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Application of Class-Based Machine Learning for Automated Well Log Interpretation

Mohammed Al-Jubouri[1], Wassem Alward[1], Ling Zongfa[2], Xu Xiaori[2], Xu Wei[2], and Zhao Yufang[2]

[1]SLB, Iraq
[2]China National Oil &Gas Exploration & Development Company, Iraq

ABSTRACT

Well logs present a concise, detailed plot of formation parameters versus depth. From these plots, interpreters can identify lithologies, differentiate between porous and nonporous rock and quickly recognize pay zones in subsurface formations. The ability to interpret a log hugely relies on interpreter's ability to recognize patterns, past experiences and knowledge of each measurement. The standard approach has been to manually correct logs for various anomalies and normalize them at the field scale, select different input parameters to calculate the formation and fluid volumes, a very time-consuming and often very subjective approach. The workload is even more time-consuming for mature fields where log data has been collected across multiple vintages of logging tools and from multiple vendors. The future of petrophysical evaluation workflows that are rapidly heading towards increased efficiency, accuracy, and objectivity through smart automation.
In this paper, we show the application of unsupervised class-based machine learning algorithm to automate well log processing and interpretation. The algorithm classifies the provided input data into set of classes that are converted to zones to drive petrophysical interpretation. The main advantage is reducing the turnaround time of the interpretation and eliminating subjective inconsistencies often encountered with standard interpretation approaches. The algorithm uses cross-entropy clustering (CEC), Gaussian mixture model (GMM) and Hidden Markov Model (HMM) that identifies locally stationary zones sharing similar statistical properties in logs, and then propagates zonation information from training-wells to other wells. The training phase involves key wells which best represent the formation and associated heterogeneities to automatically generate classes (clusters), the resulted model is then used to reconstruct inputs and outputs with uncertainty and outlier flags for cross-check and validation. The model is then applied to predict the same set of zones in the new wells that require interpretation and predict output curves.
We present examples of this algorithm applied on data from diagenetically altered carbonate & clastic reservoirs in the Middle East where the workflow speeded-up the petrophysical analysis process, reduced analyst bias and improved consistency result between one well to another within the same field.

EXTENDED ABSTRACT

INTRODUCTION

The studied field comprises of multiple, heterogenous, mixed-lithology reservoirs. The stratigraphic successions include alternating carbonate and clastic rocks across the shallower Miocene and Oligocene formations, overlaying dominantly limestone rocks, with varying shale content and traces of dolomite, across the deeper, cretaceous formations. Accurate petrophysical evaluation of these formations can therefore be a challenge. For lithology, spectroscopy measurements are ideally utilized in such reservoirs to provide direct, independent quantification of elemental and mineral fractions. However, these advanced measurements were only recently introduced in the field and are often associated with high acquisition costs, hence are not widely available. Photo-electric factor (PEF) log also provides a robust indication of lithology types, particularly in clean formations. The presence of clays, as the case in the studied formations, complicates the interpretation. PEF logs are however very sensitive to hole conditions and mud barite, and hence they are sometimes rendered less usable as compared to other conventional logs.

In absence of advanced logs and valid photo-electric factor data, alternative evaluation approaches are necessarily implemented to quantify lithology-porosity relying solely on standard logs (density, neutron, compressional slowness, and gamma-ray, in particular). Commonly, multi-mineral solvers are utilized for this purpose, and zonation is inevitably applied as the available log data will not suffice to provide accurate results without zonal constraints. Zonation serves to divide the studied interval into smaller segments with similar log characteristics (similar litho-poro traits) that can be better controlled to generate coherent outputs. The zonation task is performed manually, and hence it is highly time-consuming, particularly for long intervals, and is often subject to interpretation bias and inconsistencies. To address this, a machine-learning augmented workflow was implemented to automate the zonation process through unsupervised classification in key training wells, then propagating the same classification scheme to other wells to drive the petrophysical evaluation. This machine-learning assisted approach significantly reduces evaluation time and provides a highly consistent, unbiased interpretation of the studied well data.

METHODOLOGY

A semi-automated workflow was implemented to address the zonation task and expedite the interpretation process. An overview of the workflow is presented in Figure 1. Firstly, the selected input curves from the training well(s) undergo a randomly-initialized unsupervised cross-entropy clustering (CEC). CEC algorithm has the capability to determine the optimal number of classes and also requires minimal parameterization which reduces user influence on the outputs (Tabor and Spurek, 2014). Since CEC clustering is randomly initialized, the results are then constrained through Gaussian Mixture Model (GMM). A Hidden Markov Model (HMM) is ultimately applied to model the serial dependence between consecutive depths (Wu et al, 2018). The output clustering scheme is then stored for subsequent deployment into a reference evaluation model, and it can be iteratively re-trained if deemed necessary. The clusters (zones) are embedded into the multi-mineral solver workflow allowing the domain expert to assign different mineral types and set the optimal parameters and endpoints, as seen appropriate, for each cluster type. This reference model would then be used as an execution-ready template for any future well with the same cluster types.

Once the reference evaluation model template is established (using key/training-well logs), the workflow would then be ready to consume new data from prediction well(s). The stored CEC-GMM-HMM clustering model is applied to the new log data (supervised learning) to generate similar zonation. The new data and zones from prediction well(s) are then automatically migrated to the reference evaluation model for direct execution (no further user interference needed).

RESULTS

This workflow was first applied to key-well dataset. Figure 2 shows the extracted clustering results from the CEC-GMM-HMM workflow in the training well. A total of 14 clusters/zones were identified across the investigated interval. The model-reconstructed input logs (displayed in pink color in Figure 2) fit reasonably well with the original input curves (displayed in blue color) with a low error margin (yellow shading). The clusters noticeably alternate with depth following the highly varying log response, driven by changes in rock mineralogy and pore volume.

The clustering results were migrated to a multi-mineral solver to prepare a reference petrophysical model. As shown in Figure 3, the selection of minerals, fluids, and their corresponding endpoints are set for each zone to generate more optimized results.
The petrophysical results of the training well are presented in Figure 4. The output lithologies were validated against core description and limited spectroscopy data available.

The process was then repeated with new prediction-wells data. Supervised learning was applied to propagate the same clustering/zonation scheme to the prediction log set. The clustering results for the prediction-wells are displayed in Figure 5. The output zonation, along with input logs, was finally plugged into the interpretation model to generate the petrophysical results for the prediction-wells, as presented in Figure 6.

CONCLUSION

The machine-learning assisted workflow presented in this paper proved to be helpful to streamline the zonation task, and subsequently the petrophysical evaluation process for the studied wells. The workflow significantly reduced the time needed to prepare the zonation and evidently improved the consistency of the interpretation, all with minimal user interference.

REFERENCES

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Wu, P., Jain, V., Kulkarni, M., and Abubakar, A. 2018, Machine learning–based method for automated well log processing and interpretation, SEG International Exposition and 88^{th} Annual Meeting, P2041-2045

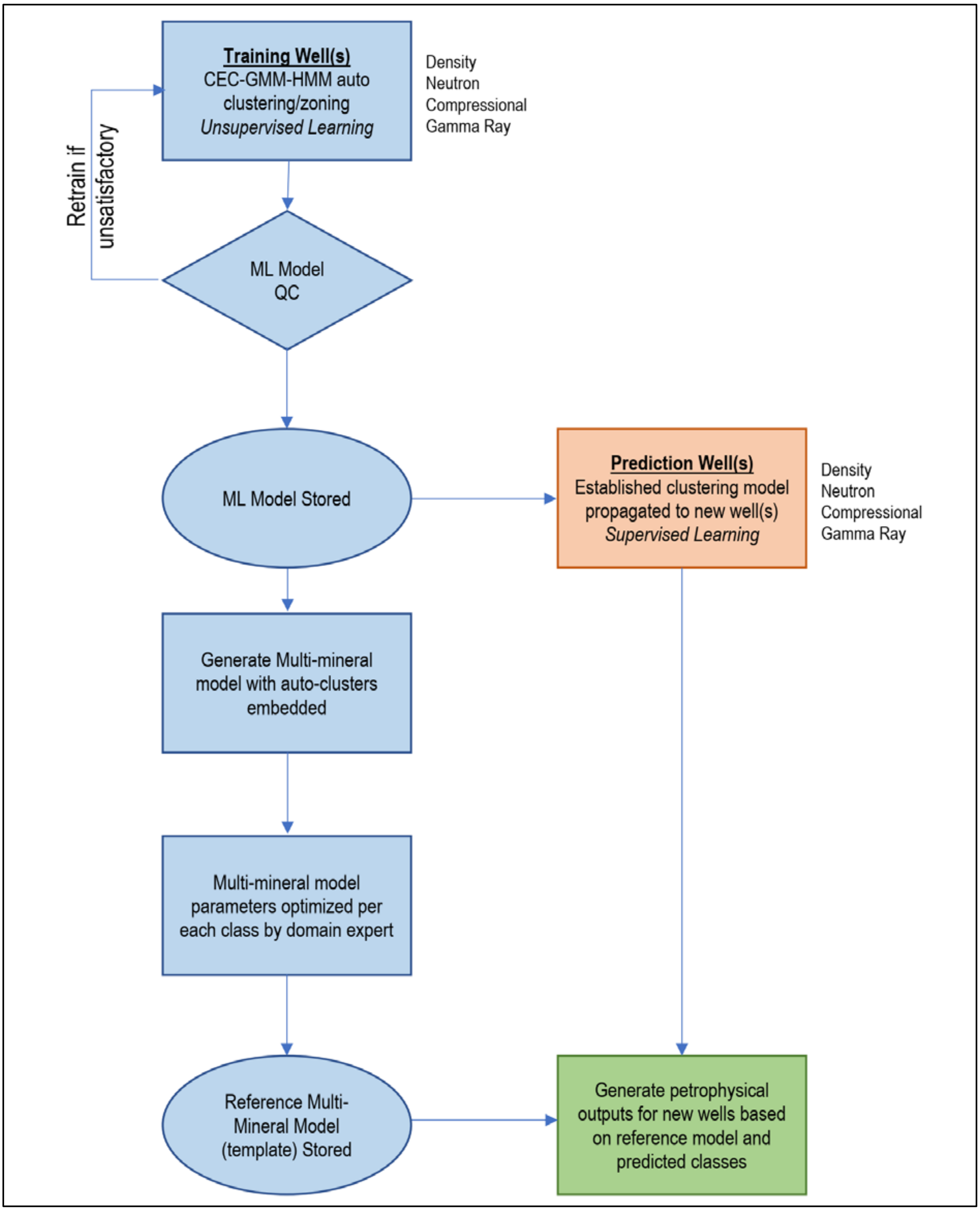


Figure 1. Semi-automated zonation & interpretation workflow

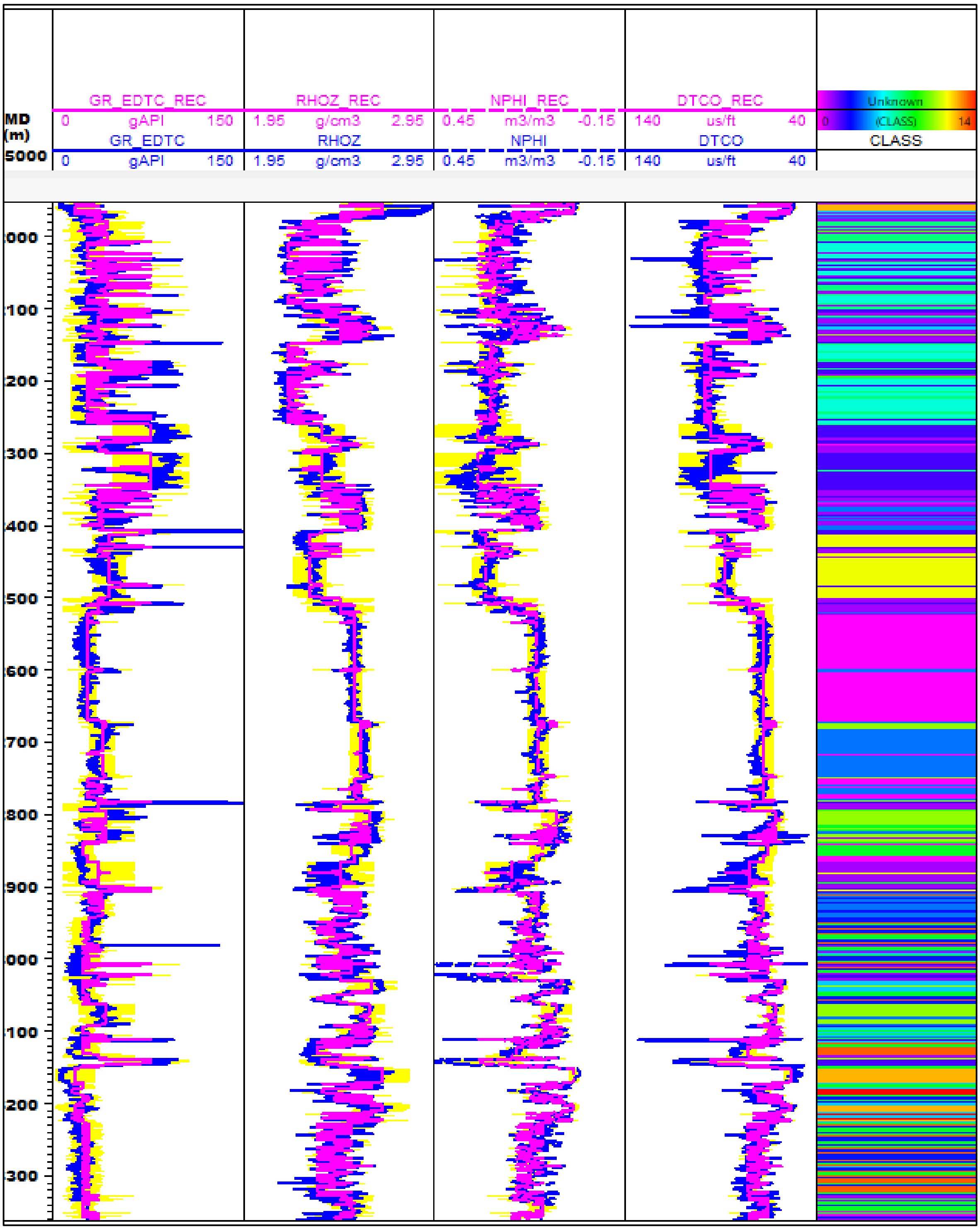
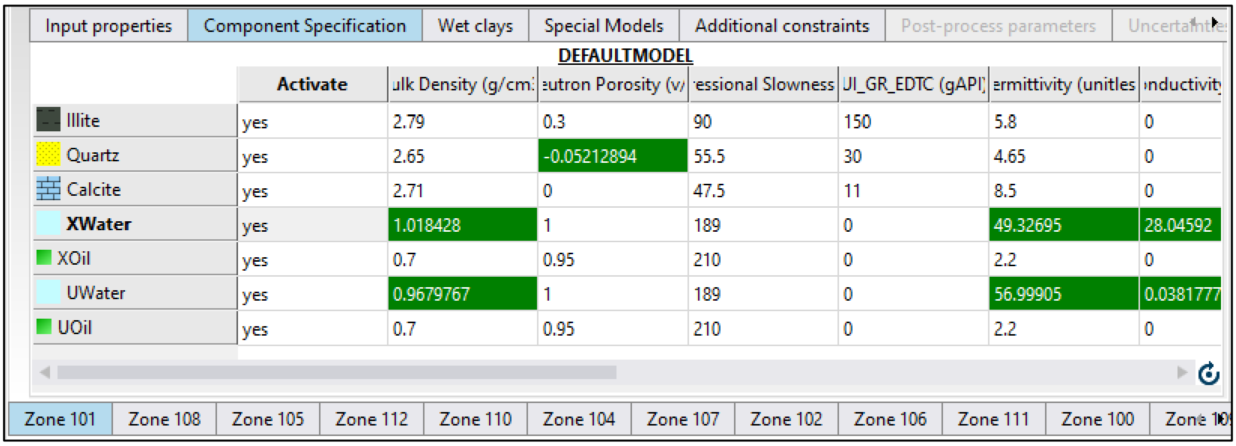


Figure 2. CEC-GMM-HMM clustering results in training well, the blue curves represent the input well logs, and the pink curves represent the data fit. The mismatch is highlighted by yellow shading.



	Activate	ulk Density (g/cm:	eutron Porosity (v/	essional Slowness	JI_GR_EDTC (gAPI)	ermittivity (unitles	nductivity
Illite	yes	2.79	0.3	90	150	5.8	0
Quartz	yes	2.65	-0.05212894	55.5	30	4.65	0
Calcite	yes	2.71	0	47.5	11	8.5	0
XWater	yes	1.018428	1	189	0	49.32695	28.04592
XOil	yes	0.7	0.95	210	0	2.2	0
UWater	yes	0.9679767	1	189	0	56.99905	0.0381777
UOil	yes	0.7	0.95	210	0	2.2	0

Figure 3. Generating a reference petrophysical model using a multi-mineral solver. The CEC-GMM-HMM clusters are embedded into the model and the parameters are optimized per zone, to be propagated for other wells.

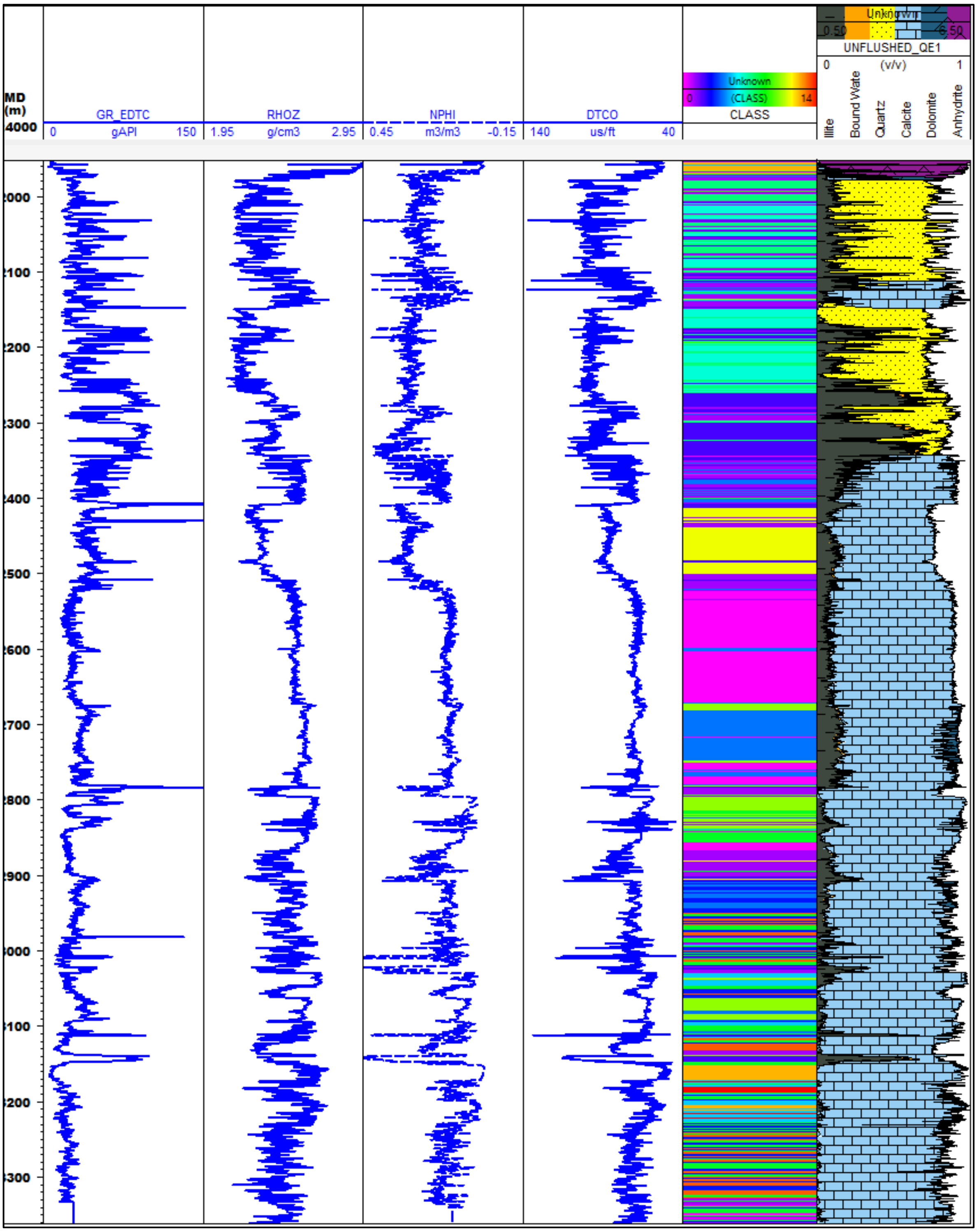


Figure 4. The petrophysical results in training well.

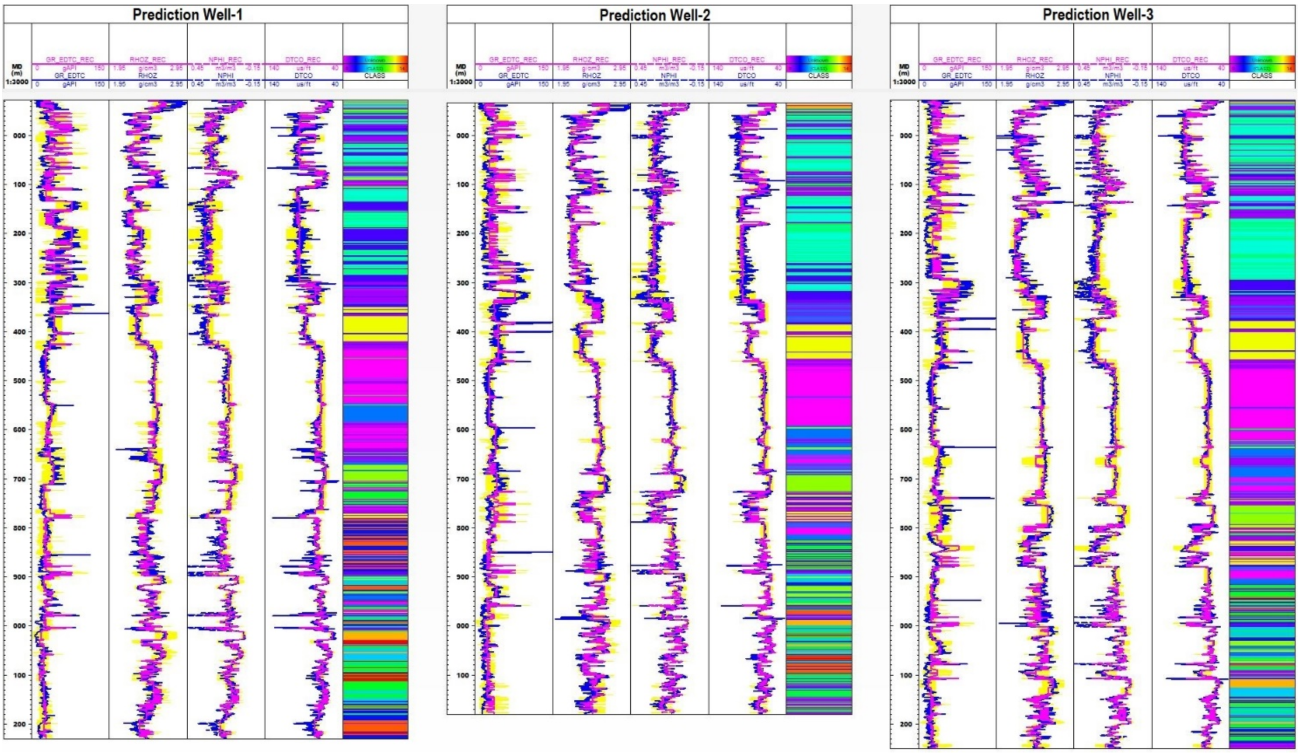


Figure 5. CEC-GMM-HMM clustering results in prediction wells. The stored zonation scheme is propagated to the new datasets.

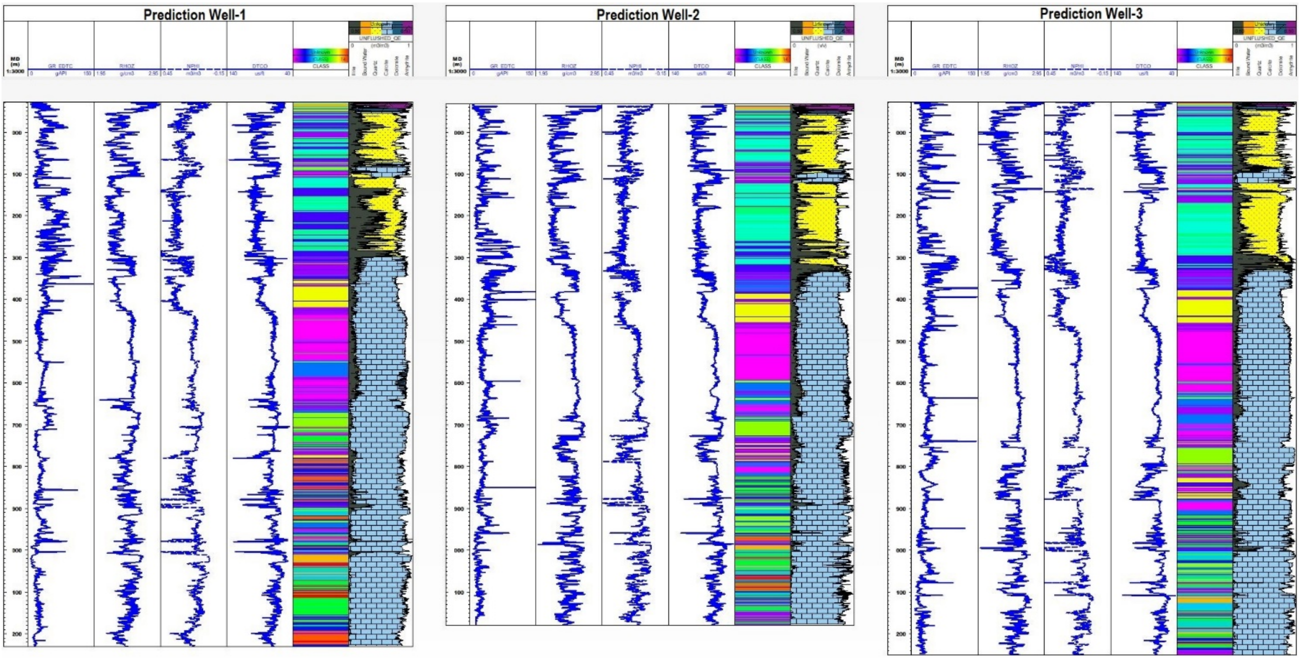


Figure 6. The petrophysical results in prediction wells.