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Genetic implanted fuzzy model for water saturation determination

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ABSTRACT

The portion of rock pore volume occupied with non-hydrocarbon fluids is called water saturation, which plays a significant role in reservoir description and management. Accurate water saturation, directly measured from special core analysis is highly expensive and time consuming. Furthermore, indirect measurements of water saturation from well log interpretation such as empirical correlations or statistical methods do not provide satisfying results. Recent works showed that fuzzy logic is a robust tool for handling geosciences problems which provide more reliable results compared with empirical correlations or statistical methods. This study goes further to improve fuzzy logic for enhancing accuracy of final prediction. It employs hybrid genetic algorithm-pattern search technique instead of widely held subtractive clustering approach for setting up fuzzy rules and for extracting optimal parameters involved in computational structure of fuzzy model. The proposed strategy, called genetic implanted fuzzy model, was used to formulate conventional well log data, including sonic transit time, neutron porosity, formation bulk density, true resistivity, and gamma ray into water saturation, obtained from subtractive clustering approach. Results indicated genetic implanted fuzzy model performed more satisfyingly compared with traditional fuzzy logic model. The propounded model was successfully applied to one of Iranian carbonate reservoir rocks.

1. Introduction

The portion of void space of reservoir rock which is occupied with non-hydrocarbon fluids is called water saturation. This petrophysical parameter has significant effects on success of drilling, well completion, and production plans. Two familiar approaches for water saturation determination include special core analysis (direct measurement) and well log data interpretation (indirect measurement). Core analysis approach, associated with huge expenses is not provided for most of wells. Therefore, most researchers seek novel methods for reservoir characterization from well log data. Hitherto, three wide categories of methods, including empirical correlations, statistical methods, and intelligent systems have been presented for determining water saturation from conventional well log data. Several empirical correlations and statistical methods for determination of water saturation can be found in number of papers and reviews (Adeniran et al., 2009; Alimoradi et al., 2011; Archie, 1942; Desbrandes and Gualdron, 1988; Hingle, 1959; Ipek, 2002; O'Meara et al., 1992; Pickett, 1963; Poupon and Leveaux, 1971; Rezaee and Lemon, 1996; Shokir, 2004; Simandoux, 1963; Waxman and Smits, 1968; Worthington, 1985). Recent years have been witness of growing tendency in utilizing intelligent systems for solving complicated petroleum related problems (Asoodeh and Bagheripour, 2012a,b, 2013a,b; Bagheripour and Asoodeh, 2013; Cuddy, 1998; Jamialahmadi and Javadpour, 2000; Kadkhodaei-Illkchi et al., 2006; Rezaee et al., 2007; Saggaf and Nebrija, 2003). Previous works showed fuzzy logic model is a robust tool for handling geosciences problems. Traditional fuzzy logic models utilize subtractive clustering (SC) for fuzzification and setting up fuzzy rules. SC assigns constant-variance membership functions to each input and no optimization is done over variances of input membership functions. Consequently, all extracted values involved in fuzzy formulation are regulated according to assigned input membership functions. Thus, extracted values are not in turn in optimal value of themselves. To extract optimal fuzzy formulation between conventional well log data (inputs) and water saturation (output), a novel strategy, called genetic implanted fuzzy model (GIFM) is proposed in this study. In this method, optimal input and output membership functions are extracted through the use of hybrid genetic algorithm-pattern search technique instead of widely held subtractive clustering approach. In this study, data belonging to seven wells (1259 data points) were used for model construction and data belonging to another two wells (488 data points) was used to assess reliability of constructed model. Results showed GIFM performed more satisfyingly compared with traditional fuzzy logic model for estimation of water saturation from conventional well log data. This study was successfully implemented in one of Iranian carbonate reservoir rocks.

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2. Genetic implanted fuzzy model

Zadeh (1965) proposed basic idea of fuzzy logic or fuzzy set theory, which defines plastic boundaries for fuzzy sets. In fuzzy sets, each value belongs to a fuzzy set with a grade of membership ranging between zero and one contrasting to crisp logic that a value may or may not belong to one set. The procedure of formulating from a set of input to desired output is done using fuzzy inference systems. The mathematical formulation behind a FIS is reviewed in this section. Supposing input Gaussian membership functions for fuzzy inference system are as follows.

$$\mu_i(\mathrm{DT}) = \exp\left(-(\mathrm{DT}-\mathrm{m}_{\mathrm{DT}i})^2/2\sigma_{\mathrm{DT}i}{}^2\right) \tag{1}$$

$$\mu_i(\mathrm{RHOB}) = \exp\left(-(\mathrm{RHOB}-\mathrm{m}_{\mathrm{RHOB}i})^2/2\sigma_{\mathrm{RHOB}i}{}^2\right) \tag{2}$$

$$\mu_i(\mathrm{NPHI}) = \exp\left(-(\mathrm{NPHI}-\mathrm{m}_{\mathrm{NPHI}i})^2/2\sigma_{\mathrm{NPHI}i}{}^2\right) \tag{3}$$

$$\mu_i(\mathrm{RT}) = \exp\left(-(\mathrm{RT}-\mathrm{m}_{\mathrm{RT}i})^2/2\sigma_{\mathrm{RT}i}{}^2\right) \tag{4}$$

$$\mu_i(\mathrm{GR}) = \exp\left(-(\mathrm{GR}-\mathrm{m}_{\mathrm{GR}i})^2/2\sigma_{\mathrm{GR}i}{}^2\right) \tag{5}$$

Where, DT, RHOB, NPHI, RT, and GR denote the sonic transit time, bulk density, neutron porosity, true resistivity, and gamma ray, respectively. m and σ refer to the mean and variance of input Gaussian membership functions. The firing strength of each rule is then determined through the following equation.

$$\mu_i = \mu_i(\mathrm{DT}) \times \mu_i(\mathrm{RHOB}) \times \mu_i(\mathrm{NPHI}) \times \mu_i(\mathrm{RT}) \times \mu_i(\mathrm{GR}). \tag{6}$$

Output linear membership function for each rule is defined by succeeding equation.

$$\mathrm{OMF}_i = \beta_{1i}\mathrm{DT} + \beta_{2i}\mathrm{RHOB} + \beta_{3i}\mathrm{NPHI} + +\beta_{4i}\mathrm{RT} + \beta_{5i}\mathrm{GR} + \beta_{6i} \tag{7}$$

Where β_j (j = 1,...,6) are constant coefficients.

Regarding above equation, mathematical interpretation of fuzzy rules is aggregated in following equation to estimate water saturation from conventional well log data.

$$S_w = \frac{\sum_i \mu_i \times \mathrm{OMF}_i}{\mu_i} \tag{8}$$

Involved parameters in Eqs. (1) through (7) are commonly determined by subtractive clustering approach. Subtractive clustering (SC) yields input Gaussian membership functions with constant variance. In other word, SC just has control on mean of membership function and no modification is done over variances. In this study, a new approach, called genetic implanted fuzzy model (GIFM) is presented to eliminate the mentioned flaw of traditional fuzzy models. This method offers use of hybrid genetic algorithm-pattern search (GA-PS) technique instead of widely held subtractive clustering for setting up fuzzy rules and clusters. For this purpose, water saturation (S_w) from Eq. (8) is considered as GIFM output and following fitness function is introduced to hybrid GA-PS technique.

$$\mathrm{MSE}_{\mathrm{GIFM}} = \frac{1}{\mathrm{N}}\sum_{k=1}^{\mathrm{N}}(S_{wk}-\mathrm{T}_k)^2 \tag{9}$$

Where, N is the number of training data and T is the target value.

Hybrid GA-PS tool can extract optimal values involved in Eqs. (1) to (7) such that the mean square error of prediction reaches its global minimum. More details about GA-PS tool are available in MATLAB user's guide (2011), and Bagheripour and Asoodeh (2013).

3. Data preparation

In this study, water saturation is going to be predicted from conventional well log data, including sonic transit time, neutron porosity, formation bulk density, true resistivity, and gamma ray. For more study about these conventional well logs refer to Asoodeh and Bagheripour (2012a, 2013a). Presence of inaccurate data for model construction leads to confusion in model and consequent shrinkage in precision of target prediction. Therefore, unreliable data must be removed before model construction. At the first stage, bad hole intervals, where caliper log increases by 20% from bit size were removed. This task removes incorrect readings of well logs. In bad hole intervals, where caliper log is much larger than bit size, there is an error owing to standoff between wireline sensors and formation. Large standoff could not be tolerated by wireline instruments and produces erroneous readings. Model construction with wrong data produces wrong model which consequently predicts wrong values. For mentioned reasons, bad hole intervals are removed from datasets. Subsequently, cycle skips in sonic transit time log were corrected by despiking process. In next stage, smoothing task is done for well logs to remove sharp pikes. Eventually, depth shifting task was done to correlate depth of well logs. All aforementioned procedure helps to provide reliable data for model construction.

4. Modeling: results and discussion

At the first stage of this study, a Takagi and Sugeno (1985) fuzzy inference system was constructed to estimate water saturation from conventional well log data. To achieve optimal fuzzy model, different clustering radii were examined and the best clustering radius resulting in the lowest mean square error was chosen as optimal clustering radius. Fig. 1 shows results of such examination. Fig. 1 shows variation of mean square error (MSE) for test and training data versus different

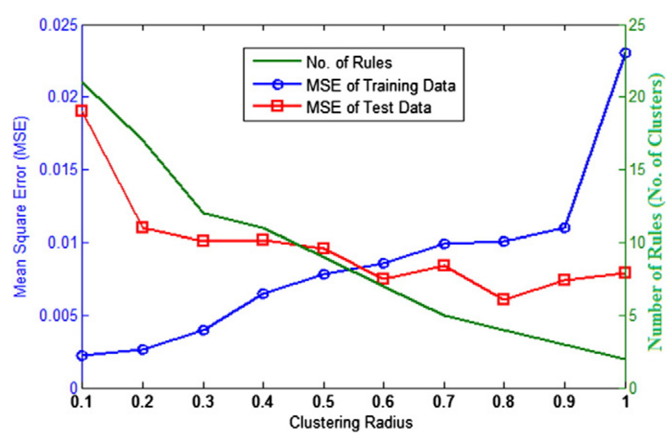

Fig. 1. Graph showing variations of MSE for training and test data versus clustering radius in company with corresponding number of rules for each clustering radius. By specification of 0.8 for clustering radius optimal fuzzy model is achieved.