INTEGRATED ANALYSIS OF CORE AND LOG DATA TO DETERMINE RESERVOIR ROCK TYPES AND EXTRAPOLATION TO UNCORED WELLS IN A HETEROGENEOUS CLASTIC AND CARBONATE RESERVOIR

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ABSTRACT

Identifying reservoir rock types and their most significant vertical and horizontal heterogeneities is an essential component of reservoir characterization process, which are among the key input parameters into a three-dimensional geological and flow simulation models.

A reservoir classification and rock typing study were carried out on the Asmari formation of the Ahwaz field, which is a mixed siliciclastic and carbonate reservoir in Iran. Detailed core analysis data including capillary pressure, core porosity, core permeability and core description were supplemented by well logs and show a complete vertical sequence of seven distinct clastic and carbonate rock types. Identification of the reservoir intervals and pay zones was carried out by means of the above results. Core based rock types were examined for each cored wells and log based rock types were selected and assigned in the uncored wells. The above data were applied as input parameters in a method based on Fuzzy Logic inference.

The Fuzzy Logic technique was calibrated in 4 cored wells and blind tested in the other cored wells to determine the rock types. After the secondary calibration of the Fuzzy Logic against the core data, this technique was applied on 28 wells without any core data. The results reveal a very good match between the core data analyses and the Fuzzy Logic determination of the rock types. This technique can be applied to reduce the uncertainty of determination of the rock typing or as a very good predictor in uncored wells.

INTRODUCTION

It is well known that accurate reservoir simulation and management requires a quantitative model of the spatial distribution of reservoir properties and an understanding of the nature of reservoir heterogeneity at many scales.
Rock type determination has presented a challenge for cases whenever no direct measurements of rock type are available. The direct determination of rock type will be carried out though the core analysis while indirect determination will be carried out through the log analyses. Typically, few wells in a field may have laboratory information such as core analysis data whereas most of wells may have electronic logs data. Wells without core are usual due to various reasons such as, time and cost associated with coring, and or impractical coring in many situations, such as in horizontal wells.

However, a method was applied based on the Fuzzy Logic inference, in some wells where core data are not available, to determine the reservoir rock types from wire-line logs data in the Ahwaz Asmari reservoir.
The Asmari formation in the southwest of Iran is one of the most important reservoirs in the world. This formation is predominately a carbonate unit, but in the central area of the Dezful Embayment, it is a mixed siliciclastic and carbonate reservoir. The Ahwaz field is situated in an area where the sandstones are interbedded with the carbonate rocks.

CORE STUDY

The core study approach was conducted on:

1) Sedimentological description of more than 2000 m of cores from 17 wells.
2) Microscopic study of more than 6000 thin sections from different cored wells.
3) Study of 16 samples from different rock types by Scanning Electron Microscopy.
4) Conventional core analysis of more than 1500 core plugs.
5) Mercury Injection Capillary Pressure, *MICP*, curve analysis on 16 core plugs.

Mineralogy, Rock Fabric and texture

Thin section petrographical analysis were carried out to determine mineralogy, rock fabric, texture, pore geometry and distribution, grain characteristics, diagenetic features and sedimentary structures for more than 6000 side wall core thin sections from 17 wells. For a detailed identification of the above characteristics, Scanning Electron Microscopy, *SEM* analysis was carried out on 16 samples selected from various rock types of wells.

Based on the petrographic observations, the rock composition of the Ahwaz-Asmari reservoir varies between siliciclastic and carbonate lithologies. In this reservoir quartz and dolomite are dominant minerals while calcite, anhydrite, clay minerals, potassium feldspar and Iron oxides are among other abundant minerals. Carbonate rocks in the reservoir show a highly variable depositional Fabric and texture. In the present study, the Dunham's classification, 1962, was applied [5]. Fabric and textural characteristics in this method depend on the depositional environments and particle types. Most of petrophysical properties, such as porosity, permeability, water saturation, mercury injection and capillary pressure data depend on fabric and textural characteristics. Siliciclastic sediments show a relatively consistent depositional fabric. In the silicilastic rock study, the great emphasis was placed up on textural attributes such as: grain size, sorting, roundness, puerility and maturity. Grain size is a highly variable and ranges in extreme cases between silt and very coarse sand grade. Sorting of various sediments ranges from poor to very well sorted with a mode of moderately well sorted.

Porosity-Permeability relationship

The permeability-porosity relationship by means of cross-plots was studied for various rocks types. In summary graphs presented in Figures 1-2, permeability-porosity trends for siliciclastic and carbonate rock types were plotted together. The results from these cross-plots study reveal that the permeability of the sandstone (Figure 1) is well defined by the porosity, whereas in the carbonate (Figure 2) has a more diffused clouds which indicating to other major factors affecting the permeability. High porosities in carbonates can be observed that does not give rise to high permeability. This property of carbonates can be interpreted as poor connectivity of the vugs. Large intra-clast mesoporosity is also a possible cause if the intra-clast porosity is connected through very small pores.
In the clay cemented sandstones, high porosity can be observed. This high porosity is mainly in the form of micro–porosity filled with chemically and physically (capillary) bound water, which is immobile. Since this high porosity does not take place in fluid flow, the permeability in the clay-cemented sandstones is low.

However the clusters of points for each rock type are not totally distinct from each other. The overlapping of depositional lithofacies in these graphs is probably cause by a number of factors including diagenesis, fracturing, similarity in pore structure produced by different depositional environment and the somewhat subjective nature of specifying rock type based on hand specimens.

Mercury Injection Capillary Pressure Curves

Mercury injection capillary pressure curves were applied to determine the pore throat size distribution of the porous rocks in the reservoir. Sixteen samples, were selected, described, photographed and made into thin sections for mercury injection capillary pressure analysis. These samples were prepared from conventional core plugs when routine core analysis was carried out on them. The reservoir samples were converted from laboratory air/mercury system to the subsurface brine/hydrocarbon system of the reservoir then the mercury injection data was applied to the reservoir samples. MICP results and pore throat size curves for selected samples are shown in summary graph, Figure 3, and summarized in Table 1. Capillary pressure data were applied to distinguish between reservoir and none-reservoir rocks, pay and none-pay, on the basis of none-wetting-phase saturations (see Table 1). This will be carried out based on empirical evaluation of a large database of reservoir rocks from fields throughout the world (Snedeir, 1987). Pore throat radius was applied to categorize the rock by pore-type, e.g. nanno, micro, meso, macro and mega.

IDENTIFYING ROCK TYPES IN CORED WELLS

Development of a rock–fluid model in the Ahwaz–Asmari reservoir was carried out with the input data from the geological and petrophysical results. The results were applied to identify various rock types in the reservoir, poor reservoirs or non-reservoir rocks. A rock type is defined as an interval of rock with unique pore geometry, determined mineralogical composition and is related to certain specific fluid-flow characteristics.

The first attempt in this study was to apply porosity-permeability ratio criteria from the routine core analysis to classify the rock type. Then these criteria were compared with visual porosity, characterized from microscopic studies in addition to the results based on log data. MICP curves were analyzed to confirm validity of the rock type classification. The capillary pressure data was also applied to distinguish reservoir rock from none-reservoir rock and pay from none-pay. A better understanding of the behavior of capillary pressure curves will be achieved when it is integrated with the information provided by the thin sections and SEM micrographs.

The reservoir rock porosity, permeability and pore throat radius ranges, by rock type are presented in Table 1. However, in this study seven rock types were designated and identified from RT1 to RT7 with individual pore geometries, mineralogy, and fluid-flow characteristics, in the Ahwaz-Asmari reservoir. In addition, by applying these criteria, the reservoir was divided into eight zones.

Table 1. Summary of petrophysical and geological properties for various rock types

Petro-physical Parameters		RT1	RT2	RT3	RT4	RT5	RT6	RT7
Lithofacies		Friable to Partialy Cemented Sandstone	Anhydritic Consolidated Sandstone	Claystone, Silticlaysone, and clayey silitstone	Grainstone / Packstone	Crystaline Dolostone / Sandy Dolostone	Anhydritic Dolostone/ Sandy Dolostone	Nodular Anhydrite
Porosity Characteristics	Maximum Air Porosity(%)	35.4	29.2	29.3	22.3	30.7	17.6	17.8
	Minimum Air Porosity (%)	12.0	1.0	0.4	0.2	1.9	0.4	0.1
	Average Air Porosity (%)	27.4	13.4	11.6	7.4	15.3	7.4	2.4
	Air Porosity	Excellent(E)	Moderately(M)	Moderately(M)	Fair (F)	Good(G)	Fair (F)	Low (L)
	Interparticle Porosity(%)	95.8	84.6	100	29.3	9.9	9.7	50
	Vuggy Porosity(%)	4.2	14.1	0	42.7	65.4	72.2	0
	Interaparticle Porosity(%)	0	0	0	25.6	9.9	6.9	0
	Moldic Porosity(%)	0	0	0	1.2	11.1	6.9	0
	Intercrystaline Porosity(%)	0	1.3	0	1.2	3.7	4.2	50
Permeability Characteristics	Maximum Heliume Permeability (md)	3000.00	1243.00	63.30	233.00	577.72	41.53	23.25
	Minimum Heliume Permeability (md)	2.15	0.01	0.01	0.01	0.02	0.01	0.01
	Average Heliume Permeability (md)	690.04	81.73	7.08	4.31	23.32	1.83	0.83
	Heliume Permeability	Excellent(E)	Good(G)	Fair(F)	Fair(F)	Good(G)	Fair(F)	Low(L)
MICPM Characteristics	C-factor (Measure of pore sortihg)	Medium(M)	Medium(M)	Good(G)	Medium(M)	Poor(P)	Medium(M)	Medium(M)
	Sm (Unsaturated pore volume) (%)	Low(L)	Medium(M)- High(H)	High(H)	High(H)	Medium(M)	High(H)	High(H)
	Pd (Entry pressure) (psi)	Very Low(VL)	Medium(M)	Medium(M)	High(H)	Low(L)	High(H)	High(H)
	Pore Size Distribution (MICPM)	Meso-Mega	Micro-Meso	Micro	Micro-Meso	Micro-Mega	Micro-Meso	Nano-Micro
Reservoir Quality		**Net Pay**	**Net Pay**	**Non Reservoir**	**Non Reservoir**	**Net Pay**	**Non Reservoir**	**Non Reservoir**

ESTIMATION OF ROCK TYPES APPLING FUZZY LOGIC

Fuzzy Logic

Fuzzy logic is an extension of conventional Boolean logic (zeros and ones) developed to handle the concept of “partial truth” values between “completely true” and “completely false”. In contrast to binary-valued (bivalent) logic, truth is ascribed either 0 or 1, multivalent logic can ascribe any number in the interval [0,1] to represent the degree of truth of a statement. This is a normal extension of bivalent logic, and it is a form of logic that humans practice naturally. Dr. Lotfi Zadeh, an Iranian professor of UC/Berkeley introduced it in the 1960's as a means to model uncertainty [8].

More common use of fuzzy logic is to describe the logic of fuzzy sets (Zadeh, 1965). These are sets that have no crisp, well-defined boundaries, and which may have elements of partial instead of full membership. For fuzzy sets, elements are characterized by a membership function that describes the extent of membership (or the degree of fit) of each element to the set. Such a membership function maps the entire domain universe to the interval [0,1].

Fuzzy mathematical techniques have been applied to solve various petroleum engineering and geological problems in the past, involving mainly classification, identification, or clustering. Toumani et al. (1994) used fuzzy clustering to determine lithology from well logs in Upper Carboniferous coal deposits of the Ruhr basin[2]. Cuddy (1997-2000) used fuzzy logic to predict permeability and lithofacies in uncored wells to improve well-to-well log correlations and 3-D geological model building [3,6,7]. Saggaf and Nebrija, 2003 used fuzzy logic approach for the estimation of facies from wire-line logs in a field in Saudi Arabia [4].

Application to well data

The Fuzzy Logic inference method was applied to identify and determine the kind of rock type in the uncored wells based on data from wire-line logs in the Asmari-Ahwaz field. Rock type determination applying the Fuzzy Logic is based on the fact that a known rock type can give any log reading although some readings are more likely than others. In this method several conditions based on wire-line data were applied to determine the rock type and reduce the uncertainty of the determination. As an example, two rock type will be discussed here, partially cemented sand (RT1) and shaly sandstone (RT3). Partially cemented sand has most likely high porosity and low gamma ray radiation while shaly sandstone has low porosity with high gamma ray radiation. It is obvious that the Fuzzy Logic inference is not just a simple probabilistic method. It is based on measured data.

The membership functions are based on determination of rock type applying the wire-line data and core description. The core determinations were derived from examination of known rock type of cored wells in the area. These membership functions will be applied to identify the rock types in an uncored well by means of wire-line log. There is no limitation on the number of input logs in this method. However, the additions of more curves may possibly not reduces the uncertainty of the determination of rock type, but, it is important to have a consistent set of logs in all wells. A sensitivity study was carried out based on five selected logs due to their relative importance in rock typing. These logs are: gamma ray (GR), effective porosity (PHIE), neutron porosity (NPHI), density (RHOB) and sonic (DT).

The membership distribution for effective porosity log in RT1 and RT6 as an example are presented in Figure 6. The membership functions were calculated from the logs and core-derived rock types in four cored-wells (B, C, D and E). In order to test the uncertainty of the determination of rock type by Fuzzy Logic method the cored-well **A** was selected and core data from other wells were applied in this well. The core description in this well was applied for a comparison with the result from the Fuzzy Logic and calibration of the input data of the method. The core-derived determination of rock types from well **B** displays in the last track of Figure 7 while the Fuzzy Logic determination displays in the last but one track. The logs of the test well **A** were passed through the Fuzzy Logic inference system to determine the rock types in this well. This determination was compared with core description from this well, see Figure 8. The determination of rock type based on the Fuzzy Logic is in agreement with the result from core analysis. This comparison between two methods reveals a good to very good results. The core analyses from 5 cored-wells were applied to determine rock types in 28 uncored wells.

These rock type's determinations were combined with the geometry of the reservoir to construct a representation of the initial (static) state of the reservoir, having a specified resolution, quality and accuracy. The section is shown in Figure 9, represents the estimated rock types over the whole field applying a geostatistical method.

CONCLUSION

High uncertainty occurs when the determination of the rock type in an uncored well will take place. Rock typing was applied for well correlation and as input data to build a 3D model of the reservoir. In this study an intelligent method was applied for rock-type analysis through the integration of core, conventional open-hole logs and geological data.

The Fuzzy Logic is inherently well suited to characterizing vague and imperfectly defined knowledge, and it can thus yield a simple and more accurate description. The Fuzzy Logic inference system allows an engineer to incorporate his basis and previous knowledge and experience, as well as general engineering principles and notions, into the inference process. Application to well data indicates that the method can determine the rock types of uncored wells with a good accuracy that rivals those of other methods, such as methods based on statistics. This method can be applied to reduce the uncertainty of determination of the rock type or as a very good predictor in uncored wells.

Applying this method requires only the standard electronics logs such as porosity and density than complex and special logging system.

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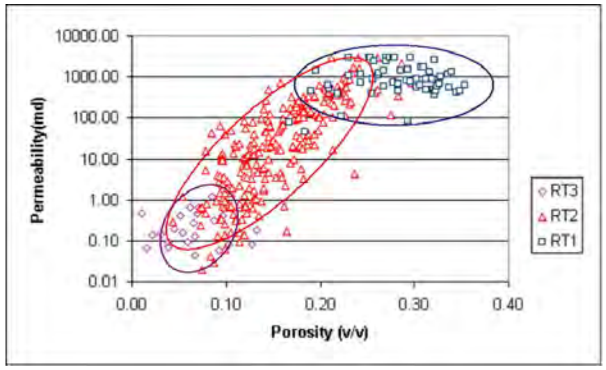

Figure 1.Permeability versus porosity, siliciclastic rock types.

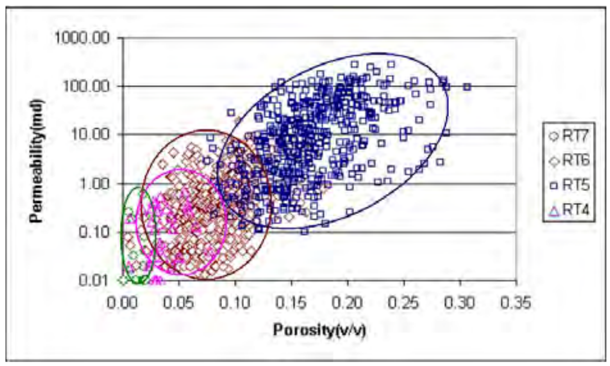

Figure 2. Permeability versus porosity, carbonate rock types.

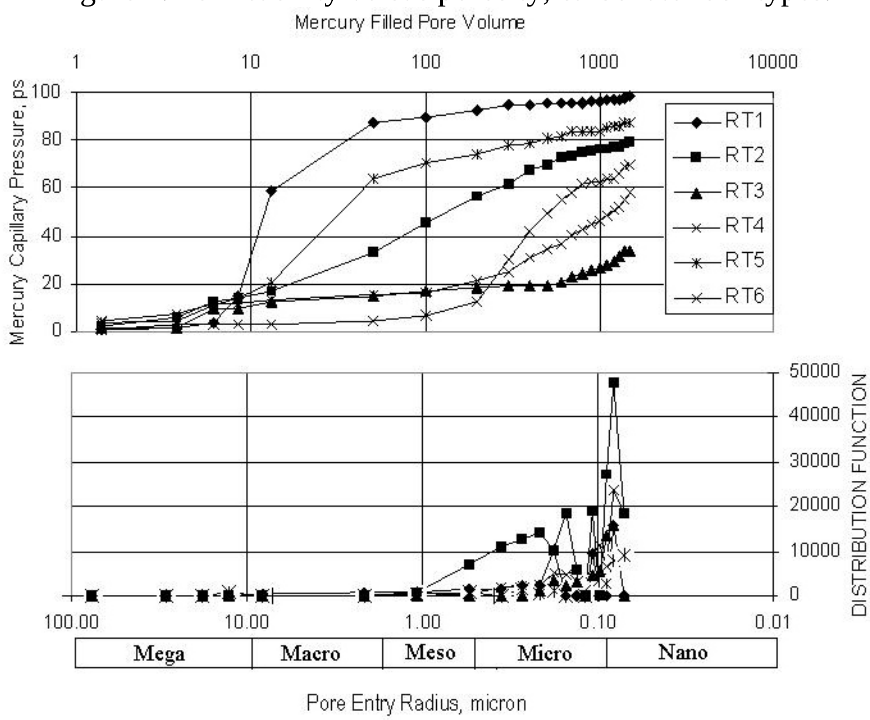

Figure 3. Capillary pressures, mercury injection method.

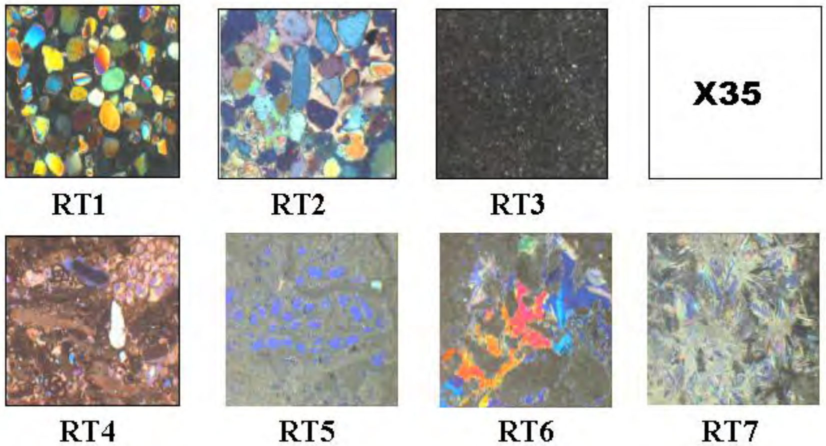

Figure 4. Thin sections Photos of various rock types.

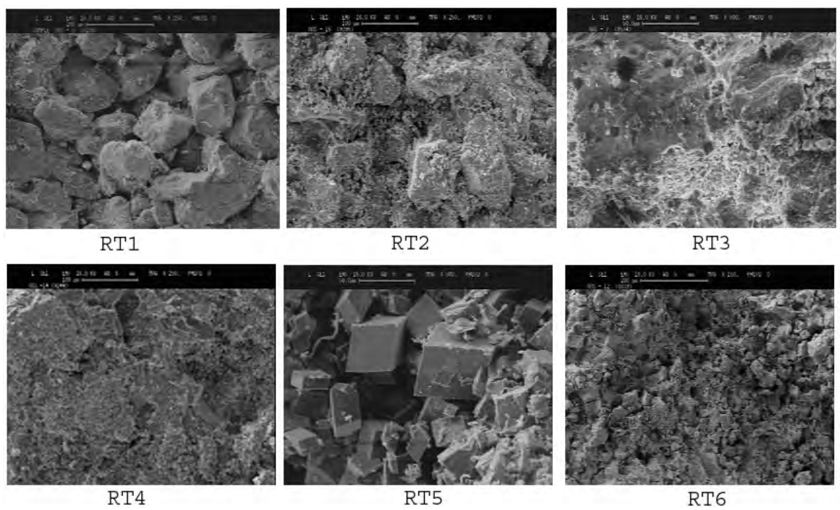

Figure 5. Scanning Electron Microscopy, SEM photomicrographs.

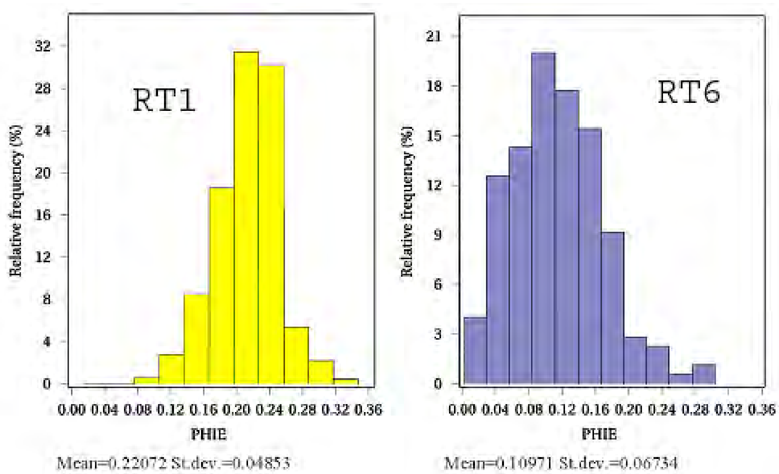

Figure 6. Membership distributions for porosity log in RT1 and RT6.

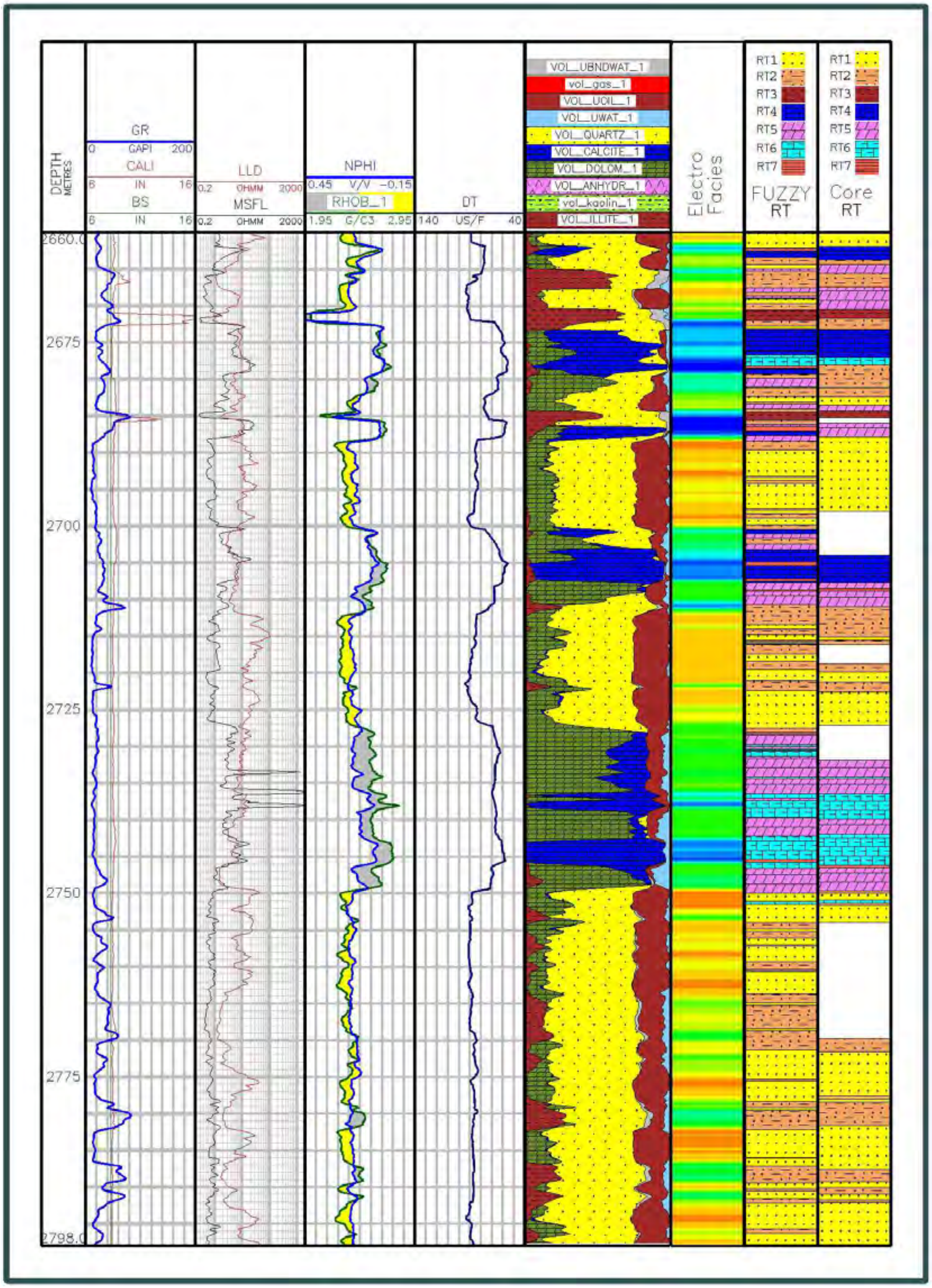

Figure 7. Comparison of the rock types determination between the Fuzzy Logic inference method and rock type determination based on core analyses, the two last tracks. The first track represents log data and interpreted lithology and facies respectively.

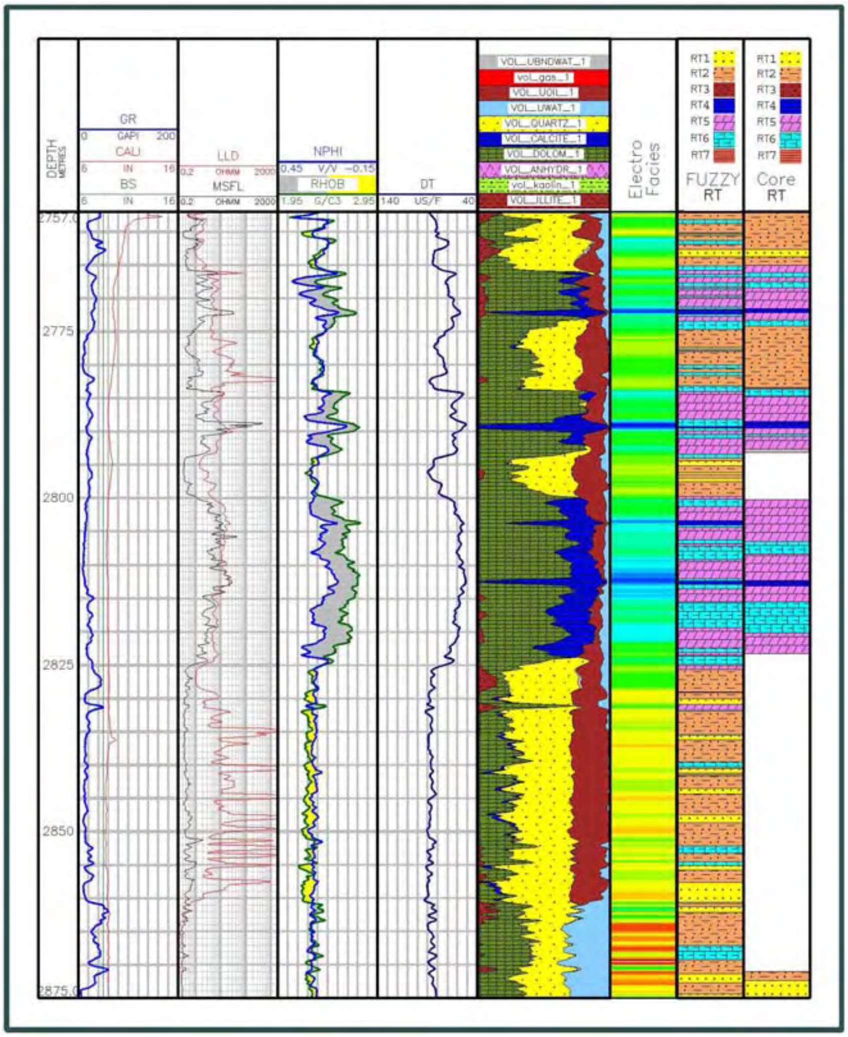

Figure 8. Blind-testing prediction in the test well **A**.

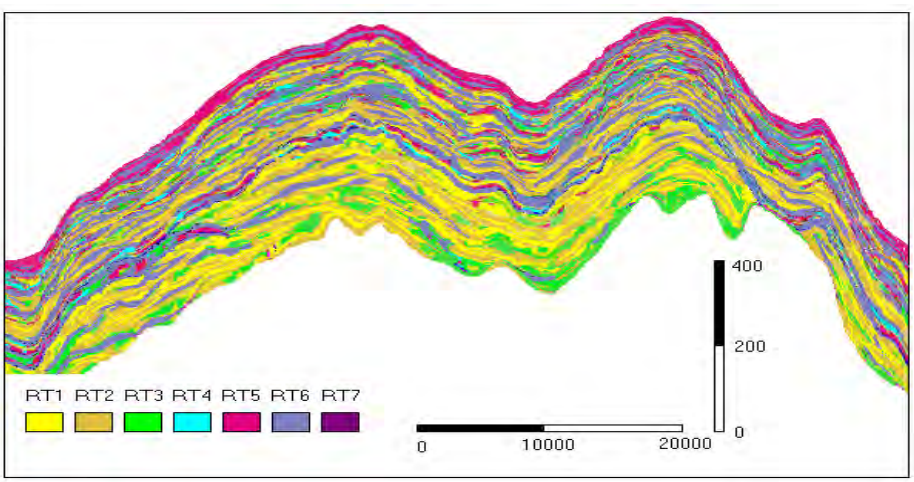

Figure 9. Cross section showing estimated reservoir rock types over the field.