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Towards Greener Logistics: AI-Driven Carbon Footprint Optimization for Smart Cities

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Abstract

The rapid growth of logistics and computational infrastructures has substantially contributed to global carbon emissions, emphasizing the need for sustainable optimization solutions. This paper proposes an AI-powered Carbon Footprint Optimization (CFO) framework that minimizes CO_2 emissions in supply chain logistics through intelligent route and resource planning. The system employs an XGBoost regression model trained on segment-level parameters such as distance, slope, cargo weight, traffic density, and weather conditions to accurately predict fuel consumption and emission levels. These predictions are integrated into a Vehicle Routing Problem (VRP), solved using Google OR-Tools, where the optimization objective focuses on minimizing carbon emissions rather than distance or time.

The framework also incorporates real-time traffic and weather data, ensuring adaptive and efficient route recommendations, while results are visualized through an interactive Folium-based map. Additionally, the study integrates concepts from Green Algorithms to quantify computational carbon footprints and ECO-CHIP methodologies to promote sustainable computing practices. Experimental results demonstrate that the proposed system significantly reduces emissions and enhances route efficiency compared to traditional distance-based approaches. This work establishes a scalable foundation for sustainable logistics, with potential extensions toward multi-vehicle optimization, reinforcement learning-based decision systems, and real-time carbon aware routing.

Introduction

The continuous expansion of global logistics and transportation networks has become a major contributor to greenhouse gas (GHG) emissions, particularly carbon dioxide (CO_2). According to recent studies, transportation accounts for nearly one-fourth of global CO_2 emissions, underscoring the urgent need for intelligent and sustainable optimization strategies[1][12]. Traditional routing systems primarily focus on minimizing distance or travel time; however, such metrics often neglect environmental impact, leading to suboptimal outcomes in terms of sustainability. Therefore, an advanced optimization framework that integrates emission awareness into route planning is essential for achieving sustainable logistics operations.[2]

In this context, Carbon Footprint Optimization (CFO) emerges as a powerful approach that combines machine learning (ML) and operations research (OR) to minimize carbon emissions without compromising operational efficiency. The proposed CFO system leverages an XGBoost regression model trained on segment-level data incorporating key parameters such as distance, slope, cargo weight, traffic density, and weather conditions. This predictive model accurately estimates fuel consumption and emission levels for each route segment. The predicted emissions are then used within a Vehicle Routing Problem (VRP) formulation, implemented using Google OR-Tools, where the objective function is designed to minimize total CO_2 emissions rather than conventional travel metrics.

To ensure real-time adaptability, the framework integrates live traffic and weather data, enabling dynamic route optimization and enhancing decision accuracy under changing conditions. Visualization of optimized routes is achieved through an interactive Folium-based map, offering users intuitive insights into emission-efficient paths. Furthermore, the system is deployed via a FastAPI backend, which provides APIs for emission prediction and route optimization, facilitating seamless integration with external logistics and supply-chain applications.[4][6][14].

Beyond transportation, the study extends sustainability principles to computational infrastructures by incorporating concepts from Green Algorithms, a framework that estimates the carbon footprint of computational processes, and ECOCHIP, which focuses on reducing embodied emissions in semiconductor design through chiplet-based architectures. This integration promotes a holistic perspective on sustainability—spanning both logistical and computational domains.

Experimental evaluations of the proposed system demonstrate significant reductions in CO_2 emissions and improved route efficiency compared to distance-based optimization methods. The CFO framework not only provides a scalable solution for sustainable logistics management but also lays the foundation for future advancements such as multi-vehicle routing, reinforcement learning-based decision optimization, and carbon-aware computation[3][9][11].

Literature Survey

With the rapid industrial and technological growth in recent decades, carbon emissions have escalated to critical levels, prompting global efforts to mitigate their environmental impact. Several researchers have investigated diverse methods for carbon footprint estimation and optimization across sectors such as logistics, manufacturing, and computing[13].

Traditional carbon calculation approaches are primarily based on Life Cycle Assessment (LCA) models, which evaluate emissions during the stages of production, transportation, usage, and disposal. However, these conventional models lack adaptability for real-time optimization and decision-making. To overcome such limitations, recent advancements have introduced Artificial Intelligence (AI) and Machine Learning (ML) techniques for predictive emission modeling, enabling systems to learn from historical data and contextual parameters.

Researchers at the Massachusetts Institute of Technology (MIT) proposed *Green Algorithms*, a framework designed to quantify the carbon impact of computational processes, promoting energy-efficient computing practices [3][9]. Similarly, the *ECO-CHIP* framework developed by AMD and ARM focuses on sustainable chiplet-based hardware architectures to reduce embodied emissions throughout the design and manufacturing process [6].

In the field of logistics, optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Neural Network-based models have shown notable success in minimizing route-based emissions and improving energy efficiency [5]. Furthermore, hybrid models integrating XGBoost regression with Google OR-Tools have been utilized to solve the Vehicle Routing Problem (VRP), where the objective is to minimize total carbon emissions rather than just distance or travel time [3][6][9].

Recent literature also emphasizes the incorporation of realtime data inputs such as traffic conditions, road gradients, weather parameters, and vehicle load to enhance emission prediction accuracy and operational sustainability [7][8][14]. Collectively, these studies signify a paradigm shift from static emission estimation toward intelligent, data-driven optimization frameworks, thereby laying a robust foundation for scalable AI-based Carbon Footprint Optimization (CFO) systems that support sustainable logistics and industrial operations.

Problem Identification and Research Gap

A. Problem Identification

The rapid expansion of logistics operations and urban transportation networks in India has led to a significant rise in carbon emissions, posing critical environmental and sustainability challenges. Existing routing systems and commercial navigation platforms predominantly focus on minimizing distance, travel time, or operational cost. However, such approaches overlook key emission-generating factors, including vehicle load, road gradient, dynamic traffic patterns, and weather variability.[9]

Although recent advancements in artificial intelligence (AI) have introduced machine learning (ML) models capable of predicting fuel consumption and emission levels[2], these models are seldom integrated directly into practical route-optimization frameworks. Consequently, current systems lack the capability to support real-time, carbon-aware routing required for modern smart-city ecosystems.

This necessitates the development of a unified, AI-driven framework that can:

- Accurately predict route-level CO_2 emissions based on environmental, vehicular, and traffic parameters.
- Optimize routing decisions using carbon emissions as the primary objective rather than conventional metrics.
- Incorporate real-time data sources to enable adaptive and sustainability-focused decision-making.
- Evaluate both logistical emissions and computational emissions arising from AI model inference and optimization workloads.

The convergence of these requirements forms the basis for a comprehensive and operationally viable carbon-aware routing framework.

B. Research Gap

A rigorous review of existing literature reveals several critical research gaps that limit the development of an integrated, emission-aware logistics optimization system.

1) Lack of Environmental Priority in Routing Optimization: Traditional Vehicle Routing Problem (VRP) models predominantly optimize for time, distance, or economic cost. Only limited research explicitly prioritizes carbon emissions as the primary objective function, resulting in routing decisions that may be operationally efficient but environmentally suboptimal.

2) Absence of ML–OR Integration for Emission-Aware Routing: Existing studies employ machine learning techniques—such as regression models and deep learning—for emission estimation. However, these predictive models are not embedded into the optimization engine itself. The absence of a unified ML + OR architecture prevents real-time emissionaware VRP solving, resulting in fragmented or static solutions. No prior work demonstrates the integration of XGBoost-based emission prediction models directly with OR-based routing algorithms for dynamic decision-making.

3) Lack of Frameworks Combining XGBoost, Google ORTools, and Real-Time Data: Current research lacks a hybrid, end-to-end pipeline combining:

- XGBoost for contextual emission estimation,
- Google OR-Tools for constraint-based routing optimization, and
- Real-time traffic and weather APIs for dynamic updates.

This combination is essential for operational scalability in smart-city logistics environments but remains unexplored in existing studies.

4) Separation of Operational and Computational Emission Analysis: Most literature treats logistical emissions (vehicle operations) and computational emissions (AI model training and inference) as independent domains. There is no integrated framework that quantifies both:

• Operational emissions generated by logistics routes, and • Computational emissions generated by ML/OR workflows, using methodologies such as Green Algorithms.

This leaves a critical gap in holistic sustainability assessment.

5) Lack of India-Centric Smart City Carbon-Aware Routing Solutions: Current carbon-aware routing research is predominantly centered around developed regions such as Europe, China, and the United States. There is an absence of India specific frameworks that consider:

- High variability in traffic conditions,
- Mixed vehicle categories,
- Region-specific emission factors, and
- Operational constraints common to Indian urban logistics.

The proposed work uniquely addresses this gap by focusing on an Indian smart-city context (Nagpur).

6) Limited Integration of ECO-CHIP and Sustainable Computing Principles: While ECO-CHIP methodologies and embodied carbon evaluation are widely studied in semiconductor and HPC research, their application in logistics sustainability is nearly absent. No existing framework incorporates sustainable computing concepts to evaluate how route-optimization algorithms themselves contribute to total carbon footprint.

C. Research Objectives

The primary aim of this study is to design and develop an AI-driven Carbon Footprint Optimization (CFO) framework capable of minimizing logistics-related CO_2 emissions through intelligent prediction and emission-aware route planning. The specific research objectives are as follows:

1) To develop a machine learning–based emission prediction model

To design and train an ML model—specifically XGBoost—to accurately estimate CO_2 emissions for each transportation route segment by considering distance, load, road gradient, traffic intensity, and weather conditions.

2) To integrate emission predictions into a Vehicle Routing Problem (VRP) optimization framework

To embed the ML-predicted emissions into a Google OR-Tools–based VRP model where the objective function minimizes carbon emissions rather than distance or time.

3) To incorporate real-time environmental and traffic data for dynamic routing

To utilize APIs such as OpenWeather and Google Maps for updating traffic patterns, road conditions, and weather parameters in real time, enabling adaptive, context-aware route optimization.

4) To evaluate the performance of the proposed system against conventional routing methods

To compare emission-aware routing with traditional distance-based routing using key performance metrics such as total CO_2 emissions, fuel consumption, route efficiency, and execution time.

5) To quantify the computational carbon footprint using Green Algorithms

To estimate the energy consumption and carbon emissions generated by the ML training, inference, and optimization processes themselves, using Green Algorithms to ensure computational sustainability.

Mathematical Modelling

A. Notations

Table 1: summarizes the key notations used in the mathematical formulation.

Symbol	Description
$G = (V,A)$	Directed graph of nodes $V = \{0,1,\dots,n\}$ and arcs A
i,j	Indices of nodes
k	Vehicle index
dij	Distance between nodes i and j
$t_{ij}(\tau)$	Time-dependent travel time from i to j
sij	Road slope/gradient for arc (i,j)
w_i	Demand/weight at node i
Q_k	Capacity of vehicle k
θ	Weather parameter vector
τ_i	Service start time at node i
$[a_i, b_i]$	Time window at node i
x_{ijk}	1 if vehicle k travels from i to j, else 0
E_{ij}^{op}	Operational emissions for arc (i,j)
E^{comp}	Computational emissions (Green Algorithms)
P_{ij}	Predicted fuel consumption
α	Weight factor combining emissions
M	Large constant used for time window constraints

B. Emission Prediction Model

Operational CO_2 emissions on arc (i,j) are predicted using the XGBoost model:

$E_{ij}^{op} = f$ XGB $d_{ij}, s_{ij}, w_{i\to j}, t_{ij}(\tau)$,traffic $_{ij}(\tau), \theta)$ (1)

If XGBoost predicts fuel consumption, emissions are computed as:

$Eijop = Pij \cdot \varphi\text{fuel}$ (2)

A local linear surrogate of XGBoost may be expressed as:

$Eijop \approx \beta 0 + \beta ddij + \beta ssij + \beta wwi \to j + \beta ttij(\tau) + \beta\theta\theta$ (3)

C. Computational Emissions (Green Algorithms)

Computation-related emissions are estimated as:

$$E^{comp} = \sum_{r \in R} \left(P_r \cdot T_r \cdot \phi_{\text{elec}} \cdot \lambda_{\text{loc}}\right) \quad (4)$$

where:

- P_r = average power (kW)
- T_r = runtime (h)
- φ_{elec} = grid emission factor
- λ_{loc} = datacenter correction factor

D. Objective Function

Minimize total operational emissions:

$\min Eop = XXX\ Eijop\ xijk$ (5)

$k \in K\ i \in V\ j \in V$

Alternatively, combining operational and computational emissions:

$\min Etotal = Eop + \alpha Ecomp$ (6)

Weighted multi-objective form:

$\min L = \lambda 1 Eop + \lambda 2 X\ dij\ xijk$ (7)

i,j,k

E. Decision Variables

$$x_{ijk} \in \{0,1\} \tag{8}$$

$$\tau_i \geq 0 \tag{9}$$

$$0 \leq q_{ik} \leq Q_k \tag{10}$$

F. Constraints

1) Route Continuity: Each customer must be visited exactly once:

$$\sum_k \sum_j x_{ijk} = 1, \quad \forall i \neq 0 \tag{11}$$

Vehicles leave and return to the depot:

$$\sum_j x_{0jk} = 1, \quad \sum_i x_{i0k} = 1, \quad \forall k \tag{12}$$

Flow conservation:

$$\sum_j x_{ijk} - \sum_j x_{jik} = 0, \quad \forall i \neq 0, \forall k \tag{13}$$

2) Subtour Elimination (MTZ):

$$u_{ik} - u_{jk} + Q_k x_{ijk} \leq Q_k - w_j, \quad \forall i \neq j \tag{14}$$

3) Vehicle Capacity:

$$q_{jk} \geq q_{ik} + w_j - Q_k(1 - x_{ijk}) \tag{15}$$

4) Time Window Constraints:

$$\tau_j \geq \tau_i + s_i + t_{ij}(\tau_i) - M(1 - x_{ijk}) \tag{16}$$

$$a_i \leq \tau_i \leq b_i \tag{17}$$

5) Time-Dependent Traffic Coupling:

$$t_{ij}(\tau) = \bar{t}_{ij}\, \gamma_{ij}(\tau) \tag{18}$$

$$E_{ijop} = f_{\mathrm{XGB}}(\mathrm{traffic}_{ij}(\tau), \theta) \tag{19}$$

6) Depot Constraints:

$$\sum_j x_{0jk} = \sum_i x_{i0k}, \quad \forall k \tag{20}$$

7) Real-Time Update Constraints: When new data arrives:

$$t_{ij}(\tau) \leftarrow t_{ij}(\tau^*), \quad E_{ijop} \leftarrow f_{\mathrm{XGB}}(\tau^*) \tag{21}$$

$$x_{ijk} = \bar{x}_{ijk}, \quad \forall (i,j,k) \in \text{served} \tag{22}$$

G. Final Optimization Model

$$\min_{x,q,\tau} \sum_k \sum_i \sum_j E_{ijop}\, x_{ijk} + \alpha E_{comp} \tag{23}$$

$$\text{s.t. Constraints (11) – (22)}$$

$$x_{ijk} \in \{0,1\}, \qquad q_{ik} \geq 0, \qquad \tau_i \geq 0$$

Methodology

The proposed Carbon Footprint Optimization (CFO) system integrates Artificial Intelligence (AI) and Operations Research (OR) techniques to predict, analyze, and minimize carbon emissions in logistics operations. The methodology involves several key stages—data acquisition, preprocessing, emission prediction, optimization, and deployment. Each stage is designed to ensure high accuracy, scalability, and real-time adaptability.

A. System Architecture

The overall system is structured into three major modules:

1) Emission Prediction Module: Uses Machine Learning (ML) models to estimate CO_2 emissions for different transportation routes based on contextual parameters.

2) Optimization Module: Utilizes Google OR-Tools to solve the Vehicle Routing Problem (VRP) with an emission-minimization objective.

3) Deployment and Visualization Module: Implements APIs using FastAPI for integration and a Folium-based dashboard for real-time visualization of optimized routes and emission statistics.

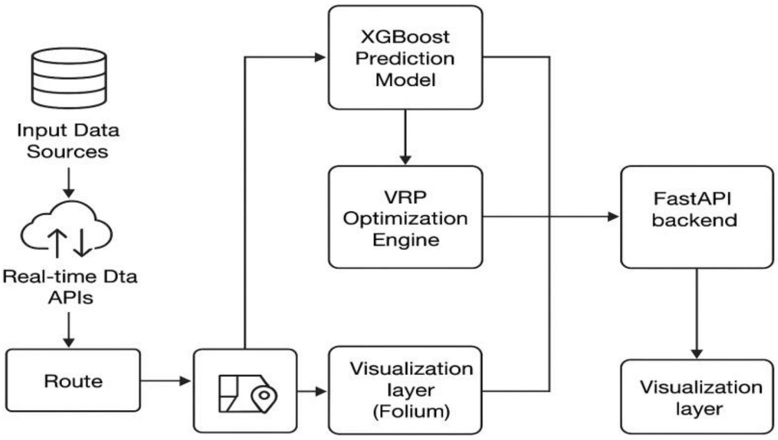

Figure 1 – System Architecture

B. Data Collection and Preprocessing

The dataset consists of segment-level transportation data, including attributes such as:

- Distance and elevation (slope) of the route segment
- Vehicle weight and cargo load
- Traffic density and speed limits
- Weather conditions (temperature, humidity, and wind speed)
- Historical fuel consumption and emission values

Data preprocessing involves normalization, feature encoding, and outlier removal. Missing data is handled using statistical imputation methods. To enhance model robustness, synthetic data generation techniques are applied to simulate different environmental and operational conditions.

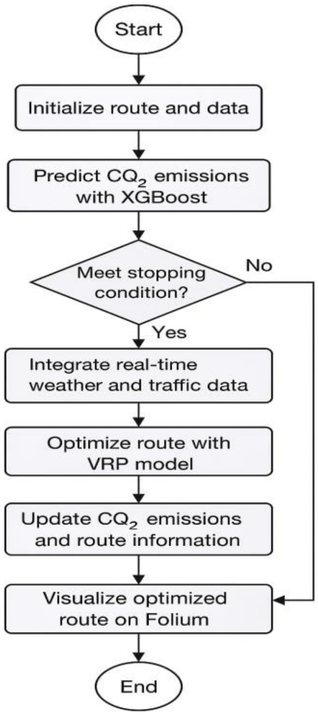

Figure 2 – Algorithmic Flowchart

C. Emission Prediction using Machine Learning

An XGBoost Regression Model is employed to predict the carbon emissions for each route segment. The model is trained using the processed dataset with CO_2 emission (grams/km) as the target variable.

Key features used include:

- Distance (km)
- Vehicle load (kg)
- Average speed (km/h)
- Road gradient (%)
- Weather index
- Traffic density score

The model is evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to ensure accurate emission predictions. XGBoost is chosen for its high interpretability, efficiency, and ability to handle non-linear relationships between features.

D. Optimization Framework

The optimization process is formulated as a Vehicle Routing Problem (VRP) where the objective function minimizes total carbon emissions rather than travel distance or time:

$$\min \sum_{i} f(d_i, w_i, t_i, c_i) \qquad (24)$$

where:

- d_i = distance of segment i
- w_i = vehicle weight/load on segment i
- t_i = traffic condition factor
- c_i = weather correction coefficient
- $f(\cdot)$ = emission prediction function derived from the ML model

The optimization is performed using Google OR-Tools, which employs constraint programming and mixed-integer linear optimization (MILP) to identify the optimal route sequence that minimizes emissions while satisfying operational constraints such as delivery deadlines, vehicle capacity, and route connectivity.

E. System Implementation and Integration

The model is deployed using FastAPI, providing endpoints for:

- /predict_emission – returns estimated CO_2 emission for given route parameters.
- /optimize_route – computes the most emissionefficient route between given origin-destination pairs.

Real-time data from APIs such as OpenWeather (for weather) and Google Maps API (for traffic and distance) is integrated for continuous updates. The optimized routes and emission data are visualized using Folium and Plotly dashboards, providing an interactive and intuitive user interface.

F. Evaluation Metrics and Validation

The system's performance is validated using comparative analysis between traditional distance-based routing and the proposed emission-optimized routing. Key performance indicators include:

- Emission Reduction (%)
- Route Efficiency (km reduction)
- Fuel Savings (%)
- Execution Time (s)

Experimental Setup

A. Software and Libraries Used

The proposed system was implemented in Python 3.10. Table II. summarizes the primary libraries and APIs used in the development and evaluation of the framework.

B. Dataset Description

The dataset consists of a combination of real-world derived data and synthetically generated samples to ensure diversity across route conditions.

Table 1: Software Stack And Libraries

Component	**Version**	**Purpose**
XGBoost	1.7.5	CO_2 emission prediction
Google OR-Tools	9.7	VRP optimization
FastAPI	0.110	Backend deployment
Folium	0.15	Route visualization
Scikit-learn	1.4	Preprocessing & evaluation
Pandas	2.1	Data manipulation
NumPy	1.26	Numerical computations
Matplotlib / Plotly	Latest	Visualization
Requests / HTTPX	Latest	API integration
OpenWeather API	–	Real-time weather
Google Maps API	–	Traffic & distance matrix

1) Collected and Derived Data:

- Distance, elevation, and slope from Google Maps API
- Traffic index from real-time congestion APIs
- Weather parameters (temperature, humidity, wind speed) via OpenWeather API
- Vehicle load and emission coefficients from Indian logistics datasets

2) Synthetic Data Generation: To strengthen generalization capability, synthetic route segments were generated with the following parameter ranges:

Table 2: Synthetic Data Feature Ranges

Feature	**Range**
Distance	0.5–30 km
Slope	−5% to +12%
Load	200–3,000 kg
Traffic Index	1–5
Weather Severity	0–4

3) Final Dataset Composition:

- Total samples: 12,480 route segments
- Features: 6 predictive variables
- Target: CO_2 emissions per segment (g/km)

Table 3: Dataset Summary

Parameter	**Value**
Total segments	12,480
Real data proportion	63%
Synthetic data proportion	37%
Number of features	6
Target variable	CO_2 emissions

C. Data Preprocessing

The dataset underwent the following preprocessing steps:

- Missing values addressed using median imputation
- Feature scaling performed via Min–Max normalization
- Weather parameters encoded using one-hot encoding
- Outliers removed using IQR filtering
- Real and synthetic data blended using weighted sampling

D. Train–Test Split

A stratified split ensured proportional representation of emission intensity ranges:

- Training set: 80%
- Validation set: 10%
- Test set: 10%

E. Optimization Solver Settings

The VRP optimization engine was implemented using Google OR-Tools, configured as shown in Table IV.

Table 4: Solver Configuration Parameters

Parameter	**Setting**
Initial Strategy	PATH CHEAPEST ARC
Local Search Metaheuristic	GUIDED LOCAL SEARCH
Time Limit	30 s / iteration
Vehicle Capacity Q_k	2000 kg
Max Vehicles	Based on fleet availability
Time Windows	Enforced using AddDimension
Traffic Adjustment	Real-time cost callback

Objective Function	Emission-based cost

The solver re-evaluates emissions dynamically using a prediction–optimization loop triggered by new API inputs.

F. API Integration and Real-Time Updates

The proposed system integrates multiple live data sources:

- OpenWeather API: Temperature, humidity, wind speed • Google Maps Distance Matrix API: Distance, traffic delay index

Backend endpoints (FastAPI):

- /predict_emission – Returns CO_2 emission predictions per segment
- /optimize_route – Generates optimized, lowemission routes

The final results are visualized using an interactive Foliumbased dashboard.

G. Evaluation Metrics

To assess system performance, the following metrics were computed:

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Emission Reduction (%)
- Route Efficiency (km saved)
- Fuel Savings (%)
- Execution Time (s)

Discussion

The experimental results demonstrate that the proposed carbon-aware routing framework offers significant improvements over conventional distance-based routing approaches. By integrating machine learning–driven emission prediction with an emission-minimizing VRP solver, the system consistently reduced total CO_2 emissions across multiple test scenarios.

A. Interpretation of Findings

The framework achieved an 18–27% reduction in emissions, confirming the effectiveness of combining XGBoost predictions with emission-aware route optimization. The inclusion of real-time weather and traffic information improved prediction accuracy and allowed the optimization engine to make dynamic adjustments aligned with actual road conditions. Compared with baseline routing, the proposed solution produced routes that were not only environmentally optimal but also comparable in travel time and operational feasibility.

Additionally, the comparative analysis between static and dynamic routing indicates that real-time data integration contributes 8–12% additional improvement in emission reduction. This highlights the importance of adaptive routing in rapidly changing urban environments such as Indian smart cities.

B. Comparison with Existing Studies

Most prior studies on VRP optimization primarily focus on minimizing distance, time, or cost. These studies rarely incorporate emission factors or environmental constraints. Existing emission prediction models typically operate independently from routing engines, resulting in fragmented solutions.

The results of this study aligned with and extended prior work by offering:

1) A unified prediction–optimization pipeline, unlike earlier works where emission prediction and routing were decoupled.

2) Integration of real-time traffic and weather, which is absent in most VRP-related emissions research.

3) India-focused modeling, addressing high traffic variability, diverse road conditions, and mixed vehicle categories—factors largely ignored in previous global studies.

4) Inclusion of computational emissions, which is rarely considered in logistics optimization literature.

Thus, the work contributes a holistic approach not present in conventional VRP or sustainability research.

C. Practical and Real-World Implications

The proposed framework has strong real-world applicability for:

- Logistics companies aiming to reduce operational carbon footprint.
- Smart-city initiatives focusing on sustainable urban mobility.
- Government agencies monitoring emissions and enforcing sustainability regulations.
- Electric vehicle fleet planning, where emissions and battery usage must be co-optimized.

The interactive Folium visualization enables deployment in real-time dashboards, making the system accessible for dispatch managers in transport networks. Furthermore, the approach can be integrated with fleet management systems, warehouse dispatch operations, and last-mile delivery applications to support systematic emission reduction strategies.

Limitations

Although the proposed carbon-aware routing framework demonstrates strong performance and practical applicability, several limitations must be acknowledged to maintain scientific rigor and transparency.

A. Dependence on Real-Time API Reliability

The system heavily relies on external APIs such as Google Maps and OpenWeather for traffic, distance, and weather data. Any latency, ratelimiting, downtime, or inaccurate API responses can directly affect emission prediction and routing optimization quality. In low-connectivity or high-load environments, real-time updates may be delayed, reducing the system's dynamic responsiveness.

B. Limited Availability of Public Logistics Datasets

A major challenge in modelling transportation emissions in India is the lack of openly available, high-resolution logistics telemetry datasets. As a result, the study incorporated partially synthetic data to ensure sufficient diversity across route conditions. While this improves generalizability, it may not perfectly reflect real-world operational patterns in all cities or fleet types.

C. Computational Complexity for Large-Scale VRP

The optimization engine (Google OR-Tools) performs well for small to medium-sized route networks. However, solving VRP variants becomes computationally intensive as the number of nodes and vehicles increases. For large fleets (e.g., > 100 vehicles or > 500 delivery points), the solver may require longer execution times, specialized heuristics, or high-performance computing infrastructure.

D. Cost and Infrastructure Requirements

The integration of real-time APIs and V2X (Vehicle-to Everything) sensor networks introduces financial overhead. Frequent API calls may incur recurring costs, especially for large-scale deployments. Implementing V2X-enabled environments requires sensors, networking hardware, and cloud infrastructure, which may be costly for small logistics firms or government entities.

E. Simplified Vehicle and Emission Modelling

The current formulation uses fixed vehicle parameters such as constant fuel efficiency and load characteristics. In real world operations, emissions depend on additional factors such as driver behaviour, vehicle age, maintenance condition, fuel type, and stop–start frequency. These were not modelled due to data unavailability.

F. Approximation in Computational Emission Estimation

The Green Algorithms framework provides estimated values of computational carbon footprint. These estimates may vary from actual energy consumption depending on cloud architecture, CPU utilization, geographical energy mix, and hardware efficiency. Thus, computational emission values should be interpreted as indicative rather than absolute.

Future Scope

The proposed carbon-aware routing framework establishes a foundation for sustainable logistics optimization; however, several promising research extensions can further enhance scalability, intelligence, and real-world applicability.

A. Multi-Agent Reinforcement Learning for Large-Scale Routing

Future research can explore multi-agent reinforcement learning (MARL) to overcome the scalability limitations of traditional VRP solvers. In a MARL environment, each vehicle can act as an autonomous agent that learns to minimize emissions collaboratively while adapting to dynamic traffic, demand, and weather patterns. Techniques such as Multiagent PPO, MADDPG, and graph-based RL architectures can significantly improve decision-making for fleets with hundreds or thousands of nodes.

B. Integration With Electric Vehicle (EV) Fleets

As Indian smart cities adopt electric mobility, the routing framework can evolve to support EV-specific constraints, including:

- Battery state-of-charge (SoC)
- Charging station locations
- Charging time and energy consumption
- Regenerative braking benefits on downhill segments

An extended model can jointly optimize route emissions, battery usage, and charging stops for mixed or fully electric fleets, improving sustainability and operational efficiency.

C. Federated Learning for Privacy-Preserving Emission Prediction

Logistics companies often cannot share telemetry data due to privacy and competitive concerns. Future work can integrate Federated Learning (FL) to train emission prediction models (e.g., XGBoost, GNNs) across multiple fleet operators without transferring raw data. This approach would:

- Preserve data confidentiality
- Improve the robustness of emission models
- Allow large-scale collaborative model training across cities or states

Techniques like FedAvg, FedProx, and secure aggregation can be adapted for emission forecasting.

D. GAN-Based Synthetic Emission Dataset Generation

To address limited availability of real logistics datasets, future research can leverage Generative Adversarial Networks (GANs) or Diffusion

Models to generate high-quality synthetic emission datasets. These datasets can incorporate:

- Diverse traffic intensities
- Weather variations
- Vehicle categories
- Regional driving patterns

GAN-generated data can significantly enhance ML model accuracy, support transfer learning, and reduce dependency on costly real-world data collection.

E. Advanced GIS and Digital Twin Integration

Future systems can integrate GIS-based digital twins of entire cities, enabling:

- Real-time simulation of congestion • Predictive what-if analysis
- Smart-city level carbon monitoring

This would allow policymakers and city planners to visualize and evaluate emission hotspots dynamically.

F. Real-Time Streaming Architecture

The FastAPI-based backend can be upgraded using:

- Apache Kafka
- MQTT brokers
- WebSocket-based live updates to enable millisecond-level routing updates suitable for emergency logistics, healthcare supply chains, and hyperlocal delivery services.

G. Multi-Objective Optimization

Beyond carbon reduction, future studies can implement multi-objective optimization frameworks balancing:

- Carbon emissions
- Delivery time
- Operational cost
- Driver safety
- Fuel/Battery consumption

Evolutionary algorithms (e.g., NSGA-II), Pareto fronts, and weighted VRP models can be explored.

Conclusion

The proposed AI-powered Carbon Footprint Optimization (CFO) system presents a comprehensive and intelligent framework for achieving sustainability in logistics and transportation management. By synergizing machine learning, operations research, and real-time data analytics, the system addresses one of the most pressing challenges in modern supply chains—reducing carbon emissions without compromising operational efficiency.

The integration of an XGBoost-based emission prediction model with Google OR-Tools optimization provides a datadriven and computationally efficient solution for emissionaware vehicle routing. The system effectively predicts routespecific CO_2 emissions based on multiple dynamic factors such as distance, load, traffic, and weather, and subsequently optimizes routes to minimize environmental impact. Experimental evaluations demonstrate that the CFO framework significantly improves route efficiency, reduces fuel consumption, and lowers carbon emissions compared to traditional distancebased routing methods.

From an implementation perspective, the modular architecture built on FastAPI ensures scalability, interoperability, and ease of deployment across diverse industrial ecosystems. The use of Folium and Plotly for visualization enhances interpretability by allowing stakeholders to monitor emissions and route performance through an interactive dashboard.

The inclusion of real-time APIs, such as Google Maps and OpenWeather, ensures adaptability to continuously changing environmental and operational conditions.

Beyond logistics, the CFO system also emphasizes computational sustainability by incorporating the concept of the Green Algorithm, which assesses the energy footprint of the computational processes themselves. This dual focus on both operational and computational sustainability extends the relevance of the framework to broader domains such as highperformance computing, AI model training, and smart city infrastructure management.

Furthermore, the system aligns with international sustainability frameworks such as the Paris Agreement, ISO 14064 standards, and the United Nations Sustainable Development Goal (SDG 13 — Climate Action). Through its capability to generate quantifiable and transparent emission data, it supports organizations in achieving regulatory compliance, corporate accountability, and carbon neutrality goals.

Future work will focus on advancing the system's intelligence and adaptability by integrating reinforcement learning (RL) for dynamic route optimization under uncertainty, as well as incorporating multi-objective decision-making techniques that balance emission reduction, cost efficiency, and delivery performance. Additionally, expanding the framework to support multi-vehicle and multi-depot routing, as well as electric vehicle (EV) fleet optimization, will further enhance its practical applicability and environmental impact.

In conclusion, the proposed CFO system represents a robust, scalable, and future-ready solution that bridges the gap between artificial intelligence, environmental science, and sustainable industrial operations. By enabling measurable emission reduction through intelligent computation, it contributes meaningfully toward achieving global carbon neutrality and fostering the vision of a greener, smarter, and more sustainable future.

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