Estimation of Reservoir Simulation Responses for Different Relative Permeability Curves

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Prediction

In oil and gas reservoir simulators, using reasonable relative permeability curves is crucial to properly represent a reservoir model and predict future reservoir performance. In practice, initially obtained relative permeability curves are modified in history matching process to decrease discrepancy between simulation results and actual production history. History matching process requires running a large number of simulations, of an order of 100-10,000. Performing a large number of simulations, however, is challenging because running each reservoir simulation is computationally expensive. In this study, linear regression and neural network fittings are explored to estimate reservoir simulation responses for different relative permeability curves without running expensive reservoir simulations.

Data

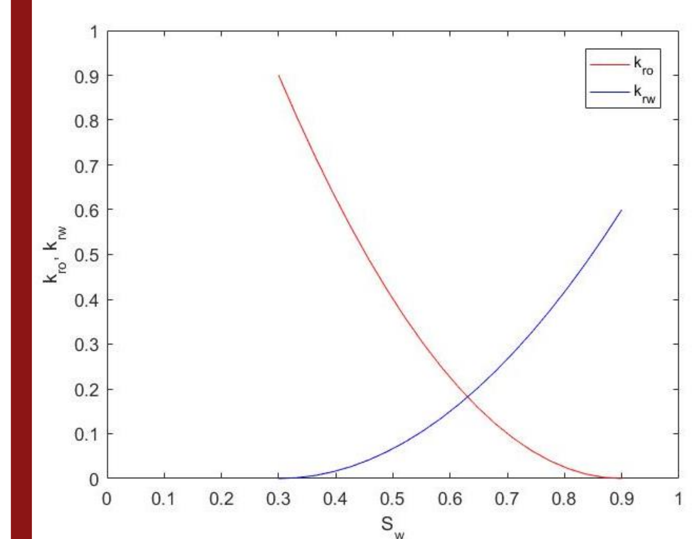
Using Stanford's reservoir simulator (AD-GPRS), 240 set of reservoir simulation outputs with different relative permeability parameters are obtained. The first 40 set is used for linear regression and neural network training and the remaining 200 set is used to test estimation accuracy.

References

[1] Howard B. Demuth, Mark H. Beale, Orlando De Jess, and Martin T. Hagan. Neural Network Design. Martin Hagan, USA, 2nd edition, 2014.

[2] S. Trehan. Surrogate Modeling for Subsurface Flow: A New Reduced-order Model and Error Estimation Procedure. PhD thesis, Department of Energy Resources Engineering, Stanford University, 2016.

Features & Output



$$k_{rw}(S_w) = krw^o\left(\frac{S_w - S_{wir}}{1 - S_{wir} - S_{or}}\right)^{n_w}$$

$$k_{ro}(S_w) = kro^o\left(\frac{S_w - S_w - S_{or}}{1 - S_{wir} - S_{or}}\right)^{n_o}$$

$$x^{(i)} = \left[1, n_w, n_o, S_{wir}, S_{or}, k_{ro}^o, k_{rw}^o\right]^T, x^{(i)} \in \mathbb{R}^7$$

Output $y_f^{(i)}$ is a vector containing amount of cumulative fluid f (f = oil or water) produced at 26 different times ($y_f^{(i)} \in R^{26}$).

Models

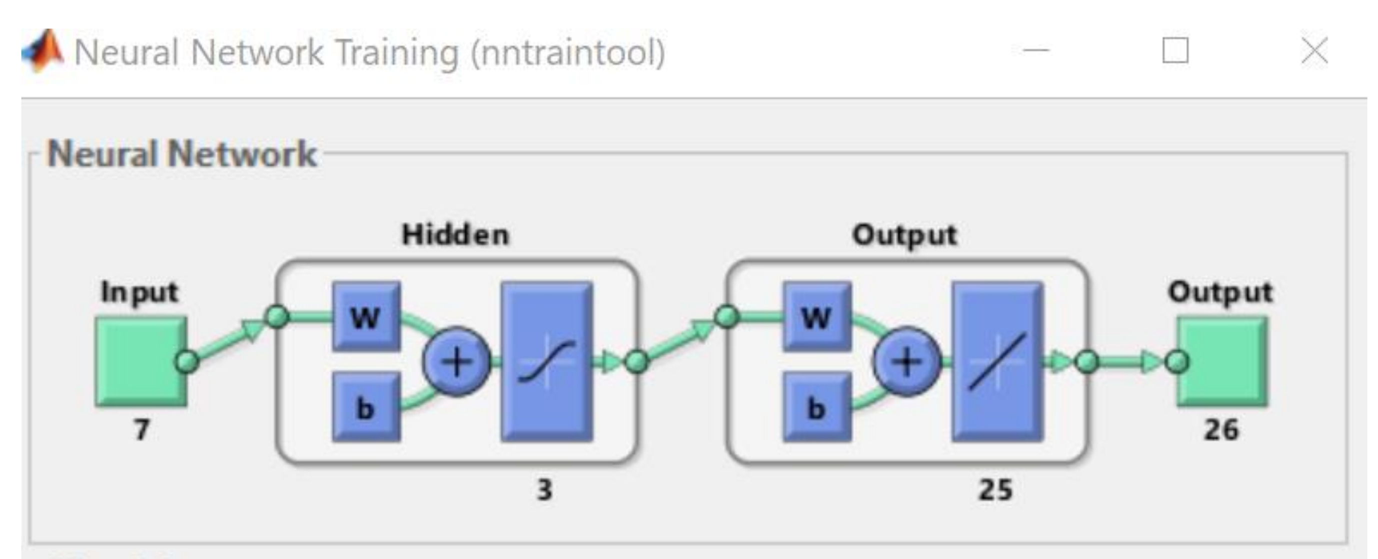
1. Linear regression

$$\begin{bmatrix} x_1^1 & x_2^1 & x_3^1 & \dots & x_7^1 \\ x_1^2 & x_2^2 & x_3^2 & \dots & x_7^2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_1^{40} & x_2^{40} & x_3^{40} & \dots & x_7^{40} \end{bmatrix} \begin{bmatrix} \theta_{1,1} & \theta_{1,2} & \theta_{1,3} & \dots & \theta_{1,26} \\ \theta_{2,1} & \theta_{2,2} & \theta_{2,3} & \dots & \theta_{2,26} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \theta_{7,1} & \theta_{7,2} & \theta_{7,3} & \dots & \theta_{7,26} \end{bmatrix} = \begin{bmatrix} y_1^1 & y_2^1 & y_3^1 & \dots & y_{26}^1 \\ y_1^2 & y_2^2 & y_3^2 & \dots & y_{26}^2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ y_1^{40} & y_2^{40} & y_3^{40} & \dots & y_{26}^{40} \end{bmatrix}$$

$$\theta^* = (X^T X)^{-1} X^T Y,$$

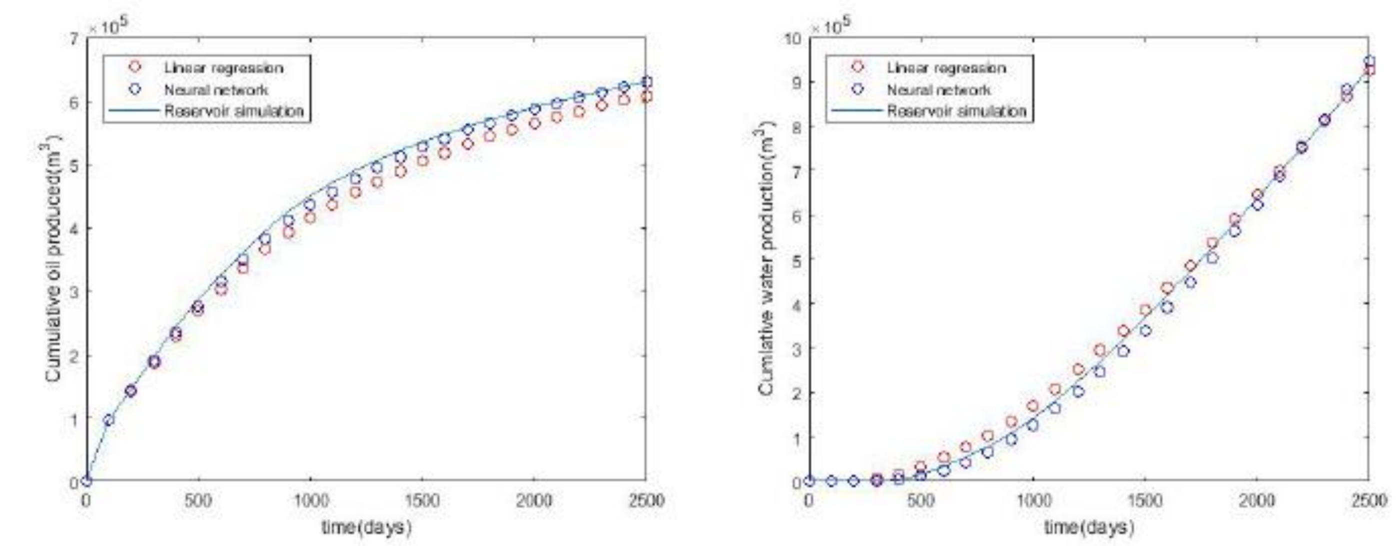
Using ϴ*, the trained liner regression model predicts reservoir simulation output for different relative permeability parameters.

2. Neural Network (MATLAB tool box)



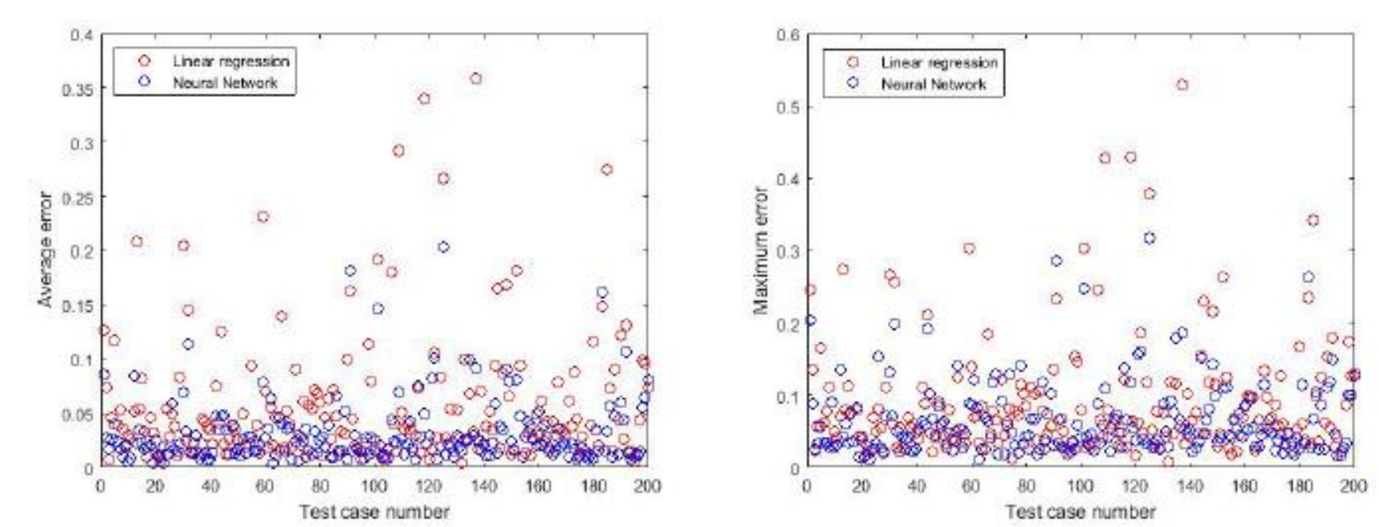
Connect the seven features to three neurons in the hidden layer and train the neural network using Levenberg-Marquardrdt[1] backpropagation algorithm.

Results



(a) Cumulative oil recovery (b) Cumulative water recovery

Figure 1. Cumulative oil recovery and water recovery obtained from linear regression, neural network, and actual simulation run from one of 200 test set.



(a) Average error in cumulative oil recovery (b) Maximum error in cumulative oil recovery

$$Error(t_n) = \frac{Q_{ML}(t_n) - Q_{Sim}(t_n)}{Q_{Sim}(t_n)}$$

$$Ave.Error = \frac{\sum_{n=1}^{N}(Error(t_n))}{N}$$

$$Max.Error = \max_n Error(t_n)$$

Figure 2. The average and the maximum errors of linear regression and neural network estimations. The error plots indicate that most of the test case show acceptable error, In addition, the estimation from neural network fitting is more reliable. 96% and 87.5% of the test set from neural network and linear regression show the average error less than 10%, respectively.

Discussion

We apply linear regression and neural network fitting to estimate reservoir simulation responses for different relative permeability parameters. For the example case considered here, both linear regression and neural network fitting show acceptable estimations from the most of test cases. We can consider to use estimation from machine learning algorithms in history matching process of relative permeability to provide significant computational savings.

Future

The estimation from machine learning algorithms is less accurate in cumulative produced water estimation than cumulative produced oil. Future work should be focused on reducing estimation error in cumulative produced water.