

Physics-aware Control and Monitoring for Energy-efficient Buildings

From Knowledge to Competitiveness

Portugal-US Partnerships 2026 Summit

MIT Portugal Program

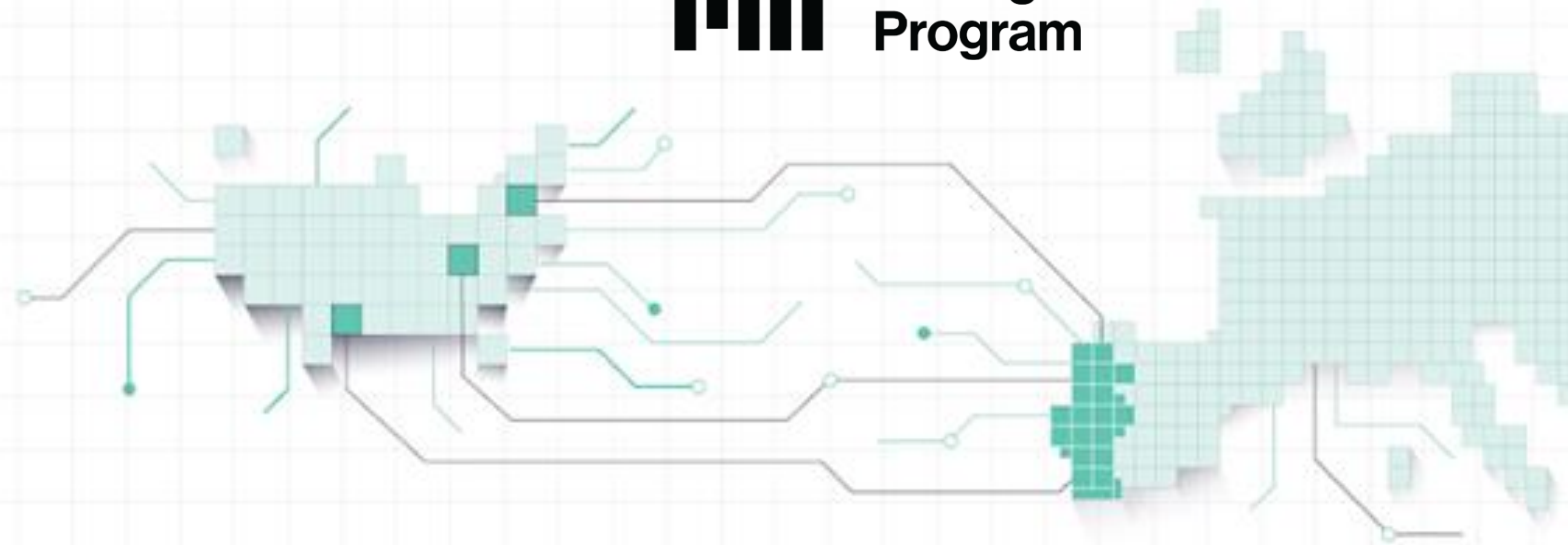


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Space, Climate and Sustainable Systems

Motivation

A significant share of building energy is wasted because of inefficient operation and control. For example, in commercial buildings and on university campuses, heating and cooling systems often operate in unoccupied spaces. Effective demand-reduction and energy-efficiency strategies therefore require *a)* optimized HVAC controls and *b)* detailed monitoring of end-user consumption. Together, these measures can lower energy use, costs, and greenhouse gas emissions. To address these needs, this project demonstrates a fast, accurate building thermal model coupled with a high-quality power-monitoring network for real-world applications.

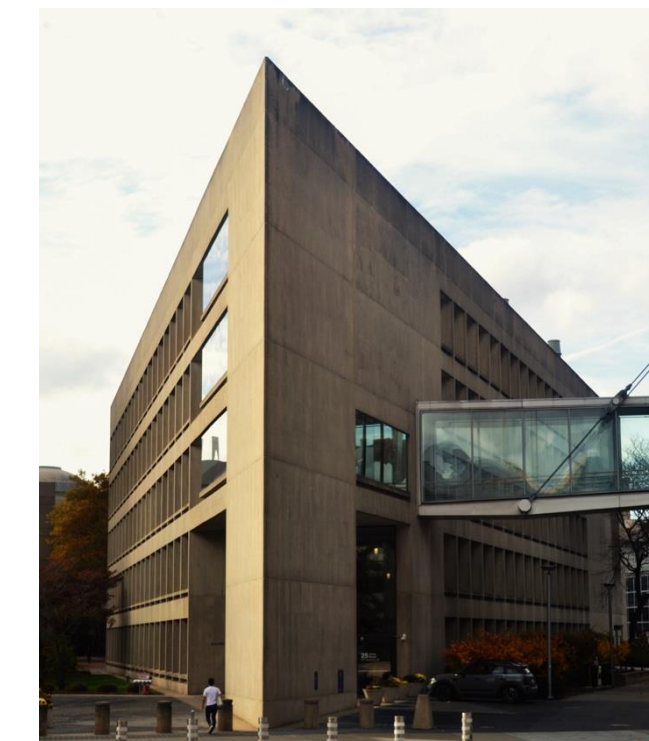


Figure 1. Building 66 at MIT campus. This building was used as a test bed for the thermal control optimization approach.

Thermal control optimization

Advanced control strategies in buildings require accurate, dynamic thermal models. These strategies are highly nonlinear, computationally expensive, and difficult to validate. In [1], a multi-zone model of Building 66 at MIT (Figure 1), combined with a genetic algorithm and numerical simulation (LTspice), produces a Pareto surface that identifies optimal trade-offs between energy consumption and occupant comfort. This work demonstrates a novel physics-informed, ML-based surrogate model for accelerating the optimization process (Figure 2).

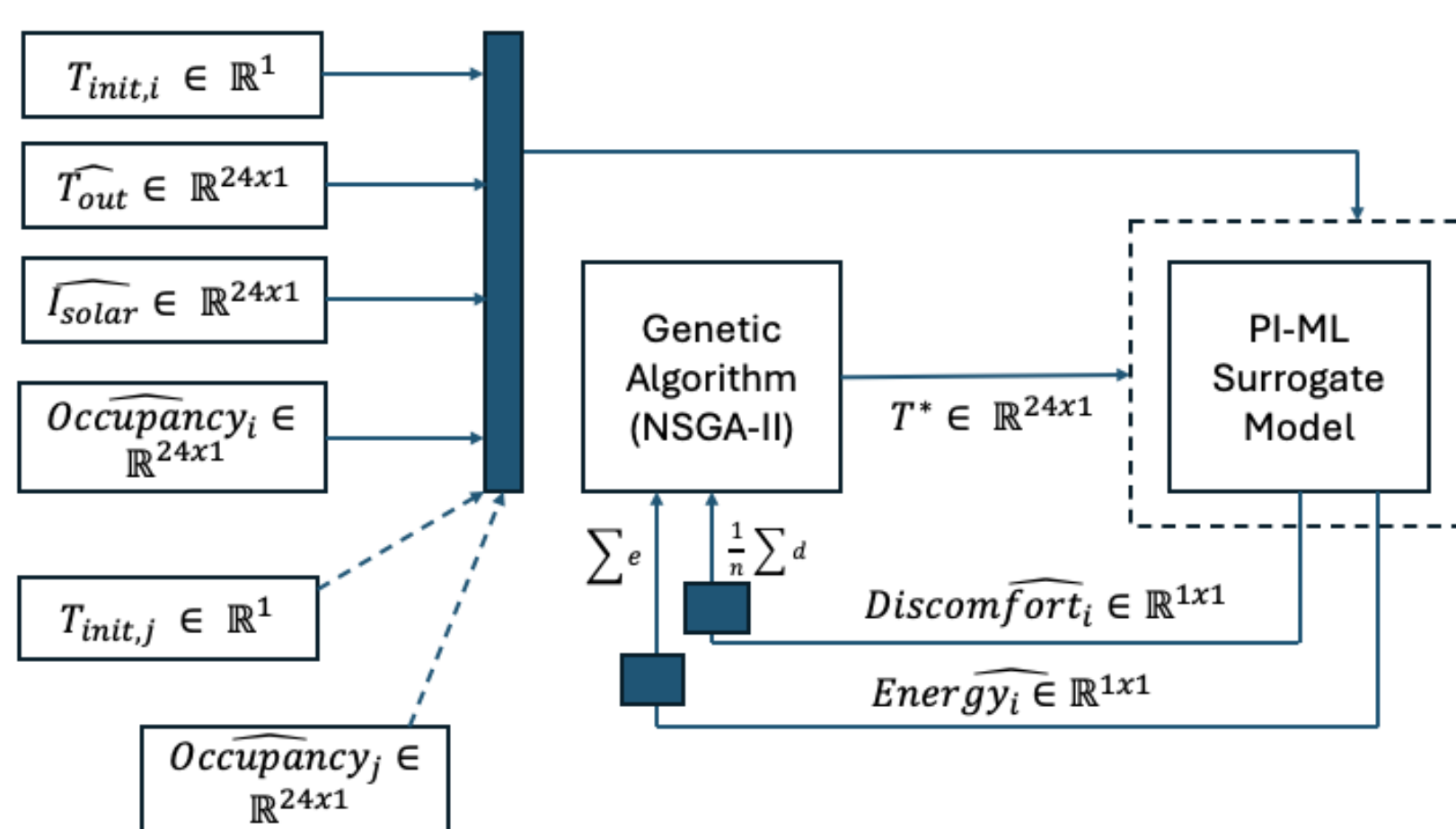


Figure 2. Flow diagram for the implementation of the ML-based surrogate model with feature and solution space.

The training dataset was constructed from 50,000 numerical simulation runs that included both real-world and synthetic temperature measurements, weather and occupancy forecasts. The architecture comprises deep neural networks with adjacency features for temperature and power estimation. The resulting inference is accurate and faster than numerical simulation (Figure 3). This speedup can support more frequent updates to HVAC setpoints and operating schedules, while the model's accuracy helps ensure that energy savings do not come at the expense of thermal comfort. This can reduce energy costs and associated emissions.

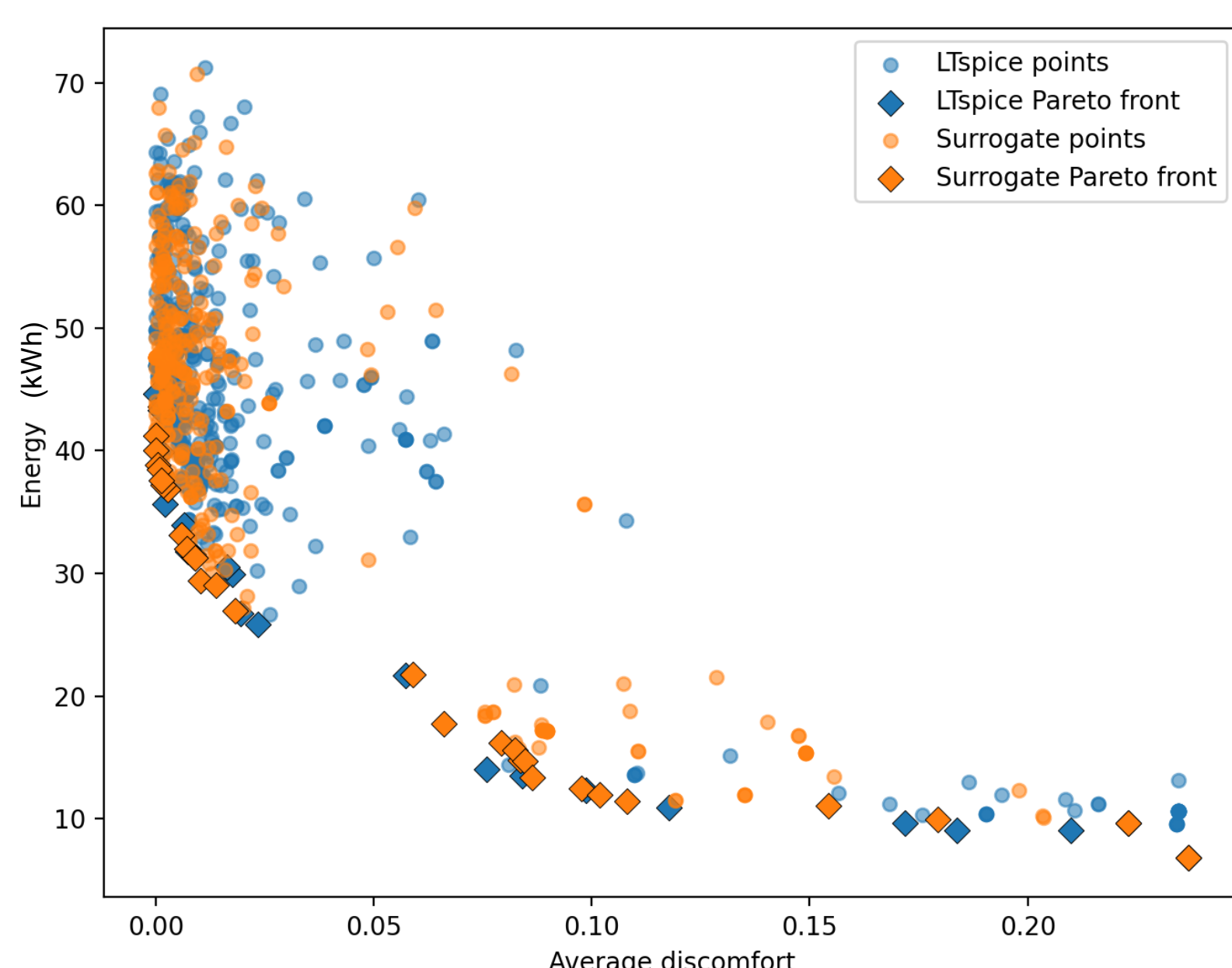


Figure 3. Comparison between the Pareto surface generated by the LTspice simulation and the ML-based surrogate model. The numerical simulation runtime is ~ 20 minutes, whereas the surrogate pipeline takes ~ 40 seconds to perform inference for the same number of candidate solutions. With respect to LTspice, the surrogate achieves an RMSE of 1.24 kWh for energy and 0.01 for discomfort.

Intelligent power monitoring and processing

Combining power data with recognition algorithms enables inference of the behavior and conditions of individual electrical loads, leading to potential peak demand reduction. Notably, high-resolution sampling can capture relevant physical phenomena that enriches the feature space, which facilitates load identification and diagnostics.

Multiple load monitoring and identification implementations rely on publicly available datasets to train their models. However, these data is often captured at inadequate sampling rates [2]. This work leverages a nonintrusive sensor network developed at MIT, called the nonintrusive load monitor (NILM) (Figure 4). A single set of voltage and current sensors provides an aggregate, high-resolution stream of time-series measurements from all loads downstream the utility point. This makes the NILM an inexpensive source of high-resolution electric load consumption data.

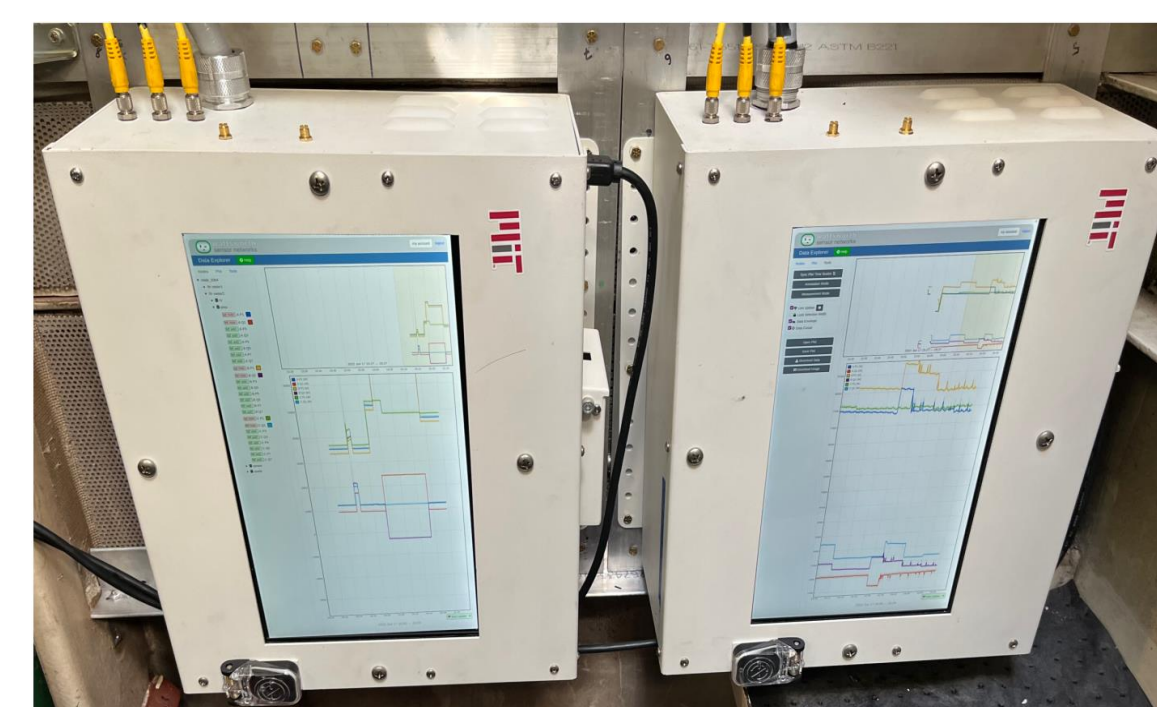


Figure 4. High-bandwidth NILM system installation.

ML methods for load disaggregation, ranging from traditional algorithms (e.g., kNN, SVM) to more sophisticated deep learning architectures (e.g., CNNs, RNNs), rely heavily on data richness. The more informative the input features, the better the algorithms can differentiate among diverse loads. Figure 5 compares the feature space produced by MIT's NILM and the feature space produced at lower sampling rates typically found in popular load datasets.

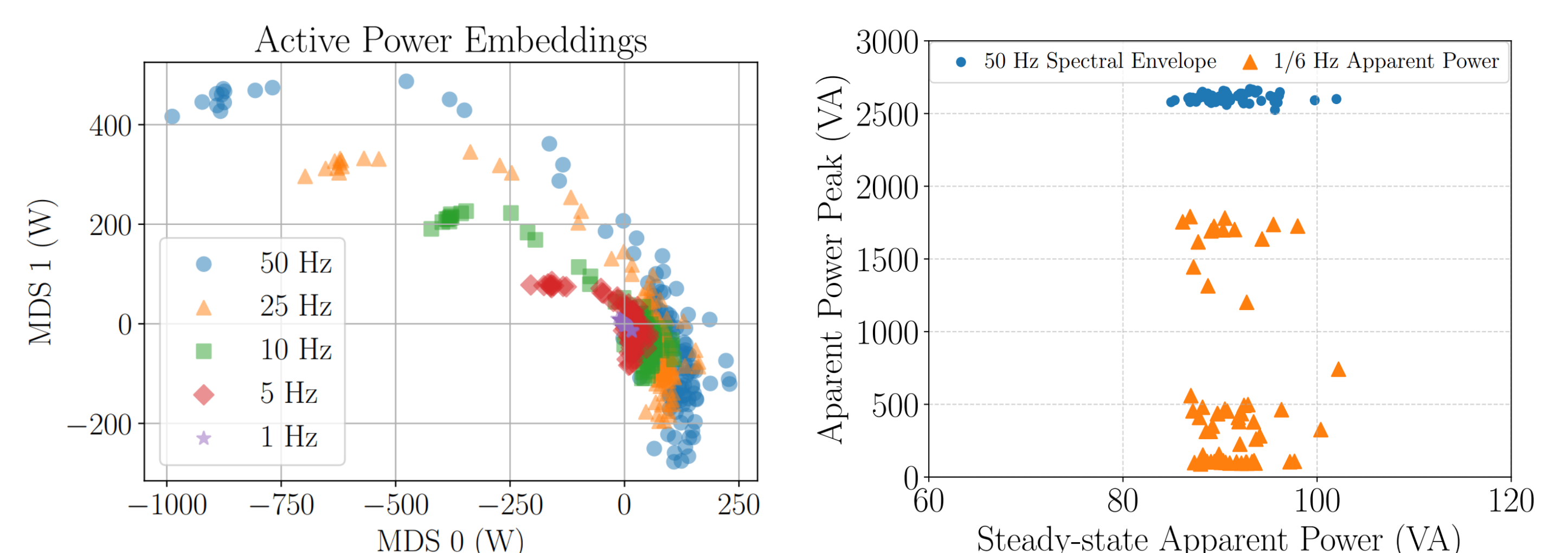


Figure 5. Feature space characterization for residential loads. Active power multi-dimensional scalings (MDS) (left), the NILM's 50 Hz resolution preserves differences across observations, whereas common, lower-resolution rates collapse into tighter clusters. In the right, a fridge turn-on event is repeated multiple times, with the NILM's resolution showing a tight cluster (since it's the same device). Lower-resolution rates show a wider spread.

Combined operation

The two proposed frameworks can operate together as a physics-aware control and monitoring loop that facilitates both energy-efficiency and demand-reduction strategies. The surrogate-based optimizer uses weather, occupancy, and thermal-state information to rapidly identify HVAC setpoints that balance energy consumption, while the NILM provides high-resolution measurements of the building's aggregate electrical behavior and enables operating conditions to be inferred from a single sensing point. Thus, the NILM can support performance verification, detection of abnormal equipment behavior, and more informed control updates.

Conclusion and future work

Modern buildings and microgrids can benefit from coordinated operation only if monitoring provides information that is both actionable and scalable. Ultimately, the project will extend these modeling techniques to allow condition monitoring and direct quantification of greenhouse gas minimization for buildings. Benchmarking results on MIT campus buildings are expected to show improved building-level efficiency and lower operational emissions.

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References

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- [2] Martínez, A., Langham, A. W., Donnal, J. S., & Leeb, S. B. (2026). The Price of Undersampling Nonintrusive Electrical Data. *IEEE Access*.