Please fill in the name of the event you are preparing this manuscript for.	2021 SPE Middle East Oil & Gas Show and Conference	
Please fill in your 6-digit SPE manuscript number.	SPE-204604-MS	
Please fill in your manuscript title.	Artificial Intelligence Aided Proxy Model for Water Front Tracking in Fractured Carbonate Reservoirs	
Please fill in your author name(s) and company affiliation.		
Given Name	Surname	Company
Yanhui	Zhang	KAUST
Ibrahim	Hoteit	KAUST
Klemens	Katterbauer	Saudi Aramco
Alberto	Marsala	Saudi Aramco

This template is provided to give authors a basic shell for preparing your manuscript for submittal to an SPE meeting or event. Styles have been included (Head1, Head2, Para, FigCaption, etc) to give you an idea of how your finalized paper will look before it is published by SPE. All manuscripts submitted to SPE will be extracted from this template and tagged into an XML format; SPE's standardized styles and fonts will be used when laying out the final manuscript. Links will be added to your manuscript for references, tables, and equations. Figures and tables should be placed directly after the first paragraph they are mentioned in. The technical content of your paper WILL NOT be changed. Please start your manuscript below.

Abstract

Saturation mapping in fractured carbonate reservoirs is a major challenge for oil and gas companies. The fracture channels within the reservoir are the primary water conductors that shape water front patterns and cause uneven sweep efficiency. Flow simulation for fractured reservoirs is typically time-consuming due to the inherent high nonlinearity. A data-driven approach to capture the main flow patterns is quintessential for efficient optimization of reservoir performance and uncertainty quantification.

We apply an artificial intelligence (AI) aided proxy modeling framework for waterfront tracking in complex fractured carbonate reservoirs. The framework utilizes deep neural networks and reduced-order modeling to achieve an efficient representation of the reservoir dynamics to track and determine the fluid flow patterns within the fracture network. The AI-proxy model is examined on a synthetic two-dimensional (2D) fractured carbonate reservoir model. Training dataset including saturation and pressure maps at a series of time steps is generated using a dual-porosity dual-permeability (DPDP) model. Experimental results indicate a robust performance of the AI-aided proxy model, which successfully reproduce the key flow patterns within the reservoir and achieve orders of shorter running time than the full-order reservoir simulation. This suggests the great potential of utilizing the AI-aided proxy model for heavy-simulation-based reservoir applications such as history matching, production optimization, and uncertainty assessment.

Introduction

Numerical reservoir simulation has become an essential tool for reservoir management and field development in the oil and gas industry (Carlson, 2003). Reservoir simulation models integrate detailed geological information with dynamic reservoir data to represent the complex subsurface fluid flow in porous media. The major goal of reservoir simulation is to predict the future performance of a reservoir and investigate the ways to enhance the oil recovery under various operating strategies. However, due to the strong nonlinearity and heterogeneity of subsurface flow systems, the computational cost can be high, particularly for mature oil fields with a long production history. Even though recent advances in computing power enable the simulation of more realistic large-scale reservoir models containing significant geological complexity, computational demands can become prohibitive for the applications involving

history matching, production optimization, and uncertainty quantification, in which a large number of simulation runs may be required (Oliver et al., 2008; Aanonsen et al., 2009; Chen et al., 2009; Emerick and Reynolds, 2012; Zhang and Leeuwenburgh, 2017; Zhang and Hoteit, 2020).

Proxy or surrogate modeling in reservoir engineering has been an active research area, whose main goal is to develop an efficient substitute for the full reservoir simulation model to significantly reduce the computational cost and meanwhile retain sufficient prediction accuracy on desired outputs (Zubarev, 2009; Amini and Mohaghegh, 2019; Jaber et al., 2019). Proxy models can be constructed based on different methods. Amini and Mohaghegh (2019) summarized the methods to develop proxy reservoir models into four different groups that include statistics-based approach, reduced-order modeling, reduced-physics modeling, and AI-based approach.

In general, statistical proxy modeling utilizes response surface methods to approximate the response of the original model for a given input setting. To properly cover the input-output space of interest, the design of experiments is typically used to identify statistically significant uncertain model variables and synthesize simulation data to create response surfaces. The computational cost increases with the growing complexity of the underlying input-output relationship to obtain a proxy model that accurately describes the system's behavior. This technique has been applied in a variety of applications such as history matching and uncertainty assessment (Manceau et al., 2001; Landa and Güyagüler, 2003; Yeten et al., 2005). Reduced-order or reduced-physics models accelerate flow predictions through either projecting the computation in the original high-dimensional state space into a low-dimensional subspace or simplifying the complex physics of numerical simulation. Wilson and Durlofsky (2013) presented a procedure for optimizing the development of shale gas field in which the developed reduced-physics model ran hundreds of times faster than the underlying full-physics model for the cases they considered. Cardoso et al. (2009) introduced a reduced-order model based on the proper orthogonal decomposition technique in which snapshot clustering and missing point estimation techniques were implemented for further reduction of computational cost. They showed that the reduced-order modeling procedures could accurately reproduce the reference simulations and could speed up the simulation up to an order of magnitude compared with the full model.

AI-based proxy modeling that utilizes machine learning and deep learning techniques has drawn increasing attention recently for researchers and reservoir engineers in the oil and gas industry. Compared with conventional modeling approaches, AI-based modeling approach has shown great potential to capture complex input-output relationships involved in fluid flow simulation, and the flexibility to be applied to a variety of reservoir problems such as uncertainty analysis, optimization, and history matching. Cullick et al. (2006) proposed a nonlinear proxy model using an artificial neural network (ANN) to reduce the computational burden for the history match process. They applied the ANN proxy model on field water injection case study which showed good performance as a proxy for numerical simulation over the trained parameter space. Amini and Mohaghegh (2019) developed a proxy model based on ANN for a real case CO₂ sequestration project in which the goal was to evaluate the dynamic reservoir parameters under various CO₂ injection scenarios. The proxy model was shown to be able to obtain pressure, saturation, and CO₂ mole fraction throughout the reservoir with much less computational effort. Zhu and Zabaras (2018) introduced a proxy model using a Bayesian deep convolutional encoder-decoder network for uncertainty quantification and propagation. Their experiments showed promising results of the proxy model in terms of predictive performance and uncertainty modeling even with limited training data.

In this study, we introduce an AI-aided proxy modeling framework for waterfront tracking in complex fractured carbonate reservoirs. The framework utilizes deep neural networks and reduced-order modeling to achieve an efficient representation of the subsurface flow dynamics to track and determine the fluid flow patterns within the reservoir. We examine the AI-proxy model on a fractured carbonate reservoir model in which the training dataset including saturation and pressure maps at a series of time steps is generated using a DPDP model.

Fractured carbonate reservoir model

Here we consider a synthetic 2D fractured carbonate reservoir box model, which is extracted and modified based on a full field geological model of a mature oil field in Saudi Arabia. Figure 1 shows a combined view of the matrix-fracture porosity and log-transformed horizontal permeability fields of the reference reservoir model. A large-scale fracture network is developed within the reservoir that dominates the production and recovery behavior. The strong contrast between matrix and fracture properties causes uneven water advancement, so that the flooding is predominantly taking place in high permeable fracture corridors.

Figure 1— Matrix-fracture log-transformed permeability (left) and porosity (right).

The reservoir covers an area of $10007 \times 8202 \text{ ft}^2$ with a varying thickness ranging approximately from 11 to 18 ft. The simulation model has dimensions of 122×100 . There are two horizontal wells that are drilled roughly parallel with approximately 4265 ft far apart. The fluid system contains two immiscible phases of oil and water. There is an aquifer connected to the west edge of the reservoir. A DPDP model is used to simulate the fluid flow dynamics in the fractured carbonate reservoir, which is implemented with the ECLIPSE reservoir simulator (Schlumberger, 2019).

Flow simulation for fractured reservoirs is typically time-consuming, due to the inherent high nonlinearity from the matrix-fracture interactions and the doubling of the number of computational gridcells for the DPDP model. The computational burden becomes challenging when performing heavy-simulation-based tasks such as history matching, production optimization, and uncertainty assessment, in which a large number of simulation runs may be required. This motivates our study to seek an efficient solution to accelerate the flow simulation of fractured reservoirs utilizing AI-aided proxy modeling techniques.

For the experimental setting, we focus on the prediction of global saturation and pressure fields of the reservoir under time-varying well controls using the AI-aided proxy model, and assume no geological uncertainty associated with the reservoir.

AI-aided proxy modeling framework

In this study, we take a deep-learning-based reduced-order proxy modeling approach which was introduced by Jin et al. (2020). This approach adopts an embed-to-control (E2C) framework (Watter et al., 2015) to predict subsurface fluid flow dynamics under time-varying well controls. The E2C framework consists of an autoencoder (AE) and a linear transition model. Figure 2 displays a schematic flowchart of the deep-learning-based reduced-order proxy modeling approach. In general, the AE component with an encoder-decoder architecture is used to obtain dimensionality reduction by learning the mapping to and from a low-dimensional representation of original reservoir states. The linear transition model is

constructed to approximate the evolution of the projected reservoir states in the latent low-dimensional subspace with time-varying production and injection well control inputs.

Figure 2—Schematic flowchart of the deep-learning-based reduced-order proxy model.

Training dataset generation

For the considered reservoir model, the simulation is run for a total of 2700 days. The injector is operated under time-varying bottomhole pressure (BHP) control, while the producer is on a time-varying liquid production rate (LRAT) control. The operating controls for both injection and production wells are altered every 90 days, which leads to 30 control time steps. Therefore, there are 60 (30×2) control parameters in total over the entire simulation time. The range for injection BHP is set between 5400 and 5800 psi, and the range for production rate is between 1000 and 2000 stb/day. To generate the training dataset, we first randomly sample the control parameters from a uniform distribution according to the specified ranges. Figure 3 shows three random realizations of the sampled well control parameters. We then perform full-order simulation runs with the sampled time-varying well controls and collect the corresponding simulation outputs. In the experiments, the dataset is composed of saturation and pressure fields for the matrix and fracture at the control time steps from 200 simulation runs, which is randomly splitted into training (80%) and test (20%) sets.

Encoder network

The workflow starts with an encoder network that takes the snapshots of saturation and pressure for the matrix and fracture as input and produce a low-dimensional representation of these full-order state variables,

$$z_t = Q_\phi^{enc}(x_t), \quad (1)$$

where $x_t \in \mathcal{R}^{l_x}$ is the full-order state variable (of dimension $l_x = 122 \times 100 \times 4 = 48800$) at time step t , and $z_t \in \mathcal{R}^{l_z}$ is the corresponding latent variable (of dimension $l_z = 50$). The value of l_z is expected to be case-dependent, which should be high enough to represent the underlying physics accurately while still sufficiently low for computational efficiency.

The operator Q_ϕ^{enc} denotes the encoder network with ϕ representing the associated training parameters with the encoder. As presented in Figure 2, the encoder network consists of a stack of four encoding

blocks, a stack of three residual convolutional (ResConv) blocks, and a dense (fully-connected) layer. The structure of each encoding block is comprised of a 2D convolutional layer, a batch normalization layer, and a ReLU (rectified linear unit) activation function. The ResConv blocks follow a similar structure of Conv-BatchNorm-ReLU for the nonlinear layers as the encoding blocks, but differ in possessing an additional identity mapping that can bypass the nonlinear layers. It turns out that the residual network architecture is beneficial in deepening the network while relieving the vanishing gradient issue related to deep neural networks (He et al., 2016). The output from these blocks is a stack of low-dimensional feature maps extracted from the saturation and pressure fields. The feature maps are then flattened to a long vector which is further reduced to a vector with specified dimension of l_z by a dense layer.

Figure 3—Randomly sampled realizations of time-varying well control profiles.

Linear transition model

The low-dimensional latent state variable z_t from the encoding network is input to a linear transition model that evolves the latent variable from one time step to the next according to given well controls. In mathematical terms, the linear transition model can be expressed as

$$\hat{z}_{t+1} = Q_{\psi}^{trans}(z_t, u_{t+1}, \Delta t), \quad (2)$$

where $\hat{z}_{t+1}$ is the predicted latent state at the next time step, u_{t+1} denotes the current well controls, and Δt is the time step size.

The architecture of the linear transition model Q_{ψ}^{trans} is basically an ANN network (ψ represents the associated training parameters of the network), which is constructed by a stack of three transformation blocks and two dense layers. Each transformation block consists of a dense layer, a batch normalization layer, and a ReLU activation function.

Decoder network

The decoder network provides an inverse mapping of the latent state variables from the low-dimensional subspace back to the original full-order space, which can be represented as

$$\begin{aligned}\hat{x}_t &= Q_\theta^{dec}(z_t), \\ \hat{x}_{t+1} &= Q_\theta^{dec}(\hat{z}_{t+1}),\end{aligned}\tag{3}$$

where $\hat{x}_t$ and $\hat{x}_{t+1}$ are the reconstructed state variable at time step t and the predicted state variable at time step $t + 1$ respectively. The structure of the decoder network Q_θ^{dec} (θ denotes the training parameters associated with the decoder) as shown in Figure 2 is analogous to the encoder network but generally constructed in reverse order. A dense layer first transforms the low-dimensional latent state vector into a stack of feature maps with reshaping operation. These feature maps are then fed to a stack of ResConv and decoding blocks, during which spatially expanded feature maps are gradually constructed. A convolution layer finally converts the expanded feature maps to saturation and pressure fields for the prediction.

Loss function

The training parameters (ϕ , ψ , and θ) for the whole framework are determined by minimizing a loss function that measures the performance of the proxy model in predicting the desired quantities. In this study, the loss function of $\mathcal{L}$ is given by

$$\begin{aligned}\mathcal{L} &= \mathcal{L}_R + \mathcal{L}_P + \mathcal{L}_T, \\ \mathcal{L}_R &= \frac{1}{N_t} \sum_{i=1}^{N_t} (\|x_t - \hat{x}_t\|_2^2)_i, \\ \mathcal{L}_P &= \frac{1}{N_t} \sum_{i=1}^{N_t} (\|x_{t+1} - \hat{x}_{t+1}\|_2^2)_i, \\ \mathcal{L}_T &= \frac{1}{N_t} \sum_{i=1}^{N_t} (\|z_{t+1} - \hat{z}_{t+1}\|_2^2)_i,\end{aligned}\tag{4}$$

where $\mathcal{L}_R$, $\mathcal{L}_T$, and $\mathcal{L}_P$ represent the reconstruction loss, the linear transition loss, and the prediction loss respectively. The parameter N_t is the total number of training data points. Therefore, the loss function is the sum of averaged mismatches between the proxy model output and the full-order model solution over all training data points. More detailed explanation of the E2C framework can be found in (Jin et al., 2020).

Experimental results

Since the range of input variables varies widely, it is necessary to preprocess the training dataset by normalization in order to make the proxy model work properly. Therefore, we implement a min-max scaling on the pressure and well control data so that the normalized pressure and rate stay in the same range $[0, 1]$ as the saturation. It is given by

$$\begin{aligned}p' &= \frac{p - p_{min}}{p_{max} - p_{min}}, \\ q' &= \frac{q - q_{min}}{q_{max} - q_{min}},\end{aligned}\tag{5}$$

where p' and q' represent the normalized (grid-block or injection well bottomhole) pressure p and production rate q respectively. The subscripts *min* and *max* denote the lower and upper bounds associated with each quantity.

The constructed proxy model is trained by minibatch gradient descent, wherein the batch size is set to 4. The optimization algorithm of Adam (Kingma and Ba, 2015) is used to minimize the loss function. The experimental result is obtained after 60 epochs for the optimization. Figure 4 displays the distributions of the loss for the training and the test datasets during the training process. We can see that the data losses for both training and test sets are gradually reduced and seem to reach an acceptable level, even though they fluctuate somewhat from iteration to iteration due to the stochastic nature of the optimization algorithm.

Figure 4—Distributions of data loss for the training and the test datasets during training process.

For visual inspection, we randomly select a representative case from the test set. Figure 5 shows the prediction of saturation evolution in both the matrix and the fracture of the reservoir using the AI-aided proxy model. Clearly, the injected water preferentially flows through the more permeable fracture corridors from the injector to the producer. Compared with the solution from the full-order model simulation, the one from the proxy model shows close visual agreement, which is further verified from the error map (absolute value of the difference between the full-order and the proxy model solutions). It suggests that the AI-aided proxy model can provide accurate prediction saturation changes in the fractured carbonate reservoir model.

Figure 5—Comparison of matrix (upper subplot) and fracture (lower subplot) saturation prediction at several time steps between full-order and proxy models for a case randomly selected from the test set.

Figure 6 shows the prediction of the corresponding matrix and fracture pressure distributions for the selected test case using the AI-aided proxy model. Even though the pressure changes exhibit fairly complex patterns, the solution of the proxy model reproduces the main features observed in the full-order model solution. The error map indicates that the AI-aided proxy model is able to achieve a reasonable accuracy on the pressure prediction of the fractured reservoir model.

Regarding the computation cost, each full-order simulation run requires on average 45 minutes on the CPUs of a desktop. The training process for the proxy model takes about 2.5 hours on a GPU node. When applying the learned AI-proxy model to a test case, the simulation takes only a fraction of a second. It means that orders of speedup can be achieved by using the AI-aided proxy model, which therefore provides a very efficient way to deal with heavy-simulation-based reservoir applications such as production optimization and uncertainty assessment.

Figure 6— Comparison of matrix (upper subplot) and fracture (lower subplot) pressure prediction at several time steps between full-order and proxy models for a case randomly selected from the test set.

Conclusions

In this study, we introduced an artificial intelligence (AI) aided proxy modeling framework for waterfront tracking in complex fractured carbonate reservoirs. The framework utilizes deep neural networks and reduced-order modeling to achieve an efficient representation of reservoir dynamics to track and determine the fluid flow patterns within complex fracture networks. In general, the AI-aided proxy model is comprised of an encoder network, a linear transition model, and a decoder network. The encoder-decoder architecture is utilized to obtain dimensionality reduction by learning the mapping to and from a low-dimensional representation of original reservoir states. The linear transition model is constructed to approximate the evolution of the projected reservoir states in the latent low-dimensional subspace with time-varying production and injection well control inputs.

We examined the AI-aided proxy model on a synthetic two-dimensional (2D) fractured carbonate reservoir model. A dual-porosity dual-permeability (DPDP) model was used to generate the training dataset that includes saturation and pressure maps at a series of time steps from two hundred full-order simulation runs. Experimental results indicated a robust performance of the AI-aided proxy model, which was shown to be able to achieve an accurate representation of the reservoir dynamics, and to track the flow patterns within the fracture network with significantly less computational cost than the full-order

reservoir simulation. The promising results suggest the great potential of utilizing the AI-aided proxy model for heavy-simulation-based reservoir applications such as history matching, production optimization, and uncertainty assessment.

References

- Aanonsen, S.I., Nævdal, G., Oliver, D.S., Reynolds, A.C., Vallès, B., 2009. The Ensemble Kalman Filter in Reservoir Engineering – a Review. *SPE J.* 14, 393–412. <https://doi.org/10.2118/117274-PA>
- Amini, S., Mohaghegh, S., 2019. Application of machine learning and artificial intelligence in proxy modeling for fluid flow in porous media. *Fluids* 4, 1–17. <https://doi.org/10.3390/fluids4030126>
- Cardoso, M.A., Durlofsky, L.J., Sarma, P., 2009. Development and application of reduced-order modeling procedures for subsurface flow simulation. *Int. J. Numer. Methods Eng.* 77, 1322–1350.
- Carlson, M., 2003. Practical reservoir simulation: using, assessing, and developing results. PennWell Books.
- Chen, Y., Oliver, D.S., Zhang, D., 2009. Efficient Ensemble-Based Closed-Loop Production Optimization. *SPE J.* 14, 634–645. <https://doi.org/10.2118/112873-PA>
- Cullick, A.S., Johnson, D., Shi, G., 2006. Improved and more-rapid history matching with a nonlinear proxy and global optimization. *Proc. - SPE Annu. Tech. Conf. Exhib.* 2, 728–740.
- Emerick, A. a., Reynolds, A.C., 2012. Combining the Ensemble Kalman Filter with Markov Chain Monte Carlo for Improved History Matching and Uncertainty Characterization. *SPE J.* 17, 418–440. <https://doi.org/10.2118/141336-PA>
- He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep residual learning for image recognition. *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.* 2016-Decem, 770–778. <https://doi.org/10.1109/CVPR.2016.90>
- Jaber, A.K., Al-Jawad, S.N., Alhuraishawy, A.K., 2019. A review of proxy modeling applications in numerical reservoir simulation. *Arab. J. Geosci.* 12. <https://doi.org/10.1007/s12517-019-4891-1>
- Jin, Z.L., Liu, Y., Durlofsky, L.J., 2020. Deep-learning-based surrogate model for reservoir simulation with time-varying well controls. *J. Pet. Sci. Eng.* 192, 107273. <https://doi.org/10.1016/j.petrol.2020.107273>
- Kingma, D.P., Ba, J.L., 2015. Adam: A method for stochastic optimization, in: 3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings. pp. 1–15.
- Landa, J.L., Güyagüler, B., 2003. A Methodology for History Matching and the Assessment of Uncertainties Associated with Flow Prediction, in: Proceedings - SPE Annual Technical Conference and Exhibition. pp. 3663–3676. <https://doi.org/10.2118/84465-ms>
- Manceau, E., Mezghani, M., Zabalza-Mezghani, I., Roggero, F., 2001. Combination of Experimental Design and JointsModeling Methods for Quantifying the Risk Associated with Deterministic and Stochastic Uncertainties - An Integrated Test Study, in: Proceedings - SPE Annual Technical Conference and Exhibition. pp. 2537–2547. <https://doi.org/10.2523/71620-ms>
- Oliver, D.S., Reynolds, A.C., Liu, N., 2008. Inverse Theory for Petroleum Reservoir Characterization and History Matching, First. ed. Cambridge University Press, Cambridge.
- Schlumberger, 2019. Eclipse 100 Reference Manual 2019.1. Schlumberger, Houston, Texas.
- Watter, M., Springenberg, J.T., Boedecker, J., Riedmiller, M., 2015. Embed to control: A locally linear latent dynamics model for control from raw images. *Adv. Neural Inf. Process. Syst.* 2015-Janua, 2746–2754.
- Wilson, K.C., Durlofsky, L.J., 2013. Optimization of shale gas field development using direct search techniques and reduced-physics models. *J. Pet. Sci. Eng.* 108, 304–315. <https://doi.org/10.1016/j.petrol.2013.04.019>
- Yeten, B., Castellini, A., Guyaguler, B., Chen, W.H., 2005. A comparison study on experimental design and response surface methodologies, in: SPE Reservoir Simulation Symposium, Proceedings. pp. 465–479. <https://doi.org/10.2523/93347-ms>
- Zhang, Y., Hoteit, I., 2020. Feature-Oriented Joint Time-Lapse Seismic and Electromagnetic History Matching Using Ensemble Methods. *SPE J.* <https://doi.org/10.2118/203847-PA>
- Zhang, Y., Leeuwenburgh, O., 2017. Image-oriented distance parameterization for ensemble-based seismic history matching. *Comput. Geosci.* 21, 713–731. <https://doi.org/10.1007/s10596-017-9652-1>
- Zhu, Y., Zabarar, N., 2018. Bayesian deep convolutional encoder–decoder networks for surrogate modeling and uncertainty quantification. *J. Comput. Phys.* 366, 415–447. <https://doi.org/10.1016/j.jcp.2018.04.018>
- Zubarev, D.I., 2009. Pros and cons of applying proxy-models as a substitute for full reservoir simulations, in: Proceedings - SPE Annual Technical Conference and Exhibition. <https://doi.org/10.2118/124815-ms>