Journal of Petroleum Science and Engineering 127 (2015) 459–468

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

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

Shear wave velocity estimation from conventional well log data by using a hybrid ant colony–fuzzy inference system: A case study from Cheshmeh–Khosh oilfield

Amir Nourafkan [a], Ali Kadkhodaie-Ilkhchi [b,*]

[a] Department of Geology, Faculty of Earth Sciences, S. Chamran University of Ahvaz, Ahvaz, Iran
[b] Department of Earth Sciences, Faculty of Natural Science, University of Tabriz, Tabriz, Iran

A R T I C L E I N F O

Article history:
Received 27 August 2014
Accepted 2 February 2015
Available online 9 February 2015

Keywords:
Shear wave velocity
Fuzzy inference system
Ant colony optimization
ACOFIS
Cheshmeh–Khosh oilfield

A B S T R A C T

Characterization of geomechanical parameters of hydrocarbon reservoirs such as compressional and shear wave velocities is a main component of petrophysical, geophysical and geomechanical studies. Compressional wave velocity is derived from sonic log. However, V_s is either obtained from core analysis in the laboratory or dipole sonic imager (DSI) tools which are both very expensive and time consuming. Recently, several methods of artificial intelligence techniques have been used to predict this fundamental parameter by using well log data. In this paper, a new methodology is presented for shear wave velocity estimation by integration of stochastic optimization in the structure of a fuzzy inference system. The proposed model, which is called ant colony–fuzzy inference system (ACOFIS), is based on the integration of fuzzy reasoning and ant colony optimization algorithm. The methodology is illustrated by using a case study from Cheshmeh–Khosh oilfield. Comparison of the results shows that the proposed novel and hybrid scheme can sufficiently improve the performance of the shear wave velocity estimation problem. Meanwhile, the developed ACOFIS model can serve as an effective tool for estimation of other reservoir rock properties.

1. Introduction

The absence of geomechanical parameters of a reservoir such as compressional and shear wave velocity in most cases imposes severe limitations during the exploitation of oil and gas reservoirs. Through calculation of such elements we attempt to find a solution to a wide range of geomechanical problems. Compressional wave velocity can be obtained directly from sonic transit time. Shear velocity is either measured at the laboratory on core samples or by means of Dipole Shear Sonic Imager tool (DSI). The accuracy of the shear wave velocity estimation schemes is especially important when performing AVO modeling (Rezaee et al., 2007). The least expensive and time-consuming way to provide a reliable shear wave velocity profile is therefore of great interest to reservoir engineers.

Several researchers have introduced empirical relationships for V_s estimation (Pickett, 1963; Castagna et al., 1985; Krief et al., 1990; Greenberg et al., 1992; Bastos et al., 1998; Domenico, 1984; Han, 1989; Murphy et al., 1993). Nevertheless, these formulas needs to be checked with field studies and globally are not applicable.

In order to overcome such problems, recently several different methods of artificial intelligence techniques have been used to predict reservoir properties using well log data. Mohaghegh et al. (1994) applied an artificial neural network for estimation of formation permeability. Jamialahmadi and Javadpour (2000), Aminian et al. (2000) and Wong et al. (2000) tried to show the ability of artificial neural network on prediction of reservoir properties. Kadkhodaie Ilkhchi et al. (2006) applied a fuzzy logic approach for estimation of permeability and rock type by using well log data. Rezaee et al. (2007) applied intellegent systems for shear wave velocity prediction. Moreover, various approaches and techniques have been employed in order to increase the accuracy and reliability of such predictions. Saemi et al. (2007) designied a neural network by using genetic algorithm and employed it for permeability prediction of reservoir rocks. Chen and Lin (2006) applied a committee machine to predict permeability from well log data. Irani and Nasimi (2012) in order to increase the accuracy of predictions, applied a hybrid system which combines artificial neural networks and artificial bee colonies. Khoukhi (2012) used genetic algorithm to enhance subtractive clustering for the parameter identification of an adaptive neuro-fuzzy inference system.

* Corresponding author: Tel.: +98 912 638 3051.
E-mail addresses: a-nourafkan@mscstu.scu.ac.ir (A. Nourafkan), kadkhodaie_ali@tabrizu.ac.ir (A. Kadkhodaie-Ilkhchi).

http://dx.doi.org/10.1016/j.petrol.2015.02.001
0920-4105/

Nomenclature

ACO	ant colony optimization
ACOR	ant colony optimization for continuous domain
ACOFIS	ant colony–fuzzy inference system
AI	artificial intelligence
ANN	artificial neural network
AVO	amplitude versus offset
C	membership function center
DSI	dipole shear sonic imager
$f(x)$	objective function
FCM	fuzzy *c*-means clustering
FIS	fuzzy inference system
FL	fuzzy logic
GA	genetic algorithm
G	Gaussian kernel
g	Gaussian function
K	solution archive size
MF	membership function
MSE	mean squared error
mu	mean
NPHI	neutron log
PDF	probability density function
Q	learning rate for ACO_R
RHOB	density log
V_p	compressional wave velocity
V_s	shear wave velocity
w	solution weight
X_{max}	maximum value
X_{min}	minimum value
X_{norm}	normalized value
σ	standard deviation
μ	grade of membership

Fuzzy modeling is a typical example of strategies that utilizes human knowledge and deductive processes to model the highly complex non linear systems. The main problem of fuzzy modeling is that the fuzzy membership function parameters are often specified by users in which they should make the decision on the parameters, either from their own experience or trial and error exercises. In order to enhance the proccess of deciding on these parameters and minimize the total error of predicted data, an optimization technique can be employed.

Ant colony optimization (ACO) (Dorigo and Stützle, 2004) is one of the most recent and poweful techniques for approximate optimization which was introduced as a novel nature-inspired method for the solution of hard combinatorial optimization problems (Dorigo, 1992; Colorn et al., 1996; Dorigo et al., 1999; Dorigo and Stützle, 2004). In comparison with other algorithms, computational simpilicity and high running speed as long as small number of control features, make ACO as a great tool for adjusting fuzzy model parameters. The inspiring source of ACO is the foraging behavior of real ants. Depending on the point of view, ACO algorithms may belong to different classes of approximate algorithms. Seen from the artificial intelligence (AI) perspective, ACO algorithms are one of the most successful strands of swarm intelligence (Bonabeau et al., 1999, 2000).

In this study, we propose a novel hybrid method which combines fuzzy modeling and ant colony algorithm in order to V_s estimation in reservoir rocks. To best knowledge of the authors, this is the first application of an integrated ACOFIS model to estimate reservoir properties. The methodology will be explained in a series of steps. The application of the method will be demonstrated via a case study from Cheshmeh–Khosh oilfield, South Iran. The study uses well logs (multiple inputs) to predict shear wave velocity (single output) in an oil well where actual V_s values are available for performance evaluation.

2. Methodology

2.1. Fuzzy inference system

Fuzzy logic is a well-known technique for computing dependent on "degrees of truth" rather than crisp logic in which includes 0 and 1 as extreme conditions of truth and various degrees of truth in between. Generally, Fuzzy Logic can be used as a model-free and nonlinear estimator helping us to attain a reliable model in order to prediction of reservoir properties using log data.

A fuzzy inference system is composed of five functional blocks, as represented in Fig. 1. It employs fuzzy logic to make decisions in an environment of uncertainty and imprecision.

One of the most well-known fuzzy inference systems is the Mamdani inference system (Mamdani and Assilian, 1975). In the Mamdani fuzzy model, the output is a fuzzy set and therefore a process of defuzzification is required in cases which the output should be a crisp value (Asadi et al., 2013). The general antecedent (if part) and consequent (then part) structure of the Mamdani inference system is given as follows.

$$\begin{aligned}
&\text{Rule}_1\text{: if } x_1 \text{ is } A_1 \text{ and } y_1 \text{ is } B_1 \ldots \text{ then } z \text{ is } C_1\\
&\text{Rule}_2\text{: if } x_2 \text{ is } A_2 \text{ and } y_2 \text{ is } B_2 \ldots \text{ then } z \text{ is } C_2\\
&\text{Rule}_3\text{: if } x_3 \text{ is } A_3 \text{ and } y_3 \text{ is } \mathrm{B}_3 \ldots \text{ then } z \text{ is } C_3\\
&\vdots\\
&\text{Rule}_k\text{: if } x_k \text{ is } A_k \text{ and } y_k \text{ is } B_k \ldots \text{ then z is } C_k.
\end{aligned}$$

where x and y are first and second input variable respectively (antecedent variable); and z is the output variable (consequent variable) and k is the numbers of rules.

Some problems such as identification of the type, shape and location of membership functions for each fuzzy variable can affect the performance of fuzzy modeling to a great extent. Another modifiable parameter which can be used to enhance the modeling

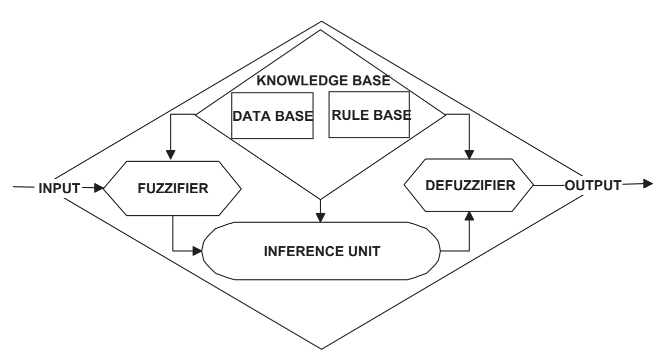

Fig. 1. A fuzzy inference system basically consists of five subcomponents: (1) a data base contains information about the membership functions of the selected fuzzy rules in the rule base, the domains of the variables and kinds of normalization; (2) a rule base of fuzzy IF-THEN rules; (usually, the rule base and data base are jointly referred to as the knowledge base); (3) a fuzzifier which receives the input variables and transfers them into fuzzy sets; (4) an inference unit performs the inference operation on the fuzzy rules; (5) a defuzzifier transforms the fuzzy results of the inference into a crisp values.