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Reservoir Quality Evaluation based on Integration of Artificial Intelligence and NMR-derived Electrofacies

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Abstract

Logarithmic Mean of Transverse relaxation time (T2LM) and total porosity of the Combinable Magnetic Resonance tool (TCMR) are the main parameters of the Nuclear Magnetic Resonance (NMR) log which provide very substantial information for reservoir evaluation and characterization. Reservoir properties, for example, porosity and permeability, free and bound fluid volumes, and clay-bound water, could be calculated through the interpretation of T2LM and TCMR. In this manuscript, an intelligent approach has been used by us to predict NMR log parameters and their corresponding electrofacies from well log data. We define NMR electrofacies as classes of NMR log parameters representing reservoir quality are defined by us. For this purpose, NMR logs and petrophysical data are available for two different formations situated in the Ahvaz field. Data from Ilam formation were applied in order to construct the intelligent models, the same as Asmari formation, data were applied for reliability evaluation of the created models. The outcome results reveal higher performance levels of the Neural Network (NN) technique compared to the neuro-fuzzy (NF) model. The synthetically generated T2LM and TCMR logs are then calculated for the four logged wells from the Ahvaz oilfield using a mathematical function, and they are named Virtual Nuclear Magnetic Resonance (VNMR) logs. Finally, VNMR logs were classified into a set of reservoir electrofacies by cluster analysis approach. Correlations between the VNMR electrofacies and reservoir quality based on porosity and permeability data helped evaluate the reservoir quality quickly, cost-effectively, and accurately.

Keywords: Virtual NMR Log, Neural Network, Neuro-fuzzy, Back Propagation, Conventional Logs, NMR Log Parameters, Electrofacies.

Introduction

Soft Computations are being confined to play a vital role in the earth sciences. Many physical phenomena and natural rules in the earth sciences are testimony to that statement. The level of data uncertainty, the enormous scale and size of data to be processed, and the versatility of the data type and their related scales are significant causes to count on unconventional mathematic tools to the same degree as soft computing [1]. Oil exploration is an eminent activity such that data acquisition, circulating the data, and gaining advantage from that knowledge are vital to lead decisions. Soft computing parameters contain some applications that deal with numerical algorithms. The advantages of intelligent methods such as Genetic Algorithm (GA) and Neural Networks, and fuzzy logic in the upstream sector of the petroleum industry have been demonstrated (by them) [2]. The possible inaccuracy of some simple mathematical models might be because of some assumptions that are used to turn those models into simpler ones to make the possible solution. From the other point of view, the models with a higher level of complexity might also be erroneous if some more equations with overestimation or underestimation to describe a phenomenon are involved. These models, in most cases, need non-measurable physical parameters. The third choice by the higher potential to inaugurate a model from data with complexity, multi- dimensionality, and also non-linearity [3] is proposed not only by using neural networks [4] but also by using fuzzy logic [5].
NMR log parameters renders advantageous information to make petrophysical studies of hydrocarbon reservoirs more straightforward. Remarkable advancements have

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been achieved in using NMR measured parameters to detect and differentiate all the formation fluids, including bound water, free water, oil, and general fluid typing of hydrocarbon-bearing reservoirs. NMR logging is an expensive operation, and because of that, there is a data limitation for this log among their full set logs to record it in all wells of a hydrocarbon field. Hence, synthesizing this log in other wells of a field seems vital to make a correlation between the electrofacies (i.e., different depositional facies which might be discriminated against using the well log tool signals) and reservoir quality. An NMR log enables us to differentiate different facies based on their reservoir quality. Several researchers have worked on estimating NMR data using expert systems. In order to make an estimation of NMR log parameters for a field in East Texas, neural-network method was applied by Mohaghegh et al. In 2000 [6], a detailed study of computing NMR porosity and permeability of NMR obtained from conventional logs was reported by Al-Ajmi and Holditch [7]. To estimate producibility by NMR data sets, applying the technique of neuro-fuzzy was proposed by Malki and Baldwin in 2002 [8]. The genetic algorithm and fuzzy-logics in separate ways for permeability prediction using NMR data obtained from NMR tool were used or utilized by Ogiliva et al in 2002 [9]. To achieve synthetic NMR log by conventional logs, a methodology was described by Mohaghegh in 2003 [10]. Labani et al. (2010) [11] applied intelligent systems in combination with a committee machine to predict effective porosity and permeability from CMR logs in a gas field named South Pars, located in the Persian Gulf basin. Estimation of more NMR log parameters and their application in reservoir characterization can be found in Eslami et al. (2013); Golsanami et al. (2014); Kadkhodaie et al. (2019); Hosseinzadeh et al. (2020); Parchekhari et al. (2020a, b), and Parchekhari (2021a, b, c) [12-20].

Using intelligent methods, former works have mainly focused on parameter estimation derived from NMR logs interpretation (porosity, permeability, and bound fluid volume). The aims of the current study are as follows:

a) Mapping conventional logs data sets versus Parameters of NMR log that are T2LM and TCMR,

b) Synthesizing virtual NMR logs for the unlogged wells by CMR tool,

c) Classification of NMR log data into NMR electrofacies using a cluster analysis approach,

d) Making a correlation between NMR electrofacies and reservoir quality based on the porosity and permeability of the core.

Materials and Methods

The CMR tool can be run with another wireline set of tools to reduce rig time. This pad-type tool can be run in 6.5 inche holes and larger. The CMR tool appoints to provide reproducible measurements that are continuous and has remarkable vertical resolution. Extended field tests, laboratory experiments, and research prove this reliable source of data gathering on water cut, permeability, and production [21]. Valuable information obtained from NMR tool is essential to reach an accurate petrophysical evaluation of hydrocarbon reservoirs. Three parameters can be calculated from the analytical study of NMR logs, including Bound fluid volume (BFV), Free fluid porosity, and permeability. Total porosity measurement is directly achievable from CMR tool. Two models can be used to calculate permeability from NMR log data: Timur-Coats and SDR.

The Mechanisms of NMR Measurements

The measurements of NMR tool are based on the relaxation time of protons found in the hydrogen atom and fluid molecules. The protons' magnetic moment acts the same as small bar magnets. Hence orientations of them might be controlled by magnetic fields. Moreover, they have spins that are similar to gyroscopes. A measurement sequence begins with aligning protons followed by these steps, including spin tipping, precession, and repetitive diphase and refocus precesses. Transverse and longitudinal relaxations are responsible for limiting a measurement's long-lasting time. When all these measurements are finished, which it takes just a few seconds, then a new measurement can be repeated [22]. There are four main steps for a NMR measurement as below:

a) alignment of protons: protons of hydrogen atoms receive a large constant magnetic field B and get aligned.

b) Tipping of spins: after proton alignment, they tipped 90 degrees using a magnetic pulse that oscillates at the resonance, or Larmor frequency.

c) Transversal Decay: when the protons go forward and proceed around the static field, they lose their synchronization step by step. In this way, the magnetic field decays in the transverse plane. The dephasing step is caused by some inhomogeneities in the static magnetic field and interactions between molecules.

d) Refocusing: spins are echoed. The dephasing process is reversibly caused by the inhomogeneity of the magnetic field B.

Mechanisms of NMR Relaxation

Three relaxation mechanisms of the NMR tool can influence T1 or T2: Relaxation of grain surfaces, molecular diffusions in magnetic field relaxation, and bulk fluid processes relaxation.

Neural Network

The common method used to train an artificial neural network (ANN) is backpropagation NN to learn an individual task's performance. The way of learning this method in estimation problems is supervised. That means you must have a set of training data and your eligible output available. The NN makes some computations to obtain the difference between the desired and computed outputs. The resultant error propagates back through the net and gains weights that have been adjusted during several epochs or interactions. The training process stops when the results are at their best-estimated values [23]. In neural networks, neurons are systems that use simplified units of computations. Each neuron is responsible for doing the process from input to output that links to other neurons [24] (Altrock, 1995). Processing elements is a phrase for neurons [25]. Two classifications for neural networks could be assumed: static and dynamic categories. Static neural networks (feed-forward) just go forward with no delay, and they have no elements for feedback, while dynamic neural networks depend on the current input, while considering all inputs and outputs before that. Special weights are assigned to inputs in the network called input weights. The weights that connect one layer to another are named layer weights. Neural networks act as a good fitting function. Evidence shows that a simple neural network can work with any practical function [26].

Neuro-Fuzzy

In soft computing, there are a variety of methodology combinations that finally lead neuro computing and fuzzy logic into neuro-fuzzy systems. A fuzzy logic system is a neural network system that is self-training. Still, it uses fuzzy logic for knowledge representation of the system behavior rules to train the system [25]. Furthermore, as the nature of geological and geophysical data deals with some uncertainties, fuzzy logic becomes a qualified candidate for combining qualitative and quantitative information with subjective observations [1].

Fuzzy logic plays an important role in conducting rules that are observation based. ANFIS (Adaptive Neuro-Fuzzy Inference System) is an effective method developed by Dr. Roger Jang [27] for this purpose. Fuzzy logic makes information production faster and cheaper compared to other methods; moreover, this process is more straightforward with ANFIS. Fuzzy logic attempts to formalize and mechanize two important human capabilities. At first, abilities such as conversation, reasoning, and rational decision-making face an imperfect information environment. Furthermore, the second one is the capability to accomplish a wide range of mental and physical functions without making computations or any measurements. Fuzzy logic is a general system, and it has so much to be offered [28].

Cluster Analysis

There is a broad spectrum of diversity of clustering approaches with various mathematical basis. Hierarchical cluster analysis (segmented or taxonomy analysis) is a model-based approach used in this study to cluster and group the data. Cluster structure is based on the similarity of objects in one cluster and distinct the differences between objects of two different clusters. This clustering method creates a dendrogram or cluster tree to make data groups over diverse scales. Clusters of one level adhere to the next level clusters; therefore, the tree is not composed of just a single set of clusters but even a multi-level hierarchy. The advantage of this clustering method by dendrograms is to choose the scale or level of clustering that is most convenient for the desired application. An approach commonly used to acquire a relative ranking from reservoir quality is subdividing the rocks based on wireline log data into single or multiple cutoffs. But here, a specific type of cluster analysis has been used by us. A clustering analysis classifies samples into clusters (i.e., facies), each with similar characteristics. NMR electrofacies is a term that we name for clustered groups of samples using NMR log data. These electrofacies are based on NMR log tool signal(s), not on sedimentology properties of the rock.

Distance Calculation

The first step finds how data are similar or dissimilar to each other between every pair of objects in the data. The determination of two element similarities is by a selection of distance measure calculations, which will influence the cluster's shape. Hence, some elements may be close to one another and further away from another. The Euclidean metric method is common for the calculation of distance data.

Linkage between Distance Data

After computing, the proximity between objects present in the dataset, determining how to turn groups into clusters should be made using the "linkage" method. This method has a function that uses distance information to link close pairs of objects into binary clusters that are made up of two objects. These recently formed clusters will link together to create bigger clusters up to the objects of the original data set linked together in a hierarchical tree.

Dendrograms

The linkage function creates a hierarchical binary cluster tree that is easier to be understood when it is in graphical form. For example, in a dendrogram, the horizontal axis demonstrates indices of the objects that are located in the original data set. The upside-down U-shaped lines represent links, while the height of U represents the distance between objects.

Cluster Generation

Determination of where to cut the hierarchical tree into clusters will finalize the last step. In this step, the pruned bottom of this tree ramifies and branches off. So, all the objects under each cut can be assigned to an individual cluster and make a data partitioning. The clustering function operates in two ways: first, by detecting natural groupings in that tree, and second, by making cutoffs at an arbitrary level in the hierarchical tree.

Data preparation and Input Selection

Before constructing any intelligent model, it is necessary to carry out some essential processes on the available dataset to obtain the best input matrixes for creating NN and NF models.

Quality Control

In the first step, outlier data must be muted. Outlier addresses the data, including null values and bad holes. Null values are always negative, and these negative recorded values are not correct. One of the main reasons for this issue is the improper and inaccurate calibration of used logging tools. Although the speed of logging and an experienced logging team are considered, inaccurate data are expected everywhere. For example, a bad hole or washout indicates depths in which the caliper size is 1.5 inches bigger than the drilling bit size.

Eliminating Out of Trend Data

One of the main concepts in using intelligent models is eliminating out-of-trend data. For this purpose, the conventional logs data are plotted against the T2LM and TCMR data, as shown in Figures 1 and 2.

To do this important step, it is essential to do a normalization process to range the data between zero and one. This process helps us to find the relationships between the available data. Data within each chart show an individual trend in linear or nonlinear form. It will allow for the recognition of out-of-trend data among the available information.

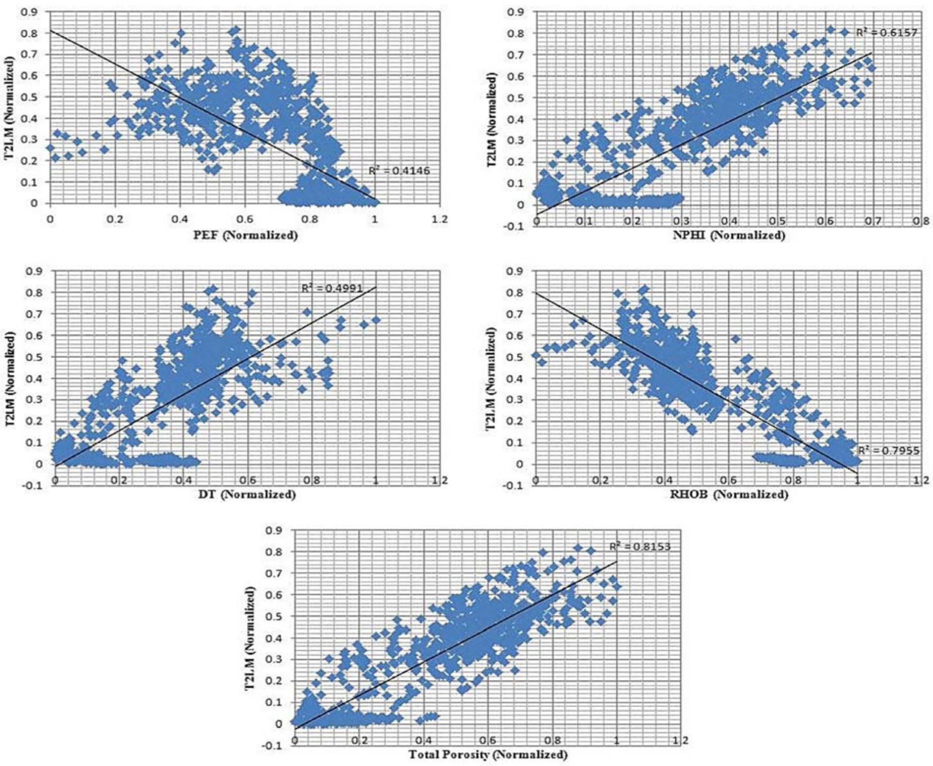

Fig. 1 Cross-plots displaying the relationship between the conventional well log data and T2LM.

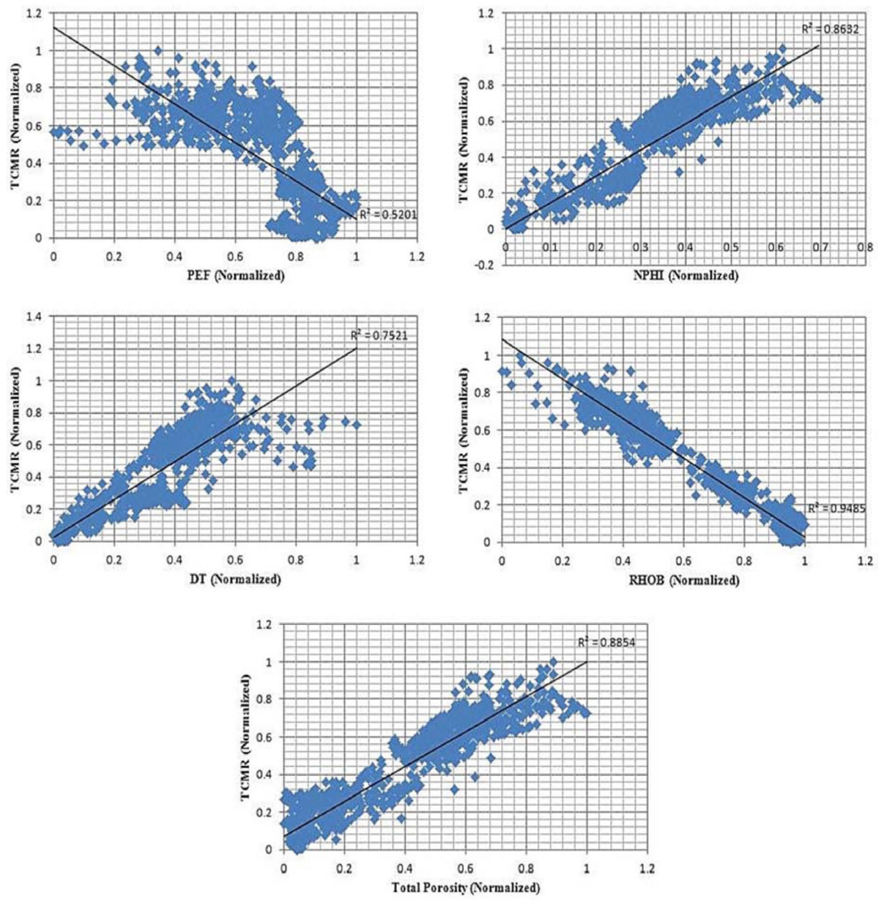

Fig. 2 Cross-plots display the relationship between the conventional well log data and TCMR.

We should always consider this important step for input selection. Otherwise, we will face errors in all determined weights, resulting in construction of noisy intelligent models.

Displays of the NMR logs used in this study are shown in Figure 3a and Figure 3b for Ilam formation and Asmari formation, respectively.

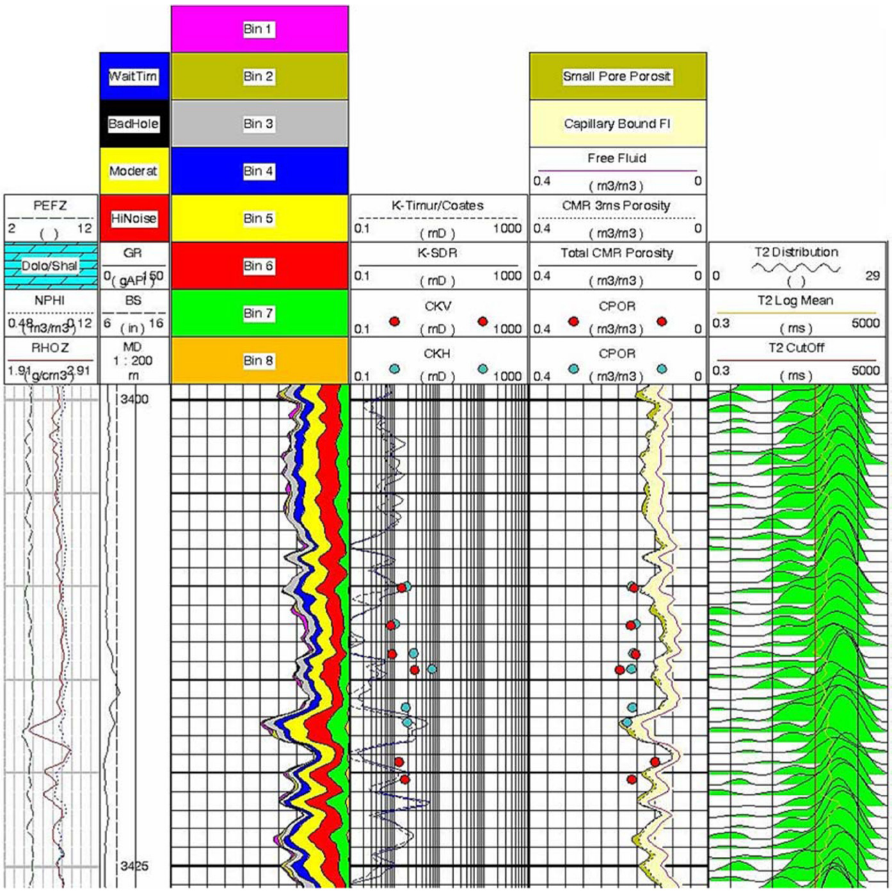

Fig. 3a Demonstration of the composite well-log data for Ilam (a) formation.

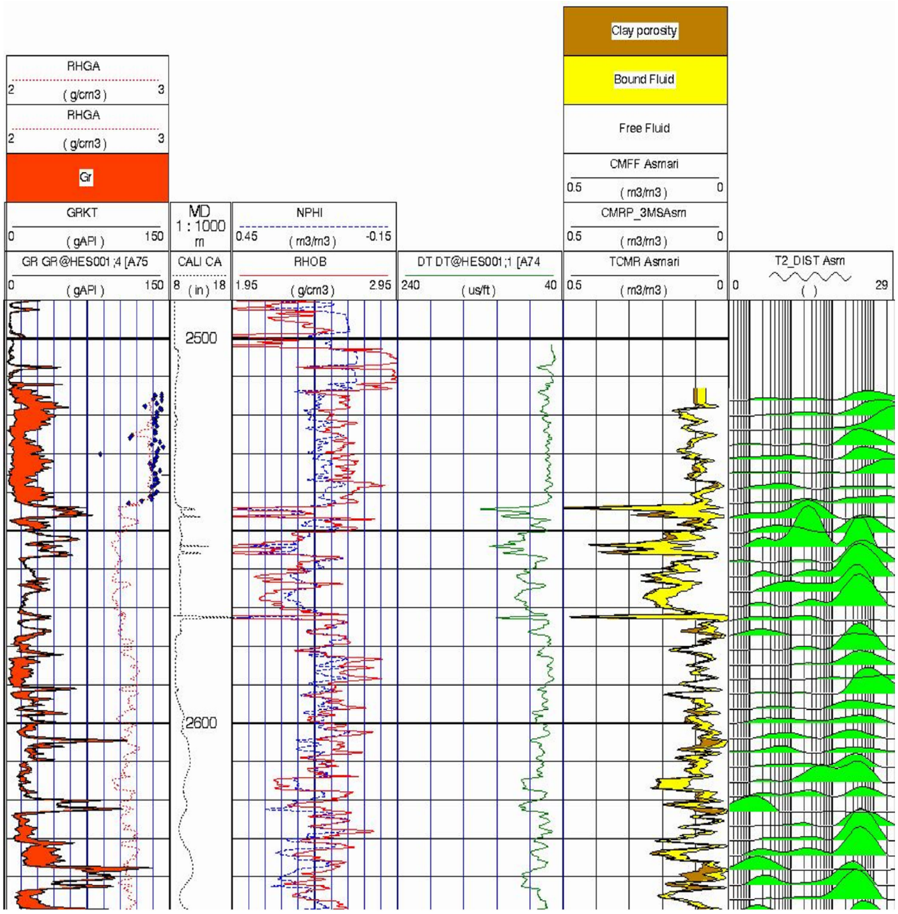

Fig. 3b Demonstration of the composite well-log data for Asmari (a and b) formation.

Processing Parameters

T2LM

T2 distributions are computed by determining signal amplitudes at preselected values of T2. A curve is then fitted through the amplitudes to give the appearance of a continuous function. The preselected T2 values are equally spaced on a logarithmic scale between T2 min and T2 max values. The number of preselected T2 values is referred to the number of components in the distribution [29]. In this study, the logarithmic mean of T2 is one of the main target logs to be estimated from the conventional logs.

TCMR

The total porosity of the Combinable Magnetic Resonance tool is also an important and useful parameter estimated in this study. It directly indicates the porosity of the logged depth point, and it can be calibrated with core porosity.

Case Study

The Ahvaz oilfield is located in the Khuzestan province, west of the Dezful embayment, with an anticline 67 kilometers in length and about 4 to 6 kilometers in width. This oilfield has a northeast to southwest strike parallel to the Zagros Mountains, and on the Asmari horizon, it looks like a horse saddle. Since crude oil in place of this oilfield is estimated to be more than 10 billion barrels, it should be considered a supergiant oilfield and maybe the biggest oilfield explored in Iran until now. In this study, the map of the used wells is shown in Figure 4. The well with real NMR data is shown with a triangle, and three other wells with conventional logs are shown with circles.

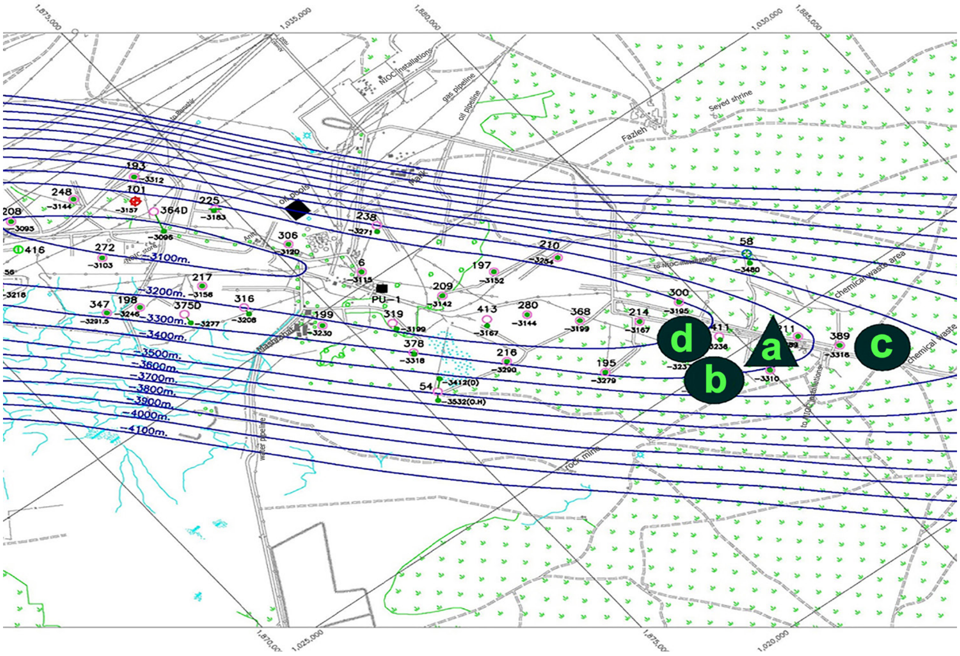

Fig. 4 The map of the used wells in this study.

The Ilam formation with limestone lithology was first introduced in the Tang-e-Garab area, North West of the KabirKuh anticline. This formation contains 190 meters of grey limestone and medium to thin layering shaly intervals. The limestones of the Ilam formation in the Khuzestan province constitute the reservoir rocks located at the Bangestan reservoir's crest. The Sarvak formation in the Dezful embayment forms the biggest economic horizon after the Asmari reservoir. The stratigraphic column of the Zagros basin for the Cretaceous Ilam formation is shown in Figure 5. It is evident that the Ilam formation is under the Asmari formation, and all the drilled wells in the Ilam formation have passed through the Asmari formation. Hence, NMR data are available for a well that passed through these two formations. The Asmari formation is situated in the southern mane of the Asmari Mountain, 45 kilometers from Masjed-I-Sulaiman (MIS) city. The thickness of this formation is 314 meters, with lithology of cream to light brown limestones. The geological age of this formation is upper Oligocene to lower Miocene.

When a complete and perfect interpretation of well log data cannot be acquired, intelligent computing (IC) methods could be applied. The Ahvaz oilfield is an example of this case that is suffering from the lack of both NMR and core data. Iran's policy on the petroleum industry is to keep the current rate of production for export purposes. Hence, the main part of the petroleum ministry budget devotes to exploring new fields and drilling more wells to develop producing wells. The remaining budget is not enough for coring and running CMR tool to obtain core and NMR data. Ahvaz oilfield has more than 400 producing wells, and there is just one well that has NMR data. Other wells, in most cases, have a full set of conventional logs or core data. The wells with a full set of conventional logs and core data are rare.

Data from four wells are used in this case study. A full set from conventional logs is available for all wells; one well has two NMR data sets from two different Asmari and Ilam formations. NMR data from Ilam formation are used to train the NN and NF networks while the other is used to make a comparison between their predictive power and robustness. In the second part of this study, all four wells (a, b, c, and d) from the Ilam formation that includes well number "a" are used for cluster analysis.

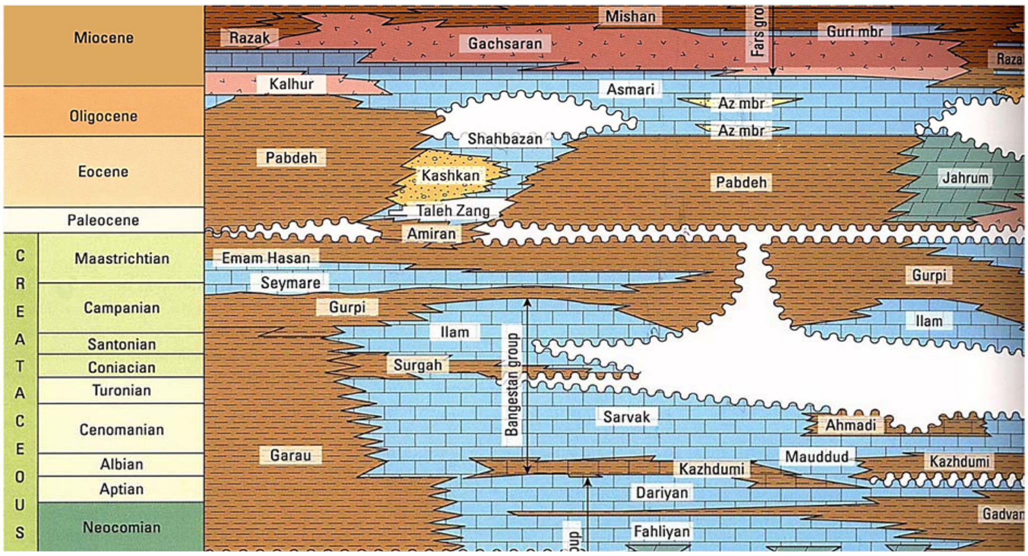

Fig. 5 The stratigraphic column of the Zagros Mountains in Cretaceous for the Ilam and Asmari formations [30].

The synthesized VNMR logs for well numbers a, b, c, and d are used to create electrofacies classifications. Because among these wells just the well number "a" has continuous core data for all intervals, the VNMR logs are synthesized for this well to make a correlation between the intelligently derived NMR electrofacies and reservoir quality.

In this study, intelligent models were employed to synthesize the T2LM and TCMR logs from available conventional log data. To evaluate the robustness and precision of the constructed models, the estimated outputs by the network and real values of NMR log were compared using root mean square error (RMS). Afterwards, the NMR electrofacies were identified through a cluster analysis algorithm. Correlation between the NMR electrofacies and reservoir quality in the framework of porosity and permeability data identified high-quality and poor-quality intervals.

Synthesizing NMR Parameters using Back Propagation - Neural Network (BP-NN) Model

Estimating the T2LM and TCMR data is done using MATLAB software's neural network fitting toolbox (nftool). All the conventional logs from the well, along with T2LM and TCMR from NMR log, are gathered in a single matrix. There are two different NMR logged formations from one well for this study. Data set from the Ilam formation is used to construct the model and the Asmari formation data set is used to evaluate the reliability of the constructed model. The neural fitting tool employs a network with two layers feed forward back propagation which also benefits from hidden sigmoid and linear output neurons. The backpropagation approach is common among the techniques proposed to train the NN models. The final aim of this learning method is to reduce and minimize the global error for output nodes by weight adjusting. It will optimize the problem and minimize errors. The levenberg-Marquardt algorithm works faster, is more robust, and is more reliable than conventional algorithms. The only disadvantage of this method is that it requires high memory levels. The conventional Levenberg-Marquardt algorithm is modified by using nonlinear statistical methods. In this study, the output of the final global error is related to the parameters of the network. Hence, the learning coefficient is modified.

The training data matrix was applied to the network during training, while the network weights were adjusted during training epochs. In order to measure the performance of network generalization, validation data were used. When this performance stops its improvement, training process will be stopped. Therefore, testing the data set has no impact on the training data set and provides an independent measurement of the network's performance during and after the training process.

In the current study, The default data percentages have been used to create the network (70% to train, 15% to validate, and 15% to test), but in some cases where the need for training was more to get better results, these fractions have changed. To achieve better network performance, the hidden neuron number in the network structure can be changed. The optimum neuron numbers in this study's hidden layers were 10, 12, and 13. Once MSE value of the validation samples tends to increase, network training stops.

Crossplots indicating comparison between measured and NN estimated T2LM (left) and TCMR (right) in the test well are shown in Figure 6.

T2LM with the unit (MS) and TCMR with the unit (V/V) are denormalized. RMS and R2 values for T2LM and TCMR of this case study are shown in Table 1:

Table 1 RMS and R2 values for T2LM and TCMR synthesized with NN.

Data set	RMS(%)	R^2
T2LM	28.4	0.898
TCMR	48.8	0.969

Synthesizing NMR Parameters using the Model of Back Propagation - Neuro Fuzzy (BP-NF)

This section uses an ANFIS editor as an alternative tool to synthesize the T2LM and TCMR data from conventional log measurements. In addition, fuzzy logic defines a new way to deal with high-complexity models [3]. The Fuzzy Inference System (FIS) has been generated in MATLAB programming environment. Membership functions and also their parameters were optimized by using an artificial neural network with a backpropagation algorithm. (BP-ANN).

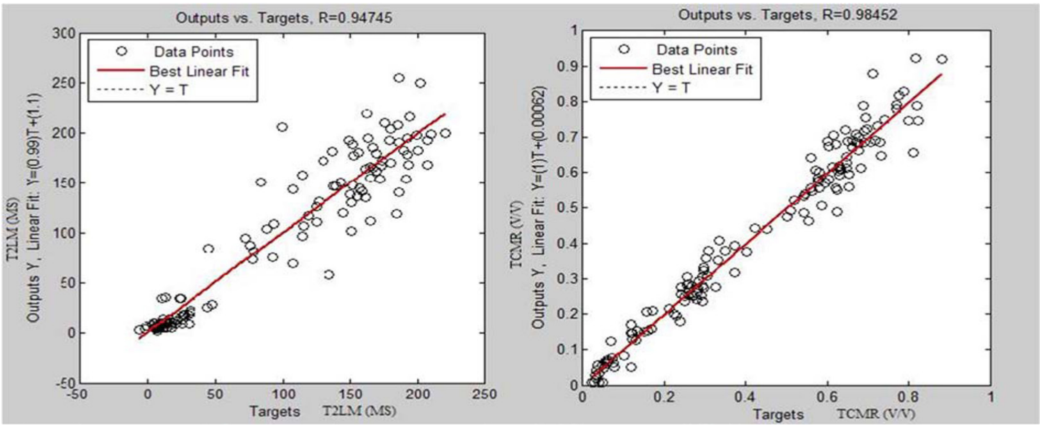

Fig. 6 Comparison between the measured and NN estimated T2LM (left) and TCMR (right).

Error tolerance was set to zero (system default), epoch value was changed several times to achieve better results. The best results were achieved when epochs were set to 30. Accept and reject ratios, squash factor, and range of influence were set to 0.5, 0.15, 1.25, and 0.5 values, respectively. As with the NN model, after construction of the neuro-fuzzy model, well log data sets were the input for the model, and virtual T2LM and TCMR data were obtained for the Ilam formation. The crossplots making a comparison between the measured and neuro-fuzzy estimated T2LM and TCMR are shown in Figure 7. T2LM with the unit (MS) and TCMR with the unit (V/V) are denormalized.

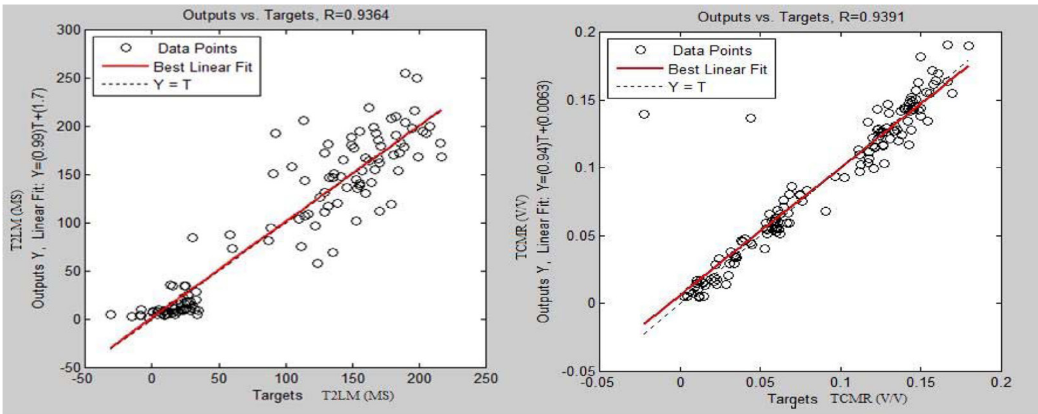

Fig. 7 Comparison between the measured and NF estimated T2LM (left) and TCMR (right).

A set of fuzzy if-then rules defines the Neuro-fuzzy approach model. The extracted FIS set of rules for T2LM and TCMR in the Ilam Formation are shown in Figures 8 and 9, respectively.

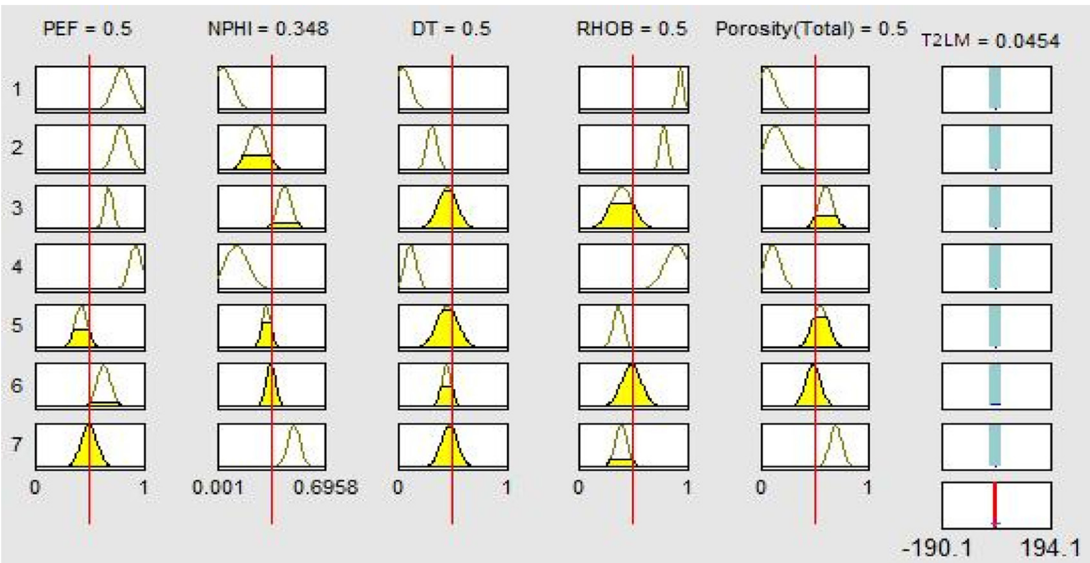

Fig. 8 FIS rules of ANFIS editor for T2LM.

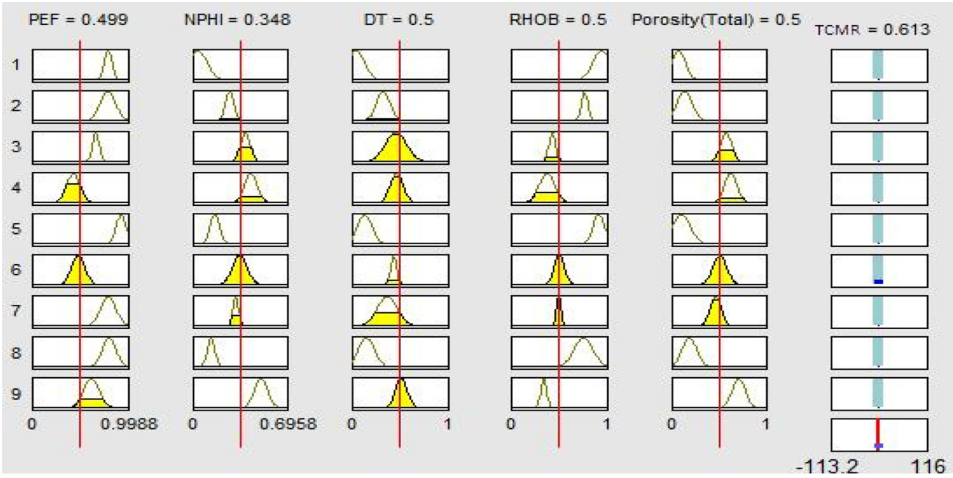

Fig. 9 FIS rules of ANFIS editor for TCMR.

Identification of NMR Electrofacies

This part of the study aims to identify NMR electrofacies and to make a correlation between the intelligently derived NMR electrofacies and reservoir quality. For this purpose, a cluster analysis algorithm was run with T2LM and TCMR inputs. The standardized Euclidean function was used to calculate distance data. Then, the average linkage function grouped the distance data into small and large clusters. The application of the linkage function is the determination of objects' proximity to each other. When objects pair into binary clusters, new clusters group into larger ones to form the hierarchical tree. As seen in Figure 10, four dendrograms show the results of the linkage function in four wells of the studied field from which core data are available only for one well. The last three wells are only logged, and no NMR and core data are available.

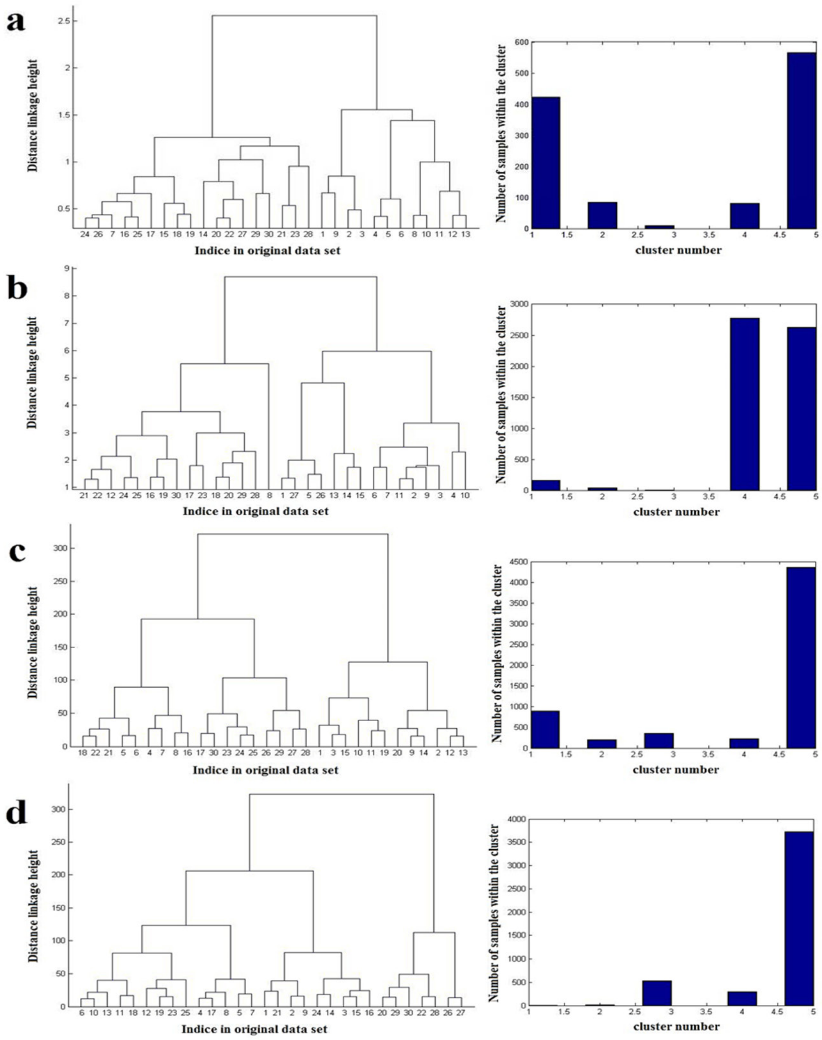

Fig. 10 Dendrograms extracted from cluster analysis for the four wells from the study area (a,b,c, and d) and histograms showing the frequency of NMR electrofacies for each well.

The histograms in Figure 10 display the frequency of the clusters extracted for each well. Running the cluster analysis algorithm allowed us to identify five classes of NMR data. The image plots shown in Fig. 11 illustrate the NMR-derived electofacies for the first well with synthesized VNMR logs and core data. The plots of synthesized T2LM and TCMR and their corresponding NMR electrofacies are displayed in Figures 11 from Ilam formation.

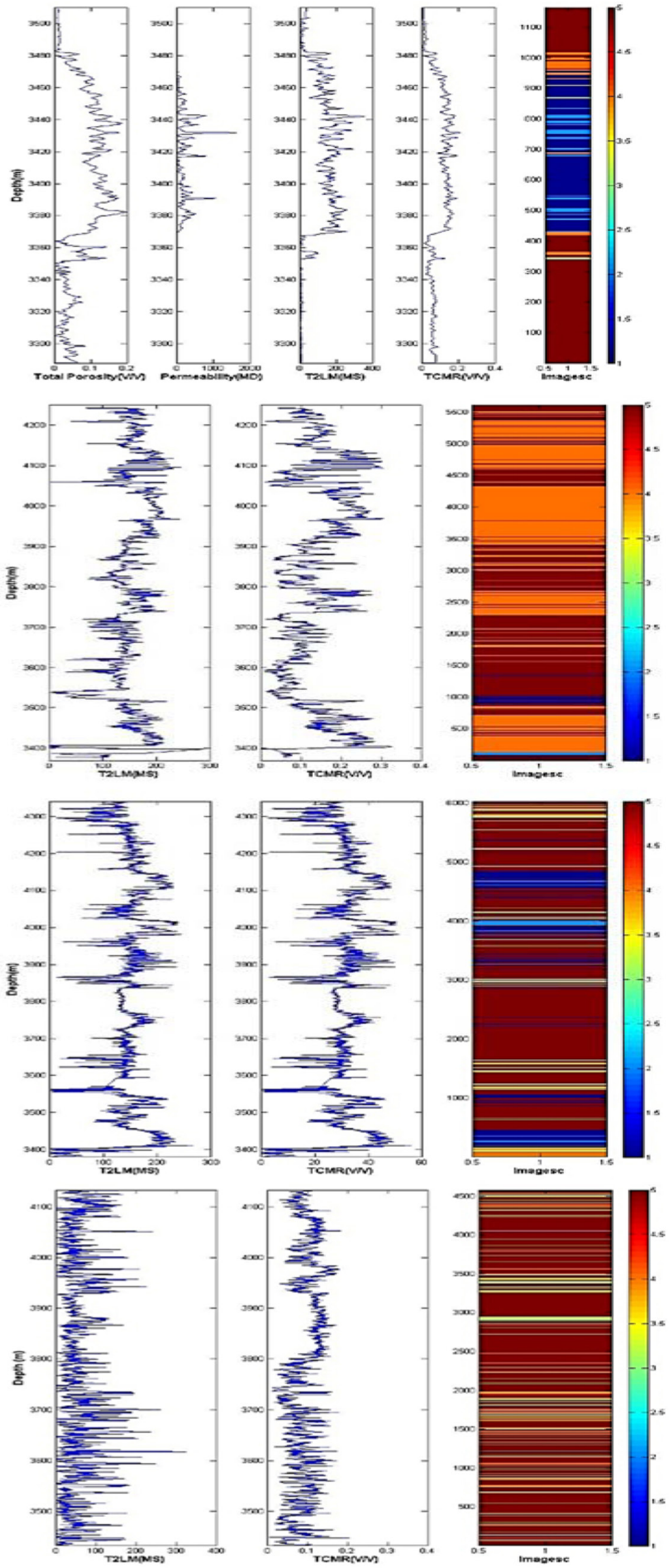

Fig. 11 Subplots show the image patterns of clustering results alongside T2LM and TCMR logs. Porosity and permeability data are also shown for the first well with core data.

Results and Discussion

Reservoir rocks properties are consequential in developing drilling plans and determining the petrophysical behavior of that reservoirs. Parameters of porosity and permeability are the elemental controlling agents in fluid movement through the porous media. Estimation methods emphasize permeability estimation more than accentuating porosity estimations because of its rule for reservoir evaluation. Accordingly, the importance of porosity estimation was considered to reach higher levels of accuracy in computations. Nowadays, porosity and permeability measurements are conceivable and even more feasible --by wireline tools or coring methods, etc.-- than in the past. However, they still cost high, are time-consuming, and are regional for logged or cored intervals.

Hence, this research paper developed a methodology for generating synthetic NMR logs by using conventional (Sonic Travel Time (DT), Neutron Porosity (NPHI), Photo Electric Factor (PEF), Density (RHOB), and total porosity) well log data. Afterwards, the synthetically generated logs are calculated using a mathematical function encompassing these measured parameters and named VNMR logs. Because of the high costs of NMR tool measurements, improvements in the new robust models' design are essential for further reservoir characterization studies. NMR logs make the in-situ measurements of reservoir characteristics. The technique is applied to a set of highly heterogeneous wells in the Ahvaz oilfield. This eminent technique can provide a better description of the reservoir and lower the cost of reserve estimation in a more realistic way.

One of the most challenging issues in reservoir characterization is to choose the best method to integrate qualitative geological descriptions. It is expected to achieve better results using hybrid Neural Network – Fuzzy Inference Systems (NN-FIS). However, individual NNs, due to their higher degree of nonlinearity, are still robust and high-performance methods for rock properties estimation. This paper compared the NN and NF models for NMR parameters estimation from a set of wireline logs available in most wells. Comparisons indicate the higher reliability of NN models over the hybrid ANFIS method. Furthermore, RMS values of the NN and ANFIS models for estimating T2LM were 28.4 and 93.6, respectively. For the TCMR case, these values were 48.8 and 93.9, respectively. The optimal hidden neuron range of 10 to 13 provided satisfactory results. The more hidden layers and neurons are added complexity to the system, and it is recommended to choose hidden neurons proportional to the number of input data in a three-layered BP-NN. Hence, it is better to get aid from NN tool to build VNMR logs for other wells of the Ahvaz oilfield that NMR tool is not run.

Figure 11 shows the generated T2LM (a) and TCMR (b) logs from conventional logs data for four wells from the Ahvaz oilfield where NMR data are not available. VNMR logs are built using wireline logs, including PEF, NPHI, DT, RHOB, and Total porosity.

From Figure 11, it could be concluded that this method successfully estimated VNMR logs and their corresponding electrofacies. The final aim of this study was to make a correlation between the intelligently derived NMR electrofacies and reservoir quality based on cluster rankings. When whole core data are absent, reservoir quality determination benefits from the wireline well logs.

For this case study, core data were available for one well. In Table 2, min, max, mean, and standard deviations of core porosity and permeability within each NMR cluster are displayed.

As shown in Table 2, cluster 2, with average porosity and average permeability of 14.49% and 422 md is ranked as the best NMR facies. Cluster No. 5 has poor reservoir quality with average porosity and average permeability of 3% and 0.021 md, respectively. Accordingly, clusters 1, 3, and 4 will get the second, third and fourth rank of reservoir quality. In the plots of Figure 11, T2LM and TCMR parameters already follow the pattern of image plots. Most formation intervals in all four wells are situated in cluster number five (poor reservoir quality). The frequency of porosity and permeability data for each NMR facies is shown in the histograms in Figure 12.

Table 2 Min, max, mean, and standard deviation of porosity and permeability for each NMR cluster.

Facies No.	Porosity (v/v)				Permeability (mD)				Rank
	Min	Max	Average	STDEV	Min	Max	Average	STDEV	
1	0.0592	0.1961	0.11657	0.02259	11.2247	505.072	128.86	95.5312	2
2	0.0967	0.1988	0.1449	0.02496	33.5069	1615.07	422.041	295.042	1
3	0.0843	0.1424	0.10557	0.01586	0.6219	40.8548	18.0326	14.6238	3
4	0.0169	0.1259	0.06282	0.02424	0.0814	33.019	4.79036	6.3253	4
5	0.0011	0.1433	0.03058	0.02129	0.000	0.8138	0.02198	0.0783	5

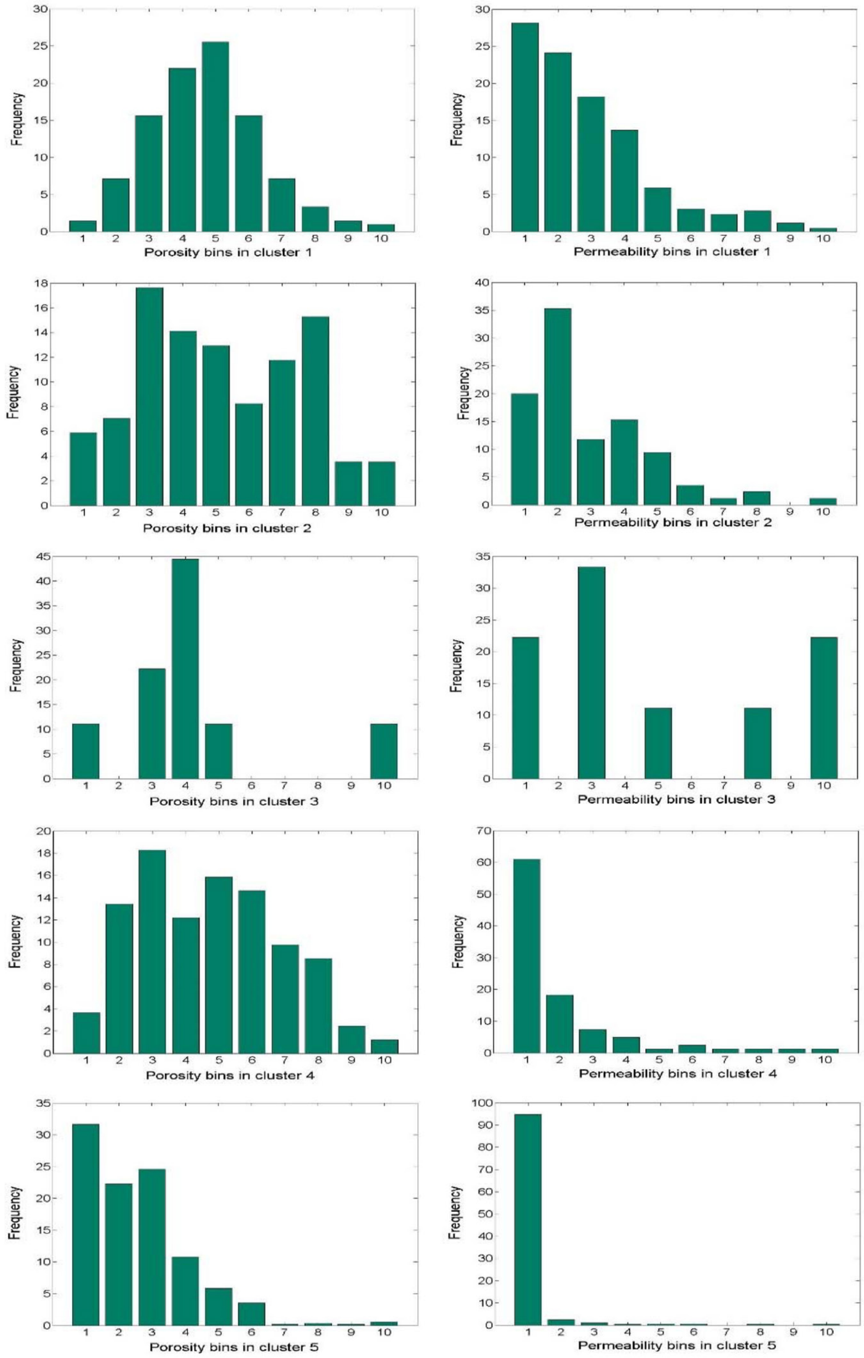

Fig. 12 Histograms of porosity (left) and permeability (right) for each cluster.

Conclusions

From this study it is concluded that NNs could be used to get better results for nonlinear function estimation and to make a good correlation between the intelligently derived NMR electrofacies and reservoir quality. These soft computing methods are applicable to solve the problems that this field suffers from them. Issues include the lack of well log data for some intervals, synthesizing these data for intervals that cannot be logged or have cased hole, synthesizing NMR data to investigate the history of wells, and generally where log data are not available or cannot be recorded. A differentiation between pay and non-pay zones could be made by using this type of cluster analysis to get better understanding from the reservoir conditions. The exactness of synthesized NMR logs is admirable because the model in the Ilam formation has been trained, and the trained model has been applied for the Asmari formation of the Ahvaz oilfield. It is applicable to other wells in this field. Finally, using the methodology stated in this study, the VNMR logs and their corresponding electrofacies, and reservoir quality can be determined for other wells from the studied field with conventional log inputs. This will help us implement a more successful approach of the future field development plans.

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