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Project management mode under the concept of low carbon environmental protection and its value in intelligent construction

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Abstract

Rapid urbanization and climate change are intertwined, making decarbonization of the built environment paramount to stabilizing the future. The commercial and residential sectors generate nearly one-third of carbon emissions. Unexpected fluctuations in operational environments face the flexibility, efficiency, and resilience of building-incorporated energy systems due to climate change and its concerns. Instead, the rapid improvement of Machine Learning (ML) and Artificial Intelligence (AI) has equipped the construction industry with the capability to learn. This paper suggests a Machine learning-based Carbon Footprint Modeling (ML-CFM) to forecast the CO₂ emissions and energy consumption in intelligent constructions. The data has been collected from the World CO₂ Emissions analysis dataset for predicting the carbon emission in residential buildings. A new method based on Deep Neural Networks (DNN) can detect the overall carbon footprint of an intelligent construction design based on the urban layout and building features. A building’s structural characteristics had the most influence on CO₂ emissions and energy consumption, followed by the appropriate micro-climate, socioeconomic conditions, and the provincial climate. The ML-CFM is the most effective forecasting model for predicting carbon emission and energy consumption reduction, which offers building managers a valuable tool to enhance decision-making levels and energy efficiency in smart buildings.

Keywords: Low carbon environment, Deep Neural Networks, Carbon Footprint Modelling, Residential Buildings
1. Introduction

Most sectors are taking sustainability seriously due to the growing awareness of the need for environmental protection [1]. In the intelligent construction industry, eco-friendly, sustainable building materials are a crucial part of reducing emissions and achieving green building certification [2]. The built environment is a noteworthy contributor to the Greenhouse Gas (GHG) emissions issue. How to reduce carbon dioxide (CO$_2$) emissions, particularly those caused by energy consumption, is a critical concern since they contribute significantly to climate change. [3]. Taking measures to decrease a building's carbon footprint has both benefits: it lowers operating expenses and communicates that the company values environmental responsibility [4]. More and more people are taking notice of low-carbon design principles nowadays [5]. Resource conservation, low-carbon environmental protection, and re-use have all benefited from the incorporation of low-carbon design notions into the planning and construction of high-rise constructions [6]. The term low-carbon and green buildings refer to structures that combine environmental protection, green environmental protection, the construction industry, low-carbon energy conservation, and low-carbon technologies [7]. Using high-performance construction covers, energy-efficient ventilation, heating, and air conditioning, as well as energy-efficient lighting, appliances, and technologies that gather on-site renewable energy sources, are all hallmarks of low-carbon buildings [8]. Carbon footprint defines the overall quantity of carbon dioxide (CO$_2$) emission caused by a structure's use and maintenance [9]. Both new and existing buildings are impacted by the need to evaluate their carbon footprint [10]. There is a critical need and strategic option to accelerate the low-carbon transformation of economic development patterns and the adjustment of economic structure, which has far-reaching implications for the growth of a low-carbon future and the conservation of energy, and the reduction of Greenhouse Gas (GHG) emissions [11]. Overcoming the above challenges is probable due to the rapid development of Building Energy Management Systems (BEMS), Information and Communication Technologies (ICT), and Building Information Modeling (BIM), plus of the concepts Smart Buildings (SB) or Intelligent Constructions (IC) [12]. Intelligent Construction collects information, analyses, stores, and processes data, and makes suitable activities or decisions that result in quality construction. As a result, the low-carbon cities discover municipalities and provinces in coastal and inland regions, involving cities with various scales, social and economic development conditions, and low-carbon environmental protection levels.
One of the most significant recent developments in technological advancement is the move toward implementing Artificial Intelligence (AI) and Machine Learning (ML) methods [13]. Advanced AI methods are better suited for the scientific prediction of building operational energy consumption carbon emissions since they can explore complex non-linear relations between these variables and building operational energy consumption carbon emissions. This is because of the wide variety of demographic structures, socioeconomic patterns, and climatic conditions [14]. A technique based on ML might make it easier for architects to evaluate a building’s environmental performance, and ML has been offered as a means to reduce carbon emissions from construction [15] dramatically. By mapping functions from a training dataset or even a series of actions in an uncertain or complicated system, ML enables the determination of non-linear relationships, such as the link between energy usage, carbon footprint, and other important aspects [16]. This learning ability as a feature of intelligent construction needs to account for the influence of factors like human and AI agent responsibilities, as well as training environment characteristics, on the learning procedure in dynamic, uncertain environments. [17]. Furthermore, there is a lack of research that details the training of autonomous, building-integrated AI systems with the ability to make autonomous decisions [18]. The carbon footprint problem may be modelled by simulating various building forms, evaluating their operational carbon, and then using these instances to train ML models. [19]. Based on the modelling frameworks’ statistical methodologies, predictions of consumer energy consumption and carbon footprints may be accurately categorized as either AI-based engineering projects or hybrid approaches [20].

2. Related Study

Minglin Sun and Jian Zhang [21] suggested the Blockchain Big Data Platform (BBDP) to construct a smart city for low carbon emissions. This study created the structure and functional information flow of the blockchain smart city data exchange model and resource sharing. The creation of a smart city big data platform was summarised by the implication of smart city, blockchain, and big data and the beneficial impacts of appropriate data technology. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method for the smart city advancement level assessment model was created based on this concern.

Lei Wen and Yang Cao [22] recommended the Enhanced Butterfly Optimization Algorithm-Least Square Support Vector Machine (EBOA-LSSVM) for exploring household CO₂
emissions justification. The study begins with determining the exact amount of CO₂ emissions from domestic energy use, and then a bivariate correlation analysis is used to examine the regional disparities in the primary influencing elements of emissions based on 13 preliminary pointers. The Kernel Principal Component Analysis (KPCA) was a unique technique for obtaining the primary information of the preceding influencing elements as input to the prediction model.

Xining Yang et al. [23] discussed the Building Information Modeling enabled Life Cycle Assessment (BIM-LCA) for analyzing the carbon footprint accounting for a domestic building. The carbon footprint of a housing building is examined in detail in this case study. To improve information flow and interoperability between LCA models and BIM models, a variety of software technologies and data sources are merged in this research Building Information Modeling (BIM) software is used to develop and compute on-site construction inputs (materials, machinery, energy, water), as well as to simulate building operating energy consumption.

Fabiano Pallonetto et al. [24] deliberated the Demand Response Algorithms (DRA) for Smart-Grid Residential Buildings. When combined with zone thermal control, a simulation model of a calibrated building was built to test the efficacy of various demand response algorithms. Rules-based and machine-learning-based demand response algorithms were used to regulate an integrated heat pump and thermal storage system in a pilot scheme. Both algorithms were put through their paces using a similar demand response pricing scheme.

Vincent J.L. GAN et al. [25] proposed the Holistic Building Information Modeling Framework (HBIMF) for the sustainable low-carbon design of high-rise constructions. Using BIM, architects and engineers can create low-carbon structures with comprehensive physical and functional qualities that may be used in conjunction with various environmental modelling methodologies. A high-rise residential structure is analyzed in case research using the suggested framework to assess the carbon operational and embodied in the building owing to different envelope designs. As a consequence of these findings, it is clear that the BIM framework may be used as a decision support tool for identifying and mitigating a building's primary sources of carbon emissions throughout its lifespan.

Muhammad Mohsin et al. [26] established the Aggregated Composite Index (ACI) for examining energy security and environmental sustainability in Greenhouse Gases (GHGs) and CO₂ emitting countries. One of the key components of their index is a comprehensive
collection of measures that includes carbon emissions and energy use. All of the indications have been combined into a single composite indicator. Higher numbers indicate improved efficiency and vice versa. There is a significant disparity in performance between the top and down-rated nations, Canada and Brazil; according to the study's findings, countries were rated from highest to lowest in this research based on efficiency scores. Policymakers may use the findings as a road map and set of recommendations for the future.

Jesús Lizana et al. [27] introduced the Advanced Low-Carbon Energy Measures (ALCEM) based on Thermal Energy Storage (TES) in buildings. Low-carbon measures in the construction industry can only be implemented if thermal energy storage technologies are used since heating and cooling account for 60% to 70% of energy use. This study summarises and organizes current developments in passive and active TES technologies for construction applications, with a focus on passive TES. To highlight the most promising uses of the commercial solutions as well as new technologies and international initiatives, researchers compared operational modes and implementation methodologies, storage materials, and advantages and obstacles.


Cost management, climate change, scheduling, procurement, and risk assessment are numerous facets of construction project management. The acceleration of natural structural damage may be neutralized through the maintenance of good health and advancements in technology, materials, and design. A rise in severe climatic conditions will produce quick damage, necessitating the spare of whole building components, which is both more obvious and often more expensive. Eco-friendly construction methods need less water, energy, and natural resources, reducing or eliminating negative environmental consequences. However, in many instances, they have a beneficial influence on the environment (in the city or building dimensions) by producing their energy or promoting biodiversity. Energy-efficient ventilation, heating, air conditioning, lighting, and appliances, as well as technology that collect on-site renewable energy sources, are all hallmarks of low-carbon buildings. Materials that need minimal energy and carbon to manufacture, assemble, and transport are viable targets for use as low-carbon construction materials. Developing the decision-making process is essential to achieving any building project's objectives. Regularly, architects need to make judgments and explain them. The time, quality, money, and relationships wasted on bad choices may add up quickly. Decisions are taken in the construction industry about the
detailing of project goals and aspirations, such as the delineation of scope, the establishment of a budget and schedule, the establishment of performance standards, and the selection of project participants. This paper presents Machine learning-based Carbon Footprint Modeling (ML-CFM) to predict the energy consumption and CO₂ emissions in intelligent construction. Deep Neural Networks (DNN) can detect the overall carbon footprint of an intelligent construction design based on the urban layout and building features.

Figure 1: Proposed ML-CFM model

Figure 1 shows the proposed ML-CFM model. ML models, such as DNN models, may be used to identify targets for unseen samples after training on sufficient data, provided that the link between the features and the targets is established. This approach is highly helpful in this situation. Using this method, the labels produced by clustering are utilized as training data for classification. A building's energy efficiency may be measured by comparing its energy consumption per square metre of floor space to standards for that type of structure in those climate conditions. An establishment's carbon footprint is the overall quantity of carbon dioxide (CO₂) released due to its daily activities and maintenance. The carbon footprint of a building is an issue that must be considered for both new and existing buildings. Overcoming
expenditures, lowering necessary budgets, completing projects on time, and maintaining quality standards are all possible with the aid of a well-thought-out plan and approach.

To compute a building’s operational emissions, this study included emissions generated to deliver the energy utilized by cooling, lighting, and heating via the consumption of natural gas, coal, and electricity. For every building and its characteristics, the overall CO$_2$ emissions have been computed utilizing the equation (1) with an open dataset [28]:

$$\text{Carbon Emission} = CE_{EL} + CE_{coal} + CE_{NG} + CE_{GAS} + CE_{HE}$$ (1)

As shown in equation (1), where $CE$ denotes the carbon emission, $CE_{EL}$ indicates that carbon emissions come from energy consumption. $CE_{NG}$, $CE_{coal}$, $CE_{GAS}$ and $CE_{HE}$ corresponds to the carbon emissions from natural gas, coal, heating, gasoline, and heating consumption.

Depending on the technique suggested by the Intergovernmental Panel on Climate Change (IPCC) for the computation of national GHG emissions, this study utilized equation (2) to transform consumption of a primary energy source (natural gas or coal) into CO$_2$ emissions.

$$CE_F = \sum^{m}_{j=1} C_{ei} \times H_{ei} \times J_{ei}$$ (2)

As inferred from equation (2), the carbon emission reduction factors are analyzed, and where $CE_F$ denotes the overall carbon emission from fuels involving natural gas and coal. $C_{ei}$ indicates the energy consumption. $H_{ei}$ signifies the energy capacity conservation. $J_{ei}$ represents carbon containment per unit consistent with IPCC estimate. The CO$_2$ emissions linked with heating and electricity consumption have been computed utilizing the suitable emissions factors.

**Step 1: Deep Neural Network (DNN) Model**

The DNN reflects inputs onto a set of fitting outputs. The representation of DNN models comprises a layer for inputs with building characteristics input node, a hidden layer of computation node, and output layers with computation nodes. Equation (3) articulates activated neurons in hidden layers.

$$net_i = \sum \omega_{ij} y_j \text{ and } x_i = f(net_i)$$ (3)

As discussed in equation (3), where $net_i$ signifies activation of $i^{th}$ neurons, $j$ denotes a neuron in the preceding layers, $\omega_{ij}$ symbolizes the weight of the connection between neurons.
\( i \) and neuron \( j \), \( y_j \) characterizes output of neurons \( j \), and \( x_i \) signifies the transmitting function as

\[
f(\text{net}_i) = \frac{1}{1 + e^{\lambda \text{net}_i}}
\]  

(4)

Equation (4) shows the transmitting function of the DNN model, where \( \lambda \) regulates the function gradients.

Weight \( \omega_{ij} \) is updated during the training progression of DNN models as expression (5). \( \Delta_{ij}(g) \) is the variance between two iterations as expression (6).

\[
\omega_{ij}(g) = \omega_{ij}(g - 1) + \Delta_{ij}(g)
\]

(5)

\[
\Delta_{ij}(g) = \eta \delta_{qj} \chi_{qj} + \beta \Delta \omega_{ij}(g - 1)
\]

(6)

As inferred from equations (5) and (6), where \( \eta \) denotes the learning rate parameter, \( \delta_{qj} \) signifies the propagated errors, \( \chi_{qj} \) signifies an output of neurons \( j \) for records \( q \), \( \beta \) denotes the momentum parameter and \( \Delta \omega_{ij}(g - 1) \) signifies the change in \( \omega_{ij} \) in the previous cycle.

**Figure 2: DNN model**

Figure 2 shows the DNN model. The DNN detects accurate statistical handling to make the input into the output. It would be a linear or non-linear relationship. The network moves by the layers computing the likeliness of every output. The building characteristics have been given as input in the DNN model. A carbon emission and energy consumption has been
predicted in the output layer. The input layer consists of the historical energy consumption, insolation, temporal, and weather information (outdoor temperatures). The hidden layer is utilized to perform the transforming calculation between input and output. The output layer comprises prediction outcomes of energy consumption in the building. In the DNNs model, a neuron is accessible by the activating functions as

\[ f(yS + a) \] (7)

As inferred from equation (7), where \( S \) is a weight and \( a \) denotes the bias function. For the DNN models, neurons are accessible by activating functions, where the affine transforms are adapted utilizing the effective operators

\[ f(b \ast (yS) + a) \] (8)

As shown in equation (8), where \( \ast \) signifies the elementwise multiplication operator.

**Step 2: Analyzing the Resource Consumption and Carbon Emission in Buildings**

![Figure 3: Resource consumption and Carbon Emission in Buildings](image-url)
Figure 3 shows the Resource consumption and Carbon Emission in Buildings. CO₂ emissions have risen in conjunction with urbanization, as measured by population density, per capita building structure, floor space, carbon emission coefficients, and building energy intensity. The created model mainly computes energy consumption related to a building’s operating phase, considering the following end uses: heating and cooling systems, lighting, household equipment, Domestic Hot Water (DHW), and elevators. The energy used by public amenities (such as street lights and water pressure systems) and the gas used by municipal garbage collection services have been analyzed to understand their impacts on urban infrastructure better.

Step 3: Examining the carbon footprint of a building and its elements

![Diagram of carbon footprint]

Figure 4: The carbon footprint of a building and its elements

Figure 4 shows the carbon footprint of a building and its elements. A building’s carbon footprint is the sum of all GHGs during its life cycle, measured in CO₂ equivalent kilos.
Everything from producing the raw materials to constructing the building to transporting the materials to the construction site to using the building to operating the building to periodically refurbishing and replacing materials to finally disposing of the building materials at the end of its useful life all contribute to the total GHG emissions. Carbon accounting is the process of calculating the effects of a building on the environment, and it may be done via a GHG emissions assessment or similar activities. Carbon emissions from buildings are mostly attributable to indirect sources, such as the energy required to generate power. Low-carbon buildings are purposefully built to reduce or eliminate their carbon footprint during their useful lifespans. To improve community health, equity, and economic prosperity, zero-carbon buildings make use of affordable, easily available technology to reduce carbon emissions dramatically.

**Step 4: Lifecycle assessment of carbon emissions**

![Lifecycle assessment of carbon emissions](image)

**Figure 5: Lifecycle assessment of carbon emissions**

Figure 5 shows the lifecycle assessment of carbon emissions. Energy usage by a household around the world is disproportionate. Most countries source energy from coal-powered plants with significantly higher CO₂ emissions than others. Some countries have a higher need for thermal comfort by increasing the heating/cooling frequency. The construction industry is one of the most polluting industries, and current mitigation efforts may not be sufficient to solve the problem. The established model’s target is achieving Zero Net Emissions only in building operations, focusing mainly on energy efficiency. In the context of the construction of buildings, the term structure refers to the method of assembling various aspects of construction to fulfil a certain purpose. This approach has to efficiently sustain the building and transfer any loads placed on it to the ground beneath. Shell, frame, and solid structures are the fundamental building blocks of every construction. Refurbishment concepts include reducing an old building's negative influence on the surrounding environment while simultaneously improving that building's ability to function following contemporary
standards. Breaking down structures, often known as demolition, entails dismantling a structure so that the valuable components may be preserved for future use.

4. Results and Discussion

The present paper suggests ML-CFM model predicts the energy consumption and CO₂ emissions in intelligent constructions. This study utilized the building dataset [28] to analyze the performance metrics of the suggested ML-CFM model. This research discusses the prediction ratio, carbon emission reduction ratio, energy efficiency ratio, decision-making level, and error rate.

(i) Energy Consumption Prediction Ratio

For intelligent construction design purposes, a reliable ML strategy based on the DNN model was developed to make forecasts about the time series of CO₂ emissions and energy consumption. As a result, accurate forecasts of energy consumption make it possible for decisions about the efficient functioning of the energy system as well as the distribution of energy resources in a balanced way. Because of its non-linear characteristics, AI approaches have been the research subject for many years. With the development of ML techniques, a growing number of hidden layers for the neural network makes the computation more power efficient, which helps achieve stability in buildings and provides higher performance than older methods. The suggested ML-CFM model enhances the prediction ratio of 98.8%. Equation (1) displays the energy consumption prediction ratio using the proposed ML-CFM model. Figure 6 signifies the prediction ratio.
Reduced carbon dioxide emissions, low-carbon city development, and enhanced citizen well-being would all benefit from DNN's robust and concise outputs. Intelligent constructions represent the most potential use of AI in urban energy systems. Many intelligent constructions include sophisticated automated monitoring and control tools that may be used to reduce energy use. These tools include sensors, subsystems, and actuators. These decreases in energy usage are accompanied by corresponding cuts in emissions of Greenhouse Gases (GHG). It was shown that smart structures have the potential to significantly influence environmental protection, operating cost reduction, and energy conservation in highly populated metropolitan regions. Figure 7 demonstrates the carbon emission reduction ratio. From equation (2), the carbon emission reduction ratio has been identified.
Figure 7: Carbon Emission Reduction Ratio

(iii) Energy Efficiency Ratio

The energy industry may learn about its features with the use of big data, which paves the way for new technological assistance for low-carbon green development, electricity efficiency improvement, conservation of energy and consumption reduction, economical operation, and system planning. On the other hand, ML and AI-based construction data analysis and processing may boost the energy system's production efficiency, enhance the quality of services provided to end users, and aid in making more informed operational decisions. This study utilized the dataset [28] to predict the overall energy utilized in construction. Figure 8 signifies the energy efficiency ratio.
This research examines the variables that impact carbon emissions during construction, particularly focusing on implementing low-carbon buildings. The CO$_2$ emission peak and carbon neutrality may be achieved with the help of this new building operating energy consumption carbon emissions database, which is a resource for decision-makers. The existing state of carbon emission for building corporations may be better understood by developing an assessment index system and approach for low-carbon buildings. As a result, relevant government agencies will be better equipped to make decisions and grasp the substance of the situation regarding low-carbon building development and the adoption of targeted actions to reduce carbon emissions. Figure 9 illustrates the decision-making level.
For assessing the suggested DNN models, the extensively utilized error metric is chosen to predict carbon emissions in buildings. Error metric of Root-Mean-Square Error (RMSE) is assumed as assessing criteria to measure the variance between the real values to the forecasting values and articulated by

\[
RMSE = \frac{\sqrt{\frac{1}{M} \sum_{m=1}^{M} (Q_f - Q_c)^2}}{\bar{Q}_c} \times 100\% (9)
\]

In the above equation (9), where \(M\) denotes the amount of dataset, \(Q_f\) indicates the prediction value, \(Q_c\) signifies the actual value and \(\bar{Q}_c\) denotes the mean of all \(Q_c\). Lesser RMSE greater predicting performance. Figure 10 demonstrates the error rate of the suggested ML-CFM model.
The proposed ML-CFM model enhances the prediction ratio, carbon emission reduction ratio, energy efficiency ratio, decision-making level, and error rate compared to other existing methods such as Blockchain Big Data Platform (BBDP), Enhanced Butterfly Optimization Algorithm-Least Square Support Vector Machine (EBOA-LSSVM), Building Information Modeling enabled Life Cycle Assessment (BIM-LCA), Demand Response Algorithms (DRA), Holistic Building Information Modeling Framework (HBIMF), Aggregated Composite Index (ACI), Advanced Low-Carbon Energy Measures (ALCEM) based on Thermal Energy Storage (TES).

Figure 10: Error Rate

As the construction industry is widely recognized as the primary source of air pollution and fossil energy consumption, optimization of construction, CO$_2$ emission, and building energy utilization has gained great attention in recent years. The ML-CFM is proposed in this research to achieve intelligent construction and low carbon emissions. This work uses AI to build a carbon-controlled monitoring system connected to long-term and real-time data, and it discusses the technique of correcting conventional carbon emission measurement. With this in mind, the foundation for the intelligent carbon monitoring platform is laid. Optimizing
building performance, decreasing CO₂ emissions, and cutting energy expenditures all start with an accurate projection of the facility's energy usage. Based on an analysis of carbon emission data, energy usage, and weather forecasts, this research suggests using a Deep Neural Network (DNN) to estimate building energy use. A model may learn from past data and use that knowledge to make predictions or develop new insights.

**Compliance with Ethical Standards:**

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**Data availability statement**

The data that support the findings of this study are available from the corresponding author upon reasonable request.

**Ethical approval**

This article does not contain any studies with human participants or animals performed by any of the authors.

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