Determination of Reservoir Facies with Seismic Data and Artificial Neural Networks

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ABSTRACT
One of the purposes in seismic interpretation and reservoir modeling is mapping the changes of anisotropy in the subsurface layers. In this study, multi-attribute analyses were applied based on ANN methods and well logs data to determine the reservoir facies alteration and heterogeneity in the Ghar reservoir of the Hendijan oil field. The Sequential Indicator Simulation (SIS) algorithm coupled with the possible trend and indicator kriging was performed for each facies. Comparison of the mentioned models with core facies shows that the accuracy of SIS algorithm coupled with the possible trend and accuracy of indicator kriging are about 95% and 92%, respectively. The results showed reservoir quality with an average porosity of 0.18 and average gamma of 29 is from moderate to high.

Keywords: Reservoir Facies, Log Data, Seismic Attribute, Artificial Neural Network

INTRODUCTION
Facies is a body of a rock that is categorized by the determined combination of physical and biological structures, and petrophysical parameters such as porosity, permeability, and lithology (Chang, 2010). The main purpose for determining the facies models is to find out the different features such as heterogeneity, controlling physical processes, and the scale (Amoyedo et al., 2016).Introducing a precise description of the lateral changes in the reservoir heterogeneity is crucial in developing a reservoir model. Based on this point of view, cores are not available in lots of well and even in case of availability of the cores; these cores are representative of a determined depth of the well due to economic and technical problems, the use of well logs to determine the petrophysical parameters and lithology can be to significantly reduce exploration costs (Bhatt and Helle, 2002). The well data cannot individually describe the changes. The well data are so scatter while the three-dimensional seismic models provides better description of the reservoir and introduce regular and compact sampling. Although the seismic data have lower vertical accuracy, coupling three-dimensional seismic data with the log data and tremendously improvement in lateral changes description. In addition, it should be noted that there is not a simple relation between seismic properties and seismic parameters such as seismic attributes and seismic amplitude. Moreover, due to the mentioned fact, the seismic facies interpreted by statistical relationship is only the relation among the adjacent well (Caetano, 2006). Artificial Neural Networks (ANNs) are capable to find highly complex nonlinear relationships. The supervised training is a training in which the desired outputs for the input vectors are presented. The training may be an unsupervised training in which no outputs are presented for the input vectors. In this type of training, some general guidelines are given to the network (Munakata, 2008).
A seismic attribute is any measure that helps to better determination of desired geological features using seismic data. There different types of attributes such as, post stack, pre-stack, horizon, inversion, velocity, four-dimensional, and multi-component. However, the most common seismic attributes, which are of this study’s concern is post stacked data (Barnes, 2001). Since 1960s, lots of researchers started studying the reservoir facies.
Pengyu Gao et al (Gao et al., 2016), utilized artificial neural network to predict the reservoir productivity of fluvial facies. These authors stated that the used method is an indirect, practical, and effective method for field applications. Hao-kun Du et al (Du et al., 2015), used empirical mode decomposition (EMD) along with self-organizing map (SOM) to acquire seismic facies. Based on the results the authors could successfully acquire seismic facies with high resolution.In this paper, it is aimed to determine reservoir facies by incorporating seismic data, log data and artificial neural network.

Methodology

At first, 1D facies are obtained using well logs. For doing this stage, Petrophysical parameters just like, porosity and gamma ray has been used. Gamma Ray is finely presenting the volume of shale, by SOM, Vsh and porosity will be clustered, and then regarding to clustering results and variance values of porosity and gamma ray logs, cut offs will be defined. Vertical facies are obtained by these cut offs. In order to generate the 3D facies, the seismic data will imported to Petrel project, after that favorable horizon, which is Ghar reservoir formation will be chosen. In this stage, suitable attributes should be applied to seismic data. Then after, K-Mean clustering shall be done on attributed seismic data. Logs facies datasets should be imported to neural network within supervising method. For optimization ANN facies, generated by logs and attributed seismic data will be result in seismic facies. After generating 3D facies modeling of reservoir, indicator kriging and sequential indicator simulation using trend modeling will be applied and the results of these methods will be compared with core data. Finally the method by minor error will applied for generating 3D reservoir facies model.

Results and Discussion

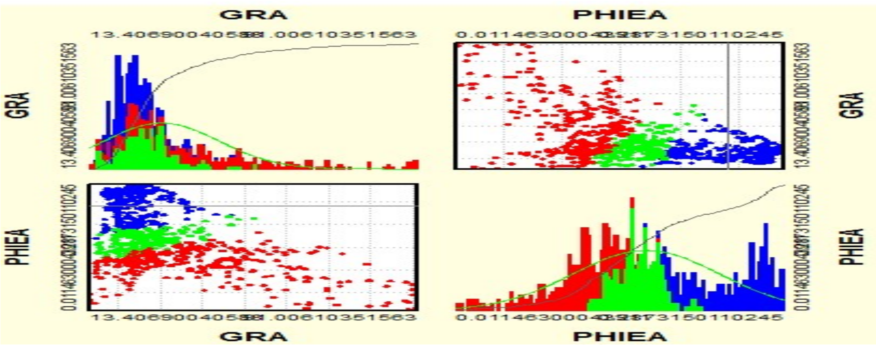
One dimensional (1D) reservoir facies model of Hendijan oil field

Figure 1 shows electerofacies of HD-1. As it is shown in the cross plot, there three classes of reservoir facies considering the SOM outputs. Facies 1 having GR and PHIE averages of respective 20.16 and 0.22 has a high quality. The mentioned values for facies 2 are 36.67 and 0.17, respectively, thus it has a moderate quality. The average GR and PHIE for facies 3 are 39.86 and 0.08, respectively, which indicative of low quality. Effective porosity and gamma values have three classes of cut off. High quality reservoir facies are shown with green color, for high quality reservoir facies PHIE>20% and GR<35. Blue color represent middle quality reservoir facies with 10 %< PHIE<20% and GR<55 and finally the low quality reservoir facies are denoted by pink color, for low quality reservoir facies PHIE<10% and GR>55. The reservoir quality logs was created by calculator of Petrel software. Figure 2 shows the reservoir quality facies for seven wells in the Ghar formation. As it can be seen, through determining the quality facies in wells of the Ghar reservoir and comparing with G1, G2, and G3 zones, it was concluded that the values of the defined cut off shows great conformity by with the three zones of Ghar reservoir.

Three dimensional (3D) reservoir facies model of Hendijan oil field

For this study, the functions of the neural network toolbox in Matlab environment are used to construct K-means cluster, train, and test the MLP neural network model. The seismic cube, which was cropped and realized including seismic attributes of chaos, envelop, GLCM, instantaneous phase, instantaneous frequency as well as log data were used as the input data. The quality log was used as the supervised facies. Seismic attribute were clustered in proper groups. Figure 3 shows the K-means clustering results. In this study, MLP network with two hidden layer with respective 10 and 4 neurons was found to be the optimum structure for this study. After that, the network was optimized trough 25 iterations, the resulted MSE was 2.41×10^{-7}. In order to improve the estimation process, a 3D facies model in well and a model with the nature of probable trend was created by stochastic methods. In this study, input is comprised of up-scaled facies well log. The trend modelling process is based on Kriging algorithm and seismic facies is incorporated as the local kriging mean. The derived possible trends in the model are such that the sum of the probability for the three up-scaled facies in each grid is equal to unity.

Facies modelling was developed using stochastic methods. In this study, the chosen approach for modeling are SIS and indicator kriging. This facies model consists of three classes of high, middle, and low. Correlation coefficient of comparison of core facies and SIS facies model is 0.947. Correlation coefficient of core facies and indicator kriging facies is 0.919.Then, the SIS facies model was chosen for facies modelling due to its higher accuracy. Figure 4 shows three-dimensional facies model of Ghar reservoir in Hendijan oil field.



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A

	FACIES	WEIGHT	GRA	PHIEA
1	1	213	25.16	22
2	2	383	36.67	17
3	3	266	39.86	8

B

Figure 1. Electerofacies of HD-1, A: Cross plot of training data, B: Properties of facies such as color, weight and average of GR and PHIE.

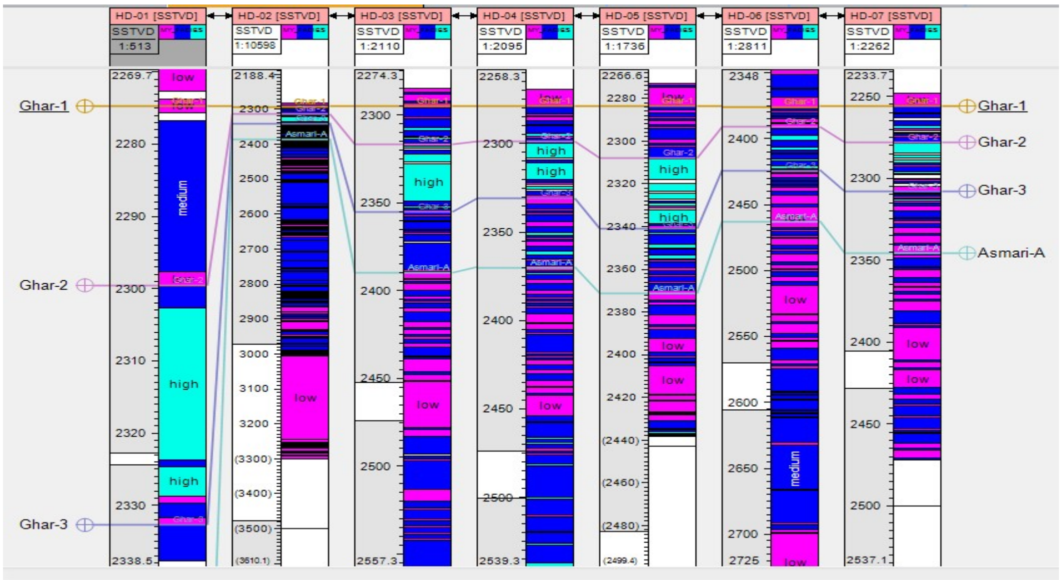

Figure 2. Reservoir quality facies in seven wells of Ghar reservoir.

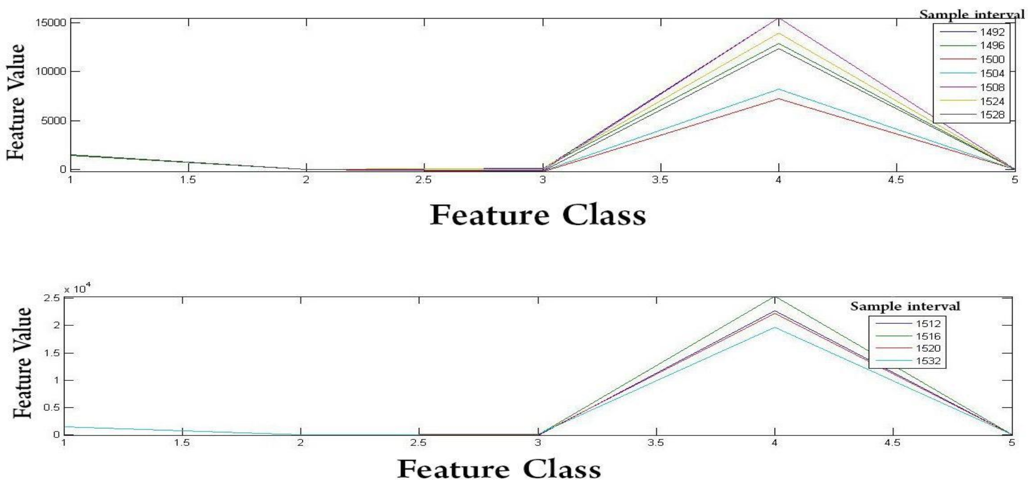

Figure 3. K-means clustering results of attributes data.

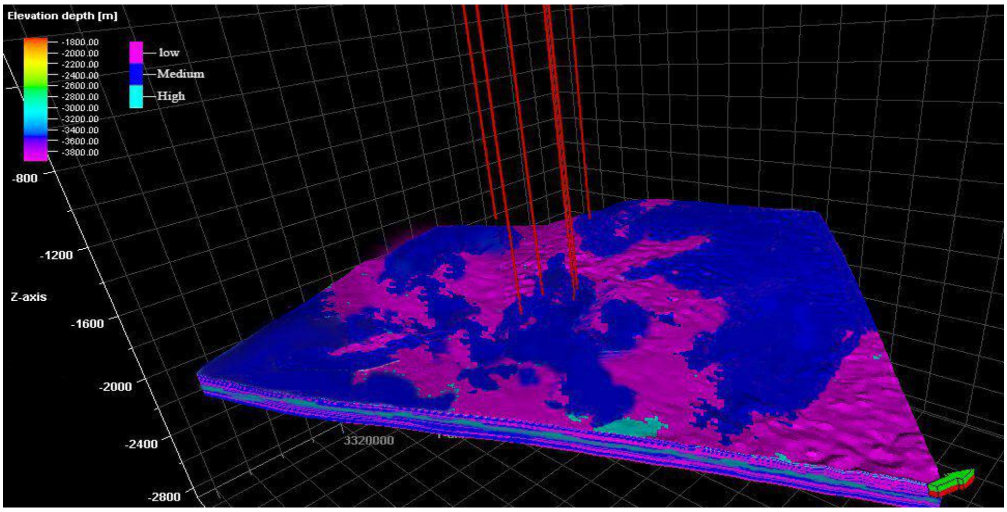

Figure 4. 3D facies model of Ghar reservoir in Hendijan oil field.

CONCLUSION(S)

The ultimate reservoir facies showed that the reservoir condition variation in the reservoir is as follows.

- ✓ In G1 zone it represents moderate reservoir quality with porosity in the range of 10-20% of index and gamma ray value is less than 55.
- ✓ In G2 zone it represents high reservoir quality with an average porosity of more than 20% of index and the gamma ray value is less than 35.
- ✓ In G3 zone just as G1 zone, it represents moderate reservoir quality with an average porosity of 10-20% of index and the gamma ray value is less than 55.

Seismic facies model was utilized along with a supervised neural network. The MLP neural network exhibited good performance in determining the seismic facies based on seismic and log data. The final error was about 2.41×10^{-7}.Facies modeling was done using SIS algorithm coupled with the possible trend and indicator kriging for each facies. The comparison between the mentioned models and core facies showed that the accuracy of the SIS algorithm coupled with the possible trend and indicator kriging are 95% and 92%, respectively. Finally, the SIS algorithm coupled with the possible trend was utilized to build the three-dimensional facies.

REFERENCES

Amoyedo, S. et al., 2016. Seismic-Consistent Reservoir Facies Modelling; A Brown Field Example from Deep Water Niger Delta, SPE Nigeria Annual International Conference and Exhibition. Society of Petroleum Engineers.

Barnes, A.E., 2001. Seismic attributes in your facies. CSEG Recorder, 26(7): 41-47.

Bhatt, A. and Helle, H.B., 2002. Determination of facies from well logs using modular neural networks. Petroleum Geoscience, 8(3): 217-228.

Caetano, H., and Jef Caers, 2006. Constraining multiple-point facies models to seismic amplitude data. SCRF Annual Report

Chang, L., 2010. Integration of facies models in reservoir simulation, Texas, 112 pp.

Du, H.-k., Cao, J.-x., Xue, Y.-j. and Wang, X.-j., 2015. Seismic facies analysis based on self-organizing map and empirical mode decomposition. Journal of Applied Geophysics, 112: 52-61.

Gao, P. et al., 2016. Fluvial facies reservoir productivity prediction method based on principal component analysis and artificial neural network. Petroleum, 2(1): 49-53.

Munakata, T., 2008. Fundamentals of the new artificial intelligence: neural, evolutionary, fuzzy and more. Springer Science & Business Media.