GENERATING LOG-MODELS OF GEOPHYSICAL PARAMETERS USING MACHINE LEARNING METHODS (GOLA FIELD)

GENERIRANJE BUŠOTINSKIH MODELA GEOFIZIČKIH PARAMETARA UPORABOM STROJNOG UČENJA (POLJE GOLA)

Ana Brcković[1]*, Jasna Orešković[1]

[1]University of Zagreb, Faculty of Mining, Geology and Petroleum Engineering, Pierottijeva 6, 10 000 Zagreb, Croatia
*corresponding author: abrckovic@rgn.unizg.hr

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In the area of the Gola field, the Upper Miocene deposits of the western part of the Drava depression represent a sequence of sediments consisting of sandstone, siltstone, marl and their transitional lithofacies. The sandstone deposits, i.e., the main reservoir rocks, mostly occur in lenticular forms (KRPAN *et al.*, 2018), which makes it difficult to spatially correlate. These deposits were formed in a brackish lake environment in the zone of the lake littoral and part of the sublittoral and represent sediments of channel fills and underwater fans deposited from turbidites (TADEJ, 2011).

In order to improve the interpretation of well logging data in the research area, different machine learning models were tested. In this study, regression analysis was used for acoustic log and porosity predictions. The regression belongs to supervised learning models, which means that the learning is based on already known values of the required variables.

Algorithmic processing of a large amount of data is only possible if the matrix of input data is not singular, i.e. its determinant is not zero. The problem with data preparation is the fact that most logging data sets are in the form of a singular matrix, that is, most wells are missing a certain number of values at certain depth intervals (MCDONALD, 2021). For this reason, the missing values were added to existing well depth intervals after predictive modelling by machine learning.

Various statistical methods used to analyse data, including correlation and regression, assume that the data have normal distribution. Most algorithms are also based on the assumption that the variables are around zero to one and that they are comparable to each other. For this reason,

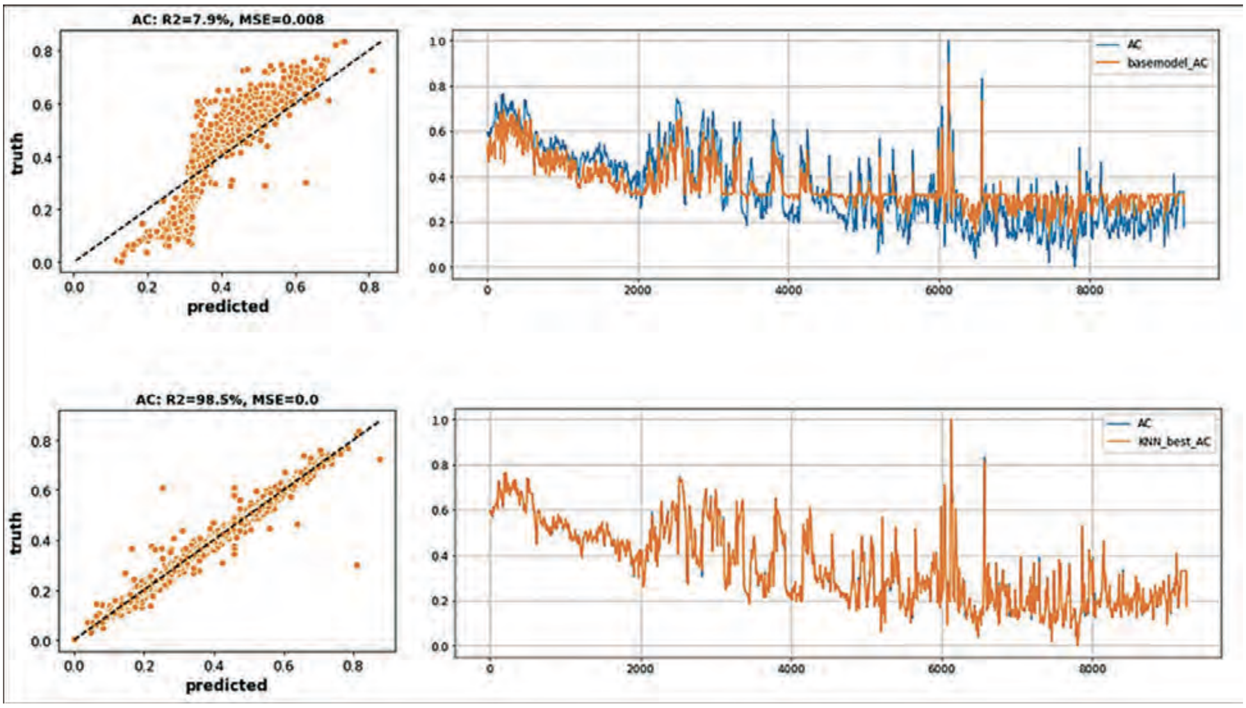

Figure 1. Acoustic log predictions of a Support Vector Regression (SVR) base model (upper images) and K-Nearest Neighbors (KNN) model as the best result (lower images)

prior to testing the algorithms, the data were standardized, normalized, or transformed depending on the algorithms used (SEMENIKHIN & BELOZEROV, 2019).

Based on the correlation matrix, 14 variables (logs) were determined for the calculation of the forecast model. A total of six regression models were used to predict the acoustic logs and porosity values. The base model was calculated using the Support Vector Regression (SVR) algorithm (Fig. 1), as the goal was to determine the boundaries of acceptable predictions.

The measure of accuracy for regression models, amongst others, is the coefficient of determination R^2, which indicates how well the predicted and measured values correlate. For the base model, at the shallower depths the predicted values follow the trend of the measured ones but at the greater depths the predictions fall out of the trend, which makes the results unreliable. The most accurate model was generated using the K-Nearest Neighbour (KNN) algorithm, where the coefficient of determination was over 0.9 (Fig. 1).

The greatest advantages of predicting the values using trained models are the ability to fill in missing logging data and the short time required to get the initial image of the subsurface. Based on the predicted values, the further processing and interpretation methods are determined more quickly.

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DETERMINING THE FORMATION OF KAOLINITE MINERALIZATION USING MINERALOGICAL ANALYSES IN MOTAJICA GRANITE COMPLEX, BOSNIA AND HERZEGOVINA

UTVRĐIVANJE MEHANIZMA NASTANKA KAOLINITA KORIŠTENJEM MINERALOŠKIH ANALIZA U MOTAJIČKOM GRANITNOM KOMPLEKSU, BOSNA I HERCEGOVINA

Tomislav Brenko[1], Sibila Borojević Šoštarić[1]*

[1]University of Zagreb, Faculty of Mining, Geology and Petroleum Engineering, Pierottijeva 6, 10 000 Zagreb, Croatia
*corresponding author: sibila.borojevic-sostaric@rgn.unizg.hr

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The aim of this abstract is to present the formation mechanism of the kaolinite and kaolin deposits in the Motajica Mt. Although several projects and investments are currently being carried out in the Motajica Mt. area, the development and formation of kaolinite mineralisation is still relatively poorly known. Kaolinite deposits are associated with the Motajica granite pluton, which is characterised by syncollisional granite of Eocene age (JURKOVIĆ, 2004). Numerous papers have been published on the Motajica kaolinites (STANGAČILOVIĆ, 1956; JURKOVIĆ & ŠINKOVEC, 1960; VARIĆAK, 1966; TRUBELJA & BARIĆ, 1979), with different authors proposing different formation mechanisms for the kaolinites. Some authors believed that kaolinitisation occurred during Tertiary marine transgression, others suggested that kaolinitisation occurred through superficial weathering, while in some cases it was considered to be the result of hydrothermal solutions.

The focus of this work is mineralogical analysis of the kaolinitised granites in the Motajica area aiming at determination of clay minerals and definition of the kaolinite deposits origin. The following analyses were performed on the samples: macroscopic determination of mineral composition, X-ray diffraction analysis on original samples, samples treatment with ethylene glycol, heating at 350 °C and 550 °C and treatment with dimethyl sulphoxide (DMSO), Fourier transformed infrared spectroscopy (FTIR) and geochemical analysis on three samples.

The semi-quantitative mineral composition of the kaolinitised granites of the original samples revealed typi-