Deep Learning Assisted Multi-Objective Optimization of Geological CO_2 Storage Performance under Geomechanical Risks

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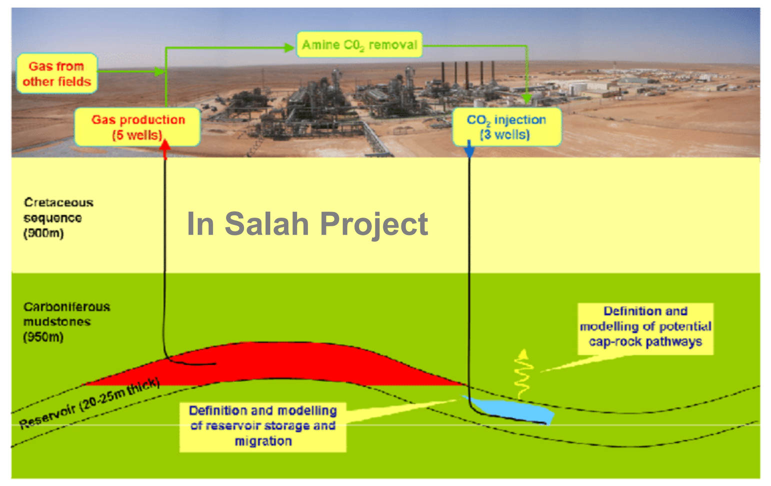
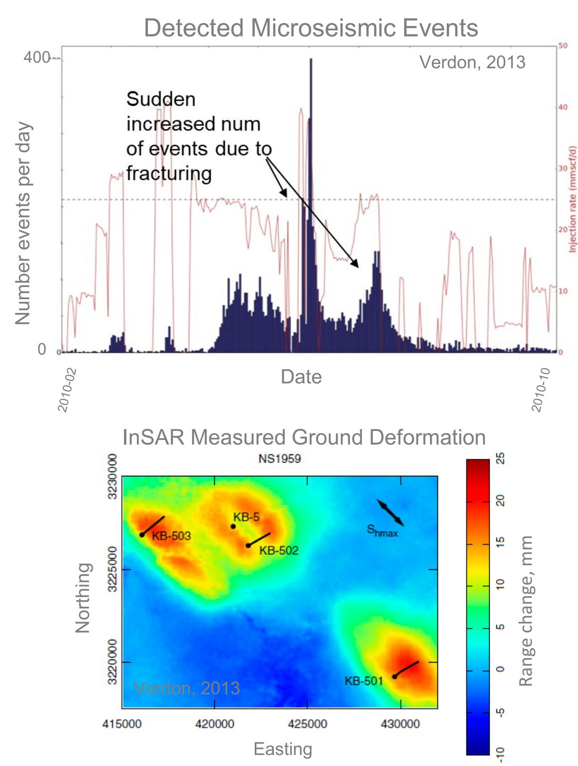
Science-informed Machine Learning to Accelerate Real Time (SMART) Decisions in Subsurface Applications

Motivation





- A total of **3.8 mega-ton** of CO_2 were injected
- **9,506** injection caused seismic events detected
- Injection of CO_2 is **opening** pre-existing **fractures**
- Maximum of **25 millimeters uplift** after 2 years

Geomechanical risks are not properly accounted.

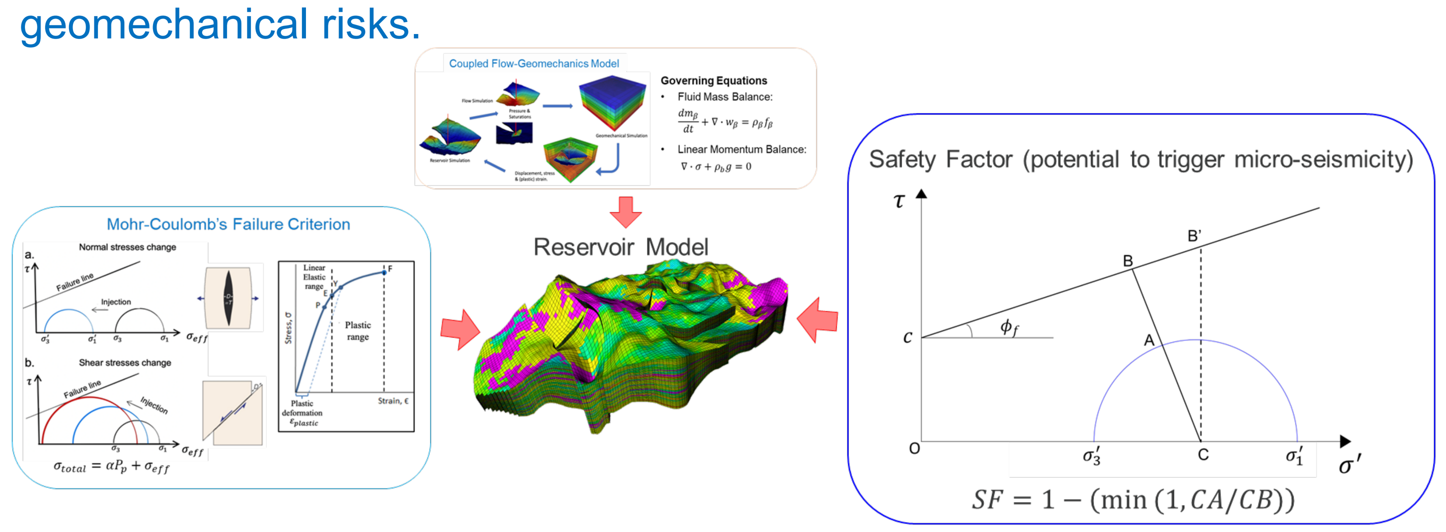
Introduction

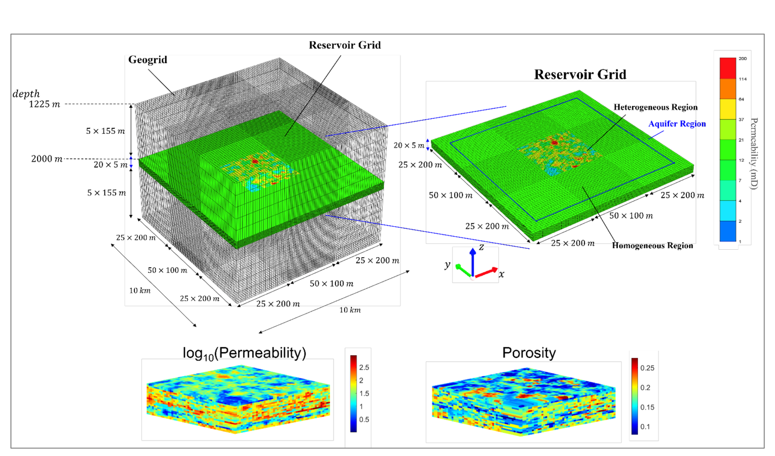
Main Objective:

Develop a **Deep Learning-assisted** optimization workflow to **optimize CO_2 storage** performance **under Geomechanical risks** such as ground displacement and induced micro-seismicity.

Major Components of Workflow:

1. Construct a physics-based CO_2 storage model and quantify the associated geomechanical risks, including ground displacement and safety factor.
2. Develop a ML-based surrogate model to output the quantified geomechanical risks.
3. Build an optimization workflow to optimization CO_2 storage while minimizing geomechanical risks.

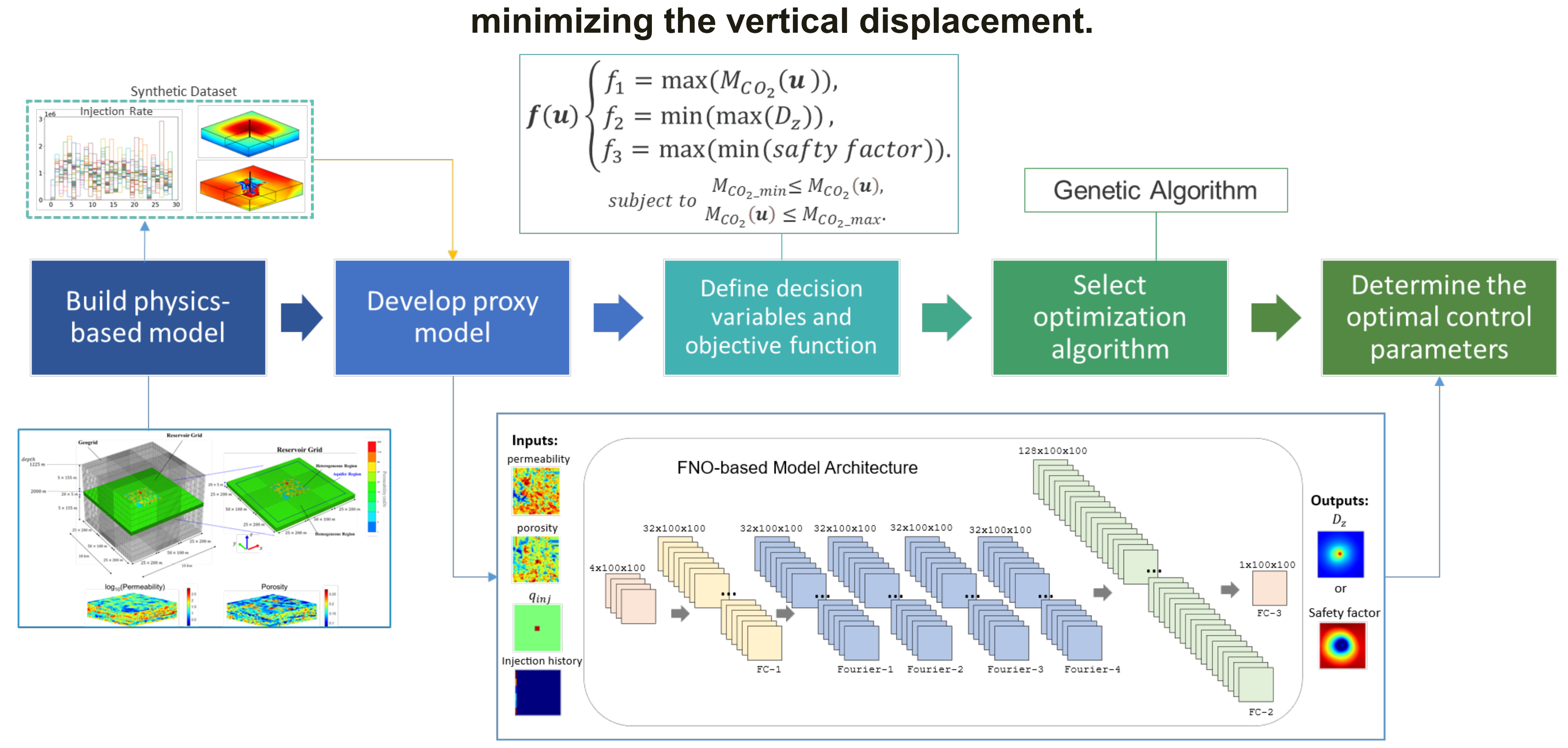




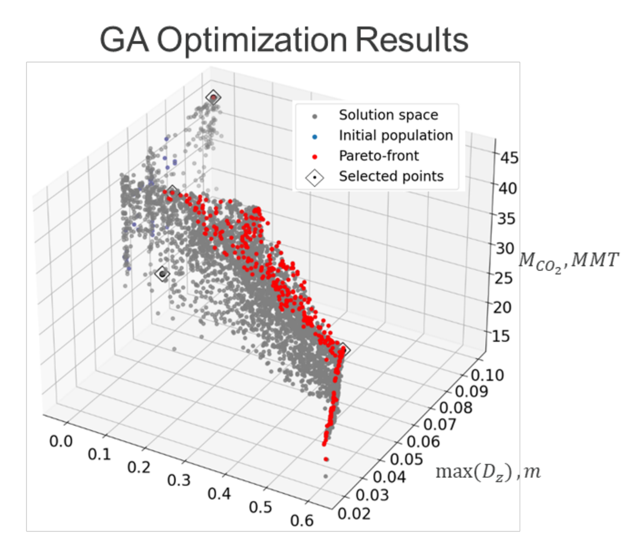
		Base case
Flow properties	Permeability (mD)	0.069 – 93.69
	Porosity	0.078 - 0.27
	Reservoir depth (m)	2000 - 2050
	pore pressure gradient (kPa/m)	9.8
	Temperature (C)	44
	Kv/kh	0.1
Geomechanical Properties	Young's Modulus (GPa)	45
	Poisson's Ratio	0.25
	Cohesion (kPa)	3000
	Friction Angle	20
	Biot's coefficient	0.8
	$\partial\sigma'_{xx}/\partial z$ (kPa/m)	10
	$\partial\sigma'_{yy}/\partial z$	12
	$\partial\sigma'_{zz}/\partial z$	13

Methodology

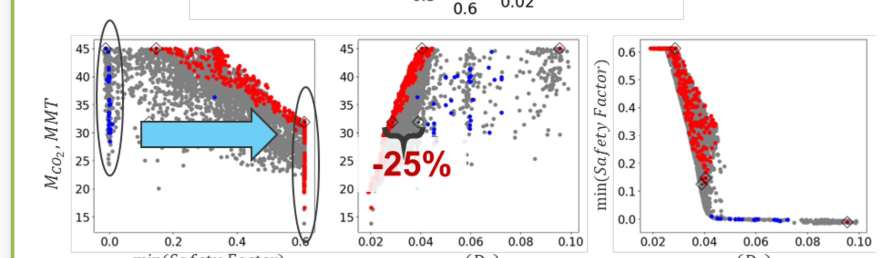
Develop a general optimization workflow to maximize CO_2 storage and safety factor while minimizing the vertical displacement.



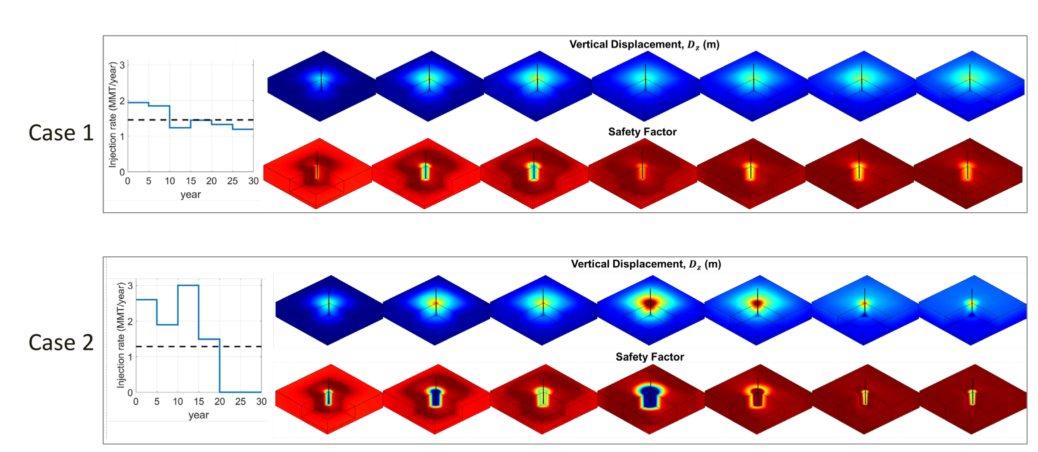
Results

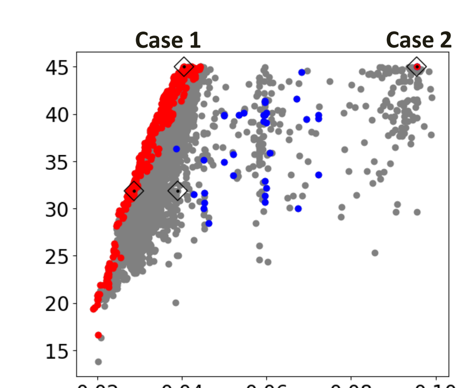


- The optimization algorithm successfully **improves** the initial population's optimal minimum safety factor from **0 (indicating rock fracturing)** to a Pareto population value of **0.61 (indicating safe injection)**.



- The optimal maximum vertical displacement also **decreased** from approximately **0.04 m** to about **0.03 m**, achieving **25% mitigation**.



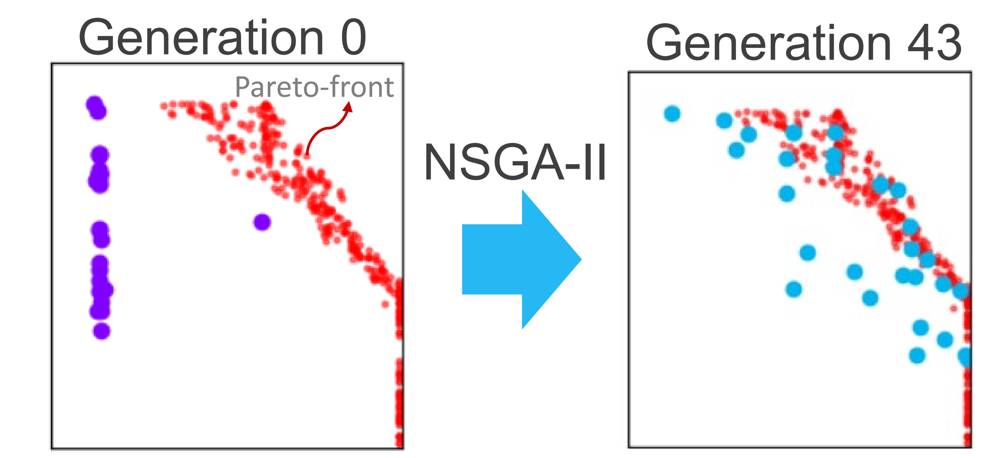


- When two cases share the **same total CO_2 storage**, injection schedules with **higher** maximum injection **rate** resulted in **higher vertical displacement** and **lower safety**.
- An **early maximum injection** allowed for **better pressure dissipation**, leading to **safer storage.**

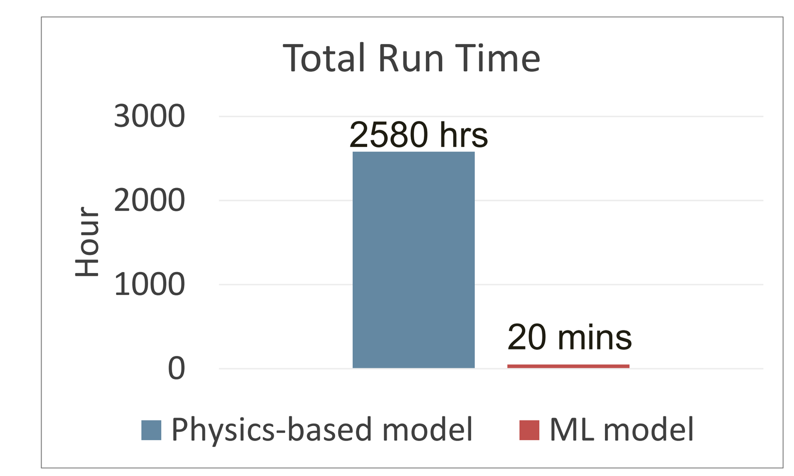
Results (cont'd)

Computational Cost

- Optimization showing a converging trend at the 43th generation.
- Each generation has 30 individuals.



- Total number of simulation evaluated = 1290
- Physics-based simulation total run time = 1290*2=**2580 hrs** (without parallel running)
- DL-model total run time ~**20mins**



80,000 times faster!

Conclusion

- ❖We demonstrated the effectiveness of using FNO-based deep learning surrogate models and the NSGA-II Algorithm for optimizing CO_2 injection strategies.
- ❖The Pareto-front indicates optimal **trade-offs** between CO_2 storage, safety, and vertical displacement.
- ❖The Pareto-front identified in the multi-objective optimization enables users to adjust the risk level according to existing local or national regulatory geomechanical safety constraints.
- ❖We achieved **80,000-fold computational cost saving**.

Acknowledgement

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