

TOWARDS DATA-DRIVEN BOILING MODELS USING A MIXTURE-OF-EXPERTS APPROACH

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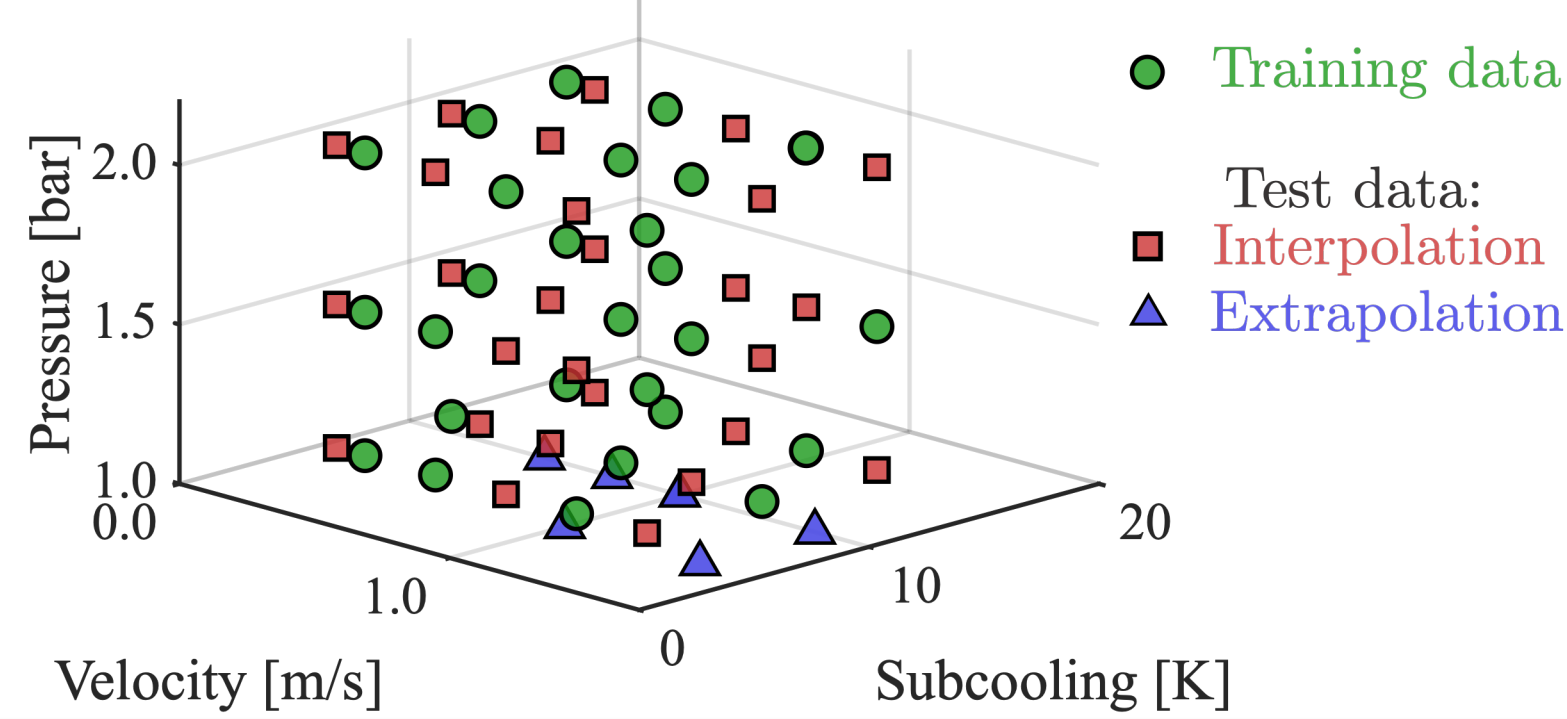
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1. MOTIVATION

- ❖ Boiling heat transfer remains difficult to predict due to complex multi-scale physics.
- ❖ Existing heat flux partitioning models rely on empirical and semi-empirical closures with limited applicability.
- ❖ No single HFP model provides reliable predictions across a wide range of operating conditions.
- ❖ We propose a neural-gated mixture-of-experts framework that combines multiple existing boiling models.

3. EXPERIMENTAL DATA

Three experimental datasets are selected for training and testing. (For extrapolation set, measurements are close to CHF conditions.)

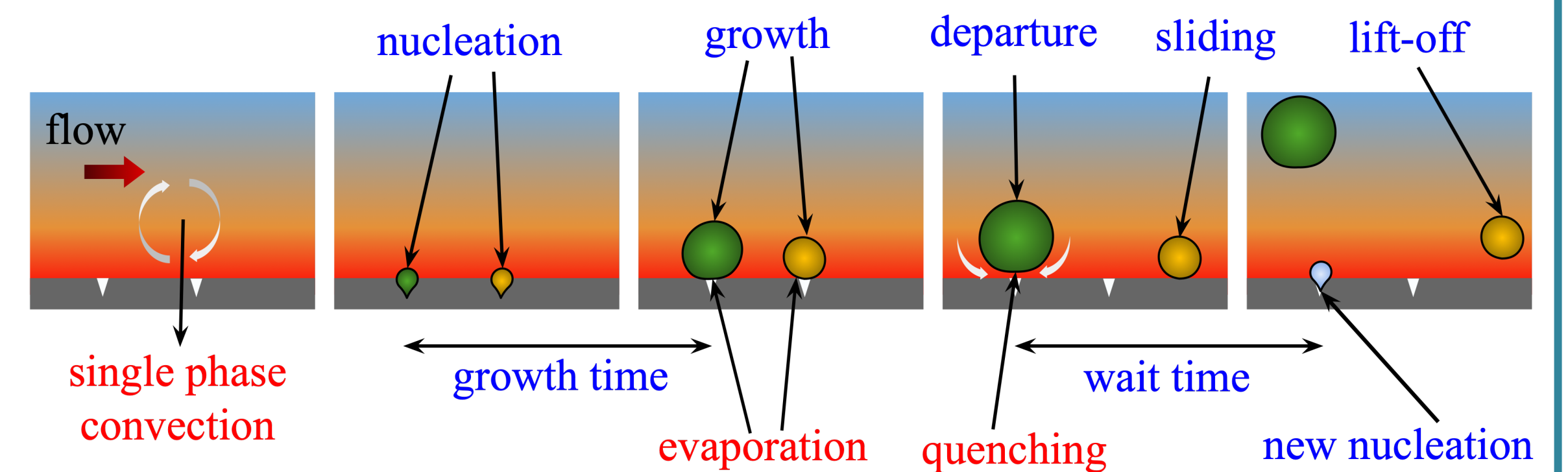


Distribution of training and testing cases in flow condition space. Total data points: 757.

2. METHODOLOGY: STANDING ON THE SHOULDERS OF GIANTS

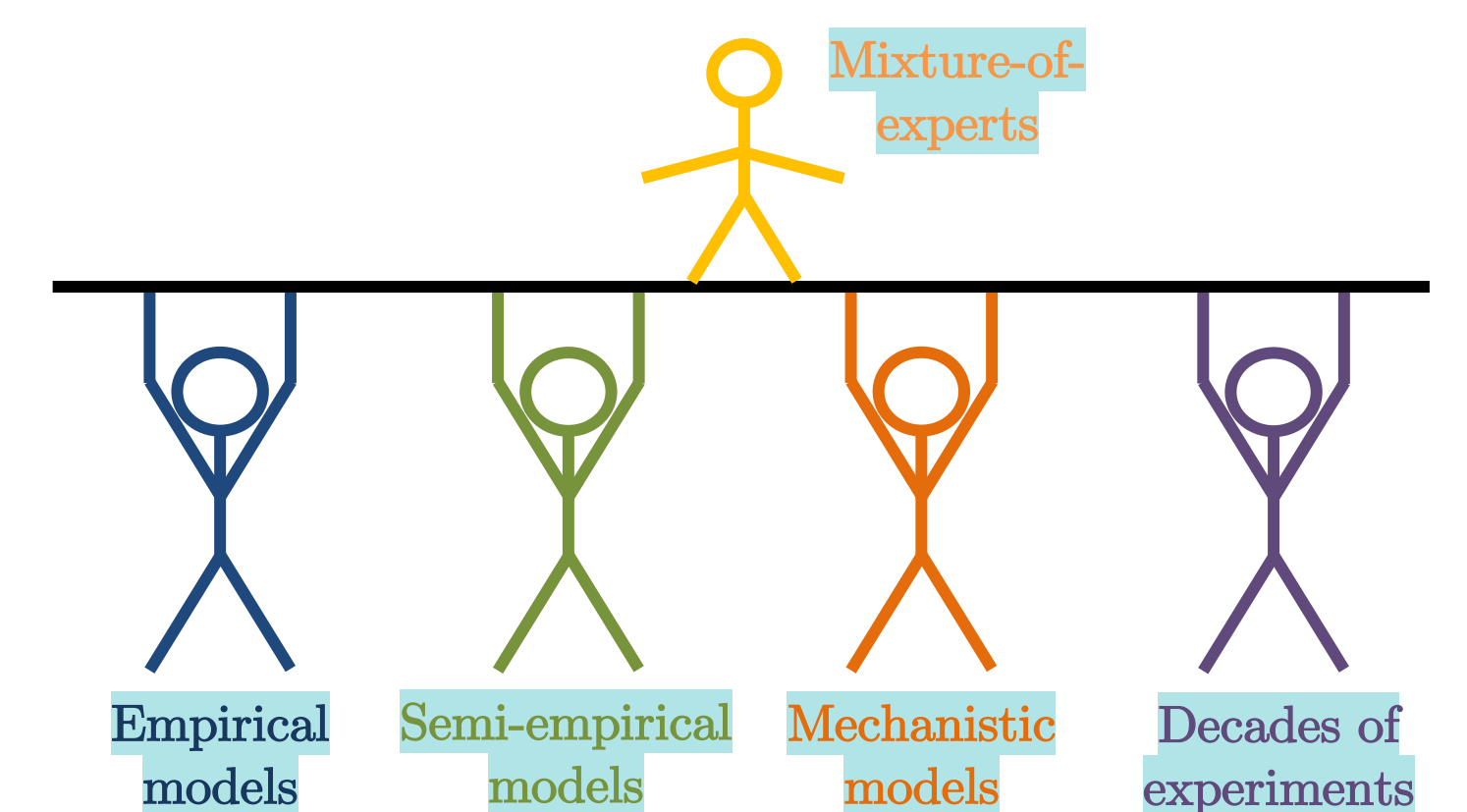
Heat flux partitioning

- Wall heat flux decomposed into multiple mechanisms.
- Require bubble dynamics closures.
- 100s of available models leading to 1000s of model combinations



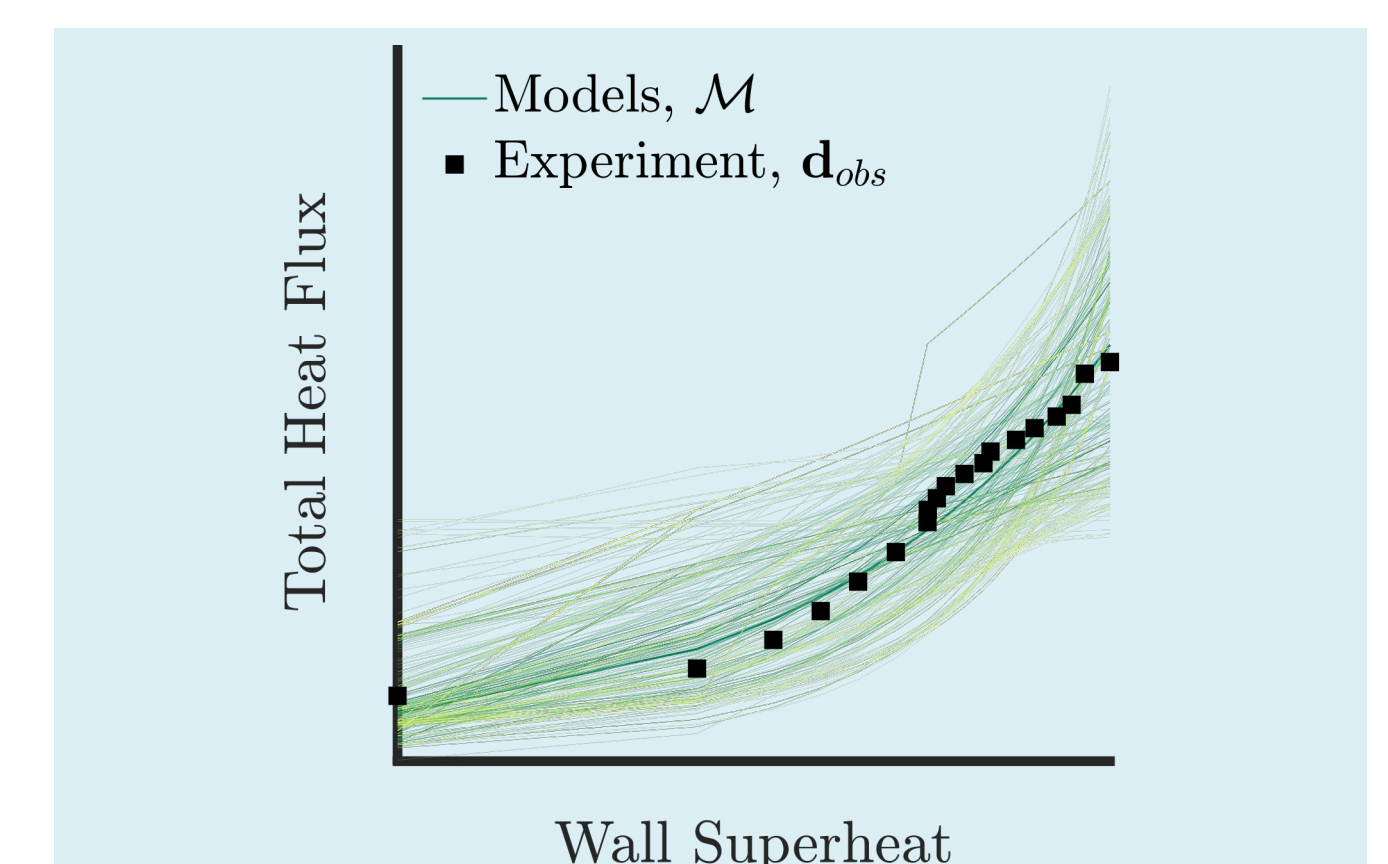
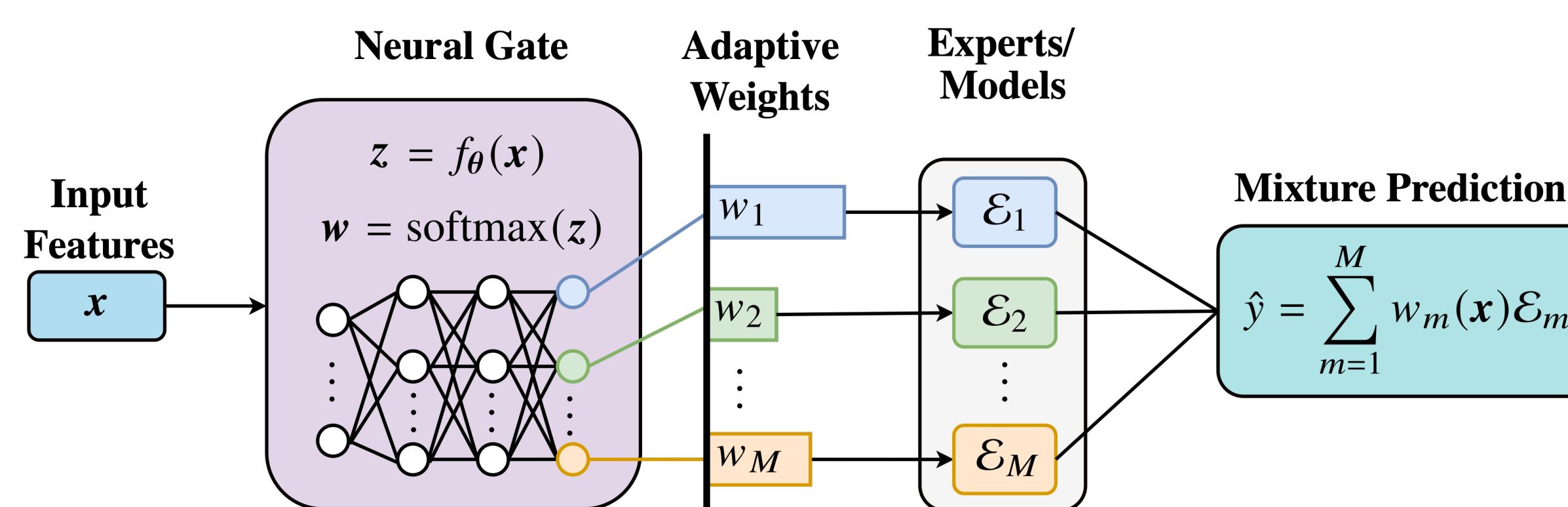
Mixture-of-experts philosophy

- Decades of research have produced a diverse library of models describing boiling phenomena.
- Rather than replacing these models, MoE learns how to blend their predictions informed by experimental data.
- The resulting predictions combine established physical knowledge with data-driven adaptation.



Mixture-of-experts architecture

- ✓ Experimental data are used to train the neural gate to assign adaptive weights to models/experts based on local operating conditions (input features).
- ✓ We retain interpretability: model contributions remains explicit through the learned weights.

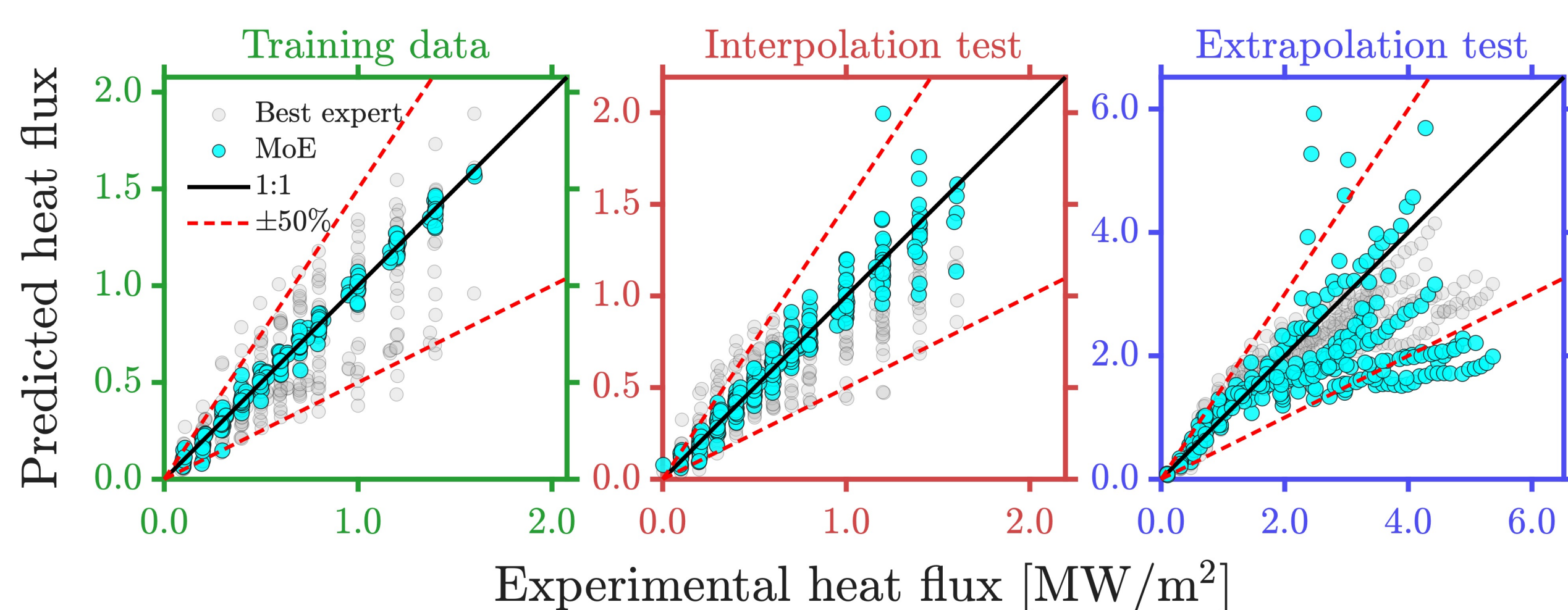


Illustrative boiling curve: each green line is a different model/expert. Given experimental measurements mixture-of-experts chooses the model(s) that match the data.

Model library: over >16,000 candidate model configurations considered; these were filtered to 215 representative experts. Each expert is a unique combination of a heat flux partitioning model with sub-models for bubble departure diameter, departure frequency, nucleation site density, growth time, wait time, and Nusselt number.

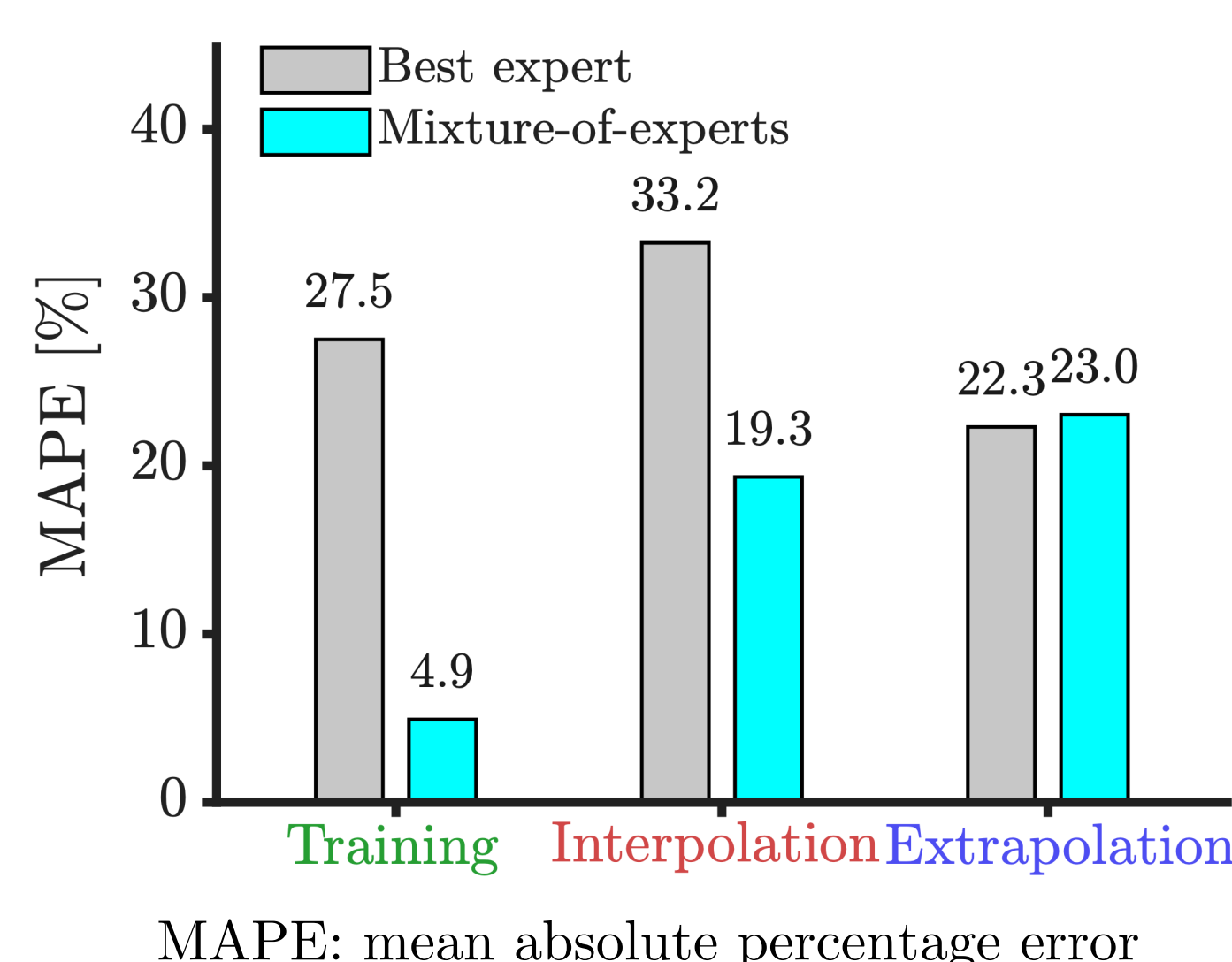
4. KEY RESULTS: PROOF OF CONCEPT

A. Mixture-of-experts (MoE) predictions: scatter plots

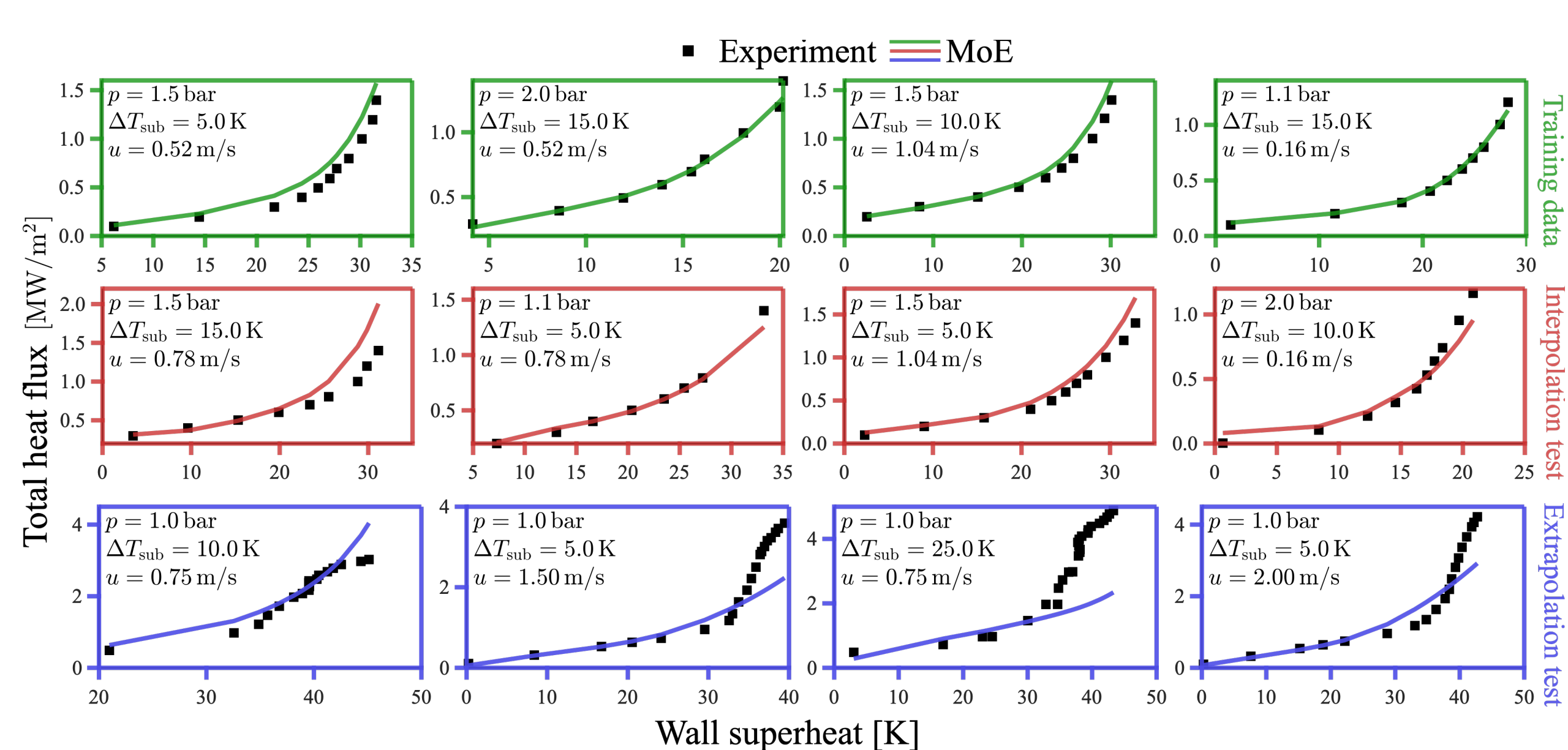


'Best expert' is the single best configuration selected for each dataset.

B. MoE prediction accuracy



C. Representative boiling curves



D. Highlights

- ✓ Adaptive weighting combines the strengths of multiple existing boiling models.
- ✓ MoE reduces prediction errors compared to best existing models.
- ✓ MoE results match experimental boiling curves.
- ✓ MoE predictive performance degrades in extrapolation scenarios (close to CHF) but is comparable to best existing model.

5. CONCLUSIONS

- Combining multiple boiling models is more effective than relying on a single model.
- The MoE improves prediction accuracy while retaining interpretability.
- MoE generalises from training to previously unseen operating conditions.

6. LOOKING FORWARD

- ❑ Use more diverse training/test datasets, including higher pressures and mass fluxes.
- ❑ Apply within CFD simulations.
- ❑ Explore MoE for other nuclear thermal hydraulics problems, e.g. critical heat flux.

Get in touch for ideas and collaboration!

