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ESTIMATION OF THE OIL SATURATION BY FUZZY INFERENCE SYSTEM IN WELL#OMNX , HASSI MESSAOUD OIL FIELD (ALGERIA)

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Abstract
The oil saturation is an important petrophysical parameter to evaluate the oil reservoirs reserve; it is calculated in the wells from log data, based on experimental equations developed for different reservoirs (clean or shaly reservoirs). In order to estimate directly the oil saturation without return to the empirical equations, the Mamadani-type fuzzy inference system is applied for the first one in well localized in Hassi Messaoud oil field (Algeria). The logs data (gamma ray, neutron porosity, deep resistivity, density and transit time) are used as input to predict the oil saturation. The membership function chosen is Gaussian. The obtained results show that the oil saturation is estimated with high accuracy, which is proved by the high correlation coefficient found between the oil saturation calculated by Archie formula and that estimated by fuzzy inference system; it is equal 0.92.
Keywords: Logging; oil saturation; fuzzy inference system; Hassi Messaoud; reservoir.

1. Introduction

The logging is a continuous record of physical parameters as a function of depth in oil or aquifer wells [1]. Since the first experiment to measure the resistivity in well executed by Conrad and Marcel Schlumberger brothers in 1924, different techniques in logging continue to be developed in order to solve various problems in oil wells for all phases, drilling (logging while drilling), reservoir evaluation (wireline logging) and during exploitation (production logging). The oil saturation is a key parameter for evaluating the oil reserves in petroleum fields; it is calculated by estimating water saturation from log data. The oil saturation is defined as the ratio of the pores volume saturated by the oil to the total pore volume [2]. It is determined directly in laboratory or from log data recorded in a continuous manner in wells. The calculation of oil saturation parameter in logging is based on empirical equations which are related to the volume and the kind of shale in reservoirs. The best-known formula is that of Archie [3], but it is applied specially for clean reservoirs. According to the nature of shale in oil reservoirs, several equations were developed based on volume and type of shale (dispersed, laminar or structural).

Simandoux [4] equation gives good results in high shaly sandstone reservoir, it takes into account shale's effect in the calculation of water saturation. Indonesian [5] equation is also used in the case of existence of shale in reservoir with possibility to change saturation exponent (n) in this equation, which is not permit in the first.

Water saturation can be measured directly in laboratory from well core samples by Den-Stark method, but this method is expensive, consuming time and practically applied to some wells and for a limited number of samples.

Although, the log data are continuous record in wells, less expensive relative to the core data and executed in a short time. But in several oil wells log data are not complete due to lack of one or several physical parameters, caused by technical problems during theirs acquisition. Hence, it is necessary to searching a complementary method that allows estimating petrophysical parameters by exploiting the conventional logs in most wells.

Fuzzy inference systems find recently wide application in many fields, but few researchers have applied it to solve various problems in petroleum. We can cite for example some works. The static properties of rocks were estimated by fuzzy inference system in Pars gas field [6] (Iran). The factors that control fracturing were studied at Hassi Messaoud field by this method [7]. Singh [8] applied the fuzzy inference system to identify the number of stratification in the subsurface from continental rise of Prydz Bay. Kadkhodaie-Ilkhchi *et al.* [9] predicted the petrophysical data from seismic attributes.

The aim of this work is to applied the fuzzy inference system in Well#OMNX localized at Hassi Messaoud oil field, in order to determine the oil saturation based on log data (gamma ray, neutron porosity, deep resistivity, bulk density, transit time) without using empirical equations found experimentally for different reservoirs. This technique allows to determining the oil saturation parameter with high flexibility using conventional well log data. The obtained results will be correlated with that calculated by +logging to see the reliability of the fuzzy interference system model.

2. Overview of the study area

Hassi Messaoud oil field is considered as the largest oil field in Algeria (Figure 1), with number of drilled wells more than (1188 wells) and recoverable reserves discovery estimated to nine billions barrels [10]. According to pression evolution in the production wells, Hassi Messaoud field is divided into 25 areas; a production area includes several wells which communicate with them and not with the other wells in neighbouring areas. The boundary of zone may be formed by permeability barriers of origin (tectonic, sedimentary, or diagenesis) which opposes the movement of hydrocarbon.

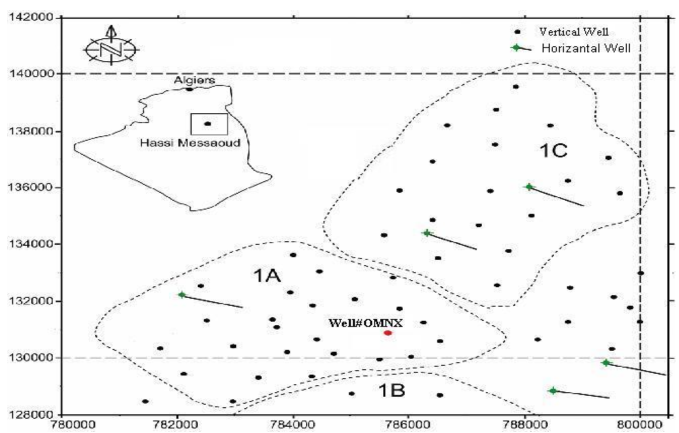

Figure 1. Location of the studied well

The Silurian is the main source rock in Hassi Messaoud oil field; it is represented by radio-active clay, with color black gray to black and rich in organic matter. Some intervals of reservoir are devoid due to Hercynian erosion [10]. This work is focused on Well#OMNX located in zone 1 of Hassi Massoud oil field. The studied well go through the reservoir anisometric Ra of Cambrian age, which composed with drains (D1, ID, D2, D3 and D4). The target is the drain D4, characterized by thickness about 40m and facies more heterogeneous than the others drain in the study area [11].

3. Fuzzy Inference System Method

The basic concept of fuzzy logic is introduced for the first time by Zadeh [12] at the university of California, Berkley. It based on the notion of fuzzy sets, which trait uncertain and imprecise problems. The fuzzy inference system consists of three main steps (Figure 2), (i) the fuzzification which allows the passage from crisp input values to fuzzy domain, and it consists to determine the membership degree of the numerical values, (ii) the fuzzy inference rule is the process of formulating the relationship functions between inputs and outputs by fuzzy logic, using language words [13] and (iii) defuzzification is the stage of transformating of fuzzy inference results into crisp output values using fuzzy implication methods (center of maxima, Maximum-decomposition and centroid defuzification).

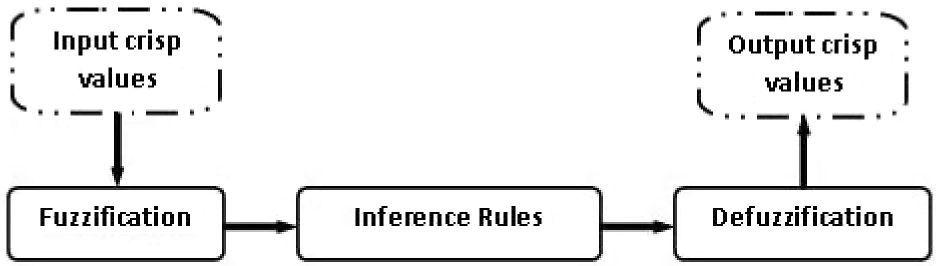

Figure 2 Fuzzy inference system diagram.

The fuzzy inference system is the process of formulating a given input to an output using fuzzy logic. There are two main types of fuzzy inference systems, Mamdani and Assilian [14], and Takagi and Sugeno [15] . Mamdani method is used to control a system by synthesizing a set of linguistic rules. Sugeno method is similar to Mamdani method but the output membership functions are different to those of Mamdani. In Sugeno method the output membership functions are constant or linear, while those of Mamdani are fuzzy sets. The selected shape of the membership function is depending on the human experience or by statistical studies. There are several types of membership functions; sigmoid, triangular, exponential, Gaussian, *etc.*

4. Results and discussions

4.1. Calculation of oil saturation by logging

The petrophysical parameters of the Well#OMNX are determined from empirical equations used in logging. The porosity is determined from the logs of density and neutron. The neutron porosity is corrected because the logging tool is calibrated in limestone and not in sandstone; the corrected neutron porosity (ϕ_{NC}) is given by the following equation:

$$\phi_{NC} = \phi_N + 4 \qquad (1)$$

where ϕ_{NC} is the corrected neutron porosity and ϕ_N is the neutron porosity measured in the well.

The porosity density (ϕ_D) is calculated buy the following equation:

$$\phi_D = \frac{\rho_{ma} - \rho_b}{\rho_{ma} - \rho_f} \qquad (2)$$

In this equation, ρ_{ma}, ρ_b and ρ_f are matrix density, bulk density and the density of the fluid in pores. The values of ρ_{ma} and ρ_f are equal 2.65 and 1.1 g/cm^3, respectively.

For oil wells, the effective porosity (ϕ) used in Archie formula is given by the following equation [16]:

$$\phi = \frac{2\phi_{NC} + \phi_D}{2} \quad (3)$$

In the studied well, due to the cleanliness of the studied reservoir marked by a low percentage of shale, which reflected by very low gamma ray, it is less than 52 (API). The water saturation is determined by Archie formula [16]:

$$S_w = \sqrt{\frac{F \times R_w}{R_t}} \quad (4)$$

where R_w is the resistivity of water contained in the pores. It is estimated in the study area by sampling and it is equal (0.025 Ohm.m). R_t is deep resistivity and F is the formation factor (F) given by equation [16]:

$$F = \frac{0.6}{\phi^{2.15}} \quad (5)$$

The oil saturation (S_o) is calculated by the simple equation:

$$S_o = 1 - S_w \quad (6)$$

The evaluation results of the Well#OMNX is shown in (Figure 3).

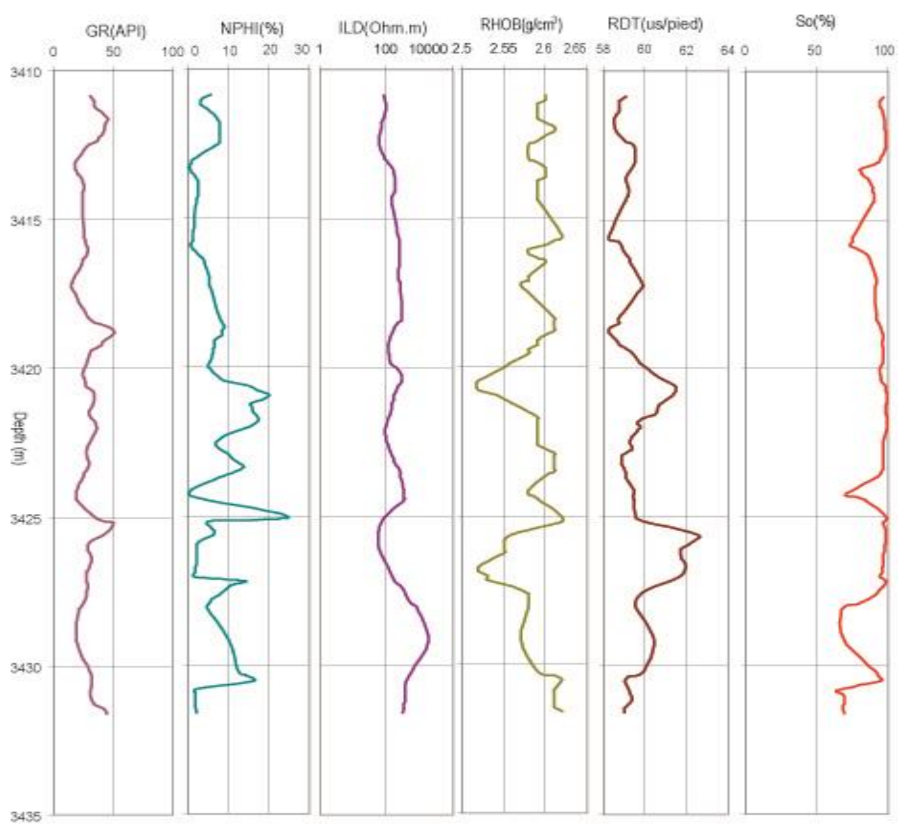

Figure 3 Well logs at Well#OMNX

4.2. Relation between well log data and oil saturation

The data set used in fuzzy inference system Mamadani type are the conventional log data recorded in situ from drain D4 of the anisometric reservoir Ra in Well#OMNX. The values of gamma ray range from 15.18 to 51.48 API (standard deviation: 7.70 API). The neutron porosity oscillates between 0.2 and 24.8 % (standard deviation: 5.21%). The deep resistivity varies between 54.26 and 1762.71 Ohm.m (standard deviation: 194.81 Ohm.m). The bulk density range from 2.52 to 2.62 g/cm^3 (standard deviation: 0.027 g/cm^3). The transit time range from 58.24 to 62.62 (μs/pied) (standard deviation: 1.07 μs/pied). The oil saturation show high values, they oscillates between 64.03 and 99.43 % with standard deviation equal 9.40%.

The correlation found between the inputs data and oil saturation show low correlation coefficient (*R*) between these parameters (Figure 4). The high correlation coefficient is obtained between neutron porosity and oil saturation (*R*=0.52) (Figure 4a). The low correlation coefficient is obtained between oil saturation and transit time (R= 0.27) (Figure 4e). These results prove the non linear relation between each log data input and oil saturation (output).

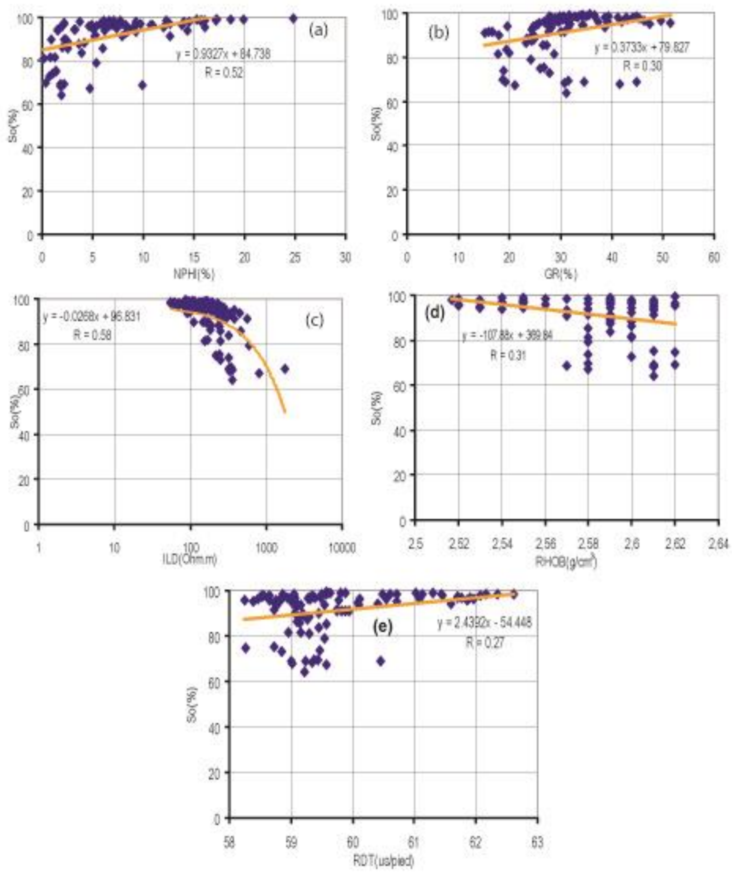

Figure 4. Correlation between inputs log data and oil saturation

4.3. Application of fuzzy inference system

In this study, the fuzzy inference system is applied for the first time to estimate the oil saturation from well log data. This method is applied in Well#OMNX localized in Hassi Messaoud oil field. The goal of this application is to demonstrate the capability of the fuzzy inference system Mamdani type to predict the oil saturation from conventional log data and compare obtained results with that calculated by logging.

The oil saturation is estimated for drain D4 on the interval (3410-3435m). The inputs of the FSI model are composed with log data which have relation with oil saturation, they include gamma ray (GR), neutron porosity (NPHI), deep resistivity (ILD), bulk density (RHOB) and transit time (RTD). There is a logical relationship between the selected inputs and the output (oil saturation). NPHI, RDT, and RHOB are logs of porosity, and they represent the reservoir storage capacity. The electrical resistivity measure the ability of rocks to conduct electrical current, the existence of oil in the rock is generally reflected by high resistivity measurements. The density is an indicator for lithology, sandstones is generally characterized by a density about 2.65 g/cm^3. The GR log measures the natural radioactivity of formation and it is used to distinguish between sandstone and clay reservoirs, intervals with low GR show higher oil saturation than clay intervals.

The inputs and output log data used in Mamadani-type fuzzy inference system are normalized to improve the model performance. The data of each variable are transformed between [0 1] using the following equation [17]:

$$\bar{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \qquad (7)$$

where $\bar{x}$ is the normalized value of x, $x_{\min}$ and $x_{\max}$ are the maximum and minimum values of data, respectively.

Fuzzy inference system of Memdani-type is applied using Matlab Toolbox. The mean square error, the correlation coefficient and the average relative error are used as performance criteria of the FSI model. The membership functions selected to build the FSI model are Gaussian for the inputs and output variables. They are divided into five linguistic terms, Very Low (VL), Low (L), Medium (M), High (H) and Very High (VH). The fuzzy logic rules are developed after analyzing all input and output data of the fuzzy inference system model. The fuzzy if-then rules were combined using the Max aggregation operator and the point prospectivity values were calculated using the centroid method. The fuzzy inference system contains five inputs to predicted one output using twenty if-then rules. The input membership function of gamma ray is given in (Figure 5).

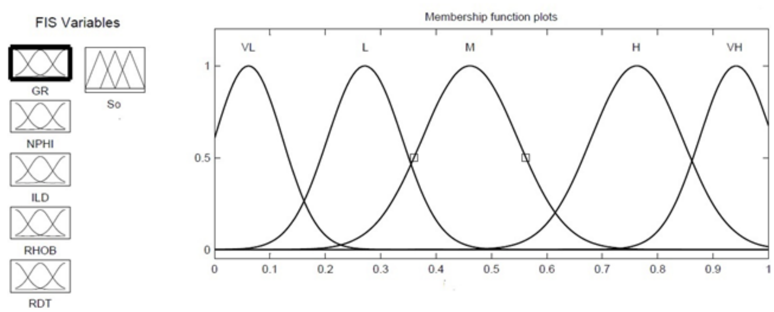

Figure 5. Membership function of input variable gamma ray

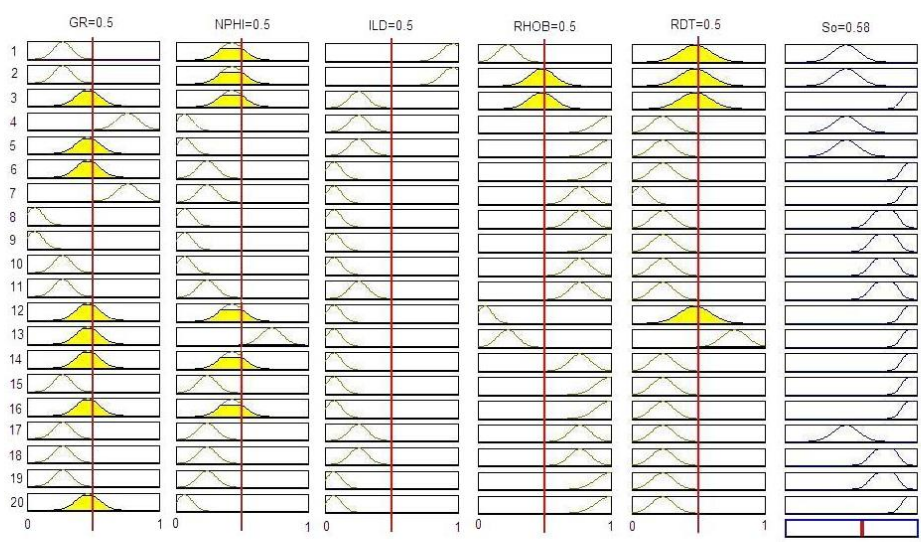

Figure 6. Fuzzy logic rules viewer for estimating oil saturation

The fuzzy rules have been made to link the inputs and the output variables basing on a series of if-then rules. The obtained FSI model is shown in (Figure 6). Despite the low application of this method in petroleum sciences compared to other artificial intelligence methods, fuzzy inference system has given good results. The oil saturation values generated by FIS are correlated with that obtained by logging; a good correlation is obtained between them (Figure 7). The mean square error, the correlation coefficient and the average relative error are equal 82 $\times 10^{-4}$, 0.92 and 7.56$\times 10^{-2}$, successively. These results prove the ability of this method to estimate this parameter without returning to the empirical equations especially in the case of lack of some log data such as interpretation parameters.

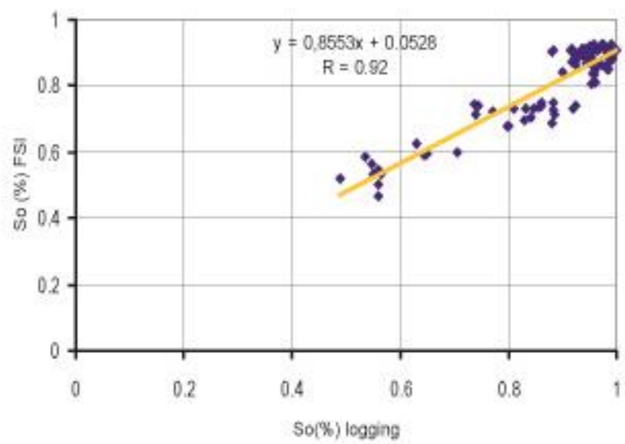

Figure 7. Correlation between oil saturation obtained from logging and that estimated by FSI

The FIS can be an effective method to estimate the oil saturation based on conventional log data recorded in the wells, which requires the good knowledge of the well log database to choose the best membership function, interval fuzzy functions and fuzzy rules. The performance of the FSI model can be evaluated by the high correlation coefficient, the less mean square and average relative errors between the oil saturation calculated by logging and that estimated by FSI.

5. Conclusion

The determination of oil saturation in oil wells is usually calculated from log data by applying empirical equations (Archie formula for clean reservoir). In this work, the fuzzy inference system Mamdani type is applied for the first time, to estimate oil saturation, using the log data and without return to empirical equations. Despite the heterogeneity of the studied drain D4 in Well#OMNX. The obtained results show that FIS have high ability to estimate oil saturation parameter, a good correlation coefficient is obtained between the oil saturation calculated by logging and that estimated by this method (R=0.92).

The FSI can be powerful nonlinear method to estimate the oil saturation petrophysical parameter in oil wells, in the case of lack log data or if the clay nature is unknown in reservoir. The methodology proposed in this study permit to estimate oil saturation for oil wells without taking into account the empirical equations used generally in logging.

Symbols

ϕ_{NC}	*corrected neutron porosity, (%)*	R_w	*resistivity of water contained in the pores, (Ohm.m)*
ϕ_N	*neutron porosity, (%)*	F	*formation factor*
ϕ_D	*porosity density, (%)*	R_w	*Water resistivity, (Ohm.m)*
ρ_{ma}	*matrix density, (g/cm^3)*	R_t	*deep resistivity, (Ohm.m)*

ρ_b	*bulk density, (g/cm³)*	S_o	*oil saturation, (%)*
ρ_f	*density of the fluid in pores, (g/cm³)*	$\bar{x}$	*normalized value of* x
ϕ	*effective porosity, (%)*	x_{min}	*minimum value of data*
S_w	*water saturation, (%)*	x_{max}	*maximum value of data*

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