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Implementation of Machine Learning for Petrophysical Reservoir Characterization in a complex Carbonate Reservoir, a Case study on Miocene Carbonate, offshore Gulf of Suez, Egypt.

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ABSTRACT

Characterization is the backbone of any oil and gas field development strategyc Reservoir quality and distribution among the field is a key Defining the flow units in the context of parameter in that reservoir characterization, modeling, and predicting the reservoir performance for optimum productivity. This is a complex and challenging task for the astic reservoirs because of the horizontal and vertical carbonate reservoirs rather than cl permeability relationship being-genesis that leads to the porosityaheterogeneity due to di inconsistent for specific flow units.

This study demonstrates the followed workflow to define the "Hydraulic Flow Units (HFU) for the Miocene carbonate reservoir in Al Hamd Field offshore the Gulf of Suez of Egypt. ure "MICP", The data from the conventional core analysis, mercury injection capillary press open hole logs, and image logs from 2 cored well and 10 uncored wells were used in the The Input data were quality checked for consistency including depth matching, .study normalization calibration, and.

The number and quality of the flow units were defined by integrating the geological and Petrophysical data (poro-perm relationships) and verified by the dynamic data such as well test and formation pressure results. Many graphical methods tried to define the flow units in the cored wells using porosity and permeability data including Reservoir Quality Index (RQI), Flow Zone Indicator (FZI), Winland R35, Pittman, and Lucia. The boundaries The results were verified by .plot between different flow units were defined using the Lorenz reservoir engineering data. Different machine learning techniques were used to predict the flow units in uncored wells using the open hole logs including multilinear regression to ncored wells, then ran the principal component predict continuous permeability in the u analysis to reduce the number of logs

The Neural Network, Fuzzy Logic, Cluster Analysis, and Self .keep the same variability and .to predict the discrete flow units from logs data were employed Organizing Map

The results were validated by contingency tables and the blind test techniques. The resulted final and continuous flow units give a new input data between wells without any additional

t model for the dynamic costs which are used as a discriminator to generate a saturation heigh reservoir simulation and lead to production optimization and new opportunities to be .predicted

Keywords:
Carbonate reservoir, Hydraulic Flow Units, Reservoir characterization, Machine learning, Saturation Height function

ABSTRACT EXTENDED

Introduction

Machine learning is an application of AI or Artificial Intelligence, that permits systems to learn and improve from the available data that focuses on analyzing and interpreting patterns making outside of -ng, reasoning, and decisionand structures in these data to validate learni .human interaction

of ML is for curve and pattern prediction and its eus In this paper, we will show how efficient and ,as carbonate s suchmaking regarding complex reservoir-valuable application in decision how this affects the production performance of any reservoir. Using two basic approaches: and unsupervised learning (without to help prediction) labeled data(supervised learning (ollowsto learn from. We made this through major seven steps as f) labeled data

- Collecting Data: used all available data from the core of two wells and logs data from ten wells.
- Preparing the Data: remove any missing values or outliers.
- Choose a model and learn from it by applying it to the two key wells having cored data.
- Train the Model on the uncored wells.
- Evaluate the Model by comparing the results.
- Parameter Tuning and QC for the predicted curves.
- Propagate the resultant curves over all the field.

The fact is similar facies types that are deposited in the same depositional environments, in most cases show divergent Petrophysical characteristics that have a great effect on the porosity-permeability relationship, water saturation, and capillary pressure. so dividing the perm figure and capillary pressure -eservoir into different flow units depending on the poror profile is a must to predict reservoir production performance.Flow unit is a key and basic unit concerning the fine description of the future reservoir (Amaefule, 1993) and this is what will be explained in the paper on how to link all the available data to transform the reservoir character from a static perspective to a dynamic one using the privilege of ML approaches to predict fluid flow and connectivity, Figure 1.

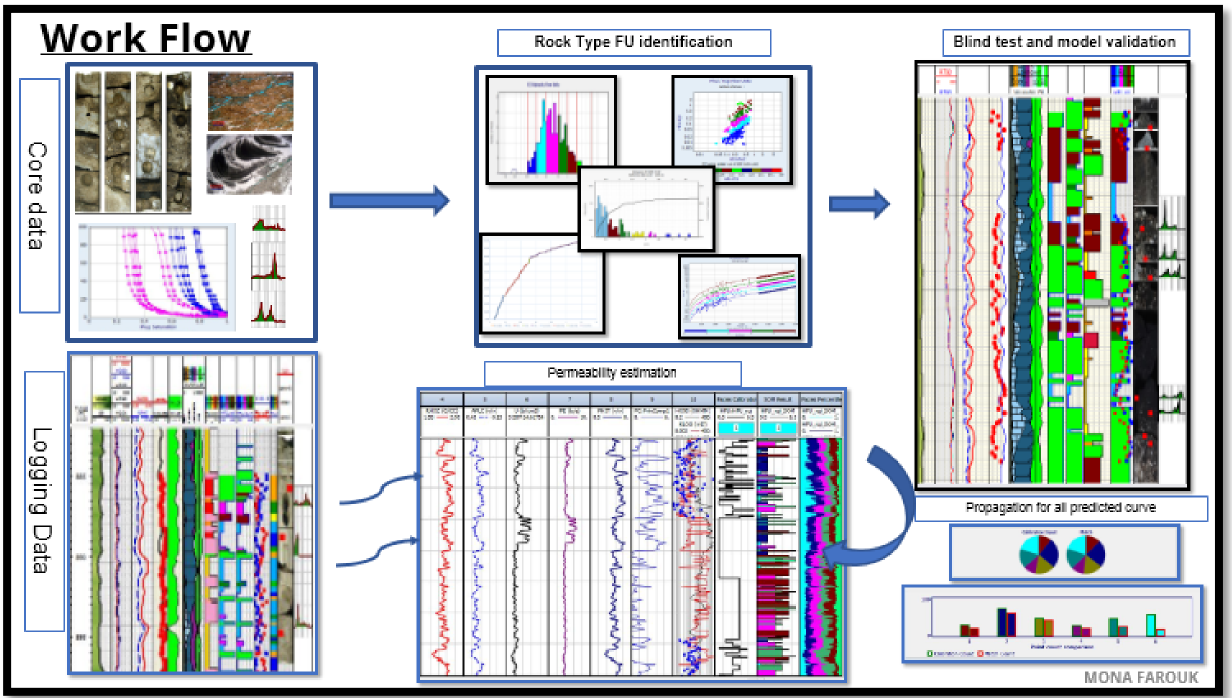
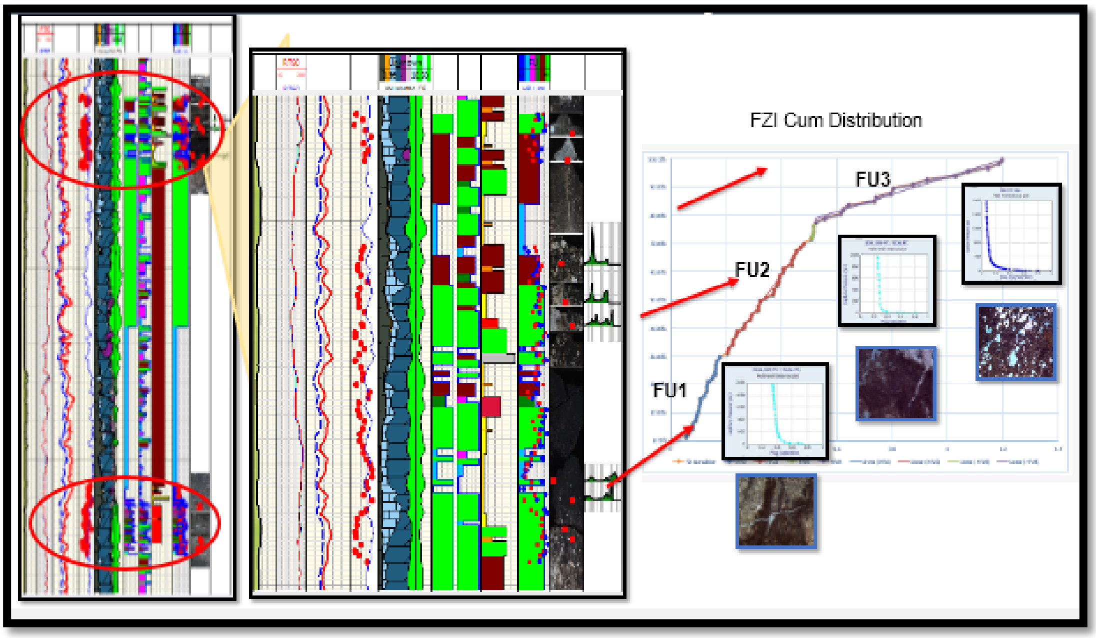


Figure1: Work Flow of this study for HFU model via integrating all data from logs core thin section and MICP

Methods

Rock typing is classifying reservoir rocks into distinct units, these units are deposited under similar conditions and they have experienced the same digenetic processes. this results in a unique porosity-permeability relationship, similar capillary pressure profile and same water saturation for a given height above the free water level for each rock type (Archie, 1950). Log and Core analysis (routine & special) data were used from two key wells figure 2,to classify reservoir into distinctive flow units using different methods as: Reservoir Quality Index(RQI)/Flow Zone Indicator(FZI)figure 3, Winland porosity-permeability plot (R35) figure4, Pittman R35 figure 5, Lucia RFN Classification figure 6, Then Using the initiated Hydraulic Flow Units (HFU) curve for each core point to develop a predictive model to create HFU from logs at every depth in each well, using ML approaches via supervised learning method as fuzzy logic figure 7, multi linear regression (MLR) and un -supervised learning method as K-means Cluster analysis, Logic and principal component analysis(PCA) figure 8, via python libraries like (Panda-Numpy-Matplotlip) Use Hydraulic Flow Units permeability via line formula to generate permeability at every depth in the-multi selected Functions for each Flow Unit from core Pc data Use predicted HFU as -wells Generate J



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well After model validation using section from geological model to identify FU continuity.

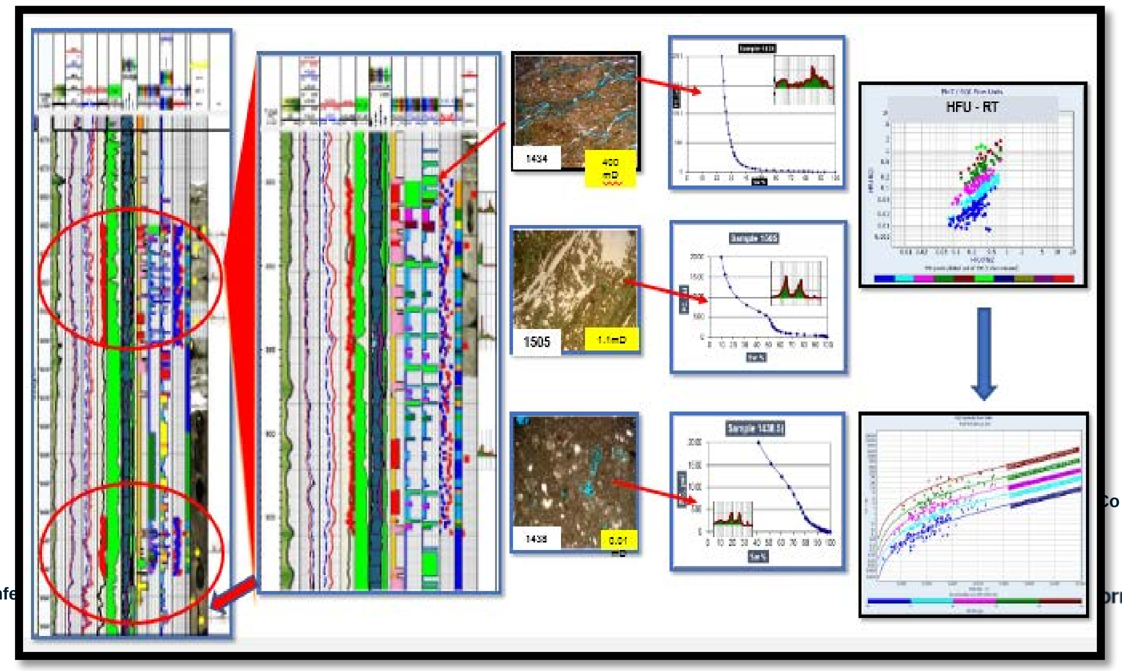


Figure2: two key wells used to establish our HFU model via integrating all data from logs core thin section and MICP

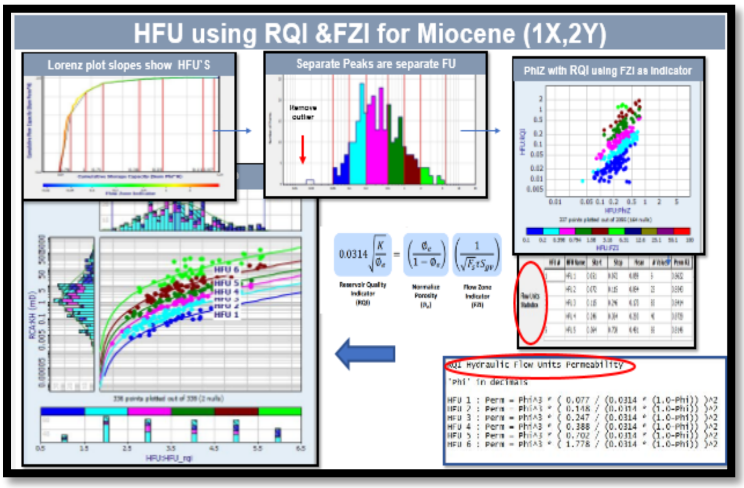


Figure3: HFU using RQI

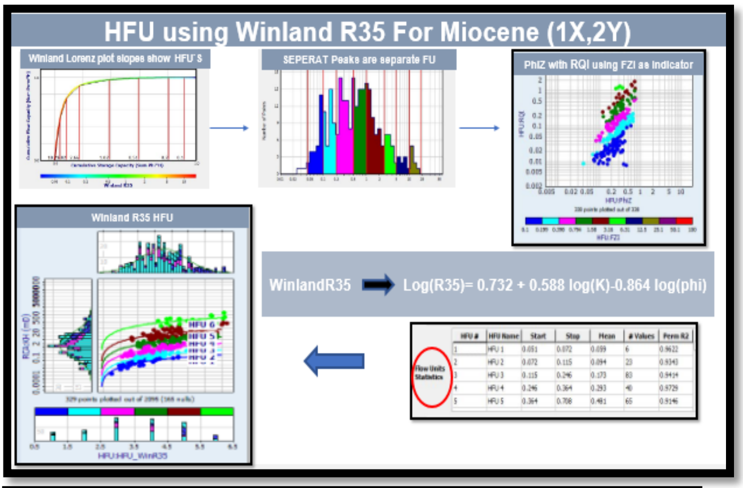


Figure4: HFU using Winland R35

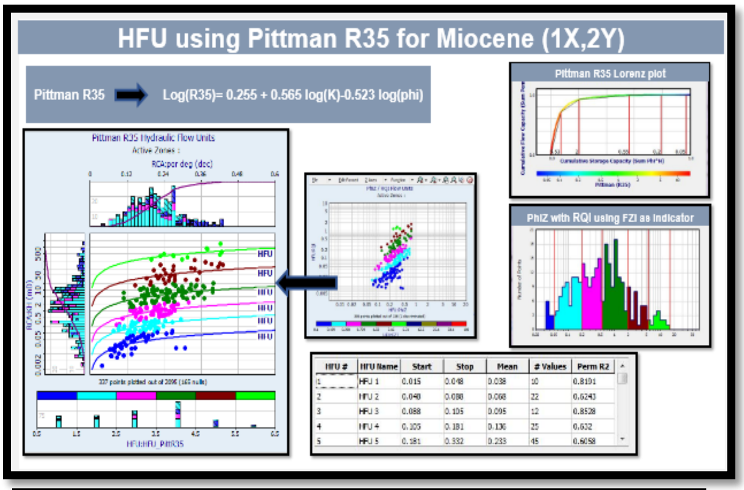


Figure5: HFU using Pittman R35

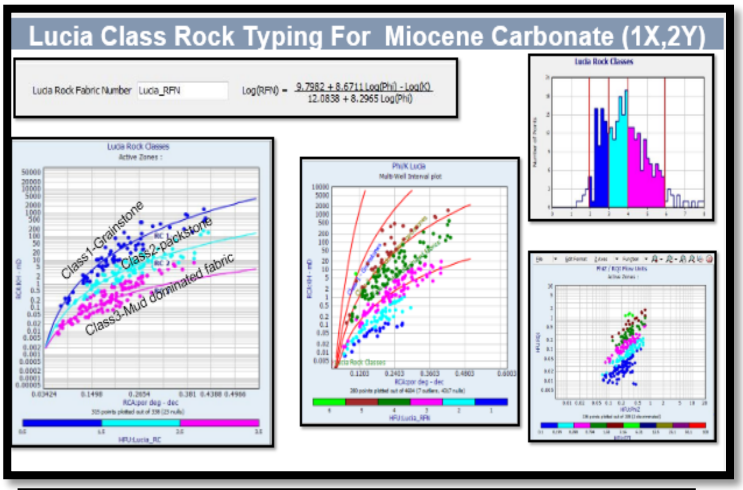
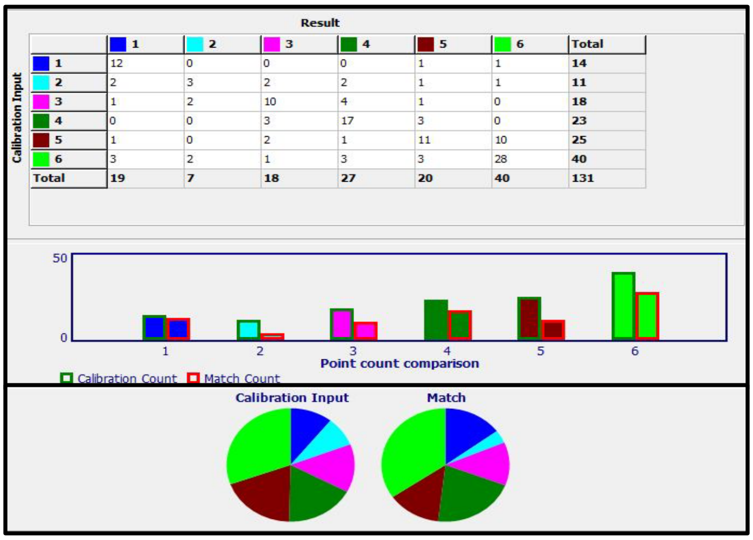


Figure6: HFU using Lucia RF

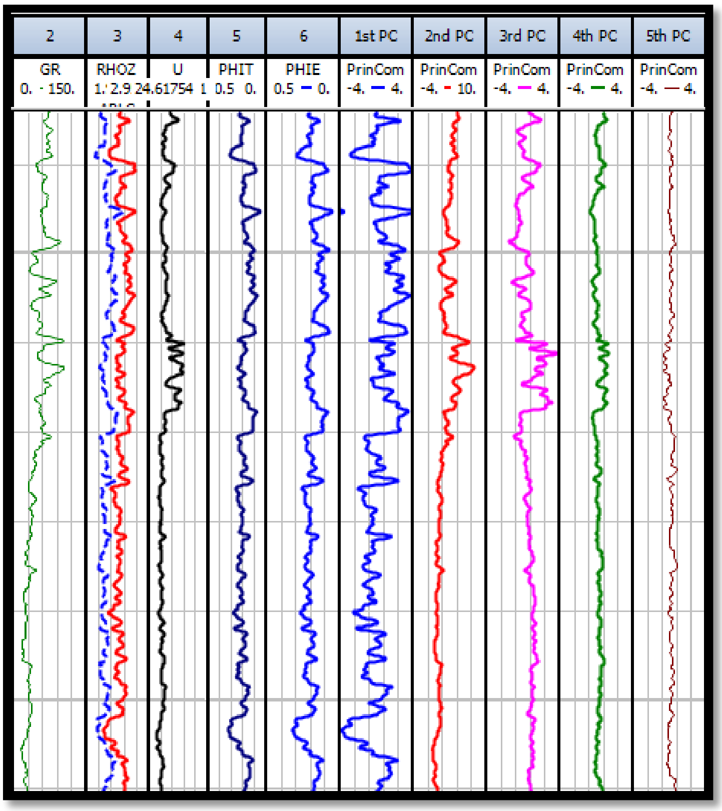
Result and Interpretation

From the above figure we notice that we could identify 6 flow units represent the studied intervals and we confirm this from more than one methods as shown (FU 1 is the lowest quality and FU6 is the highest one). after we build our model we will propagate it to the uncored intervals and then run contingency analysis method to validated the match percentage between calibrated intervals to the real one figure 9, after validation step we start to create PCA to reduce multi-dimensional data sets to lower dimensions for analysis that improve to a great extent next algorithms performance hence we used them as an input during other ML methods, 1st pc will have the largest possible variance in data figure 10,11



	1	2	3	4	5	6	Total
1	12	0	0	0	1	1	14
2	2	3	2	2	1	1	11
3	1	2	10	4	1	0	18
4	0	0	3	17	3	0	23
5	1	0	2	1	11	10	25
6	3	2	1	3	3	28	40
Total	19	7	18	27	20	40	131

Figure11: contingency analysis shows very good match between calibrated FU from core and predicted one using Fuzzy logic



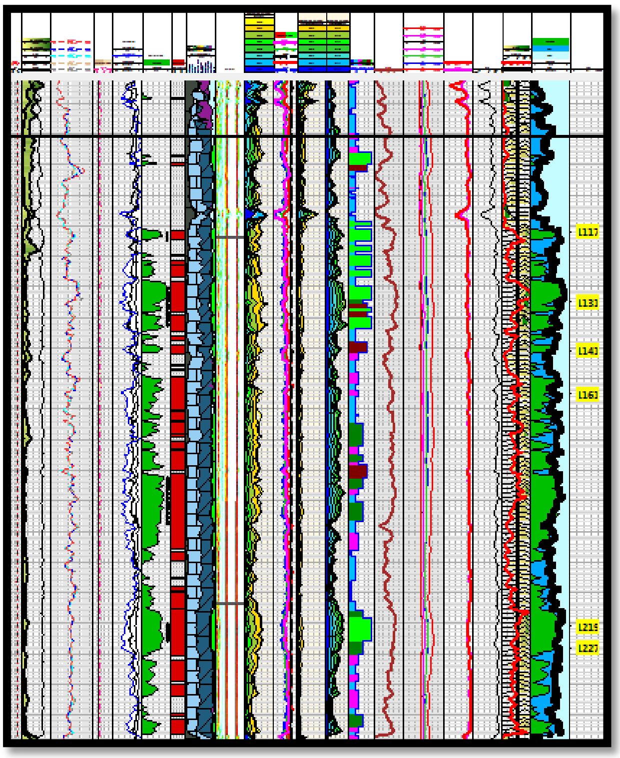
Output	Curve Name	% Variability
✓	PrinComp1	62
✓	PrinComp2	20.9
✓	PrinComp3	8
✓	PrinComp4	6.9
✓	PrinComp5	1.5
✓	PrinComp6	0.5

Figure11: in the above data >80 % of the total variability in the data can be seen in the PC1 & PC2 curves Hence the first 2 curves will contain 86.4 of the variability. so we have reduced the information in the 7 curves input to 2 curves. That will be used in each method for curve prediction.

Figure10: PCA results after making normalization for each input curve.

After model validation using blind test on one of the key wells well figure 12,we propagate model to other uncored wells using Fuzzy logic figure 13, and K-means methods to compare the results with more than one approach to fine tuning the results and then make use of predicted FU curves to create permeability curve using user input formula and again run a blind test on wells have permeability from NMR and show very good match we also use MLR to create K permeability curve used KSDR curve to learn from and compare the resulted curves figure 14 (K from ,NMR ,FU, and MLR) finally we calibrate our results with production data from production log for 4 wells beside as we using predicted FU as discriminator to build saturation height model.

Fuzzy Logic (Mathematics of Probability) Cuddy, S. (1997), Based on standard deviation and mean of all the data so all entire data is 100% repeatable that's mean (no random No generators involved) and this is an important part to relay on when we predicted fixed value input as HFU. Data Input: GR, RHOB, NPHI, PHIT, PC1, PC2, UMAX, PE. I divided it in to 6 bins to be matched with the resulting one from the two key wells I used FU from RQI method as a calibrated one, and because of the fact that fuzzy depends on probability and I generate a discrete log I have to use a variable and weighted size bin. Finally, I got a predicted FU curves for each well by mean of core data in the used key wells, that will be used to generate K-log named KUF beside Facies prediction to.



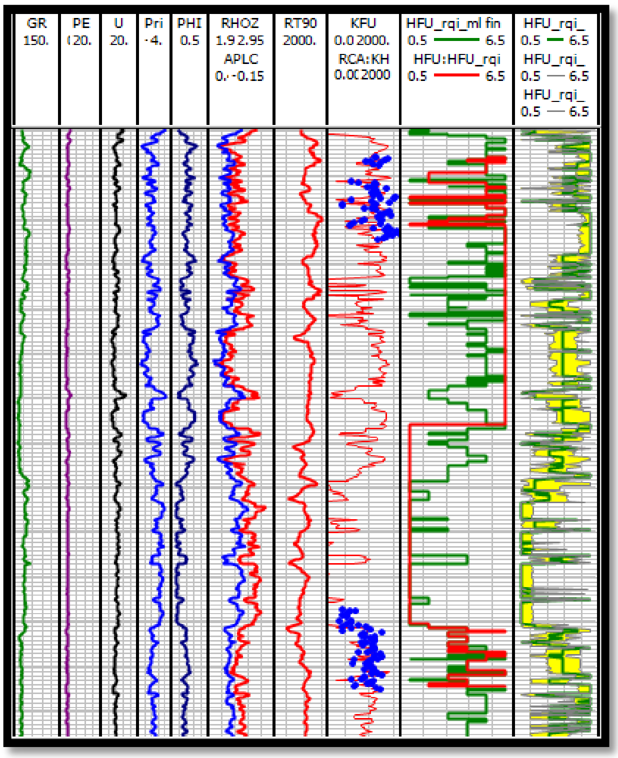


Figure13: data propagation to other we

Figure12: data validation from cored interval via blind test

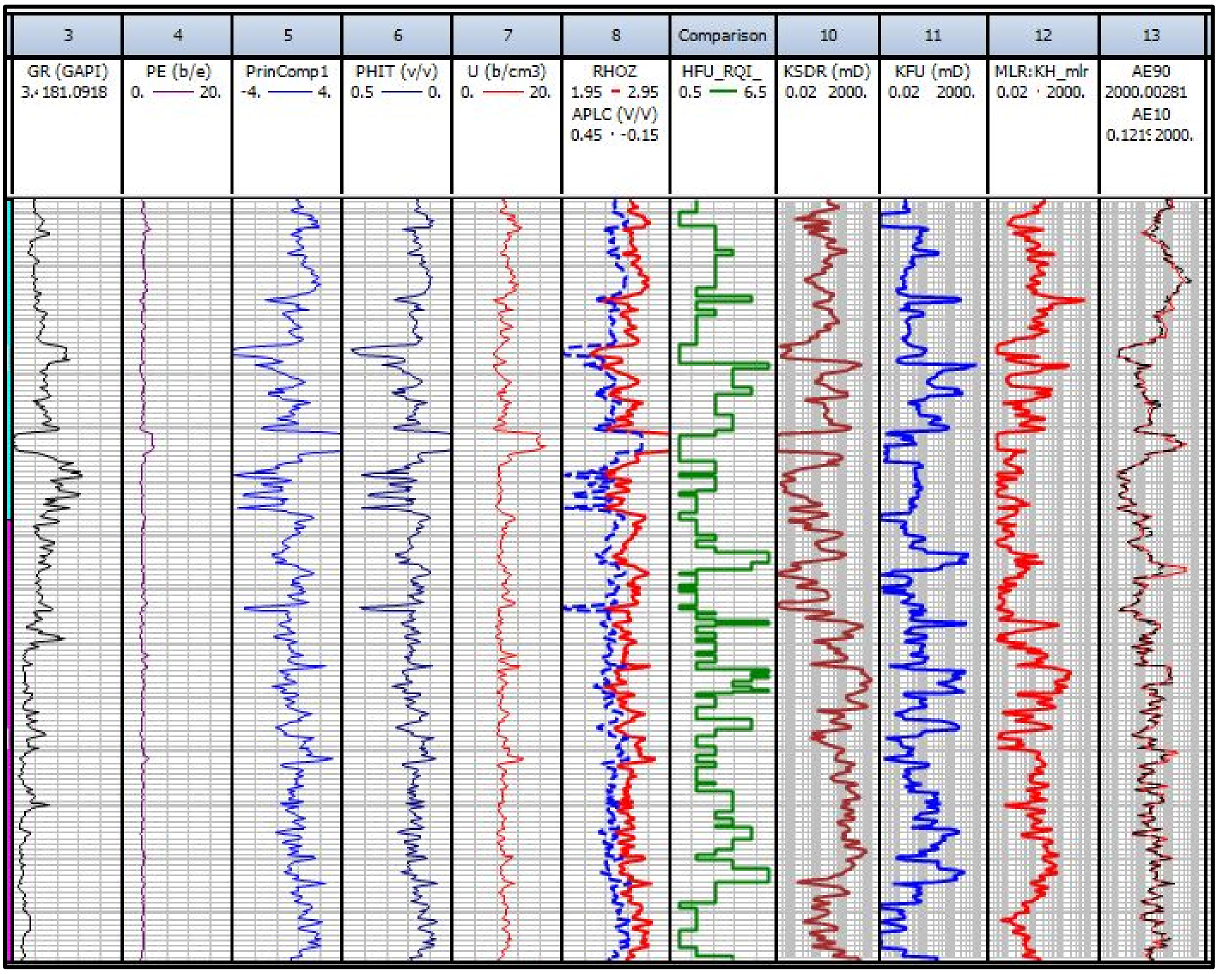
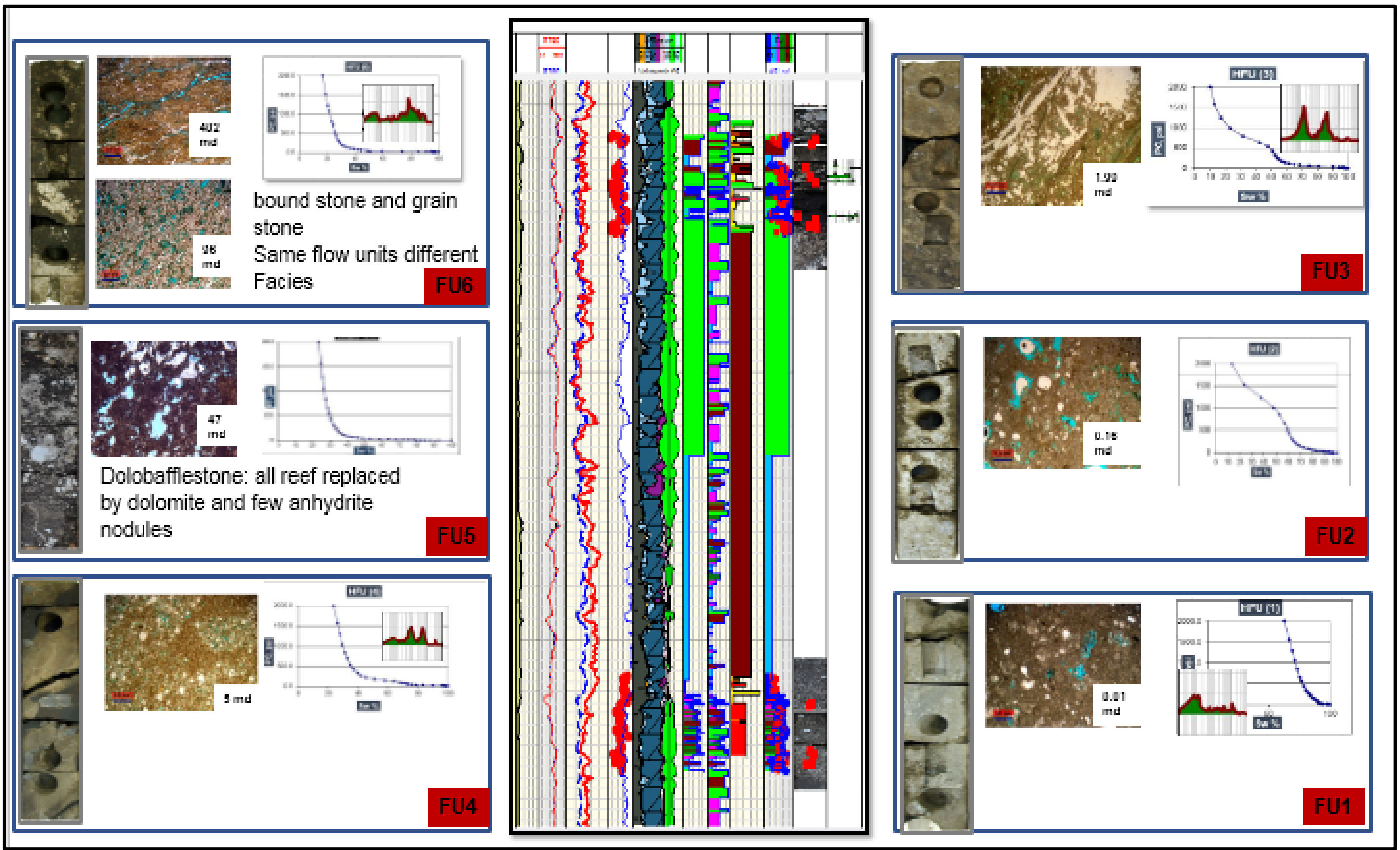


Figure14: comparing results of p Fuzzy-HFU al NMR-K K-FU KMLR-

Conclusions

In this work, we try to emphasize how efficient use of ML for curves and pattern predication and its valuable application in decision-making regarding any field development or enhanced recovery plane, especially in a complex and heterogeneous reservoir like carbonate.
The Flow Units results from this study lead to a better understanding of the reservoir performance during production and enable us to identify the layers that have the most important contribution in the fluids flow in the reservoir that have 6 distinctive flow units FU1 is the lowest reservoir quality while the FU6 is the best reservoir quality.
Capillary pressure data from mercury injection is the best way to identify pore geometry, pore size and pore-throat size. 25 mercury injection capillary pressure (MICP) analyses were available and used to validate the rock types.

In general, good match between good quality rock types with reservoir Facies beside Capillary pressure profile. FU (4,5,6) have the highest contribution in production and show very good profile in Capillary pressure data with low % of Swi While (FU 2 ,3) need more enhanced job like acid simulation and FU 1 act as a barrier boundary between different FUs no return form it even.



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