BIM-Based Calculation and Optimization of Life Cycle Carbon Emissions for a Public Building

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Abstract: *Under the guidance of the "dual carbon" goals (carbon peaking and carbon neutrality), the low-carbon transition of the construction industry has become a key issue in national strategy. But, the existing carbon emission calculation methods generally have the problems of high calculation complexity and shortcomings in the full life cycle. This study adopts a BIM-based method to calculate and improve the life cycle carbon emissions*. In this example, a case of a public building is selected, and Glodon GTJ and GQI software are used for model quantity takeoff, and GCCP is used to extract labor, materials, and machinery data. Such data are further imported into the building performance analysis platform and the Donghe Carbon Emission Platform to establish the life cycle carbon emission model. It shows that before optimization, the total carbon emissions are 67011.66 tons, with the operational stage having the highest proportion. Therefore, carbon reduction measures are targeted at this stage. Post-optimization, the total life cycle carbon emissions are reduced by 37.0%, demonstrating a significant emission reduction effect. This study highlights the immense potential of BIM tools and digital platforms in energy conservation and emission reduction, providing practical technical methods for the green and low-carbon development of buildings.

1. Introduction

In 2024, total carbon emissions from the construction sector in China amounted to 2.78 billion tons of CO_2, with residential buildings accounting for a significant portion. Operational carbon emissions reached 2.47 billion tons, representing 21.8% of the nation's total energy consumption [1]. Driven by the "dual carbon" strategic goals of carbon peaking and carbon neutrality, the green and low-carbon transition of the construction industry has become a key national priority. Due to their continuous around-the-clock operation, the wellness and healthcare buildings examined in this case study are highly energy-dependent, making them a critical target for carbon emission optimization.

While life cycle assessment (LCA) is the global standard for assessing carbon emissions from a building, the traditional methods of calculation present challenges. In traditional methods, quantity take-offs are often incomplete, and the system boundaries are not well defined [2]. For example, the embodied carbon of material by-products, transportation emissions, and demolition emissions are easily omitted. Fortunately, the popularization of Building Information Modeling (BIM) provides an effective way to solve the above problems. Some recent studies have proved that implementing LCA methodology in a BIM environment can not only improve the accuracy of the calculations but also solve issues of data barriers [3]. But, in terms of application, the searching and reading of data are frequently manual, especially for huge and complex carbon factor databases, which is inefficient and error-prone [4].

2. Project Overview and Model Development

2.1 Project Overview

To validate the proposed framework, a wellness facility in Shandong Province was chosen as the first case study for the life cycle carbon assessment. The calculation scope covers Building 5, Building 6 and the main entrance gate. The structure is constructed from reinforced concrete, which has a standard life of 50 years. It is a Seismic Fortification Category B building, with a design seismicity of 8. Total gross floor space in the model is 13,479.69 square meters.

Carbon calculations are inherently tied to physical locations. The facility analyzed here is located in Linyi, Shandong. Because this region experiences a temperate monsoon climate—featuring stark contrasts between winter heating and summer cooling demands—the baseline operational energy is highly specific. On top of that, regional power grid metrics and local material supply chains shape the carbon output during the production phase. If other researchers attempt to apply this BIM framework to projects in different cities, they must swap out these localized climatic and grid variables to maintain accuracy.

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2.2 BIM Modeling and Quantity Takeoff

2.2.1 Creation of Civil Engineering and MEP Installation Models

Based on the CAD base drawings and project overview, this study imported the CAD base drawings into the Glodon GTJ platform to generate an axis grid and set floor elevations. Detailed modeling of components such as walls, columns, beams, and slabs was then performed to complete the architectural and structural models. Subsequently, modeling for plumbing, HVAC, and electrical systems was completed using the Glodon GQI platform. To fully account for construction feasibility, this study utilized GQI's clash detection feature to identify conflicting pipelines and resolved these conflicts by adjusting clearance settings, thereby ensuring greater accuracy in the final model [5] (as visually presented in Fig. 1 and Fig. 2).

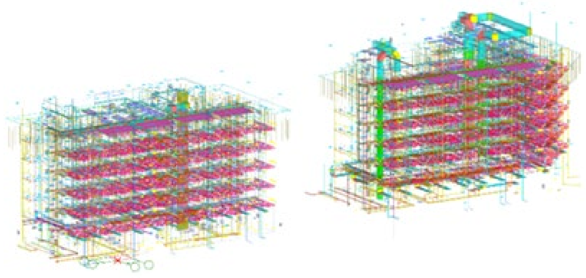

Fig. 1. MEP installation model constructed in Glodon GQI.

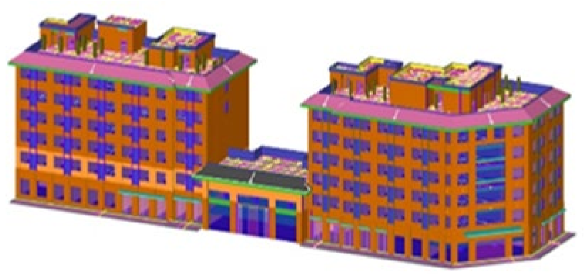

Fig. 2. Civil and structural model constructed in Glodon GTJ.

2.2.2 Preparation of the Bill of Quantities

Drawing upon the established civil and MEP models, we utilized the Glodon GCCP 6.0 cloud pricing platform to compile the tender control price documents for the unit project. We then analyzed the resource consumption, extracting and exporting detailed summary files for both materials and machinery. Consequently, it establishes a highly reliable quantitative baseline for the subsequent life cycle carbon emission assessments. Drawing upon the established civil and MEP models, we utilized the Glodon GCCP 6.0 cloud pricing platform to compile the tender control price documents for the unit project. We then analyzed the resource consumption, extracting and exporting detailed summary files for both materials and machinery. Compared to conventional manual calculations, this BIM-driven automated approach significantly enhances data accuracy [3, 6]. The specific carbon emissions of primary building materials extracted from the model are detailed in Table 1. It provides a reliable quantitative baseline for life cycle carbon emissions measurements.

3. Calculation of Carbon Emissions Across the Full Life Cycle of a Building

3.1 Calculation boundaries and basis:

Using the national standard GB/T 51366-2019 [7] and the international standard BIM-LCA [8], we defined the boundaries of the system for the carbon assessment of the building. The scope of the analysis includes five phases: production, transportation, construction, operations, and end of life demolition. Total life cycle carbon emissions are estimated using the following equation:

$$C = \sum_{i=1}^{n} Q_i \times F_i$$

Where C represents the initial carbon emissions during the building material production stage (kgCO_2e); Q is the total consumption of the i-th primary building material in m^3 or t; and F is the carbon emission factor associated with the i-th primary building material in kgCO_2e/unit of material consumed.

3.2 Carbon emissions from the production and transportation of building materials

Resource exports from GCCP show that reinforcing steel and concrete dominate the initial carbon profile (74.1%). This clearly suggests an intervention target.

Material logistics: The transportation distances were estimated using the default parameters described in the appendix to GB/T 51366-2019. These calculations show that emissions associated with transit are marginal when compared to emissions associated with manufacturing. Thus, our down-stream optimization efforts directly involve improving the building envelope and operational efficiencies.

Table 1. Carbon Emissions of Primary Building Materials in the Production and Transportation

Material	Quantity	Unit	Carbon Factor	Emissions/tCO_2e
Ready-mixed Concrete	4,707.00	m^3	295.00 kg CO_2e/ m^3	1,388.56
Aerated Concrete Block	3,481.00	m^3	213.00 kg CO_2e/ m^3	741.45
Steel Rebar	850.00	t	2,350.00 kg CO_2e/t	1,997.50
Cement & Mortar	600.00	t	735.00 kg CO_2e/t	441.00
Subtotal	-	-	-	4,568.51

3.3 Carbon emissions during the construction and demolition phases

During construction and demolition, heavy machinery is the major contributor to carbon emissions, as it consumes electricity and fossil fuel. Wanting greater precision than conventional empirical formulas can provide, we used our own energy algorithms in the Glodon Performance Analysis Platform. During this transition, we were able to calculate the emission quantities for individual construction steps within this step of the process. Using this algorithmic method, we calculated the combined total emissions for both phases as 1,681.29 tCO_2e, and the proportion of emissions across different stages is illustrated in Fig. 3.

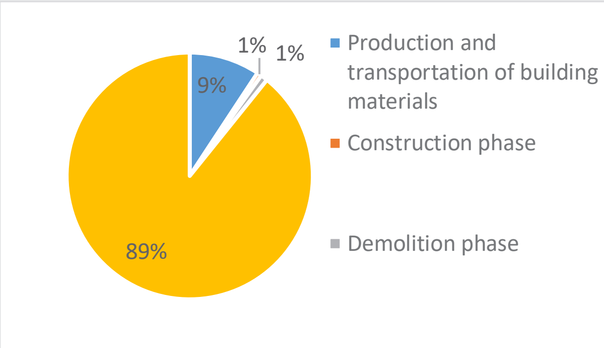

Fig. 3. Proportion of Carbon Emissions Across Different Building Life Cycle Stages

3.4 Carbon emissions during operation (energy consumption simulation)

In order to assess the operational status of our project in a precise manner, we created a 3D building model using Autodesk Revit and exported it as gbXML to use in the Glodon Performance Analysis Platform. Because healthcare facilities are operating 24/7, we simulated the occupancy, lighting, equipment and fresh air ventilation schedules over a period of 50 years. We used local variables specific to Shandong Province. For instance, we selected the time-of-use and electricity prices by tiered rate, and programmed our HVAC equipment to operate according to local cooling months and holiday seasons. Using these parameters, the platform calculated the carbon footprint at each step of the building lifecycle.

3.5 Summary of Initial Carbon Emissions Results

All four of these stages combined produce a total life cycle carbon footprint of 67,011.66 t CO_2e over a 50-year service life. These results show that the operating and material production phases make up the majority of this total. Based on these results, we will focus our efforts on optimizing these two high-carbon areas to deliver the largest reduction in carbon dioxide.

4. Strategies and Optimization Analysis for Low-Carbon Emissions Reduction

4.1 Authors and Affiliations

Since operational carbon emissions contribute up to 89% of total CO_2, the aim for this stage is to save as much as possible. This is especially true for healthcare and wellness buildings that have a high energy requirement as they operate around-the-clock [9], [10]. To meet this reduction target, the study uses a BIM performance analysis platform to implement passive and active energy-saving measures. First, without altering the main structure, the building envelope is upgraded to cut heating and cooling loads. Second, the HVAC system receives targeted efficiency improvements to maximize energy utilization. Lastly, renewable energy sources are introduced to support the transition toward green energy. This combined optimization strategy aims to effectively curb the building's overall energy consumption, offering an actionable and realistic solution for green retrofitting in modern, energy-intensive public facilities [11].

4.2 Optimization of Passive Building Envelopes

Using the performance analysis platform to identify opportunities to improve the building envelope, without altering the exterior façade or primary structural components of the building, we optimized the envelope through passive measures compared to GB 50189-2015 [12]. The thermal barriers were strengthened by changing the XPS boards. The exterior wall insulation thickness of the house increased to 100 mm (a 55 mm + 45 mm composite), the roof layer thickened to 125 mm, and a new 55 mm XPS thermal break was added on the ground floor slab. These physical changes significantly reduced heat loss from the house.

4.3 Active Systems and Renewable Energy Optimization

After exterior improvements to the envelope, we targeted the HVAC system and energy architecture for further optimization.

The original heating and cooling system was decentralized with a combination of a "hot water boiler + split-unit air conditioning," which was costly in terms of energy consumption. These were replaced by a VRF multi-split. In the performance analysis platform, the Cooling Coefficient of Performance (COP) for the outdoor units was set at 3.2, and the Heating Coefficient of Performance (COP) was set at 2.3, which meant that HVAC energy was not being used as much.

Additional renewable energy sources were used to maximise the generation at site. A 300 m^2 solar thermal array was installed on the roof and produces an estimated 246,854.25 kWh of thermal energy every year. A total of 200 m^2 photovoltaic (PV) panels with a 15% conversion rate were installed[13]. It has been estimated by software that this PV array could generate 41,471.50 kWh of clean electricity per year.

4.4 Comparison of Optimization Results

Incorporating the above carbon reduction measures, I then ran a second full-year energy simulation. The results indicate that the building's energy needs decreased dramatically since pre-intervention. Prior to intervention, the building had an annual energy demand of 2,215,900 kWh or 181.74 kWh/(m^2a) per unit area. These figures dropped to 1,396,200 kWh and 114.34 kWh/(m^2a) after optimization, resulting in an overall building energy savings of 37.0% (as shown in Fig. 4). These results show the effectiveness of implementing a combination of passive envelope changes and active systems and renewable energy for building carbon reduction.

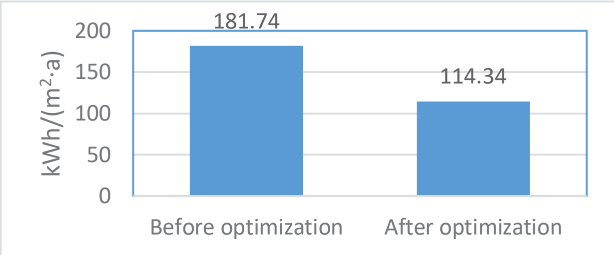

Fig. 4. Comparison of Energy Use Intensity (EUI) Before and After Optimization

5. A Discussion on the Application of AI Technology in Reducing Carbon Emissions in the Construction Industry

5.1 Conversational AI-Assisted Carbon Factor Matching

When dealing with the vast amount of carbon factor data in the Standard for Calculation of Carbon Emissions in Buildings (GB/T 51366-2019), traditional manual retrieval is not only extremely time-consuming but also prone to errors in carbon factor selection due to subjective interpretation, which severely affects the accuracy of the final calculations. In recent years, AI technology has gradually emerged as an industry trend for improving the efficiency of carbon emissions calculations. In this study, using Glodon AI, by inputting natural language descriptions of building materials from the bill of quantities (such as specific specifications and materials), the AI can deeply understand complex engineering contexts and automatically retrieve matching carbon factor data and unit conversion relationships. This intelligent approach not only significantly improves the efficiency of the carbon factor matching process—the most time-consuming step in traditional calculations—but also fundamentally resolves the systematic biases caused by manual retrieval, providing a more efficient and accurate database for precise calculations in complex projects.

5.2 Exploiting Machine Learning for Holistic Scheme Optimization

We propose leveraging artificial intelligence not merely as a passive data-matching tool, but as an active agent in broader building design optimization. This is realized by directly embedding sophisticated machine learning algorithms within the core BIM framework. Such integration transforms the standard design workflow, empowering the system to autonomously simulate thousands of design permutations. Crucially, this permits the dynamic adjustment and instantaneous testing of numerous interdependent variables, ranging from alternative material properties and varied thermal insulation thicknesses to complete HVAC system configurations. This fundamental reorientation, shifting the paradigm from recursive manual iterations to AI-driven generative exploration, holds immense potential to expedite the entire construction sector's essential transition toward net-zero emissions.

6. Conclusions and Outlook

6.1 Research Findings

Ancillary to BIM and life cycle assessment (LCA) methodologies[14], a carbon calculation and optimization methodology was implemented for the healthcare facility being evaluated. Key outcomes of this study include the following:

The operational phase accounts for the largest part of the carbon emissions reduction: the 50-year footprint is 67,011.66 t CO_2e. The operational phase accounts for 89% of the total emissions, followed by production and logistics.

The combined “passive-active-renewable” strategy yields a significant reduction in energy usage. With the passive envelope, HVAC systems with greater energy-efficiency [15], and renewable solar, the year-to-year energy demand fell from 181.74 kWh/(m^2a) to 114.34 kWh/(m^2a). This represents a 37.0% reduction in energy usage, making the green retrofitting plan feasible.

AI tools are highly effective for optimizing carbon emissions. Research has shown that the deep integration of performance analysis platforms with AI tools can effectively overcome the inefficiencies of manual searches, such as poor carbon factor matching, and significantly improve the efficiency and accuracy of carbon emissions calculations.

6.2 Practical Challenges and Future Outlook

Seeing a 37.0% energy reduction in a simulation is encouraging, but hitting those numbers in a real engineering scenario comes with hard limits. When you try to retrofit existing public buildings—like adding thicker thermal breaks—you quickly run into restrictions based on the original structural load and facade aesthetics. Active upgrades like massive solar arrays also demand a heavy upfront investment. Ultimately, turning a low-carbon blueprint into a reality means compromising between theoretical emission cuts and tight construction budgets.

Beyond financial constraints, the core limitation of what we have done here is relying purely on software. Since we haven't cross-verified the BIM outputs with an actual operating building, the numbers assume an idealized scenario. Real-life operations are messy. Equipment ages, and occupants rarely use energy exactly as predicted. To bridge this gap, our team's next phase involves wiring pilot projects with IoT sensors. Gathering live data from the field will finally let us calibrate the simulation algorithms against reality, proving whether these retrofitting strategies actually hold up over time.

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