CEMRACS 2023 mini-project proposal
2 pages maximum (references included)

Title: Embedded machine learning models for the near well region within a conventional physics-based reservoir simulator.

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1. Context

Define the scientific and technological context with a brief state of the art.

Advanced methods for data-driven modeling are becoming more important in porous media research, from data processing to numerical modeling. Recent advances include machine learning aided data analysis, machine-learning enhanced numerical methods, as well as hybrid modeling, to mention a few. For instance, the next generation of reservoir simulators will to an increasing degree couple conventional flow models with models that represent complementary physics or different spatial resolution (regional or near-well models). At the same time, today's physics-based models will be supplemented with data-driven models. Combining data-driven models and physics-based models requires improved mathematical understanding and new numerical methods that are fast and robust for combined models.

2. Description and objectives

Describe the proposed mini-project and state the foreseen results, if possible, with quantitative metrics.

This mini-project aims at providing prototypes where trained machine learning models are efficiently embedded as modules/components in existing simulation frameworks using traditional physics-based models, e.g., Dune or OPM. (dune-project.org, opm-project.org). The application will be to model the impact of fluctuating injection on reservoir performance. The aim is to provide a prototype reservoir simulator where impact of the near well region is modeled efficiently using a trained machine learning model.

3. Proposed methodology

Describe the proposed methodology for the realization of the mini project.

In reservoir models the well is traditionally modeled using a Peaceman model were the well flow into the reservoir q_w is proportional to the difference of the cell and well pressure:

$$q_w = -\,C\,(P_c - P_w). \qquad (1)$$

The proportionality factor C depends on both fluid and rock properties and the grid size. For single phase flow, from a single well in a homogenous Cartesian cell, the C factor can be derived exactly from analytical solutions for steady state solutions [1]. For the application we are considering with rapid fluctuating injection these conditions are never strictly satisfied, and we thus aim at replacing the factor C in (1) with a trained machine learning model. We will use a refined grid for the near well region to generate the data for the training and replace the C factor with the trained network in the reservoir simulator and compare it with a full refined solution for the whole reservoir. The machine learning based model should provide efficient solutions that are faster than the classical physics-based simulators on a refined grid. Different machine learning algorithms such as Neural Networks [2], Linear/Logistics Regression or

Random Forest [3] are planned to be investigated in the course of the project. The implementation will be based on Tensorflow[4] or Pytorch [5] depending on the student's level of knowledge of such frameworks.

4. Software requirements

List the required software for implementing the mini project.

Dune and OPM. (dune-project.org, opm-project.org).
Programming language: Python
Dataset with relevant initial and boundary conditions for the near-well region and the reservoir.

5. References

[1] Peaceman, Donald W (1978). "Interpretation of well-block pressures in numerical reservoir simulation (includes associated paper 6988)." Society of Petroleum Engineers Journal 18 (03): 183-194. https://doi.org/10.2118/6893-PA

[2] Gardner, Matt W. and S. R. Dorling (1998). "Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences." Atmospheric environment 32 (14-15): 2627-2636. https://doi.org/10.1016/S1352-2310(97)00447-0

[3] Breiman, Leo (2001). "Random forests." Machine learning 45: 5-32. https://doi.org/10.1023/A:1010933404324

[4] Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., ... & Zheng, X. (2016, November). Tensorflow: a system for large-scale machine learning. In Osdi (Vol. 16, No. 2016, pp. 265-283).

[5] Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., … Chintala, S. (2019). PyTorch: An Imperative Style, High-Performance Deep Learning Library. In Advances in Neural Information Processing Systems 32 (pp. 8024–8035). Curran Associates, Inc. Retrieved from http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf