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Quantification of sand fraction from seismic attributes using Neuro-Fuzzy approach

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ABSTRACT

In this paper, we illustrate the modeling of a reservoir property (sand fraction) from seismic attributes namely seismic impedance, seismic amplitude, and instantaneous frequency using Neuro-Fuzzy (NF) approach. Input dataset includes 3D post-stacked seismic attributes and six well logs acquired from a hydrocarbon field located in the western coast of India. Presence of thin sand and shale layers in the basin area makes the modeling of reservoir characteristic a challenging task. Though seismic data is helpful in extrapolation of reservoir properties away from boreholes; yet, it could be challenging to delineate thin sand and shale reservoirs using seismic data due to its limited resolvability. Therefore, it is important to develop state-of-art intelligent methods for calibrating a nonlinear mapping between seismic data and target reservoir variables. Neural networks have shown its potential to model such nonlinear mappings; however, uncertainties associated with the model and datasets are still a concern. Hence, introduction of Fuzzy Logic (FL) is beneficial for handling these uncertainties. More specifically, hybrid variants of Artificial Neural Network (ANN) and fuzzy logic, i.e., NF methods, are capable for the modeling reservoir characteristics by integrating the explicit knowledge representation power of FL with the learning ability of neural networks. In this paper, we opt for ANN and three different categories of Adaptive Neuro-Fuzzy Inference System (ANFIS) based on clustering of the available datasets. A comparative analysis of these three different NF models (i.e., Sugeno-type fuzzy inference systems using a grid partition on the data (Model 1), using subtractive clustering (Model 2), and using Fuzzy c-means (FCM) clustering (Model 3)) and ANN suggests that Model 3 has outperformed its counterparts in terms of performance evaluators on the present dataset. Performance of the selected algorithms is evaluated in terms of correlation coefficients (CC), root mean square error (RMSE), absolute error mean (AEM) and scatter index (SI) between target and predicted sand fraction values. The achieved estimation accuracy may diverge minutely depending on geological characteristics of a particular study area. The documented results in this study demonstrate acceptable resemblance between target and predicted variables, and hence, encourage the application of integrated machine learning approaches such as Neuro-Fuzzy in reservoir characterization domain. Furthermore, visualization of the variation of sand probability in the study area would assist in identifying placement of potential wells for future drilling operations.

1. Introduction

Reservoir characterization of a complex geological system involves the analysis and integration of all available datasets—mainly well log and seismic to finally construct 3D geocellular models of lithological properties. It is important to describe the status of the hydrocarbon reserves from the existing datasets; however, volumetric prediction of the reservoir properties from limited number of well logs and seismic data is viable (Hampson et al., 2001). Literature study associates the growth in reservoir characterization domain with significant advancement in the application of expert systems in the last few decades (Al-Dousari and Garrouch, 2013; Aminzadeh et al., 2000; Fung et al., 1997; Haixiang et al., 2011; Hou et al., 2008; Kadkhodaie-Ilkhchi et al., 2009; Kaydani and Mohebbi, 2013; Lim, 2003; Mohaghegh et al., 1996; Nikravesh et al., 2001; Nikravesh, 2004; Nikravesh et al., 2003; Ouenes, 2000). The objective of this type of studies is to first attune a functional relationship between reservoir properties and predictor variables at available well locations, and then apply the derived relationship to estimate the target variable over the study area from seismic attributes. Inclusion of 3D seismic attributes in the modeling empowers machine learning algorithms to estimate target properties away from the wells (e.g., Hampson et al., 2001; Hilterman, 1999; Hou et al., 2008; Kadkhodaie-Ilkhchi et al., 2009). The reliability of the prediction

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model needs to be ensured by means of testing the prediction algorithms using unseen validation set at well control points.

Geophysical well log data provides a high vertical resolution of different physical properties of the lithological units. However, in situ measurements of these properties are difficult to perform due to limited spatial accessibility and hence, most of the reservoir properties are derived from indirect measurements. The analyzed core data are normally used to guide the derivation process by comparing it with the recorded logs in the vicinity of the existing wells. On the other hand, seismic data provides higher horizontal resolution conceding the vertical resolution level to some extent. Main uses of seismic data are in the delineation of subsurface structures, and hence reservoir bodies; however less helpful in the essential task of quantifying spatial distribution of reservoir properties. Therefore, quantification of inherent relationship between seismic and log properties at the well locations provides a direction to integrate these data to get 3D model of reservoir variables. This can be achieved through systematic combined study of well log and seismic data for 3D reservoir modeling. Moreover, delineation of thin reservoir bodied creates several challenges such as availability of high resolution log data at few locations and low resolvability of seismic data. However, as wells cannot drilled everywhere due to much cost and accessibility, the only alternative is to use seismic data as predictor to model reservoir properties away from well and between the wells to get 3D reservoir model. Following paragraph enlists the literatures available in this research field.

In last three decades, several researchers have used soft computing and Artificial Intelligence (AI) techniques for reservoir characterization (RC). Literature study reveals that machine learning algorithms exhibit superior performance in terms of high accuracy and low error value compared to conventional statistical methods (Nikravesh and Aminzadeh, 2001). Some of the important articles with special emphasis on RC using 3D seismic data include Boadu (1997), Nikravesh (1998a,b), Nikravesh et al. (1998), Chawathe et al. (1997), Yoshioka et al. (1996), Schuelke et al. (1997), Monson and Pita (1997), Aminzadeh and Chatterjee (1985), Finol and Jing (2002), Hou et al. (2008), Kadkhodaie-Ilkhchi et al. (2009), Al-Dousari and Garrouch (2013), Na'imi et al. (2014), Iturrarán-Viveros and Parra (2014). Other important works on application of Artificial Neural Network (ANN), Fuzzy Logic (FL) and Neuro-Fuzzy (NF) methods for RC from well log data and core data are progressively reported by many authors (Adams et al., 1999; Aminzadeh et al., 1994; Baldwin et al., 1989, 1990; Bhatt and Helle, 2002; Griffiths, 1987; Haixiang et al., 2011; Huang and Williamson, 1994; Klimentos and McCann, 1990; Lim, 2005; Nikravesh and Aminzadeh, 2001; Nikravesh et al., 1996; Nooruddin et al., 2014; Pezeshk et al., 1996; Rogers et al., 1992; Wong et al., 1995a, b). Many research papers have been documented on reservoir characterization using statistical approaches (Doyen, 1988; Majdi et al., 2010) and its integration with neural network (Al-Dousari and Garrouch, 2013; Aminzadeh et al., 2000; Na'imi et al., 2014; Sauvageau et al., 2014). Detailed discussion on neural network and its application is well documented in a review article by Poulton (2002). The concept of fuzzy logic is useful in handling uncertainty associated with nonlinear mapping (Kadkhodaie-Ilkhchi et al., 2009; Nikravesh and Aminzadeh, 2001; Ouenes, 2000). Several studies suggest that hybrid approaches such as Neuro-Fuzzy methods, Neuro-Genetic methods, Neuro-Fuzzy-Genetic methods would be effectively applied for the accurate modeling of nonlinear variables (Ahmadi et al., 2013; Dorrington and Link, 2004; Kadkhodaie-Ilkhchi et al., 2009; Kaydani and Mohebbi, 2013; Nikravesh and Aminzadeh, 2001; Nooruddin et al., 2014; Saemi et al., 2007). However, customization of non-linear methods may be required to obtain optimum performance depending on nature of the working dataset. Kadkhodaie-Ilkhchi et al. (2009) describes a committee fuzzy inference system for prediction of petrophysical properties. Three inference systems namely Mamdani, Larsen and Sugeno are used. Most of the studies are focused to either porosity or water saturation or both. Moreover, maximum number of papers are concentrated on the modeling of reservoir properties using well log data. However, a few have discussed on effectiveness of seismic data along with logs for generating reservoir models (Al-Dousari and Garrouch, 2013; Hou et al., 2008; Kadkhodaie-Ilkhchi et al., 2009).

In the present study, the reservoir constitutes very thin layers of sand and shale which are difficult to discriminate from impedance information (Fig. 1). Analysis and interpretation of such reservoirs having thin layers is possible by accurate modeling of reservoir properties such as sand fraction or shale fraction (content) from integrated study of well log and seismic attributes. Moreover, a systematic study on the integration of different dataset and application of hybrid machine learning algorithms is rare in existing literature. Thus, the present study concentrates on the assessment of potential of the NF approaches and its comparison with ANN in the modeling of reservoir property. In this study, a hybrid approach of neural network and fuzzy logic is applied where three different inference systems are used to model sand fraction from seismic attributes. Quantification of sand/shale fraction for a reservoir system provides crucial information about sand/shale content, and hence potential reservoir.

The contributions of this study are listed as: 1) assimilation of 3D seismic data along with well logs for modeling of reservoir property; 2) assessment of thin sand layers by proposing a hybrid technique of neural network and fuzzy logic to model sand fraction from seismic attributes; in which three different categories for Adaptive Neuro-Fuzzy Inference System (ANFIS) are used; and 3) comparison has been made of the results obtained from three different NF models and ANN, where performance metrics are CC (Correlation coefficient), RMSE (Root mean square error), AEM (Absolute Error Mean) and SI (Scatter Index).

2. Description of data

In this study, the well log and seismic data are acquired from a hydrocarbon producing field located in the western onshore of India. The borehole dataset contains geophysical logs such as gamma ray, resistivity, density and other derived logs, e.g., sand fraction value, porosity, water saturation, etc. On the other hand, the seismic dataset includes different attributes, i.e., seismic amplitude, seismic impedance, instantaneous frequency, seismic envelope, seismic sweetness etc.; these attributes are mainly derived from seismic amplitude. Present study aims to model a petrophysical property from seismic attributes. In this context, choice of relevant predictor attributes from a set of attributes is a crucial job to achieve good results within a less execution

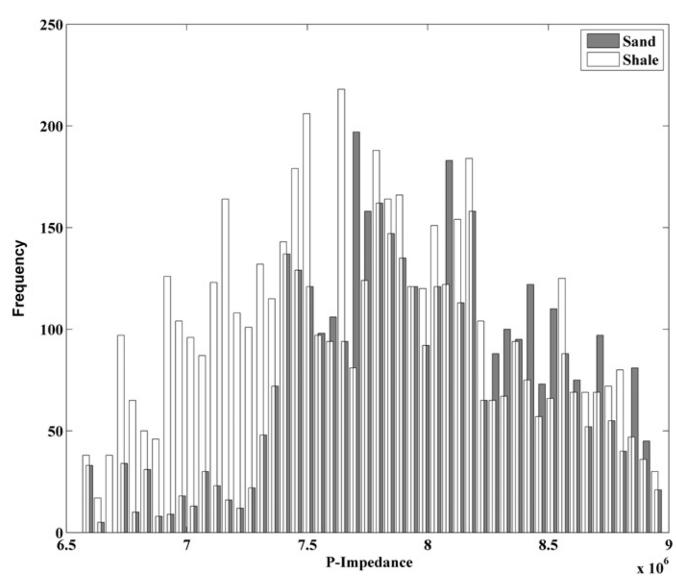

Fig. 1. Histogram plots of seismic P-impedance from all the wells.