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RESEARCH PAPER

Prediction of Reservoir Compressibility Using Subsurface Cores, Well Logs, and Seismic Data by Neural Network

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Abstract
This study predicted the three-dimensional pore volume compressibility of carbonate Sarvak Formation from the Bangestan group. Primary data of the model were petrophysical parameters, measured compressibility factor on core samples, conventional well logs, and three-dimensional seismic attributes. The proposed experimental models of compressibility prediction are based on the rock's porosity. However, due to the structural and textural complexities of carbonate formations, compressibility is not solely a function of the rock's porosity but also depends on other petrophysical parameters. Neural network algorithms were employed to propagate the compressibility data along the well and to predict the distribution of compressibility within a three-dimensional seismic acquisition area. A probabilistic neural network algorithm resulted in a better correlation than an artificial neural network algorithm. It resulted in a correlation of 85% between the predicted and measured compressibility along logged intervals of the wells. 11 optimum number of seismic attributes were extracted to find the best correlation and minimum error between the generated and target attributes. The correlation coefficient of 91% indicated the high accuracy of the model and the optimal choice of neural network algorithms. The results of this study provide insights into the application of seismic data to the field-wide prediction of static models of reservoir compressibility.

Keywords: Pore Volume Compressibility, Core, Well Log, Neural Network, Seismic Attributes.

Introduction

A hydrocarbon reservoir is a complex system of rocks with different fluids presenting in the pore spaces. Hydrocarbons and formation water flow inside the reservoir rock pore bodies. The compression of a reservoir rock results in changing the shape of pore bodies and closing flow channels, consequently reducing the formation permeability (Farahani et al., 2022). However, this compression provides part of the necessary energy for oil outflow. Pore volume compressibility (C_{pv}) is of great importance in reservoir engineering studies and is still under investigation by many researchers (Ashena et al., 2020; Cheng et al., 2020; Moosavi et al., 2022; Wu et al., 2023; Zhao et al., 2021). It is defined as fractional volume change concerning the effective overlying stress (Farahani et al., 2022). Detailed mathematical equations were presented in other articles (Ashena et al., 2020; Farahani et al., 2022).

It is vital to define compressibility to evaluate the thrust energy that the rock can provide in the production process. It is also needed for reserve estimations and geomechanical analysis. It affects the storage, production behavior, recycling, and mechanical properties of reservoir rocks. The compressibility coefficient of reservoir rocks has been reported as one of the critical

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factors in the subsidence caused by fluid extraction from the reservoir (Daïm et al., 2002; Ferronato et al., 2006). Simulation studies showed that negligence of compressibility can result 2 to 25% underestimation of hydrocarbon production prediction with the highest error in shale reservoirs (Bachir, 2014). In some cases, a constant coefficient or an empirical relationship is embedded due to insufficient information on rock compressibility (da-Silva et al., 2015).

In some cases, due to core recovery issues, enough representative core samples are not reachable for compressibility determination (Sharifigaliuk et al., 2021). Hence, normal practice is to apply C_{pv} versus porosity (ϕ) correlations derived from nearby extensive databases of core measurements (Crawford et al., 2011). Ashena et al. (2020) proposed a log‑based rock compressibility estimation for an Iranian carbonate formation. They observed a rather reliable estimation of pore compressibility, except for intervals with extremely large wellbore washouts.

In terms of structural and textural complexities of carbonate rocks, compressibility is not only a function of the rock's porosity but also depends on various other petrophysical parameters. Hence, there is a need for field-wide estimation of compressibility employing an indirect approach. Specifically, artificial neural networks (ANN) have been widely used in many aspects of geology and petroleum industry (Azadpour et al., 2015; Hassan et al., 2021; Puskarczyk, 2019; Sun & Dong, 2022; Tanko & Bello, 2020). In ANN the real measured data are used for training and validation of the model. Hence, the obtained correlations have high accuracy. ANN technique has been successfully applied to develop predictive models for the physico-mechanical rock characteristics estimation (Afshari et al., 2014; Hassan et al., 2021).

In the present study, the C_{pv} was measured on some drilling cores of four different wells. The results and well logs (density, neutron porosity, and acoustic impedance) were utilized as input data for neural network algorithms, and the reservoir formation compressibility along the well axis was predicted. Using 3-D seismic attributes, well axis C_{pv} data, artificial neural network algorithms, and expanding it along a 3-D seismic data, compressibility was predicted in a three-dimensional wide range with high accuracy. The results of this study provide insights into the application of seismic data to field-wide prediction of reservoir compressibility.

Geological description

Sarvak Fornation of the Bangestan Group in Southwest Iran (Dezful embayment and Abadan plain) was the focus of this study. The four studied wells cross different formations of this group, including Ilam, Sarvak, and Kazhdumi (Assadi et al., 2023). The Sarvak Formation, as one of the most important oil-producing zone (Mehrabi et al., 2023), is the main stratigraphic unit of the Bangestan Group in southern Iran (Fig. 1). All samples in this study were selected from the Sarvak Formation, which consists of limestone with minor shale (Rikhtegarzadeh et al., 2017). Dissolution and neomorphic caused by diagenesis, and stylolite-related dolomitization resulted in increasing the quality of the reservoir (Rahimpour-Bonab et al., 2012). Cementation, compaction, and micritization have an adverse effect on reservoir properties (Sabouhi et al., 2022).

Methodology

Fig. 2 shows the location of the studied seismic area and four selected vertical wells of a hydrocarbon field in Southwest Iran. The geological area of the studied zone was approximately 24 square kilometers. There were about 640 seismic in-lines and 240 seismic cross-lines. The wells' position was shown in terms of seismic lines and coordinates (X, Y).

320 carbonate core plug samples were prepared from the studied wellbores and underwent compressibility measurement. The petrophysical properties of the cleaned samples were routinely measured at ambient conditions. The coreLab apparatus, named CMS-300, was

employed to measure the petrophysical properties of plug samples at five different confining pressures of 5.5, 10, 15, 20, and 25 MPa. The helium gas was employed to determine effective porosity and permeability by gas expansion measurements. More details of the experimental procedures were explained in previous manuscripts (Farahani et al., 2022; Feng & Pandey, 2017).

Fig. 3 shows the workflow of the present research. Firstly, the petrophysical properties of core plug samples of the four selected wellbores were determined. The neutron porosity logs were calibrated with the data obtained from the corresponding core samples. The well logs are valuable tools for determining the petrophysical parameters along the wellbore axis due to their continuity, availability, and low cost (Moore et al., 2011). Then, the compressibility of selected samples was used to train both ANN and probabilistic neural network (PNN) models and predict the compressibility of other sections of the downhole logs along the wells. A C_{pv} log was generated for each wellbore. An equation was also derived, showing the relation between the measured compressibility and porosity. The generated equation was compared with the ones from other researchers.

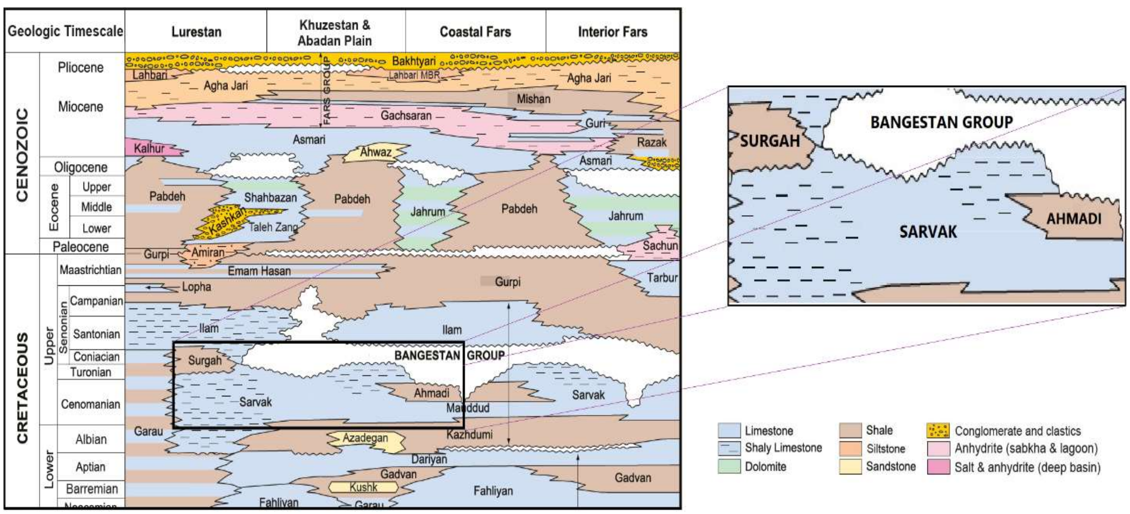

Figure 1. shows the geological section of the studied area. The lithostratigraphic column of Southwest Iran illustrates stratigraphic units of the Cenozoic and Cretaceous. Bangestan Group is shown at the right (Esrafili-Dizaji & Rahimpour-Bonab, 2019)

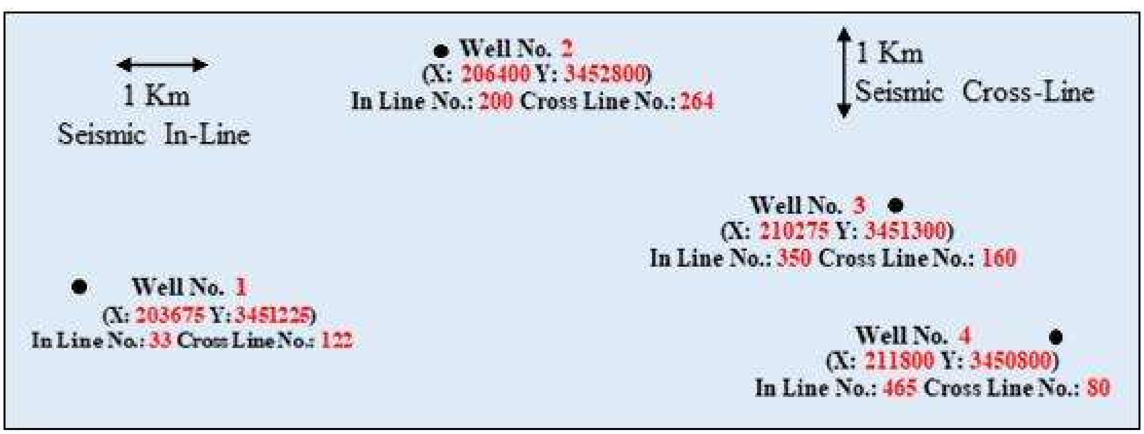

Figure 2. Shows the study area and four selected wells in the seismic data acquisition. The horizontal axis is in-line seismic data and the vertical axis is cross-line seismic data. The position of the wells was given in terms of seismic lines and coordinates (X, Y)

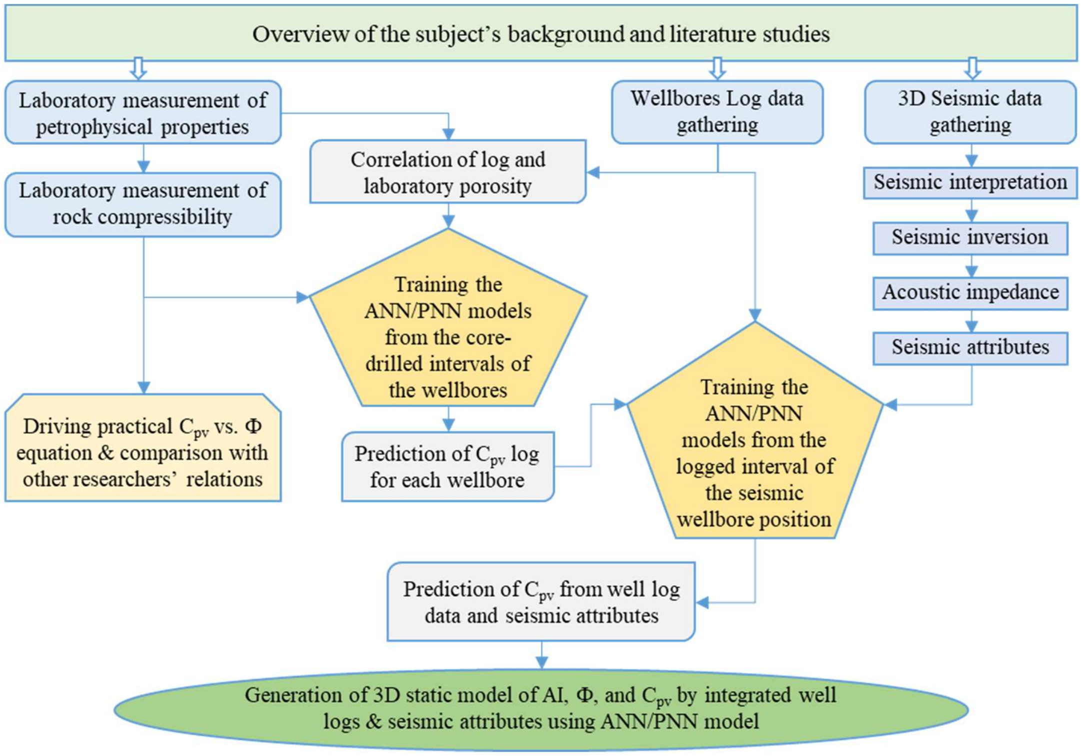

Figure 3. shows the workflow of this study

Using the optimal velocity model, the depth map of the horizons of the studied formations was determined. The workflow to prepare the seismic inversion includes seismic data averaging at sea level, data processing to reduce noise, velocity analysis, seismic data conversion to velocity model, and processing output data with XY coordinates in tracking headers. The generated C_{pv} logs were utilized to train the ANN and PNN models from the logged intervals in the seismic wellbore positions. Then, the C_{pv} values were predicted from well log data and seismic attributes.

An acoustic impedance model was developed around the seismic line and seismic interpreted horizons. The horizons define the model's geometry, while the well logs control the acoustic impedance values of each layer. To create attributes of the seismic data at the well site, the optimal correlation and error between the generated attributes and the target were evaluated. The seismic attributes were calculated from seismic amplitudes, including amplitude envelope, instantaneous frequency, instantaneous cosine phase, amplitude weighted cosine phase, weighted amplitude frequency, weighted amplitude-phase, and apparent polarity. Derivative attributes include derivative, derivative instantaneous amplitude, and second derivative. Also, they are instantaneous domain, quadratic and time attributes, etc. Finally, 3-D maps of C_{pv}, acoustic impedance (AI), and porosity were generated.

Experimental C_{pv}–ϕ relationships

Many researchers have studied the experimental relationships of compressibility, mainly versus porosity (Farahani et al., 2022). For example, Horne (1990) proposed some correlations for calculating C_{pv} based on initial porosity for limestone, consolidated, and unconsolidated sandstone rocks. Equation 1 represents a correlation for carbonate rocks.

$$C_{pv} = exp(4.026 - 23.07\phi + 44.28\phi^2) \times 6.9 \times 10^{-9}\ Mpa - 1 \quad (1)$$

Jalalh (2006a, b) investigated compressibility up to a pressure of 69Mpa at room temperature and 52°C. He showed that compressibility increases with increasing temperature and concluded that C_{pv} increases as porosity decreases.

$$C_{pv} = \left(\frac{1}{1.022^{-2} + 1.681^{-2}(\phi)^{1.05}}\right) \times 6.9 \times 10^{-9}\ MPa^{-1} \tag{2}$$

Akhoundzadeh et al. (2011) reported a C_{pv} of 18 to 71.7 $\times 10^{-9}$ Mpa^{-1} for limestone samples. They developed a robust correlation with porosity (Equation 3).

$$C_{pv} = \left(\frac{1}{0.367 + 0.099Ln(\phi)}\right) \times 6.9 \times 10^{-9}\ MPa^{-1} \tag{3}$$

In the above equations, C_{pv} is pore volume compressibility and ϕ is porosity fraction. Usually, the number of samples is limited in the experimental studies. Therefore, the proposed equations should be modified with new laboratory data for other reservoirs. So far, the proposed relations were only based on the initial porosity. Farahani et al. (2022) derived an empirical relationship between measured pore compressibility and porosity at each stress step for a carbonate reservoir. They considered the importance of the net stress effect.

Seismic reservoir characterization

Interpretation of seismic reflection data includes stratigraphical and structural interpretation. Seismic interpretation is considered the first step in building a 3D reservoir model (Wu & Hale, 2016). The primary purpose of seismic inversion is an acoustic impedance model that is an acceptable correlation and integration of seismic and well log data, especially density and compressional wave velocity logs. It is directly comparable to the properties of the reservoir. The main goal is to minimize the difference between well measurement data and model and seismic-based datasets (Jia et al., 2023). Seismic data were processed under true amplitude preservation and pre-accumulation time migration from the zero-phase attributes. Both are prerequisites for using inversion technology on seismic data (Schleicher et al., 2007).

The seismic attributes data are employed to visualize the reservoir characterization. Suitable seismic property is directly sensitive to the desired geologic feature or reservoir property. It allows us to define the structural or sedimentary environment (Chopra & Marfurt, 2007). Seismic attributes delineation can be performed on a single time slice or a group of time slices (bulk) of seismic data. Volumetric seismic attributes not only reduce the time required for seismic interpretation but also can eliminate the effect of noise in seismic data (Sahai and Soofi, 2006).

Artificial neural network

The most straightforward and efficient type of neural network is the multilayer perceptron model, which consists of an input layer, one or more hidden layers, and an output layer (Puskarczyk, 2019). Networks provide solutions for model selection, model robustness, validation set selection, validation effort size, and network architecture optimization (Burden & Winkler, 2008). Scaled Conjugate Gradient (SCG) is based upon a class of optimization techniques well known in numerical analysis as the Conjugate Gradient Methods, which is fully automated, including no critical user-dependent parameters (Karimpouli et al., 2023; Møller, 1993). In this study, the LMA technique (Levenberg, 1944; Marquardt, 1963), as a nonlinear least square method belonging to the continuous optimization domain, was used. It minimizes a multivariate function expressed as the sum square of errors (Hajian et al., 2012; Ramadasan et al., 2017). The PNN approach has widely been used as a framework for lithology classification using seismic attributes (Chaki et al., 2022). It uses a class of probability density function estimators that asymptotically approach the underlying parent density, provided that it is smooth and continuous (Soares et al., 1996). PNN was also applied for a more precise prediction. In both ANN and PNN models, 65% of the data were randomly selected for data analysis and training, and the rest for model validation.

Result and discussion

A comparison of C_{pv} of laboratory measurement data and the empirical relationships from other researchers was shown in Fig. 4. Not good compatibility between laboratory measurement data and experimental relationships of other researchers was observed. Therefore, these empirical relations cannot be used to predict the compressibility of the samples of this study.

Generation of C_{pv} log along the wellbore

Density, neutron porosity, and acoustic impedance logs are correlatable with compressibility. By using the ANN and providing these characteristics as input, it is possible to predict the compressibility. The ANN method resulted in a validation coefficient of 76%. By applying the PNN approach, the derived compressibility log data was validated nearly 85% with core measurement data for all the wellbores. To predict and estimate the target in each well, the best data must be selected. Fig. 5 shows the extraction of selected attributes at each well, using the PNN model.

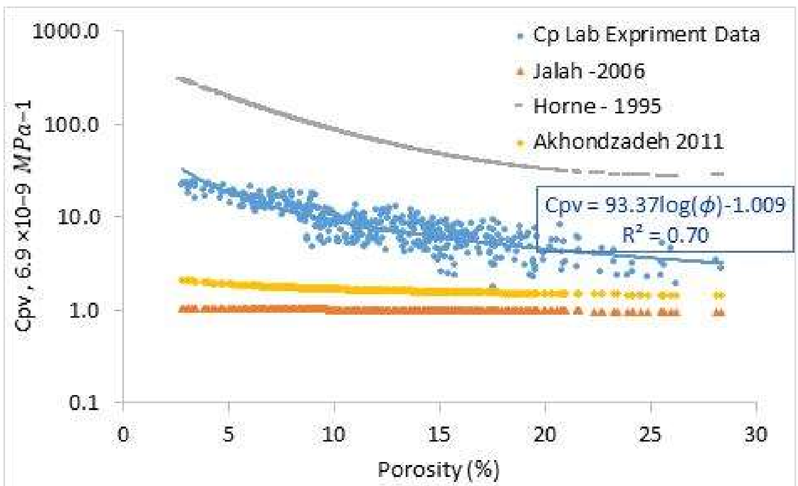

Figure 4. shows pore volume compressibility of laboratory measurement data and experimental relationships, Such as, Horne (1995), Jalalh (2006), and Akhoundzadeh et al. (2011)

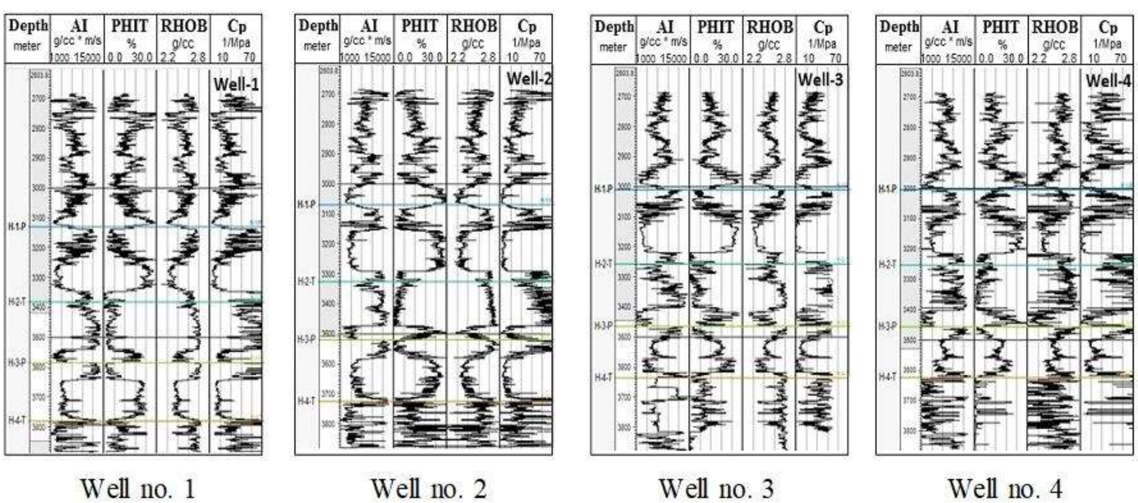

Figure 5. shows the predicted compressibility logs using the PNN approach along the wellbores by selected well attributes (Density, neutron porosity, and acoustic impedance logs)

Prediction of C_{pv} for whole seismic area

In addition to the well logs, seismic characteristics at the well position can be used to predict compressibility for the whole seismic area. Various attributes of the seismic cube data were used to find the optimal correlation and error between the generated characteristics and the targets. Fig. 6 shows that an optimal number of attributes was used to estimate compressibility with minimum error.

Using the seismic attributes at the wellbore position and C_{pv} logs, the C_{pv} values were predicted. Fig. 7 shows the acoustic impedance (AI) log versus predicted acoustic impedance (AI) from seismic attributes at each well data, applying ANN model.

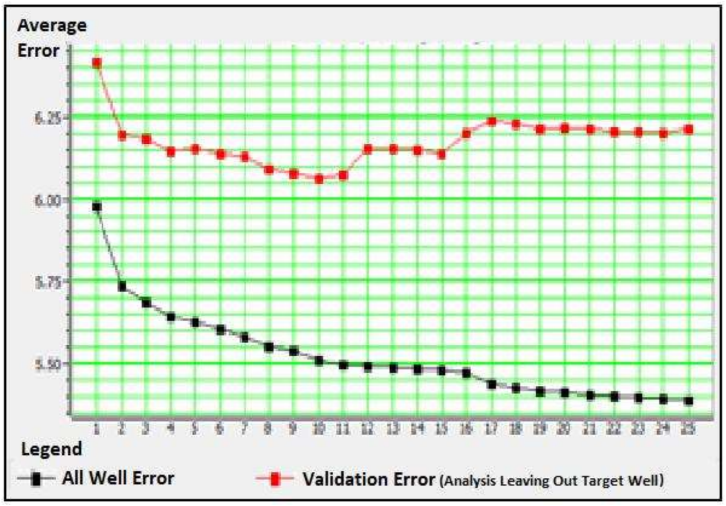

Figure 6. shows the optimal number of attributes used to estimate compressibility with minimum error

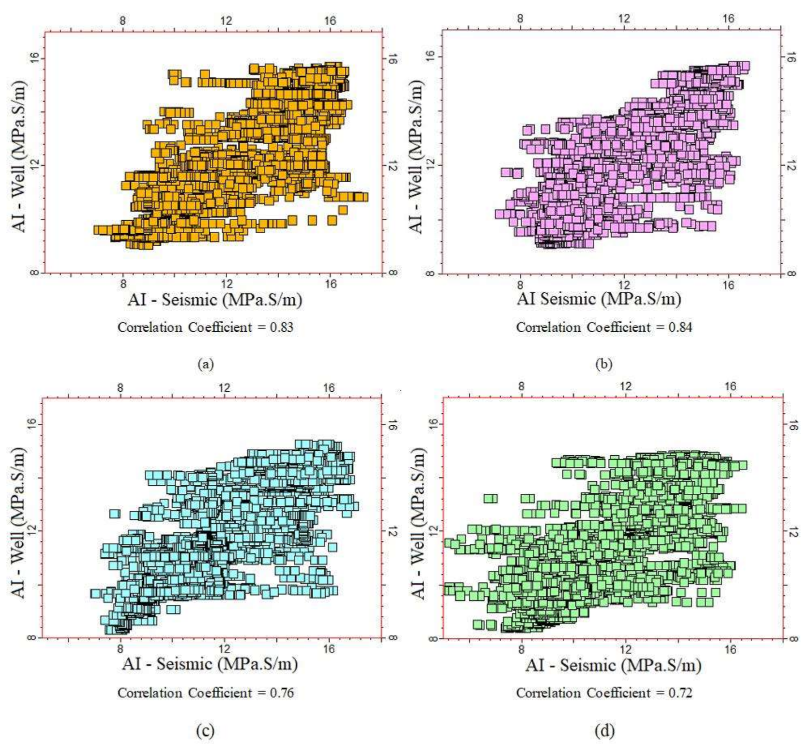

Figure 7. shows the acoustic impedance (AI) log versus predicted acoustic impedance (AI) from seismic attributes at each well data, applying ANN model

Fig. 8 shows the C_{pv} logs versus predicted C_{pv} by seismic attributes. The ANN approach was used for training and validation. The correlation coefficients of validation data were ranging from 0.7 to 0.81.

Similar to ANN approach, the same optimal number of attributes were used for PNN approach. Fig. 9 shows the correlation between predicted compressibility and the actual compressibility of the wells with coefficients ranging from 0.96 to 0.99%. Fig. 10 typically shows the high accuracy of the model and the optimal choice of PPN algorithm.

Using petrophysical and seismic data along the well-axis and neural network algorithms, reservoir parameters can be expanded along the seismic sections. Fig. 11 shows the predicted acoustic impedance, porosity, and compressibility in a cross-section across the wellbores in the Bangestan group. The PNN approach was used as it resulted in higher correlation coefficients than the ANN approach. Fig. 12 shows the prediction of the acoustic impedance, porosity, and compressibility data in the 3-D seismic volume. The proposed approach assists in a more accurate prediction of the well position from a 3-D map.

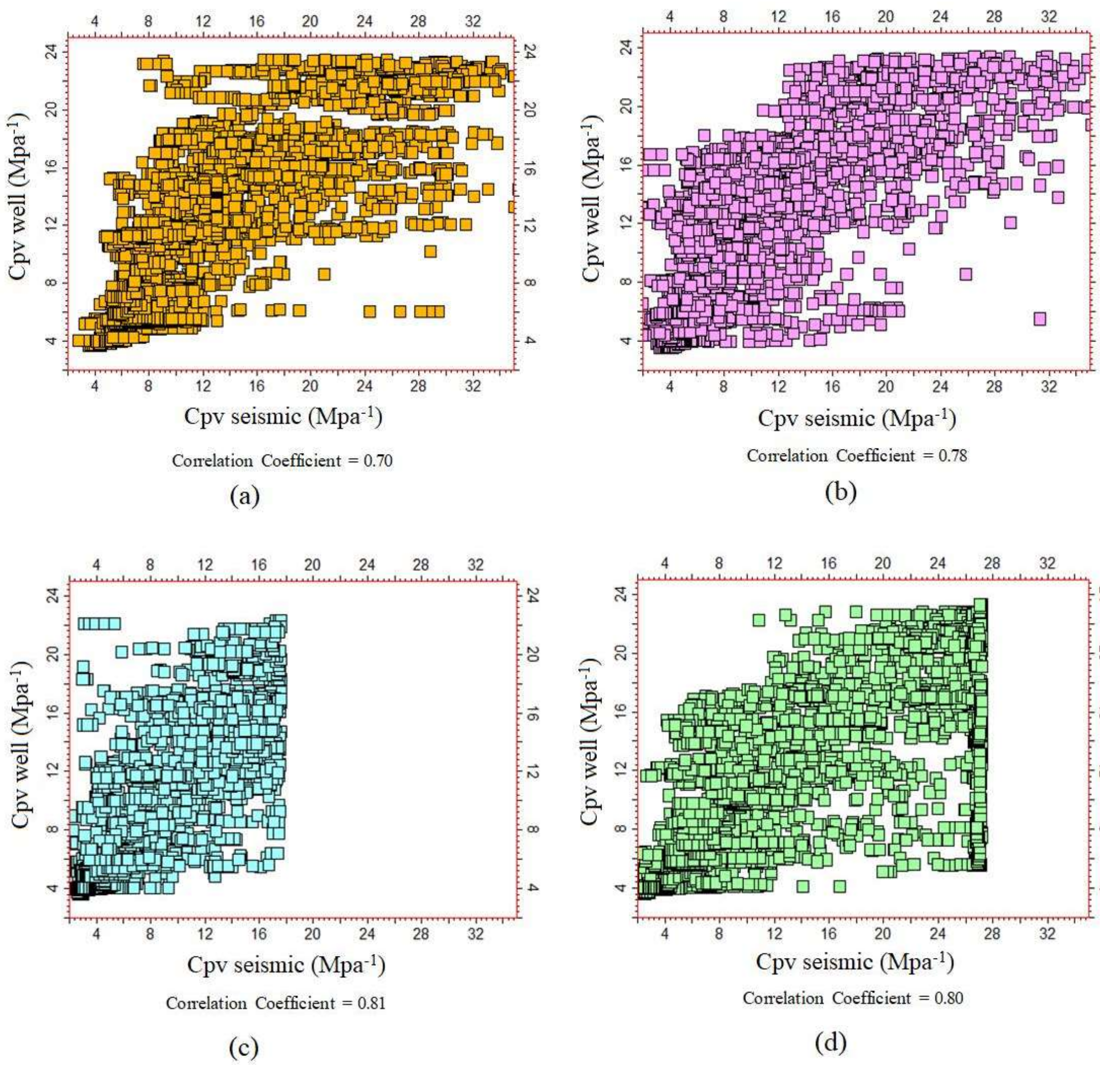

Figure 8. shows the C_{pv} log versus predicted C_{pv} from seismic attributes at each well data, applying ANN model

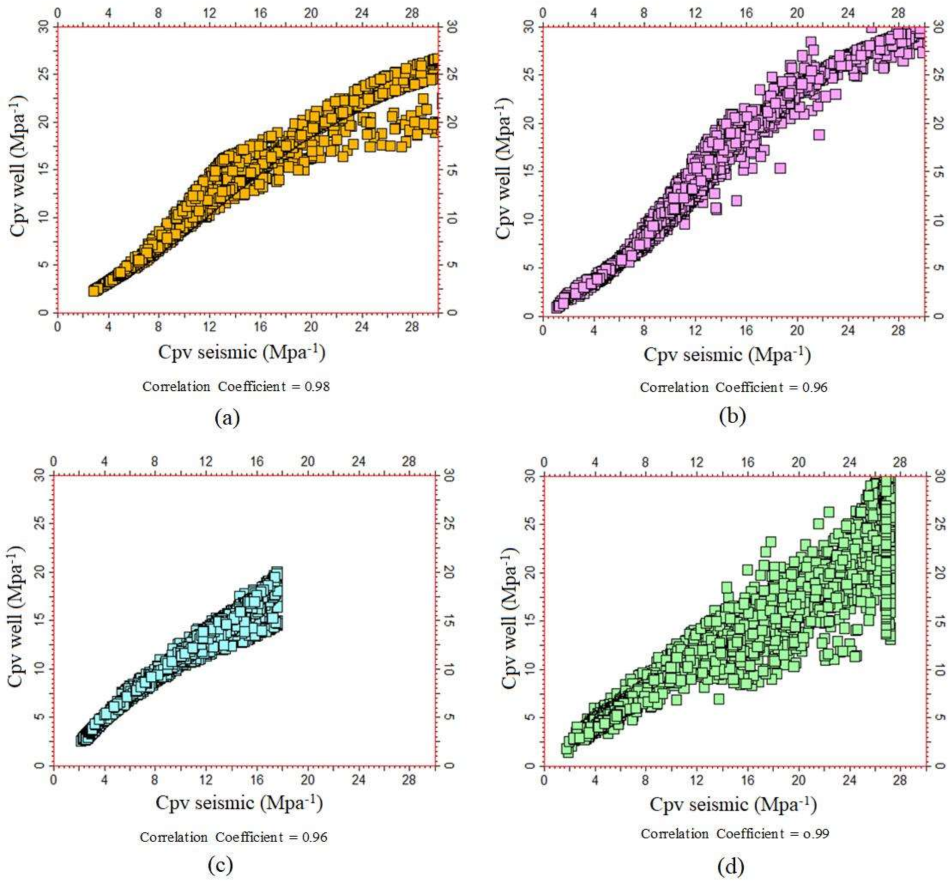

Figure 9. shows the C_{pv} log versus predicted C_{pv} from seismic attributes at each well data, applying PNN model. The correlation coefficient and equations were presented for each wellbore

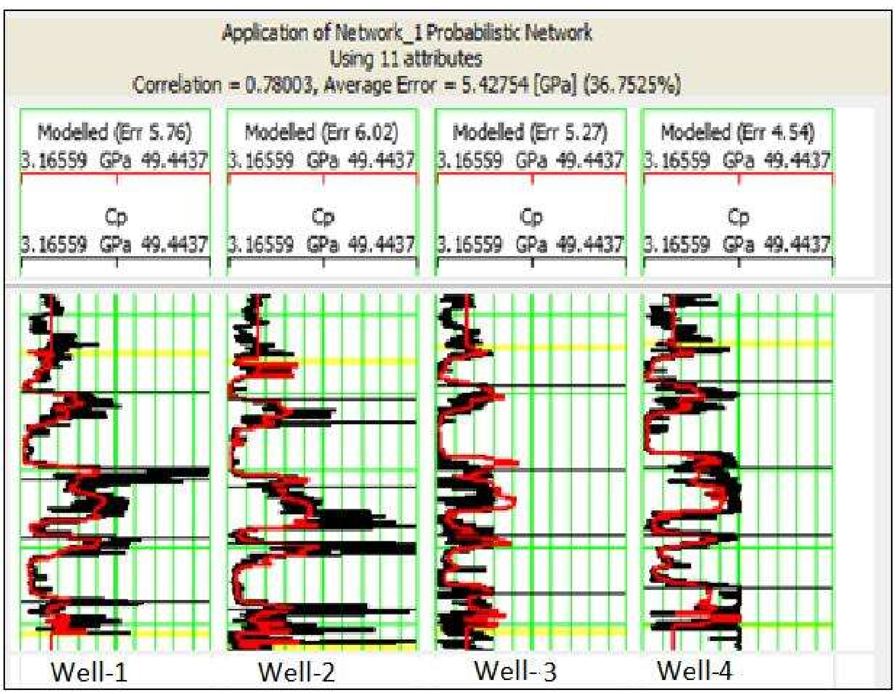

Figure 10. shows the application of PNN model (curve in red color) in predicting the compressibility parameter in all selected wells

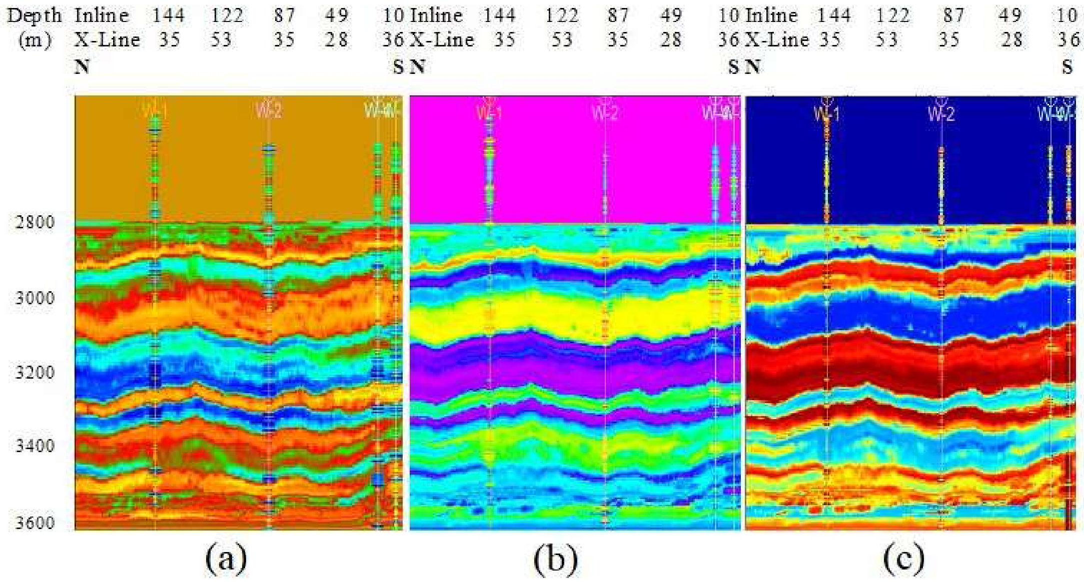

Figure 11. shows acoustic impedance (a), porosity (b), and compressibility (c) across the axis of four wells in the Bangestan group (from 2800 to 3600 m), SW of Iran

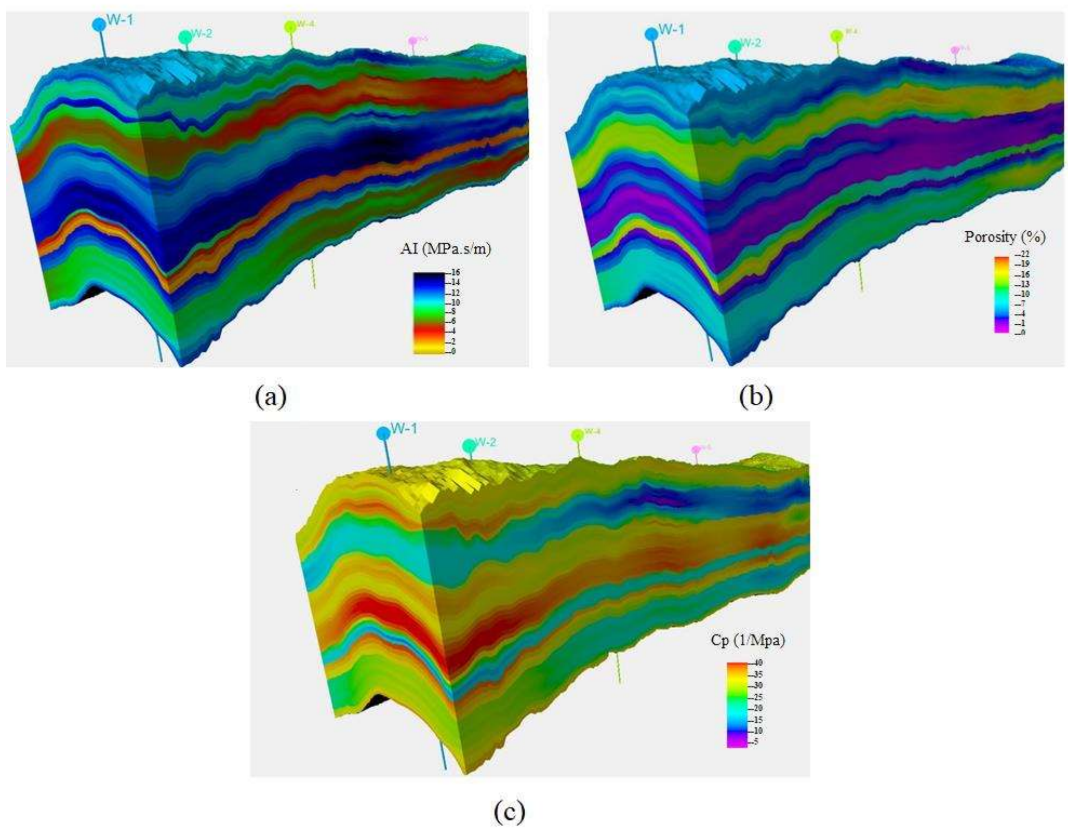

Figure 12. shows the 3-D static model of (a): Acoustic Impedance, (b): Porosity, and (c): Compressibility in intersection with four studied wells

Conclusions

In this study, the compressibility estimation was investigated and predicted using the core measurement results, and input attributes of the well logs and seismic via neural network. The following conclusions have been derived:

There is a good relationship between measured compressibility versus porosity and a semi-log equation was derived. However, the experimental relationships of other researchers cannot meet the expectations of a correct prediction for other reservoirs.

An extensive database containing a limited quantity of core samples yielded successful prediction of compressibility logs for the whole seismic area with a correlation coefficient of 70 to 80% between predicted and measured compressibility. This approach is recommended for reservoir zones with no core or low core recovery.

PNN can result in a better correlation than artificial one (91 – 99% in comparison with 70 – 81%), which is due to taking into account the most reliable data points than all the data that are used in ANN.

Using the 3-D compressibility static model, one can infer the variation of compressibility through the area and it can assist in well planning. Similarly, 3-D static models of porosity and acoustic impedance of the study zone can be generated.

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Statements and Declarations

Competing Interests: The authors have no competing interests to declare that are relevant to the content of this article.

Nomenclature

Parameters

3D: Three-Dimensional

AI: Acoustic Impedance

ANN: Artificial Neural Network

BRANN: Bayesian Regularization Artificial Neural Network

C_{pv}: Pore Volume Compressibility

LMA: Levenberg and Marquardt Artificial

PNN: Probabilistic Neural Network

SCG: Scaled Conjugate Gradient

V_p: Pore Volume

Greek letters

Φ: Porosity

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