Fire Spread Modeling Using Reduced Order Model

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Fire Spread Modeling Using ROM

Fire spread modeling using a Reduced Order Model (**ROM**) is essential due to the computational expense of Full Order Models (**FOM**). **ROM** offers a much faster alternative, enhancing simulation efficiency.

This poster presents an ongoing study to enhance fire spread modeling. We utilize a **ROM** augmented with synthetic data from Fire Dynamics Simulator (**FDS**) to develop a versatile simulation framework for swift fire dynamics analysis.

By leveraging **FDS**-generated synthetic data, we capture diverse fire behaviors, including varying heat release rates, forming the basis for constructing the **ROM**.

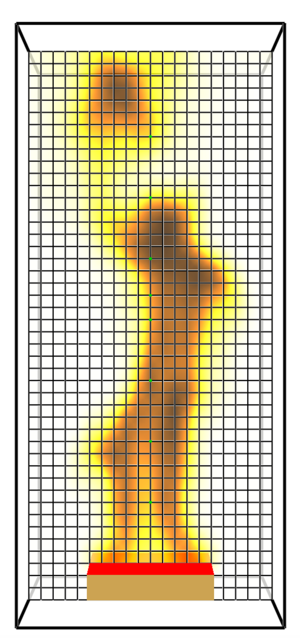
The **ROM** not only offers efficient fire spread simulation, reducing computational time, but also ensures prediction accuracy.

We further explore the integration of Proper Orthogonal Decomposition (**POD**) with Radial Basis Functions (**RBF**), adept at extracting dominant patterns, enhancing the representation and simulation of fire dynamics.

This combination significantly improves computational efficiency, enabling rapid simulations of fire spreading model.

Our proposed framework allows for efficient fire dynamics simulations with customizable boundary conditions, covering variations in materials, ventilation, and heat release rates. The synthetic data gathered forms the foundation for constructing the **ROM**.[1]

FDS Burner for Synthesis Data



Burner Temperature Slice

- **Geometry Dimensions:** 0.20m x 0.20m x 0.45m (L x W x H)
- **Fuel Types:** Methane-Propane
- **MLRPUA Range:** 0.001-0.05 (kg/m²)
- **Ambient Temperature Range:** 21-298 (C°)
- **Radiative Fraction Range:** 0.05-0.5

Data-Driven Approach with ROM

In our research, we collect snapshots of fire simulations from the central slice of FDS, storing them in a matrix $\mathbf{X}$. Each row of this matrix represents an individual snapshot. We then employ Proper Orthogonal Decomposition (POD) to identify dominant spatial modes:

$$\mathbf{X} \approx \sum_{i=1}^{r} \sigma_i \mathbf{u}_i^T \mathbf{v}_i$$

Next, we use Radial Basis Functions (RBF) to interpolate fire spread dynamics under specific conditions. This interpolation function, denoted as $f(\mathbf{x})$, is a weighted sum of radial basis functions:

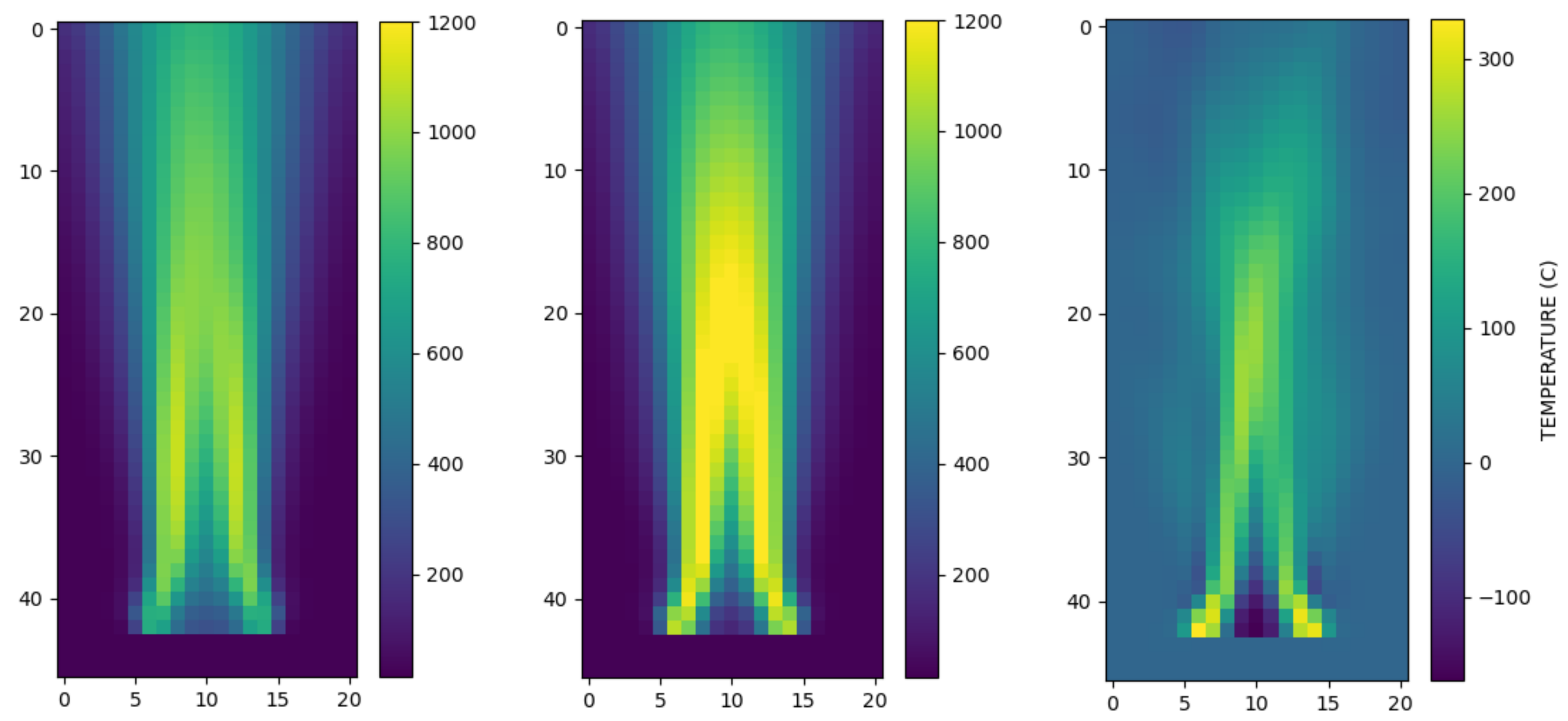
$$f(\mathbf{x}) = \sum_{i=1}^{n} \phi(\|\mathbf{x} - \mathbf{x}_i\|) w_i$$

To validate our approach, we employ K-Fold Cross-Validation. This method partitions $\mathbf{X}$ into 'k' subsets, using one for validation while the rest are used for training in each iteration. The final metric M is the average of 'k' individual metrics:

$$M = \frac{1}{k} \sum_{i=1}^{k} M_i$$

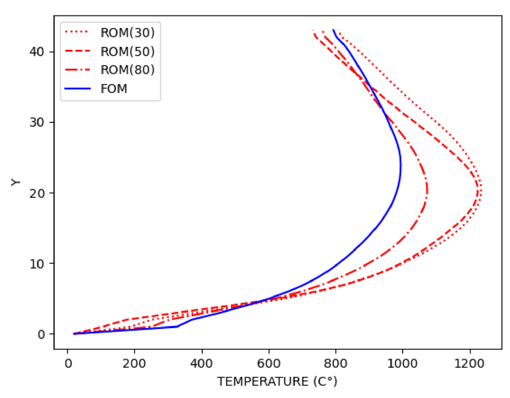
This systematic validation process ensures comprehensive evaluation of our model across non-overlapping data subsets.

Temperature Comparison FOM ROM



A comparison in the Temperature field is presented: on the left, FOM is ; in the middle, ROM is shown; and on the right, the visualization of the error between ROM and FOM is displayed.

Temperature Profile Compression

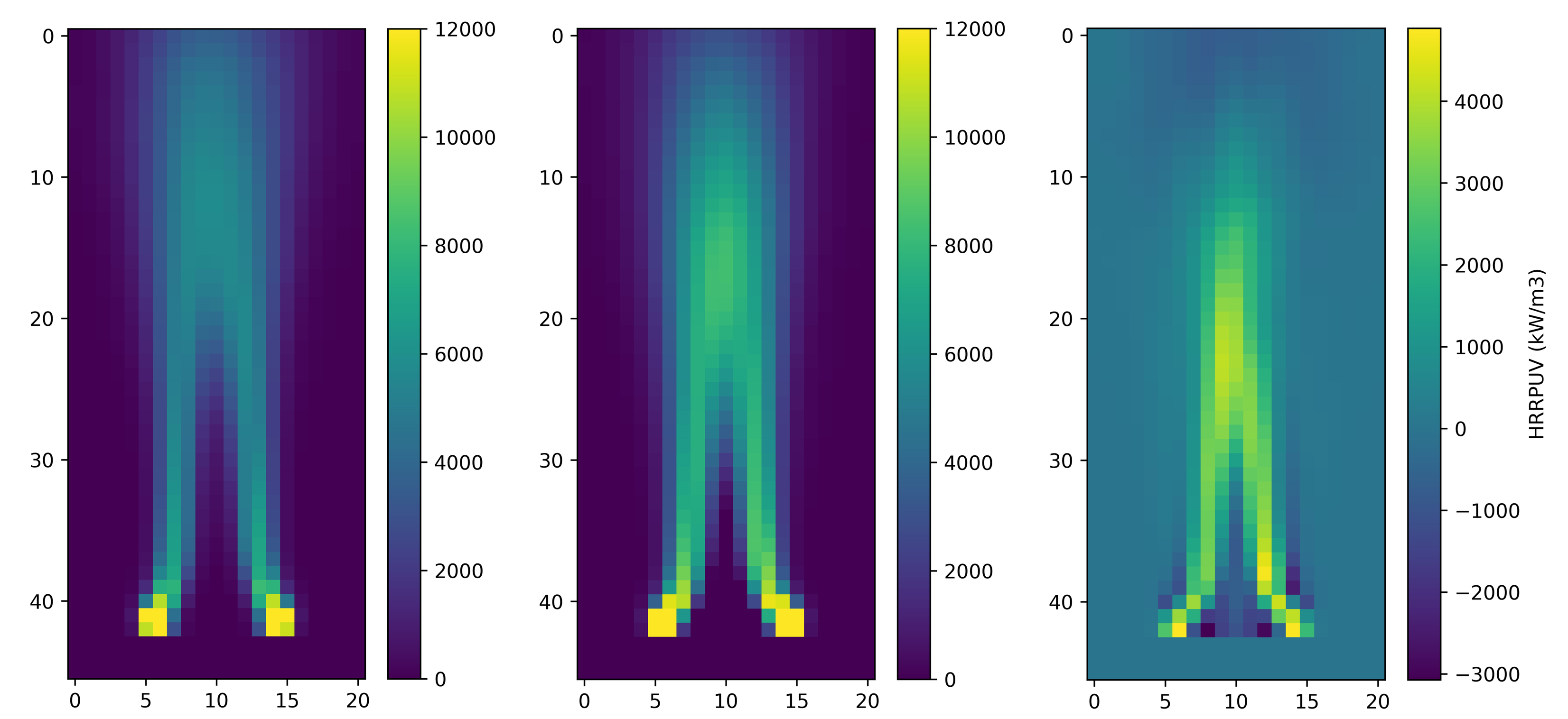


Temperature Profile

Comparison between FOM and ROM

- Analyze temperature profile comparisons between the Full Order Model (FOM) and Reduced Order Model (ROM).
- Increase the size of the training dataset to evaluate prediction accuracy.
- Observe improvements in prediction accuracy as the training dataset size increases (specifically, considering training datasets of 30, 50, and 80).

HRRPUV Comparison FOM ROM



In the figure below, a comparison in the HRRPUV field is presented: on the left, FOM is depicted; in the middle, ROM is shown; and on the right, the visualization of the error between ROM and FOM is displayed.

Tools

- Utilizing advanced computational tools, including the FireANALYSIS framework, for in-depth fire dynamics analysis.
- Enhancing Fire Dynamics Analysis with Reduced Order Modeling using the EZyRB Package.[2]
- Employing Python, a versatile and widely-used programming language, to facilitate data processing, analysis, and model implementation.

Future work

- Expanding parameters for broader boundary condition anticipation and enhancing accuracy with an extended training set.
- Investigating and accounting for transient conditions within the study.

References

[1] S. L. Brunton and J. N. Kutz. *Data-driven science and engineering: Machine learning, dynamical systems, and control.* Cambridge University Press, 2019.

[2] N. Demo, M. Tezzele, and G. Rozza. ``EZyRB: Easy Reduced Basis method''. In: *The Journal of Open Source Software* 3.24 (2018), p. 661. DOI: https://doi.org/10.21105/joss.00661.

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