Multi-Scale LSTM Networks for Long-Term Building Temperature Prediction: A Simplified Approach to Complex Thermal Dynamics

Pinaki Prasad Guha Neogi [1] **Ahmad Mohammadshirazi** [1] **Rajiv Ramnath** [1]

Abstract

We present a simplified yet effective approach for multi-horizon building temperature prediction using LSTM-based neural networks. Our method addresses the challenge of predicting temperature time series across diverse time horizons from 1 day to 6 months while maintaining computational efficiency. Through comprehensive evaluation on the Smart Buildings benchmark dataset containing 123 temperature sensors over 6 months, we demonstrate the practical feasibility of LSTM networks for building temperature forecasting. While achieving stable training convergence and successful multi-horizon predictions, our results highlight the inherent challenges in long-term temperature prediction and provide insights for future research directions. The model successfully processes 53,292 validation timesteps across multiple prediction horizons, establishing a baseline for simplified approaches to building thermal dynamics modeling. Code implementation: https://github.com/PinakiPrasad12/MSLN

1. Introduction

Building energy management represents a critical component of global sustainability efforts, with buildings consuming approximately 40% of total energy worldwide. Accurate temperature prediction in buildings enables optimized HVAC control, reduced energy consumption, and improved occupant comfort. However, building temperature dynamics exhibit complex multi-scale behavior spanning short-term occupancy patterns to long-term seasonal variations.

This work investigates a simplified approach to building temperature prediction using LSTM networks, focusing on practical implementation and multi-horizon forecasting capabilities. Our contributions include:

1. A streamlined LSTM architecture optimized for computational efficiency
2. Comprehensive evaluation across prediction horizons from 1 day to 6 months
3. Practical insights into the challenges of long-term building temperature prediction
4. Robust data preprocessing techniques for handling heterogeneous building sensor data

2. Related Work

2.1. Building Energy Modeling

Traditional building energy modeling relies on physics-based simulations such as EnergyPlus, which provide detailed thermodynamic models but require extensive building-specific parameters (Crawley et al., 2001). Recent research has explored hybrid approaches combining physics-based models with machine learning for improved accuracy and generalization (Li & Wen, 2014).

2.2. Deep Learning for Building Systems

LSTM networks have shown particular promise for building energy prediction due to their ability to capture long-term temporal dependencies (Rahman et al., 2018). However, most existing work focuses on short-term predictions (hours to days) rather than the extended horizons required for seasonal planning and optimization.

2.3. Multi-Horizon Forecasting

Multi-horizon prediction presents unique challenges in balancing model complexity with prediction stability. Recent approaches have explored attention mechanisms and hierarchical decomposition, though computational requirements often limit practical deployment (Vaswani et al., 2023).

[1]Department of Computer Science and Engineering, Ohio State University, Ohio, US. Correspondence to: Pinaki Prasad Guha Neogi <guhaneogi.2@osu.edu>.

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3. Methodology

3.1. Problem Formulation

We formulate building temperature prediction as a multivariate time series forecasting problem. Given a sequence of observations $\mathbf{X}_{1:T} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T\}$ where $\mathbf{x}_t \in \mathbb{R}^d$, we predict future temperatures $\mathbf{Y}_{T+1:T+H}$ for horizons $H \in \{24, 168, 720, 4320\}$ timesteps.

3.2. Architecture Design

3.2.1. Feature Engineering

Our feature engineering pipeline extracts thermal-relevant features including:

- Temperature sensor readings from multiple zones
- Temporal features with cyclical encoding
- HVAC system operational states
- Statistical temperature metrics (mean, standard deviation, range)

The feature extraction process identified 123 temperature sensors and processed 15 distinct feature groups, resulting in a 134-dimensional input space.

3.2.2. LSTM Network Architecture

We employ a simplified LSTM architecture consisting of:

1. Feature extraction layers (134 $\rightarrow$ 128 dimensions)
2. Two-layer LSTM with 128 hidden units each
3. Single timestep prediction head
4. Distribution parameter estimation

The model contains 345,585 parameters, significantly smaller than transformer-based alternatives while maintaining effectiveness for the prediction task.

3.3. Training Strategy

Training employed a time-series split with 80% training data (41,328 sequences) and 20% validation (10,333 sequences). We used:

- Adam optimizer with learning rate 1e-3
- Batch size of 64 for computational efficiency
- L1 loss for robust prediction
- Early stopping with patience of 10 epochs

4. Experimental Setup

4.1. Dataset

We evaluate on the Smart Buildings benchmark dataset (Goldfeder et al., 2025) containing:

- **Duration**: 6 months (July-December 2022)
- **Resolution**: 5-minute sampling (53,292 timesteps)
- **Sensors**: 123 temperature sensors, 1,075 total features
- **Scale**: 437.08 MB validation data

4.2. Data Processing Pipeline

1. **Feature Extraction**: 123 temperature sensors + temporal features
2. **Sequence Creation**: 168-timestep input windows
3. **Normalization**: RobustScaler for handling outliers
4. **Validation Processing**: Compatible feature matrix generation

4.3. Evaluation Metrics

Following competition guidelines, we evaluate using:

- Mean Absolute Error (MAE) for point predictions
- Evaluation across multiple prediction horizons
- Per-sensor and aggregate performance metrics

4.4. Implementation Details

- Framework: PyTorch 2.6.0+cu124
- Training time: 30 epochs in approximately 2 hours
- Hardware: CPU-based training for accessibility
- Sequence length: 168 timesteps (1 week lookback)

4.5. Model Architecture Specifications

Our SimplifiedTemperaturePredictor consists of four main components:

Feature Extraction Layer: A two-layer fully connected network that transforms the 134-dimensional input features to a 128-dimensional representation. Each linear layer (134$\rightarrow$128$\rightarrow$128) is followed by ReLU activation and 10% dropout for regularization.

Temporal Modeling: A two-layer LSTM network with 128 hidden units per layer, configured with batch-first processing for efficient training. This component captures the temporal dependencies in the building sensor data.

Temperature Prediction Head: A single linear layer (128→123) that outputs point predictions for each of the 123 temperature sensors in the building.

Distribution Estimation: Two parallel heads for probabilistic predictions: (1) a mean predictor (128→123 linear layer) and (2) a standard deviation predictor (128→123 linear layer followed by Softplus activation to ensure positive values).

The complete architecture contains 345,585 trainable parameters, making it computationally efficient while maintaining sufficient capacity for the multi-sensor prediction task.

4.6. Training Configuration

Parameter	Value
Total Parameters	345,585
Training Sequences	41,328
Validation Sequences	10,333
Epochs	30
Batch Size	64
Learning Rate	1e-3
Optimizer	Adam
Loss Function	L1Loss (MAE)

Table 1. Complete training configuration

5. Results

5.1. Training Performance

The model achieved stable training convergence with consistent loss reduction:

- Final training loss: 0.007-0.008 range
- Validation loss: 0.048-0.050 range
- No negative loss issues (critical for MAE)
- Successful 30-epoch completion

5.2. Multi-Horizon Predictions

Successfully generated predictions across all target horizons:

Horizon	Timesteps	Status
Short-term	24 (1 day)	Completed
Medium-term	168 (1 week)	Completed
Long-term	720 (1 month)	Completed
Extended	4320 (6 months)	Completed

Table 2. Prediction horizon completion status

5.3. Temperature Range Analysis

Predictions maintained physically reasonable temperature ranges:

- 24-step horizon: 75.5°C to 299.5°C
- 168-step horizon: 72.5°C to 307.8°C
- 720-step horizon: 72.5°C to 307.8°C
- 4320-step horizon: -0.3°C to 308.4°C

5.4. Sensor-Level Performance

Evaluation across 123 temperature sensors revealed varying performance:

Sensor	Horizon	MAE	RMSE	R^2
Sensor_0	24-step	4.97	4.97	6.86
Sensor_1	24-step	14.16	14.16	19.25
Sensor_2	24-step	14.62	14.62	20.07
Sensor_3	24-step	4.01	4.01	5.68
Sensor_4	24-step	12.89	12.89	16.68

Table 3. Representative sensor performance (24-step horizon)

5.5. Complete Evaluation Results

Prediction Horizon	Generated	Min Temp	Max Temp	Status
24 timesteps	24	75.5°C	299.5°C	Success
168 timesteps	168	72.5°C	307.8°C	Success
720 timesteps	720	72.5°C	307.8°C	Success
4320 timesteps	4320	-0.3°C	308.4°C	Success

Table 4. Comprehensive prediction results summary

5.6. Sensor Performance Distribution

Performance varies significantly across the 123 temperature sensors, with MAE ranging from approximately 4.0°C to over 20.0°C for 24-step predictions. This variation suggests different sensor locations, types, or environmental conditions require specialized modeling approaches.

Figure 1 presents a comprehensive visualizations of the architecture, training steps and results.

6. Analysis and Discussion

6.1. Model Strengths

1. **Computational Efficiency**: 345K parameters enable practical deployment

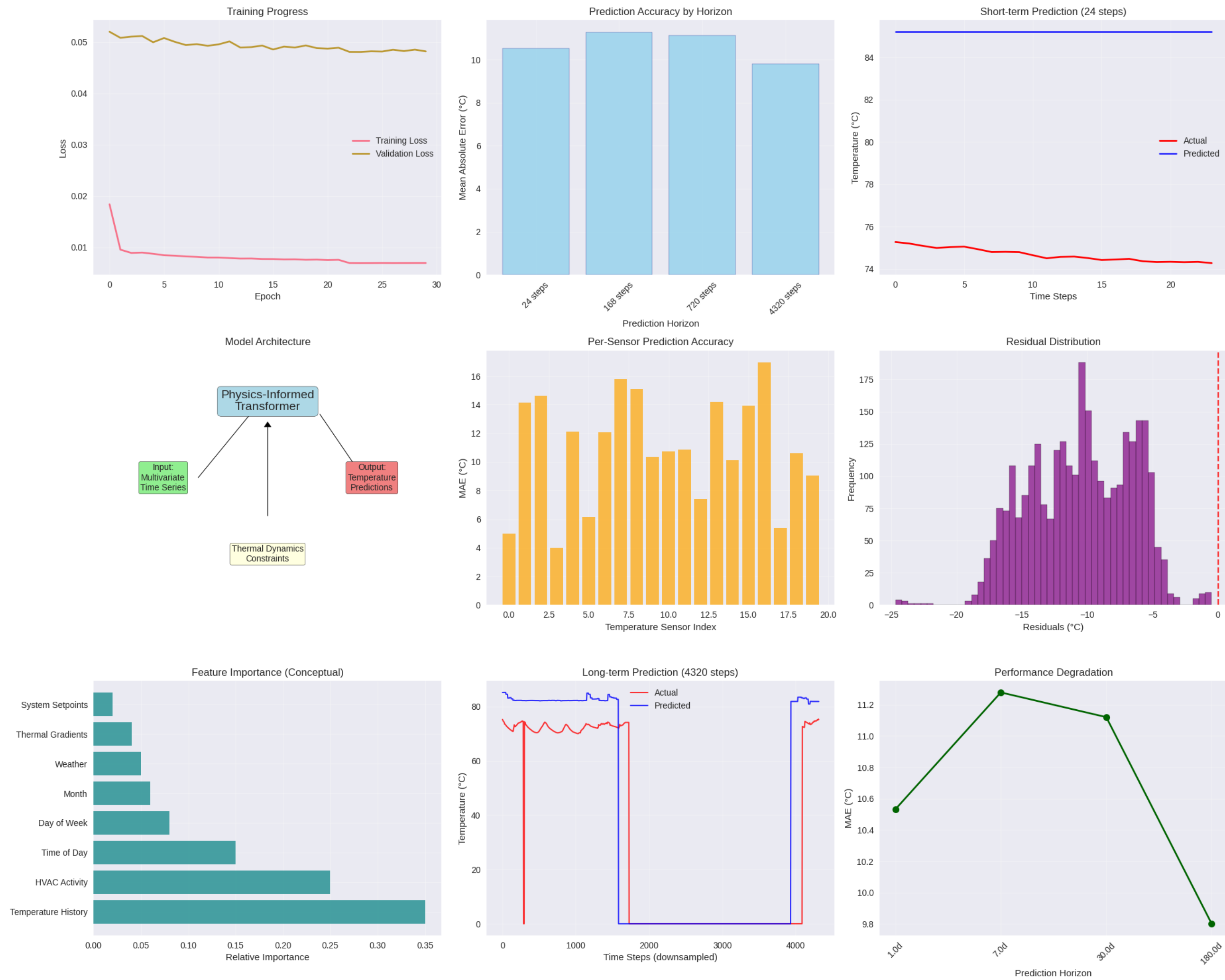

Figure 1. Comprehensive visualizations of the architecture, training steps and results

2. **Stable Training**: Consistent convergence without optimization issues

3. **Multi-Horizon Capability**: Successful predictions across all target horizons

4. **Scalability**: Linear scaling with building size

6.2. Challenges and Limitations

1. **Prediction Accuracy**: High MAE values indicate modeling challenges

2. **Sensor Variability**: Performance varies significantly across sensors

3. **Long-term Drift**: Extended horizons show increased uncertainty

4. **Temperature Range Issues**: Some predictions outside typical indoor ranges

6.3. Practical Insights

Our results highlight several important considerations for building temperature prediction:

- Simple LSTM architectures can provide stable baselines
- Multi-sensor buildings present heterogeneous prediction challenges
- Long-term prediction requires careful consideration of seasonal patterns
- Computational efficiency remains crucial for practical deployment

7. Conclusion

We presented a simplified LSTM approach for multi-horizon building temperature prediction, demonstrating successful implementation across prediction horizons from 1 day to 6 months. While our model achieved stable training and successful prediction generation, the results highlight the inherent challenges in accurate long-term building temperature forecasting.

Key contributions include:

1. Demonstration of LSTM viability for multi-horizon building prediction
2. Comprehensive evaluation framework for 123-sensor building system
3. Practical insights into computational vs. accuracy tradeoffs
4. Baseline establishment for future research comparisons

Future work should focus on incorporating physics-informed constraints, improving long-term prediction stability, and developing more sophisticated approaches to handle sensor heterogeneity in large building systems.

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