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A Comparative Study of the Neural Network, Fuzzy Logic, and Nero-fuzzy Systems in Seismic Reservoir Characterization: An Example from Arab (Surmeh) Reservoir as an Iranian Gas Field, Persian Gulf Basin

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Abstract

Intelligent reservoir characterization using seismic attributes and hydraulic flow units has a vital role in the description of oil and gas traps. The predicted model allows an accurate understanding of the reservoir quality, especially at the un-cored well location. This study was conducted in two major steps. In the first step, the survey compared different intelligent techniques to discover an optimum relationship between well logs and seismic data. For this purpose, three intelligent systems, including probabilistic neural network (PNN), fuzzy logic (FL), and adaptive neuro-fuzzy inference systems (ANFIS) were used to predict flow zone index (FZI). Well derived FZI logs from three wells were employed to estimate intelligent models in the Arab (Surmeh) reservoir. The validation of the produced models was examined by another well. Optimal seismic attributes for the estimation of FZI include acoustic impedance, integrated absolute amplitude, and average frequency. The results revealed that the ANFIS method performed better than the other systems and showed a remarkable reduction in the measured errors. In the second part of the study, the FZI 3D model was created by using the ANFIS system.The integrated approach introduced in the current survey illustrated that the extracted flow units from intelligent models compromise well with well-logs. Based on the results obtained, the intelligent systems are powerful techniques to predict flow units from seismic data (seismic attributes) for distant well location. Finally, it was shown that ANFIS method was efficient in highlighting high and low-quality flow units in the Arab (Surmeh) reservoir, the Iranian offshore gas field.

Keywords: Probabilistic Neural Network (PNN), Fuzzy Logic (FL), Adaptive Neuro-fuzzy Inference Systems (ANFIS), Flow Zone Index (FZI), Arab (Surmeh) Reservoir

1. Introduction

In recent years, the application of intelligent systems has increased in oil and gas exploration. The main goal of these systems is determining an intelligent formulation between input and output datasets. What has been of interest to these methods is exploring how seismic attributes could be

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connected to reservoir properties such as fluid content, rock types, porosity, lithology, shear wave velocity and so on. Some researchers have attempted to estimate the optimum formulation and the better prediction of reservoir properties. Trappe et al. (1995) studied the application of 3D seismic data to estimate porosity and permeability using a neural network in the Zechstein carbonate reservoir, North German basin next to the Dutch border. Balch et al. (1999) used a fuzzy logic technique to select the optimal set of seismic attributes for predicting water saturation. Nikravesh et al. (2001) found nonlinear relationships between 3D seismic data and production log data using soft computing techniques. They used k-means clustering, fuzzy c-means clustering, and neural network clustering to recognize similarity cubes in seismic data. Then, they used a neural network to formulate the seismic attributes to the water saturation. Meldahl et al. (2001) discussed how seismic attributes and a supervised neural network can transform seismic input data into a new 3D data cube in which the chimney cube is highlighted. They provided examples of the North Sea and the Gulf of Mexico gas chimneys. Russell et al. (2004) performed a multi-attribute transform using stepwise regression, probabilistic neural network, radial basis functions neural network, and multilayer perceptron to predict porosity over the seismic volume. Chopra et al. (2006) integrated AVO-derived attributes (Lamé parameters, $\lambda\rho$, and $\mu\rho$) volumes with other non-AVO derived seismic attributes to predict gamma ray, bulk density, and porosity from seismic data. Aristimuno and Aldana (2006) used attributes and artificial intelligence techniques for porosity prediction from seismic data. Usually, geophysical, geological, and petrophysical events are not sharply defined and are innately connected with ambiguity. Heretofore, fuzzy systems were introduced as modern and robust techniques to decrease uncertainties and analyze seismic data (Kadkhodaie-Ilkhchi et al., 2006; Rezaee et al., 2007). Recently, Rastegarnia and Kadkhodaie-Ilkhchi (2013) used seismic attribute analysis to predict FZI using seismic and well log data. They found an effective technique to apply FZI prediction to an oil reservoir. According to the results found, one of the major advantages of using 3D seismic attributes is that they provide images that accurately represent the areal extent of the geological features. Also, it makes the dense and regular sampling of data over the regions by using the seismic attributes. Some feature of changes not distinguished on horizontal and vertical seismic amplitude sections are easily recognized by seismic attributes. Nowadays, although there are a few hundred seismic attributes that are available, those who are sensitive to thickness, reservoir impedance, or geomorphology are more efficient to FZI prediction (Rastegarnia et al., 2013). Moreover, Yarmohammadi et al. delineated high porosity and permeability zones and used the seismic derived FZI data at Shah Deniz sandstone packages (Yarmohammadi et al., 2014). In recent years, researchers have tried to use the integration of clustering and geostatistic methods to find an optimum relationship between well logs and seismic data and build a 3D model of reservoir electrofacies (Kiaei et al., 2015).

In this study, the application of intelligent systems to finding a better relationship between seismic attributes and well log data on well locations, and to estimating the hydraulic flow units on out of well locations was discussed. Acoustic impedance, integrated absolute amplitude, and the average frequency were selected with stepwise-regression as the optimal attributes for the estimation of hydraulic flow units.

The principal objectives of the current research are as follows:

(a) The intelligent systems, including probabilistic neural network (PNN), fuzzy logic (FL), and adaptive neuro-fuzzy inference system (ANFIS) were used to predict FZI data in a 3D reservoir cube with seismic attributes;

(b) The results of the systems used to predict FZI data were compared together.

(c) The basic concepts and the validity of the applied intelligent systems in solving problems with different methodologies were verified.

2. Study area

The study area includes the world's largest non-associated gas accumulation located in the Persian Gulf (Figure 1). The samples data in this survey was extracted from four wells of Arab (Surmeh) reservoir in the south of Iran. The FZI logs and 3D seismic data were available for wells. In the studied area (Figure 1), gas accumulation is mostly limited to the Permian–Triassic stratigraphic units. The Arab formation is organic-rich and its total organic carbon (TOC) averages about 4.75 wt.% in the samples obtained from the studied oilfield in the Persian Gulf. Kerogen in Arab source rocks is primarily Type II; nevertheless, Type III kerogen in Arab formation has been reported by Rabbani and Babaii (2004). The Arab formation was drilled to its total thickness only in the central part of the Persian Gulf. Due to the shallow depth of burial, the thermal maturity of Arab formation increases toward the northwest and eastern regions of the Persian Gulf. The top of Arab formation is at the end of oil generation window in the vicinity of the Hormuz Strait. The Arab formation can be considered as a source rock for oil generation in the northwest and eastern regions of the Persian Gulf provided that it contains both good quantity and quality (kerogen type) organic matter.

Figure 1
Location map of the study area (Ghasemi-Nejad et al., 2009).

3. Methodology

In the present research, intelligent techniques were used to estimate hydraulic flow units (HFU's) from seismic and well log data. At the initiation of the process, the quality control of well logs was carried out, and then a depth matching was applied. Outlier data were eliminated, and raw well logs were corrected environmentally.

3.1. Determination of hydraulic flow units (HFU's)

Hydraulic flow units are defined as states which can be correlated and mapped zones within a reservoir controlling fluid flow. This concept is strongly related to FZI's, which are unique parameters characterizing each hydraulic flow unit. The relation between reservoir quality index (RQI), FZI, and the void ratio (ϕ_z : the ratio of pore volume to solid volume) is expressed as follows (Amaefule et al., 1993):

$$\log RQI = \log FZI + \log \varphi_z \tag{1}$$

where, $\varphi_z = \dfrac{\varphi}{1-\varphi}$

RQI and FZI can be calculated by using the following equations:

$$RQI = 0.0314\sqrt{\frac{K}{\varphi}} \tag{2}$$

$$FZI = \frac{RQI}{\varphi_z} \tag{3}$$

where, *k* is permeability in mD, and ϕ is fractional porosity. The FZI shows the relationship between the volume of void space (ε) and its geometric distribution (RQI). Rocks with a narrow range of FZI values belong to a single hydraulic unit; that is to say, they show similar flow properties (Prasad, 2003). The relationship between ε and RQI has been used to represent that the samples with similar FZI values lie close together on a semi-log plot of porosity versus permeability (Amaefule et al., 1993). The porosity-permeability relationship on the plot can be defined uniquely in each hydraulic unit. Based on the studies of Amaefule et al. (1993), permeability variations in a reservoir can be found by clustering its cored data in hydraulic units with similar FZI values. To estimate well log-derived HFU's from 3D seismic attributes—which is the main objective of this study—FZI data are calculated for 4 cored wells in one of the Persian Gulf hydrocarbon fields by using the available porosity and permeability data.

Following the identification of the flow units, they were merged with seismic traces at well locations to predict 3D FZI model. To this end, three intelligent systems in Arab reservoir were compared. The procedure of converting a 3D seismic cube to reservoir flow units is discussed in Figure 2. According to this procedure, in order to predict 3D FZI models, first of all, the best seismic attributes must be selected by means of stepwise linear regression method. Then, multivariate linear regression equations and correlation coefficients with target logs must be determined. Finally, three different artificial intelligent systems including probabilistic neural network (PNN), fuzzy logic (FL), and adaptive neuro-fuzzy inference system (ANFIS) must be designed and optimized. The results of correlation coefficients between the real and predicted logs and the prediction error in the blind test will show which method outperforms the others.

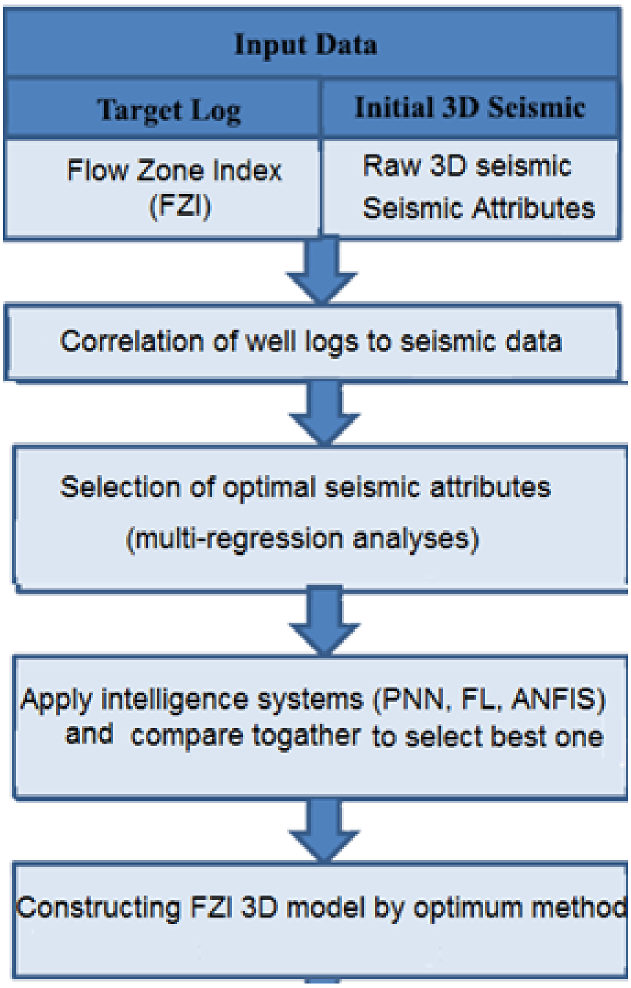


Figure 2
A schematic diagram of converting a 3D seismic cube to reservoir flow units in this study.

3.2. Producing synthetic seismograms

Firstly, to produce synthetic seismograms, well logs data were correlated to 3D seismic data. To this end, related well data A1, A2, A3, and A4 were used. Secondly, the acoustic impedance was produced by multiplying bulk density values and acoustic velocity. Subsequently, this acoustic impedance was turned to reflectivity with a proper time to depth relationship. This time-depth relation was extracted from check-shot data. In this study, depth-to-time conversion of the well logs was accomplished by applying check shot data supplied for wells A1 and A3. The curve of this time-depth relationship for well A1 is shown in Figure 3 (Track 3). In the final step, a synthetic seismogram was generated with convolving the reflectivity in time and a wavelet. The optimum wavelet was extracted from an iterative algorithm; this algorithm estimates the proper wavelet by using optimum operator that closely approximates the nearby seismic traces when convolved with the reflectivity from the well. Based on the number of wells used in the wavelet extraction procedure, the number of wavelets was defined. Finally, the optimum wavelet is produced from an average of all the extracted wavelets. The characteristics of the optimum wavelet, including frequency spectrum, phase, and amplitude are shown in Figure 4.

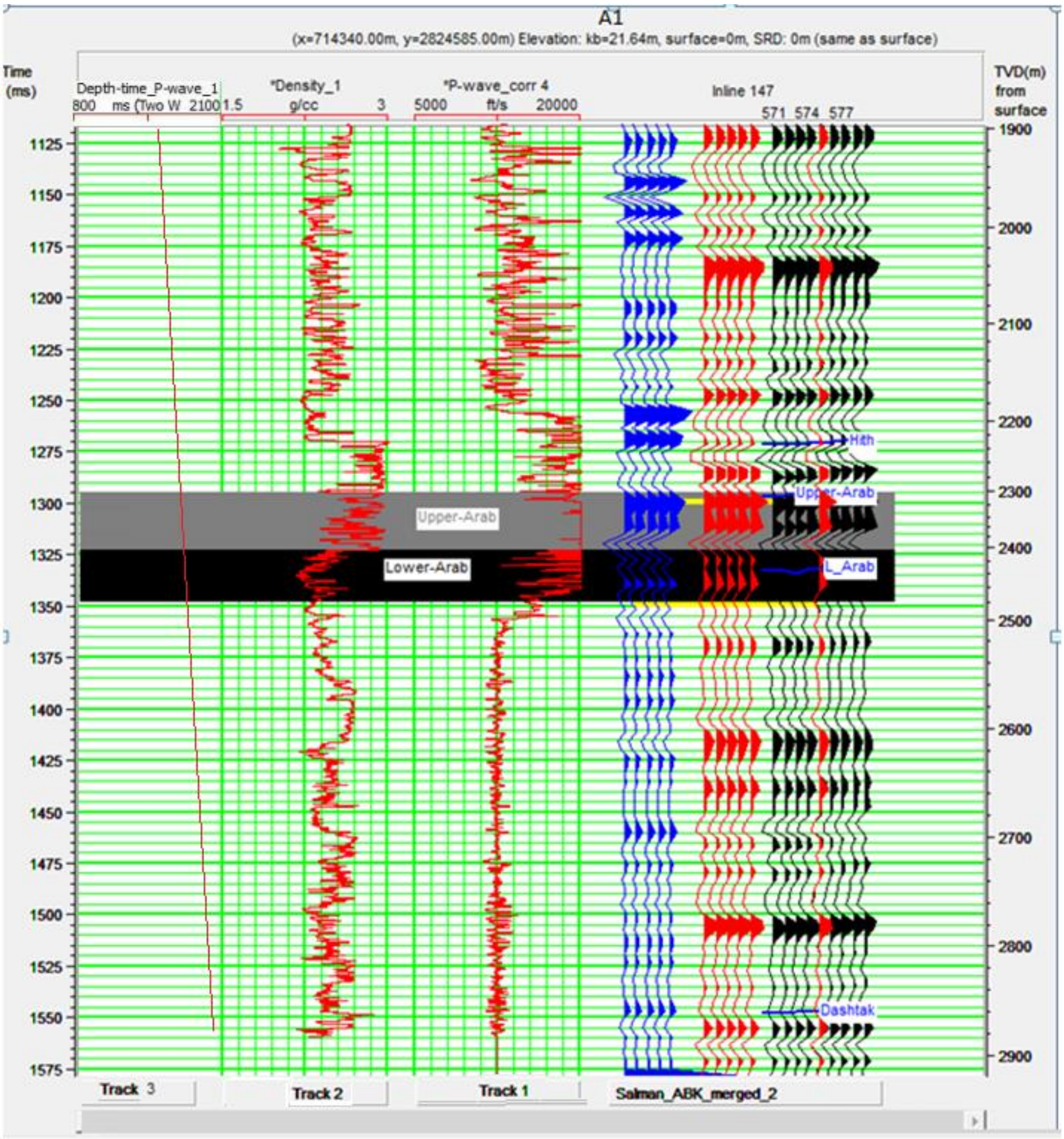


Figure 3

A sample of well to seismic tie for well A1; the correlation between the composite trace (red) and the synthetic seismogram (blue) is 0.908 at the well location.

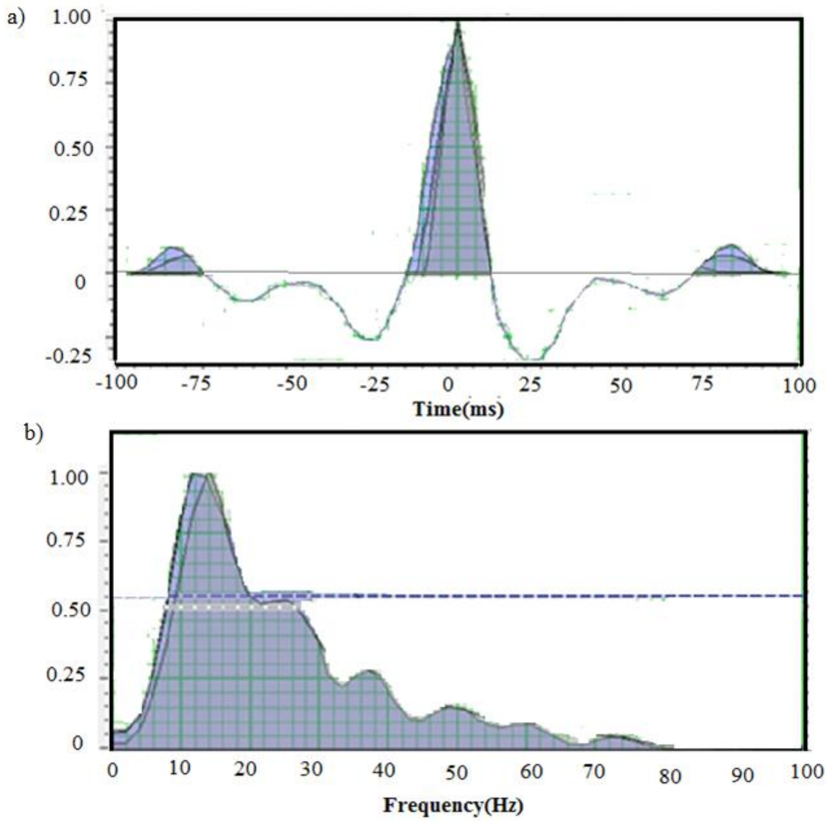


Figure 4
(a) Amplitude and (b) frequency and phase spectra of the final wavelet used for the inversion of seismic data to acoustic impedance.

Check-shot data was used for all the well logs to convert them from the depth to time domain. It was crucial to extract the wavelets to create synthetic seismogram for the position of well data on time.

This time to depth relationship could be helpful in the adaptation of seismic and well logs data in time domain. The determined well tops and horizon interpretations were employed as a support to define a time-depth formulation. The result of a depth to time procedure for well A1 is illustrated in Figure 4. The correlation coefficient between the composite trace (red) and the synthetic seismogram (blue) is 0.908.

3.3. Optimum seismic attributes selection

One of the main objectives of using intelligent systems was to detect a linear or non-linear relationship between input and output data. Actually, these models are used to detect a logical relation among the input and target parameters. In this step, a multi-regression analysis was conducted to acquire the physical relationships between seismic attributes and FZI logs. On the basis of the results from regression analyses, the optimum attributes were used to provide intelligent models. The results of multi-regression analyses used to predict FZI log are shown in Table 1. Based on Table 1, adding more attributes will enhance the improvement of the estimation. The validation error can be used as a factor determining when adding attributes to the input data should be stopped (Russell, 2004). According to Table 1, the selected attributes considered as the input set to predict FZI log include inversion result, integrated absolute amplitude, and average frequency. The result obtained from this analysis is depicted in Figure 5.

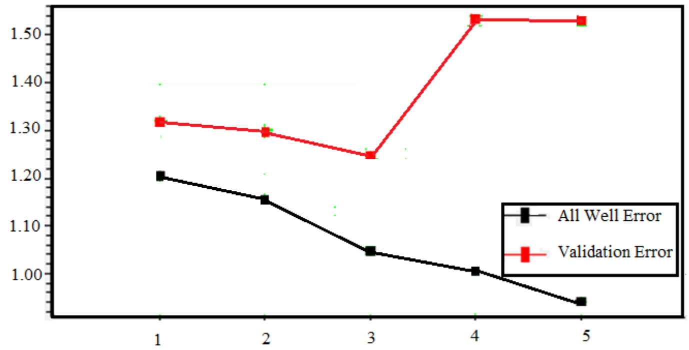


Figure 5
Determination of the number of optimum attributes by utilizing multi-regression analyses for FZI.

Table 1
Multi-attribute list for predicting FZI log.

	Target	Final attributes	Training error	Validation error
1	**log(FZI)**	Inversion result	1.205663	1.316607
2	**log(FZI)**	Integrated absolute amplitude	1.154679	1.297056
3	**log(FZI)**	Average frequency	1.048055	1.247190
4	**log(FZI)**	Apparent polarity	1.006541	1.533980
5	**log(FZI)**	Filter 45/50-55/60	0.791833	1.531778

3.4. Constructing FZI 3D models by intelligent systems

In this study, three intelligent systems (PNN, FL, and ANFIS) are used to construct 3D FZI models, and the results are compared to find out the best method. Theories of these methods are explained in following sections:

a. Probabilistic neural network (PNN) method

Probabilistic neural network (PNN) is defined as a supervised training technique that can be used to predict both discrete or continuous (classification) data, and it is composed of three layers. First, it was used by Specht (1990) to computes the difference between the calculated output and corresponding desired output from the training dataset. It has proved to be a highly efficient and fast system approximating the desired output values. For a vector of input x_i in PNN, the new sample $O_N(x_i)$ is computed by:

$$O_N(X_i) = \frac{\sum_{i=1}^{n} O_{Ni} \exp\left(-D\left(x, Px_i\right)\right)}{\sum_{i=1}^{n} \exp\left(-D\left(x, x_i\right)\right)} \tag{4}$$

where, $D(x, x_i)$ is the distance between each of the input points and the training points and is computed as follows:

$$D(x, x_i) = \sum_{j=1}^{k} \left(\frac{x_j - x_{ij}}{\rho_j}\right)^2 \tag{5}$$

where, ρ_j stands for the distance scale factor for each of the input attributes, and k is the number of input data. The scale factor ρ_j is the only parameter of the PNN that needs to be optimized. Other type of neural network, such as multiplayer perceptron needs more parameters in comparison with PNN. In addition, PNN is a simple, fast, and efficient algorithm in practice. The optimal value of ρ_j is acquired when the validation error is minimum. The validation result for the s^{th} target sample is calculated as follows (Kadkhodaie-Ilkhchi et al., 2009):

$$O_{Ns}(X_s) = \frac{\sum_{i \neq s} O_{Ni} \exp(-D(x_s, x_i))}{\sum_{i \neq s}^{n} \exp(-D(x_s, x_i))} \tag{6}$$

More details on probabilistic neural networks can be found in the works of Specht (1990), Masters (1995), and Hampson et al. (2001). In this research, to optimize distance scale factor, ρ_j range was chosen between 0.10 and 3.00. The number of ρ_j values to try was set to 21. The optimized values of ρ_j for the target (FZI log) are as follows: Inversion result= 0.752; integrated absolute amplitude= 0.361; and average frequency= 0.252.

b. Fuzzy logic system

The term fuzzy logic was introduced by Lotfi Zadeh (1965) at the University of California. Fuzzy logic uses the concept of fuzzy sets to solve some problems. In comparison with crisp sets, fuzzy sets allow partial membership which can take values ranging from 0 to 1; on the other hand, crisp sets only allow full membership or non-membership.

$$\mu_{A(x)} : X \rightarrow [0,1] \tag{7}$$

where, $\mu_{A(x)}$ is the grade of membership for element X in fuzzy set A and X that refers to the universal set defined in a specific problem which should be defined and solved (Yagar and Zadeh, 1992).

Fuzzy inference is the process of formulating a given input data to an output data using fuzzy logic. There are three different types of fuzzy inference systems (FIS) including those of Mamdani fuzzy inference systems (MFIS) and Assilian (1975), Larsen (1980), and Takagi and Sugeno (1985). These methods attempt to organize a system by synthesizing a set of linguistic control rules obtained from experienced human operators. Fuzzy inference systems consist of three major parts: (a) fuzzifier, (b) inference engine (fuzzy rule base), and (c) defuzzifier (Figure 6).

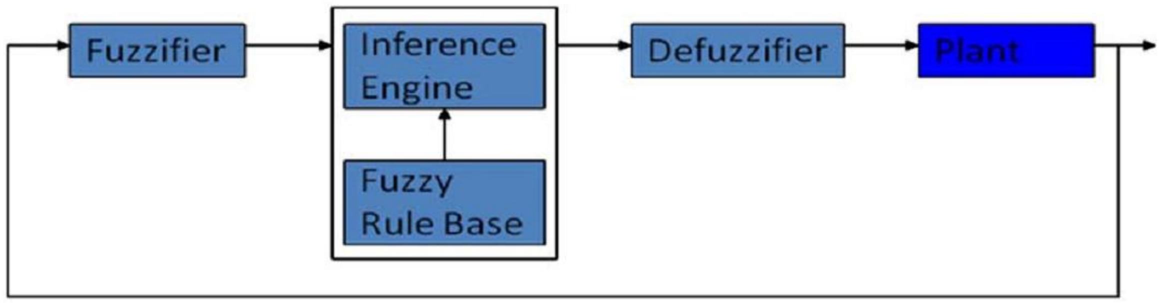


Figure 6
Main parts of an FIS (Lee, 2004).

The most important differences among fuzzy inference systems are the implication methods and types of the output membership functions used to define problems and sets. In MFIS, the output membership functions are fuzzy sets. This method uses the min operation (^) as a fuzzy implication (Mamdani and Assilian, 1975). After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. Now suppose a rule base is given in the following form (Kadkhodaie et al., 2009):

$R^i: if\ x\ is\ A_i\ and\ y\ is\ B_i\ \ then\ z\ is\ C_i, i = 1,2, \dots, n$

Then, $R^i = (A_i \wedge B_i) \rightarrow C_i$ is defined by:

$$\mu_{R_i} = \mu_{(A_i\ and\ B_i \rightarrow C_i)}(x, y, z) \tag{8}$$

The input data $x = x_0$ and $y = y_0$ pass through the above rule to produce the final output as given below (Lee, 2004):

$$\mu_{C_i'}(z) = [\mu_{A_i}(x_0) \wedge \mu_{B_i}(y_0)] \rightarrow \mu_{C_i}(z) \tag{9}$$

$$\mu_{C_i'}(z) = \alpha_i \wedge \mu_{C_i}(z) \tag{10}$$

$$\mu_{C'}(z) = \mu_{C_i'}(z) \vee \mu_{C_2}(z) = [\alpha_i \wedge \mu_{C_1}(z)] \vee [\alpha_2 \wedge \mu_{C_2}(z)] \tag{11}$$

$$\mu_{C'}(z) = \bigcup_{i=1}^{n} [\alpha_i \wedge \mu_{C_i}(z)] = \bigcup_{i=1}^{n} \mu_{C_i'}(z), C' = \bigcup_{i=1}^{n} C_i' \tag{12}$$

A graphical illustration of MFIS is illustrated in Figure 7.

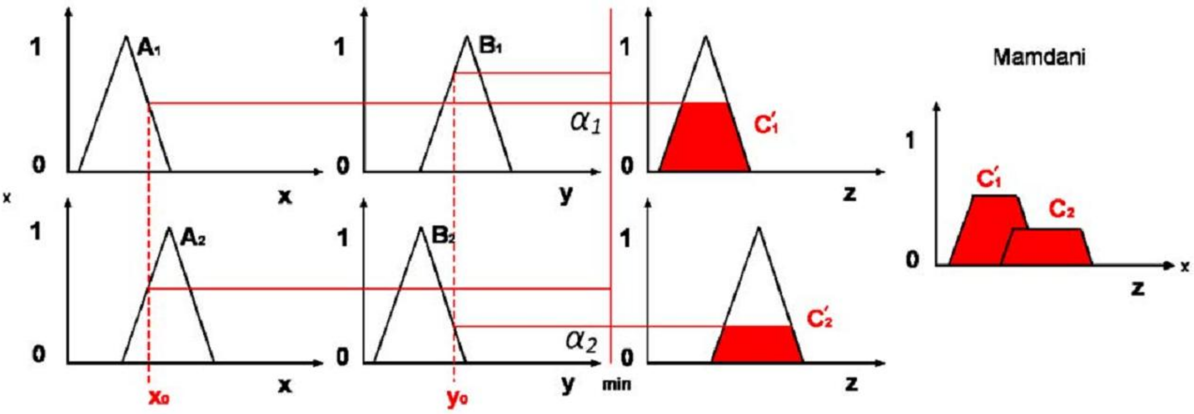


Figure 7
A graphical illustration of MFIS (Kadkhodaie et al., 2009).

c. Adaptive neuro-fuzzy inference system

In recent years, considerable attention has been paid to the application of fuzzy logic and hybrid neural network techniques. Neuro-fuzzy modeling is a technique to describe the behavior of a system using neural network structure to optimize fuzzy inference rules (Nikravesh and Aminzadeh, 2003). By using output/input dataset, adaptive neuro-fuzzy inference system (ANFIS) constructs an FIS whose fuzzy parameters are tuned using a back propagation algorithm (MATLAB User's Guide, 2007; Labani et al., 2010).

Figure 8 depicts an ANFIS system using the following fuzzy rules in layer 1 and 2 (Kamali and Mirshady, 2004):

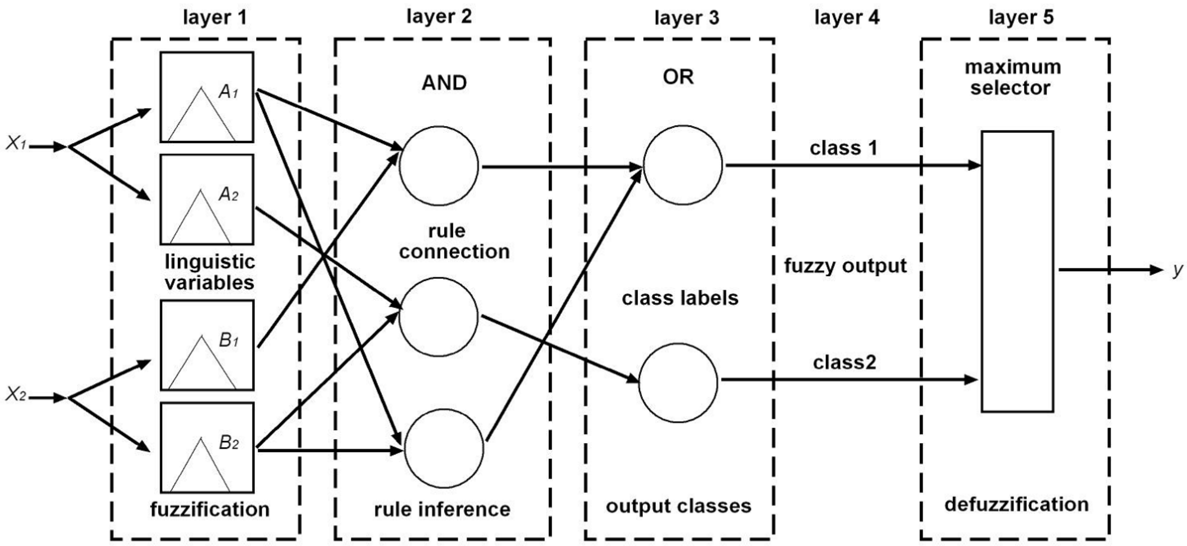


Figure 8
A schematic diagram of adaptive neuro-fuzzy system (from Kamali and Mirshady, 2004).

Rule 1: If (x_1 is A_1) and (x_2 is B_1), then (class is 1);

Rule 2: If (x_1 is A_2) and (x_2 is B_2), then (class is 2);

Rule 3: If (x_1 is A_1) and (x_2 is B_2), then (class is 1);

When several fuzzy rules have a similar result class, layer 3 combines their firing strengths. Usually, the maximum operator should be used. The fuzzy values of the classes are available in layer 4. In layer 5, the best-matching class for the input is chosen as the output if the crisp classification is required (defuzzification).

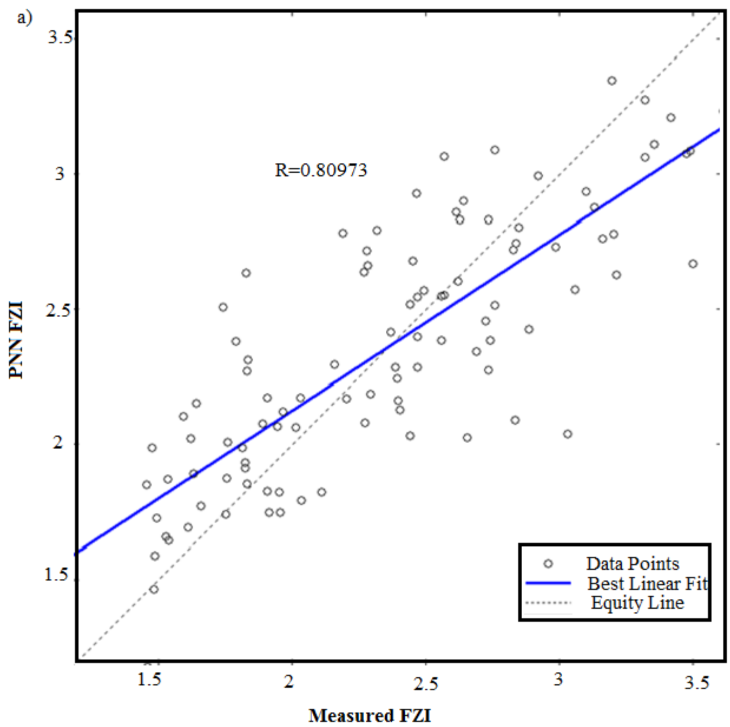
4. Results and discussion

In the current study, the test-data include well data and related seismic attributes (250 samples from 4 wells in Arab formation). 150 samples were used to model construction, and 100 samples were used to evaluate the reliability of intelligent methods. Figures 9a–c and Figures 10a-c show the correlation and graphical evaluation of the measured and predicted FZI for PNN, MFIS, and ANFIS. Based on the results shown in Table 2 and Figures 9a–c, the mean square errors of PNN, MFIS, and ANFIS models in the test data are 0.3420, 0.2673, and 0.2033 respectively, which correspond to respective correlation coefficient values of 0.8097, 0.8815, and 0.9362. It can be said that the three intelligent methods are robust tools to estimate rock properties from the integration of well logs and seismic data. They can provide an inexpensive and quick cube of rock properties in the framework of hydraulic flow units. In this study, they successfully mapped different flow units from seismic data, and validating their results with well data showed satisfactory performance. However, if their parameter is not tuned as accurate as possible or in the case of limited or uncertain core or seismic data, they can be misleading and cause errors in data integration and interpretation. The neural network is known as a black box and has powerful training algorithms to map a set of input to output data. Apart from data limitation and modeler experience, the main pitfalls of neural network model are overtraining and undertraining which can cause a model to predict well in training data but not well in validation or test data. Fuzzy models are known as gray boxes, and they are not as complex as neural nets. However, their performance highly depends on input/output space classification to find present structures in data. Apart from this issue, choosing inappropriate membership function can cause uncertainties in fuzzy "if-then" rules generation. Neuro-fuzzy models as hybrid models inherent pros and cons of both fuzzy inference system and neural net models.

Table 2

Performance of different intelligent models for FZI estimating.

Methods	**FZI**	
	Correlation coefficient (CC)	Mean square error (MSE)
PNN	0.8097	0.3420
MFIS	0.8815	0.2673
ANFIS	0.9362	0.2033



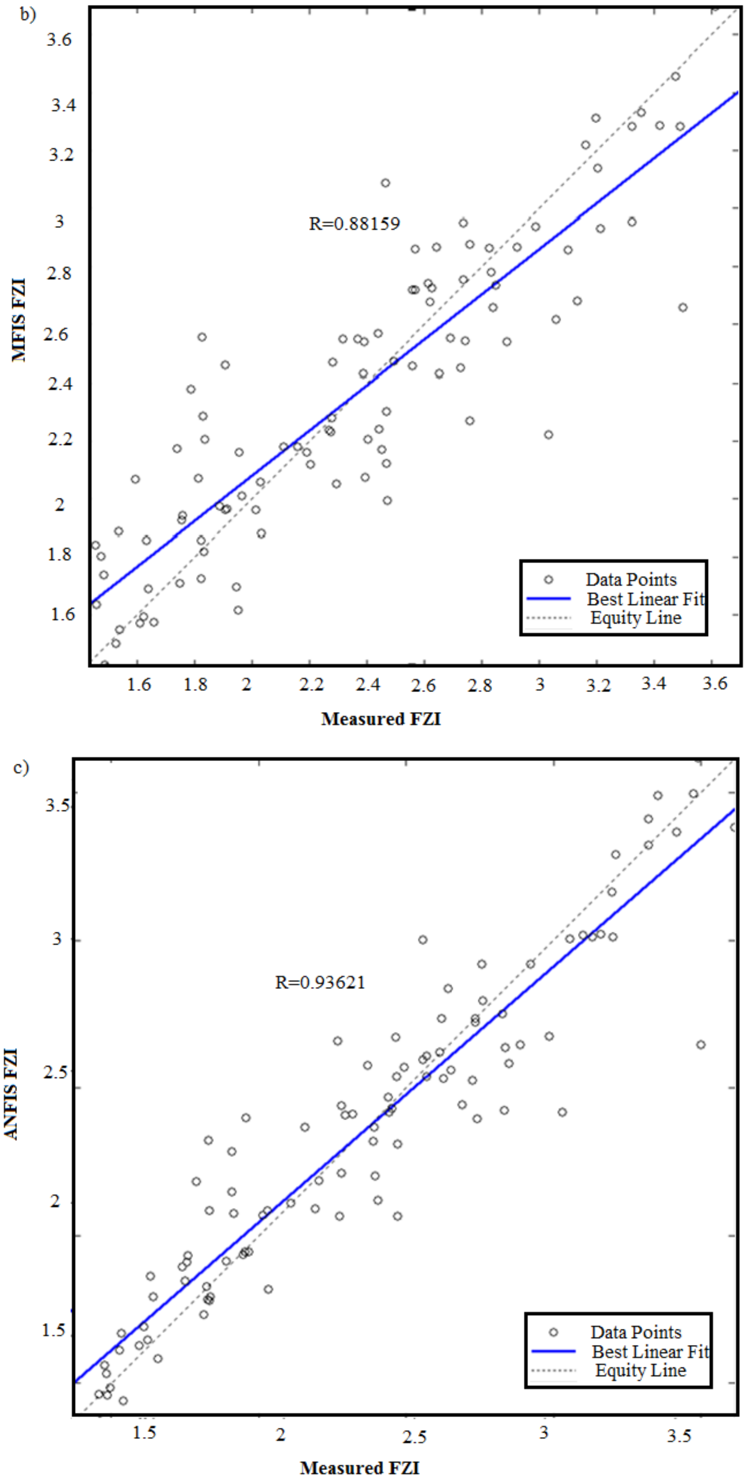


Figure 9

The correlation coefficient between the measured and predicted FZI for the test samples using (a) PNN, (b) MFIS, and (c) ANFIS.

Among the intelligent models used, ANFIS has supplied accurate results and lower errors rather than MFIS and PNN. The ANFIS indicates a remarkable progress towards the prediction of FZI from well logs and seismic attributes. Based on the results shown in Table 2 and Figures 9 and 10, the correlation coefficient and measured error are 0.8815 and 0.2673 respectively. Finally, ANFIS shows better performance in estimating FZI compared to the other methods. The mean square error (MSE) and correlation coefficient (CC) of ANFIS method are 0. 2033 and 0.9362 respectively.

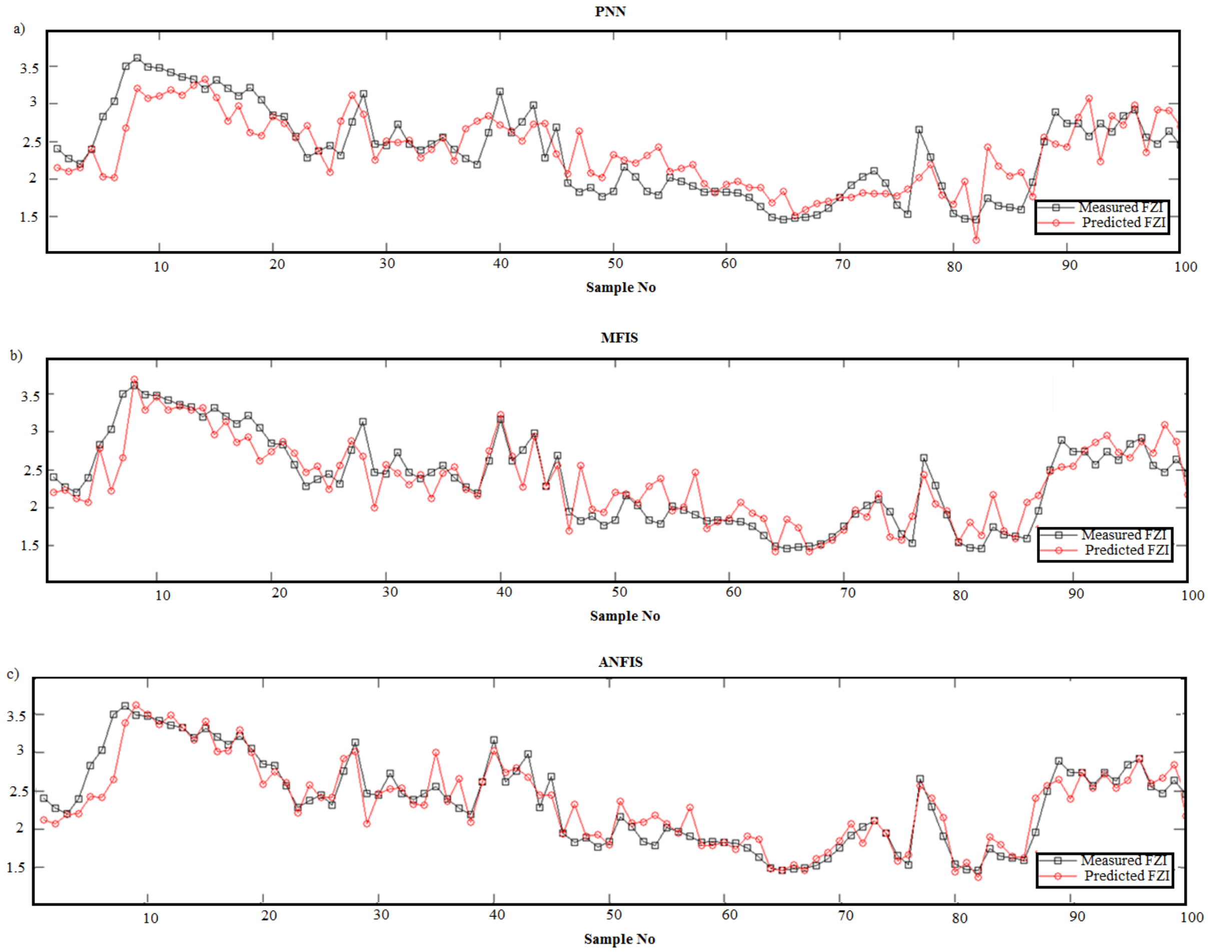


Figure 10

A graphical comparison between the measured and predicted FZI for the test samples using (a) PNN, (b) MFIS, and (c) ANFIS.

In the final step of this research, the ANFIS system was utilized to convert selected seismic attributes, namely acoustic impedance, integrated absolute amplitude, and average frequency, to 3D FZI. The distribution of the ANFIS-estimated FZI for 3D data is shown in Figures 11 and 12. These results confirm propagating the FZI through the studied seismic line and time-slice.

Accordingly, rocks with a narrow range of FZI values belong to a single hydraulic flow unit, or they share similar flow properties. As it is seen from Figures 11 and 12, the high and low values of FZI could characterize different hydraulic flow units. Although this is not the main purpose of this paper, for further studies, methods like FCM could be used to classify this FZI 3D cube into related HFU's and describe them.

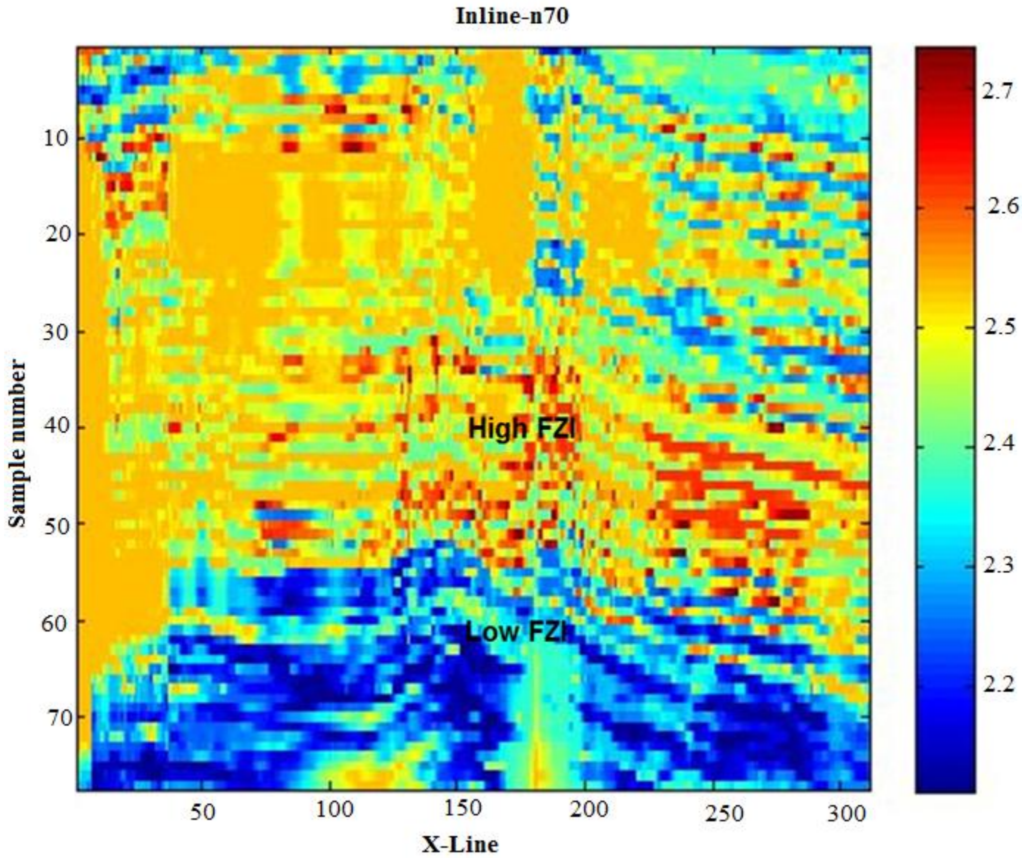


Figure 11
The section showing the distribution of ANFIS-estimated hydraulic flow units at an inline of 70; high and low FZI are shown using a color change (blue to red).

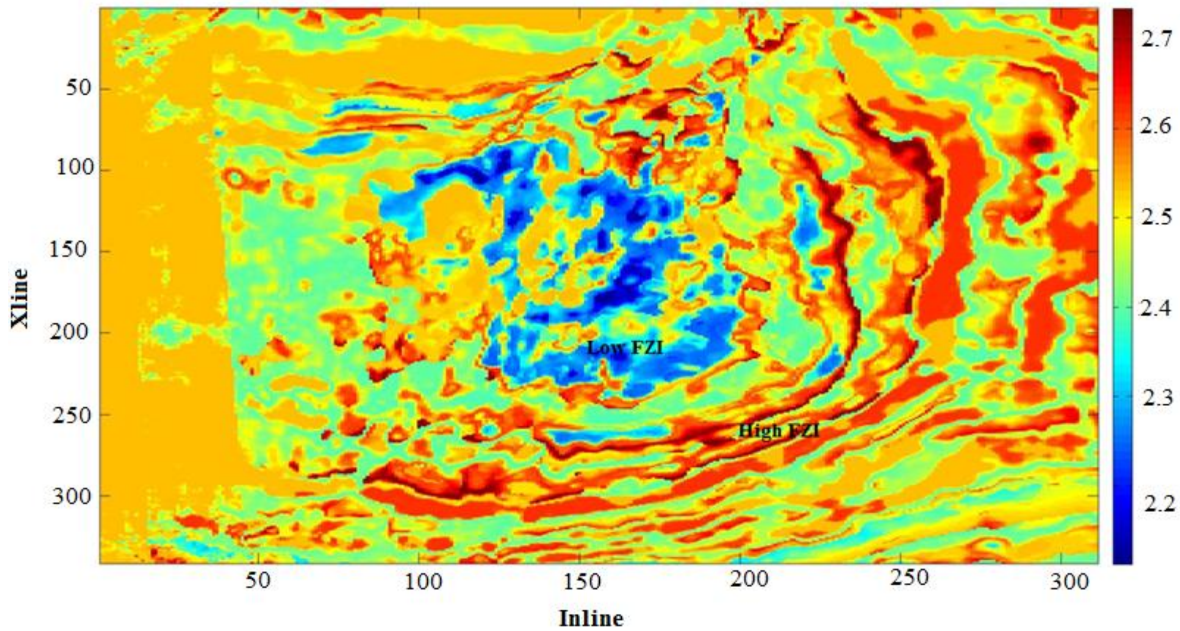


Figure 12`
The slice showing the distribution of ANFIS-estimated hydraulic flow units at 1348 ms; high and low FZI are shown using a color change (blue to red).

5. Conclusions

In this paper, inference systems, including PNN, MFIS, and ANFIS were used for the conversion of seismic attributes to 3D FZI in one of the Iranian oil fields in the Persian Gulf. Also, the integration of logs data and seismic attributes demonstrated that the use of FZI can be considered as an effective tool in reservoir characterization in this area. The final attributes used in the estimation of flow units include inversion result, integrated absolute amplitude, and average frequency.

The results indicate that the ANFIS method shows a remarkable improvement in the prediction of FZI from seismic data (seismic attributes) compared to PNN and MFIS. According to the results, ANFIS reduces the measured error to 0.2033 and increases the correlation coefficient to 0.9362. Finally, high and low FZI areas are shown at inline and time-slice sections. These values are related to different types of hydraulic flow units. According to porosity and permeability data, hydraulic flow units are in line with the pore size distributions. Since there is a strong relationship between reservoir quality and FZI, HFU models could be a good indicator of reservoir characterization.

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Nomenclatures

ANFIS	: Adaptive neuro-fuzzy inference systems
CC	: Correlation coefficient
FL	: Fuzzy logic
FZI	: Flow zone index
HFUs	: Hydraulic flow units
k	: Permeability in mD (milli Darcy)
MFIS	: Mamdani fuzzy inference system
MSE	: Mean square error
PNN	: Probabilistic neural network
RQI	: Reservoir quality index
ε	: Volume of void space
ϕ	: Fractional porosity
ϕ_z	: Ratio of pore volume to solid volume
$\mu_{A(x)}$	: Grade of membership for element X in fuzzy set A
ρ_j	: Distance scale factor for each input
$\wedge$	: Min operation

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