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Adaptive neuro fuzzy inference system for compressional wave velocity prediction in a carbonate reservoir

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ABSTRACT

Compressional-wave (V_p) data are key information for estimation of rock physical properties and formation evaluation in hydrocarbon reservoirs. However, the absence of V_p will significantly delay the application of specific risk-assessment approaches for reservoir exploration and development procedures. Since V_p is affected by several factors such as lithology, porosity, density, and etc., it is difficult to model their non-linear relationships using conventional approaches. In addition, currently available techniques are not efficient for V_p prediction, especially in carbonates. There is a growing interest in incorporating advanced technologies for an accurate prediction of lacking data in wells. The objectives of this study, therefore, are to analyze and predict V_p as a function of some conventional well logs by two approaches; Adaptive Neuro-Fuzzy Inference System (ANFIS) and Multiple Linear Regression (MLR). Also, the significant impact of selected input parameters on response variable will be investigated. A total of 2156 data points from a giant Middle Eastern carbonate reservoir, derived from conventional well logs and Dipole Sonic Imager (DSI) log were utilized in this study. The quality of the prediction was quantified in terms of the mean squared error (MSE), correlation coefficient (R-square), and prediction efficiency error (PEE). Results show that the ANFIS outperforms MLR with MSE of 0.0552, R-square of 0.964, and PEE of 2%. It is posited that porosity has a significant impact in predicting V_p in the investigated carbonate reservoir.

1. Introduction

Compressional wave velocity, in combination with shear wave velocity, makes an important parameter providing valuable information in seismic analysis, lithologic identification (Tatham, 1982; Wilkens et al., 1984) and pore fluid and pore pressure information (Duffaut and Landrø, 2007; Rojas, 2008). Its contribution to upstream oil and gas industry is not only for exploration purposes but also for production, abandoned, and environmental activities (e.g. Enhanced Oil Recovery, CO_2 injection). In carbonate reservoirs, because of the indefinite and complex physical processes associated with the formation of these materials, rock physical properties show uncertain and varied behavior. The need for a high performance predicative method is particularly critical in carbonate reservoirs which are not as well understood or studied as clastic reservoirs.

The presented study proposes a methodology for making a quantitative formulation between conventional well logs and compressional wave velocity. Few studies existed to predict solely compressional wave velocity in hydrocarbon reservoirs without involving shear wave velocity measurement (and vice versa). Due to the lack of access to useful data (e.g. inaccessible or cryptic) in the investigated oilfield, the evaluation of the reservoir's potential is adherent with complications, and could significantly hamper future development efforts. Thus the following question arises: should the efforts for better understanding of the reservoir, due to lack of sufficient data, be stopped? If the answer is *no*, is there a need for drilling new exploration well and logging/coring the reservoir interval and/or conducting laboratory tests on core plugs? The first feeling about these mentioned actions is that, the cost of the operation is substantial; however the implications have to be examined in more detail; for example, core plugs are usually taken from every few meters, over a small section of the well in question, and therefore a continues profile of the reservoir's interval is not achieved. Those questions could be expressed in an important facet: would the conventional approaches (e.g. empirical relationship and curve fitting) be trustworthy for such cases and be considered efficient techniques to improve the accuracy of the target results? Those approaches have commonly been applied (Eastwood and Castagna, 1983; Eskandari et al., 2004; Kithias, 1976; Pickett, 1963). In the case of mixed mineralogies for carbonate formations, Kazatchenko et al. (2004), Markov et al. (2006) and proposed a technique for determination of sonic wave velocity by the symmetric variant of the effective medium approximation. Assefa et al. (2003) employed two relationships (time-average and Raymer) and two theories (Gassmann and Biot), but the p-wave velocities predicted by the four approaches overestimate the measured velocities. As a deduction, those applications are limited, because, as indicated by Moos and Zoback (1983), no

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unique relationships have been found in carbonates yet. In fact, the influencing factors with interaction on V_p are complex and non-linear; it's difficult to make predictions based on not only one or more variables, but also on the complex relationship of the predictor variables with the value of response. Actually, no clear relationship is perceptible between well log parameters and p-wave velocities in carbonates.

Innovative approaches in the field of Artificial Intelligence (AI) show promising results for such cases; they were successfully developed and utilized to predict the missing information. Where empirical and statistical approaches (Augusto and Martins, 2009; Eastwood and Castagna, 1983; Eskandari et al., 2004) are mainly used to capture linear relationships, AI techniques are capable of dealing with non-linear relationship among input and output parameters. Among AI methods, ANFIS seems to be suited successfully to model complex problems where the relationship between the model variables is unknown. AI techniques recently applied to predict sonic wave velocities (Ameen et al., 2009; Asoodeh and Bagheripour, 2012; Moatazedian et al., 2011; Rajabi et al., 2011). However, their work did not examine the significant impact of input parameters on response variable, the model's ability to predict non training data, and the model's extrapolative ability of validation data set for a huge number of data.

Fuzzy propositions are statements that possess fuzzy variables. The concept of a fuzzy set is the basis of a fuzzy logic. A fuzzy set is a set without a crisp, clearly defined boundary. In addition to the above advantages, fuzzy models can be combined with Artificial Neural Network (ANN) to create ANFIS. ANFIS and ANN can be viewed as strong tools in the statistical pattern recognition algorithm and to prepare an equivalent model by virtue of their capabilities of function approximation and classification (Singh et al., 2007).

Fuzzy models offer advantages over mathematical ones; the inference process is close to human thinking and it is easier to deal with complex non-linear systems. Moreover, these approaches can be useful to non-expert modeling people. ANFIS stands for adaptive neuro-fuzzy inference systems and tunes a fuzzy inference system with a back-propagation algorithm based on collection of input/output data. The fuzzy modeling and identification toolbox constructs Takagi–Sugeno fuzzy models from data by means of product-space fuzzy clustering (using the Gustafson–Kessel algorithm) (Babuska, 1998).

Over the last few years, ANFIS has been used in many geophysical, petrophysical, geological, and engineering problems. This technique seems to be suited successfully to model complex problems where the relationship between the model variables is unknown. ANFIS model brings together the linguistic representation of a fuzzy system with the learning ability of ANNs. A review of published literature reveals that ANFIS has been used successful in injection profiles in water flooding (Wei et al., 2007), prediction of oil production (Mahdavi and Khademi, 2012), core porosity and permeability prediction (Ja'fari and Moghadam, 2012). ANFIS was used for sonic wave velocity prediction too. Predicting foundation behavior using ANFIS has been explored by Rezaee et al. (2006). The results of their study encourage the use of ANFIS in prediction of compressional wave velocity.

Motivated by the need of such advanced tool, the principal objective of this study is to predict comparatively V_p in a giant Middle Eastern carbonate reservoir by ANFIS and compare the results with MLR method. Additionally, statistical analysis will be conducted to investigate the significant impacts of input parameters on the response value (V_p). From this analysis it is expected to see which input parameter, is more important for predicting V_p and its behavior in investigated reservoir.

The paper is organized as follows. The Data selection section will show the basis for choosing the inputs for this study. In Sections 3 and 4, the employed methodologies along with the employed performance criteria are proposed. The results of conducting ANFIS and MLR approaches in the case study area are presented and the effect of the parameters will be discussed in Section 5. Finally, the results will be summed up in Section 6.

2. Data selection

Sonic velocity depends on many factors; four of the main factors among others in carbonate rocks are porosity, burial depth, bulk density, and shaliness. Rock porosity represents the main physical parameter affecting compressional wave velocities; see e.g. Wyllie et al. (1958), Raymer et al. (1980), Anselmetti and Eberli, 1993; Eberli et al. (2003), Vanorio et al. (2008). As implied by Faust (1953), due to variations in porosities, wave velocity depends upon the one–six power of the depth of burial, whereas as suggested by Anselmetti and Eberli (1993) depth should not be used solely for velocity prediction. In formation evaluation, NPHI and RHOB logs are introduced as porosity logs. The papers of Rajabi et al. (2011), Moatazedian et al. (2011), and Asoodeh and Bagheripour (2012), use neutron porosity, gamma ray, and bulk density, among others to investigate dependence of seismic velocities in carbonate formations. As indicated in literature, the mentioned parameters play a fundamental role in the variation of seismic velocities; and as a common conclusion, density, and gamma ray logs along with depth of burial and neutron porosity were selected as input data. Cross plots of depth, computed gamma ray (CGR), bulk density (RHOB), and neutron porosity (NPHI) versus V_p, are shown in Figs. 1, 2, 3, and 4, respectively. The petrophysical properties of studied reservoir's interval cover a wide range for exploration interest, with porosity from 0.02% to 20%, permeability from 0.1 to 115 mD, clay content from 0% to 0.5%, calcite content from 68% to 95% and dolomite from 1% to 24%. Fig. 5 shows gamma ray, lithology, density, and porosity along with their depth. As it is clear from Fig. 5, the dominant lithology of the investigated reservoir is limestone and conventional well log. Petrophysical wireline log data were gathered from wells and after deletion of bad hole data, all data were depth matched. All depths referred to in this paper are DSI-log depths. Table 1 shows the statistical properties of the input and output variables in this study. The table shows the maximum, minimum, average, standard deviation, variance, median, and mean of the selected variables.

3. Methodology

The aim of this study is to demonstrate the capability ANFIS for the prediction performance of V_p in a carbonate reservoir. Because MLR is widely used in this field, the results of ANFIS compared with MLR. The data set contains measured V_p derived from a DSI log of one well and conventional well log information of 31 vertical and directional wells drilled through a carbonate oil-bearing reservoir. Conventional logs, i.e., CGR, NPHI, and RHOB are available in all wells. Except for one

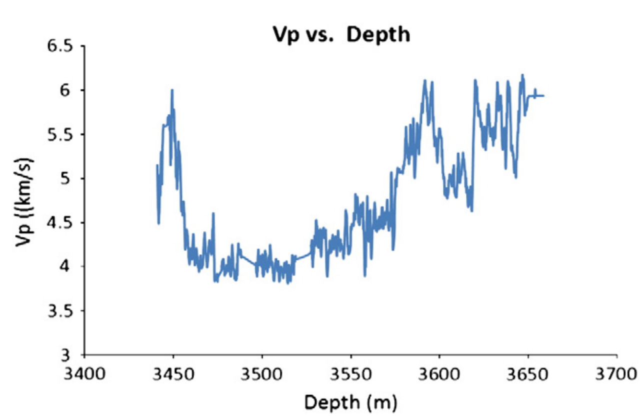

Fig. 1. Cross-plots showing the relationship between compressional wave velocity and depth.