Journal of Petroleum Science and Engineering 152 (2017) 238–249

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

journal homepage: www.elsevier.com/locate/petrol

Estimation of porosity from seismic attributes using a committee model with bat-inspired optimization algorithm

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ARTICLE INFO

Keywords:
Porosity
Seismic attribute
Alternating conditional expectation (ACE)
Committee machine (CM)
Bat-inspired algorithm (BA)

ABSTRACT

Porosity is one of the most petrophysical parameters, which has profound impact on reservoir characterization, reserves estimation, and production forecasting. This parameter is determined from experimental implementation in laboratory core analysis, as well as interpretation of porosity log. Since there exists no reliable source of porosity data (core data and porosity log data) before of drilling a well, developing a reliable model for estimation of porosity from seismic attributes is highly valuable. In current study, a merged model is proposed for identifying formulation between porosity and seismic attributes in a field which is located in the Persian Gulf. In the first step, suitable seismic attributes which have prominent influence on porosity are extracted through forward stepwise selection variable method and considered as input parameters of the model. Secondly, input variables are transformed into higher correlated data space by virtue of nonparametric method so-called alternating conditional expectation (ACE). In third step, making quantitative correlation between ACE transformed of input parameters and porosity through improved intelligence model, including optimized neural network (ONN), optimized support vector regression (OSVR), and optimized fuzzy logic (OFL) are achieved. Optimization method which embedded in intelligence models formulation for ameliorating those performances is bat-inspired algorithm (BA). In the last step, outputs of improved models are combined through a committee machine (CM) in the sake of enhancing in the prediction accuracy. Optimal contribution of improved models in overall estimation is computed by mean of the BA method. Comparison between the individual models and the CM model shows that integrating models with the CM produce results with lowest error and highest correlation and consequently is superior. The results prove that proposed strategy in this study is reliable alternative way for mapping functional dependency between porosity and seismic attributes.

1. Introduction

Porosity is one of most important petrophysical parameters of rock, which determine how much of bulk volume is occupied by fluid including water, oil, and gas. This parameter measures the fluid capacity of reservoir rock and thus has howling effect on reservoir characterization, reserves estimation, and production forecasting (Asoodeh and Bagheripour, 2013; Bagheripour and Asoodeh, 2013). In a drilled well, this parameter is determined from two ways as experimental implementation in laboratory core analysis and interpretation of porosity logs. Prior to drilling a well, determining of porosity from two aforementioned sources is limited. Porosity information is extremely important in the exploration phase of petroleum field. Since there is no porosity data source (core data and porosity log data) in this phase before drilling a well, finding a robust method for determining accurate values of this parameter is invaluable. Hence, researchers proposed seismic attributes as suitable way for estimation of porosity (Ansari, 2014; Hampson et al., 2001; Kadkhodaie-Ilkhchi et al., 2009). Recently, numerous statistical forecasting methods have been developed for modeling of porosity as a function of seismic attributes (Ansari, 2014; Hampson et al., 2001; Martin and Davis, 2013; Ogiesoba, 2010; Ahmed et al., 2010; Iturrarán-Viveros, 2012; Kadkhodaie-Ilkhchi et al., 2014; Na'imi et al., 2014a; Iturrarán-Viveros and Parrrab, 2014; Khoshdel and Riahi, 2011; Kadkhodaie-Ilkhchi et al., 2009; Russell et al., 2003;). Although the developed models have satisfactory accuracy, developing a novel model with better results is always valuable. This study presents a sophisticated based model for estimation of porosity from seismic attributes. When constructing a model for formulating porosity as a function of seismic attributes, search for achieve the influential seismic attributes as inputs of model is crucial. Aiming at to select appropriate seismic attributes, at the first stage of this study, method based on forward stepwise selection

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http://dx.doi.org/10.1016/j.petrol.2017.03.013
Received 25 May 2016; Received in revised form 4 March 2017; Accepted 6 March 2017
Available online 07 March 2017
0920-4105/

variable is proposed. At the second step, selected variable are transformed to high correlated space through alternating conditional expectation algorithm (ACE). This step simplifies the problem space. At the third step of current study, three improved models, viz. optimized support vector regression (OSVR), optimized neural network (ONN), and optimized fuzzy logic (OFL) are adopted to finding correlation between the ACE transformation of selected seismic attributes and porosity. Optimization implementation is achieved through bat-inspired algorithm (BA). Finally, committee machine (CM) is used to combining the outputs of improved models. Taking the optimized models combined by the BA, the sophisticated model that reaps the benefits of individual model is achieved. To verify the feasibility and effectiveness of the proposed scheme, the results of the proposed committee model are compared with those elements including OSVR, ONN and OFL. Correlation coefficient (R) and root mean square error (RMSE) are statistical criteria which adopted for measure the performance of the models. The comparative study concluded that the integrating the models with the CM generate the model with better precision.

2. Model description

In first step of this study, proper seismic attributes are selected through forward stepwise selection variable method. The selected seismic attributes are assigned to inputs of ACE model. In second step, input parameters are transformed into high correlated space through of ACE. In third step, three improved models including ONN, OSVR and OFL are used for relating ACE transformation of input parameters and porosity. Finally, the CM is employed for combining the outputs of improved models. Each improved model is associated with a weighting factor to determining the final value of porosity. Optimization method for achieving the optimal contribution of individual model as well as optimizing the predictive model is BA. Fig. 1 demonstrated the flowchart of integrated model for computation of porosity as a function of seismic attributes. A brief description of models which used in this study for estimation porosity is given in following section.

2.1. Alternating conditional expectation

Alternative condition expectation (ACE) is developed by Breiman and Friedman in 1985. This method has been extensively used in solving nonlinear problems which conventional regression method cannot solve it (Malallah et al., 2006; Xue et al., 1996; Shokir, 2007; Gholami et al., 2014a; Feng et al., 2014, 2015). This method solves nonlinear problems through determining the optimal transformation of input/output space (Gholami et al., 2014b; Asoodeh et al., 2015). Indeed this method transformed data space into high correlated space. To achieve detail information about the ACE formulation, reader can refer to original paper of Breiman and Friedman (1985). In this study, ACE is incorporated for simplified problem space by mean of transforming input parameters into high correlated space.

2.2. Intelligent optimized artificial neural network

Artificial neural network (ANN) is computational approach which developed based on inspiring of the behavior of the human brain (Haykin, 1999; Bishop, 1995). Akin to the human brain, ANN is competent to learn from a number of samples without pre-conditioning of mathematical relationship between input and output data. Consequently this model is felicitous for solving nonlinear problems, in which the exact formulation between input variables and response variable is ambiguous (Majdi et al., 2010; Golden, 1996). ANN consists of three layers including input, hidden, and output layers. Input layer receives the input data. Output layer produces the output data. Hidden layer extracts the underlying dependency between input and output data. This method sends the input values forward through the network, then computes the difference between calculated output and corresponding desired output from the training dataset. The error is then propagated backward through the net, and the weights are adjusted during a number of iterations named epochs. The training stops when the calculated output values best approximate the desired values (Majdi et al., 2010; Dutta and Gupta, 2010; Asoodeh and Bagheripour, 2012). After the constructing the model, ANN can estimate unseen data with good accuracy. Neural network with back-propagation learning algorithm is extremely at risk of finding the local minima instead of global minima (Afshar et al., 2014; Gholami et al., 2014c, 2015; Asoodeh et al., 2015; Asoodeh et al., 2014a, 2014b). Owing to highly dependence of ANN performance to achieving to global minima (optimal value of weight and bias), embedded the potent optimization algorithm in ANN formulation is essential. In this study bat-inspired algorithm is included in ANN formulation for determining the accurate value of weight and bias. This method is call optimized neural network (ONN) in this study.

2.3. Intelligent optimized fuzzy logic

Fuzzy logic (FL) first proposed by Zadeh (1965) provide a mathematical computation for handling uncertainty based on "degrees of truth" rather than the usual "true or false" logic calculation. Fuzzy inference system (FIS) is the process of formulating from a given input to an output using FL (MATLAB user's guide, 2012; Gholami et al., 2014d). A well-known type of FIS is Sugeno (Takagi and Sugeno, 1985) structure which has been used in this study. Sugeno model is composed of "if-then" rules in following general form:

$$R_n\text{: if } I_1 \text{ is } M_n^1 \text{ and } I_2 \text{ is } M_n^2 \text{ and } \dots \text{ and } I_m \text{is } M_n^m \text{ then } Z_n = f_n(I) \qquad (1)$$

where n refers to number of rules; I_i is input and of FIS; M_n^m is the Gaussian input membership function (MF) of mth input data and nth rule and $Z_n = f_n(I)$ is a function in the consequent. Usually, output membership function $f_n(I)$ is linear polynomial in the input variables. The output level, Z_n, is weighted by the firing strength for each rule and finally, the overall output is estimated via weighted average operator. During aforementioned learning process, associated coefficients of input and output MFs are obtained and updated with an optimization algorithm. For this purpose, the BA was used for optimizing MFs of optimized fuzzy logic model (OFL).

2.4. Intelligent optimized support vector regression

The support vector regression is a relatively new learning technique, developed by Vapnik and coworkers (1995), on the basis of statistical learning theory and structural risk minimization. Compared with other machine learning approaches, such as Artificial Neutral Network (ANN), SVR implements the structural risk minimization rather than the empirical risk minimization principle, thus SVR minimizes the upper bound of the generalization error. This method has novel feature which recently applied to variety of petroleum related problems and achieved encouraging results. Owing to successfully performance of this method, it has achieved popularity in modeling fields (Fattahi et al., 2014; Bagheripour et al., 2014; Na'imi et al., 2014b; Bagheripour et al., 2015). The most important problem with exploiting the SVR is to select the accurate value of user defined parameters, which usually requires an excessive amount of expert's effort (Fattahi et al., 2014; Mousavi et al., 2013; Liao et al., 2011; Ustun et al., 2005). Due to strong function of SVR performance to precise choose of user defined parameters, it is crucial to employ a potent optimization algorithm for searching the proper value of these parameters. Moreover, owing to interaction between parameters, optimization of each parameter individually is not sufficient to fulfill the optimal regression model and optimization implementation of SVR