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A Meta attribute for reservoir permeability classification using well logs and 3D seismic data with probabilistic neural network

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ABSTRACT Permeability is one of the most important reservoir properties for its crucial contribution to the productivity of the reservoir. This study presents a new approach to characterise reservoir parameters, specifically the permeability. The presented method consists of three major steps. Firstly, several seismic attributes such as acoustic impedance, geometric attributes, and instantaneous attributes are computed. In the second step, seismic attributes, which have good correlation with permeability logs, are selected. Finally, a Meta attribute, which extracts the permeability classes, is created using the probabilistic neural network. The results of this study indicate that the combination of several seismic attributes, each exploring a different feature of the seismic data, can be effectively used for determination of reservoir parameters, especially permeability. The current method is applied on the Asmai reservoir of an Iranian oil field located SW of Iran. A comparison of the results from this study to well-test data recorded in the field indicate that the generated Meta attribute can qualitatively predict the permeability values obtained from the well-testing.

Key words: permeability classes, acoustic impedance inversion, geometric attributes, instantaneous attributes, probabilistic neural network.

1. Introduction

Permeability is one of the most important reservoir properties. The productivity of a hydrocarbon reservoir extremely depends on its permeability. Usually, permeability measured from core analysis is evaluated as the reservoir permeability in the simulation models. The core permeability is precise, but it is only reliable in the vicinity of the wells that the cores are extracted from. Despite the good coverage of seismic surveys, a seismic attribute that can directly predict permeability has not yet been proposed. In other words, because of the reservoir heterogeneities and the large variations of the permeability values, there is no single seismic attribute that can estimate the permeability values or classify them. The researchers have mostly predicted the permeability values from the seismic data indirectly. In this context, they have generated porosity cubes and have transferred the porosity cube into permeability cubes (Hu *et al.*, 2007; Najafzadeh *et al.*, 2012; Brito Nogueira *et al.*, 2013; Dezfoolian *et al.*, 2013). Other researchers have considered the faults and fractures as conduits for fluid flow. They, therefore, have identified these structural parameters and have related them to the reservoir permeability (Kozlov *et al.*, 2009; Dejam and Hasanzadeh, 2011, 2018; Dejam *et al*., 2013, 2014; Saboorian-Jooybari *et al*., 2015, 2016; Rastegarnia *et al*., 2016; Chopra *et al*., 2017; Iravani *et al*., 2017; Mohebian and Riahi, 2017; Mohebian *et al*., 2018).

Trappe and Hellmich (1995) has applied the neural network to estimate permeability and porosity values in a carbonate reservoir in a German basin. Nikravesh and Aminzadeh (2001) have found a nonlinear relationships between production log data and seismic data, using neural network techniques. Meldahl *et al*. (2001) has discussed how a neural network algorithm could be used to transform seismic attributes to seismic 3D cube in order to discover the gas chimney area. Russell *et al*. (2004) have showed how the porosity cube can be estimated from multi-attributes data. They have used stepwise regression, neural network, and multilayer perceptron (MLP) method to obtain the porosity cube. Aristimun and Aldana (2006) have used the attributes and artificial intelligence techniques to estimate permeability from the seismic data. Moreover, Yarmohammadi *et al*. (2014) have used the flow zone index (FZI) to delineate zones of high porosity and permeability in a case study on the Shah Deniz sandstone using seismic data. Recently, Soleymani and Riahi (2012), Cranganu (2013), and Kiaei *et al*. (2015) have used the geostatistic and clustering methods to calculate a better relation between seismic and well log data in order to build the reservoir properties 3D models.

Other researchers have used the Meta attribute to recognize geological features. For example, Meldahl *et al*. (2001) have applied neural networks trained on combination of attributes to recognise features that were first identified in a seed interpretation. Aminzadeh and de Groot (2004) and Arabameri *et al*. (2018) used the Meta attribute for detecting faults, fractures, gas chimneys and salt bodies.

In this study, a Meta attribute was constructed, which classifies reservoir permeability using the probabilistic neural network. A Meta attribute is an aggregation of a number of seismic attributes combined with the interpreter's insight through a neural network to detect a particular feature or determine a reservoir property (Meldahl *et al*., 2001; de Rooij and Tingdahl, 2002; Aminzadeh *et al*., 2004; Arabameri *et al*., 2018).

In this study, the Meta attributes, constructed from multiple input seismic volumes and the derived seismic attributes, are used to predict different classes of facies in the vicinity of the reservoir. A novelty of this work is that the Meta attributes are used as a tool for facies classification in the reservoir formation. Also, as an innovation for this study, the stepwise regression analysis has been used to choose the best group of attributes. The effectiveness of this methodology is verified by applying on an Iranian hydrocarbon reservoir.

The procedure for this study includes the following four major steps: 1) data are gathered, categorised, corrected, and interpreted; 2) several seismic attributes such as acoustic impedance, geometric attributes, and instantaneous attributes are computed; 3) the seismic attributes with good correlation to the permeability logs at

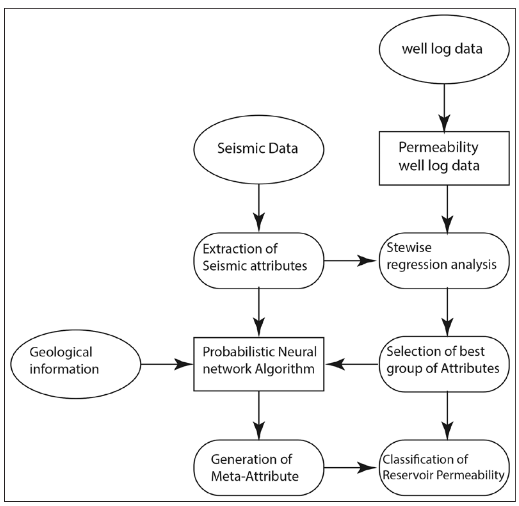

Fig. 1 - The workflow of the Meta attribute approach.

the well locations are selected using the stepwise regression analysis; and 4) a Meta attribute, which extractes the permeability classes, are created using the probabilistic neural network. The flowchart of the study is shown in Fig. 1.

2. The study area

The oil field where the study has accomplished is located on the edge of the Dezful embayment and it was discovered in 2016.

The Asmari reservoir formation is considered as the main target in this oil field. The geological studies performed in this area suggest three facies for the Asmari formation which corresponds to the tidal flat, lagoonal, and barrier/shoal. According to the geological studies, the lower part of the reservoir area is composed of clastic detritals and the upper part consists of carbonate rocks. Various facies are considered for the carbonaceous part of the Asmari reservoir and the permeability and porosity for this interval are supposed to have been affected by dolomitization processes. The lower part of the Asmari formation, which is clastic detritals, is divided into two main lithofacies, the quartzwack and coarse grain sandstone. The 3D seismic data in this oil field covers a total area of approximately 343 km^2. The vertical resolution of the seismic data in the studied reservoir is nearly 18 m.

3. Methodology

The workflow of this study was consists of three major steps.

3.1. Creation of a set of seismic attribute volumes

At this step, information related to structure, stratigraphic and fluid content of the reservoir is extracted from the seismic data. We briefly discuss the physical basis, geological significance, and methods of calculation for these seismic attributes.

3.1.1. Acoustic impedance attribute

Acoustic impedance is the main results of inverting for the post-stack seismic amplitudes; this attribute could determine physical properties of the reservoir. We invert the seismic data to obtain the acoustic impedance using a model-based inversion algorithm. This method requires an initial model and a wavelet which is estimated from the seismic data in the interval of interest. To reach a data misfit that falls below a user-defined value, the model is recursively updated. When the desired misfit is reached, the current update of the model is accepted as the objective P-impedance volume. Acoustic impedance is defined as the product of compressional velocity, υ_p, and bulk density, ρ_p. Both υ_p and ρ_p are sensitive to lithology and porosity variations. By including the acoustic impedance in the Meta attribute, the permeability variations related to either lithology or porosity variations are captured.

3.1.2. Azimuth attributes

Azimuth, ϕ, also called dip azimuth, is estimated either with regard to the north or the inline of seismic overview pivot. Azimuth is orthogonal to the geologic strike and is estimated towards most extreme descending dip (Hartmann *et al.*, 2012).

According to Taner *et al.* (1979), to calculate dip and azimuth, the instantaneous phase for adjacent traces (e.g. three traces) are computed. The dip of the central trace is estimated by laterally fitting a parabolic curve to the phase values, and adjusting it by the trace interval value. In 3D data sets, phase dips in inline and crossline directions are computed, from which the maximum dip direction and its azimuth are obtained. We perform this procedure with different spatial and temporal analysis windows such as 3×3×3, 3×3×8, 5×5×16, etc., where the first number is inline step out, the second number is crossline step out, and the last number is time sample step out. The result of this algorithm is very noisy if no filtering is applied. Therefore, the different median filter is utilised to reduce the noise of the dip and azimuth cubes.

According to Chopra and Marfurt (2007), determination of reflector end and unpretentious changes in plunge and azimuth enable geophysicists to induce reasonable progradational and transgressive bundles, and additionally more clamorous droops, fans, infill of Karsted landscapes and obviously, blame and precise unconformities.

3.2. Thin bed indicator attribute

Large variations of instantaneous frequency that can indicate the thin beds, are contained in time derivative of the phase function. Therefore, the thin bed indicator can be calculated as the difference between the instantaneous and the averaged frequencies in time. The thin bed indicator shows the interference zones. It is considered as a physical attribute because it is related to closely spaced events. It can be used in detailed studies of overlapped thin beds, when they are laterally continuous, and overlapped nonreflecting zone when it appears laterally discontinuous.

3.2.1. Absorption quality factor attribute

Seismic waves travelling through the Earth will encounter retention which means weakening and scattering in view of the versatility and heterogeneity of the medium (Li *et al.*, 2015). Absorption quality factor (AQF), which is a function of both instantaneous frequency and instantaneous bandwidth, can be considered as an indicator of seismic wave absorption. Mathematically, AQF is defined as the area beyond the dominant frequency weighted by frequency. From the petrophysical point of view, when the rock is filled with fluid, with regard to fluid type, AQF can be different. Consequently, AQF is sensitive to the type of fluids in the reservoir due to their different quality factor.

3.2.2. Other instantaneous, frequency, etc. attributes

Instantaneous phase, Amplitude envelope, apparent polarity, and instantaneous frequency are numbers of attributes that are extracted from seismic data. Each of these attributes has a geological significance and can be considered as a reservoir parameter indicator. More details on seismic attributes can be found in Hartmann *et al.* (2012), Flannery (2018) and Smith (2017).

The seismic attributes used in current study are listed in Table 1.

3.2.3. Selection of appropriate seismic attributes

According to Chinwuko *et al.* (2017), seismic attributes are extracted from the seismic data by different methods, like direct calculation or by experience or logical reasons. Some are more delicate than others to particular repositories conditions; some are better at uncovering subsurface

Table 1 - List of all seismic attribute which used in the study.

Att No.	Target	Used attribute
1	Permeability	Inverse of Acoustic Impedance
2	Permeability	Instantaneous Frequency
3	Permeability	Instantaneous Amplitude
4	Permeability	Amplitude Envelope
5	Permeability	Inverse of Thin Bed Indicator
6	Permeability	Average Frequency
7	Permeability	Log (AQF)
8	Permeability	Amplitude Envelope
9	Permeability	Azimuth a
10	Permeability	Dip a
11	Permeability	Instantaneous Phase
12	Permeability	Integrated Absolute Amplitude
13	Permeability	Apparent Polarity
14	Permeability	Filter 45/50-55/60
15	Permeability	Dominant Frequency
16	Permeability	Amplitude Weighted Frequency
17	Permeability	Amplitude Weighted Phase
18	Permeability	Second Derivative Instantaneous Amplitude

abnormalities that are not effectively perceivable. Some others have been utilised as immediate hydrocarbon markers (Iturrarán-Viveros, 2012). When more seismic attributes are accessible, there is more perplexity choosing the proper ones.

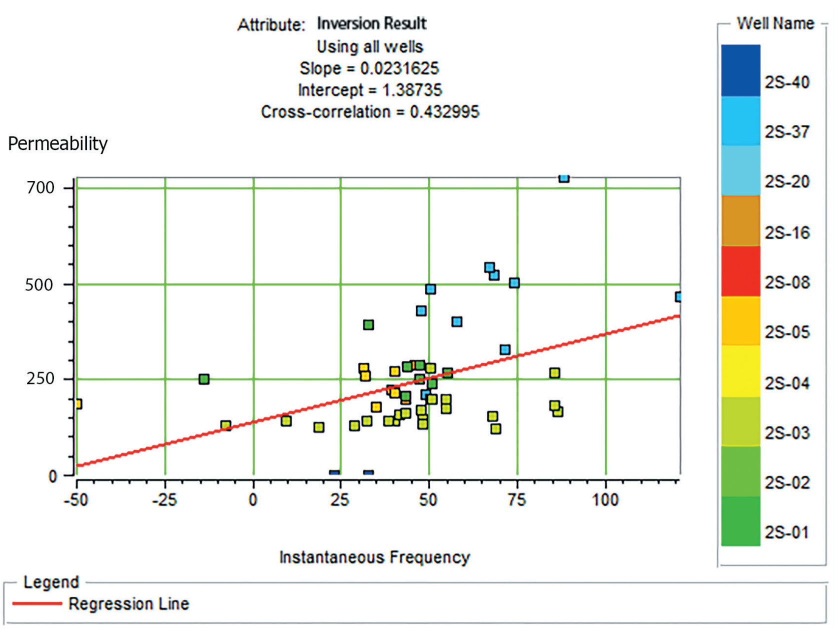

Fig. 2 - The correlation between the first attribute (inversion result) and the target log (permeability).

Stepwise regression analysis is a simple and practical method to find the list of best seismic attributes, which are related to reservoir properties. This algorithm searches on attribute space and finds the attribute which has more correlation with the reservoir property than other attributes. This correlation for first attribute (acoustic impedance) is shown in Fig. 2. The cross plot has used

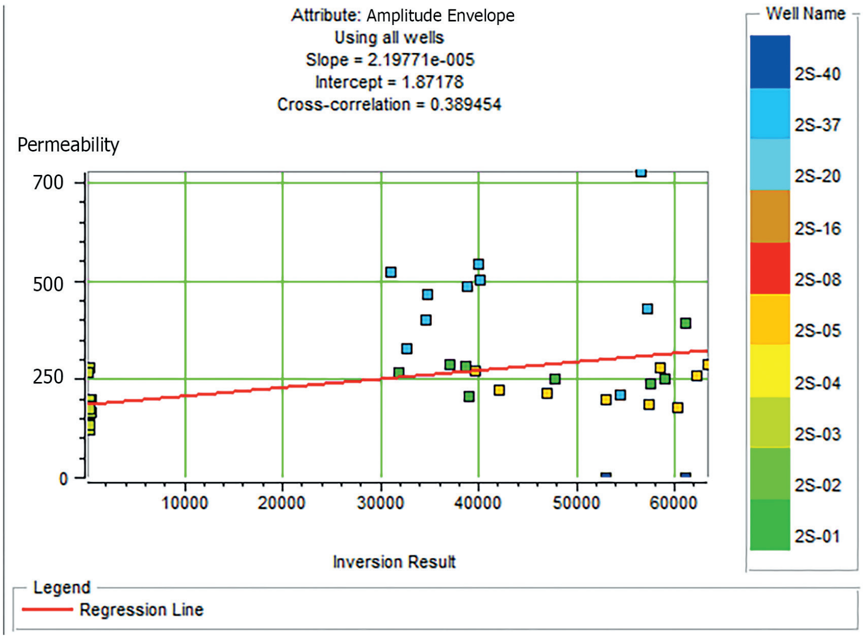

Fig. 3 - The correlation between Amplitude Envelope and target log (permeability).

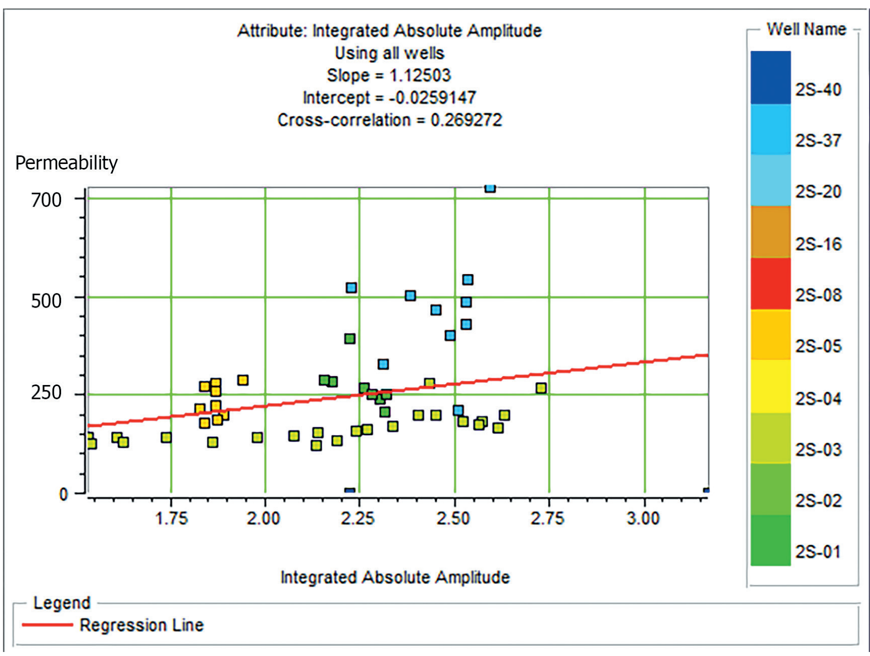

Fig. 4 - The correlation between Integrated Absolute Amplitude and the target log (permeability).

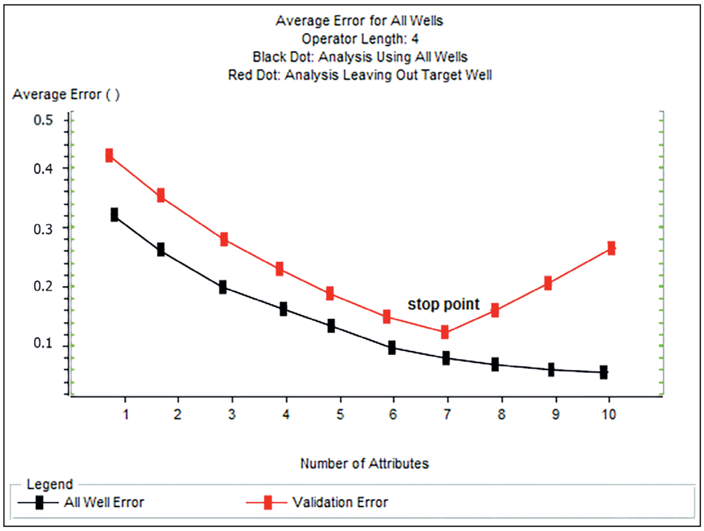

Fig. 5 - The trend of Training and Validation error, after the stopping point the validation error start to increase.

all points within the analysis windows from all wells. The vertical axis is the target permeability log value, and the horizontal axis is the selected attribute, i.e. the acoustic impedance. A regression curve is fit on the points, and the normalised correlation value of 0.39 has been printed at the top of the display. The normalised correlation is a measure of how useful this attribute is in predicting the target log. The correlation for two other attributes is shown in Figs. 3 and 4.

Then, the algorithm finds the best pair of attributes from all combinations of the first attribute and any other attribute in the list. At each step, training and validation errors are calculated. This procedure continues until the validation error starts to increase.

Data in Table 2 shows both the selected attributes and the training and validation errors. Only the first seven attributes were chosen because the validation error starts to increase if further attributes are added to the list. More details on step-wise regression can be found in Hampson *et al*. (2001) and Russell (2004).

Table 2 - Multi attribute list for classifying permeability.

Att. No.	Target	Final Attribute	Training Error	Validation Error
1	Permeability	Inverse of Acoustic Impedance	0.310056	0.360335
2	Permeability	Amplitude Envelope	0.256983	0.321229
3	Permeability	Inverse of Thin Bed Indicator	0.240223	0.321109
4	Permeability	Log (AQF)	0.198324	0.290503
5	Permeability	Azimuth[a]	0.159218	0.287709
6	Permeability	Dip[a]	0.148045	0.268156
7	Permeability	Apparent Polarity	0.131285	0.268156
8	Permeability	Amplitude Weighted Frequency	0.134078	0.374302 (increase=stopping point)

[a] created with 3×3×3 analysis windows and then filtered by 0×0×3 median filter.

3.3. Creation of Meta attribute using probabilistic neural network

3.3.1. Neural networks

The neural network can be described as scientific tools that can be prepared to solve an issue that typically require human intercession. Despite the fact that there is a wide range of neural systems, there are two manners by which they are sorted: by the kind of issue that they can tackle, and by their learning method. Neural system applications in geosciences information examination, for the most part, can be categorised as one of the two classifications: the segregation class, or the expectation value. In the segregation class issue, an information test is appointed to one of few field classes (for example, shale, sand, limestone) while in the esteem forecast issue, a particular esteem is relegated to the field test (for example, a porosity esteem). Evidently, these two methodologies meet as the number of classes approaches the number of yield tests (Russell *et al*., 2003).

Neural systems can likely be characterised by the manner in which they are prepared, utilising unsupervised learning. The neural system begins with a preparation data set for which both the information and yield esteems are known. The neural system calculation, then, takes in the connection between the input and output from this preparation data set, lastly applies the "educated" relationship to a bigger data set for which we do not have the unclear idea about the data output. Cases of the supervised learning approach are the Probabilistic Neural Network (PNN), Multi-Layer Perceptron (MLP), the Radial Basis Function (RBF), and the Generalized Regression Neural Network (GRNN).

In the unsupervised approach, the neural system is given a progression of the sources of information to search for designs itself. That is, the particular yields are not required. The benefit of this approach is that we do not have to know the appropriate response beforehand. The drawback is that it is usually hard to translate the yield (Russell *et al*., 2003). A case of this type of unsupervised systems is the Kohonen Supervised Organizing Map (KSOM) (Kohonen, 2000).

In this study, the main types of the neural networks with reference to the works of Nadaraya (1964), Watson (1964), Powell (1987), Poggio and Girosi (1990), Specht (1990), Zeidenberg (1990), Bishop (1995), and Russell *et al*. (2003) are presented. Preparing data set will comprise of an arrangement of N known preparing values t_i. Each preparation test, which is a scalar amount, is thus subject to a vector of L yield esteems, associated in time with the preparation esteems. These vectors of yields (e.g. seismic qualities) can be composed as $= (s_{i1}, s_{i2}, \ldots, s_{iL})\ T$, $i = 1, 2, \ldots, N$. The target of neural system is to discover some capacity y to such an extent that: $y(s_i) = t_i$, $i = 1, 2, \ldots, N$. When this capacity has been discovered, it can be connected to a self-assertive arrangement of M input information, (for example, seismic characteristic vectors x_k, $k = 1, 2, \ldots, M$, where the properties in the x_k vectors are indistinguishable to those in the s_i vectors; Fig. 6).

3.3.2. Probabilistic neural network (PNN)

The PNN calculation depends on the idea of "interval" in property space. To more readily comprehend this idea, look at Fig. 7, in which the three discretionary two-dimensional seismic property vectors that appeared in Fig. 6 are drawn. Note that "interval" on these diagrams is quality plentifulness as opposed to Cartesian separation. Note that two of these vectors are from the preparation data set (s_i and s_j) and one is from the application data set (x_k). As showed in Fig. 7, three conceivable separations between these vectors can be characterised as:

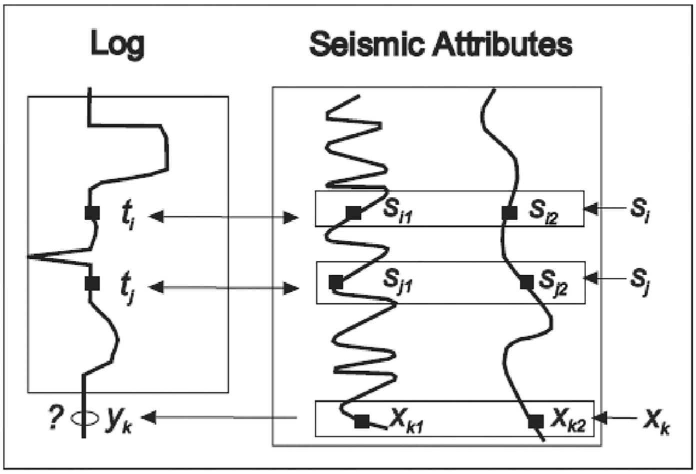

Fig. 6 - A schematic illustration of the differences between the training vectors s_i and s_j, in which the output values t_i and t_j are known and are used in the training process, and the application vector x_k, in which the output sample y_k is not known (Russell *et al.*, 2003).

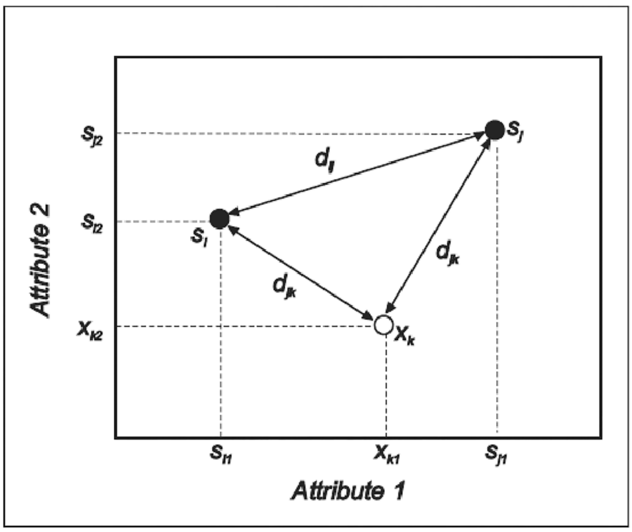

Fig. 7 - A schematic graph of the vectors s_i, s_j, and x_k from Fig. 5, where the coordinate axes represent the attribute amplitude rather than the Cartesian distance (Russell *et al.*, 2003).

$$d_{ij} = \left| s_i - s_j \right| = \sqrt{(s_{i1} - s_{j1})^2 + (s_{i2} - s_{j2})^2} \quad (1)$$

$$d_{ik} = \left| s_i - s_k \right| = \sqrt{(s_{i1} - s_{k1})^2 + (s_{i2} - s_{k2})^2} \quad (2)$$

$$d_{jk} = \left| s_i - s_k \right| = \sqrt{(s_{j1} - s_{k1})^2 + (s_{j2} - s_{k2})^2} \quad (3)$$

Here, the facilitate tomahawks explain trait sufficiency rather than Cartesian separation (Russell *et al.*, 2003). In the above conditions, there are two on very basic level diverse sorts of quality separation. The d_{ij} interval is the between preparing separation, from which the preparation coefficients will be obtained, and the d_{ik} and d_{jk} separations are the application separations, to which the forecast will be connected.

The separations themselves will not be utilised as a part of neural system applications, yet some capacity of the separations, $\phi(d)$, called a premise work will be existed. In spite of the fact that there have been various structures proposed for the premise work (Bishop, 1995), the most widely recognised shape, and the one we will use in this investigation, is the Gaussian capacity, which can be composed as:

$$\varphi(d) = \exp[-\frac{d^2}{\sigma^2}] \quad (4)$$

where σ is a smoothness parameter. Notice that σ can likewise be deciphered as the difference of a Gaussian conveyance fixated on d. Similarly, as we reduce σ, the width of the appropriation progresses toward becoming smaller.

The PNN is then characterised for each of the x_k focuses as the entirety of the conceivable $\phi(d_{kj})$ capacities, or

$$P(x_k) = \sum_{j=1}^{N} \exp[-\frac{\left|x_k - s_j\right|^2}{\sigma^2}] = \sum_{j=1}^{N} \varphi_{kj}, k = 1, 2, ..., M. \quad (5)$$

In the event that each of the focuses are utilised as a part of the preparation data set, PNN will bring about a solitary number, which will later be utilised as a normalising factor in the summed up relapse neural system (GRNN) strategy yet does not give us an extremely valuable separation method. Be that as it may, on the off chance that we break the preparation focuses into various classes, PNN turns into a grouping strategy which can be appeared to be an execution of Bayes' Theorem (Masters, 1995).

Consider the least difficult instance of two classes. On the off chance that we have class C1 with N_1 points, and class C2 with N_2 points, where $N_1 + N_2 = N$, at that point we can characterise:

$$P_1(x_k) = \sum_{j \in N_1}^{N} \varphi_{kj} \quad (6)$$

$$P_2(x_k) = \sum_{j \in N_2}^{N} \varphi_{kj} \quad (7)$$

The p_j esteems can be translated as the likelihood of participation in a class. That is if $p_1(x_k)>p_2(x_k)$, at that point x_k is an individual from class C1, or, if $p_1(x_k)<p_2(x_k)$, at that point x_k is an individual from class C2. This can be summed up to any number of classes.

In classification problems, for effective classification, the range of each class must be thoroughly representative of the actual population. The reservoir parameters will resolve more precision if a larger number of classes is given. However, there is one consideration: as the numbers of classes increase, the numbers of values which belong to each class decrease. Consequently, a classifier such as PNN cannot be trained as good as when there are enough data in each class. With above consideration in mind, we determined the numbers and range of classes as shown in Table 3.

In training step, three wells were used. To optimise the smoothing parameters, the conjugate gradient method was implemented. Data in Table 4 shows the application and cross-validation errors of the training step. After training the PNN, the network was propagated to the studied area, and Meta attribute was created. This Meta attribute exhibits the classes of permeability.

Table 3 - Permeability classes and their range.

Class No.	Permeability Range (md)
1	0.1 - 100
2	100 - 200
3	200 - 300
4	300 - 8000

Table 4 - Application and validation errors in the training step.

Reservoir property	Fractional classification error (Application step)	Fractional classification error (Validation step)
Permeability	0.17	0.25

4. Results and discussion

Permeability is a dynamic reservoir property. Therefore, a geophysicist should validate his/her model for prediction or classification of permeability with a dynamic criterion such as well production or well testing. In this study, well testing results were available for one well. The results of well testing are shown for 68 m interval and 204,338.6 m^3 and the corresponding permeability was obtained to be equal to 85.2 md.

To demonstrate the Meta attribute performance, the result of this method is compared to real data at the well location. For this purpose, the proper data set was selected, which includes well data matrix (permeability values) and related seismic attributes. The result of the comparison

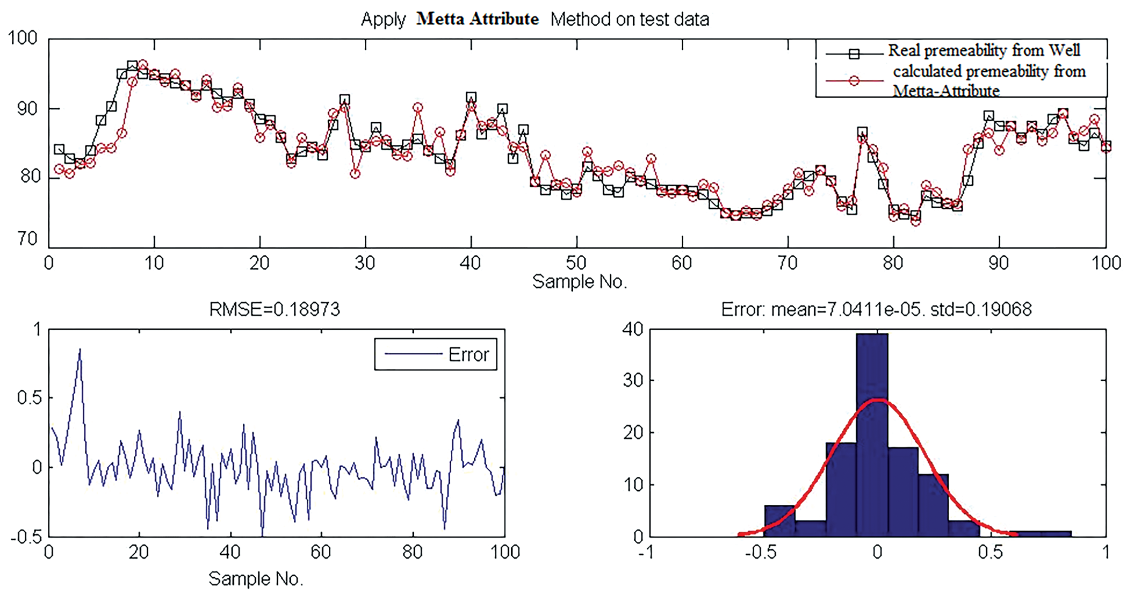

Fig. 8 - Graphical comparison between measured and predicted permeability for tested samples using the Meta attribute approach.

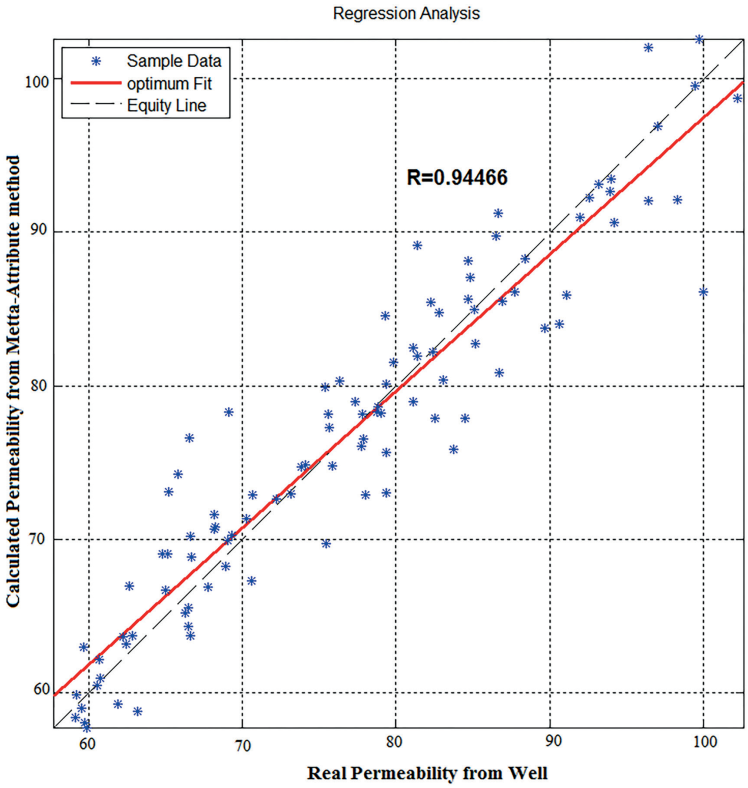

Fig. 9 - Correlation coefficient between measured and predicted permeability for tested samples using the Meta attribute approach.

between predicted and real values of permeability is shown in Fig. 8. According to the outcomes, which are shown in Figs. 7 and 8, the error in test data for the mentioned workflow is 0.18973, and the related correlation coefficient value is 0.94466.

In the studied area, the Asmari formation is consisted of five zones with approximately constant thickness (Sahraeyan *et al.*, 2013; Zabihi *et al.*, 2013; Yazdani, 2014). The interval where well test is accompolished comprises the zones 1 and 2. Therefore, the Asmari horizon was shifted to top and bottom of the well tested interval. The average of Meta attribute then was calculated between these two new horizons.

Data in Fig. 10 shows the average of Meta attribute of the well tested interval. In Fig. 11, the drainage area of the well is shown by a blue rectangle. As Fig. 11 shows, except for the area between NW and SE of well drainage area, which has a permeability greater than 100 md, other parts of the drainage area belongs to class 1. In other words, areas having a permeability less than, or equal to, 100 md are dominant. Consequently, if the well testing results indicate that the average permeability is equal to 85.2 in the well drainage area, then the Meta attribute also indicates that the dominant part of the drainage area belongs to class 1.

There are some advantages and limitations with regards to using the Meta attribute approach for reservoir permeability classification. The main advantage of using the Meta attribute for creating outputs (permeability classes) is the ability to combine different seismic attributes to benefit from their respective prediction power. This allows the interaction of the interpreter with

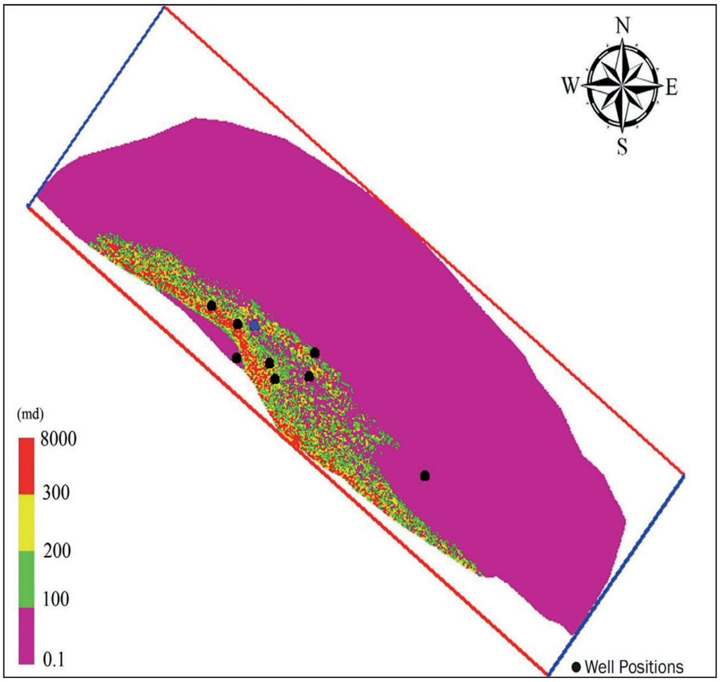

Fig. 10 - Meta attribute averaged on the well tested interval corresponding to Zone1 and Zone2 of the Asmari formation. The permeability values estimated by the Meta attribute are averaged between these two horizons. The blue circle indicates the well position for which the well test data were available.

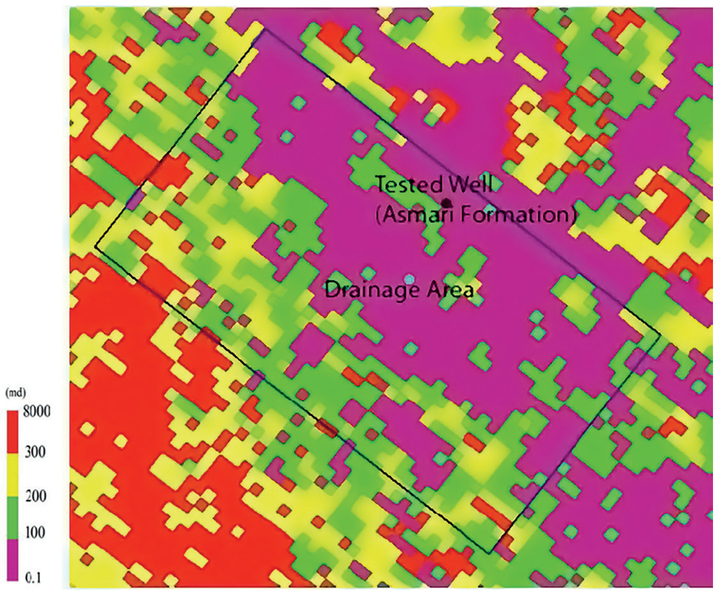

Fig. 11 - Meta attribute averaged on the well tested interval corresponding to Zone1 and Zone2 of the Asmari formation. The permeability values estimated by the Meta attribute are averaged between these two horizons. The blue rectangle indicates the well drainage area.

the neural network during its training process. Consequently, the interpreter's experience will supplement the power of various attributes and facilitate higher training of the neural network. As far as the drawbacks are concerned, the results are affected by the selected method which is used to combine different attributes, these methods include: regression analysis, principle component analysis, clustering or neural network algorithms. According to the field conditions and the target of the study a suitable method is chosen. Another issue that affects the outcomes is the list of attributes that are chosen by the stepwise regression technique. These attributes could be changed from one circumstances to another.

5. Conclusions

Due to high expenditures for drilling operations, any endeavour, which decreases the risk of drilling in non-producible zones, is valuable. To achieve this goal, we have integrated the 3D seismic attributes and the permeability logs. With regards to the geology of the studied reservoir and the range of permeability variation, the probabilistic neural network was applied to generate Meta attribute which estimate and classify the reservoir permeability. The results of this study indicates that the combination of several seismic attributes each exploiting a different feature of the seismic data, can be effectively used for determination of the reservoir parameters, such as the permeability. Comparing the permeability classification results from the Meta attribute with the well testing results, it could be inferred that the generated Meta attribute can qualitatively predict the well testing permeability. For a case of an Iranian petroleum reservoir, the well test data suggest the average permeability of the drainage area to be less than 100; this is in accordance with the results from the Meta attribute classification which indicates that the dominant part of the drainage area belongs to class 1. Whereas the reliability of the well test data is limited to the vicinity of the tested well, the permeability estimation by Meta attribute analysis has the advantage of predicting the permeability trend across the reservoir extent. According to the estimated permeability cube by the Meta attribute, the permeability and reservoir quality is increasing towards SW of the tested well.

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