Journal of the Earth and Space Physics, Vol. 47, No. 4, Winter 2022, P. 133-141 (Research)

DOI: 10.22059/JESPHYS.2022.331894.1007370

ANFIS Rules Driven Integrated Seismic and Petrophysical Facies Analysis

Mirzakhanian, M.[1] and Hashemi, H.[2*]

1. Ph.D. Student, Department of Earth Physics, Institute of Geophysics, University of Tehran, Tehran, Iran
2. Assistant Professor, Department of Earth Physics, Institute of Geophysics, University of Tehran, Tehran, Iran

(Received: 17 Oct 2021, Accepted: 10 Jan 2022)

Abstract
Different learning methods have been used to recognize seismic facies and reservoir characterization using seismic attributes. One of the significant issues in automatic facies analysis is to relate the seismic data to facies properties using the well data. According to previous studies, the role of attributes is more significant than the learning method for automatic classification. The proposed method uses supervised selection of seismic attributes for automatic facies analysis.
Extended Elastic Impedances (EEI) at different angles as seismic attributes are being increasingly utilized in both seismic facies analysis and reservoir characterization. They are representative of elastic parameters of rocks appropriately. In the presented method, proper EEI seismic attributes are selected after a feasibility study using petro-physical logs, and EEI template analysis of the well data. Adaptive Neuro-Fuzzy Inference System (ANFIS) is applied to the fuzzy coded data of the well facies to train an automatic model to predict facies from the seismic data. Subsequently, the same particular EEI attributes are prepared. The EEI attributes from the seismic data are inputs for the trained ANIFIS model to perform seismic facies analysis. In this method, the seismic facies and the well facies are compatible. Only one well data can be sufficient for the well analysis stage and well facies clustering.
The proposed method is applied on 3D prestack seismic data located in Abadan plain to discriminate hydrocarbon interval of Sarvak Formation. The results reveal that the supervised selection of attributes and fuzzy concepts present remarkable ability in dealing with imprecise seismic facies analysis and reservoir characterization.

Keywords: Seismic attributes; Extended elastic impedance; Facies analysis; Adaptive neuro-fuzzy inference system.

1. Introduction
Seismic data are used to identify the lateral changes of geology layer and reservoir properties (Brown, 2011). Seismic attributes are representative of elastic and petrophysical properties of earth layers. Automatic learning techniques can extract the relation between seismic facies and seismic attributes (Hashemi et al., 2008; Hashemi and de Beukelaar, 2017; Hadiloo et al., 2017; Wang et al., 2017; Wrona, 2018).
Automatic seismic facies analysis includes two main steps. One is selecting efficient seismic attributes, and the other is employing an appropriate classification method. Different classification methods have been applied to seismic attributes to classify the seismic facies with various degrees of success (Zhao et al., 2015; Wrona et al., 2018). According to the results, the role of seismic attributes in seismic facies analysis is more significant than the choice of classification method (Barnes and Laughlin, 2002). Among different seismic attributes, prestack ones such as Extended Elastic Impedance (EEI) attributes are more powerful to discriminate elastic parameters of rocks, as they have also knowledge of shear velocity inside them. EEI attributes play a vital role in quantitative seismic interpretation. Each EEI attribute can be proportional to a particular reservoir property (Whitcombe et al., 2002; Mirzakhanian et al., 2015, Sharifi et al., 2019; Sharifi and Mirzakhanian, 2019).
Seismic data are inherently infected with a degree of uncertainty and imprecision that certainly affects the results of seismic facies analysis. An approach to tackle this problem is the fuzzy logic, as it performs prosperous in handling uncertainty (Nikravesh et al., 2003; Khemchandani et al., 2016; Liu et al., 2019). A fuzzy clustering algorithm can separate the data into overlapping classes by assigning membership functions to each data sample to indicate the underlying structures of data samples. Aminzadeh and de Groot (2004 and 2006) discussed the application of the fuzzy logic in geosciences. Hashemi et al.

*Corresponding author: hashemy@ut.ac.ir

(2008) presented a new technique based on the unsupervised clustering with a fuzzy clustering algorithm to detect the random seismic noise.

Anand et al. (2018) used a fuzzy C-means (FCM) clustering to create fuzzy constrained inversion to improve the result of the resistivity inversion. Hadiloo et al. (2018) compared the unsupervised and supervised fuzzy clustering in seismic facies classification. ANFIS integrates both neural networks and fuzzy logic principles. Therefore, it has the benefits of the both in a single framework. A fuzzy inference system by using fuzzy rules in the form of "If-Then rules" can promote the result of the seismic classification (Zarei and Hashemi, 2019; Hadiloo et al., 2018).

In this study, an innovative method is used for supervised selection of seismic attributes to analyze the well facies. Supervised selection has a traditional meaning based on classifiers, but in this paper, the focus is finding the most relevant attributes in the middle of classification in FIS structure. FCM clustering is used to cluster the selected EEI attributes and separate the well facies. ANFIS uses the fuzzy labeled facies to provide a trained classification model based on a fuzzy inference system. The trained ANFIS model is applied to selected seismic EEI attributes to predict seismic facies. Supervised selection has a traditional meaning based on classifiers, but in this paper, the focus is on finding the most relevant attributes in the middle of classification in FIS structure.

The method was applied to a small part of 3D seismic data located in the Abadan plain to delineate the hydrocarbon distribution. The studied interval is related to Sarvak Formation as a part of Bangestan group. The late Albian–early Turonian Sarvak formation is the most significant carbonate reservoir of the Abadan Plain, southwest of Iran. The primitive EEI template analysis, essential to select supervised and effective attribute, was performed using one well data with shear velocity. The results reveal the method provided accurate and reliable seismic facies analysis. It is due to the efficiency of selected attributes and the interpreter's direct monitoring of the fuzzy rules to control the output facies of the fuzzy system.

2. Theory and Methods

Whitcombe (2002) introduced R_{EEI} (χ) or EEI reflectivity as a modified two-term linearized Zoeppritz equation's (1919) as the following:

$$R_{EEI}(\chi) = A\cos\chi + B\sin\chi. \tag{1}$$

where parameters A and B are intercept and gradient. The Chi parameter (i.e. χ) is a theoretical incident angle that varies between -90 and 90 degrees. By introducing some reference constants, he obtained the normalized dimensionless impedance values for all 181 angles. Therefore, a new-scaled formula equivalent of EI (Connolly, 1999) was developed to have a new parameter called the EEI.

$$\mathrm{EEI}(\chi) = \overline{V_P}\bar{\rho}\left[\left(\frac{V_P}{\overline{V_P}}\right)^a\left(\frac{V_S}{\overline{V_S}}\right)^b\left(\frac{\rho}{\bar{\rho}}\right)^c\right] \tag{2}$$

where,

$a = \cos\chi + \sin\chi \quad b = -8K\sin\chi$, and

$c = cos\chi - 4K\,sin\chi$ and $K = \left(\frac{V_S}{V_P}\right)^2$

EEI analysis by computing the impedance values beyond the physically observed range of actual incident angles is beneficial to discriminate different lithologies and fluid types. V_P , V_S and ρ are p-wave, s-wave and density parameters respectively. Their averages are also shown with a bar above. EEI attributes are representative of elastic and petrophysical properties of rocks (Whitcombe et al., 2002; Mirzakhanian et al., 2015; Yenwongfai et al., 2017; Sharifi et al., 2019). Sharifi and Mirzakhanian (2019) innovated the full-angle extended elastic impedance to indicate the fluid type in a carbonate reservoir by rock physics templates.

Fuzzy concepts and soft computing have a remarkable ability in dealing with the seismic and well data uncertainty. The fuzzy approach separates the data samples into overlapping groups according to their membership degrees. The fuzzy version of the k-means algorithm is introduced as FCM. The method considers membership degrees for each sample of the data set. The FCM algorithm attempts to cluster samples of the data concerning similarities and dissimilarities defined by some criterion. The FCM algorithm in an iterative scheme improves the sequence steps of clusters (Wang and Zheng, 2007). FCM depends hardly on the randomly initialized values, which are updated iteratively. The FCM algorithm differentiates clusters of the same size and shape because the distance norm is often Euclidean norm.

ANFIS is a supervised classification method. The interpreter can monitor the contribution of seismic attributes in fuzzy rules and output facies from the aggregation of different rules. An ANFIS is a kind of artificial neural network that is based on the Sugeno fuzzy inference system. It integrates both neural networks and fuzzy logic principles. Therefore, it has the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have the learning capability to approximate nonlinear functions. The architecture of ANFIS is composed of five layers. The first layer, fuzzification, takes the input values and determines the membership functions belonging to them. The second layer, as the rule layer, is responsible for generating or firing strengths for the rules and rule implications. The role of the third layer is to normalize the computed firing strengths. The fourth layer is aggregation. The last layer returns the defuzzified final output.

In this study, the role of supervised selection of EEI attributes and a trained ANFIS model by the well facies in seismic facies analysis is evaluated. Figure 1 presents the flow diagram of the study.

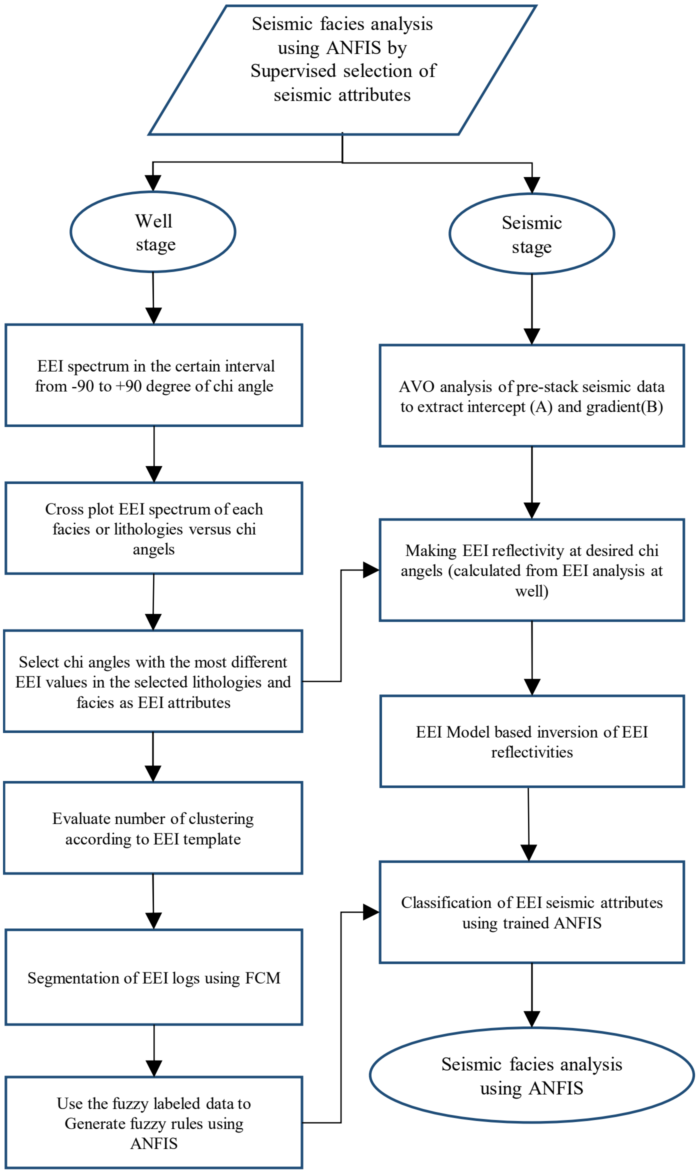

Figure 1. The workflow of the methodology. Seismic stage starts after the feasibility analysis of the well data.

In the well stage, the EEI of the studied interval is built using Equation (2). The variations of EEI logs versus χ angles ($-90°$ to $+90°$) at certain intervals of the reservoir are analyzed using petrophysical logs. Then, the EEI of each specific facies is demonstrated in a plot in the form of EEI amplitude versus χ angles as EEI template. Certain χ angles at which EEI values are the most differentiated for different facies are selected. Selected EEI logs are segmented into the significant units where each unit represents a unique facies in the studied interval, using FCM clustering. ANFIS system is applied on the prepared fuzzy labeled data to train a classification model to predict seismic facies. The seismic EEI attributes are extracted from prestack seismic data. The Intercept and Gradient from AVO analysis are used to calculate the certain EEI (χ) reflectivity data sets (Equation 1), dictated from the well analysis stage. Then, EEI inversion is applied to each EEI reflectivity to have a related EEI seismic attribute. The prepared EEI seismic attributes are input features of the trained ANFIS model to analyze seismic facies and reservoir characterization.

In this work, the clustering of the well data is performed using selected EEI logs (based on EEI template analysis) in order to label the well facies. Then the well facies distribute to the seismic data using EEI attributes extracted from pre-stack seismic data.

The results of seismic facies using the trained ANFIS model provide valid seismic facies comparable with log facies. The contribution of interpreter knowledge in the whole stages of attribute selection, rule implication, and facies analysis of the algorithm is the main achievement to improve the results of seismic facies analysis. According to the flowchart, the clustering starts from the well stage analysis, and only one well data is available for this study. Therefore, the well is required to cover all lithology. However, the chance of having all lithology columns in a well is slim for some cases. For example, the fluid content may change in the reservoir. The solution to mitigate this problem is the rock physics modeling, which provides the opportunity to provide different scenarios of the reservoir. In the proposed method, the facies are discriminated at the well according to the analysis of petro-physical logs and the selected EEI (χ) logs simultaneously to label the facies using FCM. Then similar EEI (χ) attributes are extracted from the seismic data to distribute well facies to seismic data using the trained ANFIS system. This technique brings a common perspective in facies analysis between geologists and geophysicist. Geophysicist are familiar with seismic attributes while for the geologists the well logs and core data are the main tools for facies discrimination. In this method, at the well analysis stage, the connection between the petro-physical well logs and seismic attributes is established. In previous methods, the facies were separated according to the petrophysical well logs, and then in a separate phase, the seismic attributes were selected to perform seismic facies analysis. The selection of appropriate attributes was also another challenge. However, in this method, the relation between facies, the well logs, and seismic attributes is determined in the well analysis stage, simultaneously.

3. Case study

The studied area is a carbonate oilfield in the Abadan Plain (southwest of Iran). The aim is to discriminate the hydrocarbon layer of Sarvak formation as a part of Bangestan Group. The carbonate reservoirs of the Bangestan group include Sarvak and Ilam formations. Sarvak is composed of limestone with different porosity and thin layers of shale. The Laffan shale covers Sarvak. Laffan shale is overlaid by carbonates of Ilam formation.

The study is performed on a small section of 3D seismic survey that included prestack normal move-out-corrected offset gathers. The sample rate of data acquisition is 4 ms with inline and crossline intervals of 25m and a fold coverage of 78. The seismic gathers are converted to intercept and gradient data sets performing AVO analysis. For this study, only one well in oil-bearing zones of Sarvak is available for EEI template analysis. The check-shot, density, compressional and shear velocities logs are available as well as petrophysical logs.

3-1. EEI template analysis and log data clustering

Seismic data interpreters are interested in performing seismic facies analysis comparable with the well facies. For this reason, we decided to select EEI attributes. They are significant representatives of elastic parameters of the earth layers, and they can be calculated according to the well data and extracted from the seismic data. According to the workflow (Figure 1), the analysis starts from a feasibility study at the well A-1. The EEI section is built by measured density, compressional and shears velocities logs, according to Equation (2) with the sampling rate of 0.2 m (Figure 2).

To determine the appropriate EEI attributes, the EEIs belonged to the certain facies (according to Gamma-ray, density, water-saturation and neutron porosity logs, considering the knowledge of geologist and oil engineer experts) are selected and plotted in the same chart. Figure 3 shows the EEIs related to shale, hydrocarbon limestone, and brine limestone with different porosity. According to the figure the trend of EEI values for each lithology is different from the others. This difference is more significant in some angles. For instance, shale and oil-bearing layers with lower porosity are of high contrast. However, EEIs of carbonate intervals with higher porosity for oil and water content are the same. Therefore, the separation of these two intervals is more challenging than the others are.

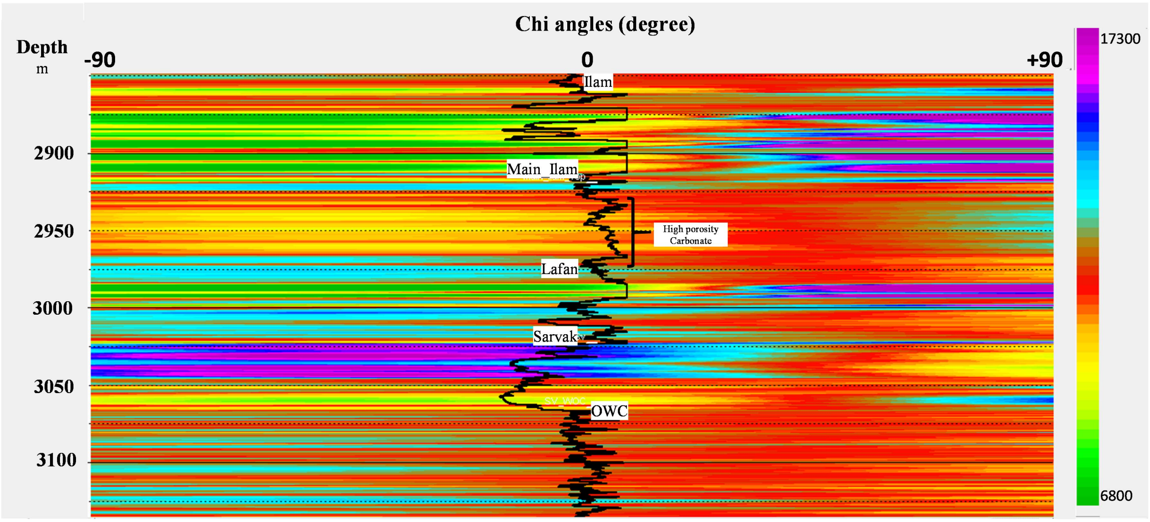

Figure 2. The EEI at the studied interval of Bangestan group, for χ angles ranging from -90 to +90 degree at the well A-1. The color scale shows EEI value in (ft/s.g/cm^3). The black log at 0 degree is water saturation.

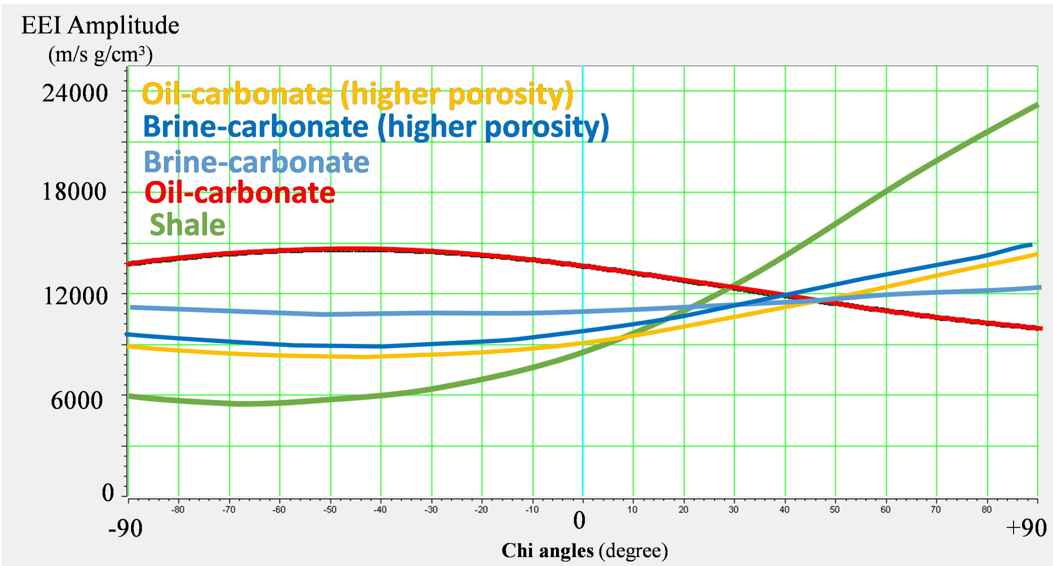

Figure 3. EEI values changes from -90 to +90 degree of χ angle for different lithologies and fluid contents at well A-1.

Finally, EEI logs related to χ angles of (-40) and (+90) degrees are selected as the optimum attributes. Selected EEI logs in the EEI analysis stage are input features for fuzzy k-means clustering of the well data. The number of cluster is an essential input of the clustering algorithm that must be identified in advance. According to geology knowledge about the main lithology of Sarvak, the numbers six to four are selected for the number of clusters. Finally, according to the EEI template analysis and results of each clustering run, the number four is chosen as the optimum number of clusters. The result of FCM clustering of selected EEI logs from the well analysis stage is presented in Figure 5. For example, the shale with high values of water saturation and CGR and low values of effective porosity is indicated by green color.

3-2. FIS generation using ANFIS

In this stage, the fuzzy segmented data from the previous stage is used as input to train an ANFIS system. To assess the algorithm's accuracy, the database is subdivided into 70% and 30% training and test datasets, respectively. In the learning algorithms, the training data is used to construct the classifier, while the testing data is employed for its evaluation. Then, the algorithm is developed based on Fuzzy Inference Systems (FIS), by using fuzzy rules in the form of If-Then to perform seismic facies analysis automatically (Table 1). The table indicates the contribution of each attribute for each rule that resulted in certain facies.

The output of this step is the appropriate FIS for seismic facies identification. For this step, the number of rules is selected more than the number of clusters from well segmentation. Initially, the FIS generation started from six clusters. Then after monitoring the effect of different rules, according to the interpreter's recognition, the redundant rules were gradually removed. Eventually, the optimum FIS, with four clusters/rules, is obtained with the best performance for seismic facies recognition (Figure 4). In another word, the ANFIS creates a new opportunity to investigate the application of rules and attributes for seismic facies analysis, in which the interpreter can select helpful rules.

In Figure 4, the red line indicates the value of each attribute and the resulted output is facies 3. The Gaussian curves show the membership functions. It should be noted that the geometry and position of each membership function is also optimized during the rule generation process. Other parameters of the solution are also updated by using an adaptive neuro network. The output of this step is the appropriate FIS for seismic facies analysis.

Table 1. Asymptotic relevant Fuzzy if-then rules comes from EEI template analysis.

If	and	then
EEI (-40) is low	EEI (+90) is high	The facies is shale
EEI (-40) is high	EEI (+90) is low	The facies is oil carbonate with medium porosity
EEI (-40) is medium, higher than shale range	EEI(+90) is medium, lower than shale range	The facies is oil carbonate with higher porosity
EEI (-40) is medium, the same as oil carbonate with higher porosity	EEI (+90) is medium, the same as oil carbonate with higher porosity	The facies is brine carbonate with higher porosity
EEI (-40) is medium, but higher than brine / oil carbonate with higher porosity	EEI (+90) is medium, but lower than brine /oil carbonate with higher porosity	The facies is brine carbonate with medium porosity

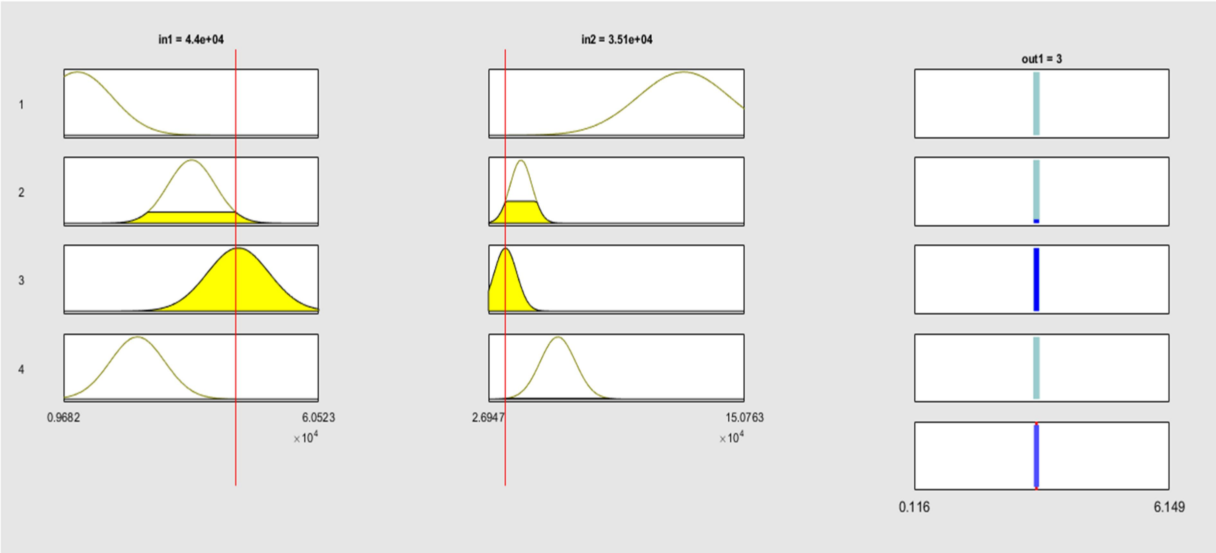

Figure 4. The rule generation with four clusters using ANFIS. The system-generated rules from two selected input attributes for FCM clustering.

3-3. Seismic EEI attribute preparation and seismic facies analysis

According to the EEI template analysis performed in the well stage, two χ angles (-40° and +90°) are chosen. The EEI reflectivity data sets related to these certain angles are built, having intercept and gradient from AVO analysis (Equation 1). To invert EEI reflectivity data to elastic impedance data, well to seismic correlation, making a Low-Frequency Model (LFM) and extracting related wavelets have been performed. Finally, EEI inversion is conducted on each EEI reflectivity (for EEI inversion, readers are recommended to study Sharifi and Mirzakhanian, 2019). The output of each inversion run is EEI data for a certain angle (EEI (-40) or EEI (+90)). Then, seismic facies analysis is performed by using the ANFIS model generated from the previous stage. Figure 5 shows the seismic facies resulted from the algorithm. The similarity of the well facies and seismic facies is addressed in this figure. The oil-bearing layer is clearly identified in the facies section by red color. The shale intervals in the section are also indicated by green color and correlated with the well facies.

4. Discussion

The algorithm starts from the well facies analysis and distributes the well facies to the seismic data. The EEI logs are calculated directly from measured logs (Vp, Vs and rho) and χ angles (Equation 2). Then, the more efficient ones are selected by EEI template analysis. However, EEI seismic attributes are extracted from prestack seismic data, using AVO attributes (Intercept and Gradient) to calculate EEI reflectivity (Equation 1) and EEI inversion. As the methods of EEI calculation from the well data and seismic data were different, the high degree of correlation between the well and seismic facies indicates the potential of the proposed method in seismic facies analysis comparable with the well facies.

According to the EEI template, the EEIs of higher porosity carbonate for oil and water content are highly similar. This similarity caused difficulty in discriminating between these two facies in the well. In addition, the seismic resolution could not distinguish oil-bearing carbonate interval with higher porosity, as the thickness of this layer is about 10 m.

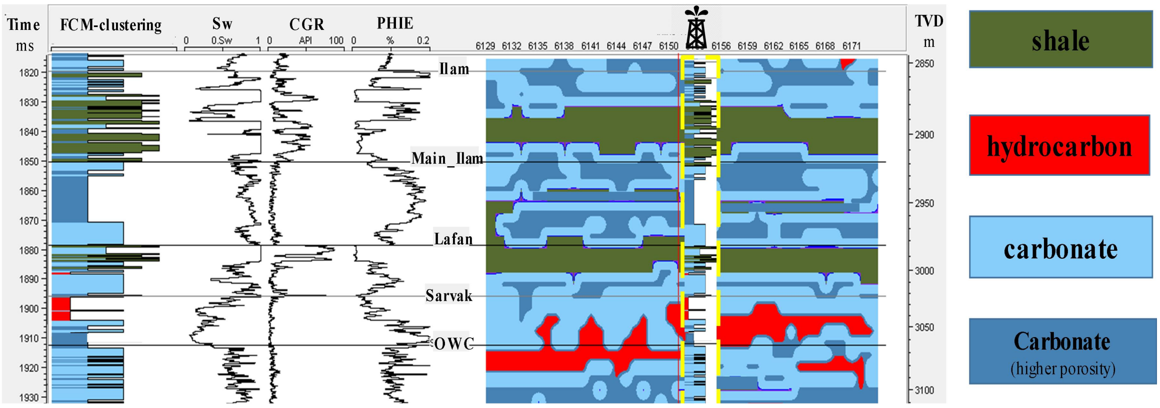

Figure 5. From left to right there are facies log resulted from FCM clustering of EEI logs, water saturation log, CGR log, effective porosity log, and finally, the seismic facies section resulted from proposed algorithm. The seismic facies is comparable with the well facies and core data.

5. Conclusion

The seismic facies analysis is an unsupervised learning method. In previous works, the physical relationship between the well facies and seismic facies was challenging. On the other hand, the selection of efficient seismic attributes has an essential role in facies recognition. This paper presents an innovative method for supervised selection of seismic attributes. The EEI attributes are representative of elastic and petro-elastic properties of earth layers. They are prestack seismic attributes with knowledge of shear velocity inside them. The analysis of the EEI template using only one well with shear information leads to selecting efficient attributes. In the presented method, the selected EEI logs/attributes are segmented to recognize different facies of the well data using FCM. An adaptive neuro-fuzzy system uses the fuzzy labeled data from the well analysis stage to generate FIS and train an ANFIS model. The trained ANFIS model classifies different seismic facies by extracting specific EEI attributes from prestack seismic data. Fuzzy concepts present an appropriate tool to mitigate the uncertainty integrated with the well and seismic data. The seismic facies analysis from this workflow is comparable with segmented facies of the well data. It is a valuable achievement in comprehensive and interpretable seismic facies analysis according to the well facies. In this method, only one well data can be sufficient for seismic facies analysis. This approach is of high importance in exploration fields with a limited number of wells. The method can be applicable for different reservoirs and lithologies after a feasibility study of EEI template analysis.

6. Data and materials availability

The National Iranian oil company provided data associated with this research. It is confidential and cannot be released. Only one well data and a small section of prestack seismic data are available.

References

Anand, S., Shashi Prakash, Sh., Irfan, A. and Vikas Chand, B., 2018, Fuzzy constrained Lp-norm inversion of direct current resistivity data, Geophysics, 83(1), E11-E24, https://doi.org/10.1190/geo2017-0040.1.

Aminzadeh, F. and de Groot, P., 2004, Soft Computing for qualitative and quantitative seismic object and reservoir property prediction, Part 1: Neural Network Applications: First Break, 22 (April), 49–54.

Aminzadeh, F. and de Groot, P., 2006, Neural networks and other soft computing techniques with applications in the oil industry: EAGE Publication BV, Houten, 161.

Barnes, A. E. and Laughlin, K. J., 2002, Investigation of methods for unsupervised classification of seismic data, 72nd Annual International Meeting, SEG, Expanded Abstracts, 2221- 2224.

Brown A. R., 2011, Interpretation of three-dimensional seismic data: Society of Exploration Geophysicists and American Association of Petroleum Geologists, 103–156.

Hadiloo, S., Hashemi, H., Mirzaei, S. and Beiranvand, B., 2017, SeisART software: seismic facies analysis by contributing interpreter and computer, Arabian Journal of Geosciences, 10(23), 519.

Connolly, P., 1999, Elastic impedance: The Leading Edge, 18, 438-452.

Hadiloo, S., Mirzaei, S., Hashemi, H. and Beiranvand, B., 2018, Comparison between unsupervised and supervised fuzzy clustering method in interactive mode to obtain the best result for extract subtle patterns from seismic facies maps, Geopersia, 8(1), 27-34.

Hashemi, H., Javaherian, A. and Babuska, R., 2008, A semi-supervised method to detect seismic random noise with fuzzy GK clustering, Journal of Geophysics and Engineering, 5, 457-468.

Hashemi, H. and Beukelaar, P., 2017, Clustering seismic datasets for optimized facies analysis using a SSCSOM technique, 79th EAGE Conference and Exhibition, Paris, France, 12-15 June, https://doi.org/10.3997/2214-4609. 201700916.

Khemchandani, R., Pah, A. and Chandra, S., 2016, Fuzzy least squares twin support vector clustering, Neural comput. and Applic, 10.1007/s00521-016-2468-4.

Liu, L., Liu, Y. J. and Tong, Sh., 2019, Fuzzy-Based Multierror Constraint Control for Switched Nonlinear Systems and Its Applications, IEEE Transactions on Fuzzy Systems, 27(8), 1519-1531.

Mirzakhanian, M., Khoshdel, H., Asnaashar, A. and Sokooti, R., 2015, Reservoir Discrimination Using EEI Analysis, 77th EAGE conference and Exhibition, Madrid, Spain.

Nikravesh, M., Zadeh, L.A. and Aminzadeh, F., 2003, Soft computing and intelligent data analysis in oil exploration, Elsevier.

Sharifi, J., Hafezi Moghadam, N., Lashkaripour, G., R., Javaherian, A. and Mirzakhanian, M., 2019, Application of Extended Elastic Impedance in Seismic Geomechanics, Geophysics, 84(3), 429-446.

Sharifi, J. and Mirzakhanian, M., 2019, Full-angle extended elastic impedance, Interpretation, 7 (4), T869-T885.

Wang, W. and Zheng, Y., 2007, On Fuzzy Cluster Validity Indices, Fuzzy Sets and Systems, 158, 2095-2117.

Wang, D., Zheng M., Li, J., Li, Z., Li, J. Q., Song C. and Chen, X., 2017, Intelligent constellation diagram analyzer using convolutional neural network-based deep learning, Optics Express, 25, 17150–17166, https://doi.org/10 .1364/OE.25.017150.

Whitcombe, D. N., 2002, Elastic impedance normalization, Geophysics, 67, 60-62.

Whitcombe, D. N., Connolly, P. A., Reagan, R. L. and Redshaw, T. C., 2002, Extended elastic impedance for fluid and lithology prediction, Geophysics, 67(1), 63-67.

Wrona, T., Pan, I., Gawthorpe, R.L. and Fossen, H., 2018, Seismic facies analysis using machine learning, Geophysics, 83(5), 83-95.

Yenwongfai, H. D., Mondol, N. H., Faleide, J. I. and Lecomte, I., 2017, Prestack simultaneous inversion to predict lithology and pore fluid in the Realgrunnen Subgroup of the Goliat Field, southwestern Barents Sea, Interpretation, 5(2), 75–96, https://doi.org/10.1190/INT-2016-0109.1.

Zarei, M. and Hashemi, H., 2019, Edge Detector Radon Transform for Seismic Multiple Attenuation-Tunisia-25 – 28 November.

Zhao, T., Jayaram, V., Roy, A. and Marfurt, K. J., 2015, A comparison of classification techniques for seismic facies recognition, Interpretation, 3(4), 29-58.

Zoeppritz, K., 1919, Erdbebenwellen VIII B, Über die Reflexion und Durchgang seismischer Wellen durch Unstetigkeitsflächen, Gottinger Nachr., 1, 66–84.