Learning CO2 plume migration in faulted reservoirs with Graph Neural Networks

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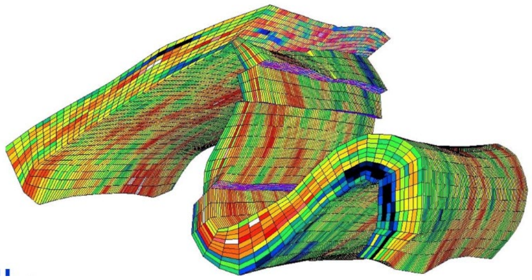


Outline

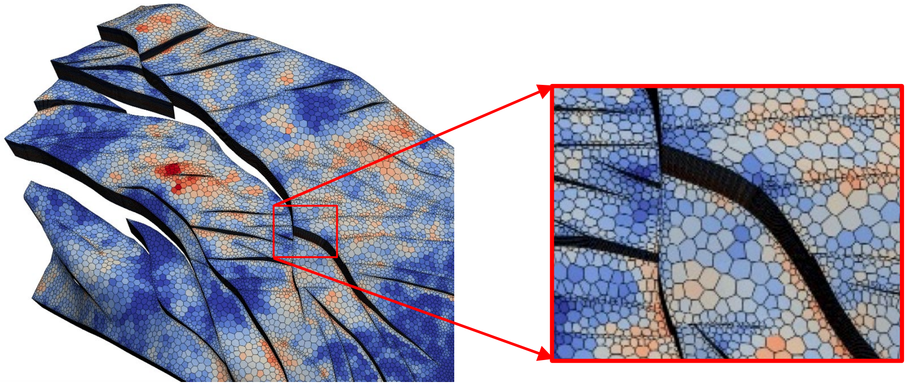
- Background & Motivations
- Methods
- Results & Analysis
- Conclusions

Predicting CO_2 plume migration in faulted geological reservoirs with DL-based models

- **Faults** could potentially lead to hazards, such as induced seismicity, or CO_2 leakage.
- Fast deep-learning-based (DL) surrogate models are needed to quantify the uncertainty in the geological model.

Predicting CO2 plume migration in faulted geological reservoirs with DL-based models

- **Faults** could potentially lead to hazards, such as induced seismicity, or CO2 leakage.
- Fast deep-learning-based (DL) surrogate models are needed to quantify the uncertainty in the geological model.
- **Unstructured** and **highly refined** mesh are used to conform to complex fault lines.

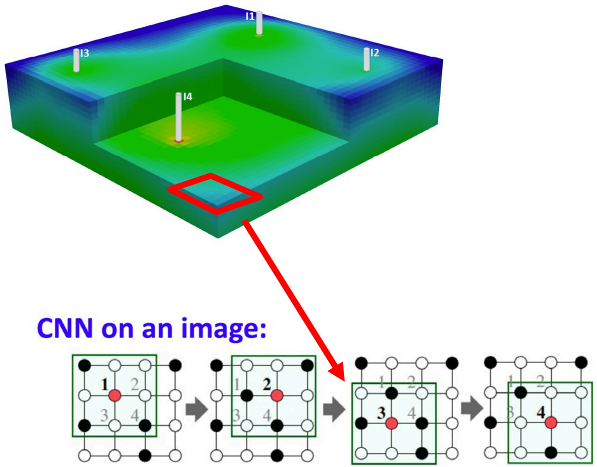


(A. Mazuyer, Sismage-CIG,B. Wendebourg, and F. Lepage)

Current limitations

- Most of current DL-based models are limited to **cartesian meshes** with **simple geometries.**

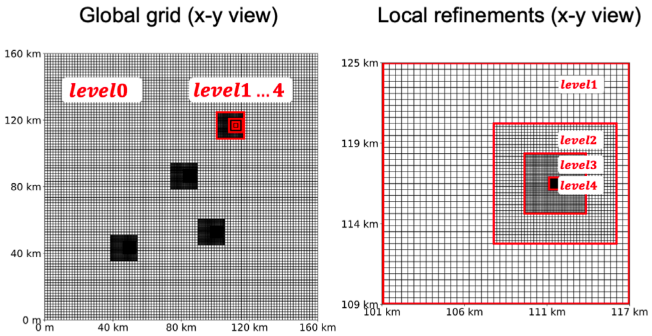
CNN-Based models



Fixed stencils

(Tang, Ju, and Durlofsky. 2022)

FNO models



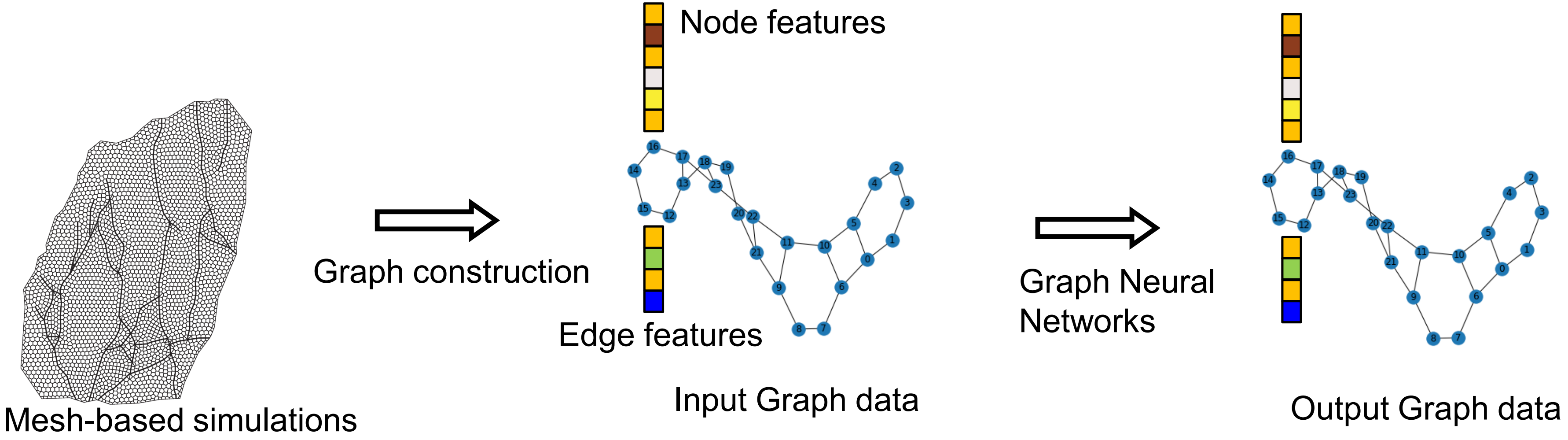
Structured grid input

(Wen et al. 2023)

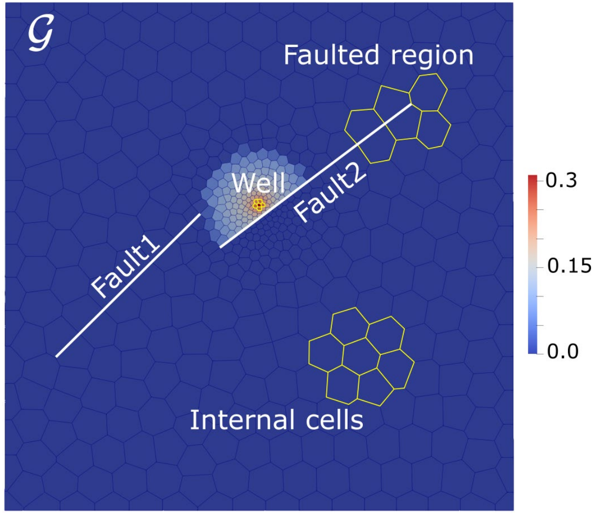
- Fixed and structured grid input.
- Difficult to handle realistic reservoir models

Our solutions: graph-based surrogate models

- All mesh-based simulations can be represented as graph data
- Graph representation allows us to handle complex geological features
- Our model can essentially operate on arbitrary subsurface simulation data



Method: Input and output graph representation



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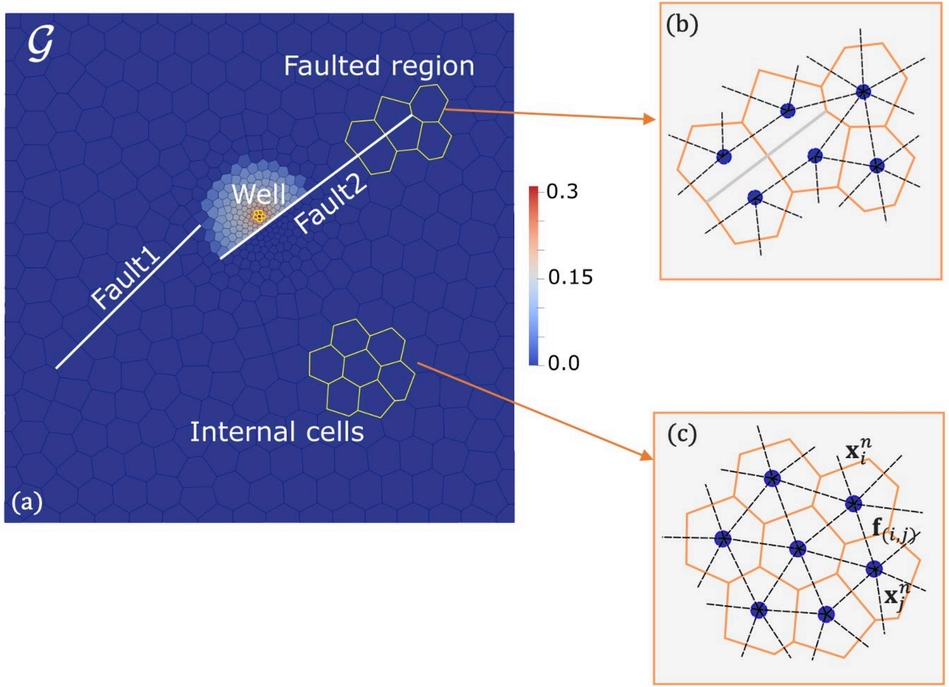
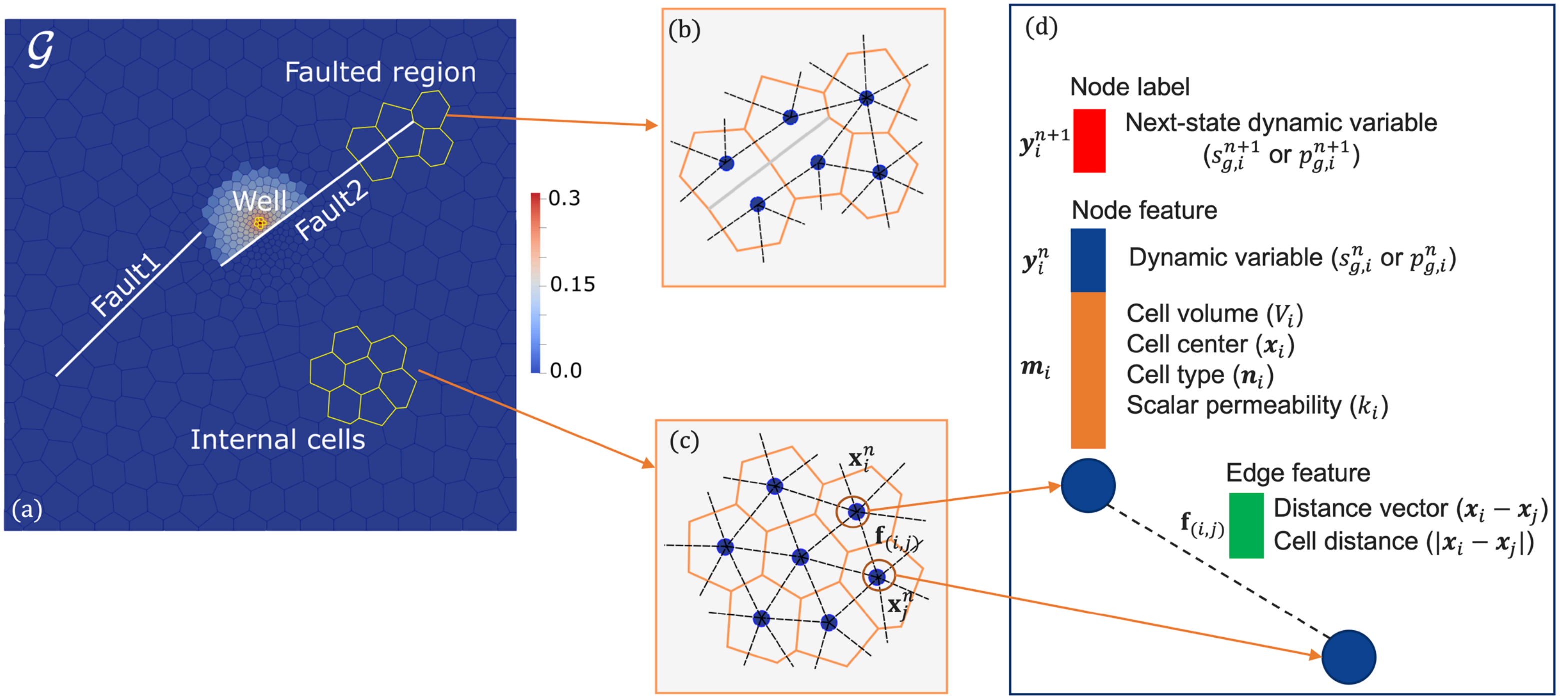
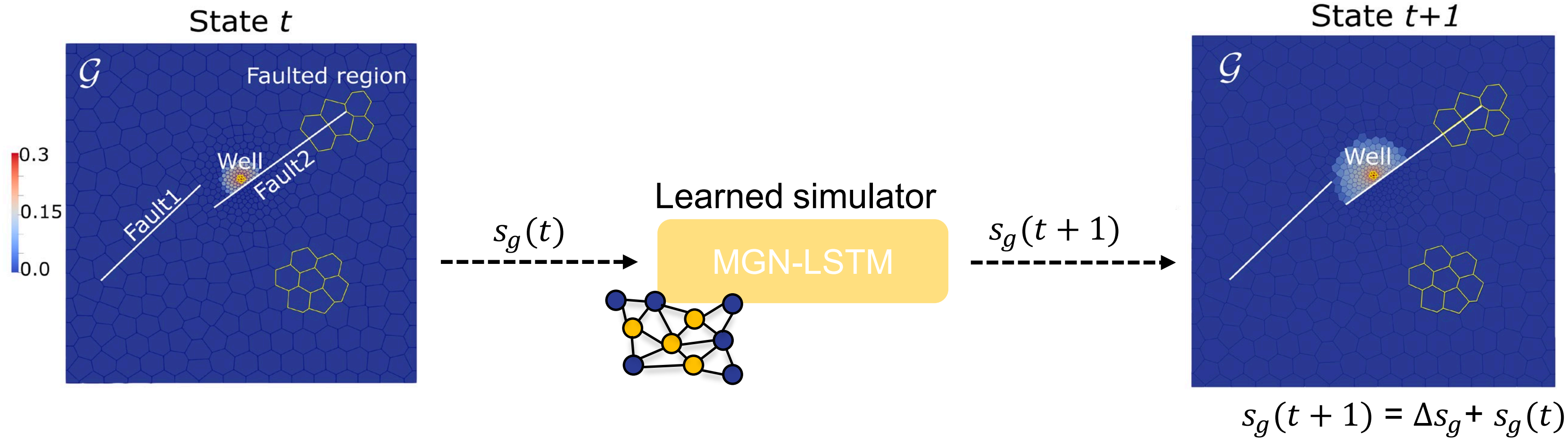


Method: Input and output graph representation

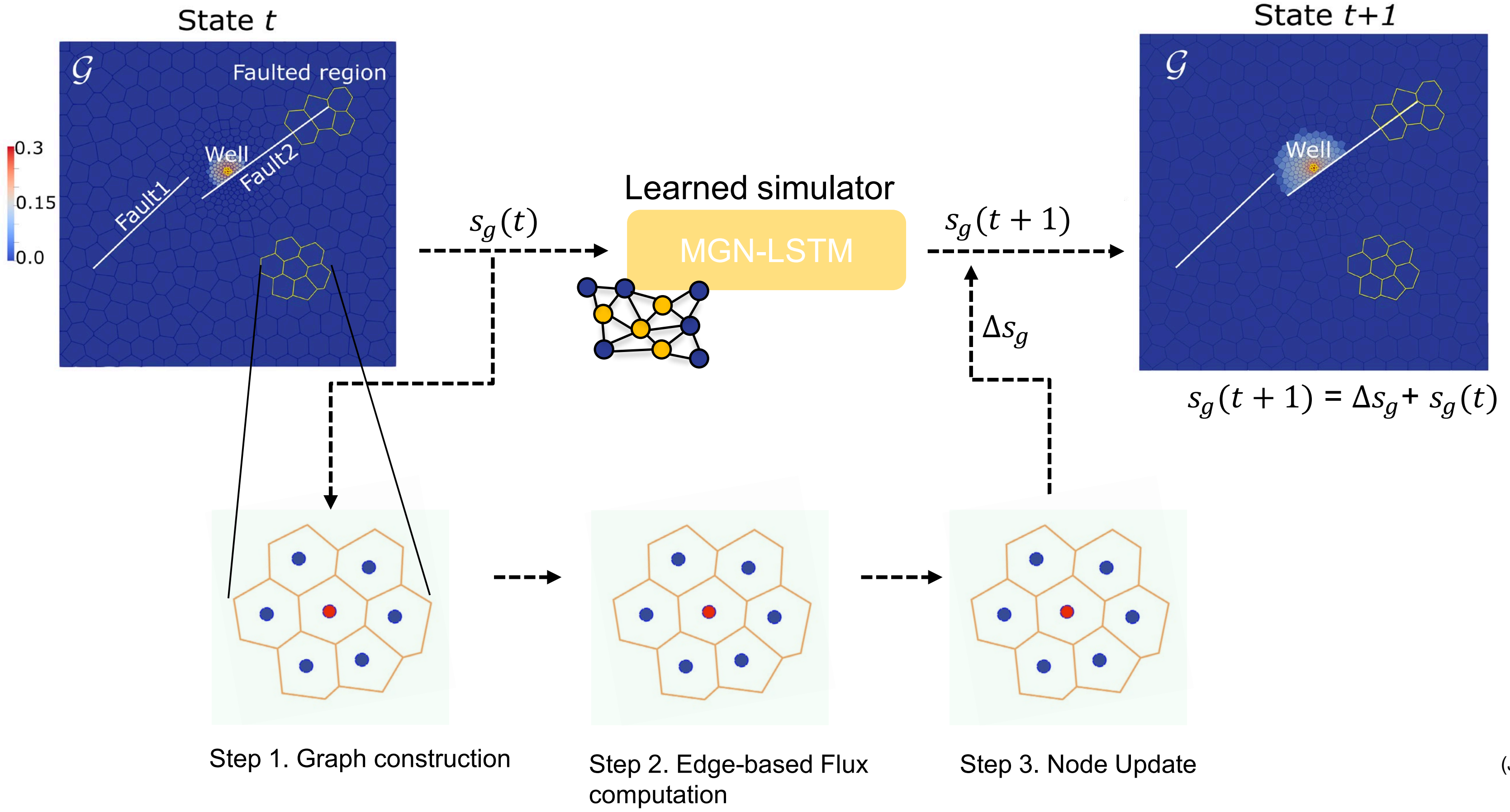


Method: Graph-based surrogate model architecture



(Ju et al. 2024)

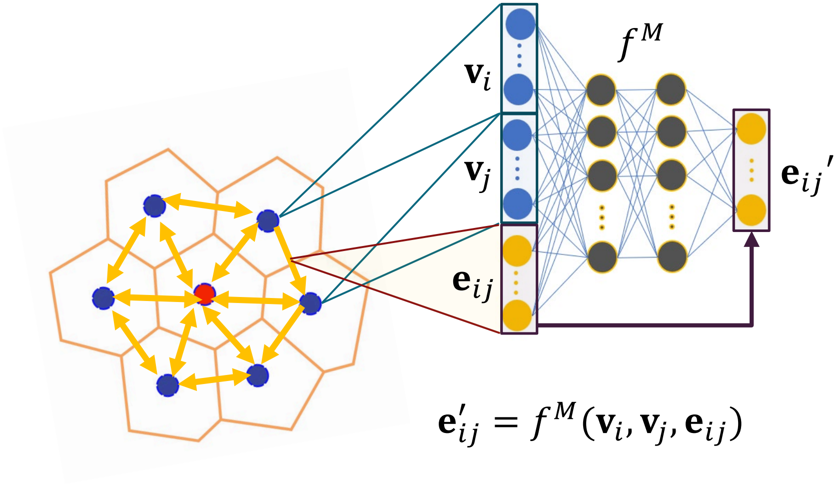
Method: Graph-based surrogate model architecture



(Ju et al. 2024)

Method: Graph-based surrogate model architecture

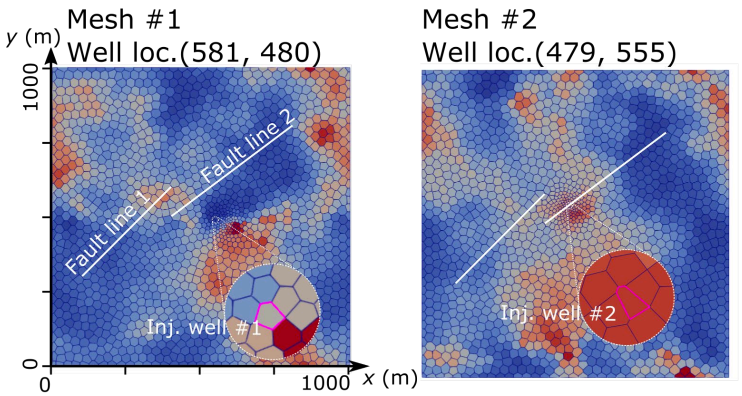
One MGN-LSTM Update



$$\mathbf{e}'_{ij} = f^M(\mathbf{v}_i, \mathbf{v}_j, \mathbf{e}_{ij})$$

Step 2: Compute all "Flux" terms from node values

Method: Training/testing dataset description and error metric



Training samples

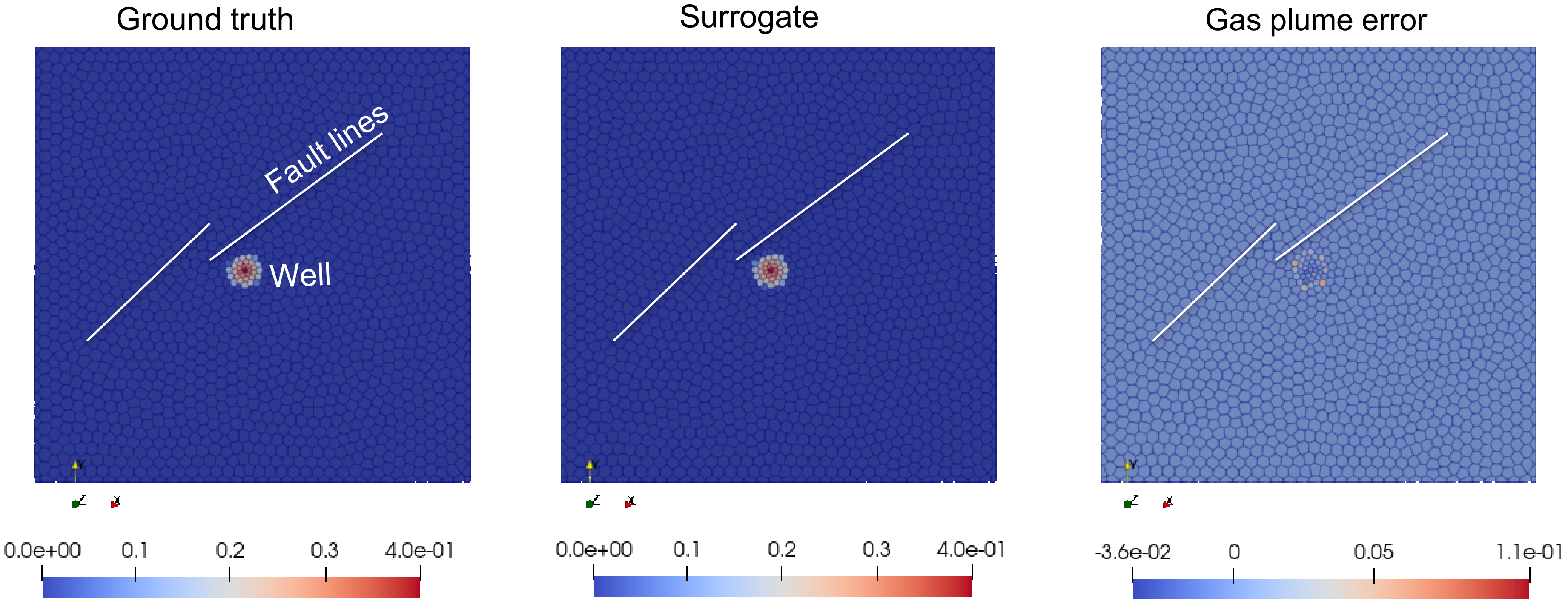
- We generate 500 realizations of 1 km x 1 km x 1 m synthetic geological models, using a **9:1** training/testing split ratio.
- The mean and standard deviation of log-permeability are 3.912 ln(mD) and 0.5 ln(mD), respectively.
- The synthetic models differ in their **permeability**, **mesh configuration**, and **well location.**
- To quantify the prediction accuracy for gas saturation, we use the **plume saturation error**, δ^{s_g}

$$\delta^{s_g} = \frac{1}{\sum_{i,n} I_i^n} \sum_{n=1}^{n_T} \sum_{i=1}^{n_C} I_i^n \left| s_{g,i}^n - \hat{s}_{g,i}^n \right|,$$

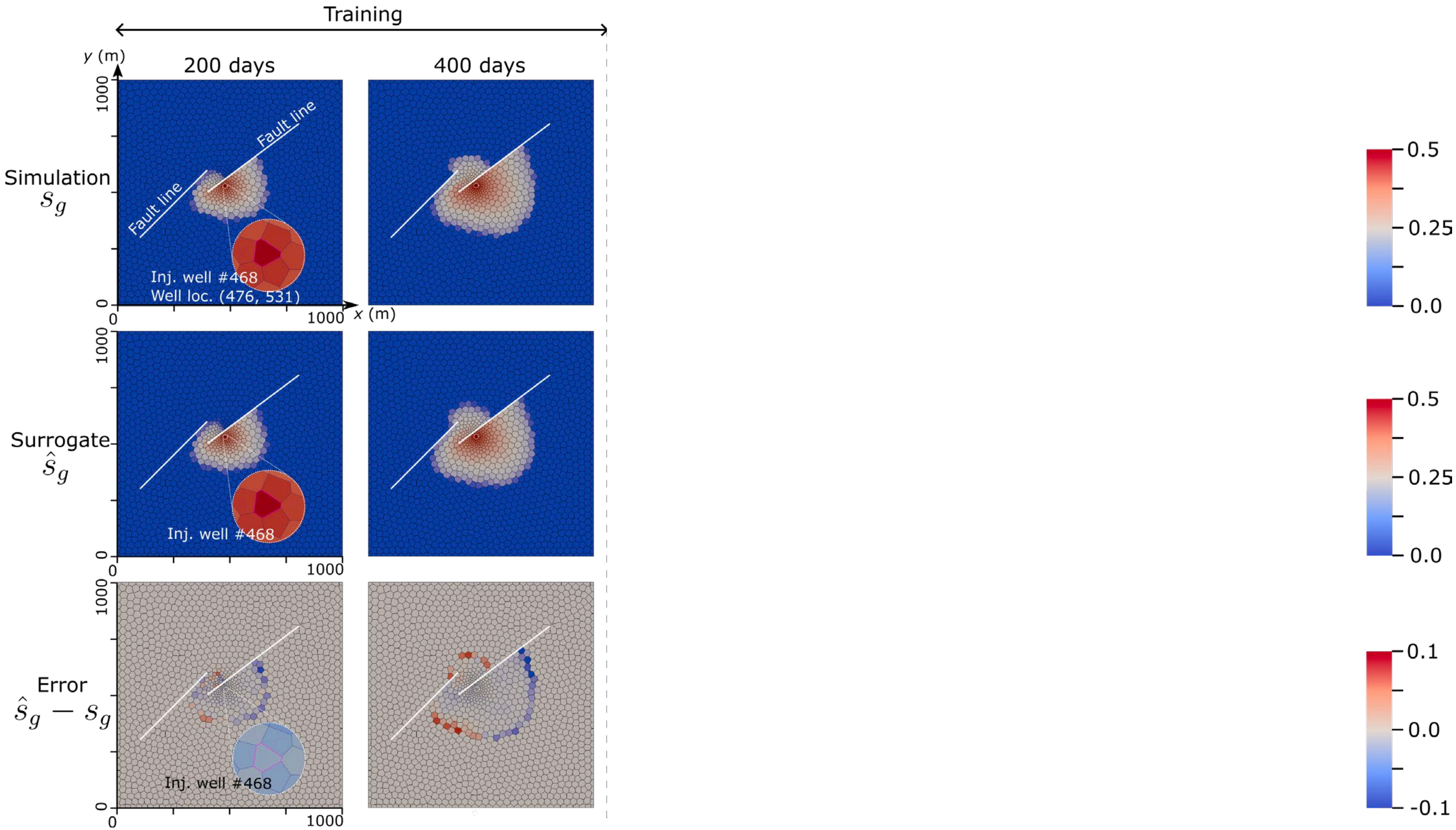
$$I_i^n = 1 \text{ if } \left(s_{g,i}^n > 0.01\right) \cup \left(\left|\hat{s}_{g,i}^n\right| > 0.01\right),$$

Predicting complex spatiotemporal dynamics in faulted storage reservoir

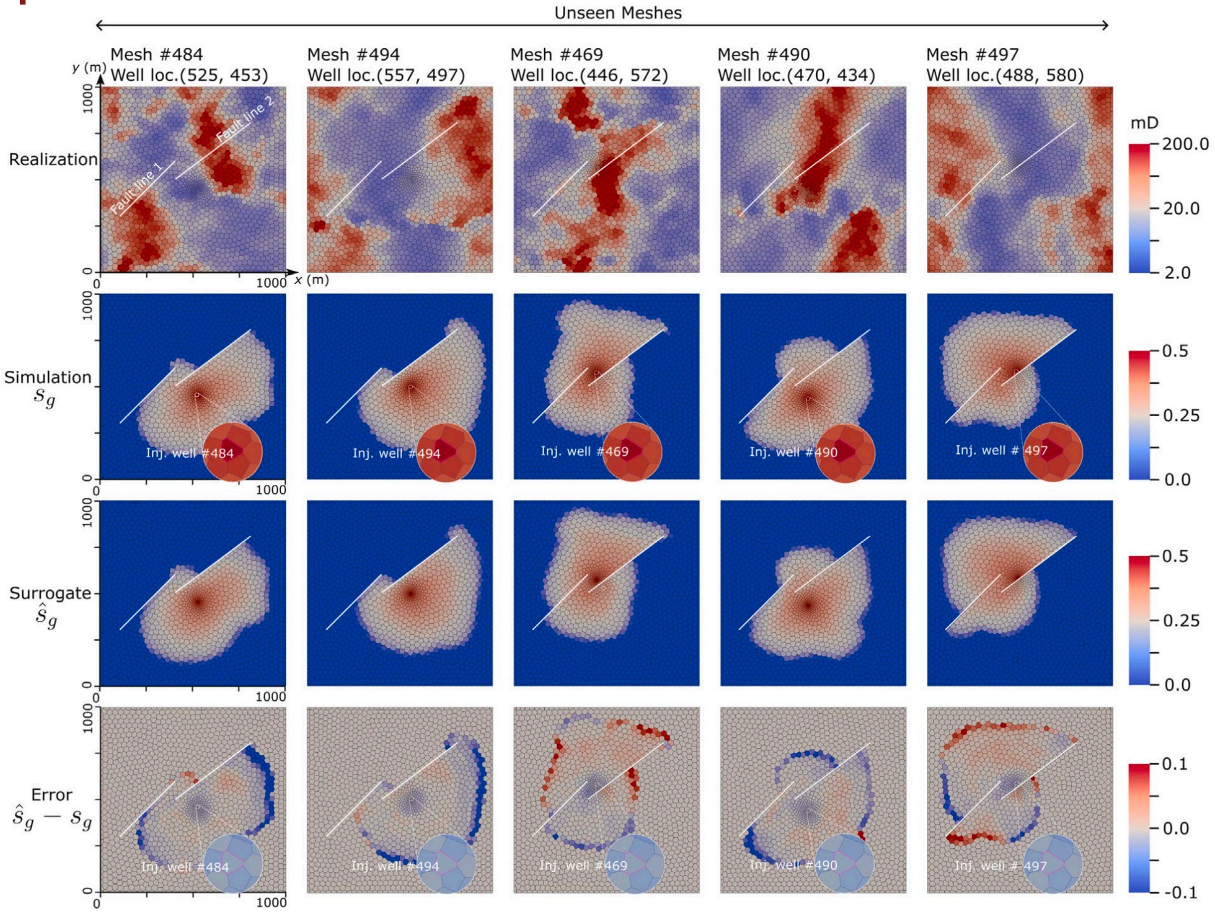
Unseen meshes (**Mesh 472**) and rolling out for **500 days (11 steps)**



MGN-LSTM can extrapolate beyond the training period

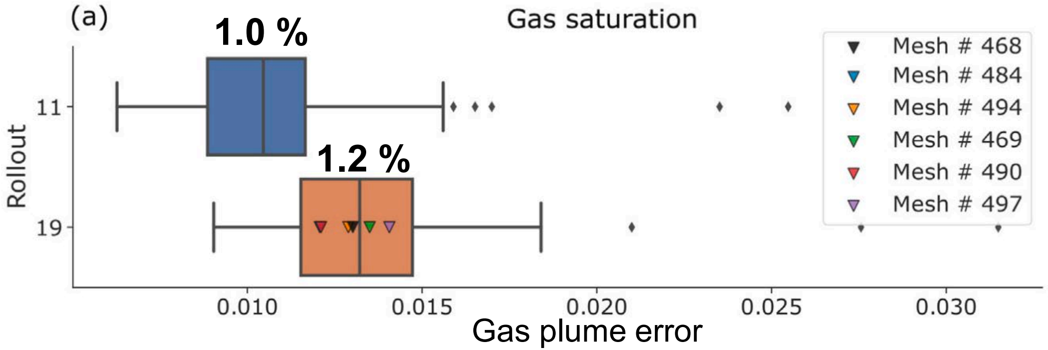


MGN-LSTM can generalize to new meshes, well locations, and permeabilities



- Five representative cases show an excellent agreement with the HF simulations after 950 days.

MGN-LSTM is an accurate and fast surrogate model



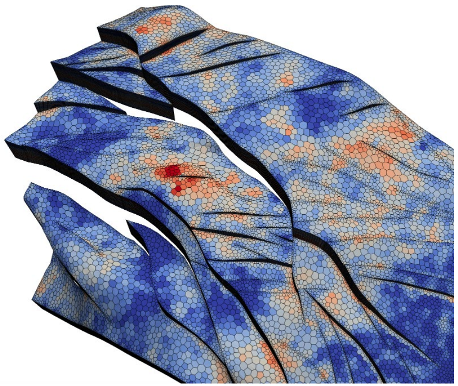
	MGN-LSTM avg. inference time (s)[a]	GEOS run time (s)[b]
11-step rollout (550 days)	**0.18**	22.12
19-step rollout (950 days)	**0.31**	49.02

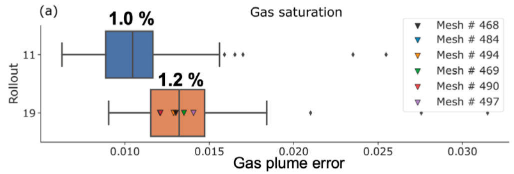
[a] On an NVIDIA Tesla A100 GPU, single-batch inference run
[b] On an Intel Xeon E5-2695 v4, single-core serial run

- The median plume error for the extrapolated ranges (950 days) in the testing set is only **1.2%**.
- MGN-LSTM demonstrates a nearly **160-fold** speedup compared to high-fidelity simulator.

Conclusions

- Developed a graph-based neural surrogate model (MGN-LSTM) that can operate on unstructured meshes and naturally handle **geological fault structures**.
- MGN-LSTM exhibits excellent generalizability to mesh configurations, well locations, and permeability fields.
- MGN-LSTM is an accurate and fast surrogate model.
- A promising tool to accelerate the process of uncertainty quantification of CCS storage formations with faults.





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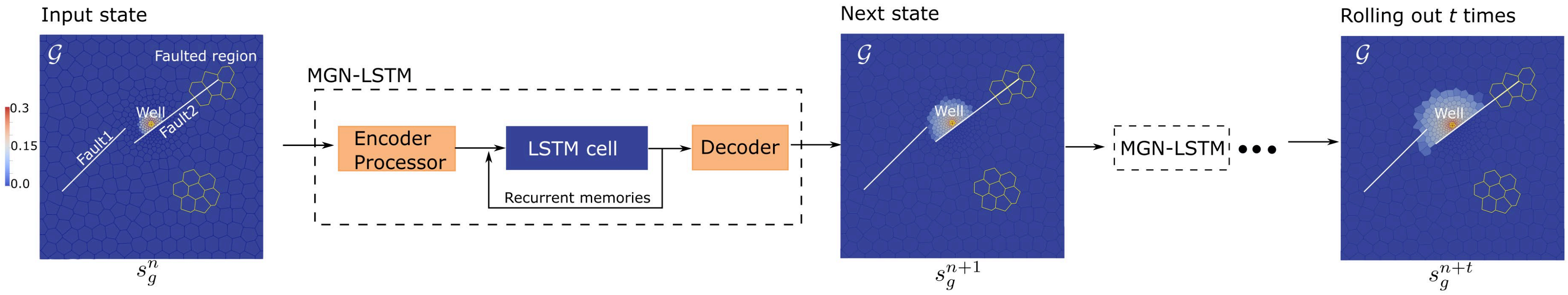
Thank you!

Method: Graph-based surrogate model architecture



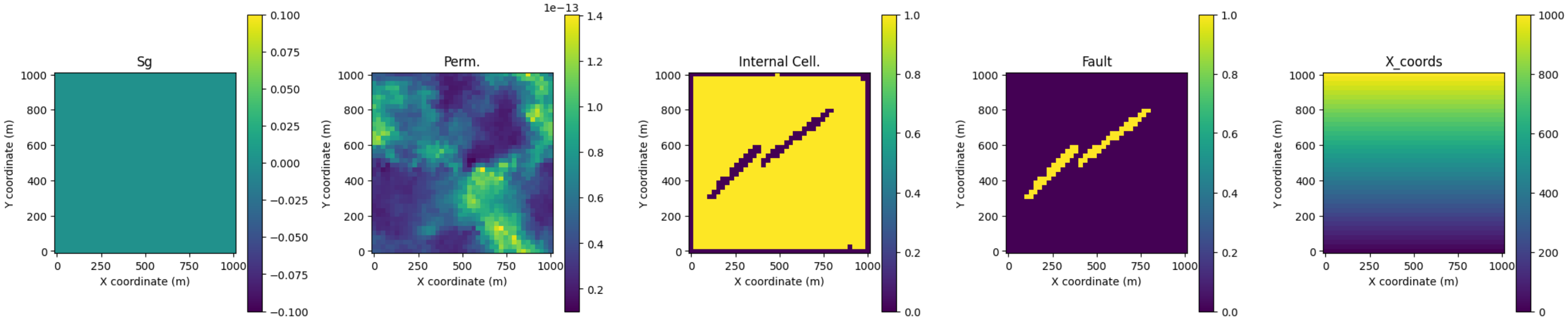
The proposed MGN-LSTM model is designed to learn the spatiotemporal evolution of the selected dynamic variable (pressure or CO2 saturation) of the two-phase flow problem:

$$\hat{\mathbf{Y}}^0 = \mathbf{Y}^0,$$
$$\hat{\mathbf{Y}}^{n+1} = f_{\text{MGN-LSTM},\theta}\left(\mathcal{G}, \hat{\mathbf{Y}}^n, \mathbf{M}, \mathbf{F}\right),\ n \in \{1, \dots, n_T\},$$

(Ju et al. 2024)

Performance comparisons against grid-based models

- Interpolated node feature



Model	11-step	19-step	# parameters
MGN-LSTM	**0.0081**	**0.01188**	1,381,501
Node-based MGN-LSTM	0.0114	0.0176	1,581,569
U-FNO	0.0450	0.0657	1,941,313
CNN	0.0504	0.0786	1,675,873

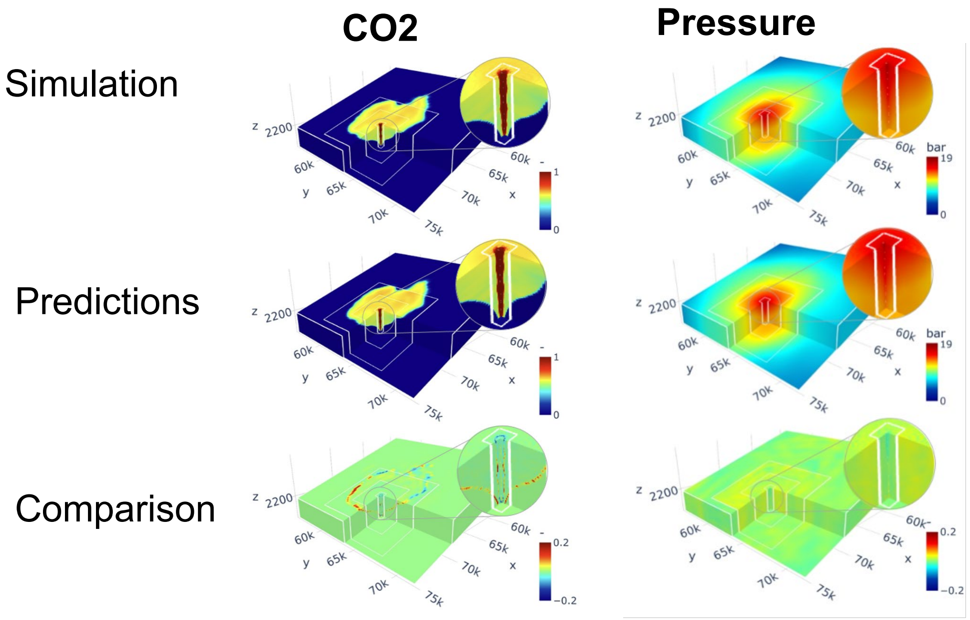
- MGN-LSTM outperforms all other models in terms of plume saturation errors over both 11-step (550 days) and 19- step (950 days) rollouts by a large margin.

(Wen et al. 2023)

Current limitations

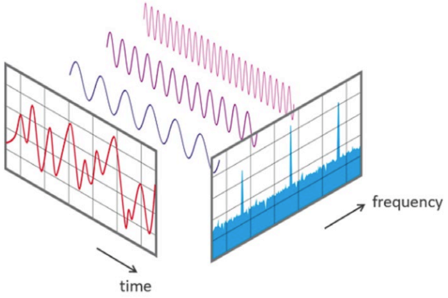
- Most of current DL-based models are limited to **cartesian meshes** with **simple geometries.**

Fourier neural operator-based models

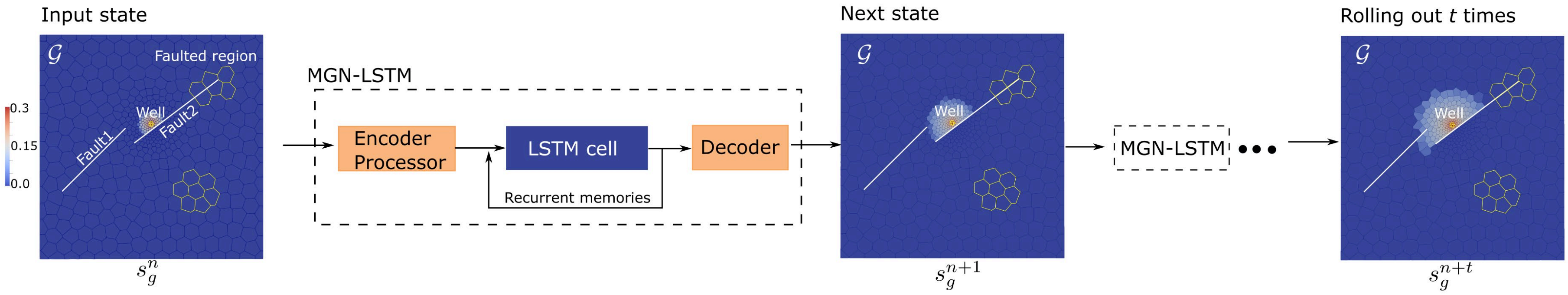


(Wen et al. 2023)

- The **Fast Fourier Transform** block used in FNO assumes that the underlying simulation data is structured



Method: Graph-based surrogate model architecture



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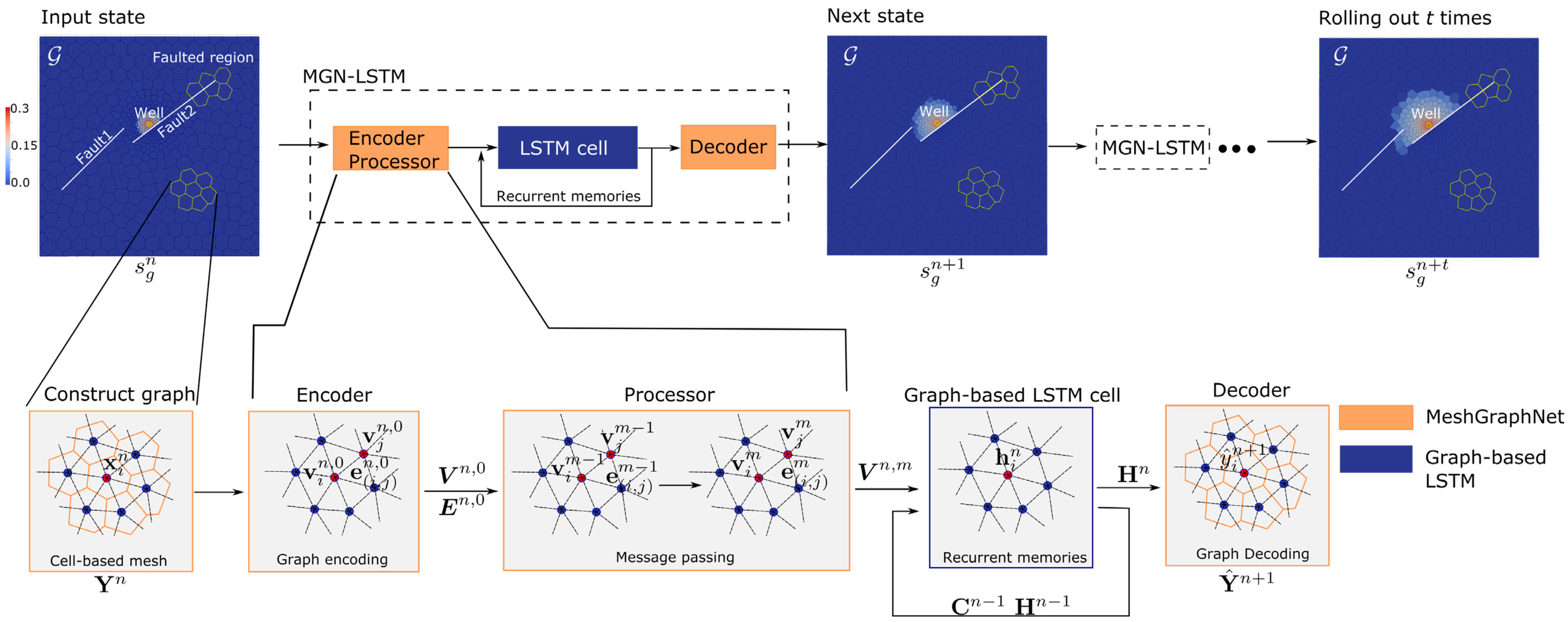
(Ju et al. 2024)

Method: Graph-based surrogate model architecture



Method: Evaluation metrics

- To quantify the prediction accuracy for gas saturation, we use the plume saturation error, δ^{s_g}

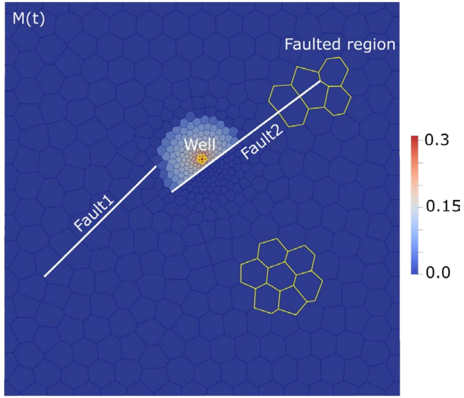
$$\delta^{s_g} = \frac{1}{\sum_{i,n} I_i^n} \sum_{n=1}^{n_T} \sum_{i=1}^{n_C} I_i^n \left| s_{g,i}^n - \hat{s}_{g,i}^n \right|,$$

$$I_i^n = 1 \text{ if } \left(s_{g,i}^n > 0.01 \right) \cup \left(\left| \hat{s}_{g,i}^n \right| > 0.01 \right),$$

- We use the relative error, δ^{p_g}, defined below to evaluate the prediction accuracy for pore pressure

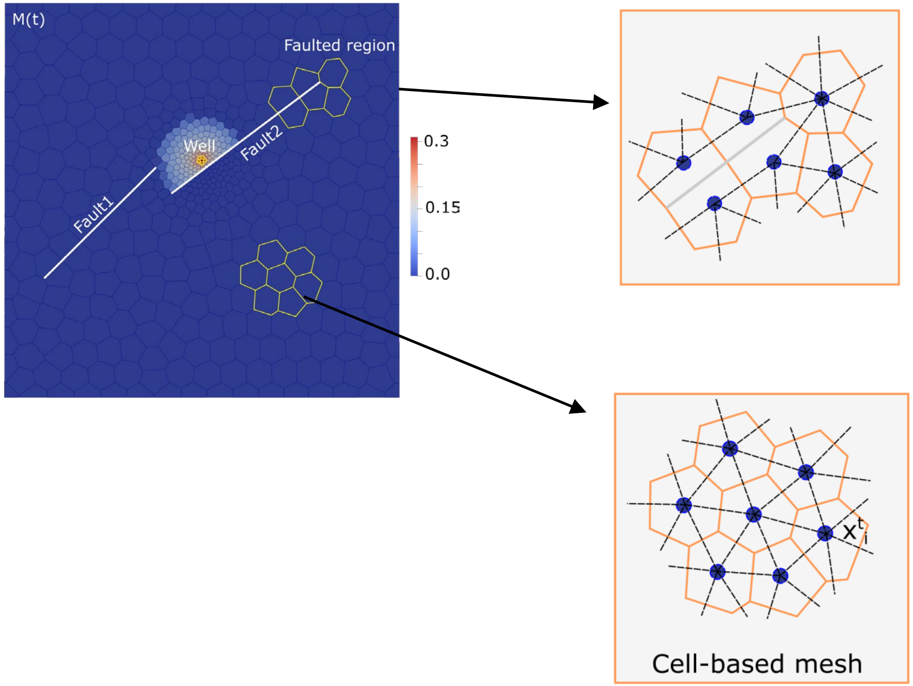
$$\delta^{p_g} = \frac{1}{n_C n_T} \sum_{n=1}^{n_T} \sum_{i=1}^{n_C} \frac{\left| p_{g,i}^n - \hat{p}_{g,i}^n \right|}{p_{g,\ init}}$$

Method: Graph construction



PEBI: Unstructured grids (a.k.a. Voronoi mesh) constructed by connecting the perpendicular bisectors of the edges of the Delaunay triangulation (Heinrich 1987)

Method: Graph construction



There are **no connection** between cells along fault lines

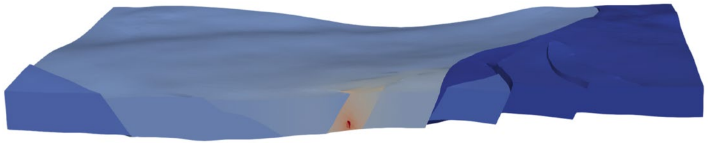
Node represents **cell**, locating at the center of each cell. The **connection** between neighboring cells forms an **edge**.

Predicting CO2 plume migration in faulted geological reservoirs with DL-based models

- **Faults** could potentially lead to hazards, such as induced seismicity, or CO2 leakage.
- Fast deep-learning-based (DL) surrogate models are needed to quantify the uncertainty in the geological model.

$$\nabla \cdot \left(\sum_j \rho_j x_j^r \mathbf{v}_j\right) + q^r = \frac{\partial}{\partial t}\left(\sum_j \phi \rho_j S_j x_j^r\right)$$

$$\mathbf{v}_j = -\frac{\mathbf{k} k_{rj}(S_j)}{\mu_j}\left(\nabla p_j - \rho_j g \nabla z\right)$$

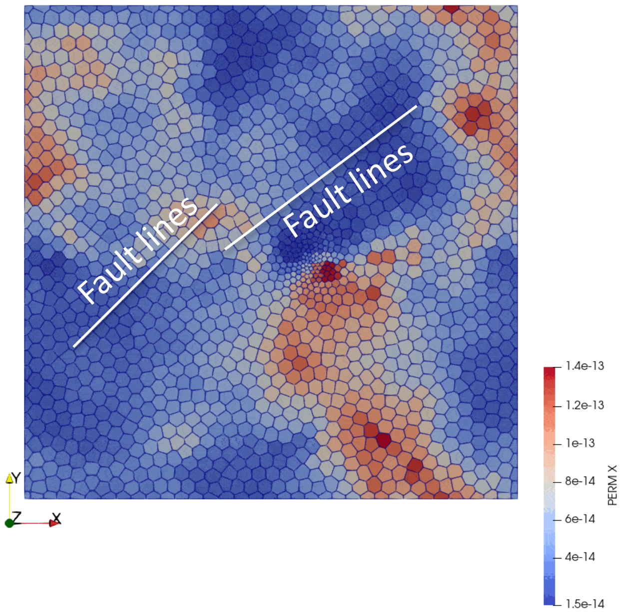


(https://www.geos.dev/)

$$\delta^{s_g} = \frac{1}{\sum_{i,n} I_i^n} \sum_{n=1}^{n_T} \sum_{i=1}^{n_C} I_i^n \left| s_{g,i}^n - \hat{s}_{g,i}^n \right|,$$

$$I_i^n = 1 \text{ if } \left(s_{g,i}^n > 0.01\right) \cup \left(\left|\hat{s}_{g,i}^n\right| > 0.01\right),$$

Method: Dataset description



- We generate a total of 500 realizations of the synthetic geological models of size 1 km x 1 km x 1 m. Each realization contains 19 timesteps.
- The mean and standard deviation of log-permeability are 3.912 ln(mD) and 0.5 ln(mD), respectively, which results in an average permeability of 50 mD in the reservoir.
- The synthetic models differ in their **geological parameters (permeability)**, **mesh configuration**, and **well location.**

Results and analysis: ablation tests

Perform better than interpolation based models

Case	Node input	Edge input	Node output
Baseline	$s_{g,i}^{n}, V_i, k_i, \boldsymbol{n}_i, \boldsymbol{x}_i$	$\boldsymbol{x}_j - \boldsymbol{x}_i$, $\lvert \boldsymbol{x}_j - \boldsymbol{x}_i \rvert$	$s_{g,i}^{n+1}$
Static transmissibility	$s_{g,i}^{n}, V_i, k_i, \boldsymbol{n}_i, \boldsymbol{x}_i$	$\boldsymbol{x}_i - \boldsymbol{x}_j$, $\lvert \boldsymbol{x}_i - \boldsymbol{x}_j \rvert$, $T_{i,j}$	$s_{g,i}^{n+1}$
Relative permeability	$s_{g,i}^{n}, V_i, k_i, \boldsymbol{n}_i, \boldsymbol{x}_i, k_{r,i}(s_{g,i}^{n-1})$	$\boldsymbol{x}_i - \boldsymbol{x}_j$, $\lvert \boldsymbol{x}_i - \boldsymbol{x}_j \rvert$	$s_{g,i}^{n+1}$
Static transmissibility Relative permeability	$s_{g,i}^{n}, V_i, k_i, \boldsymbol{n}_i, \boldsymbol{x}_i, k_{r,i}(s_{g,i}^{n-1})$	$\boldsymbol{x}_i - \boldsymbol{x}_j$, $\lvert \boldsymbol{x}_i - \boldsymbol{x}_j \rvert$, $T_{i,j}$	$s_{g,i}^{n+1}$