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A strategic analysis of fuel consumption and carbon emission reduction using an integrated multi objective optimization frame work for green freight transportation system

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Abstract

The shift to sustainable logistics is essentially a problem of strategic multi-criteria decision-making and quantitative optimization. Robust optimization models are more important than ever because global transportation parameters activities account for more than one third of the world's carbon dioxide emissions, with freight transport alone accounting for a large amount of this environmental footprint. The "Multi Objective Transportation Problem" (MOTP) in supply chain management has developed from a straightforward cost minimization exercise into a sophisticated framework that must concurrently balance social service quality, environmental stewardship, and economic viability. This study describes the process for optimizing transportation networks using weighted sum aggregation and sophisticated heuristic algorithms by utilizing the given data on inter-city distances and multi-modal fuel consumption.

Keywords: Green logistics, multi-objective optimization, fuel consumption, carbon emissions, freight transportation, heuristic algorithms

Introduction

Rapid industrialization and globalization have significantly increased freight transportation demand, leading to higher fuel construction and green house gas emissions. According to international energy assessments, the transportation sector contributes nearly one quarter of global CO₂ emissions, with freight transport accounting for a substantial share. Traditional transportation planning models emphasize cost minimization, often neglecting environmental impacts.

The multi-objective Transportation problem (MOTP) extends the classical transportation problem by simultaneously optimizing multiple conflicting objectives such as cost, delivery time, service quality, and environmental impact. Recent research emphasizes integrating sustainability indicators into transportation decision- making frameworks. This paper contributes to this domain by proposing a structured multi-objective optimization framework that explicitly incorporates fuel consumption and carbon emissions into freight routing and allocation decision.

The Primary Transportation Dataset: A Quantitative Study

The underlying scientific and spatial data form the basis of every transportation optimization model. A sample microcosm of a complex logistics network with six key Indian industrial hubs and six principal destinations is provided by the distance metrix and emission factors. Assessment of the Intercity Distance Metrix. The dataset's distance metrix demonstrates the many geographic difficulties that come with transcontinental logistics. There is a significant amount of variation in route length between Ahmadabad, Pune, Jaipur, Bhubaneswar, Indore, and Ranchi and large cities like Mumbai, Delhi, Bhopal, Kolkata, Chennai, and Hyderabad. This variation directly affects fuel consumption and carbon emission.

Origin	Mumbai	Delhi	Bhopal	Kolkata	Chennai	Hyderabad
Ahmadabad	521	977	589	2056	1771	1132
Pune	151	1364	787	1878	1199	560
Jaipur	1172	296	577	1514	2052	1425
Bhubaneswar	1592	1857	1171	443	1226	1050
Indore	587	761	193	1617	1444	805
Ranchi	1661	1356	1048	403	1735	1270

Analysis of this metrix suggests that routes such as Pune-Mumbai (151 km) and Indore-Bhopal (193 km) are ideal candidates for short-haul road freight, whereas long-haul routes like Ahmadabad-Kolkata (2056 km) or Jaipur-Chennai (2052 km) present significant opportunities for multi-modal optimization involving rail or air transport to balance time and environmental costs.

Technical Parameters for Multi-modal Transportation

The dataset offers precise fuel consumption and carbon emission parameters for three different modes: air, rail (electric and diesel), and road (diesel truck). These elements are the crucial coefficients that are utilized when creating objective functions for operational cost and environmental impact.

Mode	Technology	Fuel Consumption Rate	Emission Factor
Truck	Diesel	3.75 km/L	2.64 kg/L
Train	Electric	0.15 kWh/ton-km	0.65 kg CO ₂ /kWh
Train	Diesel	0.30 L/ton-km	2.64 kg CO ₂ /L
Air	Jet Fuel	4.8 L/seat-km	2.35 kg CO ₂ /L

The provided data reveals that while road transport has a straightforward distance-to-fuel relationship, rail transport is modelled on a per-ton-kilometre basis, highlighting the importance of cargo load in evaluating rail efficiency. Air transport, measured per seat-kilometre, underscores the high carbon intensity of aviation, which is often used as the "time-priority" objective in multi-objective models, contrasting sharply with the "environment-priority" of electric rail.

Mathematical Modelling of the Multi-Objective Transportation Problem: The formulation of a multi-objective optimization model required the definition of discrete objective functions that encapsulate the strategic goals of the organization. In the context of the provided data we defined two primary objectives: (i) Economic efficiency (minimum fuel consumption) and (ii) environmental

sustainability (minimum CO₂ emission).

Objectives Functions 1: Fuel Consumption Minimization

The first objectives Z_1 , aims to minimize the total fuel consumptions (L) across the entire logistics network. For a truck -based system, the consumption between source i and Destination j is a function of the distance d_{ij} and the consumptions Rate R (where $R=1/3.75$ liters per kilo-meter)

$$\text{Minimize } Z_1 = \sum_i \sum_j (d_{ij} \times R) x_{ij}$$

Where x_{ij} represents the decision variable indicating whether a specific route is utilized or the volume of the goods assigned to that route. The following table provides the calculated fuel consumption in litres for a single trip across the primary routes.

Origin	Mumbai	Delhi	Bhopal	Kolkata	Chennai	Hyderabad
Ahmadabad	138.93	260.53	157.07	548.27	472.27	301.87
Pune	40.12	363.73	209.87	500.80	319.73	149.33
Jaipur	312.53	78.93	153.87	403.73	547.20	380
Bhubaneswar	424.53	495.20	312.27	118.13	326.93	280
Indore	156.63	202.93	51.47	431.20	385.07	214.67
Ranchi	442.93	361.60	279.47	107.47	462.67	214.67

This data indicates that long-haul routes like Ahmadabad to Kolkata consume over 548liters of fuel per trip, emphasizing the critical need for route optimization or modal shifts to rail for these specific corridors.

consumptions in diesel engines, the emissions E_{ij} for a route is product of fuel consumptions and emission factor F (2.64 KG/L)

$$\text{Minimize } Z_2 = \sum_i \sum_j (Z_{1,ij} \times F) x_{ij}$$

Objectives Functions 2: Carbon Emission Minimization

The second objective Z_2 , Focuses on the environmental impact. Since CO₂ emissions are directly proportional to fuel

The resulting emission profiles in kilograms of CO₂ for the network are details in below:

Origin	Mumbai	Delhi	Bhopal	Kolkata	Chennai	Hyderabad
Ahmadabad	366.78	687.80	414.66	1447.43	1246.79	796.94
Pune	106.31	960.25	554.06	1322.11	844.09	394.23
Jaipur	825.08	208.38	406.22	1056.85	1444.61	1003.20
Bhubaneswar	1120.76	1307.33	824.39	311.86	863.09	739.20
Indore	413.24	535.74	135.88	1138.37	1016.58	566.73
Ranchi	1169.34	954.62	737.80	283.72	1221.45	894.09

The alignment between fuel consumption and carbon emissions is nearly perfect in a single mode diesel truck

scenario. However, once multi-modal options are introduced- such as electric rail between Ranchi and Kolkata the

relationship becomes nonlinear, as the emissions per unit of energy for electricity (0.65 kg/kWh) is significantly different from that of diesel fuel.

Advanced Weighting Methodologies in Multi-Objective Problems

When objectives are in conflict, decision-makers must assign relative importance to each goal. Weighting methods provide a systematic way to convert a multi-objective problem into a single objective one, allowing for traditional optimization techniques to be applied.

The weight sum method and normalization

The simplest approach is the weighted sum method, where each objective is multiplied by a user defined weight w , such that $\sum w = 1$

$$\text{Minimize } Z = w_1Z_1 + w_2Z_2$$

A critical drawback of this method is the sensitivity to the magnitude of the objective functions. Since fuel consumption is measured in hundreds of litres and emissions in thousands of kilogram, a direct sum would be caused the emissions objective to dominate the optimization process regardless of the weights assigned. To resolve this, normalization is required, typically by scaling each objective to a range between 0 and 1 based on its minimum and maximum possible values.

Integrating Subjective and Objective Weighting: Modern logistics optimization frequently employs a hybrid weighting approach to balance expert judgment with data-driven insights. This is achieved through the combination of the analytic Hierarchy Process (AHP) and the Entropy Weight Method (EWM)

(A) Analytic Hierarchy Process (AHP): AHP is used to drive subjective weights based on pairwise comparisons. A decision-maker might determine that environmental impact is twice as important as immediate fuel cost due to long-term carbon tax liabilities. A Judgment matrix is constructed using Saaty's 1-9 scale, and the consistency of these judgments is verified via the consistency Ratio (CR)

(B) Entropy Weight Method (EWM): EWM provides

objective weights by measuring the information content or dispersion in the data. If the distances (and thus emissions) across all possible routes are very similar, EWM will assign a lower between alternatives. Conversely, if there is a high variable as seen in the distance table provided EWM will be assigned higher weight to reflect in the importance of selecting the most efficient route.

By combining these methods using the Lagrange multiplier methods, organizations can achieve a robust weighting system that improved heuristic solution quality by an average of 112.5% in empirical trials. This hybrid approach effectively addresses the multidimensional complexity of green supply chains, identifying transport costs and carbon emissions at the most weight sensitive factors.

Heuristic and Metaheuristic Landscapes for Large-Scale Optimization:

While weight methods simplify the problem, identifying the actual optimal routes in a complex network with multiple constraints-such as vehicle capacity, delivery time windows and road congestion -requires the power of heuristic and metaheuristic algorithm.

Evolutionary Strategies: GA and NSGA-II

In a study of municipal solid waste removal, an improved version of NSGA-II was used to optimize both economic cost and delivery time out. The algorithm successfully identified 13 Pareto solutions significantly outperforming the 7 solutions found by the classical NSGA-II. This suggests that explicitly accounting for the diversity of the solution set is crucial for identifying variable trade-offs in logistic networks where cost and emissions are competing.

Swarm Intelligence: PSO and MOGWO

Particle Swarm Optimization (PSO) mimics the collective behavior of bird flocks. Each particle in the swarm moves around the search space, modifying its speed in response to both its personal optimal position and the global best of the swarm. Multi-Objective PSO (MOPSO) stores non-dominated solutions in an archive. Research indicates that MOOSO often achieves faster convergence and reduced energy management costs compared to alternative methods.

Heuristic Algorithm	Optimization Quality Score	Computational Efficiency	Primary Strength
PSO-LD	0.573	High	Global exploration and stability
MOPSO	Moderate	Very High	Fast convergence in dynamic systems
GA(standard)	0.322	High	Simplicity and speed
MOGWO	High	Moderate	Hierarchical search precision

Another effective tool that simulates the wolf leadership hierarchy is the Multiobjective Grey Wolf Optimizer (MOGWO). By balancing delivery speed and routing efficiency, MPGWO was able to minimize carbon emissions for international orders in ecommerce logistics by as much as 32.9%.

Analytical Results and Mathematical Evidence from Case Studies:

The practical application of these methods yields

mathematical results that illustrate the tangible benefits of multi-objective optimization.

Performance improvements in Economic and Environmental Metrics

Comparing an improved NSGA-II algorithm to traditional methods reveals significant statistical improvements. The following results were obtained for a logistics network with waste management focus.

Metric	Optimal Economic Solution(f_1)	Optimal temporal Solution(f_2)	Improvement vs. classical
Total cost	336,182.4 Rs.	352,732.32 Rs.	2.55%
Total timeout	921.15 min	615.16 min	2.85%(optimal)
Fuel Cost	38,172.384 Rs	40,385.952 Rs.	1.36%
Carbon Cost	8,127.216 Rs	8,598.312 Rs.	Variables

The information demonstrates that the quickest option is not the most cost-effective one. Setting time efficiency as a top priority results in a 5.8% rise in fuel use and carbon emission costs. This offers unambiguous mathematical proof of the trade curve and the need for decision makers to choose a place on the Pareto frontier that corresponds with their particular business objectives or legal needs.

Load Rate(x)	Fuel Consumption(L/km)	CO ₂ Emission (kg/km)	Emission intensity(kg/km)
0.00(No-load)	0.1842	0.4807	0.481
0.50	0.2105	0.5494	0.550
1.00(full-load)	0.2368	0.6180	0.618

According to this mathematical relationship, a full truck is significantly more efficient per unit of cargo even if it uses more gasoline overall per kilometer than an empty one (0.2368 L vs. 0.1842 L). By increasing the loading rate from 40% to 90%, the unit carbon emission intensity is reduced by over 29%, from 0.91 kg/km to 0.649 kg/km. This highlights the strategic importance of "last-mile" efficiency and consolidation in green logistics.

The Role of Carbon Policies and Global Economic Instruments

The current regulatory framework has a significant impact on the mathematical optimization of logistics; it does not happen in a vacuum. Governments use this tactic to compel the internalization of environmental costs. Carbon trade, cap, and tax systems. The best routing choices are altered when these policies are incorporated into the MOTP goal function.

Carbon Cap: This places a strict cap on overall emissions. The solution is considered unfeasible if the total emission Z_2 exceeds the cap. This frequently compels the model to choose more costly, multimodal modes of transportation.

- Carbon Tax:** This increases the economic goal by adding a direct cost per unit of emissions. The new goal is $Z = Z_1 + (Z_2 \cdot T)$ if the tax is T . The algorithm naturally favours routes with lower fuel usage as T increases, effectively.
- Carbon Cap and Trade:** This enables businesses to purchase and sell carbon permits. The mixed integer nonlinear model can maximize platform revenue while adhering to emission targets by optimizing the time and amount of permit exchanges.
- These limitations cause a major modal shift, according to research on freight transport networks. A truck only system is usually the outcome of freight cost minimization alone, but the presence of CO₂ limitations causes the mode share to move toward an intermodal hub-and-spoke network.

Strategic Implementation and Parameter Sensitivity

The success of any Optimization strategy depends on the precision of its implementation and the understanding of parameter sensitivity.

Algorithm Tuning and Convergence Stability

Large scale logistics, the metaheuristic algorithm's rate of convergence is crucial. An immune inspired MPSO algorithm reduced the overall objective function value in a study of Beijing's Fifth Ring area from 9.8 million to 3.4 million in 500 iterations, reaching stable convergence in about 280 iterations.

Additionally, sensitivity analysis shows that algorithms such as GA are extremely sensitive to parameter adjustment (e.g., crossover rate and mutation probability). "Premature

Impact of vehicle Load on Carbon Efficiency

The non-linear link between cargo load and emissions is an important finding of the study. The emissions per kilometer (t) of an 8 ton vehicle are defined by a linear regression model as $t = (0.481 + 0.137x)$, where x is a load rate.

convergence," in which the algorithm becomes trapped in a local optimum that is distant from the actual Pareto frontier, might result from improper tuning. In comparison, PSO is frequently more reliable, but if the inertia weight is set too high, it may "overshoot" optimal solutions.

Multi-Modal Shift and infrastructure Utilization

The "Regional Transport Infrastructure Utilization Index" is being used more and more in optimization models to strike a balance between environmental preservation and social contribution. This guarantees that logistics networks do not just concentrate on the quickest route but also make efficient use of the rail and waterway capacity already in place, which can lower overall CO₂ emissions by as much as 15% to 30%, depending on how developed the digital infrastructure is.

Strategic Synthesis and Practical Recommendations

A comprehensive strategy that makes use of both sophisticated algorithm execution and extensive mathematical modeling is needed to optimize fuel use and carbon emissions in transportation. The distance metrix connecting industrial centers like Ahmadabad, Pune, and Kolkata offers a high variance landscape that is perfect for optimization, according to the mathematical conclusions. An company can develop a balanced objective function that represents both short-term costs and long term sustainability goals by using integrated weighting methods, which combine the objective data dispersion of EWM with the subjective priorities of AHP.

While basic GA offers speed, variant algorithms like NSGA II and PSO LD give a more varied and superior set of solutions on the Pareto frontier, so the choice of heuristic algorithm is crucial. These algorithms are especially good at balancing the trade-offs between carbon emissions and delivery time, finding ways to optimize loading rates and route choices to cut emissions by more than 30%.

Moreover, the incorporation of carbon policies, such as taxes and cap and trade schemes, is now a strategic must rather than an option. These tools alter the economic landscape, making "green" path optimization and intermodal changes both financially and environmentally responsible.

Conclusion

The shift to green logistics is a multifaceted task that calls for a departure beyond straightforward cost cutting. By using models of transportation that are multi objective, businesses can methodically lessen their environmental impact while still fulfilling the operational requirements of the contemporary global economy. Higher truck loading rates, multimodal connectivity, and the use of strong metaheuristic optimization frameworks to handle the complexity of supply chains in the twenty first century are all supported by mathematical data.

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