AI-Driven Reduced-Order Modeling for Fire Simulation in a Passenger Train Compartment

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Motivation & Background

Fire spread modeling is essential in industries for deriving a design fire, which is strongly influenced by the choice of materials. However, full-order models (FOMs) based on Computational Fluid Dynamics (CFD), such as the Fire Dynamics Simulator (FDS), are computationally demanding and require long simulation times. This makes it difficult to efficiently assess different material sets in engineering design or safety evaluation processes.

Reduced-order models (ROMs) enable fast fire dynamics predictions with sufficient accuracy for hazard assessment. In this study, ROMs are trained on FDS data from a passenger train compartment, using two approaches: Proper Orthogonal Decomposition with Interpolation (PODI) and autoencoder-based neural networks (AE-ANN). Both allow efficient evaluation of material properties and their impact on fire development, offering a practical alternative to full CFD simulations

Surrogate Model – ROM

Two surrogate strategies are applied: PODI and AE+ANN.

Snapshot Database: Simulation outputs from selected slices are collected as snapshots and arranged into a large matrix. This snapshot matrix serves as the basis for both reduction and approximation.

PODI: Fields $\theta(x,\pi)$ are approximated as linear combinations of modes $\phi_i(x)$ with coefficients $\alpha_i(\pi)$:

$$\theta(x,\pi) \approx \theta_r(x,\pi) = \sum_{i=1}^{N_\theta} \alpha_i(\pi)\phi_i(x).$$

Modes are obtained by SVD of the snapshot matrix; coefficients are interpolated from training parameters using RBFs, Radius Neighbors, Neighbors, k-Nearest Neighbors, or Gaussian Process Regression.
AE+ANN: An autoencoder (AE) is first trained on the snapshot matrix to compress fields into a latent representation $z = f_{\text{enc}}(\theta)$. Subsequently, a separate neural network (ANN) is trained to predict this latent representation directly from the parameter set π:

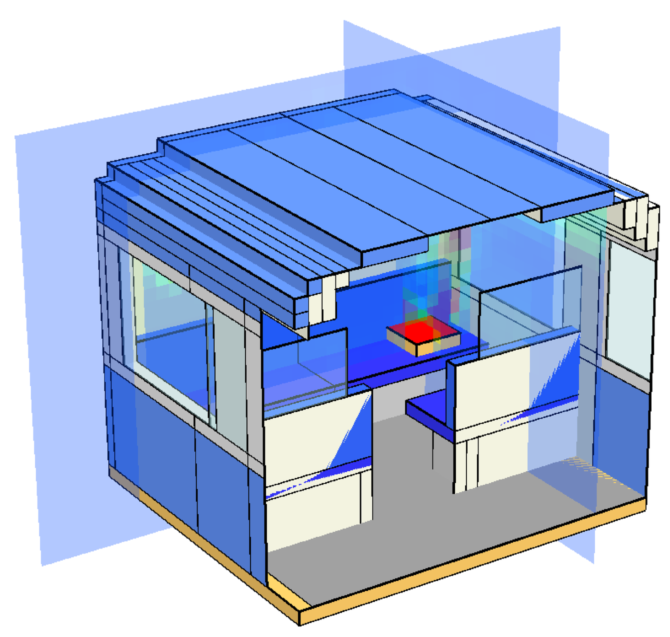
$$\hat{z} = g_{\text{ANN}}(\pi).$$

The corresponding decoder network, trained to reconstruct fields from the latent space, then maps $\hat{z}$ back to the full field:

$$\hat{\theta}(x,\pi) = f^*_{\text{dec}}(\hat{z}).$$

This pipeline combines dimensionality reduction (AE) with parameter-to-field approximation (ANN).

FDS Simulation Setup – Full-Order Model (FOM)



- **Geometry:** Passenger train compartment with two distinct slice positions.
- **Slices:** Slice–a: vertical plane at $x = 0.5$ Slice–b: horizontal plane at $y = 1.05$

- **Fields:** Temperature, HRRPUV (heat release rate per unit volume), Absorption Coefficient, and HRR-time-curve.
- **Parameters:** Ambient temperature: 15–30 °C, HRR: 50–200 kW, Radiative fraction: 0.15–0.40

Prediction – Temperature and Absorption Coefficient Slice

The figures show field comparisons on slice $x = 0.5$, where ROM predictions are compared with the FOM reference, using 5000 training data: Fig.1 (Temperature) and Fig.2 (Absorption Coefficient).

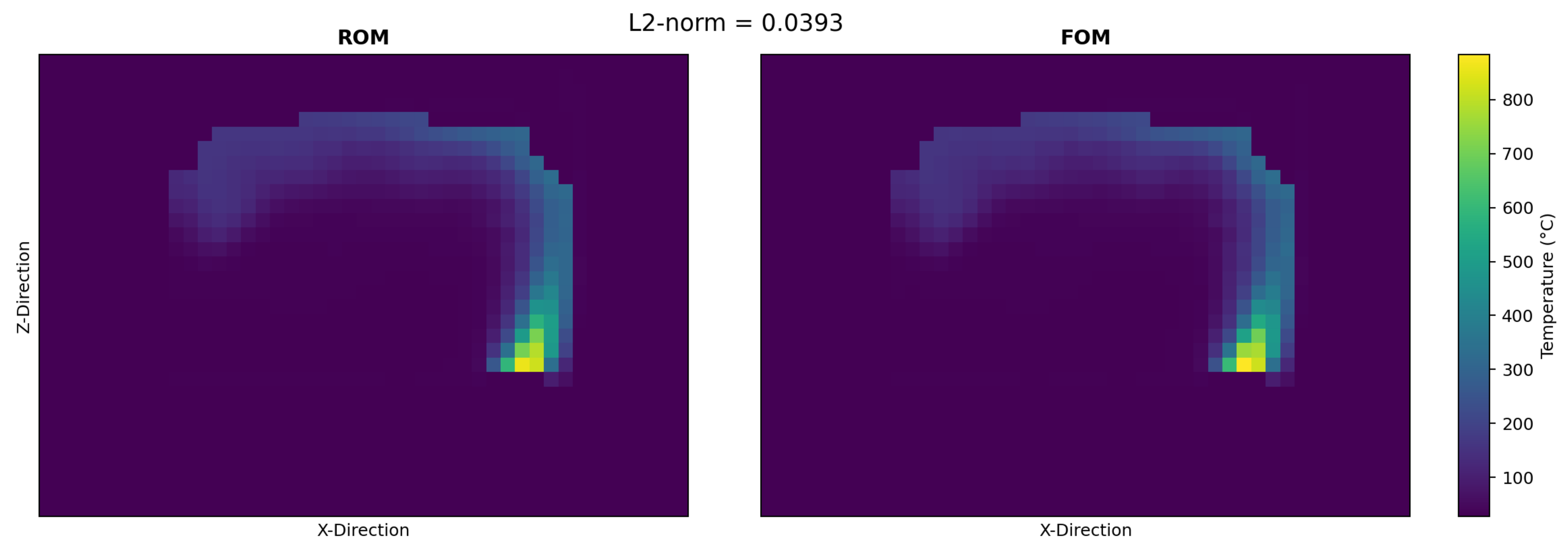


Figure 1:ROM vs FOM on slice $x = 0.5$ — Mean Temperature.

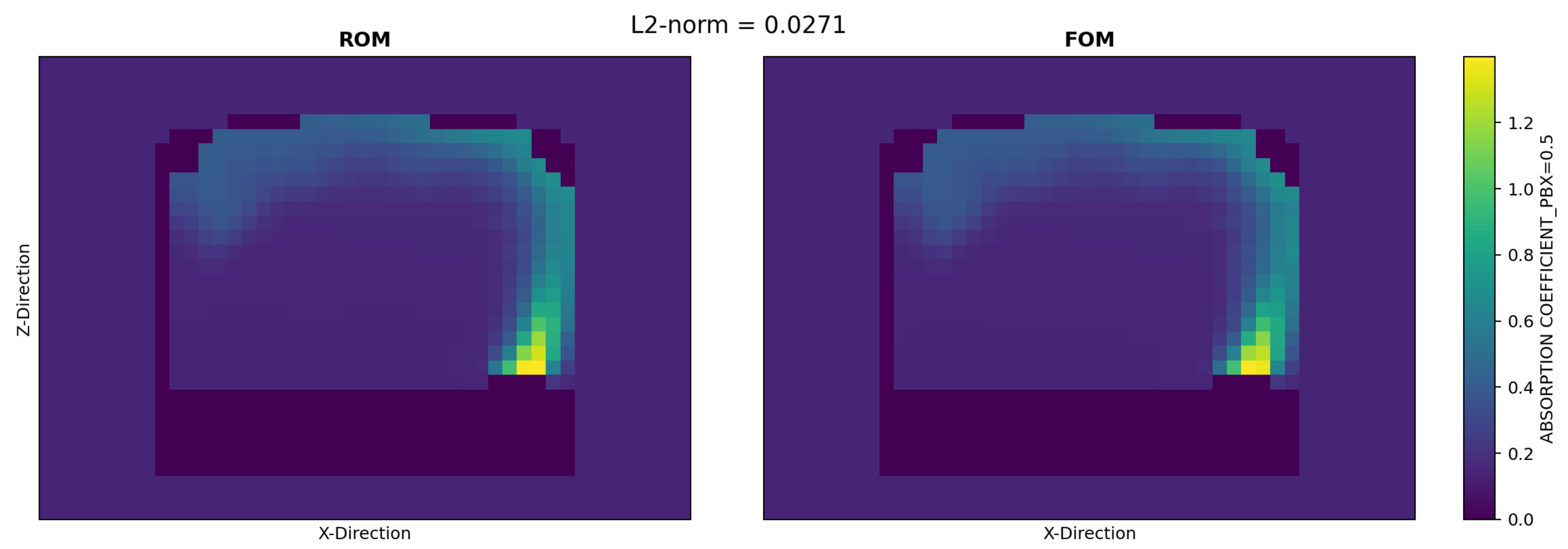
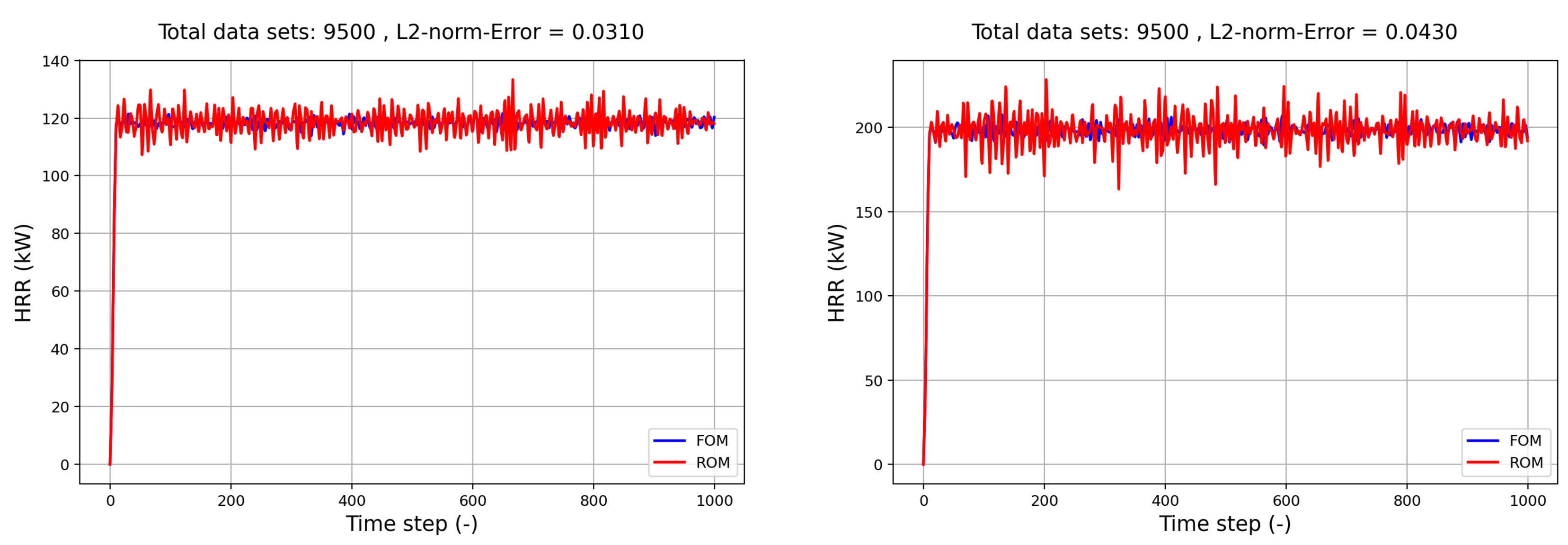
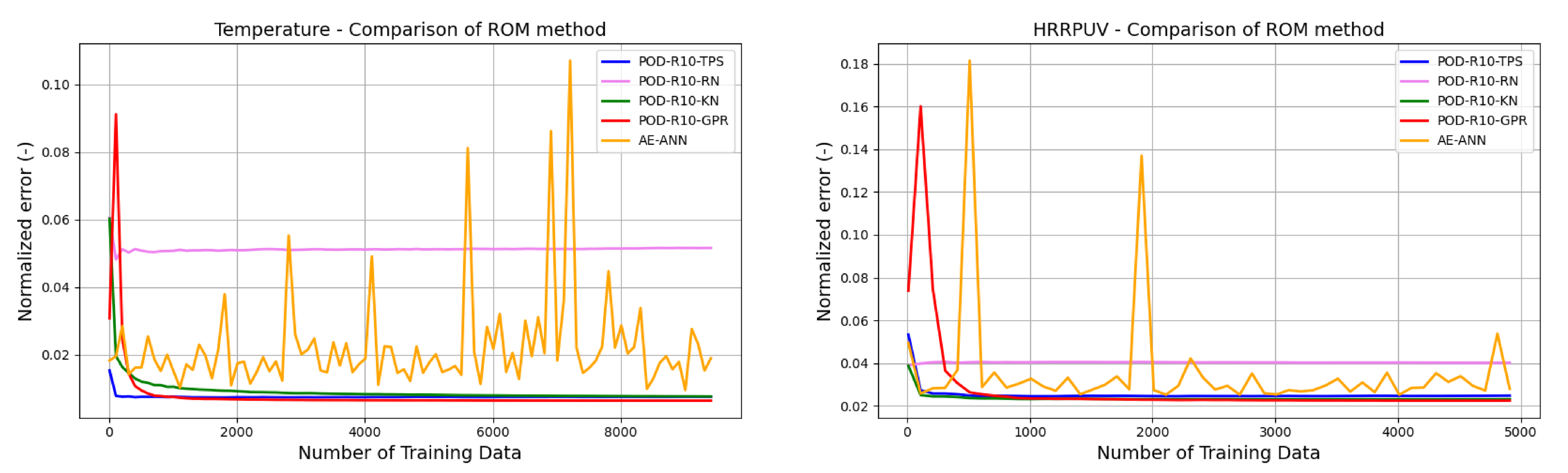


Figure 2:ROM vs FOM on slice $x = 0.5$ — Mean Absorption Coefficient.

Prediction - Time Curve



Convergence – Temperature & HRRPUV



- Both PODI and AE+ANN use log normalization.
- PODI: 10 modes with RBF, kNN, and GPR interpolation → stabilizes after ∼2000 training samples.
- AE+ANN: architectures AE([436,218,109,50],[50,109,218]) and ANN([6,25,50]) with SELU activation; error decreases with dataset size but shows a mild saw-tooth pattern.

Future Work

Future work will expand the model's applicability to flame and fire spread simulation, further broadening the practical scope and impact of this data-driven approach.

References

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[2] A. Hajisharifi, F. Romano, M. Girfoglio, A. Beccari, D. Bonanni, and G. Rozza. ``A Non-Intrusive Data-Driven Reduced Order Model for Parametrized CFD-DEM Simulations''. In: *Journal of Computational Physics* 482 (2023), p. 112355. DOI: 10.1016/j.jcp.2023.112355.

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