Reducing uncertainty in the deep-geological characterization of rocks in the inter-well area by using mathematical and statistical tools in the processing of geophysical and well data

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functional groups. Hydroxyl and methylene groups appear like anti-symmetric stretching at peak 2932 cm^{-1} and stretching at peak 2854 cm^{-1}, and carboxyl group is absent. The organic acid corresponds with humic acid in organic matter structure. It means the organic matter in the samples of both deposits is of humic source.

In conclusion, the results reveal that organic matter favors in mineralization of invisible gold on the following: (1) appearance of invisible gold detected in coexistence of organic matter and arsenian pyrite of host rocks is confirmed in Western Mecsek (where invisible gold type was a new discovery); (2) organic matter associates with invisible gold-bearing arsenian pyrite and arsenopyrite; (3) concentration of invisible gold in the minerals correlates positively with increasing TOC in the samples (from 0.2 ppm Au with C_{org} 0.1% increasing gradually to 3.2 ppm Au with C_{org} 1% in Western Mecsek and similar up to 4.0 ppm Au with C_{org} 0.47% in Bakyrchik); (4) organic matter of two deposits reveals that it is of humic origin, where likely humic acid was responsible in mobilization of the gold (5). most of the organic matter was destroyed by thermal degradation (decarboxylation) during hydrothermal mineralization removing the gold from organic matter to pyrite and arsenopyrite in the deposits. (6) the gold likely was in complex of carbonyl fraction before decarboxylation.

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REFERENCE

1. Chryssoulis S. L., Dunne R., and Coetzee A. (2004) Diagnostic microbeam technology in gold ore processing. J. Min. Metall. Mater. Soc. 56, 53–57.

2. Volkov A.V., A. D. Genkin., V. I. Goncharov V.I (2006): New data on invisible gold in disseminated sulfide ores of the Natalka deposit. 2006 / 07-08 Vol. 409; Iss. 2.

3. Martin R., Stephen E. K., Satoshi U., Christopher S. P., Stephen L. C., Rodney C. E. (2005): Solubility of gold in arsenian pyrite. Geochimica et Cosmochimica Acta, Vol. 69, No. 11, pp. 2781–2796, 2005.

4. Louis J. CABRI (1990): Comparison of in-situ gold analyses in arsenian pyrite. Applied Geochemistry, Vol. 6, pp. 225-230, 1991 Printed in Great Britain.

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REDUCING UNCERTAINTY IN THE DEEP-GEOLOGICAL CHARACTERIZATION OF ROCKS IN THE INTER-WELL AREA BY USING MATHEMATICAL AND STATISTICAL TOOLS IN THE PROCESSING OF GEOPHYSICAL AND WELL DATA

Proper assessment of the distribution of lithological composition in the subsurface is one of the key elements when evaluating the hydrocarbon potential of an area, as well as geothermal potential and possibility for the CO_2 geological storage. Spatial definition of lithology distribution is the only one step in the characterization of the subsurface.

Incompatible data are usually obtained in exploration of surface outcrops (hard data) and in the subsurface characterization (very little hard data is available, e.g. core material). The lithological composition in the inter-well area is conventionally evaluated on the basis of data obtained from the surrounding wells (cuttings, cores, logs) using either the conventional lithofacies mapping approach [1] where interpretation depends solely on the experience of the interpreter, or by making use of mathematical algorithms [2]. Such procedures have high dose of uncertainty in regional surveys where wells are widely and irregularly spaced and comparatively smaller uncertainty in the areas of hydrocarbon accumulations with large number of relatively closely spaced wells. Following the trend of technological development, it is needed to turn to mathematical and statistical tools to eliminate subjectivity when interpreting lithology, although general understanding of the geology is always invaluable [3]. In every subsurface exploration, one of the most important assignments are determing key factor—age, structural settings and lithology [4]. These have a very large influence on scientific results, as well as economic implications if the results are applied to any type of resource estimates.

The purpose of this paper was to analyze the data using both geostatistics and geological knowledge as objectively and realistically as possible. For this purpose, a small area covering a depleted oil field located within the Drava Depression of the Pannonian Basin (northern Croatia) was selected for the process. This object was chosen due to available data for lithology interpretation in the wells and 3D seismic coverage needed for the definition of lithology throughout the seismic volume. Clastic Pannonian interval (CPI) was selected for the analysis as the lithology of this unit can be generalized to three classes-sandstones and marls that occur through the whole interval and coals that are most often found in the top of the interval. Subsurface lithology was simplified in accordance with the general geological composition of the Pannonian age sediments in the research area.

For the purpose of lithology modeling, selected seismic volume was analyzed by using artificial neural networks. Two approaches to artificial neural networks (ANN) were used to observe the influence on result prediction of changing the type of the approach. First approach (DAANN) used a large number of different architecture networks, regarding different number of neurons in the hidden layer and different activation functions. Second approach (SAANN) employed the same architecture network but with different distribution of cases within the training, test and selection datasets, and with a different starting point (case) for the analysis. Out of a 1000 total cases, 100 realizations of each approach were singled out upon which the data points with probability of 50%, 75% and 90% of occurrence of certain lithology category were upscaled in the model. Six models were generated by indicator kriging.

Although in theory, the higher accuracy data should provide a more accurate result, the geologically most sound results were obtained by 50% accuracy data. In higher accuracy results, sandstone lithology was unrealistically over emphasized as a result of the upscaling process, variography and statistical analysis. Considering that majority of hydrocarbon reservoirs discovered so far are in clastic sediments, the methodology presented in this paper represents one of the possible ways of determining subsurface lithology, that can lead to new discoveries not only in the study area, but also in other sedimentary basins. Presented research can be used in all geoenergy-related subsurface explorations, including hydrocarbon and geothermal explorations, and subsurface characterization for CO_2 storage potential and underground energy storage potential as well.

REFERENCES

1. Forgotson, J.M.: Review and classification of quantitative mapping techniques. Am. Assoc. Pet. Geol. Bull. 44, 83–100 (1960).

2. Feng, R., Luthi, S.M., Gisolf, D., Angerer, E.: Reservoir lithology classification based on seismic inversion results by Hidden Markov Models: applying prior geological information. Mar. Pet. Geol. 93, 218–229 (2018). https ://doi.org/10.1016/j.marpe tgeo.2018.03.004.

3. Hohn, M.E.: Geostatistics and Petroleum Geology. Springer, Dordrecht (1999).

4. Selley, R.C., Sonnenberg, S.A.: Methods of Exploration. Elements of Petroleum Geology, pp. 41–152. Elsevier, New York (2015).