Generalization of ML-Based Surrogate Models to Dynamic Injection Schedules using Transfer Learning

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SMART

Science-informed Machine Learning to Accelerate Real Time (SMART) Decisions in Subsurface Applications

Study Highlights

- The study goal was to see whether traditional deep learning surrogate models [1,2] trained on constant rate injection scenarios could accommodate variable injection schedules (and possible other reservoirs).
- We trained a convolutional neural network model (Fig. 1) to predict pressure changes during CO_2 injection into a brine saturated carbonate reservoir.
- Our model predicted the **current month's pressure** based on the previous month's **observed pressure.**
- Training was done on **constant rate** injection scenarios (Fig. 2 left), then evaluated on **variable rate** scenarios (Fig. 2 right).
- Our work shows that the model trained on constant rate schedules (typical for reservoir simulation) does not generalize well to situations with variable injection schedules (typical of real operational settings), thus new strategies are needed.

Data

- 111 realizations of the physics-based model with one well injecting for 10 years (monthly time points):
  - **Training**: 15 realizations with five constant rates
  - **Testing**: 96 realizations with 32 variable schedules

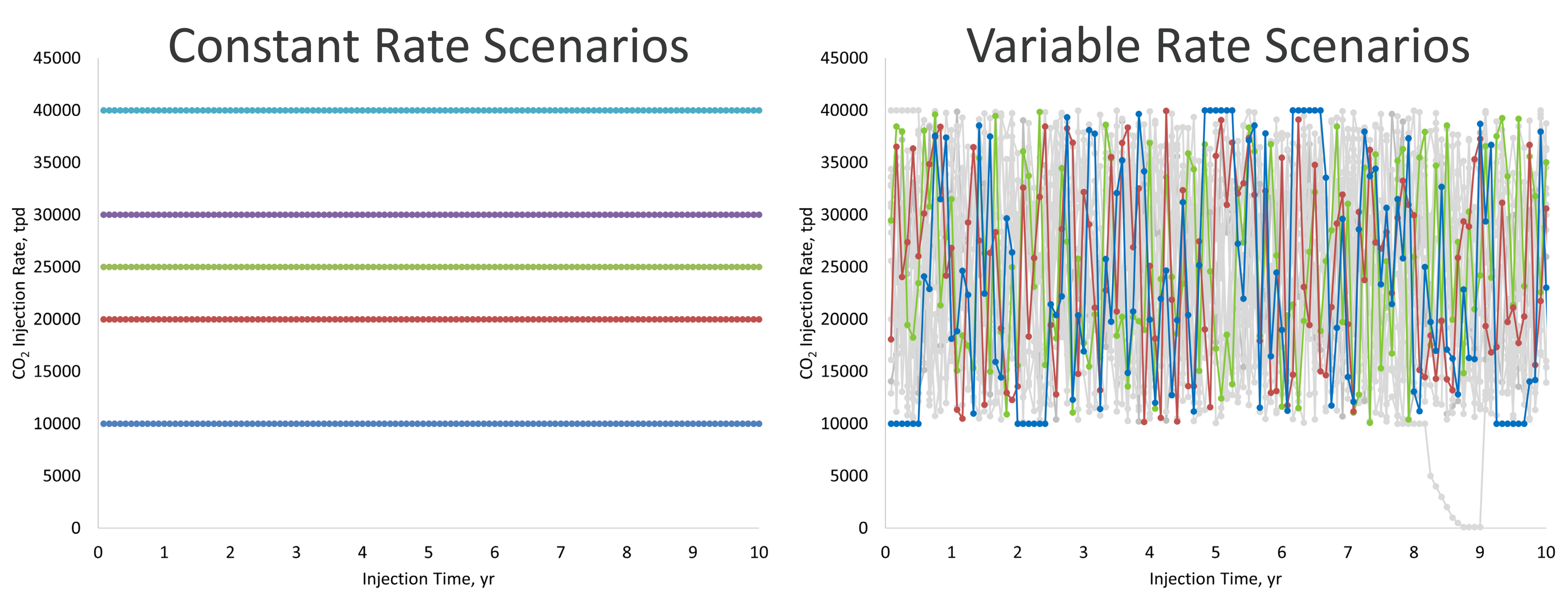

Figure 2: Constant and variable injection rate schedules

Model

- Input:
  - Delta time
  - Injection rate
  - Permeability
  - Porosity
  - Pressure
  - CO_2 Saturation
- Output:
  - Delta pressure at next time point

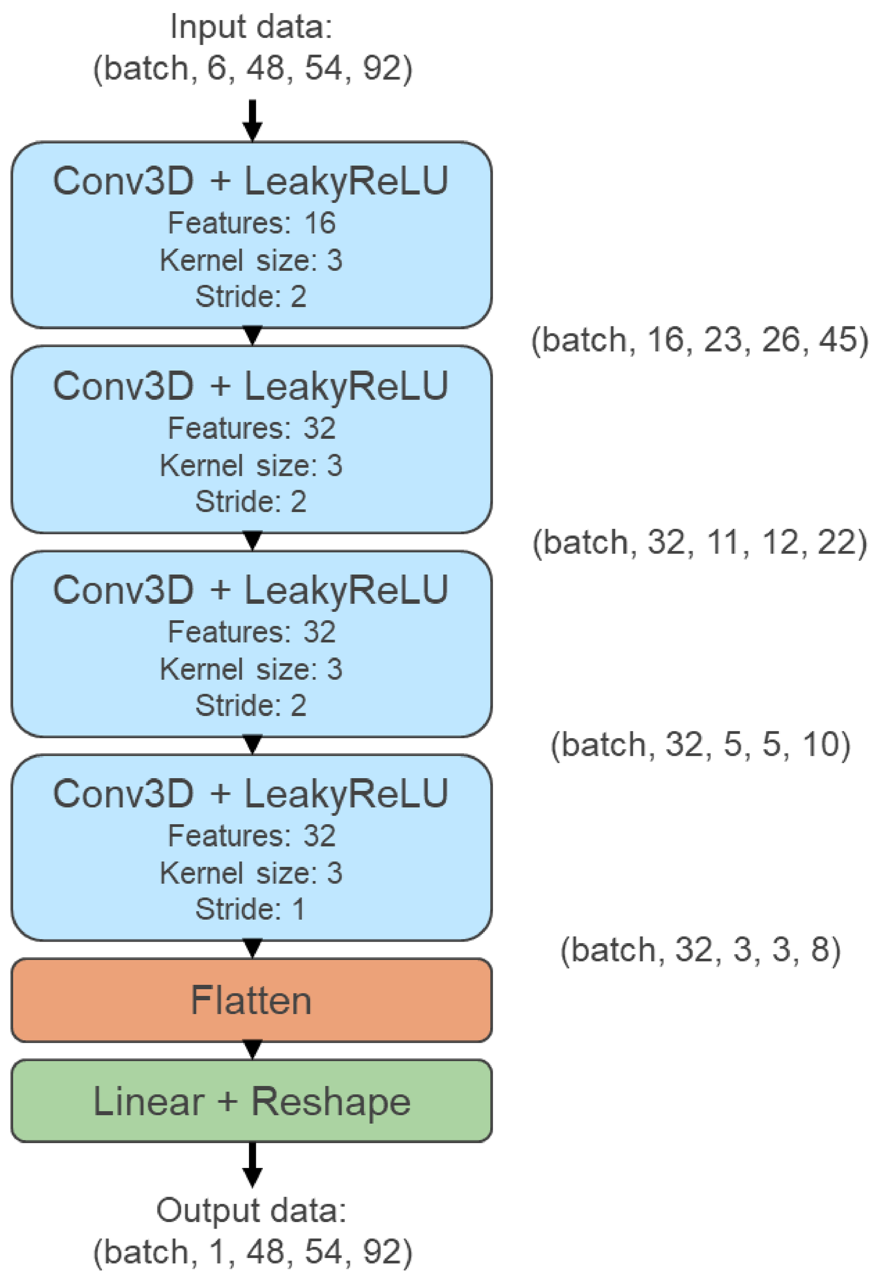

Figure 1: Model structure

Results

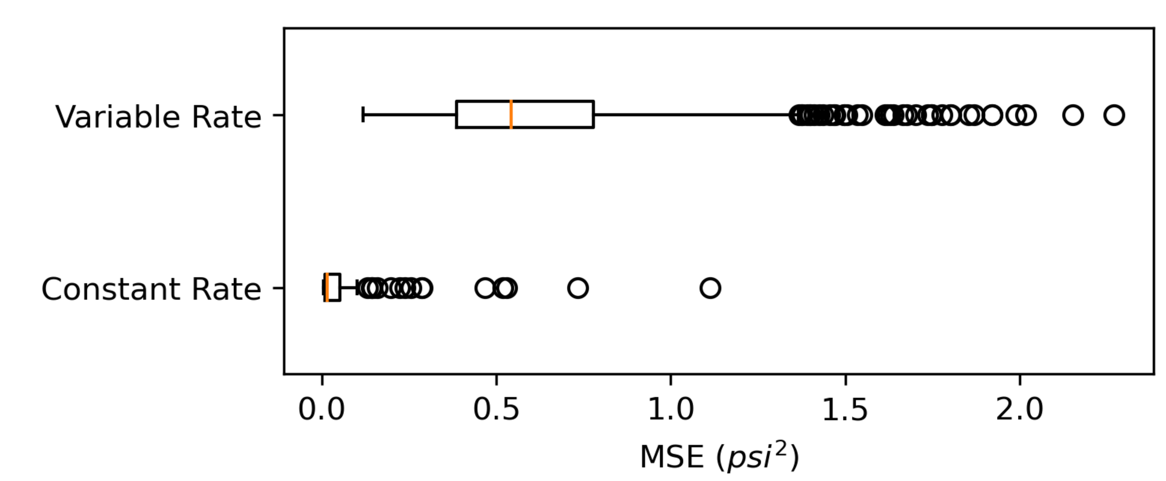

Figure 3: Pressure prediction errors for each timestep, where each dot is the average squared error over the full reservoir.

- When predictions are based on **true values** from the previous time step, prediction errors appear small (between 0 and 2 psi as in Fig. 3).
- However, when predicting recursively based on **previously predicted values**, errors will propagate and compound over time.
- Error magnitude is a function of distance from the injection well location (Fig. 4).

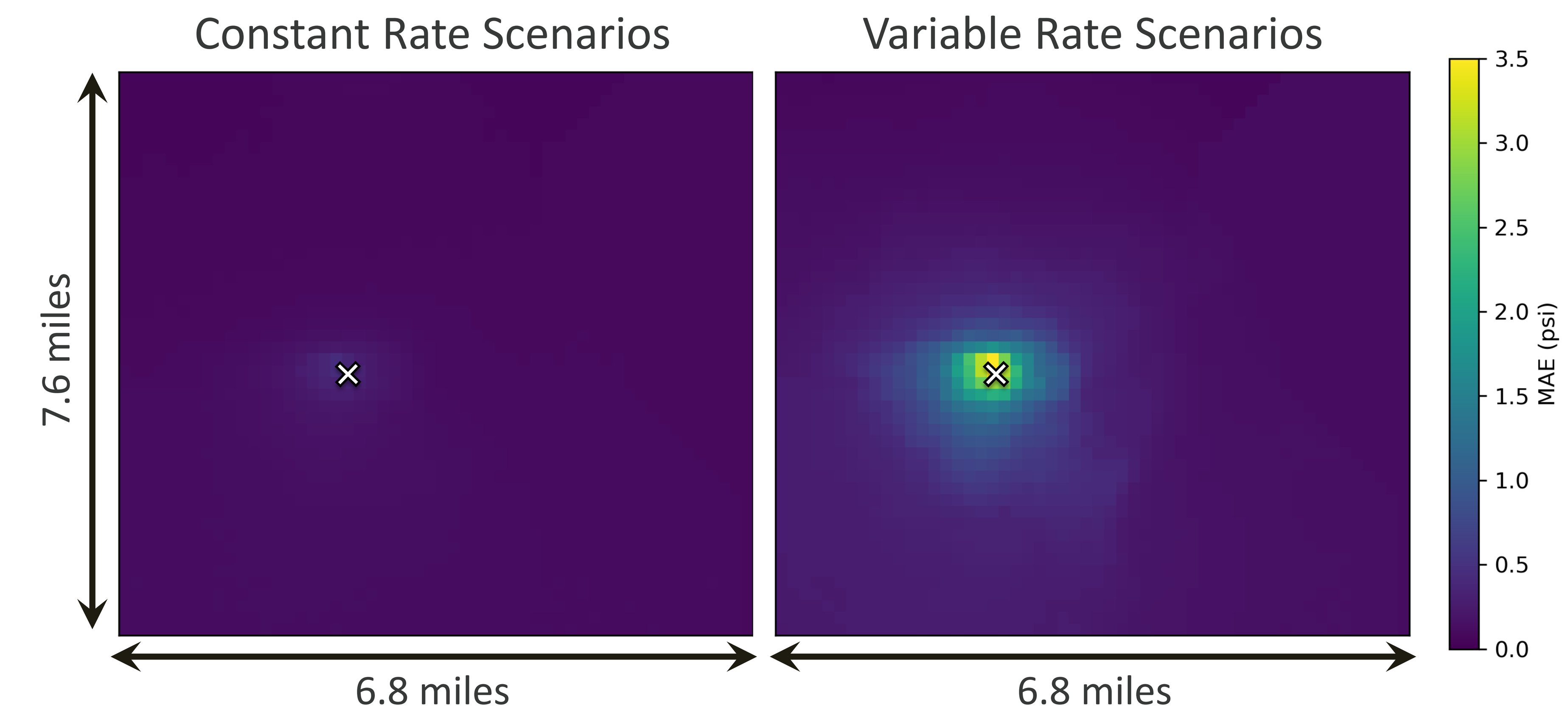

Figure 4: Comparison between the errors in the *z*-plane where the injector is perforated, where errors are averaged over all timesteps. The white cross indicates the location of the injection well.

Discussion

- Deep learning surrogate models are increasingly being used to model subsurface dynamics, but these models are often trained on simulation data that do not completely match operational realities.
- One such mismatch is between constant and variable rate injection. This study shows that models trained on constant rate injection schedules are not flexible enough to account for the daily reality of injection wells meant to operate for decades.
- Our team's current work on Phase 2 of the SMART Initiative is focused on the development of a Graph Attention Network that will enable transfer learning from constant to variable injection schedules by learning underlying fluid flow relationships between cells in the reservoir model.

References

[1] Gundersen, K., Hosseini, S., Oleynik, A. & Alendal, A., 2020. A Variational Auto-Encoder for Reservoir Monitoring. *arXiv:2009.11693.*

[2] Hosseini, S., Larson, R., Shokouhi, P., Kumar, V., Prathipati, S., Kifer, D., Garcez, J., Ayala, L., Riedl, M., Hill, B., Tamrakar, S., Schuetter, S., Mishra, S. (2022), Reservoir Modeling Using Fast Predictive Machine Learning Algorithms for Geological Carbon Storage, CRC Press.

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