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Estimating NMR T_2 distribution data from well log data with the use of a committee machine approach: A case study from the Asmari formation in the Zagros Basin, Iran

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ABSTRACT

The Nuclear Magnetic Resonance (NMR) log is one of the most valuable logs in petroleum exploration which is used to precisely evaluate the reservoir and non-reservoir horizons. Along with porosity logs (neutron, density, sonic), NMR log is used to estimate the porosity and permeability of the hydrocarbon bearing intervals. The current study focuses on estimating NMR T_2 distribution data from conventional well log data with the use of artificial intelligent systems. The eight bin porosities of the combinable magnetic resonance (CMR) T_2 distribution alongside with the T_2 logarithmic mean (T_2LM) values are predicted using the intelligent models developed in this study. The methodology applied here combines the results of the individual models in a committee machine with intelligent systems (CMIS) for estimating the NMR T_2 distribution and T_2 logarithmic mean data. The Fuzzy logic (FL), the adaptive neuro fuzzy system (ANFIS) and artificial neural networks (ANNs) are utilized as intelligent experts of the CMIS. The NN models are developed with four different training algorithms (Levenberg–Marquardt (LM), scaled conjugate gradient (SCG), one step secant (OSS) and resilient back-propagation (RP)) and the best one is chosen as the optimal NN expert of the CMIS. The CMIS assigns a weight factor to each individual expert by the simple averaging and weighted averaging methods. A genetic algorithm (GA) optimization technique is used to derive the weighted averaging coefficients. The results indicate that the GA optimized CMIS performs better than the individual experts acting alone for synthesizing the NMR T_2 curve and T_2LM data from one specific set of conventional well logs.

1. Introduction

NMR log provides an improved method to determine the reservoir petrophysical parameters. As an example since the NMR porosity is not affected by lithology and underground radioactive materials, it provides meticulous information about the porosity and pore size distribution of rocks. NMR logs have the possibility of in-situ measurement of the permeability, free fluid index, irreducible water and irreducible oil saturation. Moreover, identification of the fluid types and volumes is possible via the NMR T_2 data interpretation. Nevertheless, running NMR log in producing cased wells is not possible. On the other hand, it is one of the most expensive tools in the logging industry and its associated costs are the major limitation of its usage. Therefore, there are only a few wells for which this log is run. In opposition to such problems, artificial intelligence has proved to be a cost-effective and time saving method to virtually extract the NMR log parameters. Recent studies have investigated the use of intelligent estimators such as artificial neural networks, fuzzy and adaptive neuro-fuzzy inference systems and the intelligent optimizers such as genetic algorithms to estimate the NMR log parameters from conventional well log data in many different cases.

Wong et al. (1995, 1998) used backpropagation neural networks to predict porosity and permeability of the oil wells. Mohaghegh et al. (1996) used ANNs for petroleum reservoir characterization. Mohaghegh et al. (2001) applied intelligent systems to synthesize artificial NMR logs in a field located in East Texas. Ogilvie et al. (2002) used GA and FL techniques to predict permeability from the NMR tool data. Chen and Lin (2006) used a committee machine with empirical formulas (CMEFs) for permeability prediction. Kadkhodaie-Ilkhchi et al. (2008, 2009) developed committee machines for prediction of total organic carbon and oil content from the well log data in the South Pars Gas Field,

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Iran. Rolon et al. (2009) used artificial neural networks to synthesize specific petrophysical logs from other logs.

Most of the previous works are in relation to estimating the parameters derived from NMR log (e.g. porosity and permeability). The current study focuses on estimating the original NMR T_2 and T_2LM distribution alongside with the CMR bin porosities. Since T_2 and other NMR logs can be in relation to many other petrophysical and geological properties (e.g. facies, rock types, pore throat network, fluid saturation, wettability) it is worth synthesizing virtual NMR logs directly from one specific set of conventional well log data which are available for almost all wells. This study suggests that using the different neural network training algorithms and combining the best NN model with the FL and NF models can lead to the high accuracy of the results for construction of the synthetic T_2 curves.

The study area is located in Zagrozs basin, western Iran. The hydrocarbon bearing units of this area are Pabdeh, Asmari, Gajsaran, Agajari, etc. In the area that this research was carried out, the Paleocene to Pliocene Asmari formation is the most important reservoir unit that mainly consists of limestone, dolomite, shaly limestone and shale. The low-porosity and high-permeability Asmari formation undergoes minor lithological changes throughout the area. The latter fact provides capability of employing developed models of the current research in the neighboring fields. It is assumed that the formation contains no ions of chromium, manganese, iron, nickel or other paramagnetic ions and also no iron containing minerals which could considerably influence NMR measurements. Drilling fluid did not contain these ions neither.

2. NMR log

The nuclear magnetic resonance log is used as a tool to study the structure of porous media and their various rock–fluid interactions. This technique allows the determination of rock and fluid properties such as porosity and pore size distribution, permeability, water saturation, wettability, viscosity, etc. NMR logging exploits the large magnetic moment of hydrogen, which is abundant in rocks in the form of oil, gas and water. The NMR signal amplitude is proportional to the quantity of hydrogen nuclei present in a formation and can be calibrated to give a value for porosity that is free from lithology effects (Allen et al., 1997). The most important mechanism affecting the NMR relaxation is the grain-surface relaxation. Molecules in fluids are in constant Brownian motion, diffusing about the pore space and bouncing off the grain surfaces. Upon interaction with the grain surface, hydrogen protons can transfer some nuclear spin energy to the grain (contributing to T_1 relaxation) or irreversibly dephase (contributing to T_2 relaxation). Therefore the speed of relaxation most significantly depends on how often the hydrogen nuclei collide with the grain surface and this is controlled mainly by the surface-to-volume ratio of the pore in which the nuclei are located. Collisions are less frequent in larger pores resulting in a slower decay of the NMR signal amplitude and allowing a petrophysicist to understand the distribution of pore sizes (Kenyon et al., 1995).

3. Theory and methodology

The methodology applied in this work is based on selection of the appropriate input data. This step leads to selection of six well logs as the input data. The selection process will be explained in detail in the forthcoming section. The second step is to develop the different fuzzy, neuro-fuzzy and NN models. The NN models were developed with the four training algorithms including Levenberg–Marquardt (Hagan and Menhaj, 1994), Resilient Back-Propagation (Riedmiller, 1993), Scaled Conjugate Gradient (Moller, 1993) and One Step Secant (Battiti, 1992). The next step is selection of the

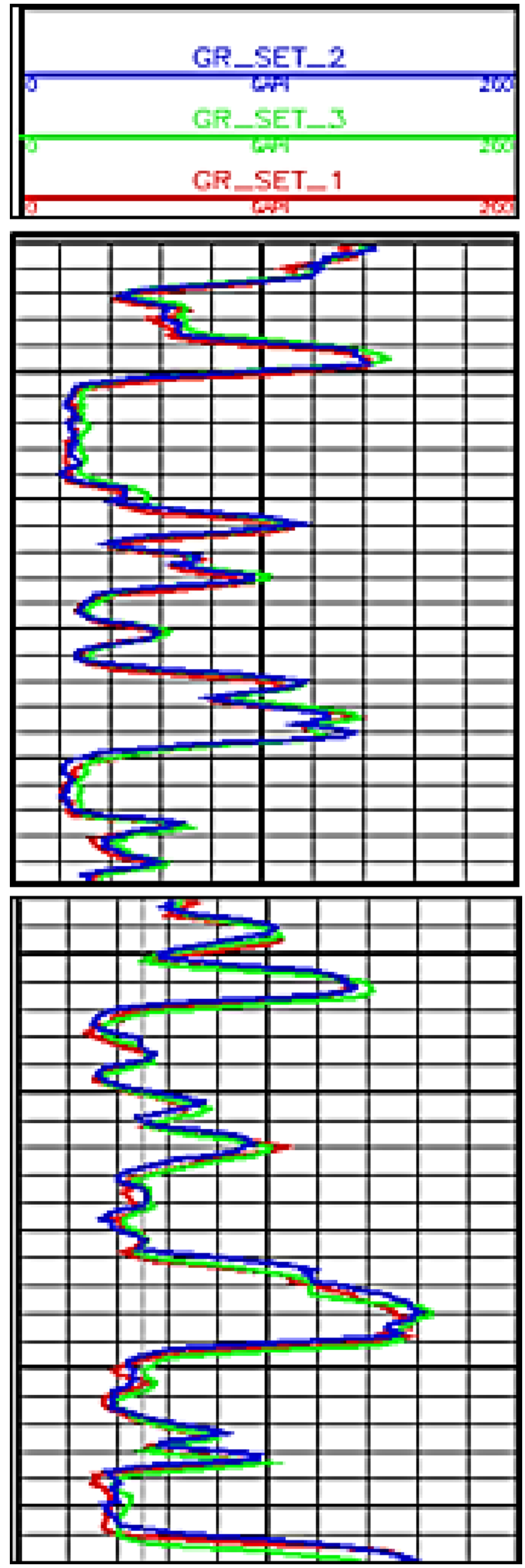

Fig. 1. GR logs from three sets of raw data used as depth controllers.