estimation in a tight shaly sandstone reservoir using artificial neural network optimized by imperialist competitive algorithm - A case study. J. Pet. Sci. Eng. 2015; 127: 347–358.
[18] Konaté AA, Pan H, Khan N, Yang JH. Generalized regression and feed-forward back propagation neural networks in modelling porosity from geophysical well logs. J. Pet. Explor. Prod. Technol. 2015; 5(2): 157–166.
[19] Russell BH. The Application of Multivariate Statistics and Neural Networks to the Prediction of Reservoir Parameter Using Seismic Attributes, 2004.
[20] Hampson DP, Schuelke JS, Quirein JA. Use of multiattribute transforms to predict log properties from seismic data. Geophysics 2001; 66(1): 220–236.
[21] Iturrarán-Viveros U, Parra JO. Artificial Neural Networks applied to estimate permeability, porosity and intrinsic attenuation using seismic attributes and well-log data. J. Appl. Geophys. 2014; 107: 45–54.

[22] Ray A, Sharma RK, Chopra S. Hydrocarbon-bearing dolomite reservoir characterization: A case study from eastern Canada. Soc. Explor. Geophys. Int. Expo. 84th Annu. Meet. SEG 2014; 2677–2682.
[23] Hermana M, Ghosh DP, Sum CW, Salim AM. In Implementation of New Seismic Attributes to Improve Reservoir Properties Prediction Using Probability Neural Network, 2016.
[24] Hermana M, Ngui JQ, Sum CW, Ghosh DP. Feasibility Study of SQp and SQs Attributes Application for Facies Classification. Geosciences, 2018; 8(2): 10.
[25] Kadhim FS, Samsuri A, Idris AK, Al-Dunainawi Y. The use of artificial neural network to predict correlation of cementation factor to petrophysical properties in Yamamma formation. Int. J. Oil, Gas Coal Technol., 2017; 16(4): 363–376.
[26] Bahramian MM, Khaksar-Manshad A, Fathianpour N, Mohammadi AH, Herki, BMA, Ali JA. Improved estimation of permeability of naturally fractured carbonate oil reservoirs using wavenet approach. Pet. Coal, 2017; 59(6): 785–796.
[27] Johnson LM, Rezaee R, Kadkhodaie A, Smith G, Yu H. Geochemical property modelling of a potential shale reservoir in the Canning Basin (Western Australia), using Artificial Neural Networks and geostatistical tools. Comput. Geosci., 2018; 120: 73–81.
[28] Zargar G, Tanha AA, Parizad A, Amouri M, Bagheri H. Reservoir rock properties estimation based on conventional and NMR log data using ANN-Cuckoo: A case study in one of super fields in Iran southwest. Petroleum, 2019; 6(3): 304–310.
[29] Saporetti CM, Goliatt L, Pereira E. Neural network boosted with differential evolution for lithology identification based on well logs information. Earth Sci. Informatics, 2020; 14(1): 133–140.
[30] Koperna G, Jonsson H, Ness R, Cyphers S, MacGregor JR. A workflow incorporating an artificial neural network to predict subsurface porosity for co2 storage geological site characterization. Processes, 2020; 8(7): 1–16.
[31] Anifowose F, Abdulraheem A. Fuzzy logic-driven and SVM-driven hybrid computational intelligence models applied to oil and gas reservoir characterization. J. Nat. Gas Sci. Eng., 2011; 3(3): 505–517.
[32] Abdulraheem A, Ahmed M, Vantala A, Parvez T. In Prediction of rock mechanical parameters for hydrocarbon reservoirs using different artificial intelligence techniques, 2010.
[33] Al-Bokhitan. Functional Networks as a Novel Approach for Predicting Reservoir Fluids PVT Properties., 2007.
[34] Anifowose FA, Labadin J, Abdulraheem A. Hybrid intelligent systems in petroleum reservoir characterization and modeling: the journey so far and the challenges ahead. J. Pet. Explor. Prod. Technol., 2017; 7(1): 251–263.
[35] Ahmed OA, Abdel-Aal RE, AlMustafa H. Reservoir property prediction using abductive networks. Geophysics, 2010; 75(1).
[36] El-Sebakhy EA, Asparouhov O, Abdulraheem AA, Al-Majed AA, Wu D, Latinski K, Raharja I. Functional networks as a new data mining predictive paradigm to predict permeability in a carbonate reservoir. Expert Syst. Appl., 2012; 39(12): 10359–10375.
[37] Tahmasebi P, Hezarkhani A. A fast and independent architecture of artificial neural network for permeability prediction. J. Pet. Sci. Eng., 2012; 86–87: 118–126.
[38] Happel B, Murre J. The design and evolution of modular neural network architectures. Neural Networks, 1994; 7: 985–1004.
[39] Chaki S, Verma AK, Routray A, Mohanty WK, Jenamani M, Chaudhuri PK, Das SK. In Quantifying sand fraction from seismic attributes using modular artificial neural network, 2013.
[40] Polikar R. Ensemble based systems in decision making. IEEE Circuits Syst. Mag. Third Quart., 2006: 21–45.
[41] Anifowose F, Labadin J, Abdulraheem A. Ensemble model of non-linear feature selection-based extreme learning machine for improved natural gas reservoir characterization. J. Nat. Gas Sci. Eng. 2015; 26: 1561–1572.
[42] Rokach L. Pattern Classification Using Ensemble Methods. World Sci. Publ. Singapore 2009, 242.
[43] Zahedi G, Fazlali AR, Hosseini SM, Pazuki GR, Sheikhattar L. Prediction of asphaltene precipitation in crude oil. J. Pet. Sci. Eng., 2009; 68(3–4): 218–222.
[44] Anifowose F, Labadin J, Abdulraheem A. Ensemble learning model for petroleum reservoir characterization: A case of feed-forward back-propagation neural networks. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics) 2013, 7867 LNAI, 71–82.
[45] Symeonidis LA, Mitkas A. Agent Intelligence through Data Mining, Mul- tiagent Systems, Artificial Societies, and Simulated Organizations Series. Int. B. Ser., 2005, 14.

[46] Giovanni A, Vincenzo L. Using FML and Fuzzy technology in adaptive ambient intelligence environments. Int. J. Comput. Intell. Res., 2005; 1(2): 171–182.

[47] Maiti S, Tiwari RK. Automatic discriminations among geophysical signals via the Bayesian neural networks approach. Geophysics, 2010; 75(1).

[48] Wang B, Wang X, Chen Z. A hybrid framework for reservoir characterization using fuzzy ranking and an artificial neural network. Comput. Geosci., 2013; 57: 1–10.

[49] Zerrouki AA, Aïfa T, Baddari K. Journal of Petroleum Science and Engineering Prediction of natural fracture porosity from well log data by means of fuzzy ranking and an arti fi cial neural network in Hassi Messaoud oil fi eld , Algeria. J. Pet. Sci. Eng., 2014; 1–12.

[50] Atashpaz-Gargari E, Lucas C. Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition. IEEE Congr. Evol. Comput. IEEE, 2007; 4661–4667.

[51] Chaki S, Routray A, Mohanty WK. Well-Log and Seismic Data Integration for Reservoir Characterization: A Signal Processing and Machine-Learning Perspective. IEEE Signal Process. Mag., 2018; 35(2): 72–81.

[52] Elkatatny S, Moussa T, Abdulraheem A, Mahmoud M. A self-adaptive artificial intelligence technique to predict oil pressure volume temperature properties. Energies, 2018; 11(12): 1–14.

[53] Qiang Z, Yasin Q, Golsanami N, Du Q. Prediction of reservoir quality from log-core and seismic inversion analysis with an artificial neural network: A case study from the Sawan gas field, Pakistan. Energies, 2020; 13(2).

[54] Hassani H, Silva ES. Big Data: a big opportunity for the petroleum and petrochemical industry. OPEC Energy Rev., 2018; 42(1): 74–89.

[55] Atakulreka A, Sutivong D. In Avoiding local minima in feedforward neural networks by simultaneous learning., 2007.

[56] Kantabutra V. Towards reliable convergence in the training of neural networks- the streamlined glide algorithm and the LM glide algorithm. MLMTA, 2006; 70–87.

[57] Sharma A.; Sharma RK.; Upadhaya PK.; Ram JN. Seismic attribute analysis and Neural network application for reservoir characterization in Lanwa Field , India ; A case study. 10th Bienn. Int. Conf. Expo. 2013; 1–6.

[58] Simoff SJ. In Handling uncertainty in neural networks: an interval approach., 1996.

To whom correspondence should be addressed: Gulbahar Yazmyradova and Maman Hermana, Centre of Seismic Imaging, Department of Geosciences, Universiti Teknologi PETRONAS, Bandar Seri Iskandar, 32610 Perak, Malaysia, E-mail: : gulbahar_18390@utp.edu.my; maman.hermana@utp.edu.my