

Field Testing and Data-Driven Modeling of Variable Refrigerant Flow (VRF) System in Buildings



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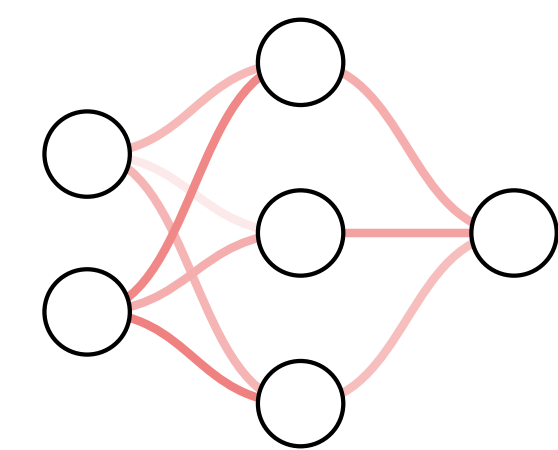
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Introduction

- Buildings account for about 30% of U.S. primary energy use^[1] and 37% of global CO₂ emissions^[2].
- HVAC systems contribute about 50% of a building's total energy consumption^[3].
- Optimized control of VRF system requires an accurate model for power consumption.
- This study presents a long-short-term memory (LSTM) model to accurately predict the power consumption of a VRF system based on the measured input features.

Which data-driven models offer the best trade-off between accuracy, computational efficiency, and data efficiency for modeling VRF systems?



Methods

- One year of field data covering all seasons was used to train the data-driven models.
- These models map selected input features to the VRF system's power consumption.
- Model hyperparameters were optimized using Bayesian optimization.

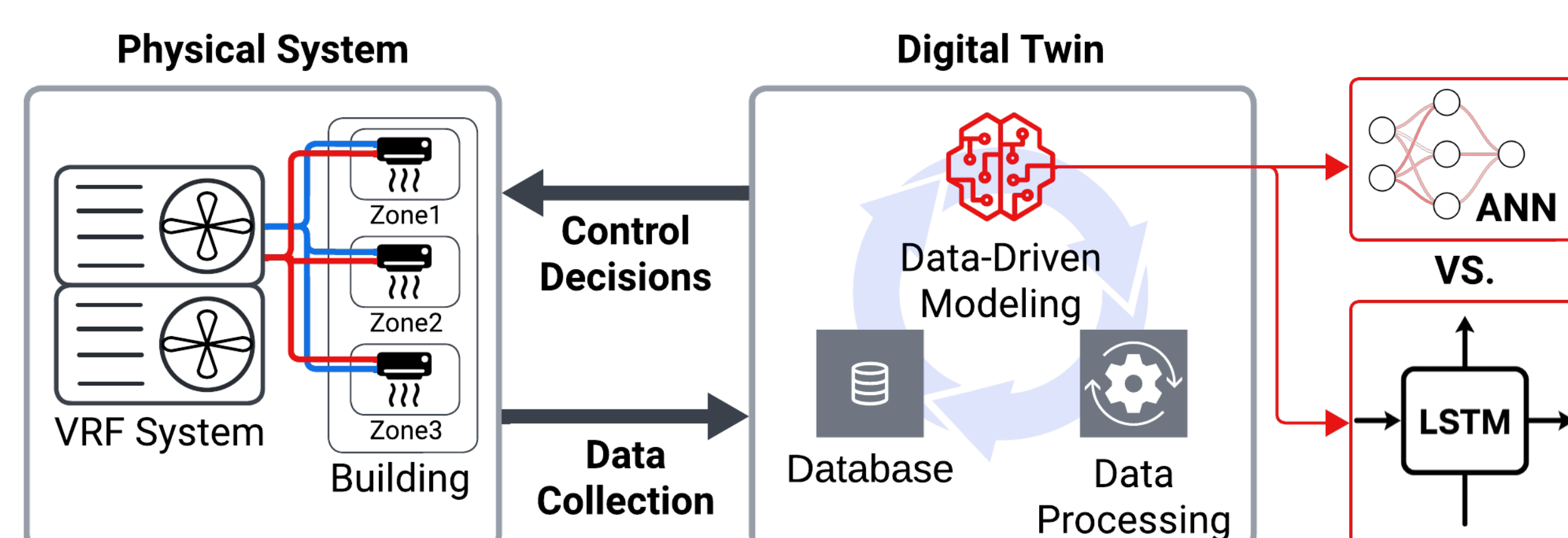


Figure 1. Flowchart of data collection, processing, and model development.

Results

Hyperparameter tuning via Bayesian optimization (TPE)^[4] is more efficient than exhaustive search

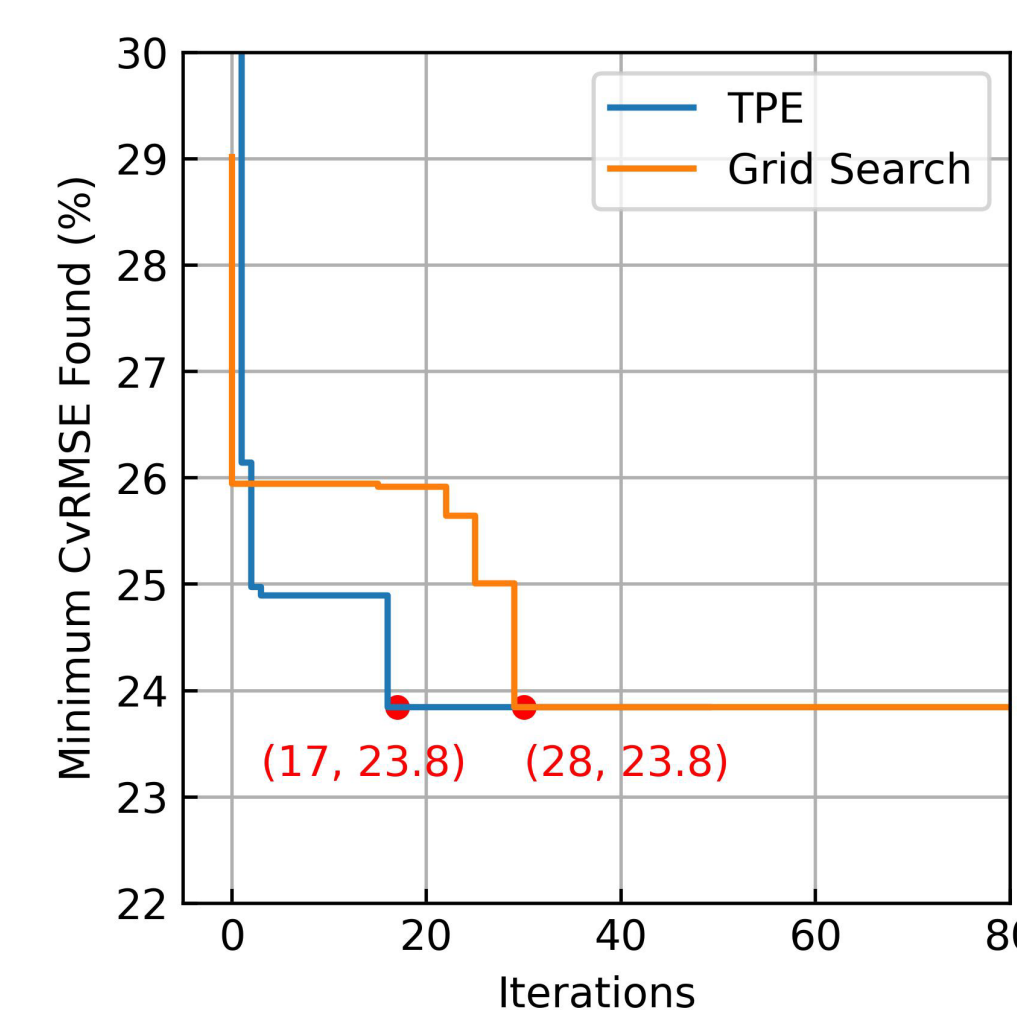


Figure 2. Minimum error observed during hyperparameter optimization.

Hyperparameters of the models.		
Models	Hyperparameters	Search Space
ANN/LSTM	Batch size	[2 ⁴ , 2 ⁵ , ..., 2 ¹⁰]
	Layer dimension	[1, 2]
	Neurons per layer	[2 ⁴ , 2 ⁵ , ..., 2 ¹⁰]
Decision Tree (DT)	Minimum samples split	[1, 2, ..., 50]
	Minimum samples leaf	[2, 3, ..., 50]

LSTM achieved greater accuracy with fewer trainable parameters than ANN

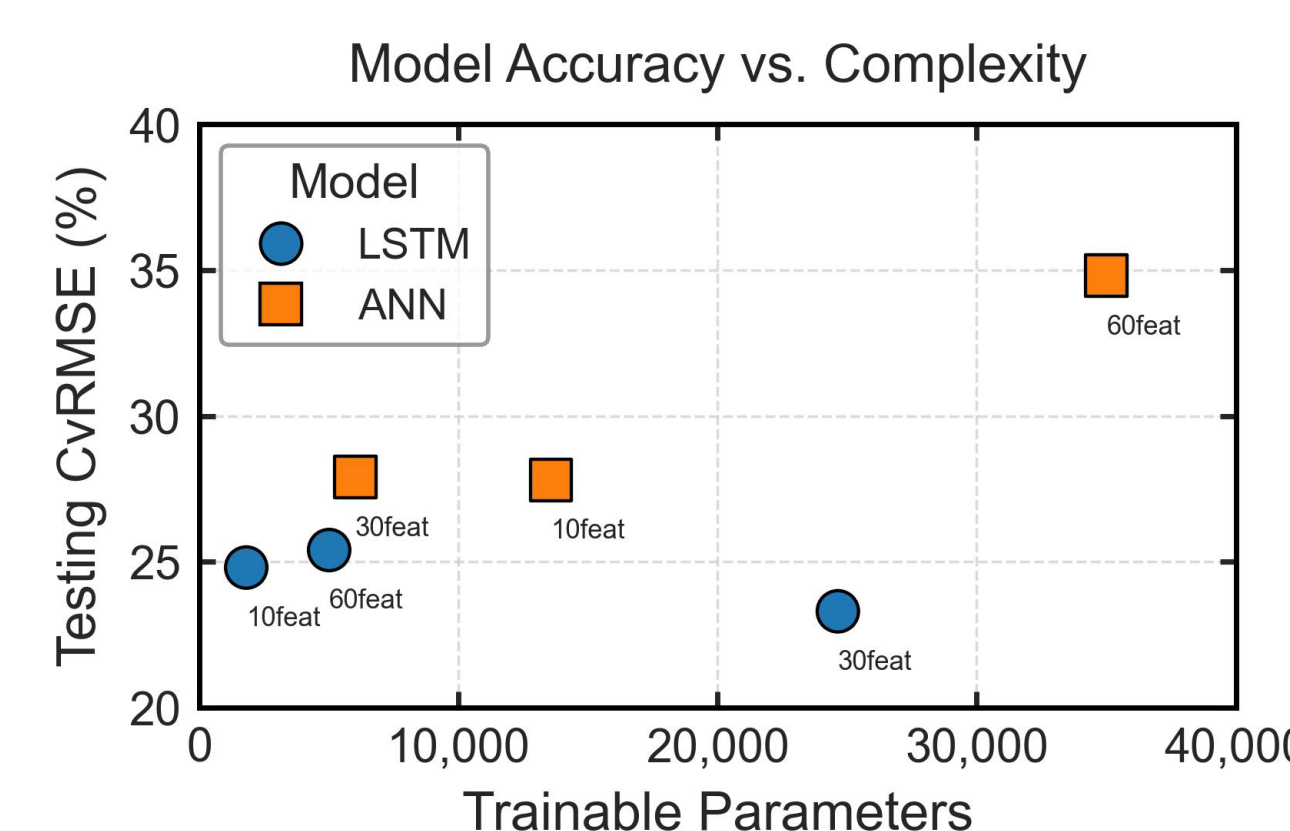


Figure 3. Models error vs. number of trainable parameters.

LSTM maintained low prediction residuals even in data-scarce regions (high-PLR)

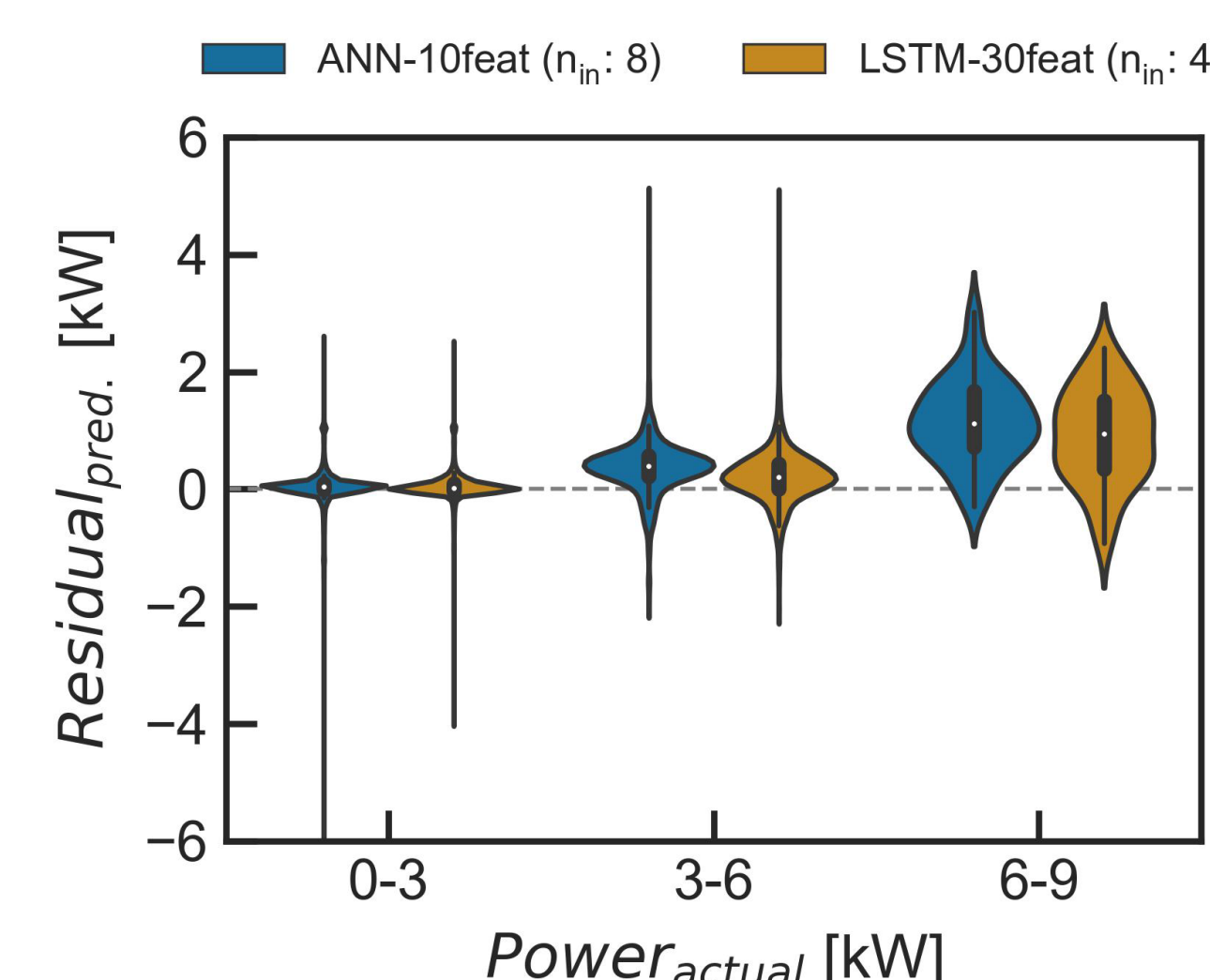


Figure 4. Distribution of prediction residuals by bin.

LSTM achieved a lower CvRMSE (22%) in power consumption prediction compared to ANN (27%) and DT (28%)

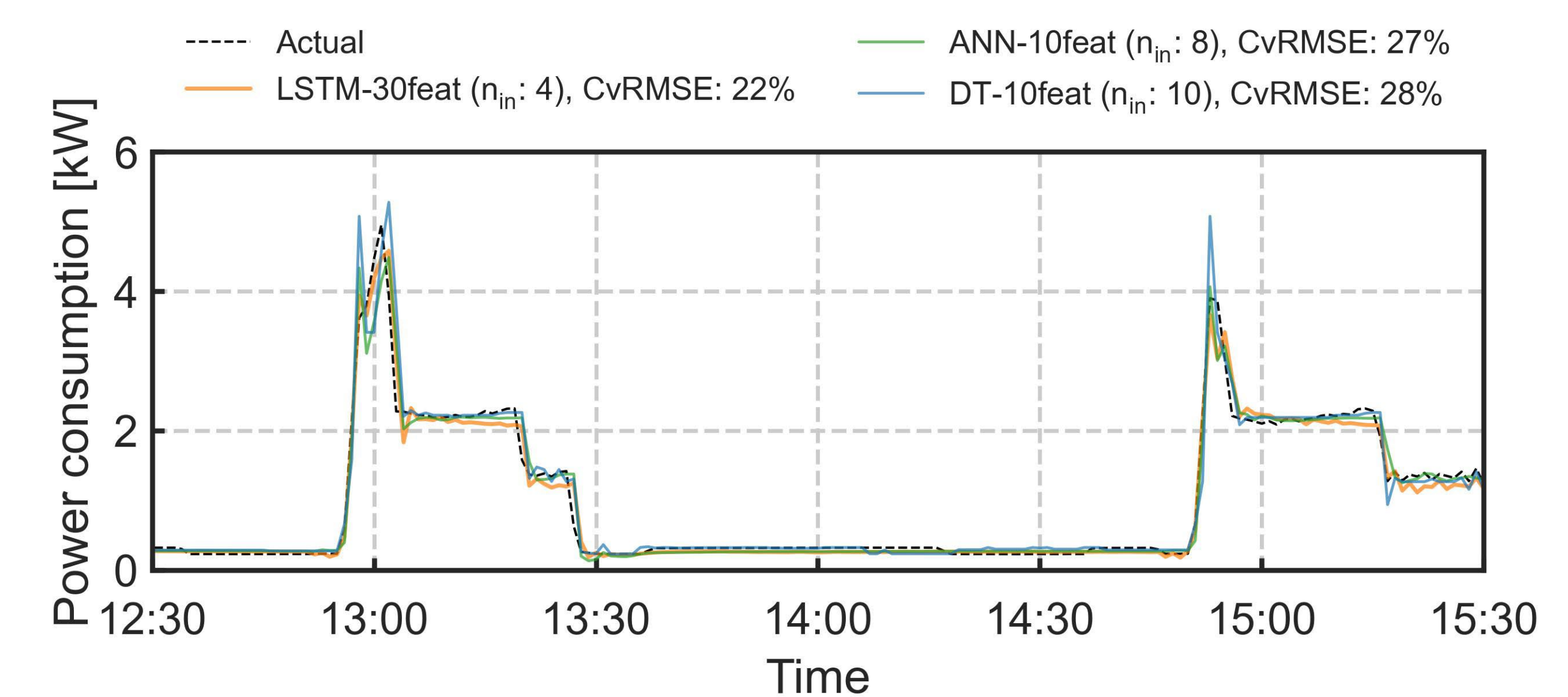
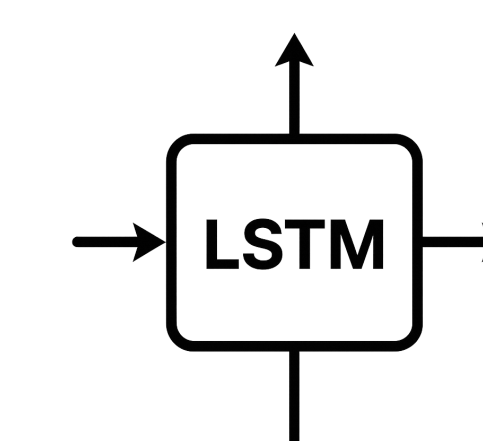


Figure 5. Model predictions for an out-of-sample winter day.

Conclusions

- LSTM-30feat achieved the highest accuracy among all models (CvRMSE: 23.3 %).
- LSTM is preferable to ANN in terms of both model complexity and accuracy.
- LSTM-30feat demonstrates greater tolerance to data scarcity.



LSTM is preferred over ANN for optimized control due to its higher accuracy, lower complexity, and greater data efficiency

Acknowledgement

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Full Paper



Poster

Website

- [1] EIA, 2023. <https://www.eia.gov/tools/faqs/faq.php?id=86&t=1>
- [2] NREL, 2022. <https://www.nrel.gov/docs/fy22osti/81670.pdf>
- [3] EIA, 2018. <https://www.eia.gov/energyexplained/use-of-energy/commercial-buildings.php>
- [4] Bergstra, J., Bardenet, R., Bengio, Y., K'egl, B., 2011. Algorithms for Hyper-Parameter Optimization. Advances in Neural Information Processing Systems. Curran Associates, Inc.