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A Novel Sparsity Deploying Reinforcement Deep Learning Algorithm for Saturation Mapping of Oil and Gas Reservoirs

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Abstract
The 4IR technology has assumed critical importance in the oil and gas industry, enabling automation at an unprecedented level. Advanced algorithms are deployed in enhancing production forecast and maximize sweep efficiency. A novel sparsity-based reinforcement learning algorithm, utilizing a surface response model approach, was developed for the estimation of hydrocarbon saturation in the interwell region. Application of the novel algorithms on a realistic reservoir box model exhibited strong performance in the estimation of the interwell saturation as well as the quantification of uncertainty. The results outline the broader application of the framework for interwell saturation mapping.

Keywords Reinforcement learning · Uncertainty quantification · Saturation mapping · Surface response model

1 Introduction

The Fourth Industrial Revolution (4IR) of technology has gained significant traction in the oil and gas industry, focusing on maximizing oil recovery and improving efficiency. From exploration to production of hydrocarbon reservoirs, 4IR technologies have led to significant advances in the industry. A major challenge in the industry is the sparsity of reservoir information that is available only close to the wellbores, from which extensive estimates of the hydrocarbon distribution inside the reservoir volumes between the wells are conducted. Although a broad number of interpolation and geostatistical techniques have been developed, these are mostly characterized by assumptions and a priori data interpretations. Reducing the uncertainties associated with the lack of direct geological, petrophysical and fluid distribution information in the interwell volumes of a field is a key opportunity to improve the understanding of a reservoir, assessing its exploitation potential and maximizing the hydrocarbon recovery from a field.

Data-driven AI approaches have found wider adoption in recent years for more accurately estimating reservoir properties far from wellbores. Ertekin et al. provided an extensive overview of the applications of artificial intelligence in reservoir engineering problems [1]. The authors present an overview about advanced machine learning approaches and more state-of-the-art artificial intelligence technologies for the reservoir engineering domain. A particular focus in the article is on advanced machine learning algorithms and their utilization for addressing challenges encountered in the extraction of hydrocarbons. Fuzzy logic and response surface model approaches are widely deployed for the categorization of reservoir zones and characterization of the properties within these zones [2]. Lim et al. presented a fuzzy logic approach for determining the porosity and permeability distribution in the reservoir from well logs. The results of combining the fuzzy curve approach together with a neural network approach allow to implement a nonlinear regression approach in determining the field's permeability and porosity properties. While the approach is quite promising, the authors solely focused on the well log parameter estimation and did not attempt to estimate permeability fields. In another article, David Wood presents a nearest-neighborhood approach for the joint estimation of porosity, permeability and saturation in well log data [3]. The utilized TOB algorithm exhibited strong performance for the estimation of the well logs; how-

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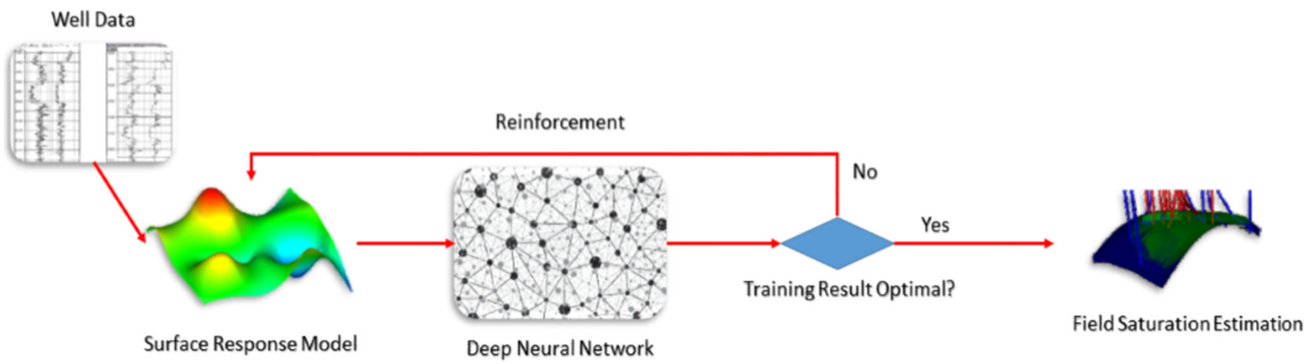

Fig. 1 Flowchart outline of the reinforcement surface response model approach

ever, it may face challenges due to overfitting when trying to predict reservoir saturation maps. A different approach by Tariq et al. utilizes a functional network model for the estimation of water saturation in carbonate rocks based on well logs [4]. While the approach delivers promising results for the data under investigation, the nonlinearity in saturation that is encountered in fractured carbonate rocks may make the approach challenging to be utilized for field saturation estimation.

Extensive research has been conducted in trying to estimate water saturation from well logs, and several algorithms have been utilized to better estimate water saturation profiles from well logs in the near wellbore area. While these approaches allow to have an accurate understanding of the saturation profile in the near wellbore profile, the estimates may be far off in the interwell region given the heterogeneity of the rock formation and lack of interwell direct measurements.

Deep electromagnetic tomography has become one of the viable solutions to have a more accurate understanding of the interwell reservoir volume, leveraging on the resistivity contrast between water and hydrocarbons [5]. Additionally, crosswell electromagnetic tomography also has been a promising solution for enhancing reservoir history matching and fluid saturation mapping via complementing well logs and production information with interwell volumetric resistivity data [6, 7].

Several crosswell electromagnetic (EM) surveys have been conducted in recent years, demonstrating the significant potential of this technology for interwell saturation mapping. A crosswell electromagnetic survey was performed between two horizontal wells, a watered out oil producer and a water injector in the reservoir section [8], followed by a 3D resistivity inversion that was developed to derive a 3D resistivity cube in the interwell space [9]. The main strength of this unique technology is how it offers an incomparable depth of investigation. It also provides a robust way to assist with the extraction of the water saturation distribution [10].

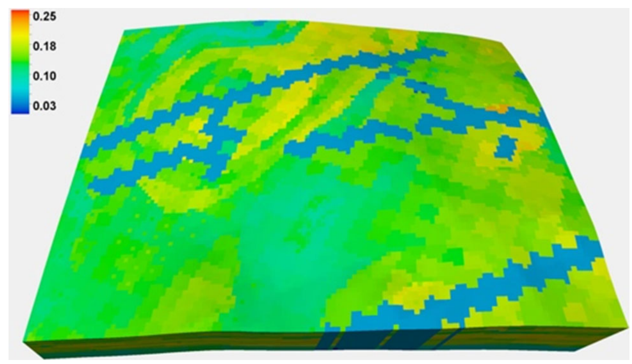

Fig. 2 3D map of the porosity distribution of the reservoir box model

Key challenge to obtain an accurate fluid distribution mapping using an analytical approach (i.e., Archie's equation) from a tomographic 3D resistivity cube, up to few kilometers in size, is the lack of knowledge of the controlling parameters, such as water salinity, cementation, factor, saturation exponent, porosity and fracture distribution, in the interwell volume. The problem is mathematically ill-posed, as we do not have direct methods to measure the volumetric distribution of such quantities in the interwell reservoir volumes. Different approaches were made to tackle this problem, such as using advanced uncertainty analysis techniques [11], integration with history matching workflows or data assimilation methods.

In this article, we present a novel AI approach, integrating a reinforcement response surface model method into a deep learning sparsity adapting neural network estimation process for the estimation of interwell saturation, taking into account the sparsity of the fracture channels. Finally, a reservoir model with complex fracture networks that are driven by mainly water injection validated the framework and estimation performance.

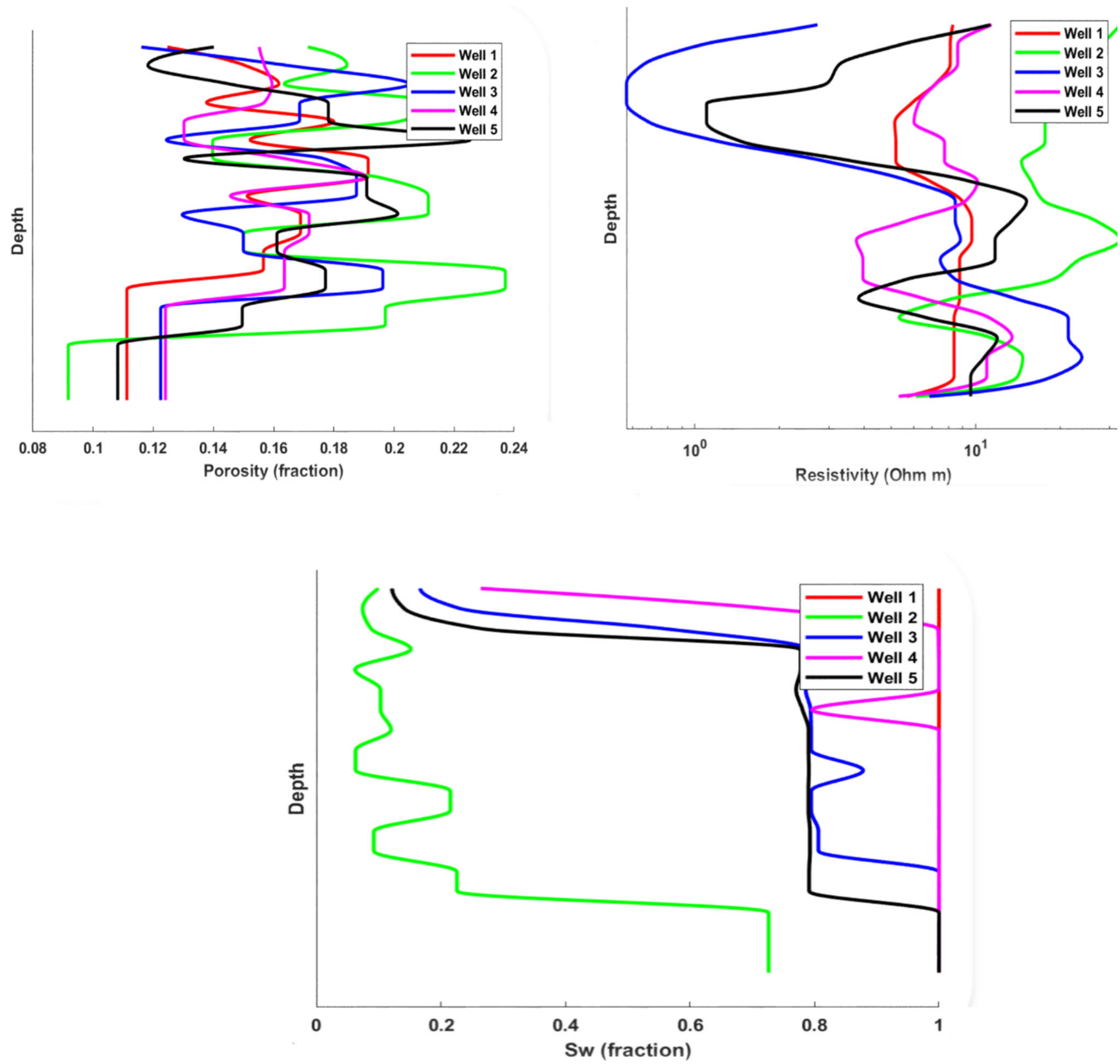

Fig. 3 Comparison of porosity (upper left), resistivity (upper right) and water saturation (bottom) well log data for the five reservoir wells

2 Experiments and Methods

We present in the article a novel spatial sparsity robust deep learning approach under uncertainty to determine the interwell saturation in the reservoir while simultaneously reducing uncertainty. Figure 1 displays the developed framework. The approach integrates a surface response model approach for determining an estimate of the uncertainty in the measurement data and utilizes it to create an uncertainty dataset for training the network. Given the spatial sparsity of the initial measurement data close to the wellbore, the surface response model simultaneously enables to estimate the water saturation in the wellbore proximity in order to increase the training data size.

The surface response model consists of a log-linear surface response model where the linear regression hyperparameters were optimized. For the hyperparameter optimization, we minimized the fivefold crossvalidation loss for a single parameter with both a support vector machine and least squares approach.

The training dataset is then utilized in the deep neural network that consists of a feedforward neural network (multilayer perceptron), where each layer is fully connected. The network consists of 50 layers, where the size of the input

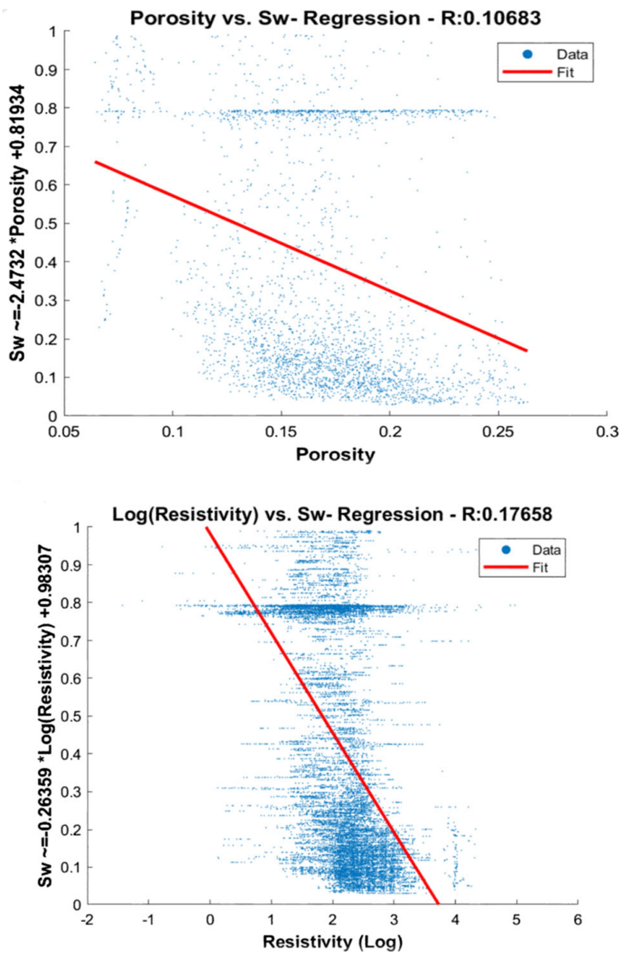

Fig. 4 Crossplot comparison of water saturation versus porosity and log resistivity. The data clearly exhibit negligible correlation between both parameters

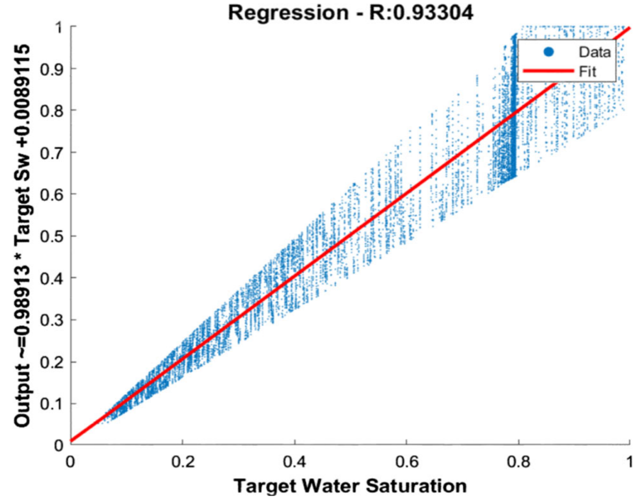

Fig. 5 Surface response model estimation removing 5% of the worst fitting data points

layer is seven, consisting of porosity, permeability, spatial information and porosity- and permeability-derived data. The full connectedness between the layers turned out to be quintessential in initial studies in order to achieve acceptable saturation estimates. The output layer is characterized by a sigmoid activation function. For the training, we employed a robust Bayesian regularization approach, which enables to achieve greater robustness during the training approach and demonstrated to be able to better deal with training datasets with greater uncertainty. The robustness of the approach is achieved via the conversion of the nonlinear regression problem into a ridge regression that is well posed and more robust to the uncertainty in the input data [12]. The estimation success is evaluated as a weighted mean between the coefficients of determination for the training and test set, and the result is considered optimal if it is above 0.95. Otherwise, a reinforcement step is applied on the initial well measurement data via adding Gaussian noise to the initial measurement data and compute the surface response model. The updated uncertainty training dataset is then utilized for retraining the neural network via weighing the new data stronger as compared to the former data, where the reinforcement learning parameter adapts the weighting of the updated training data accordingly. In terms of spatial weighting, all saturation values were equally weighted for the training in order to avoid introducing a bias.

The trained network is then subsequently applied on the estimation of the interwell saturation. The algorithm allows to deal with and integrate the spatial sparsity and strong uncertainty in the training dataset for achieving robust estimates of the saturation, in addition to generating some statistics.

3 Results and Discussion

The framework was tested and evaluated on a reservoir box model with five vertical wells and a complex fracture network structure. The reservoir box model size was $122 \times 100 \times 20$, and the porosity distribution and model geometry are outlined in Fig. 2. The well logs derived at the wellbores are outlined in Fig. 3 that show the porosity, resistivity and derived water saturation profiles.

The graphs show strong heterogeneity and difference between the individual wells and provide indications about the fracture intersections showing rather higher water saturation penetrations as compared to the surrounding areas.

When comparing both the relationships between the resistivity and porosity data in Fig. 4, it is evident that the data are strongly uncorrelated which represents a strong challenge for any framework to deliver reliable and consistent estimates. While there is a minor trend that for increasing porosity and log resistivity the water saturation is decreasing, this effect is

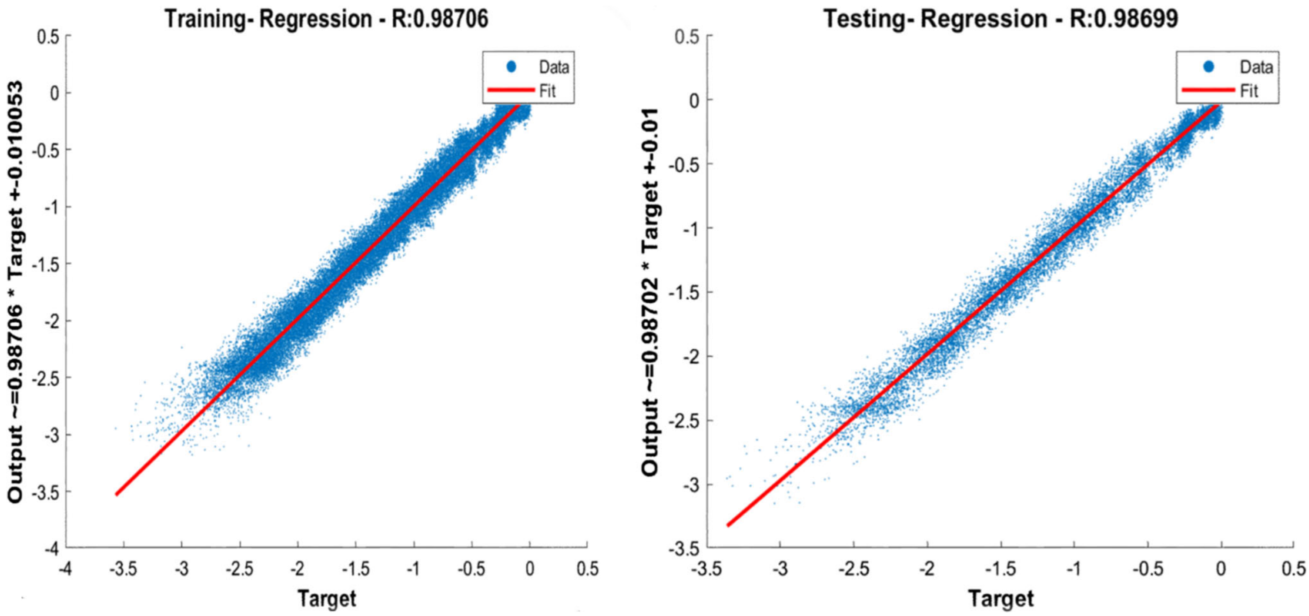

Fig. 6 Training performance of the spatial sparsity deep learning approach, comparing the training and testing data in the log space

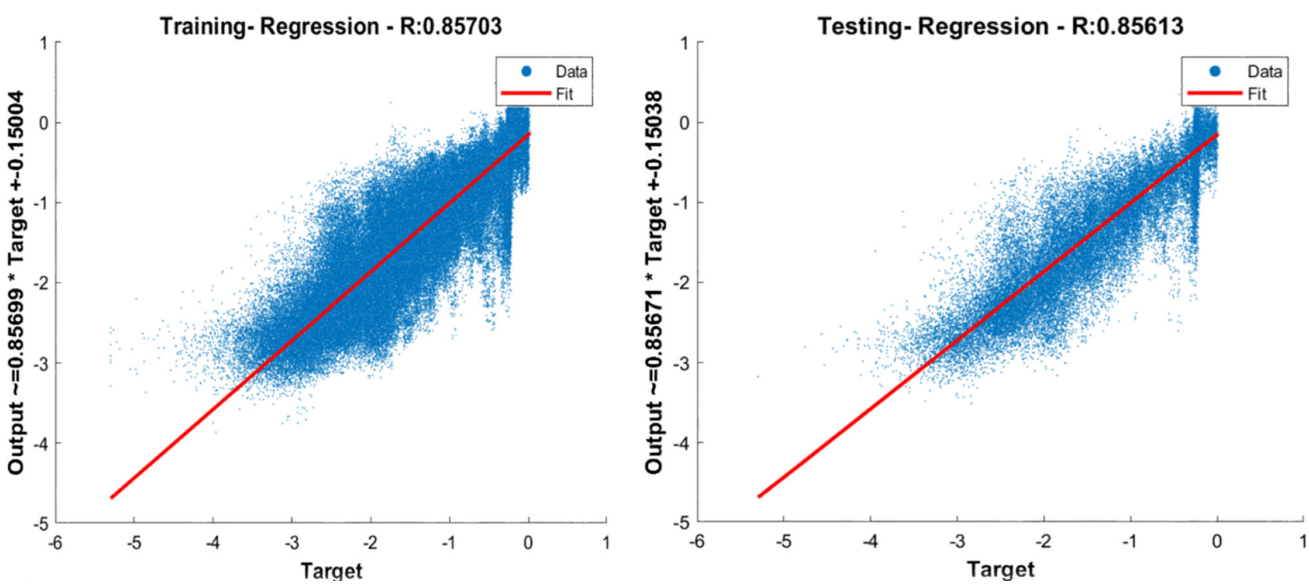

Fig. 7 Training performance of the network without a surface response model, comparing the training and testing data in the log space. The training and estimation performance is worse as compared to the combined approach

rather weak and there are significant patches in the data that do not display this behavior at all.

Figure 5 displays a comparison between the estimates of the surface response model and target well data, where a regularized support vector machine model was deployed for model estimation. Given the performed hyperparameter optimization, the support vector machine as compared to a least squares approach performed best. The optimized regularization hyperparameter for the surface response model was 0.0277. The water saturation was estimated in log form to achieve a stronger linearized response when correlating both resistivity and porosity.

With the surface response model, the adapted training dataset was created incorporating the generation of perturbed data from the initial uncertainty estimates. The incorporation of uncertainty estimates both allows for the increase in the training data size and avoids a strong bias in the network estimation due to the initial data selection. This is essential given the strong spatial heterogeneity of the water saturation levels in the reservoir. In Fig. 6, we display the training performance where the training dataset was separated into a training and

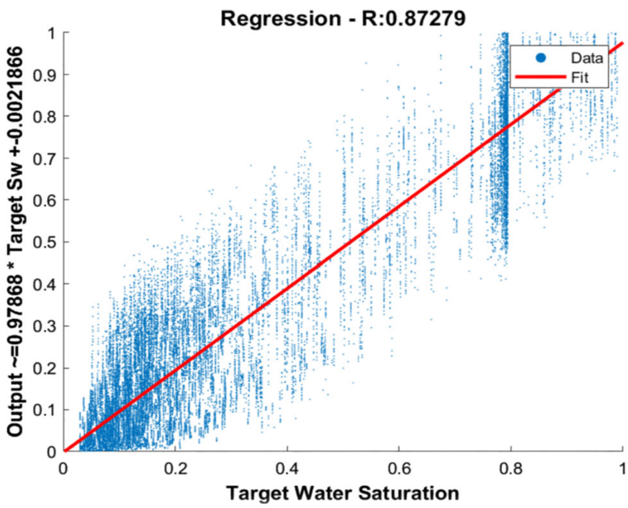

Fig. 8 Interwell saturation estimates versus the true water saturation for the model study

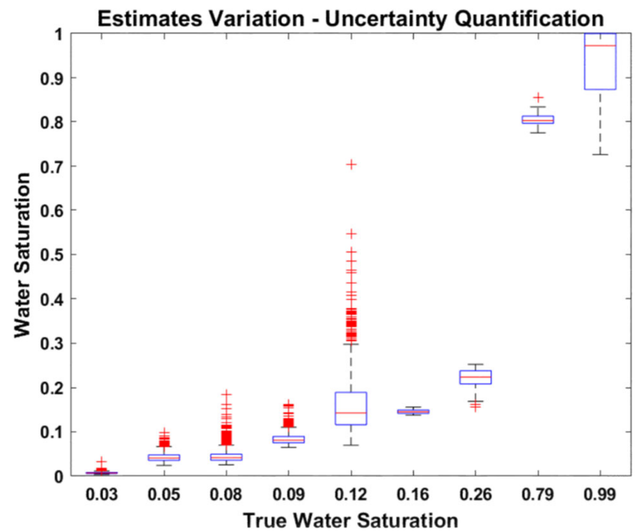

Fig. 9 Water saturation uncertainties for selected reservoir cells

testing set for improving the performance. The split was 75% and 25% of the data and clearly outlines the strong training performance. Comparing the results to Fig. 7, where the training performance is shown without having incorporated the surface response model, the performance drops significantly with a lower coefficient of determination.

The trained network was then finally applied for the mapping of the interwell region, and the results are outlined in Fig. 8. A comparison between the estimates and the true synthetic saturation field outlines the rather strong estimation ability of the technique. The method is particularly strong in the estimation at low saturation values, while exhibiting slightly higher variation for water saturation values close to 1. This can be explained from the fact that the logarithm maps the interval from zero to one, to infinity to 0, which increases the estimation ability at the lower end of the saturation values.

In order to determine the robustness of the framework for the estimation of water saturation in the interwell area as well as quantify the uncertainty in the estimates, we performed a sensitivity analysis. A total number of 1000 realizations for each data point were realized together with their water saturation estimates. In Fig. 9, we outline the estimation variation for selected reservoir cells incorporated into a boxplot. Estimation quality is fairly robust for most of the estimates that are fairly close to the benchmark water saturation in the interwell region. The boxes represent the 25th and 75th percentiles, implying that 50% of the realizations estimates are within this range. This implies that more than 500 of the 1000 realizations are encountered within this range. The number of outliers (indicated in terms of red crosses) is fairly small and less than 0.2% of the total number of realizations with the vast majority of estimates being in a fairly close range. Given the strong variation and nonlinearity between the input and output parameters, the results exhibit strong robustness in achieving good quality interwell saturation estimates.

4 Conclusions

We have presented a new sparsity reinforcement surface response AI framework for the estimation of saturation in the interwell region. The framework incorporates a surface response model for the generation of a training set incorporating the uncertainty in the measurement data. The training data are then utilized in the network training of a deep neural network that is incorporated into a feedback (reinforcement learning step) process that enhances the robustness of the trained model and improves the estimation quality. The framework was examined on a realistic reservoir box model with strong heterogeneity and uncertainty in the well measurements. The framework performed rather well, allowing to provide reliable estimates for the interwell saturation. This method may be extended to incorporate more broadly the uncertainty in the fracture network distribution utilizing discrete fracture network models as constraints. Finally, this developed method may incorporate smart pattern recognition techniques for flow feature detection and subsequent incorporation into the water saturation estimation framework.

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