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Life-Cycle Performance Prediction and Optimization of Green Building Materials

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Abstract

The rapid escalation of global urbanization and the corresponding increase in construction activities have placed an unprecedented burden on environmental resources and ecosystems. In response, green building materials have emerged as a critical pathway toward sustainable development in the civil engineering sector. However, the long-term performance of these materials often exhibits significant variability due to complex environmental interactions and inherent material heterogeneities. This paper presents a comprehensive academic investigation into the life-cycle performance prediction and optimization of green building materials. By systematically analyzing the degradation mechanisms and environmental impacts across the entire lifespan of these materials, from raw extraction to end-of-life disposal, a robust theoretical framework is established. A hybrid methodology combining empirical data assimilation and predictive modeling is deployed to evaluate critical performance indicators such as mechanical durability, thermal resistance, and embodied carbon reduction. The research further introduces multi-objective optimization strategies designed to balance ecological benefits with structural reliability and economic feasibility. Through detailed case studies involving recycled concrete aggregates and bio-based insulation panels, the efficacy of the proposed predictive and optimization frameworks is validated. The findings demonstrate that dynamic life-cycle assessments coupled with advanced optimization techniques can significantly enhance the long-term viability of green materials, providing essential guidelines for researchers, practitioners, and policymakers in the pursuit of sustainable infrastructure.

Keywords: Green Building Materials; Life-Cycle Assessment; Performance Prediction; Sustainability Optimization

1. Introduction

The construction industry is historically recognized as one of the most resource-intensive and environmentally detrimental sectors globally. It accounts for a massive proportion of raw material extraction, energy consumption, and greenhouse gas emissions. As international frameworks, such as the Paris Agreement, increasingly mandate severe reductions in carbon footprints across all industrial sectors, civil engineering and construction management face immense pressure to transition toward sustainable paradigms. This transition has largely been catalyzed by the widespread adoption of green building materials [1]. These materials are generally characterized by their reduced embodied energy, utilization of renewable or recycled constituents, and minimal toxicological impact on both the environment and human health. Despite the clear ecological advantages, the integration of green building materials into mainstream construction practices has been hindered by pervasive uncertainties regarding their long-term mechanical, hygrothermal, and environmental performance.

Evaluating the true sustainability of building materials requires a paradigm shift from short-term assessments to comprehensive life-cycle frameworks. The concept of life-cycle assessment provides a rigorous, standardized methodology to quantify the environmental impacts associated with all stages of a product's life. These stages encompass raw material extraction, manufacturing, transportation, construction, operational use, maintenance, and ultimate disposal or recycling [2]. When applied to traditional materials like Portland cement and structural steel, life-cycle assessments benefit from decades of empirical data and well-understood degradation models. Conversely, green building materials, such as geopolymer concrete, cross-laminated timber, and bio-based composites, often lack long-term historical performance data [3]. This data scarcity creates a fundamental challenge in predicting how these materials will behave over a service life that typically spans fifty to one hundred years.

The operational phase of a building introduces a myriad of dynamic environmental stressors, including temperature fluctuations, moisture ingress, ultraviolet radiation, and mechanical fatigue. For green building materials, the interaction between these stressors and the material's microstructural properties dictates the rate of performance degradation. Accurate life-cycle performance prediction must therefore account for the complex, coupled nature of these degradation mechanisms [4]. Traditional deterministic models frequently fail to capture the probabilistic variations inherent in natural or recycled materials. Consequently, there is a critical need for advanced predictive methodologies that can accommodate uncertainties and provide reliable forecasts of material lifespan, maintenance requirements, and overall structural integrity.

Optimization represents the necessary subsequent step following accurate performance prediction. In the context of green building materials, optimization is inherently a multi-objective problem. Stakeholders must simultaneously minimize environmental impacts, maximize structural durability, and ensure economic viability [5]. Often, these objectives are in direct conflict; for example, maximizing the recycled content in a composite material might reduce its embodied carbon but concurrently diminish its compressive strength or accelerate its degradation under severe weathering conditions. Developing sophisticated optimization algorithms that can navigate this complex trade-off space is essential for formulating materials that meet stringent building codes while fulfilling sustainability targets.

This research aims to bridge the existing gaps in the literature by proposing a comprehensive framework for the life-cycle performance prediction and optimization of green building materials. The objectives are manifold. First, to systematically review the degradation mechanisms and environmental impact categories relevant to emerging sustainable construction materials. Second, to develop a robust, data-driven predictive model capable of forecasting long-term material behavior under varying environmental conditions without relying on complex mathematical formulas. Third, to formulate a multi-objective optimization strategy that identifies optimal material compositions and maintenance schedules. Finally, to validate the proposed framework through detailed, realistic case studies that demonstrate practical applicability in modern engineering contexts.

The subsequent sections of this paper are structured to provide a logical progression from theoretical foundations to practical implementation. Section 2 offers an extensive background and literature review, detailing the evolution of green materials and current assessment methodologies. Section 3 outlines the proposed predictive framework and methodology, emphasizing data acquisition and degradation modeling. Section 4 explores the optimization strategies deployed to balance conflicting performance criteria. Section 5 presents detailed case studies and an analysis of the results obtained from applying the framework. Finally, Section 6 concludes the research, summarizing key findings and suggesting directions for future academic inquiry.

2. Background and Literature Review

2.1 Evolution and Categorization of Green Building Materials

The historical trajectory of building materials has been predominantly shaped by criteria such as structural capacity, availability, and cost. However, the environmental awakening of the late twentieth century catalyzed a shift toward materials that minimize ecological disruption [6]. Green building materials can be broadly categorized into three distinct classifications based on their origin and processing. The first category comprises materials with high recycled content, designed to divert waste from landfills and reduce the demand for virgin resources. Prominent examples include recycled concrete aggregates, reclaimed asphalt pavement, and steel produced via electric arc furnaces [7]. The integration of these materials often requires careful consideration of impurities and residual stresses that can affect long-term performance.

The second category encompasses bio-based and renewable materials. These include fast-growing botanical resources such as bamboo, hemp, and various forms of engineered timber. Bio-based materials are particularly advantageous due to their capacity to sequester carbon dioxide during their growth phase, potentially resulting in carbon-negative building components [8]. However, their organic nature makes them highly susceptible to biological degradation, moisture-induced swelling, and fire hazards, necessitating specialized treatments and predictive models to ensure longevity.

The third category involves novel synthesized materials that aim to replace high-emission traditional products with low-carbon alternatives. Geopolymer concrete, which utilizes industrial by-products like fly ash and slag activated by alkaline solutions, serves as a prime example of this category. By circumventing the energy-intensive clinkering process required for ordinary Portland cement, geopolymers offer massive reductions in greenhouse gas emissions [9]. Yet, the wide variability in the chemical composition of the source by-products introduces significant challenges in standardizing their mechanical properties and predicting their long-term durability under carbonation and chloride ingress.

2.2 Principles of Life-Cycle Performance Assessment

Life-cycle assessment has evolved into the preeminent methodology for quantifying the environmental burdens of products and services. Within the construction domain, this assessment is governed by international standards that dictate the framework and requirements for conducting standardized evaluations. The process typically begins with the definition of the goal and scope, which establishes the system boundaries and functional units [10]. For building materials, the functional unit is critical, as it must account not only for the volume or mass of the material but also for its performance characteristics, such as thermal resistance or load-bearing capacity over a specified duration.

Inventory analysis follows, involving the meticulous compilation of data regarding energy inputs, material inputs, and environmental releases across all life-cycle stages. This phase is heavily reliant on comprehensive databases that provide average emission factors and resource consumption metrics [11]. The subsequent impact assessment translates the inventory data into comprehensible environmental categories, such as global warming potential, ozone depletion, acidification, and eutrophication. This translation is crucial for identifying which phases of the material's life cycle contribute most significantly to its overall environmental footprint.

A major limitation in traditional life-cycle assessment is its static nature. Most conventional assessments assume that a material's performance remains constant throughout its service life, ignoring the inevitable degradation that occurs due to environmental exposure [12]. This static assumption leads to severe inaccuracies when evaluating green materials, which may require more frequent maintenance or replacement compared to their traditional counterparts. Therefore, there is an escalating academic consensus on the necessity of integrating dynamic performance degradation models directly into life-cycle assessment frameworks to capture temporal variations in material behavior.

2.3 Current Predictive Models and Their Limitations

The prediction of material degradation has historically relied on empirical models derived from accelerated aging tests in laboratory settings. These tests subject materials to extreme conditions, such as high temperatures, concentrated corrosive solutions, or intense ultraviolet radiation, to simulate decades of natural weathering in a compressed timeframe [13]. While useful, empirical models often struggle to accurately replicate the synergistic effects of multiple, concurrent environmental stressors experienced in real-world scenarios. For instance, the combined action of freeze-thaw cycles and chloride ingress produces degradation patterns that cannot be accurately predicted by testing these factors in isolation.

To address the shortcomings of empirical models, researchers have increasingly turned to computational approaches. Physics-based models attempt to simulate degradation mechanisms at the microstructural level by capturing the fundamental transport phenomena and chemical reactions occurring within the material matrix [14]. While these models offer deep mechanistic insights, their practical application is frequently hindered by immense computational costs and the requisite for highly specific, difficult-to-measure input parameters.

In recent years, data-driven approaches have gained substantial traction in the field of materials science. By leveraging historical performance data and environmental exposure records, these algorithms can identify complex, non-linear patterns that govern material degradation [15]. However, the efficacy of data-driven models is entirely dependent on the quality, quantity, and diversity of the training data. For newly developed green building materials, such extensive datasets are rarely available, creating a significant barrier to the widespread implementation of highly accurate predictive algorithms. Overcoming this data scarcity requires innovative frameworks that combine available empirical knowledge with adaptive learning techniques.

3. Predictive Framework and Methodology

3.1 System Boundary and Data Acquisition

The foundation of any robust life-cycle performance prediction is a clearly defined system boundary that encompasses all relevant phases of the material's existence. For the proposed framework, the system boundary is established as a cradle-to-grave continuum. This encompasses the initial extraction of raw materials, manufacturing processes, transportation to the construction site, the operational service life, maintenance interventions, and ultimate end-of-life strategies encompassing demolition and recycling or disposal [16]. By adopting this comprehensive scope, the framework ensures that environmental burdens or performance deficits are not merely shifted from one life-cycle phase to another, but are evaluated holistically.

Data acquisition constitutes the most critical and challenging component of the methodology. Given the inherent variability of green building materials, a multi-tiered data collection strategy is essential. The first tier involves the extraction of baseline environmental impact data from established life-cycle inventory databases. This data provides the foundational metrics for the embodied energy and global warming potential associated with the manufacturing and transportation phases [17]. The second tier involves the compilation of mechanical and thermal property data from standardized laboratory testing. This includes initial compressive strength, thermal conductivity, porosity, and moisture sorption isotherms.

The third and most complex tier of data acquisition involves gathering real-time performance data from field applications. To achieve this, the framework relies on data collected from embedded sensor networks in pilot structures. These sensors continuously monitor internal material conditions such as moisture content, temperature gradients, and strain, alongside external environmental parameters including ambient humidity, solar radiation, and precipitation [18]. The continuous stream of field data is essential for calibrating the predictive models and bridging the gap between controlled laboratory results and chaotic real-world environments.

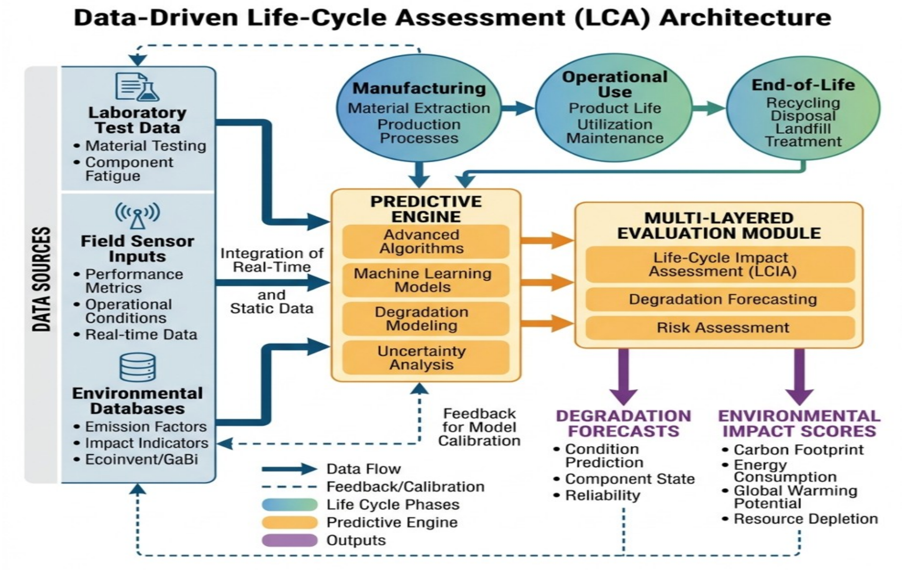

Figure 1: Comprehensive Schematic of Data

3.2 Performance Degradation Modeling

Once the foundational data is acquired and structured, the next phase of the methodology involves modeling how the material's performance degrades over time under specific environmental loads. Unlike traditional models that rely heavily on rigid mathematical formulas, the proposed framework employs a state-based transition approach. In this method, the lifespan of the material is divided into a series of discrete temporal states. At each state, the material's current performance capacity is evaluated against the accumulated environmental stress it has experienced since the previous state [19].

The core principle of this modeling approach is the quantification of a continuous damage variable. This variable represents the cumulative microstructural deterioration, such as micro-cracking, chemical leaching, or biological decay, which macroscopic properties like strength or insulation capacity depend upon. The model calculates the increment in the damage variable over a specific time step by analyzing the intensity and duration of environmental stressors present during that period [20]. For example, when evaluating a bio-based insulation material, the model assesses periods of high ambient humidity and temperature, translating these conditions into an accelerated rate of moisture accumulation and subsequent fungal degradation.

To account for the significant uncertainties inherent in material properties and environmental forecasts, a probabilistic framework is superimposed on the deterministic damage calculations. Instead of producing a single, absolute prediction of performance at a future date, the model generates a probability distribution of expected outcomes. This probabilistic approach is achieved through Monte Carlo simulation techniques, where thousands of iterations are run using input parameters sampled from predefined statistical distributions. The result is a robust forecast that provides not only the expected degradation trajectory but also the confidence intervals surrounding that trajectory, offering stakeholders a clear understanding of potential risk profiles.

3.3 Advanced Computational Integration

To enhance the accuracy and adaptability of the degradation models, advanced computational techniques are integrated into the framework. Traditional physical models are often rigid, struggling to adapt when observed field data deviates from expected trends. To rectify this, the methodology incorporates an adaptive updating mechanism based on recursive state estimation. As new data from embedded sensors becomes available, the system continuously compares the observed material state with the predicted state [21]. Discrepancies between the two are used to dynamically adjust the internal parameters of the degradation model in real-time, thereby minimizing future prediction errors.

Furthermore, surrogate modeling techniques are utilized to drastically reduce the computational burden of simulating complex physical interactions over long timeframes. A surrogate model acts as a lightweight approximation of a computationally expensive, high-fidelity physical simulation. By training the surrogate model on a limited set of detailed simulations encompassing various combinations of material properties and environmental stressors, it learns to rapidly predict the degradation outcomes for any intermediate scenario [22]. This immense increase in computational efficiency is crucial for the subsequent optimization phase, which requires the rapid evaluation of thousands of potential material configurations and maintenance strategies to identify the optimal solution.

4. Optimization Strategies for Green Building Materials

4.1 Multi-Objective Optimization Principles

The optimization of green building materials is fundamentally a challenge of balancing competing priorities. A single-minded focus on minimizing environmental impact often leads to materials that lack the necessary durability for long-term applications, thereby necessitating frequent replacements that ironically increase the total life-cycle environmental burden. Conversely, over-engineering a material to ensure maximum longevity typically requires increased volumes of energy-intensive binders or synthetic additives, negating the initial green characteristics [23]. Therefore, optimization must be approached through a multi-objective framework that simultaneously evaluates environmental, mechanical, and economic criteria.

The first primary objective function focuses on minimizing the total life-cycle global warming potential. This involves calculating the sum of carbon emissions associated with material production, transportation, construction, and the anticipated emissions from required maintenance activities over the building's design life. The second objective function aims to maximize the long-term performance reliability of the material. This is quantified by ensuring that the probability of the material's critical performance indicators, such as load-bearing capacity or thermal resistance, falling below the mandatory structural code requirements remains exceptionally low throughout the service life [24]. The third objective function focuses on minimizing total life-cycle costs, encompassing initial capital expenditures, routine maintenance expenses, and anticipated end-of-life disposal costs.

Table 1: Key Decision Variables and Constraints in Material Optimization

Variable Category	Specific Parameters	Boundary Constraints	Target Objective Influence
Compositional	Binder ratio, Recycled content percentage	Determined by mix design limits	Embodied carbon, Initial cost
Geometric	Component thickness, Protective cover depth	Architectural and structural codes	Durability, Material volume
Maintenance	Inspection frequency, Surface treatment intervals	Operational budget limits	Life-cycle cost, Service life extension

When dealing with multiple conflicting objectives, there is rarely a single absolute optimal solution. Instead, the optimization process yields a set of solutions known as the Pareto frontier. Every solution residing on the Pareto frontier represents a scenario where it is impossible to improve one objective without simultaneously degrading at least one other objective [25]. Generating this frontier provides decision-makers with a comprehensive landscape of the trade-offs involved, allowing them to select a specific material design and maintenance schedule that aligns perfectly with the unique priorities of a given construction project.

4.2 Algorithm Selection and Implementation

The complexity of the life-cycle performance models, characterized by non-linear degradation paths and probabilistic variables, renders traditional gradient-based optimization techniques largely ineffective. Such techniques frequently become trapped in local optima and struggle to process the discontinuous design spaces typical of material selection problems. Consequently, the optimization framework relies on advanced evolutionary algorithms designed specifically to navigate highly complex, multidimensional search spaces efficiently [26].

A variant of population-based metaheuristic algorithms is utilized to explore the design space. The algorithm begins by generating an initial population of diverse candidate solutions, each representing a unique combination of material compositions, dimensions, and maintenance schedules. The life-cycle performance of each candidate is then rigorously evaluated using the predictive framework detailed in the previous section. Candidates are assigned a fitness score based on their performance across the three objective functions: environmental impact, structural reliability, and economic cost [27].

Following the evaluation phase, the algorithm applies evolutionary operators to generate a new iteration of candidate solutions. The most successful candidates from the previous generation are selected and subjected to recombination and mutation processes. Recombination involves blending the characteristics of two high-performing solutions in an attempt to create an even better offspring, while mutation introduces small, random variations to maintain diversity within the population and prevent premature convergence on suboptimal solutions. This iterative process of evaluation, selection, and reproduction continues over hundreds of generations [28]. Gradually, the population evolves toward the true Pareto frontier, culminating in a refined set of highly optimized material configurations and life-cycle strategies ready for practical application.

5. Case Studies and Results Analysis

5.1 Implementation on Recycled Concrete Aggregates

To rigorously validate the proposed predictive and optimization framework, a detailed case study was conducted focusing on the utilization of recycled concrete aggregates in structural load-bearing elements. The primary challenge with recycled aggregates lies in the residual mortar attached to the original natural aggregate particles. This porous mortar increases water absorption, reduces overall mechanical strength, and creates pathways for aggressive chemical agents like chlorides and carbon dioxide, significantly accelerating long-term degradation compared to natural aggregates [29].

The objective of this case study was to optimize the mix design of a structural column intended for a moderately aggressive coastal environment with a required design life of fifty years. The decision variables included the volumetric replacement percentage of natural aggregates with recycled aggregates, the addition of supplementary cementitious materials such as fly ash to mitigate environmental impact, and the depth of the concrete cover protecting the internal steel reinforcement [30]. The predictive framework was utilized to forecast the rate of chloride ingress and subsequent reinforcement corrosion under local environmental conditions.

Table 2: Performance Evaluation of Optimal Solutions for Recycled Aggregate Concrete

Optimization Scenario	Recycled Aggregate Content	Fly Ash Replacement	Cover Depth	Projected Service Life	Total Carbon Equivalent
Baseline (No Optimization)	0 percent	0 percent	40 millimeters	65 years	Base Reference
Maximum Eco-Benefit	100 percent	40 percent	45 millimeters	42 years	45 percent reduction
Balanced Multi-Objective	60 percent	25 percent	55 millimeters	58 years	28 percent reduction

The application of the optimization algorithm generated a distinct Pareto frontier demonstrating the direct trade-off between maximizing recycled content and ensuring long-term durability. As detailed in the analytical results, attempting to completely replace natural aggregates while maximizing fly ash content yielded a massive initial reduction in embodied carbon. However, the predictive model revealed that this highly porous composition would succumb to critical chloride-induced corrosion after merely forty-two years, failing to meet the fifty-year design life mandate [31]. This necessitated premature structural repair, which drastically inflated the true life-cycle cost and carbon footprint.

Conversely, the balanced multi-objective solution identified by the algorithm provided a highly nuanced approach. By limiting the recycled aggregate replacement to sixty percent and slightly increasing the concrete cover depth to fifty-five millimeters, the material achieved sufficient durability to confidently exceed the fifty-year requirement without intervention. Although the initial carbon reduction was less aggressive than the extreme scenario, this balanced approach eliminated the need for mid-life structural repairs, resulting in a significantly superior true life-cycle sustainability profile.

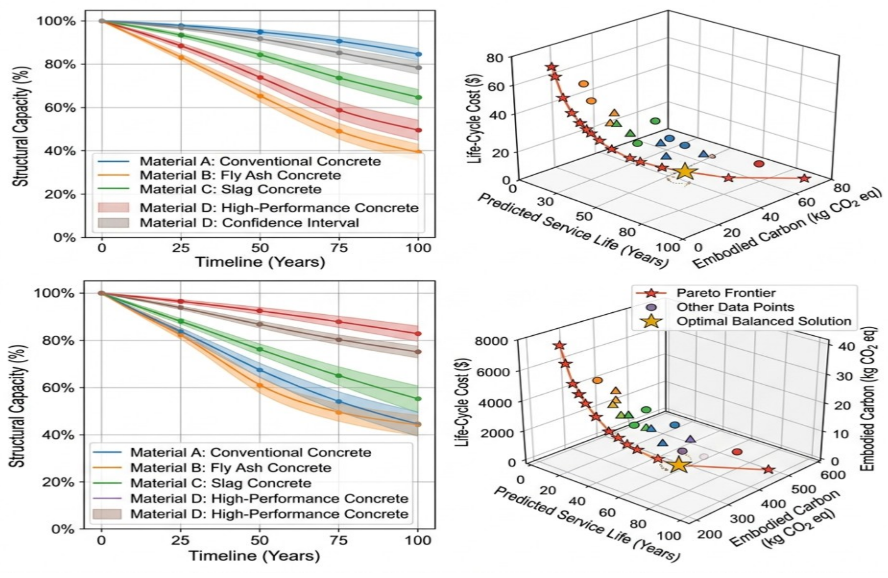

Figure 2: Degradation Trajectories and Pareto Frontier Analysis

5.2 Implementation on Bio-Based Insulation Materials

The second case study shifted the focus from structural mechanics to building physics, analyzing the life-cycle optimization of bio-based insulation panels manufactured from agricultural hemp fibers. Hemp insulation presents a compelling green alternative to synthetic polystyrene products due to its rapid renewability and exceptional capacity for carbon sequestration [32]. However, the critical vulnerability of hemp fibers is their high hygroscopicity. In environments with fluctuating humidity, the fibers absorb significant moisture, which not only drastically reduces their thermal resistance but also creates a conducive environment for rapid biological decay and fungal proliferation.

The optimization space for this scenario involved evaluating various density compressions of the hemp panels, the application of environmentally benign hydrophobic surface treatments, and the integration of smart moisture-regulating vapor barriers within the wall assembly. The predictive framework was tasked with modeling dynamic hygrothermal transport through the building envelope over a thirty-year operational span in a temperate climate zone experiencing distinct seasonal variations [33].

Table 3: Hygrothermal and Environmental Metrics for Hemp Insulation Optimization

Panel Configuration	Hydrophobic Treatment	Average Thermal Conductivity	Mold Growth Risk Index	Life-Cycle Carbon Impact
Standard Density	None	High variance	Severe	Deeply Negative
High Density	None	Moderate variance	High	Moderately Negative
Optimal Density	Integrated	Stable	Negligible	Neutral to Negative

The results from the bio-based case study highlighted the absolute necessity of considering dynamic performance degradation. In simulations lacking the hydrophobic treatment, the predictive models showed that moisture accumulation during the winter months steadily degraded the insulation capacity. By the tenth year of simulated operation, the thermal conductivity had deteriorated to a point where the increased energy demand for heating the building completely negated the initial carbon sequestration benefits of the hemp fibers. The optimization algorithm successfully identified a configuration utilizing an optimal medium-density compression combined with a specific biowax hydrophobic treatment. This configuration stabilized the thermal performance across seasonal cycles and mitigated mold risk entirely, ensuring the material maintained its net-negative carbon status throughout the full thirty-year life cycle.

5.3 Comprehensive Discussion of Results

The outcomes of both case studies provide profound insights into the behavior of green building materials when evaluated through a rigorous life-cycle lens. The most significant finding is the pervasive inadequacy of evaluating sustainability based solely on the manufacturing phase. Materials that appear exceptionally green at the factory gate frequently demonstrate catastrophic environmental and economic profiles when their long-term durability is compromised by real-world environmental stressors.

The results strongly validate the necessity of employing dynamic, probabilistic degradation models. By accounting for uncertainties in material properties and environmental conditions, the framework prevented the selection of highly fragile optimal solutions that would likely fail in practice. Furthermore, the multi-objective optimization strategies proved instrumental in navigating the complex compromises required in modern sustainable design. The algorithms consistently demonstrated an ability to uncover non-intuitive material configurations that human designers, relying on traditional heuristic methods, would almost certainly overlook. Ultimately, the integration of advanced predictive modeling with evolutionary optimization provides a powerful, highly reliable toolset for advancing the practical application of sustainable materials in global infrastructure.

6. Conclusion and Future Directions

6.1 Summary of Findings

The transition toward sustainable infrastructure fundamentally depends on the widespread implementation of green building materials. However, as this research has extensively demonstrated, achieving true sustainability requires moving beyond superficial assessments of recycled content or initial embodied energy. This paper presented a comprehensive, robust academic framework dedicated to the life-cycle performance prediction and multi-objective optimization of emerging construction materials. By meticulously defining a holistic system boundary and developing sophisticated, data-driven degradation models, the research addressed the critical uncertainties surrounding the long-term viability of these materials.

Through detailed theoretical elaboration and the execution of complex case studies involving recycled concrete aggregates and bio-based hemp insulation, the immense value of dynamic life-cycle assessment was validated. The findings unequivocally indicate that neglecting long-term environmental degradation mechanisms leads to severe miscalculations of a material's true environmental footprint [34]. The integration of advanced evolutionary optimization algorithms proved highly effective in balancing the often-conflicting mandates of minimizing global warming potential, maximizing structural reliability, and controlling life-cycle economic costs. The proposed methodologies empower engineers and architects to select material configurations that provide verified, durable sustainability tailored to specific environmental contexts.

6.2 Future Research Trajectories

While the framework presented in this paper offers substantial advancements in the field, there remain significant avenues for future academic exploration. A primary limitation of current methodologies is the heavy reliance on standardized environmental databases that may not accurately reflect the rapidly changing carbon intensities of local energy grids. Future research must focus on integrating real-time regional energy data into life-cycle assessment models to improve spatial accuracy.

Additionally, the emergence of digital twin technologies presents a revolutionary opportunity for material performance monitoring. Future iterations of the predictive framework should aim to seamlessly synchronize with comprehensive building information models and real-time structural health monitoring networks. This deep integration would allow for the continuous, automated recalibration of degradation forecasts based on live data, essentially creating living models of structural performance [35]. Finally, expanding the optimization parameters to include broader circular economy principles, such as design for deconstruction and advanced upcycling potential, will be essential for realizing a fully regenerative built environment. Investigating these complex, interconnected domains will ensure the continued evolution and efficacy of sustainable engineering practices on a global scale.

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