Permeability Prediction from CMR using the SVM classifier in shaly sand formations through the Well Takw-1 in Devonian and Ordovician. Illizi basin. Algeria.

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Abstract

The conventional methods for permeability determination are core analysis and well test techniques. These methods are very expensive and time consuming. Therefore, attempts have usually been carried out to use artificial neural network for identification of the relationship between the well log data and core permeability. In this way, recent works on artificial intelligence techniques have led to introduce a robust machine learning methodology called support vector machine.

In addition, in most reservoirs, permeability measurements are rare and therefore permeability must be predicted from the available data for the well Takw-1, Illizi basin in Algeria. CMR logs and conventional logs provide formation permeability in different ways though the parameter can be derived in the three kinds of data. Integrating the three kinds of data and comparing the change trends among the data, the rock properties of reservoirs are analyzed in this research. The nuclear Magnetic resonance (NMR) tool makes it possible independently to determine parameters such as total and effective porosities, irreducible saturation, permeability, the volume of clay, the volume of water related to clays and the distribution of the size of the grains. In particular, NMR analysis, as demonstrated from the Takw-1 well, allowed, in addition to the determination of the petrophysical parameters:

The interpretation of the magnetic resonance data recorded from the Ordovician and Devonian reservoirs made it possible to evaluate irreducible water saturation and to determine the volume of movable water. Moreover, the NMR depth log, provided measurements for the determination of accurate porosity, permeability and irreducible water saturation, which were used for enhanced formation evaluation in these reservoirs.

However, the SVM classifier approach is tested in a rock facies classification problem: classical parametric methods using Bayes' rule, and non-parametric methods using fuzzy logic, k-nearest neighbor, and feed forward-back propagating artificial neural network. The SVM classifier is compared to discriminant analysis and probabilistic neural networks. SVM predictions of the permeability are compared to that of a back- propagation and general regression neural networks. Statistical error analysis shows that the SVM method yields comparable or superior classification of the lithology and estimates of the permeability than the neural network methods. A comparison of log-based and core-based clustering reveals that permeability prediction based on core-based clustering were slightly better than that of the log-based clustering.

Keywords: CMR, SVM classifier, Devonian, Illizi Basin, Algeria.

1. Introduction

In reservoir engineering, reservoir management, and enhanced recovery design point of view, permeability is the most important rock parameter affecting fluids flow in reservoir. Knowledge of rock permeability and its spatial distribution throughout the reservoir is of utmost importance. In fact, the key parameter for reservoir characterization is the permeability distribution. In addition, in most reservoirs, permeability measurements are rare and therefore permeability must be predicted from the available data. Thus, the accurate estimation of permeability can be considered as a difficult task. Permeability is generally measured in the laboratory on the cored rocks taken from the reservoir or can be determined by well test techniques. In this recent Illizi well, conventional resistivity logs read approximately 5 to 7 ohm.m over most of the intersected sands, as shown in Fig.1. Thus, using the resistivity was not adequate in differentiating oil and water bearing zones.

High-resolution CMR combinable magnetic resonance technology is important for formation evaluation, giving you free-fluid index measurements for differentiating zones of water-free production (Freedman *et al.,* 2002). The CMR signal is processed to estimate the distribution of pore sizes. This is a wireline formation measurement you get only with the CMR tool (Hussein *et al.,* 1999).

NMR logs and magnetic resonance fluid characterization station measurements (MRF, Freedman *et al*., 2001, 2002) were also run. The NMR data was used as an aid in differentiating between low resistivity contrast oil and water bearing zones.
An understanding of reservoir directional permeability anisotropy is pertinent information for the reservoir simulator. Joanneum Research and Baker Atlas have published their theoretical- and real- data permeability anisotropy computation, using multi-component induction resistivity data available from Baker Atlas's 3D Explorer (3DEX) logging tool (Kenyon *et al*., 1997). Archie and Coates equations provide a simple petrophysical connection between resistivity anisotropy and permeability anisotropy.
Moreover, with NMR data we determined accurate porosity in these well (independent of lithology), permeability and flushed zone hydrocarbon saturation. The following sections first describe the resistivity contrast problem; then the measurement and MRF principles explained; finally, the results from the studied well are presented.

The SVM classifier approach in a rock facies classification of Devonian in the studied well aim to define the optimal boundary separating classes in feature space. This decision boundary is called the optimal separation hyper plane. The classification of new data is based on which side of the decision boundary the data point falls. The 'optimal' hyper plane is chosen based on the maximum margin principle, by choosing the boundary which maximizes the distance between classes. SVMs are able to handle problems where classes are not linearly separable by transforming the data using a kernel function such as the radial basis function (RBF) kernel. The RBF kernel is the most common choice for classification tasks and was used here. While most other algorithms tested here deal with the classification problem using a multiclass approach i.e. considering all classes simultaneously, the SVM classifier used here does not handle multiclass problems directly. It breaks the problem down into a series of binary classification problems using a one-against-one approach so that (c- 1)/2 binary classifiers are trained (where c is number of classes).

2. Experimental

The Tanezzuft-Illizi Province coincides with the Illizi Basin and is bounded on the north by the Ghadames (Berkine) Basin, on the east by the Tihemboka Arch, on the south by the Hoggar Massif, and on the west by the Amguid-Hassi Touareg structural axis.
The south-to-north plunging Tihemboka Arch separates the Illizi Basin from the Hamra Basin to the east (fig. 1) and is located near the Algerian-Libyan border (sabaou). Along the western boundary, the Amguid-Hassi Touareg structural axis separates the Illizi Basin from the Mouydir Basin of the Grand Erg/Ahnet Province.

The study carried out in the Take-1 well located in the Eastern part of Algeria very close to the In- Amenas field (Latitude: N 28 26’04.58, Longitude: E 8 16’ 14.52).
This 794-meter FMI image stretches from 2512 m up to 1718 m (MD).
The section of interest is the Devonian reservoirs as F6C, F6B, F6A, F6M2 and F6M1. This interpretation has been integrated using the Open Hole Logs CMR-HALS-SONIC. The wellsite geologist provided the following provisional tops:

The main target zones are the Ordovician reservoir units and the Upper Devonian reservoirs (F6-C, F6-B, F6-A, F6-M1).
The wells Take-1 and Takw-1 are located within the Takouazet Field in the In-Amenas area of SE Algeria (Fig. 1). This part of the Saharan platform tends to have a near flat structural dip and is thought to have been subject to the effects of strike-slip tectonics. The studied interval is believed to include a sequence of Ordovician clastic sediments.

3. Results and Discussions

3.1. Prediction of Permeability Using SVM

After building an optimum SVM based on the training dataset, performance of constructed SVMwas evaluated in testing process. Figure 2, 3, 4 and 5 are the demonstration showing the ability of SVM in prediction of permeability.
As it is illustrated in Figure 2 and 3, there is an acceptable agreement _correlation coefficient of 0.97_ between the predicted and measured permeability. In fact, the SVM is an appropriate method for prediction of permeability. Nonetheless, the performance of this method should be compared with another suitable method for highlighting the strength of SVM.

3.2 Determining T_2 cutoff with core data

After the depth of coring is corrected to the depth of CMR log, the covariance sum of core derived permeability and CMR log derived permeability can be calculated. Selecting a proper T_2 cutoff to make the sum of variance Q_a to arrive the least, (1) where KCMR is the permeability derived from Timur–Coates equation. (2) where Q_a: the sum of permeability variance md^2; *I*: series number of samples; *N*: total number of samples; KC: core permeability, md; KCMR: CMR derived permeability, md; T: CMR derived total porosity, decimal; *C*: constant, no dimension; FFV: CMR derived free fluid volume, no dimension; BFV: CMR derived bound fluid volume, no dimension MDT derived permeability can be also utilized to calibrate CMR data in the same ways).
In practice, the irreducible volume is obtained by a cut-off at T2 distribution curve:

T2cutoff = 33 msec used for training and clastic carbonates used to 92msec. The sum of the partial porosities below T2cut off-set portion of capillary water, this portion does not

contribute to water producible. The sum of the partial porosities with T2superieure T2cut off set the volume of mobile fluid.
The estimating T2cut-off is based on the irreducible core saturation and give NMR for BVI. However the information can be obtained from the capillary pressure Pc cores and core porosity: BVI (core) = Swircor * cor. Once BVI is determined, it can be integrated directly at (NMR log).

4. Comprehensive analysis of derived permeability

Using core permeability and MDT permeability derived with oil viscosity from PVT measurement, T_2 cutoff for T_2 spectra can be determined. CMR derived permeability are presented in Table 2 after the T_2 cutoff and Equations are employed.
In number varying trend, core permeability agrees well with MDT derived permeability, but the
differences between the two permeability values are pretty large. It is because core permeability and MDT permeability have different significances to fluid flow. Core permeability is the absolute permeability on the condition of lab, and on the other hand, MDT derived permeability is the effect permeability of multi-phase flows on the condition of reservoir. MDT derived permeability, obtained from pressure drawdown or build-up, shows real fluid flow on the condition of reservoir. So, it is the MDT derived permeability that owns close relation with oil and gas development. In some sampling points, such as the depth 1233.10 and 1234.80 m, core permeability shows totally different varying trends from CMR derived permeability. The main reasons for the situation may be attributed into two factors, one is disturbance from bad borehole wall, and another is the disturbance of heavy oil.

5. Conclusions

In this paper we presented a variety of NMR fluid characterization examples for evaluation of unconventional hydrocarbon bearing reservoirs with fresh formation water. We applied advanced NMR MRF logging techniques to differentiate hydrocarbon from fresh water bearing formations. Processed NMR MRF data demonstrated the application of the MRF method in such environments for the prediction of oil and water saturations, as well as, porosity, permeability and oil viscosity. Oils were distinguished from water by NMR 2D maps, thereby, helping decide which sands to complete in difficult cases.
Determination of free fluid and permeability logs also can help decide which sands and which intervals in the sands to perforate, thus, reducing perforating intervals and costs.
Our main recommendations would be that NMR has a unique role to play in the formation evaluation
of fresh water unconventional reservoirs, and can be used effectively to improve the efficiency of the interpretation workflow. For further work, it is recommended to integrate the advanced NMR logging techniques in these reservoirs with NMR core analysis and SCAL.
Moreover, NMR radial saturation profiling technology may provide additional information regarding the mobility of the detected hydrocarbons, by comparing the saturations at different depths of investigation.
For the future works, we are going to test the trained SVM for predicting the permeability of the other reservoirs in the south of Sahara. Undoubtedly, receiving meaningful results from other reservoirs using well log data can further prove the ability of SVM in prediction of petrophysical parameters incl

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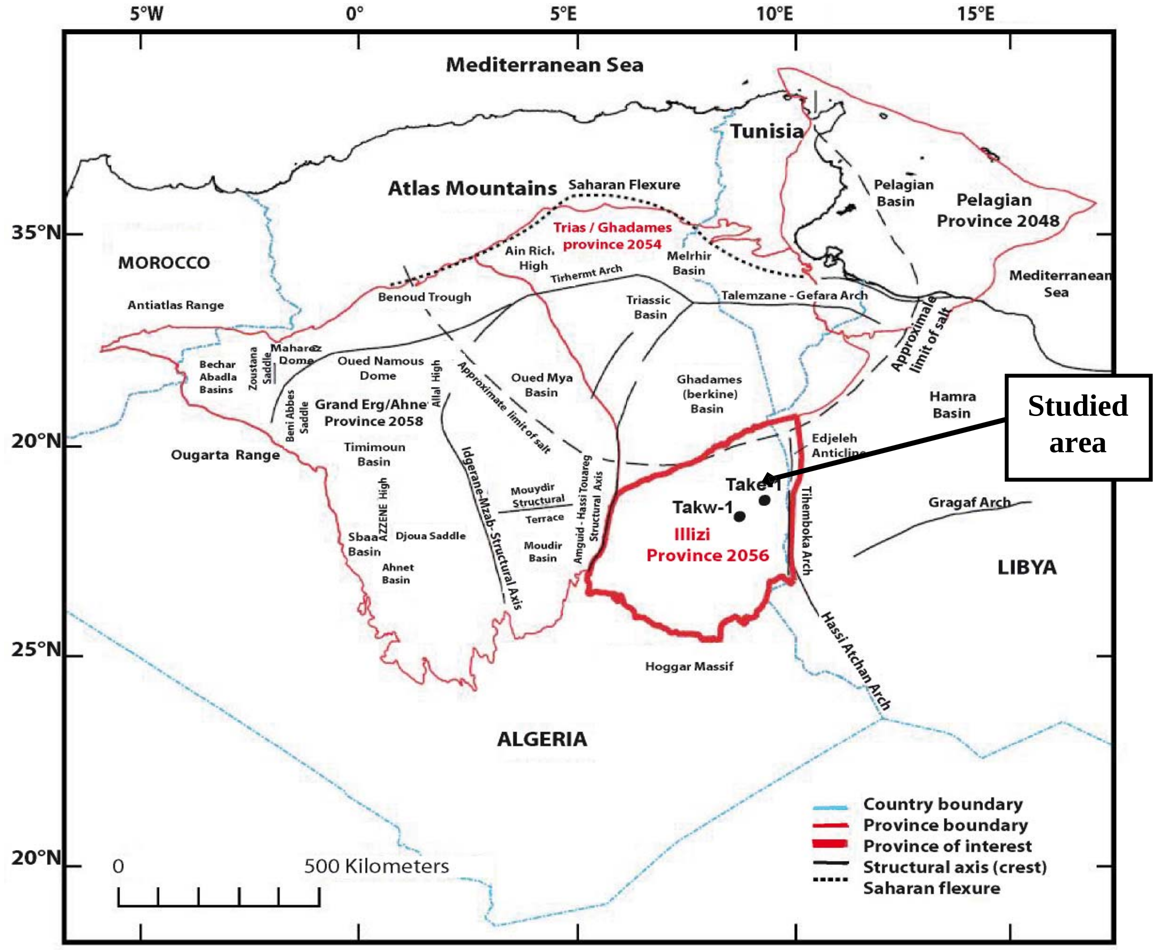
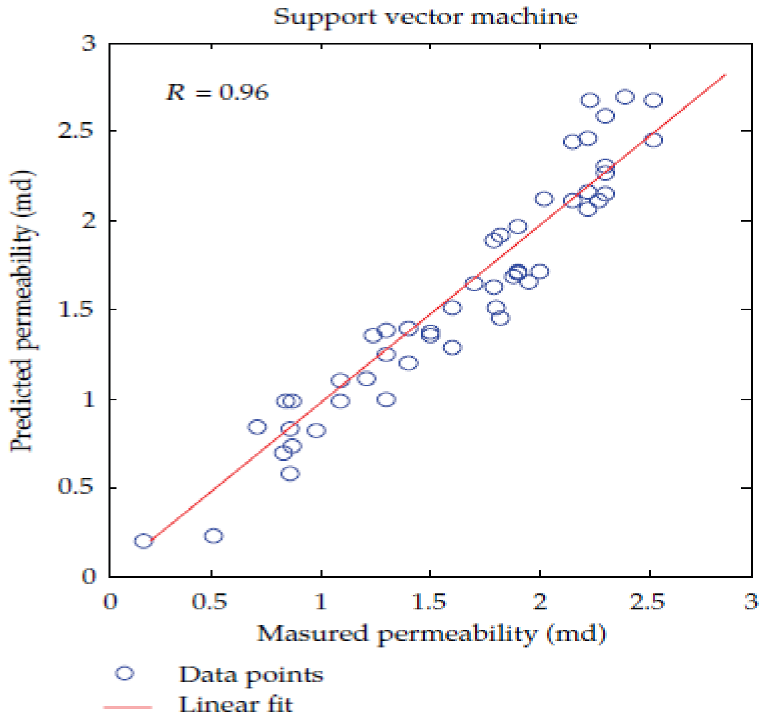
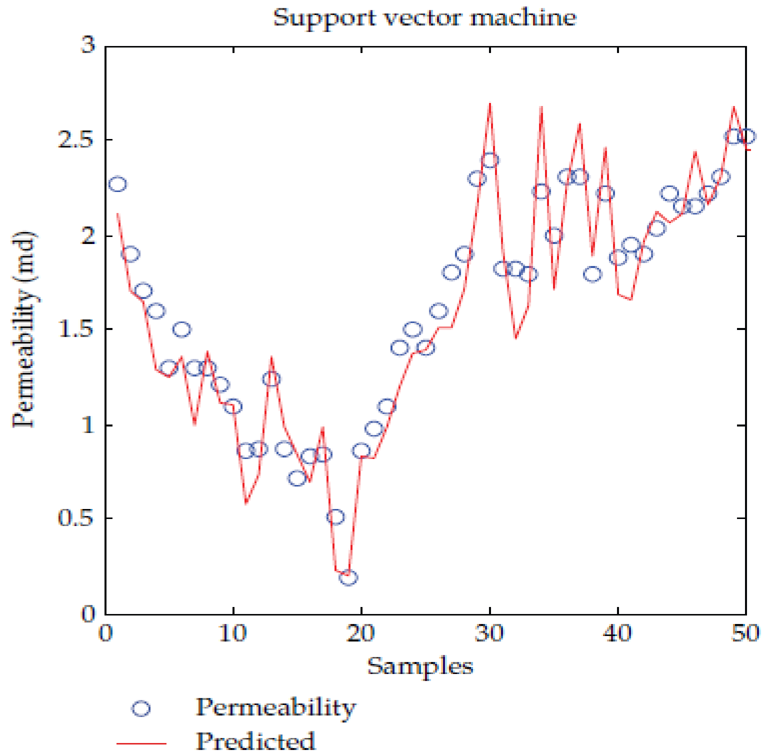


Fig. 1 - North-central Africa, showing USGS-defined geologic provinces and major structures (modified from Aliev and others. 1971; Burollet and others. 1978; Montgomery, 1994; Petroconsultants, 1996b; Persits and others, 1997).

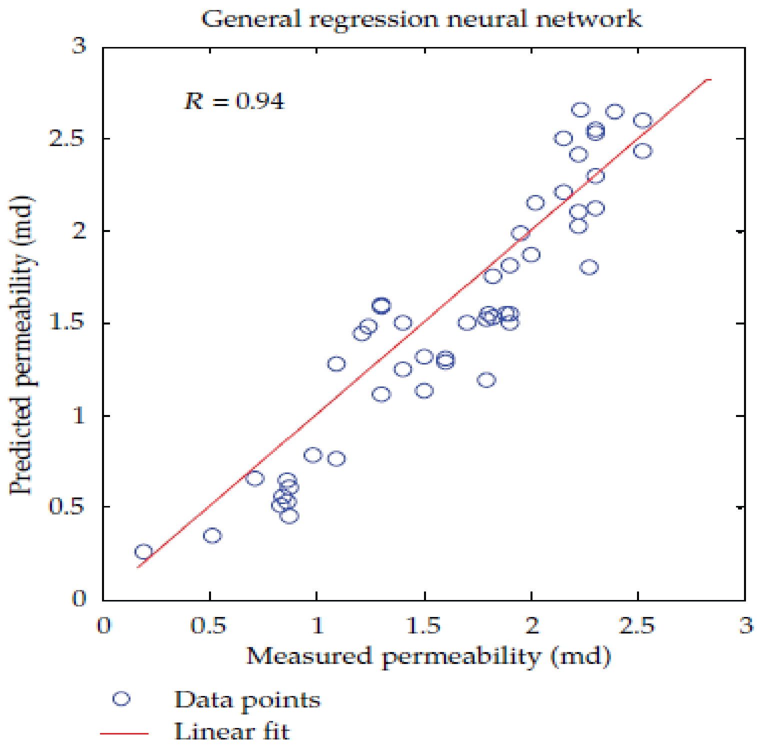


a)

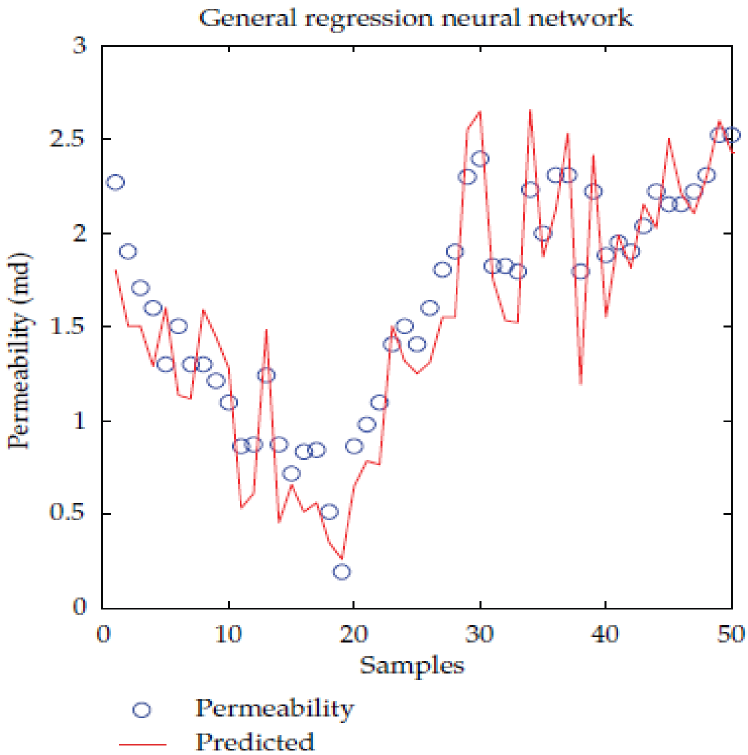


b)

Fig. 2a,b – Relationship between the measured and predicted permeability obtained by SVM: estimation capability of SVM. Well Take-1



(a)



(b)

Fig. 3a,b Relationship between the measured and predicted permeability obtained by GRNN ; estimation

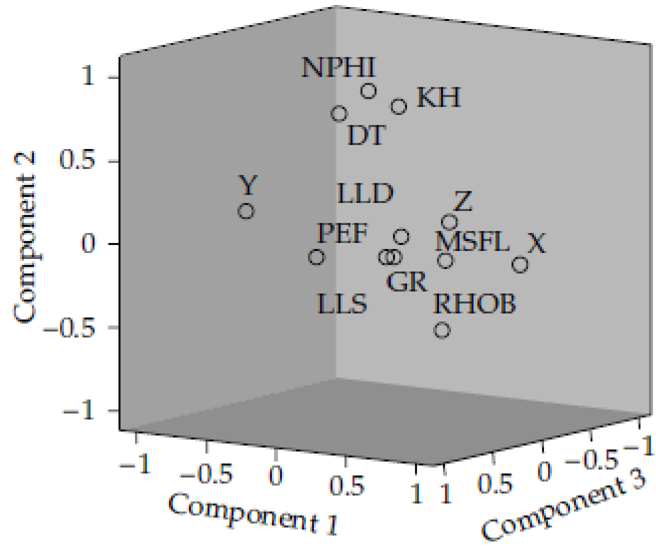


Figure 4: A graphical form of representation for showing the relationship of well logs and permeability. RHOB, NPHI, MSFL, LLD, and LLS and two coordinates, *X* and *Z*, are taken into account for prediction of permeability using the networks.

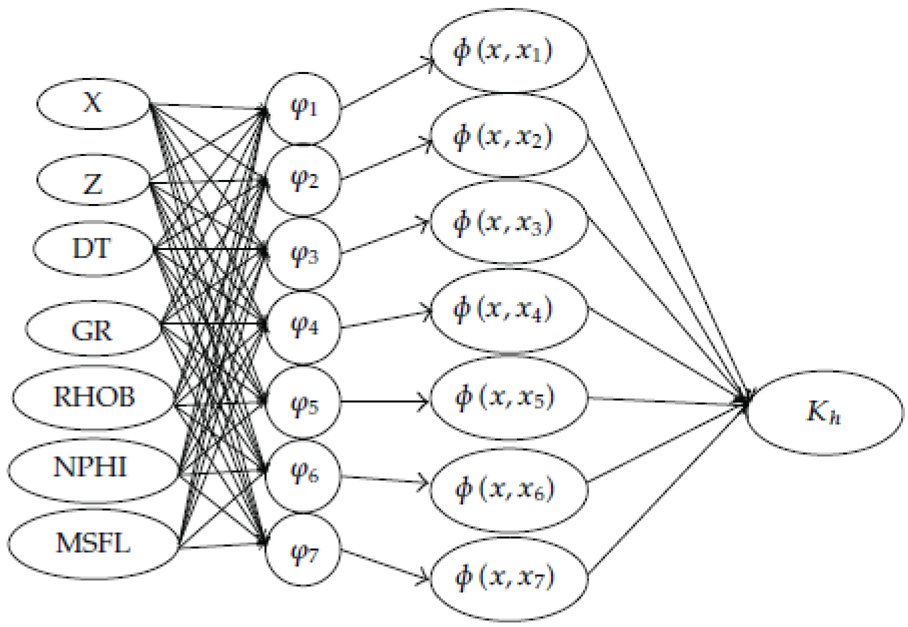


Figure 5: Schematic diagram of optimum SVM used for prediction of permeability. Well Takw-1.

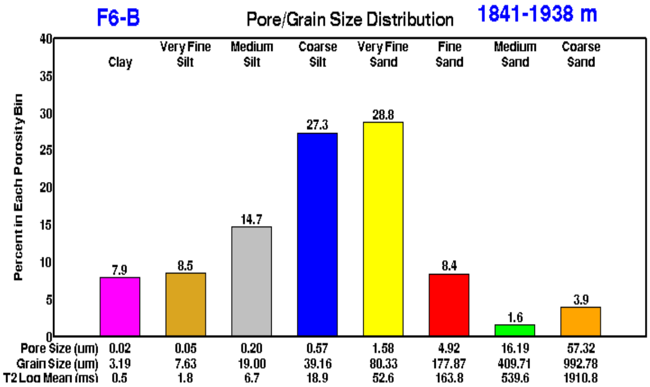
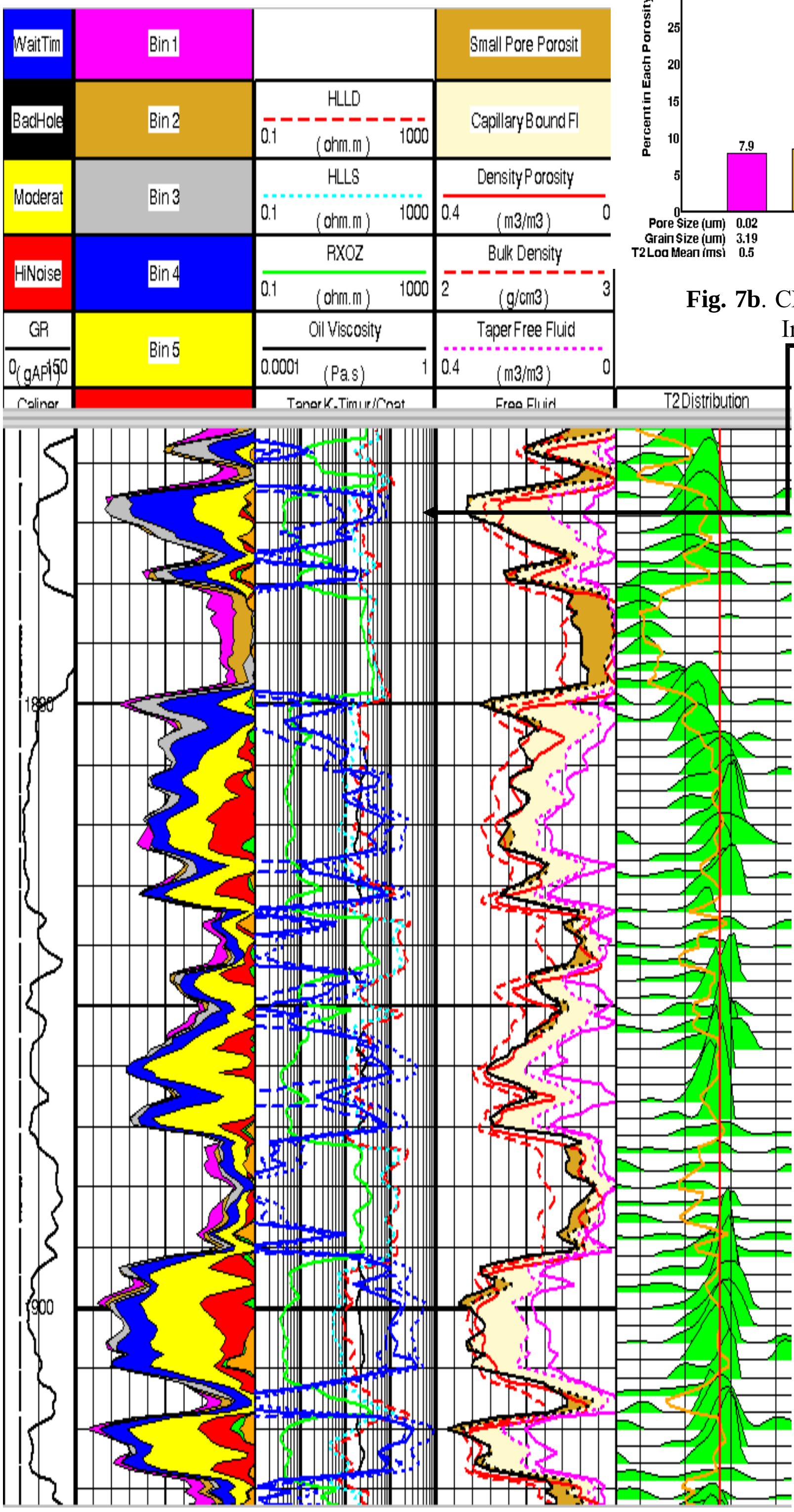


Fig. 7b. CMR pore/grain size distribution for 1841-. Interval: 1938m. Reservoir F6-B.



Ordovician IV-2	2332

Table 1 – Well Takw-1 **provisional** formation tops.

Reservoir F6-C	1776.5	1776.5
Reservoir F6-B	1841.5	1841.5
Reservoir F6-A	1880	1880
Reservoir F6-M2	1942.5	1942.5
Reservoir F6-M1	1977.5	1977.5
Silurian Shales	2050	2050
Ordovician	2397.5	2397.5

Table 2 – Well Take-1 **provisional** formation tops.

F6-C	3-12 Ωm	3-14.5Ωm	0.45 – 3.5 Ωm
F6-B	14.5-65 Ωm	6.8-10 Ωm	0.3 – 0.9 Ωm
F6-A	7.9-51 Ωm	7.2-55 Ωm	0.3 – 34.5 Ωm
F6-M2	1.6-5.6 Ωm	1.3-3.6 Ωm	0.44-1.3 Ωm
F6-M1	2.0-50 Ωm	2.4-46 Ωm	0.5-31 Ωm

Table-3. Resistivity ranges in Devonian. **Well Take-1**

Model	R (Train)	R (Test)	RMSE (Train)	RMSE (Test)
GRNN	0.998	0.94	0.16	0.35
SVM	0.998	0.96	0.16	0.28

Table-4. Comparing the performance of SVM and BPNN methods in the training and testing process.

Reservoirs	E –B (m)	Vcl (%)	KTIM (mD)	ϕ_{ef} (%)	ϕ_{CMR} (%)	Fluid Mobilty (mD/CP)
1776-1884	1776-1784	10-20	40-150	14-18	10-20	1778=5; 1781=1;1783=8 1807=0.3; 1810=08; 1811=11; 1816=300; 1826=3; 1833=20; 1838=100.
	1806-1841	15-20	60-100	12-16	10-15	
1841-1938	1869-1875	40-60	7-10	13-23	15-25	1874=7
	1879-1887	10-20	7-70	18-24	10-20	1885=600
	1889-1895	20-25	8-60	13-24	15-25	1892=100
	1898-1915	30-50	80-100	22-25	20-30	1909=90
	1917-1938	40-50	10-90	20-26	15-30	1933=200
1938-1971	1945-1953	50-70	0.4 -8	15-50	10-30	1949=70
	1958-1971	70-85	20-70	10-25	7-17	
1971-2055	1990-2000	10-30	8-15	22-25	15-20	1995=100; 2003=160 ; 2011=100; 2045=14; 2048=16.
	2036-2056	30-70	7-20	20-25	19-27	
2421-2510	2410-2446	5-10	10-90	8-11	5-12	

Table 4. NMR derived permeabilities. Reservoir: Well - Takw-1