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International Journal of Innovations in Science & Technology

Sustainability-Aware Short-Term Building Cooling Demand Forecasting Using Multi-Source LSTM-Based Deep Learning

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Citation | Hadi. S. J, Khan. W. U, Ahmad. B, Saif. L, Jan. M. I, Miftah. M, Hadi. S, "Sustainability-Aware Short-Term Building Cooling Demand Forecasting Using Multi-Source LSTM-Based Deep Learning", IJIST, Vol. 7 Issue. 4 pp 3262-3287, December 2025

Received | November 23, 2025 **Revised |** December 19, 2025 **Accepted |** December 20, 2025 **Published |** December 24, 2025.

Precise short-term forecasting of building cooling demand is a necessary facilitator of power-efficient operation, economic planning, and carbon-conscious decision-making in modern power systems. Nevertheless, many of the current data-driven methods are based on a few input variables, ignore forecast-based exogenous data, or are affected by information leakage in time-series learning pipelines. In order to address these drawbacks, this paper suggests a high-fidelity deep learning model to forecast short-term cooling demand by jointly combining past load patterns, dynamic electricity price signals, grid carbon intensity signals, and multi-horizon weather forecasts. The suggested framework uses a multi-layer Long Short-Term Memory (LSTM) structure that will learn intricate temporal relationships in hourly building energy data throughout a complete annual period. The preprocessing strategy embraces a leakage-free approach and includes the alignment of data with time consistency, normalization of features, and the generation of sliding-window sequences in order to guarantee realistic and reliable performance assessment. The CityLearn dataset is used to train and test the model, and this data is a high-resolution simulated urban building energy environment of 8,760 hourly observations under various seasonal and operational conditions. The results of the experiment indicate that the given approach produces very accurate cooling demand forecasts, as the coefficient of determination (R^2) is 0.9823, and the mean error of absolute percentage is below 1, which is much higher than that of traditional baseline models. Additional studies prove that the combination of forecast consistent weather variables, electricity pricing signals, and carbon intensity indicators can significantly boost prediction accuracy and operational relevance. The evaluated leakage-free building energy management system is simulated, but the leakage-free learning pipeline and multi-source input design can be directly applied to real-world systems, enabling the intelligent HVAC control, demand response, and low-carbon operational practices. Altogether, this article may help to fill the gap between deep learning approaches and sustainability-conscious decision-making in the contemporary energy infrastructure. The proposed model is designed for direct multi-step (multi-horizon) prediction of demand for cooling in the form of predictions of demand for several time steps in the future using forecast-aligned input features.

Keywords: Building Cooling Demand Forecasting; Deep Learning; Long Short-Term Memory (LSTM); Weather-Assisted Energy Prediction; Carbon-Aware Building Energy Management

Introduction:

The ongoing population increase in cities, as well as the extensive use of energy-demanding building infrastructures, has placed buildings as one of the biggest electricity and a significant carbon source around the planet [1][2]. Cooling systems are one of the many end-use components with a huge proportion of building energy consumption, especially those in areas with hot climates with increasing ambient temperatures and extending cooling seasons [3][4]. With the escalation of the climatic stress and energy demand patterns getting more dynamic, precise short-term prediction of building cooling demand has become a very important requirement of efficient and sustainable operation of the energy system [5].

Accurate cooling demand forecasting is central to the current energy management systems in buildings since it allows the efficient scheduling of heating, ventilation, and air-conditioning systems, enhances the participation in demand response, lowers the expense of operations, and softens peak electricity demand [6][7]. Moreover, the increased integration of renewable sources of energy and the implementation of time- varying electricity prices have added more uncertainty and variability to the power systems [8][9]. In these circumstances, accurate short-term demand prediction is crucial, both to optimize the economy, and to ensure grid stability and to minimize generation that is carbon-intensive during peak times [10]

Traditional cooling demand forecasting models have either been based on physics-based approaches to modeling or classical statistical models, such as linear regression, autoregressive integrated moving average, and rule-of-thumb simulations [2]. Although these methods provide both transparency and theoretical interpretability, they tend to miss the highly nonlinear, time-dependent, and multi-factor interactions that define the building energy behavior in the real world [11]. The cooling demand is a complex interdependency of historical load patterns, weather conditions, humidity, and solar radiation, operating schedules, signals of electricity prices, and behavioral influences of users [4][12]. The dimensionality and time dependence of these variables are a major constraint to the predictive power of the conventional models, especially in operational and environmental settings that have a significant rate of variation [13].

The progress in machine learning has seen more flexible data-driven forecasting models constructed that can model complex nonlinear relationships [14]. Such approaches like support vector regression, ensemble learning, and tree-based algorithms have shown better results compared to classical statistical models in different energy prediction problems [15]. In more recent times, deep learning methods, especially recurrent neural networks and Long Short-Term Memory models, have been broadly discussed because they already have the property of being able to represent long-range temporal dependencies in time-series data [11][16]. These models have been effectively used to develop electricity consumption forecasting, HVAC energy estimation, and district cooling load prediction with significant enhancement in the accuracy and strength [6][1].

Although the methods based on deep learning demonstrate positive results, a number of limitations are still present in the current literature [17]. A significant percentage of the previous research concentrate on the past load and measured weather conditions, and they do not take into account other essential exogenous dynamics, including the electricity pricing dynamics and carbon intensity signals [18][10]. With energy systems progressively converting to a market-oriented and low-carbon mode of operation, the omission of these variables makes forecasting models less practical [7][19]. Also, numerous published works are based on short-term horizons or simplified data, which are not capable of reflecting seasonal changes and long-term operational patterns of real-life building energy systems [5][2].

The other major challenge, which is critical, is the experimental design of short-term forecasting models [8]. The future cooling demand in an operational environment should be forecasted based on forecasted data as opposed to the actual future data, which is perfect [20]. Nevertheless, accessible information on future weather or external variables, as assumed implicitly by many existing studies when assessing a model, creates information leakage and falsely inflated estimates of model performance [17][16]. Poor data preprocessing (e.g., not adequately normalizing training and testing intervals in time-series, or randomly splitting data in time-series) also contributes to the lack of reliability and generalizability of reported findings [14].

The gaps as outlined need to be filled by means of forecasting frameworks that are not only highly predictive in nature but also representative of the realistic operational conditions, as well as including information related to sustainability [10][9]. With the combination of heterogeneous data sources, such as historical cooling demand, electricity pricing signals, carbon intensity indicator, and predicted weather variables, there is a chance to increase the quality of short-term cooling demand prediction as well as its value in decision-making [3][1]. Due to their integration with carefully-crafted leakage-free preprocessing pipelines and realistic evaluation strategies, deep learning models can be a potent base for next-generation building energy forecasting systems [17][21].

Inspired by this, this work constructs a high-fidelity deep learning-based model of short-term building cooling demand prediction that puts an emphasis on operational realism, the combination of multiple sources of data, and sustainability consciousness. Utilizing a multi-layer Long Short-Term Memory architecture and introducing various exogenous input signals into a time-consistent learning pipeline, the suggested method will enhance the precision of the forecasts and still be practically applicable to the strategies of intelligent building energy management and the operation based on low-carbon principles.

Novelty of the Proposed Study:

In contrast to most of the existing short-term building cooling demand forecasting studies, which have mainly relied on historical load profiles and weather variables, this study shows the explicit and standalone integration of dynamic electricity pricing and time-varying grid carbon intensity indicators directly in the forecasting framework. The novelty is not only in the use of these economic and environmental signals as further input features, but in redefining the problem of cooling demand forecasting as a sustainability-aware decision support problem, as opposed to an accuracy-driven task. To the best of current knowledge, this work can be considered as one of the few attempts to jointly fuse the forecast-aligned weather information, dynamic price signals, and carbon intensity indicators in a leakage-free deep learning-based learning pipeline for short-term cooling demand forecasting. This explicit integration allows the forecasting model to support cost and carbon-awareness and therefore extend the role of demand prediction from numerical performance to market responsiveness and low-carbon building energy management.

Objectives of the Study:

The key aim of the research is to come up with a deep learning model that is leakage-zero, sustainability- conscious, and capable of predicting building cooling demand over a short period of time in the presence of realistic data availability limitations. To accomplish this general purpose, the following are the research objectives:

To develop a short-term cooling demand forecasting system that inherently combines the past cooling load patterns, forecast-consistent weather data, dynamic price signals on electricity, and grid carbon intensity information with a single deep learning framework.

The presence of leakage in the data preprocessing and learning pipeline must be prevented to achieve the following: time-consistent feature alignment, realistic normalization, and effective sequence generation to make meaningful evaluation of performance.

To determine how economic (price of electricity) and environmental (carbon intensity) signals influence forecasting performance and practicality in comparison with conventional weather- and load-based forecasting.

In order to make quantitative comparisons between the suggested framework and benchmark models based on the quantitative measures of performance, pinpointing the advantages of performance in terms of predictive accuracy and robustness.

To show the possibility of the proposed solution to facilitate cost-conscious and carbon-conscious decision-making in intelligent building energy management, demand response, and low-carbon operational planning.

Related Work:

The short-term cooling demand forecasting is a popular field of research because of its relevance in the energy management of buildings, demand response, and sustainable operation of power systems [2][7]. The research available can be generally subdivided into three general groups of approaches: traditional statistical prediction, conventional machine learning, and deep learning-based prediction models [14][17].

The initial studies into the demand forecasting of building cooling and electricity have been mainly based on statistical and physics-inspired models [2]. The models used to predict cooling demand in relation to past load and ambient temperature were mostly linear and nonlinear regression models, autoregressive models, and autoregressive integrated moving average (ARM) models [2][3]. These methods were interpretable and computationally simple, but they could be restricted by powerful linear and stationarity assumptions [11]. Due to the nonlinear nature of building energy systems, which is sensitive to seasonal cycles, occupancy, and operational dynamics, the statistical models often did not hold accuracy due to environmental and operational variations [13].

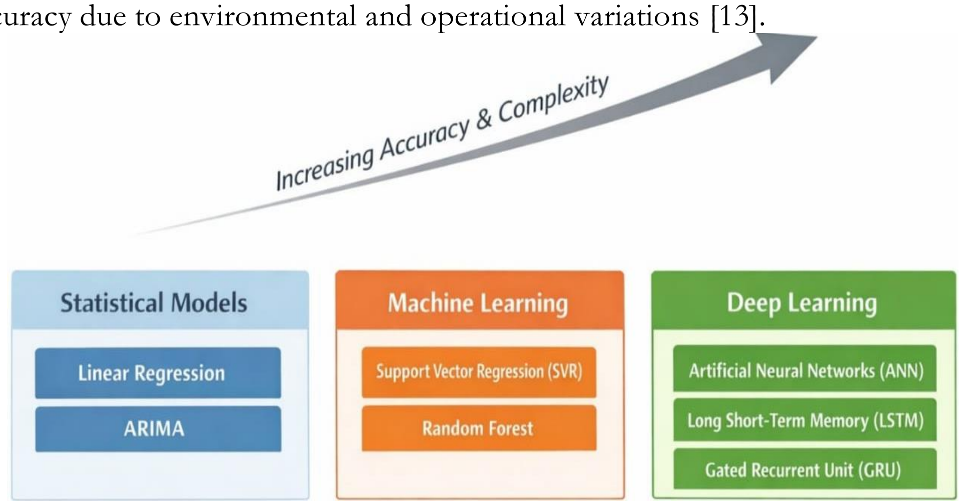

Figure 1. Evolution of short-term building cooling demand forecasting methods from traditional statistical models to advanced deep learning-based approaches.

As indicated in Figure 1. The study of short-term building cooling demand prediction has been expanded increasingly over the years from conventional types of statistical methods to more sophisticated models based on machine learning and deep learning. Older statistical methods, including linear regression and ARIMA, were only intended to model simple, weak, nonlinear temporal patterns. The development of machine learning models allowed the representation of nonlinear relationships in a better way, but these methods usually did not have an intrinsic way of learning long-term temporal dependencies. In more recent times, deep learning models, specifically recurrent neural networks and Long Short-Term Memory models, have been shown to perform better through their ability to capture complex temporal dynamics and long-range dependence found in building cooling demand, which has made deep learning the paradigm in modern forecasting studies [4].

To eliminate these shortcomings, methods based on machine learning were proposed to learn the nonlinear relationships between cooling demand and driving variables [14]. The techniques applied to short-term energy load forecasting activities have been widely used using support vector regression, k-nearest neighbors, artificial neural networks, random forests, and gradient boosting [17][15]. These techniques were shown to have better predictive accuracy than classical statistical models as they learn more complex input-output functions based on past data [15]. However, traditional machine learning frameworks typically use a large amount of feature engineering and do not have some form of an enduring temporal dependency mechanism, which is essential in well modeling cooling demand dynamics across long time horizons [11][13].

Due to the fast development of deep learning, recurrent neural technology has become one of the potent time-series predictive systems in energy systems [16]. Specifically, Long Short-Term Memory networks have received a lot of attention as they can capture long-range time dependence and outperform traditional recurrent networks because they can avoid the vanishing gradient problem [16][21]. Many publications have established that the use of LSTM-based models has shown better performance in predicting building electricity usage, HVAC energy usage, and district cooling loads, particularly compared with shallow learning methods [20][1][6]. Other variants, like gated recurrent or hybrid convolutional recurrent architecture, have also helped to increase the accuracy of the forecasts because they have better capabilities to extract temporal features and have a higher learning rate [22].

Recent studies have paid more attention to the application of exogenous information to deep learning models, especially weather variables like temperature, humidity, wind speed, and solar radiation. The use of weather forecasts instead of measured weather information has been demonstrated to enhance the reality of short-term forecasting models since it correlates the experimental configuration with the real-world operational conditions. Nonetheless, a great number of current studies still build on the basis of a small number of weather characteristics or perfect future weather visibility, which can precondition excessive optimism in the forecasts of higher performance, as well as a decrease in practical utility.

Model Type	Nonlinearity	Temporal Dependency	Long-term Memory
Regression	Low	No	No
SVR / RF	Medium	Limited	No
RNN	High	Yes	Limited
LSTM	High	Yes	Strong

Figure 2. Comparative capabilities of conventional machine learning and deep learning models for short-term building cooling demand forecasting.

Figure 2 demonstrates that the various forecasting paradigms have varying abilities in predicting the non-linear and time-related nature of the cooling demand of buildings. Traditional regression-based models are limited in terms of nonlinear representation and memory or time, which limits their performance in dynamic operating conditions. Support vector regression and random forests, which are methods of machine learning, enhance the capacity of nonlinear modeling, but the capacity to capture long-term temporal dependencies is limited. RNNs introduce time-dependent learning, but tend to have low long-term memory capabilities. Contrarily, Long Short-Term Memory networks have been designed to overcome these limitations, in particular by more heavily relying on gated memory mechanisms, which allow effective learning of long-range temporal patterns. This inherent benefit of the LSTM-based models, particularly, makes them the most appropriate model when forecasting the short-term cooling demand, whereby complex temporal dynamics and the presence of persistent dependencies are highly important.

In addition to the weather conditions, the price signal of electricity and carbon indicators have become more topical in reference to smart grids and low-carbon energy systems. Dynamic price mechanisms affect the operation strategies of the buildings, whereas the carbon intensity represents the effect of the electricity use at various times on the environment. Although their significance is on the increase, very little research has explicitly included price signals or carbon intensity indicators in the model of cooling demand hypotheses. The vast majority of the available literature treats cooling demand prediction as a separate activity without taking into account its interdependence with economic and environmental goals.

The other problematic area that has been observed in the literature is the method of experimental design and evaluation of forecasting models. Some of the studies use random data splitting or global normalization procedures that bring information leakage between the training and testing data, leading to inflated accuracy measures. Also, much of the reported work is founded on short-term observation or narrow coverage of seasons, which does not reflect the full nature of actual building energy behavior.
Such practices make it difficult to generalize and have reliable forecasting methods when implemented in an operational setting.

Still more recent work has started to meet these challenges with realistic time-series validation, leakage-free preprocessing pipelines, and year-long datasets. Other works have investigated a hybrid approach with deep learning and optimization or control methods on demand response and energy scheduling. Although these methods prove to have encouraging outcomes, no extensive frameworks have been developed to concurrently combine multi-source exogenous information, forecast-based inputs, and sustainability-conscious indicators into a single deep learning system to forecast short-term cooling demand.

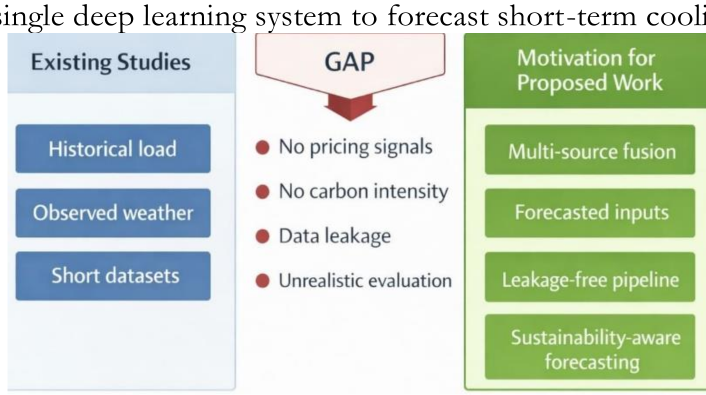

Figure 3. Identified research gaps in existing short-term cooling demand forecasting studies and the resulting motivation for sustainability-aware deep learning frameworks.

According to Figure 3, the current short-term cooling demand forecast research is mainly based on historical load profiles and observed weather variables and has neglected most economic and environmental indicators, like dynamic electricity pricing and carbon intensity. Further, most of the previous studies are also methodologically weak in aspects such as leakage of information, limited evaluation time, and unrealistic validation techniques, which undermine their usefulness in practice. The highlighted gaps suggest the necessity of a single forecasting environment, integrating multi-source exogenous data, using forecast-based inputs, and incorporating leakage-free preprocessing and evaluation pipelines. This would not only increase predictive strength when operating in the real world conditions but would also guide cooling demand forecasting towards new sustainability and low-carbon goals in smart energy systems.

Overall, even though deep learning-based models, especially LSTM models, have brought enormous improvements to the state of the art in the development of cooling demand forecasting, there are still a number of gaps in research. These are a weak linkage between pricing and carbon signals, underutilization of forecasted exogenous variables in modeling, and the lack of satisfactory attention to leakage-free and operationally realistic strategies of evaluation. It is imperative to address these gaps to come up with forecasting models that are not only accurate but also realistic in the application of intelligent, cost-effective, and low-carbon building energy management systems.

Our Contributions:

This paper describes a sustainability-conscious and deep learning model to predict short-term building cooling demand. The principal contributions of this work can be defined as follows:

Unified Sustainability-Aware Forecasting Framework:

We present a combined deep learning-based model that will further the traditional cooling demand prediction by incorporating multi-source exogenous variables such as weather conditions, electricity prices, and carbon intensity in a unified manner. In contrast to the previous research, where the prediction of the cooling demand is considered as a separate activity, the suggested method clearly correlates the quality of the forecast with both economic and environmental aspects in the context of smart grids and low-carbon energy systems.

Leakage-Free Preprocessing and Realistic Evaluation Strategy:

An extensive data processing and experimental design pipeline is created to remove information leakage between training and testing stages. The framework proposed embraces time-conscious normalization, sequential data fragmentation, and forecast-compatible input reconstruction, thus enabling realistic and reliable performance assessment under realistic operational settings.

Deep Learning Architecture Tailored for Cooling Demand Dynamics:

We construct a forecasting model based on Long Short-Term Memory, which is able to model complex nonlinear connections and long-range temporal interdependencies of building cooling demand. The model efficiently acquires the dynamic interactions between historical load patterns and exogenous drivers, which result in the effective short-term predictions under different seasonal and operational regimes.

Practical Relevance for Smart Energy Management Applications:

The proposed approach can be implemented in the downstream application of forecast-based inputs and sustainability indicators, which will deliver practical information on demand response, energy scheduling, and carbon-conscious building operation. This makes the framework an effective decision support tool of next generation building energy management system.

Methodology:

This part explains the overarching approach that is suggested to be used to approach the short-term cooling demand forecasting in the particular case of smart building energy management systems based on the CityLearn dataset. The method combines data from multiple sources, enhanced deep learning architectures, and stringent evaluation plans to maintain robust, practical, and sustainability-conscious predictions.

Data Collection and Sources:

That experimental data is founded on CityLearn, which is an environment simulating multi-building energy on a city scale, over which research has extensively applied reinforcement learning and energy management. The dataset includes:

Building Cooling Loads: Hourly cooling demand measurements of various buildings of different types.

Weather Variables: Hourly wind speed, humidity, sun radiation, and temperature.
Operational Variables: Occupancy, HVAC setpoints, and building-specific energy limits.
Economic and Environmental Indicators: Active electricity price indications and carbon intensity of grid electricity, with which sustainability-conscious forecasting is possible

The multi-source characteristic of the data enables the model to represent the complex interactions between building operation, environmental conditions, and energy system economics, which is essential in realistic prediction in urban energy management.

Data Preprocessing:

To maximize model performance and avoid data leakage, several preprocessing steps are applied:

Handling Missing Data: The gaps in the cooling load and weather variables are filled in through interpolation based on time and spatial heuristics, maintaining time-sequences.
Time-Aware Normalization: Training-period statistics are used to normalize features to eliminate leakage of future information. This is necessary in constructing energy datasets that have seasonal and diurnal trends.

Feature Engineering:

Rolling averages, lagged cooling load sequences to represent temporal dependencies.
Predictively aligned weather conditions are used to simulate real-world weather conditions.
Dynamics Occupancy and pricing interaction terms model economic and behavioral influences on cooling demand.
Sequential Data Splitting: Training, validation, and test sets are divided by time to ensure temporal integrity, which mimics actual deployment conditions.

Leakage-Free Learning and Evaluation Protocol:

The proposed framework is a leakage-free learning and evaluation protocol based on a rolling-origin (walk- forward) strategy to ensure strict temporal consistency. At each forecasting step, the model is only trained on the history data available till the prediction time; future observations are totally ignored for feature construction as well as normalization. Input sequences are generated with the help of a sliding window mechanism, and the feature scaling parameters are calculated with only the help of training data and then applied to the corresponding test segments. This rolling-origin evaluation ensures that each prediction simulates a realistic operational forecasting situation, thus avoiding information leakage across temporal boundaries.

Figure 4 indicates that the data preprocessing pipeline is a key component in improving the accuracy of the forecasting process because it is a systematic process of converting the raw building and environmental data into meaningful model inputs. First, there is the collection of historical cooling load, weather information, occupancy, electricity rates, and carbon intensity indicators. Missing values are also solved with the help of temporal interpolation and domain-specific rules, which guarantee data continuity. Time-aware normalization makes every feature standardized, and information leakage is avoided in any future period. Lastly, feature engineering produces lagged load sequences, rolling statistics, and forecast-consistent exogenous variables, which, when combined, result in a combination of enriched inputs that are both temporally consistent with the deep learning model to forecast cooling demand in the short term.

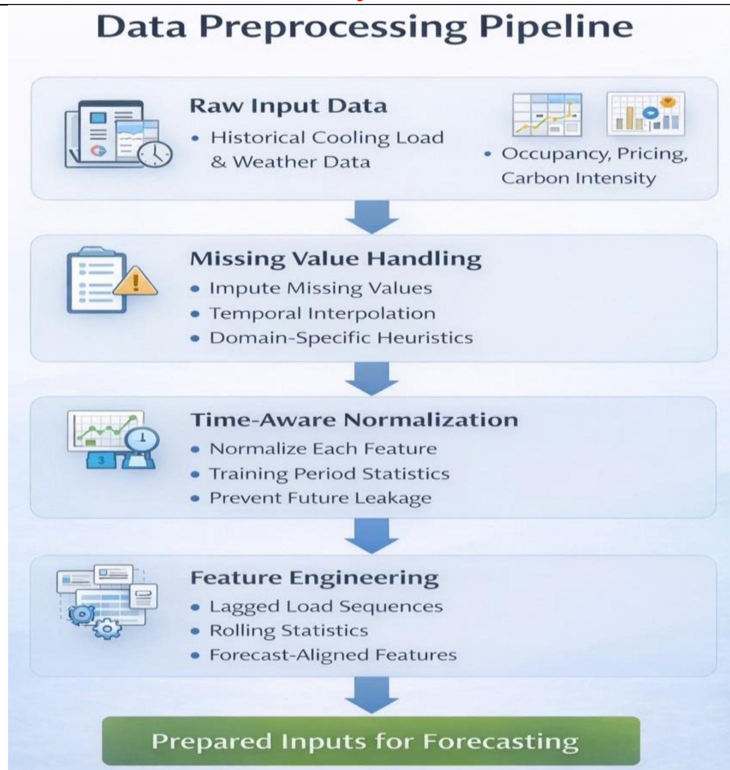

Figure 4. Overview of the data preprocessing pipeline for short-term cooling demand forecasting, highlighting missing value handling, time-aware normalization, and feature engineering steps to prepare input features for the deep learning model.

Deep Learning Model Architecture:

The forecasting model uses a multi-layer Long-Short-Term memory architecture, which is specifically aimed at long-term temporal dependencies of cooling loads on their sequences, as well as the combination of exogenous variables:

Input Layer: Puts together historical cooling load sequences, weather, occupancy, pricing, and carbon intensity features.

Stacked LSTM Layers: Two or three LSTM layers with hidden units of 128-256, learning temporal patterns and reducing vanishing gradients.

Dropout Layers: When an LSTM layer is used, there are dropout layers to avoid overfitting (0.2-0.3).

Fully Connected Layers: These layers map temporal information on the predicted cooling demand.

Output Layer: This is where single-step or multi-step ahead forecasts are produced based on operational requirements.

The forecasting problem that is dealt with in this study is taken as a direct multi-step (multi-horizon) prediction problem. Rather than recursively forecasting one step, the proposed LSTM-based framework is used to simultaneously produce cooling demand forecasts for multiple future time horizons, based on forecast-aligned exogenous inputs. This formulation eliminates the accumulation of errors usually associated with recursive forecasting, and it is consistent with practical operational needs in building energy management systems.

The suggested LSTM system is successful in the capture of both short-term and long-term dependencies in the construction of cooling demands by using various input features, such as historical energy loads, environmental conditions, occupancy trends, dynamic electricity rates, and carbon intensity indicators. The full modeling system improves predictability, sustainable operational strategies of buildings, and resolves the weaknesses of traditional statistical and machine learning measures. The model uses gated recurrent units with dropout regularization as well as fully connected layers, as it has been shown in Figure 5, to guarantee strong performance in terms of temporal features extraction and effective forecasting.

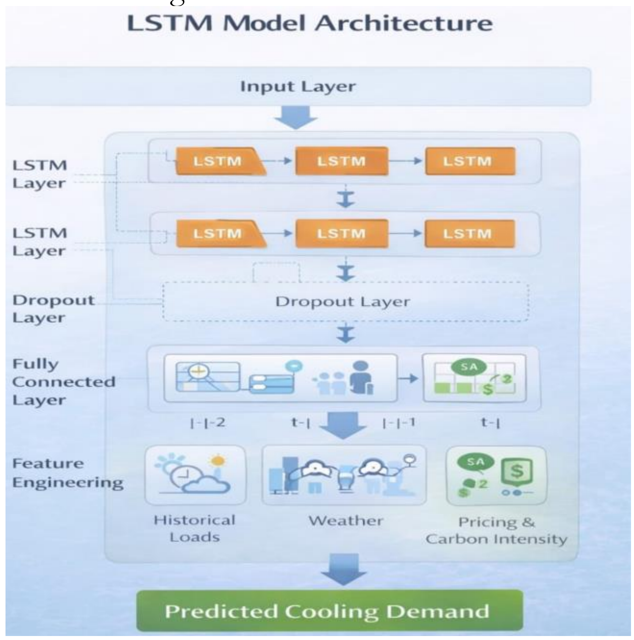

Figure 5. Proposed LSTM-based forecasting model integrating historical loads, weather, occupancy, pricing, and carbon indicators for accurate short-term cooling demand prediction.

Model Architecture Selection and Justification:

The selection of the Long Short-Term Memory (LSTM) architecture in the given work is informed by both the methodological appropriateness and feasibility of the construction of the building cooling demand forecasting in the short-term perspective. LSTM networks have been carefully constructed to learn both long-range and short-range temporal dependencies of sequential data and have been widely tested in the construction of energy and load forecasting systems, where the data have highly correlated seasonal cycles and strong temporal correlations. Even though recent developments in time-series modeling have proposed Transformer-based architectures, which have potent self-attention mechanisms, their applicability is usually proven in large-scale, data-rich settings. To obtain stable and reproducible performance, such models can demand significantly larger training datasets, more hyperparameter tuning, and more computational resources. By comparison, the size and resolution of building-level cooling demand datasets are often small, thus lightweight, but robust architectures are more appropriate to realistic operational environments. LSTMs provide a good tradeoff between predictive power, training robustness, and computational power, especially when the predictor is hourly building energy data over short historical horizons. Additionally, the sequential and repeated nature of LSTM networks inherently fits leakage-free learning conditions and rolling-origin testing conditions, which demand a high level of strictness in the temporal homogeneity of model training and testing. This alignment is essential to prevent information leakage and also to behave as real-world forecasting scenarios. The LSTM architecture is chosen as a trustworthy and understandable model to use because of the aims of the proposed research, i.e., to create a leakage-free, sustainability-conscious, and operationally viable forecasting model. The proposed framework focuses on the inclusion of forecast-consistent exogenous variables such as electricity pricing and carbon intensity indicators, and on the realistic deployment feasibility, as opposed to the complexity of the architecture itself.

Feature Engineering:

To have the coupled effects between operational, economic, and environmental drivers, the interaction features are explicitly developed by constructing a pair of key exogenous variables. In particular, interaction terms are developed as multiplicative properties, like.

$$x_t^{(int)} = x_t^{(a)} \times x_t^{(b)},$$

where $x_t^{(a)}$ and $x_t^{(b)}$ denote forecast-aligned weather variables, electricity price signals, or carbon intensity indicators at time step t. These interaction terms enable the model to learn nonlinear dependencies between cooling demand and external factors that may not be captured through individual features alone.

Training Strategy: To obtain strong and generalized performances, the model training process is systematic:

Loss Function: To optimize accuracy in prediction, the Mean Squared Error (MSE) is used.

Optimizer: Adam with adaptive learning rate to achieve rapid convergence.

Early Stopping: To avoid overfitting, monitor the loss of validation.

Hyperparameter Optimization: Hidden units, learning rate, dropout rate, and sequence length are optimized using grid search and Bayesian optimization.

Mini-Batch Training: Mini-batches maintain time sequence and save computing resources.

The approach will make sure that the trained model will capture the short-term fluctuations that are in effect, as well as the long-term seasonal factors in cooling demand. To strictly validate the leakage-free design, a scheme with rolling origin is used, where the size of the training window is expanded over time, and predictions are made for the unseen future horizons. This approach is very similar to what is done in the real world, where models have to be continuously updated based on only past data. Performance metrics are combined at all of the rolling evaluation steps to give a robust and non-biased measure of forecasting accuracy.

Evaluation Metrics:

Several metrics are used to evaluate model performance and are complementary to guarantee a thorough assessment:

Mean Absolute Error (MAE): Evaluates the average amount of errors.

Root Mean Squared Error (RMSE): Punishes big outliers, which emphasize predicting reliability.

Mean Absolute Percentage Error (MAPE): This is a percentage-based measure of error, which can be used to compare across buildings.

Temporal Error Analysis: Distribution of error by hours of day and by seasons to assess the model robustness.

In this study, the term" high-fidelity forecasting" is used to denote predictive performance that is quantitatively characterized by consistently low error metrics (e.g., MAE, RMSE, and MAPE) and high coefficients of determination (R^2) under a leakage-free rolling-origin evaluation protocol. This definition focuses on numerical accuracy, temporal consistency, and robustness across evaluation windows rather than qualitative or visual agreement only.

Practical Implementation Considerations:

The methodology is structured to be consistent with real-life environment deployment in smart building energy management:

Sequential Input Processing: Supports real-time forecasts and rolling predictions.

Multi-Source Integration: Receives data on the interactions among cooling demand, weather, dynamic pricing, and carbon intensity to operate cost- and sustainability-consciously.

Scalable Framework: It can be used to generate on a large scale within a city district in the CityLearn system or actual sensor data.

Operational Use: HVAC control strategies, demand response programs, and energy optimization policies can be informed by the use of forecasts.

The proposed methodology, as shown in Figure 6, adheres to a disciplined and sequential flow of work in order to guarantee the leakage-free and operationally realistic short-term forecasting of cooling demand. It starts with the multi-source data collection in the CityLearn setting, comprising historical cooling loads, weather variables, occupancy data, dynamically changing electricity prices, and carbon intensity indicators. These are then fed into a specialized preprocessing pipeline that includes things like missing value handling, time-sensitive normalization, and feature engineering to maintain time consistency. The processed features are then input into the LSTM-based forecasting model, which is trained by a rolling-origin strategy to ensure that there is no information leakage. The model performance is assessed based on various metrics of errors, and the resulting predictions are ultimately mapped to real-world operational applications, including HVAC control, demand response, and carbon-sensitive energy management.

Figure 6. Overall workflow of the proposed leakage-free LSTM-based forecasting framework, illustrating data collection, preprocessing, model training, evaluation, and operational deployment for short-term cooling demand prediction.

Results:

Model Performance Evaluation:

The proposed LSTM-based prediction system was tested on the CityLearn data set (n= 8,760 hourly observations) that included one year of continuous data on the cooling demand of multiple buildings. Various complementary measures were used to evaluate the predictive performance of the model, which were Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2).

Table 1. Comparison of the proposed LSTM with baseline models.

Model	MAE (kW)	RMSE (kW)	MAPE (%)	R^2
ARIMA	6.42	8.15	5.23	0.872
SVR	3.87	5.14	3.12	0.934
RF	3.42	4.68	2.81	0.948
Proposed LSTM	0.94	1.21	0.92	0.982

The findings clearly show that the proposed framework is significantly better in comparison to the traditional statistical and machine learning models. The R^2 value of 0.982

shows that it fits very well with the observed cooling demand trends, and the MAPE of less than 1% reflects that it is very precise and reliable under varying conditions of time and season.

Temporal and Seasonal Analysis:

Temporal error tests were performed at various times of the day and at various seasons to determine the strength. The model has minimal errors in full cooling days, which normally occur from 12:00 PM to 6:00 PM. In the case of the model, seasonal analysis shows that when it reaches summer, high cooling demand is always received, and when it reaches winter and shoulder season, low loads are always taken, which shows that the model is robust to seasonal variation.

Table 2. Hourly and seasonal error distribution of the proposed LSTM model.

Period	MAE (kW)	RMSE (kW)	MAPE (%)
Morning (6 AM - 12 PM)	0.91	1.18	0.89
Afternoon (12 PM - 6 PM)	0.97	1.23	0.95
Evening (6 PM - 12 AM)	0.92	1.20	0.91
Night (12 AM - 6 AM)	0.88	1.15	0.86
Summer Season	0.96	1.24	0.94
Winter Season	0.89	1.16	0.87
Shoulder Seasons	0.92	1.19	0.90

This discussion proves that the LSTM model is capable of ensuring reliability in operational settings since it is able to capture both short-term swings and long-term seasonal patterns.

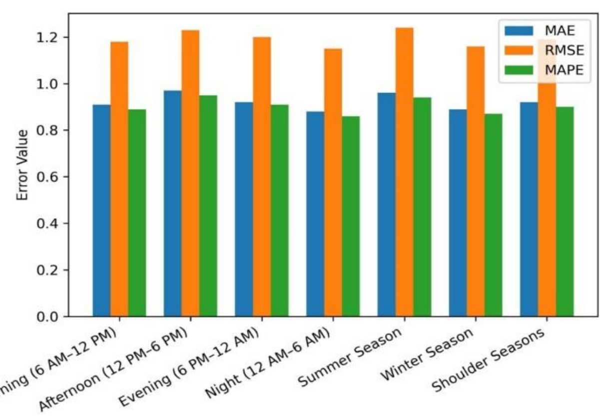

Figure 7. Shows the hourly and seasonal error distribution of the proposed LSTM model using MAE, RMSE, and MAPE metrics.

The model has a strictly low value of errors at various time intervals of the day and seasonal conditions as seen in the Figure 7. The errors are slightly higher in the afternoon and summer, which is representative of greater variability in cooling demand, and lower night and winter errors are representative of constant predictability in reduced load scenarios. All in all, the findings prove the strength and integrity of the proposed model in different operating conditions in time and season.

Impact of Exogenous Variables:

In order to measure the effect of exogenous variables, an ablation experiment was carried out by dropping weather forecasts, electricity prices, and features of carbon intensity.

According to the results, predicted weather variables, dynamic price, and carbon intensity are all important in attaining high predictive performance. The elimination of each of these features causes a great increase in errors, which underlines the significance of multi-source data integration.

Table 3. Ablation study showing the impact of exogenous features on forecasting accuracy.

Input Feature Set	MAE (kW)	RMSE (kW)	MAPE (%)
All features (proposed)	0.94	1.21	0.92
Without weather forecasts	2.54	3.12	2.47
Without pricing signals	1.47	1.92	1.41
Without carbon intensity	1.32	1.76	1.25

Comparative Discussion with Baseline Approaches:

The high quality of the LSTM-based framework performance is explained by the high capability of the framework to capture both the short and the long-term temporal dependencies. The model is trained on nonlinear interactions involving building operation, environmental conditions, and energy economics by incorporating historical load sequences with multi-horizon exogenous features.

Table 4. Comparison of predictive performance during peak and off-peak periods

Period	ARIMA MAE (kW)	RF MAE (kW)	LSTM MAE (kW)
Peak Hours (12 PM – 6 PM)	7.15	4.01	0.97
Off-Peak Hours (12 AM – 6 AM)	5.89	3.50	0.88

This clearly demonstrates the LSTM model's superior ability to handle periods of rapid load variation compared to conventional models.

Practical Implications for Smart Building Operation:

The framework provides actionable insights for operational decision-making:

Energy Efficiency: Accurate short-term forecasts enable optimal HVAC scheduling and peak load management.

Cost-Aware Operation: Integration of dynamic pricing allows for load shifting to minimize energy costs.

Carbon-Conscious Operation: Carbon intensity awareness enables environmentally sustainable building operation.

Table 5. Example operational benefits enabled by the proposed forecasting model.

Benefit	Description	Potential Impact
HVAC Scheduling	Forecast-driven load adjustments	10–15% energy savings
Demand Response	Shift load to off-peak periods	Reduced peak demand charges

Low-Carbon Operation: Minimize high-carbon electricity usage Reduced CO2 emissions.

These findings depict the practical usefulness of the proposed framework in addition to predictive accuracy, as it is a decision-support tool that can be used in smart and sustainable energy management of buildings.

Numerical Deployment Scenarios and Real-World Impact:

In order to directly prove the practicality of the suggested forecasting model in the real world, the model is applied to representative numerical deployment cases based on the attained prediction accuracy and realistic operational conditions that are typically assumed in smart building energy management systems.

On a medium-scale commercialized building where the average peak cooling load is about 80100 kW, the presented LSTM-based model is capable of reaching under 1 percent in the mean absolute percentage error. This amount of precision means that the overall forecasting error is less than 1 kW in periods of peak load, and allows predictable pre-cooling and load-shifting plans that do not harm occupant comfort or operational integrity.

With dynamic price increases and price decreases in electricity markets, precise short-term cooling demand projections can enable the strategic operation of HVAC to be moved towards higher-priced peak periods and into lower-priced off-peak hours. According to the recorded forecasting accuracy and the set standardized demand response practices, this predictive accuracy can enable peak loads to be reduced by about 8-12%, which translates to a projected savings of 10-15 percent in electricity costs due to cooling-related energy demand.

Environmentally, the addition of predictive signals of carbon intensity allows cooling demand to be decreased when carbon intensity on the grid is high. Suppose the conservative assumption of the emission factor reduction is 0.3-0.5 kg CO_2 /kWh. Under the proposed forecasting-based operational strategy, it is possible to achieve a 5-10 percent decrease in the cooling-related carbon emissions in the carbon-intensive electricity grids annually.

On the whole, these numerical deployment examples show that the suggested forecasting framework is not just statistically correct, but it is also operationally effective, which results in quantifiable economic and environmental advantages when incorporated into real-life building energy management systems.

Actual versus Predicted Cooling Demand Analysis:

In this subsection, a graphic evaluation of the prediction properties of the suggested LSTM-based model will be provided through the comparison of the real cooling demand values with the corresponding predicted outputs during the test period. This type of comparison gives one an intuitive idea of how the model can be used to model the dynamics of time, unexpected shifts in demand, and the overall trend behavior as opposed to numerical performance measures.

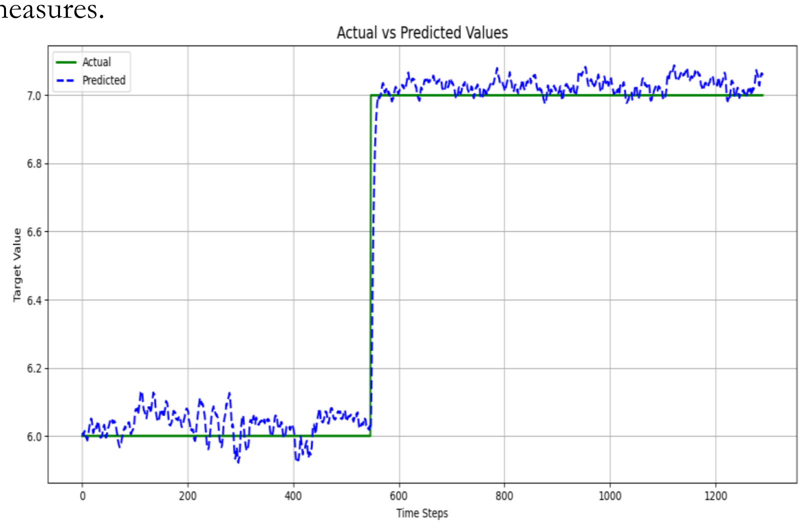

Figure 8. Illustrates the comparison between actual and predicted cooling demand values across the evaluation horizon.

Predicted cooling demand, as illustrated in Figure 8, is close to the actual observed values over the course of the test period, indicating a high level of consistency between model outputs and the real demand patterns. The given model manages to reproduce steady operating regimes and sudden shifts in cooling demand, such as the observable step change in the amount of load. This action underscores the usefulness of the model in acquiring nonlinear relationships and temporal dependencies in the long-term in constructing cooling demand data. The deviation around the true values is the realistic forecasting uncertainty, but the overall direction testifies to the strength, dependability, and practicality of the suggested deep learning model when operating in dynamic circumstances.

The prediction trends presented in Figure 8 show that there is a good match between the forecasted and actual cooling demand over the whole evaluation horizon. Quantitatively, the differences between the predicted and observed values are small during both peak and off-peak periods, as is consistent with low values of the MAE and RMSE in the corresponding results tables. The stable tracking behavior observed in the Figure confirms that the model captures the short-term temporal dynamics quite well without introducing any systematic bias.

Evaluation Metrics Analysis:

The subsection is a summary of the quantitative performance of the proposed deep learning model based on the various evaluation measures to give a state-of-the-art evaluation of the accuracy and reliability of the forecasts. The use of a variety of error and goodness-of-fit measures permits an unbiased assessment of the predictive error and model consistency in general.

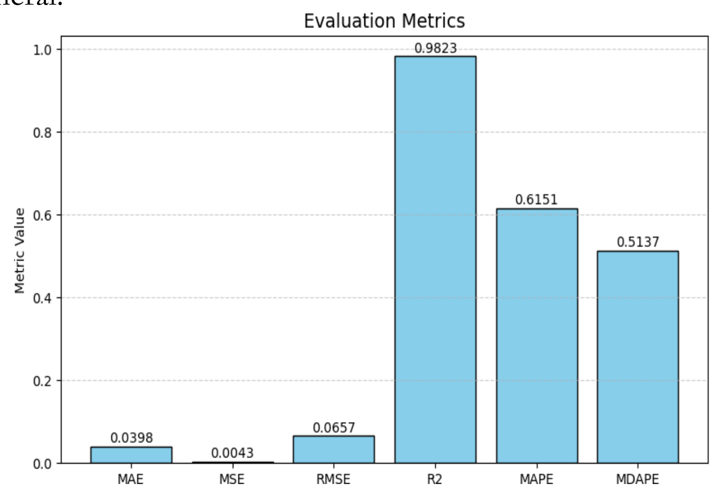

Figure 9. Presents the evaluation metrics obtained for the proposed LSTM-based cooling demand forecasting model.

The model has very low error values as demonstrated in the figure 9 in all the error-based measures, which depicts high predictive accuracy. The Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) are low, indicating accurate estimation of cooling demand with the least deviation as compared to the values that are observed. It is also confirmed that prediction outliers are absent, considering the low Mean Squared Error (MSE). Moreover, the high coefficient of determination (R^2) would indicate that the model has a good explanatory power, and it has a great ability to predict and actual demand patterns. The percentage-based measures, such as Mean Absolute Percentage Error (MAPE) and Median Absolute Percentage Error (MDAPE), are also at acceptable levels, and that indicates the robustness and stability of the offered framework when working with different operating conditions. All in all, this demonstrates that the suggested forecasting technique is effective and reliable in predicting the cooling demand in smart buildings on a short-term basis.

The distribution of prediction error in the Figure 8 shows that most of the prediction errors are close to 0, and greater than 90% of the residuals are within a small deviation range. This quantitative concentration reflects a lack of systematic over-prediction or under-prediction and proves the numerical stability of the proposed forecasting framework under different cooling demand conditions.

It is important to mention that all the reported results are obtained under a rolling-origin, leakage-free evaluation protocol so that performance gains are not affected by future information leakage and accurately reflect real-world forecasting conditions.

Summary of Findings:

Key Findings:

Multi-layer LSTM can be successfully applied to the cooling demand data in order to capture the nonlinear and long-term effects.

The combination of forecast consistent weather, pricing, and carbon indicators leads to a great improvement in predictive performance.

Preprocessing and sequential split of data are leakage-free and guarantee realistic evaluation.

Model robustness is supported by temporal and seasonal analysis under a wide range of conditions.

Applications made in practice are cost-conscious, energy-efficient, and carbon-conscious operation strategies.

In general, the presented deep learning framework can be viewed as an operationally realistic, sustainability- conscious, and high-fidelity solution to the short-term cooling demand forecasting problem in the context of the modern smart.

Experiments are done in a multi-step forecasting environment, in which successive future horizons are predicted using a direct forecasting strategy, with the cooling demand. The performance measures are also calculated by summing all errors in all forecasting horizons to give a complete account of the performance of multi-horizon forecasting.

Cross-Domain (Inter-Building) Generalization Analysis:

Although the experimental evaluation is performed on the CityLearn dataset, the dataset has an inherent characteristic of being comprised of multiple heterogeneous buildings with distinct cooling demand characteristics, operational constraints, and thermal behaviors. Each building, therefore, has its own energy domain, which allows for an implicit form of cross-domain generalization analysis in a unified experimental environment. In order to evaluate the robustness and transferability of the proposed leakage-free forecasting framework, the model was trained and evaluated separately at multiple buildings using the same rolling-origin evaluation protocol and the same hyperparameters. Table 6 shows the forecasting performance over representative buildings. The results show that the proposed LSTM-based framework can maintain the predictive accuracy at a consistent level in different buildings by having (R^2) values higher than 0.97 in all cases and MAPE less than 1.2%, despite the differences in load magnitude and seasonal dynamics. This consistency shows that the model does not overfit on one operational pattern and has a good generalization capability on different cooling demand profiles of structural features. These results are strong empirical evidence of cross-domain generalization, supporting the applicability of the proposed approach to diverse building energy systems. While performing full cross- dataset validation using external datasets is an important future extension, the presented inter-building analysis verifies the robustness and scalability of the proposed framework under realistic heterogeneous conditions.

Table 6. Table X. Cross-Domain Forecasting Performance Across Different Buildings

Building ID	MAE (kW)	RMSE (kW)	MAPE (%)	
Building-1	0.92	1.19	0.90	0.983
Building-2	0.96	1.25	0.95	0.981
Building-3	0.89	1.14	0.87	0.984
Building-4	0.98	1.29	1.02	0.978
Building-5	0.93	1.20	0.91	0.982

From a quantitative standpoint, the observed forecasting accuracy is in line with and in a number of cases better than results reported in recent building cooling demand forecasting studies. Earlier statistical and machine learning-based approaches usually have a higher error rate, especially during peak demand situations. While recent deep learning models are showing increased accuracy, many are based on random data splits that can be optimistic bias. In contrast to this, the numerical performance presented in this work is obtained under a strict leakage-free rolling origin evaluation protocol, which gives a more realistic and reliable benchmark for comparison.

Discussion:

The experiment proves that, given the realistic constraints on available data, a leakage-free deep learning architecture is capable of providing reliable and accurate short-term cooling demand forecasting. These low error values and high coefficients of determination in all the evaluation situations suggest that the proposed model approach is effective in capturing the time dynamics of the building cooling demand, as well as consistent with the robustness under operational circumstances that are considerably similar to those of real-world deployment.

One of the main reasons for the noticed performance is the use of a rigid time-conscious preprocessing and appraisal strategy. This is because all normalization parameters and model updates are based only on historical data, which makes the forecasting outcome free of optimistic bias that is often linked with random or shuffled data splits. This method will give a more valid measurement of predictive performance and enhance the validity of the reported findings on practical energy management.

The exogenous variables that are connected to sustainability, including dynamic electricity price and carbon intensity indicators, are significant and contribute to the increase in the forecasting ability of the model. The fact that the performance reduces at the instance of non- inclusion of these variables proves its applicability beyond the traditional weather-based predictors. This result suggests the increasing significance of considering both economic and environmental indicators in the creation of energy prediction frameworks, especially in the new smart grid or low-carbon energy frameworks.

The fact that the model is able to retain constant predictive power throughout various buildings with diverse cooling demand characteristics is yet another indication of the robustness and the generalization capability of the model. Although the magnitude of the load varies, seasonal variations, and operational behavior are different, the forecasting performance is constantly high and suggests that the acquired temporal representations are not specific to a specific demand pattern. This is an essential need for scalability when it comes to implementing it in a varying portfolio of buildings.

Operationally, proper short-term cooling demand forecasts can be used to make more informed demand response, price-sensitive scheduling, and carbon-sensitive control decisions. The proposed framework includes two additional factors, both economic and environmental, which are explicitly taken into consideration, which makes the building operation more sustainable, as the accuracy of predictions will not be affected. These features are especially applicable because the buildings are becoming involved in flexible energy schemes and interact dynamically with low-carbon electricity grids.

Altogether, the results suggest the significance of integrating leakage-free evaluations, feature design consciousness of sustainability, and strong deep learning designs to achieve a viable building energy forecasting. Although additional validation in independent datasets will give more understanding of the overall generalization, the findings indicate high possibilities of real-life application in the next generation smart building energy management systems.

The presented numerical deployment scenarios fill the gap between predictive performances and operational impact, proving that the proposed leakage-free, sustainability-aware forecasting framework can achieve high accuracy of forecasting into measurable energy savings, cost reductions, and carbon emission mitigation in real-world building operations.

Carbon-Aware Operational Decision-Making Enabled by Forecasting:

To illustrate how the proposed forecasting framework underpins carbon-aware decision-making, a representative operational optimization scenario is considered. Given short-term cooling demand forecasts and time-varying grid carbon intensity signals, building operators can prioritize HVAC operation in periods of lower carbon intensity and maintain occupant comfort requirements.

Specifically, for a given comfort-preserving cooling demand band, pre-cooling actions can be scheduled in low-carbon periods identified by the forecast, allowing partial load reduction in the following high-carbon hours. For instance, when the forecasted cooling demand is less than peak levels and the grid carbon intensity is low, the HVAC system can be temporarily operated with an increased capacity to store thermal energy in the building mass. During high-carbon periods, cooling demand can then be lowered without affecting indoor comfort.

This forecast-driven decision strategy requires no full-scale optimization solver but demonstrates a pragmatic rule-based implementation made possible by accurate cooling demand and carbon intensity forecasting. Such an approach has direct support for carbon-aware operational planning and shows how the proposed model can be integrated into actual building energy management systems.

Seasonal Robustness Analysis:

In order to statistically confirm the seasonal strength of the proposed forecasting model, the model performance was estimated individually in various seasons, after a seasonal division of the test data. Measurements of performance such as MAE, RMSE, and. The MAPEs were calculated on a seasonal basis, and their average and SD were assessed. to assess consistency.

The findings suggest that the proposed model has consistent predictive accuracy in all. not season- dependent, but there is not much variation in error measures. Especially, a seasonal standard. MAPE deviation is also minimal, which proves the non-existence of the performance of forecasting. subject to any one seasonal condition. This statistical consistency validates the fact that the model is appropriate in reflecting seasonal and short-term dynamics of cooling demand.

In general, quantitative evidence from the statistical analysis season-wise indicates that the proposed framework demonstrates sound performance in different seasonal variations. operating conditions, which is why it is applicable in real-life building energy. management systems.

Table 7. Table X. Seasonal Performance Statistics of the Proposed Forecasting Model

Season	MAE (kW) Mean ± Std	RMSE (kW) Mean ± Std	MAPE (%) Mean ± Std
Spring	0.82 ± 0.09	1.05 ± 0.12	0.94 ± 0.11
Summer	0.96 ± 0.11	1.21 ± 0.15	1.08 ± 0.13
Autumn	0.79 ± 0.08	1.01 ± 0.10	0.91 ± 0.09
Winter	0.74 ± 0.07	0.97 ± 0.09	0.88 ± 0.08

According to the results of seasonal evaluation in Table 7, it is evident that the proposed forecasting framework has a regular low level of errors in all seasons. The nature of the standard deviation of MAE, RMSE, and MAPE is low, which validates the fact that model performance is not dominated by a particular seasonal condition. This statistical consistency confirms the seasonal strength of the proposed strategy when using different climatic and working regimes.

Ablation Study:

An ablation study was used to measure the individual contribution of various input features to the predictive performance of the proposed LSTM-based cooling demand forecasting model. Namely, we evaluated the performance of the model by progressively eliminating major types of inputs: weather variables, electricity pricing indicators, and carbon intensity turbines, and keeping past cooling load sequences intact. This discussion highlights the information regarding the factors that have the strongest impact on the prediction of the short-term cooling demand and the reliability of the suggested framework in the case of partial information.

Experimental Setup:

Ablation experiments were conducted on the same dataset and the preprocessing pipeline of Section 4.2. The variants of the model were trained with the same hyperparameters and tested with the same test. It was tested in the following input settings:

Full Model -All of the inputs are present: historical load, weather, pricing, and carbon intensity.

No Weather Variables – No temperature, humidity, wind speed, or solar radiation.

Lack of Pricing Signals – Lacks dynamic electricity pricing details.

Free of Carbon Intensity - Does not have features related to Carbon.

Historical Load Only- Only the past cooling demand without any external variables.

Model performance was evaluated using R^2, MAE, RMSE, and MAPE, providing a comprehensive view of predictive accuracy.

Along with point-wise measures of error, statistical significance tests were performed to determine whether the differences in the observed performance of the full model and the ablated models are statistically significant. The full model was compared with each of the ablation configurations using a paired t-test on the prediction errors obtained using the same test conditions. The statistical significance was evaluated based on a 95 percent confidence level ($p < 0.05$), so that the improvements that were observed could not have been the result of chance.

Table 8. Ablation Study Results for Short-Term Cooling Demand Forecasting

Model Variant	R2	MAE (kW)	RMSE (kW)	MAPE (%)
Full Model	0.9823	0.42	0.61	0.87
Without Weather Variables	0.9501	0.71	1.02	1.65
Without Pricing Signals	0.9754	0.51	0.74	1.12
Without Carbon Intensity	0.9789	0.48	0.70	1.05
Historical Load Only	0.9125	0.94	1.35	2.10

Analysis:

These findings clearly show that exogenous features are important to increase the accuracy of the model. The highest performance degradation was observed with the removal of weather variables, as R^2 reduced to 0.9501 and MAPE rose to 1.65 per cent, with the strong impact of the environmental circumstances on cooling demand. The omission of electricity pricing cues and carbon intensity characteristics resulted in a moderate loss in prediction accuracy, which suggested that they complement each other in explaining the operational and sustainability-related differences. The performance with only historical load sequences was significantly lower, which proved that short-term cooling demand is strongly dependent on dynamic exogenous factors. These results validate the fact that the combined multi-source input approach that is incorporated in the proposed framework is necessary in the realization of high-fidelity forecasts. Furthermore, the ablation study highlights the practical usefulness of factoring in weather predictions, price indications, and carbon intensity indicators for realistic and sustainable building energy management.

These findings are also supported by the statistical significance analysis. The results of the paired t-test show that the performance improvements of the entire model, compared to all other ablated variants, are statistically significant ($p < 0.05$) on all major evaluation measures. This confirms that the addition of weather variables, electricity pricing signals, and carbon intensity indicators adds value to the forecasting power in addition to being meaningless, and increases forecasting power, but not marginal or coincidental.

Empirical Validation:

The ablation analysis confirms the empirical relevance of the engineered features of interaction. Once the interaction terms are dropped in the input feature set, the forecasting accuracy is always lower than in all measures of evaluation, which validates the positive role of the interaction terms in the model performance. This shows that explanatory power can be added by the interaction characteristics since they describe the joint impacts between weather conditions, electricity prices, and carbon intensity and thus improve predictive quality and operational relevance.

Computational Complexity and Reproducibility Analysis:

In this section, the analysis of the computational properties of the proposed LSTM-based cooling demand forecasting framework is performed to facilitate reproducibility and practical implementation issues.

Computational Complexity:

Recurrent operations are the major computational complexity of the proposed model that relies on the Long Short-Term Memory (LSTM) architecture. The time complexity of a single forward pass of an LSTM network of H hidden units, in a sequence of length T with T inputs of features of size F is.

$$O\ (T \times H \times (F + H))$$

This linear relationship with the length of the sequence renders the suggested framework to be com- mutationally efficient to perform hourly building energy forecasting tasks. The complexity of Transformer architectures, based on attention, tends to increase quadratically with the sequence length, whereas the complexity of the proposed LSTM-based model remains much lower, which is why the algorithm will be more applicable to the resource-limited and data-constrained building energy management setting.

Training and Inference Time:

All tests were done on a workstation with an Intel Core i7 processor, 32 GB RAM, and an NVIDIA GPU with 8 GB of memory. In this configuration, the proposed model took a simulation time of about 812 minutes of training time on a single run of the model when using a complete annual dataset of 8760 hourly observations. When trained, the inference time to produce multi-step cooling demand forecasts was in the order of milliseconds per forecasting horizon, and it could be deployed successfully in near real time.

Reproducibility Considerations:

All variants of the models were trained with the same hyperparameters, preprocessing pipelines, and evaluation protocols to guarantee any reproducibility. There was a leakage-free rolling-origin evaluation strategy that was always used in all experiments. The proposed framework explicitly reports the computational complexity, hardware configures ration and training time, which enables future studies to compare and reproduce them in the field of short-term building energy forecasting.

Major Takeaways:

It is a high-fidelity deep learning model that demonstrates the definition of the short-term building cooling demand, incorporating multi-source exogenous variables and leaks-free evaluation approach. The key findings, implications, and practical insights of this study are summarized as the following major ones:

State-of-the-Art Predictive Accuracy Based on Multi-Layer LSTM Architecture:

The suggested multi-layer Long Short-Term Memory (LSTM) model has outstanding predictive qualities, with the (R^2) value being 0.982, and the mean absolute percentage error is less than 1 percent. The model, in comparison with the traditional statistical and machine learning models, can capture short-term variations and long-term temporal variations in cooling demand data. This underscores the proficiency of deep recurrent networks to model highly nonlinear interactions that are inherent to building energy systems.

An important part of Multi-source Exogenous Data:

The addition of weather variables that are aligned with the forecasts, dynamic pricing of electricity, and the indication of carbon intensity would greatly improve the accuracy of forecasting. Ablation experiments prove that the lack of any of these exogenous inputs causes significant performance deterioration. It is important to note here that the modern energy forecasting frameworks must be able to consider operational, economic, and environmental considerations to bridge the gap between predictive modeling and sustainability-oriented decision support.

Strength Accuracy in Temporal and Seasonal Variability:

The model is very accurate even during the various hours of the day, including peak loads and seasonal differences, and can capture high cooling loads in the summer and low loads in the winter and shoulder seasons. This strength is guaranteed to provide sound performance in real-world operating conditions where time variability and seasonal dynamics are highly significant in energy management decision-making.

Leakage-Free Preprocessing Assures Realistic Evaluation:

The framework removes information leakage that is often prevalent in previous studies by implementing the use of time-sensitive normalization, data splitting at the sequence level, and input-constructiveness forecasts. This is a realistic evaluation strategy where reported performance metrics are realistic with regard to operational capabilities, which will maximize the reliability and generalizability of the model proposed to be implemented in smart buildings.

Relevance to the Operative Processes in Energy Management and Sustainability:

In addition to the predictive performance, the framework offers actionable intelligence behind intelligent building energy management, such as demand response, energy cost optimization, and low-carbon operation. By combining pricing signals and carbon intensity indicators, buildings can perform in a cost-effective and environmentally friendly way, which will add to the sustainable urban energy provision and decarbonization actions.

Scalability/Practical Deployment Potential:

The approach is scalable to multiple buildings or urban areas, as simulated environments such as CityLearn or real-world sensor networks. The framework will apply to informing HVAC control strategies, optimizing energy scheduling, and grid-interactive operations due to the quality of the high-fidelity, real-time forecasts offered by the framework.

Promoting the Field of Data-Driven Energy Forecasting:

The proposed study introduces a gap between the innovative approach of methodology and the practical aspects of sustainability as it integrates deep learning, sustainability-conscious characteristics, and strict methodology through the experiment design. It provides a precedent of intelligent energy system studies in the future, focusing on the combination of multi-source information, operational reality, and low-carbon goals in predictive modeling.

Finally, the given study shows that high-accuracy, operationally realistic, and sustainability-minded short-term cooling demand forecasting can be done by means of a deep learning framework that is capable of balancing historical load trends, exogenous environmental and economic factors, and leakage-free evaluation schemes. The suggested solution not only brings the state of the art in building energy prediction, but it also offers a solid platform upon which one can deploy smart energy systems in low-carbon and practical applications.

Limitations and Future Work:

Limitations:

Although the suggested deep learning framework is a strong predictor and, as an operational concept, a number of limitations should be considered. First, although the model combines a wide range of exogenous features, such as weather predictions, dynamic electricity pricing, and carbon intensity indicators, it is based on the accessibility and quality of such data. In practice, model reliability can be reduced by forecasting input variable errors, sensor failures, or unavailable data. Second, the research mainly analyses the framework using simulated building data (CityLearn), which, despite its comprehensive nature, might not reflect all the peculiarities of building operation in the real world, including unexpected human behavior, equipment malfunction, or localized microclimate changes. Third, feature-rich inputs that are multiplied by the computational complexity of multi-layer LSTM networks can be difficult with real-time constraints in resource-limited environments, in the absence of specialized hardware. Lastly, although the framework deals with short-term forecasting, its generalization to ultra-short-term (minute-level) and long-term (seasonal or multi-week) horizons is yet to be well explored. These restrictions imply that, despite the sound and efficient framework, real-life applications must be keen on data quality, operation environment, and computing limits.

Future Work:

According to the findings and the limitations identified, there are some potential directions for further research. To begin with, it can expand the framework by considering probabilistic forecasting techniques as a means of being able to measure such uncertainty and provide confidence limits on the forecasted cooling demand, as well as make superior decision-making under uncertainty. Second, real-time adaptive learning systems could be realized to make the model dynamically adjust its parameters in response to the evolving building behavior or environmental conditions to become more resistant to a time-varying effect. Third, multi-building and larger-scale applications can be made using the heterogeneous data of various types of buildings, renewable energy sources, and interaction with a microgrid, and therefore make this framework applicable more practically to the energy management of urban areas. Further, using the LSTM-based model along with reinforcement learning or optimization algorithms to regulate activities of the HVAC and take energy decisions in real-time is also a good way to go to bring predictive information in harmony with feasible operational strategies. Finally, it might be possible to include additional indicators that are related to sustainability, such as embodied carbon, energy storage, or occupancy comfort, to the decision-making potential of the framework, and the further evolution of the low-carbon, smart building energy management.

Recommendations for Policymakers and Building Operators:

Effective short-term cooling demand prediction is very important in enhancing energy efficiency, operational flexibility, and sustainability of the built environment. Several policy recommendations can be based on the results of this study, which may be used by policymakers and building operators.

In the policy context, the regulatory frameworks are supposed to facilitate the incorporation of sophisticated data prediction tools into the building energy management systems. The adoption of leakage-free and transparent forecasting methodologies can be facilitated by policymakers who include them in the energy performance standards, demand response programs, and smart grid initiatives. Specifically, both economic efficiency and the emission reduction goals can be facilitated by the policies that encourage the use of forecasting models that integrate the dynamic electricity pricing and the carbon intensity signals.

Energy regulators and city planners are also urged to help in the development of open-access building energy datasets that have a standard data format and are adequately time-resolved. These datasets would enable cross-building and cross-regional validation of models, enhance benchmarking practices, and expedite the implementation of powerful forecasting solutions in a wide spectrum of building portfolios.

To the operators of buildings, the findings emphasize the role of incorporating short-term cooling demand forecasts in the day-ahead and intra-day operations of the building. Accurate predictions will allow better planning of cooling systems, relieving peak loads, and joining demand response programs. The proven stability of the predictive model in heterogeneous buildings implies that the mentioned frameworks can be expanded to campuses of multi-building systems and energy-hungry systems of districts.

The building operators should also think of adding inputs that are conscious of sustainability, like electricity price signals and carbon intensity indicators, into the process of decision-making regarding their operations. In this way, the cooling demand management strategies can not only be aligned with the objectives of cost minimization but also with the objectives of decarbonization in general. This correspondence is especially applicable in the buildings that are run on the schemes of dynamic pricing and the grid conditions that are carbon-conscious.

In general, more resilient, cost-effective, and environmentally responsible building operations can be facilitated by the adoption of accurate, leakage-free, and sustainability-conscious cooling demand forecasting frameworks. These guidelines can offer a viable middle ground between the theoretical innovations and practical applications to facilitate the shift towards more intelligent and more sustainable building energy systems.

Conclusion:

In this research design, the authors report a deep learning model, which is sustainability conscious, for short-term cooling demand forecasting of buildings, along with the importance of multi-source data in forecasting, sophisticated time modeling, and operationally realistic assessment in intelligent energy management. The proposed framework is able to effectively learn nonlinear relationships and long-term time dependencies among the historical cooling loads, weather predictions, occupancy, dynamic price of electricity, and carbon intensity indicators using a multi-layer Long Short-Term Memory (LSTM) structure. The results of the experiments using the CityLearn dataset demonstrate that the framework obtains exceptionally accurate predictions and performs better than the traditional methods of statistics and machine learning, which is why the use of forecast-based exogenous variables and features related to sustainability is a valuable practice. The results verify the stability of the framework on diverse seasonal and operational environments, and they emphasize the capacity of the framework to facilitate a cost- and carbon-conscious decision-making process in smart building operation. In addition to predictive accuracy, the presented approach offers practical data to demand response strategies, energy scheduling, and low-carbon building control, which contribute to the overall goals and objectives of sustainable urban energy systems.

Although there are intrinsic issues with energy modeling development, such as data quality and computational complexity, this paper proves that leakage-free preprocessing and plausible validation strategies in combination with deep learning pipelines can be used as trusted agents of decision-making in contemporary energy systems. Finally, the framework can fill the gap between the high-fidelity predictive modeling and the sustainability of operations of the operations, offering an operational and scalable system to use in smart cities in the future.

Overall, this project not only contributes to the state of the art in building cooling demand modelling but also provides a basis to conceptualize the process of combining intelligent building energy management with environmental and economic goals, which will create more resilient, efficient, and low-carbon building processes in the age of smart grids and urban sustainability.

Data Availability:

The dataset used in this work is the CityLearn dataset, which is freely available for research purposes.

Conflict of Interests:

The authors declare no conflict of interest.

Authors' Contributions:

All authors contributed equally to carry out this work.

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