

Project Overview

Develop a machine learning system that can quickly adapt energy prediction models to new buildings using minimal historical data (few weeks) from the target building, leveraging knowledge from source buildings where extensive historical data exists.

Why This Matters:

- Building energy models degrade when deployed to new buildings due to climate variation, equipment differences, occupancy patterns, and operational schedules
- Retraining from scratch is expensive; using pre-trained models directly is inaccurate
- Few-shot learning solves the middle ground: Give the model 1-4 weeks of target building data, and it should predict as well as a model trained on 6-12 months
- Real companies need this (NREL, building management platforms, utilities)

Primary Research Question

"How much historical data from a target building is required for few-shot transfer learning models to achieve 90% of the baseline accuracy of a model trained on 12 months of the same building's data, and which transfer learning methods minimize data requirements while maintaining robustness across different building types and climates?"

Secondary Research Question

"What is the relationship between training data quantity (1 week, 2 weeks, 4 weeks, 8 weeks) and prediction accuracy improvement for transfer learning models applied to energy forecasting?"

"Which transfer learning method (fine-tuning vs. adapter layers vs. meta-learning) achieves the best accuracy-efficiency tradeoff for energy forecasting with limited data?"

"How does transfer learning performance vary across different building types (office buildings, residential, retail, schools) when trained on heterogeneous source data?"

Extra:

"How do few-shot models perform on out-of-distribution scenarios (unprecedented weather, new equipment, pandemic-induced schedule changes)?"

"How does model performance degrade when operating conditions change mid-deployment (e.g., occupancy schedule shifts, equipment degradation)?"

This project addresses a critical gap in building energy forecasting: How much data does a new building actually need for accurate transfer learning? While prior work (Spencer 2024, Li 2021) shows transfer learning improves accuracy, no systematic study has measured the data-accuracy trade-off across diverse building types. We conduct the first comprehensive evaluation of few-shot transfer learning across 15-20 buildings from the Building Data Genome Project 2, comparing three transfer strategies (fine-tuning, adapters, frozen) and testing robustness under realistic deployment conditions. Our findings provide actionable guidance for practitioners deploying transfer learning in data-scarce building energy forecasting.

| Phase | Weeks | Goal | Key Deliverable |
|-------------------|-------|--------------------------------|---|
| Setup | 1-2 | Environment + data exploration | Baseline LSTM trained on 1 building |
| Transfer Learning | 3-6 | Implement fine-tuning | Transfer system working |
| Adapters | 7-9 | Add adapter layers | Method comparison (RQ 3.1) |
| Multi-Building | 10-12 | Scale evaluation | Data efficiency curve (RQ 1.1 + RQ 2.1) |
| Robustness | 13-15 | Test failure modes | Robustness analysis (RQ 5.4) |
| Polish | 16-18 | Visualization + paper | Complete project report |

References:

1. For Transfer Learning Foundation:

Li et al. (2021) "Development of an ANN-based Building Energy Model..."

Established that transfer learning reduces error by 15-78% in building energy prediction.

2. For Transformer + Transfer Learning (Most Recent):

Spencer et al. (2024) "Transfer Learning on Transformers for Building Energy..."

Showed that transfer learning strategies on transformers improve forecasting and used BDG2 dataset (same as your project).

3. For Few-Shot + Meta-Learning:

Lu et al. (2025) "Few-Sample Model Training Assistant..."

Demonstrated that MAML meta-learning works for building heating load with limited data.

4. For Data Efficiency:

Xing et al. (2024) "Transfer Learning Integrating Similarity Analysis..."

Showed 70-81% error improvement for short-term and 26-65% for long-term predictions.

5. For Robustness & Continual Learning:

Conti et al. (2023) "A Physics-Based Domain Adaptation Framework..."

Addressed concept drifts and long-term model degradation.