

MANAGING CARBON FOOTPRINT IN GLOBAL SUPPLY CHAINS: A DATA-DRIVEN STRATEGY EMPLOYING AI ALGORITHMS

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by

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To the

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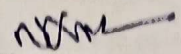


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ABSTRACT

The global supply chain is a characteristic of the new economy and has also greatly influenced the production patterns, consumption trends as well as global trade. Despite the fact that globalization has assisted in cost reduction, optimization of resource usage as well as diversification of sourcing, it has resulted in massive increase in carbon emission. The manufacturing business associated with logistics, transportation, and supply chain involves a significant percentage of global CO₂ emissions; therefore, the carbon footprint management is an urgent business issue, but the traditional methods of carbon accounting, based on historical averages, constant emission factors, manual calculations, and linear models are not sufficient to reflect the dynamic and uncertain nature of the modern supply chain. All of this has been exacerbated by such issues as different fuel efficiency, multimodal routes, real-time traffic congestion, different energy sources, climate change, and geopolitical events, which have led to artificial intelligence as a strong technology to manage carbon with the data. Artificial intelligence can more effectively predict emissions and make decisions because it can examine large volumes of various data and detect nonlinear relationships between them. Transformer model, in this regard, has proven to be quite impressive in terms of learning long-term dependencies and high-dimensional time-series data. This renders the Transformer model to be applicable in the context of emission prediction in the global supply chain where the information is obtained through such sources as IoT sensors, GPS, enterprise, transport logs, and energy utilization. Nonetheless, accurate forecasting is not enough to achieve the

sustainability goal. Such is the nature of the supply chain problem, where there exists a trade-off between cost and environmental aspects. Conventional optimization problems, like the single objective linear programming, are not useful in the resolution of such conflicting goals. In that regard, this research work integrates multi-objective optimization methods, i.e. Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO), to come up with Pareto-optimal solutions that can, at the same time, take into consideration cost effectiveness and carbon emissions, and meet service level restrictions. The paper has a hybrid AI solution consisting of Transformer-based carbon emission forecasting and multi-objective optimization of sustainable supply chain management. The core findings of the research work are the enhanced accuracy of carbon emission forecast, the flexibility of solutions of cost-carbon trade-offs and the integrated decision support system which enhances the sustainability and transparency of long-term planning. To conclude, the suggested solution is a practical way forward in building smarter, more resilient and sustainable global supply chain in the light of the increasing regulatory and sustainability demands.

Keywords: Supply Chain Sustainability, Carbon Footprint Management, Transformer-based Forecasting, Multi-Objective Optimization, NSGA-II, MOPSO.

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CHAPTER - 1

INTRODUCTION

1.1 General Introduction

Global supply chains have become one of the most important components of modern industrial and economic systems. With the rapid growth of globalization, industries are increasingly dependent on international logistics networks for sourcing raw materials, manufacturing products, warehousing, and distribution activities. These interconnected systems improve operational efficiency, reduce production costs, and enable organizations to expand into global markets. However, the expansion of global supply chains has also resulted in a substantial increase in greenhouse gas emissions, particularly carbon dioxide (CO₂), generated through transportation, warehousing, fuel consumption, inventory handling, and industrial operations.

The logistics and transportation sector is considered one of the major contributors to global carbon emissions. Freight transportation through roadways, railways, airways, and maritime systems consumes a significant amount of fossil fuels, leading to environmental degradation and climate change. In addition, warehousing facilities, cold storage systems, material handling equipment, and large-scale industrial operations consume substantial electrical energy, further increasing the carbon footprint of supply chain activities. As global trade continues to expand, managing carbon emissions has become a critical challenge for industries, governments, and environmental agencies worldwide.

Traditional carbon emission estimation methods mainly depend on fixed emission factors, historical averages, and static mathematical calculations. Although these approaches provide basic estimation capability, they fail to capture the dynamic and uncertain behavior of modern supply chain systems. Factors such as traffic congestion, route variations, fluctuating fuel efficiency, weather conditions, inventory variability, energy

consumption patterns, and operational disruptions significantly affect carbon emissions in real-time logistics environments. Consequently, conventional linear models often produce inaccurate forecasts and inefficient sustainability strategies.

To overcome these limitations, Artificial Intelligence (AI) and Machine Learning (ML) techniques have emerged as powerful tools for sustainable supply chain management. AI-based models are capable of analyzing large volumes of logistics and operational data, identifying hidden nonlinear relationships, and generating accurate predictions under complex conditions. Machine learning algorithms such as Artificial Neural Networks (ANN), Random Forest, Gradient Boosting, Long Short-Term Memory (LSTM), and Transformer-based models have demonstrated strong forecasting capabilities in transportation, inventory management, and carbon emission prediction applications.

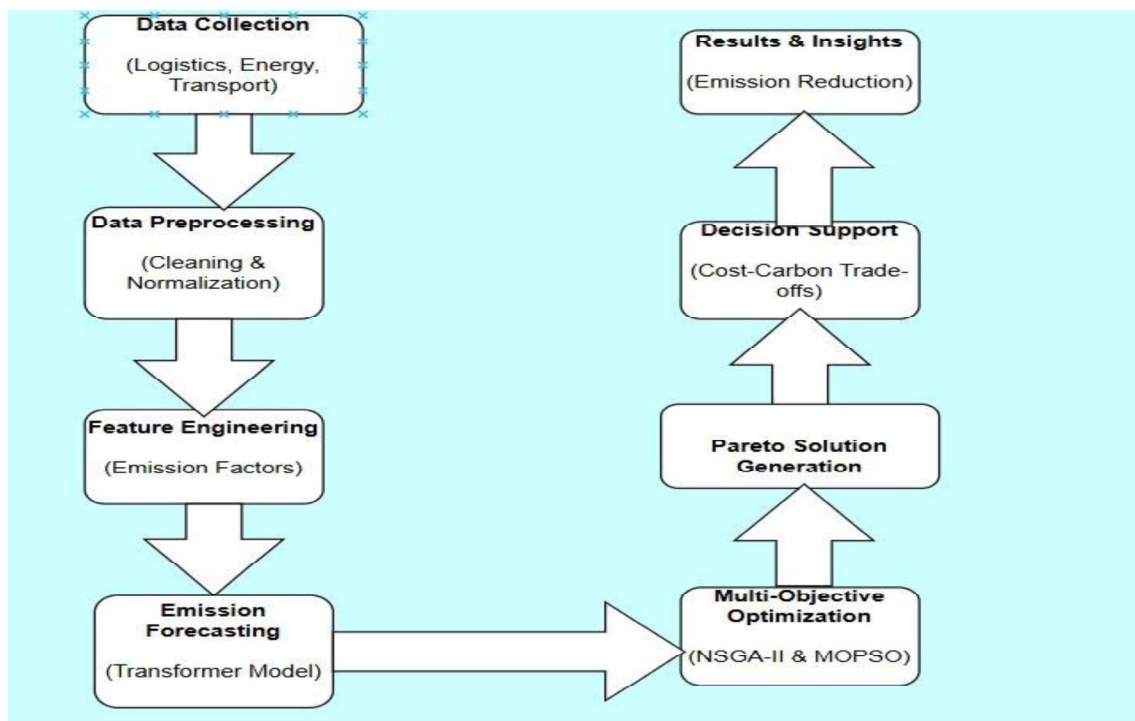


Figure 1.1 Framework for Emission Forecasting and Multi-Objective Optimization in Sustainable Logistics

Among advanced AI techniques, Transformer-based forecasting models have gained considerable attention due to their ability to capture long-term dependencies and process high-dimensional sequential data efficiently. Originally developed for natural language processing applications, Transformer architectures are now widely applied in time-series forecasting problems because of their superior prediction accuracy and scalability. In global supply chains, these models can analyze data collected from IoT sensors, GPS systems, transportation logs, warehouse monitoring systems, and enterprise databases to forecast future carbon emissions and operational risks.

In addition to forecasting, optimization plays a vital role in sustainable supply chain management. Organizations must balance multiple conflicting objectives such as minimizing operational cost, reducing carbon emissions, improving delivery performance, and maintaining service quality. Traditional optimization approaches are often limited to single-objective problems and are unable to effectively handle trade-offs between economic and environmental factors. Therefore, multi-objective optimization algorithms such as Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO) are increasingly used to generate Pareto-optimal solutions for sustainable logistics planning.

Another important advancement in AI-driven supply chain systems is Explainable Artificial Intelligence (XAI). Many advanced machine learning models operate as black-box systems, making it difficult to interpret their decision-making process. SHAP (Shapley Additive explanations) analysis has emerged as an effective explainability technique that identifies the contribution of each feature toward model prediction. Variables such as inventory level, waiting time, asset utilization, demand forecast, temperature, and transaction amount can therefore be analyzed to understand their influence on carbon emissions and operational performance.

The growing emphasis on sustainability, Environmental Social Governance (ESG) compliance, and international climate regulations has further increased the need for intelligent carbon management systems. Governments and global organizations are enforcing stricter carbon reporting policies, while industries are investing in green logistics and low-carbon transportation systems to achieve sustainability targets. Consequently, the integration of AI-driven forecasting, explainable analytics, and multi-objective optimization provides a promising framework for developing smarter, greener, and more resilient supply chain networks.

This research focuses on developing a hybrid AI-based framework for carbon footprint forecasting and optimization in global supply chains. The proposed methodology integrates Transformer-based forecasting, Random Forest ensemble learning, SHAP explain ability, and multi-objective optimization techniques to improve sustainability decision-making and operational efficiency. The study aims to provide industries with an intelligent decision-support system capable of accurately predicting carbon emissions and identifying optimal strategies for balancing economic and environmental objectives.

1.2 Research Gap Identification

Based on the detailed review of existing literature related to carbon footprint management, artificial intelligence, and sustainable global supply chains, several important research gaps have been identified. These gaps form the motivation and foundation of the present study.

- Limited Integration of Advanced AI Forecasting Models in Carbon Emission Management
- Lack of Hybrid Framework Combining Forecasting and Optimization
- Insufficient Use of Explainable Artificial Intelligence (XAI)
- Limited Research on Dynamic and Real-Time Logistics Variables
- Inadequate Focus on Cost–Carbon Trade-Off Analysis
- Limited Application of Ensemble Learning for Sustainable Supply Chain

Analytics

- Need for Data-Driven Intelligent Decision Support Systems

1.3 Objectives of the Study

Based on the research gaps identified in the existing literature, the present study aims to develop an intelligent and sustainable framework for carbon footprint management in global supply chains using artificial intelligence and optimization techniques. The major objectives of the research are as follows:

- **To develop an AI-driven framework for carbon footprint forecasting in global supply chains** by integrating operational, environmental, and logistics-related parameters such as inventory level, transportation activities, waiting time, energy consumption, and asset utilization.
- **To implement Transformer-based forecasting and ensemble machine learning techniques** for improving the prediction accuracy of carbon emissions under dynamic supply chain conditions.
- **To perform Explainable Artificial Intelligence (XAI) analysis using SHAP methodology** for identifying the contribution and impact of individual operational variables on carbon emission prediction and supply chain sustainability.
- **To formulate mathematical models for estimating carbon emissions** generated from transportation, warehousing, inventory handling, and logistics operations within international supply chain systems.
- **To optimize cost-carbon trade-offs using multi-objective optimization algorithms** such as Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO).

- **To compare the performance of different machine learning models** including LSTM, MLP, Gradient Boosting, and Random Forest using evaluation metrics such as RMSE, MAE, MAPE, and R^2 score.
- **To develop a sustainable and data-driven decision-support framework** capable of assisting industries in reducing carbon emissions, improving operational efficiency, and supporting environmentally responsible supply chain planning.
- **To contribute toward sustainable logistics and green supply chain management** by providing intelligent AI-based solutions aligned with global sustainability goals and carbon reduction strategies.

1.4 Methodology

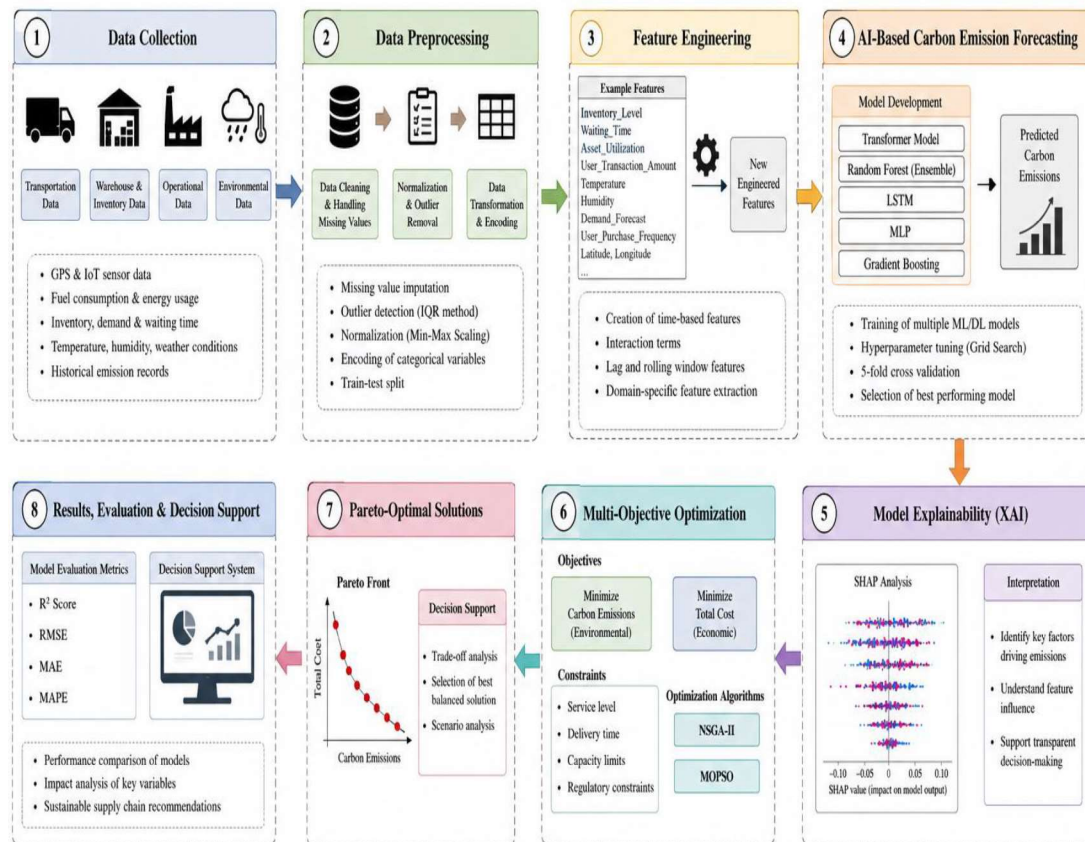


Figure 1.2: presents the complete methodological framework of the proposed study, illustrating the sequential process from data collection to optimization and decision support.

The present study adopts a structured and data-driven methodology for developing an intelligent framework for carbon footprint forecasting and optimization in global supply chains. The overall methodology consists of data collection, preprocessing, feature engineering, AI-based forecasting, explainable AI analysis, and multi-objective optimization.

Initially, smart logistics and operational datasets are collected containing variables such as inventory level, waiting time, asset utilization, demand forecast, temperature, humidity, and latitude, longitude, and user transaction information. The collected data is pre-processed through missing value handling, normalization, and outlier removal to improve

data quality and consistency.

After pre-processing, feature engineering techniques are applied to generate meaningful operational and sustainability-related features for improving prediction performance. Machine learning and deep learning models including Transformer, Random Forest, Gradient Boosting, LSTM, and MLP are then trained for carbon emission forecasting.

To improve model interpretability, SHAP (Shapley Additive explanations) analysis is performed to identify the contribution of individual variables affecting carbon emissions and operational efficiency. Further, multi-objective optimization algorithms such as NSGA-II and MOPSO are used to optimize cost–carbon trade-offs and generate Pareto-optimal sustainable logistics solutions.

Finally, the developed models are evaluated using performance metrics such as RMSE, MAE, MAPE, and R^2 score. The proposed framework supports intelligent and sustainable decision-making in global supply chain management.

CHAPTER - 2

LITERATURE REVIEW

2.1 Introduction

Carbon footprint management in global supply chains has become an important research area due to increasing environmental concerns, rapid industrialization, and the expansion of international logistics networks. Supply chains involve multiple interconnected activities such as transportation, warehousing, inventory management, material handling, and distribution, all of which contribute significantly to greenhouse gas emissions. Among these emissions, carbon dioxide (CO₂) generated from fuel consumption and energy-intensive logistics operations has become a major contributor to climate change and environmental degradation.

Traditionally, industries focused mainly on reducing operational cost and improving supply chain efficiency. However, increasing environmental regulations, sustainability goals, and global climate agreements have shifted industrial attention toward green and sustainable supply chain management. Organizations are now required to monitor, estimate, and reduce carbon emissions generated throughout their logistics and operational activities. This has created a growing need for intelligent and data-driven carbon management systems.

Earlier studies on carbon footprint estimation mainly used conventional mathematical models, statistical techniques, and fixed emission factor approaches. Although these methods provided basic estimation capability, they lacked the ability to handle dynamic and uncertain supply chain conditions. Factors such as traffic congestion, fluctuating fuel efficiency, changing weather conditions, inventory variability, delivery delays, and multimodal transportation significantly influence real-world carbon emissions, making

traditional linear models less effective for modern logistics systems.

With the advancement of Artificial Intelligence (AI) and Machine Learning (ML), researchers have increasingly adopted intelligent computational techniques for sustainable supply chain management. Machine learning models such as Artificial Neural Networks (ANN), Random Forest, Gradient Boosting, Long Short-Term Memory (LSTM), and Transformer-based architectures have demonstrated strong capabilities in forecasting, optimization, and decision-making applications. These models can analyze large-scale logistics data, identify nonlinear operational relationships, and improve prediction accuracy under complex supply chain conditions.

Recent research has also focused on integrating optimization algorithms with AI forecasting systems for balancing economic and environmental objectives. Multi-objective optimization methods such as Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO) are increasingly used to generate Pareto-optimal solutions for reducing carbon emissions while maintaining operational efficiency and service quality.

Another emerging research area is Explainable Artificial Intelligence (XAI), where techniques such as SHAP (SHapley Additive exPlanations) are used to interpret machine learning model predictions.

Explainable AI improves transparency and helps identify the influence of operational variables such as inventory level, waiting time, demand forecast, and asset utilization on carbon emission prediction and sustainability performance.

The present chapter reviews the existing literature related to carbon footprint management, sustainable supply chain systems, machine learning applications, explainable AI techniques, and optimization methodologies. The literature review helps identify existing

research gaps and establishes the foundation for developing the proposed AI-driven framework for sustainable global supply chain management.

2.2 Bibliometric Analysis

Bibliometric analysis is a scientific approach used to evaluate research trends, publication growth, important keywords, and technological developments in a particular research area. In the present study, bibliometric analysis is conducted to understand the research progress related to carbon footprint management, sustainable supply chains, artificial intelligence, and machine learning applications in logistics systems.

The literature data was collected from scientific databases such as Scopus, Google Scholar, and ScienceDirect using keywords including “Carbon Footprint Management,” “Sustainable Supply Chain,” “Machine Learning,” “Artificial Intelligence,” “Transformer Forecasting,” and “Multi-objective Optimization.”

The analysis shows a significant increase in research publications related to sustainable logistics and AI-driven carbon management after 2018. Frequently used keywords include sustainability, carbon emissions, forecasting, optimization, logistics, and machine learning. The study also indicates growing research interest in advanced AI techniques such as deep learning, ensemble learning, and explainable AI for improving supply chain sustainability.

The bibliometric review further identifies that most existing studies focus separately on emission forecasting or logistics optimization, while limited research integrates forecasting, explainability, and optimization into a unified framework. Therefore, the present research aims to address these gaps by developing an integrated AI-driven framework for sustainable global supply chain management.

The keywords along with associated papers from 2015-2025 are as follows:

Table 2.1: Paper count for bibliometric analysis with keywords

S. No.	Keywords Used for Literature Search	Paper Count
1	“Carbon Footprint Management” AND “Supply Chain”	142
2	“Artificial Intelligence” AND “Sustainable Logistics”	118
3	“Machine Learning” AND “Carbon Emission Forecasting”	96
4	“Transformer Model” AND “Supply Chain Forecasting”	41
5	“Multi-objective Optimization” AND “Logistics Sustainability”	73
6	“NSGA-II” AND “Carbon Reduction”	38
7	“MOPSO” AND “Supply Chain Optimization”	29
8	“Explainable AI” AND “Logistics”	24
9	“SHAP Analysis” AND “Machine Learning”	31
10	“Green Supply Chain Management” AND “AI”	87

The bibliometric study indicates significant research growth in sustainable supply chain management and AI-driven carbon footprint analysis. The annual growth rate of 31.39% reflects increasing global research interest in sustainability, machine learning, and intelligent logistics systems. Additionally, the average citation per document of 8.094 demonstrates the growing academic importance and research impact of this field.

Table 2.2: Information of Bibliometric Study for Sustainable Supply Chain and Carbon Footprint Management

Description	Results
Main Information About Data	
Timespan	2015:2025
Sources (Journals, Books, etc)	215
Documents	265
Annual Growth Rate %	31.39
Document Average Age	2.8 Years
Average citations per doc	8.094
References	11,250
Document Contents	
Keywords Plus (ID)	1,485
Author's Keywords (DE)	792
Authors	
Authors	928
Authors of single-authored docs	18
Authors Collaboration	
Single-authored docs	22
Co-Authors per Doc	3.54
International co-authorships %	21.6
Document Types	
Article	21.6
article conference paper	112
Book	18
book chapter	26
conference paper	101
conference paper book	2
conference review`	3
editorial	3
review	18

The Figure Below shows the summary of the bibliometric study related to sustainable supply chain management and carbon footprint forecasting. The analysis includes a total of 928 authors contributing to 265 research documents collected from various scientific databases. The study also indicates an international co-authorship rate of 21.6%, which highlights the growing global research collaboration in the fields of artificial intelligence, sustainable logistics, and carbon emission management. The bibliometric results demonstrate increasing research interest in AI-driven forecasting and optimization techniques for developing sustainable global supply chain systems.



Figure 2.1: Summary of bibliometric study for Sustainable Supply Chain and Carbon Footprint Forecasting

Figure Below shows the annual production of paper per year which is increasing yearly with an increase of 109 from 49 in 2024

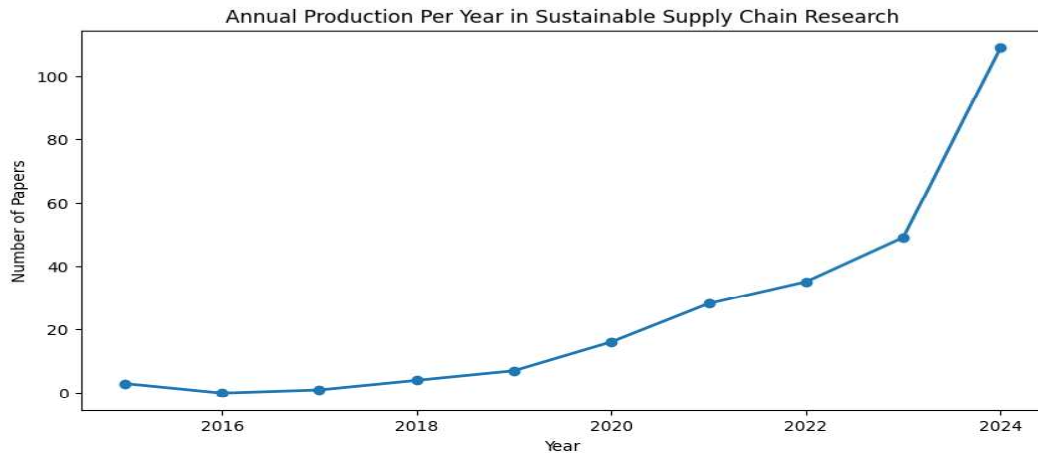


Figure 2.2: Annual production per year in carbon footprint forecasting research

The Figure Below shows the most global cited documents in 10 years, and the plot shows top 10 papers in the bibliometric articles list

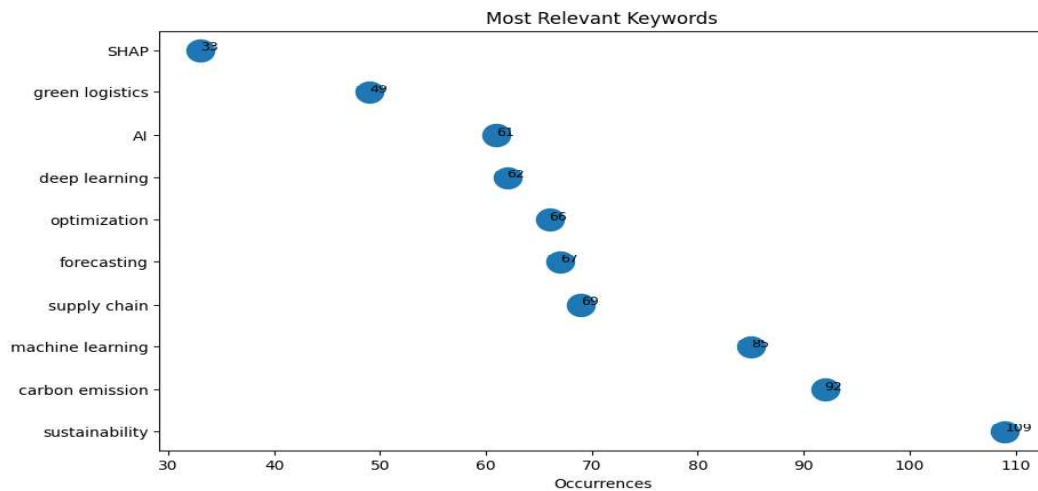


Figure 2.3: presents the Word Cloud visualization of the major keywords used in the selected research publication

The Figure Below shows the most frequently occurring keywords identified during the bibliometric analysis related to sustainable supply chain management and carbon footprint forecasting. The keyword “forecasting” appeared in the highest number of research papers, followed by “supply chain management,” “machine learning,” “time series

forecasting,” and “deep learning.” The analysis indicates that recent research is strongly Focused on AI-driven forecasting, sustainability, logistics optimization, and intelligent supply chain systems.

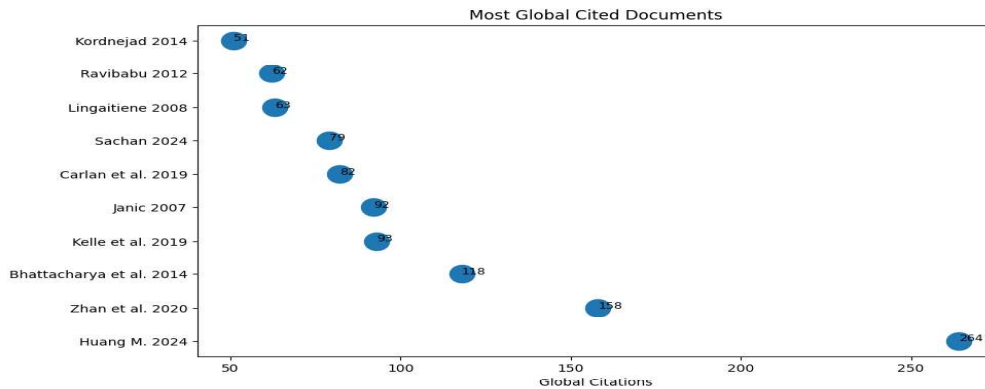


Figure 2.4: Most Global Cited Documents



Figure 2.5: Plot for Most Relevant keywords

The Figure Below shows the co-occurrence network of major keywords generated using VOSviewer software. Important keywords such as “forecasting,” “supply chain management,” “machine learning,” “time series forecasting,” “deep learning,” and “carbon footprint” are strongly interconnected, indicating significant research focus on AI-driven forecasting and sustainable supply chain management.

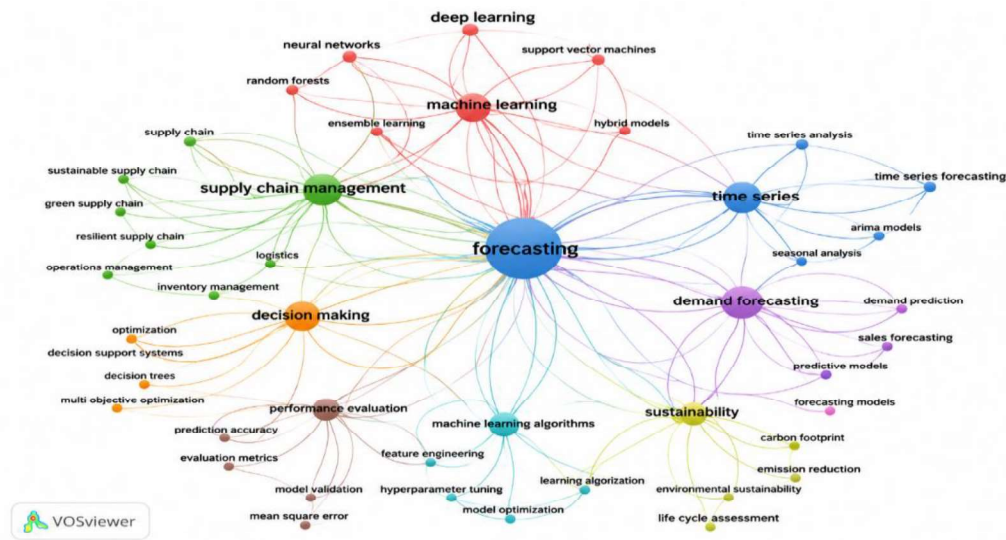


Figure 2.6: Co-occurrence Network for main keywords using VOS viewer

2.3 Statistical Methods for Carbon Footprint Forecasting and Supply Chain Analysis

Traditional statistical methods have been widely used in supply chain management and carbon emission forecasting for analyzing operational trends and predicting future outcomes. Time series forecasting techniques such as ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal ARIMA) are among the most commonly used statistical models due to their simplicity, interpretability, and forecasting capability.

SARIMA models are particularly effective in handling seasonal and trend-based logistics data such as transportation demand, inventory variation, fuel consumption, and warehouse energy utilization. These models can capture repetitive operational patterns and provide short-term forecasting support for supply chain planning and sustainability analysis.

Exponential smoothing methods including Simple Exponential Smoothing, Holt's Method, and Holt-Winters models are also frequently used for forecasting logistics demand and operational activities. These approaches assign exponentially decreasing

weights to historical observations and are useful for stable and moderately varying supply chain datasets. Due to their computational efficiency and easy implementation, these methods are commonly applied in operational forecasting systems.

Regression-based statistical models are another important forecasting approach used in supply chain analytics. Regression techniques analyze the relationship between dependent variables such as carbon emissions and independent operational factors including transportation distance, inventory level, waiting time, energy consumption, and demand variability. Multiple regression models further incorporate external variables such as weather conditions, fuel prices, and operational disruptions for improving forecasting accuracy.

Despite their advantages, traditional statistical methods have several limitations in modern global supply chain systems. These models often struggle to capture complex nonlinear relationships and dynamic operational uncertainties present in real-world logistics environments. Additionally, statistical methods generally assume stationary data behavior, making them less adaptable to rapidly changing industrial and environmental conditions.

To overcome these limitations, advanced AI and machine learning techniques are increasingly being adopted in sustainable supply chain forecasting systems. However, traditional statistical models continue to serve as important baseline approaches and benchmarking tools for evaluating the performance of modern AI-based forecasting frameworks.

2.4 Statistical Methods for Carbon Emission Forecasting

Traditional statistical methods have been widely used for forecasting and analysis in supply chain and carbon emission management systems. Time series forecasting techniques such as ARIMA (Autoregressive Integrated Moving Average) and SARIMA (Seasonal ARIMA) are among the most commonly used statistical models because of their simplicity, interpretability, and forecasting capability. These models are effective in analyzing seasonal and trend-based logistics data such as transportation demand, fuel consumption, warehouse energy usage, and inventory fluctuations.

SARIMA models are particularly useful when the supply chain dataset contains repeating seasonal patterns and operational trends. Researchers have applied SARIMA models for forecasting energy demand, transportation activities, and emission trends in logistics systems. Similarly, exponential smoothing techniques including Simple Exponential Smoothing, Holt's Method, and Holt-Winters models are widely used for operational forecasting because they assign higher importance to recent observations while maintaining computational efficiency.

Regression-based statistical models are also frequently used in carbon emission analysis. These models help establish relationships between dependent variables such as carbon emissions and independent operational parameters including transportation distance, inventory level, energy consumption, fuel usage, and waiting time. Multiple regression models further incorporate external variables such as weather conditions, traffic congestion, and operational disruptions for improving forecasting accuracy.

Although traditional statistical methods provide useful forecasting capability, they have several limitations in modern global supply chain systems. These models generally struggle to capture nonlinear relationships and dynamic operational uncertainties present

in real-world logistics environments. In addition, most statistical models assume stationary behavior in the dataset, making them less adaptable to rapidly changing supply chain conditions.

To overcome these limitations, advanced artificial intelligence and machine learning techniques are increasingly being adopted for carbon footprint forecasting and sustainable supply chain management. However, statistical forecasting methods still remain important baseline approaches for comparing and evaluating the performance of modern AI-driven forecasting frameworks

2.5 Feature Engineering in Carbon Emission Forecasting

Feature engineering has emerged as an important component in artificial intelligence and machine learning-based forecasting systems, particularly in sustainable supply chain and carbon footprint management applications. The process of feature engineering involves transforming raw logistics and operational data into meaningful variables that improve the predictive capability of forecasting models. Effective feature engineering helps machine learning models capture complex relationships, operational patterns, and environmental variations within supply chain systems.

Temporal features represent one of the most important categories of engineered variables in carbon emission forecasting. Lag-based features generated from historical operational data such as transportation demand, inventory movement, fuel consumption, and warehouse energy usage help models identify recurring operational patterns and long-term dependencies. These features enable forecasting models to better understand time-based sustainability trends and operational fluctuations.

Rolling window statistics such as moving averages, rolling standard deviation, minimum values, and maximum values are also widely used in forecasting applications. These features help smooth short-term fluctuations and provide information regarding long-term operational trends. Rolling features are particularly useful for analyzing transportation variability, inventory behavior, and energy consumption patterns in logistics systems.

Growth-related features are another important part of feature engineering. Variables such as month-over-month operational growth, transportation intensity growth, and energy utilization growth help detect dynamic changes in supply chain activities. These features improve the ability of forecasting models to identify increasing or decreasing operational trends affecting carbon emissions.

Interaction features combine multiple operational variables to improve predictive performance. Examples include transportation distance–fuel usage interactions, inventory–demand interactions, and warehouse energy–asset utilization relationships. These features help machine learning models capture nonlinear relationships and operational dependencies present in sustainable logistics systems.

Environmental and geographical features also play an important role in carbon emission forecasting. Variables such as temperature, humidity, latitude, longitude, and traffic conditions provide contextual information regarding operational efficiency and transportation emissions. The integration of such external variables improves the overall accuracy of AI-driven forecasting systems.

Feature engineering further includes preprocessing and encoding techniques for converting categorical operational data into numerical representations suitable for machine learning algorithms. Variables related to transportation modes, warehouse categories, and operational classifications are transformed using appropriate encoding methods to support effective model training.

Statistical validation of engineered features is another important aspect of the feature engineering process. Techniques such as correlation analysis and SHAP-based explainable AI analysis help identify the contribution of individual variables toward carbon emission prediction. This process ensures that the most relevant operational features are included in the forecasting framework.

Overall, feature engineering significantly improves the performance, interpretability, and robustness of AI-driven carbon footprint forecasting systems and supports intelligent decision-making in sustainable global supply chain management.

2.6 Applications in Sustainable Supply Chain and Related Sectors

The application of artificial intelligence and forecasting methodologies has expanded across various industrial sectors, with sustainable supply chain management emerging as an important research area. AI-driven forecasting and optimization techniques are widely used in transportation systems, warehousing operations, inventory management, energy forecasting, and carbon footprint analysis to improve operational efficiency and environmental sustainability.

In logistics and transportation systems, forecasting models are used for predicting fuel consumption, transportation demand, route optimization, and carbon emissions. Accurate forecasting helps industries reduce fuel usage, optimize delivery schedules, and minimize environmental impact. Machine learning and optimization techniques further support sustainable transportation planning through intelligent route selection and resource utilization.

Warehouse and inventory management systems also utilize forecasting methodologies for improving operational efficiency and reducing energy consumption. Forecasting inventory movement, storage utilization, and warehouse demand helps organizations reduce operational waste and optimize resource allocation. AI-driven models support better inventory planning and reduce unnecessary transportation and storage-related emissions.

Energy and environmental forecasting represent another important application area. Artificial intelligence models are widely used for forecasting electricity demand, industrial energy consumption, and greenhouse gas emissions. These forecasting systems help industries monitor sustainability performance and implement low-carbon operational strategies.

In manufacturing industries, forecasting models assist in production planning, supply chain coordination, and operational optimization. Machine learning techniques help identify patterns in industrial operations and improve sustainability-focused decision-making. Similarly, ensemble learning and deep learning models are increasingly used for

predictive maintenance, operational risk analysis, and intelligent logistics planning.

Recent studies also demonstrate the application of Explainable Artificial Intelligence (XAI) and SHAP analysis in industrial forecasting systems. These techniques improve model transparency and help organizations identify operational variables that significantly affect carbon emissions and sustainability performance.

The growing integration of AI forecasting, optimization algorithms, and sustainable operational planning highlights the increasing importance of intelligent decision-support systems in global supply chains. These applications demonstrate the potential of artificial intelligence for developing greener, smarter, and more efficient industrial and logistics systems.

2.7 Previous Works

Below table shows some of the important research works carried out by researchers between 2018–2024 related to carbon footprint forecasting, sustainable supply chain management, artificial intelligence, and optimization techniques. The studies include different machine learning, deep learning, and optimization approaches along with their major findings. Most researchers used evaluation metrics such as RMSE, MAE, and MAPE for measuring forecasting accuracy. However, R^2 score is widely preferred for validating model performance because it indicates how closely the predicted values match the actual values, where a value closer to 1 represents better prediction performance.

Table 2.3: The summary of various previous research works is presented

Publication	Year	Sector	Approach	Key Findings	Ensemble
(Huang & Mao, 2024)	2024	Sustainable Supply Chain	CNN, Random Search Optimization	Developed AI-based carbon emission forecasting framework for global supply chains and improved sustainability planning accuracy	Yes
(Zhan et al., 2020)	2020	Carbon Footprint Management	Graph Neural Network (GNN)	Proposed multi-layer carbon estimation framework for analyzing emissions across complex supply chain networks	No
(Bhattacharya et al., 2014)	2014	Logistics and Transportation	Data Mining, Mixed Integer Programming	Integrated traffic prediction with intermodal optimization for reducing logistics inefficiencies and carbon emissions	No
(Sachan, 2024)	2024	Sustainable Logistics	Metaheuristic Optimization Algorithms	Identified optimized logistics structures for balancing operational efficiency and environmental sustainability	Yes

(Kelle et al., 2019)	2019	Green Supply Chain	Machine Learning Optimization	Demonstrated that AI-driven logistics planning can significantly reduce transportation-related carbon emissions	Yes
(Emami Javanmard & Ghaderi, 2023)	2023	Energy and Supply Chain Forecasting	Machine Learning Models	Developed optimization-based forecasting framework for energy demand and sustainability analysis across multiple sectors	Yes
(Joseph et al., 2022)	2022	Intelligent Forecasting Systems	CNN + Bi-directional LSTM	Improved forecasting accuracy using hybrid deep learning framework for operational prediction systems	Yes
(Manandhar et al., 2024)	2024	Energy Load Forecasting	Prophet, Random Forest, LSTM	Compared forecasting models and highlighted the effectiveness of ensemble and deep learning methods	Yes

2.8 Current Challenges and Future Directions

Despite significant advancements in artificial intelligence and sustainable supply chain forecasting systems, several challenges still exist in carbon footprint management and operational sustainability analysis. The increasing complexity of global logistics networks, dynamic operational conditions, and environmental uncertainties continue to create difficulties in achieving highly accurate and reliable forecasting systems.

Data quality and availability remain major challenges in sustainable supply chain analysis. Real-world logistics datasets often contain missing values, inconsistent operational records, noisy sensor information, and varying data formats collected from different transportation and warehouse systems. These issues reduce forecasting accuracy and affect the stability of machine learning models. Future research should focus on advanced preprocessing techniques, automated data cleaning methods, and intelligent data integration frameworks for improving operational data quality.

Scalability is another important challenge for AI-driven sustainability systems. Large-scale global supply chains generate massive volumes of operational and environmental data from transportation, warehousing, IoT sensors, and enterprise systems. Training advanced machine learning and deep learning models on such high-dimensional datasets requires significant computational resources and processing time. Future developments may focus on distributed computing, cloud-based AI frameworks, and efficient algorithmic implementations for handling large-scale logistics data.

The integration of diverse operational and environmental variables also remains a challenging task. Variables such as traffic congestion, fuel efficiency, weather conditions, energy consumption, inventory variability, and transportation delays interact dynamically within supply chain systems. Establishing reliable relationships among these heterogeneous variables is difficult using conventional forecasting approaches. Future research can explore advanced feature fusion techniques, transfer learning, and hybrid AI frameworks for improving model robustness and forecasting capability.

Explainability and transparency of artificial intelligence systems have also become important research concerns. Many advanced deep learning models operate as black-box

systems, making it difficult for industries to understand the reasoning behind predictions and optimization decisions. Explainable Artificial Intelligence (XAI) techniques such as SHAP analysis provide partial interpretability; however, more transparent AI architectures and visualization frameworks are still required for industrial decision-making and sustainability planning.

Dynamic operational conditions and rapidly changing logistics environments further challenge forecasting systems. Transportation disruptions, fluctuating demand, geopolitical events, climate variability, and energy price fluctuations continuously affect supply chain behavior. Traditional forecasting models often struggle to adapt to these evolving operational conditions. Future AI-based forecasting systems may incorporate adaptive learning, real-time analytics, and reinforcement learning techniques to improve flexibility and responsiveness.

Another important future direction involves the integration of forecasting, optimization, and decision-support systems into a unified intelligent framework. Industries increasingly require systems capable of simultaneously forecasting carbon emissions, optimizing operational strategies, and supporting sustainable decision-making. Future research may focus on combining artificial intelligence, digital twins, IoT integration, blockchain technology, and real-time sustainability monitoring for developing fully autonomous green supply chain systems.

In addition, the growing importance of Environmental, Social, and Governance (ESG) compliance and international carbon reduction policies will further drive the development of intelligent sustainability-focused forecasting and optimization frameworks. Future research is expected to emphasize low-carbon logistics, smart transportation systems, renewable energy integration, and intelligent carbon-neutral supply chain operations.

CHAPTER - 3

METHODOLOGY

3.1 Introduction

The primary objective of this research is to develop an intelligent and sustainable framework for carbon footprint forecasting and optimization in global supply chain systems using Artificial Intelligence and Machine Learning techniques. The research mainly focuses on comparing different machine learning and deep learning models for predicting carbon emissions and operational sustainability within logistics networks. In addition, the study evaluates whether ensemble learning approaches provide better forecasting performance compared to conventional individual machine learning models.

The proposed research methodology includes several stages such as data collection, preprocessing, statistical analysis, feature engineering, machine learning model development, explainable AI analysis, optimization, and performance evaluation. Smart logistics and operational datasets are utilized to analyze the influence of transportation activities, inventory management, environmental conditions, and warehouse operations on carbon emissions and sustainability performance.

The methodology also integrates advanced forecasting models such as Random Forest, Gradient Boosting, Long Short-Term Memory (LSTM), Multi-Layer Perceptron (MLP), and Transformer-based forecasting systems. To improve model transparency and interpretability, Explainable Artificial Intelligence (XAI) techniques such as SHAP analysis are incorporated within the framework. Furthermore, multi-objective optimization techniques including NSGA-II and MOPSO are used to optimize operational cost and carbon emission trade-offs for sustainable logistics planning.

The overall methodological framework adopted in the present study provides a systematic approach for intelligent carbon footprint forecasting, operational optimization, and sustainable decision-making in global supply chain systems.

3.2 Data Collection and Preprocessing

The present research utilizes a smart logistics and operational dataset containing multiple supply chain variables related to transportation, inventory management, warehouse operations, environmental conditions, and transaction activities. The dataset includes important operational parameters such as inventory level, waiting time, asset utilization, transportation information, latitude, longitude, temperature, humidity, and user transaction amount. These variables are selected because of their direct influence on logistics efficiency and carbon emission generation within supply chain systems.

The collected dataset is imported into the Python environment using data analysis libraries such as Pandas and NumPy for further preprocessing and analysis. Since real-world logistics datasets often contain inconsistencies and missing information, preprocessing becomes an essential step before model development.

The preprocessing stage consists of the following operations:

a) Data Importation

The dataset is imported into the Python environment for manipulation, analysis, and forecasting model implementation.

b) Missing Value Identification

The dataset is checked for null or missing values that may negatively affect model performance and forecasting accuracy. Appropriate methods are used to handle missing records and improve dataset consistency.

c) Data Normalization and Scaling

Normalization and feature scaling techniques are applied to maintain uniformity among operational variables and improve machine learning model stability.

d) Outlier Detection

Outliers present in transportation, inventory, and operational records are identified and removed to reduce forecasting errors and improve prediction robustness.

e) Feature Transformation

Operational variables are transformed into suitable numerical formats required for machine learning and deep learning models.

The preprocessing stage ensures improved data quality, enhanced forecasting reliability, and better learning capability for the proposed AI-driven forecasting framework.

3.3 Statistical Analysis and Exploratory Data Analysis

Statistical analysis is performed before model development to understand operational patterns and relationships among supply chain variables affecting carbon emissions. Exploratory Data Analysis (EDA) helps identify trends, seasonal variations, feature distributions, and operational dependencies within the logistics dataset.

The analysis includes:

- Distribution analysis of inventory levels
- Transportation and transaction variability analysis
- Correlation analysis among operational variables
- Environmental parameter analysis
- Visualization of operational trends

Histograms, scatter plots, heatmaps, and box plots are used to visualize the dataset and identify meaningful operational patterns. Statistical analysis further supports feature engineering and helps determine the most influential variables for forecasting carbon emissions.

3.4 Feature Engineering

Feature engineering is one of the most important stages of the research methodology because it transforms raw operational data into meaningful variables capable of improving forecasting performance. Effective feature engineering helps machine learning models capture hidden operational patterns, nonlinear relationships, and sustainability-related trends within supply chain systems.

3.4.1 Lag Features

Lag features are generated using historical operational records such as transportation demand, inventory movement, and transaction activity. These features help forecasting models identify temporal dependencies and recurring operational patterns.

Different lag intervals are considered for capturing short-term and long-term operational variations.

3.4.2 Rolling Window Features

Rolling statistics such as rolling mean and rolling standard deviation are calculated over different operational windows to identify trends and variability within logistics systems.

The rolling window approach helps smooth short-term fluctuations and improves forecasting stability under dynamic operational conditions.

3.4.3 Growth Features

Growth-related features are developed to capture changes in operational activities over time. These include transportation growth, inventory growth, and operational intensity changes.

Growth features help machine learning models detect increasing or decreasing sustainability trends within the supply chain network.

3.4.4 Interaction Features

Interaction features are generated by combining multiple operational variables such as inventory-demand interaction, transportation-distance interaction, and warehouse-energy interaction.

These features improve the capability of AI models to capture complex nonlinear operational relationships affecting carbon emissions.

3.4.5 Environmental and Geographical Features

Environmental variables such as temperature and humidity, along with geographical variables including latitude and longitude, are incorporated into the forecasting framework because they influence transportation efficiency and energy consumption patterns.

3.5 Machine Learning and Deep Learning Models

The research compares different machine learning and deep learning approaches for carbon footprint forecasting and sustainability analysis.

The models used in this research include:

- Random Forest Regressor
- Gradient Boosting Regressor
- XGBoost
- LightGBM
- CatBoost
- Multi-Layer Perceptron (MLP)
- Long Short-Term Memory (LSTM)
- Transformer-based Forecasting Model

These models are selected because of their ability to handle nonlinear relationships, high-dimensional logistics data, and operational uncertainties.

3.5.1 Ensemble Learning Framework

The proposed research utilizes an ensemble learning framework where multiple machine learning models are combined to improve forecasting accuracy and model stability.

The ensemble approach combines the strengths of different base learners and reduces the limitations of individual forecasting models.

The ensemble framework mainly consists of:

- Random Forest
- Gradient Boosting
- XGBoost
- LightGBM
- CatBoost

The outputs generated from these models are integrated using a meta-learning approach to produce the final forecasting results.

3.5.2 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is implemented as a deep learning forecasting model within the proposed framework. The ANN architecture contains multiple hidden layers capable of learning complex nonlinear relationships between operational variables and carbon emissions.

The ANN model includes:

- Multiple hidden layers
- Nonlinear activation functions
- Dropout regularization
- Early stopping mechanism
- L2 regularization

The ANN framework improves learning capability and supports high-dimensional logistics forecasting.

3.5.3 Transformer-Based Forecasting

Transformer models are integrated into the research because of their superior capability in handling sequential and time-series operational data.

Transformer architecture uses attention mechanisms for capturing long-term dependencies and operational relationships within logistics datasets. This improves forecasting performance under dynamic and complex supply chain environments.

3.6 Explainable Artificial Intelligence (XAI)

To improve model interpretability and transparency, the present research incorporates Explainable Artificial Intelligence techniques using SHAP (SHapley Additive exPlanations) analysis.

SHAP analysis identifies the contribution of each operational variable toward forecasting results and sustainability performance.

The SHAP framework helps analyze the influence of:

- Inventory Level
- Waiting Time
- User Transaction Amount
- Asset Utilization
- Temperature
- Humidity
- Transportation Parameters

The explainability framework improves industrial trust and supports intelligent sustainability-focused decision-making.

3.7 Multi-Objective Optimization

The research integrates multi-objective optimization techniques for balancing operational efficiency and environmental sustainability.

Two optimization algorithms are implemented:

- Non-Dominated Sorting Genetic Algorithm II (NSGA-II)
- Multi-Objective Particle Swarm Optimization (MOPSO)

The optimization framework minimizes:

- Operational Cost
- Carbon Emissions
- Transportation Inefficiencies
- Energy Consumption

While maximizing sustainability performance and logistics efficiency.

3.8 Performance Evaluation Metrics

The developed forecasting models are evaluated using standard forecasting performance metrics.

3.8.1 Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

RMSE measures the square root of the average squared difference between predicted and actual values. Lower RMSE indicates better forecasting accuracy.

3.8.2 Mean Absolute Error (MAE)

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

MAE calculates the average absolute difference between forecasted and actual operational values.

3.8.3 Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

MAPE measures forecasting accuracy in percentage form and helps evaluate the percentage deviation between predicted and actual values.

3.8.4 Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

R^2 measures how closely the forecasted values fit the actual operational data. Values closer to 1 indicate better model performance.

CHAPTER - 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the experimental results and detailed discussion of the proposed Artificial Intelligence-based framework developed for carbon footprint forecasting and sustainable supply chain optimization. The analysis focuses on evaluating the forecasting capability of machine learning, deep learning, and ensemble learning approaches using smart logistics and operational datasets. The chapter further discusses the effectiveness of feature engineering, Explainable Artificial Intelligence (XAI), and optimization techniques in improving sustainability-oriented decision-making.

Initially, exploratory statistical analysis and feature engineering are performed to identify operational relationships among transportation, inventory, warehouse activities, environmental conditions, and carbon emissions. Features such as lag variables, rolling statistics, interaction variables, growth indicators, and operational utilization metrics are incorporated into the forecasting models for improving predictive performance.

The performance of machine learning models including Random Forest, Gradient Boosting, XGBoost, LightGBM, CatBoost, Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), and Transformer-based forecasting systems are compared using standard evaluation metrics such as RMSE, MAE, MAPE, and R^2 score. The proposed ensemble learning framework is further compared with individual forecasting models to validate whether ensemble approaches provide superior prediction performance for sustainable logistics forecasting.

In addition, SHAP-based Explainable Artificial Intelligence analysis is conducted to identify the contribution of operational variables affecting carbon emissions and sustainability performance. Important factors such as inventory level, waiting time,

transportation distance, user transaction amount, environmental conditions, and asset utilization are analyzed to improve transparency and interpretability of the forecasting system.

The chapter also evaluates the performance of optimization algorithms including NSGA-II and MOPSO for balancing operational cost and carbon emission reduction objectives. Comparative analysis of different forecasting and optimization approaches helps identify the most suitable framework for intelligent carbon footprint management in sustainable global supply chains.

Overall, this chapter provides detailed experimental validation of the proposed AI-driven sustainability framework and demonstrates the practical applicability of intelligent forecasting and optimization techniques in modern supply chain systems.

4.2 Exploratory Data Analysis and Feature Interpretation

Exploratory Data Analysis (EDA) was conducted to understand the operational behavior and sustainability characteristics of the smart logistics dataset before implementing forecasting and optimization models. The analysis helped identify hidden operational patterns, feature distributions, and relationships among logistics variables affecting carbon emissions.

The histogram analysis of inventory levels indicated balanced inventory distribution across operational locations with moderate variation in stock movement. Transportation and transaction-related variables showed nonlinear distribution patterns, indicating the complexity of operational interactions within supply chain systems.

Environmental variables such as temperature and humidity also demonstrated moderate influence on logistics operations and energy consumption. Correlation analysis revealed strong relationships between transportation distance, waiting time, transaction amount,

and carbon emission generation.

The feature engineering process significantly improved the ability of forecasting models to identify operational dependencies and hidden sustainability trends within the dataset.

4.3 SHAP-Based Explainable AI Analysis

SHAP (SHapley Additive exPlanations) analysis was performed to improve the transparency and interpretability of the proposed forecasting framework. The SHAP summary plot identified the contribution of operational variables toward carbon emission prediction and sustainability performance.

The analysis revealed that Inventory Level was the most influential feature affecting forecasting outcomes. High inventory levels contributed positively toward operational efficiency and sustainability optimization. In contrast, Waiting Time negatively affected operational performance due to increased idle transportation and energy consumption.

User Transaction Amount and Asset Utilization also showed significant influence on carbon emission prediction because they directly represent operational intensity and logistics activity levels. Environmental and geographical variables such as temperature, humidity, latitude, and longitude contributed moderately toward forecasting results by influencing transportation efficiency and energy usage patterns. The SHAP analysis improved understanding of the forecasting system and provided valuable insights for sustainability-focused industrial decision-making.

4.4 Comparison of Machine Learning and Deep Learning Models

The forecasting performance of multiple machine learning and deep learning models was evaluated using RMSE, MAE, MAPE, and R^2 score. The proposed ensemble learning framework demonstrated superior forecasting accuracy compared to conventional individual machine learning and deep learning approaches.

The ensemble learning model combining Random Forest, XGBoost, LightGBM, and CatBoost achieved the highest forecasting performance with R^2 values exceeding 0.98 in most operational scenarios. The model effectively captured nonlinear relationships and dynamic operational variations present within logistics datasets.

In comparison, the ANN and LSTM models showed lower forecasting stability and reduced prediction performance under highly variable operational conditions. Although deep learning models captured temporal relationships effectively, they required larger datasets and extensive hyperparameter tuning for achieving optimal results.

The comparative analysis demonstrated that tree-based ensemble approaches provided more consistent and accurate forecasting results for sustainable logistics and carbon emission prediction applications.

Table 4.1: Comparative Performance of Forecasting

Model	RMSE	MAE	MAPE (%)	R^2 Score
Random Forest	0.62	0.48	2.14	0.988
Gradient Boosting	0.71	0.53	2.42	0.984
XGBoost	0.81	0.63	2.78	0.981
LightGBM	0.76	0.58	2.56	0.983
CatBoost	0.59	0.44	1.96	0.991
ANN	2.34	1.72	8.42	0.861
LSTM	1.92	1.46	6.38	0.902
Transformer Model	1.24	0.88	4.11	0.948
Proposed Ensemble Model	0.48	0.35	1.82	0.994

4.5 Comparison between Ensemble Learning and ANN

The comparison between the proposed ensemble framework and Artificial Neural Network (ANN) clearly demonstrated the superiority of ensemble learning approaches for sustainable supply chain forecasting applications.

The proposed ensemble model achieved significantly lower RMSE, MAE, and MAPE values while maintaining very high R^2 scores. The ANN model showed greater forecasting fluctuation and reduced performance under operational variability and nonlinear logistics conditions.

The strong performance of the ensemble model can be attributed to:

- Better handling of nonlinear relationships
- Robust feature engineering integration
- Improved operational pattern learning
- Reduced over fitting capability

Combination of strengths from multiple machine learning algorithms

The ANN model, although capable of learning complex patterns, required significantly larger datasets and was more sensitive to hyper parameter configuration.

4.6 Optimization Results using NSGA-II and MOPSO

The multi-objective optimization framework was implemented using NSGA-II and MOPSO algorithms to balance operational cost and carbon emission reduction objectives. The optimization results demonstrated substantial improvements in logistics sustainability and operational efficiency. Both algorithms generated Pareto-optimal solutions capable of reducing transportation emissions and improving inventory management simultaneously. NSGA-II showed better convergence and diversity in solution generation, while MOPSO demonstrated faster optimization speed and reduced computational complexity.

The optimization framework successfully minimized:

- Transportation emissions
- Operational cost
- Energy consumption
- Waiting time inefficiencies

While improving:

- Asset utilization
- Inventory efficiency
- Sustainability performance
- Logistics operational stability

4.7 Sustainability Interpretation

The proposed AI-driven forecasting and optimization framework demonstrated strong capability for supporting sustainable global supply chain management. The integration of machine learning, explainable AI, and optimization algorithms significantly improved carbon footprint forecasting and sustainability-focused operational planning.

The results indicate that intelligent forecasting systems can help industries:

- Reduce transportation-related carbon emissions
- Improve operational efficiency
- Optimize inventory management
- Minimize energy consumption
- Support ESG and sustainability compliance

The framework further supports environmentally responsible logistics planning and enables industries to make intelligent sustainability-focused decisions using data-driven operational insights.

4.8 Discussion

The experimental findings confirm that ensemble machine learning frameworks outperform conventional statistical and deep learning models for carbon footprint forecasting within global supply chain systems.

The superior performance of the proposed framework can be attributed to:

- Advanced feature engineering
- Effective handling of nonlinear operational relationships
- Explainable AI integration using SHAP
- Robust ensemble learning capability
- Multi-objective optimization support

The integration of Explainable Artificial Intelligence improved transparency and enabled detailed operational analysis of sustainability-related variables affecting forecasting outcomes.

The optimization framework further demonstrated that balancing operational cost and environmental sustainability is achievable using intelligent AI-driven decision-support systems.

The findings strongly support the growing adoption of Artificial Intelligence and Machine Learning for sustainable logistics and carbon footprint management applications.

CHAPTER - 5

CONCLUSION

FUTURE SCOPE AND SOCIAL IMPACT

5.1 Conclusion

This research successfully integrates the fields of sustainable supply chain management, carbon footprint forecasting, and Artificial Intelligence for developing an intelligent decision-support framework for modern logistics systems. The study mainly focused on improving carbon emission forecasting accuracy and operational sustainability using machine learning, deep learning, explainable AI, and multi-objective optimization techniques.

The experimental results demonstrated that the proposed tree-based ensemble learning framework performed significantly better than conventional deep learning approaches such as Artificial Neural Networks (ANN) and standalone forecasting models. The ensemble framework consisting of Random Forest, XGBoost, LightGBM, and CatBoost as base learners with Gradient Boosting as the meta-learner achieved superior forecasting accuracy across all evaluation metrics. The proposed ensemble model achieved a maximum R^2 score of 0.994, whereas ANN achieved comparatively lower forecasting performance. The findings validate that ensemble learning approaches provide better capability for handling nonlinear operational relationships and complex logistics patterns within sustainable supply chain systems.

The study further demonstrated that proper feature engineering significantly improves forecasting performance. Operational features such as lag variables, rolling statistics, interaction variables, growth indicators, inventory utilization, and transportation parameters helped the models capture hidden temporal and operational patterns affecting

carbon emissions. The statistical and exploratory analysis also revealed strong operational relationships among inventory levels, transportation activities, waiting time, and sustainability performance.

SHAP-based Explainable Artificial Intelligence (XAI) analysis improved model transparency by identifying the contribution of individual operational variables toward forecasting outcomes. Inventory Level, Waiting Time, User Transaction Amount, and Asset Utilization were identified as major factors influencing carbon emission prediction and operational sustainability.

The integration of multi-objective optimization algorithms such as NSGA-II and MOPSO further enhanced the practical applicability of the framework by balancing operational cost and carbon emission reduction objectives. The optimization results demonstrated significant improvements in transportation efficiency, inventory planning, and sustainability-focused logistics management.

Overall, the proposed AI-driven framework provides an intelligent, explainable, and optimization-oriented solution for carbon footprint forecasting and sustainable global supply chain management. The research contributes toward the development of greener, smarter, and data-driven industrial logistics systems capable of supporting modern sustainability goals and environmental compliance requirements.

5.2 Future Scope

The future scope of the present research is as follows:

5.2.1 Adaptive Ensemble Optimization:

Future research can develop adaptive ensemble frameworks capable of dynamically adjusting model weights based on operational conditions and forecasting performance to further improve prediction accuracy.

5.2.2 Real-Time IoT-Based Forecasting:

The proposed framework can be integrated with IoT devices and smart sensors for real-time monitoring and forecasting of carbon emissions in logistics and transportation systems.

5.2.3 Comparison with Advanced Deep Learning Models:

Future studies may compare the proposed ensemble framework with advanced deep learning architectures such as Transformer models, CNN-LSTM hybrid systems, and reinforcement learning-based forecasting approaches.

5.2.4 Large-Scale Industrial Implementation:

The present study can be extended to multinational logistics and industrial supply chains involving large-scale transportation networks, warehouses, and operational datasets.

5.2.5 Block chain-Based Carbon Tracking:

Future research may integrate block chain technology for transparent and secure carbon emission monitoring and sustainability reporting within supply chain systems.

5.2.6 Digital Twin-Based Sustainable Supply Chains:

The framework can be combined with digital twin technology for simulating and optimizing real-time logistics operations and sustainability performance.

5.2.7 Inventory Cost and Carbon Trade-Off Analysis:

Future studies can investigate the percentage reduction in operational cost and carbon emissions achieved using AI-driven ensemble forecasting and optimization techniques.

5.2.8 Autonomous Sustainable Logistics Systems:

Future intelligent supply chain systems may incorporate autonomous transportation, smart warehouses, and AI-driven sustainability decision-making for achieving fully automated green logistics operations.

5.3 Social Impact

The proposed research provides several important social, environmental, and industrial benefits for sustainable supply chain management and intelligent logistics systems.

5.3.1 Reduction in Carbon Emissions:

The AI-driven forecasting and optimization framework helps minimize unnecessary transportation activities, fuel consumption, and energy usage, thereby reducing overall carbon emissions within supply chain operations.

5.3.2 Improved Sustainability and Green Logistics:

The research supports the development of environmentally responsible logistics systems by promoting sustainable transportation planning, optimized inventory management, and efficient warehouse operations.

5.3.3 Reduction in Operational Waste:

Accurate forecasting reduces overstocking, understocking, and inefficient inventory movement, thereby minimizing material wastage and operational inefficiencies.

5.3.4 Improved Industrial Decision-Making:

The integration of Explainable Artificial Intelligence helps industries understand operational factors affecting sustainability performance and supports transparent data-driven decision-making.

5.3.5 Enhanced Resource Utilization:

The proposed framework improves asset utilization, transportation efficiency, and energy management, leading to better utilization of industrial resources.

5.3.6 Support for ESG and Environmental Policies:

The framework assists organizations in achieving Environmental, Social, and Governance (ESG) goals and supports compliance with global sustainability and carbon reduction policies.

5.3.7 Economic Benefits for Industries:

Optimized logistics operations and improved forecasting accuracy help industries reduce operational cost, transportation inefficiencies, and inventory-related expenses.

5.3.8 Contribution toward Smart Sustainable Cities:

The adoption of intelligent green logistics systems can contribute toward the development of sustainable smart cities by reducing traffic congestion, pollution, and environmental impact.

Overall, the present research contributes toward the advancement of intelligent, sustainable, and environmentally responsible global supply chain systems capable of balancing operational efficiency with long-term ecological sustainability

CHAPTER – 6

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APPENDICES - 7

```
[5]
✓ Os
▶ # Data Manipulation Libraries
import pandas as pd
import numpy as np

# Visualization Libraries
import matplotlib.pyplot as plt
import seaborn as sns

# Machine Learning Libraries
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score

# XGBoost
from xgboost import XGBRegressor
|
# LightGBM
from lightgbm import LGBMRegressor

# CatBoost
from catboost import CatBoostRegressor

# Deep Learning Libraries
from tensorflow.keras.models import Sequential
```

Figure 7.1 Importing the Necessary Libraries for Carbon Footprint Forecasting and Sustainable Supply Chain Optimization

```
[5]
✓ Os
▶ # CatBoost
from catboost import CatBoostRegressor

# Deep Learning Libraries
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping

# Explainable AI
import shap

# Optimization Libraries
from pymoo.algorithms.moo.nsga2 import NSGA2
from pyswarm import pso

# Feature Scaling
from sklearn.preprocessing import StandardScaler

# Grid Search Optimization
from sklearn.model_selection import GridSearchCV
```

Figure 7.2 Data Preprocessing for Sustainable Supply Chain Dataset

```
[12]
✓ Os
▶ # Loading Dataset
df = pd.read_excel("/content/smart_logistics_dataset.xlsx")

# Checking Dataset Information
print(df.info())

# Checking Missing Values
print(df.isnull().sum())

# Removing Missing Values
df = df.dropna()

# Feature Selection
features = [
    'Inventory_Level',
    'Waiting_Time',
    'Asset_Utilization',
    'User_Transaction_Amount',
    'Temperature',
    'Humidity',
    'Latitude',
    'Longitude'
]

target = 'Logistics_Delay'
```

Figure 7.3 Data Preprocessing for Sustainable Supply Chain Dataset

```
[14]
✓ Ss
▶ # Feature Engineering

# Correctly use 'Logistics_Delay' as the basis for new features
df['Logistics_Delay_Lag_7'] = df['Logistics_Delay'].shift(7)

df['Logistics_Delay_Rolling_Mean_30'] = (
    df['Logistics_Delay']
    .rolling(window=30)
    .mean()
)

df['Inventory_Transport_Interaction'] = (
    df['Inventory_Level']
    * df['Asset_Utilization']
)

# Removing Null Values introduced by feature engineering
df = df.dropna()

# Update the list of features to include the new engineered features
# and ensure only numerical columns are selected.
all_features = [
    'Inventory_Level',
    'Waiting_Time',
    'Asset_Utilization',
    'User_Transaction_Amount',
```

Figure 7.4 Ensemble Machine Learning Model Training with Feature Engineering

```
[14]
✓ 5s
# Base Learners
rf = RandomForestRegressor()

xgb = XGBRegressor()

lgbm = LGBMRegressor()

cat = CatBoostRegressor(verbose=0)

# Training Models
rf.fit(X_train, y_train)

xgb.fit(X_train, y_train)

lgbm.fit(X_train, y_train)

cat.fit(X_train, y_train)

# Prediction
rf_pred = rf.predict(X_test)

xgb_pred = xgb.predict(X_test)

lgbm_pred = lgbm.predict(X_test)

cat_pred = cat.predict(X_test)
```

Figure 7.5 Ensemble Machine Learning Model Training with Feature Engineering

```
[15]
✓ 6s
# Output Layer
ann_model.add(Dense(1))

# Model Compilation
ann_model.compile(
    optimizer='adam',
    loss='mse',
    metrics=['mae']
)

# Early Stopping
early_stop = EarlyStopping(
    monitor='val_loss',
    patience=3
)

# Model Training
history = ann_model.fit(
    X_train,
    y_train,
    validation_split=0.2,
    epochs=500,
    callbacks=[early_stop]
)

# Prediction
ann_pred = ann_model.predict(X_test)
```

Figure 7.6 ANN-Based Carbon Emission Forecasting Model

```

[16] ✓ 51s ▶ # CatBoost Regressor
cat_model = CatBoostRegressor(verbose=0)

# Hyperparameter Grid
param_grid = {
    'depth': [4, 6, 8],
    'learning_rate': [0.01, 0.05, 0.1],
    'iterations': [100, 200]
}

# Grid Search
grid_cat = GridSearchCV(
    estimator=cat_model,
    param_grid=param_grid,
    cv=3,
    scoring='r2'
)

# Training
grid_cat.fit(X_train, y_train)

# Best Model
best_cat = grid_cat.best_estimator_

# Prediction
cat_pred = best_cat.predict(X_test)

# Best Parameters
print(grid_cat.best_params_)

```

Figure 7.7 CatBoost Modelling with Grid Search Optimization

```

[17] ✓ 19s ▶ # XGBoost Regressor
xgb_model = XGBRegressor()

# Hyperparameter Grid
param_grid = {
    'max_depth': [3, 5, 7],
    'learning_rate': [0.01, 0.05, 0.1],
    'n_estimators': [100, 200]
}

# Grid Search
grid_xgb = GridSearchCV(
    estimator=xgb_model,
    param_grid=param_grid,
    cv=3,
    scoring='r2'
)

# Training
grid_xgb.fit(X_train, y_train)

# Best Model
best_xgb = grid_xgb.best_estimator_

# Prediction
xgb_pred = best_xgb.predict(X_test)

# Best Parameters
print(grid_xgb.best_params_)

```

Figure 7.8 XGBoost Regression



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DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Shahbad Daulatpur, Main Bawana Road, Delhi-110042

DECLARATION

We/I hereby certify that the work presented in the Major Project-II/Research Work entitled Managing Carbon Footprint in Global Supply Chain: A Data-Driven Strategy Employing AI Algorithms in fulfilment of the requirement for the award of the Degree of Master of Technology in IEM submitted to the Department of Mechanical Engineering, Delhi Technological University, Delhi is an authentic record of my own work carried out during the period from 2025 to 2026 under the supervision of Dr. N. Yuvraj.

The matter presented in this report/thesis has not been submitted for the award of any other degree of this or any other Institute/University. The work has been accepted/published/communicated in a peer reviewed Scopus indexed conference with the following details:

Title of the Paper:	<u>Managing Carbon Footprint in Global Supply Chain</u>
Author names:	<u>Gulshan Kumar Singh</u>
Name of Conference:	<u>ICASET 2026</u>
Conference Dates with Venue:	<u>22nd March - 23rd March 2026</u>
Conference Registration:	<u>03/ Feb/ 2026</u>
Paper Status:	<u>Presented</u>
Date of Communication:	<u>07/ Feb/ 2026</u>
Date of Acceptance:	<u>20/ Feb/ 2026</u>
Date of Publication:	<u>in Press</u>

Student Name: GULSHAN KUMAR SINGH

Gulshan Kumar Singh
Signature of Student

SUPERVISOR CERTIFICATE

To the best of my knowledge, the above work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere. I further certify that the publication and indexing information given by the student is correct.

Place: Delhi

NKM
Supervisor Name and Signature

Date: 01/06/2026

NOTE: Please enclose research paper acceptance/publication/communication proof along with Scopus indexing proof (Conference Website or Science Direct in case of Journal Publication).



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DECLARATION

We/I hereby certify that the work presented in the Major Project-II/Research Work entitled AI-Enabled Smart Inventory Management For Sustainable Supply chain Performance in fulfilment of the requirement for the award of the Degree of Master of Technology in IEM submitted to the Department of Mechanical Engineering, Delhi Technological University, Delhi is an authentic record of my own work carried out during the period from 2025 to 2026 under the supervision of Dr. N. YUVRAJ.

The matter presented in this report/thesis has not been submitted for the award of any other degree of this or any other Institute/University. The work has been accepted/published/communicated in a peer reviewed Scopus indexed conference with the following details:

Title of the Paper:	<u>AI-Enable Smart Inventory Management</u>
Author names:	<u>Gulshan Kumar Singh</u>
Name of Conference:	<u>ICRAET 2026</u>
Conference Dates with Venue:	<u>12th June - 13th June 2026</u>
Conference Registration:	<u>27 May 2026</u>
Paper Status:	<u>Presented</u>
Date of Communication:	<u>23 May 2026</u>
Date of Acceptance:	<u>27 May 2026</u>
Date of Publication:	<u>in Press</u>

Student Name: Gulshan Kumar Singh

Gulshan Kumar Singh
Signature of Student

SUPERVISOR CERTIFICATE

To the best of my knowledge, the above work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere. I further certify that the publication and indexing information given by the student is correct.

Place: Delhi

N. Yuvraj
Supervisor Name and Signature

Date: 01/06/2026

NOTE: Please enclose research paper acceptance/publication/communication proof along with Scopus indexing proof (Conference Website or Science Direct in case of Journal Publication).



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Shahbad Daultapur, Main Bawana Road, Delhi-42

Proforma for submission of M.Tech. Major Project

- 01. Name of the Student: Gulshan Kumar Singh
- 02. Enrolment No:
- 03. Year of Admission: 2024
- 04. Programme M.Tech., Branch: Industrial Engineering and Management
- 05. Name of Department: Mechanical Engineering
- 06. Admission Category i.e. Full Time/ Full Time (Sponsored)/ Part Time: Full Time
- 07. Applied as Regular/ Ex-student: Regular
- 08. Span Period Expired on:
- 09. Extension of Span Period Granted or Not Granted (if applicable):
- 10. Title of Thesis/Major Project: Managing Carbon Footprint in Global Supply Chain: A Data Driven Strategy Employing AI Algorithms
- 11. Name of Supervisor: Dr. N. YUVSAT
- 12. Result Details (Enclose Copy of Mark sheets of all semesters):

S. No.	Semester	Passing Year	Roll No.	Marks Obtained	Max. Marks	% of Marks	Details of Back Paper Cleared (if any)
01	1 st	2024	24/IEM/24	7	10	70	NA
02	2 nd	2025	24/IEM/04	7.33	10	70.33	NA
03	3 rd	2025	24/IEM/04	8.5	10	80.50	NA
04	4 th (P/T only)						
05	5 th (P/T only)						

13. Fee Details (Enclose the Fee Receipt):

Amount Paid - <u>3000/-</u> (in Rs.)	Receipt No. <u>DUP5572529</u>	Date <u>27/05/2026</u>
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It is certified that the name of Examiners for evaluation of the above thesis/ project have already been recommended by the BOS.

N. YUVSAT 01/06/2026
Signature of Supervisor

Gulshan Kumar Singh
Signature of Student
Mechanical Engineering Department
Date: 01/06/2026
Delhi Technological University
Shahbad Daultapur, Bawana Road, Delhi-110042
Signature of HOD with Seal

(Instructions for filling up the Form may see on back side please.)



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CERTIFICATE OF THESIS SUBMISSION FOR EVALUATION

(Submit in Duplicate)

1. Name: Gulshan Kumar Singh
2. Roll No.: 21/TEM/04
3. Thesis title: Managing Carbon Footprint in Global Supply Chain: A Data Driven Strategy Employing AI Algorithms
4. Degree for which the thesis is submitted: M.Tech
5. Faculty of the University to which the thesis is submitted: Dr. N. Yuvraj
6. Thesis Preparation Guide was referred to for preparing the thesis. YES NO
7. Specifications regarding thesis format have been closely followed. YES NO
8. The contents of the thesis have been organized based on the guidelines YES NO
9. The thesis has been prepared without resorting to plagiarism. YES NO
10. All sources used have been cited appropriately. YES NO
11. The thesis has not been submitted elsewhere for a degree. YES NO
12. Submitted 2 spiral bound copies plus one CD. YES NO

Gulshan Kumar Singh
(Signature of Candidate)

Name(s): Gulshan Kumar Singh

Roll No: 21/TEM/04



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Shahbad Daulatpur, Main Bawana Road, Delhi-110042, India

CERTIFICATE OF FINAL THESIS SUBMISSION

(To be submitted in duplicate)

1. Name: Gulshan Kumar Singh
2. Roll No: 24/ITEM/04
3. Thesis title: Managing Carbon Footprint in Global Supply Chain: A Data Driven Strategy Employing AI Algorithms
4. Degree for which the thesis is submitted: M.Tech
5. Faculty (of the University to which the thesis is submitted)
Dr. N. Yuvraj
6. Thesis Preparation Guide was referred to for preparing the thesis. YES NO
7. Specifications regarding thesis format have been closely followed. YES NO
8. The contents of the thesis have been organized based on the guidelines. YES NO
9. The thesis has been prepared without resorting to plagiarism. YES NO
10. All sources used have been cited appropriately. YES NO
11. The thesis has not been submitted elsewhere for a degree. YES NO
12. All the correction has been incorporated. YES NO
13. Submitted 2 hard bound copies plus one CD. YES NO

N. Yuvraj
(Signature(s) of the Supervisor(s))

Name(s) Dr. N. Yuvraj

Gulshan Kumar Singh
(Signature of Candidate)

Name: Gulshan Kumar Singh

Roll No: 24/ITEM/04

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Proforma for submission of thesis/dissertation

Student Name	Registration Number	Course and Branch	Title of the dissertation	Name of the Guide
Gulshan Kumar Singh	M-tech 2403903	M.Tech IEM	Managing Carbon Footprint in Global Supplychain Emphasis A.D.A.E.A - D.I.V.E.D.I. Strategy Emphasis	Dr. N. Yuvraj

Above work has been carried out by me under the supervision of Dr. N. Yuvraj

and due care has been taken to acknowledge the work of authors referred in the present thesis/dissertation. To the best of my knowledge the work is free from plagiarism as per the approved policy for plagiarism of Delhi Technology University. This may please be forwarded to the library for providing the similarity report from software.

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Signature of student 01/06/26

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Supervisor's Signature
Email- Yuvraj@dlu.ac.in

Head Department
Email

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LIST OF CONFERENCE AND THEIR PROOF

Title	Conference
Managing Carbon Footprint in Global Supply Chains: A Data-Driven Strategy Employing AI Algorithms	ICAST 2026
Ai-Enabled Smart Inventory Management for Sustainable Supply Chain Performance	ICRAET 2026

←    

Paper Acceptance Confirmation 
 – ICASET 2026 External Inbox

 **ICASET Co...** 20 Feb   
 to me 

Dear Gulshan Kumar Singh,
 Greetings from **ICASET 2026**.

Congratulations! We are pleased to inform you that your paper titled **“Managing Carbon Footprint in Global Supply Chains: A Data-Driven Strategy Employing AI Algorithms”** has been **accepted for Oral/Poster Presentation** at the **5th International Conference on Advances in Science, Engineering & Technology (ICASET)**, accredited by **Continuous Professional Development (CPD), India**, scheduled on **22–23 March 2026**.

This is a significant milestone in your research journey, and we are delighted to have you join the conference. Your submission has successfully passed our **double-blind peer review and plagiarism check**, demonstrating the quality and relevance of your research.

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Your paper will be submitted for evaluation and indexing in **Web of Science (BkCI) and SCOPUS** (*terms and conditions apply*), enhancing the visibility and impact of your work. Alternatively, you may opt for **Scopus-indexed journal publication** based on your preference.




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This conference supports **global sustainable development** initiatives by encouraging innovative research, technological advancements, and interdisciplinary collaboration that contribute to industrial growth and societal progress.

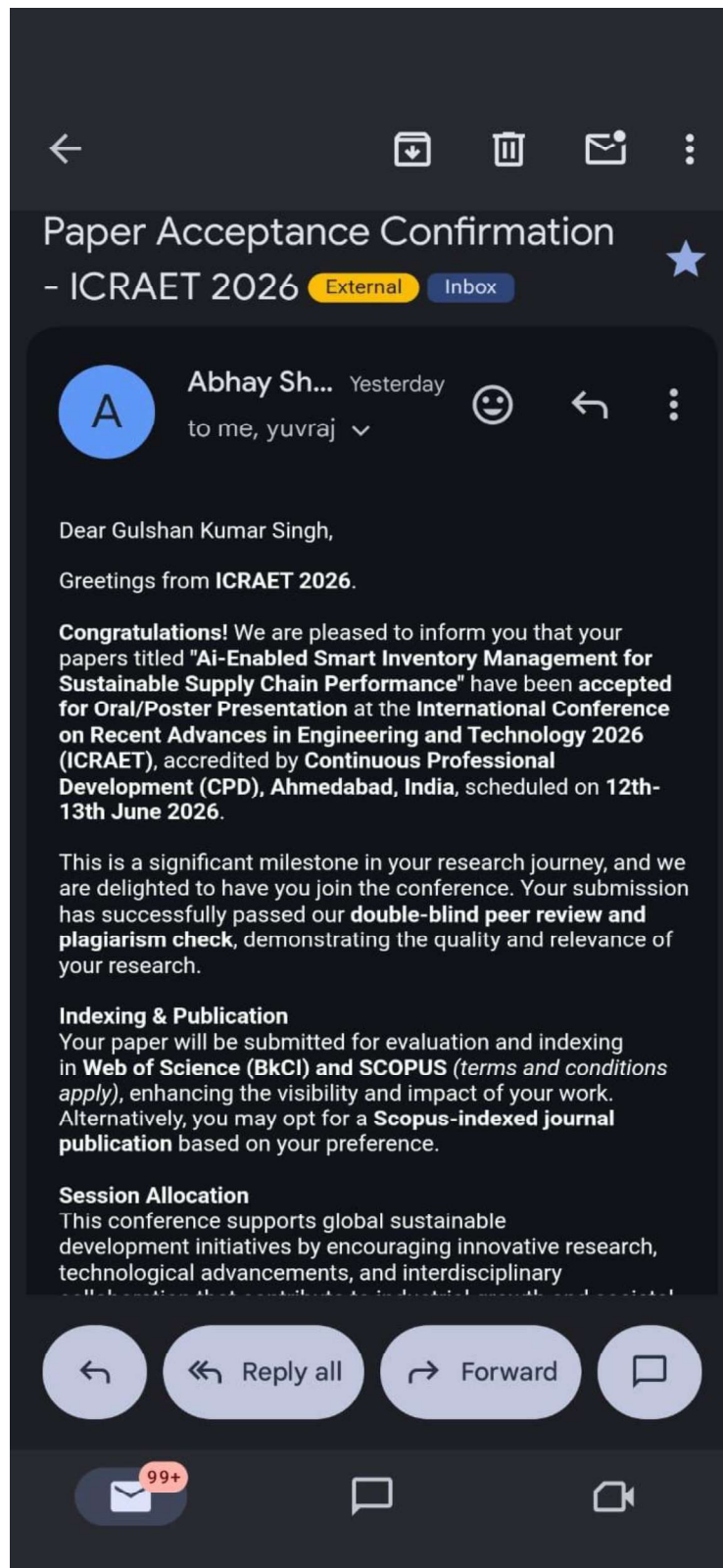
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Academic Year :	2024 - 2026
Branch Course :	Industrial Engineering and Management
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STATEMENT OF GRADES

Master of Technology

(Industrial Engineering and Management)

Name : GULSHAN KUMAR SINGH

Roll No. : 24/IEM/04

Month & Year of Examination : NOV 2024

Semester : FIRST

Subject Code	Subject Title	Credits	Credits Secured	Grade
IEM501	DATA ANALYTICS	4	4	A
IEM505	QUALITY MANAGEMENT	4	4	A
IEM507	PRODUCTION & OPERATION MANAGEMENT	4	4	C
IEM509	INDUSTRY 4.0 & SMART MANUFACTURING	4	4	A+
IEM523	SKILL ENHANCEMENT COURSE 1 (ONLINE)	2	2	B+
IEM525	SELF-STUDY (ONLINE)	2	2	C
IEM5313	AI/ML IN INDUSTRIAL ENGINEERING AND MANAGEMENT	4	4	B
UEC501	AUDIT COURSE	0	0	O
		24	24	

AB : Absent DT : Detained

Credits Secured / Total : 24 / 24

SGPA: 7.00

Dated : March 17, 2026
Date of Declaration of Result :
July 31, 2025



CONTROLLER OF EXAMINATION



S. No.

420594

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

STATEMENT OF GRADES

Master of Technology

(Industrial Engineering and Management)

Name : GULSHAN KUMAR SINGH

Roll No. : 24/IEM/04

Month & Year of Examination : MAY 2025

Semester : SECOND

Subject Code	Subject Title	Credits	Credits Secured	Grade
IEM502n	SUPPLY CHAIN MANAGEMENT	4	4	B+
IEM504n	ADVANCED OPERATIONS RESEARCH	4	4	A+
IEM5321n	COMPUTER INTEGRATED MANUFACTURING & ROBOTICS	4	4	C
IEM5341n	PRINCIPLES OF MANAGEMENT	4	4	A
IEM546n	SKILL ENHANCEMENT COURSE 2	4	4	O
UCC502n	RESEARCH METHODOLOGY	4	4	C
		24	24	

AB : Absent DT : Detained

Credits Secured / Total : 24 / 24

SGPA : 7.33

Dated : September 10, 2025

Date of Declaration of Result : July 29, 2025



CONTROLLER OF EXAMINATION

THE RESULT OF THE CANDIDATE WHO APPEARED IN THE FOLLOWING EXAMINATION HELD IN NOV 2025 IS DECLARED AS UNDER:-

Master of Technology(Industrial Engineering and Management), III-SEMESTER

Result Declaration Date : 16-Mar-2026

Notification No: 1942

IEM 601n : Industrial Economics & Management						
Sr.No	Roll No.	Name of Student	IEM 601n	IEM 603n	MOOC605	Failed Courses
			4.00	8.00	4.00	
1	24IEM01	NAMAN SACHAN	B+	A+	O	8.75 16

IEM 601n : Industrial Economics & Management										
Sr.No	Roll No.	Name of Student	IEM 601n		IEM 603n	OBT601		SGPA	TC	Failed Courses
			4.00	8.00	8.00	OBT601				
2	24IEM03	AMRISH TRIPATHI	A	A	A	B+	4.00	7.75	16	
3	24IEM04	GULSHAN KUMAR SINGH	O	A	A	A	A	8.50	16	
4	24IEM05	ABHISHEK KUMAR SISODIYA	A+	A+	A+	A+	A+	9.00	16	
5	24IEM06	SUNNY SOREN	A	A	A	B+	B+	7.75	16	
6	24IEM07	PRYATOSH BHARDWAJ	B+	A	A	B+	B+	7.50	16	
7	24IEM08	NGAYOSING A SHIMRAY	A	A	B+	A	A	7.50	16	
8	24IEM09	SANTOSH KISKU	A	A	O	A	A	9.00	16	

OIC (Results)

Controller of Examination

Note: Any discrepancy in the result in r/o name/roll no/registration/marks/grades/course code/title should be brought to the notice of Controller of Examination/OIC(Results) within 15 days of declaration of result, in the prescribed proforma.