IPTC-25237-Abstract

Accelerated History Matching In Carbon Sequestration Reservoirs: A CNN-transformer And Generative ML-based Data Assimilation Framework

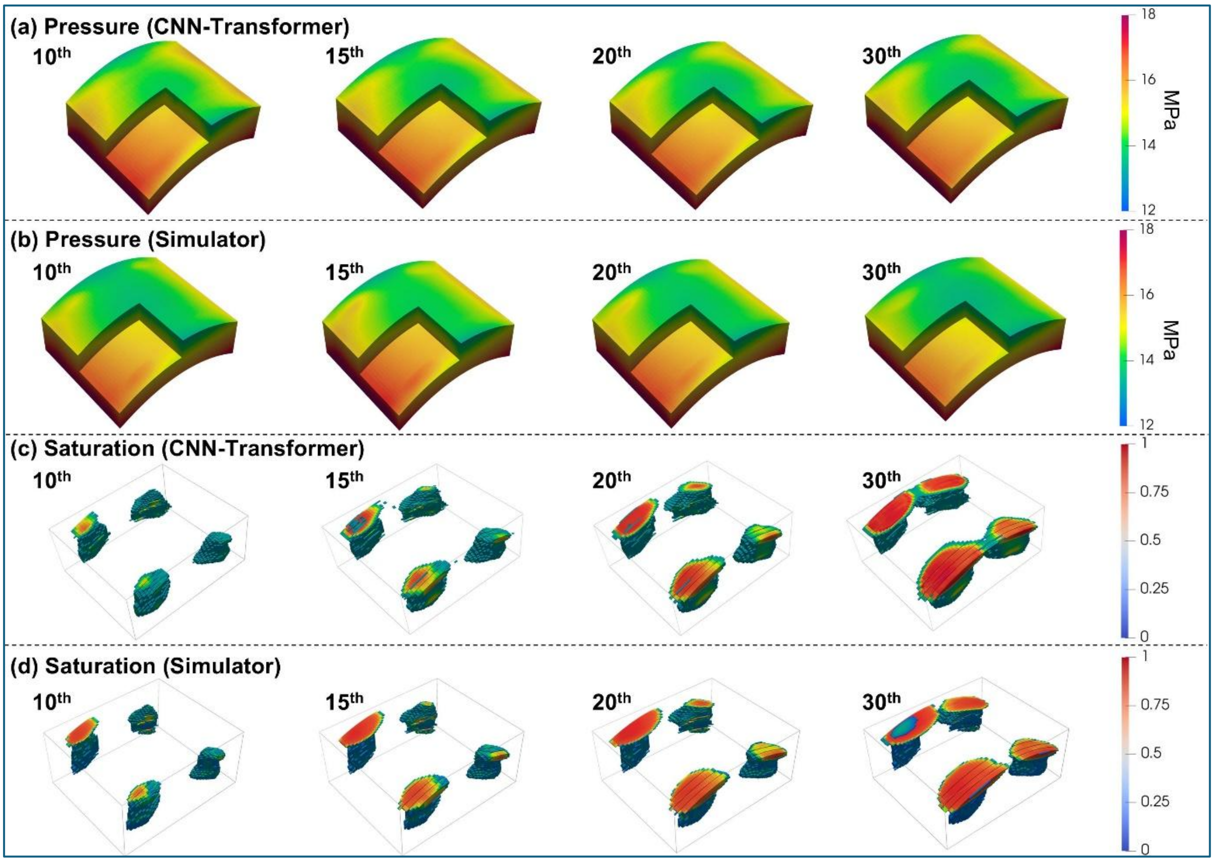
Q. Fu, King Abdullah University Of Science And Technology; M. Abu Alsaud, Saudi Aramco PE&D; X. He, Saudi Aramco PE&D EXPEC ARC; A. Manea, Saudi Aramco PE&D; T. Finkbeiner, H. Hoteit, B. Yan, King Abdullah University of Science & Tech

Objectives/Scope: Geological carbon sequestration (GCS) requires accurate subsurface characterization through history matching, where geological parameters must be adjusted to be consistent with observed field data. Traditional workflows rely on iterative reservoir simulations, which require weeks or months of computational time, severely limiting uncertainty analysis. This work presents a novel framework leveraging CNN-Transformer surrogate models integrated with a generative machine learning-based iterative local ensemble smoother (ILUES) algorithm to enable rapid parameter estimation for GCS reservoir heterogeneity characterization.

Methods, Procedures, Process: This study proposes a data-assimilation inversion framework that integrates a CNN-Transformer surrogate model and a generative machine learning-based iterative local ensemble smoother (ILUES) algorithm to estimate heterogeneous reservoir parameters. In this framework, the CNN-Transformer surrogate model enhances the computational efficiency of forward simulations, while the generative machine learning method transforms high-dimensional heterogeneity fields into low-dimensional latent vectors, thus enabling the ILUES algorithm to indirectly estimate the posterior distribution of high-dimensional heterogeneity fields.

Results, Observations, Conclusions: The results indicate that the surrogate model closely reproduces the behavior of the reference simulator, accurately predicting pressure and saturation responses across various injection scenarios and geological conditions. Meanwhile, given the synthetic observation data, the generative machine learning-based ILUES algorithm combined with the established CNN-Transformer surrogate provides reliable posterior distribution estimates of the model parameters. The uncertainty in simulation results based on the posterior distribution is significantly reduced compared to those based on the prior distribution, and these forecast results closely match the observational data. Moreover, the spatial patterns of the posterior parameter fields closely resemble those of the predesigned true fields.

Novel/Additive Information: The primary innovation integrates CNN-Transformer surrogate models with generative machine learning-based ILUES for GCS reservoir characterization. Preliminary results demonstrate that our CNN-Transformer model accurately reproduces pressure and saturation dynamics across multiple time steps, enabling efficient surrogate-based history matching with rigorous uncertainty


(a) Pressure (CNN-Transformer)
10th
15th
20th
30th
18
16
14
12
MPa
(b) Pressure (Simulator)
10th
15th
20th
30th
18
16
14
12
MPa
(c) Saturation (CNN-Transformer)
10th
15th
20th
30th
1
0.75
0.5
0.25
0
(d) Saturation (Simulator)
10th
15th
20th
30th
1
0.75
0.5
0.25
0