Designing Deep Inverse Models for History Matching in Reservoir Simulations

SenSIP INDUSTRY CONSORTIUM

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MOTIVATION

In science/engineering, we often need to learn complex mappings between independent parameters (*X*) and dependent quantities of interest (*y*) – ***Forward and Inverse maps***

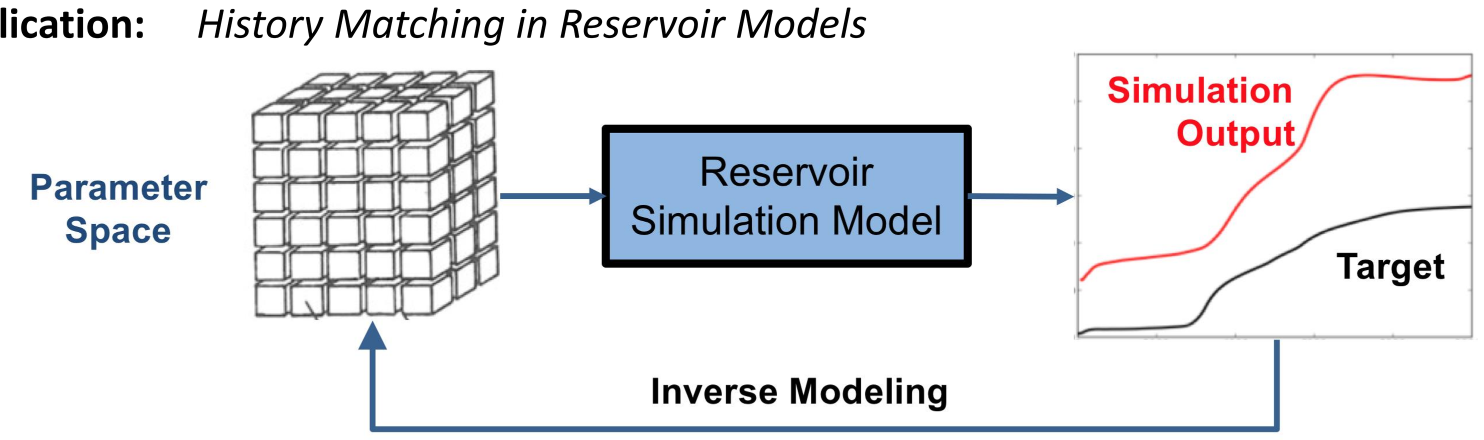
For a given dataset of observed (*X*, *y*) pairs, building inverse models is challenging in practice. Simple machine learning strategies are ineffective.

- ✓ No bijectivity
- ✓ Ill-posed
- ✓ Computationally complex

Naïve Approach: Densely sample the parameter space, run the simulator for every realization and construct the posterior *P*(*X*|*y*) – ***Computationally intractable***

Goal: Design a tractable inverse modeling approach based on deep neural networks, without requiring to use the simulator during optimization, i.e. ***only use surrogates***.

Application: *History Matching in Reservoir Models*



History Matching: Identifying and calibrating parameters of a reservoir model that best matches historical data

Key Challenges:

- High-dimensional parameter spaces – Small data regimes.
- Simulator produces multi-variate time series outputs – Lack of meaningful metrics.

Possible Solution: Fit a standalone inverse model regularized by the surrogate to estimate X – ***Introduce Self Consistency***

PRELIMINARIES

Dataset: Parameters $X \in \mathcal{R}^{2000\times 14}$; Time Series Curves $c \in \mathcal{R}^{2000\times 3\times 255}$

Step 0 – ***Learn concise latent representations***

- Train an **autoencoder (AE)** based on 1D convolutions, on the multivariate time series curves c to learn a concise latent space $y \in \mathcal{R}^{14}$.

Use effective maps $X \rightarrow y$ and $y \rightarrow X$ to build reliable inverse modeling solutions.

Proposed Solutions
- **Cyclical Training**
- **Coupled Training**

Both solutions aim to enforce self-consistency between the forward and the inverse models

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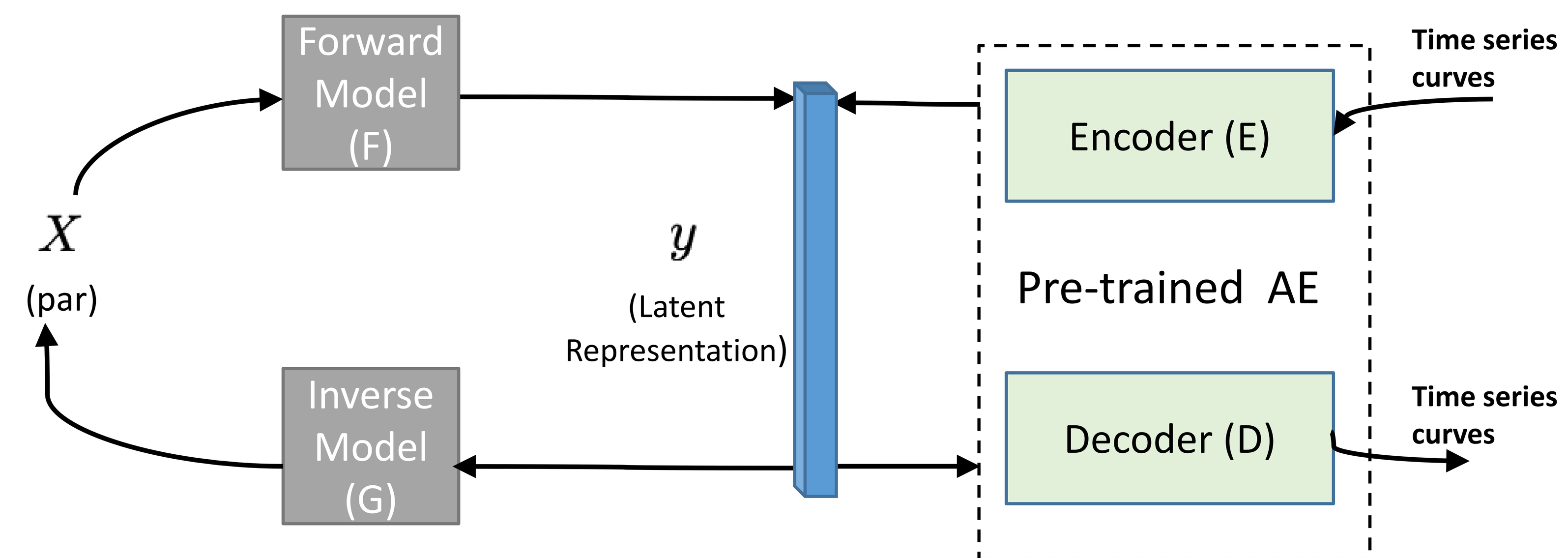
APPROACH

Proposed Solution 1: Independent models tied via Cyclical Training



F and G: Fully connected neural networks tied together with a cyclic consistency constraint

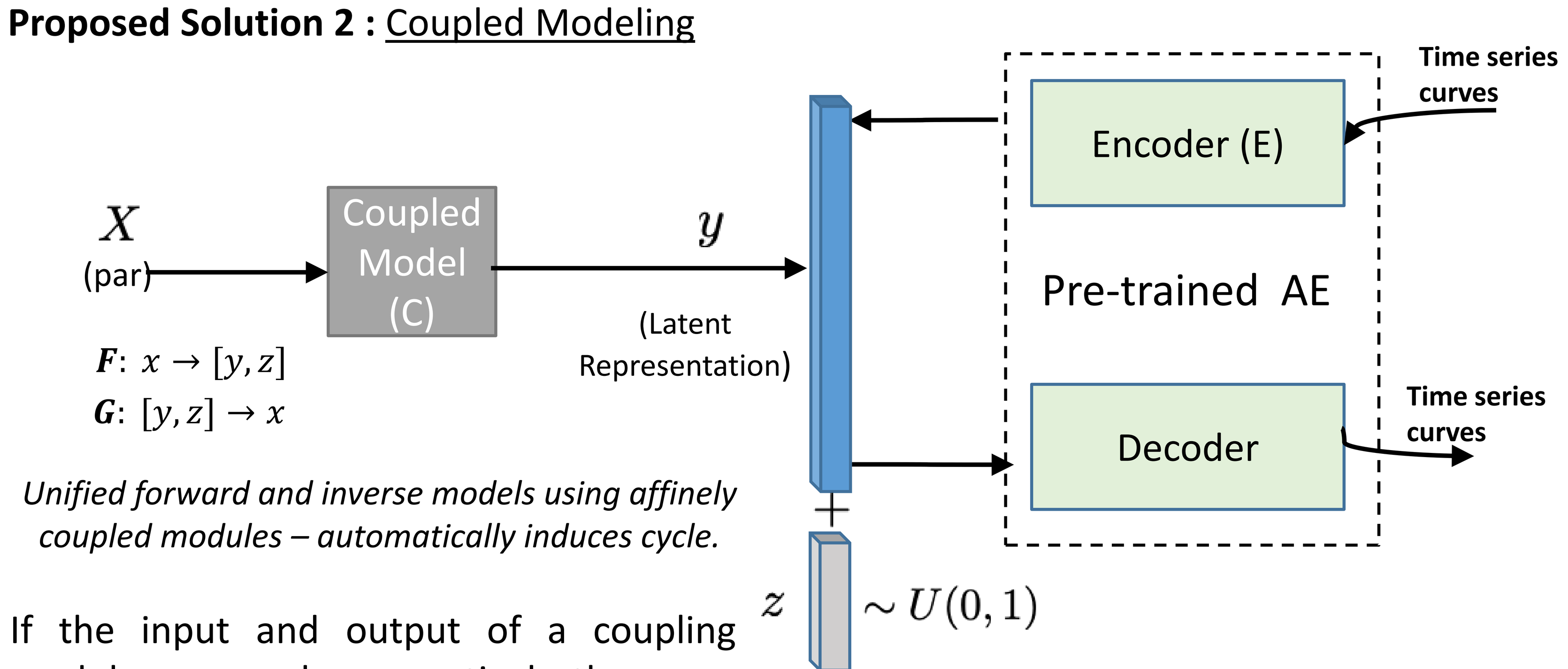
Inverse Model G: Produces mean μ and variance ϑ estimates of the input parameters X

$$L_{cycle} = \lambda_1 L_1 + \lambda_2 L_2 + \lambda_3 L_3$$

Residual $x - \mu$ is regularized by the sensitivities of the surrogate

$$L_1 = \sum_i \|\mathcal{F}(x_i) - y_i\|_2^2 \qquad L_2 = \sum_i \frac{\|\mu_i - x_i\|_2^2}{2\nu_i} + \frac{1}{2}\log \nu_i \qquad L_3 = \sum_i \|\mathcal{F}(\mu_i) - y_i\|_2^2$$

Proposed Solution 2 : Coupled Modeling



Unified forward and inverse models using affinely coupled modules – automatically induces cycle.

If the input and output of a coupling module are u and v respectively, then:

Forward | *Inverse is trivial !* | **Inverse**

$$v_1 = u_1 \odot exp(s_2(u_2)) + t_2(u_2) \qquad u_2 = (v_2 - t_1(v_1)) \odot exp(-s_1(v_1))$$
$$v_2 = u_2 \odot exp(s_1(v_1)) + t_1(v_1) \qquad u_1 = (v_1 - t_2(u_2)) \odot exp(-s_2(u_2))$$

s and t can be arbitrarily complex neural networks

Append additional independent noise variables $z \sim U(0,1)$ to the latent representation to improve the well-defined nature of the inverse.

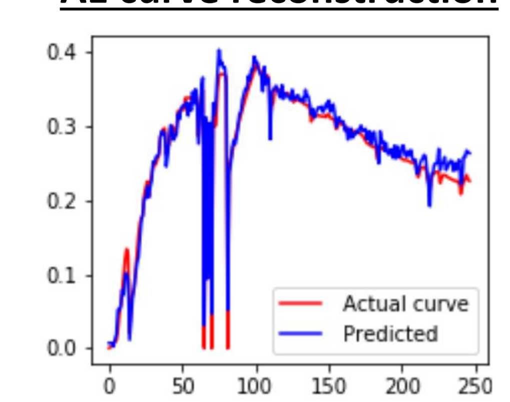
Losses defined separately for forward and inverse maps

$$L_{coupled} = \lambda_1 L_1 + \lambda_2 L_2 + \lambda_{mmd} L_{mmd}$$

Ardizzone, L., Kruse, J., Wirkert, S., Rahner, D., Pellegrini, E. W., Klessen, R. S. & Köthe, U. (2018). Analyzing inverse problems with invertible neural networks. arXiv preprint arXiv:1808.04730.

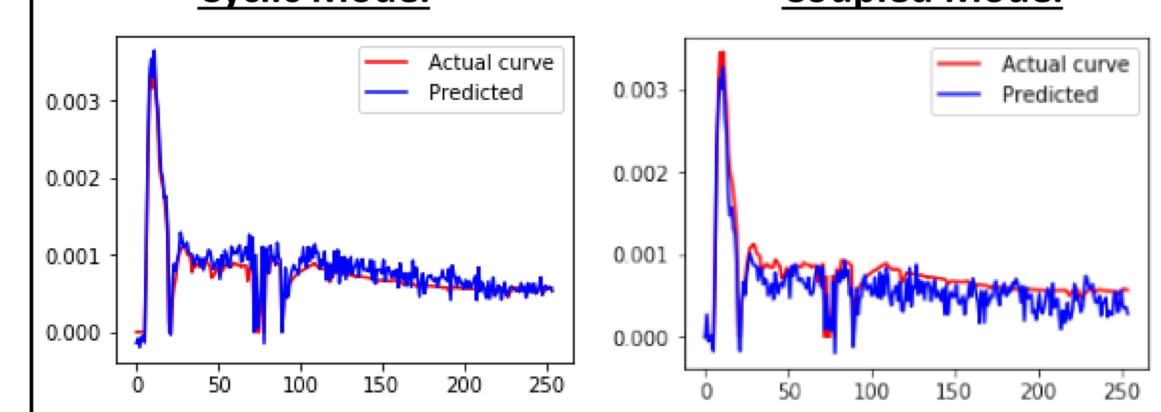
RESULTS

AE curve reconstruction

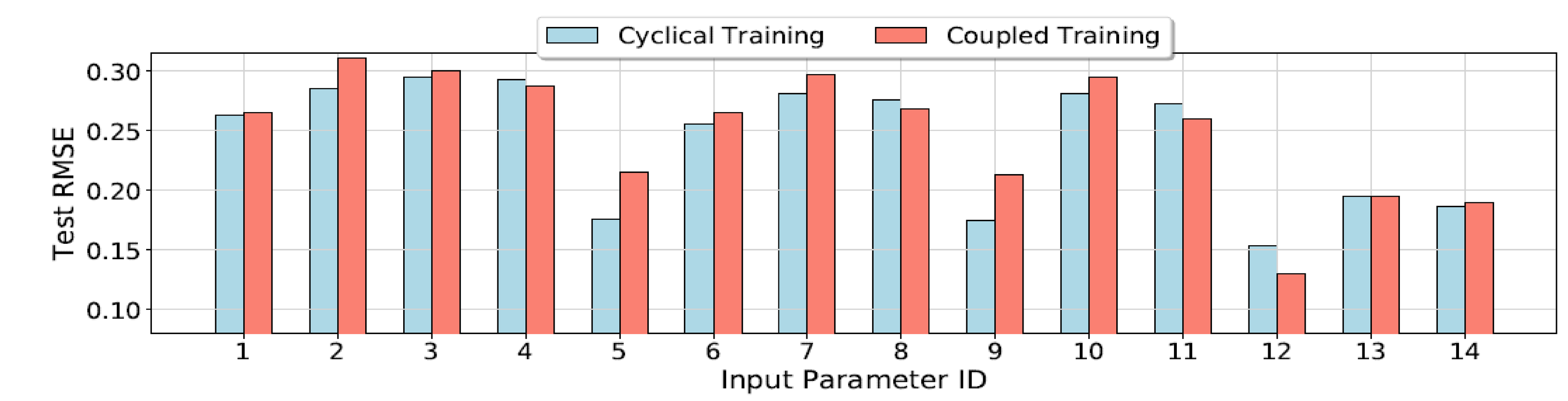


Forward Model Performance

Cyclic Model | **Coupled Model**



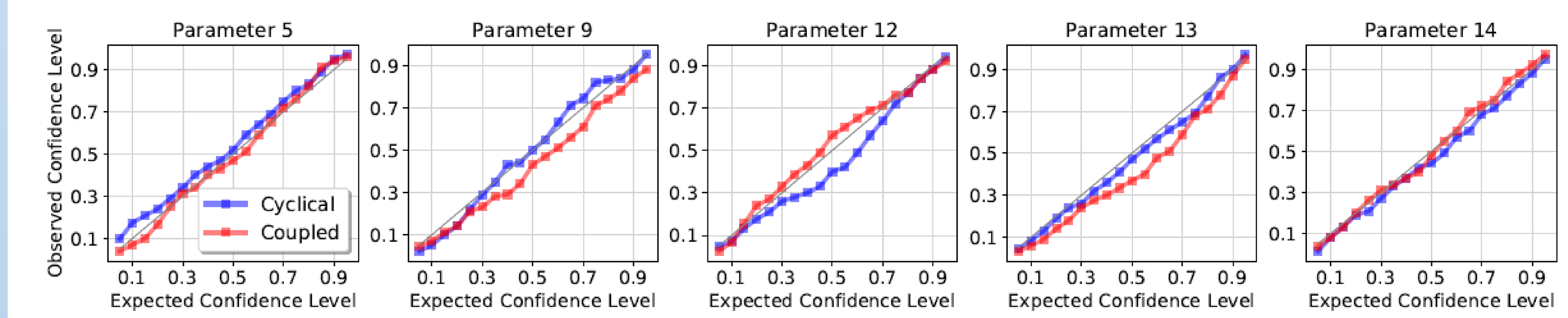
Cyclical vs Coupled – RMSE Metric



Test RMSE of the predictions obtained using our approaches for enforcing self-consistency

Some Observations
- Cyclical training produces lower RMSE.
- Parameter 12 – Low RMSE – ***Critical in curve reconstruction***

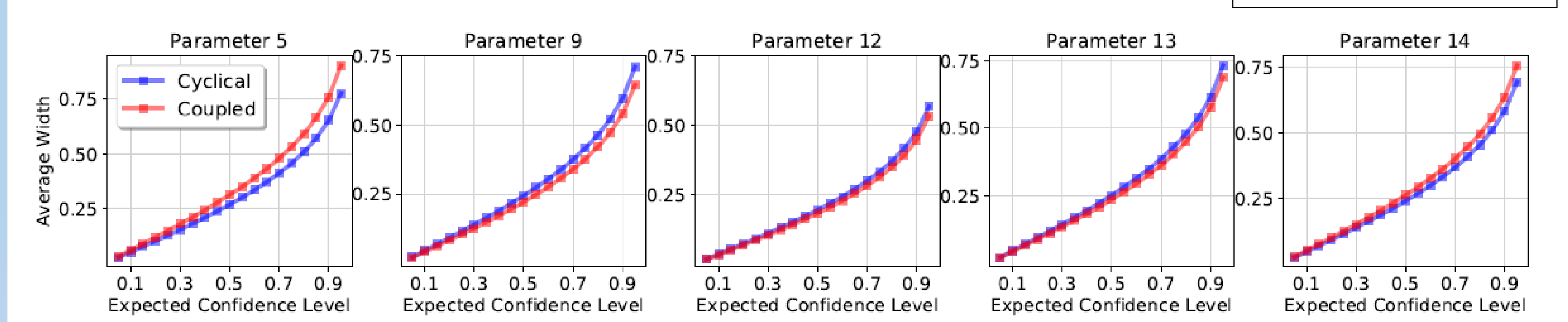
Cyclical vs Coupled – Calibration Curves & Average Width of C.Is



Calibration performance of the prediction intervals for parameters with the lowest RMSE

Calibration Curve: Desired calibration level α vs observed calibration level. For each α, C.I: $[\mu_i - \delta_i, \mu_i + \delta_i]$ can be estimated using ϑ_i as $\delta_i = z_{(1-\alpha)/2}\sigma_i$ where $\sigma_i = \sqrt{\vartheta_i}$

Both cyclical and coupled models produce well calibrated inverses



Average widths of the prediction intervals for parameters with the lowest RMSE

Average Width (AW): $\frac{1}{N}\sum_{i=1}^{N} 2\sigma_i$ *Parameter 12 – Lowest A. W*

Self-consistency is critical to produce accurate and well-calibrated inverse mappings.