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Connectionist model predicts the porosity and permeability of petroleum reservoirs by means of petro-physical logs: Application of artificial intelligence

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ABSTRACT

In this paper, a new approach based on artificial intelligence concept is evolved to monitor the permeability and porosity of petroleum reservoirs by means of petro-physical logs at various conditions. To address the referred issue, different artificial intelligence techniques including fuzzy logic (FL) and least square support vector machine (LSSVM) were carried out. Potential application of LSSVM and FL optimized by genetic algorithm (GA) is proposed to estimate the permeability and porosity of petroleum reservoirs. The developed intelligent approaches are examined by implementing extensive real field data from northern Persian Gulf oil fields. The results obtained from the developed intelligent approaches are compared with the corresponding real petro-physical data and gained outcomes of the other conventional models. The correlation coefficient between the model estimations and the relevant actual data is found to be greater than 0.96 for the GA–FL approach and 0.97 for GA–LSSVM. The results from this research indicate that implication of GA–LSSVM and GA–FL in prediction can lead to more reliable porosity/permeability predictions, which can lead to the design of more efficient reservoir simulation schemes.

1. Introduction

Porosity, which is defined as the ratio of the rock open space to its bulk volume, is generally regarded as a potential of rock in terms of fluid storage, and it is geologically categorized into two groups – primary and secondary – which are chronologically determined based on their occurrence that can be before or after the rock generation. On the other hand, permeability is one of the other important petro-physical parameters of the rock that is technically defined as the ease with which a fluid can flow through a medium, with more ease said to have a higher permeability. There is no distinctive relationship between the referred parameters and in some cases it is observed that the high porosities have been accompanied by high rates of permeability, and also in some other cases the exact opposite trend is seen as well (Nelson, 1994).

Volumetric methods of reserve estimation, which is one of the most important tasks of reservoir engineers in order to make a decision of whether a target reservoir can produce a noticeable and economic amount of petroleum or not, determine fluid saturation through implementing the Archie equation and geological characterization of reservoir based on correlations to determine the permeability of parts for which their porosity is known, are generally regarded as the main operations that could be implemented by gaining from available porosity data (Edlmann et al., 1998; Ezekwe, 2010).

Therefore, it could logically and definitely be deduced that the determination of porosity value plays a leading role in all technical aspects of reservoir engineering. As a result, numerous researchers' attentions have been drawn towards proposing precise methods of porosity calculation. These methods are generally categorized into two main groups, direct and indirect. In direct methods the core with different regular and irregular shapes has directly undergone different laboratorial methods such as displacement and gravimetric procedures and sometimes porosity can directly be measured by gaining from mercury porosity meter and gas (helium) expansion porosity meter; their details can be found in previous literatures (Heim, 1961; Leon, 1998). In indirect methods porosity is obtained by carrying out some calculations

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Nomenclature

Abbreviations

DST	drill stem test
DT	sonic transit time
FIS	fuzzy interface system
FL	fuzzy logic
GA	genetic algorithm
GLT	geochemical logging tool
HCIP	hydrocarbon in place
LSSVM	least square support vector machine
MF	membership function
MSE	mean square error
NML	nuclear magnetic log
NMR	nuclear magnetic resonance
NPHI	density tool reading
PHIT	total porosity
RFT	repeat formation testing
RHOB	bulk density

Variables

S_i	fluid saturation, fraction
A	determined attribute
a, b, c and d	parameters used to form the generality of the membership function
S_{wr}	residual (irreducible) water saturation
$k(i)$	permeability

Greek letters

σ^2	RBF kernel parameter in the LSSVM model
γ	regularization parameter in the LSSVM model
Φ	porosity

Subscripts

min	minimum
max	maximum

and analyses from data acquired from well logs such as density, sonic, neutron and nuclear magnet resonance (NMR) (Balakrishna and Narayana, 1960; Manger, 1963). The detailed technical descriptions of the mentioned logs have been addressed in previous literature about the application of different well logging methods in porosity determination (Alger and Hoyle, 1963; Tittman et al., 1966; Medlin and Alhllall, 1992; Kleinberg et al., 1993).

Furthermore, the appraisal of new technologies has led to petro-physical experts applying them in porosity determination. Seismology is one of the fields of studies where great progress in its relevant fields has been accompanied by the determination of porosity by observing the trend of adjustment in related parameters such as seismic velocity, impedance and amplitude (Yu-Mei et al., 2010). Application of laser technology and image processing in order to determine porosity has been studied in a couple of different papers (Unalmiser and Stewart, 1987; Siitari-Kauppi and Autio, 1997; Bernal et al., 2000; Sammartino et al., 2002).

As has been discussed earlier, permeability and its related derivatives like relative permeability are routinely regarded as some of the most important and sensitive parameters of rock reservoirs, which are very important factors to be known in fluid flow and chemical transport in porous media because simulation processes, history matching performance and achieving the production target of petroleum reservoirs are intensely dependent on complicated sets of issues which have strong influences in obtaining accurate information about the permeability map of different parts in a petroleum reservoir (Johnson, 1963; Abu-Khamsin, 2004; Ahmed, 2006).

Permeability is based on different methods such as well logging, core measurements and well testing. Correlating empirically the required permeability versus the measured porosity (Bloomfield and Williams, 1995), using the NMR tools to distinguish the difference between bounded and free fluid in the formation (Rezaee et al., 2012), gaining from geochemical logging tool (GLT) to clarify the mineral concentration in a determined profile (Herron, 1987), observing the trend of propagated Stoneley waves (Tang et al., 1990) and taking advantage of using repeat formation testing (RFT) tool (Ayan et al., 2001) are the main logging-based techniques that are normally applied to measure permeability in a target location.

Indisputably, deducing the permeability factor based on laboratorial core measurements is the most practical tool. The pressure difference created by an injected fluid into the core is specified in the Darcy law and the permeability is subsequently calculated. It is also possible to calculate the relative permeability based on a core relevant test, which is generally divided into two main groups of steady-state and unsteady-state methods (Thompson et al., 1987; Honarpour and Mahmood, 1988; Li et al., 2004).

While both general mentioned groups are local permeability determiners, the total situation of permeability in the reservoir needs to be known. In order to fulfill this important necessity, different types of well-testing analyses have been used such as short-term methods with a small radius of investigation (Ayoub et al., 1988; Kin et al., 2010), conventional ones which are used by recording the pressure data versus connected time as the consequence of changing the flow rate, and modern methods which have been proposed for special cases like multi-layer reservoirs (William A. Burns, 1969; Cinco-Ley et al., 1985; Jatmiko et al., 1994; Erwin et al., 2002).

After all, it must be highlighted that proposing a relationship between porosity measurements and permeability has always been favorable with different experts. Some attempts have been made to use artificial intelligence-based methods (Badarinadh et al., 2002), and some methods of permeability determination have been proposed which were gained from the coupling of core and logs information besides data of residual water saturation (Timur, 1968; Zhang et al., 1996). However, most of the scientists have paid attention to permeability calculation using logs (Balan et al., 1995). In fact, they have proposed varieties of empirical, statistical and artificial intelligence-based methods in which their input parameters and their developing techniques are different. Because of the historical and logical background on empirical models, numerous experience-based correlations have been developed so far which use the handy and basic petro-physical parameter to estimate the permeability factor. More details can be found in previous literatures (Aigbedion, 2007).

The main aim of this paper is to develop a high exactness approach to determine the porosity and permeability of reservoirs by means of petro-physical logs for reservoir simulation purposes by means of a new type of artificial intelligence, which includes LSSVM and fuzzy logic (FL). To assess the goal of this research, extensive real field data from northern Persian Gulf oil fields was utilized to