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Transformer-Based Deep-Learning for Turbulence
Modeling and Reactor System Simulations

Transformer-Based Deep-Learning for Turbulence Modeling and Reactor System Simulations

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Introduction

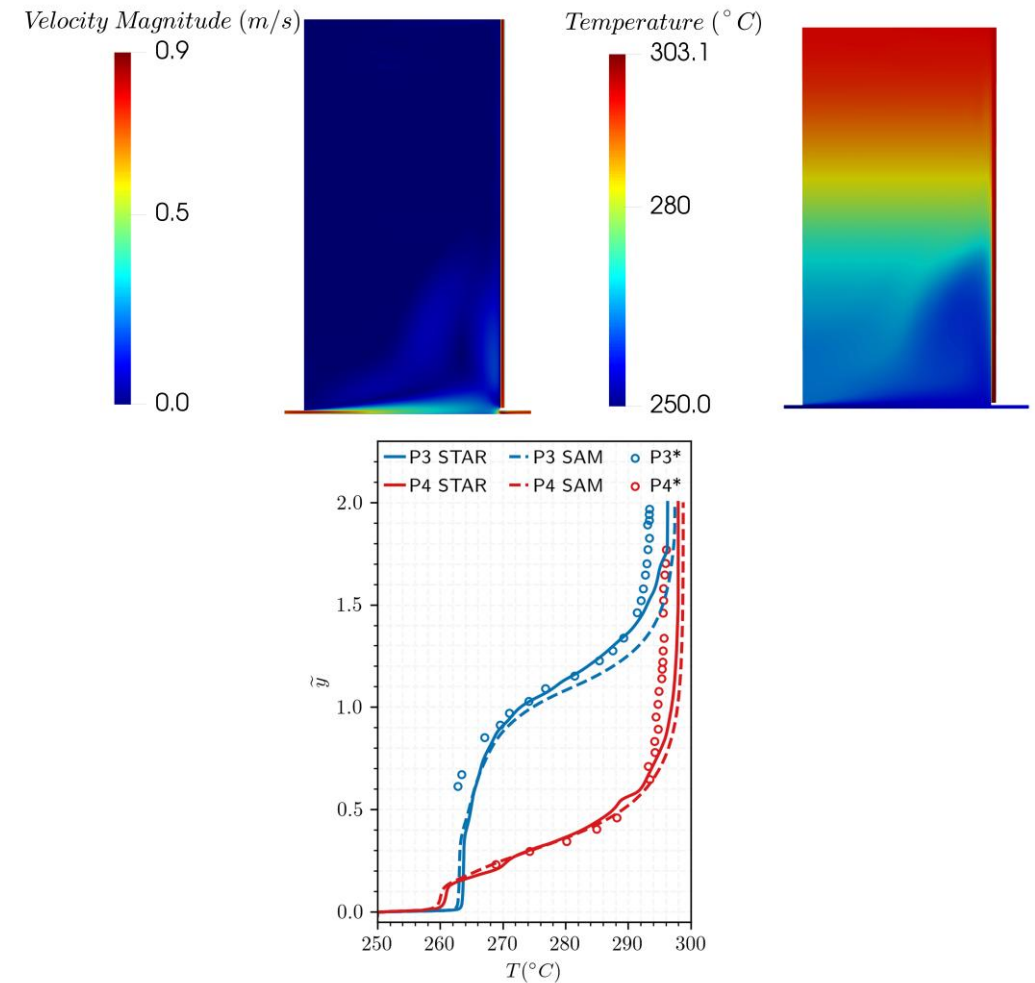
- We present a deep-learning approach to coarse-mesh turbulence modelling based on transformer architectures and the self-attention mechanism.
- The model targets coarse-mesh simulations of nuclear reactors, with the goal of improving the representation of turbulent effects in coupled 1D-3D simulation.
- The model is developed for implementation in SAM, the system analysis code for advanced non-LWR, to augment coarse-mesh flow simulations by providing data-driven turbulence closure information, in the application of thermal mixing and stratification modeling in large enclosures.



Turbulence modelling

Different approaches are available for turbulence modelling in coarse-mesh solvers:

- **RANS:** accurate but computationally expensive.
- **Zero-equations models (e.g. Prandtl mixing length)** computationally efficient but inaccurate.



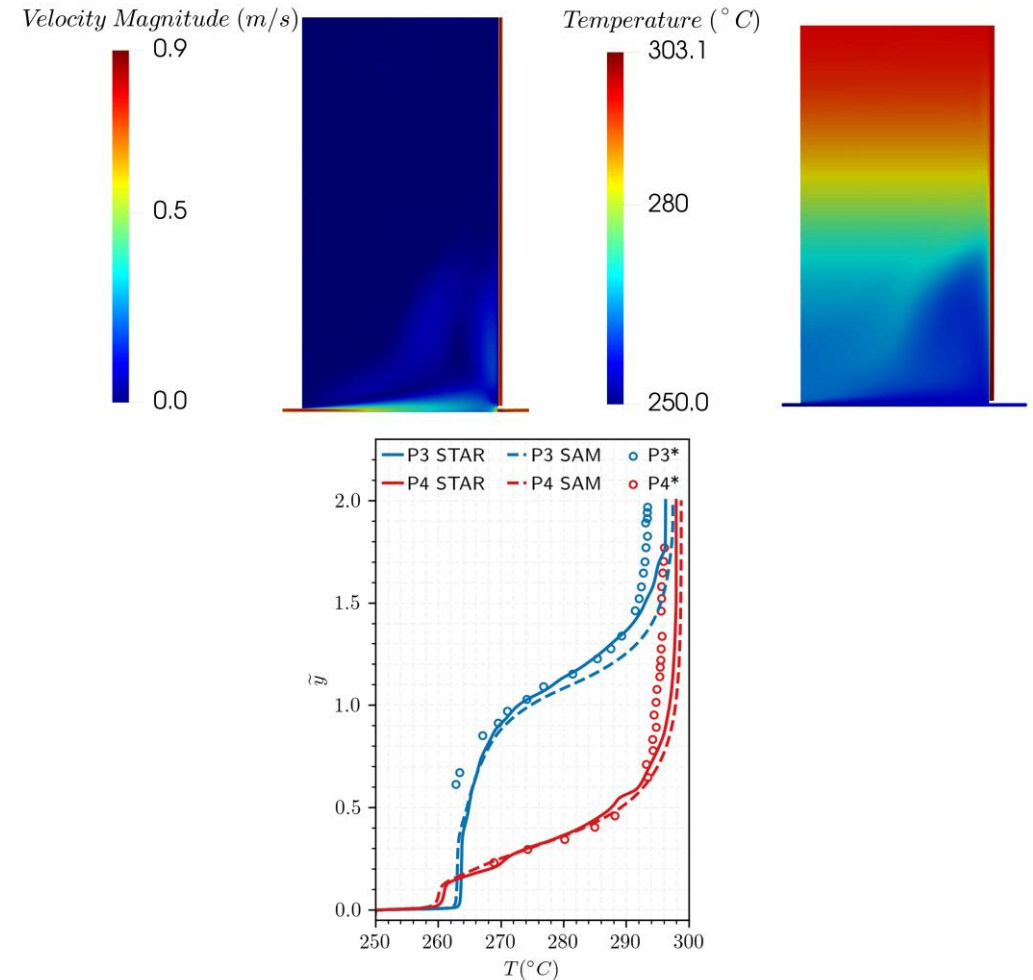
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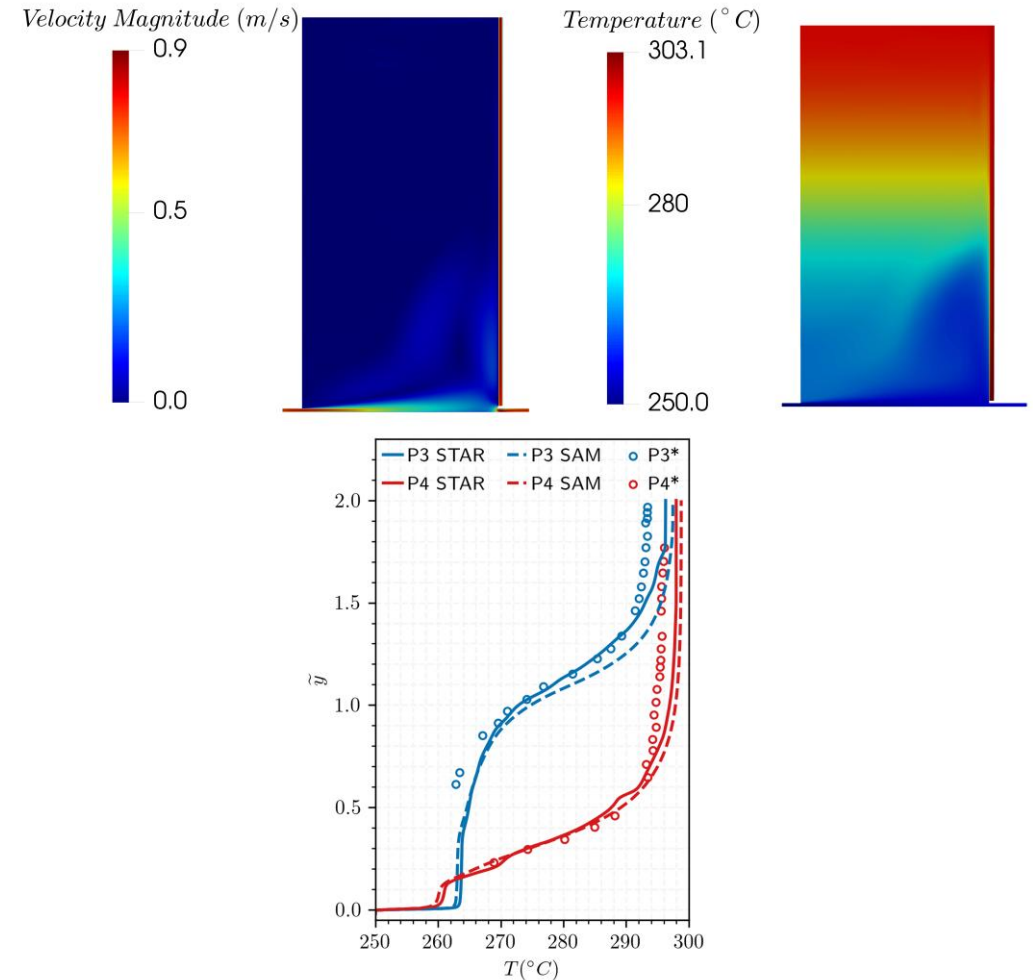
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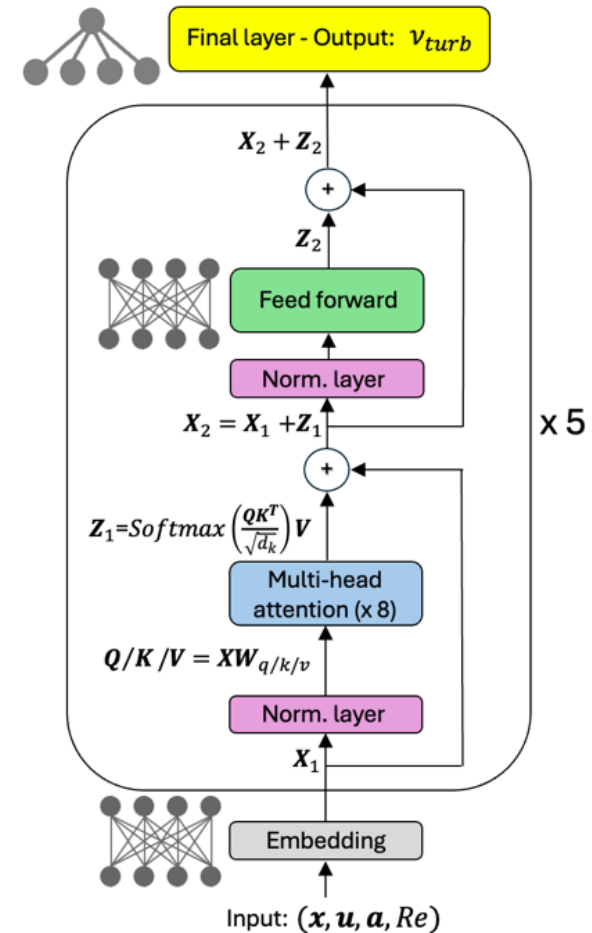
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We adopted transformers to capture both short and long-range spatial effects on turbulence (coherent eddies and recirculation).



Training and testing

In this work, we consider a tank geometry representative of the hot-pool region of liquid-metal fast reactors, where multidimensional coarse-mesh modeling is required.

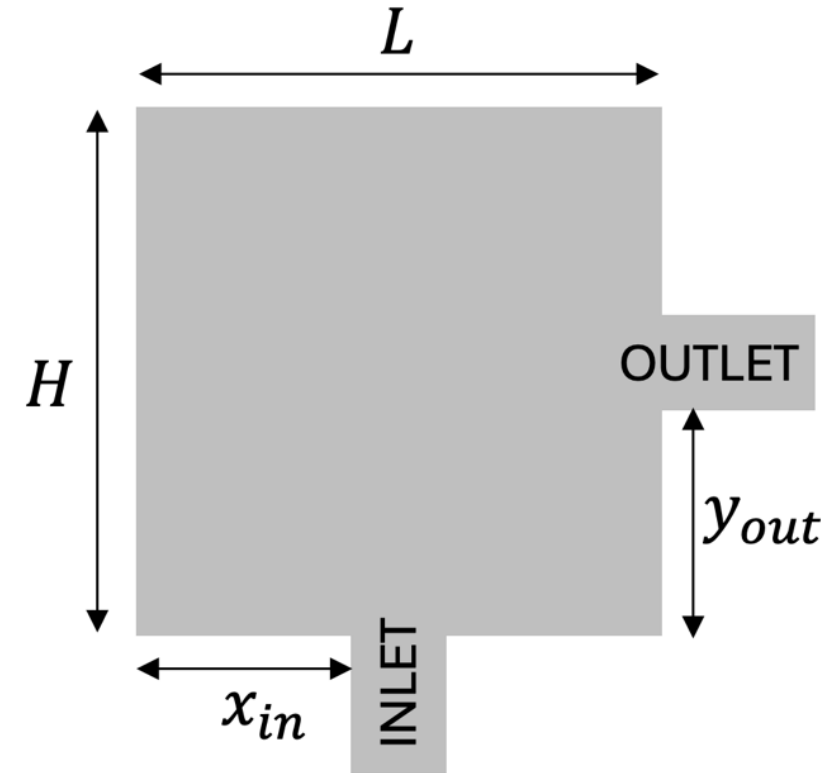
Training data were generated using CFD simulations with the $k-\omega$ SST turbulence model.

The dataset includes:

- **Different geometries:** $H/L = 1.0$ and 1.6 , with multiple inlet/outlet locations
- **Different inlet velocities:** $0-10$ m/s ($Re \approx 0-10^8$)
- **Transient data:** step-wise inlet-velocity reductions, representative of a loss-of-flow accident

After training, the model is evaluated on unseen configurations to assess generalization:

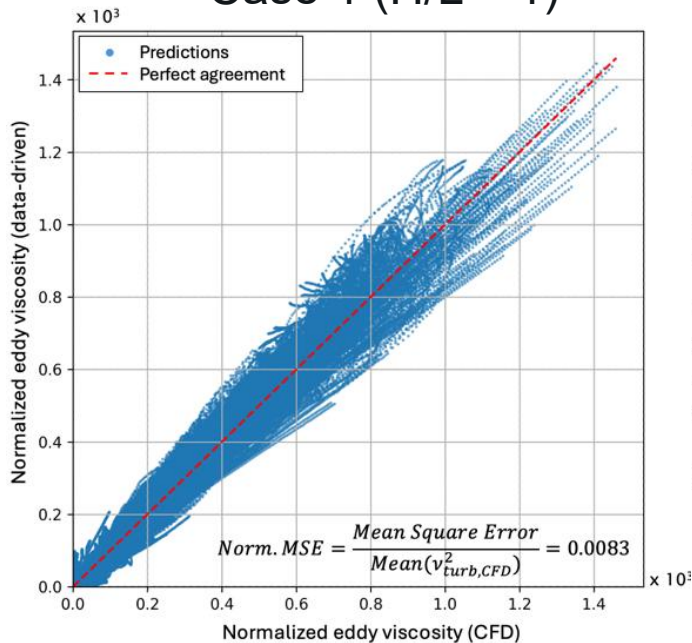
- **$H/L = 1.0$:** new inlet/outlet locations (boundary-placement sensitivity)
- **$H/L = 1.3$:** interpolation within the training range
- **$H/L = 1.9$:** extrapolation outside the training distribution



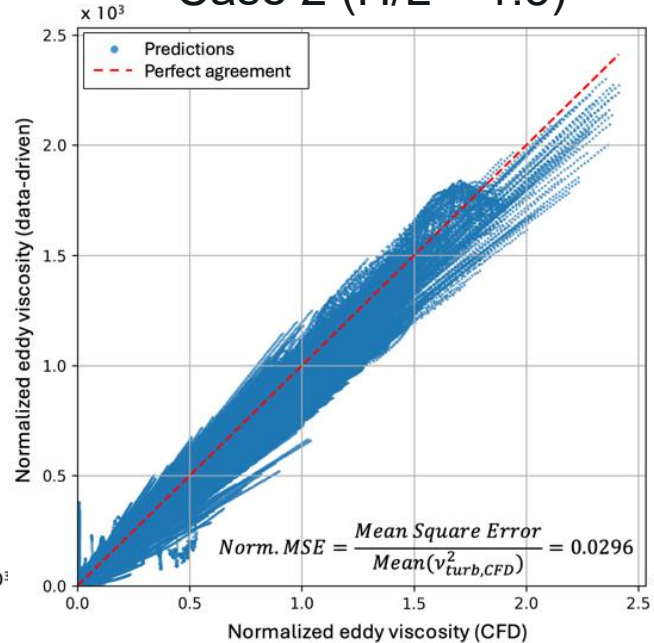
Results

Model vs. CFD eddy viscosity: each blue point is a prediction for a given location, time instant and test case. **Good accuracy with CFD is observed.**

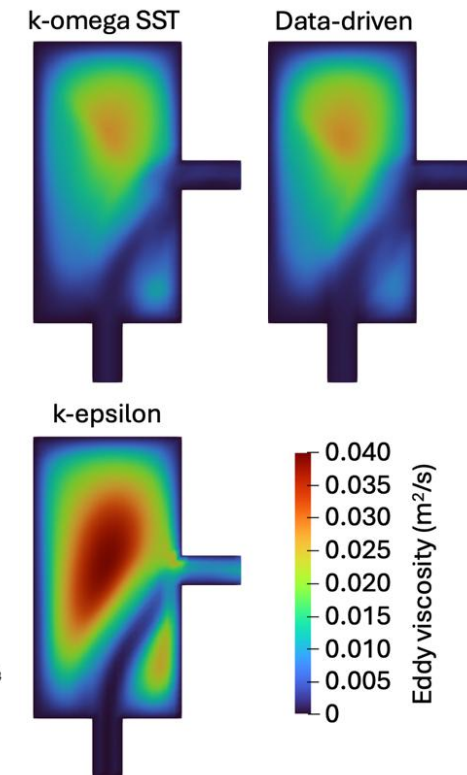
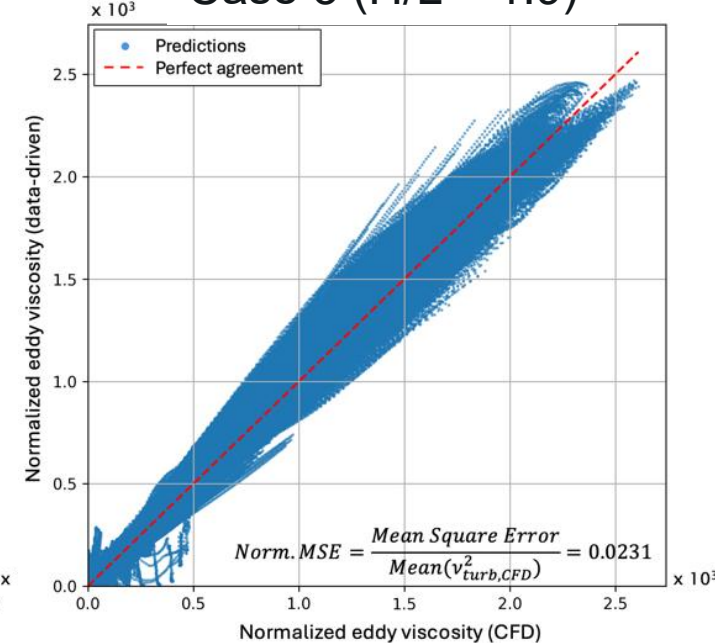
Case 1 (H/L = 1)



Case 2 (H/L = 1.3)



Case 3 (H/L = 1.9)



Conclusions

- We developed a self-attention-based deep-learning model for turbulence prediction in coarse-mesh fluid-dynamics simulations.
- Achieves high accuracy across unseen geometries, including out-of-training cases.
- Attention patterns capture physically meaningful flow features and long-range dependencies.

Next steps:

- Application in full system transient simulation.
- Application of the same approach for digital twin applications.





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