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Integrating seismic and log data for improved petroleum reservoir properties estimation using non-linear feature-selection based hybrid computational intelligence models

Fatai Anifowose [a,*,1], Suli Adeniye [b], Abdulazeez Abdulraheem [c], Abdullatif Al-Shuhail [d]

[a] Research Institute, Center for Petroleum and Minerals, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
[b] Information Technology Center, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
[c] Department of Petroleum Engineering, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
[d] Department of Earth Sciences, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia

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ABSTRACT

Various petroleum reservoir properties have been estimated in literature using only one of log, seismic or production data. The recent trend in data mining is integrating multi-modal and multi-dimensional data for improved reservoir properties prediction. The objective of this paper is to employ hybrid machine learning and feature-selection based predictive models to estimate the permeability of carbonate reservoirs from integrated seismic and well log data. Hybrid models of Type-2 Fuzzy Logic System (T2FLS) and Support Vector Machine (SVM) with Functional Networks (FN) as the non-linear feature selection algorithm are proposed. Five seismic attributes were integrated with six commonly used Well logs. Data were collected from 33 oil Wells but only 17 of them had a complete matching seismic-log pair. The performance of the hybrid models were compared to those of the individual models without the non-linear but with the conventional feature selection algorithm. The comparative results showed improved prediction accuracies with the hybrid models and more excellently with the FN-SVM model. A blind test on the models revealed that the FN-SVM hybrid model gave an (R-Square) of 0.82, root mean square error of 0.46, and mean absolute error of 0.42 compared to the lowest performing T2FLS model with 0.40, 0.77 and 0.65 respectively. This demonstrates the significance of the hybrid machine learning paradigm in solving petroleum engineering problems with improved accuracies. The study presented some lessons learned from the data limitation challenges experienced in this work and proposed recommendations to chart further research directions.

1. Introduction

The capabilities of Computational Intelligence (CI) techniques have been widely appreciated in Petroleum Engineering, in particular, and in other fields. Some of the areas of petroleum technology where the CI paradigm has been successfully applied include seismic pattern recognition, porosity and permeability predictions, identification of sandstone lithofacies, drill bit diagnosis, analysis and improvement of gas well production, analysis, prediction, and optimization of well performance, bed thickness, proximity to faults, slopes and curvatures of the structure, irreducible water saturation and oil and gas portfolio management (Anifowose et al., 2013). CI relies on heuristic algorithms such as in Fuzzy Systems, Neural Networks, Support Vector Machines and Evolutionary Computation. In addition, CI also embraces techniques that use Swarm Intelligence, Fractals and Chaos Theory, Artificial Immune Systems, Wavelets, etc. (Sumathi and Surekha, 2010).

A good number of studies have been carried out on the use of various CI schemes to predict the characteristics of oil and gas reservoirs such as depth, temperature, pressure, volume, migration mechanism, structure and seal, diagenesis, well spacing, wellbore integrity, porosity and permeability, using various techniques (Duch et al., 1997; El-Sebakhy, 2011; Guojie, 2004; Hosmer and Lemeshow, 2000; Lauría and Duchessi, 2006; Salah et al., 2005). Well logs have been used to predict permeability using CI methods. However, such predictions can be made only along the depth of a given well for which well logs are available. Reservoir simulation requires that these values are available throughout the

* Corresponding author.
E-mail addresses: fanifowose@gmail.com (F. Anifowose), suli@kfupm.edu.sa (S. Adeniye), aazeez@kfupm.edu.sa (A. Abdulraheem), ashuhail@kfupm.edu.sa (A. Al-Shuhail).
[1] This author is now with the Advanced Research Center, Exploration and Petroleum Engineering Center, Saudi Aramco, Dhahran, Saudi Arabia.

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reservoir. Recent developments in CI and seismology can therefore potentially be used to predict the core permeability distribution in a given reservoir where seismic and log data are available. Rock permeability is an important parameter in reservoir characterization and simulation, because it influences the hydrocarbon rate of production, ultimate recovery, optimal placement of wells, pressure and fluid contact evaluation, etc. Thus, proper determination of permeability is of paramount importance because it affects the economy of the whole venture of development and operation of a field. Estimation of permeability in un-cored but logged wells is a generic problem common to all reservoirs.

The most reliable data of permeability have been taken from laboratory analyses of core samples. But extensive coring is very expensive (Wheatley, 2009) and thus is available only for some of the wells in a field, and for some limited intervals in a well. For that reason, in terms of practical use, there was the need to develop relationships that can represent the permeability value for each cored well using the existing log and seismic data. The objective of this paper is to investigate the possibility of improving petroleum reservoir permeability prediction by integrating log and seismic data using some novel CI techniques based on the hybrid methodology.

2. Literature survey

2.1. Conventional approach to permeability prediction

Traditional approaches for the estimation of permeability are based either on simple linear regressions or empirical inferences that use correlations among various well log responses. Some of the popular correlations are based on the Darcy's equation that considers the fluid properties namely flow rate, viscosity, cross-sectional area and pressure difference (Shang et al., 2003) and the Kozeny-Carman equation that considers other properties such as the shape factor, tortuosity and the surface area per unit grain volume (Carman, 1937; Kozeny, 1927). From the latter, several extensions were proposed. These include the correlations proposed by Amaefule et al. (1993), Coates and Denoo (1981), Timur (1968), Thomeer (1983), and Wyllie and Rose (1950). In recent times, Dastidar et al. (2007) considered the pore throat radius in their empirical model (Nooruddin et al., 2013). Other correlations such as Purcell, Swanson, Winland, Walls-Amaefule, Katz-Thompson, Kamath, and Huet-Blasingame have been extensively studied and compared in Comisky et al., (2007). It has been however argued that all these correlations can be expressed in linear terms (Anifowose et al., 2014a).

The regression methods assume that a linear relationship exists between core porosity and the logarithm of core permeability. This method explicitly ignores the scatter of data about the regression lines and implicitly attributes any scatter to measurement errors. A partial improvement is achieved by first identifying lithological categories of the formation and then calculating linear regression lines for petrophysical core measurements that belong to each lithology class. As the regression methods smooth data, the predicted permeability values from these regression models lack the variability seen on actual core data. Despite these deficiencies, the linear regression methods were still found to outperform the empirical correlations (Eskandari et al., 2004). However, with relevant data representing the dynamics of the subsurface, CI techniques have reportedly outperformed the statistical regression tools (Al-Marhoun et al., 2012; El-Sebakhy, 2009).

The recent use of seismic technology in reservoir characterization (Brahmantio et al., 2012; Maity and Aminzadeh, 2012) has become increasingly common. It has also been combined with production data for reservoir management (Nalonnil and Marion, 2010; Liang et al., 2011; Suman et al., 2011) as well as history matching (Jin et al., 2011; Kazemi and Stephen, 2010) and stratigraphic trap identification (Lertlamnaphakul et al., 2012). Trial studies have been carried out to explore the possibility of predicting permeability from seismic data (Behzadi et al., 2011; Liang et al., 2011). The latter is a major motivation for this study. Seismic and log data have not been integrated in the prediction of petroleum reservoir permeability.

A large volume of data has been generated and acquired over the years through the traditional coring followed by aggressive laboratory analytical procedures as well as through advanced logging activities and massive seismic campaigns. The cost of the expensive, laborious and time-taking coring procedures is huge and the accuracy of the mathematically-derived correlations is low. These serve as the motivation to investigate the benefits of the hybrid intelligent system being proposed in this paper. These historical data have remained perpetually locked up in secured warehouses and storage devices. The significance of this study is to utilize the learning capability of CI techniques to mine the pattern stored in these data and extract the useful information in them for future decision-making. The implication of this study is to expand the scope of application of CI techniques in the petroleum business to the level of utilizing the power of hybrid learning machines. Harnessing the power of data will lead to reduced cost of exploration, improved accuracy of predictions, increased availability and turn-around of critical information, and improved efficiency of production operations.

2.2. Seismic attributes

Seismic data are the results of seismic investigations made to describe geological structures in the bedrock. On either land or sea, signals are transmitted from the land or ocean surface (pings), and the echoes are captured by special measuring instruments namely geophones and hydrophones respectively. They are used to localize occurrences of hydrocarbons. They can be of any of the 3 types: 2-D, 3-D or 4-D. A 2-D seismic data is a vertical section of seismic profile consisting of numerous adjacent traces acquired sequentially. A 3-D seismic data are a set of numerous closely-spaced seismic lines that provide a high spatially sampled measure of subsurface reflectivity. Typical receiver line spacing can range from 80 m to over 600 m, and typical distances between shot points and receiver groups range from 34 m to 67 m (onshore US), and 25 m offshore and outside the US (Deco Geophysical, 2007). The resultant data set can be "cut" in any direction but still displays a well sampled seismic section. Computer-based interpretation and display of 3-D seismic data allow for more thorough analysis than 2-D seismic data. A 4-D seismic data is 3-D seismic data acquired at different times (time-lapse) over the same area to assess changes in a producing hydrocarbon reservoir with time. Changes may be observed in fluid location and saturation, pressure and temperature. A seismic attribute is any measure of seismic data that helps to better visualize or quantify features of interpretation interest. Seismic attributes fall into two broad categories – those that help to quantify the morphological component of seismic data and those that help us quantify the reflectivity component of seismic data. The morphological attributes help to extract information on reflector dip, azimuth, and terminations, which can in turn be related to faults, channels, fractures, diapirs, and carbonate buildups. The reflectivity attributes help to extract information on reflector amplitude, waveform, and variation with illumination angle, which can in turn be related to lithology, reservoir thickness, and the presence of hydrocarbons.

In the reconnaissance mode, 3D seismic attributes help to rapidly identify structural features and depositional environments. In the reservoir characterization mode, 3D seismic attributes are