Deep Learning Model for Subsurface Flow Prediction with Multifidelity Data

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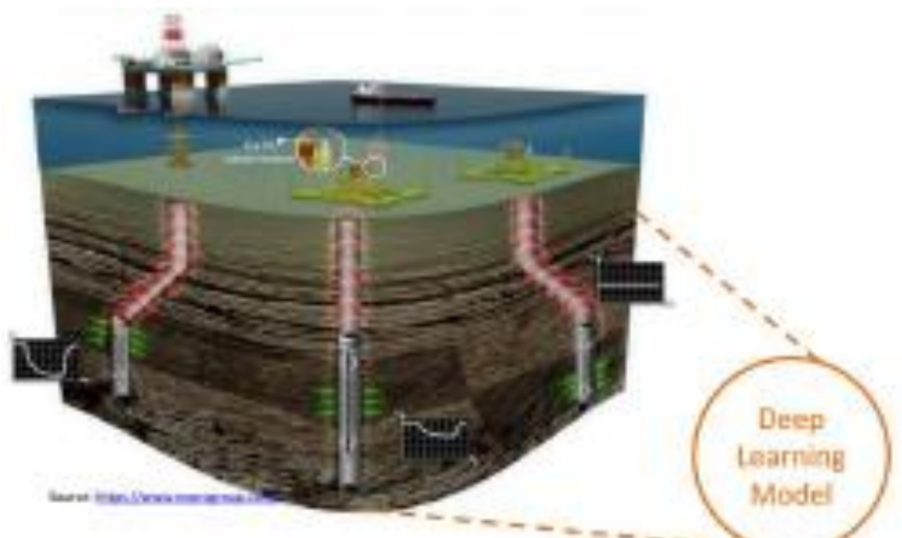
Introduction

Goal: Develop a deep learning model that predicts flow from the subsurface using multi-fidelity data.

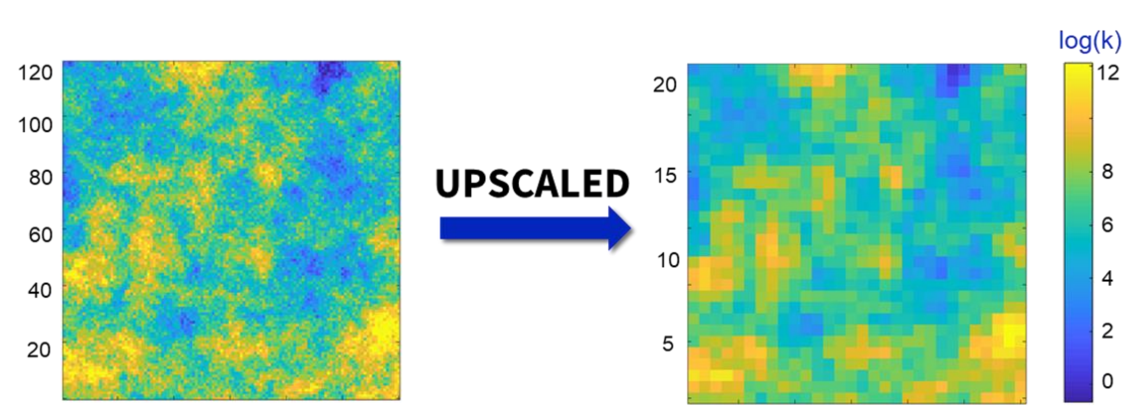
Why is it important?

- The use of numerical reservoir simulators for the forward simulation is computationally expensive.
- Lots of data required to obtain good accuracy. Utilize cheap ow fidelity data to reduce cost of training deep earning model.



[From Tita Ristanto]

Dataset



High Fidelity **Low Fidelity**

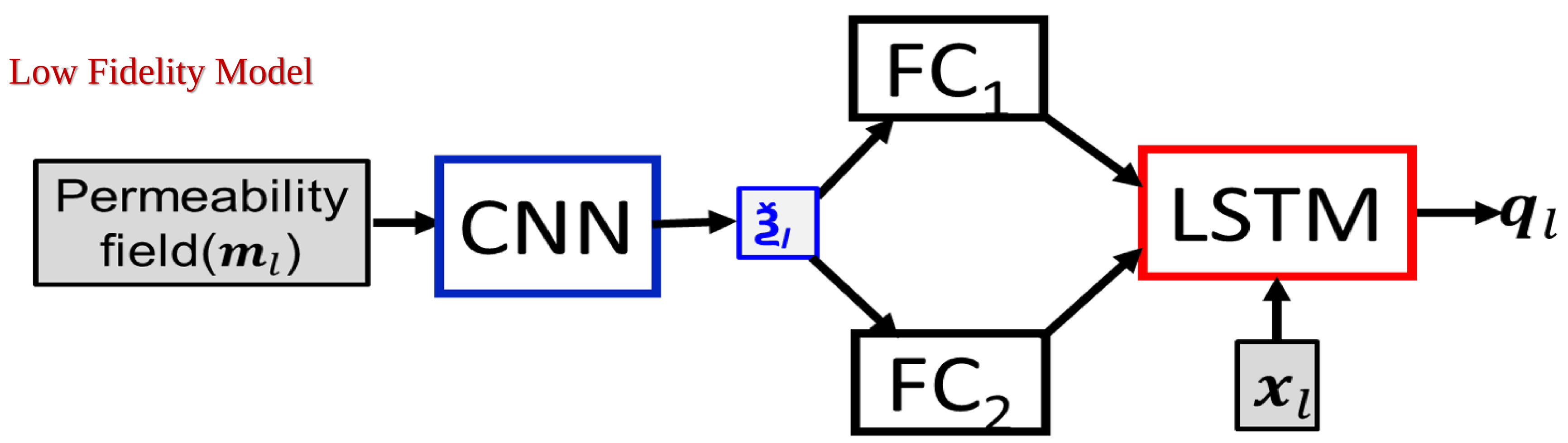
- **Input for low-fidelity DL model**: upscaled model ($\boldsymbol{m}_l$), well pressure settings ($\boldsymbol{x}_l$).
- **Input for high-fidelity DL model**: fine model ($\boldsymbol{m}_h$), well pressure settings ($\boldsymbol{x}_h$), low dimensional representation of $\boldsymbol{m}_l$, ($\boldsymbol{\mathfrak{z}}_l$)

$$\boldsymbol{x}_h \ll \boldsymbol{x}_l$$

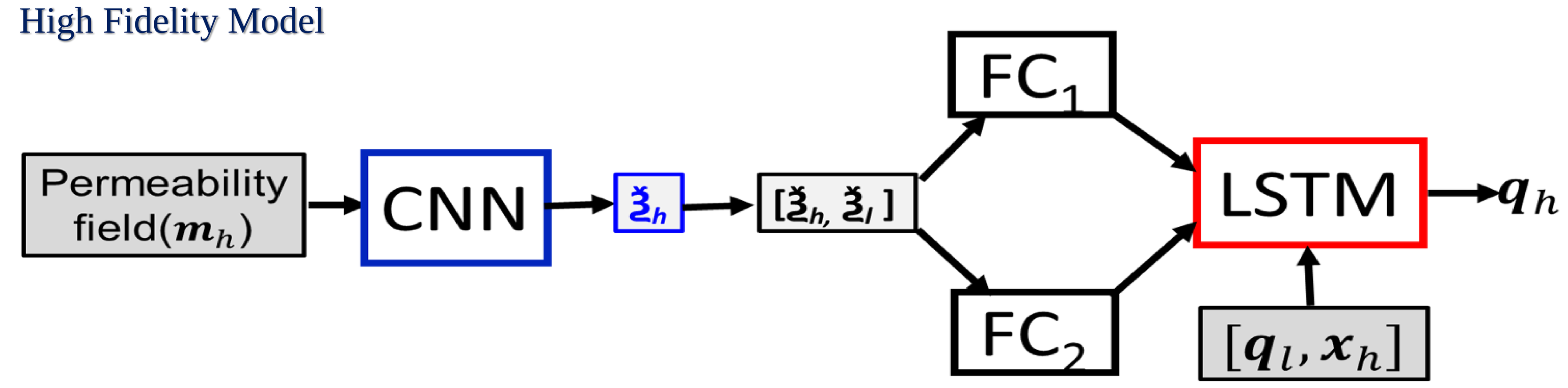
- **Low fidelity data**: 20000 flow simulations (400 well pressure settings and 50 geologic realizations). Took 7 hrs.
- **High fidelity data**: 2500 flow simulations (50 well pressure settings and 50 geologic realizations). Took 41.5 hrs.
- Stanford Automatic Differentiation General Purpose Research Simulator (AD-GPRS) used for flow simulation.
- Preprocessing: applied min-max scaling to input and output separately.

Model

Low Fidelity Model



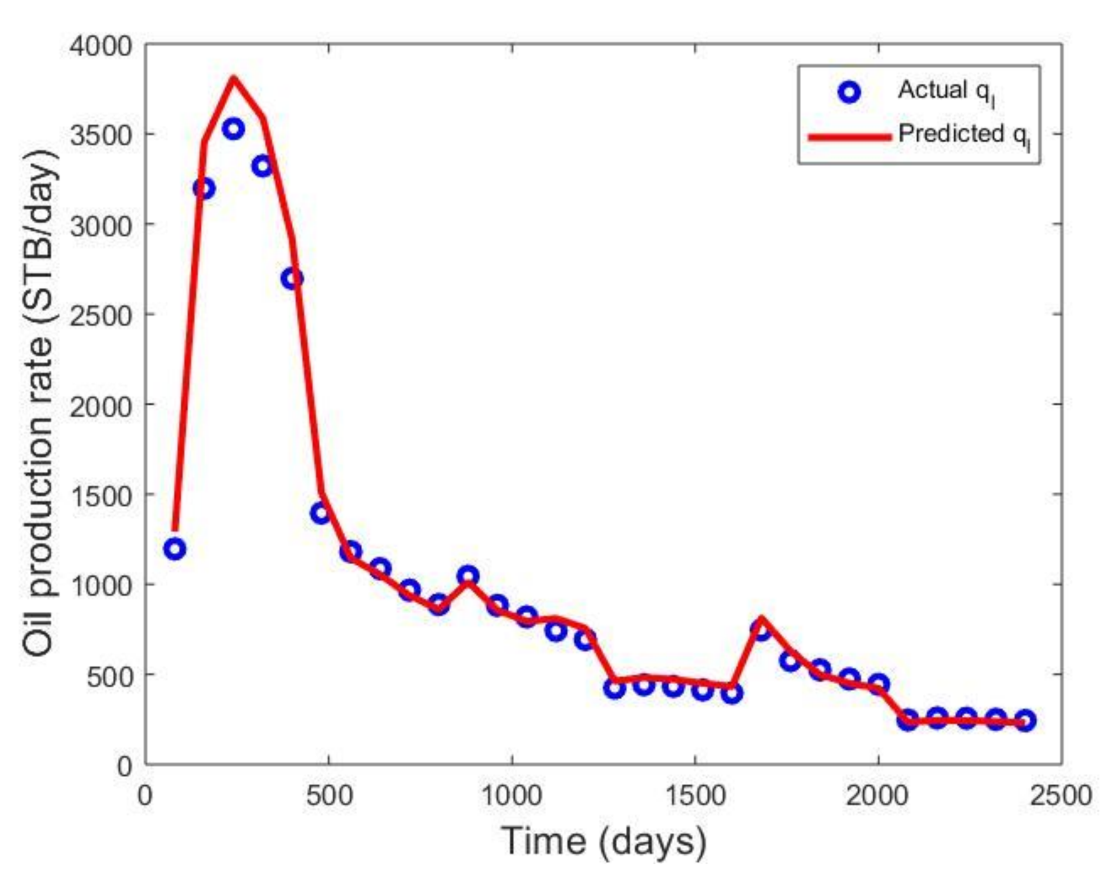
High Fidelity Model

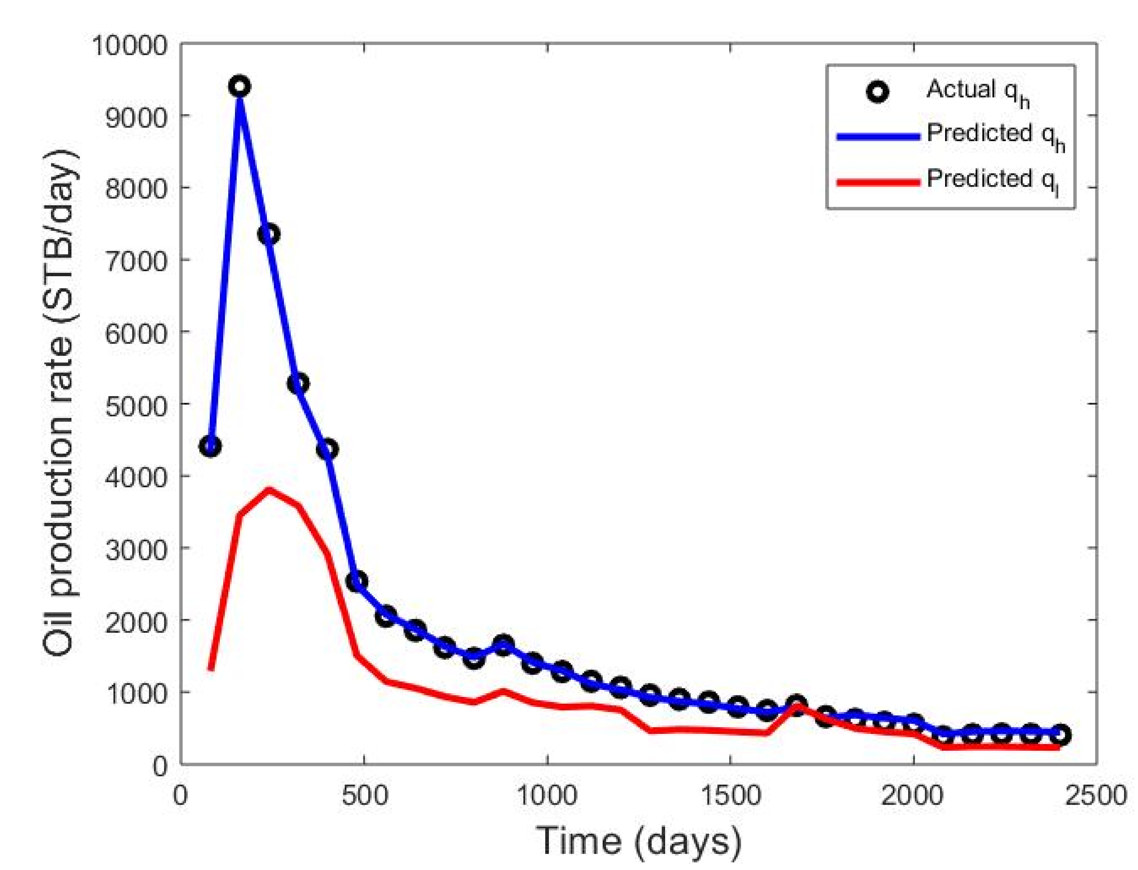


Loss function: $L_l = \frac{1}{N_t}\sum_i^{N_t}\left|\hat{q}_l^{(i)} - \boldsymbol{q}_l^{(i)}\right|$ $\quad L_h = \frac{1}{N_t}\sum_i^{N_t}\left|\hat{q}_h^{(i)} - \boldsymbol{q}_h^{(i)}\right|$

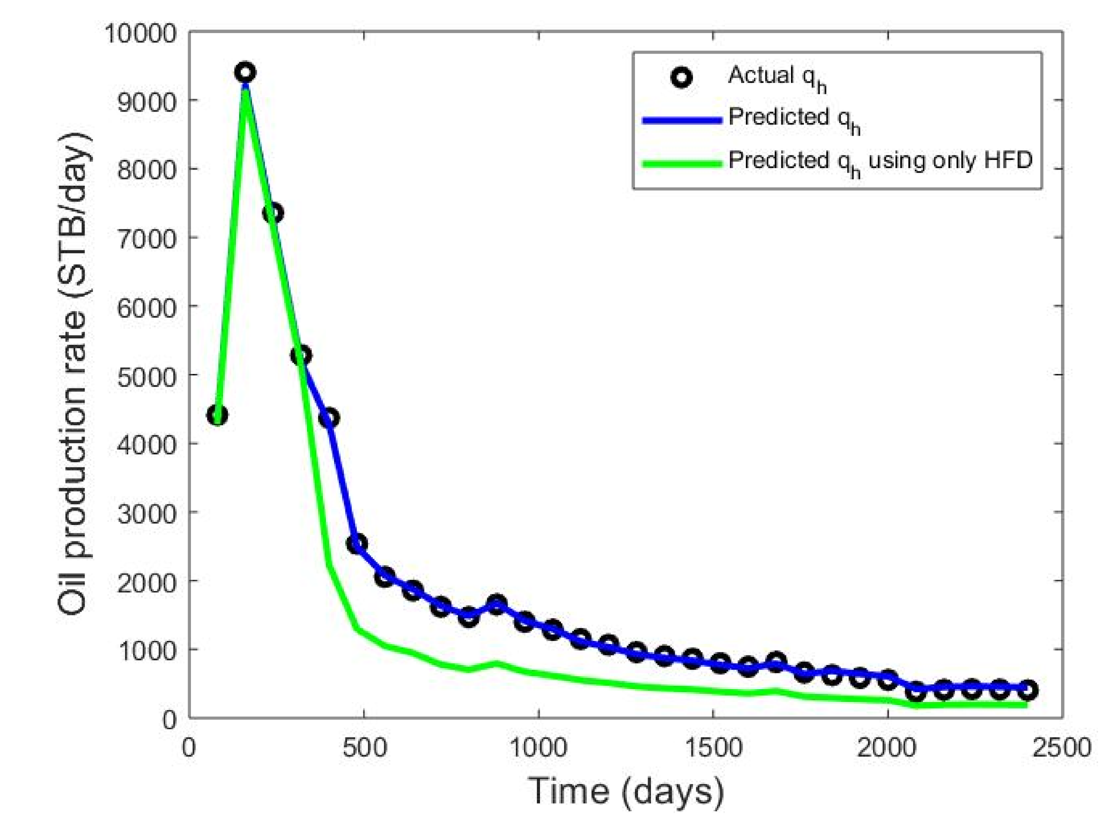
Hyperparameters	Value
Learning rate	0.03
Number of epochs	250
Batch size	16
Dropout rate	0.2

Results





Model	Training MAE	Dev MAE	Test MAE
Low fidelity	77	82	74
High fidelity	65	72	68
Only high fidelity	107	111	115



Conclusion

- Accurate flow prediction using multifidelity data.
- Obtained 7 times speed up by using a combination of low and high fidelity data
- Test MAE as low as 68 was obtained.

Future Work

- Apply to optimization
- Predict water production and injection rate.

Acknowledgement

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- Stanford CEES.

References

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