Integrating Deep Learning Models for Urban Building Energy Modeling: A Fusion-Based Approach

Said Bolluk, Özyeğin University, Istanbul

said.bolluk@ozu.edu.tr

ABSRACT

This study introduces a hybrid statistical UBEM that integrates dynamic and statistical models to capture building energy consumption patterns. The model incorporates building characteristics, local weather data, and thermal interactions between buildings. The methodology involves the following steps: (1) A dynamic UBEM generates synthetic building energy consumption data at hourly resolution. (2) A hybrid statistical model is developed using the early fusion technique over a time-series model for the time-dependent features and a feed-forward model for the static and thermal interaction features. (3) Finally, the hybrid statistical model assesses retrofit scenarios. Once applied to a sample district in Istanbul, the hybrid model predicts hourly building energy consumption with around **4% MAPE** and identifies retrofitting measures that can achieve up to **13% energy savings**. The proposed hybrid model offers valuable insights for urban planners in identifying high-demand areas and implementing energy-efficient interventions on urban building stocks.

TABLE OF CONTENTS

1. INTRODUCTION 4

2. METHODOLOGY 5

2.1. Generating Synthetic Energy Consumption Data 5

2.2. Creating GNN Embeddings 7

2.3. Creating A Hybrid Statistical Model 9

3. CASE STUDY 10

4. DISCUSSION 14

5. CONCLUSION 15

REFERENCES 15

LIST OF FIGURES

Figure 1. GNN Structure 7
Figure 2. The architecture of the hybrid statistical model 10
Figure 3. Neighborhood conditions on the campus 11

LIST OF TABLES

Table 1. Optimal hyperparameter combination of the hybrid statistical model 12
Table 2. Time-series regression performance of the hybrid statistical model 12
Table 3. Retrofit results 14

1. INTRODUCTION

Building energy consumption resulted in a 60-million-ton increase in greenhouse gas (GHG) emissions globally in 2022 [1]. This substantial emission is driven by urban building stock's embodied and operational energy consumption, which accounts for approximately 30-40% of the world's total energy consumption in 2022 [1]. It is essential to thoroughly investigate the characteristics of urban building energy consumption to manage and reduce this massive energy use. However, the lack of comprehensive data for characterizing and validating building energy consumption and uncertainties arising from the diversity in urban building morphology, including variations in construction methods, building use types, and occupant behaviors, make it challenging to assess building energy performance reliably [2,3].

Various approaches have been developed to analyze urban building energy use in this sense. Swan and Ugursal classified these into top-down and bottom-up approaches [4]. The top-down approach relies on historical data to make predictions, and it examines the overall energy consumption of urban building stocks to develop long-term plans that incorporate urban planning, economic growth, and technological advancement strategies in cities [4]. On the other hand, the bottom-up approach focuses on understanding the factors influencing the energy consumption of urban building stocks [4]. This approach demands in-depth insights into regional climatic conditions and the characteristics of the buildings and occupants within the chosen district [5].

Bottom-up UBEMs are categorized into dynamic and statistical models [4]. Dynamic UBEMs can provide high temporal (e.g., hourly) and spatial (e.g., building-level) resolution simulation results as they offer in-depth insights into time-dependent variations and thermal interactions among neighboring buildings [5]. However, dynamic models require comprehensive datasets and significant computational resources to represent the local climate and building morphology within the observed district [6]. To that end, statistical UBEMs are promising options as they can effectively capture building energy consumption patterns using historical building characteristics and metered consumption. However, these models usually provide building energy consumption predictions at lower temporal (e.g., monthly or annual) and spatial (e.g., district level) resolutions. Statistical UBEMs may struggle to incorporate time-sensitive variables, such as unstable climate conditions, building operation schedules, and thermal interactions between buildings. Advanced time-series regression models provide a viable solution to incorporate time dependency. However, another constraint arises from the static nature of the available building characteristics. Even though some parameters, such as weather data and operational schedules, are time-dependent, most parameters that have a significant impact on building energy consumption, like insulation details of building facades and details of HVAC systems, are static.

Another limitation of UBEM is that building-level metered energy consumption data at hourly resolution is rare [7]. High temporal and spatial resolution metered energy consumption data is essential for developing and validating UBEMs [8]. The insights from such comprehensive are vital to evaluating energy-saving measures and designing sustainable urban built environments [9]. The scarcity of metered energy consumption data poses a significant challenge to the reliable utilization of UBEMs in sustainable urban planning. To that end, synthetic data generation through properly characterized dynamic UBEMSs offers a promising solution [10].

This study proposes a hybrid UBEM framework to address these challenges. The methodology involves generating synthetic hourly building energy consumption through a dynamic UBEM and utilizing a hybrid statistical model to predict building energy consumption and assess retrofitting scenarios. The novelty of the proposed hybrid model lies in separating the effects of time-dependent and static building attributes on hourly building energy consumption and ensuring the contribution of thermal interaction parameters in the time-series analysis. Once applied to a sample district in Istanbul, the hybrid model predicts hourly building energy consumption with **a 4.031% MAPE** and achieves around **13% energy reduction** through assessing retrofitting scenarios.

2. METHODOLOGY

The methodology involves three stages. First, synthetic hourly energy consumption data is generated for the buildings of a sample district using a dynamic simulation tool. The geometrical attributes of buildings and the neighborhood conditions between them are then modeled using Graph Neural Network (GNN) embeddings. Finally, a hybrid statistical model is created to predict hourly building energy consumption.

2.1. Generating Synthetic Energy Consumption Data

Several modeling tools in the literature have been developed to create dynamic models of building stocks and simulate their energy consumption. Among these tools, the Urban Modeling Interface (UMI) [11] was selected due to its user-friendly modeling interface, validated simulation accuracy

[12], and proven reliability in urban planning studies worldwide [13]. UMI is integrated into a computer-aided design (CAD) program called Rhinoceros 3D (Rhino) [14], which offers an accessible and effective environment for modeling and simulation. UMI is designed to explore the impact of buildings on urban environments with a series of analyses, such as operational and embodied energy simulation, district energy modeling, urban food production simulation, and land-use accessibility analysis for walking and cycling [11]. Four fundamental inputs must be collected to create a dynamic UBEM with UMI.

- The first input is **Geometrical Building Data**, which includes all the necessary information to create building geometries in the dynamic model. Building geometries can be created from building footprints obtained with absolute coordinates from online mapping services (e.g., Google Maps or Yandex Maps) or Geographic Information System (GIS) software (e.g., ArcGIS).
- Another input is **Non-Geometrical Building Data**, which includes building envelope thermo-physical features, internal heat gain details, HVAC system properties, domestic hot water (DHW) details, and building operational schedules. Non-geometrical building data can be obtained from relevant sources, such as energy audit reports, building project drawings, and building inspection surveys. Suppose there is no prior knowledge about the energy-related parameters of the selected buildings. In that case, the non-geometrical data can be assumed from building literature, including technical and academic studies, building codes, and building standards.
- The final input is **Weather Data**, which includes comprehensive meteorological properties of a region, such as temperature, humidity, wind speed and direction, amount of precipitation, and solar radiation recorded at an hourly resolution. The weather data can be acquired from the weather stations closest to the case study district.

Once all the necessary input data is collected, the dynamic model of the sample district is created. The non-geometrical building attributes in the dynamic model include time-dependent features, such as building operational schedules, as well as static features, like wall U-value and heating setpoint. The static features will remain constant throughout the hours of the year. Thus, they will now exhibit variation in the final training data. To solve this problem, scenarios from the combinations of certain static features are created. These scenarios are simulated through UMI, and synthetic hourly energy consumption data is generated per scenario. These hourly consumption values form the target values in the training dataset.

2.2. Creating GNN Embeddings

Factors such as building location, three-dimensional features, and neighborhood conditions can significantly influence thermal interactions on urban building stocks. For example, the surrounding buildings can influence solar radiation on a building's surface. Likewise, the wind effect in outdoor corridors formed by building settlement causes significant changes in the temperature of building facades. Thermal interaction parameters should be considered when modeling the energy performance of the urban building stocks.

In this sense, graph representation of the buildings is constructed to model the thermal interactions between buildings in the selected district. Each building is represented as a node, and the relationships between buildings are captured as edges, with attributes derived from spatial and geometric characteristics (Figure 1).

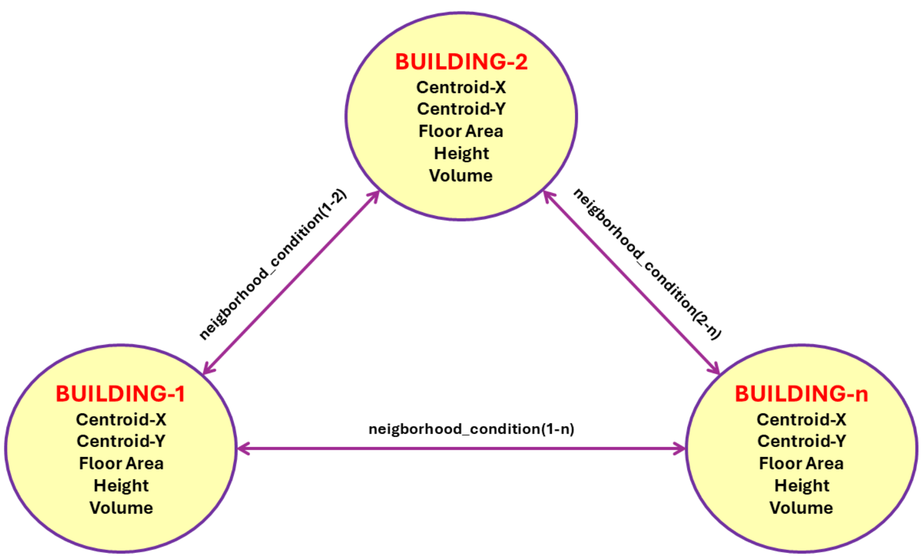

Figure 1. GNN Structure

To create neighborhood conditions between building pairs, the centroid of each building footprint, which is a polygon, is calculated using the 2D centroid formula in Equation 1 [15]:

$$C_x = \frac{1}{6A}\sum_{i=1}^{n}(x_i + x_{i+1})(x_i y_{i+1} - x_{i+1} y_i)$$
$$C_y = \frac{1}{6A}\sum_{i=1}^{n}(y_i + y_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \tag{1}$$

where $\boldsymbol{A}$ is the area of the polygon, determined using the closed polygon area formula in Equation 2 [15]:

$$A = \frac{1}{2}\left|\sum_{i=1}^{n}(x_i y_{i+1} - x_{i+1} y_i)\right| \tag{2}$$

Using the centroids and areas, each building footprint is approximated as a circle with an equivalent area. This is for the simplicity of the neighborhood representation in densely populated building stocks since the building footprints are highly complex polygons. The radius of each circle is calculated as (Equation 3):

$$r = \sqrt{\frac{A}{\pi}} \tag{3}$$

For each pair of buildings, the centroidal distance is calculated as the Euclidean distance between their centroids using Equation 4:

$$d_{ij} = \sqrt{\left(C_{x_i} - C_{x_j}\right)^2 + \left(C_{y_i} - C_{y_j}\right)^2} \tag{4}$$

Finally, the shortest distance between two building surfaces, which indicates the neighborhood condition of a given building pair, is then determined by subtracting the radius values of the respective buildings as shown in Equation 5. This process produces **a pairwise distance matrix** with dimensions of $(n \times n)$, where $\boldsymbol{n}$ is the number of buildings in the selected district.

$$d_{ij,surface} = d_{ij} - (r_i + r_j) \tag{5}$$

The resulting graph incorporates building-specific attributes as node features, including centroid coordinates (C_x, C_y), floor area, floor count, building height, and building volume. The edge attributes are derived from the calculated shortest distances between building surfaces from the pairwise distance matrix. This graph representation is then utilized to generate Graph Neural

Network (GNN) embeddings, where each node and edge is encoded into a single-dimension vector of a specified length. The proposed graph structure facilitates modeling thermal interactions between buildings by integrating spatial and geometric relationships as GNN embeddings into the training dataset for time-series building energy consumption prediction.

2.3. Creating A Hybrid Statistical Model

The final training dataset incorporates features and targets from multiple scenarios. The feature set is categorized into three distinct groups:

- **Time-dependent features**: These include weather data and building operational schedules (e.g., heating and lighting schedules).
- **Static features**: These are fixed building attributes, such as wall U-value, infiltration ratio, and lighting power density.
- **Thermal interaction features**: These are the building-specific geometrical attributes and pair-wise neighborhood conditions from the GNN embeddings.

The primary motivation of this research is to investigate the role of static building attributes in predicting hourly building energy consumption. To achieve this, the static building attributes and GNN embeddings are fed into a Multi-Layer Perceptron (MLP) model, while the time-dependent features are utilized to create hourly sequences for a Long Short-Term Memory (LSTM) model.

An **early fusion technique** is employed to merge the outputs of these two models. In this approach, the individual models transform their respective inputs for a given observation at time $\boldsymbol{t}$ without directly generating predictions. These intermediate outputs are concatenated and passed into another MLP model with two dense layers. The final MLP model produces predictions for hourly building energy consumption. The architecture of the hybrid statistical model is illustrated in Figure 2.

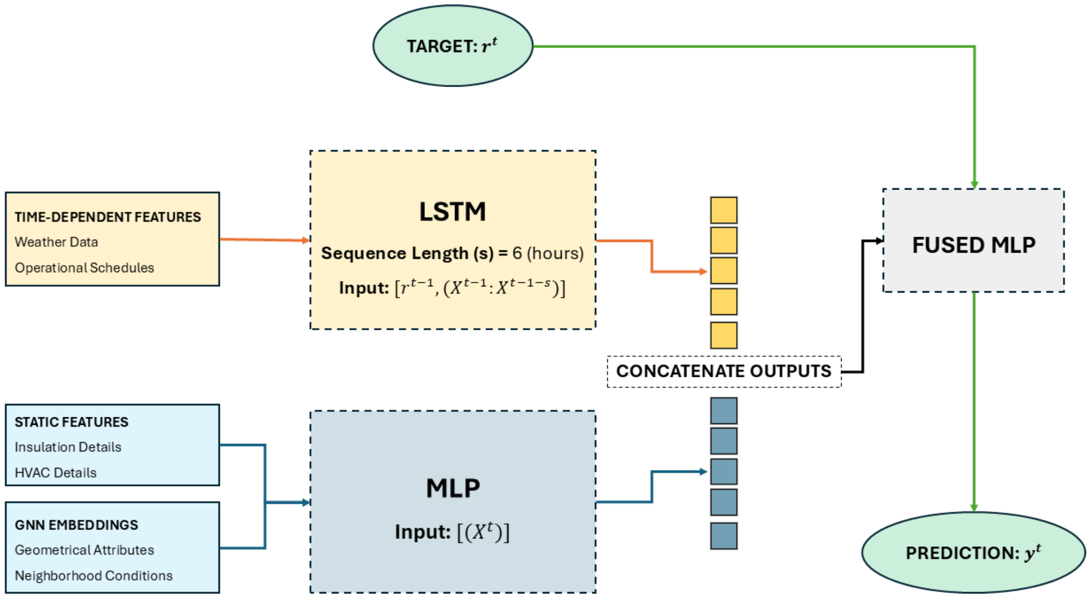

Figure 2. The architecture of the hybrid statistical model

3. CASE STUDY

The proposed methodology was tested on a campus operated by the Istanbul Metropolitan Municipality (IBB), which was designed to accommodate and rehabilitate elderly and needy citizens. The campus is in Ataşehir, Istanbul, and it hosts approximately 30 buildings with diverse use types, including nursing homes, offices, social buildings, and places of worship. However, this study focused on 19 buildings for which data was available.

Geometrical and non-geometrical data for the campus buildings were obtained from the campus administration, while weather data was sourced from the nearest weather station with permission from the Turkish State Meteorological Service (TSMS) [16]. A dynamic model of the campus was developed using these inputs. Thirty scenarios were simulated within the dynamic model by varying non-geometric attributes, including wall U-value, roof U-value, window U-value, heating set point, and lighting power density. These simulations, conducted using UMI software, generated synthetic hourly energy consumption data. The simulation parameters, weather data, and the generated energy consumption data formed the training dataset for this study.

Next, the geometrical attributes of the buildings were used to construct GNN embeddings. Node attributes were derived from building characteristics such as height, floor area, and volume, while edge attributes represented the shortest distances between building pairs. These pairwise distances were calculated using the coordinates of building polygons, which were used to model the neighborhood relationships among the campus buildings (Figure 3). The resulting graph representation was used to generate GNN embeddings, which were integrated into the training dataset. The complete training data included 8,760 hourly observations per building for each scenario. With 30 scenarios and 19 buildings, this amounted to 4,993,200 data points.

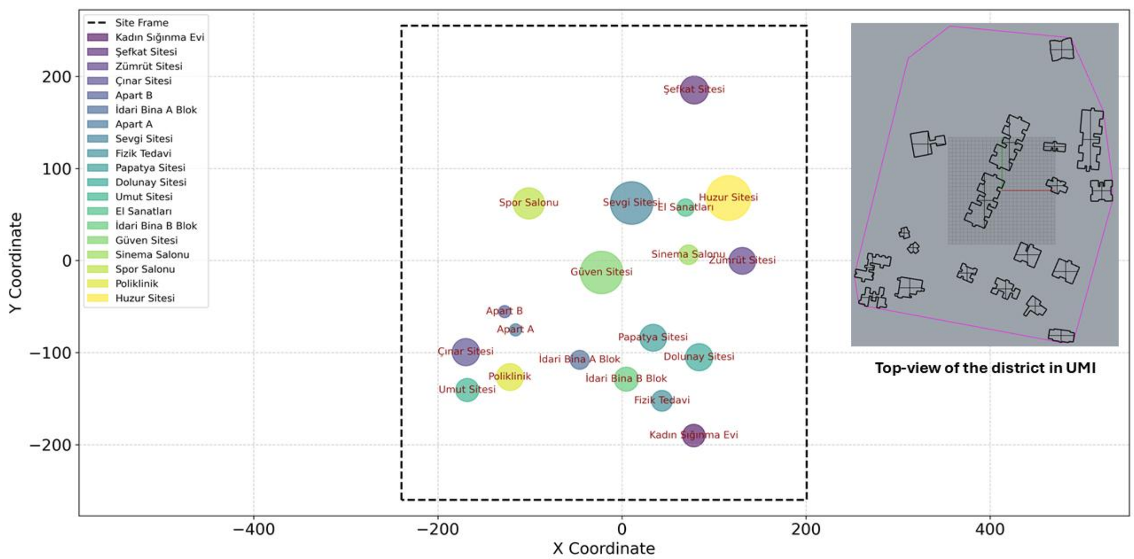

Figure 3. Neighborhood conditions on the campus

The next step was to develop a hybrid architecture for the statistical model after completing data collection. The training data was separated into time-dependent features, static features, and GNN embeddings. The time-dependent features like building operational schedules and weather data were fed into an LSTM model with a single LSTM layer and a single dense layer with a specified output size. The sequence length of the LSTM model was fixed to 6 hours for simplicity as the training data size was too large. The static features and the GNN embeddings were inserted into a two-layer MLP model with a specified output size. The outputs coming from these two models were then concatenated and inserted into a final MLP model with two dense layers and a single output layer that produces a prediction for the hourly energy consumption of the given building.

Several values of the hyperparameters, including batch size, the output sizes of the LSTM and the first MLP models, the number of hidden units in the dense layers of the final MLP model, number of epochs, learning rate, and dropout ratio, were tested within a hyperparameter tuning. The data was separated into training, validation, and test sets with 80%, 10%, and 10% respectively. The hybrid model was trained using the training set, and the validation data was used to observe the performance of different hyperparameter combinations during hyperparameter tuning. The optimal hyperparameters of the hybrid model are given in Table 1.

Table 1. Optimal hyperparameter combination of the hybrid statistical model

HYPERPARAMETER	**OPTIMAL VALUE**
Batch Size	1440
LSTM Output Size	96
MLP-1 Output Size	64
Final MLP Joint Hidden Size-1	96
Final MLP Joint Hidden Size-2	64
Number of Epochs	200
Learning Rate	5e-04
Dropout	No
Early Stopping	No

The hybrid model was trained using the optimal hyperparameter values over 90% of the training data, which combines the training and validation sets. The performance of the model was then evaluated on the test set with several regression evaluation metrics, including Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), Coefficient of Variation of the Root Mean Squared Error (CV-RMSE), and R-Squared, as shown in Table 2.

Table 2. Time-series regression performance of the hybrid statistical model

EVALUATION METRIC	**RESULT**
MSE	12.295
MAPE (%)	4.031
CV-RMSE (%)	4.548
R-Squared (%)	99.804

The hybrid model demonstrates excellent predictive performance. It achieves a low percentage error with a MAPE of 4.031%. Additionally, an R-squared value of 99.804% confirms the model's ability to effectively explain nearly all variance in the target variable. The CV-RMSE value can further validate the model's regression performance. ASHRAE suggests that the simulation (or prediction) error should be at most 30% at the hourly resolution based on the evaluation metric CV-RMSE (Equation 6) [17]. A CV-RMSE of 4.548% further validates the model's regression performance, well below ASHRAE's suggested threshold of 30% for hourly resolution. These results confirm the model's robustness and potential as a reliable statistical UBEM for analyzing energy-efficiency scenarios in the given district.

$$CV - RMSE = \frac{1}{\bar{r}} \sqrt{\frac{\sum_{t=1}^{N} (r^t - y^t)^2}{N}} \qquad (6)$$

Retrofitting analysis is a key application of UBEMs, which focuses on upgrading existing buildings to enhance energy efficiency, reduce operational costs, and improve occupant comfort. Common retrofitting measures include adding facade insulation, replacing windows, upgrading HVAC systems, and integrating renewable energy solutions. Among the various static features in dynamic and static UBEMs, wall U-value, roof U-value, window U-value, lighting power density, and heating setpoint were explicitly analyzed in this study. These features were selected as they represent the only static attributes used in training the hybrid model. From the combinations of these static feature values, 162 retrofit scenarios were evaluated using the trained hybrid model. Table 3 highlights the five best scenarios that achieved the highest energy reductions compared to the baseline scenario. **Scenario 115** showed the most significant improvement, with a 13.07% energy reduction. This was achieved by decreasing the wall U-value by 20.63%, roof U-value by 89.95%, window U-value by 75.00%, lighting power density by 16.67%, and heating setpoint by 12.50%.

Table 3. Retrofit results

SCENARIO	WALL U-VALUE	ROOF U-VALUE	WINDOW U-VALUE	LIGHTING POWER DENSITY	HEATING SETPOINT	CHANGE (%)
S115	0.9	0.3	0.8	2.5	21	13.07
S112	0.9	0.3	0.8	2	21	12.83
S127	0.9	0.3	1.2	1.5	21	12.81
S130	0.9	0.3	1.2	2	21	12.67
S133	0.9	0.3	1.2	2.5	21	12.66
Baseline	1.134	2.984	3.2	3	24	-

4. DISCUSSION

This study demonstrates the effectiveness of utilizing LSTM for time-dependent features and MLP for static features, combined with GNN embeddings, within an early fusion framework to generate hourly building energy consumption predictions. This unique hybrid architecture achieved a notable regression accuracy, with **a MAPE of merely 4.031%**. The results highlight the model's ability to capture the interactions between static building attributes and hourly building energy consumption, as well as effectively incorporating time-dependent features. Furthermore, including neighborhood conditions and geometric building attributes as GNN embeddings facilitated the modeling of the thermal interactions among building pairs on the campus.

Despite these strengths, a key limitation of this study is the lack of model comparisons. Due to the significant training time required, a plain LSTM model incorporating both time-dependent and static features was not analyzed. A comprehensive comparison could have validated the benefits of separating data types, using specialized models, and integrating them in a hybrid framework.

Nevertheless, the hybrid model's application to building retrofitting demonstrated its practical utility. The retrofitting achieved **a 13% reduction in energy consumption**, equivalent to an annual operational energy savings of approximately **1,007,132 kWh** on the campus. The hybrid model can efficiently evaluate various energy efficiency scenarios without relying on exhaustive simulations, including insulation adjustments, zone conditioning setups, and operational schedule variations. Furthermore, by incorporating weather data as an input, the hybrid model can forecast and mitigate the impacts of climate change on the studied area. These capabilities underscore the model's potential for advancing sustainable urban planning.

5. CONCLUSION

A hybrid statistical UBEM architecture incorporating both time-dependent and static building attributes was developed for this study. The model also integrated buildings' geometric attributes and neighborhood conditions to account for thermal interactions between buildings. The proposed methodology was tested on a sample district, where a time-series regression predicted hourly building energy consumption with **a MAPE of 4.031%.** The robust hybrid model was then applied to building retrofitting, resulting in up to a **13% improvement** in the annual operational energy consumption of the buildings in the sample district.

Future work should focus on comparative analyses through a plain LSTM model that uses both time-dependent and static building attributes to further validate the performance of the proposed hybrid architecture. Additionally, exploring the impact of data augmentation on the model's prediction performance could offer valuable insights. For instance, comparing the weights of models trained on individual scenarios with those of the hybrid model through heatmaps or other explainable AI techniques could illustrate how the model evolves as the training dataset expands. Another future work could investigate more detailed thermal interaction parameters relying solely on neighborhood conditions. For example, solar radiation maps on building surfaces and wind corridor effects could be analyzed and processed using CFD simulations to enhance thermal interaction features. Overall, the proposed hybrid models hold significant potential for investigating various energy efficiency scenarios in urban building stocks. Municipalities and central authorities can utilize this model to develop strategies to improve building energy consumption on regional and national scales.

REFERENCES

1. CO2 emissions in 2022. (2023). https://doi.org/10.1787/12ad1e1a-en
2. Oraiopoulos, A., & Howard, B. (2022). On the accuracy of Urban Building Energy Modelling. Renewable and Sustainable Energy Reviews, 158, 111976. https://doi.org/10.1016/j.rser.2021.111976

3. Santin, O. G., Itard, L., & Visscher, H. (2009). The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock. Energy and Buildings, 41(11), 1223–1232. https://doi.org/10.1016/j.enbuild.2009.07.002
4. Swan, L. G., & Ugursal, V. I. (2009). Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. Renewable and Sustainable Energy Reviews, 13(8), 1819–1835. https://doi.org/10.1016/j.rser.2008.09.033
5. Ferrando, M., Causone, F., Hong, T., & Chen, Y. (2020). Urban building energy modeling (UBEM) tools: A state-of-the-art review of bottom-up physics-based approaches. Sustainable Cities and Society, 62, 102408. https://doi.org/10.1016/j.scs.2020.102408
6. Johari, F., Peronato, G., Sadeghian, P., Zhao, X., & Widén, J. (2020). Urban building energy modeling: State of the art and future prospects. Renewable and Sustainable Energy Reviews, 128, 109902. https://doi.org/10.1016/j.rser.2020.109902
7. Davila, C. C., Reinhart, C. F., & Bemis, J. L. (2016). Modeling Boston: A workflow for the efficient generation and maintenance of urban building energy models from existing geospatial datasets. Energy, 117, 237–250. https://doi.org/10.1016/j.energy.2016.10.057
8. Sokol, J., Davila, C. C., & Reinhart, C. F. (2017a). Validation of a Bayesian-based method for defining residential archetypes in urban building energy models. Energy and Buildings, 134, 11–24. https://doi.org/10.1016/j.enbuild.2016.10.050
9. Roth, J., Martin, A., Miller, C., & Jain, R. K. (2020). SynCity: Using open data to create a synthetic city of hourly building energy estimates by integrating data-driven and physics-based methods. Applied Energy, 280, 115981. https://doi.org/10.1016/j.apenergy.2020.115981
10. Han, M., Johari, F., Huang, P., & Zhang, X. (2023b). Generating hourly electricity demand data for large-scale single-family buildings by a decomposition-recombination method. Energy and Built Environment, 4(4), 418–431. https://doi.org/10.1016/j.enbenv.2022.02.011
11. Reinhart, C., Dogan, T., Jakubiec, A., Rakha, T., & Sang, A. (2013). UMI – an urban simulation environment for building energy use, daylighting and walkability. Building Simulation Conference Proceedings. https://doi.org/10.26868/25222708.2013.1404
12. Dogan, T., & Reinhart, C. (2017). Shoeboxer: An algorithm for abstracted rapid multi-zone urban building energy model generation and simulation. Energy and Buildings, 140, 140–153. https://doi.org/10.1016/j.enbuild.2017.01.030

13. Ang, Y. Q., Berzolla, Z. M., Letellier-Duchesne, S., Jusiega, V., & Reinhart, C. (2022). UBEM.io: A web-based framework to rapidly generate urban building energy models for carbon reduction technology pathways. Sustainable Cities and Society, 77, 103534. https://doi.org/10.1016/j.scs.2021.103534
14. McNeel, R. (2008). Rhinoceros: NURBS modeling for Windows. Robert McNeel & Associates, 862.
15. Shoelace Theorem. (n.d.). Retrieved January 1, 2025, from https://artofproblemsolving.com/wiki/index.php/Shoelace_Theorem?srsltid=AfmBOorG1heHXifZXeuULM2jJY3931fAdbkuD3HlfIj43CIYI2stK7Br
16. Mgm. (n.d.-a). About | Turkish State Meteorological Service. MGM. Retrieved August 20, 2024, from https://www.mgm.gov.tr/eng/about.aspx
17. ASHRAE, A. (2002). Ashrae guideline 14: measurement of energy and demand savings. American Society of Heating, Refrigerating and Air-Conditioning Engineers, 35, 41-63.