International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 17 (2025) pp. 261–276

Article

Green Capacitated Vehicle Routing Problem under Traffic Congestion

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Received date: 2 November 2024; Accepted date: 9 March 2025; Published online: 27 March 2025

Abstract: The transportation system has grown significantly and quickly in the past few years. This growth is natural to the development of societies, producing positive externalities that support the economic growth of the regions 'activities, but it also brings about negative externalities, particularly Traffic congestion. Congestion substantially increases fuel consumption and carbon emissions, exacerbating environmental challenges. This paper introduces a novel approach to model and resolve the Green Capacitated Routing Problem (GCVRP), incorporating traffic congestion and CO_2 emissions. Objectives are to minimize the total travelled distance and the associated carbon emissions. This bi-objective problem is NP hard. We propose to convert it to a mono-objective one. The proposed model transforms real distance metrics into a virtual distance adjusted to account for CO_2 emissions and congestion levels. Exact solution methods is applied for finding optimal solutions using CPLEX solver with AMPL programming language. Using numerical experiments, the comparison between the real model and the suggested virtual model shows that the new methodology improves computing efficiency and solution quality. These results demonstrate how the model can help make more sustainable and efficient decisions about transportation logistics.

Keywords: capacitated vehicle routing problem (CVRP); CO_2 emissions; traffic congestion; virtual model; mono-objective optimization

1. Introduction

The transport sector is an essential link in development. A source of wealth, equality, and well-being, transport is of crucial importance for any nation. Transport is evolving to enable more people to go further, and faster. In recent decades, the quantity, diversity, and length of passenger flows have increased. Transportation has taken up more and more space in our quotidian. Economic growth, trade, population growth, and the concentration of populations in large cities intensify the demand for transport services. Of course, this growth is inherent in the development of societies, generating positive externalities contributing to the economic development of the territories through their activities. Still, this mobility also induces negative externalities such as noise pollution, insecurity, congestion, and increased CO_2 emissions.

In this article, we will focus on the Green Capacitated Vehicle Routing Problem considering congestion and CO_2 emissions. Road congestion can be defined as the condition wherein a rise in vehicle traffic results in an overall slowdown in traffic [1,2]. Traffic congestion causes delays and bottlenecks because the infrastructure cannot control traffic flow.

The transportation system has a considerable impact on the ecological environment. Since road transportation contributes significantly to CO_2 emissions, extensive studies have been done in the last ten years on how to create vehicle routing that is both economical and environmentally friendly. In this context, Erdogan et al. [3] developed the green vehicle routing problem (Green-VRP), a relatively new research area, as an extension of the traditional routing problem. Green-VRPs seek to reduce fuel use to reduce energy consumption in fleet operations, and it is a way to apply effective routes to address financial indices and environmental issues while balancing the economic and environmental costs. The Green Capacitated Vehicle Routing Problem (GCVRP) is one of the GVRP's versions and one of the most significant transportation challenges.

The GCVRP problem is NP-hard and can only be precisely and optimally solved for small-size situations utilizing exact approaches. Therefore, workable and good, but not always guaranteed, optimal solutions are developed while requiring appropriate amounts of processing time using heuristic and meta-heuristic methods. Modeling the GCVRP problem considering congestion is challenging. A range of features have been suggested for a measure of congestion [4–6].

Several authors have studied the impact of congestion on CO_2 emissions [7–10], but to our knowledge, there is no work that has proposed methodologies to integrate congestion into the GCVRP problem.

To integrate traffic congestion into the GCVRP problem, our goal is to present a new modeling approach to the GCVRP problem, minimizing the complexity of multi-objective problems. This approach is based on the conversion of the problem of minimizing traveled distance and CO_2 emissions into a model that minimizes the total virtual traveled distance. Virtual travelled distances include the real distances and the distances equivalents to the quantity of emissions and traffic congestion.

The structure of this document is as follows: A concise multi-objective GCVRP under traffic congestion literature review is presented in the second section, along with suggested techniques for estimating CO_2 emissions and traffic congestion. A formulation of the suggested approach is presented in Section 3. Additionally, the fifth section will present the tests and results. Finally, a general conclusion is presented in Section 5.

2. GCVRP under Traffic Congestion: State of The Art

2.1. The Green Capacitated Vehicle Routing Problem (GCVRP)

The GCVRP can be efficiently solved for small-scale cases, but as the problem size increases, finding the best solution becomes more challenging. To address this, alternative approaches are used to generate high-quality solutions within a reasonable computation time, even if they do not always guarantee optimality. Several methods have been proposed to solve the GCVRP. Table 1 provides a thorough summary of recent research on the Green Capacitated Vehicle Routing Problem (GCVRP), contrasting their main goals and the different approaches taken to solve them. These studies look at a variety of strategies meant to maximize vehicle routing considering environmental factors like lowering CO_2 emissions and controlling traffic congestion. The table illustrates the variety of approaches used, ranging from precise algorithms to heuristic and metaheuristic approaches.

Table 1. Green capacitated vehicle routing problem: brief review.

Author	Title	Description	Resolution Method
Li et al. [11]	Bibliometric review of the Green Vehicle Routing Problem: Research trends, challenges, and future directions	Conducted a bibliometric analysis of GCVRP research, emphasizing important patterns such as the growing emphasis on environmental sustainability. Their research highlights how energy consumption and CO_2 emissions must be considered when developing vehicle routing solutions, and they point out that metaheuristic algorithms like ant colony optimization and genetic algorithms are frequently used in this field.	Review of Exact, heuristic and metaheuristic methods
Alam et al. [12]	A deep learning-based approach to predict CO_2 emissions in vehicle routing and its application in the Green Capacitated VRP	This study uses deep learning models, including LSTM and BiLSTM, to predict CO_2 emissions from traffic vehicles. The model analyzes vehicle attributes and traffic data to support sustainable transportation management and reduce environmental impact.	deep learning-based approach
Zachariadis et al. [13]	A hybrid metaheuristic algorithm for the vehicle routing problem with simultaneous delivery and pick-up service	This paper addresses the Vehicle Routing Problem with Simultaneous Delivery and Pick-Up (VRPSDP), where each customer requires both delivery and pick-up services. The authors propose a hybrid metaheuristic algorithm combining local search and tabu search techniques to optimize vehicle routes, aiming to reduce transportation costs and improve service efficiency	Tabu Search and Local Search

Heydari et al. [14]	A mathematical model of routing problem for hazardous biomedical waste: A multi-objective particle swarm optimization solution approach	This study addresses a Green Heterogeneous and Stochastic Capacitated Vehicle Routing Problem, incorporating risks and environmental hazards, and proposes a multi-objective particle swarm optimization approach to solve it	using a particle swarm optimization (PSO) algorithm
Xu et al. [15]	A Model for Capacitated Green Vehicle Routing Problem with Time-Varying Vehicle Speed and Soft Time Windows	Proposes a mathematical model to address the Capacitated Green Vehicle Routing Problem (GCVRP). This model integrates time-varying vehicle speeds and soft time windows, considering the dynamic nature of traffic conditions and customer time flexibility. The goal is to minimize the total fuel consumption and emissions, while optimizing vehicle routes and satisfying customer demand within the given time windows	NSGA-II (Non-dominated Sorting Genetic Algorithm II
Shuib et al. [16]	Mixed Integer Multi-Objective Goal Programming Model For Green Capacitated Vehicle Routing Problem	The Green Capacitated VRP (GCVRP) while reducing total fuel consumption, total distance traveled, and total carbon dioxide emissions, The MATLAB intlinprog solver is used to resolve the suggested model	Mixed Integer Goal Programming (MIGP) based on a preemptive GP strategy
Soysal et al. [17]	A heuristic approach for green vehicle routing	the GCVRP problem that incorporates the concepts of restriction, simulation, and online control of parameters	Dynamic Programming-based strategy/ the k-nearest neighbor (kNN) algorithm
El Bouzekri et al. [18]	A genetic algorithm for optimizing the amount of emissions of greenhouse gaz for capacitated green vehicle routing problem in green transportation	Elbouzekri et al. (2013,2014,2016) Integrated CO_2 emissions into the CVRP model, with the main goal being to reduce greenhouse gas emissions, particularly carbon dioxide (CO_2), utilizing a recognized set of benchmarks to show the model's efficacy	genetic algorithm simulated Hybrid
El Bouzekri et al. [19]	A hybrid ant colony system for green for capacitated green vehicle routing problem in sustainable transport		hybrid ant colony system
El Bouzekri et al. [20]	A hybrid Metaheuristic to minimize the carbon dioxide emissions and the total distance for the vehicle routing problem		Metaheuristic based on an ant colony system
Úbeda et al. [21]	Solving the green capacitated vehicle routing problem using a tabu search algorithm	showed the difficulty of estimating CO_2 emissions which depend on several factors such as speed, weather conditions, load, and distance, then adopted a methodology to calculate them based on approximations	tabu search algorithm

Urban surroundings and the quality of life are negatively impacted by the rapid growth of urban transportation demand. Over the last few decades, greenhouse gas emissions, such as carbon dioxide, have considerably increased. Transportation is a major source of emissions throughout all spheres of society.

While the Green Capacitated Vehicle Routing Problem (GCVRP) has received significant attention in recent years, focusing on optimizing emissions and distance, it remains primarily concerned with static road conditions. However, in real-world scenarios, traffic congestion plays a crucial role in shaping vehicle routing decisions. The effects of congestion—such as increased travel times, fuel consumption, and CO_2 emissions are often overlooked in traditional GCVRP models. As urban transportation systems continue to expand and face greater congestion, it becomes essential to incorporate these dynamic factors into vehicle routing models. The next section discusses the integration of traffic congestion into vehicle routing problems, exploring recent advancements in this area and highlighting the need for combining congestion with environmental objectives.

2.2. Integrating Traffic Congestion and Vehicle Routing Problems

Traffic congestion is a major transportation problem and one of the primary drivers of the decline in urban air quality. poor traffic flow control and the massive growth of private transportation options. Increased car ownership and related infrastructure, the growth of ridesharing and delivery services, and a dense population all make driving more challenging and add to the ongoing global issue of traffic congestion [22], which raises vehicle emissions during peak hours of the day.

Researchers have addressed congestion in several ways. Most often, the word "congestion" refers to traffic flow when demand for travel exceeds existing road capacity. According to the delay-travel time perspective, congestion occurs when a significant number of cars obstructs the normal flow of traffic, resulting in longer travel times [23], as stated by Aftabuzzaman et al. [5]. Most urban places exhibit congestion for a variety of reasons. Congestion can be categorized as recurrent or nonrepeating based on these numerous factors. The overabundance of traffic during peak hours is the primary cause of frequent congestion [24]. Conversely, non-regular congestion is caused by irregular events, such as construction zones, weather, accidents, and special events [25,26].Time-varying traffic congestion is the main emphasis of Pereira et al.'s review of the heterogeneous green vehicle routing and scheduling challenge. They give a cutting-edge summary of the approaches employed in the field and draw attention to the difficulties in incorporating environmental and traffic elements into the vehicle routing problem. Additionally, their analysis highlights important research gaps and makes recommendations for future directions in the integration of these two intricate components in green vehicle routing [27].

Traffic congestion has recently had a negative impact on the environment, the economy, and society [7,28]. The urban transportation system is impacted by congestion, which results in significant delays and costs, particularly in densely populated area, authors in [4,29] summarizes the most innovative traffic congestion-reduction techniques now on the market, assesses their feasibility and differences with regard to traffic condition monitoring, and balances the benefits and drawbacks of each technique. For a range of vehicle trajectories, the average vehicle speed has a significant effect on CO_2 emissions, according to studies by Barth and colleagues [9,10]. In general, CO_2 emissions can be significantly impacted by even little variations in traffic speed. It is generally known that CO_2 emissions and gasoline consumption rise in tandem with the severity of traffic congestion. Driving style has a big influence on CO_2 emissions and fuel usage. Traveling at a steady-state pace will result in significantly reduced emissions and fuel consumption than a stop-and-go driving pattern, as highlighted by several "eco-driving" systems. Lower CO_2 emissions can be achieved by reducing stop-and-go driving, which is common in crowded areas. As part of their investigation into how traffic congestion affects CO_2 emissions, the fleet mix's projected CO_2 emissions are depicted as a function of average operating speed. Every time traffic congestion reduces the average vehicle speed to less than 45 mph (for a motorway scenario), there is generally a negative net effect on CO_2 emissions. The amount of time spent driving increases CO_2 emissions. Therefore, in this instance, lessening traffic will also result in fewer CO_2 emissions.

The time-dependent vehicle routing issue with time windows (TDVRPTW) is examined by Liu et al. [30]. A number of factors are considered, including capacity, journey time, time-dependent vehicle speeds, and others. The objective is to lower the overall fixed costs of the vehicles as well as the expenses related to the drivers, fuel consumption, and carbon emissions. A congestion avoidance method is proposed to prevent traffic congestion during peak hours and during specific times of the day. The issue is then resolved using an enhanced ant colony algorithm with a congestion avoidance method (IACACAA).

In order to address the issue of ineffective vehicle routing brought on by traffic congestion, Ng et al. [31] proposed multiple colonies of an artificial bee colony algorithm based on a developed re-routing strategy to solve the online vehicle routing problem, which is a development of the capacitated vehicle routing problem.

Xiao et al. [32] proposed a combined partial MIP optimization algorithm and an iterative neighborhood search algorithm (P-MIP-INS) based on the concepts of variable neighborhood search in order to solve a complex Mixed Integer Linear Programming (MILP) model and construct GVRP for a heterogeneous group of vehicles operating in time-varying traffic conditions with multiple intervals and time windows determined by customer requirements or vehicle availability. This article attempts to integrate the TDVRP and GVRP into a time-dependent green vehicle routing problem (TDGVRP) in order to design a time-varying vehicle planning alternative with the aim of lowering carbon emissions from vehicles that have a positive linear relationship with vehicle fuel consumption. Using green traffic situations like congestion, Luo et al. [33] investigate dynamic green vehicle routing for perishable products. By taking traffic dynamics into account during the routing process, their study presents an optimization framework that lowers carbon emissions and operating costs. This strategy tackles the problems caused by transportation congestion while enhancing the sustainability of urban logistics.

2.3. Estimating CO_2 Emissions and Congestion: State of the Art

2.3.1. Estimating the CO_2 Emissions Factor

The literature has put forth several techniques for calculating CO_2 emissions in vehicle routing, each with unique benefits based on the model's complexity and data availability.

Fuel-Based Techniques: According to Palmer in [34] and Sheu et al. [35], fuel-based approaches compute emissions by multiplying fuel consumption by the CO_2 emission factor unique to each kind of fuel. When comprehensive information on car characteristics and fuel usage is available, these techniques are quite accurate. They do, however, need a lot of input data, including driving circumstances, fuel type, and vehicle-specific fuel efficiency. This approach is not feasible in our situation, as such detailed data is not available.

Models of Analytical Emissions: Analytical emissions models (EM) were introduced by authors such as Paulo Roberto et al. [36] and Hickman et al. [37,38]. These models connect emissions to many elements such road slopes, vehicle speed, and travel distance. Because they take dynamic elements like speed fluctuations into account, these models—which are frequently nonlinear—offer excellent precision. They are computationally demanding, though, and necessitate accurate input data—like real-time speed and gradient information, which is outside the purview of this investigation.

Distance-Based Approaches: Distance-based approaches, such as those put out by Palmer in [34] and Ubeda et al. [38], calculate emissions in relation to vehicle load and travel distance. These techniques are appropriate for situations with restricted data availability because they strike a balance between accuracy and simplicity. Specifically, Ubeda method offers a useful framework for predicting CO_2 emissions without the need for fuel-specific data by using emission factors (ϵ) adjusted to load and distance. According to Soysal et al. [17] vehicle speed was the main factor in determining fuel consumption and CO_2 emissions. A nonlinear function of speed determines the overall production of transportation emissions (E) (g/km).

According to Palmer [34] and Úbeda et al. [38] the emissions matrix can be used to demonstrate the linearization of flow and emissions for the arc ij as fellow:

$$\text{Min } \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{m} e_{ij} z_{ijk} \quad (i \neq j) \tag{1}$$

The authors considered that each vehicle's overall CO_2 emissions are influenced by its trip distance and an emission factor ($\boldsymbol{\epsilon}$) calculated in Table 2. Because of this, it is important to account for route planning while calculating the environmental matrix, which must also consider the load transported between each pair of nodes (qv_{ij}) and the distance matrix

$$e_{ij} = d_{ij} \times \epsilon(qv_{ij}) \; \forall i,j \in [1, \dots \dots n] \tag{2}$$

They stated that utilizing this method to estimate the environmental matrix prior to route design is not viable since the information about the iterator and the nodes to be visited is only available after the optimization. The environmental matrix in this scenario can be estimated by figuring out the emission factor ($\boldsymbol{\epsilon}$) between each pair of nodes using the initial demand for each node (qi) and the distance between each pair of nodes (dij) as shown in equation (3).

$$e_{ij} = d_{ij} \times \epsilon(q_j) \; \forall i,j \in [1, \dots \dots n] \tag{3}$$

Table 2. Estimation of CO_2 emissions Factor.

State of the Vehicle	Weightladen (%)	Consumption (l/100 km)	Fuel Conversion Factor (kg CO_2/l)	Emission Factor Kg CO_2/km
Empty	0	29.6	X2.61	0.773
Lowloaded	25	32.0		0.831
Halfloaded	50	34.4		0.9
High loaded	75	36.7		0.958
Full load	100	39.0		1.018

Fuel-based methods are particularly valuable for achieving high precision when the fuel type is well defined, making them ideal for specific applications. However, they require detailed fuel consumption data, which may not always be readily available or accurate. Analytical models, on the other hand, offer the advantage of incorporating dynamic factors such as vehicle speed, providing a more realistic representation of the routing scenario. Despite their benefits, these models are computationally intensive and rely heavily on large datasets, which may limit their applicability in data-scarce situations. Distance-based methods are widely used due to their scalability and practicality, especially when data is limited. While they offer a more straightforward approach, they tend to have moderate accuracy and often depend on simplifying assumptions, such as constant travel speeds, which may not hold true in all real-world contexts.

Among these approaches, Palmer's distance-based method provides a useful and generally recognized framework for situations in which vehicle performance data (such as engine characteristics or fuel efficiency) is not available.This method provides a solid theoretical basis for incorporating emissions into distance-based routing algorithms. Adapting to Situations with Limited Data.

2.3.2. Estimation of Congestion Index

Several methods have been proposed in the literature to model and estimate traffic congestion. Below are some proposed works:

Time-Dependent Congestion Models: Luo et al. [39] created a time-dependent green vehicle routing problem (TDGVRP)that considers congestion as a dynamic factor that changes over a number of time intervals. Real-time traffic data was used to model congestion, which was then included in an optimization framework. in the same context Liu et al.[40] tackle the Time-Dependent Green Vehicle Routing Problem with Time Windows (TD-GVRP-TW), aiming to optimize vehicle routes in urban logistics while considering traffic congestion and service time windows. They propose a Branch-Cut-and-Price (BCP) algorithm to solve this complex problem, integrating environmental concerns like CO2 emissions. The algorithm demonstrates efficiency and high-quality solutions for large-scale problems, offering significant improvements for sustainable transportation planning.

Congestion Models Based on Speed: Soysal et al. [41] used a nonlinear relationship between speed and emissions to link congestion to vehicle speed. Higher pollutants and traffic were linked to slower speeds.

Simulation-Based Approaches: To dynamically avoid congested roadways, Luo et al. [42] suggested a simulation-based rerouting technique. Their approach uses predictive algorithms and real-time data to modify routes.

Empirical Research: in an empirical investigation of urban congestion patterns, Aftabuzzaman used historical data to pinpoint recurrent hotspots for congestion [43].

While significant progress has been made in optimizing vehicle routing with environmental considerations, most existing methods focus on either reducing CO_2 emissions or minimizing travel distance, often neglecting the influence of traffic congestion. Despite its critical role in urban logistics, congestion is rarely incorporated into routing models in a way that fully captures its impact on sustainability and operational efficiency.

To address this gap, our approach introduces a more comprehensive method that simultaneously accounts for emissions and traffic congestion within the routing process.Given the complexity of real-world traffic dynamics and the limited availability of relevant datasets, our work initially focuses on developing a solid theoretical foundation. The proposed framework is validated through small-scale experiments to assess its feasibility and effectiveness before scaling to scenarios that are more complex.

To the best of our knowledge, not much study has been done on how to include congestion in the vehicle routing (VRP) and GVRP difficulties. Although GVRP and traffic congestion have been the subject of several studies, few of them combine the two. We have not found any studies that optimize the total distance traveled and CO_2 emissions while accounting for congestion, specifically for the green-capacitated VRP variation. The following sections outline the methodology for integrating CO_2 emissions and congestion into the distance metric, forming the basis of our proposed solution.

3. Proposed Approach to Model the GCVRP under Traffic Congestion

3.1. Description

Our approach to solve the problem GCVRP is carried out in two steps. The first step is to define an initial model, M1, which minimizes only the total distance traveled, without considering CO_2 emissions or traffic congestion. This model is optimized to determine the optimal route based solely on real distance.

Once this route is obtained, we use known data on CO_2 emissions and congestion between customers to calculate their impact retrospectively on this itinerary.

In the second step, we develop another model M2, which takes a novel approach by minimizing not the real distance, but a "virtual distance" that implicitly integrates the effects of congestion and CO_2 emissions.

Finally, a comparison between M1 and M2 is conducted to evaluate the performance of this approach and demonstrate the benefits of incorporating environmental and traffic factors into route optimization.

3.2. Adopted Technique to Estimate CO_2 Emissions in Distance

As already mentioned, since vehicle-specific data is not available, our study estimates CO_2 emissions using a random matrix. This approach is commonly used in literature as a first step to validate optimization models when accurate or large datasets are not available, we assign values within a predetermined range [0,1] to represent various levels of emissions indices projected based on a variety of possible circumstances, as shown below:

$$\text{Emission Matrix} = \begin{pmatrix} 0 & \delta_{12}D_{12} & \delta_{13}D_{13} & \dots & \delta_{1n}D_{1n} \\ \delta_{21}D_{21} & 0 & \delta_{23}D_{23} & \cdots & \delta_{2n}D_{2n} \\ \delta_{31}D_{31} & \delta_{32}D_{32} & 0 & \cdots & \delta_{3n}D_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \delta_{n1}D_{n1} & \delta_{n2}D_{n2} & \delta_{n3}D_{n3} & \cdots & 0 \end{pmatrix}$$

$$\delta_{ij}: \textit{emission index associated to road ij with } \delta_{ij} \in [0,1]$$

Using a random matrix to overcome data restrictions is a short-term, practical method that enables model validation and proof of concept. This method lays the foundation for incorporating more precise data as it becomes available and shows the adaptability required to address real-world issues. Although our method is simpler, it nevertheless improves on popular distance-based techniques such as Palmer's and Ubeda et al. The workable solution of employing a random emissions matrix for preliminary validation is justified under data constraints. Our method enables easy proof-of-concept testing, unlike analytical or fuel-based models that need substantial volumes of inaccessible input data.

3.3. Congestion Estimation in Distance

Several congestion measures have been developed to quantify the congestion level considering different criteria.

Allie et al. [44] proposed six measures to calculate the congestion index which are presented in Table 3.

Table 3. Proposed measures for congestion index.

Measure	Description
delay/km	minutes of a road segment's delay divided by the distance traveled on the segment
congestion/km	the number of minutes of traffic on a road segment divided by the distance traveled on the segment
time/km	the number of minutes spent on a segment divided by the distance traveled on that segment
Congestion index	percent of the time beneath cruising speed
congestion index in km	percentage of segment length beneath cruising speed

If we take the example of the first measure proposed by [44] which is delay/km assuming, according to the author, at every second on a road section, we know the congestion level (FF) and the actual speed or speed. When the concrete speed is lower than the congestion rate, we can estimate the delay in seconds using [$\mathbf{1} - \boldsymbol{s}$/FF]. For example, if the cruising speed is 40 km/h and the current speed is 20 km/h then the delay associated with this observation second is half a second.

The length of each road segment is different. The metric is therefore adjusted to reflect the total distance traveled by all users in partition (D). The measurement must be changed to reflect the percentage of length traveled on the ramp because entering or exiting the segment is always possible.

We presume that a road segment is observed for n seconds. The total number of minutes of delay per kilometer is calculated using the formula:

$$\textbf{Delay/KM} = \left(\sum_{i=1}^{n}\left(\mathbf{1} - \frac{si}{FFi}\right)\frac{ki * \delta i}{D * 60}\right) \tag{4}$$

ki is the percentage of a road segment's distance traveled relative to observation i, and $\boldsymbol{\delta i}$ an indicator of whether the speed is below the FF congestion level, or 0 otherwise.

Our aim objective is to calculate the virtual distances considering the traffic congestion, for this we convert the retard /km generating by congestion to a travelled distance. To do this, the total delay generated over the distance D is multiplied by the speed limit FF. An explanatory diagram is shown in Figure 1.

This method uses the following formula to determine the virtual distances:

$$\boldsymbol{D_v} = D_r + D_d = D + d_1 + d_2 + d_3 \tag{5}$$

D_v: virtual distance

D_r: real distance

D_d: distance associated to congestion delay

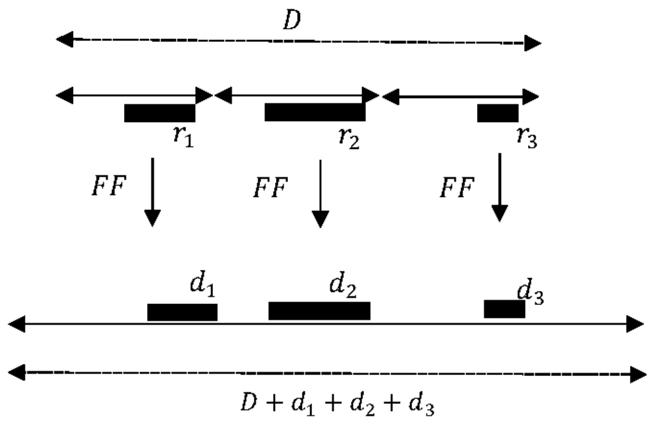

Figure 1. Distance proportional to Traffic congestion delay.

By transforming traffic-induced delays into equal trip distances, this method offers a more accurate way to calculate congestion indices. Even though this method necessitates comprehensive traffic data, which is not yet available, its theoretical foundation guarantees that the model can smoothly incorporate real-world data when it becomes available.

Due to the lack of easily accessible real-time traffic and vehicle-specific data as a preliminary test of the proposed approach, we estimated the congestion index between n cities. As shown in the matrix below, we accomplished this by assigning a congestion value to every road according to the state of traffic congestion; in our instance, we used the congestion index as a function of the distance between cities.

$$\text{Congestion Matrix} = \begin{pmatrix} 0 & \alpha_{12}D_{12} & \alpha_{13}D_{13} & \dots & \alpha_{1n}D_{1n} \\ \alpha_{21}D_{21} & 0 & \alpha_{23}D_{23} & \cdots & \alpha_{2n}D_{2n} \\ \alpha_{31}D_{31} & \alpha_{32}D_{32} & 0 & \cdots & \alpha_{3n}D_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \alpha_{n1}D_{n1} & \alpha_{n2}D_{n2} & \alpha_{n3}D_{n3} & \cdots & 0 \end{pmatrix}$$

$$\propto_{ij} \text{ is } a\ congestion\ coefficient\ associated\ to\ road\ ij\ \ with \propto_{ij} \in [0,1]$$

$\propto_{ij} = 0$ if there is no congestion

$\propto_{ij} = 1$ if the road is extremely congested.

D_{ij}: The real distance between the customer i and j.

The proposed method aims to assess congestion in the absence of detailed traffic data. By adding a congestion coefficient αij to the distance calculation, it accounts for the overall impact of congestion on routing. It provides a practical means of initially validating the optimization framework, despite its lack of accuracy in comparison to speed-based or time-dependent models. When more comprehensive data becomes available, the strategy can be extended to incorporate dynamic congestion patterns, real-time traffic statistics, and more sophisticated prediction techniques.

3.4. Total Virtual Distance Calculation

As was already noted, the impacts of CO_2 emissions and traffic congestion are taken into consideration when calculating the virtual distance as a function of the real distance.

Virtual distances are calculated using this formula:

$$\begin{gathered} \boldsymbol{D}_{\mathbf{ijv}} = D_{\mathrm{ij}} + \delta_{ij}D_{ij} + \propto_{ij} D_{ij} \\ \boldsymbol{D}_{\mathbf{ijv}} = \left(1 + \delta_{ij} + \propto_{ij}\right)D_{ij} \end{gathered} \tag{6}$$

While

D_{ijv}: Virtual distance

D_{ij}: Real distance

$\propto_{ij}$, δ_{ij}: Congestion and CO_2 emissions indexes

Using this formula, we can generate the virtual distances matrix as presented below:

$$\text{Virtual distances Matrix} = \begin{pmatrix} 0 & \beta_{12}D_{12} & \beta_{13}D_{13} & \cdots & \beta_{1n}D_{1n} \\ \beta_{21}D_{21} & 0 & \beta_{23}D_{23} & \cdots & \beta_{2n}D_{2n} \\ \beta_{31}D_{31} & \beta_{32}D_{32} & 0 & \cdots & \beta_{3n}D_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \beta_{n1}D_{n1} & \beta_{n2}D_{n2} & \beta_{n3}D_{n3} & \cdots & 0 \end{pmatrix}$$

With:

$$\beta_{ij} = 1 + \delta_{ij} + \propto_{ij}$$

This is the first attempt, as far as we know, to model GCVRP by redefining inter-city distances as "virtual distances" that incorporate traffic congestion and CO_2 emissions. This strategy is a major advancement in environmentally friendly and effective vehicle routing.

3.5. Mathematical Model

An introductory example of the route adjustment employed in our case using both actual and virtual models is shown in Figure 2. Assume that when the six customers (A, B, C, D, E, and F) depart and return to the same depot, two cars must serve them. Just the separations of the arcs (AB, AC, DE, EF, BO, CO, and FO, DO) are shown on the graph, the matrix of distances between all other customers follows the same logic. Real distances (di) between customers are shown by solid lines, while virtual distances (d_{ei}), which are proportionate to the number of CO_2 emissions along the arc ij, are shown by dashed lines while virtual distances (d_{ci}) proportionate to traffic congestion along the arc ij, are shown by dashDot ones. As a result, the original routes will now change as we plan new routes based on the updated distance information. In this scenario, the overall distance of our model, for instance, between clients A and B, will be as follows:

$$\boldsymbol{d_{AB} = d_1 + d_{e1} + d_{c1}}$$

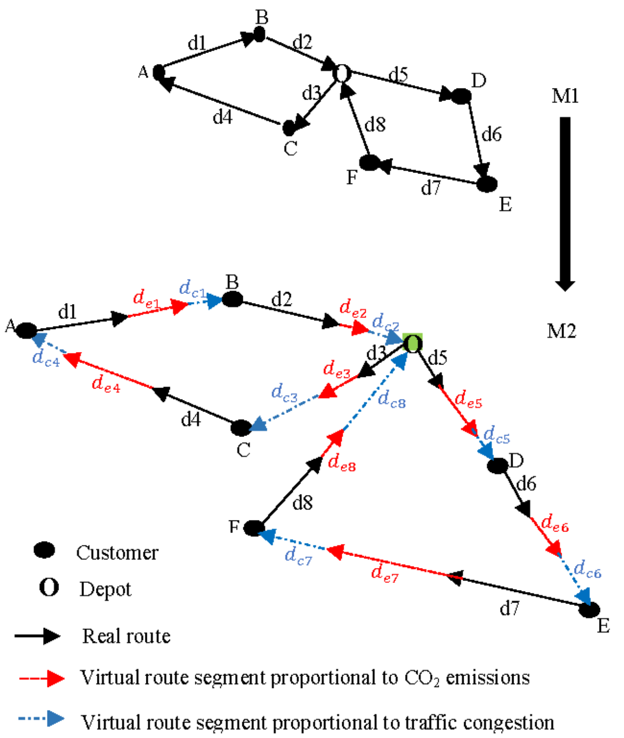

Figure 2. graphical example of Real and virtual models (M1& M2).

Our model can be presented as follows:

A complete weighted digraph G = (V, E), where V = {0, 1… n} while node 0 representing the depot and other nodes from 1 to n representing the number of clients, the fleet of vehicles is denoted by K =

{1, 2… m}.

To present the entire linear programming model for VRP, the following variables are introduced:

Q: capacity of vehicle

dij: distance between nodes i and j.

qi: the demand of node i, where node i represents a single customer

The decision variables are:

z_{ij}^k Is a binary variable equal to 1 if the vehicle k visit customer j after customer i

z_{ij}^k= 1: the vehicle k has crossed the road ij

$z_{ij}^k = 0$: otherwise

Objective function:

Our problem considers two different objectives, the first one is to minimize the total traveled distance and the second is minimizing the level of vehicle emissions.

The total traveled distance by all vehicles can be expressed by:

$$\sum_{k\in K}\sum_{(i,j)\in E} d_{ij} z_{ij}^k \tag{7}$$

While

$$\boldsymbol{d_{ij} = d_{ijr} + d_{ije} + d_{ijc}}$$

$\boldsymbol{d_{ijr}}$: Real distance between customer i and j

$\boldsymbol{d_{ije}}$: Distance proportional to CO_2 emissions between customer i and j

$\boldsymbol{d_{ijc}}$: Distance proportional to traffic congestion between customers i and j

Constraints:

$$\sum_{k\in K}\sum_{i\in V, i\neq j} z_{ij}^k = 1 \ \forall j \in V \setminus\{0\} \tag{8}$$

$$\sum_{j\in V\setminus\{0\}} z_{0j}^k = 1 \quad \forall k \in K \tag{9}$$

$$\sum_{i\in V\ i\neq j} z_{ij}^k - \sum_{i\in V} z_{ji}^k = 0 \ \forall j \ \in V, \forall k \in K \tag{10}$$

$$\sum_{i\in V}\sum_{j\in V\setminus\{0\}, i\neq j} q_j z_{ij}^k \leq Q \ \forall k \in K \tag{11}$$

$$\sum_{k\in K}\sum_{(i,j)\in S, i\neq j} z_{ij}^k \leq |S| - 1 \ S \subset V \setminus\{0\} \tag{12}$$

$$z_{ij}^k \in \{0,1\} \ \forall k \in K, \forall (i,j) \in E \tag{13}$$

The Objective function (7) minimizes the total virtual traveled distance of all vehicles,

Constraint (8) means “only one visit per vehicle and per customer location” and constraint (9) means “departure from stock”, for constraint (10) the number of vehicles entering and leaving a customer's location are the same, (11) notices the capacity of each vehicle must not exceed the maximum capacity, binding (12) prohibits creating side tours. Finally, integrity constraints related to the decision variables are included (13)

Computational experiments are used to compare M1 with M2 in order to assess the impact and feasibility of the suggested strategy. The efficiency of M2 in striking a balance between reducing travel distance and attending to traffic and environmental issues is evaluated against M1.

4. Computational Results

4.1. Presentation of Data and Results

To assess the viability of our approach and demonstrate the impact of implicitly accounting for traffic congestion and CO_2 emissions in the travel distance on a set of randomly created instances with 10 to 30 requests, we evaluated the performance of the M1 and M2 models. The fleet of vehicles is infinite and homogeneous, with a capacity of 25000 kg per vehicle, and it consists of the depot point (0, 0) and a set of client spots, whose coordinates are chosen at random from the region [0 Km, 100 Km].

The service time for consumers is set at 15 minutes, and their demand falls within the range [500 Kg, 2500 Kg].

Python is used to code models M1 and M2, and CPLEX 20.1.0 is used to solve the problems, with a 15-second execution time constraint. Using a computer with a 2.40GHz core i5 processor and 4Go of RAM.

The analysis's data set includes matrices that were produced automatically by a Python application. The values in the emission index matrix, which are chosen at random from 0 to 1, represent the different amounts of CO_2 emissions connected to each route. In a similar manner, varying degrees of traffic congestion are represented by the congestion index matrix, which is likewise constructed using random values between 0 and 1.

As a result, the program generates three outputs: execution time, suitable route, and the optimal distance. To compare the two models using the program's ideal plan, we compute the other three outputs, which are the quantity of emissions, the congestion, and the total working time corresponding to each event.

With N being the number of clients and columns D, E, C, and T representing the total distance traveled, CO_2 emission, traffic congestion, and total trip time for models M1 and M2, respectively, Tables 4 and 5 display the best results for nine different scenarios with 10 to 30 requests.

Table 4. Results obtained for M1 Model.

N	**M1**			
	D1	**E1**	**T1**	**C1**
10	365.562	494.312	29134.312	50.635
13	375.630	539.129	31775.804	67.348
15	394.212	657.106	38729.238	83.289
18	430.853	692.946	39947.743	98.356
20	466.677	709.049	41790.760	130.25
23	484.554	716.439	42226.267	158.68
25	492.853	769.111	45330.733	167.29
28	525.854	834.807	49202.786	186.28
30	685.114	1033.028	60885.773	204.36

Table 5. Results obtained for M2 Model.

N	**M2**			
	D2	**E2**	**T2**	**C2**
10	380.153	420.115	26798.781	41.356
13	398.756	510.325	28679.764	59.364
15	425.116	598.859	33168.118	80.364
18	445.759	611.243	34980.268	85.346
20	486.571	681.112	41857.166	110.34
23	498.235	702.024	42004.258	122.37
25	522.689	754.736	43786.063	156.32
28	570.448	798.235	46987.284	170.02
30	700.025	930.238	61001.097	193.62

The ideal solutions for the two models, M1 and M2, for instance N=15, are shown in Figures 3 and 4.

For M1

vehicle1: 0➔8➔11➔10➔15➔13➔9➔12 ➔0

Vehicle2: 0➔1➔2➔3➔6➔14➔4➔5➔7➔0

For M2

Vehicle1: 0➔1➔8➔11➔10➔15➔13➔9➔0

Vehicle2: 0➔2➔3➔6➔14➔5➔4➔7➔12➔0

Figures 5–8 provide a graphical representation of the obtained results, illustrating the performance of the proposed models across various metrics. These visualizations enable a clear comparison of key indicators such as distance, CO_2 emissions, traffic congestion, and total travel time, highlighting the differences between the models and the impact of the proposed approach he graphical format aids in understanding the trends and T relationships within the data, offering valuable insights into the effectiveness of the methodology.

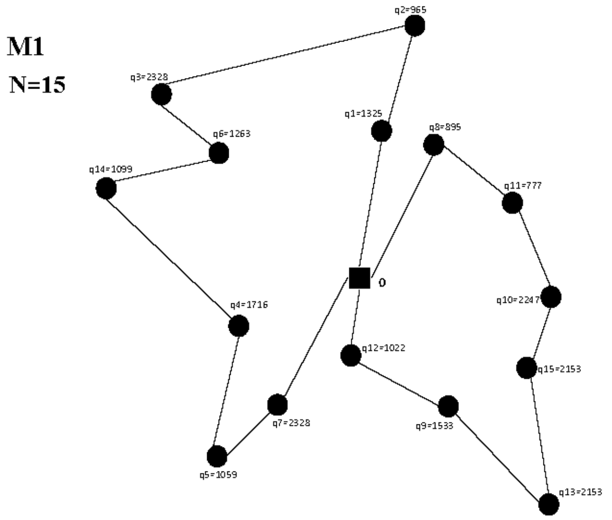

Figure 3. An illustration of the M1 model's solutions for the situation of N = 15.

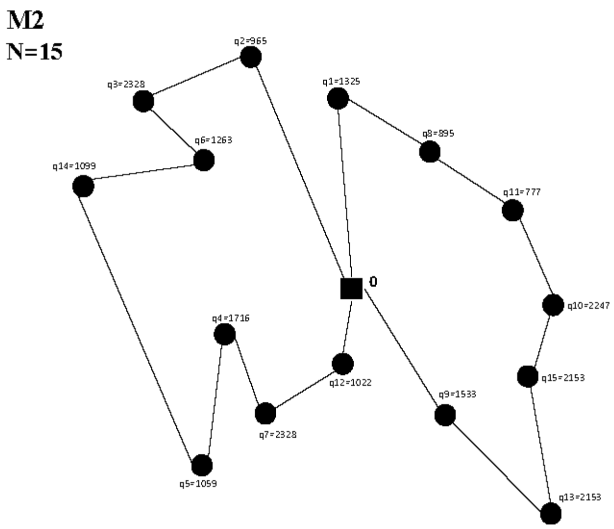

Figure 4. An illustration of the M2 model's solutions for the situation of N = 15.

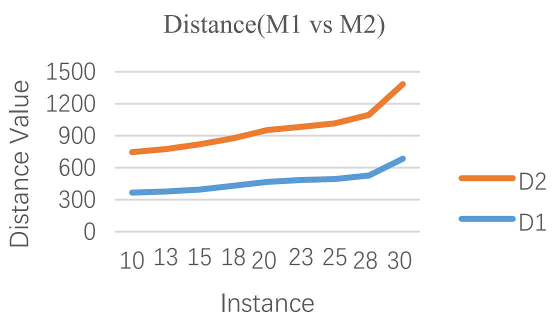

Figure 5. Results obtained for distance (M1 and M2).

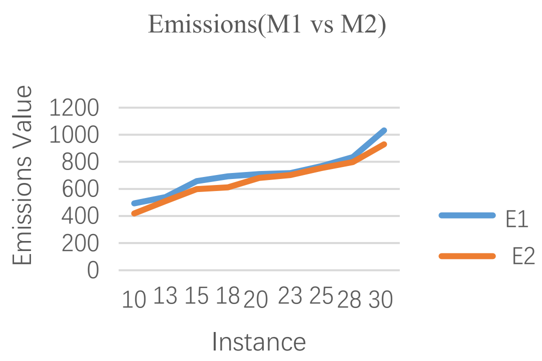

Figure 6. Results obtained for Emissions (M1 and M2).

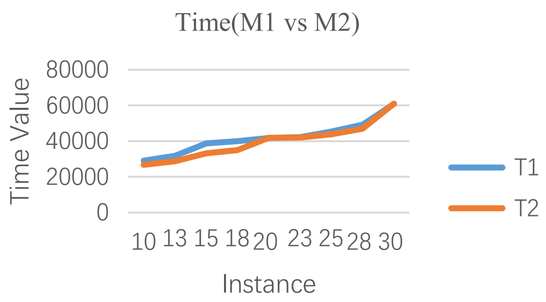

Figure 7. Results obtained for Time (M1 and M2).

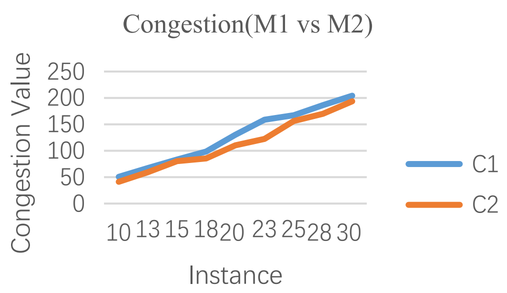

Figure 8. Results obtained for Congestion (M1 and M2).

4.2. Discussion and Future Work

The models M1 and M2 are compared on nine examples in Figures 7 through 10. The results show that the distances calculated using the M2 model are systematically higher than those calculated using the M1 model. This is expected as the model M2 incorporates additional parameters and constraints.

However, the improved performance of the M2 model in other areas deserves special attention. Specifically, there are notable decreases in CO_2 emissions and traffic congestion when switching from model M1 to model M2. These improvements demonstrate the effectiveness of the suggested approach, which directly incorporates emissions and traffic into the distance measurement. This integration shows that the methodology is feasible and has the potential to produce environmentally friendly, optimized solutions.

In terms of travel time, there is a decrease in seven cases and an increase in two others. This phenomenon makes sense because travel time depends on both the distance traveled and delays caused by traffic.

Even if the present outcomes are encouraging, more work is required to confirm and broaden the application of the suggested strategy. To demonstrate scalability and resilience, future work will concentrate on assessing the models using larger and more intricate instances. To improve the model's realism, other characteristics will be incorporated, such as vehicle type, fuel efficiency, and time windows.

Lastly, to guarantee the methodology's practical application and to offer insights that are more pertinent to real-world situations, the utilization of real-world data will be given priority. These developments will increase the approach's potential applications and reinforce its validation.

5. Conclusion

This paper has introduced a novel method for modeling GCVRP. The suggested model is mono-objective and minimizes the total virtual traveled distance, considering the quantity of CO_2 emissions and the traffic congestion index. The methodology used to calculate CO_2 emissions and traffic conditions in terms of distance is presented in the article. The proposed approach presents also a transition from a GCVRP multi-objective that minimizes three objectives, distance, CO_2 emissions and congestion to a GCVRP mono-objective that minimizes only one objective, the virtual traveled distance integrating implicitly emissions and congestion. The M2 model's successful outcomes support the viability and applicability of the methods suggested in this work. To have better visibility, the introduced model needs to be improved, along with validation on huge instances, which will be covered in subsequent efforts.

Author Contributions

Conceptualization, Asma Oumachtaq and Latifa Ouzizi; methodology, Asma Oumachtaq; software, Asma Oumachtaq; validation, Asma Oumachtaq, Latifa Ouzizi and Mohammed Douimi; formal analysis, Asma Oumachtaq; investigation, Asma Oumachtaq; resources, Asma Oumachtaq; data curation, Asma Oumachtaq; writing-original draft preparation, Asma Oumachtaq; writing-review and editing, Asma Oumachtaq, Latifa Ouzizi and Mohammed Douimi; visualization, Asma Oumachtaq; supervision, Latifa Ouzizi and Mohammed Douimi; project administration, Latifa Ouzizi. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Data Availability Statement

No new data were created or analyzed in this study. Data sharing is not applicable to this article

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