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CVRP Model with Environmental Aspects

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Abstract

The current competitive environment is drawing increasing attention to green logistics. Road transport is a significant source of carbon emissions, which contribute to environmental pollution. Multi-objective algorithms are typically used to represent transportation problems like the Green Capacity Vehicle Routing Problem (GCVRP). These problems are NP-difficult and provide a Pareto front with incomparable solutions. In this context and in order to divert these issues, the purpose of this article is to propose a new approach to modeling the GCVRP problem in the form of single-objective programming. The idea is to look for the shortest path in a new virtual graph that is designed by integrating CO_2 emissions into actual distances. This new modeling approach facilitates digital resolution and decision-making. The numerical results show the effectiveness of the model. In addition, the calculation time and the quality of the solution are much better.

Keywords
Capacitated vehicle routing problem (CVRP); mono-objective optimization; CO_2 emissions; virtual model.

Introduction

The transportation system has become a crucial link in a logistics chain as a result of rising freight quantities brought on by expanding populations, technology, internationalization of markets, and globalization. One of the biggest issues facing the logistics industry is to improve the effectiveness of freight logistics while reducing the energy use of existing logistics systems and transforming them to be environmentally friendly. Meanwhile, the logistics process aims to reduce the cost of transportation by reducing factors like journey time, distance, and reliability. Additionally reducing air pollution, especially carbon dioxide (CO_2). The construction of a set of routes for a fleet of vehicles carrying items to a set of clients falls under the broad category of challenges known as vehicle routing. Finding a set of ideal routes for a fleet of similar vehicles (with fixed capacity) that, from a central depot, service the demand of the customers is the fundamental model of the Vehicle Routing Problem (VRP) that we explore in this article (Toth and Vigo 2002).

The green vehicle routing problem (GVRP) is described by (Lin et al. 2014) as 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), one of the GVRP's versions and one of the most significant transportation challenges in logistics, is presented in this article. The goal is to serve a limited number of clients. Taking into account a fleet of vehicles with uniform and limited capacities while reducing overall transportation costs and CO_2 emissions. Only for cases of small sizes can we solve the extremely NP-hard GCVRP accurately and optimally using exact methods. Heuristic and meta-heuristic methods are therefore used to develop workable and good, but not necessarily guaranteed, optimal solutions while consuming reasonable amounts of processing time. CO_2 emissions and fuel usage are influenced by a number of factors, including individual driving style, vehicle and road types, vehicle load, distance traveled, traffic circumstances, etc. Additionally, fuel usage and speed of the vehicle also contribute to CO_2 emissions. It is often difficult to combine and integrate all these criteria into a multi-objective problem.

To minimize the complexity of multi-objective problems and gain in terms of resolution time, our goal is to present a novel model approach to the GCVRP problem based on the reduction of the multi-objective GCVRP into a single-objective problem while reducing the total traveled distance. The present paper is organized as follows: The second section presents a brief multi-objective GCVRP literature review. The third section presents a formulation of the GCVRP problem plus a brief state of the art of proposed methods for estimating CO_2 emissions. Further, in section 4 we present the proposed approach; the experiments and results will be presented in the fifth section. Finally, a general conclusion is presented in section 6.

2. Literature Review

Green Capacitated VRP (GCVRP)

The routing research community has recently paid close attention to the green vehicle routing problem (G-VRP), a significant variant of the vehicle routing problem (VRP) (Emrah et al. 2014,Canhong et al. 2014), with numerous reviews taking its analysis into account in a variety of practical contexts. These studies (Kopfer et al. 2014, Küçükolu et al. 2013) were carried out to investigate the costs of various types of pollution and their effects on the environment. We introduce the Green Capacitated Vehicle Routing Problem (GCVRP) in this paper as a variant of the Capacitated Vehicle Routing Problem (CVRP) (Toth and Vigo 2002) that takes into account greenhouse gas emissions and environmental concerns. The major goal is to reduce the overall distance traveled while minimizing the total CO_2 emissions.

The traditional Vehicle Routing Problem (VRP), which primarily focuses on minimizing travel distance, journey time, and the number of vehicles, has evolved into the Green Capacitated Vehicle Routing Problem (GCVRP), which incorporates broader objectives that account for environmental impacts. The pioneering works of Sbihi and Eglese (2007) and Palmer (2007) were among the first to explore the role of the CVRP in promoting environmentally sustainable transportation. Notably, Palmer proposed integrating both logistical and environmental considerations within a unified freight demand model.

GCVRP is very NP-hard and can only be precisely and optimally solved for small-scale scenarios utilizing exact methods. Therefore, while taking a fair amount of processing time, heuristic and meta-heuristic methods are employed to generate practical and good, but not always guaranteed, ideal solutions. Several methods of resolution have been proposed to solve the GCVRP, the majority of authors have referred to metaheuristics to solve the problem and little work has used exact and heuristic methods for this type of hard NP problem. (Shuib et al. 2001) developed a Mixed Integer Goal Programming (MIGP) based on a preemptive GP strategy to solve 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. (Soysal et al. 2021) provide a Dynamic Programming-based strategy for solving the GCVRP problem that incorporates the concepts of restriction, simulation, and online control of parameters. The information on customers' locations was also initiated using the k-nearest neighbor (kNN) algorithm. Other authors have used the genetic algorithm to solve the GCVRP, for example,(El Bouzekri et al. 2013) introduced a new genetic algorithm to integrate CO_2 emissions into the CVRP model, with the main goal being to reduce greenhouse gas emissions, particularly carbon dioxide (C02), utilizing a recognized set of benchmarks to show the model's efficacy. The same author respectively in 2013, 2014, and 2016 proposed a hybrid ant colony system, an evolutionary algorithm, and simulated Hybrid Metaheuristic based on an ant colony system to minimize the Carbon Dioxide Emissions and the Total Distance for the same problem.

Úbeda et al. (2014), 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, the author proposed a tabu search algorithm to solve the GCVRP problem with the objective is to design routes that generate the lower levels of CO_2 emissions to the atmosphere. The majority of the studies that have been recently published on the GCVRP are related to electric vehicles, among which is cited that of (Zhang et al. 2016) Studied alternative fuel-powered vehicles (AFVs) for distributing products with limited capacity. AFVs are assumed to have low fuel tank capacity. They used a two-phase heuristic algorithm and a meta-heuristic based on an ant colony system. In the same context, (Wang et al. 2019) studied the capacitated green vehicle routing problem (CGVERP) for alternative fuel-powered cars (AFV) with the goal of minimizing the total distance traveled. The author then suggested a memetic algorithm with competition (MAC) to solve the problem (GCVRP). (Normasari et al. 2019) formulate the mathematical model of the GCVRP and propose a simulated annealing (SA) heuristic for its solution in which the GCVRP is set up as a mixed integer linear program (MILP), the objective of the GCVRP is to minimize the total distance traveled by an alternative fuel vehicle (AFV).

GCVRP problems are multi-objective problems; the particularity of these types of problems is that they are significantly more challenging to solve than their mono-objective counterparts. Generally, the objectives are contradictory; there is no total relationship between them. One solution may be better than another on some objectives and less good on others. Because of this, it is uncommon to discover a single solution that precisely satisfies every goal's criteria. The solution in this case is no longer a single solution but a set of solutions satisfying the constraints of the problem and achieving a compromise between all the objectives. This set is called the Pareto front. It's difficult to maintain a variety of Pareto-optimal solutions for more reasons, for example, whether the Pareto-optimal front is convex or not and whether solutions are not distributed equally throughout the Pareto-optimal front. Another difficulty of multi-objective problems lies in the choice of the best Pareto front solutions; the decision maker must integrate other criteria in order to be able to select solutions satisfying his preferences among Pareto set solutions.

The authors have discussed techniques for turning multi-objective problems into mono-objective ones in order to avoid the challenges of multi-objective optimization, such as the method of aggregation, the ϵ-constraint, or other techniques.in this context,(El Bouzekri et al. 2014) used the aggregation method to transform the bi-objective problem (PBO) into a mono-objective problem which combines the various functions of the problem into a single objective function using aggregation factors $\beta_1$et β_2 reflecting the relative importance of the objectives while determining the values of $\beta_1$et β_2 is a political decision, the difficulty of this method lies in the choice of factors $\beta_1$et β_2, the discomfort is that a simple change in these values will affect final solutions, therefore, in this case, it is difficult to find an optimal solution that achieves the best compromise between the two objectives. In addition,(Xiao et al. 2011)developed a fuel consumption optimization model for the capacitated vehicle routing problem(GCVRP) by integrating the Fuel Consumption Rate (FCR) as a load-dependent function, while considering two objectives .

The first one is the sum of fixed costs of the vehicles, and the second is the sum of the fuel costs of all the vehicles, the authors transformed the multi-objective model into a single objective model considering one objective which is the sum of defined objectives without considering any aggregation factors, otherwise, the author supposed that the two objectives have the same importance. (Ubeda et al. 2014) has studied the GCVRP considering the minimization of CO_2 emissions as the only objective, but it has not taken into consideration the other objectives of total distance traveled or total travel time.The same context informs our work, which has the goal of examining the multi-objective GCVRP while taking into account the two objectives, total distance traveled and CO_2 emissions. We propose a new strategy that will enable us to integrate the CO_2 emissions as a key aspect in the minimization of the total distance traveled. Otherwise, we create a new single-objective virtual model that reduces the overall virtual distance traveled, which takes into account both actual customer-to-customer distances and distances proportional to the amount of CO_2 emissions emitted.

2.1 GCVRP Formulation

The GCVRP system identifies a set of delivery routes that meet the needs of distribution locations, achieve the lowest travel costs and lowest volume of CO_2 emissions while visiting each client just once, departing and returning to same depot, taking into account the problem restrictions such as, known and homogeneous fleet, single depot; deterministic demand and Limited vehicle capacity.

Notation

The GCVRP can be modelled mathematically through a complete weighted digraph G = (V, E), where V = {0, 1,, n} is a set of nodes representing the depot or vehicle warehouse (0) and n customers and E = {(i, j) | i, j ∈ V} is a set of edges connecting each node, The set of available vehicles are denoted by K = {1, 2… m}.
For presenting the integer linear programming model for VRP, the variables below are introduced:

Q: capacity of vehicle

dij: distance between the 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 customer j is visited immediately after customer i by vehicle k

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

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

Objective function

Our problem consider 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:

$$\sum_{k\in K}\sum_{(i,j)\in E} d_{ij} z_{ij}^k \qquad (1)$$

The function of emission emitted by the vehicle is:

$$\sum_{k\in K}^{n}\sum_{(i,j)\in E}^{n} e_{ij} z_{ij}^k \qquad (2)$$

Constraints

$$\sum_{k\in K}\sum_{i\in V, i\neq j} z_{ij}^k = 1 \quad \forall j \in V \setminus\{0\} \qquad (3)$$

$$\sum_{j\in V\setminus\{0\}} z_{0j}^k = 1 \qquad \forall k \in K \qquad (4)$$

$$\sum_{i\in V\ i\neq j} z_{ij}^k - \sum_{i\in V} z_{ji}^k = 0 \qquad \forall j \in V, \forall k \in K \qquad (5)$$

$$\sum_{i\in V}\sum_{j\in V\setminus\{0\}, i\neq j} q_j z_{ij}^k \leq Q \qquad \forall k \in K \qquad (6)$$

$$\sum_{k\in K}\sum_{(i,j)\in S, i\neq j} z_{ij}^k \leq |S| - 1 \quad S \subset V \setminus\{0\} \qquad (7)$$

$$z_{ij}^k \in \{0,1\} \quad \forall k \in K, \forall (i,j) \in E \qquad (8)$$

The first Objective function (1) minimizes the traveled distance of all vehicles, Relation (2) is the second objective function to be minimized including the total emission produced by the running vehicles Constraint (3) means “only one visit per vehicle per customer’s location” and constraint (4) means “depart from depot”, constraint(5) expresses that the number of vehicles coming in and out of a customer’s location is the same, constraint (6) announce that the delivery capacity of each vehicle should not exceed the maximum capacity, constraint(7)prohibits the creation of sub-tours. Finally, the integrity constraints associated with decision variables are included in (8).

2.2 Emission Estimation

As already mentioned the answer to the "green vehicle routing problem" identifies a set of delivery routes that satisfies the needs of distribution centers and obtains the minimum total emission while minimizing the amount of fuel consumed for all vehicles.CO_2 emissions and fuel usage are influenced by a number of factors, vehicle weight, and speed have a direct impact on fuel economy because heavier vehicles require more energy to run, and the rate of CO_2 emissions per mile traveled drop as vehicle operating speed rises up to around 55 to 65 mph, and then they begin to grow once more(Aronsson et al. 2006), weather and headwinds reduce fuel efficiency since it takes more power from the engine to move the car through the wind. Fuel consumption is also impacted by traffic congestion because moving at a steady-state speed will lower emissions and fuel use dramatically compared to a stop-and-go movement. As traffic congestion worsens, CO_2 emissions rise along with fuel consumption. Therefore, eliminating stop-and-go driving can help to reduce CO_2 emissions (Boriboonsomsin et al. 2010).

Several approaches have been proposed for estimating CO_2 emissions (Palmer 2007, Sheu et al. 2005) introduced two types of approach, the fuel-based approach and the distance-based method, the CO_2 emission factor for each type of fuel is multiplied by the fuel consumption in the fuel-based approach. In contrast side, the distance-based approach enables the use of distance-based emission factors to calculate emissions. Based on the fuel's heat content, the percentage of carbon in the fuel that is oxidized, and the carbon content coefficient, a fuel-based emission factor is created. When vehicle activity data in the form of distance traveled is known but fuel economy characteristics are not, the distance-based technique can be employed. The choice of strategy is significantly influenced by the availability of data (The Greenhouse Gas Protocol Initiative: Calculating CO_2 emissions from mobile sources. Guidance to calculation worksheets (2005).El Bouzekri et al. (2013) considered that the exhaust gases and hydrocarbons created by gasoline evaporation are the principal sources of emission from motor vehicles. An engine consumes fuel inefficiently and produces more pollutants when starting below its normal operating temperature than when it is hot.

Paulo Roberto et al. (2018) Proposed An alternative approach based on an analytical emission model (EM) (Hickman et al. 1999), the approach considers that CO_2 emissions depend on the distance traveled and an EF emission factor by the following relationship: Emissions = EF $*$ d**,** EF depends on several parameters, such as speed and weight, the author proposed two models to estimate the EF factor, a speed model and a road gradient model. In the same context,(Soysal et al. 2021) believed that the primary determinant of fuel usage and CO_2 emissions was vehicle speed (Boulter et al. 2009)The total amount of transportation emissions (E) (g/km) produced is a nonlinear function of speed. According to (Palmer, 2007) and (Úbeda et al. 2014) the emissions matrix can be used to demonstrate the linearization of flow and emissions for the arc ij as fellow:

$$\text{Min} \quad \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{m} e_{ij} z_{ijk} \quad (i \neq j) \qquad (9)$$

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 1. Because of this, it is important to account for route planning while calculating the environmental matrix, which must also take into account the load transported between each pair of nodes (qv_{ij}) and the distance matrix

$$e_{ij} = d_{ij} \times \epsilon\left(qv_{ij}\right) \ \forall i,j \ \in [1, \dots \dots n] \qquad (10)$$

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 eq.(11).

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$$e_{ij} = d_{ij} \times \epsilon\left(q_j\right) \ \forall i,j \ \in [1, \dots \dots n] \qquad (11)$$

Table 1. Estimation of the 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

This method remains one of the other methods proposed in the literature to estimate CO_2 emissions based on the total distance traveled and the load of the vehicle. There are several other methods and approaches proposed in the literature for estimating CO_2 emissions since we do not have data concerning the type of vehicle and fuel, the speed of vehicles, heating values, etc. We have only data concerning the total distances traveled and the weight of the vehicles, so the method adopted by Palmer (2007) is the closest to our case, but that does not prevent any other estimation methods from being applied to our approach once the data is available.

2.3 Proposed Approach to model the GCVRP

Description

As already mentioned above, this work seeks to develop a new approach to model the Green capacitated vehicle routing problem by converting the GCVRP multi-objective model minimizing two objectives: total distance traveled and CO_2 emissions into a virtual single-objective model having as an objective to minimize a virtual distance implicitly integrating the number of CO_2 emissions. The major goal is to reduce the overall distance traveled while focusing on CO_2 emissions as the primary factor. The first model presented in this work is the mono-objective Green capacitated vehicle routing problem (M1) that minimizes the total traveled distance without taking CO_2 emissions into consideration. The second model is the virtual mono-objective Green vehicle routing problem (M2) that considers CO_2 emissions as the main factor implicitly integrated into the total virtual distance as shown in figures 1 and 2. We propose to compare these two main models to study the viability and the impact of the developed approach.

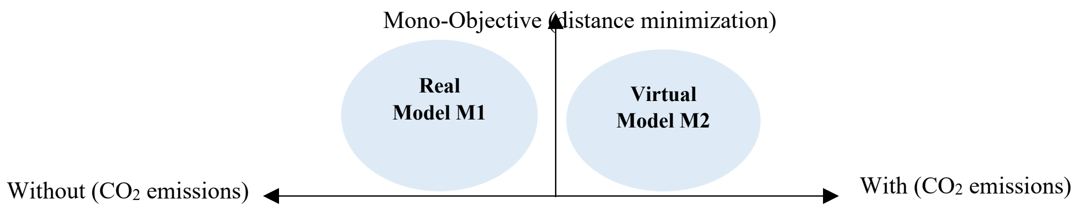

Figure 1. Real and virtual models

A As already mentioned, we propose a mono-objective virtual model that minimizes the total distance traveled by implicitly integrating into the CO_2 emission rate. To our knowledge, this is the first time that such a model is presented, which consists of quantifying the CO_2 emission rate and converting it into distance traveled. In other words, we build a virtual model where the distances between cities are no longer real distances, but virtual distances are updated according to CO_2 emissions as shown in Figure 2.

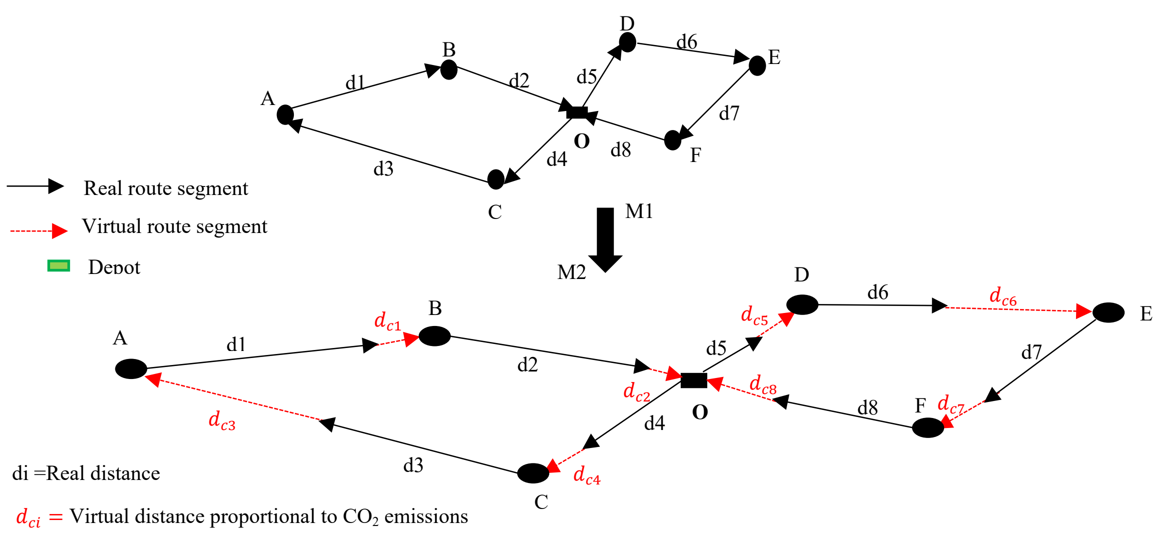

Figure 2. Converting a real GCVRP model to a virtual model

Real and virtual models are shown in Figure 2 to demonstrate an example of the route adjustment implemented in our situation. Let's assume that there are sex customers (A, B, C, D, E, and F) who must be served by two vehicles leaving and returning to the same depot .Only distances between the arcs (AB, AC, DE, EF, BO, CO, 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 (dci), which are proportionate to the number of CO_2 emissions along the arc ij, are shown by dotted lines. 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:

$$\mathrm{d_{AB}} = \mathrm{d_1} + \mathrm{d_{c1}}$$

2.4 Estimation of CO_2 emissions factor in distance

For the estimation of the emission rate we can use the approach presented in section 3 for the model M1 inspired by the method of (Ubeda et al. 2011), which estimates the CO_2 emissions according to the distance traveled d_j and the load of vehicle in each road ij using Eq.(11).

If we consider High loaded vehicles then $\boldsymbol{\epsilon}$ =0.958

$$e_{ij} = 0.958\, d_{ij} \quad \forall i, j \in [1, \dots \dots n]$$

As already mentioned, this method or any other method in the literature to estimate CO_2 emissions remotely can be implemented in the proposed optimization methodology. We can also for a first validation of the model, generate a random matrix estimating CO_2 emissions as a function of the total distance travelled, as shown below.

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

$$\delta_{ij}: \textit{emission index associated to road ij with } \delta_{ij} \in [0,2]$$

3.Computational Results

Data presentation and results

In order to evaluate the effectiveness of our approach and to prove the effect of considering implicitly the CO_2 emissions in the travelled distance. We tested the performance of M1 and M2 models on a set of instances generated randomly of 10 to 30 requests. With the depot point coordinate (0, 0) and a set of customer points, which coordinates randomly belong to the region [0 Km, 100 Km], the fleet of vehicles is unlimited and homogenous, and the capacity of each one is 25000 kg. The customer's demand belongs to the interval [500 Kg, 2500 Kg], and the service time of customers is fixed at 15 min.

Table 2. Results obtained for M1 Model

	M1		
N	D1	E1	T1
10	365.562	494.312	29134.312
13	375.630	539.129	31775.804
15	394.212	657.106	38729.238
18	430.853	692.946	39147.743
20	466.677	709.049	41790.760
23	484.554	716.439	42226.267
25	492.853	769.111	45330.733
28	525.854	834.807	49202.786
30	642.114	1002.028	60885.773

Table 3. Result obtained for M2 Model

	M2		
N	D 2	E2	T2
10	369.930	443.968	30902.858
13	390.486	475.129	33003.73
15	417.270	558.361	40909.329
18	430.907	572.286	41930.025
20	470.676	641.070	43784.111
23	490.482	712.000	44964.684
25	507.552	727.998	47728.764
28	558.465	787.619	60921.604
30	670.348	1028.568	62432.351

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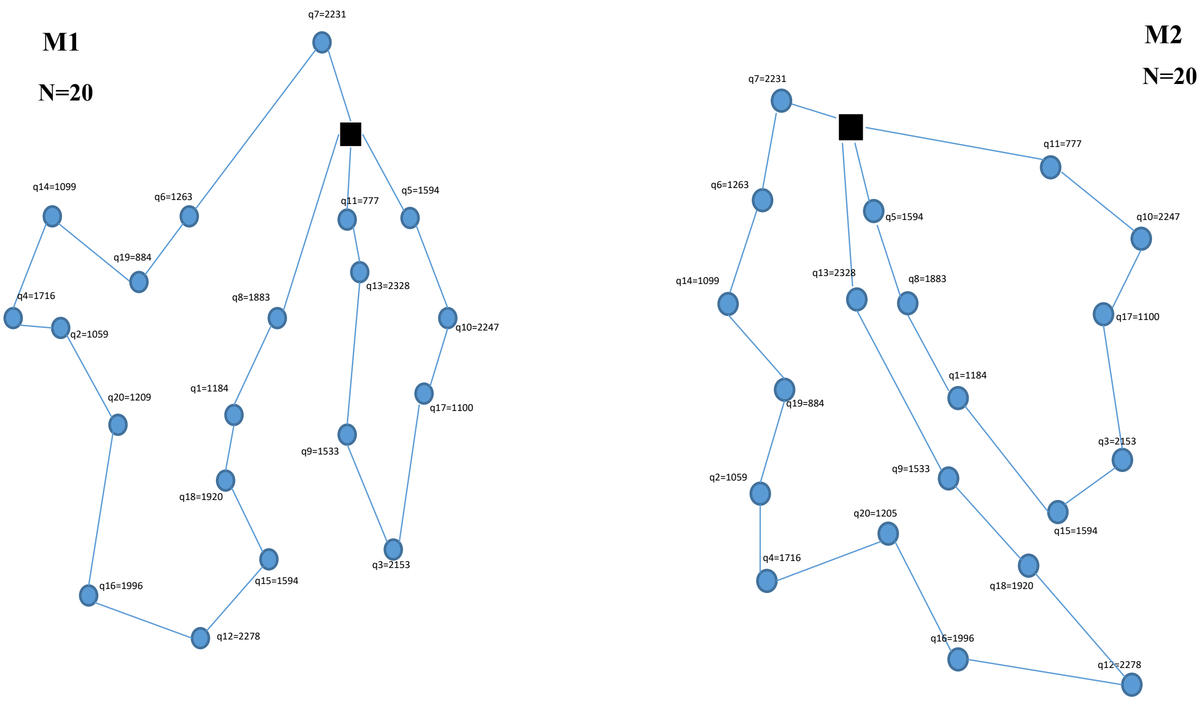

Figure 3. Example of solutions obtained for M1 and M2 in instance 20

The models M1 and M2 are coded with python and solved with CPLEX 20.1.0 with an execution time limit fixed at 15s. On a machine with a core i5 processor, 2,40GHz, 4Go of RAM.

The program gives as result 3outputs, which are the optimal distance, the corresponding itinerary, and the execution time, In order to be able to compare the two models, based on the optimal plan generated by the program, we calculate the other 2 outputs which are the number of emissions and the total working time corresponding to each instance. Tables 2 and 3 show the best results found for 9 different instances of 10 to 30 requests, where n is the number of customers columns D, E, and T are respectively the total distance traveled, CO_2 emission and the total traveled time for models M1 and M2. Figure 3 presents the optimal solutions obtained for models M1 and M2 in the case of N=20, while Figure 4 provides a comparative analysis of the results for M1 and M2 across all instances.

For M1

vehicle1: 8➔1➔18➔15➔12➔16➔20➔2➔4➔14➔19➔6➔7

Vehicle2: 11➔10➔17➔3➔9➔13➔5

For M2

Vehicle1: 13➔9➔18➔12➔16➔20➔4➔2➔19➔14➔6➔7

Vehicle2: 11➔10➔17➔3➔15➔1➔8➔5

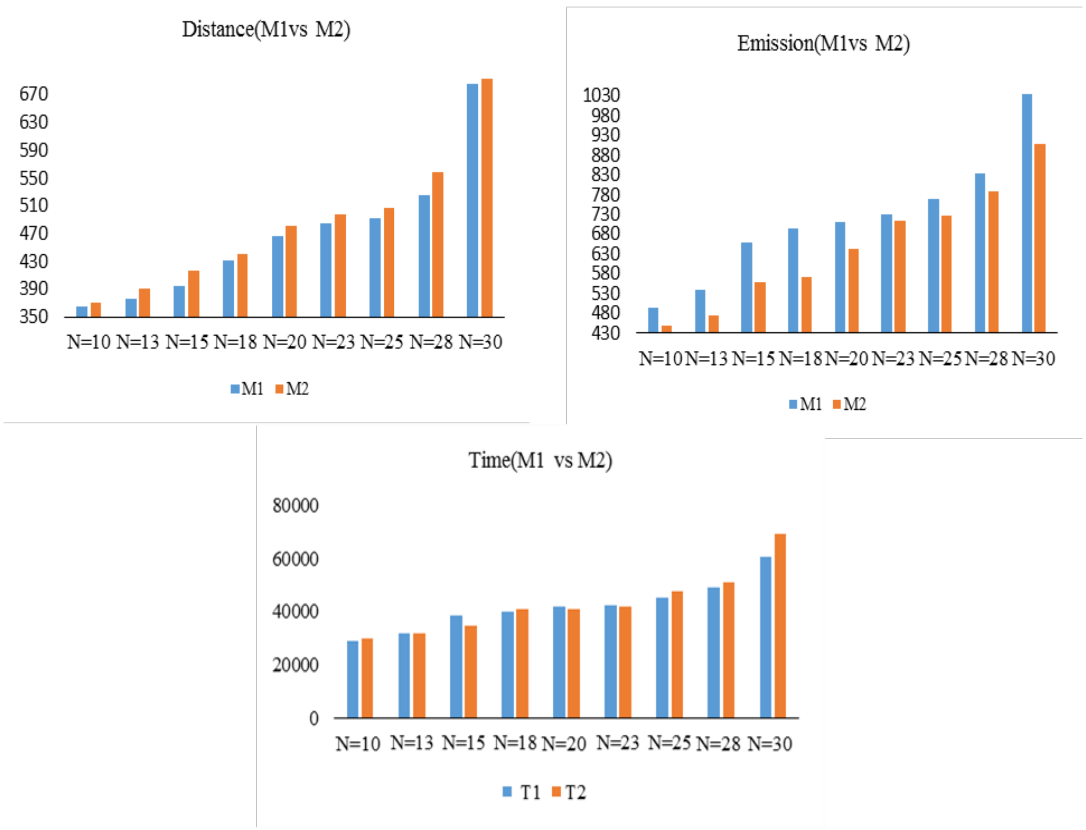

Figure 4. Comparison of M1 and M2 results in terms of distance, emissions and time

4. Discussion

As anticipated based on the model's adjustments, Tables 2, 3, and the graphs in Figure 4 clearly show that the distance values generated by Model M2 are consistently higher than those of Model M1 are across all nine instances. However, a significant reduction in CO_2 emissions is observed when transitioning from Model M1 to Model M2. This decline highlights that, despite the increase in distance, the changes introduced in Model M2 prioritize environmental sustainability. As for travel time, it increases in some instances and decreases in others—an expected outcome, given that time is influenced not only by distance but also by factors such as emissions and, notably, congestion. These findings offer preliminary support for the methodology, showing that it is both practical and efficient to incorporate CO_2 emissions straight into the distance computation. The findings demonstrate the model's potential for future development and practical use in sustainable logistics and transportation by demonstrating its capacity to produce ecologically beneficial results without sacrificing its applicability.

Although preliminary testing of the suggested method on small samples offers a basic grasp of its efficacy, it is insufficient to make trustworthy or broadly applicable inferences. The next stage is to expand the validation process to larger and more complicated situations in order to obtain more reliable and representative results. This will enable a more thorough evaluation of the method's scalability and usefulness. To address these larger cases, we intend to use more sophisticated metaheuristics in subsequent work. The approach will be improved, and its efficacy in resolving real-world issues will be ensured by the use of metaheuristics, which are renowned for their capacity to effectively explore vast and intricate solution spaces. By bridging the gap between theoretical validation and real-world implementation, this process will offer a more thorough review.

5. Conclusion

To conclude, this article introduces a new approach to model the GCVRP, the proposed model is mono-objective minimizing the total virtual traveled distance, including the number of CO_2 emissions. The article presents the methodology adopted to quantify CO_2 emissions in distance and the passage from a GCVRP multi-objective that minimizes two objectives, distance and CO_2 emissions to a Virtual GCVRP mono-objective minimizing only one objective which is the virtual traveled distance. The M2 model has given good results justifying the possibility and feasibility of the methodology proposed in this work. An improvement of the introduced model plus a validation on large instances is necessary to have better visibility which will be presented in next works.

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