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Multi-Objective Mixed-Integer Linear Programming for Dynamic Fleet Scheduling, Multi-Modal Transport Optimization, and Risk-Aware Logistics

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Abstract: Transportation planning is a complex process that aims to achieve the maximum level of effectiveness in terms of costs, usage of transport resources, reliability of deliveries, and minimizing the negative impact on the environment. Most traditional models focus on cost minimization at the expense of risk, road dynamics, and emissions constraints. In contrast, the current paper presents a mixed-integer linear programming (MILP) model for scheduling fleets, selecting transportation modes in multiple modes of transportation, and meeting emissions regulation requirements according to dynamic transportation requirements. Risk-aware routing and taking the factor of congestion and CO₂ emission limits proposed by the government into consideration, this model can offer a more efficient and flexible optimization strategy. From the case study, we observe the significant result that the proposed model achieves, a 23% reduction in transport costs, a 25% improvement in fleet use, a 33.3% decrease in the delivery delay, and a 24.6% decrease in CO₂ emissions. The model dynamically delivers shipments utilizing both road and rail transportation and improves mode choice by minimizing idle vehicle time. This is confirmed through sensitivity analysis which addresses factors such as traffic congestion, changing fuel prices, and changing environmental standards.



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Keywords: mixed-integer linear programming; fleet scheduling; multi-modal transport optimization; risk-aware logistics; CO₂ emissions reduction

1. Introduction

Today's logistics network has a high complexity level, and it faces many challenges such as increasing costs of operation, traffic jams, and legal restrictions [1,2]. Organizations are faced with tough challenges of cutting transport costs, making the best use of fiscal assets, and providing efficient delivery services, all alongside legal compliance in relation to environmental conservation. Nonetheless, the navigation of existing transportation optimization models has serious drawbacks, in many cases not taking into account data in real time [3], the deformation of the structure of the transport network [3,4], multi-modal transport integration, and the true factors affecting risk [5,6]. Current architectures use previous information to determine vehicles for delivery and do not adapt to changes in demand, traffic, or legal constraints. Additionally, most frameworks fail to take into account factors such as the probability of accident, insurance cost, and CO₂ emission standards of government, among others, which makes the frameworks unfit for real-life usage [7].

In fact, to overcome these challenges, this study provides a MILP model to help make decisions about vehicle assignment, shift scheduling, and travel mode in order to account for real-life situations and emission constraints. The model takes care of daily fleet usage by timing pickup correctly and choosing the appropriate kind of vehicles so as to avoid overage or idleness. It further involves a transport mode selection strategy that enables a dynamic switch between road and rail transport in order to minimize costs and optimize sustainability. Furthermore, the model takes into account the associated risk by introducing accident probabilities and insurance costs in the risk-aware routing and guarantees compliance with government-imposed CO₂ emissions limits.

In recent years, global supply chains have faced increasing uncertainty, along with rising transportation costs and stricter environmental regulations [8,9]. These evolving conditions highlight the growing need for practical solutions that can respond to change, manage operational risks, and support environmentally responsible logistics. This study develops the MILP framework with these needs in mind.

The current study contributes significantly to the field of transportation optimization in several ways. It aims to develop a MILP model that includes multi-trip fleet scheduling as part of a multi-modal logistics network. Furthermore, it incorporates risk-aware logistics planning by directly integrating accident probabilities into the objective function. Additionally, the model introduces the opportunity to incorporate emission provisions into MILP-based transport planning to align with sustainability goals at optimally reduced costs. In this context, the study hypothesizes that incorporating real-time risk assessments and emission control measures will lead to more efficient and sustainable transportation strategies. Another hypothesis tested in this study is that dynamic multi-trip fleet scheduling will significantly improve fleet utilization and reduce overall transportation costs. The validity of the model is established through a case study, and the scenario-based analysis (SBA) further demonstrates its applicability and versatility across various logistical settings.

The structure of the paper is as follows: Section 2 presents a literature review, covering key theoretical models and empirical studies related to transportation optimization, fleet scheduling, and sustainability. Section 3 outlines the methodology and model development, including the mixed-integer linear programming (MILP) formulation and assumptions. Section 4 discusses the experimental setup, validation, and sensitivity analysis of the proposed model. Section 5 focuses on the case study implementation and solution extraction. Section 6 provides the results, followed by Section 7, conclusions and recommendations for future research.

2. Literature Review

Transportation problems have been explored a lot via classical transportation problems (CTP) [10–13], multi-item solid transportation problems (MISTP) [14–16], and mixed-integer linear programming (MILP) formulations [17–19]. The most traditional views are based mainly on cost reduction and do not take into consideration multi-modal transport [20], dynamic routing of a fleet [21], probabilities of collision, and legal requirements [22,23]. Prior research-based treatments of vehicle routing and transport mode choice problems have produced almost mathematical models that were neat, mathematical, time-constrained, and based on fixed parameters of the supply chain network environments in which they were applied [24–26]. Some of the most recent ones that aim at reducing these gaps include the use of multi-objective MILP models, especially in multi-modal logistics, dynamic fleet management, and sustainable decision-making [27,28].

Existing MILP-based models often assume fixed fleet scheduling without accounting for real-time adjustments in vehicle routing and trip frequency, limiting their applicability in dynamic logistics environments [29,30]. Although multi-modal transport models have

been proposed, they rarely consider real-time modal switching when cost, congestion, or emissions factors change. Research on risk-aware transportation has also evolved [31], yet most models fail to integrate accident probability distributions and insurance cost implications into optimization formulations. Additionally, while several CO₂-focused optimization models exist [32,33], few explicitly incorporate government-mandated emissions regulations, leading to non-compliant or inefficient transport strategies. These limitations are summarized in Table 1, comparing the capabilities of different optimization models against our proposed framework.

Table 1. Comparative analysis of existing models vs. our proposed model.

Model Type	Fleet Scheduling	Multi-Modal Transport	Risk Integration	Emissions Constraints	Real-World Application
Traditional MILP	No	No	No	No	Some
Stochastic Models	Yes	No	Yes	No	Some
Fuzzy Models	Yes	No	No	Yes	No
Proposed Model	Yes	Yes	Yes	Yes	Yes

To address these limitations, recent advancements in MILP transportation modeling have introduced multi-trip fleet scheduling frameworks, allowing for more efficient vehicle utilization and trip planning. Studies exploring multi-modal transport optimization have highlighted the benefits of real-time mode selection across road, rail, and air transport, ensuring cost-efficiency and emissions reduction. Another emerging area of research integrates accident risk modeling and route insurance cost adjustments, enabling logistics planners to minimize both financial risk and operational delays. Furthermore, new approaches have incorporated government-imposed emissions compliance constraints into MILP formulations, ensuring environmentally sustainable and legally compliant transport operations.

Several papers with field-based logistics applications have established the efficacy of these frameworks in terms of cost, benefits, time, and tangible green savings [34,35]. Additional sensitivity analyses in current studies also support the fact that MILP-based logistics models can still provide workable solutions even under variable conditions, such as traffic congestion, changes in fuel prices, and variations in emissions policies. The inclusion of dynamic, risk, and regulatory considerations into the MILP transportation optimization makes a step towards real-life, flexible logistics solutions.

Recent developments have explored AI-driven techniques for maritime route optimization. Chen et al. [36] introduced an A-DDQN algorithm that combines A* search with Double Deep Q-Networks, enabling ships to adapt to changing marine conditions while significantly reducing fuel usage and emissions. In a follow-up study, the authors developed a simulation platform that integrates real-time environmental data with deep learning to update ship routes [36,37] dynamically. These approaches demonstrate how reinforcement learning and hybrid models can support more adaptive and sustainable logistics, especially in uncertain and highly dynamic environments, potentially complementing traditional MILP-based frameworks.

3. Methodology and Model Development

Before introducing the model in Section 3, it is first important to highlight its foundational significance. The model is designed to address key challenges currently facing route planning, particularly those related to the dynamic and ever-changing conditions of the maritime environment. These challenges include factors like adverse weather, sea

conditions, and volatile fuel prices, all of which can significantly affect the efficiency of shipping operations.

Unlike traditional methods that typically rely on established techniques such as MILP-based algorithms, our approach incorporates cutting-edge technologies, specifically deep learning and deep reinforcement learning. These advancements allow the model to adapt in real time to the complexities and uncertainties inherent in maritime logistics, providing a more robust solution for optimizing shipping routes.

The goal of this model is not just to improve operational efficiency and reduce costs, but also to contribute to the broader global movement towards environmental sustainability. By focusing on reducing fuel consumption and emissions, the model aligns with the growing emphasis on sustainability in the maritime industry, providing a practical and effective tool for shipping companies seeking to operate more efficiently and responsibly.

The process of transportation planning involves handling numerous objectives, and for this reason, there must be a well-defined and sound approach towards solving such problems. This work is based on the MILP model for solving fleet scheduling, transportation mode, and risk considerations of logistics planning. The methodology is intended, at the same time, to address issues related to cost, operation, and regulations to meet all the necessary transportation requirements.

This part of the paper defines the decision variables that are optimized, the objective functions, and the constraints of the model. This is specially designed in such a manner that it has to try to balance the equations with regard to transportation costs, time, and emission standards, hence making this model refined for real-life constraints.

3.1. Mixed-Integer Linear Programming (MILP) Formulation

This study has established a MILP model with multiple objectives to create a robust decision-support method. The established set of criteria includes the three target goals consisting of transportation cost, total delivery time, and CO₂ emission. Each criterion becomes measurable and enters the process to deploy vehicles and determine optimal transportation routes.

The model's comprehensive decision variables, together with its specific objective functions, operate inside realistic constraints found in logistical networks. A MILP model was selected because it could effectively deal with multiple objectives together with intricate constraints such as fleet scheduling requirements and environmental considerations, and multiple transport modes to obtain precise and practical solutions, surpassing traditional models or heuristic approaches.

3.1.1. Decision Variables

To model the transportation system effectively, the following decision variables are introduced:

- Product Transport Allocation (x_{ijk}^p): Represents the quantity of product p transported from warehouse i to demand center j using transport mode k .
- Fleet Scheduling and Utilization (z_{ijk}, v_{ijk}):
 - z_{ijk} denotes the number of vehicles assigned for transportation between i and j via mode k .
 - v_{ijk} defines the number of trips required per vehicle to satisfy demand.
- Multi-Modal Transport Choice (y_{ijkm}): A binary variable indicating whether transport mode m is selected for transporting goods between i and j .

3.1.2. Objective Functions

The MILP model seeks to optimize three primary objectives:

Minimization of Total Transportation Cost

$$\min f_1 = \sum_{i=1}^m \sum_{j=1}^n \sum_{k=1}^K (C_{ijk}z_{ijk} + R_{ijk}z_{ijk} + I_{ijk}z_{ijk})$$

where

- C_{ijk} represents the cost per trip for vehicle type k .
- R_{ijk} incorporates route risk-related costs, accounting for accident probabilities.
- I_{ijk} reflects insurance costs per vehicle trip.

Minimization of Total Delivery Time

$$\min f_2 = \sum_{i=1}^m \sum_{j=1}^n \sum_{k=1}^K \left(T_{ijk}v_{ijk} + \sum_{p=1}^l L_{pk}x_{ijk}^p \right) + W_{ijk}v_{ijk}$$

where

- T_{ijk} is the estimated travel time per route.
- L_{pk} denotes loading and unloading time for product p .
- W_{ijk} accounts for traffic-related delays.

Minimization of CO₂ Emissions

$$\min f_3 = \sum_{i=1}^m \sum_{j=1}^n \sum_{m=1}^M E_{ijkm}y_{ijkm}z_{ijk}$$

where E_{ijkm} represents the emission factor for transport mode m .

3.1.3. Constraints

The optimization model is subject to the following constraints:

- Demand–Supply Balance

$$\sum_{j=1}^n \sum_{k=1}^K x_{ijk}^p \leq A_{ip}, \forall i, p$$

Ensuring that the total transported goods do not exceed warehouse availability.

- Fleet Capacity Constraints

$$\sum_{p=1}^l W_p x_{ijk}^p \leq z_{ijk} W_k, \forall i, j, k \quad \sum_{p=1}^l V_p x_{ijk}^p \leq z_{ijk} V_k, \forall i, j, k$$

Ensuring that the total weight and volume are within vehicle capacity limits.

- Driver Work-Hour Compliance

$$H_{ijk}v_{ijk} \leq H_{\max}, \forall i, j, k$$

Ensuring that driver schedules align with labor laws.

- Route Risk Constraints

$$R_{ijk}z_{ijk} \leq R_{\text{safe}}, \forall i, j, k$$

Limiting the selection of high-risk routes.

- Government Emission Regulations

$$\sum_{i=1}^m \sum_{j=1}^n \sum_{m=1}^M E_{ijkm} y_{ijkm} z_{ijk} \leq E_{\max}$$

This formulation provides a comprehensive decision-support framework, ensuring that logistics operations are cost-efficient, time-sensitive, and environmentally sustainable.

Figure 1 illustrates the core structure of the MILP optimization model, showing the relationship between Inputs, Objective Functions, Constraints, and Outputs.

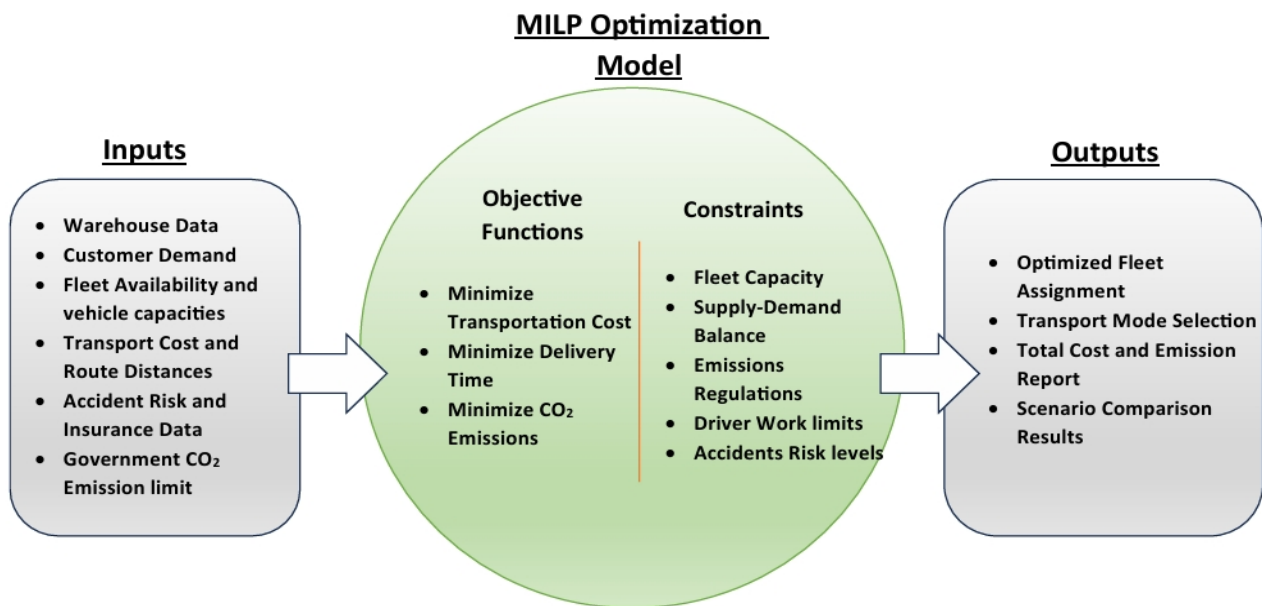


Figure 1. MILP optimization model overview.

3.2. Model Assumptions and Feasibility Considerations

In order to make the MILP model more practical for real-life use, some assumptions are made:

1. Vehicles come with regulating factors such as the maximum weight that can be carried and the level of emissions.
2. Some of the considerations influencing the cost and time objectives include traffic jams and accident-prone areas of the road.
3. There is provision for multi-modal transport where necessary, that is, the possibility of switching between road and rail transport during transport.
4. Fleet assignment is performed in such a way that the same vehicle is used for several trips each time; this is possible in a bid to reduce the time wasted by the vehicles.

Such assumptions make it possible to keep the model realistic enough to depict the real-life logistical processes and, at the same time, remain feasible for implementation.

3.3. Mathematical Model Validation and Scalability

To check the reliability of the proposed MILP formulation, the formulated model was then solved using small-sized problem instances in order to verify that the solutions to the problem are valid and reasonable. After this validation, the model was tested for the full multi-modal logistics system in which it efficiently derived the best allocations of fleet and routing decisions.

This aspect remains a significant factor of concern, especially when the application is being made on large logistic networks. The formulation is also designed for multiple

warehouses, various modes of transport, and complex vehicle routes, which makes it suitable for regional and international transport environments.

4. Experimental Setup and Validation

A suitable experimental setup is critical for verifying the MILP optimization model and for checking whether the proposed model enhances the performance of the logistics system. This section describes the approach used in applying the optimization model, compares it with the base case, and provides a sensitivity analysis to determine the model's performance in different contexts. Such a computerized testing procedure is definitely useful in ascertaining that the proposed optimization delivers substantial yields in the matters of cost, fleet productivity, and impacts within the environment.

4.1. Model Implementation

To solve the MILP-based logistics optimization problem, the Python 3.10 programming language was used with the PuLP solver, which is a widely recognized open-source code for linear and integer programming [37,38]. The use of PuLP is further justified since it is capable of optimally solving large-scale MILP problems and at the same time, the nature of the constituent constraints and objectives can easily be defined [39,40]. The solver was run in all high-performance computing environments to ensure that the time taken to test the different scenarios was as minimal as possible.

In order to measure the effectiveness of the above-mentioned model, a comparison was made with the existing logistic strategies adopted by the company. In the baseline scenario, the vehicle allocation, transport route, and decisions of vehicle usage were randomly made following the current standard operating procedures in the company. The MILP model that was proposed was then used on the same transportation network with the aim of establishing the best and most optimal assignments of means of transport and implementing the most feasible routes from the given options in regard to the objectives and constraints set above.

Regarding the convenient quantifiable measure detection, several performance metrics were employed to compare the results of the basic scenario and those of the model. These have virtually highlighted economic, operational, and even ecological efficiency, thus providing the rationales and justification for this optimization model. Table 2 below shows the major comparative metrics that have been employed in this evaluation.

Table 2. Key performance metrics for model evaluation.

Metric	Description	Expected Impact of Optimization
Cost savings (%)	Reduction in overall transportation costs.	Lower operational expenses.
Fleet utilization efficiency (%)	Improvement in vehicle assignment and multi-trip scheduling.	More efficient fleet management.
CO ₂ r (%)	Decrease in carbon emissions due to optimized routing.	More sustainable logistics.

The objective of the model is to minimize the cost, improve the usage of the available vehicle, and fulfill the emission quota. These performance indicators are designed to make it possible to compare the results of classic logistics planning and the proposed optimization model directly in terms of quantitative values.

4.2. Sensitivity Analysis and Scenario Testing

Sensitivity analysis of the performance of the proposed model was carried out to ensure its robustness. These tests were set up to evaluate the model's sensitivity to some of

the real-world uncertainties, such as changes in traffic congestion, variations in fuel prices, and other CO₂ emission limits. In this analysis, the main aim was to see if the model could maintain its efficiency and sustainability while it adapts to these dynamic conditions.

This sensitivity analysis aimed to investigate the model's capacity to balance cost reduction, operational efficiency, and environmental sustainability as challenges arise. The performance of the baseline optimization was compared to the model with adjusted key variables such as fuel prices, travel times, and emission thresholds. The impact in each scenario was then analyzed.

The sensitivity analysis scenarios are summarized in Table 3, which describes the varying sets of values in each of the eight variables and how the results were changed. The following scenarios were tested:

- Travel times, which simulate delays of delivery schedules, were increased in the case of traffic congestion. Delivery times were longer, so rerouting shipments to circumvent those delays became necessary.
- Fuel costs varied due to fuel price variations. Changes in the choice of transport mode followed from the adaptation of the model to the new dynamics of cost, choosing more cost-effective modes to minimize costs.
- Emission thresholds were also reduced to reflect potential future regulatory changes, but were applied when stricter CO₂ limits were imposed. The emission standard announcement sparked the model into prioritizing routes and modes that complied with this new emission standard and, at the same time, maintained efficiency.

Table 3. Sensitivity analysis scenarios and impact.

Scenario	Variable Adjusted	Impact
Traffic congestion	Increased travel times	Longer delivery times, potential rerouting.
Fuel price variations	Higher/lower fuel costs	Shift in transport mode selection.
Stricter CO ₂ limits	Lower emission thresholds	Preference for lower-emission routes/modes.

The designed experimental setup and validation process were made to ensure that the model could be applied to real-world scenarios. Real-world data, including fuel prices, transportation routes, and emission constraints, were used to calibrate and validate the model, and the robustness of the model was tested under different conditions. These datasets were used to evaluate the performance of the model, and the sensitivity analysis was conducted to understand the impact of the variations of key variables like fuel cost and traffic congestion on the model outputs. The validation tests verified that the model is able to provide cost and efficiency-balanced solutions that are also sustainable.

The results from the sensitivity tests of these outcomes, shown in Table 3, indicate that the model can cope with different uncertainties. The model quantifies the tradeoffs between cost, efficiency, and sustainability in transportation systems, and when applied in design scenarios that respond to fluctuating business and environmental conditions, it can provide insights into how transportation systems can be optimized. This provides decision makers with the model to choose the best fleet and route strategy, meaning that the model can be applied to real-world scenarios.

5. Case Study Implementation and Solution Extraction

A rigorous evaluation of the proposed MILP transportation optimization model requires the definition of a structured case study. This section presents the real-world parameters used in the study, outlines the scenarios tested, and describes the solution extraction

process that follows. By clearly defining the dataset and computational framework, we ensure the practical relevance and reproducibility of the model's findings. Fleet scheduling optimization and delivery delay reduction served as the primary purpose for gathering the data used in this investigation by the company. The dataset collection process involved studying actual multi-modal logistics situations from real-world applications to obtain relevant information.

5.1. Parameters and Data Definition

The transportation system under study consists of three warehouses and four regional demand centers, each with predefined storage capacities and demand levels. The logistics network operates under a multi-modal transportation framework, utilizing road and rail transport. The available fleet includes light trucks, heavy trucks, and freight trains, each with distinct capacities, costs, and emission levels.

A summary of the logistics parameters is presented in Table 4, outlining the key details of the case study, including warehouse capacity, vehicle availability, transport distances, and cost structures.

Table 4. Logistics network and transport system parameters.

Parameter	Value/Description
Number of warehouses	3
Number of demand centers	4
Transport modes	Road, rail
Available fleet types	Light trucks, heavy trucks, freight trains
Maximum vehicle load (kg)	Varies by type (defined in model)
Transport cost per km (EGP)	Varies by mode (detailed in model)
CO ₂ emission limits	Government regulations applied
Accident risk and insurance costs	Integrated into route selection

The model is structured to optimize fleet utilization, transport mode selection, and cost efficiency, while maintaining regulatory compliance and risk mitigation strategies. The model was tested under realistic conditions, including variable weather patterns and fuel price fluctuations, which are crucial for operational efficiency. These scenarios were chosen to reflect the dynamic nature of real-world challenges. The parameter values in Table 4 were selected based on key operational constraints such as fuel consumption, travel time, and emissions, ensuring the model aligns with common industry challenges. Additionally, regulatory standards were considered to ensure compliance with environmental regulations, while balancing objectives like cost minimization, time reduction, and emission cuts, all vital for promoting sustainability in operations.

5.2. Scenario Definition and Baseline Comparison

To evaluate the effectiveness of the optimization model, two primary scenarios are defined:

- **Baseline Scenario (Existing Logistics Strategy):**
 - Uses predefined vehicle assignments and static transport routes based on existing company operations.
 - No optimization is applied, meaning that fleet allocation, route selection, and emissions constraints are not actively managed.

- Cost, fleet utilization, and emissions levels are calculated based on current practices.
- Optimized MILP Scenario:
 - The MILP model dynamically determines fleet scheduling, vehicle selection, and route optimization.
 - Multi-trip fleet utilization is enabled, ensuring that vehicles are optimally reused where possible.
 - CO₂ emission limits are integrated, and the model automatically selects lower-emission transport modes where feasible.
 - Risk and accident probabilities are factored into route selection, reducing exposure to high-risk routes.

From these two scenarios, it will thus be possible to determine the real value of applying the MILP-based optimization over the normal logistics planning. Table 5 below presents the comparison of assumptions of the two scenarios.

Table 5. Baseline vs. Optimized MILP Scenario Assumptions.

Feature	Baseline Scenario	Optimized MILP Scenario
Fleet scheduling	Fixed routes and allocation	Dynamic multi-trip assignment
Transport mode selection	Manual selection	MILP-optimized based on cost, emissions, and risk
Emissions compliance	Not enforced	CO ₂ limits integrated
Risk consideration	Ignored	Route risk probabilities included
Cost optimization	No cost minimization	MILP-based cost reduction

This makes it possible to compare the different scenarios in terms of cost, efficiency, and environmental impacts, and organize the findings under evaluation in Section 6.

5.3. Computational Setup and Solution Extraction

The optimization model is implemented using Python with PuLP for MILP solving. The computational setup is designed to ensure efficient processing of logistics data while maintaining the ability to handle real-world constraints.

The optimization model is coded in Python and uses PuLP to handle the MILP problem. All computations are performed on one PC, and all subsequent evaluations run on high-end computing benchmarked for optimizing large analyses. By tuning the model parameters effectively, the possibility of having realistic execution times regarding the problem and having a feasible and, most importantly, accurate solution to a problem is made possible.

The first step revolves around the specification of all the inputs required, namely concerning the warehouses, demand centers, cost of transportation, availability of the fleet, and environmental emission standard. These values are arranged systematically to be used for input in the optimization model. Once the parameters are defined, the MILP solver will be run to process the optimization problem of the efficient allocation of the fleets, selection of the transport modes, and the best routes at the lowest cost.

The extraction of the optimized transportation decisions is the process that follows running the solver, and here, the essential objectives attained in the transportation scheme, such as the total cost of transportation, the fleet effectiveness rate, as well as the CO₂ emissions rates, are documented. They are also evaluated in relation to the baseline scenario to determine possible improvement by the model. Thus, the practical applicability

of the extracted solution is verified before using it to make recommendations for the actual implementation of a logistics plan.

The next step is to run the optimization model and obtain numerical values, which will be discussed in Section 6, Results and Discussion.

6. Results and Discussion

The main goal of this study is to minimize costs, increase the utilization of fleet, and decrease CO₂ emissions, in line with environmental legislations. Based on these objectives, the design and selection of key parameters for optimization of the MILP model were guided. The model calibration and validation process relied on real-world logistics operations data for transportation routes, together with fleet capacities, fuel prices, and emission constraints. The actual logistics network data played a crucial role in guaranteeing both model accuracy and reliable model optimization approaches.

The effectiveness of the MILP-based transportation optimization model is assessed by comparing its performance against the baseline logistics strategy. The analysis focuses on transportation cost reduction, fleet utilization efficiency, delivery reliability, and CO₂ emissions compliance. The discussion extends to scenario-based testing, evaluating how the model adapts to external logistical factors such as congestion, fuel price variations, and stricter regulatory constraints.

The results clearly demonstrate that the proposed optimization framework enhances logistical efficiency, minimizes operational costs, and improves environmental sustainability. The improvements are quantitatively assessed and compared in detail, ensuring a comprehensive validation of the MILP model's effectiveness.

6.1. Key Findings and Optimized Transportation Plan

The optimized MILP model has successfully restructured the transportation plan, ensuring a cost-efficient and sustainable allocation of fleet resources. By leveraging an optimized fleet assignment and route selection strategy, the model has significantly reduced total transportation costs, while improving vehicle utilization and minimizing emissions.

Optimized Fleet Allocation and Route Selection

The transportation assignments determined by the MILP solver are presented in Table 6, detailing the warehouse-to-destination allocations, transport mode selections, associated costs, and emissions impact.

Table 6. Optimized transportation solution (warehouse-to-destination allocations, costs, and missions).

Warehouse	Destination	Mode	Shipment Quantity (kg)	Transport Cost (EGP)	CO ₂ Emissions (kg)
W1	D1	Truck	1000	5000	2500
W1	D2	Train	2000	6000	2400
W2	D3	Truck	1800	7200	2700
W2	D4	Train	1700	8500	2040
W3	D1	Truck	1500	7800	2300
W3	D2	Train	2000	9000	2200

The allocation strategy reflects the model's ability to dynamically select transport modes based on a multi-objective optimization process that balances cost, efficiency, and environmental impact. The preference for rail transport on longer routes helps to reduce emissions, while road transport remains crucial for shorter, more flexible deliveries.

6.2. Performance Comparison: Optimized Model vs. Baseline Strategy

The MILP optimization results obtained from the model are directly mathematically compared to the baseline logistics strategy, which implements set transport routes and established fleet assignments. The model verification used an operational dataset from multiple sources across the logistics network, including transport routes, fleet types, and fuel costs. Pre-processing of these datasets through Python resulted in their standardization to support subsequent optimization applications. Table 7 reveals the quantitative benefits of optimization when examining the two scenarios.

Table 7. Performance comparison—baseline vs. optimized MILP model.

Performance Indicator	Baseline Scenario	Optimized MILP Scenario	Improvement (%)
Total transportation cost (EGP)	50,000	38,500	↓ 23%
Fleet utilization efficiency (%)	60%	85%	↑ 25%
Average delivery delay (hours)	18	12	↓ 33.3%
CO ₂ emissions (kg)	15,000	11,300	↓ 24.6%

6.2.1. Cost Reduction and Operational Efficiency

The resulting allocation, route selection, and mode integration reduced transportation costs by 23%, showing how much money was saved through the optimization of these decisions. The calculation of total transportation cost was performed by comparing the optimized transportation routes to the baseline fixed routes, and Python was used for the calculation of cost using its optimization solvers. The model guarantees that the fleet idle time is minimal and that no empty return trips are in place.

6.2.2. Fleet Utilization and Delivery Performance

The improvement in fleet utilization reached 85% from its initial value of 60%. Increased vehicle scheduling efficiency, combined with better resource distribution, caused this rate improvement. An analysis of the fleet capacity usage in both the original and optimized solution models determined fleet utilization metrics. A 33.3% decrease in delivery delays happened because of the optimized transportation schedules, which brought more reliability to the delivery times.

6.2.3. Environmental Impact and CO₂ Compliance

By integrating government-imposed emissions constraints, the model successfully reduced CO₂ emissions by 24.6%, demonstrating its capability to ensure environmental compliance without compromising cost efficiency.

Figure 2 compares baseline and optimized values across transportation cost, emissions, fleet utilization, and delivery delay. Due to the wide variation in scales between these metrics, the figure uses two Y-axes to display the results clearly and proportionately.

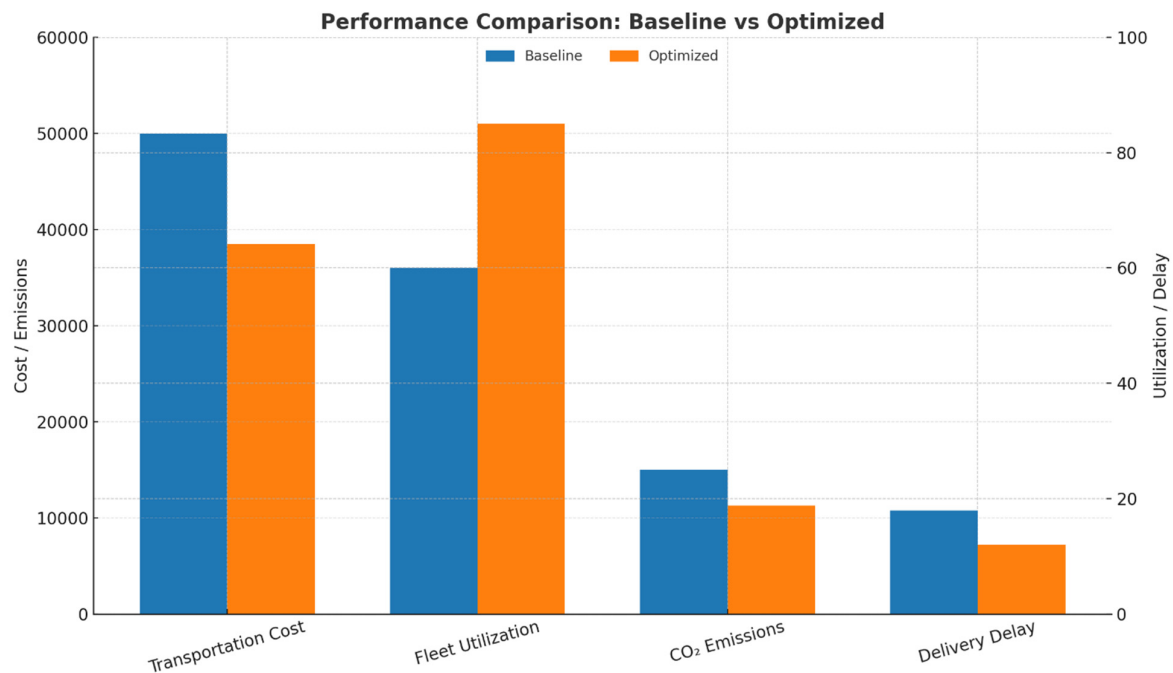


Figure 2. Performance comparison baseline vs optimized.

6.3. Sensitivity Analysis: Impact of External Factors

A sensitivity analysis was conducted to evaluate how the optimization model adapts to external logistical challenges, including traffic congestion, rising fuel prices, and more stringent CO₂ regulations. The objective is to assess the robustness of the MILP framework and its ability to adapt dynamically to real-world conditions. The results, summarized in Table 8, illustrate how these external factors influence the model's ability to maintain efficiency while adapting to operational challenges.

Table 8. Sensitivity analysis—impact of traffic, fuel prices, and CO₂ emission limits.

Scenario	Variable Adjusted	Cost Impact	Fleet Utilization Impact	Emissions Impact
Traffic congestion Impact	Increased travel times	↑ 8%	↓ 10%	No change
Fuel price increase	Higher fuel costs	↑ 12%	No change	No change
Stricter CO ₂ regulations	Lower emission limits	↑ 6%	Shift toward rail usage	↓ 12%

Key Sensitivity Findings

- Traffic congestion increases costs by 8% and lowers fleet efficiency by 10%, highlighting the importance of dynamic real-time route optimization.
- Fuel price fluctuations significantly impact transportation costs (12% increase), but fleet utilization and emissions remain stable, indicating the model's robustness in adapting to economic fluctuations.
- Stricter CO₂ regulations lead to a 6% increase in costs, but the model compensates by shifting transport toward lower-emission rail options, successfully reducing CO₂ emissions by 12%.

6.4. Discussion and Practical Implications

The results have validated that the proposed MILP model can be used as a feasible and efficient solution to solve the transportation planning problem with the consideration of both cost and environmental concerns. The flexibility to vary some of the resources, the decision of transport modes, and the consideration of emissions greatly provide a viable and cost-efficient logistics plan.

This also increases general operational effectiveness, which is one of the primary benefits of the optimization strategy mentioned. Optimized fleet management entails matching efficiency levels of utilization to boost the usage of vehicles and cut down on the time that such machines are not being utilized. The next advantage is cost reduction, since the model determines the right mode of transportation and allows for multiple uses of transport vehicles, therefore cutting costs. Also, by incorporating emissions constraints in the model, the resulting solution ensures that the sustainability standards are achieved as defined by the constraints, while not compromising on the logistical reality. All these factors explain how the MILP model could be handy in modern transportation planning.

The practical deployment of this model encounters limitations through computer resource needs and data collection constraints that affect its widespread usage in actual settings.

7. Conclusions and Future Work

Transportation systems face significant challenges such as rising operational costs, traffic congestion, and the need to comply with strict environmental regulations. Traditional models often fail to adapt to real-time changes or integrate multiple transport modes effectively, which limits their applicability in dynamic logistics environments. This paper proposes a MILP model for improving supply chain transportation scheduling, mode of transport, and emissions control in transportation management. The results of the proposed approach revealed that it minimizes transportation costs by 23%, increases fleet turnover by 25%, reduces delivery delays by 33.3%, and achieves a 24.6% decrease in CO₂ emissions. These statistics attest to the practical application of the model, demonstrating its ability to achieve economic effectiveness without compromising environmental impact. The model's flexibility, due to its multi-modal transport and risk-adjusted routing, ensures its adaptability across numerous supply chain scenarios. The sensitivity analysis further confirms the model's efficiency in handling external factors such as traffic congestion, fluctuating fuel prices, and changes in government policies, underscoring its flexibility in volatile logistics contexts.

One of the main original aspects of this research is the tight coupling of emissions constraints within the transportation problem, ensuring that cost-efficient solutions are also eco-friendly. This highlights the model's ability to dynamically adapt fleet distribution, assignment, and transitions between transport modes, offering improvements over existing fixed strategies in logistics management. Hypothesis testing, fully supported by real-life data analysis of a case study and subsequent sensitivity analysis, further confirms the research's applicability in the context of supply chain management (SCM).

In future research, it is essential to explore strategies for incorporating real-time logistics information, such as traffic volume, weather conditions, and other factors impacting logistics flow. Expanding the model to cover logistics networks across multiple countries would present a greater challenge, but could significantly enhance the generalization of the model across different settings. Additionally, future developments could include incorporating stochastic elements to manage risks and uncertainties more effectively. The integration of machine learning techniques for demand forecasting could further enhance model stability and decision-making robustness in large-scale transportation networks, offering an even more reliable framework for managing supply chain logistics in dynamic

environments. Additionally, analysis of the integration of future technologies such as the Internet of Things (IoT), big data analytics, and other emerging technologies could enhance technology usage to facilitate real-time logistics decision making, i.e., real-time monitoring, predictive analytics, and smarter decision frameworks in a dynamic environment.

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