DOI 10.4430/bgo00432

Prediction model of reservoir porosity via incorporating Particle Swarm Optimisation into an Adaptive Neuro-Fuzzy Inference System; application to Triassic reservoirs of the Hassi R'mel field (Algeria)

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(Received: 31 December 2022; accepted: 8 August 2023; published online: 30 November 2023)

ABSTRACT Conventional methods for estimating porosity from core data are often limited by their spatial coverage, time-consuming nature, high cost, and inability to capture the entire underground reservoir. To address these challenges, this paper proposes a soft computing method using an Adaptive Neuro-Fuzzy Inference System (ANFIS) to estimate porosity in a conventional gas reservoir. The approach involves integrating well-logging data and the ANFIS model with a Particle Swarm Optimisation (PSO) training algorithm to predict the underground porosity model in the Hassi R'mel region of the Algerian Sahara. The choice of this hybrid method was based on its superior performance compared to other models. Although the Hassi R'mel reservoirs are of Triassic clay sandstones, originated by the fluviatile depositional environment that lay on top of the Hercynian surface, the characterisation of their properties still requires refinement to improve the reservoir performance and address the problems faced using appropriate technologies. With an average porosity of 15% and permeability ranging from 250 to 650 mD, the ANFIS method shows excellent accuracy compared to core data, and a reliability of 85%. Overall, the ANFIS-PSO hybrid model proves to be a dependable and efficient technique for porosity prediction, surpassing traditional methods.

Key words: Porosity prediction, Adaptive Neuro-Fuzzy Inference System (ANFIS), Particle Swarm Optimisation (PSO), hybrid machine learning systems, neuro-fuzzy.

1. Introduction

The field of Hassi R'mel, in south Algeria, is one of the most important gas fields in the country and is considered a super-productive field (Boote *et al*., 1998), comprising most of the gas fields. The reservoirs of this field are mainly composed of clay sandstones of fluviatile deposits of the Upper Triassic. The geological analysis of these reservoirs has shown a porosity ranging from 10% to 16%, with a permeability exceeding 200 mD (Sonatrach and Schlumberger, 2007). Although this field reached maturity in terms of development long ago, there is still room for implementing new technologies, to address the problems of reservoir performance, and improvement.

Porosity estimation is one of the most challenging steps in reservoir characterisation. It is a crucial step in the workflow to ensure an optimum description of the state of the oil and gas reservoir, which plays a major role in the exploitation of the latter. Usually, due to underground heterogeneity, the process for calculating porosity is empirical. Therefore, it mainly depends on the experts' knowledge of the region and its properties. However, the rise of Machine Learning (ML) and soft computing methods, the long, complex nature of the classic methods of porosity estimation, as well as the vague relation between the actual porosity and the recordings of well-logging tools, have pushed researchers to adopt these advanced methods in order to reduce the computational cost.

ML is the application of automated methods that mimic human thinking to calculate values that are either very complex or take a considerable amount of time to be calculated using the conventional method. Most researchers have proposed employing these methods in different aspects of reservoir characterisation. Aliouane *et al*. (2018) proposed using two algorithms for permeability prediction: the Backpropagation and the Hidden Weight Optimisation algorithms, and the implementation of a Multilayer Perceptron (MLP) Neural Network (NN) with the Levenberg-Marquardt algorithm (Aliouane, 2022) for the prediction of clay volume. For the prediction of porosity, permeability, and water saturation, Okon *et al*. (2021) used a Multiple-Input and Multiple-Output (MIMO) Artificial Neural Network (ANN). Lithology classification had its share of applications. Extreme Gradient Boosting and Bayesian Optimisation showed great accuracy in identifying formation lithology (Sun *et al.,* 2020). Within the same scope, fuzzy clustering showed great potential in lithology classification; its results are as accurate as the lithology classes identified using core data (Cherana *et al*., 2022).

Many scholars saw the value of NNs in petrophysics as early as the 1990s. One of the first applications is the Backpropagation Neural Network (BNN) for predicting porosity (Wong *et al*., 1995). The use of BNNs continued in the early 2000s and 2010s, to predict both permeability and porosity (Helle *et al*., 2001), and to estimate porosity only using an updated NN version (Singh *et al*., 2016). In 2009, Kraipeerapun *et al*. (2009) proposed the application of the bagging technique to feedforward BNN to predict porosity, and Aliouane *et al*. (2012) proposed using MLP and Radial Basis Function (RBF) to predict porosity permeability and water saturation. Conversely, another successful application in achieving reservoir properties from seismic attributes of 3D seismic data was proposed by applying Self-Organising Maps (SOMs) to classify reservoir lithology, and the backpropagation algorithm to predict porosity (Al Moqbel and Wang, 2011). Within the same scope, many comparative studies were performed on the different types of NN, among which MLP and RBF (Aliouane *et al*., 2012), for the prediction of porosity. In addition to ANNs, in the past two decades, fuzzy logic had its share of applications in predicting reservoir properties. One of the early applications is a linguistic paradigm based on fuzzy logic to predict both porosity and permeability (Fang and Chen, 1997). In the first applications of different neuro-fuzzy systems, for the prediction of reservoir properties, some authors compared combinations of hybrid systems and their advantages (Anifowose *et al*., 2013). Afify and Hassan (2010) tested the accuracy of a neuro-fuzzy system, in which fuzzy logic was applied to obtain the parameters best related with the reservoir properties, and NN to predict the properties from the training data.

Recent studies have demonstrated the efficacy of ML applications in geophysics, particularly in analysing well-logging and seismic data. For instance, Hadiloo *et al*. (2018) found that the unsupervised Gustafson Kessel method outperformed other methods in accurately detecting subtle patterns in seismic facies maps. Similarly, Laudon *et al*. (2021) utilised a Convolutional Neural Network (CNN) and an unsupervised SOM to improve the quality of reservoir structural and stratigraphic models by fault detection. Hybrid ML algorithms have also gained popularity in petrophysics due to the complexity of reservoir characterisation. Rajabi *et al*. (2021) and Hu *et al*. (2023) investigated fracture density and fracture porosity evaluations, respectively, and proved the benefits of using hybrid and deep learning methods. These studies highlight the importance of using ML techniques in geophysics, and their potential to improve the accuracy and efficiency of various tasks.

Despite the recent advancements made in petrophysics, porosity prediction is still one of the main tasks in the steps of reservoir characterisation. Many recent works, introducing innovative approaches for predicting porosity, have been published. Erofeev *et al*. (2019) presented a comparative study of different ML methods, which are linear regression (simple, with L1 and L2 regularisation), decision tree, random forest, gradient boosting (two different implementations, with and without regularisation), NN, and support vector machines, to compare their predictive power. A Particle Swarm Optimisation (PSO) - Support Vector Machine (SVM) method, with an integrated approach, was proposed to predict permeability and porosity in a heterogeneous dolomite reservoir (Zhang *et al*., 2021). Deep learning had its share in the application for the prediction of different parameters, among which the multilayer long short-term memory network (Chen *et al*., 2020) and a combination of one-dimensional CNN and Bidirectional Gated Recurrent unit (Bi-GRu) NN (Wang and Cao, 2021).

The successful applications of the Adaptive Neuro-Fuzzy Inference System (ANFIS) - PSO in various domains have convinced us of a promising application in predicting porosity. In their paper, Rini *et al*. (2013) showed the testing of the ANFIS-PSO in three different applications with enhanced prediction accuracy and reduced complexity. Shamshirband *et al*. (2019) proposed the application of this method for intelligent monitoring due to its acceptable accuracy in predicting mercury emission, which is one of the most perilous environmental contaminations. Another successful application was performed by Noushabadi *et al*. (2020) for estimating cetane numbers of biodiesel and diesel oils, where the ANFIS-PSO showed the highest prediction accuracy compared to the Nuclear Magnetic Resonance (NMR) model.

What made the ANFIS-PSO combination very useful in this work was the combination of the advantages of both methods to obtain a better optimised system. The ANFISs combine the advantages of both fuzzy logic and NNs, where the robustness and interpretability of fuzzy logic meets the generalisation and computational efficiency of NNs. The PSO enables the optimisation and tuning of the ANFIS to fit the data, as it efficiently handles non-linear data without the need for gradient data.

In this study, the application of a hybrid system was discussed to better define the relationship between the well-logging recordings and the underground porosity for a better prediction of the latter. This method is based on a Sugeno fuzzy system combined with BNN and least mean square estimation (Abraham, 2005), which is a high-performing system that is computationally expensive. To overcome such computational cost, the system is combined with PSO, which also guarantees the success of the learning process with an optimal solution, due to its ability to prevent the system from being trapped in a local solution, and to distribute the computational load on several parallel processors.

2. Theory and methods

The proposed algorithm combines the ANFIS and PSO.

2.1. The Adaptive Neuro-Fuzzy Inference System (ANFIS)

The ANFIS is a hybrid combination between a fuzzy system and the node functions of an adaptive network. This model is a multilayer feedforward and adaptive network (Jang, 1993).

It is an integrated neuro-fuzzy system with the advantage of data structures and knowledge representation from ANN and fuzzy logic. The need for these systems originated from their compatible and complementary natures. Hence, they combine the advantages of both methods.

The performance of the model was improved using different parameters, chosen on the basis of trial and error, so as to define the best-constructed model. Ultimately, the best-estimated results were chosen based on the output with the minimum error. The different metric models used to investigate the system performance are the coefficient of correlation (*CC*), the coefficient of determination (R^2), the mean square error (*MSE*), and the root mean square error (*RMSE*):

$$CC = \frac{n(\sum_{i-1}^{n} x_i^{core}.x_i^{pred.}) - (\sum_{i-1}^{n} x_i^{core})(\sum_{i-1}^{n} x_i^{pred.})}{[n\sum_{i-1}^{n}(x_i^{core})^2 - (\sum_{i-1}^{n} x_i^{core})^2][n\sum_{i-1}^{n}(x_i^{pred.})^2 - \left(\sum_{i-1}^{n} x_i^{pred.}\right)^2]} \quad (1)$$

$$R^2 = 1 - \frac{\sum_{i-1}^{n}(x_i^{core} - x_i^{pred.})^2}{\sum_{i-1}^{n}(x_i^{core} - x_i^{pred.})^2} \quad (2)$$

$$MSE = \frac{\sum_{i-1}^{n}\left\| x_i^{core} - x_i^{pred.}\right\|^2}{n} \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i-1}^{n}\left\| x_i^{core} - x_i^{pred.}\right\|^2}{n}}, \quad (4)$$

where n is the number of data points, x_i^{core} is the i-th value, and $x_i^{pred.}$ is the corresponding prediction of each value.

To simplify the architecture description of the ANFIS, we assume that it only has two inputs and one output. It is a Sugeno model with a set of two different if-then rules as follows:

Rule 1: if x is A1 and y is B1, then: $f1 = P1x + Q1y + r1$;

Rule 2: if x is A2 and y is B2, then $f2 = P1x + Q2y + r2$.

The choice of the Takagi-Sugeno (TS) system was based on its ability to model complex nonlinear relationships between input and output variables. This is due to the fact that the TS system adopts a set of linear models able to capture different local system behaviours. Additionally, TS systems require less computational time, and present a simplified rule base, which leads to a reduced number of rules. This simplifies the modelling process and makes the interpretation of the results more straightforward.

The reasoning mechanism is shown in the architecture of the ANFIS model (Fig. 1), which consists of five layers.

Layer one is for defining the x and y inputs to the nodes and the linguistic labels associated with each of these nodes. Each of these inputs is mapped to the fuzzy sets through the membership functions. This process is called fuzzification. These functions are defined as indicated in Eqs. 5 and 6:

$$O_{1,i} = \mu A_i(x) \qquad i = 1, 2 \quad (5)$$

$$O_{1,j} = \mu B_i(x) \qquad j = 1, 2. \quad (6)$$

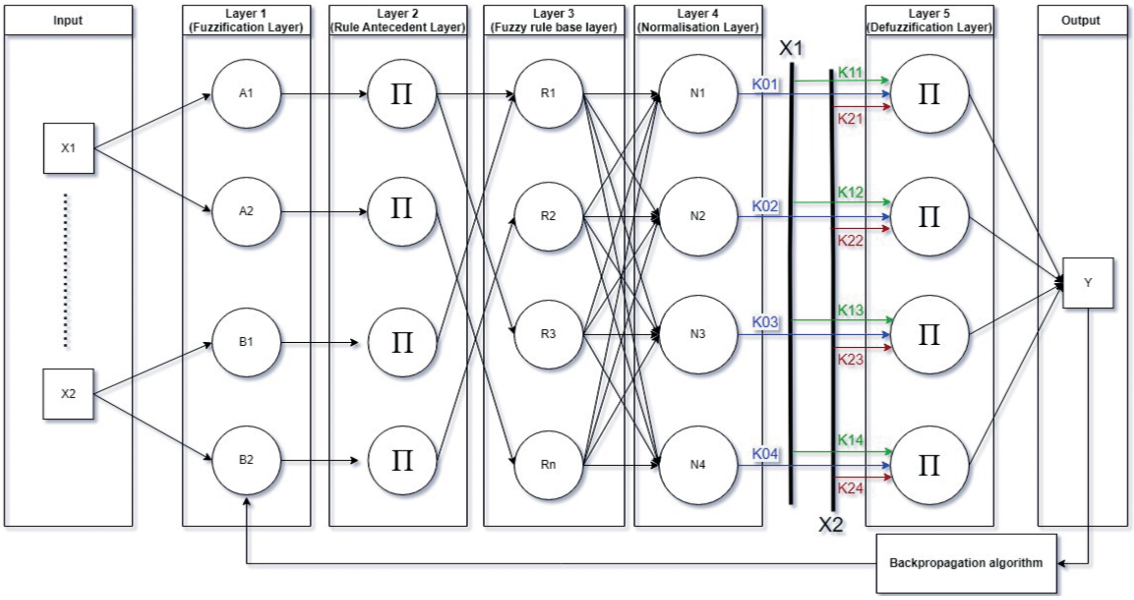

Fig. 1 - Scheme of the intelligent ANFIS.

In layer two, the firing strengths of each input are used after combining all the inputs. The T-norm is applied as the node function to obtain the layer output. Layer three, where the ratio of the firing strength of the *i*-th rule is calculated in conjunction with the sum of the firing strengths of all the rules. In layer four, the output of layer three of the 'normalised firing strengths' are multiplied by the Sugeno fuzzy rule to obtain the 'consequent parameters'. Ultimately, all the outputs of the previous layers are summed in layer five, which is a single node layer. The defuzzification process is, then, performed to obtain a neat output from the fuzzy outputs.

The model chosen in this work is more complicated than the one described above, and presents seven inputs and one output. Hence, an adequate optimisation method is needed to overcome the issues arising during the calculation process.

Despite the superiority of this model, compared to the Fuzzy Inference Systems (FISs) and to the ANNs, separately, the need for an optimisation method for the ANFIS model persists. This need originates from the difficulty of curing a problem in the event of unsatisfactory results, as the parameters of the adaptive systems cannot be exploited.

The system optimisation process is based on determining the loss function by maximising the gains and minimising the losses, by trying to calculate the best model predictions and finding the optimum solution. For the model in this work, PSO was used. This optimisation method was chosen on the basis of its superiority compared to other optimisation methods. Its advantages were proved in the application in different domains, with a comparison between PSO and genetic algorithms (Ceylan *et al.,* 2018), Ant Colony Optimisation (Moayedi *et al.,* 2019), and Differential Evolution algorithms (Elzain *et al.,* 2021). The steps of this optimisation model are shown in the diagram in Fig. 2. Further explanations are presented in the following section.

2.2. Particle Swarm Optimisation (PSO)

PSO was first proposed by Kennedy and Eberhart (1995). As presented by the authors, it is a simple paradigm based on the simulation of organisms in flocks of birds and schools of fish. It can

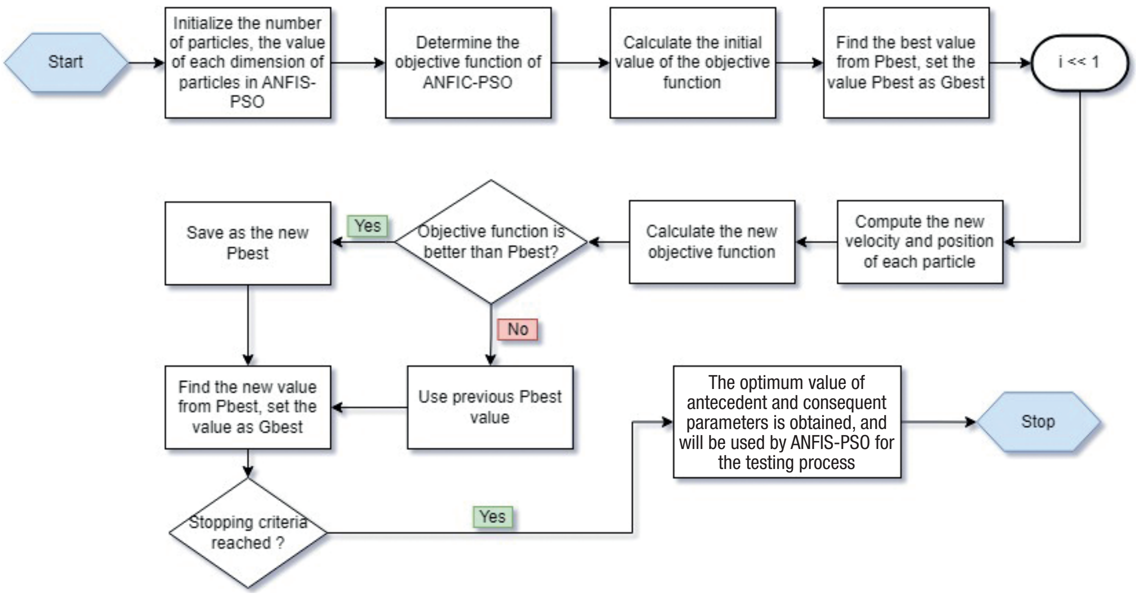

Fig. 2 - Diagram of the applied PSO algorithm workflow.

be implemented in various fields, requires simple mathematical concepts, and is computationally inexpensive.

The optimisation problem concerns the minimisation or maximisation of the cost function, which depends on the proposed optimisation formulation of the *f*(*X*) function, where *X* is the position vector representing the variable model. The *f*(*X*) function is also known as the 'fitness function' or 'objective function'.

The details of this method are thoroughly described in the works of Clerc (2006), who defines PSO as a movement towards a promising area to obtain a global optimum. When travelling, each particle of the swarm dynamically adjusts its velocity according to its flying experiences and group members. It keeps track of its best result, also known as Personal Best (P_b), and the best value of any particle, known as Global Best (G_b). Ultimately, each particle modifies its position according to its current position, velocity, distance between its current position and P_b, and distance between its current position and G_b.

PSO is based on moving towards a promising area to find the global optimum, G_b. To build the PSO algorithm, initially, a population (A) of agents (particles), uniformly distributed over X, is created. Then, the position of each particle (X_i) is evaluated, by means of the objective function:

$$Z = f(x,y) = \sin x^2 + \sin y^2 + \sin x \cdot \sin y \tag{7}$$

where *f* is the objective function.

The position is updated if the present position of the particle is better than its previous best position, P_b. Accordingly, the location of the best particle is based on the last best place of the particle. Next, the particle velocities are updated through the following equation:

$$V_i^{t+1} = W \cdot V_i^t + c_1 U_1^t\left(P_{b_1}^t - P_i^t\right) + c_2 U_2^t\left(g_b^t - P_i^t\right) \tag{8}$$

where: V_i = velocity of the particle or agent, W = inertia weight, c_1 = cognitive constant, U_1, U_2 = random numbers, c_2 = social constant.

Furthermore, the particles are moved to their new positions:

$$P_i^{t+1} = P_i^t + v_i^{t+1}. \tag{9}$$

These steps are repeated until the stopping criteria are satisfied.

Despite its weak optimum local searchability, PSO is very efficient for a global search when in the presence of few algorithm parameters. In addition, it is easily parallelised for concurrent processing, which allows the distribution of the processing on all the available nodes. Moreover, this optimisation method is derivative-free, and, in the case of well-logging data, it is an advantage because the relation between the measured parameters and the underground porosity is unknown as a result of underground heterogeneity. A detailed description of this optimisation model can be found in the work of Clerc (2006).

The PSO algorithm was used to optimise the membership function parameters of the ANFIS model. Such parameters are crucial in determining the accuracy of the model and for finding the optimal values in the parameter space of the ANFIS model. The PSO algorithm starts with a set of randomly generated candidate solutions, called particles. These move in the search space on the basis of their current position and velocity. The fitness of each particle is evaluated according to the objective function, and the best particle and its corresponding parameters are updated during each iteration. This process continues until a satisfactory solution is found or the predefined stopping criterion is met. This solution represents the optimal value that minimises the objective function.

A simplified workflow of the ANFIS-PSO algorithm is presented in Fig. 3. A more thorough description was given by Juang (2010) and Basser *et al*. (2015).

3. Data and geological concepts

The study area includes one of the gas fields in the Algerian Sahara (Fig. 4). It is one of the largest and most renowned gas fields in Algeria. This paper discusses the application of an ANFIS to predict porosity from well-logging data. The data set in this study derives from six wells in the Hassi R'mel field. Training and testing of the model were performed with 365 points from Well 1, 201 from Well 2, 552 from Well 3, 411 from Well 4, 277 from Well 5, and 315 from Well 6.

Figs. 5, 6, and 7 are a representation of the input and output values of three of the six wells (Well 1, Well 4, and Well 6) used for the algorithm training. The data selected as system input are the gamma ray (GR), neutron porosity (NPHI), density (RHOB), deep resistivity (LLD), shallow resistivity (LLS) logs, and microspherically focused resistivity log (MSFL), plus the core driven porosity obtained from the laboratory analysis and used as the output of the supervised algorithm. The algorithm inputs were chosen on the basis of the direct impact of the formation porosity on these logs, despite the lack of a mathematical or linear representation of the relation between them. These logs are all valuable tools in assessing porosity in the reservoir as each provides different pieces of information that can be combined to provide a comprehensive understanding of the reservoir porosity distribution and fluid content, which are crucial for reservoir characterisation and hydrocarbon exploration. The GR log enables lithology identification and estimation of shale content, which significantly influences effective porosity,

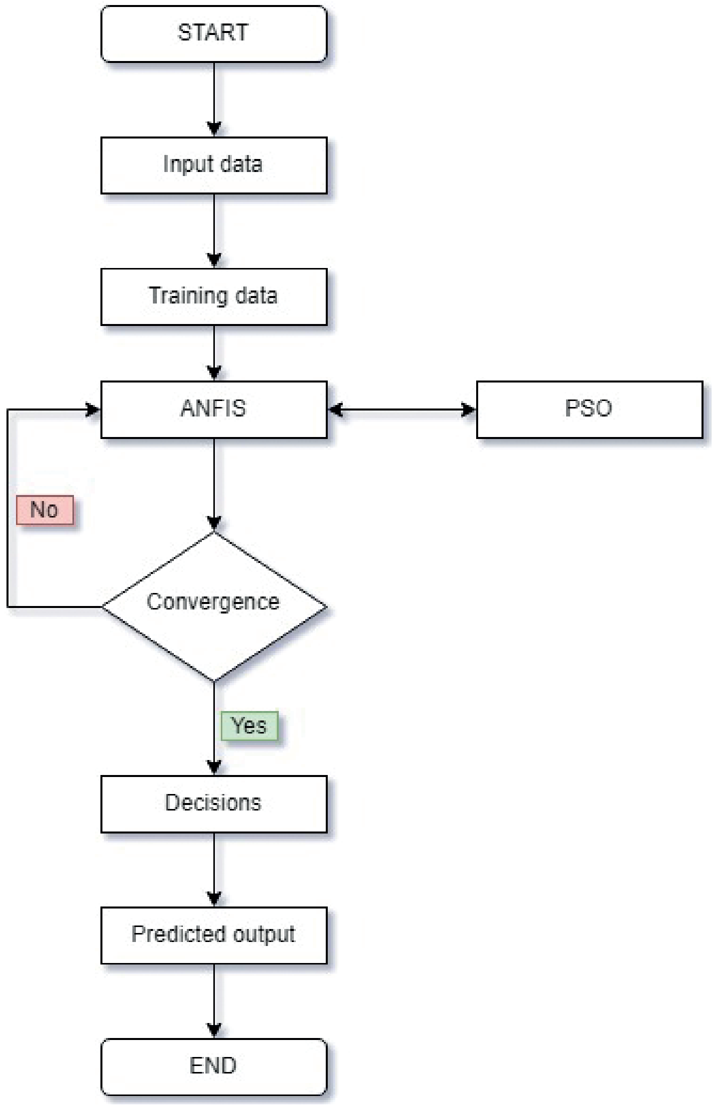

Fig. 3 - Diagram of the optimised ANFIS using the PSO algorithm.

whereas the porosity log provides a direct measurement of the formation porosity, offering information of utmost importance on the potential storage of fluids, such as hydrocarbons. Conversely, the density log assesses the bulk density of the formation, offering indirect inferences about porosity as it relates to the presence of fluid. An increase in porosity leads to a reduction in bulk density due to fluid filling the pore spaces. Additionally, resistivity logs play a pivotal role in analysing the electrical resistivity of the formation, thus providing insights into fluid presence and rock mineralogy. As porosity rises, electrical resistivity decreases due to increased fluid conductivity relative to the solid rock matrix. Altogether, these logs collectively contribute to a comprehensive understanding of the reservoir porosity distribution and fluid content, crucial for effective reservoir characterisation and hydrocarbon exploration.

The statistical description of each log containing input points used in this study, i.e. maximum, minimum, mean, and standard deviation, is represented in Table 1.

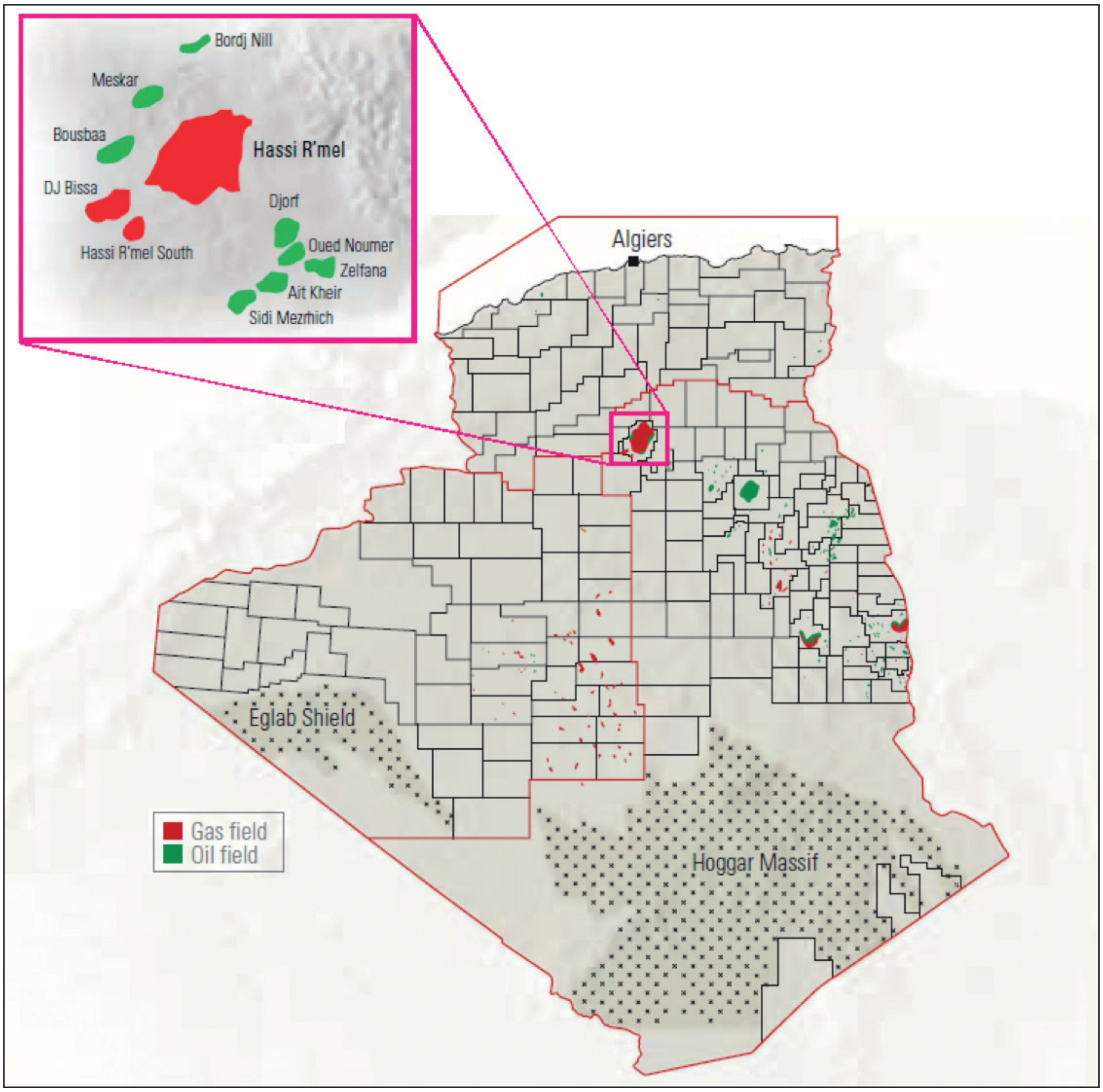

Fig. 4 - Geological map of Hassi R'mel, northern Sahara, Algeria (Sonatrach and Schlumberger, 2007).

Table 1 - Statistical properties of the well-logging parameters.

Parameters	Minimum	Maximum	Mean	ST deviation
GR (GAPI)	20.654	150	64.89292	38.54801
DT (US/F)	42.375	97	77.94184	8.964971
RHOB (g/cm^3)	2.125	2.771	2.421625	0.131828
NPHI (V/V)	0.011	0.366	0.153108	0.055639
LLD (Ω·m)	0.475	217.829	14.72156	25.04013
LLS (Ω·m)	0.316	181.216	12.73062	22.4931
MSFL (Ω·m)	0.202	400.248	5.050762	16.9622

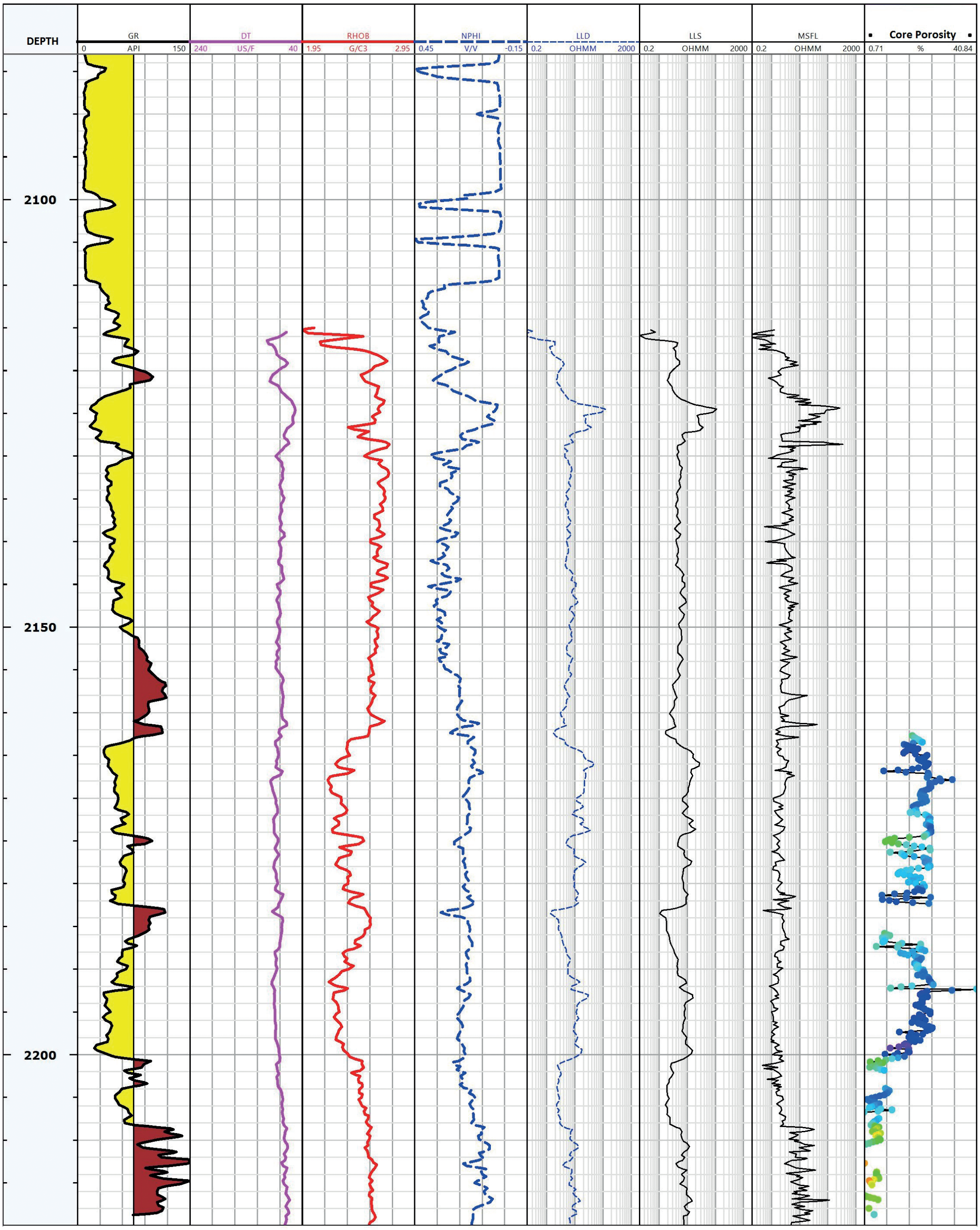

Fig. 5 - The petrophysical recordings of the Triassic reservoir of Well 1: a) GR log, b) sonic log, c) RHOB log, d) NPHI log, e) LLD log, f) LLS log, g) MSFL, and core driven porosity log.

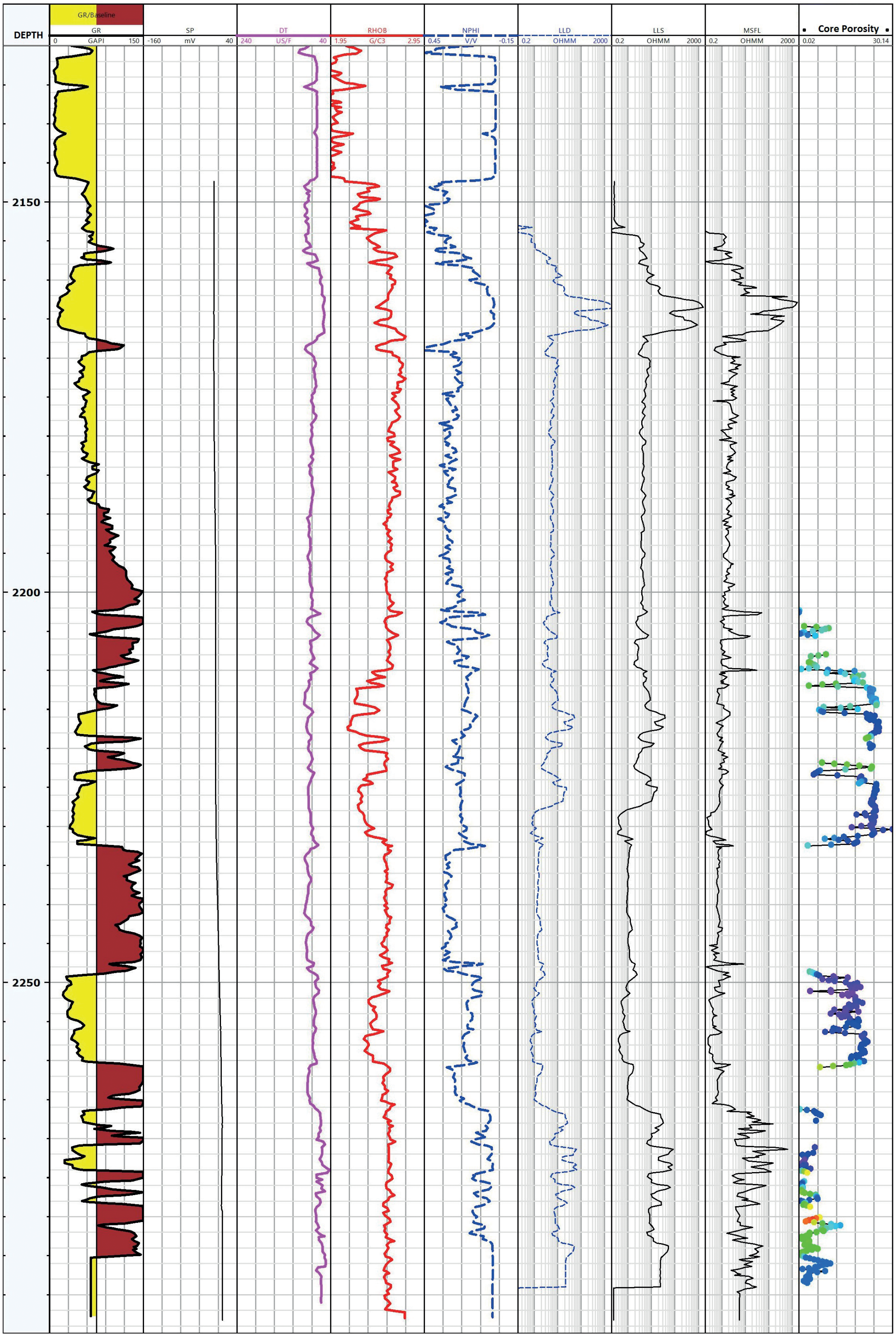

Fig. 6 - The petrophysical recordings of the Triassic reservoir of Well 4: a) GR log, b) sonic log, c) RHOB log, d) NPHI log, e) LLD log, f) LLS log, g) MSFL, and core driven porosity log.

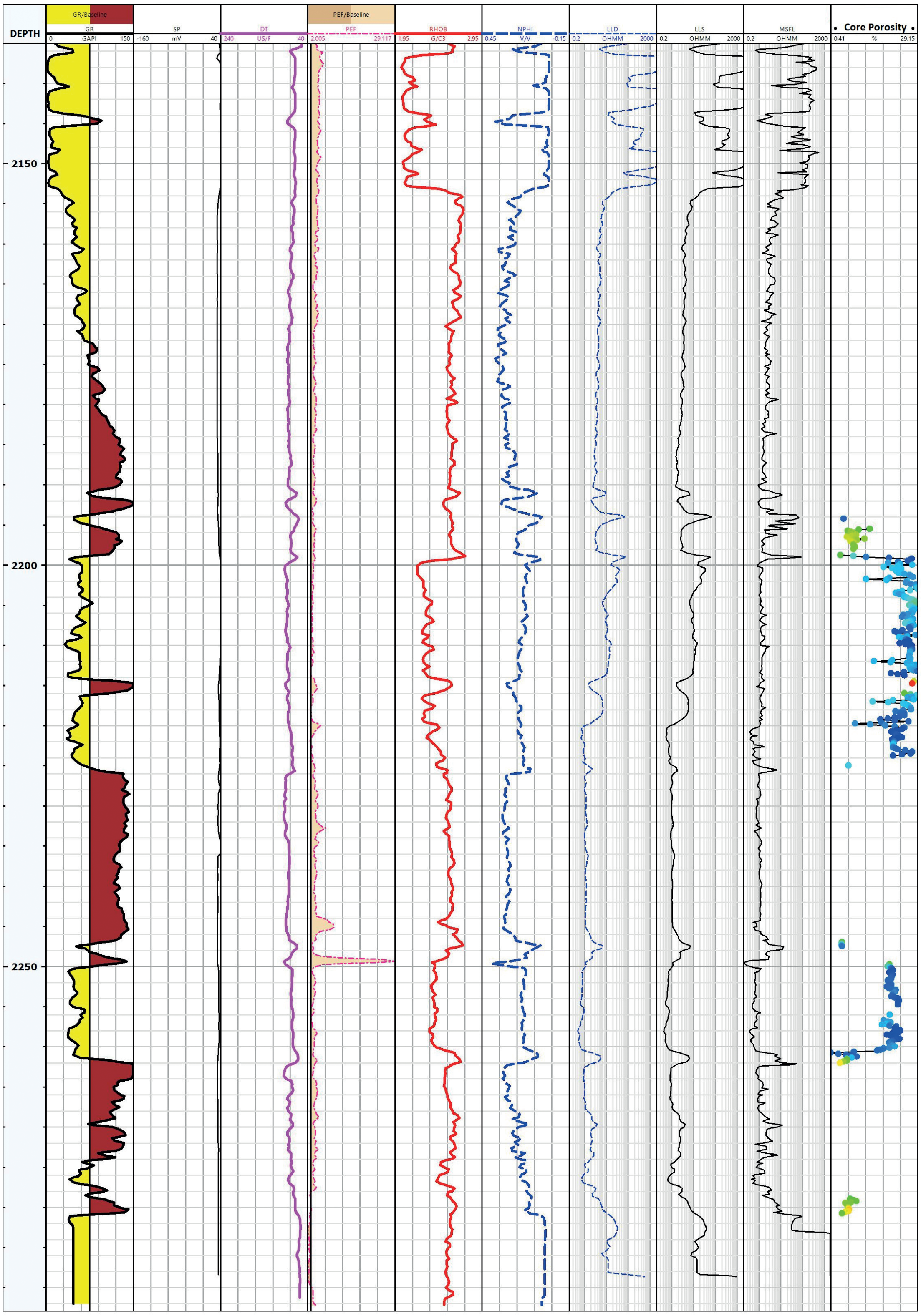

Fig. 7 - The petrophysical recordings of the Triassic reservoir of Well 6: a) GR log, b) sonic log, c) RHOB log, d) NPHI log, e) LLD log, f) LLS log, g) MSFL, and core driven porosity log.

3.1. Conventional porosity estimation methods

Conventional methods used to evaluate and estimate porosity are core data or well logs. The well-logging measurements can never measure the porosity directly as they depend on other reservoir properties. Therefore, porosity is usually deduced using theoretical and empirical equations. This renders the task complex and time-consuming, given the non-linearity and heterogeneity of the reservoirs. In addition, due to the different formation and wellbore conditions, many log corrections are needed, and the logs are evaluated together for better porosity estimation.

Conversely, with the presence of core data, well-logging measurements are calibrated for better porosity estimation. After retrieving the core samples, many methods are used to determine porosity after estimating bulk, grain, and pore volumes.

4. Results and discussion

The model used in this application is a PSO algorithm applied to an initial FIS. The code is a modified version of the code of Gilardi (2021).

The membership functions are the tuning parameters optimised using the PSO algorithm. 70% of the data is used for training, while the remaining 30% is left for testing. This random split of the training and testing data is to provide an unbiased evaluation of the model as the split is not influenced by any specific patterns or data characteristics. This also allows more flexibility as any data subset can be used for either training or testing. Furthermore, this data split can be scalable to data of any size, as well as reproducible, making this approach replicable by other researchers, thus helping to ensure valid results.

The parameters of the PSO are: K, the average size of each agent's group of informants; Phi, the coefficient to calculate the two confidence coefficients; vel_fact, the velocity factor for calculating the maximum and minimum velocities allowed; conf_type, the confinement type (on the velocities); IntVar, the list of indexes specifying which variables should be treated as integers; Normalise, to specify if the search space should be normalised (to improve convergence); Rad, the normalised radius of the hypersphere centred on the best particle.

The parameters of the ANFIS-PSO are: mu_delta, the variation allowed for the mean, expressed as a fraction of the corresponding data range; s_par, the centre value and variation allowed for the standard deviation in the premise function, where the centre value is scaled based on the corresponding feature data range; c_par, the range of allowed values for the exponent in the premise functions; A_par, the range of values allowed for the coefficients in the consequent functions; N_mf, the number of premise functions of each feature, having the same length as the number of features; N_Pop and epochs, the number of agents (population) and number of iterations, respectively.

The network training process was reiterated several times to ensure consistent model results. The developed five-layer ANFIS combines the BNN to minimise output errors.

The ANFIS-PSO method was applied to six wells in Hassi R'mel on the readings of conventional Triassic gas reservoirs. The input data fed to the system were the GR log, the sonic log, the RHOB log, the NPHI log, and the resistivity logs. In addition to these, the PS log was fed for wells 4, 5, and 6. The algorithm was separately applied to every well, and, then, to the whole of the data available for comparison purposes. As previously mentioned, 70% of the data was used for training the model, and the remaining 30% was used for testing it. This random split of data for training and testing is preferred over a more structural method as it offers each data sample the possibility to be selected for either purpose, ensuring fairness and giving credence to the results. The results, given in Fig. 8, show an excellent correlation between the predicted and core porosity for all wells.

The output of the testing data was compared to the core data porosity to evaluate the precision of this algorithm. The results are displayed in Fig. 9, where the values show a significant

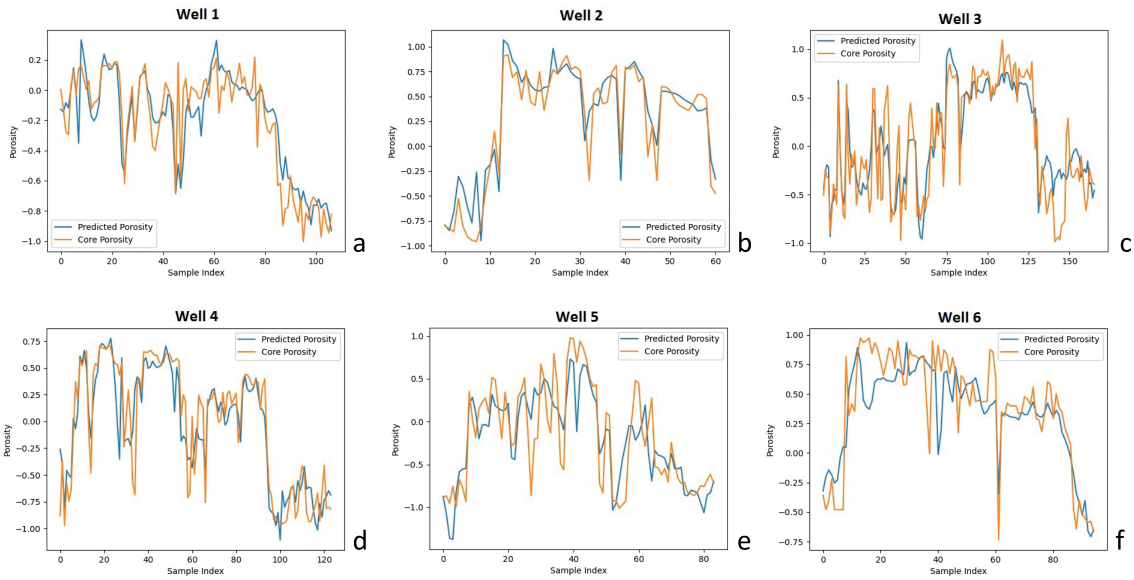

Fig. 8 - Testing performance of the ANFIS-PSO using target and predicted porosity values. The graphs represent the predicted and core porosity values against the sample indexes of: a) Well 1, b) Well 2, c) Well 3, d) Well 4, e) Well 5, and f) Well 6.

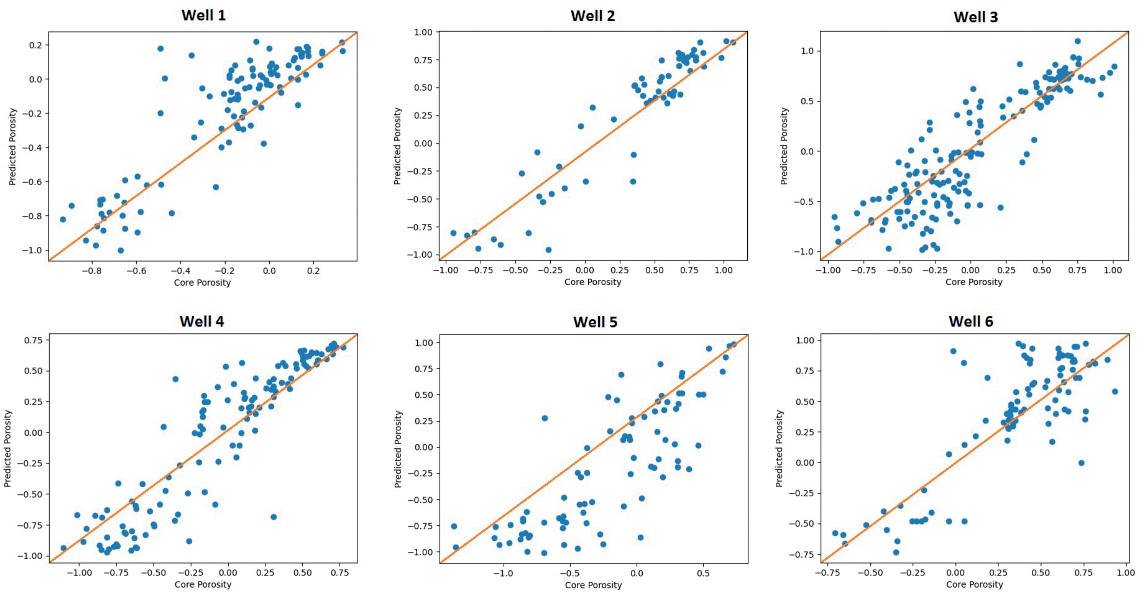

Fig. 9 - Regression derived between the core data and estimated porosity values of the six wells.

correlation between the output of the ANFIS-PSO model and the targeted values. The error in the training data is *MSE* = 0.041 and *RMSE* = 0.20, and *MSE* = 0.045 and *RMSE* = 0.21 in the testing data. The related *CC* values are 85% and 84% for the training and testing, respectively. Alternatively, the squared correlation coefficient is 0.73 for the training and 0.71 for the testing. This reflects a rather high correlation between the core porosity values and those predicted using the ANFIS-PSO.

For a better representation of the efficiency of this method, the algorithm was individually applied to each well. The comparison of the results, represented in Tables 2 and 3, shows that the performance of the model was better in some wells compared to others. From the results of Well 2 (PS log absent) and Well 4 (PS log available), we observe that the PS log had no significant impact on the porosity prediction. For this reason, the absence of the PS log has no effect on the application and efficiency of this method in predicting porosity.

The training results presented in Table 2 show that the *CC* values for all wells range from 0.845 to 0.918, indicating a relatively strong positive correlation between the training well-logging data and the output data or core porosity. The R^2 values for all wells range from 0.713 to 0.842, indicating that the input well-logging data explain a good portion of the variance in the core porosity. The *MSE* and *RMSE* values for all wells range from 0.032 to 0.099 and from 0.179 to 0.315, respectively. These measurements indicate the average magnitude of the error between the predicted values and the actual values of the training data. Lower values indicate greater accuracy. Overall, the ANFI-PSO algorithm seems to perform similarly across all wells, with the combined analysis of all wells showing slightly better performance (higher *CC*, R^2, and lower *MSE*

Table 2 - Performance analysis of the ANFIS-PSO in the training data.

Training well	**Statistical tools**			
	CC	R^2	***MSE***	***RMSE***
Well 1	0.886	0.785	0.032	0.179
Well 2	0.918	0.842	0.045	0.212
Well 3	0.877	0.769	0.070	0.265
Well 4	0.914	0.835	0.056	0.236
Well 5	0.845	0.713	0.099	0.315
Well 6	0.850	0.722	0.073	0.270
All wells	0.855	0.730	0.042	0.204

Table 3 - Performance analysis of the ANFIS-PSO in the testing data.

Training well	**Statistical tools**			
	CC	R^2	***MSE***	***RMSE***
Well 1	0.884	0.781	0.027	0.164
Well 2	0.941	0.885	0.043	0.207
Well 3	0.881	0.775	0.075	0.274
Well 4	0.914	0.835	0.054	0.233
Well 5	0.813	0.660	0.118	0.343
Well 6	0.834	0.696	0.072	0.269
All wells	0.841	0.708	0.045	0.213

and *RMSE* values) compared to individual well analyses.

In general, the results in Table 3 are slightly lower than those in Table 2, which is expected since the model is being tested on unseen data. In observing the statistical tools, the *CC* values for all wells, in both tables, are above 0.8, indicating a strong correlation between the predicted and actual values. The R^2 values are also relatively high, indicating a good fit of the model to the data. In terms of error metrics, the *MSE* and *RMSE* values in Table 3 are slightly higher than those in Table 2, indicating a slightly worse performance on the testing data. However, the values for all wells are still relatively low, indicating good predictive performance of the ANFIS-PSO model. Overall, the ANFIS-PSO model appears to perform well in both the training and testing data, with strong correlations and low error metrics.

Based on the predicted results, the efficiency of the ANFIS-PSO in estimating porosity is relatively high compared to the core values.

We proposed a neuro-fuzzy model to predict the porosity of a gas reservoir in the gas field of Hassi R'mel. Our findings suggest that the ANFIS-PSO technique enhanced the porosity prediction in these wells. The relationship between well-logging data and reservoir properties is complex and nonlinear, but neuro-fuzzy systems can deal with this. In ideal situations, the estimation of reservoir properties is direct and straightforward. However, it is not easy to run petrophysical inversion to address the challenges of the underground heterogeneity. Therefore, the application of hybrid ML methods is effective and practical in estimating reservoir properties.

5. Conclusions

The ANFIS using PSO enhanced the learning cost saving and minimising the system processing time, optimised the cost function, and enhanced the overall performance of the system. Porosity predicted using the ANFIS-PSO, in comparison with the core data porosity, shows a good correlation. Applying these types of hybrid systems to petrophysical data is a good practice and can be applied to predict and classify other underground parameters.

PSO has proven its advantages when combined with the ANFIS. This combination opens the way for more applications of this hybrid system, in predicting other reservoir properties, such as permeability and saturation. However, a comparative study with other optimisation methods, i.e. gradient methods, may prove the superiority of this optimisation method when applied to these types of problems or the possibility to deliver an even better approach for predicting underground properties.

Acknowledgments. The data underlying this article were provided upon permission by SONATRACH, and cannot be shared publicly due to confidentiality issues. The data will be shared upon reasonable request to the corresponding authors.

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