

ML Based Newton preconditioner

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Numerical simulation of Carbon storage

Advantages

Safety

Parametric studies

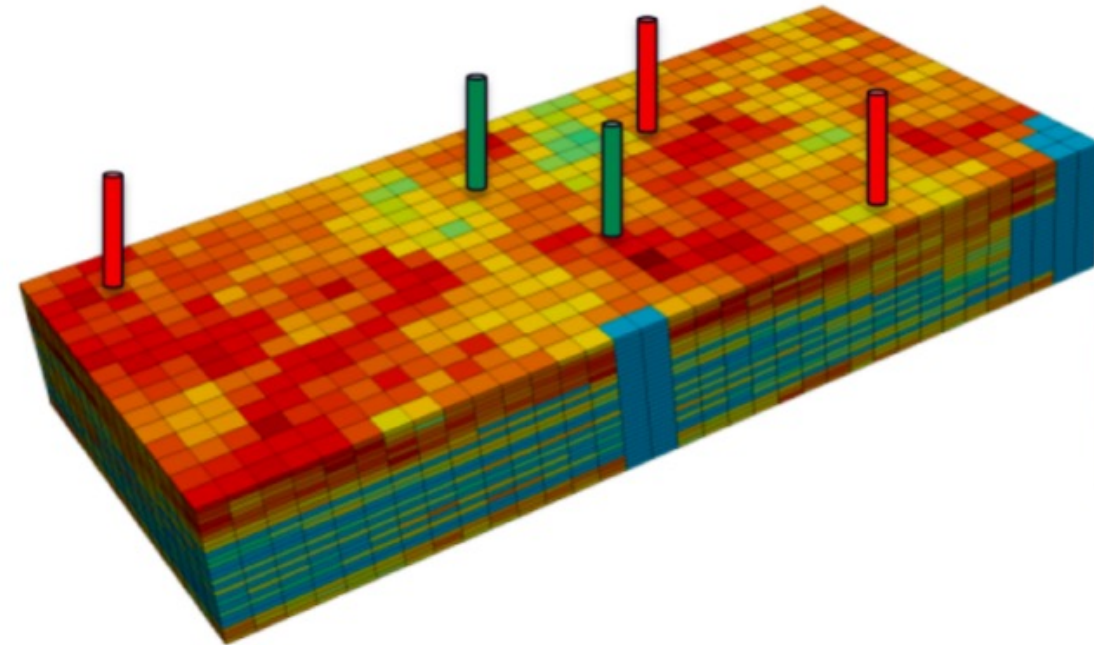
Cost and time efficiency

Drawbacks

Model uncertainties

Parameters uncertainties

Computational resources



2) Bicheng Yan et al.

CO₂ storage requires important amount of simulations

→ Modify parameters to test scenarios

Explore recent breakthroughs in Artificial Intelligence to accelerate numerical simulation

Outline

- Mathematical model and numerical resolution
- Global Hybrid Newton
- Results
- Conclusion

Mathematical model and Numerical resolution

Mathematical model

- Incompressible two-phase flow in porous medium

$$\phi \frac{\partial}{\partial t}(1 - S) + \operatorname{div}(\mathbf{v}_w) = 0, \quad \phi \frac{\partial}{\partial t}(S) + \operatorname{div}(\mathbf{v}_g) = q_g, \quad \text{Mass conservation}$$

$$\mathbf{v}_w = -\frac{Kk_{r_w}(1 - S)}{\mu_w} \nabla P, \quad \mathbf{v}_g = -\frac{Kk_{r_g}(S)}{\mu_g} \nabla P, \quad \text{Darcy's law}$$

$$S = S_g = 1 - S_w, \quad \text{Closure law}$$

Numerical Resolution

1

P, S as main unknowns

$S_w = 1 - S$ auxiliary unknown

2

Discretization

- Finite volume in space
- Implicit Euler in time

Numerical Resolution

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2

Discretization

- Finite volume in space
- Implicit Euler in time

- Fully Implicit scheme

$$\begin{cases} R_g(S^{n+1}, P^{n+1}) & = 0, \\ R_w(1 - S^{n+1}, P^{n+1}) & = 0. \end{cases}$$

→ **Non-linear** system of equations solved using **Newton's method**

→ **Unconditionally stable** but large time steps can prevent Newton's method from converging

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2

Discretization

- Finite volume in space
- Implicit Euler in time

Python library:

Yads: Yet Another Darcy Solver



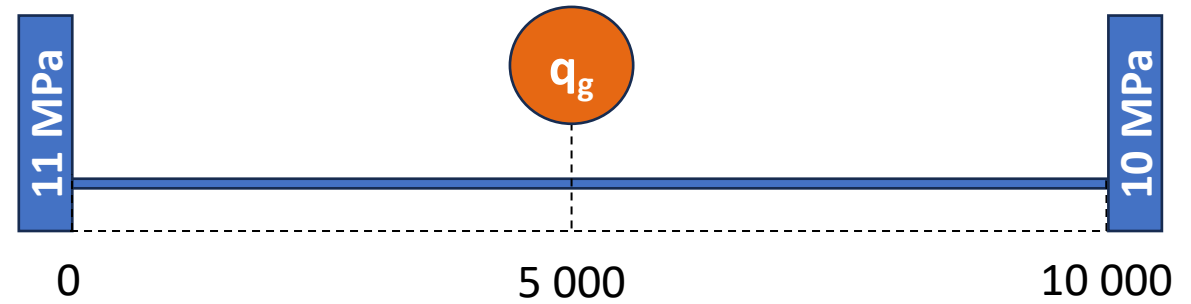
Reservoir geometries

1D

200 cells

Variable parameters :

- Well injection flow rate: q_g
- Time-step: dt



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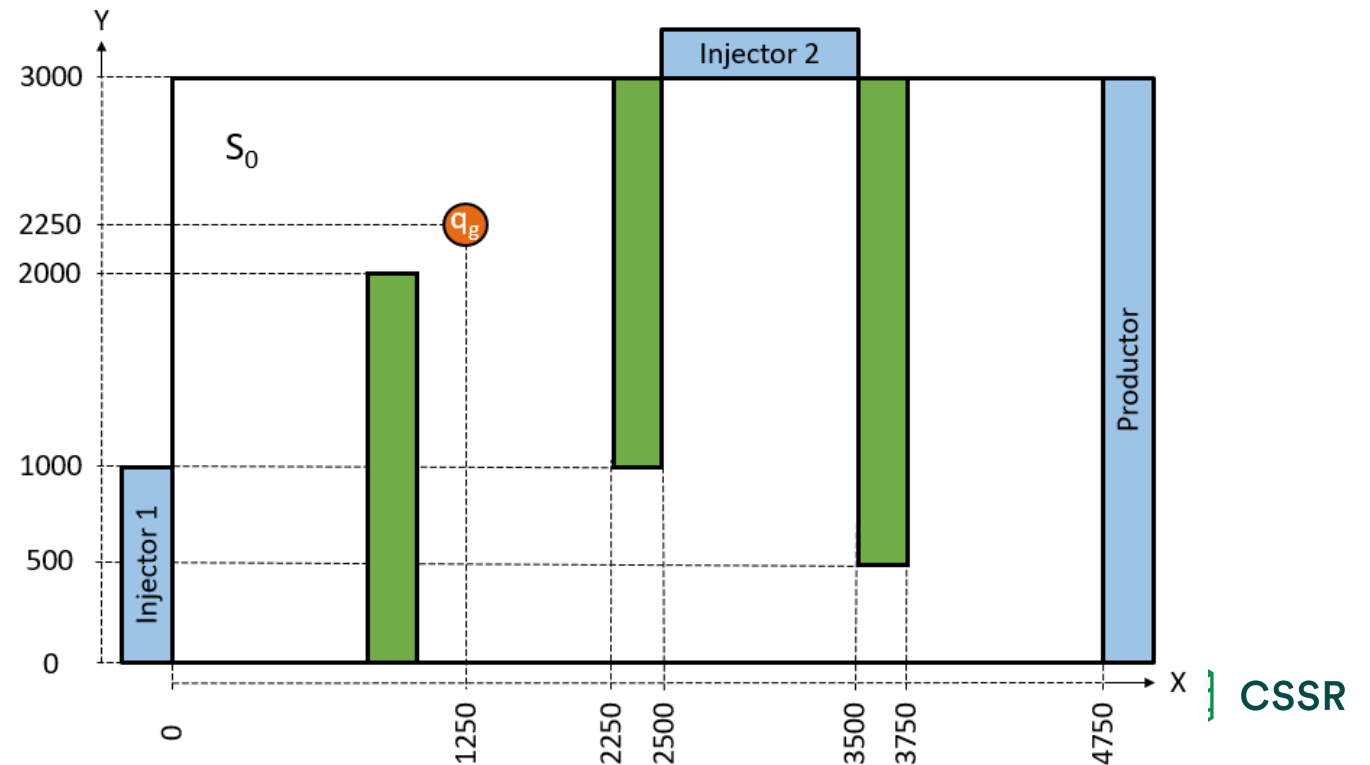
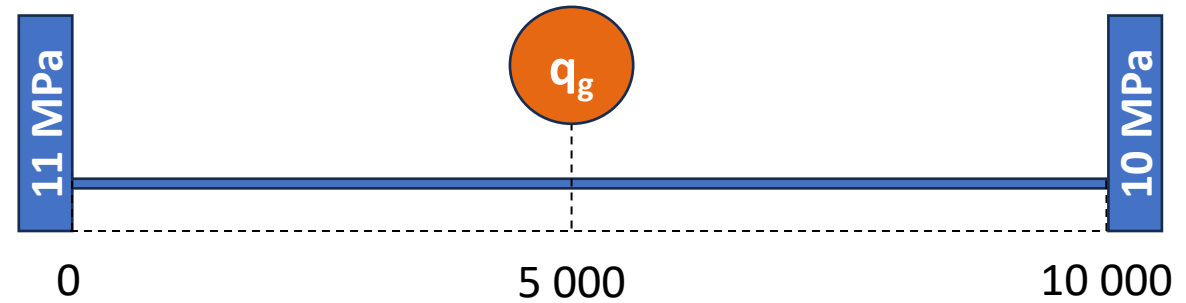
2D

SHPCO2 benchmark¹

95 X 60 cells

Variable parameters :

- Initial saturation: S_0
- Well injection flow rate: q_g
- Time-step: dt



1) Florian Haerberlein 2011 Time Space Domain Decomposition Methods for Reactive Transport — Application to CO2 Geological Storage.

Global Hybrid Newton

Global Hybrid Newton

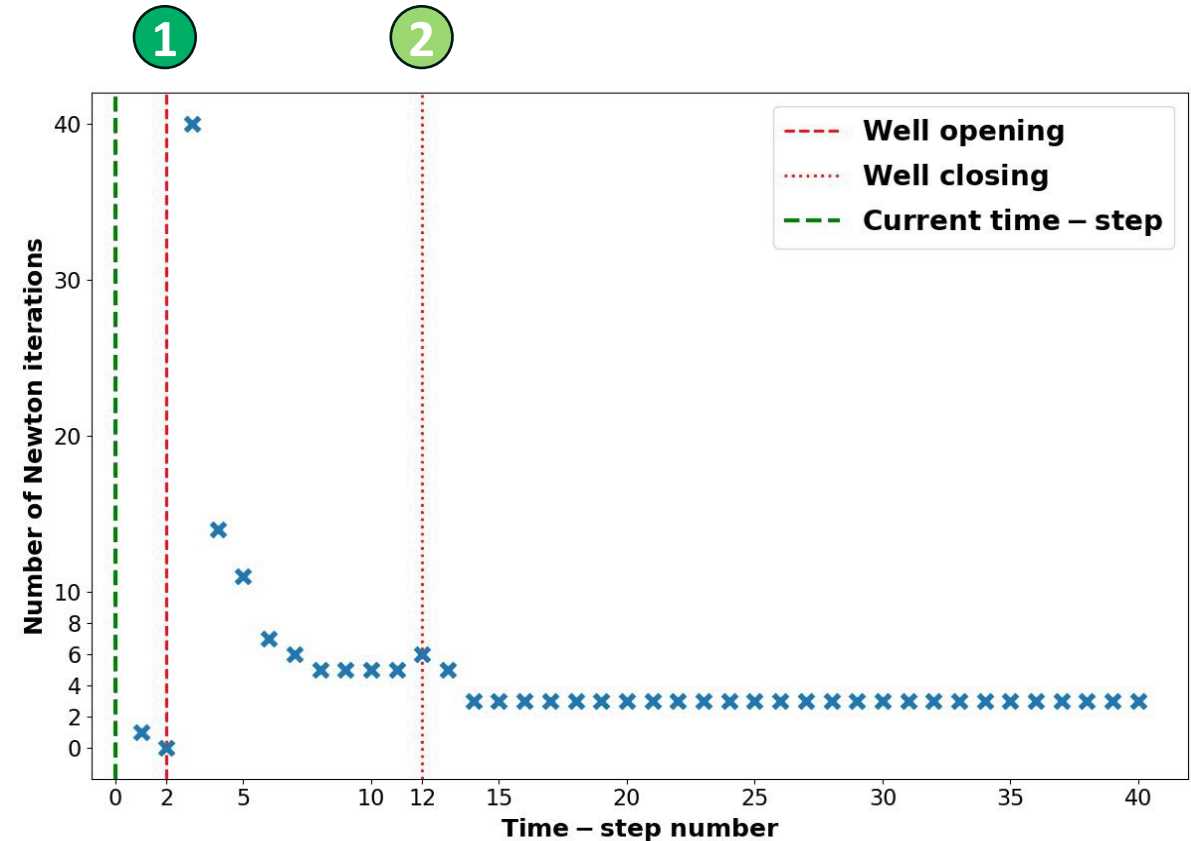
- Scenario :
 - 1 Well opening
 - 2 Well closingTransport



Global Hybrid Newton

- Scenario :
 - 1 Well opening
 - 2 Well closingTransport

Computational cost?



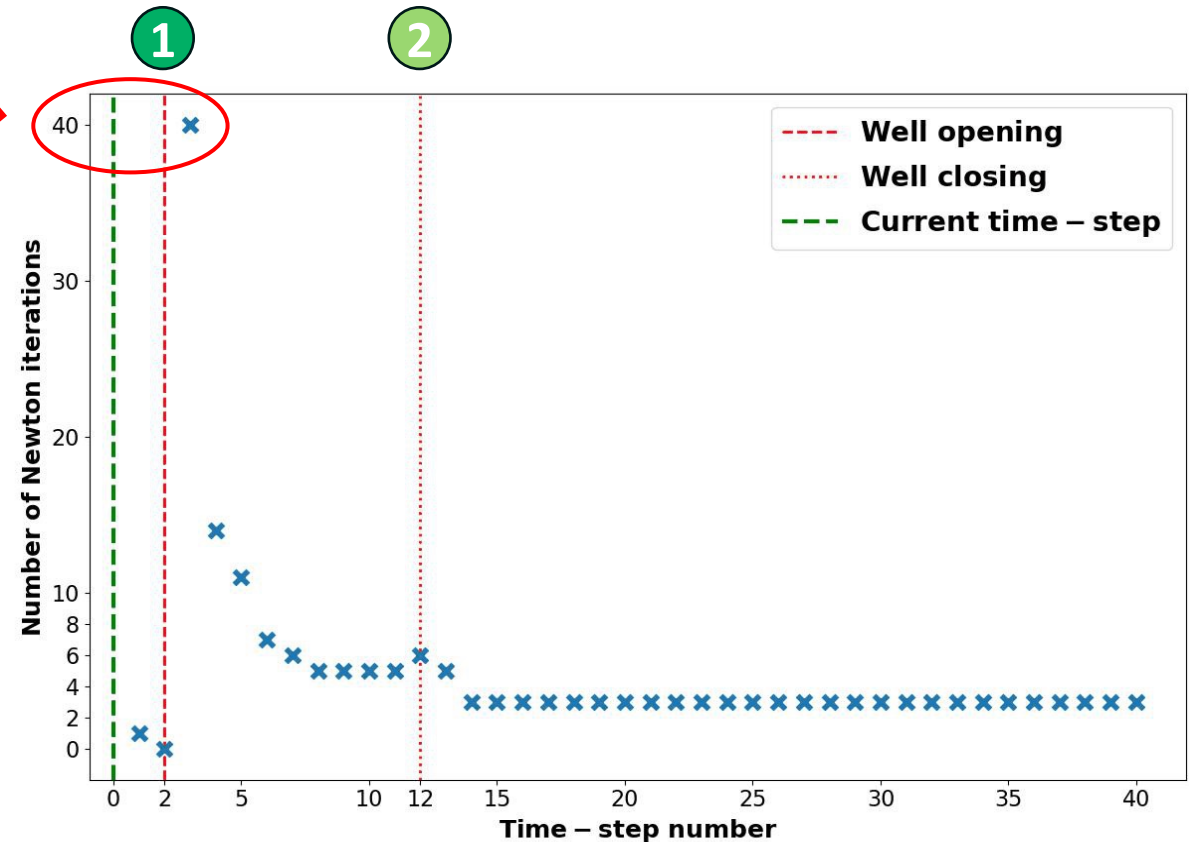
Global Hybrid Newton

- Scenario :

- 1 Well opening
 - 2 Well closing
- Transport

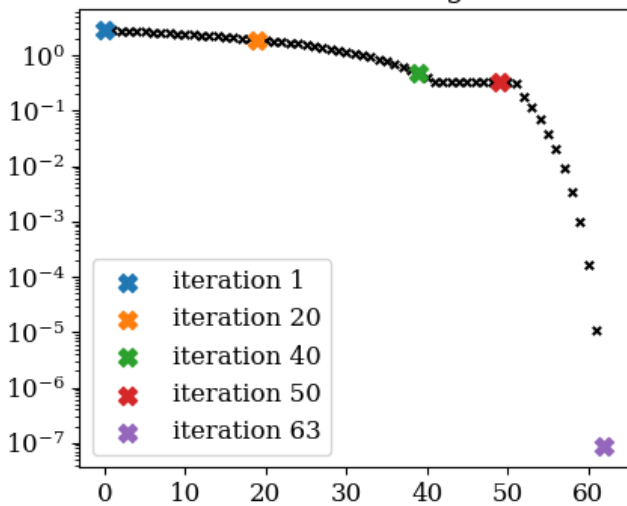
Computational cost?

Well opening requires 40 Newton iterations



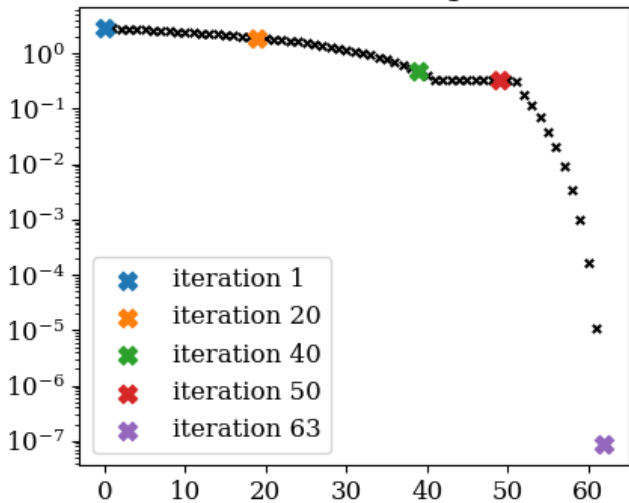
Hybrid initialization: 1D example

Residual evolution through iterations

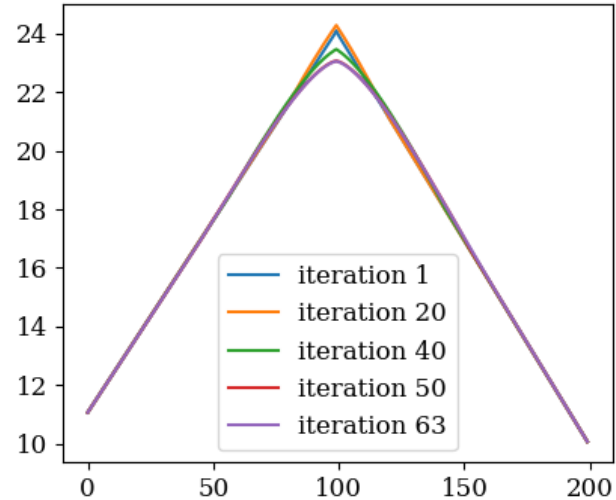


Hybrid initialization: 1D example

Residual evolution through iterations



Pressure evolution through iterations



Pressure

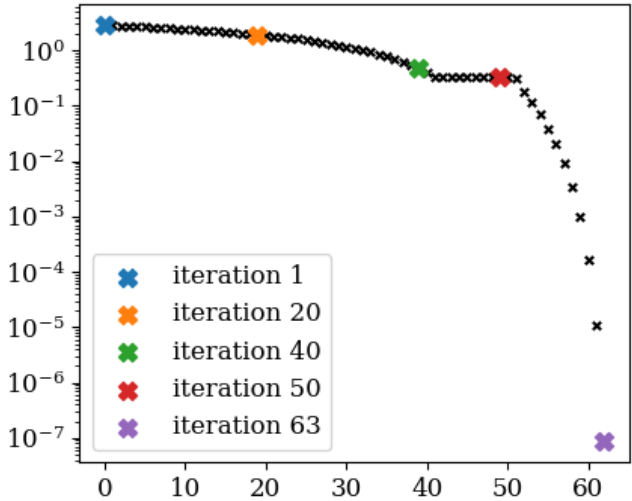
Implicit Pressure Solver

→ Solve linear system

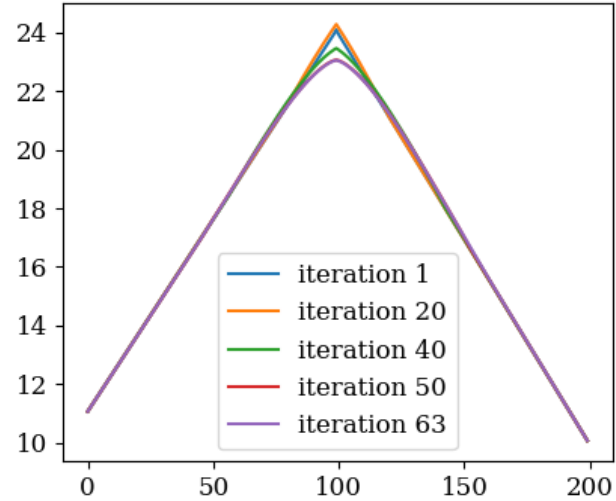
$$\operatorname{div}(v_w(P^{n+1}, 1 - S^n)) = 0, \quad \operatorname{div}(v_g(P^{n+1}, S^n)) = q_g.$$

Hybrid initialization: 1D example

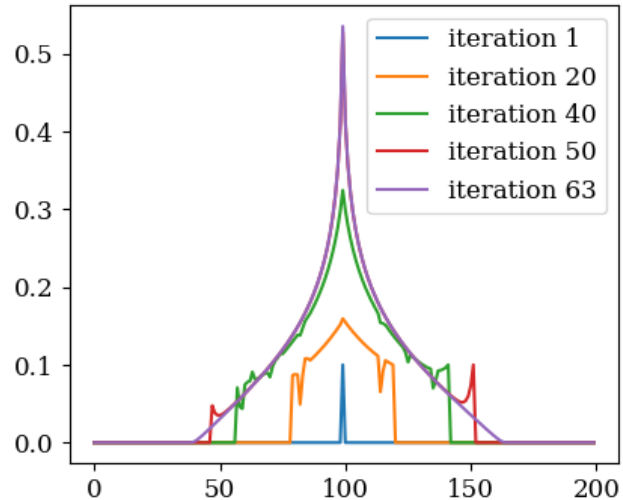
Residual evolution through iterations



Pressure evolution through iterations



Saturation evolution through iterations



Pressure

Implicit Pressure Solver

→ Solve linear system

$$\operatorname{div}(v_w(P^{n+1}, 1 - S^n)) = 0, \quad \operatorname{div}(v_g(P^{n+1}, S^n)) = q_g.$$

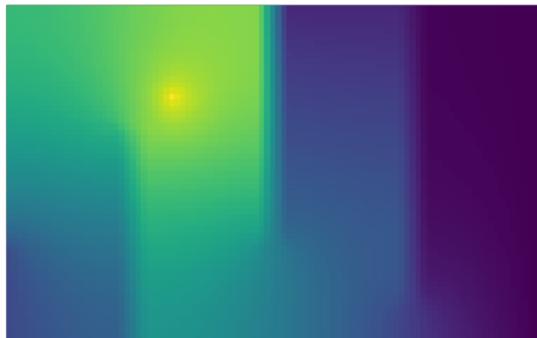
Saturation

Well events are similar in space and time

→ Machine Learning model

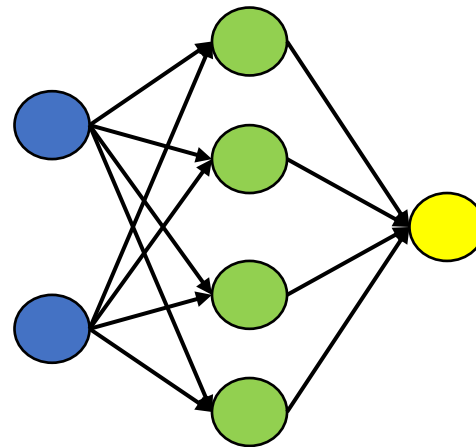
Workflow

Generate data



→ Cover large range of well events

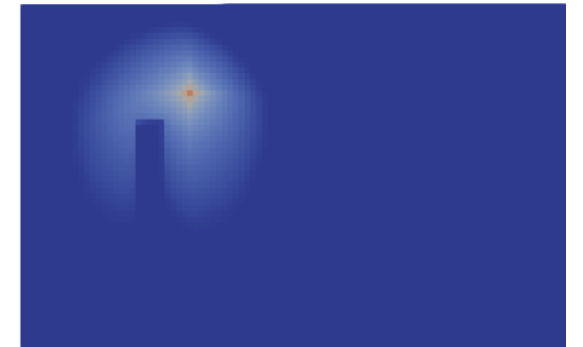
Supervised training of Saturation model



→ Fourier Neural operator

$$S_{\text{guess}} = f_{\theta}(P_{\text{imp}}, S, q_g, dt)$$

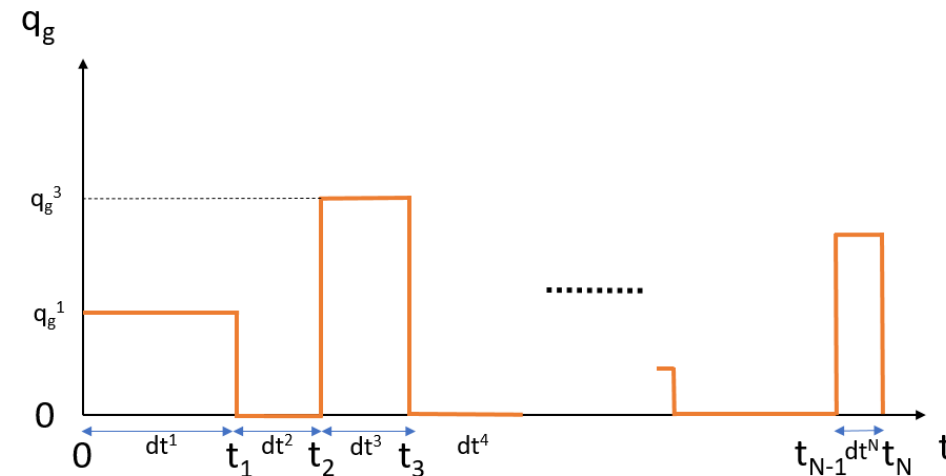
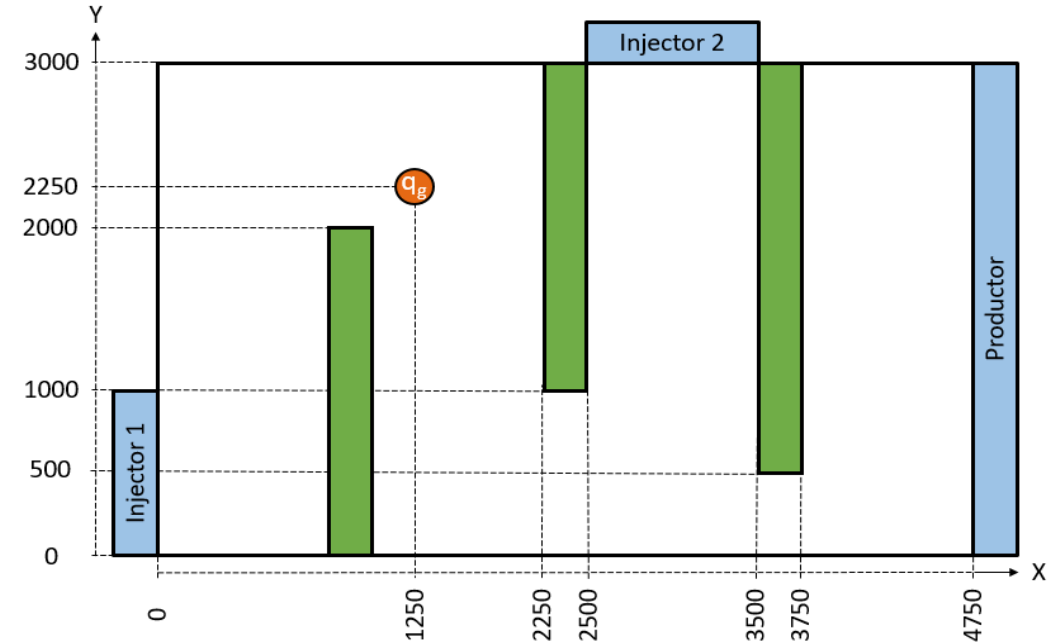
Plug saturation model in Newton's method



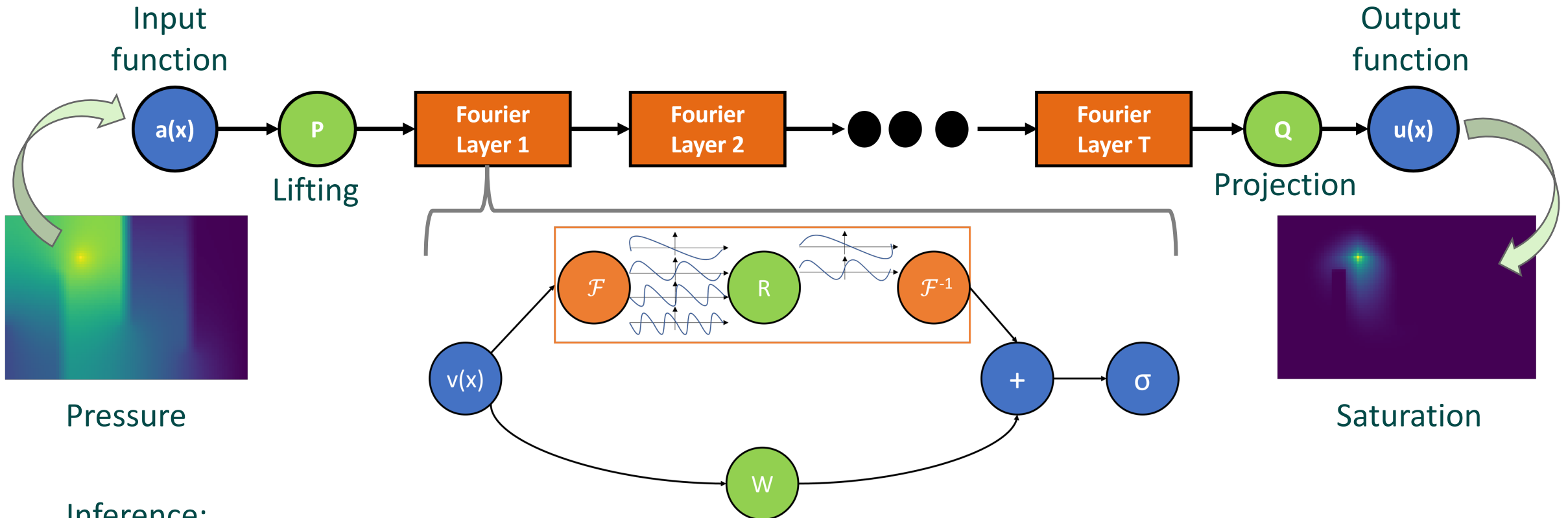
→ Compare Hybrid with Standard Newton's method

Data Generation

- Variable parameters
 - Well injection flow rate: $q_g \in [10^{-5}, 10^{-3}] \text{ m}^2/\text{s}$
 - Well opening time: $dt \in [1, 10]$ years
 - Reservoir gas saturation: $S \in [0, 0.6]$
- Generate realistic saturations S
 - Consecutive well opening and closing
 - 3 600 parameters combination
 - 18 000 samples
- Computational cost
 - Run in parallel using MPI
 - 360 CPUs
 - ≈ 36 hours



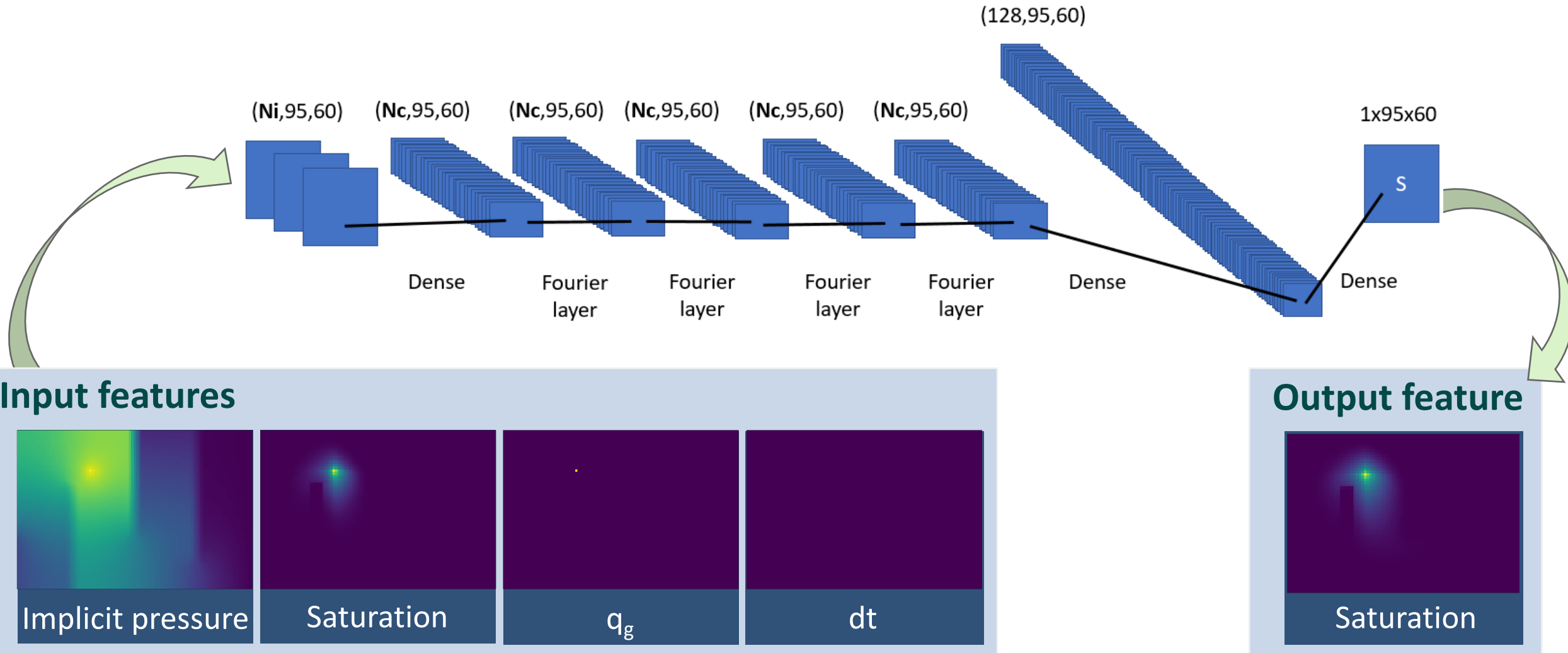
Fourier Neural Operator¹



Inference:

Majority of the inference cost is in the Fourier Transform !
Fast Fourier Transform $\rightarrow N \log(N)$

Saturation model - Architecture



Saturation model - Training

- Dataset

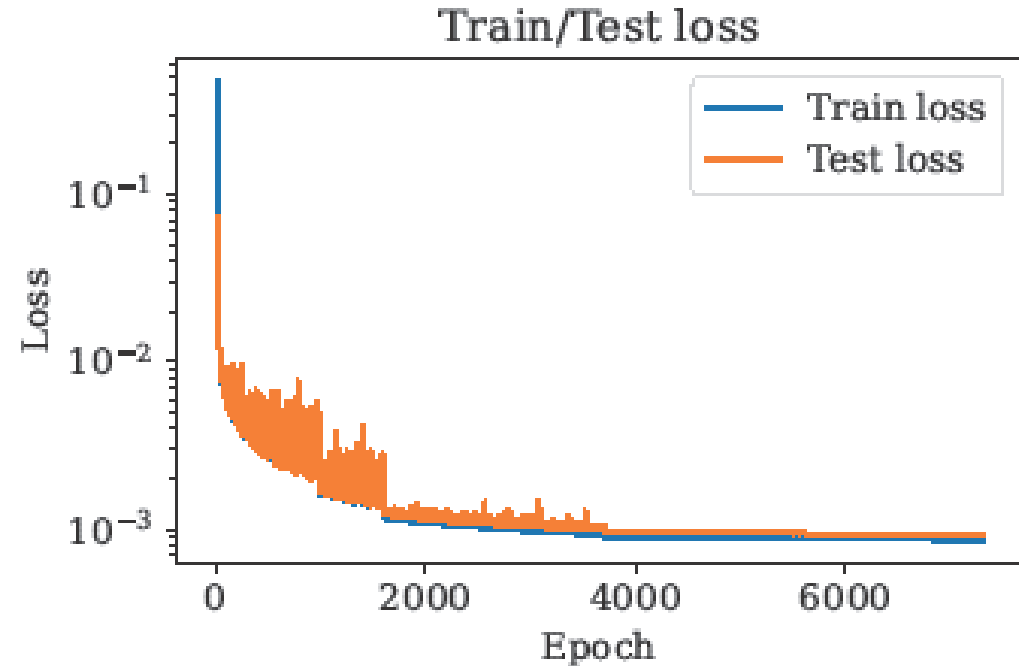
- 80% train / 20% test

- Computational cost

- 132 hours on NVIDIA V100 GPU

- Hyperparameters

- Loss: $\frac{1}{N} \sum_{i=1}^N \frac{\|s_i - \hat{s}_i\|_2}{\|s_i\|_2}$
- Batch size: 128
- Adam optimizer
- Starting learning rate: 10^{-4}
- Momentum: 0.9
- Weight decay: 10^{-4}



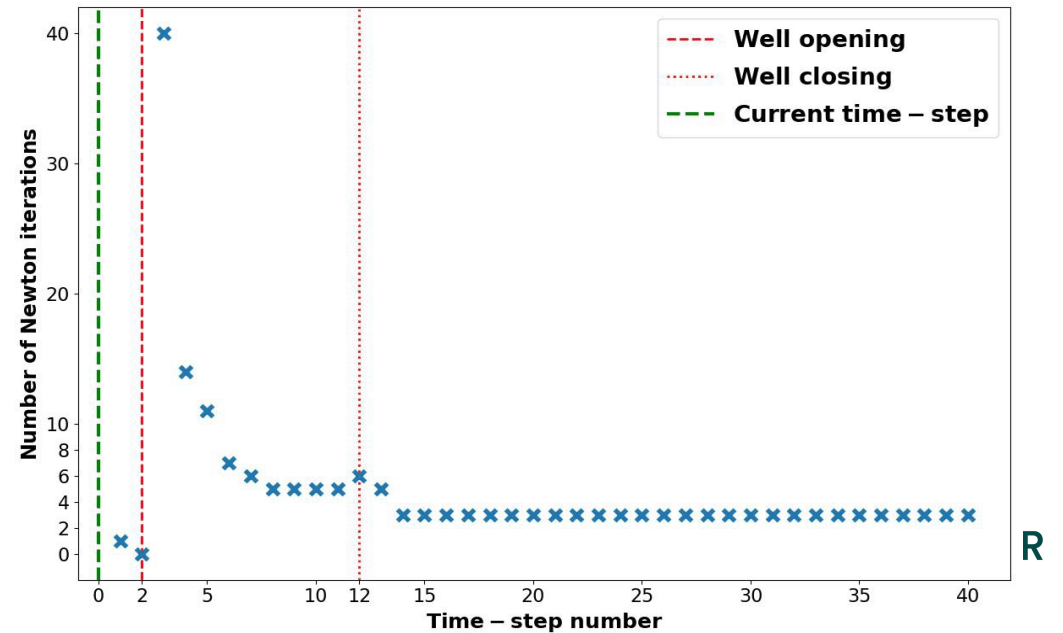
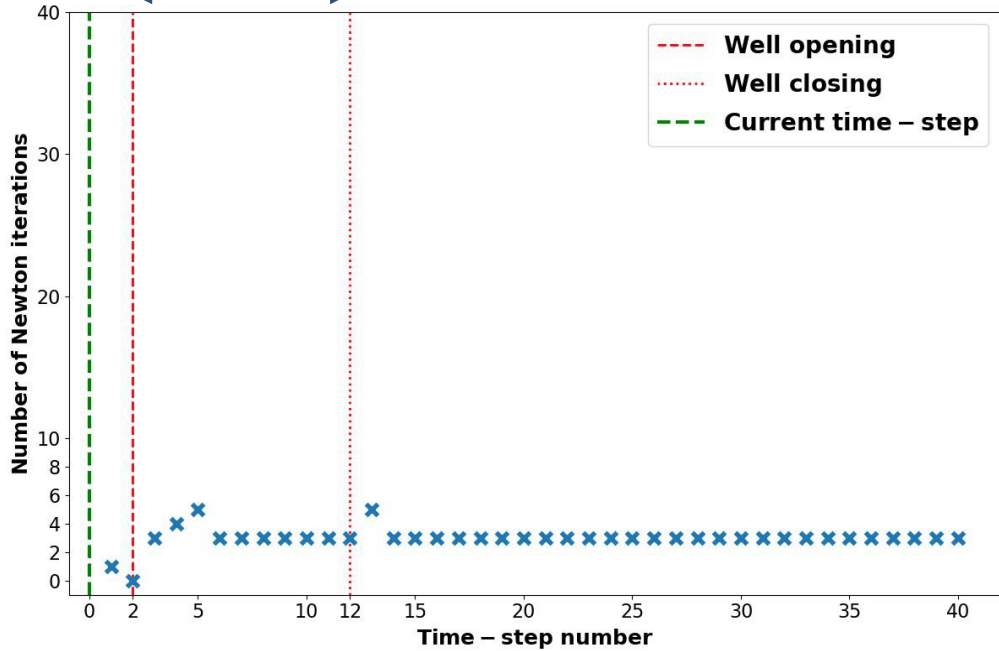
Best model	epoch 7295
Test loss	8.7×10^{-4}
Train loss	9.3×10^{-4}

Results



Hybrid Newton

Standard Newton

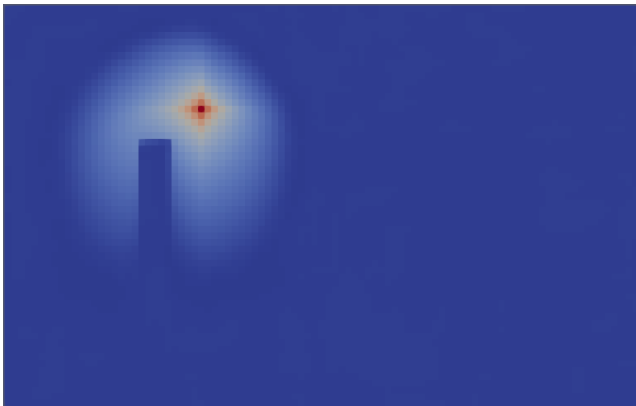


Results

Saturation initializations :



Standard



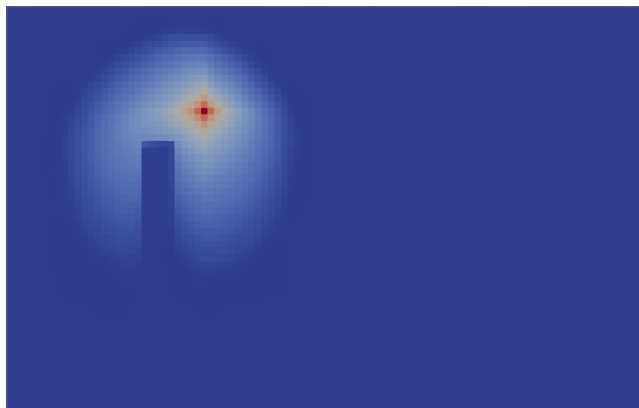
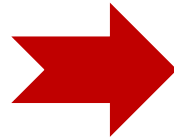
Hybrid

Results

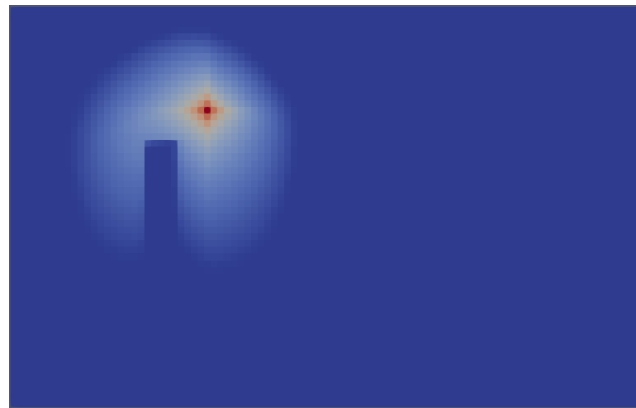
Saturation initializations :



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Hybrid



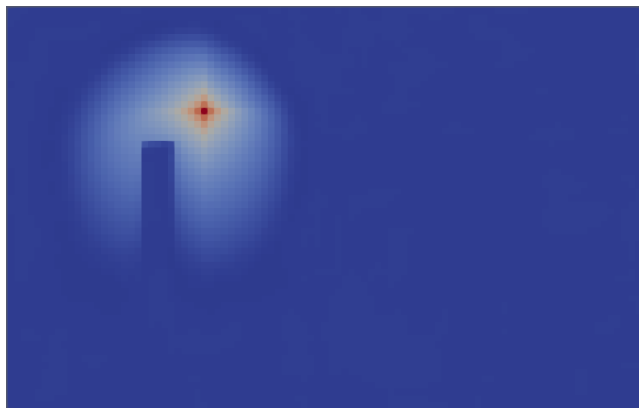
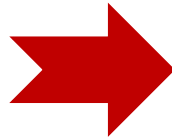
Solution

Results

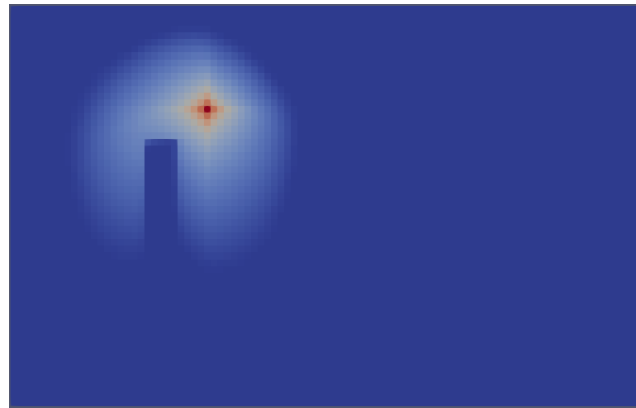
Saturation initializations :



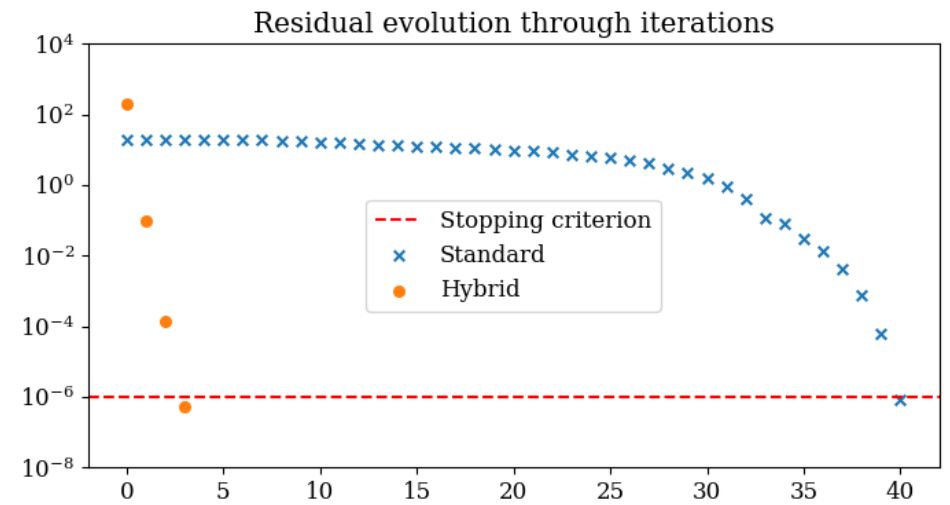
Standard



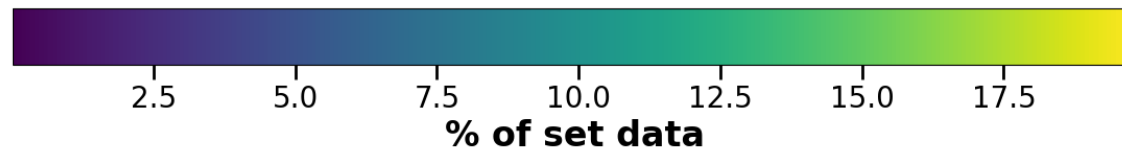
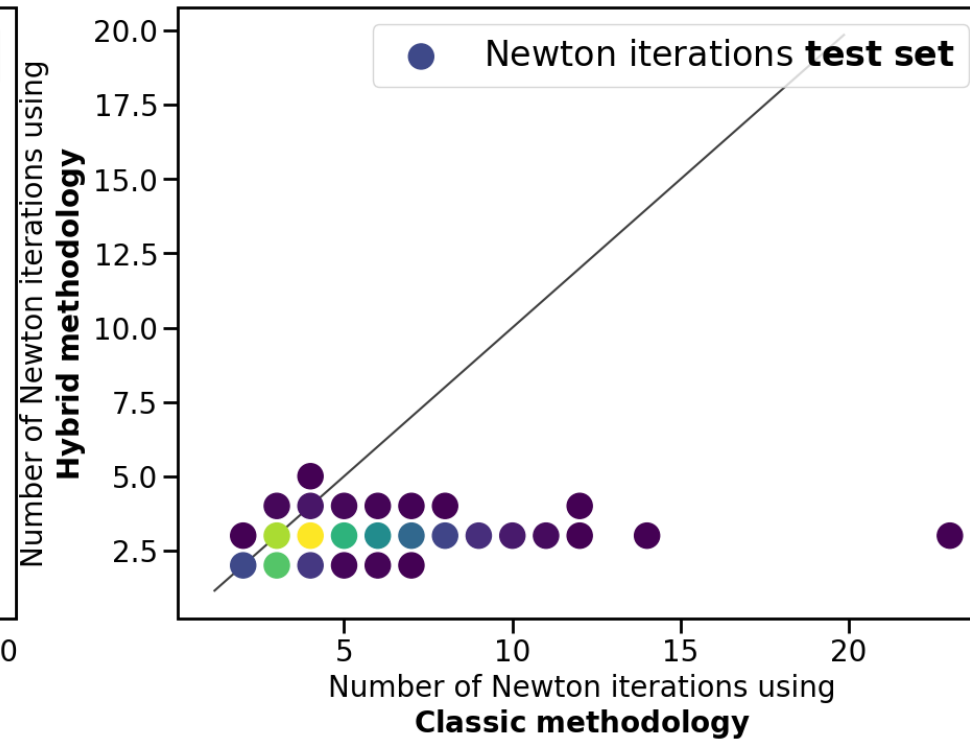
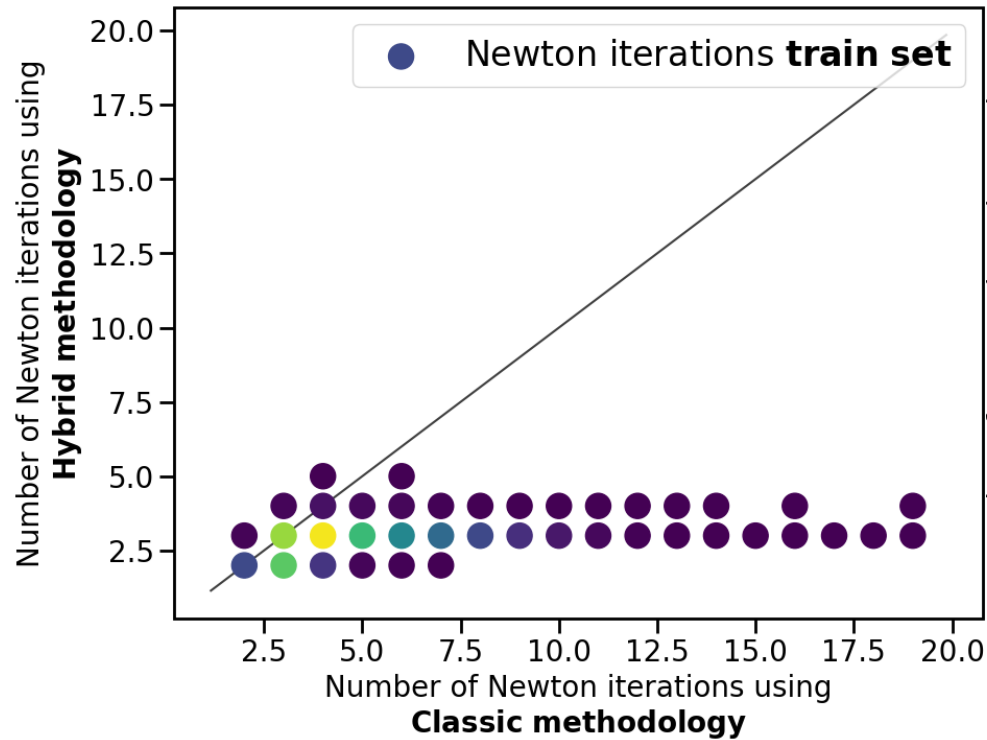
Hybrid



Solution



Results



	Acceleration
Test	39%
Train	39%



Summary of Global Hybrid Newton

Advantages

Acceleration of numerical simulation for a large range of well events

Online phase affordable

Drawbacks

Offline phase expensive :

- Data generation
- Model training

Constant well location

Conclusion and perspectives

- Integration of Hybrid Newton preconditioning in OPM
- Challenges:
 - More complex physical model
 - **Training data generation cost**
 - **Multi-well handling**
 - Heterogeneities
 - Discretization
- Current developments:
 - Local Hybrid Newton → Reduce training cost / Multi-well handling
 - Generalized well model → Reduce Dataset generation cost

References

1. Hybrid Newton

- *Alban Odot, Ryadh Haferssas, and Stéphane Cotin. Deepphysics: a physics aware deep learning framework for real-time simulation. CoRR, abs/2109.09491, 2021.*
- *Ichrak Ben Yahia, Jean-Pierre Merlet, and Yves Papegay. Mixing neural networks and the Newton method for the kinematics of simple cabledriven parallel robots with sagging cables. In ICAR 2021 - 20th International Conference on advanced robotics, Ljubljana, Slovenia, December 2021.*
- *Jianguo Huang, Haoqin Wang, and Haizhao Yang. Int-deep: A deep learning initialized iterative method for nonlinear problems. Journal of Computational Physics, 419:109675, 2020.*
- *Subhrajyoti Bhattacharyya and Aditya Vyas. A novel methodology for fast reservoir simulation of single-phase gas reservoirs using machine learning. Heliyon, 8(12):e12067, 2022.*
- *Joubine Aghili, Emmanuel Franck, Romain Hild, Victor Michel-Dansac, Vincent Vigon. Accelerating the convergence of Newton's method for nonlinear elliptic PDEs using Fourier neural operators. 2024. {hal-04440076}*

2. Other citations

- *Bicheng Yan, Bailian Chen, Dylan Robert Harp, Wei Jia, Rajesh J. Pawar, A robust deep learning workflow to predict multiphase flow behavior during geological CO2 sequestration injection and Post-Injection periods, Journal of Hydrology, Volume 607, 2022, 127542, ISSN 0022-1694, <https://doi.org/10.1016/j.jhydrol.2022.127542>.*

3. Github repository

- <https://github.com/PINN-Well-opening-and-closing-events/Yads.git>





Centre for Sustainable Subsurface Resources

Research for optimal reservoir operations and value generation in the green transition

Energy-efficient petroleum production

Strategies to synchronize water injection with intermittent energy

Energy storage in the subsurface

Scalable solutions for subsurface storage of hydrogen, air, and heat

CCS: Carbon storage

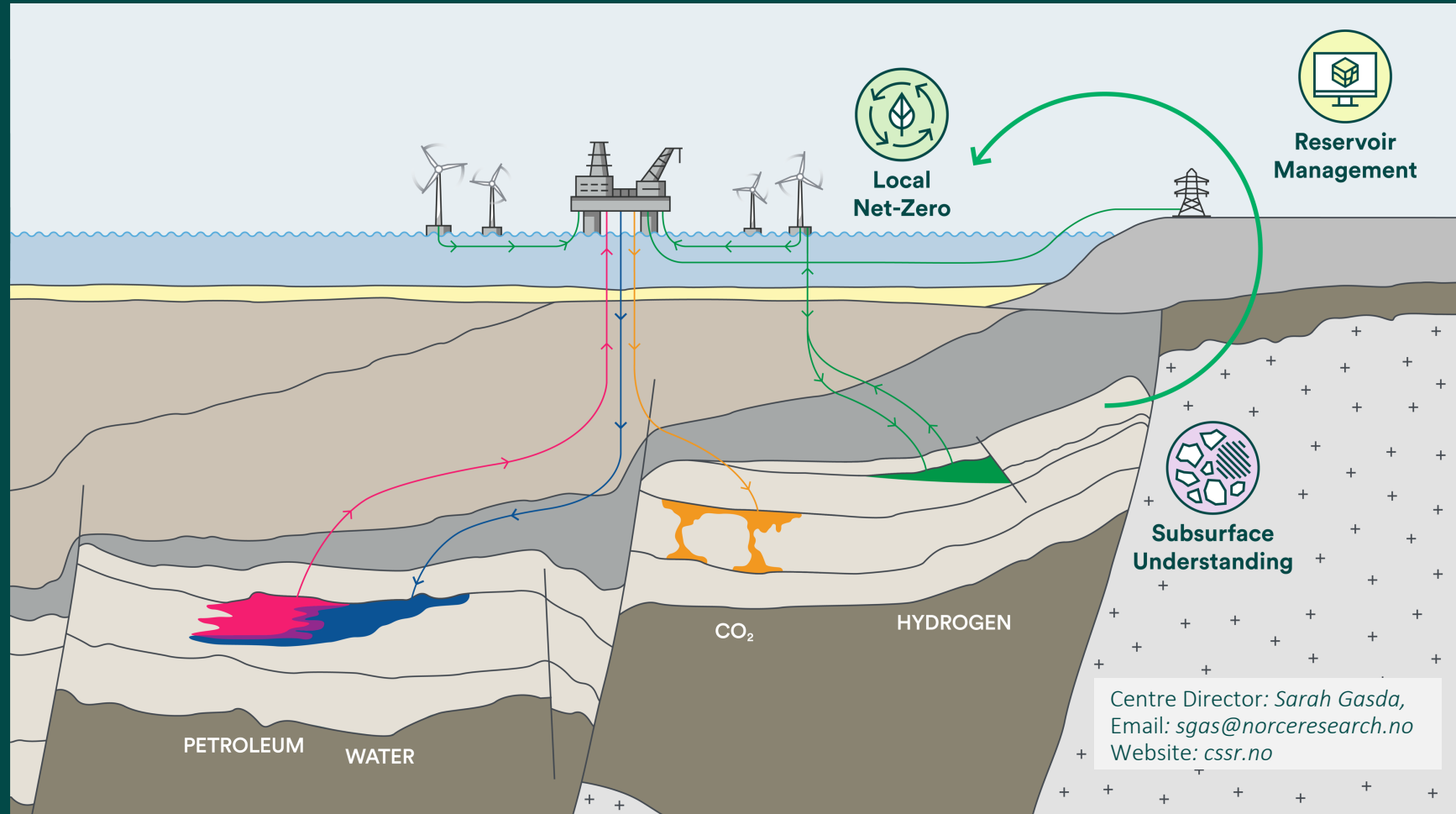
Flexible solutions for CO₂ storage in depleted reservoirs

Digitalization of subsurface management

Update workflows to increase predictive capacity and harness the value of subsurface data

Interdisciplinary research and education

Reservoir physics, geosciences and applied mathematics



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