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Optimizing a Capacitated Vehicle Routing Problem with Scheduled Arrival, Split Deliveries within Time Windows and Emission Consideration

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Abstract: The Capacitated Vehicle Routing Problem (CVRP) has gained significant attention in both academic and industrial circles due to its pivotal role in optimizing logistic systems. In the context of evolving distributor companies and the growing integration of logistics with broader societal concerns such as climate considerations, this paper delves into a CVRP variant that includes time windows and split deliveries. Real-world assumptions are incorporated to enhance the practical applicability of the study. A mathematical model is proposed to minimize both economic costs and pollutant emissions. Given the unavailability of cost information for all possible routes, a cost function is estimated through multiple linear regression, considering both distance and time factors simultaneously, in order to associate to each link costs and emissions. To validate the effectiveness of the proposed model, a real-world case study involving an industrial distribution company is investigated. The results demonstrate a significant improvement compared to the company's current operational procedures.

Keywords: GHG emissions, capacitated vehicle routing problem, cost estimation, split delivery, multiple linear regression

1. INTRODUCTION

Logistic problems have been a subject of extensive investigation by researchers, governmental bodies, and industrial organizations over the past few decades. Since the introduction of the Vehicle Routing Problem (VRP) in the late fifties, it has become a pivotal component in various industries. Numerous variants within this field have been explored, including the Capacitated Vehicle Routing Problem (CVRP), Vehicle Routing Problem with Time Windows (VRPTW) (Wu et al, 2024), VRP with Backhauls, and VRP with Pick-up and Delivery (Toth & Vigo, 2014). The economic significance of transportation is evident as it plays a crucial role throughout the entire production and distribution systems. Notably, the transportation process represents a substantial component, typically contributing between 10% and 20% to the overall cost of goods (Moghdani et al 2021).

The work by Asghari and Al-e in 2021 vastly investigated on Green Vehicle Routing Problem (GVRP) literature by categorizing it into two primary domains: problem characteristics and solution methodologies. Regarding the problem characteristics of GVRP, existing research has concentrated on diverse objectives, scenarios, and their integration with conventional supply chain models. Various studies have delved into nuanced aspects, thereby enriching the understanding of the problem within the broader context of traditional research frameworks.

In parallel, a substantial body of recent contributions has been focused on solution methodologies for GVRP. Methodologies can be broadly categorized into exact methods and heuristics/meta-heuristics. Exact methods, such as Linear Integer Programming, Tree Search Methods, and Dynamic Programming, aim to provide optimal solutions. On the other hand, heuristics and meta-heuristics, exemplified by approaches like the Saving Method, Clustering-Based Algorithms, and Population-Based Search for Meta-Heuristics, strive for effective solutions within reasonable computational time (Asghari & Al-e 2021).

In the recent literature addressing the GVRP, a predominant focus has been directed towards understanding and mitigating pollutants emitted during the transportation phase of the supply chain, particularly stemming from the use of fossil fuels (Asghari & Al-e 2021). A parallel stream of research has emerged, exploring the Electric Vehicle Routing Problem (EVRP) and its integration for environmentally conscious objectives (Amiri et al 2023). Further investigations delve into the optimization of electric vehicle consumption (Lera-Romero, Bront, & Soulignac 2024) and the strategic placement of charging stations (Ferro, Paolucci, & Robba, 2020).

Diversifying the scope, some studies introduce complexity by incorporating uncertainty into GVRP considerations (Zarouk, Mahdavi, & Rezaeian, 2022). Others extend the inquiry to hazardous material transportation within the GVRP framework (Rahbari et al., 2023). Some of the investigations tried to address real-world complexities, such as considering

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the Time-Dependent Fleet Size and Mix Green Vehicle Routing Problem (TD-FSMGVRP), with a focus on algorithmic solutions (Alinaghian, Jamshidian, & Tirkolaee, 2022).

Categorically, in terms of fleet, GVRP can be segmented into three domains: (1) GVRP involving conventional vehicles, (2) GVRP featuring alternative fuel vehicles, and (3) GVRP considering a mixed fleet of vehicles. Within these broad categories, specific subcategories have been identified for GVRP with Conventional Vehicles (CV) and Alternative Fuel Vehicles (AFV), demonstrating the nuanced variations and specialized areas of inquiry (Sabet and Farooq, 2022).

The primary objective of this study is to formulate a green optimization problem, specifically tailored to address the challenges associated with the distribution of industrial products. We intend to estimate economic costs by leveraging historical data to establish a reliable objective function. Additionally, drawing insights from existing literature, we propose a function to compute the total emission factors of diesel engines, thereby integrating environmental considerations within the optimization framework. To assess the accuracy and efficacy of our model, we apply it to solve a real-world case involving the distribution of industrial products on a medium scale. We aim to showcase the various features and capabilities of our proposed model. This validation process will demonstrate the practical applicability of our optimization approach and highlight its potential to contribute to greener and more sustainable practices in the distribution of industrial goods.

The principal contributions of this work are as follows:

- Formulating a mathematical model for Green Capacitated Vehicle Routing Problem (CVRPTW) using a real-world case assumption, taking into account the scheduling of arrival times and the split deliveries among trucks.
- Addressing a real-world case study through the application of the proposed model, showcasing the results obtained their distinctive features.

In the following, in Section 2, we conduct an analysis of economic costs by estimating different truck types through multi-linear regression. This analysis is based on real data, and aims to identify an actual cost function. Simultaneously, a formula for calculating the total emission factors resulting from this transportation is applied. In Section 3, we propose a Mixed Integer Linear Programming (MILP) mathematical model, grounded on real-case assumptions. This model not only considers economic costs but also the total emissions generated during the distribution process. Section 4 showcases and evaluates the proposed model's results to a real-world case, offering insights into its practical implications and effectiveness. Finally, in Section 6, we conclude our research and recommend potential avenues for future investigation.

2. EMISSION AND COST ANALYSIS

2.1 Cost function

In the considered real case, the costs of all node-to-node connections in the network are not completely known, apart from a small subset of such connections. Besides, there is no evidence of the rule by which such available values have been generated. So, to deal with this lack of data (and of a suitable model) a multiple linear regression (MLR) has been applied to estimate the rest of the missing costs on the basis of the available real costs (Uyanık & Güler, 2013). Regression analysis is a statistical method employed to estimate relationships between variables exhibiting cause-and-effect dynamics. Univariate regression, a key focus, involves scrutinizing the relationship between a dependent variable and a single independent variable, thereby formulating a linear equation that captures their interdependence. When the model incorporates one dependent variable and multiple independent variables, it is termed multilinear regression (Uyanık & Güler, 2013). Obviously, the cost of each route by each truck depends on factors like distances between nodes and travel time between nodes. In this part, a multiple linear regression based on the distances, travel time and fixed cost is provided. Based on the real data that were received this regression was accomplished within three different models: i) based on the distance between nodes ($dist_{ij}(km)$) and fixed cost, ii) on travel time between nodes ($t_{ij}(hour)$) and fixed cost, and iii) on the distance, travel time and fixed cost. This analysis is carried out separately for each type of truck. The estimation is based on the minimization of the Sum Square Error (SSE of the estimation compared with some of the real costs As it is shown in (2). The numerical analysis are presented in section 4.1. Equation (1) represents the linear regression in which $K1_h$ (€/km), $K2_h$ (€/hour) and $K3_h$ (€) are the coefficient of distance of the link (i, j), coefficient of travel time of link (i, j) and fixed cost of using each type of vehicle h respectively and ec_{ijv} is the available real cost of the link (i, j) by vehicle v.

$$c_{ijh} = K1_h.dist_{ij} + K2_h t_{ij} + K3_h \qquad \forall i \in N, j \in J, h \in H \tag{1}$$

$$Min \;\; E_h = \sum_{i \in N} \sum_{j \in N} \left(ec_{ijh} - K1_h dist_{ij} - K2_h t_{ij} - K3_h \right)^2 \forall h \in H \tag{2}$$

2.2 Emission Cost

Given that controlling the emission of pollutants, particularly carbon dioxide (CO_2), is crucial in addressing the CVRPTW for large-scale problems, this section applies a method derived from the literature to calculate the emission amount and convert it into a monetary cost. Among the various pollutants, CO_2 is selected as the most representative, and its emission cost is quantified. Integrated assessment models (IAMs), encompassing around 36 models, have been extensively studied for estimating the social cost of emissions. Wang et al. (2019) analyzed 578 scientific works and found that the mean social cost for CO_2 was approximately 0.0000536 [€/gCO2]. The method employed for emission cost considers the CO_2 emission rates for three types of diesel engine-based vehicles: Delivery Van, Medium Duty Truck, and Heavy-Duty Vehicle. These emission rates are reported as 252, 450, and 678 [gCO_2/km], respectively (Krause et al., 2020). Equation (3) is utilized to calculate the social emission cost $EC_v^{CO_2}$ for CO_2

based on the type of truck (v) for one kilometer of travel. In the formula, $e_v^{CO_2}$ [gCO_2/km] represents the emission of truck v (per unit distance), and EP^{CO_2} [€/gCO_2] indicates the social emission price of one gram of CO_2.

$$EC_v^{CO_2} = EP^{CO_2} e_v^{CO_2} \quad \forall v \in V \tag{3}$$

3. CVRPTW MATHEMATICAL MODEL

In this section, a Mixed Integer Linear Mathematical model based on real-case assumptions is proposed. The model assumes capacitated vehicle routing with time windows and split delivery between trucks to satisfy the store's orders. In the following, in section 3.1 the model notations are presented, and in section 3.1 the problem and all assumptions are provided followed by the mathematical model with all definitions.

3.1 Sets, parameters and variables

In this section, prior to introducing the mathematical model, Table 1 provides definitions for various notations, encompassing sets, parameters (representing input and known information), and decision variables (reflecting the model's output after solution).

Table 1. Sets, parameters and decision variables

Notation	Definition
	Sets
N	The set of all nodes (DC and Stores), $\forall i, j \in N$
$J \subseteq N$	A subset of N that include only store nodes $\forall i, j \in J$
V	The set of all trucks with different characteristics and capacities $\forall v \in V$
	Parameters
c_{ijv}	Cost of path from *i* to node *j* by vehicle *v*, $\forall i, j \in N, v \in V$
$dist_{ij}$	Distance of path from *i* to node *j*, $\forall i, j \in N$
t_{ij}	Travel time between nodes *i* and *j* $\forall i, j \in N$
d_j	Aggregate demand of the customer *j* $\forall j \in J$
Q_v	Capacity of truck *v*, $\forall v \in V$
a_j	Earliest possible arrival time at the node *j*, $\forall j \in J$
b_j	Latest possible arrival time at the node *j*, $\forall j \in J$
S_{jv}	Service/unloading time at the node *j*, by truck *v*, $\forall j \in J, v \in V$
UV	Upper bound for the number of visits in each tour
M	A large number
	Decision Variables
x_{ijv}	Binary variable equal to 1 if truck *v* includes link *(i,j), 0* otherwise
z_{ijv}	Load of truck *v* transferred between link *(i,j)*
w_{jv}	Arrival time at the node *j* by truck *v*
g_{jvl}	Binary variable equal to 1 if truck *v* arrives at node j before truck *l*, 0 otherwise

3.2 Mathematical Formulation

This section presents a Mixed-Integer Linear Programming (MILP) mathematical model based on a real industrial case. The scenario involves two distinct types of nodes: warehouses and stores, distributed across various cities. The predetermined association of stores to distribution centres is a given parameter in this problem formalization, focusing solely on deliveries from warehouses to the assigned stores. The warehouse receives orders from its associated stores at the commencement of each day or the preceding night. These orders comprise essential information, including the store name, aggregate demand, and time windows for order delivery. Each day, only one delivery to each store is required, and the delivery process involves one or more trucks. During each day after receiving the orders, the stores cannot change the orders. Despite the potential diversity in product classes within a store's demand, we treat each order as a volume of a single category of items, specifically pallets. The deliveries are executed using a fleet of trucks with heterogenous characteristics, as each category has a specified capacity. Certain stores may only be accessible by specific categories of trucks. Vehicle types and driver constraints limit the number of stores to visit on each route. Each truck initiates its route from a known position (the depot), with the last store in its route marking the completion of the journey. The routing problem's objectives are stated as follows:

a) Minimizing the overall economic cost incurred on the designated day;
b) Minimizing the total emission of pollutants in relation to the designated routes.

By considering the above assumption, we propose the following mathematical model:

$$Min\ \ Z = \sum_{i \in N}\sum_{j \in N}\sum_{v \in V} x_{ijv}\left(K1_v dist_{ij} + K2_v t_{ij} + K3_v\right) + \sum_{i \in N}\sum_{j \in N}\sum_{v \in V} x_{ijv} dist_{ij} EP^{CO_2} e_v^{CO_2} \tag{4}$$

Subject to

$$\sum_{j \in J} x_{1jv} \le 1 \quad \forall v \in V \tag{5}$$

$$\sum_{\substack{i \in N \\ i \ne j}}\sum_{v \in V} x_{ijv} \ge 1 \quad \forall j \in J \tag{6}$$

$$z_{ijv} \le x_{ijv} Q_v \quad \forall i \in N, j \in J, i \ne j, v \in V \tag{7}$$

$$\sum_{\substack{i\in N\\ i\neq j}} z_{ijv} \geq \sum_{\substack{k\in J\\ k\neq j}} z_{ikv} \quad \forall j\in J, v\in V \tag{8}$$

$$\sum_{i\in N}\sum_{v\in V} z_{ijv} = d_j + \sum_{k\in J}\sum_{v\in V} z_{jkv} \quad \forall j\in J \tag{9}$$

$$\sum_{\substack{i\in N\\ i\neq j}} x_{ijv} \geq \sum_{\substack{k\in J\\ k\neq j}} x_{jkv} \quad \forall j\in J, v\in V \tag{10}$$

$$w_{iv} + t_{ij} + S_{jv} - w_{jv} \leq \left(1 - x_{ijv}\right)M \quad \forall i\in N, j\in J, i\neq j, v\in V \tag{11}$$

$$w_{jv} \geq a_j \sum_{i\in N} x_{ijv} \quad \forall j\in J, v\in V \tag{12}$$

$$w_{jv} \leq b_j \sum_{i\in N} x_{ijv} \quad \forall j\in J, v\in V \tag{13}$$

$$w_{jv} \geq w_{jl} + S_{jl} - \left(1 - g_{jlv}\right)M \quad \forall l, v\in V, l\neq v, j\in J \tag{14}$$

$$g_{jvl} + g_{jlv} \leq 1 \quad \forall l, v\in V, l\neq v, j\in J \tag{15}$$

$$g_{jvl} + g_{jlv} \geq \sum_{\substack{i\in N\\ i\neq j}} x_{ijv} + \sum_{\substack{i\in N\\ i\neq j}} x_{ijl} - 1 \quad \forall l, v\in V, l\neq v, j\in J \tag{16}$$

$$\sum_{\substack{i\in N\\ i\neq j}}\sum_{\substack{j\in J\\ j\neq i}} x_{ijv} \leq UV \quad \forall v\in V \tag{17}$$

$$\begin{aligned} & x_{ijv}\in\{0,1\}, z_{ijv}\in R_+ \quad \forall i,j\in N, \forall v\in V \\ & g_{jvl}\in\{0,1\} \quad \forall j\in N, \forall v,l\in V \\ & w_{jv}\in R_+ \quad \forall j\in N, \forall v\in V \end{aligned} \tag{18}$$

The cost to be minimized in (4) takes into account the total economic and emission costs. Constraints (5) stipulates that each trip must commence from the warehouse node, representing the initial node. To ensure comprehensive coverage, constraints (6) mandates that every customer must be visited at least once. Constraints (7) imposes a limitation on the total product volume carried, ensuring it does not exceed the capacity of each truck. Constraints (8) maintains a balance between the inflow and outflow of load at customer node j for each truck. Moreover, (9) are flow conservation constraints calculating the load of truck that must be transferred between nodes, accounting for each customer's demand. Constraint (10) effectively manages the inflow and outflow of trucks at each customer node. Time windows for customer satisfaction are guaranteed by constraints (11)-(13). Constraints (14)-(16) specifically address scenarios where the delivery for a store is split among multiple trucks, ensuring their non-simultaneous arrival. Constraints (17) establishes an upper limit on the number of visits for each tour within the model. Lastly, constraints (18) outlines the type of decision variables in the model.

4. REAL CASE STUDY AND RESULTS

4.1. Multi Linear Regression Analysis

As the results of this estimation procedure which is presented in section 2.1, Table 2 was obtained. It turns out that the best model is that taking into account the distance, travel time and fixed cost together. The minimization in (2) is a simple optimization problem that allows to determine the coefficients of the regression model that optimizes the sum of the square errors.

Table 2. Results of the linear regression for the cost function for three different vehicle types.

Considered criteria	$K1$	$K2$	$K3$
	Vehicle Type 1		
Distance, Time and Fixed cost	2.4	67.6	23
Distance and Fixed cost	3.4	-	24
Time and Fixed cost	-	230.1	23
	Vehicle Type 2		
Distance, Time and Fixed cost	1.8	44.6	0
Distance and Fixed cost	2.5	-	0
Time and Fixed cost	-	165.6	0
	Vehicle Type 3		
Distance, Time and Fixed cost	1.7	12.5	0
Distance and Fixed cost	1.9	-	0
Time and Fixed cost	-	129.6	0

4.1. Mathematical Model Results

This section investigates a real case of distributing industrial goods from a warehouse to stores. The case involves 20 nodes, with the first node being the warehouse and the remaining nodes representing various stores in different cities. There are 16 available trucks, each with capacities ranging from 12 to 33 pallets. The assumed unloading time for each truck at every store is one hour. After implementing the model in Python and executing the sample using the Gurobi Optimizer solver version 10.0.2, we obtained results for the case in one day. Figure 1 displays the optimal routes after solving the model, while Table 3 presents detail of a part of optimal result, including the optimal values of the decision variables (x_{ijv}, z_{ijv} and w_{jv}). The optimality gap is less than 4% and the computation time was 8000 seconds which corresponds to the maximum time limit for the solver. According to the results, the demand for certain stores is splited and fulfilled by multiple trucks. The split delivery is achieved by scheduling the arrival times of the trucks, ensuring they arrive one after the other following the loading time. As evident from Table 3, certain stores, such as Store 11 and Store 3, experience a split in deliveries among trucks. For instance, in Store 11, the delivery is divided between Truck 2 and Truck 11, with Truck

2 arriving before Truck 11. The time gap between their arrivals is one hour, which equals the unloading time of the first truck. Similarly, in the case of Store 3, the optimal result involves the distribution of orders among three different vehicles, as illustrated in Table 3. The scheduling of arrival times is notable for this store. Vehicle 16 arrives first at 8:00, followed by Truck 6 at 9:00, and the final truck, Truck 10, arrives at 10:00. The objective function of the result indicates that the total economic and emission cost is €3742. This suggests that the optimal procedure results in approximately a 20 percent reduction in the total cost compared to the actual distribution centre's procedure for the same day, as implemented in this paper. In terms of distance, the total distance traveled by all vehicles in the experiment was 1453 km. In the real-world scenario, however, the vehicles covered approximately 1900 km, indicating a 23 percent improvement. The study involved 10 heterogeneous vehicles, consisting of 2 large trucks, 6 medium-sized trucks, and 2 small-sized trucks. In contrast, the real-world application utilized 16 trucks, including 5 large trucks, 9 medium-sized trucks, and 2 small-sized trucks. This demonstrates a 60 percent and 33 percent improvement in the number of large and medium-sized trucks, respectively, compared to the real-world case. In the study, split delivery was implemented for 2 stores. In contrast, in the real-world scenario, the company executed it for only 1 store.

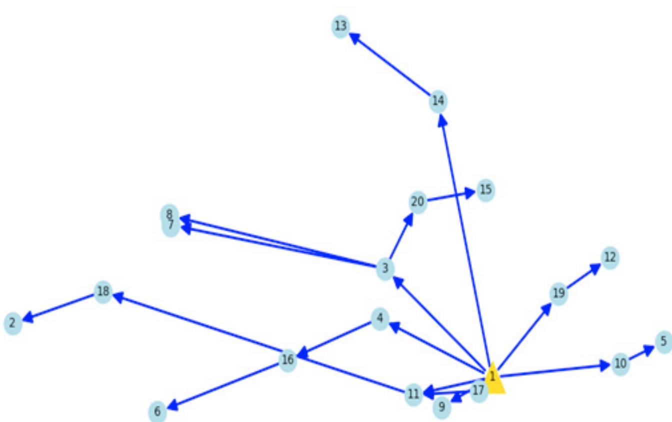

Figure 1. Optimal routes after solving the MILP model

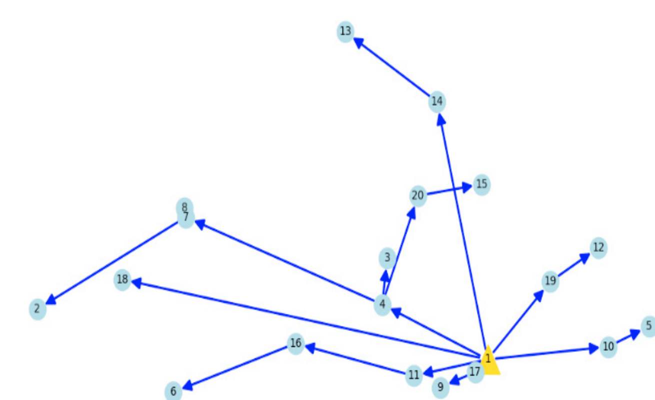

Figure 2. Optimal routes considering emission cost as the objective

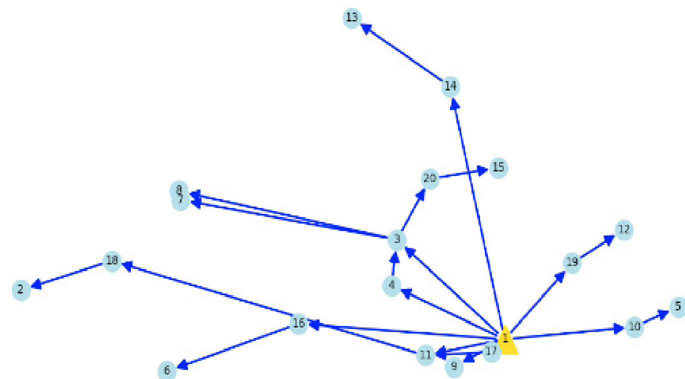

Figure 3. Optimal routes considering econommic cost as the objective

Table 3. Optimal results and parameter ranges

Optimal Results							
Vehicle 2							
Optimal Path (x_{ijv})	1	→	11	→	18	→	2
Load of Truck (z_{ijv})	-		33		23		11
Arrival Time (w_{jv})	-		8:00		10:00		12:00
Vehicle 6							
Optimal Path (x_{ijv})	1	→	3	→	7		
Load of Truck (z_{ijv})	-		17		9		
Arrival Time (w_{jv})	-		9:00		11:00		
Vehicle 10							
Optimal Path (x_{ijv})	1	→	3	→	20	→	15
Load of Truck (z_{ijv})	-		18		14		6
Arrival Time (w_{jv})	-		10:00		11:00		13:00
Vehicle 11							
Optimal Path (x_{ijv})	1	→	17	→	11		
Load of Truck (z_{ijv})	-		17		13		
Arrival Time (w_{jv})	-		8:00		9:00		
Vehicle 16							
Optimal Path (x_{ijv})	1	→	3	→	8		
Load of Truck (z_{ijv})	-		12		10		
Arrival Time (w_{jv})	-		8:00		10:00		

Upon further analysis, the model was applied with two distinct objectives: minimizing emission cost and minimizing economic cost. A comparison of the final routes for these scenarios was conducted. Figure 2 illustrates the outcome when solely focusing on emission cost, revealing a notable 5% percent improvement. However, this gain comes at the expense of increased resource utilization, with 11 vehicles utilized, including one large truck. Notably, when both objectives were considered concurrently, only 10 trucks were needed, and two of them were large. Figure 2 visually highlights significant alterations in routes and their sequences. Conversely, when economic cost served as the sole objective function, only a single path underwent a change, resulting in a marginal improvement in economic efficiency (Figure 3). Remarkably, the number and types of trucks mirrored those used in the bi-objective scenario. This implies that the economic cost had a more stable impact on the final routes compared to the emission cost. The consequence of this analysis firmly establishes the dominance of economic considerations over social emission costs. The final routes derived from the bi-objective approach closely resembled those optimized for economic efficiency. In contrast, the scenario focusing solely on emission cost exhibited considerable route changes. This stark contrast underscores the narrative that economic efficiency significantly outweighs the impact of social emission costs in shaping optimal logistics routes.

5. CONCLUSIONS AND FUTURE WORK

In this paper, we develop a Mixed-Integer Linear Programming (MILP) model to minimize both the total economic and emission costs for a real-world industrial product distributor. A multi-linear regression model is formulated and analyzed for the economic cost using past data, yielding a functional representation for cost calculation. The model is then solved using commercial solvers, and optimal solutions are obtained for a practical case study. The results indicate that the optimal solution for the sample case exhibits the model's key features, such as split delivery to fulfill orders and scheduling arrival times at stores based on realistic assumptions. Furthermore, the optimal result demonstrates a significant deviation from the actual procedures employed by the company. Daily operational decisions in the real world involve addressing an NP-hard problem. As the problem size increases, finding efficient solutions within a reasonable time frame becomes crucial. Thus, exploring reliable heuristics or exact methods for solving the problem is a promising area for future research.

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