MTECH THESIS REVISED

by Gulshan Kumar Revised

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

Gulshan Kumar Singh

ABSTRACT

The global scale of supply chains has grown significantly due to the growth of global trade and industry. But for logistics operations like transportation, warehousing, and manufacturing, carbon emissions are significant, posing serious environmental concerns. Traditional carbon estimation methods tend to be based on fixed calculations and historical data, which cannot cope with the varying circumstances of contemporary supply chain systems.The study is dedicated to predicting carbon emission in Global Supply Chains by means of Artificial Intelligence (AI) technique and optimization. Logistics data from transport records, GPS tracking systems, warehouse operations, and energy usage data were analyzed using a prediction model based on a Transformer. The model has been developed to enhance the ability to predict the amount of carbon emissions in various operational conditions.For improved supply chain planning, the study also used two optimization techniques: Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO). The following methods were used to balance transportation cost, service performance, and carbon emission reduction. The developed system provided various solutions for planning that enabled a joint discussion between costs and environmental impact.

The results indicated that the AI-based prediction model outperformed the traditional methods in predicting carbon emissions. The optimization methods also assisted in determining realistic logistics plans that are lower in emissions and have improved operational performance. It is a valuable study for businesses looking to minimize their environmental footprint without compromising the effectiveness of their supply chain. In summary, the research underscores the potential of AI and optimization methods to contribute to sustainable and efficient global supply chain management amidst growing environmental and regulatory challenges.

Keywords: Eco-friendly Logistics, Carbon Emission Reduction, AI Predictive Model, Supply Chain Management, NSGA II Technique, MOPSO Technique

TABLE OF CONTENTS

List of Tables

List of Figures

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
neural AI model	Artificial Neural Network
MLP	Multi-Layer Perceptron
RF	Random Forest
XGBoost	Extreme Gradient Boosting
LightGBM	Light Gradient Boosting Machine
SHAP	SHapley Additive exPlanations
XAI	Explainable Artificial Intelligence
SSCM	eco-friendly Supply Chain Management
GSCM	Green Supply Chain Management
ESG	Environmental, Social and Governance
GPS	Global Positioning System
EDA	Exploratory Data Analysis
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
MOPSO	Multi-Objective Particle Swarm improvement
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
R	is the coefficient of determination. R^2 is coefficient of determination.
CO_2	Carbon Dioxide

CHAPTER 1

INTRODUCTION

1.1 General Introduction

Global supply chains have turned into one of the most critical elements of the current industrial and economic system, [1, 2] now days. As globalization progresses, the industries are dependent increasingly on international logistics networks to access their raw materials and to manufacture and distribute their products, as well as to store the products. These interlocking systems will contribute to an reliable operation and reduced costs, while taking our production capabilities to world market.At the same time, the globalisation of supply chains has brought about a marked jump in the pollution of harmful gases (GHG) , especially carbon dioxide (CO_2), because of transport, warehousing, fuel use, keeping inventory, and certain industrial procedures . So, even while the networks get more connected, the ecological cost goes up.

Logistics and transportation are among the primary contributors to global carbon pollution, making them critical areas for green practices and carbon emission level reduction efforts [3, 4, 5]. The use of fossil fuel for freight transport on roads, railways, airways and maritime transport contributes to environmental degradation and climate change. Furthermore, the electricity usage of warehousing, cold storage, material handling systems and large-scale industrial activities contributes clearly to the overall carbon emission level of supply chain activities. With the rapid growth of global trade, carbon emission management is a major problem for industries, governments and environment agencies across the globe.

Existing approaches for carbon emission estimation are mostly tied to fixed emission factors and historical averages, plus a kind of static mathematical treatment. Even if these methods can give you a rough estimate, they often fail to mirror the moving, uncertain behavior of today's supply chain systems. In real time logistics, outcomes depend on many things at once, like traffic congestion , different routing choices, fuel usage that shifts along the way, weather swings , inventory oscillations, energy demand, and random disruptions during operations. So in practice the usual linear forecasting strategies, and even many eco-friendly operation indicators, can end up being not very reliable . Given these restrictions, artificial intelligence (AI) and machine learning (ML) have emerged as viable solutions in the realm of eco-friendly supply chain management (SCM). There's all sorts of logistics and working data, and it has hidden, non-linear patterns too, that AI models can unravel and then learn from to make more accurate predictions. A number of AI techniques such as Neural Networks, Random Forest, Gradient Boosting, and LSTM are employed for estimation of logistics and carbon footprint in supply chain processes [6, 7].

The Transformer-based forecasting model is one of the newer, more popular AI techniques playing the spotlight these days, and no offense, but it sure seems like it works pretty darn well for high-dimensional sequences and it just has the ability to grab long-term dependencies. While the Transformer architectures were first used with NLP, they've become quite common these days, particularly for time-series forecasting, with the advantage of being able to offer good prediction performance, and scaling up nicely. In the real world, The models employ logistics information like GPS tracking, transportation information, and warehouse data to project carbon dioxide emissions and problems in the supply chain.

improvement is also a pretty crucial part of supply chain management, for eco-friendly operation, like in a general sense. It's kind of about how you streamline the whole flow so less resources are wasted, and everything stays a bit more viable over time, even

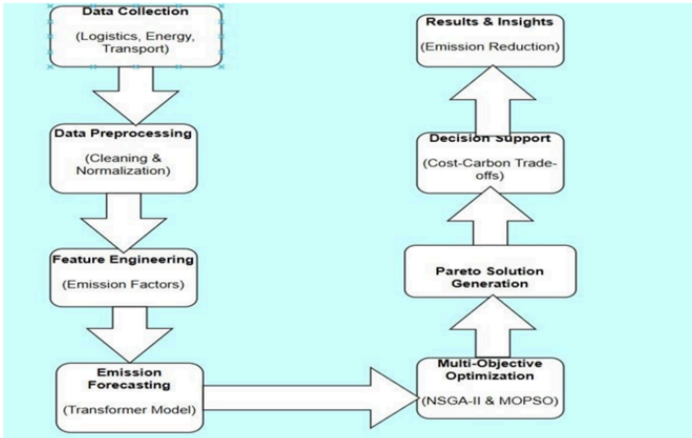

Figure 1.1: Emission Forecasting Process and Multi-Objective improvement for the eco-friendly operation in Logistics.z

if it sounds simple at first. Many conflicting goals and requirements include working cost minimization, carbon emission reduction, performance of deliveries and quality of service. Standard improvement methods cneural AI modelot be applied to multi-objective problems, and they can be bad at balancing the economic and environmental dimensions of problems. As a consequence, Multi objective improvement algorithms are getting more popular lately to reach Pareto fronts for greener logistics plneural AI modeling,One of the well known algorithms is and also the Multi-Objective Particle Swarm improvement (MOPSO). One point that often comes up is that it is a balancing act and that one should be able to find those non-dominated answers without adding needless complications.

Explainable Artificial Intelligence (XAI) is another significant AI system development for supply chains. There are many machine learning models that are 'black box' meaning that the process by which they make a decision is hard to understand. SHAP (Shapley Additive Explanations) analysis has become a quite effective explainability method, which determines the importance of every feature in the model prediction. This information can therefore be used to analyze variables like inventory level, waiting time, asset utilization, demand forecast, temperature, and transaction amount and understand how these variables affect both carbon pollution and working performance.

As eco-friendly operation grows in importance, along with compliance with the Environmental Social Governance (ESG) and international climate rules, The need for smart carbon management systems keep getting stronger, kinda, year by year. Governments and global organisations are putting in place stricter carbon reporting systems, while industries are putting money into greener logistics and low-carbon transport systems to hit their eco-friendly operation targets. And, in conclusion , bringing together AI- driven forecasting, explainable analytics, and multi-objective improvement seems like a solid way to build supply chain networks that are smarter, cleaner, and also more resilient overall.

Thus, the research theme for this is to develop a hybrid AI solution for SF forecasting and improvement along global supply chain. The suggested method combines a Transformer-based forecasting method, ensemble learning with Random Forest, explainability with SHAP, and multi-objective improvement methods. The aim is to take eco-friendly operation decision making forward and also to drive day to day working efficiency. Finally, the study aims to support industries in implementing an smart planning support system that allows them to predict the carbon pollution with high accuracy and select the optimal trade-off between economic and environmental objectives.

1.2 Research Gap Identification

After a thorough analysis of the relevant literature available on carbon emission level management, artificial intelligence and eco-friendly global supply chain, the following research gaps are identified. The motivation and foundation of the present study is the gaps.

- Carbon emissions prediction tools based on advanced AI techniques are yet to be put into extensive use.
- There is a shortage of Hybrid System Combining Forecasting.
- Shortage of appropriate usage of Explainable Artificial Intelligence (XAI)).
- Currently, there is no research that takes into account dynamic and real-time logistics variables.
- Not enough attention is placed on the cost and carbon trade off analysis, it feels like a blind spot in the flow. combined AI learning for eco-friendly Supply Chain Analytics, yes, but a bit limited in practice.
- More smart, data driven planning support systems are also needed, especially when things change.

The aim of the study is kind of to answer these questions:

The objective of this research can be outlined as the development of an intelligent and environmentally friendly carbon emission management system through the utilization of artificial intelligence in conjunction with various improvement techniques. This is due to certain lacunas in the existing literature related to this field; thus, the developed system will not only be theoretical, but it should be applicable as well. The objectives of the current research are:

- To create an artificial intelligence predictive model of carbon emissions in global supply chain processes.
- To conduct a study on the principal factors influencing carbon emissions, such as transportation activity, inventory, waiting time, energy consumption and asset usage. [8, 9, 10].
- To enhance accuracy of carbon emission prediction with Transformer-based and en-

semble machine learning models.

- To investigate the effect of various operating parameters on carbon emission forecasting with Explainable AI (XAI) methods..
- To develop mathematical models of emission sources for transportation, warehousing, handling and logistics.
- To use the NSGA-II and MOPSO optimization technique to maximize cost efficiency and minimize carbon emissions.
- Compare the performance of various AI models like LSTM, MLP, Gradient Boosting, and Random Forest based on RMSE, MAE, MAPE, R^2 evaluation metrics.
- To create a data-driven planning system to assist industries in lowering emissions and making decisions around supply chains.

1.3 Methodology

The approach of this research work is almost structured but data driven to develop an smart system for forecasting and improvement of carbon emission level through the global supply chain. In total, the trip involves collecting data, pre-processing the data, generating features, forecasting them through an AI model, analyzing the forecasts with understandable AI (XAI), and optimizing them with multi objective improvement.

We collect smart logistics and working data such as stock levels, waiting time, asset usage, demand estimation, temperature, humidity, latitude, longitude data and even user transaction data. After that, the information is pre-processed to boost data integrity and consistency, for instance, fixing missing values , normalizing the dataset, and performing outlier spotting then removing those points.

Then the whole set is once again meticulously pre-processed and processed using data preparation techniques to generate more meaningful indicators that can make a predic-

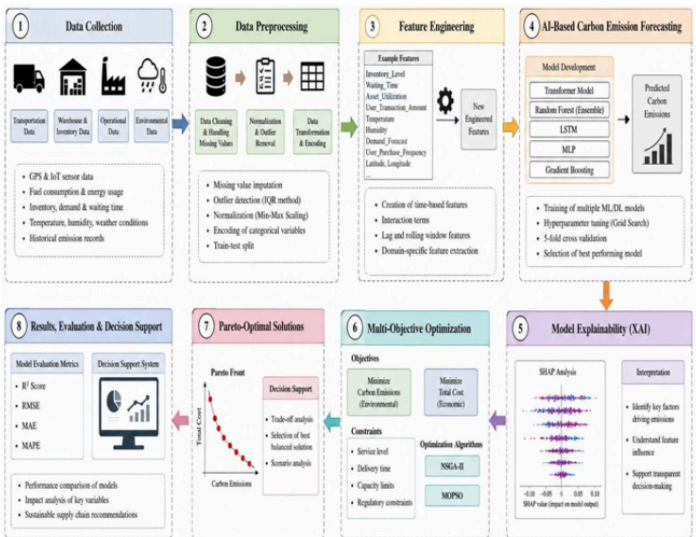

Figure 1.2: The entire method scheme of the developed study is presented, which reflects the sequence of data collection to improvement and support decision-making.

tion better from an working perspective as well as eco-friendly operation perspectives. Machine learning and advanced AI learning models are then trained for forecasting carbon emission.

To make the model more interpretable, the model was modified using SHAP (Shapley Additive Explanations) analysis in order to gain a bit more insight into how each variable affects carbon pollution and overall working efficiency. Moreover, multi objective improvement techniques like NSGA-II and MOPSO lead to a kind of cost versus carbon compromise, and Pareto optimum eco-friendly logistics solutions, respectively.

In the end, the capability of the developed models is evaluated with RMSE, MAE, MAPE and the R^2 score. Overall, the developed solution helps support smart yet eco-friendly decision making for the global supply chain , too.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Supply chains consist of several interconnected activities including transportation, distribution, inventory management, warehousing, material handling etc. which have significant GHG pollution. One of these pollution is CO_2 pollution resulting from fuel use and energy-intensive transport activities and has become a significant contributor to climate change and environmental degradation.

Company were Totally concerned about reducing their working costs and optimizing the supply chain in the past.the increase in environmental laws and regulations, eco-friendly operation and global climate commitments have begun to place an emphasis on green and eco-friendly supply chain management throughout industries. Now, organizations are responsible for monitoring, measuring and reducing their carbon emission levels in logistics and process activities. This has also created a need for more smart data-driven carbon stewardship systems of like-kind. Previous studies of the development of a carbon emission level were based primarily on classical mathematical modeling, statistical methods and emission factor methods. Those approaches provided only a bit more limited estimation functionality - not the flexibility one needs in a dynamic and uncertain supply chain environment. Well the traditional linear models don't work as well in today's logistics environments because they fail to accurately account for fluctuations in real-world carbon pollution, changes in fuel efficiency, weather variations, inventory variations, delivery delays, or multi-modal transportation.

The advancement of the technology of AI and ML seems to be pushing researchers to more and more smart computational approaches for eco-friendly Supply Chain Management (SSCM). Models such as neural AI model, RF, GB, LSTM, and Transformer-based architectures have in fact proven to be effective in forecasting, optimizing, and even aiding in decision-making tasks in this space[11, 12, 13]. They can ingest a tremendous amount of logistics data, and be able to find that nonlinear relationship between operations and results, so that the prediction is more accurate, particularly in that kind of messy logistics environment.

More recently some research attempts to combine improvement algorithms with AI forecasting tools, as people are looking for a compromise that still takes into account both economic goals and environmental pressures. When the goal is to reduce the carbon pollution while maintaining the same or similar working efficiency and service quality, multi-objective improvement methods like NSGA-II and MOPSO is gaining significant traction. The bottom line is that together they contribute to Pareto-optimal solutions, but it can sometimes feel a bit different in each paper.

A newer research field that is gaining a large amount of momentum is Explainable Artificial Intelligence (XAI), which serves to explain the decisions made by machine learning systems, such as SHAP (SHapley Additive exPlanations). The application of understandable AI will help enhance transparency and, in varying degrees of usefulness, enable individuals to understand how working inputs like inventory levels, wait times, demand forecasting and asset utilization ultimately contribute to the carbon emission forecasting outcomes, and the eco-friendly operation side effects.

For this reason, the previous studies in this chapter is summarized throughout the carbon emission level management, eco-friendly supply chain systems, machine learning applications, understandable AI methods and improvement methodologies. This previous studies can be used to identify gaps in existing research. It also gives the groundwork for the design of the developed AI based eco-friendly global supply chain management (SCM) system. That is, it is the foundation for development, and for determining what the next research steps should be.

2.2 Bibliometric Analysis

Bibliometric analysis is a scientific technique that can assist in the estimation of research trends, publication growth, significant keywords and even technological advances in a particular research field [14, 15]. The current study uses bibliometric analysis to gain a more accurate perspective of the current state of research in carbon emission level management, eco-friendly supply chain, and the application of AI and ML in logistics systems.

The literature was collected from scientific databases including ScienceDirect, Google Scholar and Scopus. This was achieved by conducting queries on topics such as carbon emission level Management, eco-friendly Supply Chain, ML, AI, TF and MOOP.

results indicates an overall growth in literature over the last years, especially for eco-friendly logistics and AI-enabled carbon management, after 2018. eco-friendly operation, carbon pollution, forecasting, optimisation, logistics and machine learning are all recurring themes, as described. The study also points to a rising attention towards more sophisticated AI approaches, like advanced AI learning , combined AI learning and understandable AI, mainly to enhance supply chain eco-friendly operation [14, 15].

Moreover, it can be observed that much of the research has been conducted independently either on emission forecasting or on logistics optimisation and only a few studies consider both forecasting and explainability and optimisation. So, in the present study, it is planned to fill these gaps, by developing an AI-integrated solution in the supply chain management of the global supply chain.

The keywords, along with the related papers for 2015–2025, are given below:

bibliometric analysis reveals a high and noticeable increase in research on the topic of

Bibliometric analysis words are listed below.
While counting papers for the bibliometric analysis, keywords are used.

S. No.	Leading words in literature search	No. of Papers
1	carbon emission level Management" AND "Supply Chain".carbon emission level Management" AND "Supply Chain"	142
2	AI + eco-friendly Logistics" is a weekly column dedicated to eco-friendly logistics and artificial intelligence for the benefit of the global freight transport industry.	118
3	Machine Learning" intersects with "Carbon Emission Forecasting.The following terms intersect: "Machine Learning" AND "Carbon Emission Forecasting".	96
4	sequence prediction model AND Supply Chain Forecasting	41
5	Logistics eco-friendly operation".'Multi-objective improvement' AND 'Logistics eco-friendly operation".	73
6	"NSGA-II" AND "Carbon Reduction"	38
7	MOPSO, supply chain improvement	29
8	understandable AI" AND "Logistics"	24
9	"feature impact analysis" AND "Machine Learning"	31
10	"Green Supply Chain Management" AND "AI"	87

eco-friendly Supply Chain Management and, with this, the AI based carbon emission level analysis. A quick look at the compound annual growth rate (CAGR) suggests that the entire research sphere of eco-friendly operation, machine learning and smart logistics systems has been growing in the global interest for the last year, with a CAGR of 31.39%. Additionally, with an average of 8.094 citations per document, this stream appears to be growing more and more relevant to the academic world and has a high research impact as well.

So the findings from this bibliometric study about eco-friendly supply chain management and the forecasting of carbon emission level are kind of summarized below. The analysis really works with 928 authors, and 265 research documents pulled from different scientific databases. It also suggests an international co-authorship rate of 21.6%, which is sort of a sign that the world is increasingly collaborating on research in this field of AI, eco-friendly logistics and managing carbon pollution.

This is a sample of information about a bibliometric study for eco-friendly Supply Chain and carbon emission level Management.

Description	Results
The following is the main information about the data:	
Timespan	2015:2025
Sources (Journals, Books, etc)	215
Documents	265
Annual Growth Rate %	31.39
Calculate Average Age of Document (years)	Average Age of 2.8 Years
Average citations/ doc	8.094
References	11,250
Inside the Documents	
Keywords Plus (ID)	1,485
Author's Keywords (DE)	792
Authors	
Authors	928
Single authored docs	18
How Authors Collaborate	
Single-authored docs	22
Co-Authors per Doc	3.54
International co-authorships %	21.6
Types of Documents	
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

Overall, the bibliometric output indicates that there is increasing interest in the use of forecasting and improvement methods based on AI within these eco-friendly global supply chain systems at least according to the results of this study.

Figure 2.1: eco-friendly Supply Chain and carbon emission level Forecasting.

The figure below shows the annual production of paper per year, which is increasing every year with an increase of 109 from 49 in 2024 and this progression continues over time.

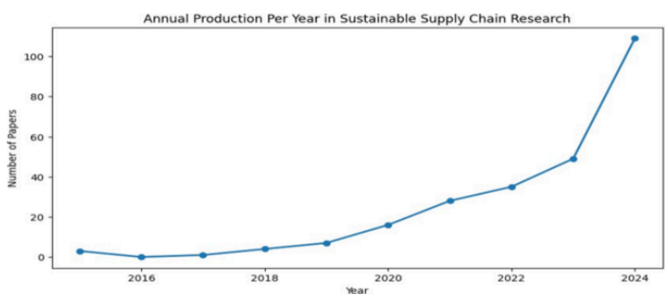

Figure 2.2: Annual production per year in carbon emission level forecasting research.

The most frequent keywords retrieved from the literature based on the keywords of the study on eco-friendly scm and carbon forecasting are represented in the figure below. The most cited papers contained the word ”forecasting,” after that the papers cited

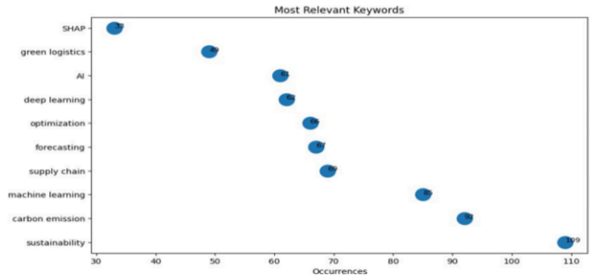

Figure 2.3: Word Cloud visualization of the major keywords.

with the word "SCM," "ML," "TSF," and "advanced AI learning," respectively. The analysis highlights that recent research has been predominantly focused on forecasting, eco-friendly operation, logistics improvement, and smart supply chain systems, with AI playing a significant role in these areas.

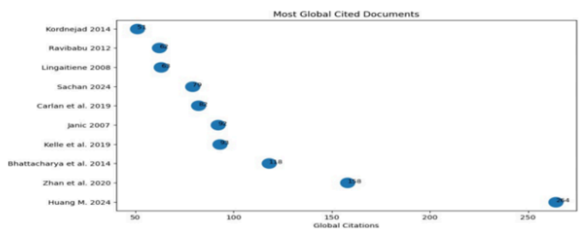

Figure 2.4: Most Global Cited Documents.

The co occurrence network of major keywords, obtained with the VOSviewer software, is shown below. The key terms "forecasting," "supply chain management," "machine learning," "time series forecasting," "advanced AI learning," and "carbon emission level" look tightly linked , so it seems like there's a clear attention on forecasting and supply chain management, but with AI involved as a kind of catalyst.

Figure 2.5: Plot for Most Relevant Keywords.

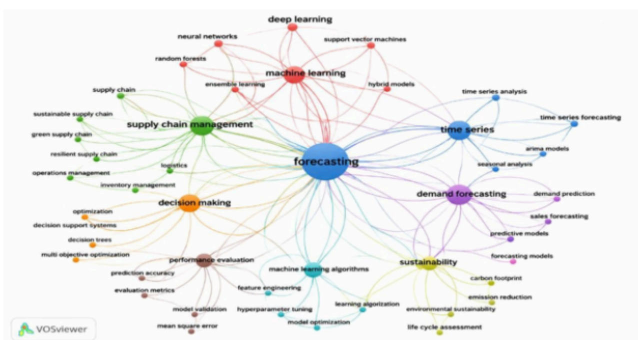

Figure 2.6: Co-occurrence Network for main keywords using VOS viewer.

2.2.1 carbon emission level forecasting, and Supply Chain Analysis using Statistical methods

For a long time working trends and the possible future outcomes have been studied with traditional statistical tools in supply chain management, and in carbon emission forecast too. The commonly used and widely applied time series prediction models include AutoRegressive Integrated Moving Average (ARIMA), and Seasonal AutoRegressive Integrated Moving Average (SARIMA). They are commonly chosen due to their simplicity, interpretability, and their forecasting power is still fairly good [16].

The logistics data also has a seasonal pattern, and may have some slow trend, such as transportation demand, inventory shift, fuel burn, and warehouse energy use; in these cases, SARIMA models prove to be a particularly good fit. They can be helpful for forecasting repetition of cycles in the short-term, and provide support in supply chain planning, or even eco-friendly operation analysis[7, 6].

In addition to SARIMA, other frequently-used forecasting methods for logistics demand and normal daily operations of a business are exponential smoothing techniques. Consider Simple Exponential Smoothing, Holt's and Holt-Winters models. These techniques are based on weights that decrease by an exponential factor, making them effective when the underlying signal is moderately changing, but otherwise fairly regular in time. They are also easy to implement and computationally reliable; you will find them in many working forecasting pipelines, all the time.

Other essential forecasting tools, which are applied in SC analytics, are statistical models based on regression. Regression techniques are used to study the relation of the dependent variables (e.g., CO_2 pollution) with the independent working factors (e.g., transport distance, inventory, waiting time, energy consumption and energy demand variability). In addition, some external factors, such as weather, fuel prices and working disturbances will be incorporated into the multiple regression models to further enhance the accuracy of the forecasts, just a little more than before.

Although traditional statistical methods have benefits, they do have certain limitations in today's world global supply chain systems. They are not as effective as modelling high order or non-linear relationships, and working uncertainties in real life logistics situations. Moreover, statistical tools are not well suited to rapidly evolving industrial and environmental conditions and typically rely on the assumption of stationarity of the behaviour of data.

To address these challenges, cutting-edge AI and machine learning technologies are being implemented in more and more eco-friendly supply chain forecasting applications[17, 18]. Traditional statistical models remain useful baseline methods and benchmarks for assessing the performance of the modern AI-based prediction models, though.

2.3 The statistical approaches to carbon emission predictions

Earlier, the traditional statistical approaches are widely applied in forecasting and analysis systems for supply chain settings and carbon emission management systems. Most frequently, people lean on time series forecasting systems. Because they stay simple, reasonably interpretable , and they still have strong predictive capability. These models also tend to fit well when you're looking at seasonal plus shifting patterns in logistics records, like the transportation demand, fuel consumption, energy use inside warehouses, inventory variations ,and similar working traces.

SARIMA models can be useful for the supply chain data which exhibits repeating seasonal patterns and operating trends. SARIMA models have been used to forecast the energy demand, transportation activities, and emission trends for logistics systems. Likewise, the Simple Exponential Smoothing, Holt's Method and Holt-Winters models are common working forecasting methods since they give more weight to recent information and are less complex to compute.

Regression-based statistical models are used for analyzing carbon pollution. Models such as this help in forming relationships between a dependent variable (such as carbon pollution) and other independent working factors (transportation distance, inventory level, energy consumption, fuel consumption and waiting time). Additional external variables (weather, traffic congestion and working problems) are incorporated into multiple regression models in order to improve forecasting ability.

Although traditional statistical methods can provide effective forecasts, modern global supply chain systems pose a number of constraints. These models are inadequate at describing the non-linear relationship and dynamic working uncertainty present in real-world logistics scenarios. Most statistical models are also based on stationary data, which does not lend itself to flexible prediction in the face of changing supply chain times.

To overcome these challenges, AI and Ml technologies are becoming a widely-used solution for carbon emission level forecasting, as well as eco-friendly scm. Despite this, statistical forecasting techniques continue to be significant reference methods to compare and assess the capabilities of state-of-the-art AI-powered forecasting systems.

2.3.1 Carbon Emission Forecasting: Feature Engineering

The data preparation plays a fundamental part in improving the predictive accuracy and model interpretability of the AI and ML forecasting systems, particularly for eco-friendly supply chain management and carbon emission level analysis. data preparation is the procedure to transform raw Logistics and Operations (LogOps) data to useful features that enhance the predictive performance of the prediction models. data preparation is a significant component in building a machine learning model that can detect complex relationships, working patterns, and environmental variables present in supply chain systems.

Among the important categories of engineered features used for carbon emission forecasting are those of temporal nature. The prediction models can use them to detect patterns in terms of similar operating cycles, as well as relationships in terms of longer cycles of operation. These include transportation demand, movements in the inventory, fuel consumption, and even energy used at the warehouse. These types of features are built through the use of lag-based features.

the warehouse-can allow prediction models to identify typical patterns occurring in day to day operations as well as longer term trends. Due to these qualities, the forecasting system gains context to effectively interpret time-varying patterns of eco-friendly operation and transient fluctuations typical to LogOps.

The other common features used in forecasting systems are rolling window statistics (like rolling standard deviation, maximum and minimum values). These features help mitigate the short term variance effects and represent information of longer term nature. The Rolling features have a specific benefit in assessing transportation and inventory variability, and steady working dynamics.

The growth-oriented aspects are also an important part of data preparation. This sort of feature assists the prediction models to assess the direction and pace of changes in the supply chain operations from a perspective of pollution output.

The interaction features of multiple working factors can be introduced to further strengthen the predictive power of a ML system[19, 20]. The most typical ones include interaction features between transport distance and fuel consumption, between inventory level and demand level, and between energy consumption in a warehouse and assets. With these features, machine learning models will be able to detect nonlinear relationships and working dependencies.

Environmental and geographical data are also significant to predict carbon pollution. Context information such as traffic conditions, latitude, longitude, humidity and temperature gives clues on efficiency of operations and transportation related pollution. By feeding environmental features into the AI forecasting system the system becomes somewhat more accurate, and slightly more reliable over time.

The pre-processing and encoding of the working data, in order to make them suitable for use with machine learning algorithms, is also an important task of data preparation. Especially the categorization features of transportation means, warehouse types and working classification have to be properly coded in order for the machine learning models to train.

The statistical evaluation of the engineered features, in terms of how relevant are the created features in the prediction of carbon pollution is another critical part. The correlation analysis, as well as understandable AI approaches, such as SHAP, can be used in order to analyze the impact of each engineered feature on the prediction of carbon pollution and thereby selecting those, which will eventually be utilized in the forecasting system.

The overall effect of data preparation is that it enables better accuracy, better explainability, and better stability in AI-based carbon emission forecasting and supports decision making for eco-friendly supply chain management. These features are used in eco-friendly supply chain management but also related applications in other fields.

In recent years, artificial intelligence and forecasting techniques have been increasingly utilized across different industries, and eco-friendly supply chain management (SSCM) is among them. In the transportation sector, AI technology has been applied in forecasting and improvement; for warehousing and inventory management, as well as energy forecasting and carbon emission level analysis among others.

prediction models can be applied to logistics and transportation systems to predict fuel usage, transportation demand, optimize routes, and calculate carbon pollution. Good forecasting can lower the amount of fuel used, optimize delivery schedules, and lower environmental impact[16]. The incorporation of machine learning and improvement methods enhances eco-friendly transportation planning by optimizing routes and managing resources.

Forecasting techniques are also used in warehouse and inventory management systems to optimize operations and minimize energy usage. Predicting inventory flow, space usage, and warehouse demand can minimize losses and reliable resource allocation. AI models can aid in optimizing inventory, minimizing transportation and storage pollution.

Another area of application is energy and environmental forecasting. AI models are extensively applied in predicting electricity demand, industrial energy usage and greenhouse gas pollution. These forecasting tools can aid industries in tracking environmental performance and adjusting their working practices towards a lower carbon emission level.

In the manufacturing sector, prediction models can, sorta help with production planning supply chain management and optimizing operations. Machine learning algorithms are used in detecting patterns within industrial operations and also for making improved decisions meant to enhance eco-friendly operation. Kinda similarly to above, combined AI learning and advanced AI learning models get used a lot in predictive maintenance, operation risk assessment, and for smart logistic planning, though the details vary by case.

The inclusion of Explainable Artificial Intelligence XAI, and feature impact analysis in industrial forecasting systems has been seen in recent studies too, and people report clearer insight into why the models decide things the way they do. Such approaches enhance the transparency of the model and enable organisations to understand the factors that have a significant impact on carbon pollution and eco-friendly operation.

These examples, powered by AI forecastings, improvement techniques, and eco-friendly operating plan, indicate how smart planning support systems play a crucial role in the global supply chains. The developed applications prove the strength of AI for designing more eco-friendly, reliable, smart, and so on, industrial and logistic systems.

2.3.2 Related Works

The table below summarizes major scientific works from 2018 to 2024 focusing on carbon emission level forecasting, eco-friendly supply chain management, Ai, and improvement algorithms. The conducted studies essentially integrate Ml, advanced AI learning (DL) techniques with improvement algorithms and present a number of findings. Typically, in ML/DL approaches for time-series forecasting, prediction performance are usually evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Additionally, the R^2 coreliable, otherwise named determination coreliable, is frequently reported since it can describe how well the fitted model representates the observations. Higher value close to 1 reveals a better fit.

Here's a rewritten version:

2.3.3 challenges

Although AI and eco-friendly supply chain forecasting systems have made great strides, there are still some challenges in carbon emission level management and working eco-friendly operation analysis. Global logistics networks are becoming increasingly complex, and the working conditions are changing as well as the environment, which continues to pose challenges to the development of highly accurate and reliable forecasting systems.

Table 2.1: Summary of Previous Work

Publication	Year	Domain	Methodology	Key Contributions	Ensemble
Huang and Mao	2024	eco-friendly Supply Chain	CNN, improvement via random search	Developed an AI based carbon emission prediction system for global supply chains and enhanced the accuracy of eco-friendly operation decisions.	Yes
Zhan et al.	2020	Carbon Footprint Management	Graph Neural Network, GNN	Proposed a stacked carbon estimation methodology for analyzing pollution within complex supply chain graphs.	No
Bhattacharya et al.	2014	Logistics and Transportation	Data mining, mixed integer programming	Integrated traffic forecasting with intermodal improvement, to reduce logistical delays and carbon pollution.	No
Sachan	2024	eco-friendly Logistics	Metaheuristic improvement algorithms	Identified optimal logistical configuration designs that balance daily operations with long term resilience to climate shocks.	Yes
Kelle et al.	2019	Green Supply Chain	Machine learning improvement	Demonstrated that AI driven planning can significantly decrease transportation related carbon pollution.	Yes
Emami Javanmard and Ghaderi	2023	Energy and Supply Chain Forecasting	Machine learning models	Constructed an improvement-oriented forecasting framework for evaluating energy demand and eco-friendly operation impact across various sectors.	Yes
Joseph et al.	2022	smart Forecasting Systems	CNN + bi-directional LSTM	Reported improved forecasting accuracy by implementing a hybrid advanced AI learning architecture supporting working prediction systems[21].	Yes
Manandhar et al.	2024	Energy Load Forecasting	Prophet, Random Forest, LSTM	Their work compared various prediction models and highlighted the benefits of ensemble and deep learning approaches[22].	Yes

Data quality and availability are still the great challenges for eco-friendly supply chain analysis. Logistics data in real world can be missing, inconsistent records, noisy sensor data, and different data formats from various transportation and warehouse systems. These problems cause low accuracy of the forecasting process, and they impact the stability of machine learning models. More research is needed to address the challenges of working data quality through advanced cleaning, automated data cleaning and smart data integration systems.

Another key hurdle with AI-driven eco-friendly operation systems is scalability. Massive amounts of working and environmental data are created in large-scale, global supply chains from transportation, warehousing and enterprise systems as well as IoT sensors. With the huge count of dimensions and objects sitting in these datasets, getting machine learning and advanced AI learning models trained becomes pretty computing intensive, and honestly a bit time consuming too. The next steps could involve further advancements in distributed computing, cloud-based AI models, and optimizing algorithm implementations to manage vast amounts of logistics data.

The incorporation of a variety of working and environmental parameters is also a difficult task. Traffic congestion, fuel efficiency, weather, energy, inventory variation, and transportation delays are variable elements that interact in a dynamic manner within a supply chain system. Forecasting methods are not suitable to establish reliable relationships between these heterogeneous variables. Advanced feature fusion, transfer learning, and hybrid AI systems can be explored for enhanced model reliableness and forecasting in future research [23].

In many advanced advanced AI learning models, the system is a 'black box' and it is challenging for industries to understand why the model is making a prediction or improvement decision. While there are some effective XAI methods like feature impact analysis that offer some degree of interpretability.

Forecasting systems are also further challenged by dynamic conditions of operation, and rapidly changing logistics environments. Supply chain behavior is constantly influenced by transportation disruptions, volatility of demand, geopolitical issues, climate variability and energy price changes. The traditional prediction models often fail to adjust to the changing working situation. Future AI forecasting systems can be designed to include adaptive learning, real-time analytics, and reinforcement learning methods, which will enhance flexibility and responsiveness.

Another promising future research direction is to put forecasting, improvement, and planning support systems together, like into one coherent smart system, kinda as a single engine. In more and more industries, they are asking for systems that can at the same time forecast carbon pollution, tune and optimize their working strategies, and help people make eco-friendly choices. Possible future research can, for example, involve combining Artificial Intelligence with Digital Twins, IoT, Blockchain, plus real time eco-friendly operation monitoring, so that you can build fully autonomous green supply chain systems.

Also, smart forecasting and improvement systems that help firms comply with international carbon reduction policies and Environmental, Social and Governance ESG requirements will keep evolving.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The central aim of this research is the development of an smart and eco-friendly system designed to predict and optimize the carbon emission level across a global supply chain system using AI and machine learning techniques, what you can imagine like a loop that close. This work explores a wide range of advanced AI learning and machine learning algorithms, in terms of carbon emission forecasting and working environmental performance in the logistics network. This work examines whether the ensemble techniques results in better forecasting performance than the old way, using single models that were not so complex to be used.

The developed method involves various steps including: Data collection, cleaning, statistical analysis, data preparation, machine learning models building, understandable AI and then improvement and performance validation of models. The smart logistics and working logistics data were applied for analysis of transportation activities, inventory control, environmental status and warehouse operations impact over carbon emission and working eco-friendly operation level of logistics network.

The method also explores more advanced prediction models, such as LSTM, MLP and Transformer-based forecasting system, Random Forest, and Gradient Boosting[24]. In this proposal, explainable Artificial Intelligence methods (like feature impact analysis) were employed for making the models interpretable, while multi-objective improvement algorithms (like NSGA-II and MOPSO) were used to attain an optimal trade-off between working cost and carbon emission performance of the system. It is for more eco-friendly logistics operation than relying on one metric at a time.

An end-to-end methodological system was leveraged for the present study in order to propose a structured pathway for the construction of an smart system for forecasting carbon emission level, optimizing operations, and informing eco-friendly decision making throughout the entire supply chain system.

3.2 Data Collection and cleaning

A smart logistics and working logistics dataset was used in this work. It comprised numerous features relating to transportation segments, warehouse management, inventory management, environmental factors, and transaction records. The dataset also contains relevant working information, such as inventory levels, waiting time, asset utilization, traffic related features, longitude, latitude, temperature, humidity and overall volume of user transactions. The features chosen for analysis directly represent the variables that effect the performance of logistics network and carbon emission levels.

The relevant statistical data was imported into the Python platform with the use of analysis library like Pandas and NumPy for further statistical analysis and cleaning of the data. In a real-world logistics dataset, there are usually a lot of errors and incomplete data which can have detrimental effects over the overall model and the prediction accuracy; thus the data cleaning stage is critical for successful model construction.

cleaning includes:

Data Import

The collected data is first imported into the Python platform for further manipulation and analysis; in other words, for using it to build the forecasting model.

Missing Value Detection

The next task is to find the missing or null data within the data set which are identified for their potential adverse effects on the model's performance and predictive accuracy. Different techniques are utilized for handling and filling these missing values so as to achieve data set completeness.

3.3 Data normalization and Data Scaling

working data will be normalized and scaled for consistency and stability of the model.

Identification of Outliers

To increase forecast quality and dependability, outliers found in transportation, inventory, and operations records will be found and eliminated.

Transforming Features

In order to feed working data variables into ML/DL models, they will be converted into an appropriate numerical form.

In pre-processing, the stage ensures data quality, leading to reliable and accurate predictions from the developed AI-based forecasting system.

3.3.1 Statistical analysis and Exploratory data analysis

The procedure of statistical analysis and exploratory data analysis is outlined as follow. The statistical analysis and exploratory data analysis are given below.

The data will be subjected to statistical analysis to better understand operation patterns and interactions between variables affecting carbon pollution within the supply chain. EDA will be employed to find patterns, seasonality, feature distribution and interrelationships among the logistics dataset's operations. This analysis includes:

- Analysis of stock distribution. Analyze working transport and transaction variance; consider the variance of transport and transaction operations.
- working variable correlations will be studied as per usual convention.
- Tabulated data for a clearer picture.
- working trends will be visualized in a cleaner presentation form.

The data will be visualized using histograms, scatter plots, heatmaps, box plots and other graphs in an effort to identify meaningful working patterns. Statistical analysis is vital for data preparation and selection of crucial variables predicting carbon pollution.

3.4 Feature Engineering

This research will also include data preparation which is important for turning raw working data into insightful features to increase prediction accuracy. systems[19].

Lag Features

Lag features will be developed by using past working information, such as transportation demand, inventory movements, and transaction volumes, in order to analyze short and long term temporal dependence and pattern in operations[25].

Rolling Window Features

To track overall working trends and variations within the logistic system,rolling operations likerolling meanaandrolling standard deviationwill be developed by various rolling window. Rolling window analysis would also aid in smoothing out the fluctuations in the operations data to develop a more stable and consistent prediction model.

Growth Features

Growth features will be designed to capture daily trends of working activities across different time frames, considering fluctuations in the transportation sector, inventory growth and the intensity of the operation, among others. The growth features allow machine learning models to identify emerging eco-friendly operation trends in a supply chain network, both positive and negative.

Interaction Features

Interaction features will be formulated through the combination of various working features; for example, transportation-distance interaction, inventory-demand interaction and warehouse-energy interaction to increase the capability of ML models in extracting complex and non-linear patterns and trends affecting carbon pollution.

3.4.1 Environmental and Geographical Features

Apart from working features, environmental (temperature, humidity etc.) and geographical (latitude and longitude etc.) features will be taken into consideration to incorporate the environmental factors impacting the transport efficiency and also the overall energy utilization within operations.

3.5 Machine learning and advanced AI learning models

Various ML and DL models will be evaluated for forecasting carbon emission level and also for analyzing the system eco-friendly operation[26, 27, 28]. The selected ML and DL models that would be employed in this analysis are mainly a combination of tree based models and neural network architectures, namely:

- Random Forest Regressor The prediction task would be handled by Gradient Boosting Regressor. The use of Gradient Boosting Regressor for prediction is selected.
- XGBoost
- LightGBM
- CatBoost
- Multi-Layer Perceptron (MLP)
- LSTM A forecasting method using sequence prediction model has been developed, a transformer based forecasting model is developed once again.

These models were selected due to their ability to process high-dimensional logistics data, deal with working uncertainties and their capacity to detect complex, nonlinear trends in the operation[29, 30].

3.5.1 combined AI learning Framework

Our research relies on the approach of combined AI learning, a method where multiple models are combined together in order to get better forecast accuracy and also make the model's behavior steadier[31, 32, 33, 20]. Ensemble method allows taking advantage of the strengths that models offer, and avoid a lot of the problems derived from the usage of a single forecasting model.

The ensemble system involves the usage of these components:

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

These models output some results which are combined by the meta-learning mechanism to obtain the final forecasts[32].

3.5.2 Artificial Neural Network (neural AI model)

The Artificial Neural Network (neural AI model) is applied in this research as the advanced AI learning forecasting mechanism. The neural AI models in the developed system are composed by many internal layers, thus can learn effectively the non-linear and complicated relation among the operation and carbon pollution, quite well.

Our neural AI model is a system built with many components; these are:

- Multi-layered structure-meaning the network is composed of various hidden layers nested in one another.
- Machine learning models for pattern discovery in data-driven manner.
- Non-linear activation functions-modeling non-linear behavior patterns, and non-linear associations with operation attributes.
- Dropout regularization-stabilizing the training phase of neural AI models, and lowering down the generalization error.
- Early stopping mechanism-this is to prevent over-fitting, since training is stopped when improvement is no longer possible.
- L2 regularization-This method makes the weights within an neural AI model more controlled, by adding a quadratic penalty.

So, an neural AI model is able to improve the learning capability; it turned out to be a very good approach in high dimension logistics forecasting[21], and also in practice.

3.5.3 Transformer-Based Forecasting

Our inclusion of transformers in this research is quite direct; these models can work well with sequences like working data with time-series important parts. The sequence prediction model is the first application using attention-based learning, so it could identify dependencies and operation relations in the logistics data in a higher time span. Therefore, forecasting is rendered accurate, especially with complicated and dynamic supply chain settings, in the case when configurations change.

3.6 understandable AI (XAI)

This study adopts the method of EAI (Explainable Artificial Intelligence) techniques applying SHAP (SHapley Additive exPlanations) analysis to allow the model to be as interpretable and clear as possible. feature impact analysis enables identifying what each working variable contributes to the forecasts and environmental performance of the model.

The SHAP system could analyze the contributions of all factors, such as:

- Inventory Level
- Waiting Time Calculate and quantify the volume of each transaction.
- Asset Utilization
- Temperature
- Humidity
- Transportation Parameters

This transparency mechanism could improve trust among stakeholders and contribute to smart decision making to improve eco-friendly operation.

3.7 Multi-Objective improvement

This study employed multi-objective improvement approach so that the project may attain a good compromise solution between working efficiency and environmental eco-friendly operation. Practically, the two optimizing algorithms were employed to interact within the decision space; they are:

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

The task that we are going to perform in this project is to minimize those targets as follows:

- working Cost
- Carbon pollution,
- Transportation Inefficiencies
- Energy Consumption

And to maximize the environmental performance, and logistics efficiency as well.

3.8 Performance Evaluation Metrics

Root Mean Square Error (RMSE)

RMSE quantifies the difference between forecast values and observed values. If the forecast values tend to cluster closely around the observed ones, the RMSE is lower and the forecast is better.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum i = 1^n (yi - \hat{y}_i)^2} \tag{3.1}$$

Mean Absolute Error (MAE)

MAE calculates the average magnitude of all the errors in a set of forecasts; i.e., it takes the absolute value of each forecast and observes the difference with the observed value and then calculate their average.

$$\text{MAE} = \frac{1}{n}\sum i = 1^n |yi - \hat{y}_i| \tag{3.2}$$

Mean Absolute Percentage Error (MAPE) The accuracy of a forecast may be measured using the MAPE calculation; it shows the mean error in percentage terms, i.e. Average of differences between forecasted value and observed value, scaled by the observed value in percentage term.

$$\text{MAPE} = \frac{1}{n}\sum i = 1^n \left|\frac{yi - \hat{y}i}{yi}\right| \times 100\% \tag{3.3}$$

The coefficient of determination (R^2) is another model performance assessment that could be utilized. When the points of the forecast data and real data come closer, R^2 is increased, so if R^2 tends to approach 1, model performance is regarded as higher.

$$R^2 = 1 - \frac{\sum i = 1^n (yi - \hat{y}i)^2}{\sum i = 1^n (y_i - \bar{y})^2} \tag{3.4}$$

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the results obtained from the performed experiments and the detailed discussion of the Ai-based system to forecast carbon emission level and optimize supply chains eco-friendly operation. In summary, the aim of the analysis is to verify the prediction capabilities of various machine learning, advanced AI learning, and combined AI learning models in smart logistics and working data, and to highlight the successful application of data preparation, XAI and improvement. The input features for the machine learning models were carefully selected, after Exploratory statistical analysis and data preparation were conducted, to establish working interrelationships between transportation, inventory, warehouse operations, environment factors and carbon pollution. The models used time lag variables, rolling statistics, interaction terms, trend, growth variables and the inputs of working metrics to make predictions on the carbon pollution. Various machine learning, advanced AI learning and combined AI learning models were assessed and compared based on metrics of RMSE, MAE, MAPE and R^2 score such as Random Forest, Gradient Boosting, XGBoost, LightGBM, CatBoost, neural AI model, LSTM, Transformer-based models and the developed combined AI learning system to forecast the working and environmental data to analyze their applicability to the eco-friendly logistics environment. A contrast of individual ML models and the ensemble model were given to prove the effectiveness and efficiency of the ensemble model in the eco-friendly transport activities prediction. We also utilized Explainable Artificial Intelligence in particular SHAP method, to reveal the relationships between the working and environmental inputs and their direct influences to carbon pollution and eco-friendly operation. Then, improvement algorithms, NSGA-II and MOPSO, were performed to identify the ideal levels for operations, so that we achieve our eco-friendly working goals which are minimum operation cost and reduced carbon pollution. In the end, different ML, DL and ensemble approaches for forecasting and improvement algorithms are compared to analyze the efficiency of the chosen system for the management of smart carbon emission levels in globally eco-friendly supply chains.Overall, extensive experimental evidence for the developed system for eco-friendly operation and for "smart" prediction and improvement in the era of AI is shown and explained, so that the applicability of such techniques are successfully demonstrated for the existing supply chain systems.

4.2 EDA and interpretation of features

Before forecasting and improvement model building, we analyzed how the smart logistics dataset is operated and eco-friendly operation trends. In general, EDA was performed to have a clear view of the working and eco-friendly operation attributes of the logistics data before we analyze and forecast using ML models. In the EDA process, hidden working trends were identified, and the distribution and correlation between the logistics and carbon pollution data were also understood. Distribution by histogram was observed for the logistics inventory levels; most of the operation locations maintained fairly even levels of stock, with moderate fluctuations in inventory movements. Also, working relationships were observed between logistics processes; especially between variables of transportation and transaction. Environmental variables (temperature and humidity) had a moderate impact on transport activities and energy consumption; correlations were also made between transportation distance and waiting time and amount of transaction and generation of carbon pollution. The application of data preparation had clearly enhanced the prediction capability of the models as it highlighted existing working connections and unexplained eco-friendly operation issues in the data.

4.3 understandable AI Analysis using SHAP

In order to demonstrate the transparency and understandability of the developed forecasting system, the SHAP (SHapley Additive exPlanations) analysis was performed. The analysis revealed that inventory level has the strongest impact on the forecasting results; extra stock leads to more effective operations and enhanced eco-friendly operation while Waiting Time poses a negative influence on working performance. Also, the Amount of user transactions and asset utilization was revealed as highly important features as they illustrate the volume of working and logistics activities. Environmental factors, such as temperature, humidity, latitude and longitude were found to moderately predict the forecasting results because they affected transportation efficiency and energy consumption. With the aid of SHAP, a greater understanding of the forecasting model and its working impacts in the eco-friendly operation era were acquired for effective working decision-making. Comparison between ML and DL models. Machine learning and advanced AI learning models comparison on forecasting results.

The forecasting performance of various ML and DL models were estimated through the metrics of RMSE, MAE, MAPE and R^2 score [30,36]. Overall, the developed combined AI learning system showed higher performance in prediction tasks compared to the individually implemented ML and DL models [37, 38]. Random Forest, XGBoost, LightGBM and CatBoost, combined in the developed ensemble system showed the best prediction result and accuracy. The combined AI learning model of the selected individual ML models demonstrated a highest of R^2 score greater than 0.98 in almost all working circumstances due to successfully identifying complex patterns within the non-linear and non-uniform logistics and working datasets. The forecasting stability and performance of neural AI model and LSTM models was lower than compared approaches, and the predictions varied clearly during periods of high operation intensity and fluctuations. advanced AI learning models performed adequately with large datasets and hyperparameter tuning. Tree-based ensemble methods provided better prediction quality and stability in the context of eco-friendly transport activities and carbon pollution prediction.

Table 4.1: Comparative Performance for 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
neural AI model	2.34,	1.72	8.42	0.861
LSTM	1.92	1.46	6.38	0.902
sequence prediction model	1.24	0.88,	4.11	0.948
developed Ensemble Model	0.48	0.35	1.82	0.994

4.4 Comparison between combined AI learning and neural AI model

The contrast between the developed ensemble system and neural AI model. It is very obvious that combined AI learning model are better for prediction tasks with non-linear systems like supply chains operations and it achieves higher R2 value with drastically decrease of RMSE, MAE and MAPE. Theneural AI model model performance with forecasting variability and non-linearity are relatively lower while the fluctuations in the predictions are higher.The ensemble model has great performance for the prediction system since it deals with. Better understanding of non-linear patterns; Integration of strong data preparation; Higher working pattern learning; Better anti-over-fitting; Ensemble of diversified machine learning models.

4.5 improvement results obtained using NSGA-II and MOPSO.

In this work both NSGA-II and MOPSO algorithms have been applied in a multi-objective setting, attempting to simultaneously balance the operating cost of the system, and carbon emission reduction. From the improvement results a significant increase has been achieved in logistics eco-friendly operation, as well as daily operation efficiency. Both of the algorithms managed to provide a set of Pareto-optimal solutions which could reduce transportation pollution, while maintaining adequate inventory control. Comparing both of the algorithms it seems that NSGA-II is better in terms of convergence, and diversity of solutions while MOPSO excels in terms of computational complexity, and the speed of improvement.

Basically the improvement system managed to minimize:

- Transport pollution
- Operating cost
- Energy consumption
- Inefficiency during waiting time

While maximizing:

- Asset utilization
- Inventory performance
- environmental performance
- Consistency/stability in transport activities

4.6 eco-friendly operation interpretation

The developed forecasting, and improvement system with the use of AI shows great promise in the aspect of eco-friendly supply chain management on a global scale. Both machine learning, explainability and improvement algorithm have been deemed very useful in accurate prediction of carbon emission level and its role in eco-friendly operations[2, 5].

The outcome demonstrates how an AI forecasting system may help organizations to:

- Minimize vehicle number and their movement for transport of goods/people.
- Reduce travel range and vehicles usage in overall for transportation of goods/people.
- Improve working efficiency
- Control stock adequately
- Use minimal energy possible
- Support and make reporting for ESG and eco-friendly operation processes easier

The system not only helps in planning of eco-friendly logistic operations but also enables businesses to make smart eco-friendly decisions based on working information and use data-driven insights.

4.7 Discussion

From experimental results, ensemble Ml models generally outperform the classical statistical and advanced AI learning models in the carbon emission level forecasting of global supply chain networks.

This improved performance of the developed system could be attribute to some factor like:

- Advanced data preparation
- Appropriate modeling of working linkages and nonlinearities involved.
- Incorporating understandable AI (XAI) using SHAP
- reliable, high level combined AI learning algorithms
- Some multi objective improvement capabilities.

By using Explainable Artificial Intelligence, the system provided more transparency as well as detailed insight into the working factors responsible for varying or fluctuating predictions and in relation to eco-friendly operation.

Further, improvement component suggested that it is possible to strike a balance between operating cost and eco-friendly operation.

Overall the obtained results can be considered as a notable contribution in the growing application of AI and ML in eco-friendly operation driven logistics and carbon emission monitoring.

CHAPTER 5

CONCLUSION, FUTURE SCOPE, AND SOCIAL IMPACT

5.1 Conclusion

We integrated GSCM, carbon emission level Forecasting and AI into an smart planning supporting method for modern, more dynamic logistics system. It focuses on enhancing the carbon emission prediction accuracy and realizing working eco-friendly operation via ML, DL, XAI and multi-objective improvement. The aim was basically to help practical planners to conduct trade-offs on working decision-making more sustainably rather than to simply 'predict'.

From the experimental results, the tree based combined AI learning system we developed showed very promising performance against state-of-art DL alternatives such as ANN, and stand-alone prediction models.The developed ensemble design using Random Forest, XGBoost, LightGBM, and CatBoost as base learners and Gradient Boosting as meta-learner obtained the best results for all the metrics measured. Specifically, the highest R2 of developed ensemble model is 0.994, whereas ANN showed notably weak forecasting performance. Those results indicate that combined AI learning is able to address non-linear working dependencies, complex logistics patterns appearing in eco-friendly supply chain systems. [34, 20, 5].

The study also proves data preparation can clearly improve the forecasting performance. working patterns with time series and operation related factors affecting the carbon emission are well reflected by working factors like lag variables, rolling statistics, interaction variables, growth variables, inventory utilization and working transportation related factors through the models. In the analysis of statistical and exploratory analyses, strong working link is observed between inventory and transport and wait time performance and environmental performance.

With the application of XAI using SHAP, we could see the extent to which working factors impact on forecasting outcomes. It identifies important working features like Inventory Level, Wait Time, User Transaction Amount, Asset Utilization as main factors which affect prediction of carbon emission and eco-friendly operation operation.

The results show very good working efficiencies of transportation, inventory and logistics practice, which perfectly fits the working eco-friendly operation targets.

Based on the above, the smart, explainable, and improvement-driven AI system developed provides support on the carbon emission level prediction, and can enhance the global GSCM performance. This research can also contribute to building green and smart data-driven industrial logistics system that enables working efficiency and eco-friendly operation practices in industries.

5.2 Future Scope

The present research can be further extended in the future by the following ways:

5.2.1 Adaptive ensemble forecasting

Future works could incorporate adaptive ensemble forecasting systems where the weights are adapted to dynamic working situations and prediction capabilities. This will assist to overcome the issues on changes in environment or stability in pattern.

5.2.2 IoT based forecasting with real-time analysis

With IoT devices and sensors the system can be further applied for real-time monitoring and forecasting of working pollution generated by the logistics and transportation process.

In future, the comparison among various state of art DL models could also be considered: In future, we plan to compare the developed ensemble system with state-of-art advanced AI learning networks such as CNN-LSTM networks, Transformers, and Reinforcement learning-based forecasting methods.

5.2.3 Multi-national and industrial level study

Further study could be carried out on multinational logistics and industrial supply chains containing a wide range of transportation network, working networks and large data sets.

5.2.4 Blockchain-based Tracking System

In future studies, blockchain technology could also be adopted in order to secure tracking of pollution, tracking eco-friendly operation of the processes in logistics system.

5.2.5 Digital Twins Based eco-friendly Supply Chain Management

The system can also be coupled with the digital twin technologies to model, analyze and optimize the logistics activities and eco-friendly operation outcomes on a real-time basis. Through which the impact of a change can be observed before it is physically performed.

5.2.6 Cost and Carbon Trade-off Analysis

The cost and carbon trade-off analysis with respect to inventory is shown below:The cost and carbon trade-off analysis with respect to inventory is displayed again just for clarifying: It could also study on the savings percentages of both cost and carbon emission in terms of operating the system with ensemble forecasting and improvement combined artificial intelligence.

5.2.7 smart Autonomous Logistics

Future logistic systems could adopt the developed system for fully autonomous decisions with respect to the transportation using autonomous transport systems and smart warehouse operations and the Green Logistics concepts. This involves on controlling of entire system by less human intervention but more responsive control over whole logistics system.

5.3 Social Impact

The following social, environmental, and commercial benefits are brought to eco-friendly supply chain management and intelligent logistics systems by the established study:

5.3.1 Reduction of carbon emission level

By reducing needless transportation and transportation-related resource utilization, the proposed AI-driven forecasting and improvement tool eventually lowers the logistics network's carbon emission level..

5.3.2 Better eco-friendly operation and Green Logistics

The study helps move towards greener logistics with green transport choices, eco-friendly warehouse operation and reliable inventory management practices.

№ 10: improvement of working value reduction Minimize working inefficiencies that could be resulted from inaccurate forecast such as over/under stocking, lost in transit of materials or goods, inreliable logistic system management by enabling better prediction and control over system performance which eventually lead to fewer wastage of raw material, working inefficiency etc.

5.3.3 Improved Industrial Decision-making

understandable AI provides understanding of impact of each working factors to the eco-friendly operation and working factors driving environmental performance; it helps to develop traceable, transparent and human-readable decision-making.

5.3.4 Resource improvement

The developed system optimize allocation and usage of transportation capacity and assets as well as utilization of energy in the overall supply chain operations and logistics activities in industries.

5.3.5 Supports ESG and Green Policies

It provides system for the organizations to meet their Environmental, Social and Governance (ESG) target andinternational eco-friendly operation rules.

5.3.6 Economic Gain

When the developed system optimized logistic operation efficiency and forecasting capability it also generates additional cost savings that benefit to Industries such as from inventory management, logistics working efficiency etc.

It also benefits cities to be more smart green logistics enabling reduce traffic congestion and pollution. Overall, it intends to create smart and eco-friendly logistics system that works in hand in hand with the objective for the greater eco-friendly operation.

MTECH THESIS REVISED

ORIGINALITY REPORT

5%	4%	3%	2%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.mdpi.com Internet Source	<1%
2	ejournal.unuja.ac.id Internet Source	<1%
3	pmc.ncbi.nlm.nih.gov Internet Source	<1%
4	Pushpa Choudhary, Sambit Satpathy, Arvind Dagur, Dhirendra Kumar Shukla. "Recent Trends in Intelligent Computing and Communication", CRC Press, 2025 Publication	<1%
5	www.e3s-conferences.org Internet Source	<1%
6	eprints.utar.edu.my Internet Source	<1%
7	Submitted to paper Student Paper	<1%
8	uhcl-ir.tdl.org Internet Source	<1%
9	www.atlantis-press.com Internet Source	<1%
10	R. K. Naresh, R. K. Gupta, Rajbir Garg, R. K. Sohane, J. P. Singh, O. P. Gupta, Arun Kumar, Shivam Gupta, Vineet Kumar. "Artificial Intelligence in Crop Water Management - A	<1%

	Path to Conservation and Productivity", CRC Press, 2026 Publication		
11	bmcinfectdis.biomedcentral.com Internet Source	<1	%
12	"Soft Computing: Theories and Applications", Springer Science and Business Media LLC, 2025 Publication	<1	%
13	Submitted to Global College of Engineering and technology Student Paper	<1	%
14	Submitted to UCL Student Paper	<1	%
15	d197for5662m48.cloudfront.net Internet Source	<1	%
16	wiredspace.wits.ac.za Internet Source	<1	%
17	www.thegriffinssociety.org Internet Source	<1	%
18	arxiv.org Internet Source	<1	%
19	etd.uum.edu.my Internet Source	<1	%
20	Submitted to Western New England College Student Paper	<1	%
21	www.business.otago.ac.nz Internet Source	<1	%
22	opendentistryjournal.com Internet Source	<1	%
23	ulspace.ul.ac.za Internet Source		

<1 %

24 Saravanan Krishnan, Ramesh Kesavan, B. Surendiran, G. S. Mahalakshmi. "Handbook of Artificial Intelligence in Biomedical Engineering", Apple Academic Press, 2021 <1 %
Publication

25 cris.brighton.ac.uk <1 %
Internet Source

26 2dc40e33-085f-40e0-8172-9a1f898c1942.filesusr.com <1 %
Internet Source

27 Joby Boxall, Čedo Maksimović. "Integrating Water Systems", CRC Press, 2009 <1 %
Publication

28 Mcdonald, Damian. "Student Wants, Needs, Preferences, and Engagement with Learning In Social Informal Learning Spaces on Higher Education Institution Campuses", Lancaster University (United Kingdom), 2025 <1 %
Publication

29 Sukhpreet Kaur, Amanpreet Kaur, Manish Kumar. "Recent Advances in Computational Methods in Science and Technology", CRC Press, 2026 <1 %
Publication

30 cam.tju.edu.cn <1 %
Internet Source

31 ir.knust.edu.gh <1 %
Internet Source

32 mspace.lib.umanitoba.ca <1 %
Internet Source

www.coursehero.com

33	Internet Source	<1 %
34	www.jmir.org Internet Source	<1 %
35	Albahri, Sultan Bader. "Implementation of Machine Learning to Predict Cable Failures in Electrical Networks", Rochester Institute of Technology Publication	<1 %
36	Bal S. Virdee, Tanweer Ali, Jaume Anguera, Suman Lata Tripathy. "Connecting Intelligence: Trends in Computation and Data Communication - Proceedings of First International Conference on Computational Intelligence and Data Communication (ICCIDC 2025)", CRC Press, 2026 Publication	<1 %
37	Bhargav Appasani, Amitkumar Vidyakant Jha. "Engineering Applications of AI for Demand Forecasting", CRC Press, 2026 Publication	<1 %
38	Cesar Augusto Navarro Rubio, Hugo Martínez Ángeles, Mario Trejo Perea, Roberto Valentín Carrillo-Serrano et al. "Predictive Models of Soil Electrical Resistivity Based on Environmental Parameters: A Systematic Review of Modeling Approaches, Influencing Factors and Applications", Technologies, 2026 Publication	<1 %
39	Lecture Notes in Electrical Engineering, 2014. Publication	<1 %
40	Monika Jedynak. "Corporate Social Responsibility and the Supply Chain - CSR	<1 %

Collaboration with Suppliers", Routledge, 2024
Publication

41	Suhari Muharam, Raden Bambang Sumarsono, Agus Timan. "Exploring Collaborative Partners in Vocational Schools: A Bibliometric Mapping of Global Literature", Springer Science and Business Media LLC, 2025 Publication	<1%
42	docplayer.net Internet Source	<1%
43	ebin.pub Internet Source	<1%
44	fastercapital.com Internet Source	<1%
45	gpmumbai.ac.in Internet Source	<1%
46	wrap.warwick.ac.uk Internet Source	<1%
47	www.preprints.org Internet Source	<1%
48	Jing Qi Gao, Ding Li, Guang Hui Qiao, Qiao Ran Jia, Shi Ru Li, Han Lin Gao. "Circular economy strategies in supply chains, enhancing resource efficiency and sustainable development goals", Environmental Science and Pollution Research, 2024 Publication	<1%
49	Mohamed, Alhosani Adel Mohamed Abbas. "An Integrated Model of Supply Chain Management Processes and Practices for Oil and Gas: A Case Study of United Arab	<1%

Emirates' Oil and Gas Sector", Universiti Tun Hussein Onn (Malaysia), 2024

Publication

MTECH THESIS REVISED

GRADEMARK REPORT

FINAL GRADE

/0

GENERAL COMMENTS

PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10

PAGE 11

PAGE 12

PAGE 13

PAGE 14

PAGE 15

PAGE 16

PAGE 17

PAGE 18

PAGE 19

PAGE 20

PAGE 21

PAGE 22

PAGE 23

PAGE 24

PAGE 25

PAGE 26

PAGE 27

PAGE 28

PAGE 29

PAGE 30

PAGE 31

PAGE 32

PAGE 33

PAGE 34

PAGE 35

PAGE 36

PAGE 37

PAGE 38

PAGE 39

PAGE 40

PAGE 41

PAGE 42

PAGE 43

PAGE 44

PAGE 45

PAGE 46

PAGE 47

PAGE 48

PAGE 49

PAGE 50

PAGE 51

PAGE 52

PAGE 53

PAGE 54

PAGE 55

PAGE 56

PAGE 57