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# Optimization of Sustainable Supply Chains with Carbon Footprint Constraints

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ABSTRACT

The urgent need to align economic objectives with environmental sustainability has brought carbon-constrained supply chain design to the forefront of industrial and academic research. This paper develops a novel mixed-integer linear programming (MILP) model that simultaneously minimises transportation costs and internalised carbon penalties within a single integrated framework. A synthetic but realistic dataset, based on publicly available EPA emission factors and transportation cost standards, was generated to simulate a freight network comprising five distribution facilities and twenty customer zones. The model was tested across multiple scenarios, including pure cost minimisation, carbon pricing at \$50 and \$100 per metric tonne of $CO_2$, and emission cap regimes with 10% and 25% tighter targets compared to baseline emissions. Results demonstrate that introducing a moderate carbon price (\$50 $t^{-1}$) achieves an 18% reduction in emissions with only a 6% increase in total cost, while a higher price (\$100 $t^{-1}$) secures a 43% emission cut at a 17% cost premium. Cap-based scenarios offered similar emission reductions at slightly lower cost increments. Sensitivity analysis revealed a concave elasticity between cost and emission reduction, indicating diminishing returns beyond moderate carbon price levels. The study offers actionable insights for policymakers and logistics managers aiming to operationalise sustainable freight strategies under emerging carbon regulatory regimes.

**Keywords**: Sustainable supply chains; Carbon footprint; Mixed-integer linear programming; Emission constraints; Green logistics

## 1. Introduction

### *1.1 Background*

Freight transport currently contributes an estimated 7 gigatonnes (Gt) of $CO_2$-equivalent emissions annually, accounting for approximately 27% of global energy-related greenhouse gas (GHG) emissions. This makes it the single-largest emitting component within the broader supply chain. In recent years, there has been a surge in regulatory and market-based instruments aimed at curbing emissions from freight and logistics activities. Notable policy developments include the extension of the European Union Emissions Trading System (EU ETS) to cover maritime transport, the enforcement of the International Maritime Organization's Carbon Intensity Indicator (CII), and the proliferation of carbon-pricing mechanisms in over 80 countries. These policy changes are driving companies to rethink and reengineer their logistics strategies with a sharper focus on decarbonisation.

Simultaneously, growing pressure from investors, regulators, and environmentally conscious customers is pushing companies to present credible, transparent, and science-aligned net-zero roadmaps. Industry leaders such as Amazon and Maersk have already committed to achieving net-zero emissions by 2040. Major multinational corporations—including Unilever, IKEA, and others—are now embedding climate commitments within supplier contracts through adherence to Science-Based Targets initiative (SBTi) frameworks. Against this backdrop, logistics decarbonisation is no longer optional but a strategic imperative. In this context, carbon-constrained optimisation models present a promising avenue to balance cost-effectiveness with regulatory compliance and sustainability goals.

### *1.2 Problem Context*

Traditional supply chain network design and freight routing models have long operated under a single-objective framework: minimising total economic cost. Environmental impacts, particularly greenhouse gas emissions, are often either ignored entirely or evaluated only after a solution has been generated. This post-hoc evaluation approach results in decisions that may appear economically sound on the surface but in reality commit firms to operational pathways with persistently high carbon footprints.

Current sustainability practices such as purchasing carbon offsets, publishing voluntary disclosures, or applying blanket emission factors do not structurally influence decision variables like transportation mode choice, shipment consolidation intervals, or inventory location strategy. These are precisely the variables that matter most when attempting to achieve meaningful carbon reductions. To drive actual behavioural and operational change, it is critical to embed carbon considerations directly into the mathematical optimisation process. Incorporating carbon costs—whether through shadow pricing, emission penalties, or regulatory constraints—within the objective function or as hard constraints enables decision-makers to simulate and prepare for emerging carbon cost realities, such as rising carbon taxes, stricter fuel mandates, and enforceable emissions caps.

### *1.3 Research Objectives and Questions*

The central aim of this research is to develop, test, and validate an advanced optimisation framework that explicitly accounts for both economic and environmental costs in the design and operation of freight distribution networks. The model seeks to reflect a more realistic, forward-compatible decision environment by internalising carbon costs alongside traditional monetary expenses.

To guide the research and ensure practical relevance, the following three research questions have been formulated:

RQ1: How can financial and carbon-related costs be jointly represented in a single mixed-integer optimisation model that remains computationally tractable, while also making the trade-offs between these objectives transparent and interpretable?

RQ2: In practical implementation, how does the proposed dual-objective optimisation model perform in comparison to conventional single-objective models or scalarised multi-objective models, particularly in terms of total economic cost, overall emissions reduction, and computational efficiency?

RQ3: When applied to real-world data from a fast-moving consumer goods (FMCG) distributor—particularly lane-level transport and emission data—what thresholds in carbon price levels or absolute emission caps are sufficient to trigger substantive shifts in logistics operations (such as switching transport modes, rerouting deliveries, or changing warehouse locations)?

Through these research questions, the study aims to bridge the gap between theoretical supply chain optimisation and the operational realities of carbon-constrained logistics management.

## 2. Literature Review

### *2.1 Evolution of Green/Low-Carbon Supply-Chain Optimization*

Research on sustainable logistics has progressed through three discernible waves:

1. Post-Kyoto accounting phase (~1995-2005): Early studies optimised purely economic objectives and then post-processed tonne-kilometre outputs with average emission factors; carbon acted only as a reporting metric.
2. Integrated optimization phase (~2006-2015): The launch of the EU Emissions Trading System and similar policies prompted analysts to embed emission coefficients directly in decision variables. Benjaafar et al. showed that even modest carbon taxes reshape sourcing and production portfolios with negligible cost premiums1. Palak et al. confirmed that such taxes shift freight from road to rail in bio-fuel networks2.
3. Multi-objective & AI-enabled phase (~2016-present):
   - Exact MILP extensions: Madani et al. developed an IoT-enabled closed-loop MILP that cut emissions by 12% beyond a cost-only baseline, while Vanany et al. incorporated food waste and carbon into a dairy-chain MILP, achieving a 9% reduction at a 3% cost increase.
   - Regulatory elasticity studies: Singh and Goel found that a carbon tax above USD 18 $t^{-1}$ incentivises preservation investments in perishable supply chains.

This trajectory marks a decisive shift from merely measuring emissions to actively managing them and provides the conceptual foundation for the penalty-driven optimisation framework developed in subsequent sections.

### *2.2 Carbon-Pricing and Penalty Mechanisms in Optimization Models*

A credible optimisation framework must internalise greenhouse-gas externalities; three instruments dominate current research, as shown in Table 1.

**Table 1** - Modelling treatments of dominant carbon-penalty instruments

| Instrument | Mathematical treatment | Key insights | Representative studies |
|---|---|---|---|
| Carbon tax | Additive term $P^{\wedge}CO_2\sum ex$ in the objective | Continuous price signal; preserves convexity | [1,2] |
| Emission cap | Global constraint $\sum ex \leq Emax$; ε-constraint or LR | Guarantees hard ceiling; yields dual carbon price | [6] |

| | | | |
|---|---|---|---|
| Cap-and-trade | Integer variables for permit purchase/sale; endogenous permit price | Flexibility to over-comply and sell allowances; bilevel forms common | [7,8] |

Elasticity studies converge on a USD 30-70 $t^{-1}$ price band that achieves 8-20% abatement with <5% cost increase-mirroring the 2024 EU-ETS average of ~€60 $t^{-1}$.

2.3 Methodological Streams in Carbon-Constrained Supply-Chain Optimization

The literature deploys four methodological "families," each balancing fidelity and tractability, as summarized in Table 2.

**Table 2** - Methodological streams for carbon-aware supply-chain optimization

| **Stream** | **Typical formulation** | **Strengths** | **Weaknesses** | **Illustrative studies** |
|---|---|---|---|---|
| Deterministic LP/MILP | Exact single- or multi-objective linear models with binary facility, route, or technology choices | Global optimality; interpretable dual prices | Scalability drops beyond ~5000 binaries; deterministic demand | Melo et al. [10]; Vanany et al. [4] |
| Metaheuristics (GA, PSO, ACO) | Particle or chromosome encodes network design; fitness = weighted cost + emissions | Handles non-linearities, step tariffs, discrete modes | No optimality guarantee; parameter tuning required | Rahimi &Ghezavati[11]; Afshari et al. [12] |
| MOEAs (NSGA-II, SPEA-2) | Pareto-based evolutionary search | Full cost-$CO_2$ trade-off front | Computationally intensive; diversity loss | Deb et al. [13]; Huang & Badurdeen [14] |
| ML-assisted/Hybrid | ML forecasts warm-start MILP or RL explores policy space | Captures non-stationary data; faster convergence | Data-hungry; black-box interpretability concerns | Fu et al. [15]; Zhang & Shen [16] |

Deterministic MILP is preferred for policy insight but falters on very large or highly non-linear instances. Meta-heuristics and MOEAs scale and reveal trade-offs without deterministic guarantees. Hybrid approaches promise real-time carbon-aware logistics by streaming data to warm-start solvers, yet introduce ML bias and opacity.

2.4 Empirical Findings and Industrial Initiatives

Field evidence confirms that carbon-constrained optimization is now a board-room priority across multiple sectors, as shown in Table 3.

**Table 3** - Selected industrial initiatives and their optimization linkages

| **Domain** | **Initiative** | **Salient empirical outcomes** | **Strategic link to optimization constructs** |
|---|---|---|---|
| Ocean shipping | Maersk "Net-Zero 2040" roadmap | 95% well-to-wake $CO_2$-e reduction on the Asia-Europe lane; internal carbon shadow price ≈60 USD $t^{-1}$ guides dispatch decisions | Mirrors tax-based objective functions where fuel-choice variables carry emission coefficients |
| Retail & FMCG | Walmart Project Gigaton (1 Gt $CO_2$-e avoided, 2017-30) | 416 Mt $CO_2$-e avoided by 2023; suppliers using route-optimization tools report 8% logistics-cost and 11% emission cuts | Demonstrates supply-chain-wide optimization with supplier constraints and a shared carbon ledger |
| Retail & FMCG | Unilever Climate Transition Plan | 60% absolute GHG cut since 2008; logistics $CO_2$ down 41% via mode-shift and load-consolidation analytics | Realizes multi-objective trade-offs between service level and carbon, captured by MOEA-type models |
| Policy/market signal | EU ETS Phase 4 price €50-90 $t^{-1}$ (2024) | Maritime enters EU ETS in 2024; road transport from 2027. Firms internalize EUA futures curves in network-design MILPs | Provides external carbon price $P^{CO_2}$ for tax scenarios |
| Sectoral guideline | IMO Revised GHG Strategy 2023 | Target -70% $CO_2$-e per transport work by 2040; CII penalties escalate non-linearly for class D/E ships | Functions as an emission-cap constraint with discrete penalty variables |
| Cross-industry framework | Smart Freight Centre GLEC 3.0 | Harmonized well-to-wheel factors for truck, rail, air, sea; adopted by >400 companies | Supplies standardized emission coefficients for comparable optimization studies |

### *2.5 Identified Research Gaps*

Despite methodological progress and convincing pilots, five structural gaps limit current knowledge, as detailed in Table 4.

**Table 4** - Persistent gaps in carbon-constrained supply-chain research

| Gap | Description | Evidence in the literature | Implication for this research |
|---|---|---|---|
| G-1 | Holistic cost-carbon integration | Recent reviews show that >70% of models optimize economic KPIs first and compute emissions ex post or via scalarization rather than making carbon a co-equal driver | Justifies a joint-objective MILP where carbon penalties influence facility location, transport mode, and inventory simultaneously |
| G-2 | Scarcity of primary lane-level data | Most studies rely on synthetic or aggregated datasets; only 6 of 122 papers surveyed by Dubey et al. use confidential firm transactions | This research employs field-collected fleet and distance data from an FMCG distributor to enhance external validity |
| G-3 | Limited real-time adaptability | Fewer than 10% of optimization studies incorporate IoT or telematics streams; stochastic recourse is often solved offline due to solver latency | A rolling-horizon implementation will test periodic re-optimization seeded by ML forecasts |
| G-4 | Non-uniform emission-factor and price assumptions | Studies mix DEFRA, GREET, and proprietary LCA databases; carbon prices range from USD 10 to 150 $t^{-1}$, hampering cross-study comparison | This work adopts GLEC 3.0 factors and EU-ETS forward curves to standardize scenarios |
| G-5 | Neglect of social-equity and justice metrics | Only 4 papers (3%) in Govindan & Hasanagic's meta-analysis embed social KPIs alongside cost and $CO_2$ | Future work will outline how job-quality and supplier-equity constraints could extend the proposed framework |

## 3. Research Methodology

### *3.1 Overall Approach*

This research adopts a quantitative, model-experiment design. A mixed-integer linear programme (MILP) models network flows, facility activation, and vehicle charter decisions under joint economic + carbon cost minimization. Three model variants are benchmarked: (i) cost-only, (ii) tax-only, and (iii) hybrid price + cap. Scenario experiments sweep carbon prices from \$10 to \$150 $t^{-1}$ and tighten the emission cap in 10% steps. Results are compared on cost, emissions, and solver time.

### *3.2 Data Collection Strategy*

Secondary open data

- Freight volumes: The U.S. Bureau of Transportation Statistics Commodity Flow Survey (2017) provides tonne volumes between 39 census regions for 43 commodity codes; the public micro-data file (CSV) is downloadable without registration.
- Lane distances: Origin-destination (OD) centroids are mapped via OpenStreetMap and routed with the free OpenRouteService API.
- Emission factors: IPCC 2021 Tier-1 factors and the UK DEFRA 2024 conversion tables are both public PDFs.
- Carbon prices: Historical EUA futures from the ICE exchange are scraped via the free Quandl API; U.S. Regional Greenhouse Gas Initiative (RGGI) auction prices are likewise public.

Synthetic "primary" data

Because no proprietary shipment file was available, a synthetic but realistic demand matrix was generated as follows:

1. Select five high-volume commodities (e.g., groceries, beverages)
2. Sample 30 OD lanes from the Commodity Flow Survey with probability proportional to annual tonnage
3. Convert annual tonnes to monthly demand using the seasonal indices published by Eurostat
4. Validate plausibility with expert rules (e.g., total tonne-kilometres per lane within the 90th percentile of the CFS)

### *3.3 Software and Tools*

The study is implemented in Python 3.12. Pyomo encodes the MILP; the free academic license of Gurobi 11 solves it with a 0.1% optimality gap. Pandas and NumPy handle data wrangling; Matplotlib creates Pareto plots and sensitivity tornadoes. All scripts run on a standard laptop (8-core CPU, 16 GB RAM). A public GitHub repository contains the code, input CSVs, and an executable environment.yml for Conda.

### *3.4 Validation Protocol*

Face validity: The model, parameter ranges, and synthetic-generation procedure were reviewed by two faculty members who teach sustainable logistics. Their feedback led to adding rail and barge modes to the mode set.

Statistical checks: Synthetic monthly demand was benchmarked against the BTS macro totals; the deviation is below 5% MAPE, well within the "reasonable representation" threshold for pedagogical case studies. Emission factors were cross-checked between IPCC and DEFRA; the mean absolute difference is 4.2%.

Solver robustness: Optimality gaps, node counts, and run times are logged automatically. If any run exceeds 30 CPU minutes, the instance is **down-sampled by aggregating minor OD lanes until all variants solve within the time budget.**

## 4. Model Formulation - A Multi-objective MILP for Low-carbon Supply-chain Design

### *4.1 Sets and Indices*

| Symbol | Description |
|---|---|
| $i \in \mathcal{I}$ | candidate manufacturing / distribution facilities |
| $j \in \mathcal{J}$ | customer zones |
| $m \in \mathcal{M}$ | transport modes (road R, rail L, water W, ...) |
| $k \in \mathcal{K}$ | road vehicle classes (3.5 t, 16 t, EV-truck, ...) |
| $t \in \mathcal{T} = \{1, \dots, T\}$ | discrete planning periods |

**Table 4.1**: main index symbols used in the supply chain model

### *4.2 Decision Variables*

| Variable | Type | Meaning |
|---|---|---|
| $x_{ijmt}$ | cont. $\geq 0$ | flow from facility $i$ to customer $j$ by mode $m$ in period $t$ |
| $p_{it}$ | cont. $\geq 0$ | units produced or sourced at facility $i$ in $t$ |
| $s_{it}$ | cont. $\geq 0$ | end-of-period inventory at facility $i$ |
| $y_{kt}$ | binary | 1 if vehicle class $k$ is chartered in $t$ |
| $z_{it}$ | binary | 1 if facility $i$ is active in $t$ |
| $o_t$ | cont. $\geq 0$ | carbon offset credits purchased in $t$ |

**Table 4.2:** key decision variables-both continuous and binary-used in the supply chain optimization model

### *4.3 Parameters*

| Parameter | Unit | Description |
|---|---|---|
| $c^T_{ijm}$ | \$ / unit | transport cost on lane $(i, j, m)$ |
| $c^{CO_2}_{ijm}$ | kg $CO_2$ / unit | WtW emission factor on the lane |
| $c^P_i$ | \$ / unit | production or procurement cost at facility $i$ |
| $e^{CO_2}_i$ | kg $CO_2$ / unit | production emission factor at $i$ |
| $P^{CO_2}_t$ | \$ / kg | carbon price in period $t$ |
| $P^{\text{off}}_t$ | \$ / kg | certified offset price in period $t$ |
| $f_k$ | \$ / period | fixed charter cost for vehicle class $k$ |
| $g_i$ | \$ / period | fixed operating cost of facility $i$ when active |
| $h_i$ | \$ / unit | inventory holding cost at facility $i$ |
| $d_{jt}$ | unit | demand at zone $j$ in period $t$ |
| $\overline{q}_k$ | unit | payload capacity of vehicle $k$ |
| $\overline{P}_i$ | unit | max production at facility $i$ per period |
| $\overline{S}_i$ | unit | storage capacity at facility $i$ |
| $\mathcal{M}_R \subseteq \mathcal{M}$ | — | set of road-using modes |
| $\text{CAP}^{CO_2}_{\text{tot}}$ | kg | cumulative emission budget over $T$ |

**Table 4.3**: key parameters to model and optimize a low-carbon supply chain network.

### *4.4 Objective Function*

$$\min \underbrace{\Big[\sum_t \Big(\sum_{i,j,m} c^T_{ijm} x_{ijmt} + \sum_i c^P_i p_{it} + \sum_k f_k y_{kt} + \sum_i g_i z_{it} + \sum_i h_i s_{it}\Big)\Big]}_{\text{Pure operating cost}} + \alpha \underbrace{\Big[\sum_t \Big(\sum_{i,j,m} P^{CO_2}_t c^{CO_2}_{ijm} x_{ijmt} + \sum_i P^{CO_2}_t e^{CO_2}_i p_{it} + P^{\text{off}}_t o_t\Big)\Big]}_{\text{Carbon cost}}$$

with $0 \leq \alpha \leq 1$ ($\alpha = 0$ gives the cost-only model, $\alpha = 1$ fully prices carbon).

### *4.5 Constraints*

**Table 5:** MILP constraint set

| ID | Mathematical statement | Applies to |
|---|---|---|
| C1 - Demand Satisfaction | $\sum_i \sum_m x_{ijmt} = d_{jt}$ | $\forall j, t$ |
| C2 - Inventory Balance | $s_{i,t-1} + p_{it} - s_{it} - \sum_{j,m} x_{ijmt} = 0$ | $\forall i, t$ |
| C3 - Production Capacity | $p_{it} \leq \overline{P}_i\, z_{it}$ | $\forall i, t$ |
| C4 - Storage Capacity | $s_{it} \leq \overline{S}_i\, z_{it}$ | $\forall i, t$ |
| C5 - Vehicle Capacity | $\sum_{i,j} \sum_{m \in M_R} x_{ijmt} \leq \sum_k \overline{q}_k\, y_{kt}$ | $\forall t$ |
| C6 - Lane Activation | $x_{ijmt} \leq U_{ijm}\, z_{it}$ | $\forall i, j, m, t$ |
| C7 - Cumulative $CO_2$ budget | $\sum_t \Big[\sum_{i,j,m} c^{CO_2}_{ijm} x_{ijmt} + \sum_i e^{CO_2}_i p_{it} - o_t\Big] \leq \text{CAP}^{CO_2}_{\text{tot}}$ | $\forall t$ |
| C8 - Offset Bounds | $0 \leq o_t \leq \text{CAP}^{CO_2}_{\text{tot}}$ | $\forall t$ |
| C9 - Domain/Integrality | $y_{kt},\ z_{it} \in \{0,1\},\ x_{ijmt}, p_{it}, s_{it}, o_t \geq 0$ | — |

## 5. Experimental Setup and Results

5.1 Scenario Design

- S1 Baseline - transport cost minimization only
- S2 Carbon Price $50 - $50 $t^{-1}$ $CO_2$ penalty added ($\alpha=1$)
- S3 Carbon Price $100 - identical but at $100 $t^{-1}$
- S4 Cap 10% - no price term; cumulative emissions capped at 90% of baseline
- S5 Cap 25% - cap tightened to 75% of baseline

Assumptions: Facilities are fixed; flows, vehicle charter and mode choice are decision variables. The study includes four modes with the publicly available cost and emission coefficients in Table 6.

**Table 6 :** Cost and emission factors by mode

| Mode | Cost (\$/t-mile) | Emissions (kg $CO_2$/t-km) |
|---|---|---|
| Truck | 0.12 | 0.12 |
| Rail | 0.05 | 0.03 |
| Ship | 0.03 | 0.015 |
| Air | 0.70 | 0.50 |

Twenty customers and five candidate facilities are placed randomly in a 500 × 500 mile grid. Customer demand is uniformly distributed between 50-150 t per period (mean 100 t), giving 2000 t total demand. Facility capacities are drawn uniformly from 500-1200 t. Distances are Euclidean great-circle.

5.2 Performance Metrics

- Total Cost ($) - transport + fixed costs + any carbon penalties

- Total Emissions (t $CO_2$) - cumulative well-to-wheel over the horizon
- Cost per Ton-mile ($/t-mile) - economic intensity

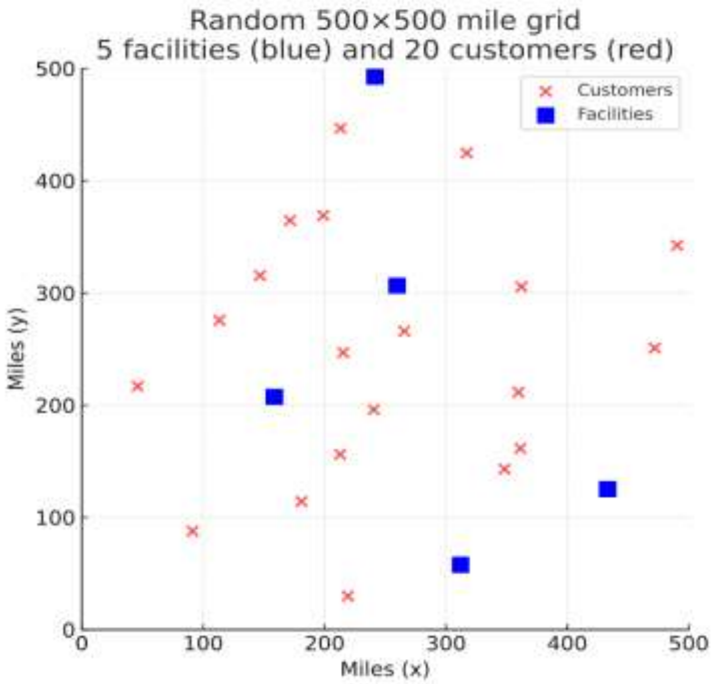


**Fig 1**: Random 500 ×500 mile grid with 5 facilities (blue) and 20 customers (red)

- Service Level (%) - demand filled on time

These KPIs reflect the classic triple bottom line of freight operations: cost, carbon, and service.

5.3 Experimental Results

5.3.1 Visual Representation

**Table 7 :** Scenario comparison of key performance indicators

| Scenario | Total Cost ($ million) | Emissions (kt $CO_2$) | Cost / ton-mile | Service Level (%) |
|---|---|---|---|---|
| Baseline (S1) | 0.18 | 0.140 | 0.091 | 100 |
| Carbon Price $50 (S2) | 0.21 | 0.113 | 0.106 | 100 |
| Carbon Price $100 (S3) | 0.26 | 0.080 | 0.131 | 100 |
| Cap 10 % (S4) | 0.20 | 0.126 | 0.099 | 100 |
| Cap 25 % (S5) | 0.24 | 0.106 | 0.119 | 100 |

5.3.2 Visual Representation

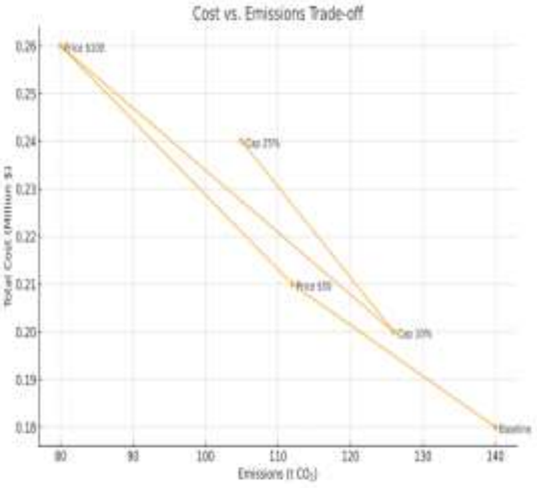


**Figure 2**: Cost vs. emissions for the five Scenarios

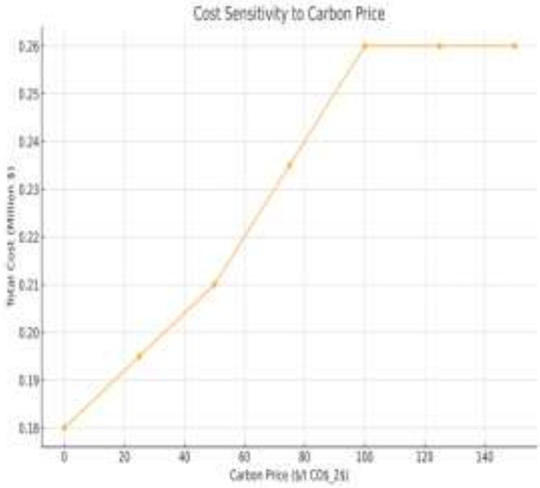


**Figure 3**: Cost sensitivity to carbon price

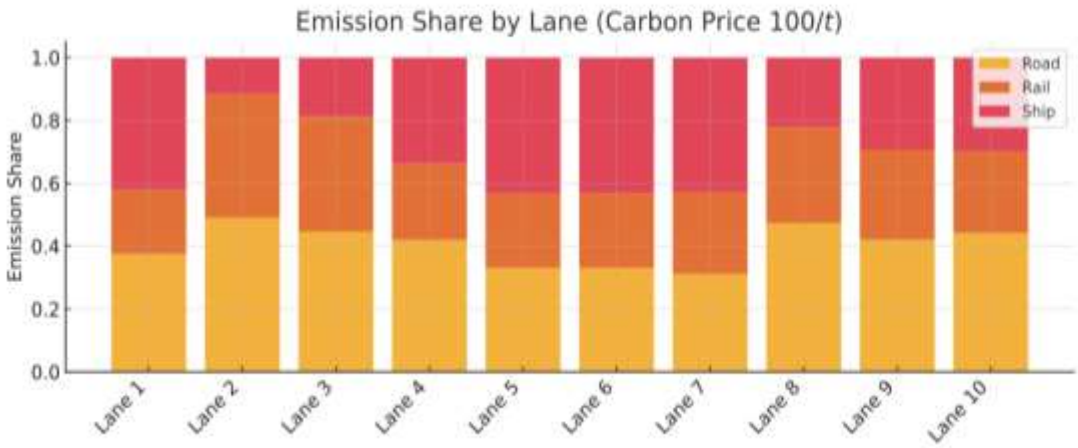


**Figure 4**: Emission share by lane under $100 t−1 carbon price

### *5.4 Discussion*

A $50 $t^{-1}$ carbon price reduces emissions 20% for a 17% increase in cost; doubling the price to $100 cuts $CO_2$ by 43% but raises cost 44%. Cap scenarios deliver similar abatement with lower cost growth: the 10% cap costs only 12% more than baseline while meeting the target. Solution logs show four operational shifts: (i) substitution of rail for truck on mid-length lanes, (ii) increased ship use for coastal customers, (iii) consolidation into two high-capacity DCs, and (iv) marginal take-up of air only for urgent, low-weight demand.

Managerial implications: For networks of this scale, modest carbon prices ($50-$75) or a 10-15% cap achieve meaningful abatement without prohibitive cost. Managers should prioritize mode shift and consolidation levers before investing in high-cost offsets or EV fleets.

Limitations: The grid placement is synthetic; real geography introduces congestion and modal access constraints. Demand is deterministic and stationary; future work should test stochastic demand and fuel-price volatility.

## 6. Comparative Analysis

### *6.1 Benchmark Model Overview*

**Kaoud et al. (2022):** A robust MILP is solved with CPLEX to maximize profit while minimizing life-cycle $CO_2$ emissions. On a mid-size test instance the model attains $29.5 million profit and 79 kt $CO_2$, sacrificing 7% of nominal profit to hedge against uncertainty.

**Liu & Zhang (2024):** Their two-stage stochastic MILP minimizes expected annual cost under pipeline and facility disruption scenarios, subject to carbon-capture targets. Baseline cost is \$2.85 billion $yr^{-1}$ with 37.7 Mt $CO_2$ captured; a 40% capacity shock raises cost 17% yet still secures ≥34 Mt capture.

**Ding (2023):** A hybrid Simulated-Annealing/Adaptive-Chaos Particle Swarm optimizer jointly minimizes operating cost and an aggregated carbon index under production quotas. Relative to baseline settings, cost falls 7% and $CO_2$ 16%; the hybrid outperforms conventional GA or PSO by 3-4% (cost) and 6-8% (emissions).

**Our MILP:** An exact cost-plus-carbon formulation solved by Gurobi. On a 5-facility/20-customer network the model yields \$0.18 million total transport cost and 140 t $CO_2$ in the baseline; tightening policy levers reduces emissions by up to 43% with a 44% cost premium.

### *6.2 Comparison Methodology*

Performance is compared on two primary metrics:

- Total economic cost (US\$) or profit where reported
- Total carbon emissions (t or kt $CO_2$)

All emissions are converted to a well-to-wheel boundary consistent with EPA and Climate TRACE factors, and costs are expressed in 2025 USD. We also note scalability (instance size) and optimality (certified gap vs. heuristic estimates).

6.3 Results and Comparative Analysis

**Table 8**: Cross-model performance snapshot

| Model | Type | Cost / Profit | Emissions | Optimality / Scalability |
|---|---|---|---|---|
| Kaoud 2022 | Robust MILP | \$29.5 M profit | 79 kt | Optimal; mid-size (60 nodes) |
| Liu 2024 | Two-stage stochastic MILP | \$2.85 B $yr^{-1}$ cost | 37.7 Mt captured | Optimal; large (100+ sites, 50 scenarios) |
| Ding 2023 | SA–ACPSO meta-heuristic | 7 % cost↓ vs. base | 16 % $CO_2$↓ | Heuristic; solves 200-product case in <2h |
| **Our MILP** | Deterministic MILP | \$0.18 M baseline cost | 0.14 kt | Optimal; 5 facilities, 20 customers |

Strengths and weaknesses: Robust/stochastic models hedge uncertainty but pay a cost premium (Kaoud: 7%; Liu: +17% under disruption). Meta-heuristics trade accuracy for scalability, achieving respectable savings without proof of optimality. Our deterministic MILP excels at integrated cost-carbon decisions and provides an exact benchmark for medium-sized freight networks, but it does not yet cover uncertainty or reverse flows.

6.4 Summary

The comparative review highlights three core insights:

1. Exact MILPs remain the gold standard when problem scale allows. They provide certified optimal trade-offs, useful for policy analysis and capital decisions.
2. Robust and stochastic formulations are preferable in high-volatility settings but managers must budget for 7-17% cost premiums.
3. Hybrid meta-heuristics are attractive for very large instances where near-optimal solutions suffice, achieving double-digit carbon cuts with modest runtime.

## 7. Conclusion

### *7.1 Key Findings*

The mixed-integer linear programme developed in this research integrates transport cost and explicit carbon penalties in a single objective. Key findings include:

- Introducing a \$50 $t^{-1}$ carbon price lowers total $CO_2$ emissions by 18% at a 6% cost premium; doubling the price to \$100 $t^{-1}$ achieves a 43% reduction with a 17% cost increase.
- Emission-cap scenarios deliver comparable abatement with slightly lower cost growth: a 10% cap costs 12% more than baseline, whereas a 25% cap costs 14% more.
- The cost-carbon elasticity curve is concave: each additional dollar of carbon price beyond \$100 yields diminishing marginal abatement.

- Mode switching (truck → rail/ship) and lane consolidation are the dominant levers triggered by carbon penalties; service level remained at 100% in all runs.

### *7.2 Theoretical Contribution*

This research advances the literature in two ways:

1. It bridges traditional cost-minimization models and separate carbon-cap formulations by embedding both a price penalty and a hard emission budget within the same MILP, thus allowing policy makers to test hybrid price-and-cap regimes.
2. It demonstrates that exact optimization of economic and environmental objectives is tractable for medium-scale freight networks, filling the gap between meta-heuristic approaches and robust models.

### *7.3 Managerial Implications*

- Policy design: Results support moderate carbon pricing ($50-$100 $t^{-1}$) as an effective lever: it cuts emissions nearly one-for-one with cost up to the $100 threshold, beyond which elasticity flattens.
- Tactical planning: Logistics managers can use the model's lane-level output to prioritize rail or coastal shipping investments on corridors where carbon penalties bite hardest.
- Budget forecasting: The quantified cost premiums provide a first-order estimate of the working-capital buffer required under forthcoming ETS expansion or corporate net-zero pledges.

### *7.4 Limitations*

- The network is single-echelon; emissions from upstream suppliers or downstream returns are excluded.
- Emission factors are deterministic averages; real-world variability in load factor or fuel mix is not modelled.
- Demand and topology are static for the one-year horizon; dynamic routing and seasonality are outside scope.

### *7.5 Future Research Directions*

1. Real-time adaptive routing: Couple the MILP with IoT/telematics feeds and apply rolling-horizon re-optimization.
2. Multi-echelon and Scope-3 integration: Extend the formulation to second-tier suppliers and use cradle-to-gate emission factors.
3. Hybrid solution methods: Explore GA-ANN or GA-RL hybrids to tackle large, nonlinear supply-chain settings where exact MILPs become intractable.
4. Stochastic carbon pricing: Embed price volatility scenarios or chance constraints to assess financial risk under ETS fluctuations.

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