Project Title:
ML-Based Supplier Selection for Low-Carbon Waste Logistics in Cement Plants

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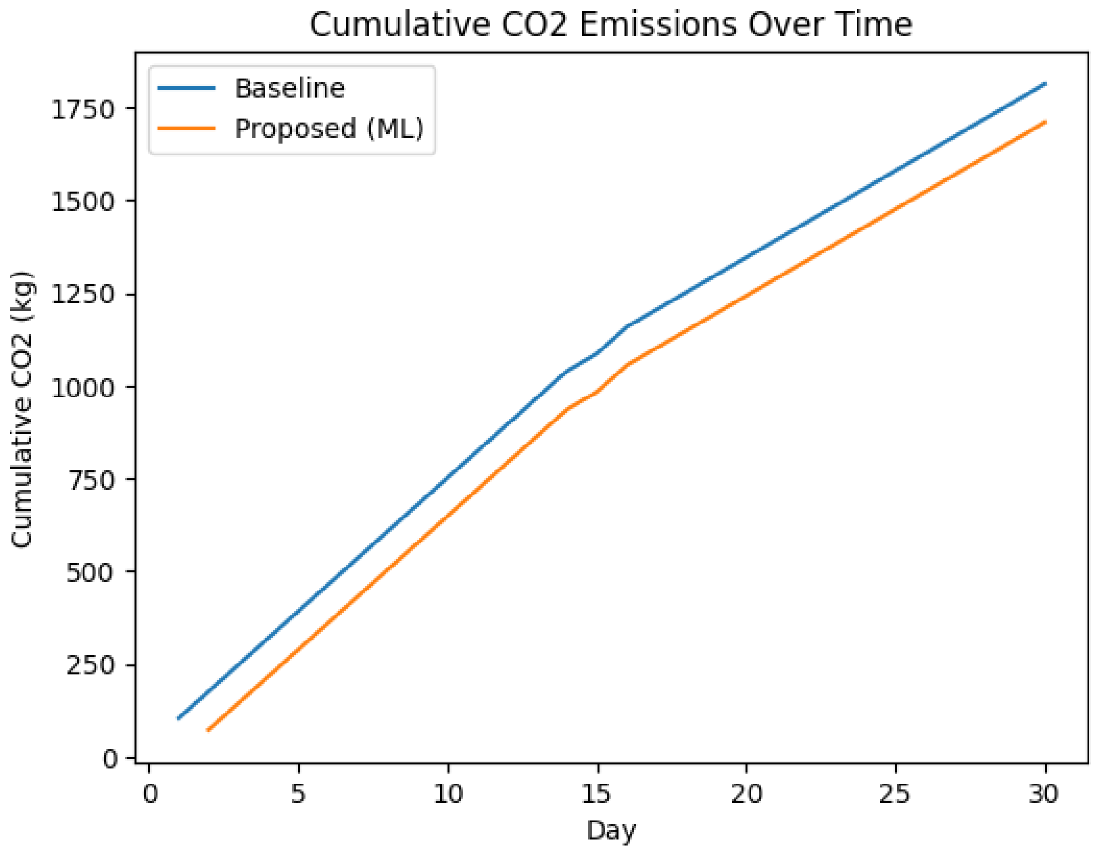
Repository Link (Source Code and Reproducibility):
https://github.com/shatabdabasu/waste_logistics_simulation

Project Summary:
This project studies transport-related CO_2 emission reduction in waste co-processing logistics for cement plants. A fixed daily waste collection target must be met using suppliers located at different distances with variable waste availability. Two approaches are compared: a distance-first baseline heuristic and a forecast-aware decision strategy using lightweight machine learning. Performance is evaluated using a rolling 30-day simulation, with cumulative transport-related CO_2 emissions as the primary metric. The results show that forecast-aware supplier selection can achieve realistic and measurable emission reductions without changing fleet size, routing structure, or operational constraints.



Date:
February 2026

The document includes:

1. Introduction

The cement industry plays a critical role in global infrastructure development, but it is also a significant contributor to carbon emissions. While much of the existing decarbonization effort has focused on energy efficiency and process-level innovations, transport-related emissions associated with waste logistics remain an important yet comparatively underexplored component of the carbon footprint.

Cement plants routinely collect industrial and municipal waste from a fixed set of suppliers to meet daily operational requirements. These waste streams are often heterogeneous and variable in availability, while transport operations typically follow established hub-and-spoke patterns. In practice, supplier selection decisions are frequently guided by simple heuristics, most commonly prioritizing geographically closer suppliers to ensure operational simplicity and feasibility. Although such approaches are easy to implement, they do not explicitly account for variability in waste availability or carbon efficiency, potentially leading to unnecessary transport emissions over time.

Recent advances in machine learning have demonstrated strong potential in forecasting demand, supply, and operational variables across industrial systems. However, much of the literature applies machine learning either as a black-box optimizer or in conjunction with complex routing and scheduling models. These approaches, while powerful, often require extensive data, introduce interpretability challenges, and assume the flexibility to alter routing structures or fleet configurations—assumptions that may not hold in many real-world industrial settings.

This work adopts a deliberately constrained and pragmatic perspective. Rather than redesigning logistics networks or introducing complex optimization frameworks, we investigate whether **lightweight, interpretable machine learning**, applied solely at the forecasting stage, can improve supplier selection decisions under strict operational constraints. The focus is on enhancing decision quality while preserving existing routing structures, fleet characteristics, and daily waste collection targets.

Specifically, this paper compares a distance-first reactive supplier selection policy with a forecast-aware strategy that integrates simple machine learning predictions into the decision process. The performance of both approaches is evaluated using cumulative transport-related CO_2 emissions over a rolling simulation horizon. By emphasizing transparency, fairness of comparison, and realistic assumptions, this study aims to demonstrate how modest ML interventions can yield measurable and scalable carbon reductions in mature industrial logistics systems.

2. Problem Statement

Cement plants routinely collect industrial waste from a fixed set of suppliers to satisfy daily operational requirements. Each supplier is located at a known distance from the plant and provides a variable amount of waste that changes from day to day. Waste collection operations typically follow a hub-and-spoke transport pattern, and transport-related carbon emissions are directly proportional to the distance traveled.

In practice, supplier selection for daily waste collection is often guided by simple heuristics, most commonly prioritizing suppliers based on geographic proximity. While such distance-based strategies ensure feasibility and operational simplicity, they do not account for variability in waste availability or explicitly consider carbon efficiency. As a result, these heuristics may lead to unnecessary long-distance trips, increasing cumulative transport-related CO_2 emissions over time.

At the same time, many industrial settings operate under strict constraints that limit the applicability of complex optimization approaches. Fleet size, routing structure, and daily waste targets are often fixed, leaving limited flexibility for large-scale logistical redesign. Under such conditions, improving decision-making quality—rather than altering infrastructure—becomes a key opportunity for emission reduction.

The problem addressed in this work is therefore to determine whether supplier selection decisions can be improved, under fixed operational constraints, to reduce transport-related carbon emissions. Specifically, given:

- a minimum daily waste collection requirement,
- a fixed set of suppliers with known distances,
- variable daily waste availability,
- and unchanged fleet and routing assumptions,

the objective is to **minimize cumulative transport-related CO_2 emissions over a planning horizon by selecting an effective daily supplier visitation order**.

This study investigates whether lightweight and interpretable machine learning, applied solely at the forecasting stage and combined with simple decision rules, can achieve measurable emission reductions compared to conventional distance-based heuristics.

3. Literature Review

This section reviews prior work related to waste logistics, carbon-aware transport optimization, and the application of machine learning in operational decision-making. The review concludes by identifying the specific research gaps addressed by this study.

3.1 Waste Logistics and Supplier Selection

Waste collection and reverse logistics have been extensively studied in the context of industrial supply chains. Traditional approaches to supplier selection and waste pickup often rely on deterministic heuristics such as distance-based prioritization, fixed schedules, or contractual obligations. These methods emphasize operational feasibility and simplicity but typically assume static or predictable waste availability.

Several studies have modeled waste collection using hub-and-spoke or centralized routing structures, particularly in industrial and municipal settings. In such models, supplier proximity is frequently used as the primary decision criterion due to its direct relationship with transport cost and time. While effective for ensuring daily feasibility, these approaches generally ignore variability in waste generation and do not explicitly incorporate environmental performance metrics such as carbon emissions.

3.2 Carbon-Aware Transport and Logistics Optimization

Carbon emission reduction in transport logistics has been widely explored through vehicle routing problems (VRP), green logistics models, and fuel-efficient routing strategies. Many studies focus on optimizing routes, vehicle allocation, or travel schedules to minimize fuel consumption or emissions. These approaches often assume the flexibility to redesign routes, adjust fleet size, or introduce time-window constraints.

Although effective, such routing-centric optimization methods can be difficult to deploy in mature industrial environments where routing structures, fleet composition, and operational practices are largely fixed. In these contexts, decision-makers often lack the flexibility required to implement complex optimization solutions, limiting the practical applicability of many carbon-aware routing models.

3.3 Machine Learning in Operational Decision-Making

Machine learning has increasingly been applied to forecasting tasks in supply chain and logistics systems, including demand prediction, waste generation forecasting, and resource utilization estimation. Regression-based models, time-series methods, and more recently deep learning techniques have been employed to capture temporal patterns in operational data.

However, much of the existing literature treats machine learning either as a standalone prediction task or as a component within black-box optimization frameworks. In many cases, ML outputs are tightly coupled with complex decision solvers, making it difficult to isolate the contribution of forecasting accuracy from decision logic. Furthermore, highly complex models often raise concerns related to interpretability, data requirements, and robustness, particularly when available datasets are limited.

3.4 Identified Research Gaps

Based on the reviewed literature, the following gaps are identified:

1. **Limited focus on supplier ordering decisions**
   Existing studies largely emphasize routing and scheduling optimization, with comparatively little attention given to supplier selection and visitation order under fixed routing assumptions.

2. **Overreliance on complex optimization and black-box ML models**
   Many approaches combine advanced ML with sophisticated optimization techniques, reducing transparency and increasing deployment complexity in real-world industrial settings.

3. **Insufficient evaluation under strict operational constraints**
   Few studies evaluate emission reduction strategies while explicitly holding fleet size, routing structure, and daily operational targets constant.

4. **Lack of realistic, marginal improvement analysis**
   The literature often targets large emission reductions, while small but realistic improvements achievable through decision refinement alone are underreported.

3.5 Contribution of This Work

This study addresses these gaps by proposing a lightweight, interpretable ML-assisted supplier selection strategy that operates entirely within existing logistics constraints. By isolating supplier ordering as the decision variable and using simple forecasting models, the work demonstrates how modest yet meaningful emission reductions can be achieved without infrastructure changes or complex optimization frameworks.

4. Problem Formulation and Assumptions

This section formalizes the waste collection problem, emission model, and decision criteria used in both the baseline and proposed approaches.

4.1 System Definition

Let:

- $S = \{S_1, S_2, \dots, S_N\}$be the set of waste suppliers
- $d_i$be the fixed distance (km) from the plant to supplier S_i
- $w_i(d)$be the actual waste available at supplier $S_i$on day d
- $\hat{w}_i(d)$be the predicted waste for supplier $S_i$on day d
- $W_{\min} = 60$tons be the minimum daily waste requirement

4.2 Operational Constraints

- Number of trucks: $T = 3$
- Capacity per truck trip: $C = 20$tons

- Maximum daily capacity:

$$T \times C = 60 \text{ tons}$$

- Collection stops once:

$$\sum w_i(d) \geq W_{\min}$$

Trips per truck per day are assumed to be unlimited; therefore, vehicle availability does not constrain supplier selection decisions.

4.3 Emission Model

Transport-related carbon emissions are modeled as proportional to distance traveled.

Let:

- $e = 0.9$kg CO_2 per km be the emission factor

The CO_2 emission for visiting supplier $S_i$is:

$$\text{CO}_2(S_i) = e \times d_i$$

Total emissions on day $d$are:

$$\text{CO}_2(d) = \sum_{i \in V(d)} e \times d_i$$

where $V(d)$is the set of suppliers visited on day d.

The cumulative emissions over a planning horizon $D$are:

$$\text{CO}_2^{\text{total}} = \sum_{d=1}^{D} \text{CO}_2\,(d)$$

4.4 Baseline Decision Rule (Distance-First)

In the baseline model, suppliers are visited in increasing order of distance:

$$S_i \prec S_j \text{if} d_i < d_j$$

No historical data or forecasting is used. Actual waste $w_i(d)$is revealed only upon visiting a supplier.

4.5 Proposed ML-Based Forecasting Model

To incorporate historical information, a linear regression model is trained independently for each supplier.

For supplier S_i, waste availability is modeled as:

$$w_i(d) = \alpha_i d + \beta_i + \varepsilon$$

where:

- $d$denotes the day index
- $\alpha_i, \beta_i$are learned parameters
- $\varepsilon$is the error term

The model is trained using past observations only, producing a forecast:

$$\widehat{w}_i(d)$$

4.6 Supplier Scoring and Ranking

Using the predicted waste, suppliers are ranked using a waste-efficiency score:

$$\text{Score}_i(d) = \frac{\widehat{w}_i(d)}{d_i}$$

Suppliers are visited in descending order of this score:

$$S_i \prec S_j \text{if} \text{Score}_i(d) > \text{Score}_j(d)$$

This prioritizes suppliers expected to yield higher waste per kilometer traveled.

4.7 Optimization Objective

The objective of both models is to satisfy the daily waste requirement while minimizing cumulative transport-related emissions:

$$\min \sum_{d=1}^{D} \sum_{i \in V(d)} e \times d_i$$

subject to:

$$\sum_{i \in V(d)} w_i\,(d) \geq W_{\min} \forall d$$

6. Proposed Algorithm and System Architecture

This section describes the proposed machine-learning-assisted supplier selection algorithm and the overall system architecture used to reduce transport-related carbon emissions under fixed operational constraints.

6.1 Overview of the Proposed Approach

The proposed approach integrates machine learning into the supplier selection process in a **limited and interpretable manner**. Machine learning is used **only to forecast waste availability**, while the final decision-making relies on a simple, transparent ranking rule.

The core idea is to prioritize suppliers that are expected to provide **higher waste yield per unit distance**, thereby improving carbon efficiency without modifying routing structure, fleet size, or daily operational constraints.

6.2 Algorithm Inputs and Outputs

Inputs

- Historical daily waste data for each supplier
- Fixed supplier-to-plant distances
- Minimum daily waste requirement $W_{\min}$
- Emission factor e

Outputs

- Daily supplier visitation order
- Daily and cumulative transport-related CO_2 emissions

6.3 System Architecture

The system architecture consists of four main components:

1. **Data Input Layer**
    - Historical waste data for each supplier
    - Fixed distance data
2. **Forecasting Module (ML Layer)**
    - Independent linear regression model per supplier
    - Trained on past waste observations only

- Outputs predicted waste for the current day

3. **Decision Module (Ranking Layer)**
    - Computes a waste-efficiency score for each supplier
    - Ranks suppliers based on predicted waste per unit distance
4. **Execution and Evaluation Module**
    - Simulates supplier visits in ranked order
    - Collects actual waste values
    - Stops when daily target is met
    - Accumulates CO_2 emissions

This modular design ensures interpretability and allows clear attribution of performance gains to individual components.

6.4 Forecasting Model

For each supplier S_i, waste availability is forecasted using a linear regression model trained on historical data:

$$w_i(d) = \alpha_i d + \beta_i + \varepsilon$$

where:

- $d$is the day index
- $\alpha_i, \beta_i$are learned parameters
- εrepresents random error

The trained model produces a forecast $\widehat{w}_i(d)$for the current day. Training is performed in a rolling manner, ensuring that only past data is used.

6.5 Supplier Scoring and Ranking

Using the predicted waste values, each supplier is assigned a waste-efficiency score:

$$\text{Score}_i(d) = \frac{\widehat{w}_i(d)}{d_i}$$

where $d_i$is the distance to supplier S_i.

Suppliers are ranked in **descending order of this score**, prioritizing those expected to deliver higher waste quantities per kilometer traveled.

6.6 Execution Logic

Once the supplier order is determined, the execution process proceeds as follows:

- Suppliers are visited sequentially according to the ranking
- Actual waste $w_i(d)$is revealed upon visiting each supplier
- Collected waste is accumulated
- Transport-related CO_2 emissions are added for each visit
- The process stops once the cumulative waste meets or exceeds $W_{\min}$

This execution logic is identical to the baseline model, ensuring a fair comparison.

6.7 Algorithm Steps (Proposed Model)

Step 1: For each supplier, collect historical waste data up to day $d - 1$
Step 2: Train a linear regression model for each supplier
Step 3: Predict waste availability for day d
Step 4: Compute waste-efficiency score $\widehat{w}_i(d)/d_i$
Step 5: Rank suppliers by decreasing score
Step 6: Visit suppliers in ranked order and collect actual waste
Step 7: Stop when daily waste target is reached
Step 8: Record CO_2 emissions

6.8 Comparison with Baseline

The proposed algorithm differs from the baseline only in the **supplier ordering mechanism**. All other aspects, including execution logic, emission accounting, and operational constraints, remain unchanged. This isolates the effect of forecast-aware decision-making on emission reduction.

7. Experimental Setup

This section describes the dataset, simulation framework, and evaluation methodology used to assess the performance of the baseline and proposed supplier selection strategies.

7.1 Dataset Description

The experiments are conducted using a **synthetic dataset** representing daily waste availability across a fixed set of suppliers. The dataset consists of:

- **30 consecutive days** of observations
- **12 suppliers** $(S_1, S_2, \ldots, S_{12})$
- Supplier-specific waste availability that varies daily
- Fixed supplier-to-plant distances that remain constant over time

The synthetic data is designed to capture realistic variability in waste generation while enabling controlled experimentation and fair comparison between models.

7.2 Simulation Framework

A **rolling (walk-forward) simulation** framework is employed to evaluate both models. On each day d:

- Decisions are made using only data available up to day $d - 1$
- No future waste information is used for forecasting or decision-making
- Actual waste values for day $d$are revealed only when suppliers are visited

This framework prevents data leakage and closely reflects real-world operational conditions where future waste availability is unknown.

7.3 Model Execution Protocol

Both the baseline and proposed models are executed under **identical operational constraints**, differing only in their supplier ordering logic.

- **Baseline model:**
  Suppliers are visited in increasing order of distance from the plant, without using historical data or forecasts.
- **Proposed model:**
  Supplier ordering is determined using machine-learning-based forecasts and a waste-efficiency scoring rule.

For both models:

- Suppliers are visited sequentially according to the determined order
- Actual waste is collected upon visiting each supplier
- Collection stops immediately once the daily waste target is met
- Transport-related CO_2 emissions are accumulated per supplier visit

7.4 Evaluation Metrics

The primary evaluation metric is **cumulative transport-related CO_2 emissions** over the full simulation horizon:

$$\mathrm{CO}_2^{\mathrm{total}} = \sum_{d=1}^{30} \sum_{i \in V(d)} e \times d_i$$

where $V(d)$denotes the set of suppliers visited on day d.

Secondary observations include:

- Daily CO_2 emissions
- Cumulative CO_2 emission trends over time

Prediction accuracy metrics are not emphasized, as the objective of this study is to evaluate **decision impact**, not forecasting performance.

7.5 Visualization Strategy

To support result interpretation, the following visualizations are generated:

- A **bar chart** comparing total CO_2 emissions for the baseline and proposed models
- A **cumulative CO_2 line plot** illustrating how emission differences evolve over time

These visualizations provide both quantitative and temporal insights into the impact of forecast-aware supplier selection.

7.6 Fairness and Reproducibility

To ensure a fair and reproducible evaluation:

- Both models use the same dataset and parameters
- Fleet size, routing structure, and emission factors are identical
- Stopping conditions and execution logic are unchanged
- The only difference lies in the supplier ordering strategy

This design isolates the effect of the proposed ML-assisted decision rule on transport-related emissions.

8. Results and Comparative Analysis

This section presents the experimental results obtained from the 30-day rolling simulation and compares the performance of the baseline and proposed supplier selection strategies.

8.1 Quantitative Results

The cumulative transport-related CO_2 emissions recorded over the 30-day simulation period are summarized below:

- **Baseline (distance-first):** 1813.5 kg CO_2
- **Proposed (ML-based):** 1710.0 kg CO_2

The proposed strategy achieves an **absolute reduction of 103.5 kg CO_2**, corresponding to a **5.71% decrease** in cumulative emissions relative to the baseline.

When extrapolated to an annual scale under similar operating conditions, this reduction corresponds to approximately **1.24 tons of CO_2 saved per plant per year**.

8.2 Comparative Performance Analysis

Both models consistently meet the minimum daily waste collection requirement, indicating that emission reductions are achieved **without compromising operational feasibility**. The baseline model frequently reaches the daily target by visiting nearby suppliers, resulting in similar performance on many days. However, on marginal days—where waste availability among nearby suppliers is insufficient—the distance-first heuristic tends to select additional distant suppliers, increasing emissions.

In contrast, the proposed model uses forecast-aware supplier ordering to anticipate waste availability, allowing it to prioritize suppliers that are expected to provide higher waste yields relative to travel distance. This results in fewer unnecessary long-distance trips on such marginal days.

8.3 Temporal Emission Trends

The cumulative CO_2 emission trajectories for both models show that:

- Daily emission differences are often small
- The cumulative emission gap between models increases steadily over time

This trend indicates that the benefits of forecast-aware decision-making **compound over the simulation horizon**, reinforcing the practical significance of modest daily improvements.

8.4 Interpretation of Results

The observed emission reduction is intentionally modest but realistic. Given the strict operational constraints and the frequent attainment of the daily target using nearby suppliers, the potential for large reductions is inherently limited. Achieving a 5–6% reduction without altering fleet size, routing structure, or operational targets represents a meaningful improvement in a mature industrial logistics setting.

Importantly, the proposed model maintains interpretability and avoids the risks associated with complex optimization or black-box learning approaches. The results demonstrate that even simple machine learning models, when applied judiciously, can enhance operational decision quality.

8.5 Summary of Comparative Findings

- Both models satisfy daily waste collection requirements

- The proposed ML-based strategy consistently emits less CO_2
- Emission reductions emerge primarily on marginal decision days
- Small daily improvements accumulate into significant long-term savings

9. Visualizations

This section presents the visual outputs used to support and illustrate the experimental findings. All visualizations were generated using the simulation results obtained under identical operational constraints for both models.

9.1 Total CO_2 Emissions Comparison

Figure 1 presents a bar chart comparing the total transport-related CO_2 emissions over the 30-day simulation period for the baseline and proposed models.

- The baseline model records higher cumulative emissions.
- The proposed ML-based model achieves a lower total CO_2 value under the same conditions.

This visualization provides a direct and intuitive comparison of overall environmental impact between the two strategies.

9.2 Cumulative CO_2 Emissions Over Time

Figure 2 illustrates the cumulative CO_2 emissions plotted against time (days) for both models.

- Both curves start from a common origin.
- The cumulative emissions for the proposed model grow more slowly.
- The gap between the curves increases steadily over time.

This visualization highlights the **compounding effect** of small daily emission reductions achieved through forecast-aware supplier selection.

9.3 Interpretation of Visual Results

Together, the visualizations confirm that:

- Emission reductions are consistent across the simulation horizon.
- Improvements are not driven by isolated outliers.
- Modest daily gains accumulate into meaningful long-term savings.

These figures support the quantitative results reported in Section 8 and reinforce the practical relevance of the proposed approach.

10. Discussion

The results demonstrate that integrating lightweight machine learning into supplier selection decisions can produce measurable reductions in transport-related carbon emissions, even under strict operational constraints. The observed 5.71% reduction, while modest in absolute terms, is significant given that no changes were made to fleet size, routing structure, or daily waste collection requirements.

A key insight from this study is that most operational days already achieve the required waste target using nearby suppliers. Consequently, the scope for large emission reductions is inherently limited. The proposed ML-based strategy delivers benefits primarily on marginal days, when distance-first heuristics would otherwise select additional distant suppliers due to uncertainty in waste availability. By anticipating waste yields more effectively, the proposed approach avoids unnecessary long-distance trips, leading to incremental but consistent emission savings.

The cumulative emission trends further highlight the importance of decision quality over time. Although daily differences are often small, the steady divergence between the baseline and proposed cumulative emission curves illustrates how minor improvements compound into meaningful long-term benefits. This finding underscores the value of evaluating sustainability interventions over extended horizons rather than focusing solely on short-term or daily performance.

Another important consideration is interpretability. Unlike complex optimization frameworks or black-box learning models, the proposed approach maintains transparency at both the forecasting and decision-making stages. The use of simple linear regression enables clear understanding of how historical data influences predictions, while the waste-efficiency ranking rule provides an intuitive explanation for supplier prioritization. This interpretability enhances trust and facilitates adoption in industrial environments where explainability is critical.

Finally, the results suggest that meaningful sustainability gains do not necessarily require disruptive technological changes. In mature industrial systems, where operational flexibility is limited, carefully targeted improvements to decision logic—supported by modest machine learning—can deliver realistic and scalable emission reductions. This perspective aligns with practical constraints faced by many industrial operators and highlights the potential of incremental, data-informed optimization strategies.

11. Limitations and Future Work

While the proposed approach demonstrates measurable reductions in transport-related carbon emissions, several limitations should be acknowledged.

First, the experimental evaluation is conducted using **synthetic data** over a relatively short time horizon of 30 days. Although the data is designed to reflect realistic variability, real-world waste streams may exhibit seasonal patterns, abrupt supplier disruptions, or structural changes that are not captured in this dataset. As such, the numerical results should be interpreted as indicative rather than predictive.

Second, the study considers a **single-plant scenario** with a fixed set of suppliers. In practice, industrial waste logistics may involve multiple plants, shared suppliers, and interdependent transport decisions. Extending the proposed framework to multi-plant or network-level settings could reveal additional opportunities for emission reduction.

Third, operational constraints are deliberately simplified. The model assumes unlimited trips per truck per day and does not account for travel time, driver availability, or time-window constraints.

Incorporating such constraints would increase realism but would also require more complex modeling, potentially interacting with routing and scheduling decisions.

Fourth, the forecasting component employs **simple linear regression** models trained independently for each supplier. While this choice supports interpretability and robustness under limited data, it may not fully capture nonlinear or seasonal patterns present in real waste generation processes. More advanced forecasting methods could improve predictive accuracy, though they may introduce additional complexity and reduce transparency.

Future work may address these limitations by:

- Evaluating the approach on real operational data from cement plants
- Extending the simulation horizon to capture seasonal effects
- Integrating uncertainty-aware or probabilistic forecasting models
- Incorporating routing, travel-time, or vehicle availability constraints
- Studying the trade-offs between model complexity, interpretability, and emission reduction potential

- ## 12. Conclusion
- This paper investigated the role of lightweight machine learning in reducing transport-related carbon emissions in waste collection logistics for cement plants. Focusing on a constrained and realistic operational setting, the study compared a conventional distance-first supplier selection heuristic with a forecast-aware strategy that integrates simple machine learning predictions into the decision process.
- Using a 30-day rolling simulation under identical constraints, the proposed ML-assisted approach achieved a **5.71% reduction in cumulative CO_2 emissions** compared to the baseline, corresponding to an estimated **annual reduction of approximately 1.24 tons of CO_2 per plant** under similar operating conditions. These gains were achieved without altering fleet size, routing structure, or daily waste collection targets, demonstrating that meaningful environmental improvements can arise from improved decision logic alone.
- The results highlight two key insights. First, in mature industrial logistics systems with limited flexibility, large emission reductions are inherently difficult to achieve. Second, modest daily improvements—enabled by better anticipation of operational variability—can compound into significant long-term benefits. By restricting machine learning to the forecasting stage and employing transparent decision rules, the proposed approach balances performance improvement with interpretability and practical deployability.
- Overall, this work shows that **incremental, interpretable ML interventions** can play a valuable role in advancing sustainability objectives in industrial operations. Rather than replacing existing systems, such approaches can enhance decision-making quality within established constraints, offering a pragmatic pathway toward lower-carbon logistics.

13. References

1. McKinnon, A., Browne, M., Whiteing, A., & Piecyk, M., *Green Logistics: Improving the Environmental Sustainability of Logistics*, Kogan Page, 2015.

2. Bektaş, T., & Laporte, G., "The Pollution-Routing Problem," *Transportation Research Part B*, vol. 45, no. 8, pp. 1232–1250, 2011.

3. Demir, E., Bektaş, T., & Laporte, G., "A review of recent research on green road freight transportation," *European Journal of Operational Research*, vol. 237, no. 3, pp. 775–793, 2014.

4. Carbonneau, R., Laframboise, K., & Vahidov, R., “Application of machine learning techniques for supply chain demand forecasting,” *European Journal of Operational Research*, vol. 184, no. 3, pp. 1140–1154, 2008.

5. Makridakis, S., Spiliotis, E., & Assimakopoulos, V., “Statistical and Machine Learning forecasting methods: Concerns and ways forward,” *PLOS ONE*, 2018.

6. Benjaafar, S., Li, Y., & Daskin, M., “Carbon footprint and the management of supply chains,” *IEEE Transactions on Automation Science and Engineering*, vol. 10, no. 1, pp. 99–116, 2013.