Virtual Sensing for Real-Time Well Monitoring in CCS projects

Introduction

Carbon Capture and Storage (CCS) stands as the primary operational technology capable of achieving emissions reductions in essential industries. To ensure the long-term integrity of geological storage and mitigate the risk of CO_2 leakage, national and international regulations mandate the implementation of comprehensive monitoring plans, see as example European Parliament (2009) and European Commission (2025). Consequently, monitoring presents a significant challenge in CCS projects, as it must deliver the critical data needed for operational management while satisfying stringent regulatory oversight.

In this context, real-time well monitoring relies on continuous bottom-hole gauge measurements of pressure and temperature during CO_2 injection and post-injection. Comparing these measurements with model-based predictions enables the timely detection of operational deviations, see Bilogan et al. (2019), Sahu et al. (2021) and Shchipanov et al. (2023). It can trigger adjustment of operational parameters to prevent and mitigate safety hazards, ensure regulatory compliance, and preserve storage integrity. Virtual Sensors (VS) offer a powerful solution by estimating these critical variables from other available measurements, as stated by Martin et al. (2021). This approach not only enables continuous performance tracking but also enhances operational reliability by monitoring the health of physical sensors. A discrepancy between a sensor's measurement and its corresponding VS estimate can signal sensor malfunction, a valuable capability in the oil and gas industry, particularly for downhole sensors that are inaccessible or difficult to service.

While the application of machine learning (ML) for virtual sensing has been extensively documented, the application of ML for virtual sensing in Petroleum application is predominantly focused on flow-rate estimation in oil production, see as example Franklin at al. (2022) and Yan et al. (2022), leaving its potential to address the unique challenges of CO_2 injection largely untapped. This paper presents a novel framework using ML-based virtual sensors to monitor critical bottomhole parameters in CO_2 injection wells

Objective

This study introduces a novel Deep Neural Network (DNN) framework for the real-time virtual sensing of bottom-hole pressure and temperature in CO_2 injection wells. Current methods face significant trade-offs: empirical correlations struggle with accuracy near complex phase boundaries, while numerical simulations are computationally prohibitive for real-time applications. To overcome these challenges, the proposed data-driven model leverages surface operational data to provide accurate, real-time bottom-hole estimations, offering a superior alternative to traditional correlation-based models.

Method

Compared to the approach presented in Figueroa et al. (2024), the proposed workflow comprises an ensemble of N deep neural networks. As reported in Figure 1, each neural network is trained in a two-stage process to ensure robustness against the noisy data typical of operational environments. The first stage relies on a denoising-autoencoder (DAE) which reconstructs the monitoring data like wellhead pressure and temperature, trained in an unsupervised manner. The motivation of using a DAE is to construct a high-level noise-free latent representation of the input data by the encoder – see Vincent et al. (2008). This is critical to ensure Virtual Sensing application in an operating environment, where sensor data are inevitably associated with a level of noise. Then, in the second step, a fully connected layer is stacked on top of the encoder and trained in a supervised manner to provide estimation of bottomhole pressure and temperature (BHP and BHT). This two-stage training procedure is repeated N times to build an ensemble of deep neural networks for accurate estimation. The testing and training dataset was enriched by integrating high-frequency field data with data from dynamic multiphase flow simulations. This hybrid approach provided a more comprehensive representation of the relationship between wellhead and bottomhole parameters.

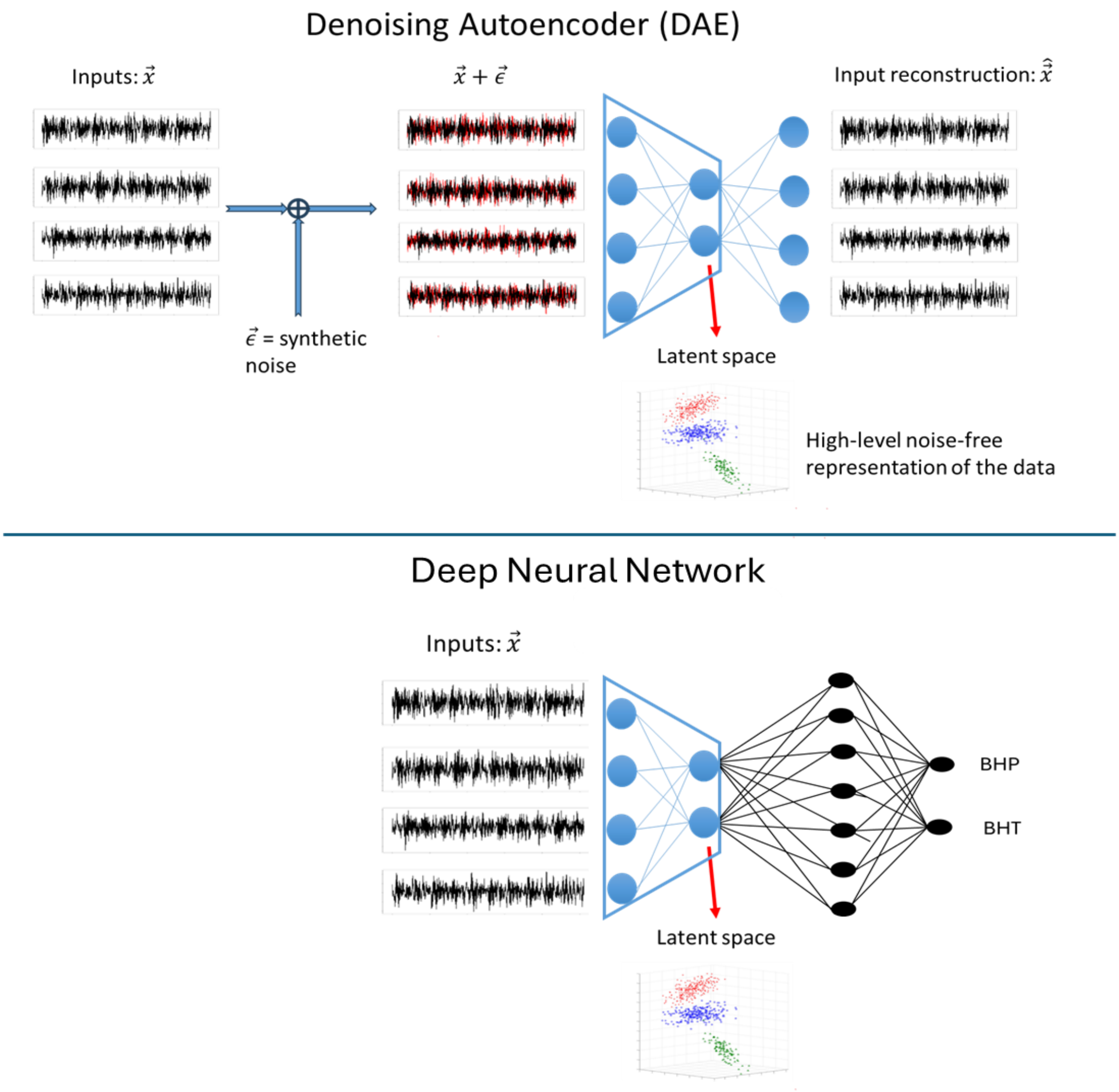

Figure 1 *Schematic of the n-th deep neural network, illustrating the two-stage training process. An unsupervised denoising autoencoder (DAE) reconstructs the input data to learn a noise-free latent representation, upon which a supervised fully connected layer is trained to predict BHP and BHT*

Example

The case study focuses on an offshore CO_2 injection well in the Adriatic Sea, injecting into a depleted sandstone reservoir. A major strength of this study is the availability of a complete, high-frequency dataset spanning a full year of operations, which inherently accounts for seasonal environmental effects. The wellbore instrumentation included discrete pressure and temperature gauges at key points, complemented by Distributed Temperature Sensing (DTS) for continuous thermal profiling.

The analysis was performed focusing on the periods where the well was in stable condition, although different strategies were tested to extend the application also on transient conditions like a restart after a well shut-in or a ramp-up of injection rate. Specifically, it was observed that including as input measurements intermediate temperatures acquired from the DTS improved the performance of the VS on transients, reducing the overall prediction error.

By leveraging this rich field data alongside dynamic multiphase flow simulations for training and validation, the Virtual Sensor achieved high levels of accuracy. Table 1 reports the performance of the proposed method in terms of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) over the test set. The variability of the results is obtained from a cross-validation procedure, where a different

portion of training data is used across folds. Note that the test set focuses on the last three months of production, including only data not used in the training process of the ensemble of deep neural networks. To quantify the value of the downhole thermal data, the performance of the proposed method (VS-A) was compared against a second model (VS-B). VS-B utilizes the same architecture and training data but excludes the DTS measurements as an input. As shown in Table 1, the inclusion of DTS data measurably reduces prediction error and variability, confirming the superior accuracy and robustness of the VS-A model for real-time applications in CCS projects.
Figure 2 shows the measured and predicted values of BHP and BHT over a three month period. It can be observed that the proposed VS-A is more accurate than VS-B over the whole test set. Specifically, the value of the DTS data is most pronounced during transient conditions. In these periods, VS-A demonstrated a 39% reduction in MAE for BHP (from 1.12 to 0.68 bar) and a 42% reduction for BHT (from 0.52 to 0.30 °C) compared to the surface-data-only model (VS-B).

	VS-A (with DTS)		VS-B (surface only)	
Metrics	BHP (bara)	BHT (°C)	BHP (bara)	BHT (°C)
RMSE	**0.92 ± 0.02**	**0.49 ± 0.02**	1.30 ± 0.15	0.68 ± 0.06
MAE	**0.65 ± 0.02**	**0.32 ± 0.02**	1.06 ± 0.13	0.50 ± 0.06

Table 1: *Comparison of VS-A and VS-B performance on test data.*

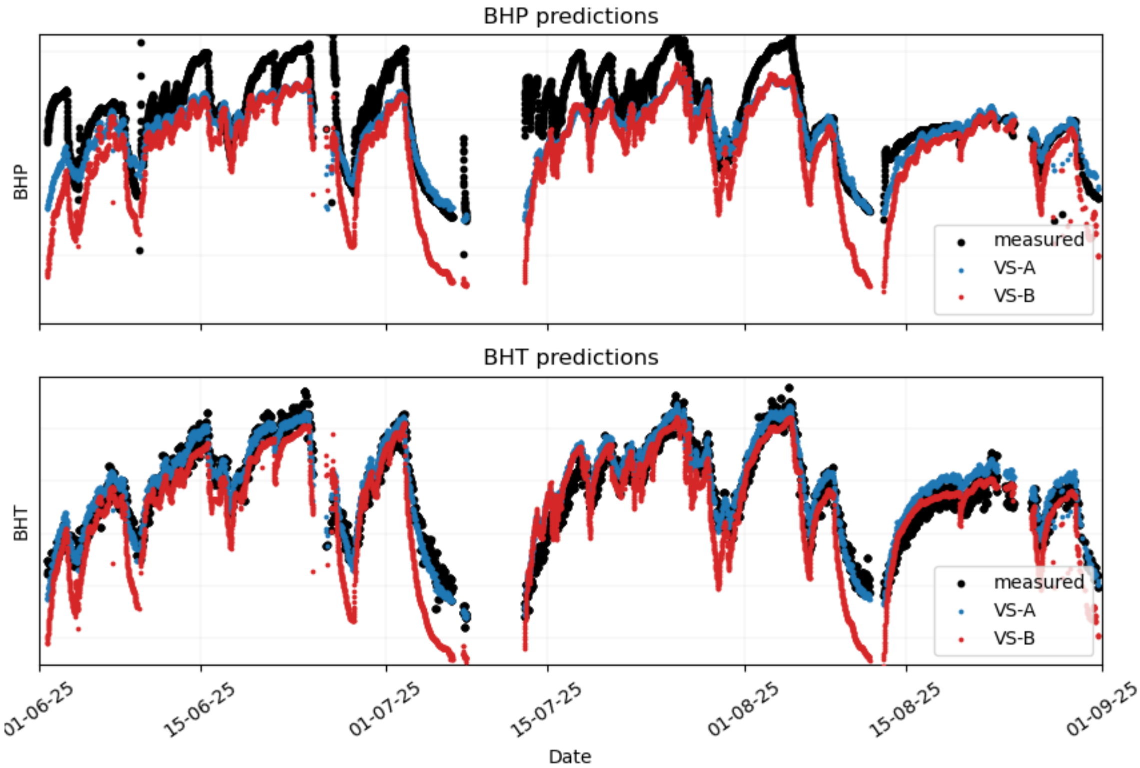

Figure 2*: measured and predicted BHP and BHT over the test set. Note that the numerical values on the y-axis have been omitted for confidentiality reasons. Y axis spans a range of 8 bar for the top graph and 6 °C for the bottom one.*

Conclusions

A robust Virtual Sensing workflow was developed to accurately estimate Bottom Hole Pressure and Temperature during a year-long test of CO_2 injection in a depleted reservoir. This capability is critical for maintaining storage integrity, as it ensures uninterrupted monitoring even if physical downhole gauges fail. The tool's performance was verified through an extensive testing campaign spanning multiple seasons and operating regimes. However, some challenges remain, such as the necessity of detecting the occurrence of concept drifts -the change over time in the statistical relationship between surface measurements and bottom-hole targets, as stated by Widmer and Kubat (1996)- and of developing adaptive solutions to maintain model performance. In CO_2 injection wells, this relationship can shift due to evolving operating regimes (e.g. seasonality), changes in the fluid properties, sensor degradation, and physical degradation of the well that alters hydraulics and heat transfer.

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