geoconvention
Virtual Event
September 21-23
2020
CSPG • CSEG • CWLS • GAC • MAC • IAH

Electrofacies, a guided machine learning, as a foundation for improving facies logs for the practice of geomodeling

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Summary

The initial foundation for achieving goals in integrated reservoir studies is a sound conceptual geological model which includes deposition, stratigraphy and structure. A key impact on reservoir studies is a rigorous strategy around facies for modeling. Decisions on facies, how to define them and how to model them are an important factor in creating reservoir models that are useful. The modeled facies provide local geological features, patterns and properties. Facies are derived from many sources with varied concepts, definitions, scales and purposes. Classically, facies are a visual interpretation of the face of a rock driven by geological concepts. The interpretation of facies from outcrops is made in terms of depositional processes, by their genetic relationships, thus leading to a depositional environment interpretation. Subsequently, we derive an understanding of stratigraphy, the depositional architecture and stacking patterns. In petroleum reservoirs, we commonly use these surface observations of ancient analogues compared to modern settings, in addition to sparse and imprecise subsurface information to determine facies logs. Is this adequate? The under used application of electrofacies modeling provides a robust and encompassing framework of methods to bring consistency to facies logs thus enhancing the integration of multi-scale data for reservoir modeling.

The current industry best practice for modeling reservoir heterogeneities related to flow is to apply a hierarchical workflow of simulation of facies first, followed by property simulations within each modeled facies. Model facies are a categorical variable used for hard conditioning in geomodels. For modeling purposes, the input facies categories each represent consistent statistical properties, stationary domains, across a study area. Fluid distributions as well as flow and mechanical properties are dependent on the characterization by each facies. Accounting for known physical behavior, percolation and capillarity, when distributing properties by facies facilitates reasonable physical responses in flow models.

Methods and Workflow

The classification of lithofacies involves various approaches. There are visual methods such as combining rock fabric, pore space and petrophysics (e.g. Lucia, F. J., 1995) and these may include detailed description of depositional and diagenetic processes from core or image data. Petrofacies classification involves defining rules-based petrophysical categories, e.g. using log cutoffs or cross-plot polygons. Electrofacies classification typically applies multivariate statistics using wireline logs and visual core or image description. The advantage of electrofacies is combining both the important geological classifications with the petrophysical data.
Visually interpreted facies must be checked for petrophysical consistency, i.e. the distinctness of petrophysical distributions, which is not guaranteed. Application of electrofacies, multivariate classification can improve consistency and is beneficial for the hierarchy of modeling workflows (Martinius et al. 2017). The result is to enforce the lithological characteristics based on distinct

rock properties measured and to be distributed in models at the log curve scale. (Garner et al., 2014; Manchuk et al., 2015). A brief discussion of five assumptions underlying a basic linear discriminant analysis application (Davis, 1986) provides practical guidance on checking, cleaning and improving useful facies inputs whether the facies are used directly for modeling or as a part of the training set (visual facies and well logs) for other numerical classification methods. These five assumptions are all violated to some degree by the training sets.

Discriminant analysis described by Davis, 1986, although useful to understand, is a parametric method applicable to simply organized data distributions and clusters, and is not optimal for typically complex geological facies log data distributions. When using visual facies and well logs as the training sets for electrofacies classifications, non-parametric methods (Nivlet, et al., 2002; Ye and Rabillier, 2000) tend to be most effective given the varied sizes and shapes of the facies in the “hyper-space”, the multivariate distributions.

Electrofacies modeling workflow steps are not widely established in the industry practice or promoted by the software vendors. There is a lack of best practice guidance and training. Misuse or sub-optimal application and lack of widespread dissemination of software to G&G staff beyond petrophysicists holds back the technology. Treating the electrofacies practice as an interpretive one, a guided machine learning process, is part of successfully obtaining results.

To emphasize the workflow, thorough training set preparation is imperative for electrofacies methods to succeed. The visual facies may be considered to be at a different scale or resolution than well logs, are prone to slight errors, and have overlapping distributions. Cleaning involves inspecting and trimming input facies based on the outlier tails of the distributions for each log parameter. Paradoxically, cleaning the training set entails interpretive judgement and alters the statistical measures used to check the results, e.g. increasing the percentage of correctly assigned facies and changing initial facies proportions. However, once deemed cleaned, different model parameter options may be consistently compared. If enough wells are available with core facies, withholding some for blind tests and for model validation can be beneficial. The final electrofacies logs will be judged not only by correct assignment rates, reasonable proportions, but for consistency with the geological concepts. Assignment errors tend to be a reclassification to an adjacent quality facies, feasibly aiding consistency for future heterogeneity modeling. Thus the process is guided and not statistically unbiased. Examples from a few fields will be shown along with aspects of the workflows. The industry practices around preparing facies logs for modeling are diverse and can benefit from the controlled application of electrofacies classification and the associated thought processes.

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