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Prediction of Petrophysical Properties from Well Log Data using the Adaptive Neuro-Fuzzy Inference System (ANFIS)

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The Deadwood Formation of the Williston Basin has been in the spotlight for underground CO_2 storage geothermal energy in recent years. It is the deepest sedimentary unit within the Basin deposited during the Late Cambrian to Early Ordovician, and uncomformably overlying the crystalline basement rocks of the Precambrian (LeFever et al. 1987). In Saskatchewan, the Deadwood formation thickness varies from a regional maximum of over 440 m in the west where Lloydminster area has the thickest 500 m, and thinning eastward to zero at the Saskatchewan–Manitoba border. It is primarily characterized as quartz-rich fine/coarse rounded sandstones interbedded with siltstones and shale, interpreted to range from deeper water marine (shales) to upper and lower shoreface settings (siltstones to sandstones). The basal sandstone unit of the Deadwood is composed of a conglomerate and sandstone zone, which unconformably overlies the Precambrian basement (Kreiss 2004). The siliciclastic portions of the Deadwood, carbonate beds and cementation, are more commonly seen within the middle and upper zone.

Among all geological factors that influence the success of a CO_2 storage project in the saline aquifer, porosity and permeability are two of the most important properties to evaluate, as the former determines storage capacity and the latter affects injectivity. Acquiring actual core samples for laboratory measurements can be highly expensive and time-consuming. There are only over 30 wells in the province that contain routine core analysis for the Deadwood formation, whereas over 500 wells have logs of different types available. The goal of this work is to develop an artificial intelligence (AI) model that can predict the porosity using well logs with reasonable confidence. While the nature of well logging entails much lower precision, i.e., the log response is influenced by the overlying and underlying layers, than the lab-measured core analysis with exact sampling location, it requires certain “fuzziness” to account for log–porosity correlation. Also due to complex affecting factors on any logging tool, it could be overly simplified to model a petrophysical property with single log type data, in spite of generally decreasing/increasing trend of the log response.

These challenges were tackled with the Adaptive Neuro-Fuzzy Inference System (ANFIS) method. First introduced by Jang (1993), the method combines the learning capability of a neural network with the approximate representation of knowledge found in a fuzzy system. In essence, a neuro-fuzzy system is a fuzzy inference system (FIS) in which its membership functions and rule base are trained by a neural network-learning algorithm. Using a ground-truth input/output data set, the ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned with either a back propagation algorithm or in combination with a least-squares type of method. This allows the fuzzy systems to learn from the measured data they are modeling without considering actual physics in the data.

After examining the Pearson correlation coefficients of measured porosities with available logs, three logs, namely neutron porosity, density porosity, and bulk density logs are selected for ANFIS modeling. A total of 690 data is randomly divided into the training set (500) and validation set (190) to minimize over-fitting. The Sugeno type-1 ANFIS architecture with the generalized bell membership function, hybrid method was adopted for training and 3-input and 1-output structure. The ANFIS keeps updating the membership function parameters (66 in total) that specify their shapes and partition of membership function during each training epoch. The optimization approach employs back propagation for updating the parameters associated with the input membership functions, and the least-squares estimation for the parameters associated with output membership function. The model reached convergence after 100 epochs, with minimal training RMSE=3.1134 and validation RMSE=3.7161, as shown in Fig. 2 the crossplot of measured and predicted porosities.

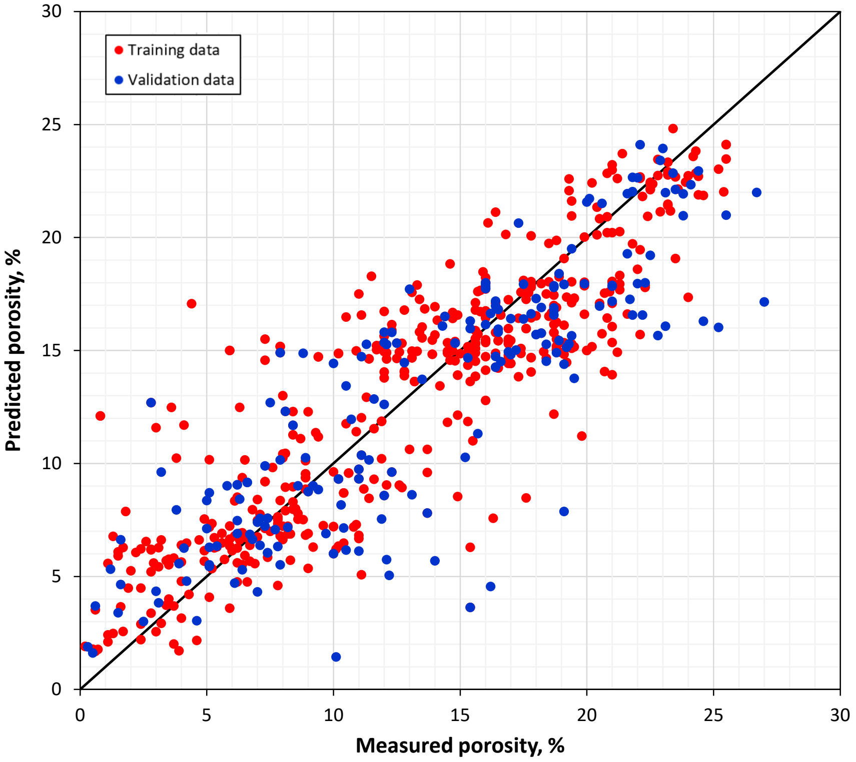

Fig. 1 Crossplot of measured and predicted porosities

Fig. 2 shows two example Deadwood wells in the Regina area of modeled porosity versus measured neutron porosity, and density porosity curves. It is well known that that neutron logs read spuriously high values in shaly sands or shale, which are commonly present in the Deadwood formation. The modeled porosities have corrected that shale effect and present consistently lower values the neutron density readings. In such cases the method is advantageous by taking into account all three logs rather than relying on any single type.

In the following-up research, permeability modeling has been undertaken using the same methodology. Traditionally permeability can be estimated from porosities through Kozeny-

Carman type correlation. With inter-bedded shale contents in the Deadwood formation, the permeability-porosity data suffer from low correlation coefficient (R^2=0.0115 for Saskatchewan Deadwood cores). Applying the ANFIS method, other affecting factors can be considered by incorporating pertinent log response for better modeling their non-linear re.

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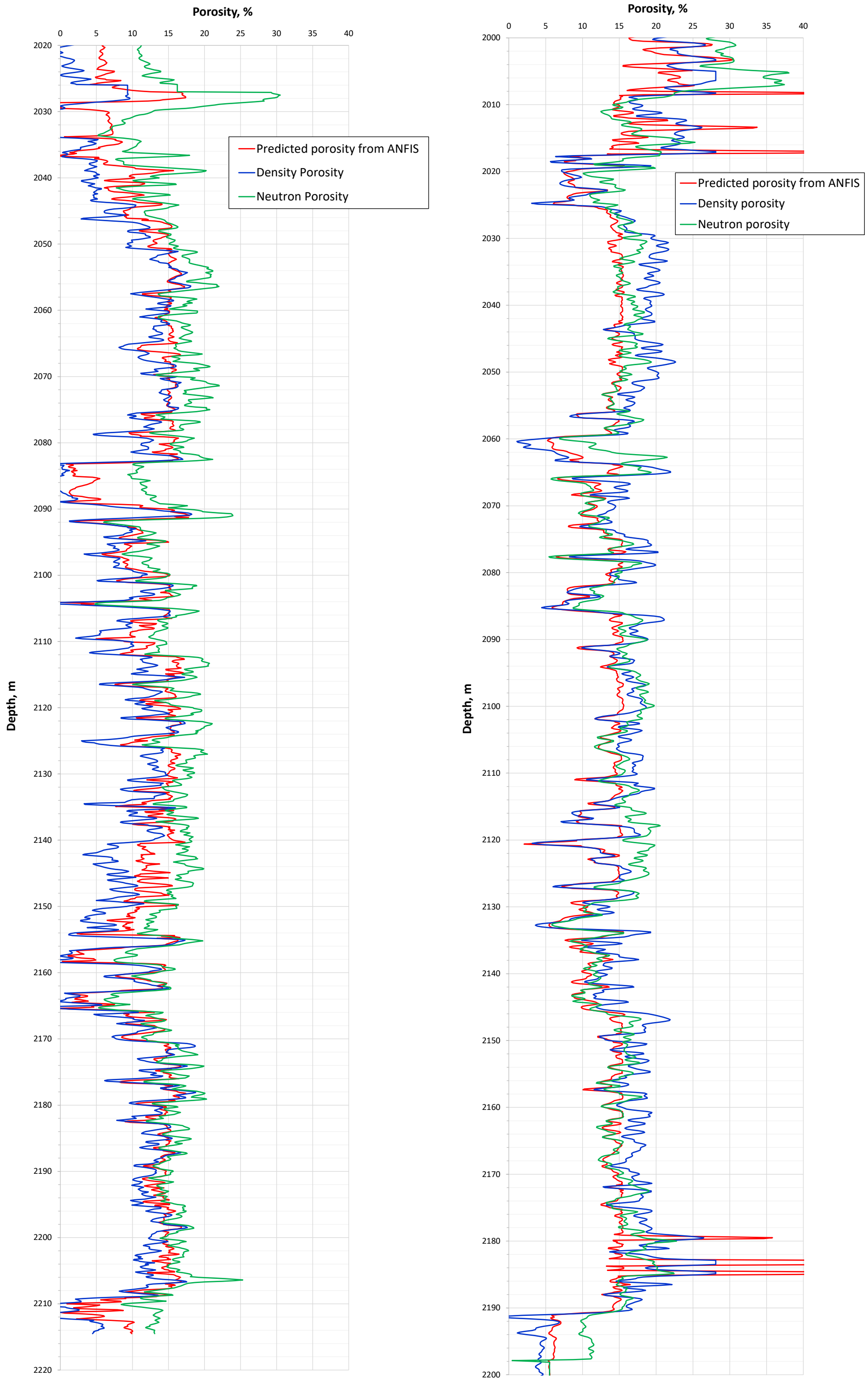

Fig. 2 Comparison of neutron porosity, density porosity, and predicted porosities for Wells 3-8-17-19W2M and 4-4-18-19W2M