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A New Approach in Reservoir Characterization Using Artificial Intelligence

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Abstract

The basic characteristics of a reservoir system are normally distributed spatially. Since there is no immediate measurement for the lithological parameters, they are to be computed from other geophysical logs or seismic attributes. In this study, oil field data from the exploration wells including logs and seismic data were used and studied using AI Artificial Intelligence to select the best locations for drilling according to porosity distribution. Moreover, the objective of this project is the study of reservoir characteristics and distribution using Artificial Intelligence (AI). The studied area is the Asma area in India where all seismic and well-logging data were collected. The process is first aligned in finding the porosity of the well-logging interpretation using density log and sonic log and then shed the prediction of porosity using seismic data using the reflected waves of the structure to estimate the acoustic impedance. The neural network was used to predict porosity. There were three outputs for each of well-logging, logging-seismic and seismic. All the outputs were compared where the accuracy was good with a ratio of 95% and a small error percentage of 5%. A map of the area was created where the porosity distribution of each of the outputs was determined. The best areas were identified for drilling the future production wells depending on the porosity and the type is sandstone.

Introduction

The demonstration of the structure of a reservoir model that joins every one of the reservoirs of the repository to store hydrocarbons and produce them is named 'Reservoir Characterization (RC). The heterogeneous and non-linear physical subsurface properties make reservoir properties very complex to measure. The underlying advance of this characterization is a forecast property of the reservoir (such as water saturation, fluid saturation, sand fraction, porosity, shale fraction, permeability, etc.) or class variations of these properties from well logging and attributes from seismic. The expectation of petrophysical properties is related to various complex assignments, for example, information combination (a combination of information from different sources), information mining (for example data recovery after breaking down that information), definition and treatment of the uncertainty.

The use of AI is progressively factual, and design acknowledgment procedures for such issues have machine learning, advanced statistical, and pattern recognition techniques to such problems have gotten significant enthusiasm among the scientists in the division of oil-gas. This also requires process the involvement of specialists for calibrating the forecast outcomes. Standard retreated techniques aren't suitable for this issue because of the high level of obscure nonlinearity. The issue is more complicated due to the vulnerabilities related to lithological units. However, in any oil/gas reservoir, an understanding of subsurface structure is a fundamental part of the characterization of the reservoir. The seismic properties of the reservoir in heterogeneous oil/gas reservoirs are fundamental to determining some of the ambiguities in reservoir characteristics. Thus, the practical approach consists of incorporating the impact of the oil/gas reservoir heterogeneity in modeling reservoir porosity. Thus, obtaining an accurate three-dimensional model of reservoir properties, such as porosity and permeability. Obviously, due to the importance of such data in decision-making for production management, they have to be modeled by the most precise and advanced methods. Although direct sampling of reservoir rocks and fluids may provide the most accurate data for reservoir properties, such as porosity, however, it is limited by time and capital and suffers from its certainty in other parts of the reservoir. Therefore, interpretation and modeling based on seismic data and understanding of porosity distribution in the reservoir is an alternative in reservoirs with sparse well locations (Lawrence and David 2015).

Reservoir portrayal and demonstration gotten by this data are keys to coordinating the production profile and well arranging in oil fields. However, reservoir model structure has turned into a pivotal step in field enhancement, as reservoir modeling gives a venue to integrate and reconcile geologic concepts and all available data. One of the key challenges in reservoir characterization is an accurate representation of reservoir porosity, which requires a precise structural frame and detailed stratigraphic interpretation, and sufficient well logs with appropriate distribution in the reservoir. The structural frameworks outline significant compartments of a reservoir and frequently give the main order controls on the fluid movement and volumes in the reservoir. The stratigraphic model also defines the relationship between different zones in the reservoir. To generate the 3D porosity distribution model, it is important to utilize advanced techniques such as AI/Machinery or geostatistical methods. The property model development is considered the investigation of phenomena variety utilizing an accumulation of AI systems to depict the spatial distribution in a reservoir (Ghahri 2018).

A standard study in the modeling of reservoir properties contains the reservoir classification, petrophysical zonation, stratigraphy and, the development of a 3D model grid, and finally fills these grids by calculated characteristics such as porosity. In this investigation, a methodology would be exhibited for characterizing seismic and well logs of the porosity distribution model dependent on cutting-edge techniques using artificial intelligence (AI) methods. This model then could be used to precise the reservoir geometrical and geological characterizations for well location proposal. For this reason, a cube of seismic data was used beside the required sonic and density well logs (Siddiqui et al 2018).

Artificial Neural Network linear function transforms one value to its respective output with a direct relationship. Sigmoid task labels output values in a range between 0 and 1. There are various sorts of activation work from a numerical or algorithmic perspective, namely, Hard limit work (output is either 1 or 0). Neural Networks are created according to learning algorithms to be trained (Hamada et al 2018). The sigmoid position is demonstrated to be the most appropriate for multilayer neural networks as it is trained to utilize the 8 backpropagation calculation and has a particular non-decreasing behavior, shown in Figure 1.

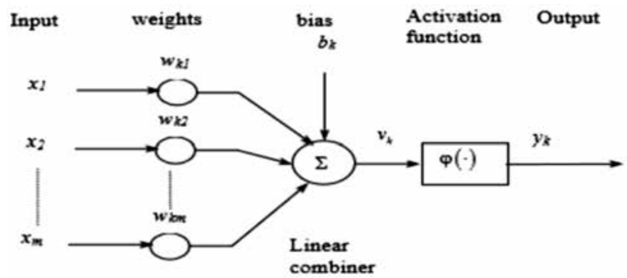

Figure 1—Artificial Neural Network flowchart (Hamada et al 2018)

Five types of well log data: (GR) Gamma-Ray, (LLD) Latero-log Deep, (RHOB) density, (NPHI) Neutron, and (PEF) Photoelectric Factor, were used to improve properties of petrophysical by the neural-network approach. Porosity distribution can be anticipated by the neural network approach. The outputs were plotted against depth in correlation with the core data and the conventional method. Hydrocarbon pay zones which are potential were assessed using log data by setting cut-off values of the volume of shale, and porosity. Any segment of the well which fulfilled the accompanying criteria was a hydrocarbon pay zone. More studies with many different methods on different field data are recommended for extra evidence of the success of ANN usage in petrophysical evaluation (Hamada et al 2018).

Hybrid intelligent systems are a methodology for quantitatively delineating distinctive reservoir characteristics in spatial fluctuation utilizing accessible field and lab information. It is the procedure of structuring reservoir models ordinarily between the disclosure period of supply and its administration stage by merging certain characteristics that have to do with its ability to store and make hydrocarbons. A conclusive purpose of describing the oil reservoir, the procedure is to decide the characteristics of the reservoir structure to find the perfect creation methodologies that will enhance the production methodology expressed in Figure 2. Reservoir properties adopt a basic role in the administration of current repositories. It increases the mix of multidisciplinary data and information and hence evolves the accuracy of reservoir predictions. A definitive objective is a reservoir model with practical resistance to imprecision and vulnerability (Fatai 2016).

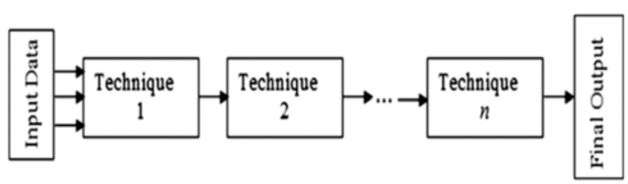

Figure 2—Hybrid intelligent systems flowchart (Fatai 2016)

Development of a Framework

The borehole data contains different logs such as bulk density (ρb), gamma-ray (GR), P-sonic (DT), spontaneous potential (SP), neutron porosity (NPHI), acoustic impedance (AI), and shallow resistivity (RS) logs, different resistivity, medium resistivity (RM), and logs such as deep resistivity (RT). The porosity is derived from these log properties. After the determination of important features among accessible logs, we have used GR, RHOB, DT, and NPHI logs as input attributes to classify level. The rock characteristics of the subsurface structure can be interpreted from these factors. Grams per cubic centimeter is the unit of the density log in the account. It varies according to the mineralogy and porosity estimates. Travel time is recorded a as P-sonic log of P-waves versus depth in microseconds per foot. The fourth pointer variable for instance neutron porosity log is touchy to peruse the represented porosity and genuine porosity per unit (Soumi 2015).

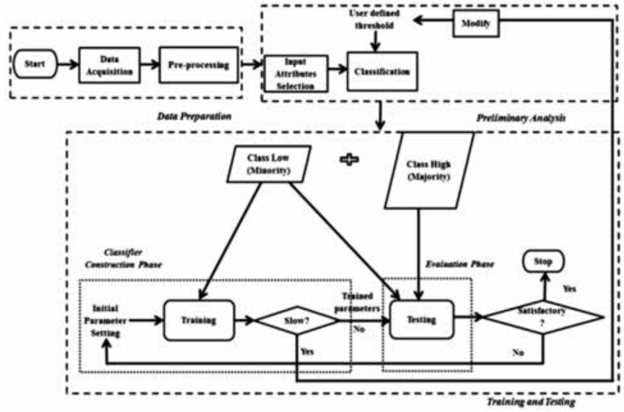

Figure 3—Development of a Framework to Classify porosity from Well Logs (Soumi 2015)

Particle Swarm Optimization (PSO)

Artificial neural networks (ANNs) were built based on the function and formation of the human brain, neural networks, and complex learning and reaction procedures. It expects to create target estimate parameters from information data through inward calculations and investigation. This method includes a well-associated model with a straightforward preparing part (or neuron) equipped for knowing the right connections among reliant and free parameters. A multilayered neural system ANN is an acceptable framework, where neurons are orchestrated in different layers: shrouded, yield, and info. Commonly, multi-layer neural systems feed at least one shrouded layer, which can system to frame non-direct and entangled capacities. The concealed layer is accountable for exchanging significant data between the information and system arrangements through a functioning methodology. ANNs interface is communicated through the neurons of the information layer and the yield of the reliant variable (s) is transmitted through the neurons of the output layer. Hold every neuron in concealed layers and produce an exchange work that demonstrates the interior actuation. The output of neurons is normally accomplished by changing over its data sources utilizing a contrary exchange is shown in Figure 4 (Mohammad et al 2015).

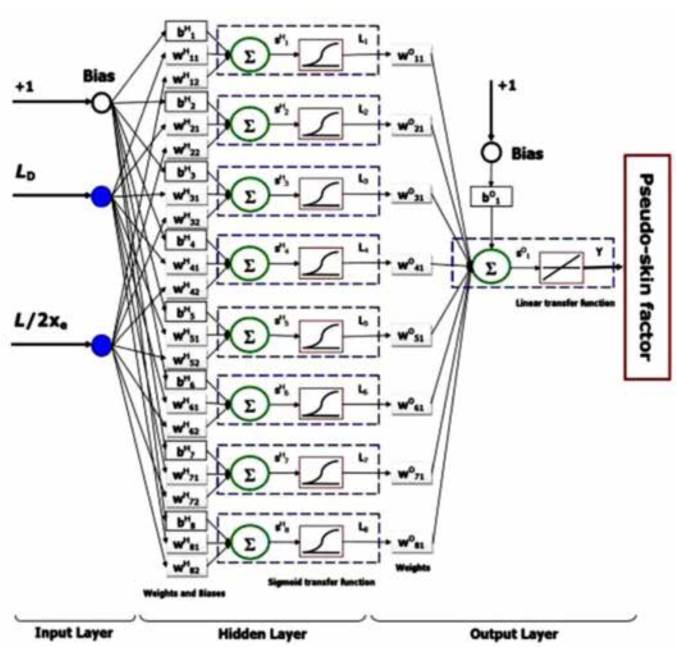

Figure 4—Structure of the proposed three-layer feeds forward neural network model (Mohammad et al, 2015)

AIS algorithms can be utilized to learn ANN by changing the weights and the changes of the values to achieve the least mean squared error as the methodology of the process as shown in Figure 5. The immune response (or cell) is coded, and it outlines the weights and the predispositions of the system with the goal that the length of every counteracting agent is equivalent to the number of weights and inclinations. The learning is performed by applying AIS advancement calculations to change the antibodies to locate the base mean squared blunder (maximum – ve mean squared error) (Saad and Saleh 2018).

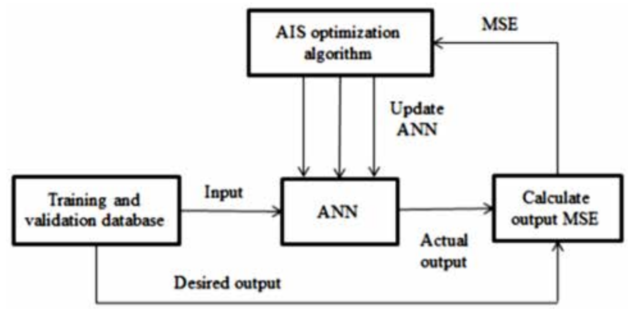

Figure 5—The modified artificial immune network algorithm (Saad and Saleh 2018)

This strategy is computationally effective, simple to actualize, and has been demonstrated to perform superior to the root mean squared prop (RMSprop) optimizer. Inclination rescaling is dependent on the sizes of parameter updates. The Adam streamlining optimizer doesn't require a stationary object and can work with progressively meager inclinations (Bui et al 2019).

To make the feed-forward networks (FNN) architecture, initially an estimate of the number of layers of each kind and the number of hubs in every one of these layers is needed. In an ANN, at least one concealed layer of sigmoid neurons is frequently found, in this manner pursued by an output layer containing direct neurons or hubs as shown in Figure 6 (Bui et al 2019).

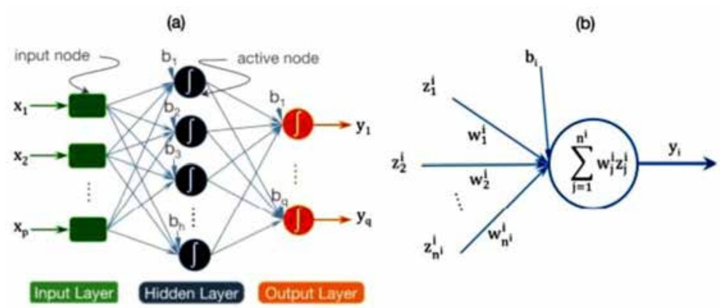

Figure 6—Discrete element method and artificial neural network (Bui et al 2019)

Reservoir Characterization

The basic characteristics of a reservoir system are normally distributed spatially in a non-linear manner and non-uniform. The extraction of lithological data from obtainable datasets is an important step in the process of reservoir characterization. Since there is no immediate measurement for the parameters of lithological, they are to be computed from other geophysical logs or seismic attributes.

Integration of Dataset

Preparation of the master dataset joining data obtained from various sources before demonstrating and characterization of lithological properties. For instance, seismic attributes and well logs are gathered by various strategies with various inspecting rates, and resolutions. The issue of non-extraordinary testing of seismic data and well log. Well, logs, different scales of seismic, and other reservoir data to likewise be satisfactorily adequately handled by developing generalized methodologies that may be independent of the target reservoir characteristic.

1. Few inputs and poor data quality: data procured from a study zone with poor data quality, or a predetermined number of inclusions isn't useful to carry out reservoir characterization. It is hard to plan a forecast or classification-based model utilizing poor data. Pre-processing methodologies are to be fine-tuned to accommodate this fact. Vulnerabilities related to gained dataset additionally add to the poor execution of a structured model.
2. Information content: in the event of structuring an AI model to foresee lithological properties from seismic sources of inputs, a key test is the data value of the indicator factors.

The main objective of this research is (to identify a potential zone for drilling a new well). This research was also designed to achieve the objectives of evaluating the reservoir characteristics and distribution using (AI) Artificial Intelligence, improving, and estimating the accuracy of reservoir characteristics, and reducing the cost of drilling and well logging operations.

Hydrocarbons move from the source through the porous rock to the reservoir rock for brief temporary. The movement of hydrocarbons in the cap rocks gets seized. In that capacity, proof of enriched formations of hydrocarbon by the properties of each layer Introduction in the borehole is very necessary to the explorers (Masoud 2018).

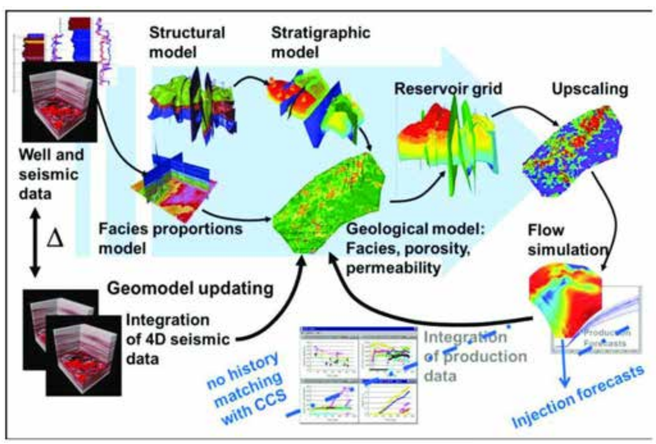

Figure 7—Reservoir modeling and porosity (Masoud 2018)

Seismic Attributes

The seismic data are obtained in the time where depth is estimated in milliseconds two-way travel-time rather than meters. The time required for the sound wave to reach the reflector from the source and get back to the collector in the wake of hitting the reflector is known as two-way travel time. In the event of shallow reflectors, high frequencies are reflected, though, the lower recurrence substance of the sound sign enters the ground further down. The wavelength and velocity increase with the depth, unlike the frequency.

In this manner, the seismic resolution reduces with increasing depth. First, the well logs are changed over from the profundity area to the time at 0.15 milliseconds inspecting interim utilizing the given velocity profile coming about because of well seismic-tie (Abdelmoneam 2016).

Hence, the band-limited seismic attributes are reconstructed at each time instant corresponding to the well logs by a sonic interpolator while adhering to the Nyquist–Shannon sampling theorem. The absolute attribute of impedance which was used in this research can be created with any Sei-slog type impedance inversion or a model-based inversion shown in Figure 8 (Abdelmoneam 2016).

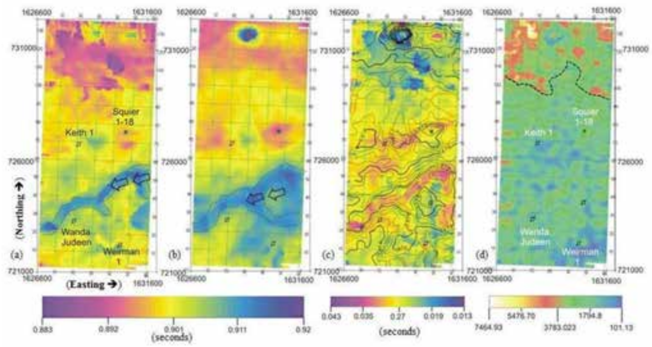

Figure 8—Seismic attributes (Abdelmoneam 2016)

Well Logs

Well-logging narratives, depths, subsurface arrangements, and events encountered while penetrating. Well, logs can incorporate visual observations or be made by instruments brought down into the well during drilling. Information on seismic is gathered through a gigantic study zone, while well logs are reachable at explicit areas in a similar zone. Also, the seismic qualities vertical goals are more component to that of the well logs because of the more prominent testing interim. By and large, the information of seismic is useful to display a reservoir; while it is hard to assess the vertical appropriation of the reservoir characterization with the supporting of the seismic sign. Subsequently, data from both well logs and seismic are imperative to describe a reservoir characteristic with high goals in both horizontal and vertical bearings. The structure of any such normal for petrophysical has pivotal significance in this examination area (Soumi 2015).

Advantages:

- Continuous measurements
- Easy and quick to work with
- Short-time acquisition
- Better resolution than seismic data
- Low cost

Limitations:

- Indirect measurements
- Limited by tool specification
- Affected by the environment
- Varying resolution

The well log incorporates the header, which gives explicit data about the well, such as the type of log run, well information, and the operating company, as well as the graph or the main log section. Additions are found throughout the diagrams at each real area of the log, recognizing each bend. Bend on the log, likewise, called follows, readings or estimations. The last piece of the log incorporates the adjustments made when the log was led, guaranteeing that the log is exact.

Methodology

This part presents the strategy used by this research. It describes every component involved in conducting this research on the new approach in Reservoir Characterization using Artificial Intelligence. At long last, this part gives a detailed description of the chosen method of investigation utilized and data gathering strategy.

Research Approach

As this project aimed to identify a potential zone for drilling a new well, it was decided that the best method was to use Artificial Intelligence / Machine Learning to take a new method approach to cost reduction.

The evaluations of well logs data and seismic data as input data obtained the results of the reservoir porosity based on programmed codes, then based on the results, we can select the best location to drill production and injection wells. The procedure to obtain the results is explained here:

- A pre-processing scheme to improve the prediction ability of the field algorithms by data filtering for the prediction of a lithological property from seismic and well logs.
- A complete development framework to carry out well tip guided reservoir horizon from well logs and seismic.
- Development of a classification framework to classify formations' porosity from well logs.
- Modification of the mentioned classification framework to find formations porosity from seismic.

Data Collection Instruments

This study involved the analysis of data received from the oil field. The porosity distribution has the biggest effect on reserves and production forecasts, and thus on the economy of a prospect. The difficulty of assessing it comes from the way that porosity may vary altogether over a reservoir volume, however, must only be sampled in well areas, often using different technologies at different scales of observation. The solution to the mentioned problem requires the integration of surface seismic, and petrophysics which also includes well logging to guarantee consistency of analysis and results.

This project focuses to use artificial intelligence, while conventional methodologies have been used for porosity distribution like drilling more wells, these are considered appropriate in this project for confirmation.

Proposed Methodology and Flow Chart

The evaluations (1) and (2) that are shown in orange boxes of the flowchart (Figure 9) are the first step of evaluation of the study field which includes Well logging and Acoustic impedance data. This evaluation is divided into two processes (Pre-processing and Model building and validation). Pre-processing plays a pivotal role in the performance fine-tuning of a machine learning algorithm. The pre-processed dataset was used in model building and validation.

Pre-processing, the two evaluation (Well logging and Acoustic impedance data) passes through two stages which are:

1. Collection of the input data well-logging data (density and sonic logs) for the first evaluation and acoustic impedance data for the second evaluation, the data collected from geologists come in the form of Excel sheets.
2. Data interpretation, data analysis using an advanced calculator, plotting logs as a single well plot, and moreover, conducting cross-sectional plots to compare each well log data, including Geological Pore Pressure Predictions.

Model building and validation pass through six stages which are:

1. Machine training analysis of well log curves and seismic data, as well as functions that manipulate tables. To interpret seismic data, build reservoir models, perform well correlation, visualize

reservoir simulation results of porosity distribution, calculate porosity, and produce maps and design development strategies.

2. Porosity distribution and 3D model of the field, from commercial modeling and simulation platform to petrophysical interpretation.
3. Predict output, in this stage where all the results achieved from previous stages are gathered.
4. Output collection, at this stage, the first and second assessment data are collected (Well logging and Acoustic impedance) and evaluated with porosity recordings taken from both logging and seismic survey from known exploration well were drilled. Then, it was correlated with the remaining area, which only takes seismic data which means this remaining area has not been drilled yet.
5. Upscaling assessment, which is testing and analysis, analysis of the comparison between the tests and the results.
6. The result validation, to check the results to be achieved in this project which are appropriate to the objectives which are (to identify the potential area for drilling a new well, increase the accuracy of reservoir characteristics, reduce the cost of drilling and logging wells).

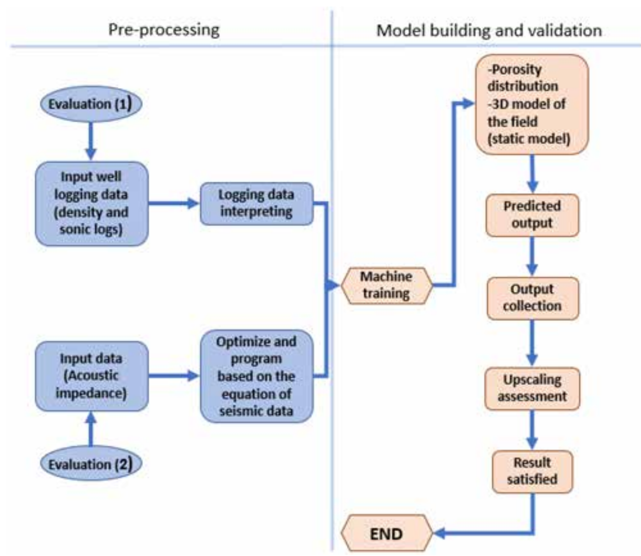

Figure 9—Flow chart of this study

Artificial intelligence/machine learning is using programs that pass from many algorithmic questions to create the porosity distribution model and others of the reservoir characterization.

Acoustic impedance (Z) is the ratio of (P) which is acoustic pressure to (Q) volume flow of acoustic. Therefore, we define Z = P/Q. Z which often shifts unequivocally when the frequency is changed. The acoustic impedance at a specific recurrence shows how much stable weight is produced by the frequency of that given air pulse.

$$Pt=(R\times Q)(t) \tag{1}$$

$$Qt=(P\times Q)(t) \tag{2}$$

$$G=R\text{-}1 \tag{3}$$

- (p) is the acoustic pressure
- (Q) is the acoustic volume flow rate
- (R) is the resistance of acoustic in the time domain
- (G) is the acoustic conductance in the time domain (R −1 is the convolution inverse of R).

Seismic reflection data records the two-way travel time (TWT) to a reflection occasion from the surface. The depth change is the procedure by which translated seismic skylines (time-area seismic itself) are changed over from the movement time-traveled to the depth. The depth movement is a seismic imaging system that improves reflector situating. Depth relocated information is regularly changed over back to time and afterward depth changed over customarily as this gives more prominent adaptability for testing elective speed models. The depth comparison with the logging depth defined from the trace and the two-way time (TWT) as:

$$Vp=2h/TWT \tag{4}$$

$$Trl=2/Vp\times\left(\left(D/2\right)2+h2\right)0.5 \tag{5}$$

$$h=TWT/2\times\left(D/2\right)\times\left(Trl2-TWT2\right)0.5 \tag{6}$$

$$Sin\left(ic\right)/V1=sin\left(90^{o}\right)/V2 \tag{7}$$

$$Trr=2h\cos\left(ic\right)/V1+D/V2 \tag{8}$$

$$h=V1T_{rr}/2\cos\left(ic\right) \tag{9}$$

where:

- h = depth
- Vp = Primary velocity
- TWT = Two-Way Times
- Trl = Reflected Time
- D = Distance between geophones ic = Refracted time angle
- V1 = Refracted velocity of the first structure
- V2 = Refracted velocity of the second structure
- Trr = Refracted Time

In geophysics for oil and reservoir exploration studies, there are two systems (logging and seismic survey) to obtain a reservoir model. These systems play an increasingly important role in soil investigations of reservoir properties. Each of these systems has a different process and a different principle as is shown in Figure 10.

The most common way to determine porosity is with well Logs. Well-logs are tools that are used during drilling operations to collect a core sample for laboratory tests and some of the tools are used to collect values of data on the reservoir properties. Because of the calculation of obtaining basic samples, a few wells are usually drilled. Wells that are drilled are usually wells early in the life of the reservoir (exploration wells) and main wells throughout the reservoir. On the other hand, well logs are routinely run in wells if only to determine the depths of productive intervals. The two open-hole logs used to assess porosity are (sonic and density logs).

While none of these logs measure porosity directly, porosity can be calculated based on theoretical or empirical considerations. Because many variables may affect logs readings, corrections should be applied to logs interpretations and the two logs are usually evaluated together to determine the best estimate of the porosity of the rock formations. Registry evaluations are also calibrated basic porosity in wells where both core samples and logs are available.

The objective of seismic interpretation is to acquire a reasonable geographical story from the guide of prepared seismic reflections. At its most straightforward level, seismic translation includes following and associating alongside consistent reflectors all through the 2D or 3D dataset and utilizing these as the reason for the subsurface understanding. The point of this is to deliver auxiliary maps that mirror the spatial variety from top to bottom of certain topographical layers. Utilizing these maps hydrocarbon traps can be recognized and models of the subsurface can be made that enable volume computations to be made. However, the seismic dataset rarely gives a clear enough picture to do so. This is mainly due to vertical and horizontal seismic accuracy, but noise and processing difficulties often also lead to reduced image quality. The head wave breaks at an interface, moving with it, into the lower center, and produces an oscillatory motion parallel to the facade. This movement causes a disturbance in the upper middle that is detected on the surface. Because of this, there is always a degree of uncertainty in seismic interpretation and a particular data set can contain more than one solution that fits the data. In such a case, more data will be needed to restrict the solution, which filters seismic and meteorological data, as this will help to determine the sound impedance based on the velocity of the P wave (primary wave). Analysis of seismic features involves the extraction or derivation of a quantity of seismic data that can be analyzed to enhance the information that may be more accurate in a conventional seismic form, leading to a better interpretation of porosity data.

The determination of acoustic impedance from well-logging by using the synthetic principle, which is similar to the seismic acoustic principle that includes Vp (Primary-velocity). By using deep learning to train both the acoustic impedance of well-logging and seismic to find the better ratio of porosity, if the rate ($0.5<R<1$) the estimation of the porosity is good from both acoustic impedances, that leads can estimate the porosity from the seismic acquisition after density correlation by using deep learning.

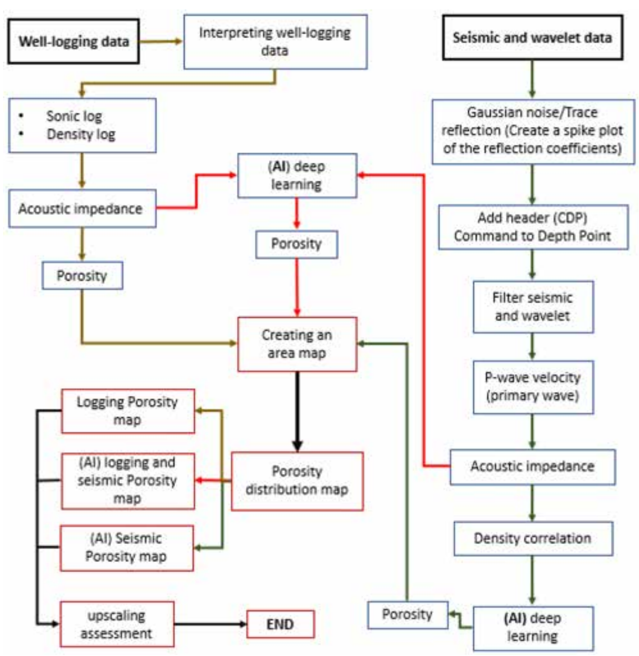

Figure 10—Overall block diagram of the entire system

Results

The results of porosity distribution show that we can predict the porosity from the seismic survey. To show the output of the porosity distribution we need to use an area map.

Well-Logging Porosity Map

Figure 11 shows the porosity distribution derived using well-logging which is the first case for approving the porosity distribution from the seismic. The map shows the porosity average which is around 23% and the porosity range is between 2-37%. The selection of the best zones for drilling is one of the research objectives.

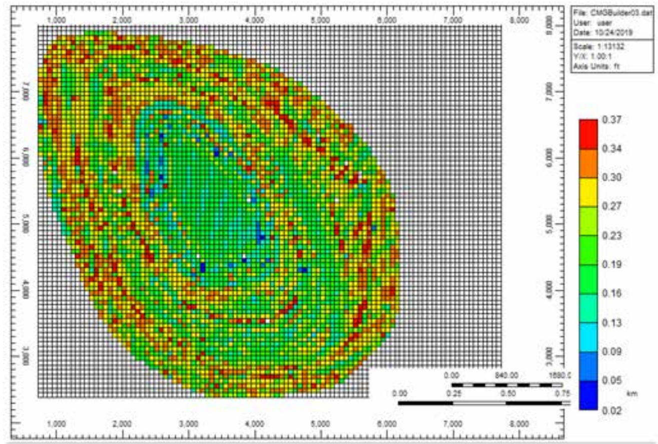

Figure 11—Well-logging porosity map

The zones with high porosity percentage will be the best to drill which include more volume of the hydrocarbon, the shadowed zones as shown in Figure 12 are the best zones for drilling with porosity >15% which is a good range of sandstone porosity.

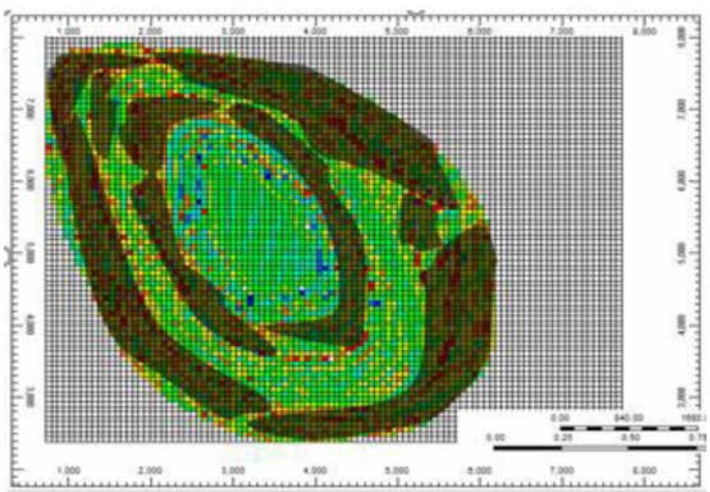

Figure 12—Zones will be the best to drill based on the well-logging porosity map

AI Well-Logging and Seismic Impedance Porosity Map

Figure 13 displays the porosity distribution derived by using (AI) well-logging and seismic impedance which is the second case for finding the relation between both distribution porosity from the seismic and logging. The map shows that the average porosity is around 23% and the porosity range is between 2-37% which is the same average and range of the well-logging porosity distribution and the different percentage between both porosity maps is 7%. Also, we need to select the best zones for drilling to see the difference between them. The shadowed zones as shown in Figure 14 are the best zones for drilling with porosity >15% which is a good range of sandstone porosity. The map shows there is one more zone on the top of the map which is caused by the 7% difference.

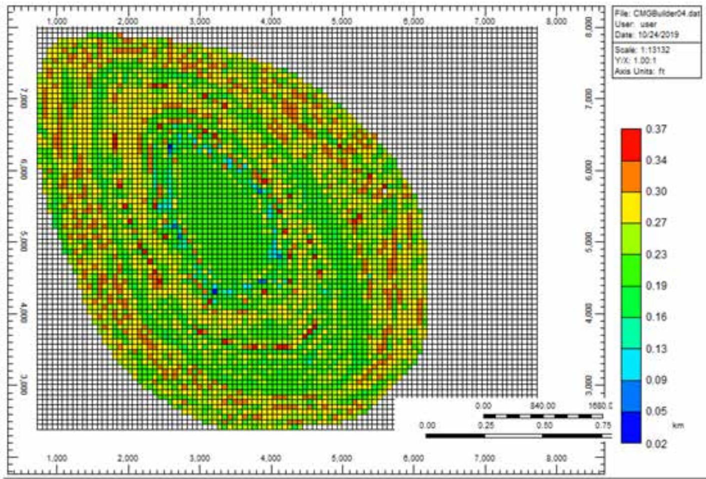

Figure 13—Well-logging and seismic impedance porosity map

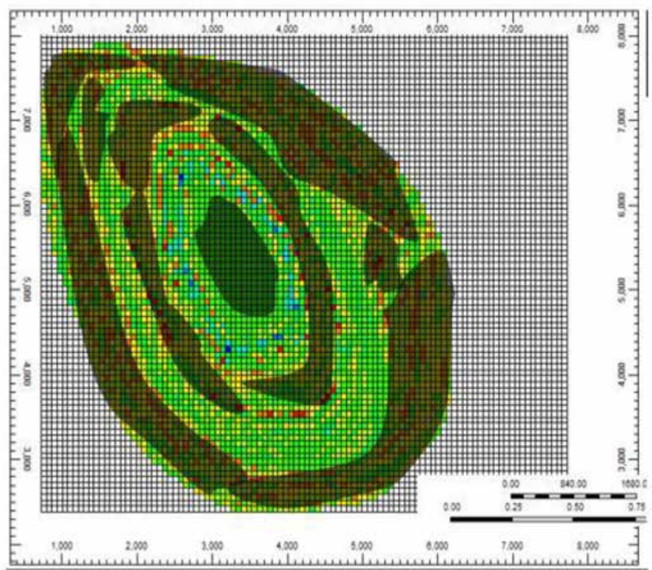

Figure 14—Zones will be the best to drill based on well-logging and seismic impedance porosity map

Seismic Impedance Porosity Map

Figure 15 shows the porosity distribution by using seismic which is the base case for finding the distribution porosity in this project. The map shows that the average porosity is around 23% and the porosity range is between 2-37% which is the same average and range of the well-logging porosity distribution and the different percentage between both porosity maps is 5%.

Also, need to select the best zones for drilling to see the difference between them. The shadowed zones as shown in Figure 16 are the best zones for drilling with porosity >15% which is a good range of sandstone porosity. The results of porosity distribution prove it can predict the porosity under any condition from the seismic survey, which leads to predicting the reservoir properties.

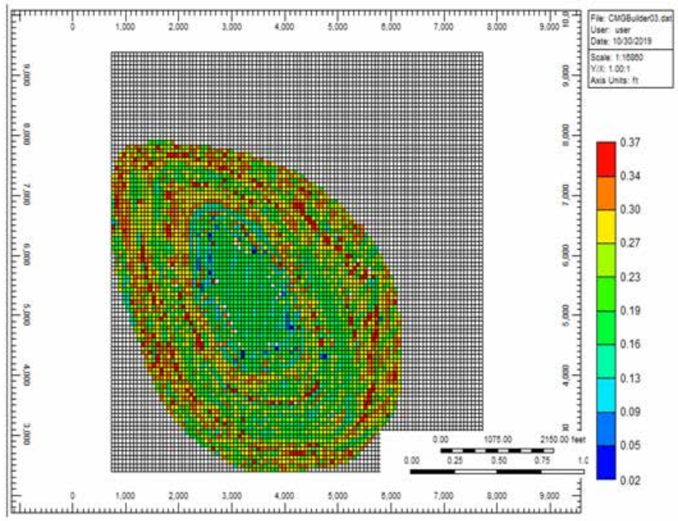

Figure 15—Seismic impedance porosity map

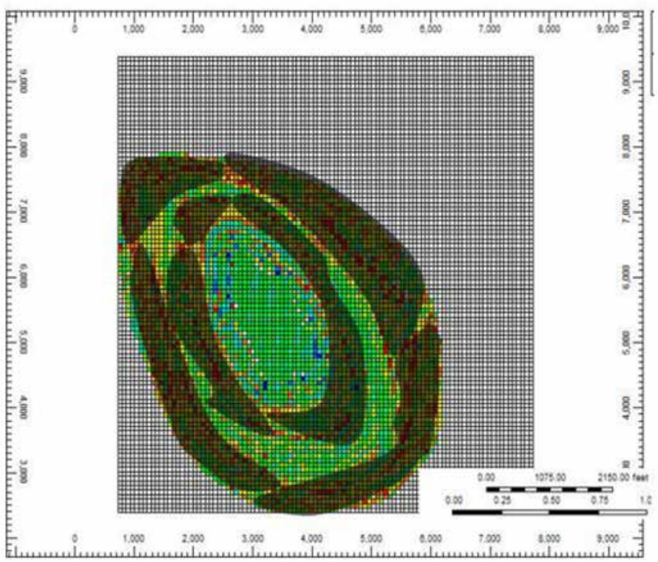

Figure 16—Zones will be the best to drill based on seismic impedance porosity map

Training. Neural network training is the process of finding values of weights and biases. In most scenarios, training is done using what can be described as a train-testing technique. The available data, which defines the input and output values, is divided into a training group (usually 80 percent of the data) and a test group (the remaining 20 percent) but in this scenario, it is divided into a training group (70 percent of the data) and a test group (the remaining 30 percent) is the best-divided ratio for scenarios.

The training dataset is used to train the neural network. The different values for weights and biases are checked to find the set of values so that the calculated output values closely match the correct output values. In other words, training is the process of finding values for weights and biases so that this error is minimized. There are many training algorithms, particularly posterior reproduction, and improved particle swarm.

During training, test data is not used at all. After the training is completed, the accuracy of the weights and biases of the resulting neural network model is applied only once to the test data. The accuracy of the model on the test data gives you a very rough estimate of the accuracy of the model when you submit it with new data that was not previously visible.

One of the main challenges when working with neural networks is a phenomenon called overtaking. Typical endurance occurs when the training algorithm works for a long time. The result is a set of values for weights and biases that generate outputs that exactly match the training data, but when those weights and bias values are used to make predictions of new data, the model is very accurate.

The train validation test process is designed to help determine the time when the model begins to be heavily equipped so that training can be stopped. Instead of dividing the available data into two groups, training and testing, the data is divided into three groups: a training set (typically 70% of the data), a validation set (15%), and a test set (15%).

Figure 17 shows the training set of the logging-seismic scenario with (R=0.9272) size of the ratio, and the training ratio created by the output target (acoustic impedance from both logging and seismic) Vs the output data. So, the accuracy between the logging acoustic impedance and seismic acoustic impedance is very good which reaches more than 90%.

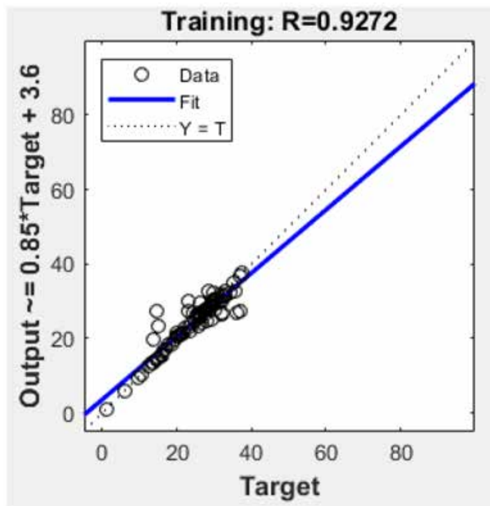

Figure 17—A training set of logging-seismic

Figure 18 shows the training set of seismic scenarios with (R=0.94972) size of the ratio, and the training ratio created by the output target (acoustic impedance, velocity, and density from seismic only) Vs the output data. So, the accuracy of seismic data is very good to predict the porosity which reaches more than 90%.

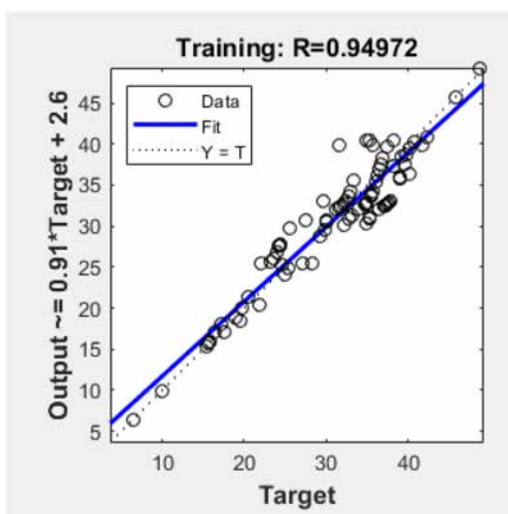

Figure 18—A training set of seismic

Testing. Figure 19 shows the testing set of logging-seismic scenarios with (R=0.86337) size of the ratio. This step is critical to test the generalizability of the model. The testing ratio created by the output target (acoustic impedance from both logging and seismic) Vs the output data. So, the accuracy of the test between the logging acoustic impedance and seismic acoustic impedance is very good which reaches more than 80% which fits the training dataset. This corresponds to the final evaluation that the model goes through after the training phase.

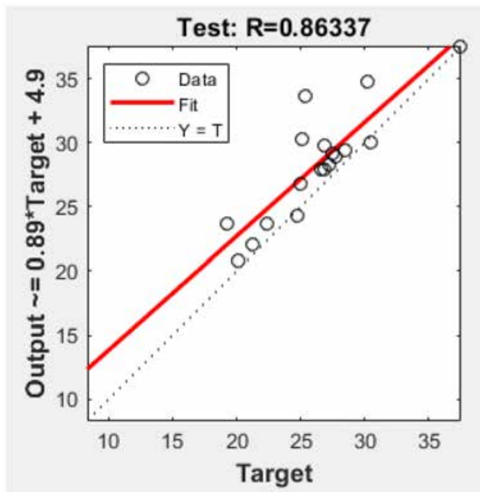

Figure 19—A testing set of logging-seismic

Figure 20 shows the testing set of seismic scenarios with (R=0.94522) size of the ratio. The testing ratio created by the output target (acoustic impedance, velocity, and density from seismic only) Vs the output data. So, the accuracy of the test of seismic data is very good to predict the porosity is very good which reaches more than 90% and fits on the training dataset. This corresponds to the final evaluation that the model goes through after the training phase.

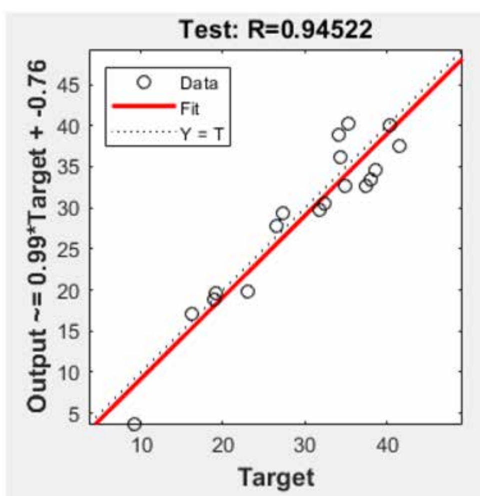

Figure 20—A testing set of seismic

Validation. Figure 21 shows the validation set of the logging-seismic scenario with (R=0.76156) size of the ratio, and the validation ratio created by the output target (acoustic impedance from both logging and seismic) Vs the output data of the testing set that was validated. that the percentage of the data set of testing and validation is the same as 15%. So, the accuracy of the testing set that was validated is good which reaches more than 70%.

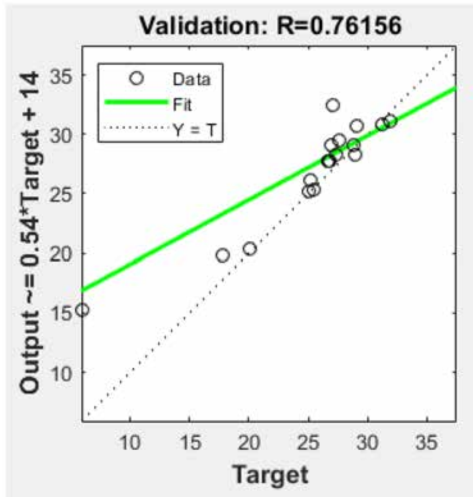

Figure 21—Validation set of logging-seismic

Figure 22 shows the validation set of the seismic scenario with (R=0.92533) size of the ratio, and the validation ratio created by the output target (acoustic impedance, velocity, and density from seismic only) Vs the output data of the testing set that validated. that the percentage of the data set of testing and validation is the same 15%. So, the accuracy of the testing set that was validated is very good which reaches more than 90%.

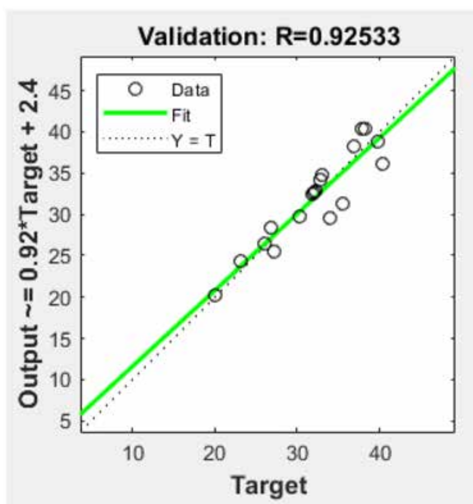

Figure 22—Validation set of seismic

The acoustic impedance has a different assumption of estimation and principles for each one of both logging and seismic which used to find the porosity, but the results of the acoustic impedance for both are in the range between 15000-35000rayl as it is shown in Figure 23, which prove the relation between them to predict the reservoir characteristics like porosity.

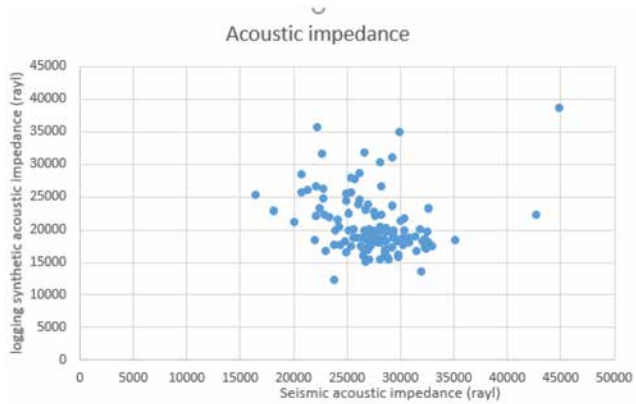

Figure 23—Acoustic impedance of logging and seismic

Figure 24 shows the relationship between logging porosity and (AI) logging-seismic porosity in percentage. Logging porosity predicts by using theoretical and calculated values of density used as input data, which was explained in the previous part, which is the common way to determine the porosity by using logging. (AI) logging-seismic porosity predicts by using a neural network. The distribution results of (AI) logging-seismic porosity prediction is very good with 7% errors compared to logging porosity.

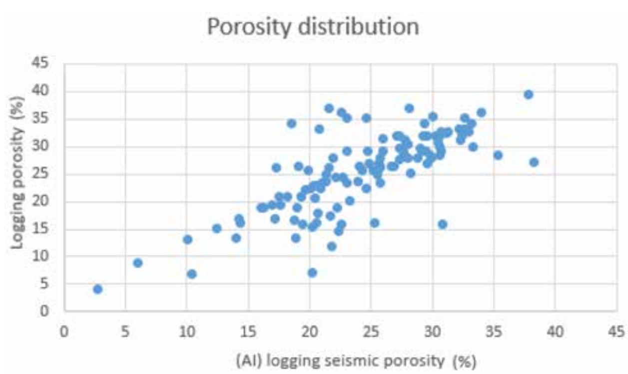

Figure 24—Logging porosity and (AI) logging-seismic porosity

Figure 25 illustrates the relationship between logging porosity and seismic porosity. Seismic porosity predicts by using a neural network that cannot determine by using theoretical and calculated values of density like logging which had many errors of prediction as it is shown in Figure 25. The distribution results of seismic porosity prediction are very good with 5% errors compared with logging porosity.

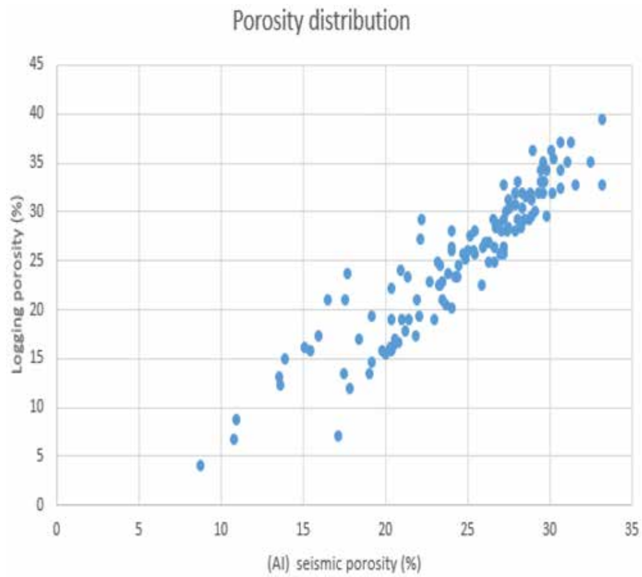

Figure 25—Logging porosity and seismic porosity

Figure 26 illustrates the relationship between logging porosity and seismic density porosity. Seismic density porosity predicts by using theoretical and calculated values of density which are determined from the seismic acoustic impedance. The distribution results of seismic density porosity prediction are very poor with more than 70% errors compared with logging porosity. That proves cannot use the same principle of logging directly with seismic.

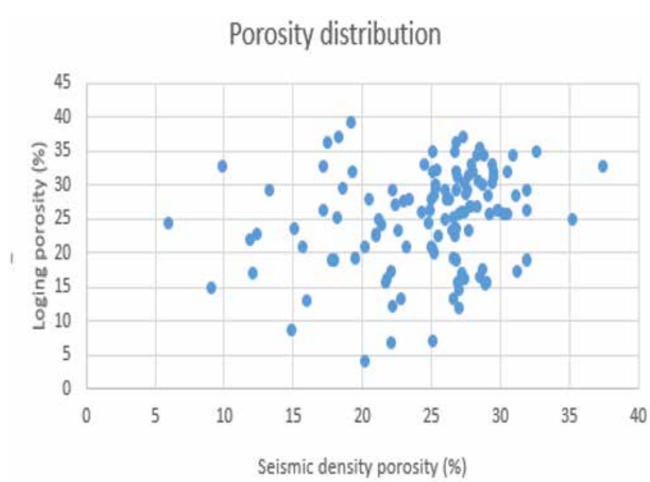

Figure 26—Logging porosity and seismic density porosity

The calculated values of the porosity from the well-logging interpretation are necessary for the comparison. It is not possible to find and calculate the porosity and any reservoir characteristics from the seismic survey data directly unlike the well-logging interpretation where it goes through a lot of processes. Table 1 below illustrates the discrepancy and the difference between theoretical/calculated and Deep learning-neural network results of seismic porosity.

Table 1—Discrepancy and the difference between theoretical/calculated and Deep learning-neural network.

Correlation	Deep learning-neural network
The prediction of porosity is weak compared with the interpretation of the well-logging where the percentage of difference of more than 70%. This is due to the lack of values of correlation of seismic density interpretations. Because the type of lithology is anonymous in seismic surveys.	The prediction of porosity is very good compared with the interpretation of the well-logging where the percentage of difference of less than 5%. This is due to the possibility of entering several values of the seismic interpretation (acoustic impedance, P-wave velocity, and density) in contrast to the theoretical/calculated prediction where the only possibility is to predict the values of the density.

Conclusions

The characteristics of the reservoir were evaluated using a neural network that depend based on the patterns of the input and output. The characteristic of the reservoir focus of this research is porosity. The porosity assessment was first based on the evaluation of the well-logging of the values of densities and sonic logs to find acoustic impedance. Depending on the evaluation the well-logging it is shown that the porosity ratio is high and that the rock is optimal for this sandstone. The porosity evaluation was secondly based on seismic surveys in addition to the well-logging by using a neural network for gathering the acoustic impedance values of both. It was shown that the assessment was very close and good with a low error rate of around 7%. The porosity assessment was finally done based on seismic survey values, which include density, acoustic impedance, and velocity using the neural network to gather them to find the porosity. The evaluation of the compression was very close and good as it predicted porosity with an approximate ratio with the porosity of logging with a 5% error ratio.

To improve and estimate the accuracy of reservoir characteristics, accurate estimation of the porosity of the sandstone reservoir has been a challenge, due to the enhanced effect of pore structure. Porosity has been estimated by sound waves reflected from the structure where it faces many fractures during travel, and this may affect the higher estimation of values. To estimate the values and avoid errors, theoretical principles were used to avoid negative values of the reflected waves which reduces the values of the seismic impedance. Also, the inferred depth of the seismic survey and comparison with the depth of the well-logging confirm the path of the process to assess the correctness of prediction in the specific depth of the layer. To improve the porosity prediction values, all seismic parameters such as sonic, density, and acoustic impedance were collected and incorporated into deep training.

To reduce the cost of drilling and well logging operations, porosity prediction is carried out by drilling several exploration wells either by sending logging tools (sonic, density, and neutron logs) or collecting core samples, these ways are very expensive. It was proved that it is possible to predict the porosity of the seismic survey using artificial intelligence which will help to predict the other characteristics, which does not cost up to a quarter of the cost of drilling a single exploration well which is tasked to collect reservoir characteristics data only.

The porosity prediction shows the most porous zones through a porosity a map of the area. The high percentage of porosity areas contain the most proportion of fluids and are the potential zones for drilling future production wells.

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