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Uncertainty assessment of porosity and permeability by clustering algorithm and fuzzy arithmetic

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ABSTRACT

A hybrid clustering-fuzzy arithmetic algorithm is here proposed, which uses cluster analysis to quantify porosity uncertainty, then the uncertainty is projected to the irreducible water saturation and permeability by the means of fuzzy arithmetic. The proposed method is applied to five wells of the carbonate Sarvak Formation, in an Iranian onshore oil-field. First, cluster analysis is applied to the porosity logs including neutron porosity, bulk density and sonic transit time. The uncertainty range of porosity is defined by the range of neutron porosity in each cluster. In order to estimate the core porosity, neutron porosity is calibrated to the core porosity in each cluster. Due to the average of error, the calibrated clustering-based porosity is at least 33% more accurate than the conventional methods. Based on the generalization ability of porosity estimators, a homogeneous porosity zone is determined northward. Irreducible water saturation, analyzed by the proposed method, has less overestimation, compared to the conventional evaluation of irreducible water saturation. Permeability fuzzy number is compatible with core tests, except in well S1, which is drilled in a location, compressed by two stress regimes (N-S and NW-SE). Two criteria are defined for validating the fuzzy numbers by core data: (i) Crit1 finds an average α-cut of core values; (ii) Crit2 finds the best α-cut to optimize uncertainty interval of the fuzzy number. The $\alpha > 0.90$ is the most appropriate for porosity and permeability studies.

1. Introduction

Porosity and permeability (porperm) of reservoir rocks are either measured (in the cored intervals) or estimated (in the logged intervals). Since the estimation is an indirect method, the results are uncertain. This uncertainty is effective on the results of field-scale studies, e.g. production forecast (Riva et al., 2010). Each porperm investigation belongs to one or two of the following categories: (i) Deterministic approach (up to about 1997): The primary porperm researches were about to find the best-fit experimental model for estimation, which ignores the uncertainty. (ii) Intelligent studies (since about 1997), which could be conducted either in deterministic or probabilistic approaches. (iii) Probabilistic approach (since about 2004), which assesses the porperm uncertainty by Probability Distribution Function (PDF).

Archie (1952) was one of the first researchers who investigated on petrophysical parameters (porperm, water saturations, resistivity and formation factor), and developed the empirical relations between them. Timur (1968) explored the relationships between porperm and irreducible water saturation, which is introduced and used in this article. For permeability estimation, Turban and Robert (1989) proposed using production equation and formation pressure. It is reported that permeability estimation in hydraulic units separately, improves the results (Altunbay et al., 1997).

In the recent decades, the intelligent methods are incorporated in petrophysical evaluations. The fuzzy theory was hired in studying rock facies, fractures, porperm and water saturation estimation (Abdulazeez et al., 2007; Cuddy, 1997, 2000). Fang and Chen (1997) proposed a hybrid method for predicting porperm of sandstones, using cluster analysis and fuzzy arithmetic. In this method, the inputs are compositional and textural parameters: grain size, Trask (1930) sorting coefficient, relative amounts of ductile grains, rigid grains and detrital matrix. The output data (porperm) are clustered using fuzzy c-means (FCM) algorithm. FCM provides the degree of membership of the inputs to each cluster prototype. Using fuzzy reasoning, the fuzzy rules are generated between the inputs and the outputs, which will be used in a fuzzy inference. Clustering is also used for studying productive zones (Moradi

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Nomenclature

α_c	α of core porosity
α_{ref}	Reference α
φ_{DN}	Estimated porosity by density-neutron (shaly sand) cross-plot
$\varphi_{DN}^{(q)}$	Estimated porosity by quick look method of density-neutron cross-plot
φ_e	Effective porosity
φ_{LC}	Estimated porosity by the method of complex lithology
φ_{log}	Estimated porosity by a one-log porosity method (neutron or density)
φ_{NPHI}	Estimated porosity by one-log porosity method, based on neutron porosity
φ_{RHOB}	Estimated porosity by one-log porosity method, based on bulk density
$^{\alpha}A$	α-cut of the fuzzy membership function A
ANN	Artificial neuron network
C_k	Constant of Wylie-Rose relation
CM	Consistency measure
Crit1(2)	First (second) criterion
CT	Computer tomography
DT	Sonic transit time
FCM	Fuzzy c-means
FN	Fuzzy number
fr	Fraction
GG	Gath-Geva
GK	Gustafson-Kessel
GR	Gamma ray
Int_{ave}	Average of cluster intervals
J	Performance index
$k_{Buckles}$	Buckles number
k_{WR}	Estimated permeability by Wylie-Rose relation
KM	k-means
LLD	Deep laterolog
log	Calculated petrophysical well-log
log_h	Petrophysical value of hydrocarbon
log_{ma}	Petrophysical value of matrix
$log^{(s)}$	Scaled petrophyical value (well-log)
log_{sh}	Petrophysical value of shale
log_w	Petrophysical value of water
m	A parameter in Wylie-Rose relation
m_f	Fuzzifier
m_s	A parameter related to irreducible water saturation
mD	Millidarcy
n	A parameter in Wylie-Rose relation
$\mathbb{N}_c$	Sets of cluster number
$\mathbb{N}_n$	Sets of data points
NMR	Nuclear magnetic resonance
NPHI	Neutron porosity
$NPHI^{(s)}$	Scaled NPHI
$NPHI_{sh}^{(s)}$	Scaled NPHI value at the line of pure shale
$\mathscr{P}$	Fuzzy partition
PDF	Probability distribution function
PM	Precision measure
RHOB	Bulk density
$RHOB^{(s)}$	Scaled RHOB
$RHOB_{sh}^{(s)}$	Scaled RHOB value at the line of pure shale
RMSE	Root mean square error
S_w	Water saturation
S_{wir}	Irreducible water saturation
S_{XO}	Water saturation in invaded zone, in fraction
SSE	Sum square error
ten%	Unit of order, e.g. 56% = 5.6 ten%
$v_i^{(t)}$	Cluster center of the ith cluster at the tth iteration
V_{sh}	Shale volume, in fraction
VLSA	Volumetric laminated sand analysis
VRmf	Vertical resolution membership function

et al., 2015), saturation or permeability variations (Masoudi et al., 2016).

The permeability determination was enhanced when the data was clustered by principal component analysis and cluster analysis, then the fuzzy logic model was applied to each cluster (Ibrahim Sami and Adel, 2010). The Artificial Neural Network (ANN) was used in porperm estimation, showing high precision in the north sea (Helle et al., 2001). For porperm estimation, the ANN is much more accurate than the regression-based methods (Jalali Lichaei and Nabi Bidhendi, 2006). Since the histogram of permeability has lognormal distribution, it has to be transformed to the normal (Gaussian) distribution for a successful ANN-based permeability estimation (Masoudi et al., 2011). Aïfa et al. (2014) reported that application of neural network and fuzzy logic prediction techniques showed correlation coefficients of >0.91. However using a neuro-fuzzy model, the correlation coefficients increased to >0.98 and > 0.96 for porosity and permeability estimations, respectively.

Kharraa et al. (2013) investigated the porosity distribution using Nuclear Magnetic Resonance (NMR) logging. In the dolomitic formation, neutron-density porosity is the most accurate method. But in clean limestones, NMR is the most accurate tool for porosity study. Kharraa et al. (2013) also discussed that differences between the porosity determinations originate from the differences in their tools mechanisms. As an example, the effective porosity is measured in the core laboratory, while the total porosity is estimated by neutron porosity well-log. By NMR well-log, the distribution of pore sizes micro (smaller than 0.5 μm), meso (between 0.5 and 5 μm) and macro (larger than 5 μm) could be determined, separately. Or using Computerized Tomography (CT), the pore shapes and their connections in the core samples can be visualized. In a recent publication, factor analysis was performed on NMR T2 distribution to estimate free-water filled and bound-fluid-filled porosities (Li and Misra, 2017).

Volumetric Laminated Sand Analysis (VLSA) is a probabilistic method for evaluating hydrocarbon pore-thickness, when the beds are thinner than 1 ft (30 cm). The method uses Monte-Carlo simulation for generating realizations in the intervals of 47.6 ft (14.5 m). 400% improvement in accuracy of hydrocarbon pore-thickness estimation is reported by this method (Passey et al., 2004, 2006). In this article, VLSA is introduced and used as a base method for validating the outputs of the proposed method. Bachrach (2006) concluded that incorporating shear impedance reduced the porosity uncertainty by 15%. He used standard deviation as a measure of uncertainty of porosity and water saturation estimations.

The uncertainty is a property, so it should be quantified (not to be removed). It is often desired to have the least uncertainty but should not be minimized, however we try to minimize the error. There are many definitions and categorizations of the uncertainty in the literature. Fang and Chen (1990) categorized it into vagueness (equivalent to fuzziness, haziness, cloudiness, unclearness and sharplessness) and ambiguity (non-specifity, diversity, divergence, generality, variety and one-to-many). In the well-logging, the uncertainty type is ambiguity since an average value is attributed to a volume of investigation (diversity, generality or one-to-many). The volumetric Nyquist frequency is formulated for assessing this ambiguity quickly (Masoudi et al., 2017b), and the Dempster-Shafer Theory of evidences was used to quantify the ambiguity for whole the well-log (Masoudi et al., 2017a). The uncertainty categorizations are not yet accepted universally. So in this paper,