Irreducible water saturation from Nuclear Magnetic Resonance raw data using Deep Learning

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The amount of irreducible water saturation (SWirr) in a reservoir is a key petrophysical property that is usually estimated using Nuclear Magnetic Resonance (NMR) data. Laboratory data is commonly used to improve the accuracy of SWIRR logging estimates; the technique used for upscaling is however a matter of choice and can lead to some questions. In this work we use Deep Learning (DL) as a natural candidate for this task. It has emerged as a powerful tool to solve (or at least speed up) several tasks in different fields, including petrophysics. Here, we use NMR data from carbonate reservoirs to infer SWIRR directly from magnetic decays using a multi-scale convolutional network. Due to the scarcity of laboratory data, we perform a data augmentation scheme which combines the SWirr measurements and the NMR decays to produce a new synthetic sample. Our best model achieves a coefficient of correlation of 90% on a blind test set. This work is one of the first to provide a completely model-independent way to estimate SWirr in carbonate rocks with satisfactory accuracy, and paves the way for more challenging tasks, such as using noisier logging data instead of laboratory plugs.

SWirr is a key quantity to assess the total amount of oil in a reservoir. Techniques used to estimate the water saturation usually involve different types of logs and models that connect the SWirr with other quantities, such as porosity and permeability. Here, we use DL to estimate the SWirr in a completely model-independent way from the raw magnetic decays of lab plugs.

The data used to train and test our DL models come from different carbonate reservoirs in the pre-salt region of Brazil, decharacterized. Basic petrophysical quantities are also available together with SWirr and decay values. We preprocess the decays by selecting only those with at least 1000 echoes; performing the phase rotation such that signal is kept in one channel, while the other is mostly noise; and cutting all decays to 1000 echoes. Furthermore, we split the set into those that are fully saturated with water (SW) and those that have two fluids (SWI), water and oil based mud filtrate; preliminary testing showed that this split produces better results since the models will not have to process different sample states decays to estimate the same SWirr value, which was causing confusion. After this split, we selected a part to be our blind test set for each sample. Due to the scarcity of data, we employ a data augmentation scheme consisting of weighted means of the decays (normalized to be in the [0,1] range) and the SWirr.

The architecture chosen for both samples consist of a series of multi-scale convolutional blocks, followed by a series of fully connected layers. We used the training sample to optimize the hyperparameters of the models: kernel sizes, activation functions, number of convolutional filters, number of convolutional blocks, number of fully connected layers and units in each layer. The set of hyperparameters that achieved the lowest validation loss was chosen as the best model, and retrained from scratch. The training was performed using a 5-fold cross-validation scheme: at each fold, 20% of the plugs were selected as a validation set, and the rest was augmented and used to train the model. The validation sets are different for all the folds, so that we can assess the performance of the models across all plugs in the training set. The best models for each fold are then evaluated using the blind test set.

The results for the SW sample are satisfactory, with all five models having similar coefficient of correlation (R2); the best model achieves an R2 value of 0.9, while the mean is 0.86 with a standard deviation of 0.02. The SWI sample was more challenging, with a mean R2 of 0.67 with a standard deviation of 0.08 and a best value of 0.72.

This work shows that DL is a powerful tool in petrophysics, and can be applied to more challenging situations such as well logging NMR, which is far noisier than laboratory measurements.