



Petrophysical parameters estimation of a reservoir using integration of wells and seismic data: a sandstone case study

Ahsan Leisi¹ · Mohammad Reza Saberi²

Received: 14 October 2022 / Accepted: 13 November 2022 / Published online: 1 December 2022
© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2022

Abstract

Estimation of reservoir parameters (reservoir characterization) including lithology, porosity and water saturation is crucial in the oil and gas industry. These parameters can be calculated in the wells and/or laboratories but these methods are time-consuming, costly, and can cover only a small part of the reservoir. Therefore, integration of seismic and well data for reservoir characterization has received special attention in the oil and gas industry since it provides information from the entire volume of the reservoir. In this study, to establish a relationship between the seismic attributes and the petrophysical parameters of a reservoir at the location of the wells, seismic inversion was performed using model-based, linear programming sparse spike, and maximum likelihood sparse spike algorithms, and the acoustic impedance were calculated accordingly. The model-based inversion method has provided a better answer than the other two methods by providing 99% correlation between the actual and estimated acoustic impedance. Therefore, this method was used to calculate the acoustic impedance in the space between the wells. In the next step, porosity, water saturation, and lithology (quartz and dolomite volume) were estimated from different seismic attributes. In this paper, the multi-attributes regression (MAR) method and artificial neural network (ANN) were used to estimate each of the petrophysical parameters of the reservoir, and we found out that the ANN provided a more accurate estimate than the MAR method for our given dataset. The correlation between the actual and estimated values using the ANN method for porosity, water saturation, quartz volume and dolomite volume is 86, 93, 93 and 95% respectively in the training data and 75, 78, 79 and 82% in the validation data.

Keywords Seismic inversion · Acoustic impedance · Seismic attributes · Petrophysical parameters · Multi-attributes regression · Artificial neural network

Introduction

One of the important goals of determining a model for petrophysical parameters (e.g., porosity, saturation, and lithology) within a reservoir is to identify production reservoir zones (Soubotcheva and Stewart 2004). These parameters can be calculated directly in the laboratory from cores or in the wells from well logs. Acquiring well log and core data

are expensive processes and can calculate reservoir properties only along the well path, and at some given intervals (Das et al. 2017). Seismic reservoir characterization is the recommended technique to address these issues by including all available information (e.g., well logging, seismic, core and geological data) to produce a full image of the subsurface reservoir (Serajamani et al. 2021). It integrates well logging data which has a good vertical resolution with seismic data with an acceptable horizontal resolution (Oldenburg et al. 1983). Therefore, a better reservoir model can be achieved even with a limited number of wells which is the scenario for the reservoirs in the pre-development phase (Brown 2001; Taner 2001). This makes seismic reservoir characterization as an optimal tool to understand reservoir properties such as thickness, net-to-gross ratio, porosity, saturation, and lithology (Chopra and Marfurt 2006).

There are many studies that used seismic reservoir characterization for reservoir property estimation. Oldenburg

Communicated by H. Babaie

✉ Ahsan Leisi
ahsan.leisi.1995@gmail.com

¹ Faculty of Mining Engineering, Sahand University of Technology, Tabriz, Iran

² GeoSoftware, the Hague Area, 2591 XR Den Haag, the Netherlands

et al. (1983) recovered acoustic impedance from reflection seismic data to estimate petrophysical parameters. Doyen (1988) estimated reservoir porosity from seismic attributes using geostatistical algorithms. Kalkomey (1997) and Schuelke et al. (1997) estimated porosity from seismic attributes. Chen and Sideny (1997) used seismic attributes for reservoir monitoring. Hampson et al. (2001), Russell (2004) and Leite and Vidal (2011) estimated reservoir porosity from seismic attributes. The results of their studies have introduced artificial neural network (ANN) method as a fast, accurate and cost-effective tool for porosity estimation. Jalalhosseini et al. (2014) estimated porosity by combining well and seismic data. Na'imi et al. (2014) and Viveros and Parra (2014) estimated petrophysical parameters of a reservoir from well logging and seismic data using intelligent algorithms. Zahmatkesh et al. (2017) estimated reservoir lithology and porosity using seismic data inversion. Das and Chatterjee (2016) and Gogoi and Chatterjee (2019) estimated petrophysical parameters using different seismic characterization methods. Saadu and Nwankwo (2018) determined reservoir quality using well and seismic data. Leisi and Falahat (2021) investigated and compared the conventional methods of porosity estimation using seismic data and introduced the probabilistic neural network method as a better method for porosity estimation.

In this case study, first we will compare the acoustic impedance results at well locations using three different inversion algorithms: model-based, linear programming sparse spike, and maximum likelihood sparse spike algorithm within a sandstone reservoir. Then, the efficiency of each method is examined using the correlation between the actual and estimated acoustic impedance in the wells. We will use the method with the least error as the optimal algorithm for calculating acoustic impedance in the entire reservoir. Furthermore, the acoustic impedance results (from the chosen algorithm) are converted to porosity, water saturation and the lithology using multi-attributes regression (MAR) and artificial neural network (ANN) methods. The amount of error and correlation between the actual (well logs) and estimated values in both methods are investigated and the method that has the highest correlation and the lowest error is introduced as the optimal method for converting acoustic impedance to the reservoir properties in the studied sandstone reservoir.

Geological background

Our dataset comes from one of the Persian Gulf sandstone oil reservoirs. This offshore field is in the northwest of the Persian Gulf and located inside the Dezful embayment (Fig. 1). Geologically, the studied field is an anticline with a

north-south structural trend. This anticline is located in the depressed part of the folded Zagros zone and is considered a part of Abadan plain. The structure of this field is influenced by two fault systems: One from the Arabian plate with a north-south trend and the other is from the Zagros folding system with a northwest-southeast trend. In this field, the older sediments are oriented in the north northwest-south/southeast direction, but the younger formations, including Asmari and Ghar, are more oriented in the northwest-southeast direction. In this field, there are four reservoirs that produce hydrocarbons: Nahar Omar, Sarvak, Asmari and Ghar (Soleimani et al. 2013). Ghar sandstone reservoir is the focus for this study. It is mainly composed of quartz sandstones with dolomite cement along with thin layers of sandy dolomites. The Ghar formation in this field can be divided into three zones in terms of reservoir quality, and these zones are separated by shale layers (Leisi et al. 2022). In this reservoir, presence of porous sand layers has provided suitable conditions for hydrocarbon accumulation. The source and cap rock of the Ghar reservoir are the Kazdumi and the Gachsaran Formations, respectively (Fig. 2).

Database and methods

Our dataset includes three wells with a full suite of well logging data such as density, compressional wave velocity, porosity, water saturation, quartz volume, and dolomite volume (Fig. 3).

All the wells have checkshot information. The dataset also includes: a 3D post stack seismic cube, interpreted horizons, and well tops. To estimate petrophysical parameters (porosity, water saturation, quartz, and dolomite volume) of our reservoir using integration between wells and seismic data, the following steps have been taken (Fig. 4):

- First, we corrected the time to depth relationship using checkshot data.
- Then, a statistical method is implemented to extract the wavelet to generate synthetic seismogram (at each well) to achieve the highest cross-correlation with the seismic traces.
- We proceed with inverting our seismic cube to the acoustic impedance cube using model based, linear programming sparse spike, and maximum likelihood sparse spike algorithm. In the model-based inversion algorithm, first, the low-frequency model must be built. This low frequency information comes from well log data to build the initial model. This initial model, furthermore, is used as the starting point for the comparison between synthetic and seismic traces. This model will be updated to achieve the best match with the seismic data. This

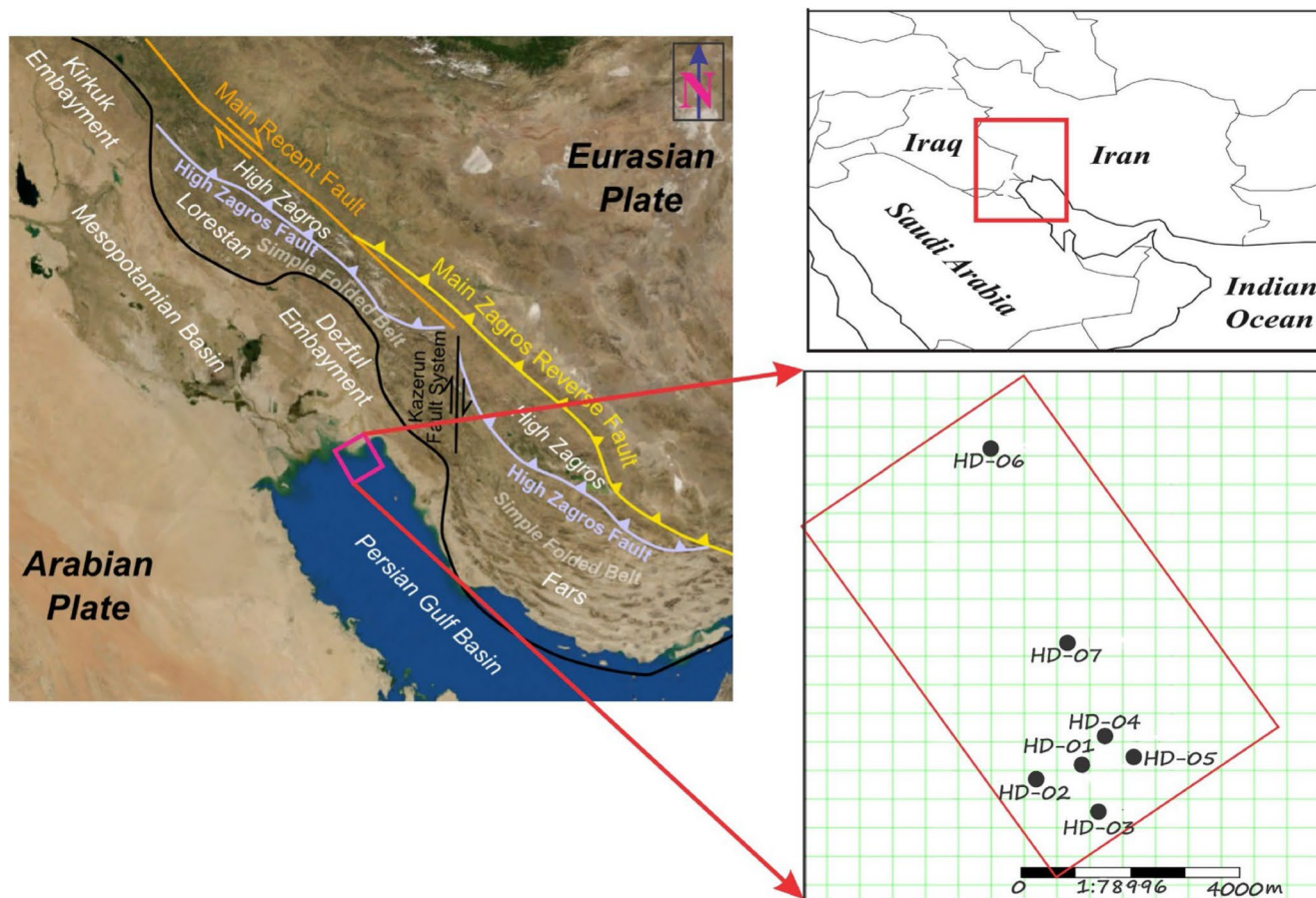


Fig. 1 The studied field location in this work (Abdolahi et al. 2022)

method is sensitive to the constructed initial model and seismic wavelet. In the sparse spike inversion method, the reflection coefficients series are calculated from the seismic trace, and the goal is to fully reconstruct the frequency bandwidth. In this method, it is assumed that there is no noise in the acquisition of seismic data. Unlike the model-based method, the sparse spike method is less sensitive to the wavelet and the initial model. The sparse spike inversion method is divided into two algorithms: linear programming sparse spike and maximum likelihood sparse spike. These two algorithms are not physically different from each other and only differ from each other in terms of the number of adjustable parameters. In this inversion algorithms, first, a composite trace is extracted from seismic data near the well locations to invert for P-impedance. This inverted P-impedance at the well locations are then compared with the original impedances calculated from the well data (Serajamani et al. 2021). The inversion parameters are optimized until we achieve an acceptable match between both P-impedances, and the best algorithm is selected accordingly. In the end, the inversion parameters of the selected

algorithm is extended to invert the entire 3D seismic volume into P-impedance cube (Das et al. 2017).

- Finally, porosity, water saturation and lithology (quartz and dolomite volume) are estimated using multi-attribute regression method and artificial neural network from the P-impedance cube. Here, the optimal number of seismic attributes for estimation are determined using the cross-validation method (Russell et al. 2003). In the cross-validation method, the amount of validation error at the point where it reaches its lowest value gives the optimal number of attributes for estimating these reservoir properties. In addition to determining the optimal number of attributes, the operator length was also determined. This parameter is used to eliminate the frequency difference between well and seismic data (Russell 2004). After the optimal number of attributes and the operator length are selected, each of the petrophysical parameters of the reservoir are estimated using different seismic attributes. We used multi-attributes regression and artificial neural network to calculate these reservoir properties.

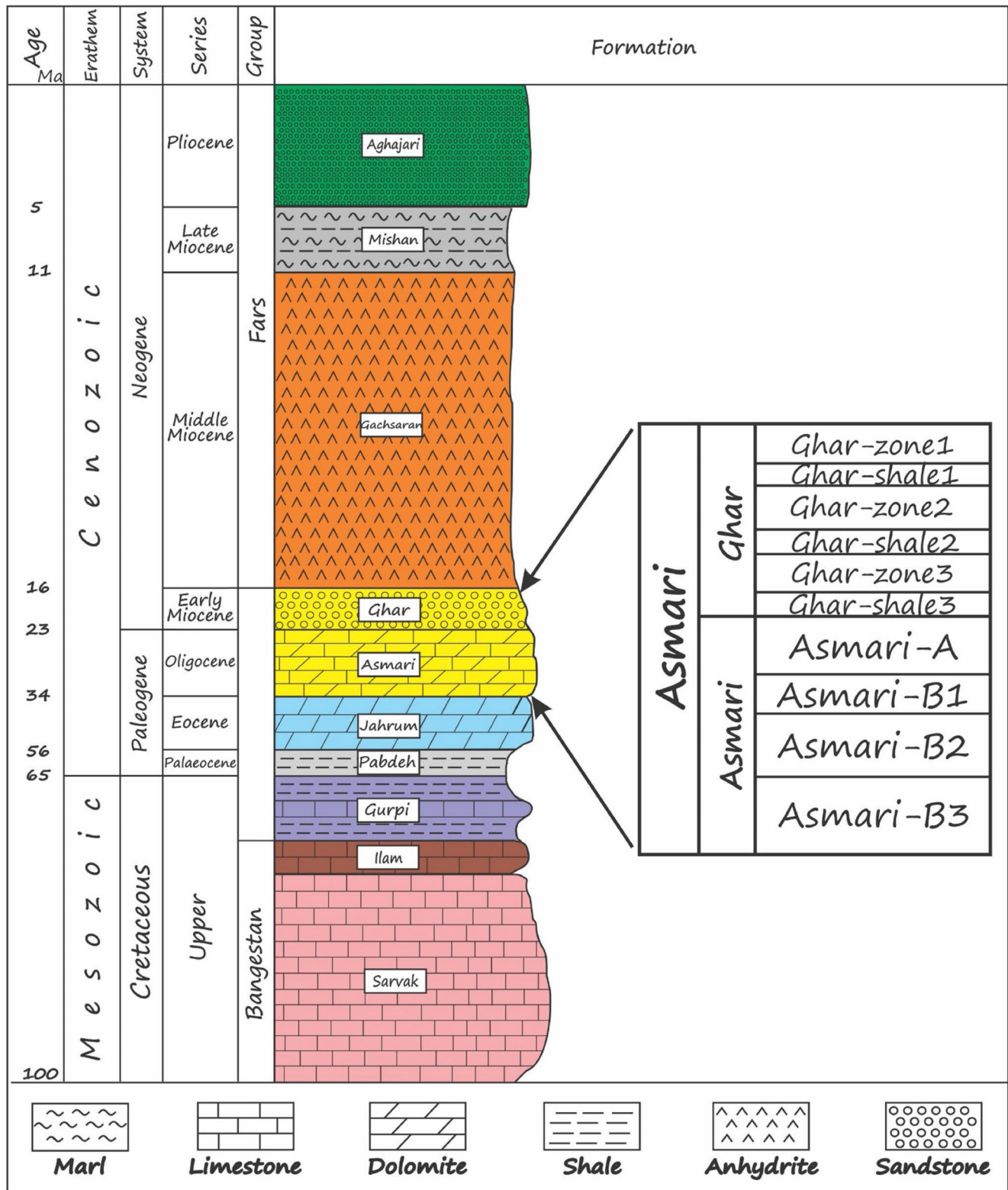


Fig. 2 The stratigraphy of the studied field in this paper (Abdolahi et al. 2022)

The multi- attributes regression (MAR) method works like the multivariate regression method. In this method, the output parameter (target) is estimated

from seismic attributes as input. In the artificial neural networks (ANN), a set of data is given to the network as input and output, and the network is trained and

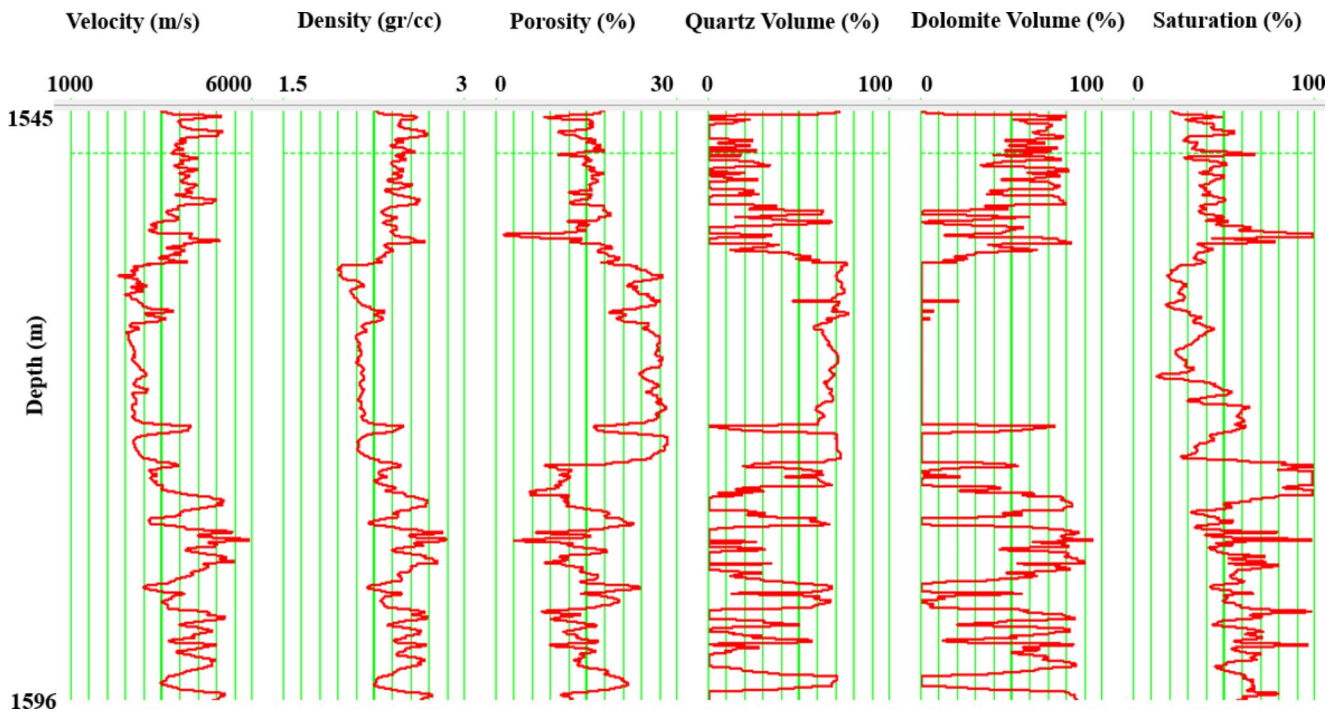


Fig. 3 Log data used in this study. From left to right: velocity, density, porosity, quartz volume, dolomite volume, and saturation log

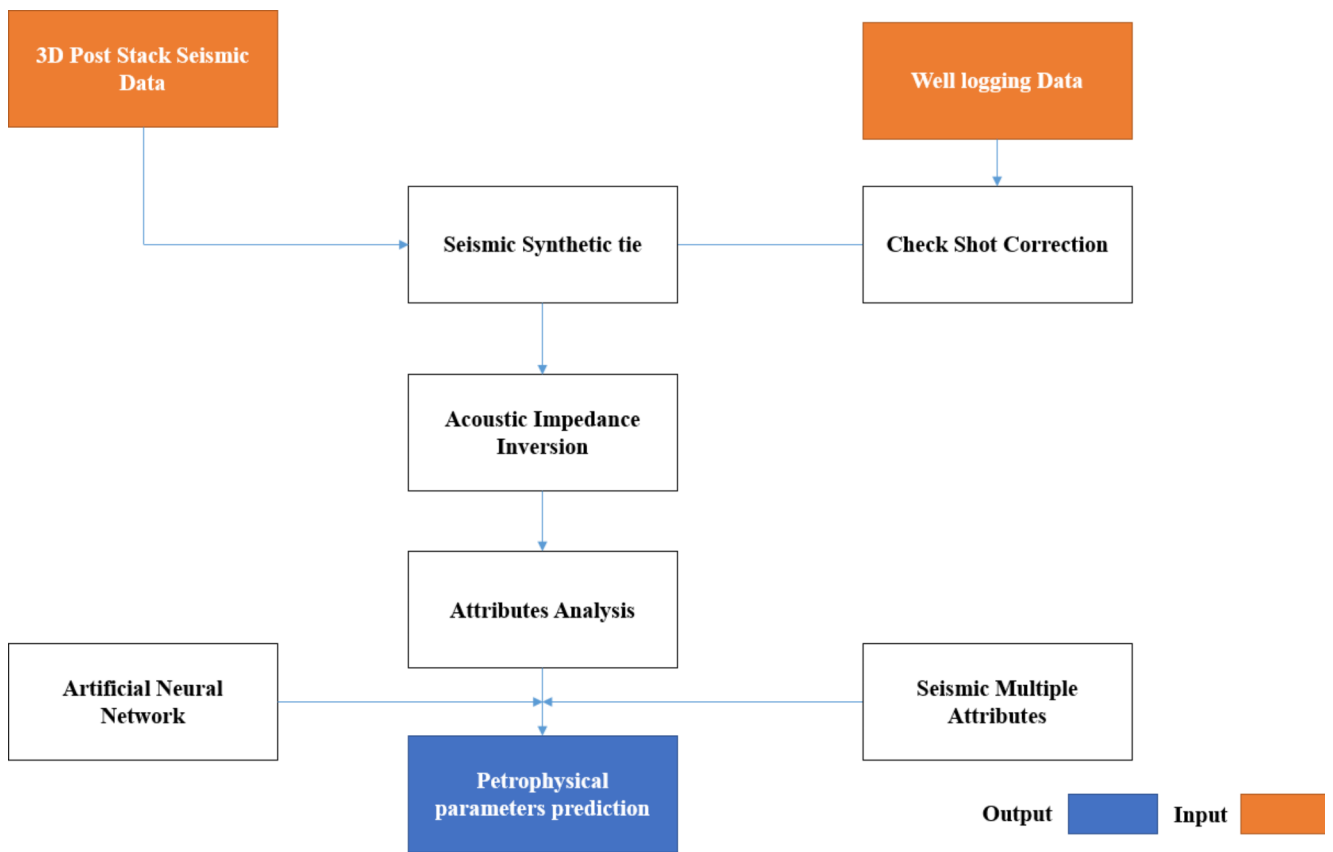


Fig. 4 The applied flowchart for integrating well logs and seismic data

Table 1 Average error and correlation between real and estimated acoustic impedance

Method	Cross-Correlation	Error
Model-based	0.99	0.13
Linear programming sparse spike	0.97	0.23
Maximum likelihood sparse spike	0.93	0.34

adjusts the input and output weights in such a way that it estimates the output if new inputs are given. Therefore, an artificial neural network consists of an arbitrary number of computational units (neuron) located in the layer(s) that connect the input to the target and specify a nonlinear relationship between them. One of the reasons for using artificial neural networks is that they have a higher ability than other methods in estimating non-linear and complex relationships between input and output parameters. Therefore, to achieve this goal, sufficient data must be available to train the network so that the network can optimally adjust the weights of the inputs. In both methods, first the relationship between each of the petrophysical parameters and seismic attributes at the wells is determined and then the distribution of each of the parameters in the space between the wells (the entire reservoir area) is calculated. In the end, we selected the best method and used it to invert the cube of P-impedance into reservoir properties.

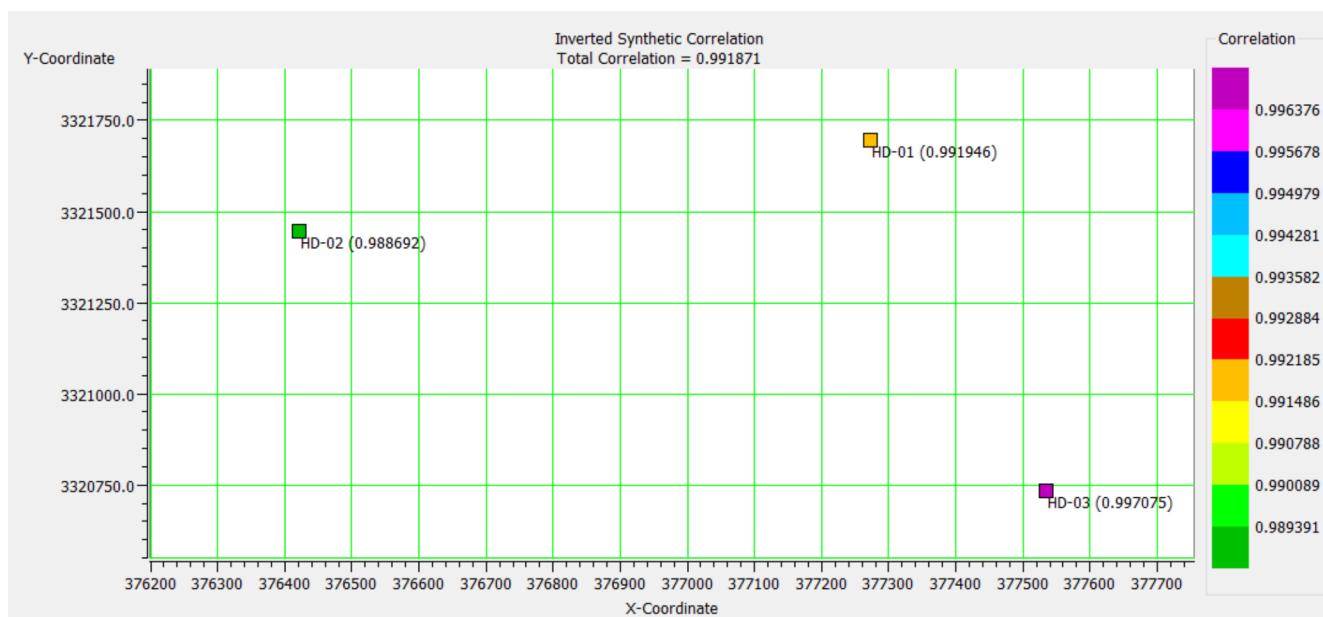
Results and discussion

We applied the given workflow on our reservoir to calculate its petrophysical parameters including porosity, water saturation and lithology (quartz and dolomite volume). We used all three wells in our dataset to train the algorithms. Then, their results are validated by ignoring the data of one well and estimating the same properties using other wells. This procedure is repeated for all three wells. Finally, the overall correlation (between true and predicted values) is calculated. Validation of each method is done to avoid overfitting. The results are given as following:

Seismic inversion results

Seismic inversion was performed using three different algorithms: model-based, linear programming sparse spike, and maximum likelihood sparse spike algorithm. We applied these three algorithms on our dataset and the results are presented in Table 1. Note that the reported values in Table 1 represent the average error and correlation in all wells (3 wells).

According to Table 1, the model-based inversion method has provided better results than other seismic inversion methods. In Fig. 5 the correlation between the actual and estimated acoustic impedance using the model-based seismic inversion method at the location of each well is shown. Also, in Fig. 6, the correlation between synthetic and composite seismogram at the location of Well 3 is shown. The cross plot between the actual and estimated acoustic impedance using the model based seismic inversion method is

**Fig. 5** Correlation between actual and estimated acoustic impedance using the model-based inversion method at each well location

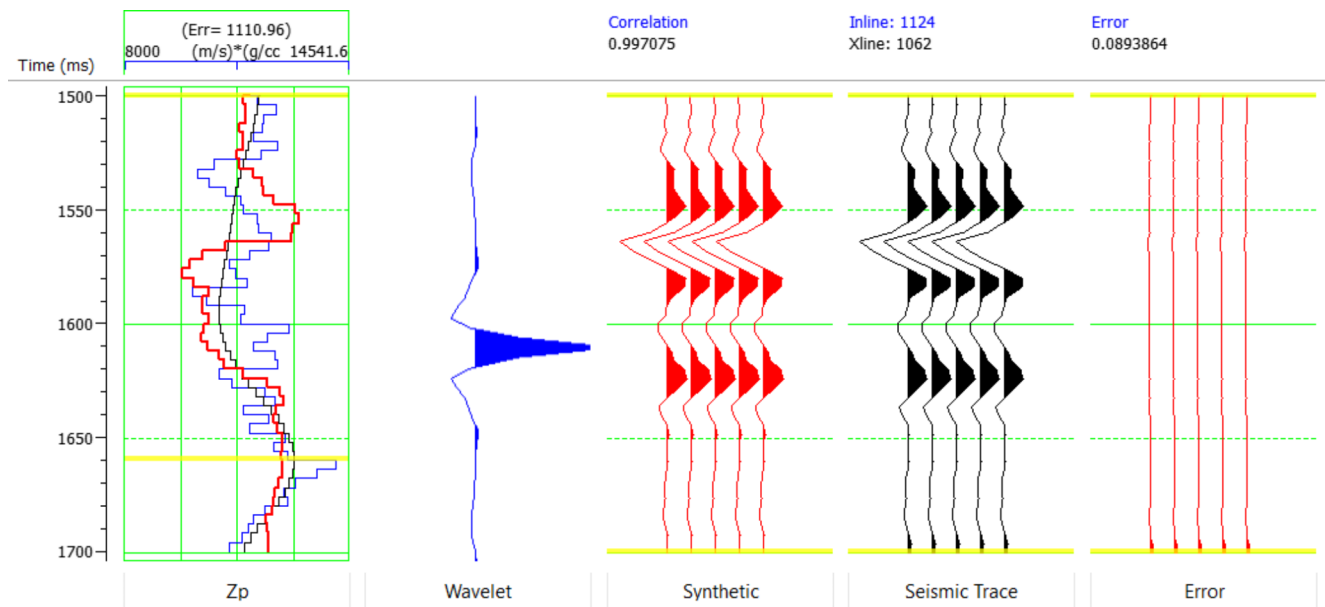


Fig. 6 The correlation between synthetic and composite seismogram at the location of Well 3 using model-based inversion algorithm

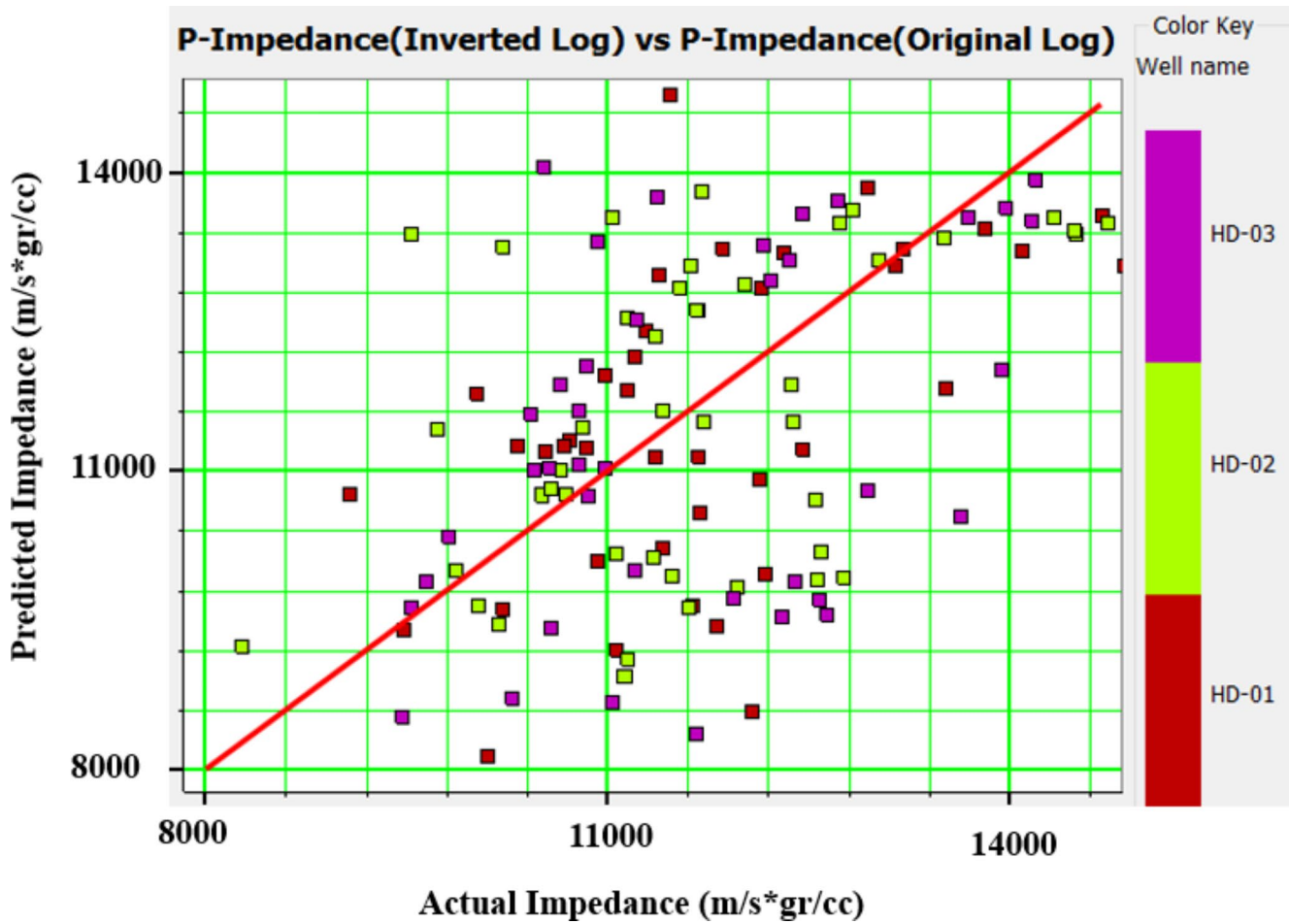


Fig. 7 The Cross plot between actual and estimated acoustic impedance using model-based inversion algorithm

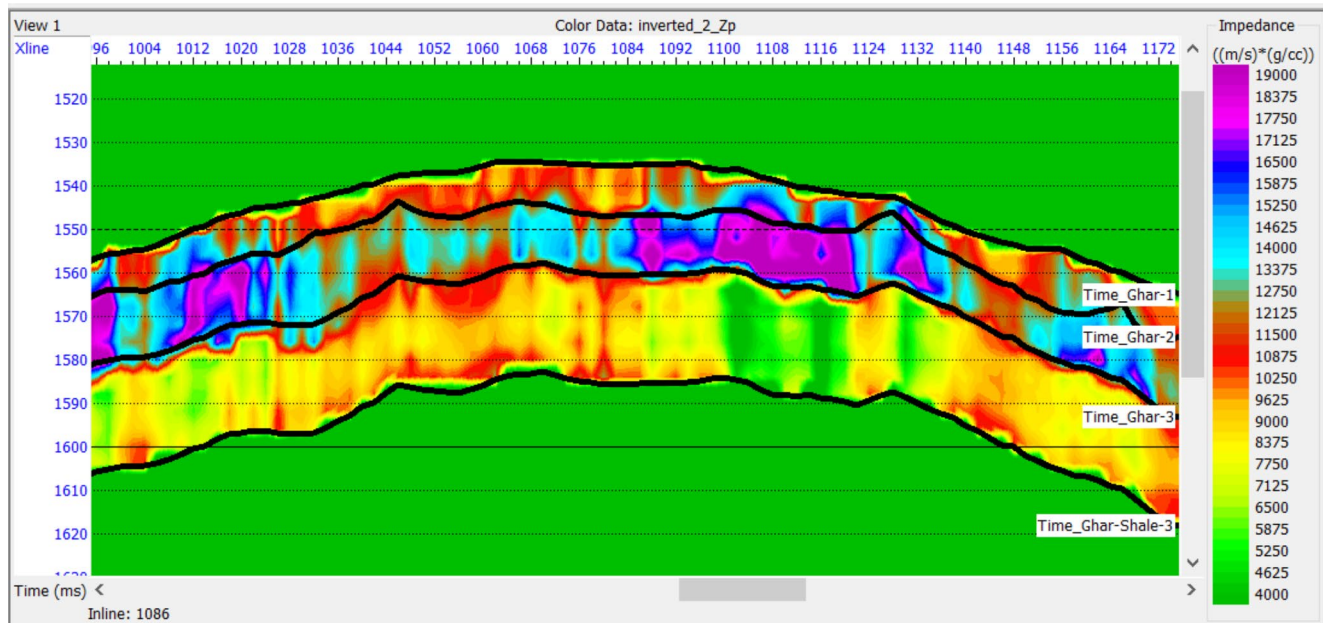


Fig. 8 The acoustic impedance section using the model-based inversion method

Table 2 List of the used attributes for porosity estimation

Attribute	Training Error	Validation Error
Derivative	0.036	0.044
Amplitude Weighted Frequency	0.032	0.041
Integrated Absolute Amplitude	0.031	0.039

Table 3 The amount of correlation and error resulting from the used methods to estimate porosity

Method	R_{Train}	E_{Train}	$R_{\text{Validation}}$	$E_{\text{Validation}}$
MAR	0.83	0.031	0.74	0.039
ANN	0.86	0.029	0.75	0.036

shown in Fig. 7. According to Fig. 7, there is a good correlation between the actual and estimated values.

By examining and comparing the results of each of the seismic inversion methods, we observed that the model-based inversion method provided a better answer than other methods. Because the correlation between the actual and estimated acoustic impedance in this method is higher than the other two methods and has less error. Therefore, this method has been used to calculate the acoustic impedance in the space between the wells (the entire area of the reservoir). Figure 8 shows the acoustic impedance section obtained by the model-based inversion method.

Porosity estimation results

After seismic inversion and acoustic impedance calculation, the petrophysical parameters of the reservoir were estimated from seismic attributes. The first estimated parameter in this paper is porosity. We tested multi-attributes regression

(MAR) and artificial neural network (ANN) for calculating porosity. In both methods, three seismic attributes were used to estimate porosity (Table 2). These attributes have been selected using the cross-validation method, and the reason for selecting these attributes is that they have the least error and the most correlation with porosity. Table 3 shows the correlation and error of each of the used methods to estimate porosity.

According to Table 3, the ANN method has provided a better answer than the MAR method as the correlation (between actual and estimated values) of this method is higher in both training and validation data with less error. Therefore, we used ANN to convert acoustic impedance to porosity. Figures 9 and 10, and Fig. 11 display the correlation between the real and estimated porosity in the training and validation data, the comparison between real and estimated porosity logs, and a section of the estimated porosity using ANN, respectively.

Water saturation estimation results

Water saturation is the second reservoir parameter which was estimated from the acoustic impedance cube. We used MAR and ANN methods for calculating water saturation and compared their results. Here, three seismic attributes have been used in both methods to estimate water saturation (Table 4). After choosing the optimal attributes for estimation, water saturation was estimated using MAR and ANN. Table 5 shows the correlation and error (between actual and predicted values) of these two methods.

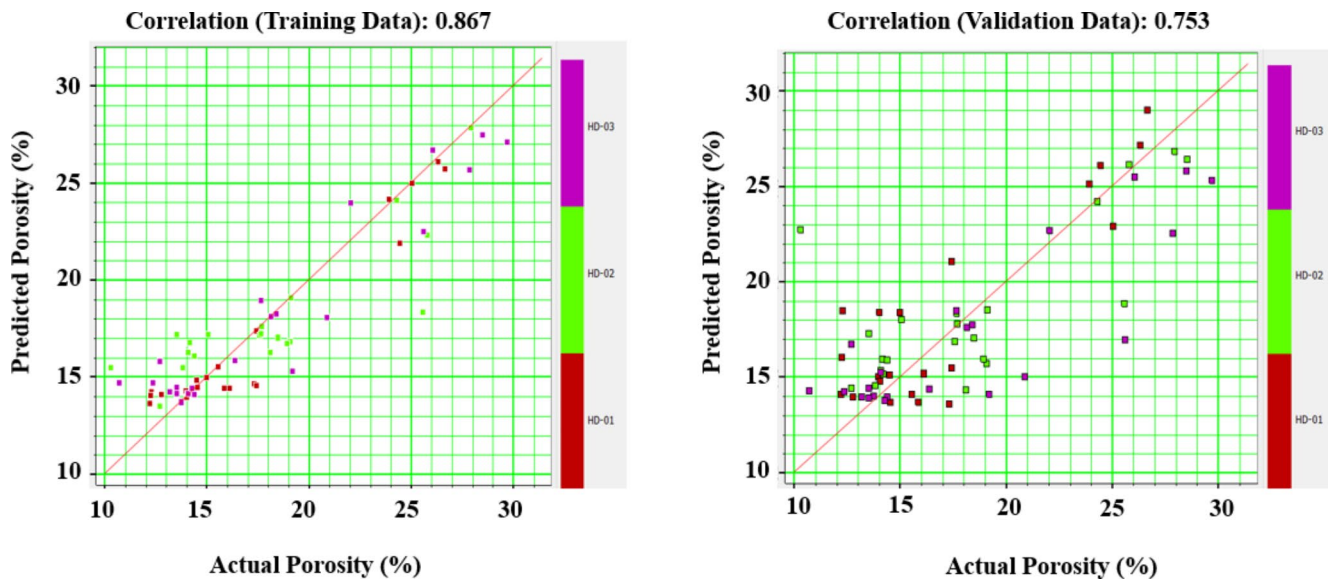


Fig. 9 Correlation between actual and estimated porosity in the training and validation data using ANN method

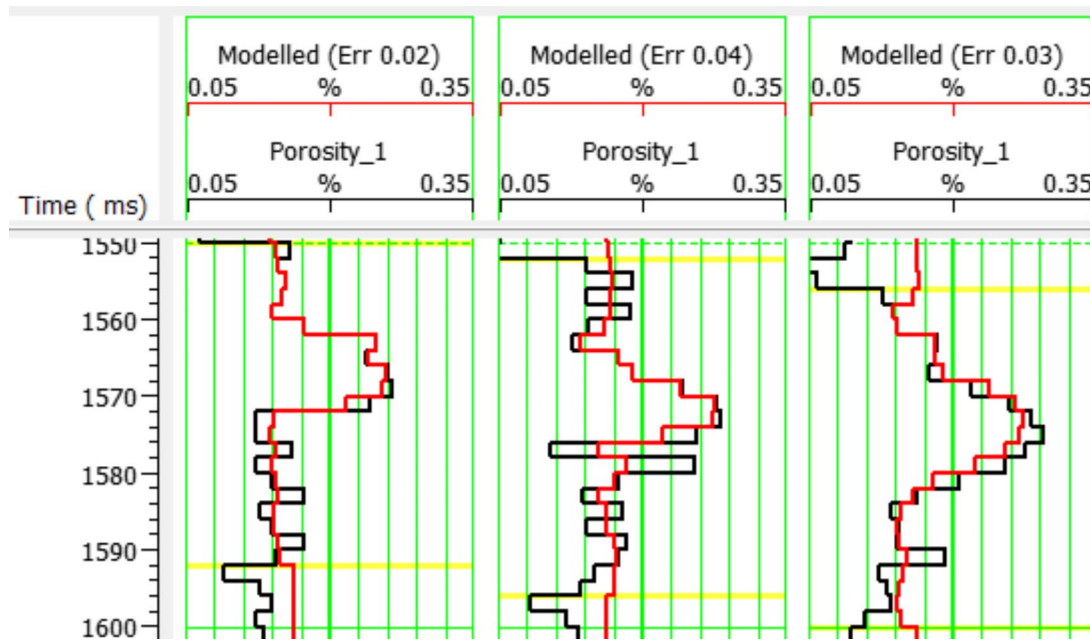


Fig. 10 Comparison between the actual and estimated porosity logs using ANN method

We observe that ANN method provides a more accurate estimate of water saturation compared with MAR. Figures 12 and 13, and Fig. 14 display the correlation between the real and estimated water saturation in the training and validation data, the comparison of real and estimated water saturation logs, and a section of water saturation obtained using ANN, respectively.

Lithology estimation results (quartz and dolomite volume)

The last estimated reservoir parameter in this study is reservoir lithology (quartz and dolomite volume). The used methods to estimate each of the petrophysical parameters in this paper are the same, but different attributes have been used to estimate their parameters (the attributes that are most related to the target parameter). Considering that the studied reservoir is mainly composed of quartz sandstones with dolomite cement along with thin layers of sandy

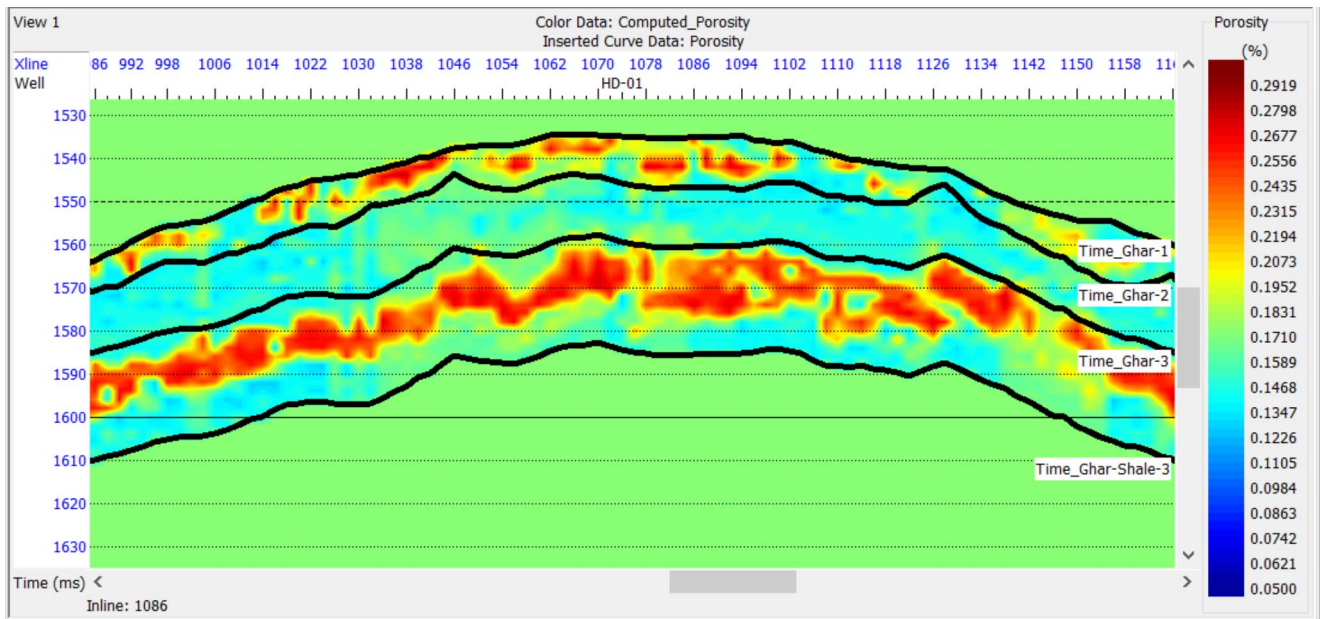


Fig. 11 Porosity section calculated using ANN method

Table 4 List of the used attributes to estimate water saturation

Attribute	Training Error	Validation Error
Filter 15/20–25/30	0.13	0.15
Filter 35/40–45/50	0.12	0.14
Integrated Absolute Amplitude	0.11	0.12

Table 5 Correlation and error resulting from the used methods to estimate water saturation

Method	R_{Train}	E_{Train}	$R_{Validation}$	$E_{Validation}$
MAR	0.78	0.11	0.73	0.12
ANN	0.93	0.06	0.78	0.11

dolomites, therefore, in this article, the volume of quartz and dolomite has been estimated. Table 6 shows the list of selected attributes for estimating the volume of quartz and dolomite. Table 7 presents the results of each of the used methods to estimate the volume of quartz and dolomite.

We again observe that ANN has provided a more accurate estimate for both quartz and dolomite volume compared with MAR. Figures 15 and 16 display the correlation between actual and estimated values in training and validation data for quartz and dolomite volumes, respectively. Figures 17 and 18 show the comparison between actual and estimated logs for quartz and dolomite volumes,

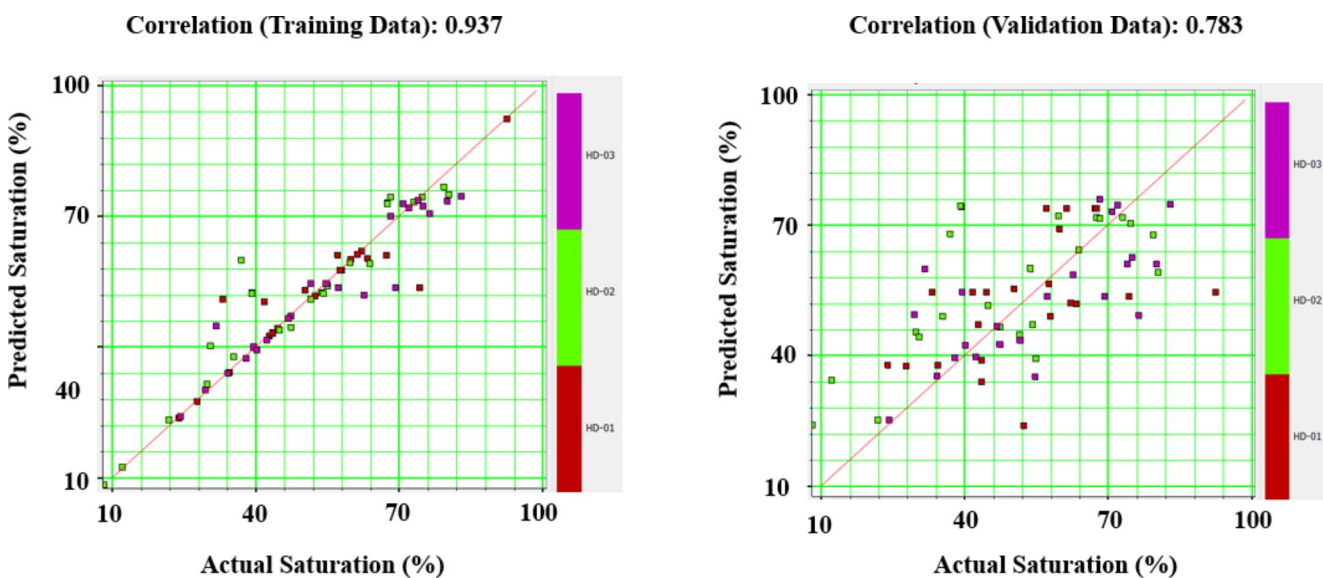


Fig. 12 Correlation between the actual and estimated water saturation in training and validation data using ANN method

Fig. 13 Comparison of the actual and estimated water saturation logs using ANN method

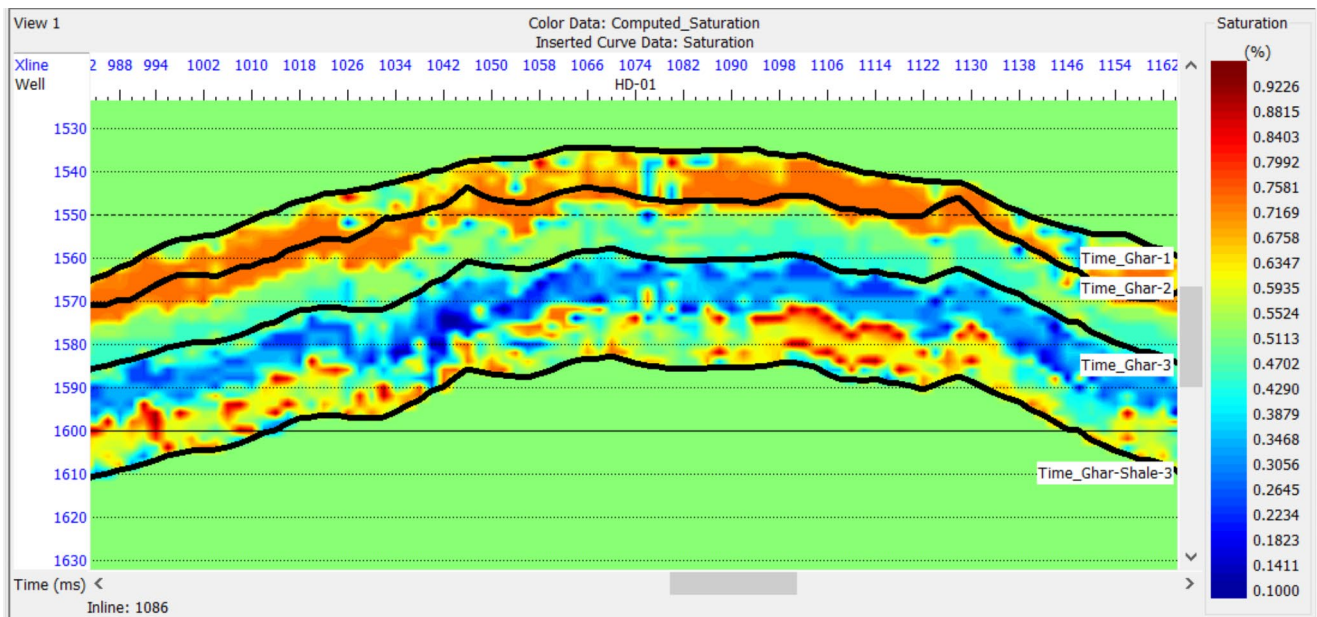
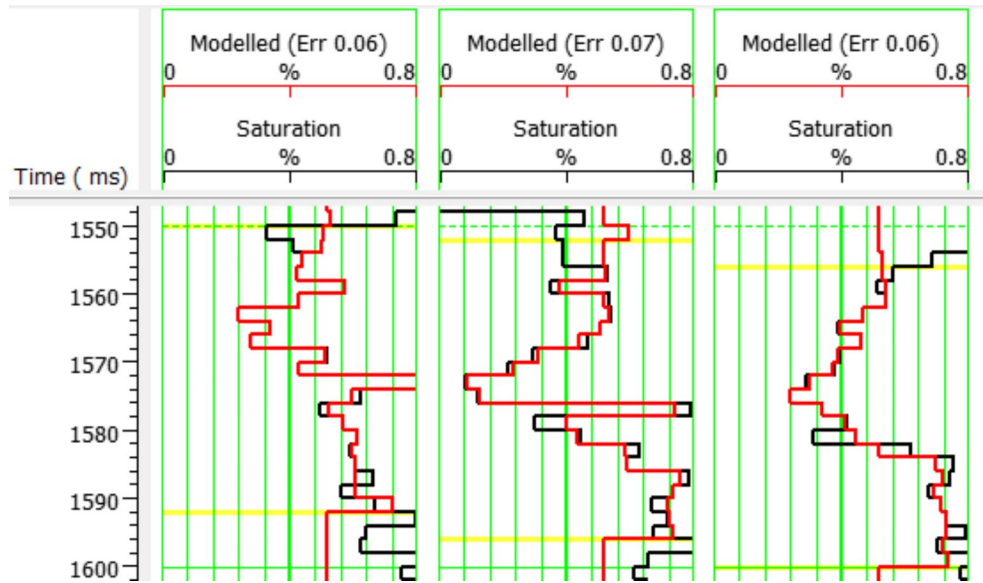


Fig. 14 Water saturation section obtained using ANN method

Table 6 The used attributes to estimate the volumes of quartz and dolomite

Quartz Volume		
Attribute	Training Error	Validation Error
Filter 25/30–35/40	0.15	0.19
Apparent Polarity	0.14	0.17
Filter 15/20–25/30	0.13	0.16
Amplitude Weighted Frequency	0.12	0.14
Dolomite Volume		
Filter 25/30–35/40	0.18	0.21
Amplitude Weighted Frequency	0.16	0.18
Filter 0/10–50/60	0.15	0.17
Filter 5/10–15/20	0.14	0.16

Table 7 The results of each of the used methods to estimate the volumes of quartz and dolomite

Dolomite Volume				
Method	R-Value _(Train)	Error _(Train)	R-Value _(Validation)	Error _(Validation)
MAR	0.86	0.14	0.82	0.16
ANN	0.95	0.08	0.82	0.16
Quartz Volume				
MAR	0.89	0.11	0.73	0.18
ANN	0.93	0.09	0.79	0.15

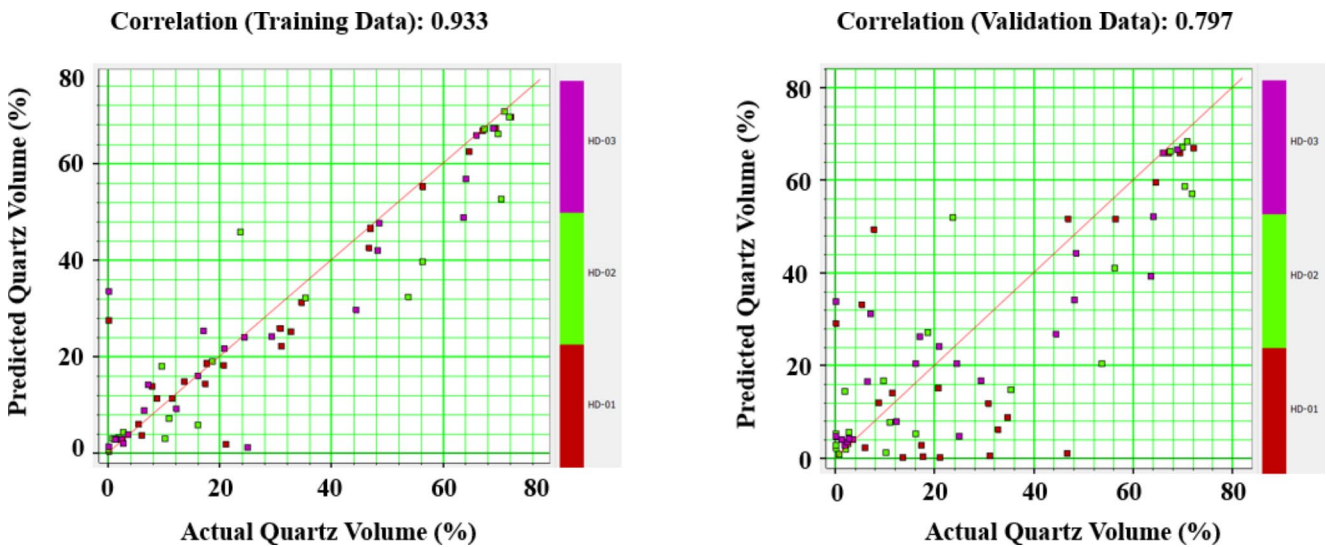


Fig. 15 Correlation between the actual and estimated quartz volume in training and validation data using ANN method

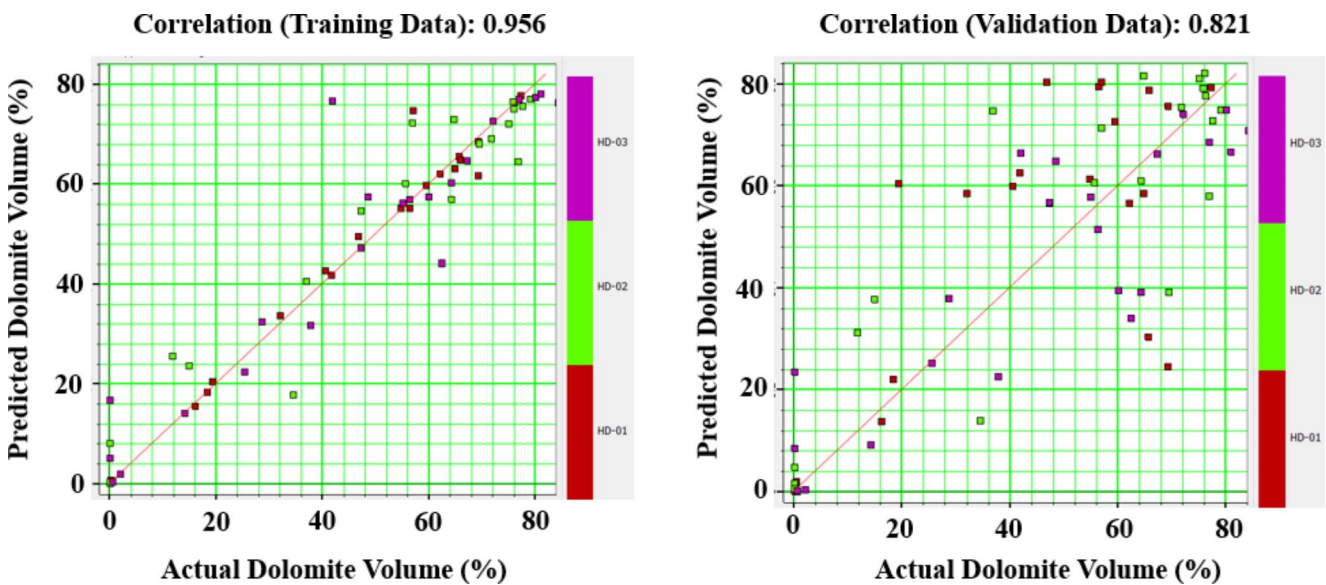


Fig. 16 Correlation between the actual and estimated dolomite volume in the training and validation data using ANN method

respectively. Figures 19 and 20 display the obtained section by ANN method for the volumes of quartz and dolomite, respectively.

In this study, as an effective tool for hydrocarbon field exploration and development, modelling of reservoir properties such as porosity, saturation, and lithology has been carried out to characterize their spatial distribution pattern. Our results confirm that Ghar 3 has good reservoir potential (high porosity and low water saturation) and can be considered as one of the good candidates for further field development in this area. The average maps (slice) of porosity, water saturation, and quartz and dolomite volume in the studied reservoir are shown in Figs. 21 and 22. It shows the distribution of each parameter in the reservoir.

Conclusion

In this paper, petrophysical parameters of a sandstone reservoir (porosity, water saturation, quartz volume and dolomite volume) were estimated from seismic attributes using multi-attributes regression and artificial neural network. To achieve this goal, in the first step, seismic inversion was performed using model-based, linear programming sparse spike, and maximum likelihood sparse spike algorithm to calculate the acoustic impedances. Then, the optimal inversion algorithm was chosen using the correlation and error between the real and estimated acoustic impedance at the well locations. We observed that the model-based inversion algorithm (99% correlation and 13% error) provides

Fig. 17 Comparison of the actual and estimated quartz volume logs using ANN method

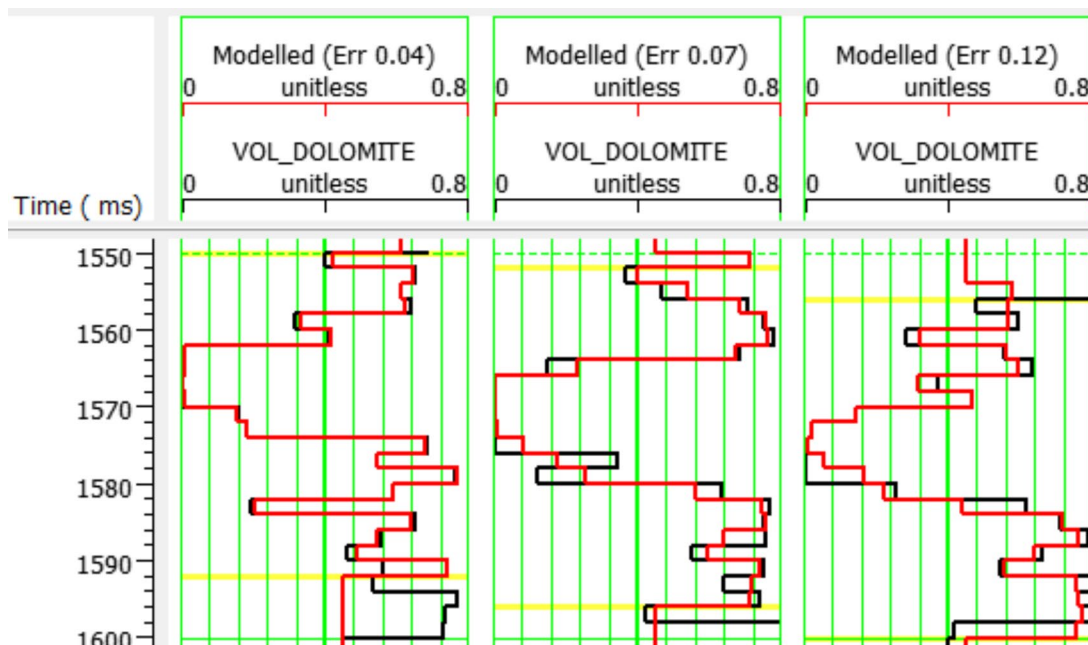
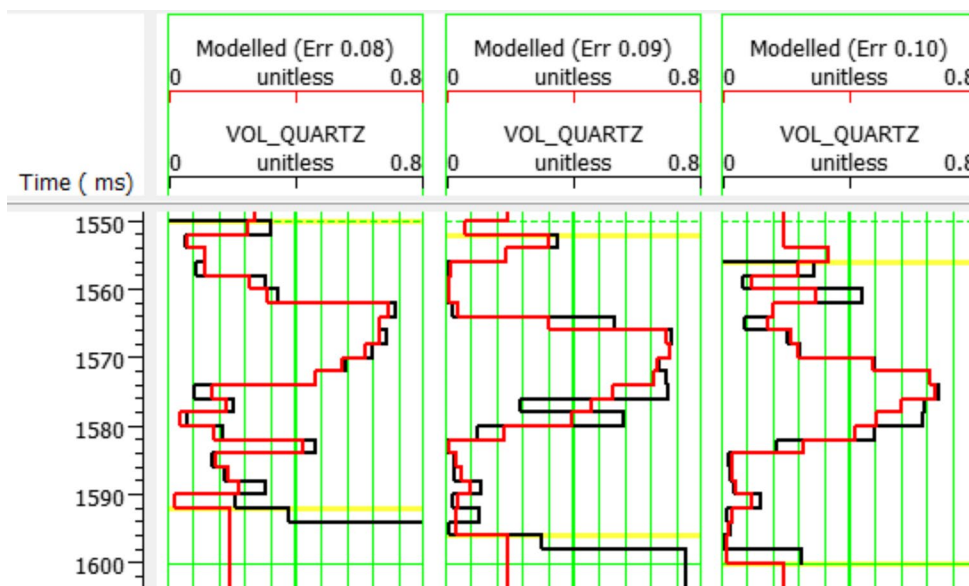


Fig. 18 Comparison of the actual and estimated dolomite volume logs using ANN method

better results in our studied reservoir compared with the other two methods. Then, porosity, water saturation, quartz volume and dolomite volume are estimated from different seismic attributes including the inverted P-impedance cube. For this purpose, the multi-attributes regression method and artificial neural network were used. We observed that the artificial neural network method provided more accurate estimation compared with the multi-attributes regression method. The correlation between the actual and estimated values in the ANN method for porosity, water saturation, quartz volume and dolomite volume are 86, 93, 93 and 95%, respectively in the training data and are 75, 78, 79 and 82%

in the validation data. In addition to correlation, the error of the ANN is lower than the MAR method. The reason that the ANN has provided a better answer than the MAR method is linked to the fact that neural networks have a high ability to estimate nonlinear and complex relationships between the input and the target parameters. We found out that the model-based inversion algorithm combined with the artificial neural network method is an optimal workflow to estimate petrophysical properties in reservoirs with similar geology to our dataset. Our results also show that the studied reservoir is mainly composed of quartz and dolomite

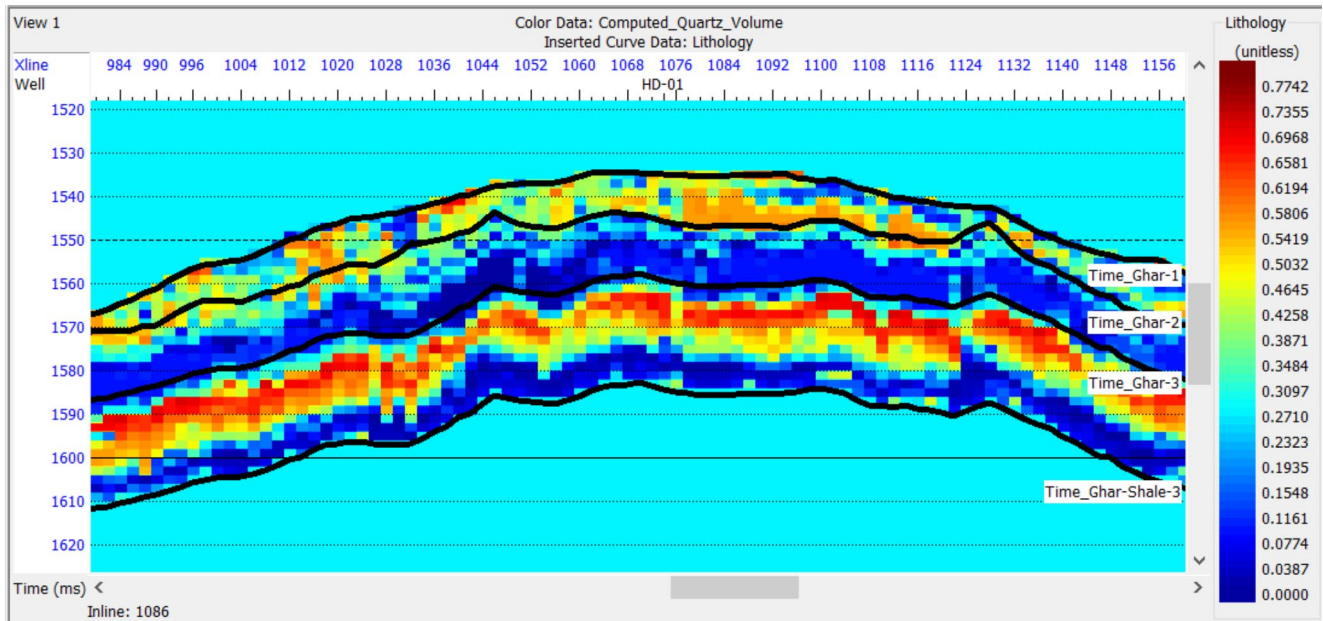


Fig. 19 Quartz volume section obtained using ANN method

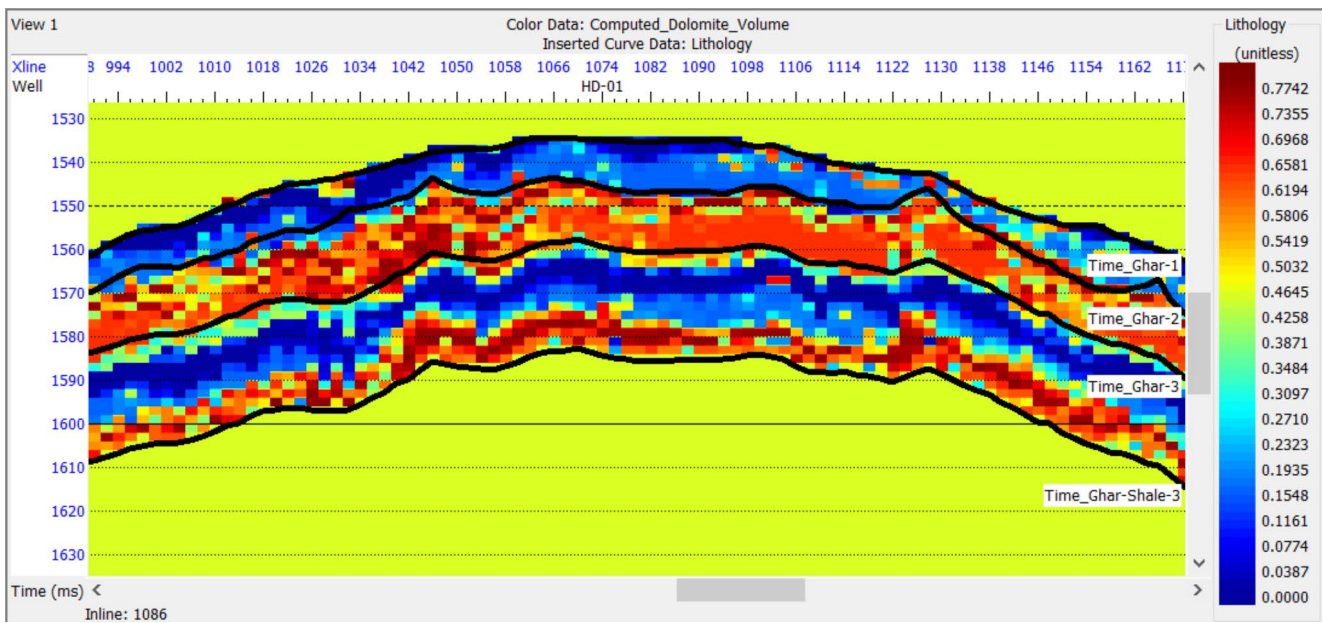


Fig. 20 Dolomite volume section obtained using ANN method

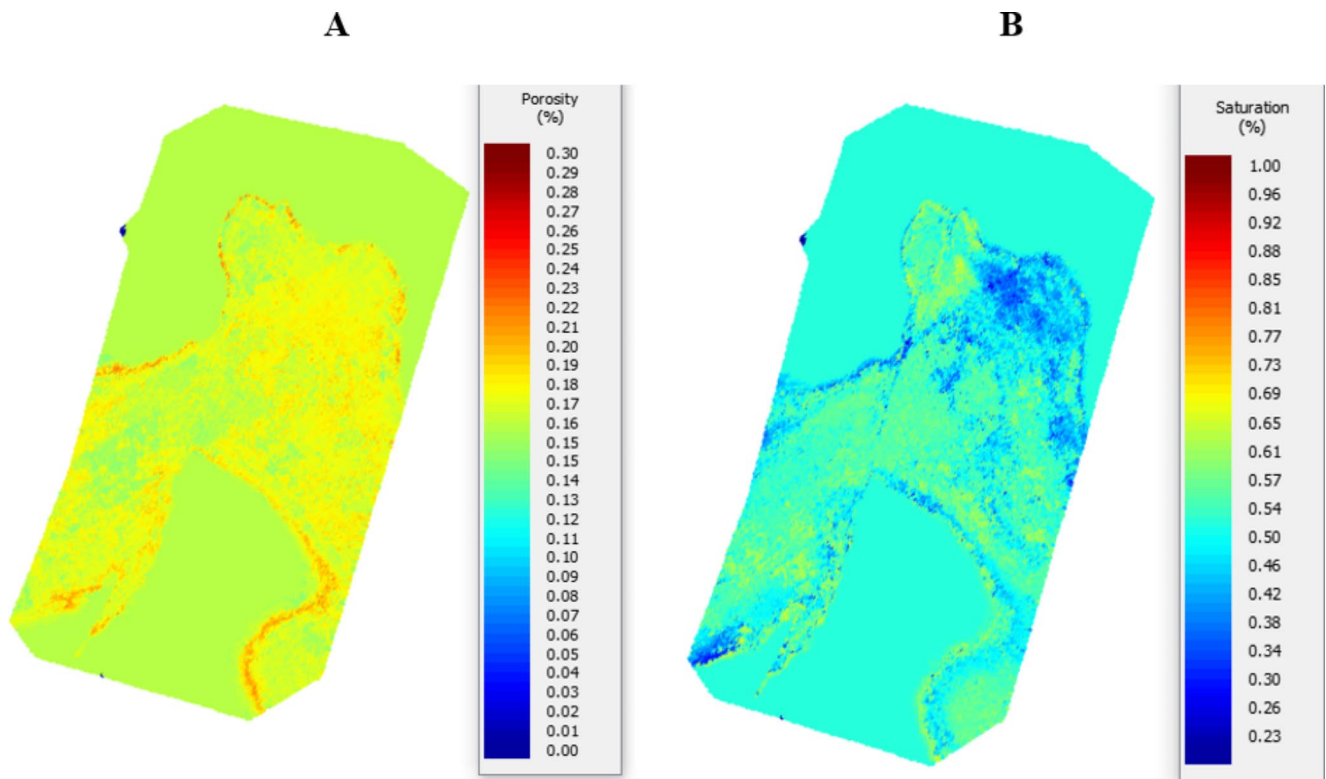


Fig. 21 The average map (slice) of: (A) porosity, and (B) water saturation in the studied reservoir

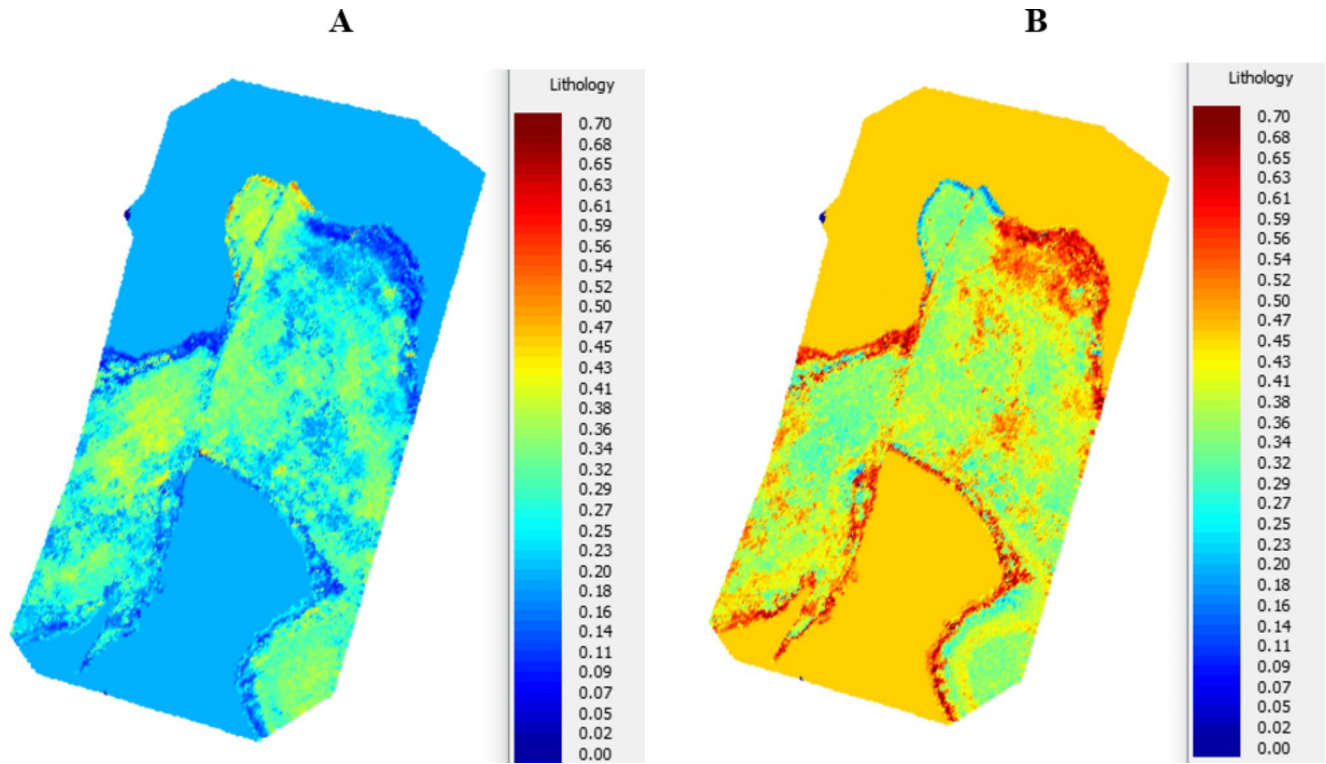


Fig. 22 The average map (slice) of: (A) Quartz volume, and (B) Dolomite volume in the studied reservoir

and in the porous zones, the volume of quartz become more than the dolomite and hydrocarbon presence increases.

Author's contribution Both authors have played a significant role in preparing the article. Ahsan Leisi has done modeling and simulation, and Mohammad Reza Saberi has interpreted the results.

Funding No funding was obtained for this study.

Signed by all authors as follows:

Ahsan Leisi.

Mohammad Reza Saberi.

Data availability If you need the used data in this article or the methods of use, contact Ahsan Leisi, who is the responsible author for this article.

Declarations

Competing interests This research was carried out according to the agreement of the authors and did not have any financial support or financial competition.

References

- Abdolahi A, Chehrazi A, Kadkhodaie A, Amir Abbas Babasafari (2022) Seismic inversion as a reliable technique to anticipating of porosity and facies delineation, a case study on Asmari formation in Hendijan field, southwest part of Iran. *J Petroleum Explor Prod Technol* 12:3091–3104. <https://doi.org/10.1007/s13202-022-01497-y>
- Brown AR (2001) Understanding seismic attributes. *Geophysics* 66(1):47–48
- Chen Q, Sideny S (1997) Seismic attribute technology for reservoir forecasting and monitoring. *The Leading Edge*
- Chopra S, Marfurt K (2006) Seismic attributes- A promising aid for geologic prediction. *CSEG Recorder* 31(5):110–120
- Das B, Chatterjee R (2016) Porosity mapping from inversion of post-stack seismic data. *Georesursy* 18(4):306–313. <https://doi.org/10.18599/grs.18.4.8>
- Das B, Chatterjee R, Singha Dk, Kumar R (2017) Post-stack seismic inversion and attribute analysis in shallow offshore of Krishna-Godavari basin, India. *J Geol Soc India* 90(1):32–40
- Doyen PM (1988) Porosity from seismic data: a geostatistical approach. *Geophysics* 53(10)
- Gogoi T, Chatterjee R (2019) Estimation of petrophysical parameters using seismic inversion and neural network modeling in Upper Assam basin, India. *Geosci Front* 10:1113–1124. <https://doi.org/10.1016/j.gsf.2018.07.002>
- Hampson DP, Schuelke JS, Quirein JA (2001) Use of multiattribute transforms to predict log properties from seismic data. *Geophysics* 66(1):220–236
- Jalalhosseini SM, Ali H, Mostafazadeh M (2014) Predicting porosity by using seismic multi-attributes and well data and combining these available data by geostatistical methods in a South Iranian oil field. *Petroleum Sci Tech* 32(1):29–37. <https://doi.org/10.1080/10916466.2011.584102>
- Kalkomey CT (1997) Potential risks when using seismic attributes as predictors of reservoir properties. *The Leading Edge*

- Leisi A, Falahat R (2021) Investigation of some porosity estimation methods using Seismic Data in one of the South Iranian Oil Fields. *Petroleum Res* 31(119):22–25. <https://doi.org/10.22078/pr.2021.4438.3007>
- Leisi A, Kheirollahi H, Shadmanaman N (2022) Investigation and comparison of conventional methods for estimating shear wave velocity from well logging data in one of the sandstone reservoirs in southern Iran. *Iran Journal Geophys.* <https://doi.org/10.30499/IJG.2022.320098.1385>
- Leite EP, Vidal AC (2011) 3D porosity prediction from seismic inversion and neural networks Emilson. *Comput Geosci J* 37:1174–1180. <https://doi.org/10.1016/j.cageo.2010.08.001>
- Na'imi S, Shadzadeh S, Riahi MA, Mirzakhani M (2014) Estimation of reservoir porosity and water saturation based on seismic attributes using support vector regression approach. *J Appl Geophys* 107:93–101. <https://doi.org/10.1016/j.jappgeo.2014.05.011>
- Oldenburg DW, Scheuer ST, Levy S (1983) Recovery of the acoustic impedance from reflection seismograms. *Geophysics* 48(10):1318–1337
- Russell B (2004) The application of multivariate statistics and neural networks to the prediction of reservoir parameters using seismic attributes. *Ph.D. Dissertation*. University of Calgary, Alberta
- Russell B, Hampson D, Lines L (2003) Application of the radial basis function neural network to the prediction of log properties from seismic attributes. *ASEG Ext Abstracts*. <https://doi.org/10.1071/ASEG2003ab151>
- Saadu YK, Nwankwo CN (2018) Petrophysical evaluation and volumetric estimation within Central swamp depobelt, Niger Delta, using 3-D seismic and well logs. *Egyptian J Petroleum* 27:531–539. <https://doi.org/10.1016/j.ejpe.2017.08.004>
- Schuelke JS (1997) Reservoir architecture and porosity distribution, Pegasus Field, West Texas -- an integrated sequence stratigraphic-seismic attribute study using neural networks. *INT* 5.2
- Serajamani M, Nikrouz R, Kadkhodaie A (2021) Estimation of Acoustic Impedance of the tight Sandstones using seismic inversion methods: a Case Study from Whicher-Range Gas Field in the Perth Basin, Australia. *Petroleum Res* 30(115):17–19. <https://doi.org/10.22078/pr.2020.4018.2829>
- Soleimani B, Bahadori A, Meng F (2013) Microbiostratigraphy, microfacies and sequence stratigraphy of upper cretaceous and paleogene sediments, Hendijan oilfield, Northwest of Persian Gulf, Iran. *Nat Sci* 5(11):1165–1176
- Soubotchev N, Stewart RR (2004) Predicting porosity logs from seismic attributes using geostatistics. *CREWES Research Report* 16
- Taner TM (2001) Seismic attributes. *CSEG Recorder* 26(7):49–56
- Viveros U, Parra JO (2014) Artificial neural networks applied to estimate permeability, porosity and intrinsic attenuation using seismic attributes and well-log data. *J Appl Geophys* 107:45–54. <https://doi.org/10.1016/j.jappgeo.2014.05.010>
- Zahmatkesh I, Kadkhodaie A, Soleimani B, Gholzadeh A, Azarpour M (2017) Estimating vsand and reservoir property from seismic attributes and acoustic impedance inversion: a case study from the Mansuri oilfield, SW Iran. *J Petrol Sci Eng.* <https://doi.org/10.1016/j.petrol.2017.11.060>

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.