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New Insights on Water Saturation Determination of Carbonate Reservoirs Using Artificial Intelligence Approach (AIA) and Conventional methods

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Abstract

Carbonate reservoir rocks are considered heterogeneous and it is due to complex pores pattern caused by different diagenetic factors that are modifying the microstructures and matrix system. parameters and finally leading to significant petrophysical heterogeneity and anisotropy. Water saturation determination in carbonate reservoirs is crucial parameter to determine initial reserve of given an oil field. Water saturation determination using electrical measurements is based on Archie's formula. Consequently, accuracy of Archie's formula parameters affects seriously water saturation values. This work focuses on calculation of water saturation using Archie's formula. Different determination techniques of Archie's parameters such as conventional technique, CAPE technique and 3-D technique have been tested and then water saturation was calculated using Archie's formula with the calculated parameters (a, m and n). This study introduced parallel self-organizing neural network (PSONN) algorithm predict Archie's parameters and determination of water saturation. Results have shown that predicted Archie's parameters (a, m and n) are highly accepted with statistical analysis lower statistical error and higher correlation coefficient than conventional determination techniques. The developed PSONN algorithm used big number of measurement points from core plugs of carbonate reservoir rocks. PSONN algorithm provided reliable water saturation values. We believe that PSONN can improve or may replace the conventional techniques to determine Archie's parameters and determination of reserve estimate in carbonate reservoirs.

Introduction

Carbonate reservoirs contains more than 50% of proven oil and gas reserve in the world. However, carbonate rocks are characterized by complex porosity systems e.g. vugs, oolites and fractures and very heterogeneous permeability distribution and pattern. This makes carbonate reservoirs seriously petrophysically heterogeneous reservoirs [1,2,3,4]. The use of experts' knowledge and statistics to the use of artificial intelligence (AI) models can provide good prediction of reservoir petrophysical properties from well-logs data. There are several AI models for this purpose available in the literature. The main target of present study is introducing Artificial Neural Network (ANN) algorithms to estimate reliable values of Archie's parameters and then getting accurately the water saturation of reservoir rocks. In order to reach this target, in first place developing a technique to obtain an unbiased accuracy measure from a finite set core samples. This will allow for meaningful comparison between NN method; hybrid system of parallel self-organizing neural network (PSONN) and currently used techniques namely CAPE, 3-D and conventional method targeting ultimately an accurate water saturation determination. The developed model (PSONN) has shown more accurate prediction with respect to some existing ones such as back propagation NN and multi-layer learners in the same time, the developed PSONN model is replicable as its threshold weights and biases required to replicate the model are made available, unlike other models in the literature. Hence, the developed NN model is a more robust tool to predict reservoir's porosity, permeability and water saturation in carbonate reservoirs. [5,6,18,19,22]

Water saturation is keystone parameter in estimation of initial oil reserve as it is included in the caluaction of the initial oil in place. Determination of water saturation is very critical parameter for an accurate estimate of reserve also optimum reservoir recovery from oil fields. Reservoir heterogeneity affect the accuracy of determination techniques of Archie's parameters. Reservoir fluids heterogeneous distribution and changes in lithofacies properties and the inclusion of shale are most important aspects of heterogeneity. The main issue with the understanding of heterogeneous reservoirs is addressing the right relationship between lithofacies properties and petrophysical characteristics and then reservoir performance [3,5,6,7,11,12,14,20]. Reservoir wettability, pore size distribution and pore geometry mainly affect the saturation exponent (n) and to certain degree cementation exponent (m) and tortuosity factor (a) is also affected. Cementation exponent changes radically with wettability changes induces radical effect on water saturation calculation using electrical measurements. Reservoir rock and mainly carbonates have mixed wettability or fractional wettability. Wettability changes either in reservoir or in coring operation and handling create serious problems in the determination of water saturation exponent. Wettability alteration is embarrassing factor in reservoir evaluation of clean and shaly reservoir rocks clay minerals aggravates the perception of heterogeneous reservoir complexity. [8,9,10,13,15,16,17,21,23,24,25]

Conventional Determination Methods of Archie Equation Parameters

In the field of formation evaluation and calculation of initial oil in place using electrical logging data, Archie water saturation model is the key stone. Therefore, Archie's parameters should be accurate. Currently there are three techniques for Archie's parameters a, m and n determination; conventional technique, CAPE technique and 3-D technique.

Conventional Determination of Archie's Parameters

Archie, [16] presented imperial formula relating rock resistivity, Rt, and porosity, φ, and water saturation Sw;

$$Sw^n = a\,Rw / \phi^m\,Rt = Ro / Rt = 1/Ir \quad \ldots\ldots\ldots\ldots (1)$$

To calculate water saturation exponent, Eq.1 is arranged in the form:

$$\log Ir = -n \log Sw \quad \ldots\ldots\ldots\ldots (2)$$

The coefficients a and m are determined by plotting F vs Φ of the equation $F = a/\Phi^m$:

$$\log F = \log a - m \log \Phi \quad \ldots\ldots\ldots\ldots (3)$$

Core Archie-Parameter Estimation (CAPE)

Maute et al [17] presented CAPE technique for Archie's parameters (a, m and n) determination using numbers of electrical measurements (I) for numbers of plugs (j). CAPE is based on setting accepted minimum error (ε) between measured water saturation and calculated water saturation using assumed a, m and n values on core plugs using following equation.

$$\varepsilon = \sum_j \sum_i [Swij - (aRwij / \phi i^m\, Rt\, ij)^{1/n}]^2 \quad \ldots\ldots\ldots\ldots (4)$$

Three Dimensional Regressions (3D) Hamada and Assal [7] introduced new method to determine Archie's parameters (a, m and n), it is based on three dimensional techniques (3-D technique) using electrical measurements on core plugs. 3-D technique arrange water saturation equation (1) and taking the form of equation (5) where water saturation, Sw is variable and considering it as three dimensional regression version of Rw/Rt, Sw, and ⍰.

$$\log Rw / Rt = -\log a + m \log \phi + n \log Sw \quad \ldots\ldots\ldots\ldots (5)$$

These conventional methods have been tested on core plugs and results of each method are shown in following sections. It is worth to note that 3-D and CAPE methods have provide an acceptable and reliable values of Archie's parameters.

Artificial Intelligence Determination of Archie's Parameters

Parallel self organizing neural networks (PSONN) is based on considering cluster of points randomly distributed within studied band. Each point was identified as element. Elements fly having definite speed and the task is to find the right location (gbest) followed to certain number of iteration. At the end of iteration process, the particle would be retained as a point in an N-dimensional space that manages relevant speed forwarding to designed momentum and relevant effect of its target (pbest) and also the target position of its surrounding elements (gbest), Figure (1) shows the elements of flying model used in the development of the algorithm. [9,18]
Following to determination of the two best values of PSONN, elements continuously changes its speed (V) and locations (S) according to equations. [6,7]

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$$V_i^{(k+1)} = \omega * V_i^{(k)} + w_1 * \left(pbest_i - S_i^{(k)}\right) + w_2 * \left(gbest_i - S_i^{(k)}\right) \quad (6)$$

$$S_i^{(k+1)} = S_i^{(k)} + V_i^{(k+1)} \quad (7)$$

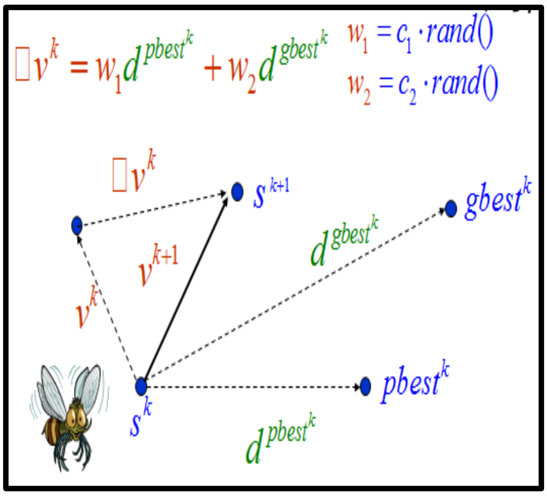

Figure 1 particle flying model[9]

Hybrid Parallel Self-Organizing Neural Network (PSONN) Model

Neural Network (NN) is defined as learning and improving where machine learning technique enables it to learn from experience, generalize on their knowledge, make errors and does not need to be reprogrammed. Hybrid system of parallel self-organizing neural network (PSONN) uses the concept of combination algorithm of the Particle Swarm Optimization (PSO) with the back-propagation Neural Network (BPNN). PSO and NN should be integrated to achieve the convergence around global search faster. On the other side, combining of PSO and NN could minimize the constraints of the individual application. PSONN algorithm englobe the aspects of PSON and BB, this would lead to big improvement of Neural Network efficiency. Particles positions in PSONN are set of weight for current nonlinear iterations. Each particle has a dimension which is the weighting numbers that is connected with the selected network. Root Mean Squared Error (RMSE) is considered as the learning error of this network which have been deduced using particles mobilizing within the weighting spaces targeting minimum learning errors. Learning process of PSONN was based on two steps: First step; PSO is designed for an optimal connected weights during neural networks, second step; it is the back propagation learning and training algorithm and applied to manipulate the final weights. Figure (2) illustrates the PSONN technique learning performance that has reached 0.049926 at epoch of 417. In this case study, the neural network parameters (weights and basis) have been optimized by the PSO algorithm and the selected input parameters of neural network and system have been adopted as three layers. One hidden layer (tensing) is taken as intermediate function and other two hidden layers (purlin) are used as a transfer function to get final output. [19,20]

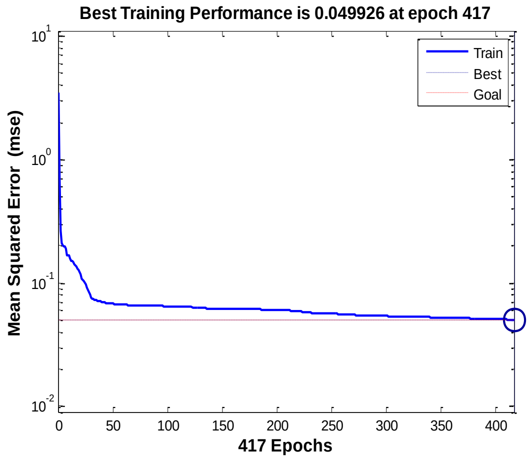

Figure 2 Training performance of PSONN.

Data Description

Artificial intelligence technique (PSONN) has been trained, tested and validated using 1440 input points from 1440 carbonate core plugs from three wells in carbonate reservoir. The design of hybrid system (PSONN) was tailored according to the number of points available keeping in mind reaching the minimum absolute average percent relative error (AAPRE) and also optimizing the relative different errors, correlation coefficient and root mean square error for given set points for studied core plugs as shown in table 1 and figures 3 and 4.

Validation

The statistical analyses showed a good agreement between actual and calculated water saturation using parallel self-organizing neural network (PSONN**). Figure 3** illustrates the statistical errors of the current techniques namely conventional, CAPE and 3-D methods and PSONN algorithm, it is obvious that the average error, standard deviation and RMS errors of PSONN is lower than the current methods and conventional method has higher error. **Table 1** shows the absolute errors and correlation coefficients of the current methods and PSONN algorithm, and it is found that PSONN has high correlation coefficient (0.95) and minimum error (0.09).

Results and Discussion

In order to reach minimum error and getting reliable values, PSONN network configuration was designed as follow: numbers of hidden Layers = 3., Hidden Neurons numbers= 35., Max Iteration essay = 120., Conjugate factor (c1, set number 80, number of particles 600, no. of generated points 700, inertia weight (w), 0.67., maximum speed 3.75 and dimension numbers 150, dimension numbers have to be referred to numbers of bias and weights that are direct function of the feeding parameters in PSONN modelling scheme. PSONN arrangement was used to estimate Archie's parameters a, m and n and consequently predicting water saturation values using Archie' formula. It was planned to test the correlation coefficient of the five techniques in water saturation, **Figure 4** that shows that CAPE (m,1, n) and conventional methods have low correlation coefficient while PSONN and 3-D have reasonably high correlation coefficients. **Table 1** depicts statistical error analysis of water saturation values which are absolute errors, minimum and maximum absolute error, correlation coefficient, standard deviation and finally the root mean square relative error of the three current methods and proposed PSONN algorithm. **Figure 5a** depicts measured water saturation profile as reference profile and water saturation profiles determined by three conventional methods; Conventional, CAPE and 3-D and PSONN. Water saturation profiles in **Figure 5b** have shown that PSONN water saturation is closer to measured water saturation profile and conventional water saturation profile is far from measured saturation profile. Comparison of the five water saturation profiles in studied section of a producing well leads to the conclusion that 3-D is better than CAPE and conventional and PSONN algorithm proved high correlation coefficient and low statistical error, thereby it can be supplement or may be replacing the current Archie's parameters determination methods and ultimately more accurate water saturation profile.

This study demonstrates the idea of the application of AI algorithms, such as PSONN to predict water saturation from well-logging data. **Figures 3, 4 and 5 a,b** revealed that PSONN might be promising tool in water saturation prediction from well log data collected by the authors without relying on a resistivity log. These methods can be applied to reduce the cost of core measurements and well-logging services. In all combinations of predictors considered, Super Learner is proved to be useful to combine the merits of base machine learning algorithms and enhance predictive robustness on water saturation.

Table 1 Statistical errors in of Four methods determining Archie's parameters

Methods	Absolute Error			E_{rms}	S	R
	E_a	E_{min}	E_{max}			
Conventional Technique	0.18	0.0059	1.078	0.33	0.21	0.28
CAPE (m,1,n) Technique	0.15	0.0014	0.37	0.157	0.12	0.20
CAPE (m,a,n) Technique	0.12	0.0012	0.334	0.123	0.10	0.15
3-D. Technique	0.11	0.0032	0.512	0.134	0.09	0.14
PSONN T Technique	0.06	0.0012	0.323	0.093	0.07	0.09

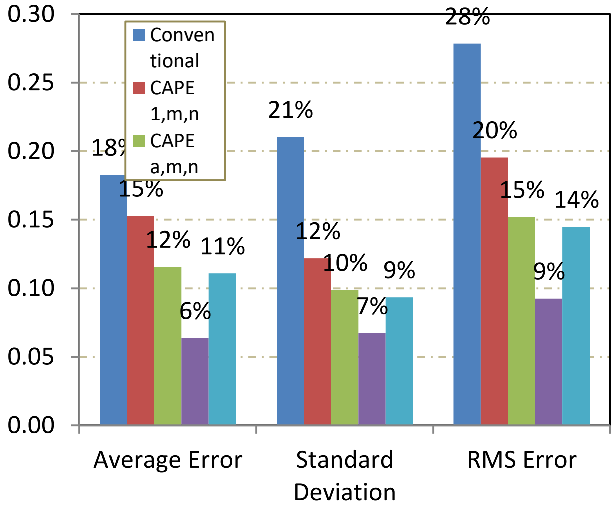

Figure 3 RMS, Standard deviation and average error for five techniques

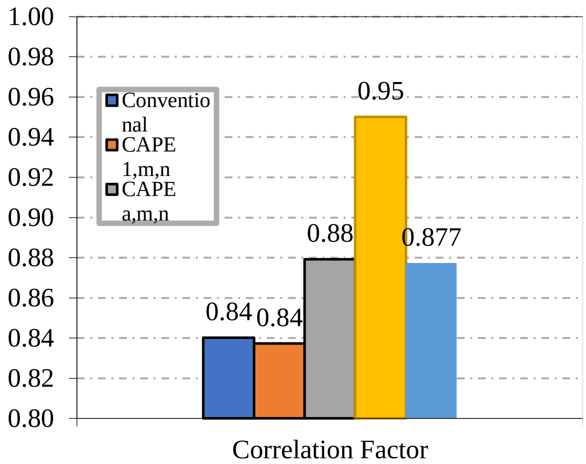

Figure 4 Correlation coefficients values for five techniques

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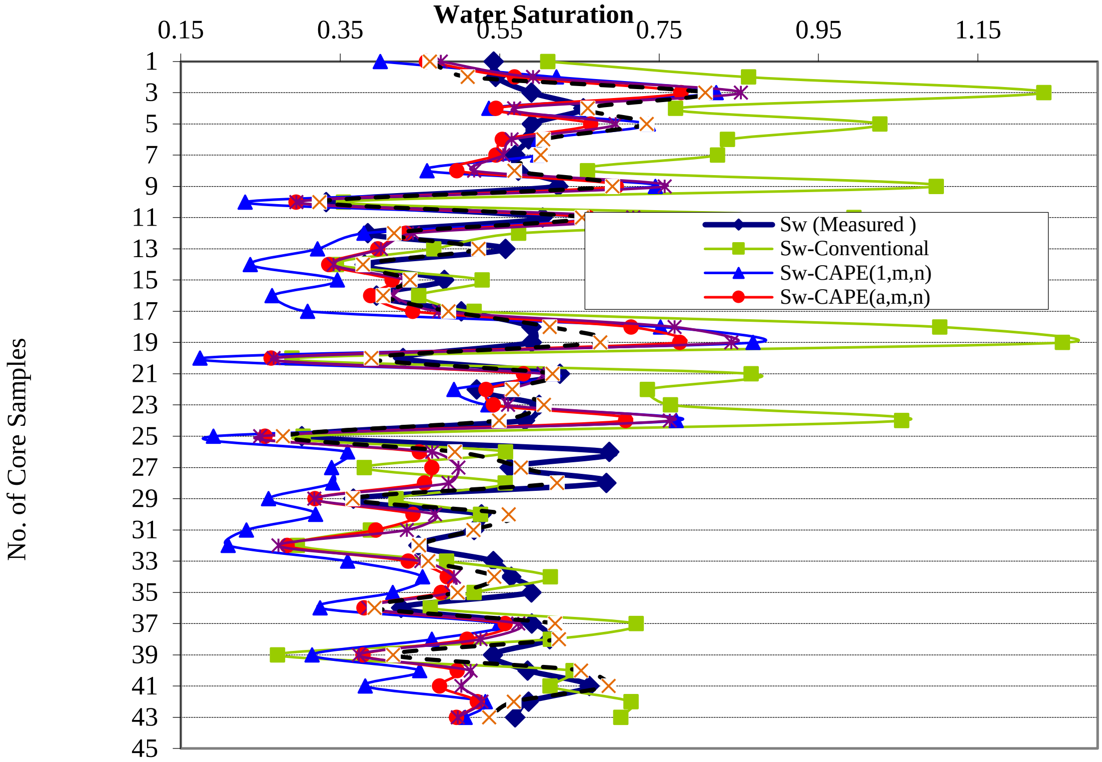

Figure 5a Profiles of water saturation calculated by Archie's formula using five determination techniques, water saturation profile and b) Relative errors curves

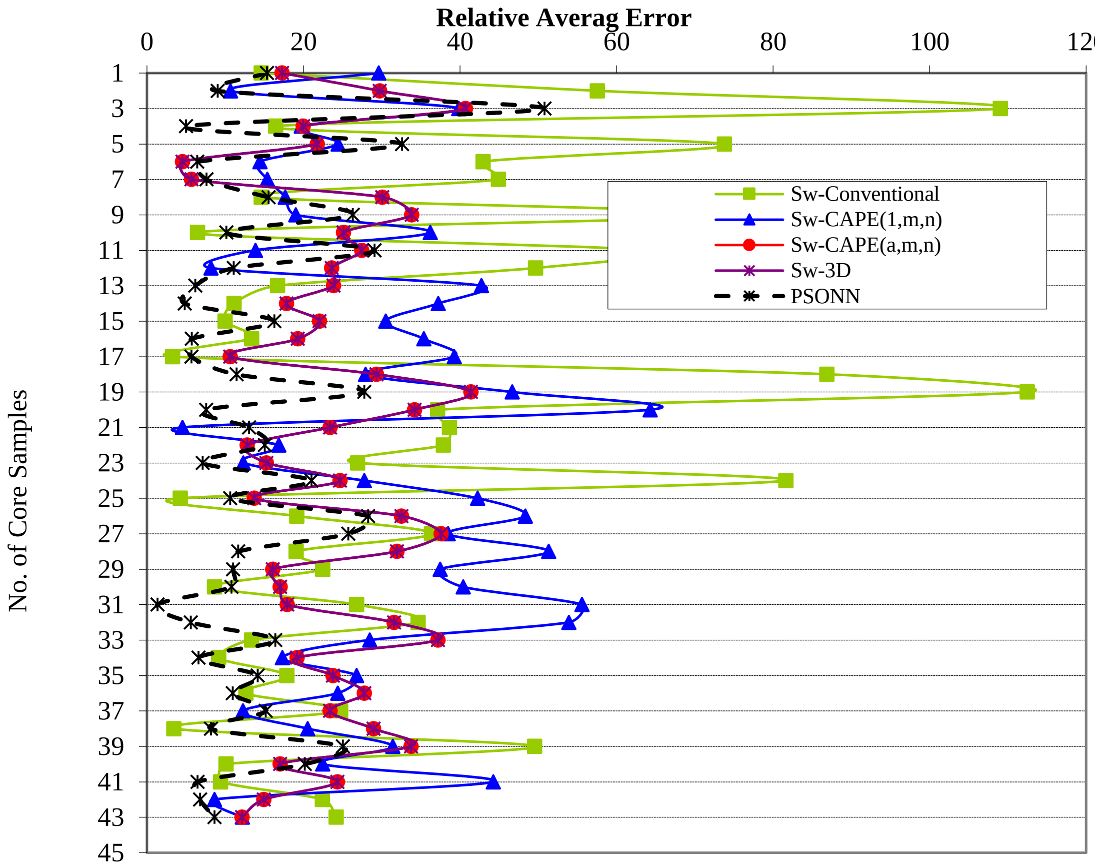

Figure 5b Profiles of water saturation calculated by Archie's formula using five determination, Relative errors curves

It is of high importance to get an accurate determination of Archie’s parameters in order to well evaluate water saturation from well logging data. potential to increase the accuracy of well logs interpretation in wells, where some data are not available. Two different datasets were used in this study to observe the effect of diverse variables. In this study, three conventional techniques have been implemented to determine Archie’s parameters and consequently evaluation more reliable method with reference to CAPE and conventional methods. The application of artificial intelligence techniques and mainly PSONN approach has shown excellent results in calculating water saturation based on an accurate Archie’s parameters values. Figure 5 has shown that PSONN water saturation curve is more reliable than CAPE and conventional curves and also PSONN outcomes do not rely mainly on resistivity data which is meaningful aspect in parameters prediction. PSONN algorithm may be used in developing static reservoir modelling and also in predicting certain reservoir petrophysical parameters such as porosity and permeability in future research activities

Conclusion

Carbonate reservoir rocks are generally heterogonous which causes problems in reservoir assessment processes. Water saturation from resistivity data is determined using Archie’s formula. Archie’s parameters must accurately be determined to get reliable water saturation values for securing an accurate reserve estimate. Results of 3-D technique, CAPE and conventional methods to determine Archie’s parameters a, m and n have shown that 3-D gives better results than CAPE and conventional techniques and more accurate water saturation values.

PSONN algorithm has proved that it can give good estimate of Archie’s parameters and water saturation. PSONN can provide Archie’s parameters where current methods are not available or difficult to be applicable due to missing parameters. Different artificial intelligence techniques such fuzzy and ML in addition to PSONN can contribute heavily in the evaluation of the reservoir petro physical properties. It is imperative to select the right approach giving more accurate results for given data.

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Conflicts of Interest
This research has no conflict of interest with other research and researchers.

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