A Data-Driven Approach to Achieve Low-Carbon Building Energy Optimization by Using BIM Technology

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***Abstract*—Low-carbon building energy optimization is the environmental aspect that is impacted due to the construction sector. The integration of Building Information Modelling (BIM) with Artificial Intelligence (AI) techniques offers the design and operation of buildings with a reduced carbon footprint. Usually, such systems lack flexibility and the precision of dynamically optimizing energy usage. This work proposes a novel data-driven framework that merges AI and BIM to optimize the building energy system for low-emission design using Carbon Major Emission Datasets. It aids materials and energy source selections by identifying highly emitting commodities to reduce operational carbon footprints. Initially, data acquisition and emission analysis are performed on the Carbon Majors database to identify high-emission materials. Subsequently, emission factors are linked with the BIM elements using plug-ins such as One Click LCA, which allow the annotation of embodied carbon values. Further, operational energy is optimized by Multi-Agent Assisted NSGA-II, which optimizes parameters and material selection. Additionally, AI-assisted energy prediction supported by the SqueezeNet model and energy simulation techniques was used for minimizing building energy consumption. The results reveal a high-energy prediction accuracy of 0.0212 for MAE, 0.0376 for MSE, and 0.9814 for the R^2 score. It further helps to reduce carbon emissions by 1155 tons and improve the cost efficiency of 570.25 million, promoting low-carbon building solutions from the earliest stages of design.**

***Keywords*—Low-carbon buildings; building information modelling; carbon emissions; operational energy optimization; SqueezeNet; energy simulation**

I. Introduction

Low-carbon building in energy optimization is the strategic design, construction, and operation of buildings with the goal of minimizing carbon dioxide (CO_2) and greenhouse gas emissions throughout their life cycle [1]. This method is in reaction to the huge contribution of the built environment toward global climate change, whereby buildings contribute around 39% to global annual CO_2 emissions, 28% from building operations, and 11% from materials and construction (embodied carbon) [2]. The urbanization, industrialization, and energy demand across the world have increased the carbon intensity of building infrastructure over the last four decades [3]. Perceiving climate change mitigation as a global agenda, the Paris and the United Nations sustainable development goals stresses the urgent necessity of decarbonizing the construction sector. More than 75% of the building stock in 2050 will be built today; hence, the optimization of new and existing buildings is paramount [4]. This leads further to the development of advanced energy modelling and carbon accounting tools with policy-inspired benchmarks for the reduction of the lifecycle carbon footprint of buildings [5]. Over the past 15 to 20 years, the emergence of carbon emission trajectories in climate models has brought into sharp relief the prominence of energy optimization for low-carbon building and thereby situated it as one of the key pillars in sustainable urban development worldwide [6].

Due to the increasing demand for sustainable construction, Building Information Modelling (BIM), combined with low-carbon building technology, has been identified as a transformational approach [7]. A BIM system is a digital representation of a building's physical and functional attributes through a 3D model-based process, thus facilitating multidisciplinary collaboration among design, construction, and operation phases [8]. The carbon emission data, along with energy performance, could be embedded into the BIM platform, enabling stakeholders to simulate, analyze, and optimize design alternatives [9]. Price types and potential hybrid modes of construction based on carbon emissions could be informed by such integration [10]. In 15 to 20 years, BIM will graduate to a platform-based 5- and 6-dimensional solution [11]. This has propelled BIM ahead of its contemporaries regarding carbon-aware building methods, hence providing a striking tool for the reduction of embodied and operational carbon footprints early in scheme planning and design, an important activity since over 70% of a building's lifecycle cost and impact are determined during the initial phases [12].

A rapid rise in the practice of BIM-based low-carbon design optimization is being witnessed in developed and emerging countries, owing to varied regulations on carbon, increased concern regarding climate risk, and growth in digital technologies for construction [13]. BIM mandates and sustainability frameworks have been adopted by governments and industries around the globe, with carbon performance increasingly within these frameworks [14]. The incorporation of historical datasets of carbon emissions within BIM environments enables architects and engineers to trace the carbon intensity of a material (such as cement) or goods (such as coal) to the producers for emission-conscious supply chain decisions [15]. This data-oriented integration of BIM and Artificial Intelligence (AI) -based optimizers allows for-going carbon assessments and predictive modelling of energy consumption to be evaluated with surgical precision [16]. This way, it enables buildings to comply with environmental standards, maintain energy efficiency, and sustainable building

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design solutions, thereby drastically cutting carbon emissions and green-resilient structures towards the building agenda. This AI has helped in considerably minimizing carbon emissions, enhancing design efficiency, saving costs through energy optimization, improving regulatory compliance, and creating environmentally resilient and future-ready buildings [17]. Thus, this work provides a data-driven framework to integrate BIM technology into historical carbon emission data through the AI-aided analysis of energy performance and support for low-carbon design decisions.

Research Questions:

1) How can Building Information Modelling (BIM) be integrated with historical carbon emission datasets to support low-carbon material selection in early design stages?

2) In what ways can Artificial Intelligence (AI), particularly deep learning models such as SqueezeNet, improve the accuracy of building energy consumption prediction?

3) How can a multi-objective optimization approach (MAA-NSGA-II) simultaneously balance energy efficiency, carbon reduction, comfort, and cost in building design?

4) To what extent can the proposed AI-BIM framework achieve both embodied and operational carbon optimization across the entire building lifecycle?

The major contributions of the proposed work are:

- Formulate a data-driven framework where the AI-BIM is integrated with the Carbon Majors Emissions Dataset to orient low-carbon building energy optimization about material selection and operational strategies through historical emissions intelligence.
- Analyse carbon emission data to aggregate emissions from coal, cement, oil, and gas to parent entities to identify high-emission materials for sustainable construction planning.
- Integrate emissions data with BIM by connecting emission coefficients with building components with One Click LCA (life cycle assessment) to enable the visualization and annotation of embodiment carbon values within the BIM environments.
- Optimize operational carbon emissions using a Multi-Agent-Assisted NSGA-II (MAA-NSGA-II) algorithm by considering the simultaneous positioning of multiple design parameters and shading configurations for multi-objective energy efficiency.
- Simulate predictive energy demands with an AI-based model that characterizes building energy consumption using a SqueezeNet model for compressing buildings and assessing actual operational energy demand, while maintaining thermal comfort and indoor quality.

The study is organized into sections as follows: Section II is concerned with the study of related literature and existing approaches. Section III describes the AI-based simulation methodology proposed. Section IV provides analysis and discussion of the results in Section V. Finally, Section VI draws the conclusions.

II. Literature Survey

Recently, the convergence of Internet of Things (IoT), AI, and big data analytics has immensely expanded the functional scope of BIM applied in construction and visualization. According to Ho et al. [18], a data-centric approach with ant colony optimization method for low-carbon prefabricated component production is introduced. The study highlighted the importance of prefabrication in reducing environmental impacts in the construction sector. In the same vein, Razi et al. [19] used a multi-objective prediction model for time, cost, energy consumption, and CO_2 emissions. Applying decision-making methods to identify influencing factors and utilizing eleven machine learning (ML) algorithms, the study forecasted the four competing priorities and balanced them. Another work by Popa et al. [20] developed a predictive tool that cohered energy consumption data under the IoT to assign energy performance ratings. Their model tested the capability of an efficiency label for buildings by using minimal input features of floor area. Between these developments, Myintet al. [21] focused on carbon estimation during numerous stages of construction, including raw material processing and transportation, by using data acquired from a residential project. Yet, challenges in integrating emission data and allow for a holistic low-carbon optimization in BIM workflows.

BIM has been transformative in embedding energy performance and carbon footprint assessment throughout a building's lifecycle. For instance, Zhao et al. [22] developed a BIM approach with 3D laser scanning to generate energy models for the building. The method was employed to analyze retrofit options to convert existing buildings into operational nearly zero-energy systems. Similarly, Shen et al. [23] introduced a full-life-cycle net-zero carbon building framework. Their work utilized an ontology-based approach in BIM to delineate key decision variables that cover design, construction, and operation, thus allowing seamless data integration and decision-making based upon it. Also, Tahmasebinia et al. [24] utilized regression models within BIM environments to simulate energy-efficient design. The study showed that multi-linear regression was used to estimate energy consumption for different architectural shapes and materials, revealing that triangular shapes produced the best energy performance. Another survey by Zhuang et al. [25] explored a performance-oriented BIM framework to optimize environmental impact and energy usage throughout the building life cycle. They employed a school building to analyze the effects of different envelope structures on indoor environment conditions and cost-effectiveness. However, lacked dynamic integration of emissions data to enable true holistic optimization.

Advancements in data-driven technologies, especially AI, BIM, and big data analytics, have increased opportunities for optimizing the energy performance of buildings. Mehraban et al. [26] studied residential buildings' energy behaviour in hot climatic zones by applying a BIM-ML approach. The approach involved simulating energy use via platforms such as green building studio and insight with respect to building orientation, fenestration, floor area, wall constitution, infiltration rates, and daylighting. Four ML methodologies were used to predict energy use intensity and thus generated information on the design's energy use. Likewise, Wang et al. [27], Arsiwala [28], and Giannelos et al. [29], among others, have studied carbon emission prediction at the initial stages of construction, focusing on integrating BIM-ML techniques. They studied 35 public buildings in China to measure emissions caused by material selection. In parallel, digital twin models combined with ML were employed to engineer the monitoring of CO_2 emissions from operational buildings. Also, they used ML to predict emission levels at various stages of the life cycle in the building sector. Despite significant achievements, many of the solutions faced limitations with respect to predicting emissions across varied climates, materials, and emission scenarios, hence paving the way for generalizable emissions-informed BIM-AI frameworks. Table I presents the limitations of previous studies and the solutions proposed in this study.

TABLE I. LIMITATIONS OF PREVIOUS STUDIES AND SOLUTIONS PROPOSED IN THIS STUDY

Study	Limitations	Proposed Solutions
Ho et al. [18]	Looked only at parts, not the full building carbon.	Covers both building materials and energy use with AI.
Razi et al. [19]	Balanced cost, time, energy, but not a full low-carbon design.	Optimizes energy, emissions, and comfort together.
Popa et al. [20]	Used very few inputs; no detailed carbon data for materials.	Adds detailed carbon data of materials into BIM for better design.
Myint et al. [21]	Did not fully connect carbon data in BIM.	Links carbon data directly in BIM with One Click LCA.
Zhao et al. [22]	Focused only on retrofit energy, not the full life cycle.	Handles both embodied and operational carbon for the full life cycle.
Shen et al. [23]	Did not use changing data during building use.	Uses AI for dynamic updates over the life of the building.
Tahmasebinia et al. [24]	Looked at energy, but not much carbon.	Combines both energy and carbon.
Zhuang et al. [25]	No real-time adjustment for energy and carbon.	Adds AI for real-time changes across the life cycle.
Mehraban et al. [26]	Only studied hot-climate houses.	Uses a global dataset, so it works in all regions.
Wang et al. [27]	Looked only at carbon at construction start.	Covers both short-term and long-term carbon with AI + BIM.

A. Problem Statement

Despite advances in integrating BIM with data-driven technologies, it still has not been able to develop fully optimized low-carbon building energy systems. Most of the methods consider operational carbon and embodied carbon, but they are not linked with emission data from materials such as cement, coal, and natural gas, known to be major contributors to the carbon footprint of the building sector [30]. Also, they present different explanations of energy simulation tools that exert generalized assumptions and do not provide internalized insight into carbon-intensive commodities, compromising their early-stage design decisions [31]. Retrofit models are also limited by small datasets, lacking dynamic adjustment through building lifecycles, or are limited to a narrow geography and climatic condition [32]. Besides, AI methodologies are used for energy prediction but rarely consider carbon emission data, especially from databases based on emissions of global actors [33]. Therefore, a clear gap exists as existing research either remains limited to operational optimization, neglect material-level carbon data, or fail to integrate dynamic lifecycle adjustments. Few approaches combine embodied and operational carbon within a unified BIM-AI framework, which restricts their real-world applicability. To overcome these challenges, this study proposes a novel data-driven methodology that integrates BIM and AI, with an infusion of historical emissions data to define low-carbon decisions throughout the building life cycle, achieving both embodied and operational carbon optimization.

III. PROPOSED AI-BIM LOW-CARBON ENERGY FRAMEWORK

This framework presents a data-driven low-carbon building energy optimization framework integrating BIM with historical emissions data and AI-trained optimization techniques. The proposed algorithms are especially effective when applied to detailed and high-dimensional datasets, such as BIM models enriched with material-level carbon factors and time-series operational data (e.g., HVAC loads, occupancy, lighting). Their strength lies in handling multi-variable scenarios where both embodied and operational carbon must be optimized together, whereas performance may be less comprehensive when applied to small or low-detail datasets. Utilizing the carbon emissions dataset allows identify the commodities with high emissions and trace the carbon responsibility to particular entities. The framework starts with an investigation of emissions, wherein data is aggregated by commodity and entity to identify high embodied carbon materials. This is followed by a data embedding process into BIM environments, which associates carbon coefficients with building components and thus allows for graphical exposition of environmental impact. Similarly, an MAA-NSGA-II algorithm is used to perform multi-objective optimization of crucial operational parameters, while the AI-assisted prediction model simulates building energy use to reduce operational emissions and work alongside human comfort to design carbon-aware energy-efficient buildings. The general synthesis of the proposed framework is shown in Fig. 1.

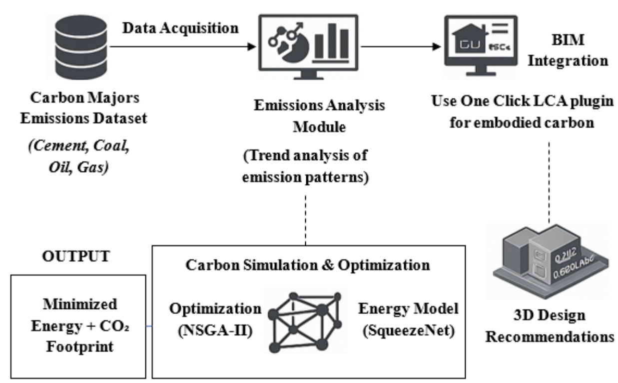

Fig. 1. AI-BIM Integrated framework for low-carbon building energy optimization.

A. Data Acquisition

The dataset adopted in this work consists of carbon emissions, providing a history of emissions data from 1854. The data are provided by the Climate Accountability Institute. It compiles production and emissions data from 122 major fossil fuel and cement producers. This database was selected due to its being one of the most authoritative and comprehensive in existence, reporting over 72% of global fossil fuel and cement emissions since the onset of the industrial era. Its broad coverage and granularity by commodity and producer make it incredibly well-suited to associating emission factors with BIM components and facilitating sound low-carbon design choices. The data for emissions analysis were obtained from corporate disclosure, national inventory, and academic research, guaranteeing reliability. This study entails the variables year, parent entity, commodity type (coal, cement), production quantity, and total emission observed in $MtCO_2e$ to capture emission-intensive materials and producers over time.

B. Emissions Analysis

During this stage, the emissions data is accumulated and analyzed to build a carbon-intensive materials and emission contributors. Emissions are grouped by type of commodity, specifically by coal, cement, oil, and gas, on parent entity ownership models considered by type of ownership from the investor. This sets the basis for understanding with level of granularity with which materials and producers have contributed in the past toward global carbon emissions. In the analysis, it produced material-wise emission coefficients towards informing low-carbon design in BIM environments. These coefficients serve as quantified indicators of embodied carbon, allowing architects and engineers to identify and consequently circumvent or lessen high-emission materials at the conceptual design phase level.

This study, using the aggregation of measurements provided by the dataset (1854- Present), identifies carbon-intensive materials by a detailed dataset from commodity type and parent entity (state-owned versus investor-owned). These coefficients guide the annotation of BIM components toward carbon-conscious design and planning (for instance, annotations may encourage the use of Portland cement substitutes consisting of lower embodied carbon).

C. BIM Integration

Once the emissions analysis is conducted, the framework incorporates emission intelligence into the BIM environment. This is done through One Click LCA, the premier platform for LCA and embodied carbon calculations, used to make environmental data, mainly emission coefficients for high-carbon materials like cement, coal-based steel, and fossil fuel derivative chemicals, feed into design decisions on the digital stage. Incorporation of emissions data in the LCA platform follows a multi-step procedure,

1) Initially, emission coefficients are retrieved from the dataset. The coefficients stand for average carbon emissions per unit of material. For instance, 0.95 $MtCO_2e$ per tonne of cement. The materials are arranged according to their commodity type, production source, and historical emissions; thus, they represent more realistic environmental impact metrics.

2) A highly detailed digital building model was imported from Autodesk Revit into One Click LCA via a plugin. The plugin reads and interprets the BIM model in terms of basic structural and architectural elements, and it extracts quantities and dimensions, material specifications, and location-based metadata for all components (such as slabs, beams, insulation, and facades).

3) One Click LCA features an extensive environmental database, carrying thousands of building materials around the world and their environmental profiles. It automatically maps BIM materials to corresponding emission profiles so that tailored emission coefficients can be manually assigned to each material element in the model.

4) After materials get mapped, One Click LCA calculates the embodied carbon for each building component by multiplying the emission factor by the quantity extracted from the BIM model. Subsequently, these values are annotated into the respective model elements, thus enabling the user to visualize the particular components, contributing to the overall carbon footprint of the building.

5) Finally, this tool also prepares detailed LCA reports and carbon impact dashboards showing total embodied emissions of the building, material or construction-phase-wise breakdowns, and comparison across design alternatives. Such information is then available to architects and sustainability engineers to make informed decisions, based on data, either on low-carbon cement alternatives or structural systems optimization from a carbon perspective.

By embedding emission coefficients and embodied carbon within the BIM environment, this integration elevates the static 3D models into living, carbon-conscious digital twins. The initiative enables stakeholders to simulate and optimize the environmental performance of a building before embarking on physical construction, therefore supporting the overarching goal of a design that leads to energy-efficient, low-carbon buildings from the emissions data.

D. Carbon Simulation and Optimization

Further improvements in building energy efficiency and operational carbon emission reduction are achieved by considering the use of MAA-NSGA-II within the proposed framework. This multi-objective optimization within a BIM environment addresses critical design and operational parameters, enabling maximizing conflicting objectives at the same time, such as minimizing energy consumption and maximizing occupant comfort and material sustainability. The overall system of the MAA-NSGA-II optimization outline is shown in Fig. 2.

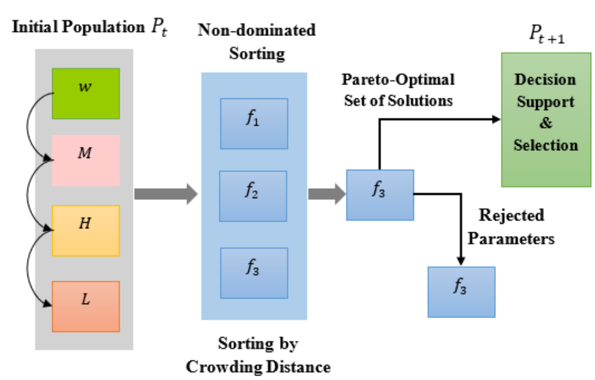

Fig. 2. Illustration of the MAA-NSGA-II optimization framework.

The primary parameters selected for optimization include:

- Window size and orientation (affecting solar gain and daylight utilization).
- Building envelope materials and insulation levels.
- HVAC system configuration and efficiency.
- Lighting and shading strategies.

The initial population of candidate design vectors ($\vec{X}$) for the design alternatives is mathematically modelled as in Eq. (1):

$$\vec{X} = [x_1, x_2, x_3, x_4] = [W, M, H, L] \tag{1}$$

where, $x_1 = W$ signifies window sizes and orientations, $x_2 = M$ includes building materials and their insulation parameters, $x_3 = H$ represents types and configurations of HVAC systems, and $x_4 = L$ represents lighting strategies and shading devices. These variables influence energy demand and emissions through the building life cycle. This optimization is conducted to minimize the operational energy and consequently emissions of the building while maximizing thermal comfort. Then, the mathematical formulation of this multi-objective optimization is indicated in Eq. (2):

$$\min_{\vec{X}} \begin{cases} f_1(\vec{X}) = E_{\text{total}}(\vec{X}) \\ f_2(\vec{X}) = C_{op}(\vec{X}) \\ f_3(\vec{X}) = -C_{\text{int}}(\vec{X}) \end{cases} \tag{2}$$

Here, $f_1(\vec{X})$ quantifies total energy consumption (E_{total}) in kWh, $f_2(\vec{X})$ reflects carbon emissions (C_{op}) in kilograms of CO_2-equivalent, and $f_3(\vec{X})$ captures the inverse of the comfort function (C_{int}), where represented using the predicted mean vote to ensure indoor thermal satisfaction.

Energy use throughout the period of operation of the building is dynamically simulated by Eq. (3):

$$E_{\text{total}}(\vec{X}) = \int_0^T \left(Q_{HVAC}(t) + Q_{\text{lighting}}(t) + Q_{\text{equipment}}(t)\right)dt \tag{3}$$

where, $Q_{\text{HVAC}}(t)$, $Q_{\text{lighting}}(t)$, and $Q_{\text{equipment}}(t)$ represent time-variant energy loads of respective systems over a total simulation time T. These load profiles are compressed and represented using an AI model, enabling efficient processing within multi-agent systems. Then the operational carbon emissions are directly related to the energy consumed by various systems, weighted by their emission factors. This relationship is formalized as in Eq. (4):

$$C_{op}(\vec{X}) = \sum_{i=1}^{n} (\eta_i \cdot E_i) \tag{4}$$

where, E_i is the energy usage of the i^{th} building subsystem (lighting), and η_i is the corresponding CO_2e emission factor for grid-supplied electricity (n). This provides a direct estimation of emissions based on design choices.

To ensure occupant well-being, the thermal comfort function $C_{\text{int}}(\vec{X})$ is evaluated in the model embedded within a thermal comfort agent, as shown in Eq. (5):

$$C_{int}(\vec{X}) = f(T_a, T_r, RH, V_a, G, I_{cl}) \tag{5}$$

where, T_a and T_r denote air and radiant temperatures, respectively, RH is relative humidity, V_a is air velocity, G is the metabolic rate, and I_{cl} is the clothing insulation index. The function $f(\cdot)$ computes the score to estimate comfort from -3 (cold) to +3 (hot). Correspondingly, multiple intelligent agents (m), each with their own utility functions $\phi_j(\vec{X})$, evaluate candidate designs in parallel. These evaluations are then aggregated to compute a global fitness score using a weighted summation (Φ), as expressed in Eq. (6):

$$\Phi(\vec{X}) = \sum_{j=1}^{m} \omega_j \cdot \phi_j(\vec{X}) \tag{6}$$

Here, ω_j are user-defined weights reflecting the priority of each agent (comfort, cost, emissions), and $\phi_j(\vec{X})$ are individual agent outputs. This enables modular and adaptable evaluation supporting BIM feedback. The evolutionary facet of MAA-NSGA-II is used to evolve a Pareto-optimal population in time, preserving diversity and convergence. Therefore, the output of the whole process is a solution set of the non-dominated solutions, as defined in Eq. (7):

$$F = (P_t) = \{\vec{X}_1, \vec{X}_2, \dots, \vec{X}_k\} \in \text{ Pareto Front} \tag{7}$$

where, P_t is the population at generation t, and F is the final set of trade-off solutions between emissions, energy, and comfort. This Pareto front aids architects and engineers in selecting optimal design configurations early in the design process. Algorithm 1 shows the MAA-NSGA-II for low-carbon building optimization.

Algorithm 1: MAA-NSGA-II for Low-Carbon Building Optimization

Input: Initial population ($\vec{X}$)
Output: Final Pareto-optimal front of low-carbon design solutions (F)
Begin
Initialize $\vec{X}$ with random design vectors
For each $\vec{X}$ in Population do
Evaluate $f_1(\vec{X}), f_2(\vec{X}), f_3(\vec{X})$
For each agent m
Compute agent utility: $\phi_j(\vec{X})$
End For
Compute global fitness: $\Phi(\vec{X}_i) \leftarrow \sum_j=1^m (\omega_j \times \varphi_j(\vec{X}_i))$
End For
For $t = 1$ to G do
Perform Non-Dominated Sorting on P_t
Calculate Crowding Distance
Select Parent Set using Tournament Selection
Generate Offspring ϕ_j using Crossover and Mutation
Evaluate objectives and agent utilities for ϕ_j
Select Next Generation P_{t+1}
End For
Extract final Pareto Front (F)
End

E. *AI-Assisted Energy Prediction*

After optimization of parameters, refined building design parameters, dynamic energy consumption predictions are made through an AI-assisted approach using the SqueezeNet model, ensuring the best possible accuracy in predicting operational energy usage, which is the direct cause of carbon emissions in the building environment. The overall architecture of the proposed SqueezeNet framework is shown in Fig. 3.

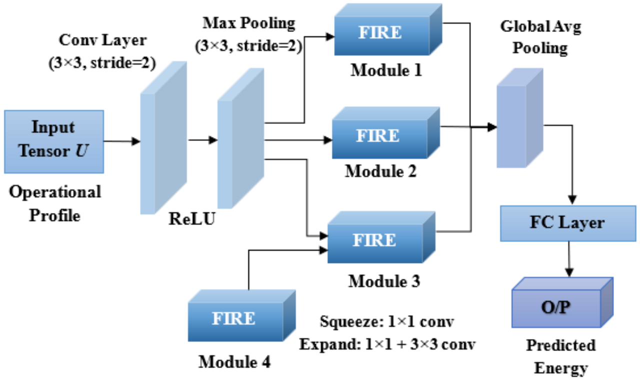

Fig. 3. Architecture of the SqueezeNet for building energy prediction.

The high-dimensional spatiotemporal datasets were considered for training of this model, wherein each input sample represents some operational state of a building over time. The data is in three-dimensional tensor form, $\mathrm{U} \in \mathbb{R}^{T\times Z\times F}$, where T is the number of time steps, and Z corresponds to spatial zones inside the building, such as rooms or floors. Also, F represents feature channels detailing contextual variables, including temperature, occupancy levels, lighting usage, HVAC operations, and daylighting contribution. The first convolutional layer in the model extracts low-level spatial features F_0 according to Eq. (8):

$$\mathrm{F}_0 = \sigma(\mathrm{W}_0 * \mathrm{U} + \mathrm{b}_0) \quad (8)$$

Here, W_0 learned weights of the convolutional filters, b_0 is the bias term, $*$ is the convolution operator, and σ is the ReLU operator used as an activation function to add non-linearity. These extracted features are the basis on which the subsequent layers of the model will extract more complicated building dynamics.

One of the main aids of the model is the Fire modules, which cut down model complexity to a huge extent while maintaining its performance. Each module includes a squeeze layer with 1×1 convolutions that reduce the number of input channels, followed by an expand layer that applies both 1×1 and 3×3 convolutions. Thus, the Fire module F_i can be computed as follows in Eq. (9):

$$\mathrm{F}_i = \phi\left(\mathrm{Conv}_{1\times1}(\mathrm{F}_{i-1}) \| \mathrm{Conv}_{3\times3}(\mathrm{F}_{i-1})\right) \quad (9)$$

Here, $\|$ represents concatenation, and ϕ is a function that merges the expanded feature maps from both convolution paths. This modular design enables SqueezeNet to drastically reduce parameter count and computation time when integrated within large-scale BIM systems for energy prediction.

After passing through a stack of Fire modules, the final compressed feature representation F_n is forwarded to a regression head with a fully connected output layer that predicts the total energy consumption $\grave{E}_{\text{total}}$. The regression function is formulated, as in Eq. (10):

$$\grave{E}_{\text{total}} = \mathrm{w}_e^T \cdot \mathrm{F}_n + b_e \quad (10)$$

where, w_e is the learned weight vector for regression, and b_e is the corresponding bias. This ensures that the model iteratively learns to minimize prediction error across diverse operating scenarios. Algorithm 2 presents the AI-assisted energy prediction using SqueezeNet.

Algorithm 2: AI-Assisted Energy Prediction Using SqueezeNet

Input: Optimized Extract parameter vector (F)
Output: Predicted total energy consumption (in kWh)
Begin
Initialize model
Load AI architecture with Fire Modules
For each timestep t from 1 to T do:
Extract U ⟵ usage profile at time T
Apply initial convolution U
For each Fire Module i:
Perform squeeze operation → reduces input channels ($Conv1x1$)
Perform expand operation → parallel $Conv1x1$ and $Conv3x3$
Concatenate results to produce F_i
End For
Aggregate final feature vector F_n from last Fire Module
Compute predicted energy $\grave{E}_{\text{total}}$
Return $\grave{E}_{\text{total}}$
End For
End

This phase is crucial in the optimization of building energy systems and low-carbon architectural design through advanced simulation aided by AI. The system provides an energy usage predictor employing a forecast with the SqueezeNet model. Within it resides the power to make a prior judgment on the configurations that stand to be the least energy-consuming and environmentally sustainable design options. This will make data-driven decisions in the early stages of the design process and take the biggest potential for impact-control on CO_2 emissions away before construction begins.

This intertwining of predictive modelling with BIM enables architects to create incremental design alternatives in a way that operational energy consumption, embodied carbon, indoor thermal comfort, as well as compliance with local standards are considered. It allows designers and engineers to further reduce operational carbon and energy while still maintaining occupant comfort, which is essential in designing and constructing low-carbon and energy-efficient buildings.

IV. Results and Discussions

This study contains the assessment and comparative analysis of the proposed framework for optimizing low-carbon building energy, developed and simulated using Python. Simulation parameters considered building geometry, material emission coefficient, HVAC configuration, insulation level, and solar orientation. Multi-objective optimization was used to balance energy efficiency and carbon reduction, while AI served as a model to compress usage profiles for energy prediction. The framework identified the design configurations to lower total CO_2 emissions, proving its application in guiding the early design phase for carbon-conscious decisions.

A. Dataset Description

Carbon Majors Emissions Dataset, a globally recognized and authoritative source of historical carbon emission data. Emissions are broadly covered by the dataset from 1854 to date. Its peculiar dataset traces well beyond over 1.42 trillion tons of carbon dioxide equivalent (CO_2e) emissions, almost 72% of global fossil fuel and cement-related emissions since the dawn of the Industrial Revolution in 1751, hence ranking it as one of the most thorough repositories for emissions tracking and attribution.

This dataset is developed for multidimensional analysis while including major variables such as.

- Year of emission record,
- Parent entity and its type (investor-owned, state-owned, or nation-state),
- Commodity type (including Oil, Gas, various Coal types, and Cement),
- Production quantity and units (million barrels, billion cubic feet, or million tons),
- Total emissions (in $MtCO_2e$).

The dataset is curated from producers ranked among the top 122 in the globe in oil, gas, coal, and cement, such as:

- 75 investor-owned companies,
- 36 state-owned companies, and
- 11 nation-states.

It comprises 82 oil producers, 81 gas producers, 49 coal producers, and 6 major cement producers. Apart from this, the dataset is also provided at a low, medium, and high level of granularity, which facilitates scaling analysis from aggregated trends to much finer emissions at the entity and commodity levels. It also facilitated carbon-aware decision-making via dynamic annotation and optimization of building components. Therefore, the dataset acts as a historical record and, concurrently, as an enabler of opposite-looking low-carbon design strategies in a data-driven building energy optimization framework.

Dataset link: Carbon Majors Emissions Data.

B. Performance of Emissions Analysis

This section undertakes a thorough analysis of carbon major emissions data for high-emission materials and responsible entities. This analysis, by aggregating emissions from commodity types and ownerships of the entities, brings to light emission hotspots for low-carbon considerations in BIM design.

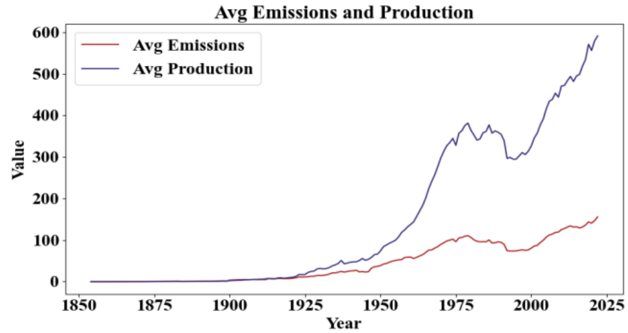

Fig. 4. Time trends of Emissions vs. Production (1854–2024).

Fig. 4 presents the historical average carbon emissions and production volume trends over time, from the Carbon Emissions dataset. This shows steep growth, especially post-1950, with production and emissions soaring with industrialization of fossil fuels. By 2024, average production had peaked at around 584 units, while emissions reached nearly 140 $MtCO_2e$. This peak of carbon emissions and commodities helped these BIM-integrated decisions to lessen carbon impact through informed decisions for the choice of material and source of energy.

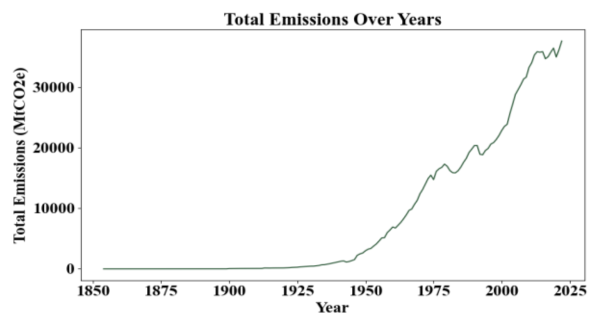

Fig. 5. Historical surge in carbon emissions accumulation.

Fig. 5 exhibits the long-term time trend of total emissions (in MtCOe) from 1850 to 2024. This indicates how emissions have a historical upward trend, becoming drastically steeper after 1950. By 1975, total emissions surpassed 15,000, after which total emissions show even a sharper rise to finally breach the 30,000 $MtCO_2e$ mark by 2020. This corresponds to industrial time, and, thus, brings to attention the need for limiting emissions in the present design and policy framework. Both of these historical viewpoints are aware of the legacy emission loads and planning for data-driven pathways for building environment and energy systems.

Fig. 6 displays the fine-grained analysis of different features contributing to carbon emissions. Product emissions $MtCO_2$ received the highest score of 0.200, followed by commodity type (~0.155), year (~0.125), and production value (~0.100). The fugitive methane emissions $MtCO_2e$ (~0.090), total operational emissions $MtCO_2e$ (~0.080), and parent entity (~0.080). Then there were lesser influential to be noted as own fuel use emissions $MtCO_2$ (~0.065), total emissions $MtCO_2e$ (~0.060), and flaring emissions $MtCO_2$ (~0.050). It helps to elucidate where emphasis is placed in the emission-aware design decisions within the BIM frameworks, thus ensuring that the targeted mitigation measures are applied to high-impact contributors.

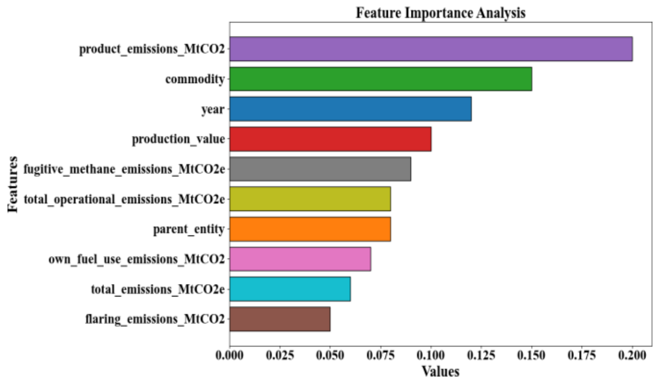

Fig. 6. Feature importance insight of influential drivers in carbon emissions.

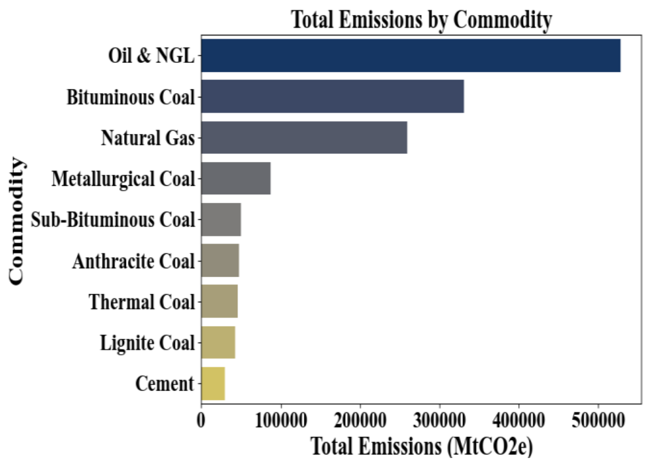

Fig. 7. Emission intensity by commodity – sectoral breakdown of carbon burden.

Fig. 7 provides an analysis of total carbon emissions (in MtCO2e) by commodity type from the dataset. It reveals that Oil & NGL is the most carbon-intensive sector, with emissions of over 500,000, followed by Bituminous Coal at roughly 350,000 and Natural Gas at around 270,000. The carbon emissions include Metallurgical Coal (~130,000), Sub-Bituminous Coal (~75,000), Anthracite Coal, Thermal Coal, and Lignite Coal, each emitting between 50,000. Finally, cement comes under 40,000 MtCO2e. This helps in identifying the most carbon-intensive sectors on which to focus the decarbonization interventions in commodity-specific policies and sustainable design practices.

The embodied carbon emissions for construction materials are summarized in Table II, which shows the emission coefficient and corresponding embodied carbon values for cement, steel, and glass, with steel recording the highest carbon emissions among these materials. Table III shows total carbon emissions globally by parent entity type, thus stressing the implications of material choice in BIM systems, and the effects of organizational ownership on the assignment of global emissions accountability; therefore, this bears on material choice and emission governance strategies in sustainable infrastructure development.

TABLE II. CARBON QUANTIFICATION FROM CONSTRUCTION MATERIALS

Material	Emission Coefficient	Quantity	Embodied Carbon ($MtCO_2e$)
Cement	0.95	1000	950.0
Steel	2.10	500	1050.0
Glass	1.40	200	280.0

TABLE III. TOTAL EMISSIONS BY PARENT TYPE

Parent Type	Percentage of Total Emissions
Nation State	36.3%
State-owned Entity	32.7%
Investor-owned Company	31.0%

C. Performance Evolution

Here, evaluate the aggregate performance of the SqueezeNet integrated optimization framework in minimizing carbon emissions and energy use. It measures improvements through simulation and establishes that data-driven design choices greatly improve the environmental performance of a building initial stages of planning.

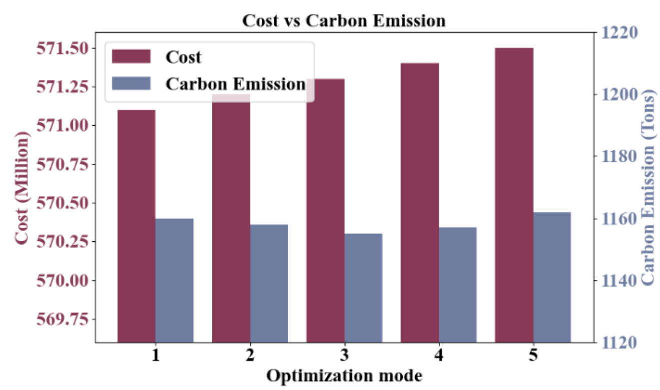

Fig. 8. Multi-objective trade-off between cost and carbon emission across optimization modes.

Fig. 8 analyzes cost (in millions) and carbon emission (in tons) across different optimization modes, based on the proposed BIM-integrated framework using an MAA-NSGA-II approach. Mode 3, thus optimized, recorded the lowest carbon emissions (~1155 tons) at a fairly low cost (~570.25 million), setting an almost-best trade-off. Equally, Mode 5 yields the most expensive costs (~571.45 million), albeit emissions were slightly reduced (~1165 tons), allowing engineers to select the most sustainable and cost-efficient configurations available for early-stage building design.

Fig. 9 compares the actual energy consumption data against predictions from the AI model. With almost exact values, the model proved its ability to accurately interpret patterns of energy consumption from building design parameters and profiles, thus validating its use in early-stage building design for the estimation of operational energy. This predictive capability favors the implementation of early-phase optimizations of energy systems toward a low-carbon design strategy.

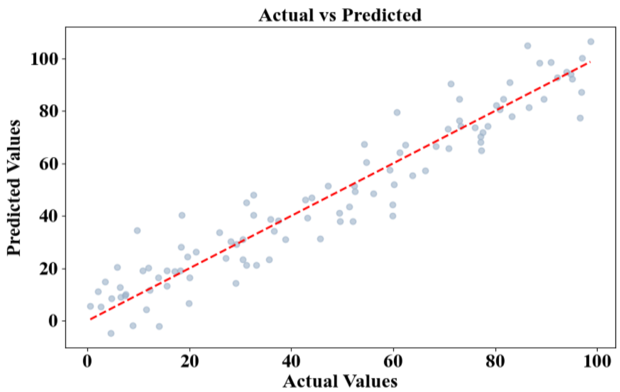

Fig. 9. Energy usage prediction accuracy using SqueezeNet.

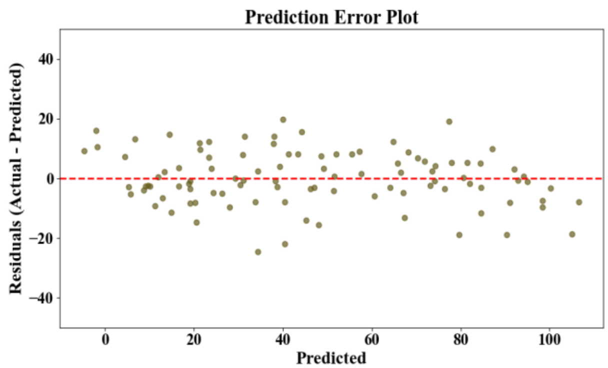

Fig. 10. Prediction error plot of energy consumption.

Fig. 10 shows the distribution of energy consumption prediction errors, highlighting the actual and predicted energy use for the various building configurations. The low clustered error values point to high model precision and minimal error in energy load prediction and thus reflect the model's capability of capturing complicated energy behavior patterns. Such a low error in prediction instils confidence in the designed framework, with attention to energy-efficient considerations in the building design process while being carbon-conscious.

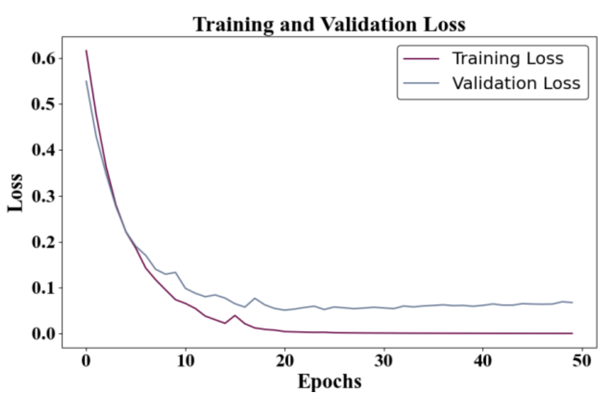

Fig. 11. Training and validation loss curve of the energy consumption.

Fig. 11 represents the training and validation-loss development of the DL model for building energy consumption prediction. The training loss gauges the ability of the model to fit the training data and turns out to be 0.00354. The validation loss, however, is slightly higher at 0.09634, yet it indicates that the predictive capabilities are good and no extensive overfitting. Through monitoring the changes in losses during the model training, it attains a trade-off between accuracy providing reliable energy consumption forecasting for building energy optimization tasks.

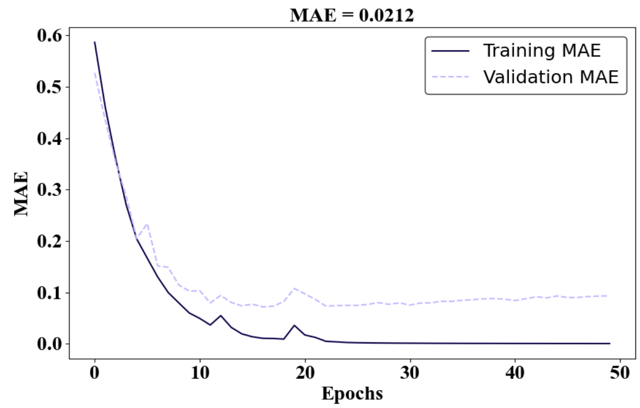

Fig. 12. Training and validation of MAE evolution.

Fig. 12 shows the training and validation Mean Absolute Error (MAE) of the model in predicting building energy consumption. This MAE considers the average magnitude of errors in prediction and ignores their direction. An overall MAE of 0.0212 shows that the model predicted energy consumption values to the actual energy consumption with high reliability.

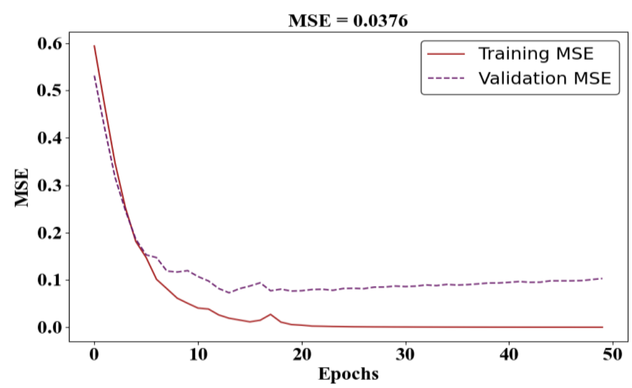

Fig. 13. Training and validation MSE analysis.

Fig. 13 shows the evolution of training and validation of Mean Squared Error (MSE) during the model training process. It quantifies the average squared difference between predicted and actual values, thus giving an indication of model accuracy. The research records an overall final MSE of 0.0376, showing that this predictive model for building energy consumption performs well in predicting the energy use of low-carbon building design.

In Fig. 14, the coefficient of determination (R^2 score) of the predictive model gives the proportion of variance of the observed data explained by the AI model. Along with this, the RMSE (Root Mean Squared Error) measure how far the observation values are from the predicted ones. Thus, the model achieved an overall R^2 score of 0.9814 and the RMSE of 0.1060, showing excellent predictive accuracy that confirms the reliability of the data-driven framework to produce accurate energy consumption.

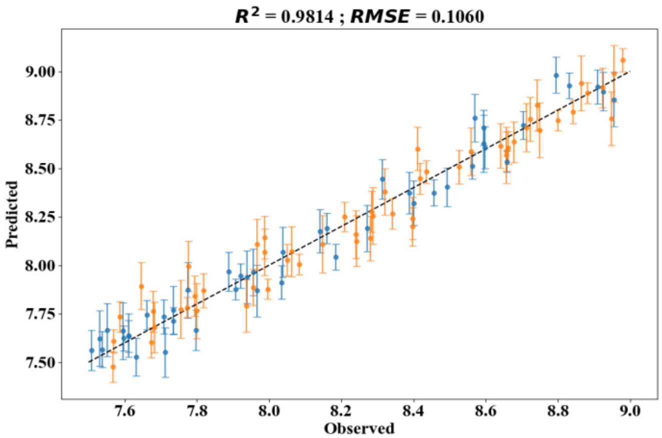

Fig. 14. Model performance evaluation using R² score and RMSE.

The above outcomes present the comprehensive analysis of the performance of the proposed framework. For the sake of further interpretation of such results in light of relevant studies and practical usage, the following section includes the discussion.

V. Discussion

A. Comparative Analysis

In this study, the comparative evolution reveals consistent improvements with regard to energy prediction accuracy and carbon reduction, confirming the efficacy of the data-driven AI optimization process through the development stages.

TABLE IV. Comparative Evaluation of AI Models for Carbon Emission Prediction

Models	MAE	MSE	RMSE	R² score
GAN [34]	0.2600	-	-	86.00
LSTM [35]	46.10	4570.14	67.60	96.00
GB [36]	24.06	-	35.18	91.00
SqueezeNet	0.0212	0.0376	0.1060	98.14

Table IV provides a comparative analysis between the proposed AI-driven method and state-of-the-art techniques, such as GANs (Generative Adversarial Networks), LSTMs (Long Short-Term Memory), and GBs (Gradient Boosting), for the prediction of carbon emissions from energy consumption forecasts. Compared to these models, the AI-based framework proposed model outperforms them tremendously. In particular, the SqueezeNet-based prediction had the lowest MAE, MSE, and RMSE values, along with the highest R^2 score, proving superior accuracy. Moreover, the integration with MAA-NSGA-II provides multi-objective optimization that balances cost, energy use, emissions, and comfort at the same time, which most existing models fail to address. This accommodation of the model to low-carbon building design through emission forecasting, to the efficient integration in SqueezeNet to account for complex temporal dependencies.

VI. Conclusion

This study effectively developed and implemented an intelligent and data-driven framework that integrates BIM with the SqueezeNet architecture for exact prediction and optimization of building energy consumption. This framework further supports low-carbon construction strategies by allowing the early-stage evaluation of design alternatives, based on the carbon major's emissions dataset. The model was enhanced by incorporating MAA-NSGA-II to balance two conflicting objectives, such as maximization of energy efficiency and minimization of emissions. This analysis revealed that an MAE of 0.0212, an MSE of 0.0376, and an R^2 of 0.9814 were achieved, indicating an impressive accuracy in prediction and generalization capacity. These results are even better than the conventional models, further supporting the energy performance superiority of the proposed method. The framework showcased its practical effect by reducing carbon emissions by 1155 tons while achieving cost savings of about 570.25 million, confirming that it offers both environmental and economic advantages. The comparative analysis also highlighted its superiority over GAN, LSTM, and GB models, establishing the framework as both highly accurate and computationally efficient. This integrated framework comprises reduced computational complexity due to AI-based design considerations, emission feedback aimed at BIM integration, and robust Multi-objective optimization for sustainable architectural decision-making. This work ultimately presents the novel, scalable, and interpretable method inherently applicable to different building typologies, thus assisting in the world shift towards low-carbon city development and climate action decisiveness. Yet, this study does have some limitations since it was primarily validated against historical emission datasets and simulations. How it performs on operational real-time data or under extremely diverse regional contexts still needs to be tested. Future work will improve the framework by using more detailed data and real-time sensors, adding better comfort models for different users and climates, improving occupant behavior prediction with AI, and applying the approach to groups of buildings or whole districts for sustainable city planning.

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Conflicts of Interests

Authors do not have any conflicts.

Data Availability Statement

The data generated and analyzed during the current study are available from the author Shu Haowen upon reasonable request but are not yet publicly available due to ongoing research.

Code Availability

Not applicable.

Authors' Contributions

Xin Yu, Guoliang Ren, are responsible for designing the framework, analyzing the performance, validating the results, and writing the study. Jie Niu is responsible for collecting the information required for the framework, provision of software, critical review, and administering the process.

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