Enhanced Carbon Storage Forecasting Via Cross-Geology Transfer Learning

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TRANSFER LEARNING







SOURCE SITE: SACROC

SACROC GEOMODEL



SACROC unit is the oldest CO2-EOR site in the US (~75 years).

AM



POROSITY AND PERMEABILITY



4000 m by 8200 m by 250 m represented using 36x16x25 grid cells

TRAINING DATASET



4000 m by 8200 m by 250 m represented using 36x16x25 grid cells



Miscible & Immiscible Displacement; Oil Swelling; Viscosity Reduction; IFT reduction; Carbonic Acid; Pressure Maintenance; Sweep

RAPID FORECASTING USING NEURAL OPERATOR



Mapping the spatial distribution of transport/engineering parameters to spatiotemporal pressure & saturation

Ā M

Pressure Forecast

Pressure at time zero







CMG at layer 22





FNO at layer 10



FNO at layer 22



Saturation Foreca

True



Predicted



CMG at layer 10



CMG at layer 22 Sg 0.8 10 0.6 15 0.4 20

25







FNO at layer 22



10

FNO-I Performance for Pressure





FNO-II Performance for Saturation





Improved FNO-I

Model Architecture





SPARSE REPRESENTATION





- Inference speed-up is possible using sparse neural network developed using RigL Library
- At regularly spaced intervals, remove a fraction of connections and then activate new.
- First layer is kept dense.
- Update is based on ΔT , Fraction, Decay, T_{end}
- GeLU within, Modified ReLU for final

TARGET SITE: IBDP

IBDP Site



- U.S. DOE carbon storage project located in Illinois Basin
- 15.6km x 15km x 2.14km (126x125x110)
- Heterogeneous Sandstone (layered)





Transfer Learning from SACROC to IBDP







SACROC Geomodel (SOURCE)

Fe

• 4km x 8.2km x 0.2km (36 x 14 x 25)







- **IBDP** Geomodel (TARGET)
- 15.6km x 15km x 2.14km (126 x 125 x 110)

Differences between SACROC and IBDP



Parameter	SACROC <mark>(Source)</mark>	IBDP (Target)	
Input Variables	q, Q, Kx, poro, t, prod locs	q, Q, Kx, Kz, poro, t	
Injection Period (years)	30 (monthly and yearly)	3 & 1 (monthly)	
Relative Perm	Tight Rock: Carbonate/Dolomite	Sandstone	
Distinct Geomodels	5 (regular grid)	100 (tartan grid)	
No of Injection Wells	2	1	
No of Producer Wells	2	0	
Injection Type	Constant	Variable/Intermittent	
Injection Rates Range (MT/yr)	5.6 - 40.8	0.5 – 1.5	
Perforation zones	All through z-axis	3 non-continuous zones	
Train – Val – Test Split	133 - 20 - 20	10 – 10 – 80 (or 20 – 10 – 70)	

Base Transfer Learning with Fine-Tuning





• Fine-tuning with constant learning rate (LR) all through training epochs

Transfer Learning with Adaptive Fine-Tuning





• Fine-tuning with learning rate (LR) that adapts all through training epochs





• Fine-tuning by training blocks of layers with specific LR all through training epochs



Pressure Forecast with 10 Train Samples





Sample 53

- Cross plots for test samples over all time-steps and layers
- Plots majorly within the 2% error range
- Training+Validation set: 20, Test set: 80



Error plots for Pressure Forecast





Pressure MAE: 10 Train Samples

- Adaptive LR gave the best results of the TL techniques
- Overall MAE: 4.47psia for all samples, time-steps and layers
- 87% data reduction (7 times)

Error plots for Saturation Forecast





- Base fine-tuning gave the best results of the TL techniques
- Overall MAE: 0.086 for all samples, timesteps and layers
- 80% data reduction (5 times)

Saturation Forecast with 20 Train Samples

0.

0.6

0.5

0.4

0.0

Predicted CO₂ Saturation



- Cross plots for test samples over all time-steps and layers
- Plots majorly within the 10% error range
- Training-Validation set: 30, Test set: 70

















 S_g







0 5 10 15 20 25 30 35 40

Simulation - Layer 6

5 10

15

20

25

30

35

3479.0

3380.8

3282.6

3184.4

3086.2

2988.0

P [psia]

10

15

20

25

30

35







27

Reducing Training Datasize



PRESSURE





Key Takeaway



- Transfer Learning was implemented on the SACROC-based Neural Operator that was trained on only 20 simulation runs for IBDP Site
- SACROC and IBDP Sites have several significant differences in geology and engineering parameters.
- Pressure forecast has less than 9 psi error
- Saturation forecast has less than 8% error
- Traditional simulator takes 1 hour for a single scenario, while neural operator takes less than 1 minute to forecast.

Transfer Learning Benefits



Model	Train	Validation	Test
Source Pressure & Saturation	133	20	20
Target Pressure	10	10	80
Target Saturation	20	10	70

	Source	Target
Pressure (MAE) [2K to 4K psi]	2.4 psia	8.7 psia
Saturation (MAE) [0 to 1]	0.05	0.08
Average Training Time (hrs)	4	1.5
Training Data Storage (GB)	28	2.8
RAM Required (GB)	200	64

Thanks for your Attention !! More Info on Google Scholar (Sid Misra) Email: misra@tamu.edu