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Porosity and permeability prediction in shaly Triassic reservoirs of the Hassi R'mel Field (Algeria) from well log data using fuzzy logic

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ABSTRACT Petroleum reservoir characterisation is the process of quantitatively describing the various characteristics of reservoirs in spatial variability using available data. It plays a crucial role in modern reservoir management, decision making, and improving the reliability of reservoir modelling. In this paper, we present an inexpensive approach based on fuzzy logic (FL) type-two, as an artificial intelligence technique, to estimate the porosity and the permeability in shaly Triassic reservoirs from well log data. Porosity and permeability are the main properties of reservoir characterisation, especially in sandy reservoirs, since they have a direct impact on the petrophysical parameters such as water and hydrocarbon saturations. Indeed, clay volume and its distribution in the reservoir considerably affect the porosity and permeability values of the reservoir under study. For that reason, this case study is dedicated to the use of the FL type-two algorithm to estimate, with less uncertainty, the porosity and permeability values of the shaly Triassic reservoir in the Hassi R'mel field in the Algerian Sahara. The application of the proposed approach on the well data of the studied reservoirs enabled comparing the obtained porosity and permeability values to the results measured in the laboratory by using cores. Furthermore, the correlation between the obtained results and laboratory data has improved the fuzzy model predictability degree far from the wells. More precisely, a Mamdani-type fuzzy model was formulated to predict porosity and permeability. Three 'if-Then, fuzzy rules with three Gaussian type membership functions have been created in the fuzzification phase in order to transform the fuzzy set into a net value. A centre of gravity method has been used in the defuzzification phase. The obtained results showed a good agreement, which means that the curves generated by the proposed algorithm are very close to the real curves of the measured values. Moreover, the correlation coefficients (R^2) of the FL model in the training step were 0.90 and 0.91 for the well HR01 and 0.90 and 0.89 for the well HR02 for porosity and permeability respectively. The Root Mean Square Errors (RMSEs) instead were 4.56×10^{-2} and 3.47×10^{-2} for HR01 and 3.81×10^{-2} and 4.21×10^{-2} for HR02. Furthermore, R^2 of the FL model in a testing step were 0.89 and 0.92 for HR01 and 0.91 and 0.87 in HR02 for porosity and permeability respectively, while the RMSEs were 4.65×10^{-2} and 3.59×10^{-2} for HR01 and 3.54×10^{-2} and 4.38×10^{-2} for HR02. The main contribution of this study is that we have considered an FL type-two approach; this technique has not been considered before for superior, intermediate, and inferior levels of the shaly Triassic reservoir in the Hassi R'mel field. Thus, the obtained results can provide an added value to the petrophysical scientific community. Besides, this methodology provides a precise estimation of porosity and permeability without the need for too many measurements, and with a minimum use of coring process. It

can therefore help in better understanding such type of reservoirs and consequently optimising their exploration costs in Algeria.

Key words: porosity, permeability, shaly sand reservoir, fuzzy logic, Hassi R'mel petroleum field.

1. Introduction

Accurate reservoir characterisation is an important step to increase oil and gas recovery. Indeed, enhanced characterisation requires cheap sources of data, which may rely entirely on the prediction of rock porosity and permeability. It has been noted in the last decades that fossil fuels are still the most used energy source in the world and the demand for this type of energy does not cease increasing. However, due to the small number of new field discoveries and their limited net pays, it is necessary to master the development of reservoir properties and their characterisation with minimum uncertainties because most of the empirical reservoir models have been developed for specific regions with a predefined geological setting. From another side, the fuzzy logic (FL) applications have been extended notably in the last decades to several disciplines like oceanography, climatology, and bio-energy and geosciences. Therefore, it is becoming a more powerful tool in all science domains including geophysics and petrophysics. Cuddy (2000) has proposed new interpretation techniques based on FL to predict permeability and lithofacies in uncored wells. In seismic interpretation, Klose (2002) has described a simple approach to the geological interpretation of seismic diffraction stack images by using FL, in which a fuzzy rule-based expert system was developed to classify lithology and tectonic rock units by interpreting those seismic images. Later on, in seismology, D'Ayala and Esperanza (2003) proposed an FL system to define measures of damage and vulnerability. In petrophysics, Lim (2005) applied

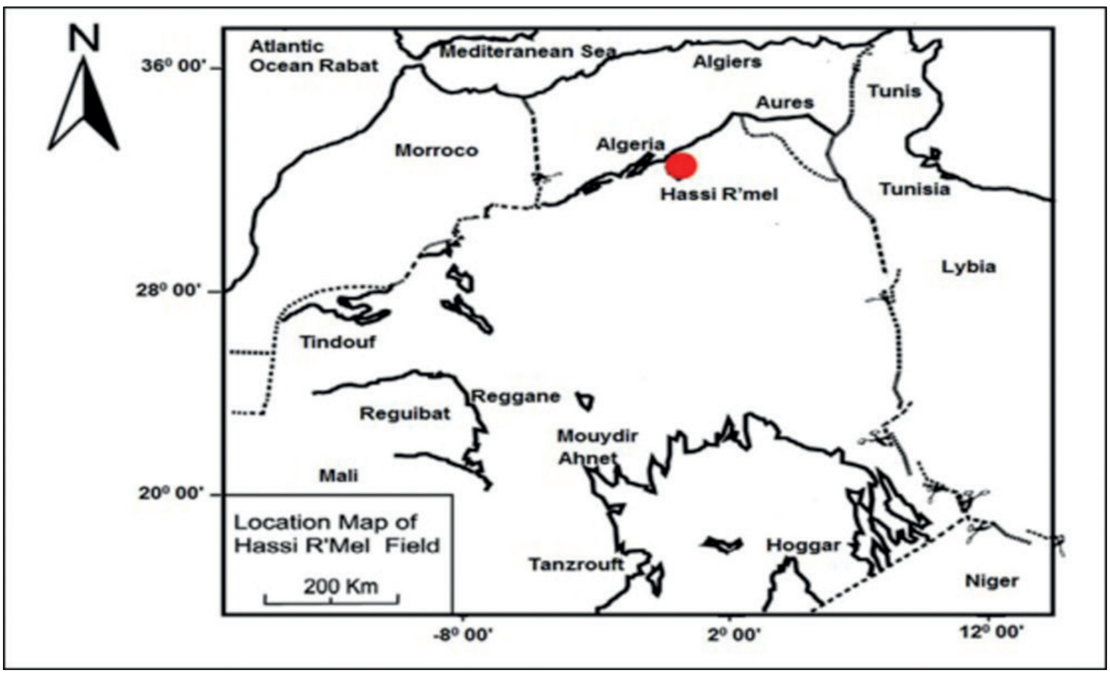

Fig. 1 - The geographic location of the Hassi R'mel field (Rossi *et al.*, 2002).

the fuzzy classification to choose the best logging curves that have an effect on the porosity and permeability of the cores. Thereafter, Kadkhodaie Ilekchi *et al*. (2006) have also conducted a study on presenting the importance of the FL approach to predicting rocks types from well log responses.

The main objective of this case study is to design a methodology for estimating porosity and permeability with minimal acceptable errors, based on the FL type-two algorithm in the Hassi R'mel field in Algeria. This field is located in the north-western part of the Triassic basin, about 550 km south of Algiers, 100 km NW of the city of Ghardaïa and 80 km SE of the city of Laghouat, as shown in Fig. 1.

The main novelty of this case study is the use of the FL algorithm type-two to predict porosity and permeability with optimised number of core data at the shaly Triassic reservoir in the Hassi R'mel field. Two wells (HR01 and HR02), which cross the shaly lower series of Triassic reservoirs, have been studied in detail in this study. In these series, the presence of clay affected considerably the petrophysical parameters, mainly porosity and permeability. Hence, the estimation of these two key parameters using conventional methods and cross-plots led to high uncertainties due to the facies variation (Aliouane *et al*., 2018; Sajid *et al*., 2021; Aliouane, 2022; Doghmane *et al*., 2022). The application of the proposed FL model type can thus be advantageous in this case due to the specifications of the Hassi R'mel geological settings.

The steps of this study are set out in the sections as follows: first, the geological settings are described in detail in Section 2 in order to familiarise the readers with the region under study. Then, the methodology has been presented in Section 3. The porosity and permeability prediction by FL are then detailed in Section 4. The results are demonstrated and discussed carefully in Section 5. Finally, this manuscript ends with the conclusions and perspectives for future works.

2. Geological settings

The Hassi R'Mel field, which covers an area of around 3700 km², produces condensate gas at a rate of 235 g/m^3, with the presence of a large oil ring on its eastern and southern periphery (Rossi *et al*., 2002). Since the objective of this study is related to the Triassic interval, only the stratigraphic and structural settings of the Triassic formations have been considered here (Figs. 2 and 3). The average thickness of the Triassic is 200 m in the north and 75 m in the south and its basic limit is the Hercynian non-conformity. As demonstrated in Fig. 2, the Triassic of Hassi R'mel includes from bottom to top the following lithological units:

a) the lower clayey-sandstone Triassic: called the Lower Series; this series is represented by an alternation of green indurated clays, sometimes brown, and by fine and well- classified sandstones; it is characterised by the presence of volcanic flows (andesites). This series rests unconformably on the Palaeozoic formations;
b) the upper clay-sandstone Triassic: it consists of three main reservoirs, called A, B, and C, separated from each other by clay basins with a wide extension, and the cover consists of clayey Triassic and the saliferous Lias. Concerning the characteristics of the reservoir rocks of the Triassic interval, protected by thick layers of salt that form an excellent cover, there are three main levels (Aggoune *et al*., 2006):
   1. the upper level, level A: it is the most stable and the most extensive one, forming an excellent reservoir with porosity of 15% and a permeability of up to 800 millidarcies;
   2. the medium level, level B: it is the thinnest and least stable, the maximum thickness is 20 m;
   3. the lower level, level C: it forms the most important part in the thickness of the

reservoir and containing 30% of the total reserves; its thickness ranges from 10 to 60 m, its porosity is 15 to 22%, and its permeability is 400 to 2300 millidarcies;

c) the clayey Triassic: called the lower clayey; it is made up of indurated chocolate-brown clays, traversed by veins of anhydrite and salt;
d) the Triassic salifer: it is made up of a large series of salt and clay (Aggoune *et al*., 2006).

The structures of Hassi R'mel extend towards the SW by the small anticlinal structure of Djebel Bissa and towards the south by that of Hassi R'mel South, as shown in Fig. 3. Its structure appears in the form of a NNE-SSW oriented anticline. This structure is characterised by a network of oriented faults that can reach a height of 100 m and plays an important role in the compartmentalisation and accumulation of hydrocarbons. The structure of Hassi R'Mel is characterised by the individualisation of three zones marked by numerous peaks and depressions of variable magnitude where:

a) South Zone: it is formed by a series of undulations of notable dimensions (5×10 km^2), of strong vertical amplitude (50 m) and affected by numerous faults of 100 m height;
b) Central Zone: structurally high, it appears as a slightly undulating plateau for Mesozoic formations. On the other hand, the importance of the structural falls of the east and west flanks ensure a good structural closure;
c) North Zone: this zone is strongly affected by tectonic movements, particularly for post-Jurassic formations with deep faults favouring Mio-Pliocene deposits.

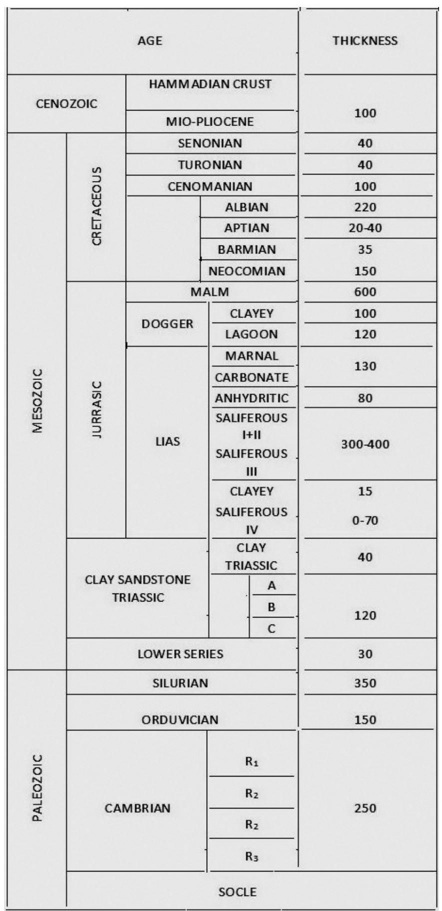

Fig. 2 - The stratigraphic column of the Hassi R'mel field (Aggoune *et al*., 2006).

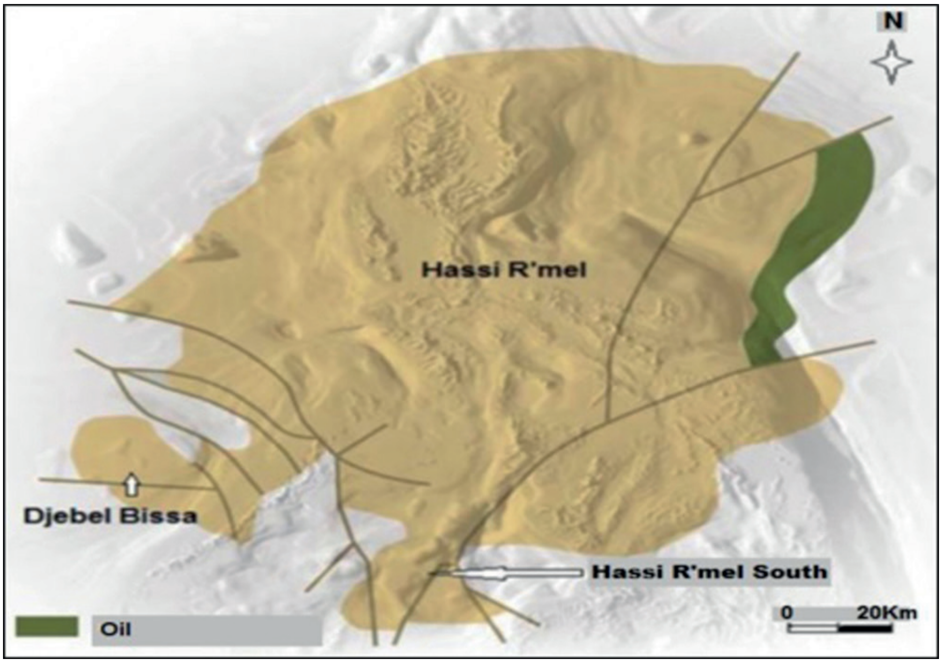

Fig. 3 - Structural setting of the Hassi R'mel field (Aggoune *et al.*, 2006).

3. Methodology

3.1. Data set

The data set of the Triassic reservoirs, used in the study, was collected in Trias stratification in the Hassi R'Mel region, where the cores have provided more accurate information and more materials for analysis. They can give us much information on tectonics (cracking, faults, etc.), sedimentation environment, morphogenesis, etc. Two core wells (including porosity and permeability measurements) indicate the presence of thick layers of salt. Thus, data of wells HR01 and HR02, where the stratifications have been prepared and validated in order to be used as inputs for the FL interference system type-two.

The input data of the fuzzy system are: acoustic logs, natural and induced log curves represented by natural gamma rays (GRs), resistivity of deep laterolog (LLD), bulk density (RHOB), transit time (Delta T), and neutron porosity (NPHI). The output data sets include fuzzy porosity (FUZZYPOR) and fuzzy permeability (FUZZYPERM) as shown in Figs. 4 and 5, respectively.

The FL algorithm is powerful and simple and can be modified according to our requirements. It can handle different types of inputs simultaneously and can make accurate decisions using shortened functions. Moreover, the method used in this study is simple, it can be built easily and can make decisions readily because it is similar to human thinking in its logical system, which makes it easier to solve more complex problems. Besides, the FL system can be easily reprogrammed if good results are not obtained. In addition, the mathematical form is not required and the rules can be controlled to obtain good results. Expressing the system rules in natural language (and therefore qualitatively) does not make it possible to prove that the system will have optimal behaviour. All settings that the programmer has to enter into the system are done in a completely customised way. Thus, this method cannot guarantee that the system is stable, accurate or perfect, nor even guarantee that the rules entered by the programmer will not be contradicted. In addition to that, the accuracy of these systems is compromised because the system often operates on inaccurate inputs data and there is no single systematic way to solve a problem using FL.

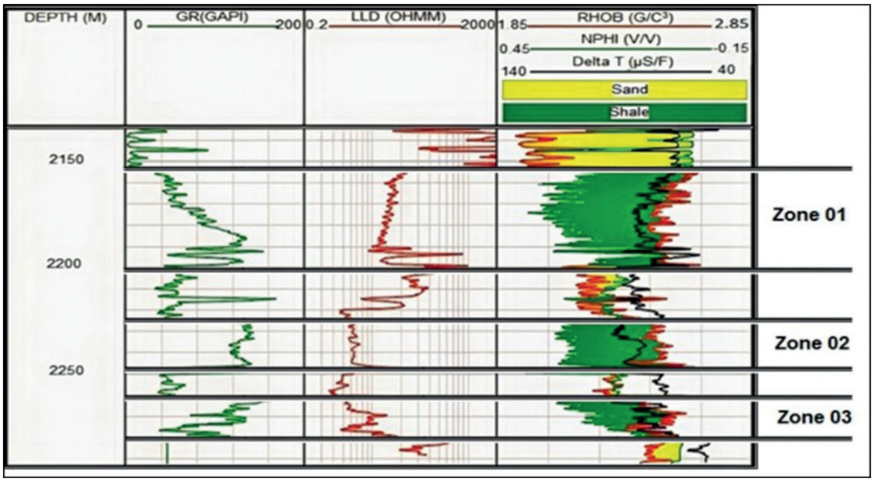

Fig. 4 - Petrophysical parameters of the shaly Triassic reservoir in Well HR01. GR is the natural gamma rays, LLD resistivity of deep laterolog, and RHOB bulk density, NPHI neutron porosity, and Delta T is transit time.

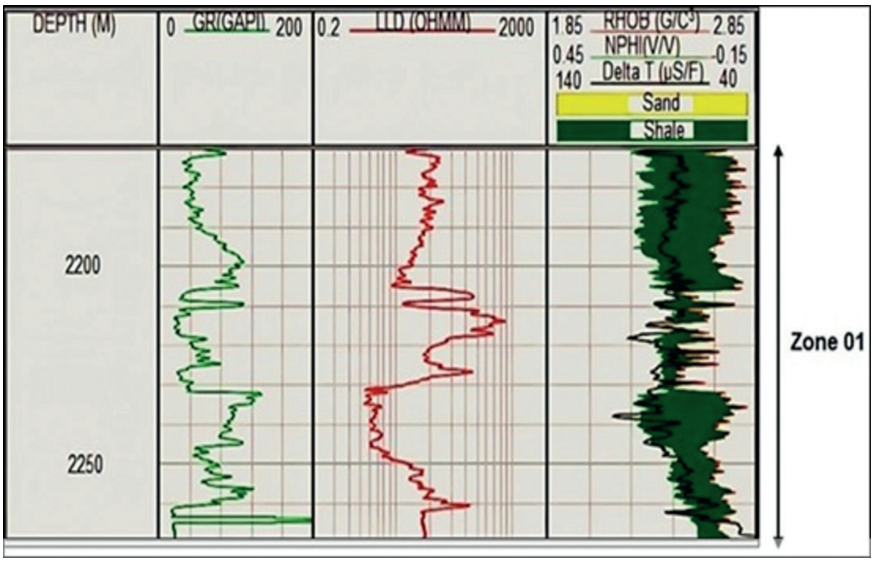

Fig. 5 - Petrophysical parameters of the shaly Triassic reservoir in well HR02.

A large number of data points were collected over a wide range of porosity and permeability measured in the laboratory by using cores (Fig. 6), where in well HR01 (298 points have been plotted out of 1265) and in the well HR02 (190 points have been plotted out of 1073).

The distribution of porosity and permeability values in the two boreholes investigated (Fig. 6) is due to the heterogeneity of the reservoir. The scatter in these two diagrams indicates that this

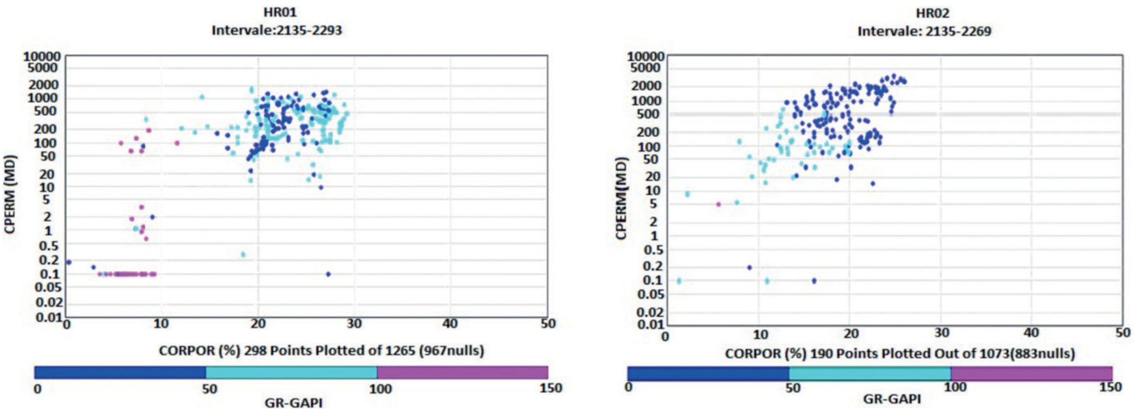

Fig. 6 - Variation of the permeability according to the porosity of the shaly Triassic reservoir in the wells HR01 and HR02. HR is Hassi R'mel, CORPOR is porosity core, and CPERM is permeability core.

property is very complex and has a strong non-linearity between porosity and permeability, making it impossible to predict using conventional approaches. On the other hand, the results obtained from the input data in Figs. 4 and 5 showed the presence of clay in the three depth zones 2155-2200 m, 2228-2250 m, and 2261-2280 m in the well HR01, and the zone 2170-2270 m in the well HR02.

The clay is a very restrictive parameter for the porosity and permeability determination in the reservoirs under study, which leads to the problem of finding a relationship connecting the two parameters. For that reason, we propose to estimate the reservoir parameters by FL; in this case the knowledge of a mathematical relation is not necessary. In fact, the FL architecture just needs to be trained using input data corresponding to desired outputs, which are porosity and permeability in this study.

3.2. FL method

In this work, the Mamdani fuzzy inference system (MFIS) has been used and compared to the Sugeno fuzzy inference system. It demonstrated more precision in the encryption algorithm and is well-suited because its variables are defined by fuzzy sets and a fuzzy reasoning process that belongs to a linguistic reasoning type. On the other hand, due to the defuzzification rules, a net result is obtained in the MFIS. Therefore, the MFIS is created from three major elements: an input part, that includes the input data (GR, LLD, RHOB, Delta T, NPHI), an intermediate part called 'fuzzy inference engine', which invokes each appropriate rule and generates the results for each variable, and combines the results of the rules and the output part, which includes FUZZYPOR and FUZZYPERM and converts the combined results to a specific output value.

To calculate the output values of the porosity and permeability, seven steps have been followed in this work:

1. data normalisation and fuzzy clustering;
2. determination of a set of fuzzy rules;
3. fuzzify inputs using input membership function and linguistic variables;
4. combine the fuzzy inputs according to the fuzzy rules to establish a rule conclusion;
5. finds the consequence of the rule by combining the conclusion of the rule and the output membership function;
6. combine consequences to get output data;
7. defuzzify output data.

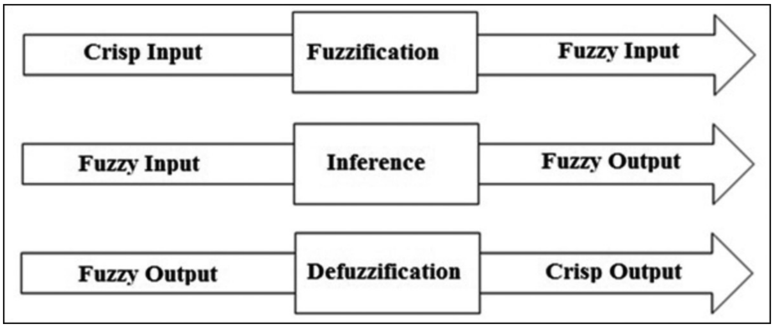

Fig. 7 - Schematic diagram of the three components of a fuzzy inference system.

4. Porosity and permeability prediction by FL

A fuzzy inference system aims to transform input data into output data from the evaluation of a set of rules formulated in natural language, for which there is compatibility between the input data, these rules and the output parameters. The generated structure for FUZZYPOR and FUZZYPERM are shown in Fig. 8, with input represented by node in the left and output represented by node in the right. The three fuzzy rules that are connected by 'and' are represented in the schematic diagram by the three blue nodes.

The workflow has been implemented by using the fuzzy approach based on the steps described in the following sections.

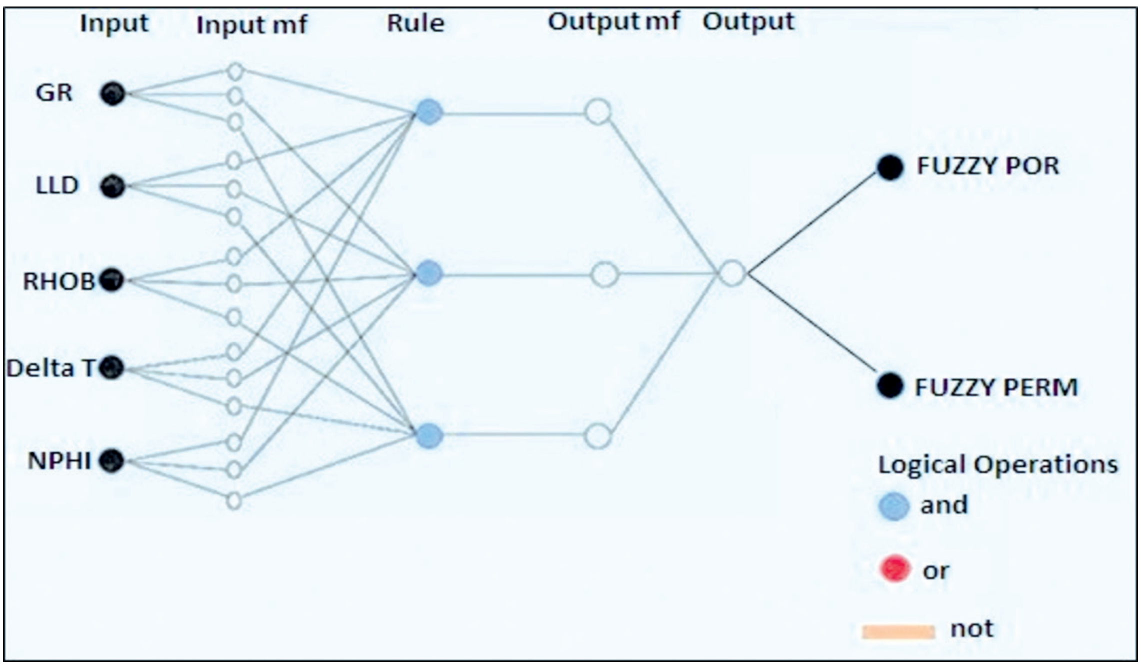

Fig. 8 - Fuzzy model architecture for FUZZYPOR and FUZZYPERM of Hassi R'mel in wells HR01 and HR02, mf is membership function, FUZZYPOR is fuzzy porosity, and FUZZYPERM is fuzzy permeability.

4.1. Data normalisation and fuzzy clustering

In this step, data normalisation is achieved by using the maximum and minimum values of the logging data inputs (Cherana *et al.*, 2022). The range of variation of the input and output variables should be between 0 and 1, so that, the normalisation operations can be operational. To divide the data set into subgroups, a *k*-mean algorithm has been used, where this algorithm is distinguished from other algorithms by the following:

1. acceptable calculation time as the algorithm works quickly, even for large data sets;
2. the simplicity of the clustering since it contains only two steps, the cluster assignment step and the move centroid step;
3. if we are looking for an unsupervised learning algorithm that is easy to implement and can handle large data sets, then *k*-mean clustering is a good starting point because its convergence can be guaranteed in this method. Also, the method is known to be one of the most popular algorithms and it is implemented in many machine learning packages.

By using *k*-means, three centres resulting from clustering or the fuzzy model have been created based on three fuzzy 'if-then' rules with three-membership function for the FUZZYPOR model and FUZZYPERM (Cherana *et al.*, 2022). The data set was divided into 80% for training and 20% for testing and validation. The *k*-mean algorithm, used in this work, is based on minimising the objective function given by:

$$F_p = \sum_{J=1}^{C} \sum_{i \in Sj} \|Z(i) - Cj\|^2 \to_{Cj}^{Min} \quad (1)$$

where C is the number of clusters, C_j is the centres of the clusters (prototypes).

The sets S_j contain the data samples, which belong to cluster j. That is to say, those located closest to the centre of the cluster C_j (Cherana *et al.*, 2022).

We introduce the *k*-mean algorithm in the following steps:

1. initialise the centres of the C clusters C_j, $j = 1 \dots C$;
2. assign all data samples to nearest cluster centres;
3. calculate the centre of gravity (average) of each cluster then readjust each cluster centre in relation to its centre of gravity using the expression:

$$C_j = \frac{\sum i \in Sj \ \mathrm{Z(i)}}{Nj} \quad (2)$$

where N_j is the number of elements of the set S_j.

The statistical characteristics of each input curve used in this study are summarised in Tables 1 and 2.

Table 1 - Input data set statistics of well HR01.

Values	Min	Max	Mean	Median	Mode	Standard Deviation
GR(GAPI)	2.082	168.956	75.639	61.777	47.138	41.471
LLD (OHMM)	0.475	51619.051	871.410	3.846	516.661	5209.819
NPHI(V/V)	-0.011	0.382	0.188	0.199	0.017	0.102
Delta T(µS/F)	53.100	96.292	78.515	79.790	83.766	9.043
RHOB(G/C^3)	2.022	2.756	2.490	2.559	2.602	0.173

Table 2 - Input data set statistics of well HR02.

Values	Min	Max	Mean	Median	Mode	Standard Deviation
GR(GAPI)	5.895	300	56.563	41.375	160.238	143.354
LLD (OHMM)	0.2	80.658	8.743	6.825	12.634	25.102
NPHI(V/V)	-0.024	0.244	0.1123	0.145	0.167	25.102
Delta T(µS/F)	40	113.182	76.947	62.825	80.125	74.423
RHOB(G/C^3)	1.727	2.801	2.546	2.635	2.476	74.423

4.2. Fuzzification

The main role of this process is to transform the modelled value *X* into a fuzzy part to allow modelling the inputs of a system mainly in the form of curves called membership functions. In this case study, we have three subsets: Low, Moderate, High porosity and permeability as shown in Fig. 9. Eq. 3 expresses the Gaussian distribution function used in this fuzzy system (Cherana *et al.*, 2022):

$$F(x, \sigma, c) = exp^{-(x-c)^2/2\sigma^2} \quad (3)$$

where *C* and *σ* are the normal distribution parameters showing the mean and the standard deviation of the logging data, respectively. Fig. 9 shows an example of input membership function of natural GRs in well HR01.

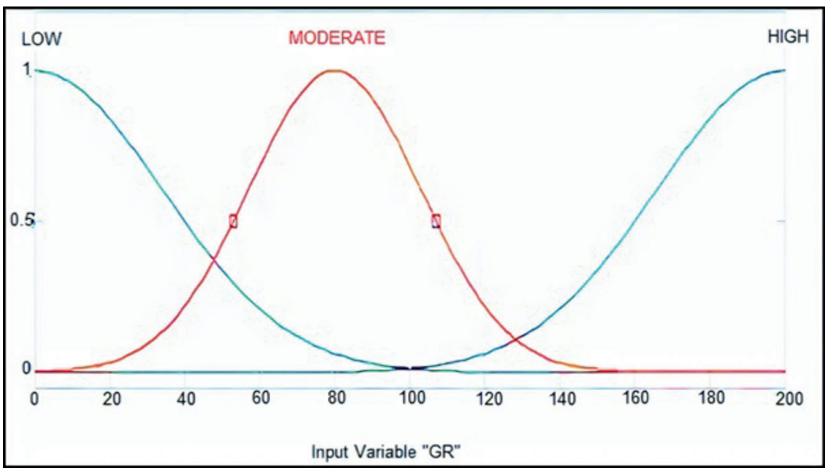

Fig. 9 - An example of membership function for natural GRs in well HR01.

4.3. The inference engine and fuzzy rule

The fuzzy rules are used to formulate the conditional instructions that compose the FL; they allow the information of a system to be condensed through a set of defined rules (Mamdani and Assilian, 1975). The rules for formulating the petrophysical input data of FUZZYPOR and FUZZYPERM are expressed in the next subsections.

a. For the FUZZYPOR:
   - a.1. if GR is high and LLD is low and RHOB is low and Delta T is moderate and NPHI is moderate, then FUZZYPOR is low;
   - a.2. if GR is moderate and LLD is moderate and RHOB is moderate and Delta T is moderate and NPHI is moderate, then FUZZYPOR is moderate;
   - a.3. if GR is low and LLD is high and RHOB is high and Delta T is high and NPHI is high, then FUZZYPOR is high.

b. For the FUZZYPERM:
   - b.1. if GR is low and LLD is low and RHOB is high and Delta T is moderate and NPHI is low, then FUZZYPERM is low;
   - b.2. if GR is moderate and LLD is moderate and RHOB is moderate and Delta T is moderate and NPHI is moderate, then FUZZYPERM is moderate;
   - b.3. if GR is high and LLD is high and RHOB is low and Delta T is high and NPHI is high, then FUZZYPERM is high.

A graphic illustration showing the steps of formulating inputs of the petrophysical data for the FUZZYPOR and the FUZZYPERM by using three fuzzy 'if -then' rules is highlighted in Figs. 10 and 11. They are generated by the fuzzy inference system, where each figure displays a roadmap for the whole process of fuzzy inference. The plots represent the antecedents, the FUZZYPOR and the FUZZYPERM as results of the rules, where each rule is a row of plots and each column is a variable.

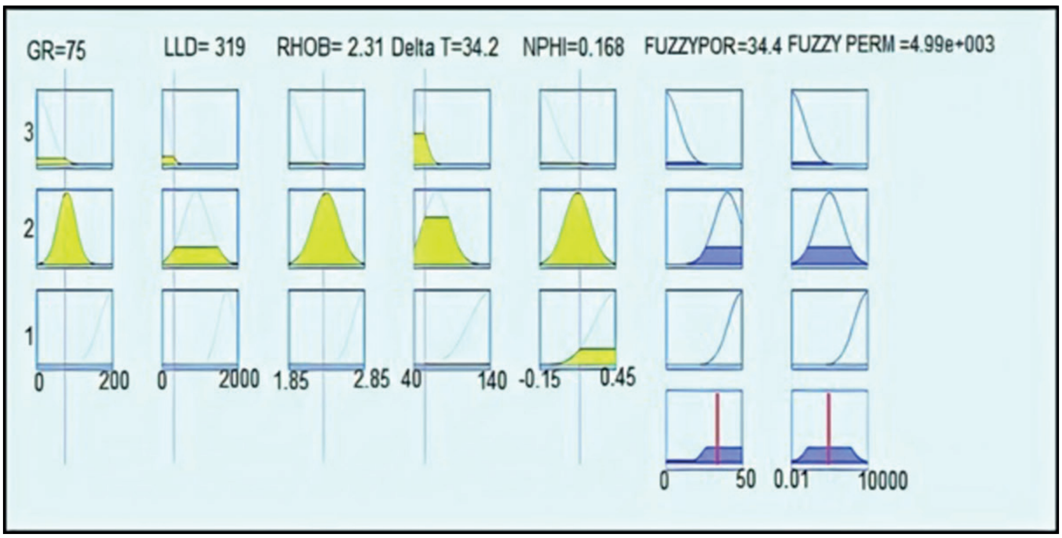

Fig. 10 - Fuzzy inference system rules viewer for FUZZYPOR and FUZZYPERM generation of Well HR01.

4.4. Defuzzification

In this part of the research work, the gravity centre method has been considered; it involves the calculation of the centre gravity position for the resulting membership function. Wherein, the abscissa of this centre of gravity becomes the output (Al-Gabalawy *et al.*, 2020), the *X* value

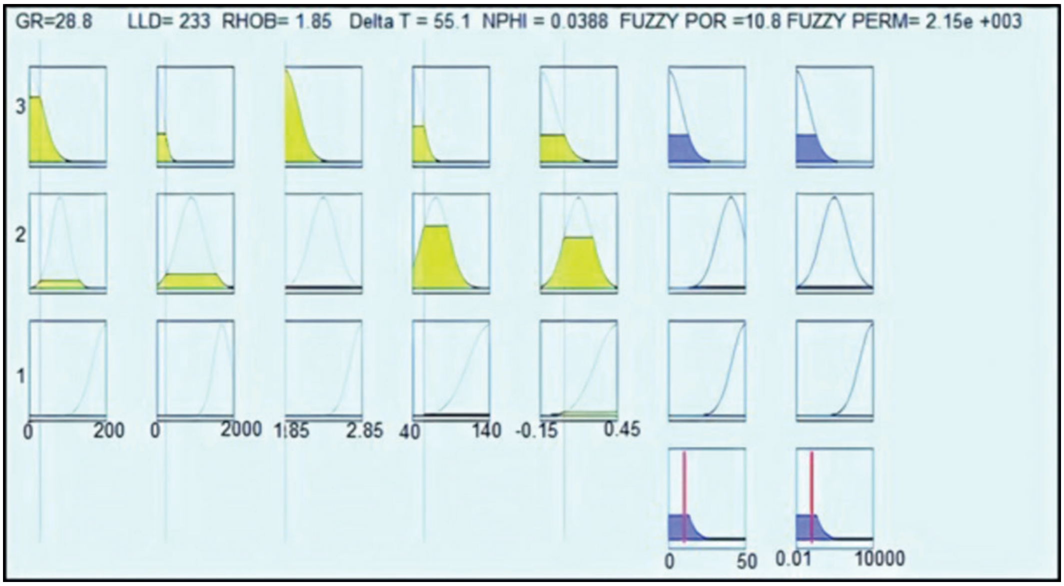

Fig. 11 - Fuzzy inference system rules viewer for FUZZYPOR and FUZZYPERM generation of Well HR02.

obtained by defuzzification is calculated by:

$$X = [\int X \mu_F(x) dx] / [\int \mu_F(x) dx] \tag{4}$$

where *X* is the numerical variable, $\mu_F(x)$ is the membership function of the variable *X*.

Figs. 12 and 13 show the prediction of the FUZZYPOR and FUZZYPERM for the wells HR01and HR02, respectively. The logging data have been recorded in a conventional way, so that each log contains six tracks.

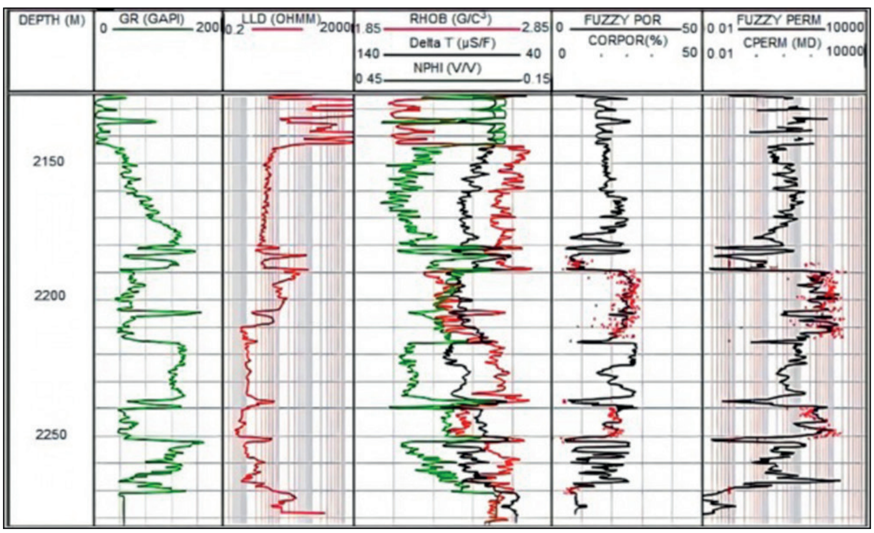

Fig. 12 - Prediction of porosity and permeability by FL in well HR01.

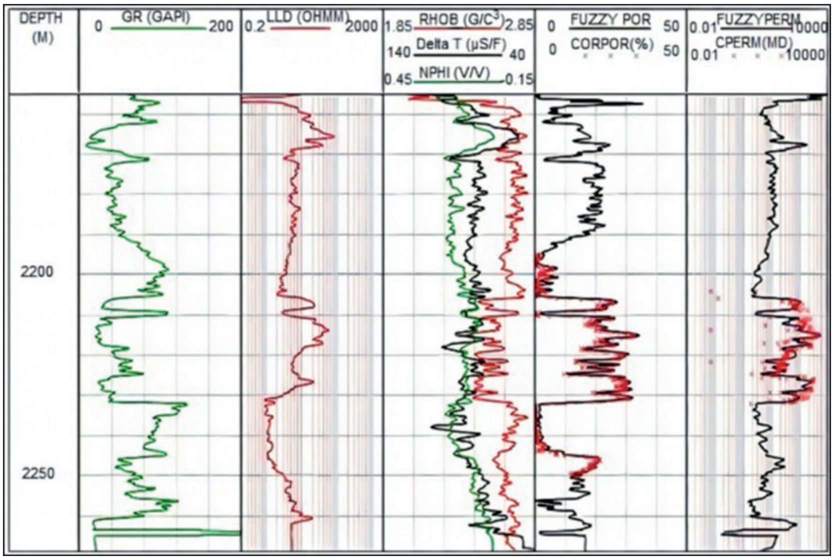

Fig. 13 - Prediction of porosity and permeability by FL in well HR02.

5. Results and discussion

From Figs. 12 and 13, a comparison between the measured values from cores (CPERM, CORPOR) and the values predicted by FL (FUZZYPERM, FUZZYPOR) showed a good correlation, which means that the curves generated by the FL are very close to the real values, especially at some depth intervals, more precisely in [2195-2222 m] and [2250-2260 m] of porosity and permeability for the well HR01, and in [2195-2250 m] of porosity and [2205-2232 m] of permeability for the well HR02. Furthermore, the inputs and outputs data curves have been divided into number of data classes used in the model. Then, the results of each analysis are accumulated and displayed in distributions called 'bins', where the number of bins must be between 2 and 100, but only 10 bins have been demonstrated in the case study.

To demonstrate the effectiveness of the obtained results in this study, the results have been compared with the results obtained by Aliouane *et al*. (2012). The main objective of the latter work was to use the Multilayer perceptron (MLP) and Radial Basis Function (RBF) neural network models to estimate petrophysical parameters from well log data, which is collected from a typical Triassic oil reservoir of the Hassi R'Mel field in south-eastern Algeria.

A statistical comparison of correlation coefficient (R^2) and the Root Mean Square Errors (RMSEs) between FL and MLP to estimate porosity and permeability is provided in Table 3 and the graphical comparison is highlighted by Figs. 12 and 13. Fig. 14 shows the correlation coefficient between the predicted values by the FL method and the measured values. The obtained model demonstrated relatively lower prediction errors with the FL method, where the R^2 and the RMSEs in the training step compared to the testing step indicate that:

i) R^2 of the FL model in training step are 0.90 and 0.91 in HR01 and 0.90 and 0.89 in HR02 for porosity and permeability, respectively. While the RMSEs are 4.56×10^{-2} and 3.47×10^{-2} in HR01 and 3.81×10^{-2} and 4.21×10^{-2} in HR02;
ii) R^2 of the FL model in testing step are 0.89 and 0.92 in HR01 and 0.91 and 0.87 in HR02 for porosity and permeability, respectively. While the RMSEs are 4.65×10^{-2} and 3.59×10^{-2} in HR01 and 3.54×10^{-2} and 4.38×10^{-2} in HR02.

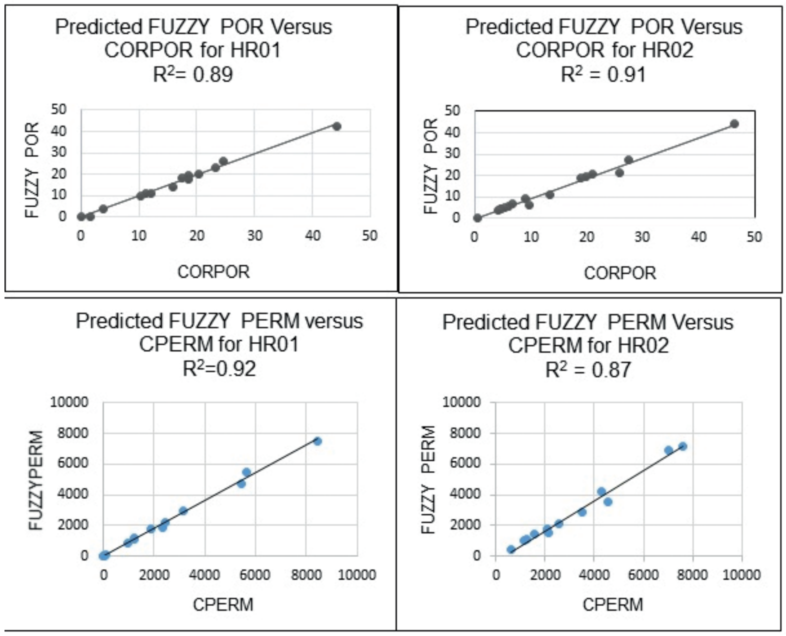

Fig. 14 - R^2 between predicted and measured value of the porosity and permeability in wells HR01 and HR02.

This statistical comparison summarised in Table 3 demonstrated the successful application of the FL technique and its effectiveness especially in reservoirs where the clay volume is considerable and its distribution affects the porosity and permeability values. The limitation of the proposed method is that if the data is inaccurate in the system, then, the human cannot acquire knowledge or infer any relationship. It is hoped that future research will lead to the solution of this problematic, hence the treatment of inaccurate data and the inference inherent in human thinking. These are the two main limits facing the FL approaches.

Table 3 - A statistical comparison of R^2 and the RMSEs between FL and MLP to estimate porosity and permeability in wells HR01and HR02.

Model			**Training step**		**Testing step**	
			R^2	**RMSE ($\times10^{-2}$)**	**R^2**	**RMSE ($\times10^{-2}$)**
MLP	HR01	Porosity	0.87	5.846	0.81	8.3125
		Permeability	0.88	5.212	0.72	11.2207
FL		Porosity	0.90	4.56	0.89	4.65
		Permeability	0.91	3.47	0.92	3.59
MLP	HR02	Porosity	0.85	6.078	0.81	9.4287
		Permeability	0.90	3.74	0.89	3.87
FL		Porosity	0.90	3.81	0.91	3.54
		Permeability	0.89	4.21	0.87	4.38

6. Summary and conclusions

In this study, we have used the FL-based type-two approach to estimate the porosity and permeability in the Hassi R'Mel field (Algerian Sahara). To evaluate the performance of the FL model in comparison to MLP, the values of R^2 and the RMSEs have been used, which indicated that the FL provided a better prediction when compared with the MLP model. In addition, this study compared the results obtained from FL with core data. It was found that FL is able to estimate reservoir parameters, essentially porosity and permeability. R^2 of the FL model in the test step was 0.89 and 0.92 in HR01 and 0.91 and 0.87 in HR02 for porosity and permeability, respectively.

The FL has been tested for the prediction of porosity and permeability; it is a simple tool for conforming known connections and a strong predictor in unexplored wells. This approach improved the estimation of reservoir properties to handle the interpretation more precisely and obtain a more reliable model. Thus, in order to meet the increasing oil demand, it will be helpful to consider such type of new techniques to evaluate, with less uncertainty, new reservoirs and make effective use of existing resources. Thence, FL can greatly contribute to such type of applications. To obtain satisfactory results when using the proposed FL in other future case studies, we recommend the following points:

1. in order to predict reservoir porosity and permeability, it is necessary to use appropriate input data clustering method such as fuzzy *k*-means to control and determine the number of fuzzy rules;
2. it is preferable to select at the beginning relatively simple membership functions such as (Gaussian and triangular) in the fuzzification part;
3. for a better estimation of the reservoir parameters, we recommend the use of a separate fuzzy model structure for each petrophysical parameter (porosity and permeability), which may provide results closer to the measured parameters;
4. the selection of an appropriate method in the defuzzification step plays a major role in obtaining accurate results in a short time.

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Errata Corrige

Porosity and permeability prediction in shaly Triassic reservoirs of the Hassi R'mel Field (Algeria) from well log data using fuzzy logic

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