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DeepSWIrr: Determining irreducible water saturation from raw Nuclear Magnetic Resonance decays using deep learning

Bernardo Fraga (Centro Brasileiro de Pesquisas Físicas), Clecio De Bom, Bernardo Coutinho (Petrobras)

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Abstract Summary

Estimating the Irreducible Water Saturation (S_{wirr}) of a reservoir is an important but challenging task, typically accomplished using Nuclear Magnetic Resonance (NMR) data. Laboratory data is used to complement logging data to improve accuracy; however, the technique used for upscaling is a matter of choice, potentially leading to different results using the same data. Here, we try to circumvent this problem by estimating SWIrr directly from the echo trains using deep learning (DL), without any modeling. We obtained raw laboratory NMR data from carbonate reservoirs and used it to train a multi-scale convolutional network. Due to the scarcity of labeled laboratory data, we employed a data augmentation scheme that combines two or more samples.

After optimizing the hyperparameters of the network, our best model has a coefficient of correlation of 90% on a blind test set. This serves as validation of the methodology before applying it to noisier logging data.

Introduction

The amount of Irreducible Water Saturation (S_{wirr}) is closely related to the amount of oil that can be extracted from a reservoir. It is, therefore, one of the important quantities to determine during reservoir characterization. However, determining S_{wirr}most of the time involves knowing the T_2 distribution, and determining a cutoff value, from where S_{wirr}can then be inferred. Determining the T_2 distribution is a complex matter, where an inverse Laplace transformation is needed, and different noise models can give rise to different T_2 distributions even when the signal-to-noise ratio (SNR) is the same. Even so, finding a cutoff value in the T_2 distribution is still problematic, and different methods have been proposed (e.g. Liu et al., 2022; Solatpour et al., 2018). Efforts have been made to mitigate these shortcomings (ref), but still the determination of the T_2 distribution from magnetic decays is an ill-posed problem with no obvious solution.

Here, we try to eliminate this problem by using a DL model to estimate $S_{\mathrm{wirr}}$from NMR data directly, without intermediary steps or complex modeling. Deep Learning (DL) is a natural approach for this task, and has been used extensively for several applications with borehole data: lithology classification (Valentín et al., 2019), porosity and permeability determination (Bom et al., 2021), determination of subsurfaces (Kurup and Griffin, 2006), among others.

To avoid the need for modeling or calculation the T_2 distribution, we use laboratory samples from carbonate reservoirs, where $S_{\mathrm{wirr}}$was measured directly, without resorting to modeling or setting cutoff values.

Method

We built a dataset composed of 873 laboratory NMR samples (decharacterized) from carbonate reservoirs in the pre-salt region of Brazil, containing the echo trains and basic petrophysical properties such as S_{wirr}, porosity, and permeability. The sample was cleaned and preprocessed by the following steps:

- Cut all samples where at least one of the echo trains had less than 1000 points;
- Perform a rotation so that all noise is concentrated in one channel, while the other has just the signal;
- Cut both channels to 1000 decays.

After all these cuts, we are left with 821 samples. Besides the properties, measurements were done when the plug was saturated with water or with water and an oil-based mud filtrate; henceforth, we will call these states SW and SWI, respectively. Although the echo trains for a given plug are slightly different in the two states, $S_{\mathrm{wirr}}$is the same. Initial testing showed that this was a source of confusion for the neural network. We therefore further split our dataset into SW (372 plugs) and SWI (449 plugs) states. Finally, we chose 50 plugs that are common to both states to serve as a blind test sample; our training SW sample contains 322 plugs, while the SWI sample contains 399.

Since DL models are notoriously data-hungry and we only have less than five hundred samples per state, we employed a data augmentation scheme where pairs (or even triplets) of plugs can be combined to create a synthetic one, with new decays and S_{wirr}:

$$m(w) = w \times m_1 + (1 - w) \times m_2 \tag{1}$$

$$S_W(w) = \frac{w \cdot S_{W1} \cdot V_{B1} \cdot \phi_1 + (1 - w) \cdot S_{W2} \cdot V_{B2} \cdot \phi_2}{w \cdot V_{B1} \cdot \phi_1 + (1 - w) \cdot V_{B2} \cdot \phi_2}. \tag{2}$$

Where m are the magnetic decays, S_W is the S_{wirr}, w is a weight, V_B is the bulk volume and ϕ is the porosity. Our dataset, however, lacks information about the bulk volume. We therefore normalize the decays to the range $[0, 1]$; in this way, we can assume that $V_B \cdot \phi = 1$.

Our architecture is a multi-scale convolutional network, depicted in Figure 1. By choosing different kernel sizes for each convolutional block, we aim to capture the different structures of the echo train. Each state (SW and SWI) will have a different model, trained specifically for that state. We furthermore optimize the hyperparameters for each model using 50 plugs from the training set as a validation: the best set of hyperparameters is the one that achieves the lowest validation loss. After optimization, we retrain the network using a 5-fold cross-validation, wherein the augmented training data is split into five different groups, and five iterations of training are performed. At each iteration, one of the groups is used for validation, while the rest is used for training. In the end, the model with the lowest validation loss at each iteration is chosen as the best.

Results

Here we report the results for the test set, comprising 50 plugs common to both SW and SWi states. In Figure 2, a scatter plot of the true vs. the predicted values is shown, for both states. It can be seen that the results are satisfactory, with a coefficient of correlation approximately 0.9 for both states.

The bulkiness of a sample is a measure of how much bulk processes influence the relaxation time:

$$\beta(T) = 1 - \left(1 - \frac{T}{T_B}\right)^2. \tag{3}$$

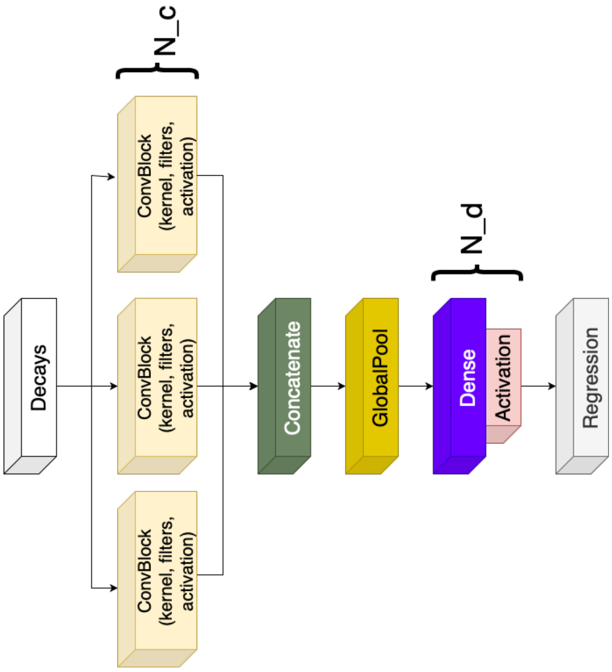

Figure 1: The multiscale convolutional neural network. Each convolutional block has a differente kernel size.

We calculate it by fitting a second-order polynomial to the first 40 points of the echo train, imposing the condition that the independent term is equal to the porosity. Plugs with high bulkiness are less likely to be affected by the magnetization, since the pores are larger, and therefore the connection between magnetic decays and $S_{\mathrm{wirr}}$is less evident. Looking at Figure 3, we can see that for the results are better for the low bulkiness (defined as $\beta \leq 0.5$)sample, when compared to high bulkiness.

Conclusions

This work showed a first effort to obtain S_{wirr} directly from magnetic decays using laboratory plugs using neural networks. The model was able to perform satisfactorily, recovering S_{wirr} from a blind test sample with good accuracy for both states. As expected, results for low bulkiness are better than for high bulkiness. More work needs to be done to apply this methodology to logging data, which is significantly noisier.

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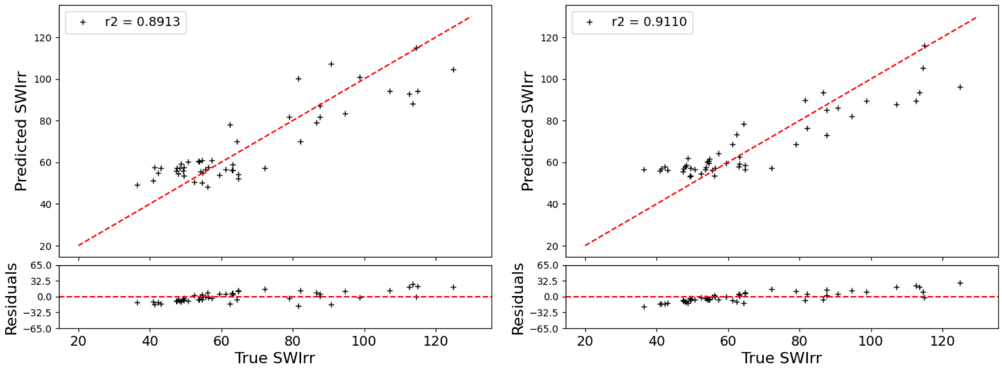

Figure 2: True vs. predicted values of S_{wirr} for the SW state (left) and for the SWI state (right). Both show good agreement between predicted and true values.

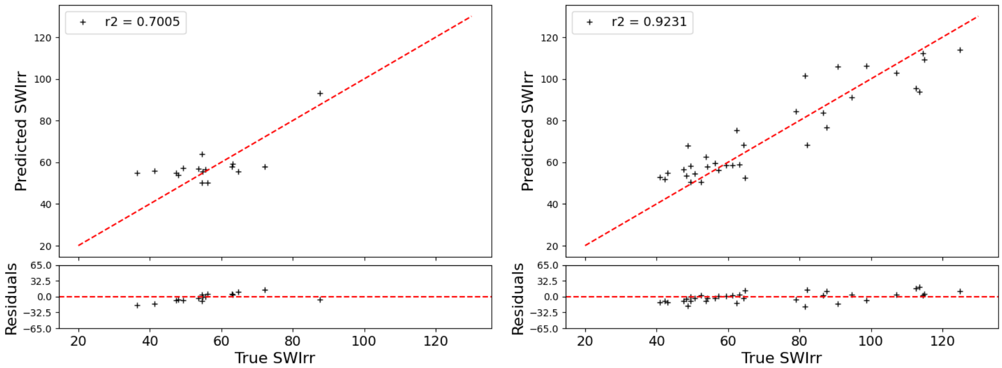

Figure 3: True vs, predicted values for a sample in SW with high bulkiness (left) and low bulkiness (right).

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