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Artificial Intelligence–Driven Carbon Footprint Assessment: A Cross-Sector Review of Methods, Challenges and Future Directions

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Abstract
The growing feeling of urgency in regard to the need to reduce climate change has amplified the need to make the calculation of carbon footprint in different industrial sectors more accurate and efficient. The traditional approaches, which include the Life Cycle Assessment (LCA) approach, the Emission Factor Approach, and the Standard Approach, provide a platform upon which the calculation of greenhouse gas emissions can be done. Nevertheless, some recent investigations undertaken on behalf of different industrial sectors, including manufacturing sector, construction sector, logistics sector, transportation sector, and digital infrastructure sector, state that the traditional means of estimating greenhouse gas emissions are limited, including the application of fixed-valued emission factors, rigidity, and high levels of uncertainty in Scope 3 emissions. Meanwhile, Artificial Intelligence (AI) and Machine Learning (ML) techniques are being developed as promising solutions for improving the carbon footprint models. Data science techniques like deep learning networks, ensemble learning, predictive analysis, and IoT monitoring systems can help forecast and monitor the emissions and carbon footprint in real-time. However, the connection between AI-based prediction systems and standardized carbon accounting systems is still fragmented. The research gaps are identified in the areas of inconsistency in boundaries, interoperability, the absence of automation in the calculation of Scope 3, and the need for better modeling of uncertainties. A conceptual framework for the application of AI-based techniques in the calculation of carbon footprint is proposed based on the analysis.India.

Keywords: *Carbon Footprint, Life Cycle Assessment, Carbon Accounting, Greenhouse Gas Emissions, Process-Level Analysis, Digital Carbon Tracking, Industrial Sustainability, Decarbonization.*

1. Introduction
Climate change has emerged as one of the significant global challenges. It requires precise assessment of carbon footprint in various industries. Recent studies indicate that structured carbon accounting is essential to achieve net-zero goals effectively [1–8]. Several studies have been conducted on various industries to assess carbon emissions in prefabricated housing [1, 2], corporate industries [3], energy [4], logistics [5], livestock [6], tourism [7], carbon tracking technologies [8], etc. These studies indicate that carbon accounting is becoming more prominent to ensure sustainable development goals are achieved effectively. Although various studies have been conducted on various industries, there are various challenges that need to be addressed. The system boundaries, data sources, calculation methods, etc., are not consistent across various studies. These studies are not comparable with each other [8, 9]. The same has been identified in textile industries [10], digital industries [9], etc., in terms of process-based carbon accounting [11].On the other hand, Artificial Intelligence (AI) and Machine Learning (ML) are increasingly recognized as viable options for carbon modeling. AI-based approaches for the prediction of energy in vehicles [12] and optimization-based approaches in electric transportation [13] indicate better prediction accuracy, especially with the ability to handle uncertainties. These approaches are also useful for real-time analysis, which is not possible with traditional Life Cycle Assessment (LCA) methods.Previous studies have helped in the development of carbon accounting in the construction

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sector [14,15], industrial systems [16], digital infrastructure [17], and product life cycle models [18]. Other studies in the field of energy systems and sustainability have further enhanced these methods [19-21]. Basic studies on digital platforms [22], logistics [23], and corporate carbon reporting [24,25] have also helped in the development of standardized carbon assessment methods. Though traditional methods of LCA are well structured, these methods are based on fixed emission factors and assumptions. On the other hand, AI methods are more dynamic, as these methods can handle complex problems and dynamic conditions. However, these methods are not integrated.Objectives of the Review: This review aims to assess various methodologies for carbon footprints in different sectors, the role of AI and ML in improving these methodologies, and propose a new AI-based methodology for carbon footprints for sustainable development.

2. Literature Review

2.1.Sector-Specific Carbon Footprint Assessment:

Recent research has revealed that research on carbon footprint is increasing in various industrial sectors. In the construction sector, many researchers have studied the carbon footprint of prefabricated housing through material-based and life cycle approaches. The results of these research articles revealed that the production stage is one of the major stages in the life cycle of building materials.In the corporate sector, many researchers have developed carbon accounting systems to measure the carbon footprint of companies through their operational activities.In the energy sector, many researchers have studied the carbon footprint of power transformer components. The results of this research article revealed that the operation stage is one of the major stages in the life cycle of power transformer components. Similarly, many researchers have studied the carbon footprint of pharmaceutical logistics. The results of this research article revealed that transportation is one of the major stages in the life cycle of pharmaceutical logistics.In addition to these sectors, many researchers have also studied the carbon footprint of livestock systems, tourism activities, textile industries, and digital platforms such as social media.Though many researchers have studied the carbon footprint of various sectors through different approaches and assumptions, there is inconsistency in their research articles.

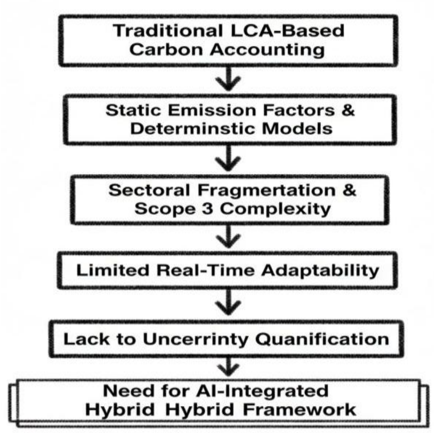

Figure 1 Evolution from Traditional Carbon Accounting to AI-Integrated Framework

2.2.Methodological Frameworks and LCA-Based Approaches

The most widely used method for carbon footprint analysis is Life Cycle Assessment (LCA) [1]. Most studies utilize emission factor databases and standard reporting systems for this purpose [2,18].In construction-related studies, methods based on LCA are further enhanced with clear system boundaries and structured data [14,15].A few review studies emphasize that carbon footprint is an important tool for sustainable development [9]. However, other studies emphasize that there is no standardization in methods and reporting systems for this purpose [8].
A few studies emphasize that there are limitations to static emission factors and simple modeling approaches [10,11]. Scope 3 emissions are particularly difficult to assess due to complex supply chains.Even though LCA methods are reliable, they are inflexible and cannot adapt to changing scenarios in real time.

2.3.Carbon Tracking and Digital Monitoring Technologies

Recent studies have focused on digital technologies for carbon tracking. For instance, IoT, blockchain, and data analytics technologies are being used for carbon tracking systems [8].From various studies

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conducted on digital technologies, it is evident that activities in user systems and data centers should be taken into consideration in calculating carbon emissions [22]. In the logistics sector, detailed models should be developed to improve accuracy in calculating emissions from transport activities [5].Despite the fact that these technologies have improved carbon tracking, they are still not integrated with predictive or optimization models.

2.4.AI and Machine Learning in Carbon Modeling

Artificial Intelligence and Machine Learning have started to play a vital role in carbon modeling. AI-based vehicle energy prediction models have shown high accuracy levels. Optimization models used in electric transport systems also contribute to emission reduction. These models can cope with non-linear relationsandcanadjust to new conditions.Uncertainty, large data processing, and prediction scalability are also aided by AI. However, most AI models operate only in particular sectors and are not incorporated into ISO or GHG protocols.

2.5.Identified Research Gaps

Based on the literature, several gaps are identified:

- Different sectors use different methods, leading to fragmentation [1–7,10,22]
- Lack of integration between carbon tracking systems [8]
- Strong dependence on static emission factors [14,18]
- Poor handling of Scope 3 emissions
- Limited integration of AI with LCA-based methods [12,13]

These gaps show the need for a unified framework that combines standard methods with AI-based modeling and uncertainty handling

3. Research Gaps and Critical Challenges

Despite the increasing number of research works, there are some challenges associated with this. The literature indicates that there is fragmentation in the current carbon accounting methodologies and their integration with computational techniques.

3.1.Methodological Fragmentation Across Sectors

Various sectors have different methodologies for carrying out carbon footprint analysis. In the construction sector, material and production phases are considered [1,14], whereas in the logistics sector, carbon footprint analysis is carried out based on transportation phases [5], and in the digital sector, energy usage is considered [22].It is hard to compare the results of carbon footprint analysis because there is no single standard approach applicable to all sectors..

3.2.Limitations of Static LCA-Based Models

The conventional LCA techniques employ pre-defined emission factors and make assumptions. These techniques are simple to apply but cannot respond to changes in real time. The emission factors are often averaged and cannot account for changes in sources of energy, transportation modes, and supply chains. This is a major problem for a dynamic network like the electricity grid. Additionally, Scope 3 emissions are hard to estimate due to a lack of data and complex supply chains.

3.3.Insufficient Uncertainty Quantification

In most studies, the emission results are provided as a single value without taking the uncertainties into account. However, real-world data does vary.In some studies based on AI, it has been shown that the uncertainties can be taken care of using more advanced models like ensemble learning [12]. However, these models have not yet been widely used.

3.4.Limited Integration of AI and Standardized Carbon Accounting

The potential of AI and ML in emission prediction and optimization is high. However, these models are used only in specific sectors.These models are not properly linked with the conventional carbon accounting system, i.e., ISO or GHG. A unified system is still not available to incorporate AI with conventional methods.

3.5.Need for Adaptive and Scalable Frameworks

The following are the requirements for modern carbon systems:

- Comparable across sectors
- Adaptive to real-time data
- Robust to uncertainty
- Scalable for large data sets
- Compatible with digital technologies

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However, current research does not offer an integrated framework that includes all these requirements.

3.6.Summary of Research Gaps

The identified gaps are as follows:

- Fragmented methodologies are being followed in the sectors
- Dependence on static emission factors
- Insufficient Scope 3 modeling
- No uncertainty analysis
- No integrated AI-based methodology

The next section proposes a conceptual AI-integrated carbon footprint methodology.

4. AI-Integrated Carbon Footprint Assessment Framework

Below, the concept of the framework, which results from using the conventional approaches to carbon accounting along with modeling tools offered by Artificial Intelligence, is discussed. The goal of creating this framework is improving the accuracy and effectiveness of carbon footprint assessment. As mentioned above, the proposed framework relies on the traditional approaches to life cycle assessment.

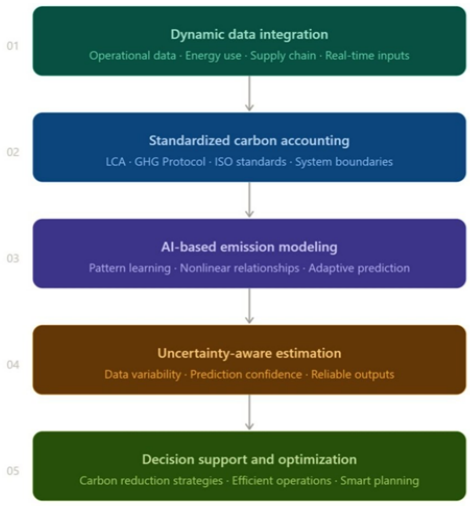

Figure 2 AI-Integrated Carbon Footprint Assessment Framework

4.1.Standardized Carbon Accounting Foundation

This framework is built based on the conventional approaches to carbon accounting, including LCA, GHG Protocol, and ISO. It assists in making emission calculations within the given boundaries and based on a particular functional unit and emission sources .The proposed approach creates a strong basis for achieving comparable results. It is characterized as static since it does not consider any real-world changes.

4.2.Dynamic Data Integration

Unlike the conventional models, the proposed framework utilizes dynamic data from various sources. It includes operational data, energy consumption, transportation activities, and supply chain data. It can also include real-time data, such as the carbon intensity of the electrical grid or environmental conditions.The utilization of dynamic data allows the framework to be more responsive to the real world. It improves the accuracy of the estimation of the carbon footprint, thus making the system more realistic.

4.3.AI- Based Emission Modeling

Artificial Intelligence plays a vital role in this framework. AI models are used to understand complex relationships between different factors that influence emissions. These factors may include operational conditions, environmental changes, and system performance.Unlike traditional methods, AI models are capable of handling complex relationships and are flexible in nature. This helps in better predicting emissions for different scenarios. Hence, carbon footprint assessment is more flexible in nature.

4.4.Uncertainty-Aware Estimation

Another significant improvement of this framework is the inclusion of the concept of uncertainty. It is a known fact that data may be incomplete or variable. This is not taken into consideration while applying the conventional methods. They provide a fixed value for the data.In the proposed framework, the concept of uncertainty plays a significant role. It helps to achieve more reliable results for the estimation of carbon.

4.5.Decision Support and Optimization

The last part of the framework deals with the use of carbon data in decision-making. The framework does not only help in calculating carbon emissions; it can also aid in reducing carbon emissions.It can be used in deciding routes in transportation, energy usage, or efficiency. The framework, therefore, makes carbon footprint prediction an effective tool for sustainability.

4.6.Overall Significance of the Framework

This approach links conventional carbon accounting with new AI-based methods. It ensures the accuracy of conventional approaches, while offering flexibility, adaptability, and intelligence in carbon accounting.It can be used for cross-sector applications and can manage large and complex data sets. This approach is one step forward in developing more advanced and intelligent carbon footprint management systems.

5. Discussion

In this study, both the conventional models of carbon footprints' measurement and novel AI-based modeling were analyzed within a number of industries. The purpose of the current research is to highlight the strengths of the existing models along with their weaknesses.

5.1.Theoretical Implications:

Conventional methodologies for the calculation of carbon footprints, especially Life Cycle Assessment, can be considered the starting point in estimating CO2 emissions. These models provide quite a solid basis and help to identify the areas and objects of analysis. They also ensure the consistency in reporting.However, conventional models are rather static since they assume the clear relationships between particular actions and their consequences. In some cases, a dynamic approach to analysis may be required due to continuous evolution.The proposed approach to carbon footprints' analysis based on artificial intelligence provides an alternative solution to the issue. AI makes it possible to develop an adaptive model based on the learning algorithm.

5.2.Methodological Implications:

In particular, the review highlights a crucial point where each industrial sector uses a unique method of carbon footprint calculation. This, therefore, makes it difficult to compare results. Moreover, there is high dependency on emission factors, which ignore possible variances within the industry.AI-based models can make it easier for carbon footprint assessments to become consistent because they consider dynamic information. However, there is no integration of such models into the current models of carbon footprint assessment.From the above discussion, therefore, it can be seen that future models should take advantage of all the strengths of the two model types. In particular, the current models offer some structure, while the latter offers more flexibility.

5.3.Practical and Industrial Implications:

On a practical basis, having better models of assessing carbon footprints will ensure proper decision-making. For example, the use of better models will allow industries to identify the sources of emissions and mitigate them accordingly.Examples of such applications in various sectors include route planning in transport networks to reduce emissions, optimal energy consumption in production processes, and proper management of data centers.

5.4.Policy and Governance Implications:

Similar trends in carbon modelling can bring about a variety of implications for policy and governance. Firstly, one should keep in mind that along with the increased accuracy in results, there should be appropriate guidelines established in order to deal with reporting.In addition, decision-makers should bear in mind that transparency and reliability are important factors that are likely to affect policy decisions. In addition, uncertainties play an important role when it comes to policy decisions regarding complex systems.

5.5.Limitations of the Study:

Even though this study is highly informative, it cannot claim to have no limitations at all. The first problem lies in the fact that the literature review conducted herein is based solely on academic studies. Furthermore, another problem concerns the fact that there was no validation of theoretical framework proposed.Finally, it is important to mention that the current issue remains rather dynamic owing to constant advances made in AI development.

6. Future Directions:

The research areas below will be instrumental in improving future research activities in carbon footprint evaluation. Firstly, there is a need to develop a hybrid model consisting of an LCA model and an AI-based model. In most cases, LCA models have a defined structure. On the other hand, AI-based models have a dynamic structure. Developing a hybrid model will be instrumental in advancing the methods used in carbon footprint estimation [12,13]. Secondly, future research efforts should focus on developing improved models for calculating Scope 3 emissions. The major sources of carbon footprint are the Scope 3 emissions that emanate from supply chains. However, calculating Scope 3 emissions can be difficult due to the complexity involved and lack of information. Thus, future research efforts should focus on estimating Scope 3 emissions through use of sophisticated techniques like AI models [5,8].Thirdly, future research efforts should concentrate on real-time carbon footprint estimation models. Current models of carbon footprints utilize historical data. However, future models of carbon footprints will incorporate real-time data.Furthermore, there is a lack of studies dedicated to uncertainty-aware modeling of carbon footprints. The current approach gives users single-valued results and does not account for any variability in the data. AI technology may come handy in incorporating uncertainties into the system and making carbon footprint estimates more accurate [12].The next area of future research will be the integration of digital solutions, like Internet of Things, blockchain technology, and cloud computing, into carbon footprint monitoring systems [8].Finally, a framework for incorporating AI into the carbon footprint monitoring process should be developed in order to standardize procedures and ensure comparability [3,9].To summarize, future Research Must Focus On The Creation Of Intelligent Carbon Footprint Monitoring Systems Capable Of Integration With Other Systems And Scale-Up To Other Areas Of Operation.

Conclusion

This Paper Analyzed Various Methods Employed For Calculating Carbon Footprints In Different Industries. The Study Revealed That Traditional Methods, Mainly Lca, Offer A Standardized Way Of Quantifying Emissions. This Is Achieved Through The Use Of Static Emission Factors. In Addition, Assumptions Made Under Traditional Methodologies Are Limiting In Terms Of Dealing With Dynamic Situations [2,18].Another Point Brought Out By This Analysis Is That Use Of Ai And Ml Offers An Improvement In Carbon Footprint Calculation Methods. This Methodology Can Effectively Manage Complex Correlations And Massive Data Sets, As Well As Enable Real-Time Analysis [12,13]. Nevertheless, There Is Still No Widespread Use Of Ai And Ml In Carbon Footprint Calculations [8].Some Of The Identified Issues Include Disjointed Methods Used, Not Accounting For Scope 3 Emissions, Lack Of Uncertainty Analysis, And Lack Of Ai Application In Current Methodologies [5,8,9]. All These Issues Have Adverse Effects On The Accuracy Of Results Obtained And Their Comparability.The Proposed Solution To Such Issues Is Development Of An Ai-Driven Carbon Footprint Model. This Model Combines All The Strengths Of Traditional Approaches And Artificial Intelligence, As Well As The Ability To Work With Real-Time Information.Hence, Current Practices Should Move Away From Traditional Approaches That Are Inflexible To More Flexible, Yet Effective Ones. The Hybrid Ai-Lca Model To Be Developed In This Study Will Serve Better.

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