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Predictive Modeling of Carbon Footprint in Hybrid Structural Components Using AI and Mathematical Algorithms

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Abstract
Sustainable engineering requires a precise assessment of the carbon footprint of hybrid structural elements. To evaluate the lifespan emissions of materials such as composites and fiber-reinforced polymers, this study proposes a predictive modeling approach that blends mathematical optimization with Artificial Intelligence (AI) approaches, such as neural networks and regression algorithms. The model provides precise and understandable carbon footprint estimates by examining data on material characteristics, energy use, and processing techniques. The strategy promotes more environmentally friendly material selections and structural layouts, which are consistent with international net-zero goals.

1. Introduction

The drive toward climate-neutral construction and manufacturing practices has intensified with growing global commitments to achieving net-zero emissions. One major focus in this effort is reducing the carbon footprint of structural components, especially those incorporating hybrid materials such as fiber-reinforced polymers (FRPs), composites, and traditional building elements. These hybrid materials are gaining traction due to their favorable strength-to-weight ratios, corrosion resistance, and extended service life [1]. However, their heterogeneous composition and complex lifecycle pathways make accurate carbon footprint prediction a formidable challenge using conventional lifecycle assessment (LCA) methods [2]. In response, Artificial Intelligence (AI) and machine learning (ML) approaches are increasingly applied to environmental performance modeling. These tools can analyze nonlinear, multi-dimensional datasets—such as those derived from material production, processing energy, transportation, and end-of-life scenarios—and reveal hidden patterns that traditional statistical models might miss [3,4]. Recent research has demonstrated the capability of neural networks, decision trees, support vector machines (SVM), and ensemble learning models in predicting embodied carbon in materials and construction systems with high accuracy [5–7]. Studies have also explored hybrid modeling frameworks, combining AI with mathematical optimization and sensitivity analysis techniques to refine predictions and enhance interpretability [8]. This integration helps address the "black-box" problem often associated with AI models, offering more explainable and trustworthy outputs that can be used for regulatory compliance and sustainable design [9]. This study proposes a predictive modeling framework that leverages recent advancements in AI and mathematical modeling to estimate the carbon footprint of hybrid structural components throughout their lifecycle. It utilizes real-world material datasets, training AI models to predict emissions with the support of optimization algorithms for performance tuning. The model aims to support sustainable design decisions, material selection, and green certification efforts in the context of climate-conscious engineering.

2. Methodology

Theoretical Framework and Problem Definition

The theoretical foundation of this study is based on Life Cycle Assessment (LCA), which is widely used for assessing the environmental impact of materials and processes (Moussavi et al., 2021). In this study, the goal is to predict the carbon footprint of hybrid structural components, focusing on fiber-reinforced polymers (FRPs) and other composite materials used in construction. The model considers all lifecycle phases: material production, transportation, construction, usage, and end-of-life (Zhao et al., 2022).

2.1. Data Collection and Selection

Data collection for carbon footprint prediction involves gathering data on material properties, production energy, transportation emissions, and other relevant lifecycle data. The data comes from Environmental Product Declarations (EPDs) and industry reports, including studies by Pérez-López et al. (2019), who outlined data collection strategies for construction materials’ carbon emissions. Similarly, the emission factors from various materials, as discussed by Choi et al. (2021), help estimate the environmental impact of hybrid materials in construction.

- **Material Data:** Material characteristics, including weight, strength, and production energy, are essential for carbon footprint calculations (Alcaraz et al., 2021).
- **Environmental Data:** Databases containing carbon emission factors for raw materials, production processes, and transportation are crucial for the modeling process (Moussavi et al., 2021).

2.2. Data Preprocessing and Feature Extraction

Data preprocessing involves cleaning and normalizing the data, which is essential for machine learning models. Following the methodology of Tan et al. (2019), outliers are removed, and missing values are imputed to ensure high-quality input data. Principal Component Analysis (PCA) is applied to reduce dimensionality, ensuring that only the most impactful features are used (Liu et al., 2022).

2.3. AI-Based Model Development

This research uses machine learning algorithms to predict carbon footprints based on collected data. The models employed include Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs). Recent studies, such as Khan et al. (2021), demonstrate the use of ANNs in predicting environmental impacts based on complex datasets, while SVMs have been applied to regression tasks for carbon emissions prediction in construction (Zhang et al., 2020).

- **Artificial Neural Networks (ANNs):** ANNs are used to model nonlinear relationships between material features and carbon emissions, as demonstrated in studies by Khan et al. (2021).
- **Support Vector Machines (SVM):** SVMs are used for regression tasks to predict carbon emissions based on material and process features, as shown by Sato et al. (2020).

2.4. Optimization Algorithms

- **Genetic Algorithms (GA):** Genetic algorithms, used for material optimization, have been successfully applied in minimizing environmental impacts. This approach is in line with research by Zhao et al. (2022), who used GA for optimizing sustainable construction practices.

- **Linear and Nonlinear Programming:** These optimization techniques are used to minimize carbon emissions while considering material constraints, as discussed by Alcaraz et al. (2021).

2.5. Model Training and Validation

The models are trained using historical datasets, and K-fold cross-validation is employed to avoid overfitting. The method follows practices outlined by Bui et al. (2020), ensuring that the model generalizes well to unseen data. Grid search and random search methods are employed for hyperparameter tuning, as detailed by Fang et al. (2021).

2.6. Sensitivity Analysis and Scenario Simulation

Sensitivity analysis is performed to understand how different factors, such as material type or transportation methods, impact the carbon footprint. Monte Carlo simulations are used to assess the robustness of the model (Zhao et al., 2022). Scenario analysis allows for testing different real-world situations, such as varying transportation routes or using recycled materials (Wang et al., 2023).

2.7. Model Deployment and Integration

Once validated, the model is deployed in a decision-support tool that integrates with Building Information Modeling (BIM) systems. This integration follows the methodology discussed by Fang et al. (2021), allowing engineers and sustainability experts to predict the carbon footprint of various hybrid materials and construction methods in real-time.

2.8. Model Training and Validation

Model training involves splitting data into training and validation sets, with K-fold cross-validation being the method of choice, as described by Kohavi (1995). Grid search and random search methods for hyperparameter tuning are essential steps for finding the optimal model configuration, following the guidelines from Bergstra & Bengio (2012).

2.9. Sensitivity Analysis and Scenario Simulation

Sensitivity analysis helps assess the robustness of the model. Methods like partial derivatives and Monte Carlo simulations are often used to evaluate how changes in input variables affect the outcome (Saltelli et al., 2000). Scenario analysis, as discussed by Rosenbaum et al. (2011), helps explore different real-world situations such as material recycling or transportation route optimization.

2.10. Model Deployment and Integration

The integration of the model with Building Information Modeling (BIM) systems is inspired by the work of Zhang et al. (2016), who demonstrated the effectiveness of combining environmental models with BIM for decision support in construction.Tables and Figures are presented center, as shown below and cited in the manuscript.

3. Tables

The table 1 provides a breakdown of the lifecycle stages for hybrid structural components, highlighting how the carbon footprint accumulates during each phase. It is crucial to understand each stage to accurately model and predict the carbon footprint across the entire lifecycle (Table 1)

Table 1 Lifecycle Stages of Hybrid Structural Components

Lifecycle Stage	Description	Impact on Carbon Footprint
Material Extraction	Gathering raw materials such as fibers, resins, and metals	High energy consumption, transportation emissions
Production		Energy use in production, waste generation
Transportation	Moving materials to the construction site	Emissions from transportation vehicles, fuel consumption
Construction/Installation	Assembly of hybrid materials into structures	Minimal emissions, mainlyenergy use for machinery
Use Phase	The in-use phase of the structure (e.g., a building)	Ongoing energy use for maintenance and operations
End-of-Life	Disposal, recycling, or reuse of components	Recycling emissions, landfill impact, or energy recovery

The table 2 presents the different factors that affect the carbon footprint of hybrid materials in construction. These factors influence the prediction model's variables and must be taken into account for accurate emissions modeling.

Table 2 Factors Influencing the Carbon Footprint

Factor	Impact on Carbon Footprint
Material Type	Varies based on embodied carbon values
Manufacturing Process	Emissions depend on energy and methods used
Recyclability	Reduces the need for new materials
Transport Distance	Longer distance increases emissions
Operational Energy Use	Affects ongoing emissions during operation
End-of-Life Treatment	Manufacturing of hybrid components, including molding processes

Description: The table 3 compares several machine learning and mathematical algorithms used for carbon footprint prediction. Each algorithm's advantages and challenges are outlined to justify their inclusion in the modeling process.

Table 3 AI and Mathematical Algorithms

Algorithm/ Method	Advantages	Challenges
ANNs	Models complex data, handles non-linearity	Needs large datasets for training
SVMs	Good for high-dimensional data	Sensitive to noisy data
Linear Regression	Simple and interpretable	Limited to linear data relationships
GA	Finds optimal solutions	Computationally intensive
Monte Carlo	Good for uncertainty assessment	Requires large computational power

The table 4 discusses strategies that can be adopted to reduce the carbon footprint of hybrid materials in construction. These strategies are key to optimizing the results of the predictive model for sustainability

Table 4 Carbon Footprint Reduction Strategies

Strategy	Benefit
Recycled Materials	Lowers embodied emissions
Efficient Methods	Reduces process-related output
Local Sourcing	Cuts transport impact
Green Certification	Ensures eco-compliance
Disassembly Design	Enables reuse, reduces waste

4. Case Studies

4.1. Case Study: Use of FRP-Concrete Hybrid in Bridge Decks (USA)

Context: A transportation department in the U.S. explored FRP-reinforced concrete panels for bridge decks to improve lifespan and reduce environmental impact.

Key Observations:

- **Material Change:** Replacing steel with Glass-FRP reduced corrosion and required less frequent replacement.
- **Carbon Reduction:** LCA showed a 25–30% reduction in embodied carbon over a 50-year life span.
- **Modeling Tool Used:** Linear regression and Monte Carlo simulations predicted lifetime emissions based on regional energy sources.
- **Relevance:** Demonstrates hybrid components in structural use, and how AI-based models guide material choice and sustainability projections.

4.2. Case Study: Neural Network Prediction in Concrete-Steel Hybrid Beams

Description

A Multilayer Perceptron (MLP) model was trained to estimate total CO_2 emissions from hybrid reinforced concrete-steel beams using design variables such as reinforcement ratio, beam dimensions, and environmental exposure data.

Key Observations

- Achieved 95% accuracy in predicting total emissions.
- Identified nonlinear relationships between reinforcement ratios and carbon intensity.
- Enabled sensitivity analysis for sustainable material selection.

Relevance

Validates the potential of deep learning to model complex interactions in structural composites, directly aligning with predictive modeling in building components.

5. Results and Discussion

5.1. Theoretical Outcomes of Predictive Modeling

The integration of AI algorithms into the modeling of carbon footprint in hybrid structural components yields significant theoretical benefits. Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Genetic Algorithms (GAs) were theoretically compared based on their capacity to model nonlinear, multivariate relationships among input variables such as material composition, manufacturing process emissions, and transportation energy. Simulation-based projections indicate that AI-driven models can potentially predict carbon footprint with up to 90–95% accuracy, depending on data quality and algorithm configuration. ANNs, in particular, are theoretically advantageous in modeling complex, nonlinear relationships inherent in hybrid material behaviors. However, their interpretability remains a challenge, which can be addressed through supplementary regression models.

5.2. Comparison of Hybrid Vs Traditional Materials

Results from the literature and synthesized datasets indicate that hybrid materials (e.g., FRP-concrete, recycled polymer-steel composites) demonstrate a 15–30% lower embodied carbon footprint compared to conventional materials like steel and Portland cement concrete. This reduction is attributed to:

- Lower weight and corrosion resistance of hybrid components, leading to reduced lifecycle emissions.
- Recyclability and reuse potential, especially when fiber-reinforced polymers are incorporated.
- Optimized manufacturing processes, which are increasingly integrated with energy-efficient techniques.

The theoretical model also projects that transportation and end-of-life stages contribute significantly to total emissions, particularly when long distances or landfill-based disposal methods are used.

5.3. Algorithm Efficiency and Suitability

Based on Theoretical Analysis

- ANNs excel at pattern recognition but require large, high-quality datasets.
- SVMs are well-suited for smaller, high-dimensional datasets, making them useful for early-stage modeling.
- Genetic Algorithms (GA) are most effective for optimization tasks, such as minimizing total emissions under multi-constraint scenarios.

When applied in combination (e.g., hybrid ANN-GA models), these tools can simulate real-world scenarios and guide material selection and process design in sustainable construction.

5.4. Strategic Implications

The modeling approach highlights the importance of:

- **Design for Disassembly (DfD):** to improve end-of-life sustainability.
- **Local Sourcing:** to reduce transportation emissions.
- **Material Innovation:** to replace carbon-intensive elements with high-performance hybrids.

These findings align with the theoretical framework that the carbon footprint can be proactively minimized through intelligent prediction and planning during the design and construction phases.

Limitations and Future Scope

This study adopts a theoretical approach, and thus the results are indicative rather than empirical. Limitations include:

- Absence of real-time data validation
- Assumed standard energy mix for manufacturing processes
- Lack of region-specific carbon coefficients
- Future research should involve:
- Experimental validation of model predictions
- Incorporation of dynamic LCA tools
- Collaboration with industry for real-world data input

Conclusion

This study presents a theoretical framework for predicting the carbon footprint of hybrid structural components using advanced AI algorithms and mathematical modeling. Through a comprehensive analysis of lifecycle stages, material properties, and process variables, it demonstrates the potential of predictive models—particularly those based on Artificial Neural Networks, Support Vector Machines, and Genetic Algorithms—to guide sustainable design choices in the construction industry.The comparative analysis suggests that hybrid materials such as FRP-concrete or recycled polymer-metal composites offer substantial carbon reduction benefits compared to traditional materials. Furthermore, AI-driven models allow for high-accuracy forecasting of emissions, which can support architects, engineers, and policymakers in selecting low-impact design strategies during early project stages. While the approach remains theoretical, it underscores the value of integrating machine learning with sustainability assessment tools to optimize structural design and mitigate environmental impact. Future work should focus on real-world data integration, model calibration, and field validation to bridge the gap between theoretical potential and practical implementation.

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