A Fully Integrated Method for Dynamic Rock Type Characterization Development in One of Iranian Off-Shore Oil Reservoir

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Abstract

Rock selection in modeling and simulation studies is usually based on two techniques; routinely defined rock types and those defined by special core analysis (SCAL). The challenge in utilizing these two techniques is that they are frequently assumed to be the same, but in practice, static rock-types (routinely defined) are not always representative of dynamic rock-types (SCAL defined) in the real reservoir. There is also no significant link between these two techniques. To fill this gap, we integrate the well log data for identification of the optimal number of rock-types, and SCAL data with its high interpretive potential in a given reservoir zonation.

In this paper, we propose a method in one of Iranian offshore oil reservoir with a tight carbonate formation for dynamic rock type characterization. In this method, with the integration of well logs and core description data using multivariate statistical methods, different static rock-types can be identified, but these rock types cannot be assigned for fluid flow simulation. So, with our approach based on capillary pressure curves, different flow behavior can be classified. This technique can be done by using integration of similar capillary pressure curves due to the inlet pressure corresponding to the log parameters.

Finally, with integration of capillary pressure and well log data, two different dynamic rock-types with distinct flow behavior were identified. This method can be used for the development of rock-type characterization and deriving of saturation height functions for calculation of initial water saturation in any heterogonous reservoir and it is an applicable solution for inputs in Geomodel and also simulation models.

Keywords: Dynamic rock-typing, Multivariate statistical, Mercury injection, Capillary pressure, EQuivalent Radius method (EQR)

Introduction

The Geologist, Petrophysicists and Reservoir Engineers in charge of a detailed reservoir description face with a complex challenge, as they must significantly identify the regions that have similar features for better characterization, modeling and simulation of reservoir. These similar regions are called as Rock types which have definable and statistically predictable properties. By now, no direct borehole measurement can provide a complete record of rock-type representative throughout the volume of reservoir. Rock-type's distribution is also the key information to define layering and to select the best options for production test interpretation.

Various disciplines have different imaginations of rock types due to their different work scales. A geologist characterizes a rock type based on similar depositional and digenetic environment using core description and core analysis in cored wells and calls it as "litho- facies". A petrophysicists characterizes a rock type based on similar responses of log measurements in a whole well profile and calls it as "electro-facies". Each electro-facies is assigned as a number that can be plotted against depth. In addition, a reservoir engineer characterizes a rock type based on similar pore size distribution, capillary pressure and relative permeability curves at a given wettability in the limited depths. These disciplines are not considering the rock types in the same way, and also there is no distinct correlation between them. This poor acceptance can be traced to the dimensionality problem(i.e. log space is not equivalent to geological space,

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and two points that are close to each other in log space may not be geologically similar). Experience suggests that the problem of dimensionality cannot be solved if unilaterally addressed, that is from either log data or core description data or SCAL data by themselves. Now the question is that which of them to be considered as a reference. Log data are subject to environmental conditions and have a limited resolution. Core description and core analysis have a limited coverage and are subject to interpreter's bias. Also, SCAL data are limited and sensitive to interpretation.

Few literatures have been proposed for multidisciplinary identification of rock types. In 2000, Shin-Ju [1] Ye and Philippe Rabiller presented a new tool for electro-facies analysis as Multi-Resolution Graph-Based Clustering (MRGC). This method automatically determines the optimal number of clusters using only well log data. The electro-facies obtained, are only based on log data and no other data (core description and SCAL data) were used for investigation of flow behavior.

In 2003, G.Hammon [3] showed that usual rock-typing methods might not capture the actual variability of relative permeability curves for describing behavior production. Therefore, he proposed that multivariate description, including petrophysical characteristics, mineralogical data and wettability indicator, succeeds in capturing the actual variability of relative permeability curves and should be the basis for the generation of multiphase flow rock-types. But in this method the spatial distribution of these rock-types are not described. Moreover, other approaches for identification of rock types have been used based only on well logs or core analyses or special core analysis 4, 7.

In this paper, we want to propose a new approach for rock type characterization based on both well logs and core description and Special Core Analysis that show their spatial distribution in reservoir. In our case study there are a number of limited data, so we used a procedure to get the best result. First, the electro-facies is derived from well logs using multivariate statistical methods, and next the two-step classification methodology was used based on correspondence analysis and observational methods. Then, the number and position of static rock-types is optimized with the core description data. Furtheremore, the dynamic rock-types based on the correlation of SCAL data with static rock-types within reservoir zonation are identified. Finally, these rock-types which their references are logs and based on multi phase flow, were derived to be utilized, accurately, for geomodeling and simulation of reservoir.

1. Objective and Methodology

The aim of this study is to develop a methodology for dynamic rock-typing in reservoir characterization and modeling. Our proposed method is a multidisciplinary approach to identify an optimal number (statically) and effective (dynamically) rock-types, from well logs, core description, Routine Core Analysis and SCAL data based on partitioning and correlation. This approach is used with the support of multivariate statistical, neural networks and Equivalent Radius (EQR) methods. Basically, the method consists of four major parts: (a) data partitioning and electro-facies determination (b) electro-facies derived correlation with core description using correspondence analysis for identification of optimal number of static rock types (c) permeability prediction and pertinent parameters (RQI, m) and (d) dynamic rock-typing.

To characterize and identify electro-facies groups, we utilize a multivariate analysis of well-log data with combination of factor analysis (FA) and cluster analysis (CA). Based on these two parameters, a classification of the logged sequences due to physical and chemical properties can be done. Similar properties of well log measurements are grouped into one cluster, reflecting one lithologic and sediment unit.

Regarding to that, there is a dimensionality problem between log data and lithology which makes it difficult to tie any log data partition to a sedimentologically relevant description. Therefore, this problem is solved with the aid of the two-step classification methodology as a correspondence analysis technique using correlation of core description and electro-facies.

For permeability prediction, neural networks method and also relationships between porosity and permeability in each obtained static rock type using routine core analysis data have been used. Moreover, other pertinent parameters like reservoir quality index (RQI) and cementation factor (m) can be calculated, also for characterization of dynamic rock-types the shape of MICP cannot separate the dynamic rock-types, so we propose a new normalized capillary pressure method which is known as EQR (EQuivalent Radius method) for visual grouping of capillary curves, after that with corresponding of well logs can find a significant correlation between them (SCAL and well log).

2. Procedure

The procedures of this integrated approach are discussed as follows:

A. Electro-facies determination.

First, in this step, the multivariate factor analysis method is used to effectively summarize the data and to reduce the dimensionality of the data without significant loss of important information, resulting in factor logs that are helpful tools for further interpretation. In addition, factor analysis constitutes an alternative form of displaying the data, thereby allowing better knowledge of its structure without changing the information [6]. Then, the two or three most significant factors can be classified into groups that are internally homogenous, using the cluster analysis. Among of the most common methods of complete linkage hierarchical clustering is the Ward method [8], which was used in this study. The identified clusters can be viewed as distinct Electrofacies groups that reflect hydrologic, lithologic, and diagenetic characteristics. B. Optimal static rock-typing with correspondence analysis.

Considering the detailed structure of multidisciplinary data by a two-step methodology simultaneously or iteratively and using correspondence analysis, proved to be the useful solution to set up an interpretation model. In the first step of such a methodology, according to previous stage, log data are classified into a given number of clusters using cluster analysis. In the second step, one manually merges small clusters into electrofacies to more similar statistical and geological characteristics.

C. Permeability prediction.

Once the static rock types are identified, a correlation between permeability and other well log responses for each static rock-type is developed with core data analysis. First, the relationship between porosity and permeability of cores in each static rock-type is drawn; then equation of their relationship was employed if there was a clear relationship between them, otherwise the neural network method is used for permeability prediction. Finally, a reservoir zonation is applied between the wells based on the correlation of petrophysical and geological facies and permeable and impermeable zones.

D. Dynamic rock-typing.

With regard to traditional rock-typing methods, they may not capture the actual variability of relative permeability curves. Therefore, for the generation of multiphase flow rock-types workable for input in simulation model, multivariate description such as capillary pressure and relative permeability curves, wettability, pore network and structural position within reservoir zonation and static rock-types were used 11,12,13,14.

It was therefore required to develop a new capillary pressure normalization procedure. The new normalization procedure, called the Equivalent Radius method is based on a split of the drainage capillary pressure curve into three separate functions:

· Capillary entry pressure (Pce).

· Irreducible water saturation (Swir).

· Capillary shape function (CSF).

Capillary entry pressure (Pce) expresses the minimum pressure to allow the non-wetting phase to invade into a continuous network of pores in the matrix. Irreducible water saturation (Swir) expresses the minimum wetting phase saturation, which represent the wetting phase saturation left in the pore system at infinite high capillary pressure (Pc).

Finally, the capillary shape function (CSF) represents the change in normalized non-wetting phase saturation (Snw') as function of capillary pressure. CSF is a representation of the distribution in pore throat sizes as well as how the pore throats are connected.

CSF is in the EQR-method expressed as a function of Pce/Pc, called equivalent radius or in short EQR. Pce/Pc is a measure for the minimum pore throat radius in a connected pore system that allows the non-wetting phase to intrude.

The fundamental equation(s) for the EQR-model can be expressed as follows, where CSF(EQR) expresses CSF as function of EQR:

$EQR = Pce/Pc$ (1)

$Snw = CSF(EQR) \times (1-Swir)$ (2)

The split of the drainage capillary pressure function into three separate functions and the expression of CSF as a function of EQR has allowed a de-coupling between the three basic capillary pressure properties (Pce, Swir and CSF) and has provided a simple plotting technique for the derivation of basic capillary pressure properties for a given core sample.

Plotting of normalized non-wetting saturation (Snw' = Snw/(1-Swir)) versus EQR offers a simple way of extracting a combination of Pce, Swir and CSF for a given sample.

For, clarity of exposition, a flow chart detailing the steps in our proposed method is given in Fig. 1.

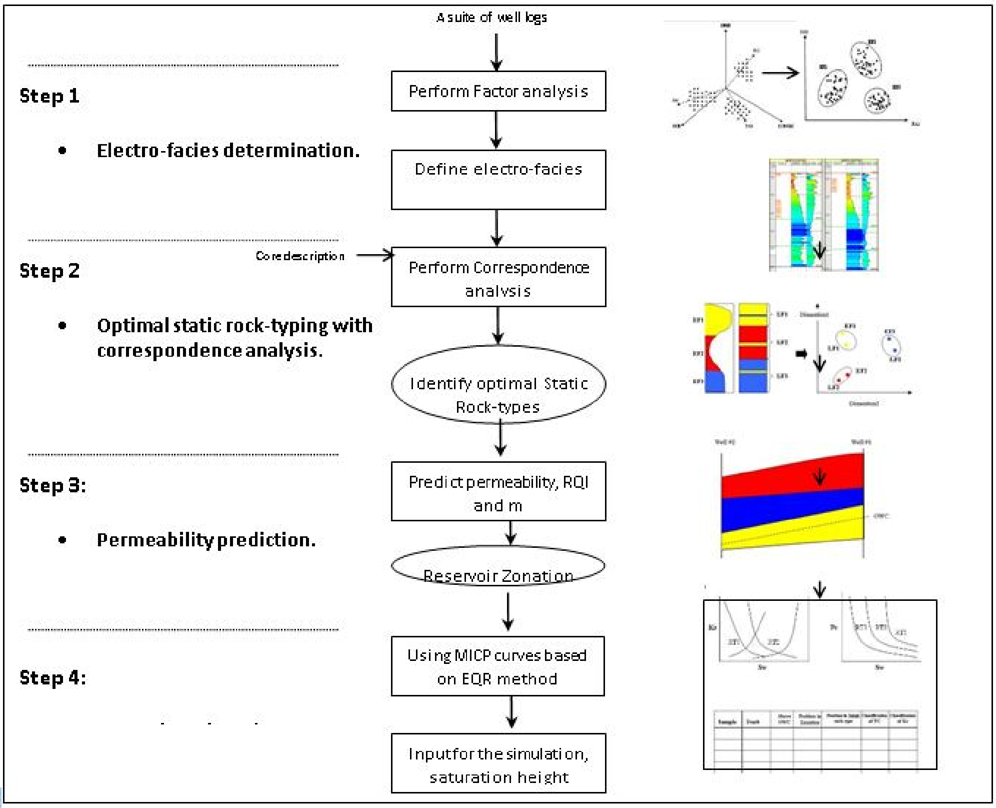

Figure1: Flow diagram summarizing the integration of data suite into dynamic rock-type characterization

3. Data Collection and Preparation

Our case study which is one of Iranian offshore oil reservoirs is located in Persian Gulf. This case study contains three formations, named as Mauddud (MD), Upper Dariyan (UD) and Lower Dariyan (LD), contains oil with different API° range from 19 to 22. All these reservoirs are slightly undersaturated; none of them contain a gas cap. All formations consist of slightly argillaceous limestone, moderately heterogeneous, without significant fracturing, with average porosity of 25% and permeability range of 1 to 5 md. DST data indicate higher permeability and well productivities as estimated from core data. The rock wettability is uncertain, so the classifications range from strongly oil wet over neutral wet to lightly water wet.

Well logs, core description, routine core analysis (RCAL) and Special Core Analysis (SCAL) are available. A suite of well logs including logs of Caliper, Gamma ray, Density, Acoustic transit time, Neutron and Resistivity, Core description for only one well is available. Core samples and plugs that are used to measure porosity and permeability were available, together with the pressure data of repeat formation tester (RFT).

All conventional core analysis data, core descriptions, special core analysis and logs are collected and validated. Then, between all of core and log data rigorous depth matching has been performed, especially for porosity curves. All of these data were qualitatively controlled based on depth shift, core-log calibration and curve values. The main objective of core-log integration in this study is to train the log to recognize permeability and RQIs. Finally, two main databases in the spreadsheet of MS_EXCEL were made. The first database includes a suite of well logs data, Core analysis data (porosity, permeability and RQI) and core descriptions. Second database include SCAL data for all of the samples and it consists of mercury injection capillary pressure (MICP), pore throats, relative permeability and wettability.

4. Applications and Results

Our proposed technique was applied for a giant carbonate in one of off-shore Iranian oil reservoir.

We start the procedure for the data available as the following:

Step 1: Electro-facies determination. First, a suite of well logs is selected for the analysis and are combined together in a data sheet. In this field, we have eight well logs: caliper, gamma ray (CGR), sonic (DT), neutron (PHIE), density (ρhob), and three different resistivity logs [lateral log deep (LLD), lateral log shallow (LLS), and microspherically focused log (MSFL)]. For more characteristics of electrofacies, ten variables of logs and ratios (caliper, CGR, DT, MSFL, LLD, density, PHIE, (Density-neutron), LLD/LLS, and LLD/MSFL) were chosen. In addition, for running the statistical methods described in this paper all of the distribution data sets were normalized if necessary.

Factor analysis was applied to obtain the principal components from well log data. With respect to the eigenvalues of the components, only three major principal components that approximately explain 81% of the variation for the whole data set was selected for the next analysis. In Table 1 the results of factor loadings as varimax rotation have been showed. The first component appears to indicate formation porosity against density. The second component shows a strong correlation with the existence of hydrocarbon, and the third component corresponds to shaleness of formation.

Then, cluster analysis is initially performed to define ten distinct groups; each cluster (electro-facies) can be treated as an electrofacies that reflects the hydrologic, lithologic, and digenetic characteristics.

Step 2: Optimal static rock-typing with correspondence analysis. In this step, we statically discuss the optimal number of electerofacies. First, correspondence analysis was used for two coupled data, one facies log-derived and the second facies core-derived. The measure of correspondence could indicate the similarity, affinity, confusion, association, or interaction between the row (coupled facies between wells) and column (facies in the well profile) variables. Table 2 shows the summary of correlation of electrofacies data (10 electro-facies) and core description data (10 litho-facies) in the well no.1, laterally.

Table 1: The results of varimax factor loadings for data set of two wells under study

Variable	Component		
	1	2	3
Rhob	0.888	-0.137	
(Density- neutron)	0.851	0.273	0.379
MSFL	0.801	0.129	-0.230
DT	-0.756	-0.337	-0.292
PHIE	0.750-	-0.374	-0.443
LLD/LLS		0.911	-0.106
LLD/MSFL		0.898	0.277
LLD	0.501	0.812	0.108
CGR	0.161		0.783
Caliper		0.549	0.637

In this analysis as you look at the summary table three dimensions were selected that their interia (a measure of the variation in the data) has the maximum distribution amount of 90 %. The first dimension displays as much of the inertia as possible about 54 %, the second is orthogonal to the first and displays as much of the remaining inertia as possible about 23 %, and third displays about 12 % of the total interia. The singular values can be interpreted as the correlation between the row and column scores and for each dimension, the singular value squared (Eigen value) equals the inertia.

Fig 2 shows two scatter plots of the row and column scores for the three-dimensional solution, which graphically illustrate the underlying relationships between electro-facies and litho-facies. A symmetrical normalization is used to distribute the inertia over the row scores and column scores.

As it is indicated both in fig 2 (a) and (b) the first dimension separates the electrofacies of 3, 4, 1 and 7(none reservoir) from other electrofacies and also the second and third dimensions show the separation of the other electrofacies.

Table 2: Summary table of correspondence analysis for two nominal variables (Litho-facies and electrofacies)

Dimension	Singular Value	Inertia	Proportion	
			Accounted	Cumulative
1	0.684	0.468	0.541	0.541
2	0.446	0.199	0.230	0.771
3	0.321	0.103	0.119	0.890
4	0.230	0.053	0.061	0.951
5	0.171	0.029	0.034	0.985
6	0.103	0.011	0.012	0.997
7	0.041	0.002	0.002	0.999
8	0.024	0.001	0.001	1.000
Total		0.865	1.000	1.000

In these bi-plots the correlation of electrofacies and lithofacies can be identified, easily. As you see the Corresponding electro-facies 1 with litho-facies 4 and 5, electro-facies 2 with litho-facies 6 and 7, electro-facies 3 and 4 with litho-facies 12, electro-facies 5 with litho-facies10, electro-facies 6 with litho-facies 8, electro-facies 7 with litho-facies 13, electro-facies 8 and 9 with litho-facies 9 and 11. Finally, with regard to these plots, graphically, the optimal number facies (we called in terms of static rock-type) was identified with the combination of well logs and core descriptions.

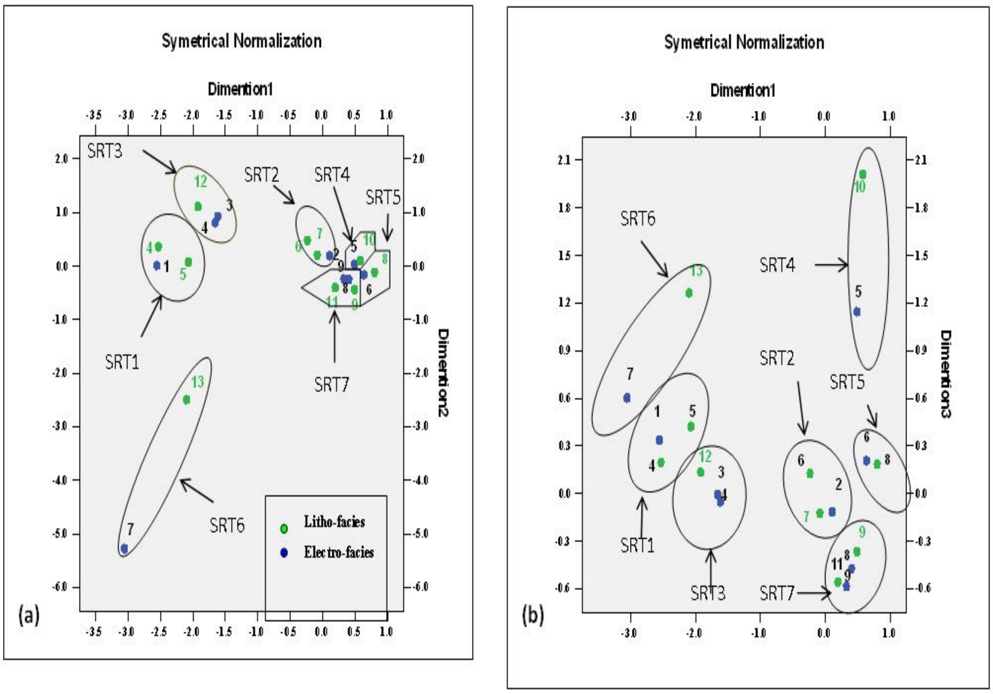

Figure 2: Biplots of electeo-facies and litho-facies correlation with correspondence analysis, Digits are facies number as nominal

Table 3: Optimal number static rock-types from the electrofacie merged with their geology descriptions

Static Rock-types Finalized	ElectroFacies Number	Description of corresponding Litofacies
1	1	Musdstone/DoloMudstone-Mudstone [4]- Skeletal Wackestone- Bioturbated, Skeletal [5]
2	2	Wackestne/Dolo Skeletal Wackestone [6]- Peloid, Skeletal Wackestone-Packstone [7]
3	3, 4, 10	Echinoderm, Oligostigina Wackestone-Packstone [12]
4	5	Coral, Rudist Boundstone [10]
5	6	Peloid, Skeletal Packstone [8]
6	7	Peloid, Pelagic Foram, Oligostigina Packstone [13]
7	8, 9	Ooid, Skeletal Packstone-Grainstone [9]- Ooid, Skeletal Grainstone [11]

It is worth noting that because there is no electrofacies in cored wells, then an allocation function is determined by discriminate analysis. So, we could find its group membership of log responses similar to electrofacies 3 and 4. Table 3 shows the seven optimal static rock types accompanying their geology descriptions. In this table the numbers in brackets are litho-facies number in correspondence analysis.

Step 3: Permeability prediction and zonation. After determining the static rock types, the relationship of porosity and permeability for each rock type is plotted which is showed in Fig 3. For the perditions permeability in the static rock types whose correlation coefficient is less than 0.8 (SRTs of 1, 2, 5, 6) neural network artificial (NN) were utilized and for the others their relationship equation was obtained.

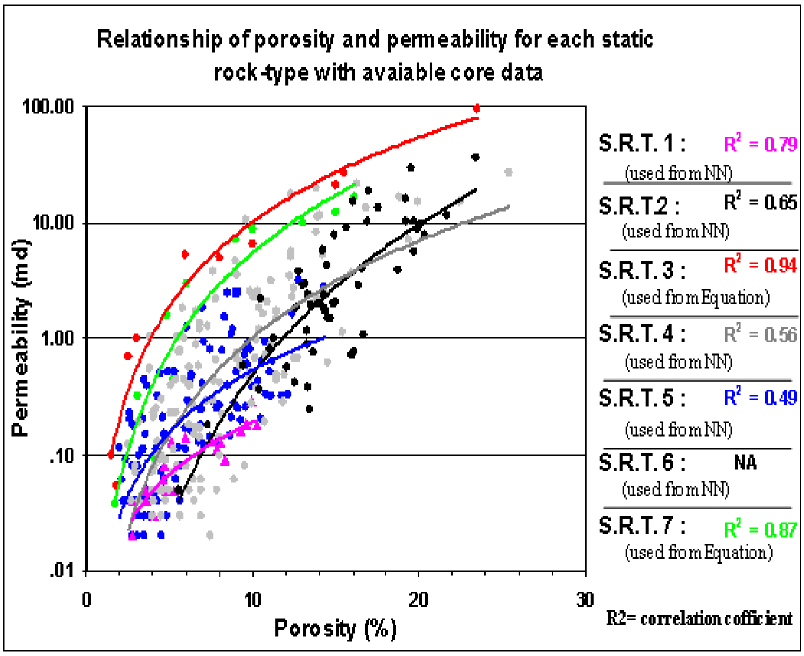

Figure3: Relationship of porosity and permeability for each SRT in well no.

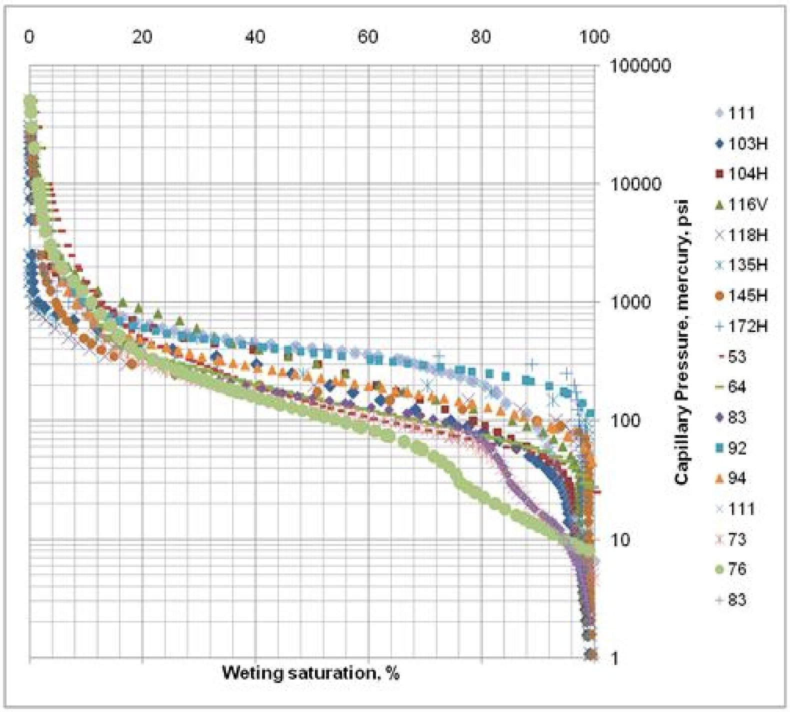

Figure 4: Mercury injection capillary pressure for available data

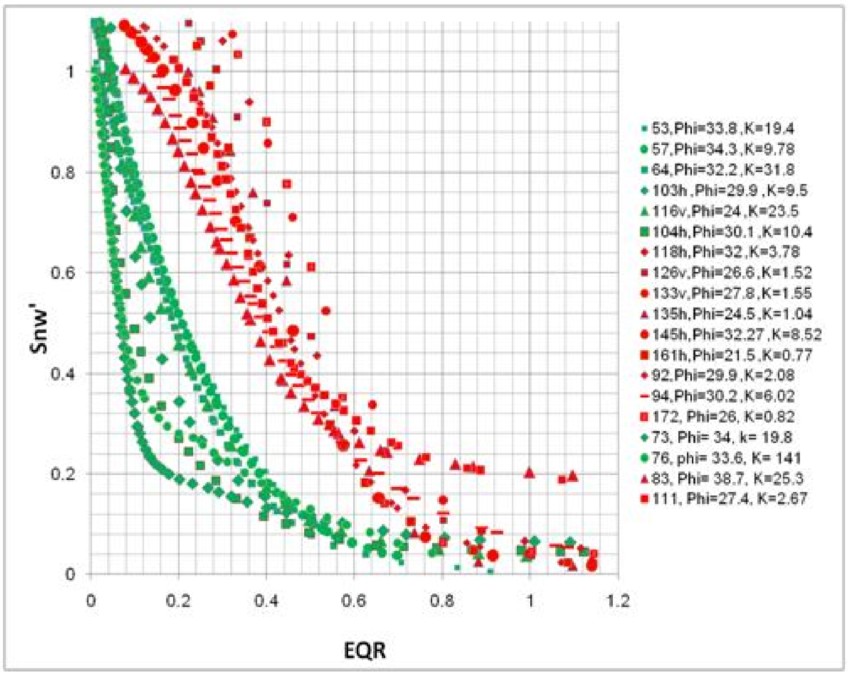

Figure 5: EQR plot for available data

Table 4: Positions of available SCAL data in zonation and SRT with their classifications

Sample no.	Well no.	Depth (m)	Position in Zonation	Position in Static Rock-type	Pc Class	k (md)	Φ (%)	RQI	Swi (%)	Sor (%)	r35 (μ)	Amott Wettability Index
s.1	2	2838.5	2	4	B	2.39	14.99	0.125	21.4	53	1.07	0.051
s.2	2	2827.5	1	6	B	23.7	23.48	0.315	27.92	36	5.38	-0.101
s.3	2	2841.4	2	4	A	15.14	22.45	0.257	27.92	33	1.15	NA
s.4	2	2849.1	2	5	A	18.6	20.72	0.3	19.5	28	1.15	NA
s.5	2	2849.5	2	5	A	15	25.43	0.24	26.94	34	1.15	-0.087
s.6	1	2728.3	1	1	B	0.132	6.41	.045	NA	NA	0.1	NA
s.7	1	2729.9	1	2	B	0.332	11.07	.054	NA	NA	0.23	NA
s.8	1	2900	4	5	A	3.02	20.29	0.121	24.82	49	0.53	0.092
s.9	1	2900.3	4	5	A	3.09	14.15	0.146	20.85	51	0.53	0.135
s.10	1	2900.6	4	5	A	0.288	10.34	0.052	11.81	58	0.53	0.162

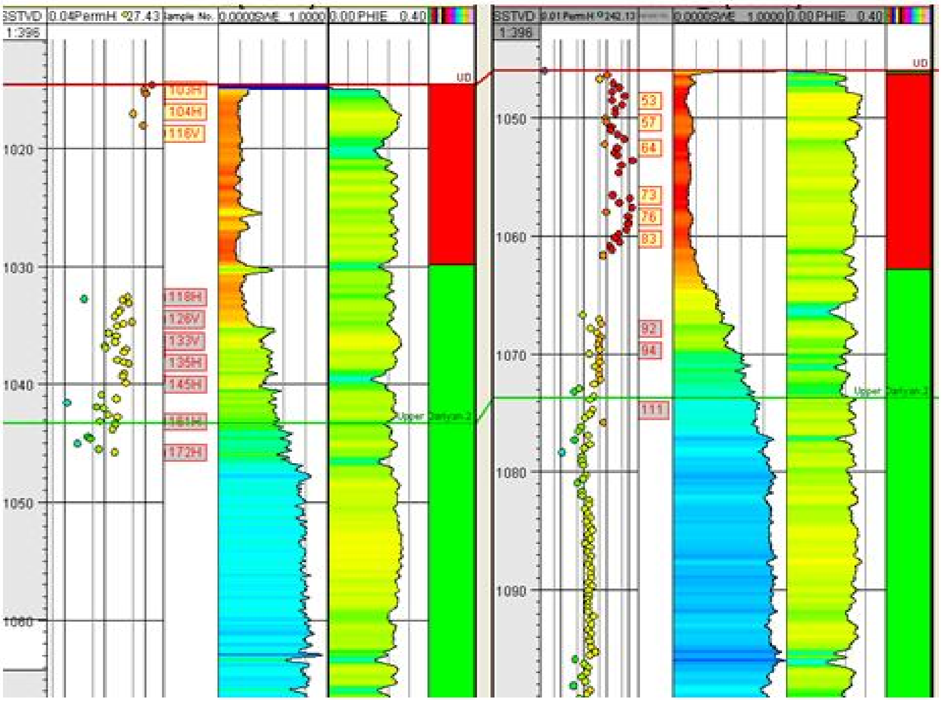

Figure6: A well section of availability MICP samples with well logs (porosity and Sw)

In NN modeling, the 356-sample data set was selected for training. Input layer consists of factor1, factor2 and factor3 resulting of factor analysis and output layer consists of core permeability and Reservoir quality index (RQI). For validation, we used the core data set from other well that was omitted for use in blind test. We obtained a strong correlation between the measured and calculated data. Overall, it indicated that the predicted permeabilitis and RQIs based on log data match well with the core data.

Step 4: Dynamic rock-typing. For a detailed description reservoir needs to be considered to have two-phase flow behavior using SCAL data. First, the cross plot of mercury injection capillary pressure curves for all of SCAL data were drawn as can be seen in Fig. 4.

With the aid of EQR graph (Fig.5) dynamic rock-types can be classified due to their shape and curvature of curves.

Next, a table similar to Table 4 was prepared that consists of the number and the depth of sample in the well, its position within included reservoir zone, its position within static rock- types, results of classification PC curves (2 class), porosity, irreducible water saturation, residual oil saturation and Amott wettability .

As you see in Fig.6, we can separate 2 dynamic rock-type in this formation that also these rock-types can be correlated with well logs properties.

In this formation, relationship of dynamic rock-types with log properties showed that this two rock-type can be correlated with an active zone in above of formation and transition zone below active zone. Fig.7 shows the capillary shape function and their equations for each dynamic rock-type in the reservoirs.

Finally, with knowing the number of dynamic rock-types, the saturation height-functions as drainage can be calculated by EQR method. According to equation 1 and 2 irreducible water saturation can be calculated using correlation of effective porosity versus water saturation in pay zone of reservoir (Fig.8).

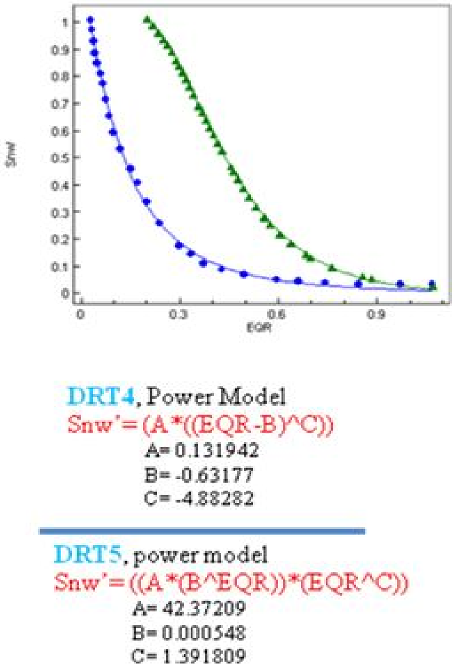

Figure7: Separation of capillary shape functions and their equations

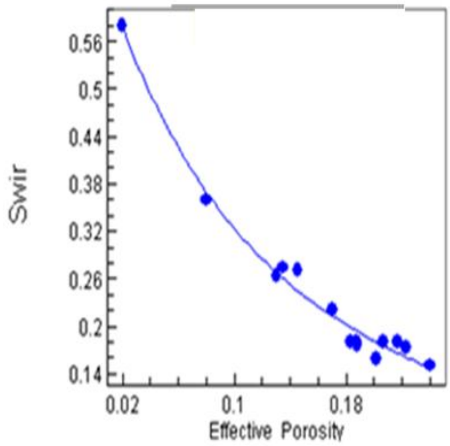

Figure8: Correlation of irreducible water saturation versus effective porosity based on pay zone

Also, saturation height functions were obtained for that was best match as has been shown in **Fig.9.**

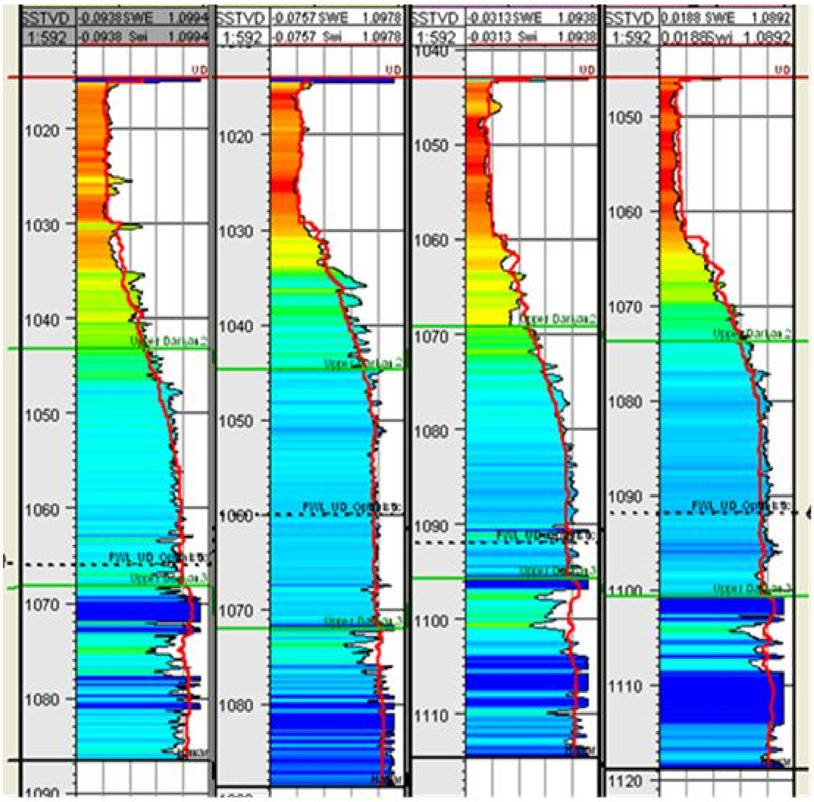

Figure9: Comparison of water saturation of measured versus calculated

5. Discussion and Conclusions

As can be seen, there are differences between static rock-types and dynamic rock-types in reservoir zonation. These differences exist despite the fact that there are not similar responses of a certain depositional environment with its fluid flow behavior. However, the differences can be attributed to the environment and included fluid and it is better to evaluate these differences in separate zones. Sometimes, the difference in the Kr curves of similar SRTs can be seen in various zones. This difference is due to variation of wettability, pore geometry, fluid distribution and its position relative to OWC. Therefore, with the aid of this method, well logs, core description and SCAL data in combination with multivariate statistical methods can be integrated. It can provide an applicable solution for the best characterization of effective rock-types in simulation models.

Several conclusions can be drawn from the data presented in this paper: A new approach has been developed to improve the rock-type characterization as static rock-types (input for geomodeling) and dynamic rock types (input for simulation models) in combination with core description, well logs and SCAL data in a giant complex carbonate reservoir. This approach works better than the industry standard methods.

1. Application of multivariate statistical methods e.g. factor analysis, cluster analysis and correspondence analysis with core description and well logs shows a significant and suitable tool for static rock-typing characterization in complex carbonate reservoirs.
2. The proposed correspondence analysis method, significantly describes the relationships between lithofacies (geological facies) and electrofacies (petrophysical facies) graphically in a multidimensional space.
3. Usually, lithofacies with electrofacies cannot be tied due to the difference of environmental conditions and different scale. Therefore, in this paper, a combination of these two as static rock types for identify optimal number facies is introduced.
4. For permeability prediction based on either neural network method or correlation equation with respect to its relationship in each SRT was applied. Consequently, strong permeability predictions were obtained.
5. There is a strong correlation between the cementation factor and RQI so that the water saturation can be accurately calculated.
6. Reservoir zonation using SRTs and permeable and impermeable regions, significantly, improve the interpretation of SCAL data for determination of dynamic rock-typing.
7. With respect to wettability data and the relative permeability curves and endpoints, the reservoir under study is a mix-wetted system.
8. Difference of relative permeability curves in similar SRTs is due to its structure position and wettability change in different zones.
9. More study on saturation -height functions for each DRT in each reservoir zone is recommended.
10. It is recommended to use well-known techniques for relative permeability correlation in Lake of Kr information.
11. It is recommended to rely on RQI, Sor, wettability and pore size cut-off to separate and assign the relative permeability curves in each zone and each rock-type.
12. It would be interesting to extend the proposed method to other reservoir wells and to use more SCAL data for obtaining the most accurate results
13. Calculation of initial water saturation as most important in volumetric calculation and simulation of fluid flow need to be developed using the saturation height-functions based on a dynamic rock-typing.
14. Saturation height-functions can be developed based on dynamic rock-typing

15. Saturation functions can be considered as end-point scaling with assuming the distribution of irreducible, residual and initial water saturation.

6. Nomenclature

RQI = Reservoir Quality Index
M = cementation factor
FA = factor analysis
CA= Cluster analysis
SCAL = special core analysis laboratory
RCA = routine core analysis
CGR = compensated gamma ray
DT = acoustic transit time
PHIE = effective porosity
LLD = lateral log deep
LLS = lateral log shallow
MSFL = microspherically focused log
FWL= free water level
OWC= oil water contact
SRT= static rock type
DRT= dynamic rock type
Pc= capillary pressure
Kr= relative permeability
Sor = residual oil saturation
Swi= irreducible water saturation
MICP = mercury injection capillary pressure
FRF = formation resistivity factor
NN =neural network
k= permeability
r35= pore size in 35% of the mercury saturation
EQR= EQuivalent Radius

7. Acknowledgments

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