Modelling Approach to Reservoir Characterization of the Camal Field-Masilah Basin-Yemen

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***Abstract*— The significant impact of reservoir characteristics including porosity, permeability, and saturation on the well productivity calls for concerted research effort towards developing promising models for high accuracy prediction. In this work, a new model for estimating rock properties of Camal field was developed using various approaches of Artificial Intelligence (AI) such as neural networks and hybrid neuro-fuzzy techniques.**

In order to achieve the objective of this study, actual porosity, permeability and saturation data collected from laboratory analysis of the core samples obtained from eight wells in Camal field. In addition, the logs data (bulk density, gamma ray, induction) was also gathered for the same wells. Among different AI approaches were applied in this study to estimate reservoir characteristics. Hybrid method are also used such as adaptive neuro-fuzzy inference system (ANFIS) for estimation reservoir properties for Camal field. The proposed models were validated through the graphical and statistical error analysis.

An AI models to estimate different rock properties such as porosity, permeability and saturation were presented using actual field data in this work. The obtained results showed that the hybrid neuro-fuzzy method had a great potential in predicting reservoir properties among the other AI approaches. Statistical analysis and comparative study showed that the performance of proposed hybrid neuro-fuzzy model is the best one with lower root mean square error (0.05) and higher accuracy of correlation coefficient (0.98) than those obtained with other models. It was observed that artificial intelligence modeling is reliable and accurate for prediction reservoir rock properties applied for this field.

The modeling approach presented in this work can be used as alternatives methods for determining petrophysical properties. These methods are accurate and less expensive techniques of reservoir description.

Keywords— Reservoir properties, Model, Artificial Intelligence, Yemen.

I. INTRODUCTION

The process of characterizing different reservoir features utilizing all the data that has been acquired from various experiments is known as reservoir characterization. The complexity of the geology and the availability of sample data influence how reservoir attributes are described. Petroleum engineers need to understand the petrophysical characteristics of reservoir rocks at a fundamental level. An essential component of reservoir management is reservoir characterization. The characteristics of the reservoir rock and the fluid saturation largely determine the amount of recoverable petroleum in a reservoir and the rate at which it can be produced. The two main sources of this data are well logging and core analysis.

Geophysical well logs, often referred to as wireline well logs, can be used to assess the attributes of reservoir rock, such as porosity, permeability, and fluid saturation, or they can be obtained by laboratory methods. Although this porosity evaluation approach is not very exact, it has the benefit of continuously supplying porosity data. After these logs are acquired and transformed into a porosity log, they can be used as an extra trustworthy resource for evaluating the porosity distribution and calibrated using core-sample porosity data.

The formation resistivity factor (F), the microresistivity log (which yields F), the neutron-gamma log, the density (gamma-gamma) log, and the acoustic (sonic) log can all be used to assess porosity. The description, heterogeneities, and permeability of a reservoir are revealed by well test analysis. Laboratory examinations of cores from the reservoir under evaluation are used to identify the characteristics of the rock. Following the removal of the cores from the reservoir, changes occur in the core bulk volume, pore volume, reservoir fluid saturations, and, occasionally, the wettability of the formation.

This work presents a modelling approach for determining reservoir properties. This method is quite affordable. Unlike well testing, well logging, or the core laboratory method, it does not necessitate stopping production, and the results are similar to those obtained from laboratory measurements of cores.

II. PREVIOUS WORKS

Reservoir characterization is an important step in the exploration and production of oil and gas reservoirs. In the past, data from different sources, including seismic surveys, core samples, and well logs, have been analyzed to characterize reservoirs. But now that AI has arrived, there are more sophisticated and effective ways to analyze data. During reservoir characterization, massive amounts of data are collected, including seismic data, well logs, and drilling data, which can be evaluated using AI techniques. Based on multiple research articles (Talebkeikhah, Sadeghtabaghi, and Shabani 2021), an extensive examination of the state of the art in the field of permeability prediction in oil and gas reservoirs using various machine learning and computational intelligence models (Babadagli, Alberta, and Worldwide 2004). These studies address a variety of subjects, such as the prediction of porosity and permeability in heterogeneous reservoirs through the application of artificial neural networks, fuzzy logic, and genetic algorithms (Ahmed A. Adeniran et al., 2019); (Al-bulushi et al. 2009); (Anifowose, Abdulraheem, and Fahd 2010); (Kalule et al. 2023); (Malki, Baldwin, and Kwari 1996); (Mohaghegh et al. 1994, 1996, 1997), the development of competitive ensemble models for permeability prediction (Ahmed A. Adeniran et al. 2019), permeability prediction using convolutional neural networks, and the application of machine learning algorithms for classification of flow units in oil fields (Ranjbar, Kafi, and Keshavarz, 2023). Milad and Farmer (2022), while others investigated the application of machine learning for forecasting permeability reduction owing to scale deposition (Ahmed A Adeniran et al. 2019). Some articles concentrated on specific reservoir types, such as carbonate reservoirs (Babadagli, Alberta, and Worldwide 2004); (Milad and Farmer 2022). Using machine learning algorithms, they developed an ensemble model that is competitive for predicting permeability in heterogeneous oil and gas reservoirs. The model attained over 90% accuracy. Machine learning was utilized by Ahmadi and Chen (2020) to forecast permeability deterioration brought on by scale deposition. Over 95% accuracy was attained by the model. The applicability of several machine learning methods, such as neural networks, support vector machines, and linear regression, for the prediction of certain rock features was investigated by (Erofeev 2018). Artificial neural network models for fluid distribution and water saturation were created by Al-bulushi et al. (2009). Over 90% accuracy was achieved by the models. Stacked ensemble machine learning was utilized by Kalule et al. (2023) to forecast the carbonate rock plugs' total porosity and permeability. Over 95% accuracy was attained by the model. Machine learning was utilized by Sheykhinasab et al. in 2022 to forecast the permeability of highly heterogeneous petroleum sources from traditional petrophysical logs. The model attained over 90% accuracy. Aldombi and Al-khudafi (2019) modified an artificial neural network model (ANN) to create new models for estimating the porosity and permeability of rocks. The models for forecasting the porosity and permeability of the reservoir rock in the Biyad formation of the Kharir oil field were successfully demonstrated

III. GENERAL DESCRIPTION OF RESERVOIR

The Camal Field is located in Block 14 of the Masilah Basin, Yemen. Since the field was discovered in 1993, it has produced approximately 6.3 million stock tank barrels and 91.5 mmstb at the end of 2005 of the total original barrels of oil in place (234 mmstb). The eight wells that have been completed in the clastic Qishn Formation's sandstones have produced oil. The basin in general and the Camal field in particular suffer from the fall in pressure of the reservoir. Since 1992, when the first well in the Camal field was drilled, which negatively affects the production of oil, we have been addressing that fall through the process of water injection on the outskirts of the field (specifically in wells located outside the installation of a higher) in order to maintain the rate of total production, which produces 23,000 barrels of oil and 1.8 million barrels of water daily.

Roughly 90% of the reserves are located in the Qishn Formation's Upper Qishn Clastics Member, which dates to the Lower Cretaceous. Along with fractured Cambrian granitic basement rocks, oil can also be found in at least seven other distinct reservoir units made up of Lower Cretaceous, Middle to Upper Jurassic clastics and carbonates. Therefore, in this study, we focus on Qishn clastic formation.

The Qishn clastics of formation categories into multiple sedimentation environments major and minor according to the results of the types of rock and its contents, as well as facies and environmental analysis by using cores and well logs in the study, which divided the upper and lower Qishn clastics of the formation. The upper part of the Qishn clastic was divided into three units of reservoir sand (S1, S2, S3), and reservoir S1 was subdivided into three subunits (S1A, S1B, S1C) depending on the rock types interbedded into the clastic sandstone of the formation. For that, the S2 and S3 unites have a good porosity, while S1 (S1A, S1B, and S1C) have a porosity range of good to medium. The S1 unit is a widespread littoral sand with permeabilities (1-2) that grade down where clay cement occurs. This results in a difference from one to another.

The lithology of reservoir units in general consists of sandstone with some carbonate and shale interbedded in some units. Zones S2 and S3 are quite different from one another in lithology. S2 contains sandstone with shale overlap (interbedded tidal channel sands and shales with occasional crevasse splay sands), while S3 is characterized by clean sandstone (a laterally extensive and massive sequence of stacked tidal channel), so it is the unit with the best reservoir properties.

Reservoir sandstones and possible sealing shales in the C-4 and C-5 intervals are determined by sedimentary facies and depositional systems. Throughout the region, a delta system prograde from east to northeast, depositing the C-4 and C-5 sediments. The east-west (up structural dip) orientation of reservoir sandstones is more continuous than the north-south orientation, suggesting a higher degree of reservoir heterogeneity and the possibility of bypassed and unexplored reservoir compartments in the former direction. The C-4 and C-5 intervals' shally or fine-grained facies were deposited in tidal flats, shallow marine environments, and low-energy inter-distributaries. A few thin layers of shale stretch out over brief distances. Sand-on-sand contacts resulted in stacked channel-fill deposits as a result of distributary channels locally eroding through the shales and depositing channel-fill sands. Furthermore, sandy.

VI. MATERIAL AND METHODS

A. AVAILABLE DATA:

Porosity, permeability, and saturation analyses of the reservoir were derived from logs for wells C-2, C-4, C-5, C-7, C-8, C-30, C-44, and C-4 as well as from laboratory examination of the core sample taken from wells C-2, C-4, C-7, and C-8. Well log curves were converted into digital format to use as inputs for modelling. Five well logs (GR, DT, LDL, CNL, and LLD) are selected as the input to the network for estimating permeability and fluid saturation. In addition to these logs, the MSFL log is used as input for porosity modelling. Spatial coordinates and geological information (zones).

B. METHODOLOGY

An artificial intelligence software program was used to design and optimize different neural network models for forecasting reservoir properties. The approach used in this study was that the different diagrams of the neural system were tested to find the most accurate method for modelling the reservoir properties. Among the methods used are MNN, MLP, GRNN, and RBF.

C. MODELING

The approach used in this study was that different diagrams of the neural system were tested to find the most accurate method for modelling the reservoir properties. Among the methods used are MNN, MLP, GRNN, and RBF. It was found that fuzzy logic is the best method for estimating the properties.

1. *The neurofuzzy model*

The modelling of reservoir properties carried out using a hybrid neurofuzzy approach. The MATLAB program designed, and 11 parameters, including well logs, geological data, and well location, used as input for the model. The model output is a reservoir property.

2. *Models of Neural Networks*

An intricate relationship between input and output variables is represented by a neural network, which is made up of layers with nodes and weights. The input variables (independent variables) that the problem specifies are represented by the input nodes in the first layer. A hidden layer node generates output for the nodes in the following hidden layer by adding the weighted outputs of the layer before it and the sigmoid function. Through experimentation and optimization, the number of nodes in each layer and their weights are found. Finding the ideal weights to provide the best value for the output layer's nodes—the dependent variable—is the neural network's main goal.

The neural network approach has a number of benefits. An explicit functional relationship between the input and output variables is not necessary for it to work. It can be taught to learn and approximate the nonlinear relationships to any accuracy level using previously available data. It works with systems that have multiple variables. The requirement for input node specifications in advance is one of the neural network approach's major disadvantages. Neural network analysis does not readily yield information about the kind of input variables or the ideal quantity of input variables.

3. *Fuzzy*

Although they have demonstrated their ability to solve many problems, fuzzy logic and neural networks have not yet been able to fully solve complex problems. Fuzzy systems and neural networks can be combined to offset the shortcomings of one method with the advantages of the other. A combination of fuzzy set theory and neural networks, known as "neuro-fuzzy" (Jang and Sun, 1995), mimics the decision-making process of humans and has the advantage of handling any type of information (numeric, linguistic, logical, etc.) as well as managing imprecise, partial, vague, or imperfect information to resolve conflicts through aggregation and collaboration. Some characteristics of fuzzy logic and neural networks are similar, such as the distributed representation of knowledge. Estimating without a model and managing uncertain data

Every one of the aforementioned characteristics—data selection, ANN parameters, etc.—was chosen and taken into account for the modelling. Prior to modelling, it is preferable to clarify a few important CANFIS and GA parameters. The Gaussian-shaped curve and the bell-shaped curve are the two types of fuzzy MFs. Compared to the Gaussian-shaped MF, which has two free parameters, the bell-shaped curve has three, making it slightly more flexible. As a result, the employed membership function is the bell-shaped one. There are always two types of learning updates: batch learning, which updates the network after the entire training set is presented, and online learning, which updates the network after each exemplar is presented. In this study, we made use of the latter update. Additionally, we chose momentum and axon.

V. Results and Discussions

The developed model was used for determining reservoir properties for MLP, RBF, MNN, and neurofuzzy. Various kinds of well logs, including induction, gamma ray, and bulk density along with spatial coordination and geological information were used as input parameters for the model. Table 1 gives a list of examples of computation input and output parameters for the calculation of porosity.

Bulk density adds to the permeability of the formation because it can be thought of as a symbol of the rock's porosity, regardless of how linear or non-linear this relationship may be. The gamma-ray log response provides information about the formation's clay or shale content. This characteristic of the rock affects how well it conducts liquids. The usual method for determining the water saturation of rocks is deep induction. Water saturation may contribute in some way to rock permeability since it may be a sign of water movement or migration in the rock over geologic time.

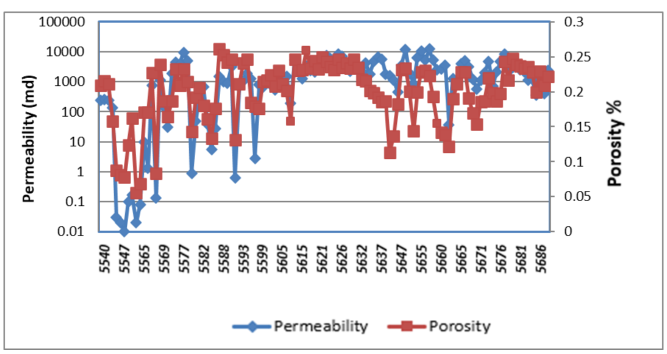

Fig. 1 Represents a cross-plot of Porosity and permeability core data as a function of depth for well C-7.

An investigation of the performance and accuracy of the proposed models was performed by comparing theiperformance to predict different rock properties against laboratory values using graphical representation. The results of the comparison between experimental and estimated permeability, oil saturation, porosity, and water saturation are shown in figures 2 through 13.

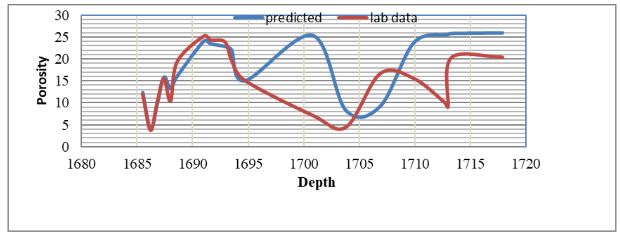

Fig. 2 Predicted porosity by GFF vs. laboratory core data

The neural network's predicted porosity value is displayed in Figures 2 through 5 in comparison to the porosity measured in a lab.

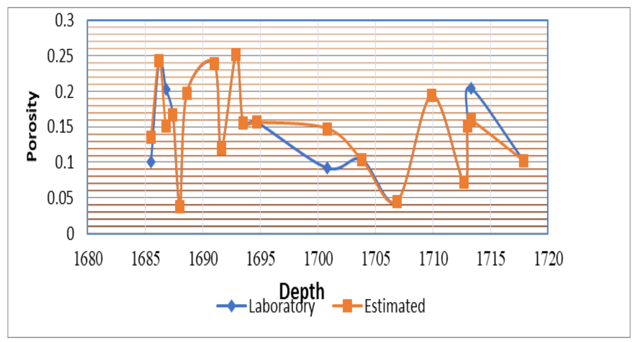

Fig. 3 Predicted porosity by fuzzy vs. laboratory core data

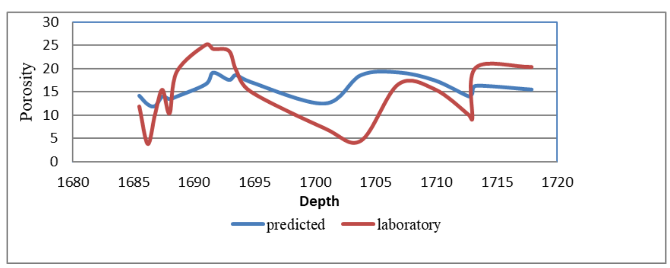

Fig. 4 Predicted porosity by MNN vs. laboratory core data

The permeability prediction made by different modelling approaches (GFF, MNN, fuzzy) in the neural network model in comparison with the measured permeability by the core sample is represented in figures 6 through 10. It is obvious from the figures that most of the actual values are quite close to the values predicted by most models. It may be concluded that the actual values of permeability and porosity are reasonably close to the predicted values by the model.

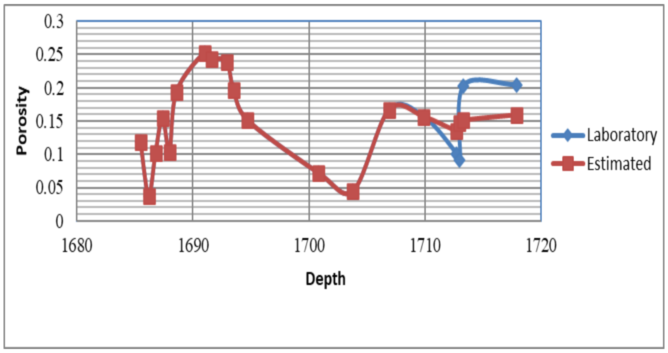

Fig. 5 Predicted porosity by Fuzzy vs. laboratory core data

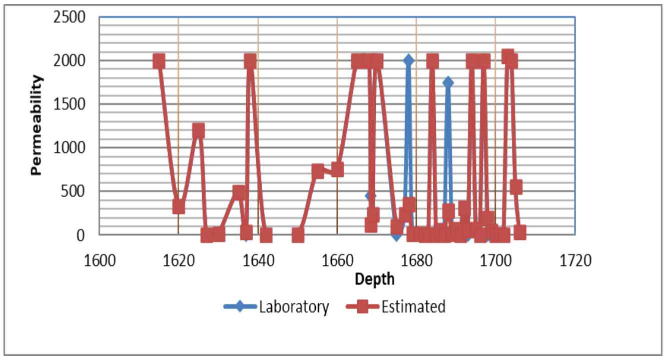

Fig. 6 Predicted porosity by Fuzzy vs. laboratory core data

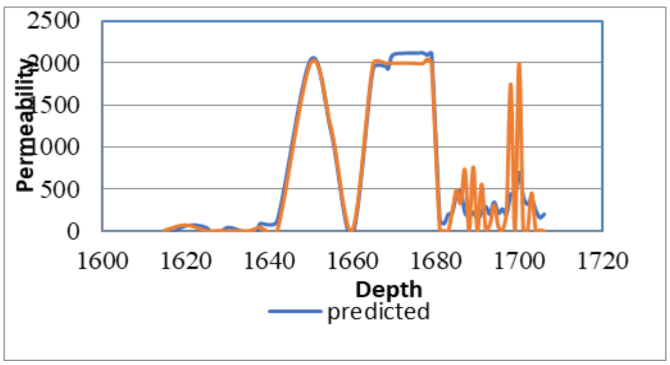

Fig. 7 Predicted porosity by MNN vs. laboratory core data

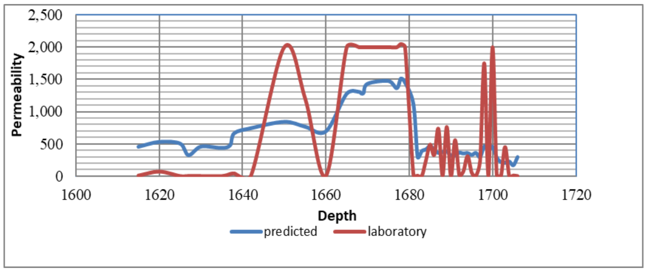

Fig. 8 Predicted porosity by RBF vs. laboratory core data

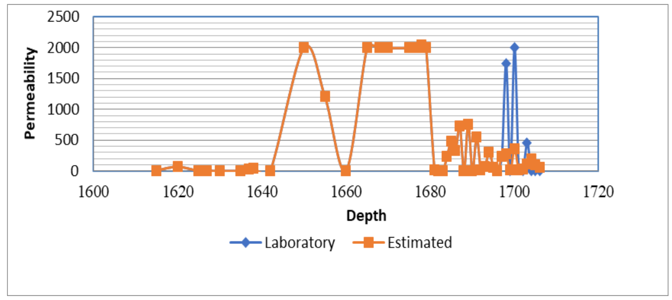

Fig. 9 Predicted Permeability by Fuzzy vs. laboratory core data

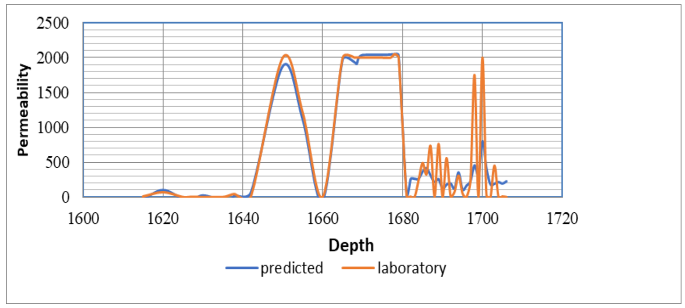

Fig. 10 Predicted Permeability by MLP vs. laboratory core data

The fuzzy model is the best model for calculating water saturations, as shown in figures 11 through 13. It indicates a good degree of correlation between estimated and experimental values.

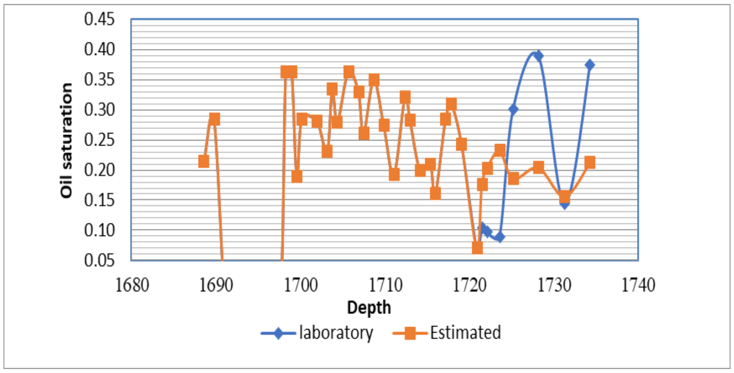

Fig. 11 Predicted Permeability by MLP vs. laboratory core data

Table.1 Example of input and output for modeling-well# C-4–Camal field

depth,	Well log data						Coordinates		Zones					Output
m	LDL	LLD	GR	CNL	MSFL	DT	x	y	S1A	S1B	S1C	S2	S3	Porosity
1685.5	2.4	400	9	0.15	100	75	292200	1730000	1	0	0	0	0	**0.119**
1686.2	2.33	800	8	0.13	380	75	292200	1730000	1	0	0	0	0	**0.038**
1686.8	2.33	700	8	0.18	60	81	292200	1730000	1	0	0	0	0	**0.102**
1687.4	2.26	350	8	0.185	40	81	292200	1730000	1	0	0	0	0	**0.155**
1688	2.24	450	9	0.19	40	84	292200	1730000	1	0	0	0	0	**0.104**
1688.6	2.27	350	10	0.18	40	82	292200	1730000	1	0	0	0	0	**0.194**
1691	2.45	25	10	0.07	10	67	292200	1730000	1	0	0	0	0	**0.252**
1691.6	2.6	12	32	0.12	13	67	292200	1730000	1	0	0	0	0	**0.243**
1692.9	2.4	63	28	0.19	70	74	292200	1730000	1	0	0	0	0	**0.239**
1693.5	2.4	45	30	0.12	45	70	292200	1730000	1	0	0	0	0	**0.197**
1694.7	2.1	10	45	0.33	10	85	292200	1730000	0	1	0	0	0	**0.151**
1700.8	2.45	20	30	0.12	35	70	292200	1730000	0	0	1	0	0	**0.072**
1703.8	2	9	68	0.27	10	90	292200	1730000	0	0	1	0	0	**0.045**
1706.9	2.15	6	75	0.37	8	96	292200	1730000	0	0	1	0	0	**0.167**
1709.9	2.3	18	60	0.24	18	80	292200	1730000	0	0	1	0	0	**0.156**
1712.7	2.3	50	28	0.21	40	82	292200	1730000	0	0	1	0	0	**0.101**
1713	2.27	50	28	0.18	35	79	292200	1730000	0	0	0	1	0	**0.092**
1713.3	2.4	45	45	0.19	45	73	292200	1730000	0	0	0	1	0	**0.203**

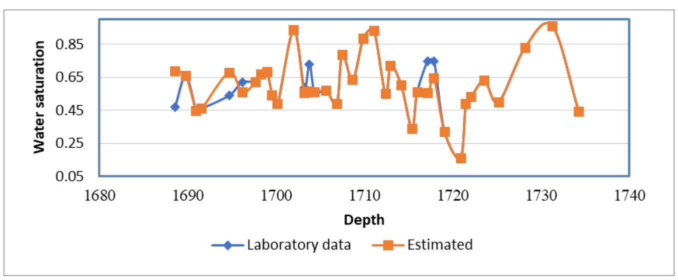

Fig. 12 Predicted oil saturation by fuzzy vs. laboratory core data

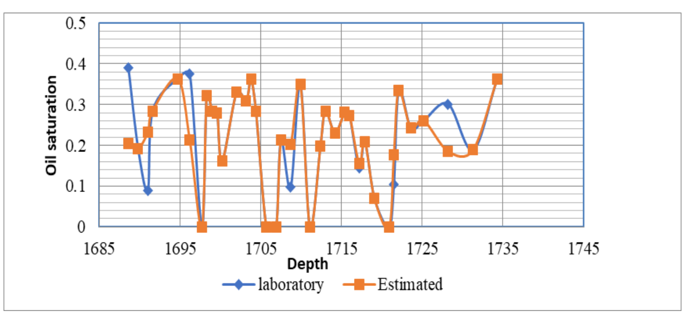

Fig. 13 Predicted water saturation by fuzzy vs. laboratory core data

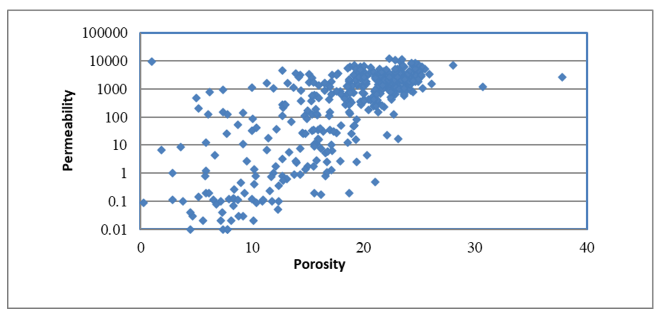

Fig. 14 Permeability vs. Porosity

Figure 15 illustrates a scatter plot of predicted results versus experimental data for water saturation generated by a fuzzy model. This plot indicates the agreement between the actual and predicted values. It is clear from the figure that the fuzzy model has a good capability of predicting water saturation. The neural network models (MLP, MNN) also showed high accuracy in predicting reservoir properties.

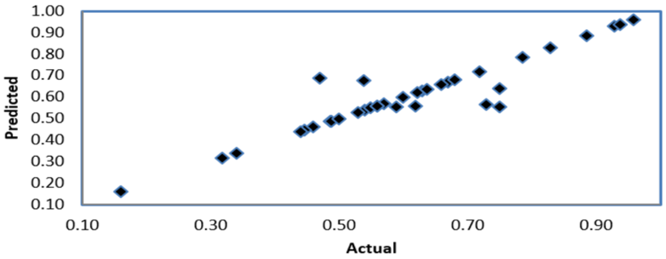

Fig. 15 Crossplot of predicted and actual water saturation (fuzzy model)

Fig. 16 shows a crossplot between estimated and experimental porosity, where good correlations are seen. As shown in the figure, There doesn't seem to be any connection between permeability and those log responses. From these results, it is observed that intelligence modelling has good prediction capability.

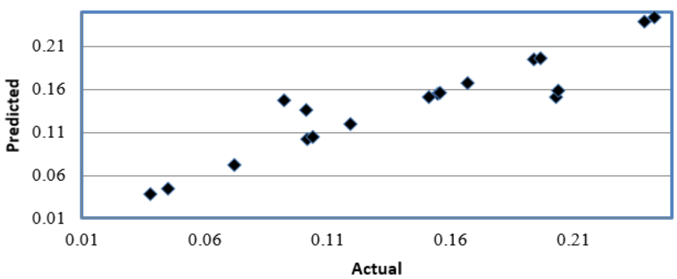

Fig. 16 Crossplot of predicted and actual porosity (fuzzy model)

VI. Conclusion

The conclusion of the study is that artificial intelligence modeling, specifically neural networks and neuro-fuzzy inference systems, are reliable and flexible for predicting reservoir rock properties. The combination of fuzzy logic and neural networks showed great potential for predicting reservoir properties. The models demonstrated acceptable results even with a limited number of data points. The neural network models (MLP, MNN) and the fuzzy model both showed high accuracy in predicting reservoir properties such as permeability, porosity, and oil saturation.

Furthermore, the study found that the combination of neural networks and fuzzy systems, known as neuro-fuzzy, can compensate for the drawbacks of each technique and handle any kind of information, including numeric, linguistic, logical, and imprecise data. The study used a bell-shaped membership function and employed online learning for the neural network models. Genetic algorithms were used to find the optimal values for processing elements, step size, and momentum rate. The Tsukamoto fuzzy model and the TSK fuzzy model were both considered for the modeling

Nomenclature

AI- Artificial intelligence
LDL- density log
CNL- neutron log
GR- gamma ray log
LLD- deep induction log
DT- sonic log
MSFL- shallow literal log
RBF= radial basis feed-forward neural networks
GA=genetic algorithm
MLP- Multilayer perceptron
ANN= artificial neural networks
CANFIS= co-adapted neuro-fuzzy inference system

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