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Decomposition-based Matheuristics for Green Vehicle Routing Problems

by

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Alejandro Fernández Gil

Valparaíso, December 2, 2023 ____________________________

To Margot and Arnaldo

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Abstract

The fast development of logistics industries has encouraged an increase in the sharing of logistics resources as well as in the reduction of environmental pollution in freight transport. Although transportation companies are relevant drivers of economic growth, they are one of the leading causes of carbon dioxide emissions. The transportation of goods impairs local air quality, produces noise and vibration, and contributes significantly to global warming. This circumstance has been widely studied in green logistics, which considers the efficient use of resources within logistics activities and the modification of distribution strategies. The central purpose is to minimize energy use, reduce waste, and properly manage its treatment in order to achieve an eco-friendly, respectful, and sustainable transport scheme that reduces environmental and social impacts within logistic operations.

Nowadays, many companies still need to efficiently address the transportation of pickup or/and delivery of goods over the routes. The complexity of planning routes that optimize transportation costs by satisfying a large number of restrictions generates challenging problems that involve vehicle fleets in the industry. Moreover, adopting environmental aspects in transport plans requires extensive analysis to harmonize environmental costs and financial costs. This encourages studying and developing optimization techniques involving mathematical programming models and algorithms to assist fleet managers and decision-makers when planning transportation operations.

This thesis is positioned within green logistics and computational logistics areas, especially in problems related to green vehicle routing problems (GVRP) and resolution hybrid algorithms. The GVRPs are characterized by incorporating factors concerning the environment, such as energy consumption, emission reduction, and noise mitigation. In order to fully grasp and map the GVRP variants and how the algorithms have been used to solve them, an in-depth study of heuristics and hybrid algorithms for solving GVRPs considering emissions is presented. For each variant of GVRP, we discussed how the emissions are addressed by presenting the main characteristics related to the compositions of the restrictions, objectives, emission models, and types of emissions. Also, we reported the heuristics' main features and heuristics hybridizations developed for solving these problems by highlighting the leading strategies and methodologies employed in each solution method. Lastly, we indicated a detailed description of the benchmark instances proposed in the related literature and used it to assess the algorithms' performance.

Based on the study carried out, we proposed two studies that consider novel emerging GVRP variants.

The first study defined the cumulative vehicle routing problem with time windows (CumVRP-TW), intending to minimize a given cumulative cost function while respecting customers' time window constraints. The CumVRP-TW considered two types of time windows, i.e., soft time windows (CumVRP-STW) and hard time windows (CumVRP-HTW). For each version, we formulated a mathematical model for solving small-sized instances of the problem, while a matheuristic decomposition algorithm was presented for solving all instances' sizes. The last approach was based on a cluster first-route second approach by considering the integration of a greedy randomized adaptive search procedure (GRASP) with each mathematical model. The solution approaches are tested on instances proposed in the literature as well as on a new benchmark suite proposed for assessing the soft time windows variant. The computational results show that the mathematical formulations provide optimal solutions for scenarios of 10, 20, and several 50 customers within suitable computational times. Nevertheless, the same performance is not observed for several medium as well as for all large scenarios. In those cases, the proposed matheuristic algorithm is able to report feasible and improved routes for those instances where the exact solver does not report good results. Moreover, we verify that fuel consumption and carbon emissions are reduced when the violation of the time windows is allowed in the case of soft time windows.

The second study proposed the multi-depot green vehicle routing problem with pickup and delivery operations (MDGVRP-PD), where the objective was to construct a set of vehicle routes considering multiple depots and one-to-one pickup and delivery operations that minimize emissions through fuel consumption. The way emissions were determined during the route depended on weight and travel distance. To solve this problem, a mathematical model and a matheuristic approach based on a clustering procedure and a partial optimization metaheuristic under special intensification conditions (POPMUSIC) framework were proposed. To validate the previous approaches, we proposed modified benchmark instances based on the literature on pickup and delivery VRPs and addressed inherent characteristics related to real locations considering pickup and delivery partner association in multi-depot contexts. The results show that if the weight carried on the routes as part of the fitness measure is considered, our matheuristic approach provides an average percentage improvement in emissions of 30.79%, compared to a fitness measure that only takes into account the distances of the routes.

The results shown in this thesis indicate that the management of green routing problems by means of decomposition approaches is beneficial for reducing emissions while showing competitive time performance. In this regard, the literature analysis reports the relevant impact that the matheuristic methods, such as those proposed in this thesis, have on solving different variants of GVRPs. Furthermore, the definition of new GVRPs permit evaluating the impact of cumulative cost through arcs and the soft and hard time windows concerning fuel consumption. Lastly, the results on decomposition matheuristics indicate that they are suitable and comprehensive solution approaches to solve GVRPs.

Publications Arising From the Thesis

(2 journal papers have been published. 2 conference papers have been published)

Journal Articles

1. Fernández, A., Lalla-Ruiz, E., Gómez, M., and Castro, C. (2023). The cumulative vehicle routing problem with time windows: models and algorithm. *Annals of Operations Research (ANOR)*, 1-29. 10.1007/s10479-022-05102-7

2. Fernández, A., Lalla-Ruiz, E., Gómez, M., and Castro, C. (2022). A review of heuristics and hybrid methods for green vehicle routing problems considering emissions. *Journal of Advanced Transportation (JAT)*, 2022:5714991. doi:10.1155/2022/5714991

3. Fernández, A., Lalla-Ruiz, E., Mes, M., and Castro, C. A matheuristic approach to solve the multi-depot green VRP with pickups and deliveries. (Working paper).

Lecture Notes and Indexed Conference Proceedings

1. Fernández, A., Lalla-Ruiz, E., Mes, M., and Castro, C. (2021). Optimization of green pickup and delivery operations in multi-depot distribution problems. In *International Conference on Computational Logistics (ICCL 2021)*, pages 487-501. Springer. doi:10.1007/978-3-030-87672-2_32

2. Fernández, A., Gómez, M., Lalla-Ruiz, E., and Castro, C. (2020). Cumulative VRP with time windows: a trade-off analysis. In *International Conference on Computational Logistics (ICCL 2020)*, pages 277-291. Springer. doi:10.1007/978-3-030-59747-4_18

Other outputs

(1 journal paper have been published. 1 conference paper have been published)

Journal Articles

1. Fernández, A., Gómez, M., Castro, C., and Pérez-Alonso, A. (2022). A mixed-integer linear programming model and a metaheuristic approach for the selection and allocation of land parcels problem. *International Transactions in Operational Research (ITOR)*. Wiley. doi:10.1111/itor.13115

2. Gómez, M., Lalla-Ruiz, E., Fernández, A., Castro, C., and Voß S. (2022). Resource-Constrained Multi-Project Scheduling Problem: A survey. *European Journal of Operational Research (EJOR)*. doi:10.1016/j.ejor.2022.09.033

3. Gómez, M., Masip, Y., Fernández, A., Castro, C., Nuñez, S.M. and Pedrera, J. (2020). A mathematical model for the optimization of renewable energy systems. *Mathematics*. doi:10.3390/math9010039

4. Gómez, M., Lalla-Ruiz, E., Mes, M., Fernández, A., and Castro, C. The resource-constrained multi-project scheduling problem with resources mixed accessibility. *Expert Systems with Applications (ESWA)*. (Under Review).

Lecture Notes and Indexed Conference Proceedings

1. Fernández, A., Gómez, M., Castro, C., and Masip, Y. (2019). A mixed integer linear programming approach for the 2D strip packing problem with different size options for plots of land in smart floating farms. In *III International Conference on Agro BigData and Decision Support Systems in Agriculture (BigDSSAgro 2019)*, pages 69-72. isbn:978-956-356-095-4

2. Gómez, M., Fernández, A., and Castro, C. (2019). Integrating a SMT solver based local search in ant colony optimization for solving RCMPSP. In *2019 IEEE Latin American Conference on Computational Intelligence (LA-CCI)*, Guayaquil, Ecuador, pages 1-6. IEEE. doi:10.1109/LA-CCI47412.2019.9036765

3. Masip, Y., Fernández, A., Gómez, M., Castro, C., & Nuñez, S. M. (2019). Optimization of a smart integrated renewable energy system for isolated rural villages using integer linear programming. In *2019 7th International Engineering, Sciences and Technology Conference (IESTEC)*, Ciudad de Panamá, Panamá, pages 161-166. IEEE. doi:10.1109/IESTEC46403.2019.00-83

Research Projects

1. Optimization and modeling based on matheuristic methods for solving vehicle green routing problems. 2020-2022. *Regular Research Line Project DGIIE-UTFSM* PI_LIR_2020_67. Universidad Técnica Federico Santa María. Chile.

2. Hybrid algorithms for the green vehicle routing problems. 2020 - 2021. *Scientific Initiation Incentive Program (PIIC)* DGIP-UTFSM 013/2020. Universidad Técnica Federico Santa

María. Chile.

3. The Multiple Balanced Academic Curriculum Problem with Quotas Balanced for Academics Periods. *Scientific Initiation Incentive Program (PIIC)* DGIP-UTFSM 014/2019. Universidad Técnica Federico Santa María. Chile.

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Chapter 1

Introduction

At the end of the 19th century, Karl Benz established the beginning of the automobile era, the internal combustion engine became a symbol of German engineering and the automobile became a mass production after the Second World War (Welle, 2021; Winner and Wachenfeld, 2016). In the mid-1950s, the United Kingdom recorded rail strikes and port delays (SNAP, 2019). Similarly, in the United States, the railroad fell into decline, and dozens of companies merged and eliminated rail lines in an effort to survive competition with the automobile (Maglev, 2018). This way, the transport load was more directed to the roads, allowing vehicles to connect with suppliers and customers. The new and improved road network grew rapidly and revolutionized freight logistics, increasing vehicle size and fuel efficiency and reducing travel times. Since then, freight transportation via roads has been the engine for the economies of many countries (Ranaiefar and Amelia, 2011).

Beyond road transportation, the development of research and studies by the scientific community and logistics distribution companies to manage freight transport problems has been a growing interest since the late 1950s. The work of Dantzig and Ramser (1959) introduced the vehicle routing problem (VRP), which is a well-known problem in the freight transportation sector, artificial intelligence, and combinatorial optimization field. The authors defined the VRP as the problem of determining an optimal set of routes where a fleet of delivery trucks must visit a given set of service stations. In 1964, Clarke and Wright (1964) generalized the previous problem by employing a linear optimization model that considers serving a set of customers geographically distributed around a central depot using a fleet of vehicles with different capacities. After these initial works, there were many routing problems derived from VRP, such as VRP with time windows (VRP-TW, Laporte (1984); Laporte et al. (1988)), VRP with pickup and delivery operations (VRPPD, Parragh et al. (2008)), VRP and scheduling problem (VRSP, Bodin and Golden (1981)), among others. A book that serves as a primer on VRP and its variants, providing general and comprehensive coverage of concepts, mathematical models, and methodologies on this problem, can be found in Toth and Vigo (2014).

In recent years, the freight transportation sector has generated a growing concern at the governmental, business, and social levels due to the negative impacts caused to the environment (Roper, 2012). Burning fossil fuels causes approximately 80% of global environmental pollution, and about 60% of this fuel is consumed in the transportation sector (Sahin et al., 2009). Thus, many logistics companies like UPS (UPS, 2019), DHL (DPDHL, 2021), FedEx (FedEx, 2021), or transport services are looking to manage carbon emissions efficiently (Yang and Sun, 2015). Consequently, many objectives were considered in the literature such as: the minimization of emissions, operational cost, and high-quality transport service.

This consideration is involved in the optimization of VRP and is an emerging research topic in green logistics. Green logistics considers the study of the environmental impact of production and distribution strategies of goods (Sbihi and Eglese, 2010). For example, energy optimization in logistics activities, reduction of greenhouse gas emissions (GHGs), and management and treatment of waste.

In this regard, developing efficient goods distribution plans considering sustainability factors has become a fundamental objective (Bektaş et al., 2019). Since the beginning of this century, several variants of VRP related to ecological transport began to be identified in the literature, resulting in the introduction of the Green VRP[1] area. Green VRP is dedicated to studying green vehicle routing problems, which aims to harmonize environmental and economic costs by implementing effective routes to meet environmental concerns and financial indicators. According to Lin et al. (2014), the current problems in Green VRP can be classified as (i) green vehicle routing problem (GVRP[1]), which is oriented to the study of the energy consumption of the means of transportation (commonly expressed in terms of fuel consumption), (ii) pollution-routing problem (PRP), is oriented to the study of GHGs during the vehicle routing process, and (iii) VRP in reverse logistics (VRRPL), which is associated with the optimization of distribution channels in reverse flows (reuse of products and materials) of a supply chain.

The existing investigations for solving VRPs involve sophisticated resolution methodologies and numerous subroutines to exploit each problem structure (Booth, 2021). These resolution methodologies can be divided into three main categories: (i) exact approaches, (ii) approximate approaches, and (iii) hybrid approaches. Exact approaches guarantee a global optimal solution depending on the problem dimension. However, these problems are often classified as non-polynomial hard problems (NP-Hard), which implies these are complex to treat (Lenstra and Kan, 1981). To handle this intractable type of problem, approximate approaches find locally optimal solutions (heuristic/meta-heuristic solutions) with reasonable times, while there are no guarantees on the quality of that solution (Talbi, 2009). Similarly, hybrid approaches (e.g., mathematical model-heuristic, exact-heuristic, and heuristic-metaheuristic) inte-

[1]Using Green VRP as a field of research, and GVRP as a problem.

grate different artificial intelligence and/or operational research techniques into the resolution procedure (Goel and Bansal, 2020). Choosing a suitable combination of algorithmic concepts can be the key to achieving top performance in solving many hard optimization problems (Blum et al., 2011). These latter approaches have been an actively growing area because mitigating the inherent weaknesses of exact techniques and approximate techniques to hybridize those methodologies.

In an effort to solve VRPs efficiently using the advantages of exact and approximate algorithms, researchers have made ongoing contributions to the combination of both types of techniques known as matheuristics. Matheuristic approaches involve heuristics that incorporate phases where mathematical programming approaches are solved (Archetti and Speranza, 2014). In this sense, models for routing problems typically involve the following two main decisions: the clustering of customers, which are assigned to each vehicle, and the sequencing of customers in vehicle routes. Then, due to the nature of these problems, decomposition optimization techniques are relevant approaches to solve them, since they can be used to divide the original problem into smaller and simpler subproblems and apply a specific exact method to solve each subproblem (Maniezzo et al., 2021; Santini et al., 2021).

Considering the above discussion and increasing interest in GVRPs, in this dissertation we investigate the development of decomposition matheuristic approaches for emerging green vehicle routing problems considering emissions. Moreover, we investigate the importance of providing efficient solutions by proposing matheuristic algorithms, specifically those based on decomposition.

1.1 Routing problems

This section discusses the incremental progress towards GVRP. In doing so, Section 1.1.1 describes the vehicle routing problem (VRP) starting from the traveling salesman problem (TSP) and a generalization of it, named multiple TSP (mTSP). Section 1.1.2 builds upon those problems to define the green vehicle routing problem (GVRP).

1.1.1 The vehicle routing problem

Routing problems can be classified into node routing problems, where nodes in a road network can represent the customers, and arc routing problems, in which the service is performed on the arcs of a road network (Corberán et al., 2021). The first type has been the most traditionally used, and to model this type of problem.

The models presented in the remainder of this chapter use the following notation. Let $G = (V, A)$ be a graph, where V is a set of vertices (i.e., customer and depot) and A is a set of arcs. A travel cost, $c_{ij} > 0$, is associated with A and defined for each arc between each pair of vertices $(i, j), i, j \in V, i \neq j$. In several applications, c can also be interpreted as a distance or travel time matrix. A binary variable x_{ij} takes the value of 1 if any vehicle goes from i to j, 0 otherwise.

One of the most studied problems in operations research is the well-known traveling salesman problem (TSP). This problem considers determining a minimum distance circuit visiting each vertex once and only once. Such a circuit is known as a tour or Hamiltonian circuit. This tour starts and ends from an initial depot vertex (see Figure 1.1). Moreover, this problem can be considered symmetrical, i.e., when $c_{ij} = c_{ji}$ or asymmetrical $c_{ij} \neq c_{ji}$ with $\forall i, j \in V$. Also, c is said to satisfy the triangle inequality if and only if $c_{ij} + c_{jh} \geq c_{ih}$ $\forall i, j, h \in V$. This occurs in Euclidean problems, i.e., when V is a set of points in $\mathbb{R}^2$ and c_{ij} is the straight-line distance between i and j.

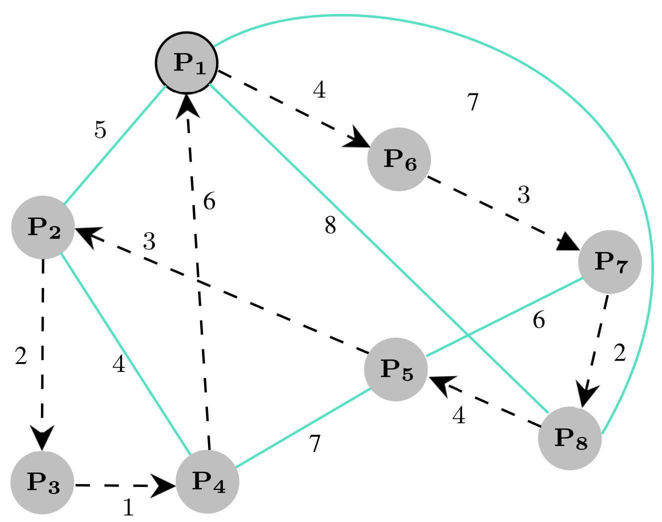

Figure 1.1: A Hamilton cycle of the graph $\{P_1, P_6, P_7, P_8, P_5, P_2, P_3, P_4, P_1\} \in G$ with minimum travel cost of 25.

Dantzig et al. (1954) proposed one of the initial formulations for TSP, named DFG, based on integer linear programming (ILP), as described below.

The objective function clearly describes the cost of the optimal tour:

$$\text{minimize} \quad \sum_{i \neq j}^{|V|} c_{ij} x_{ij} \tag{1.1}$$

$$\text{subject to:} \quad \sum_{j=1}^{|V|} x_{ij} = 1, \quad \forall i \in \{1, \ldots, |V|\}, \tag{1.2}$$

$$\sum_{i=1}^{|V|} x_{ij} = 1, \quad \forall j \in \{1, \ldots, |V|\}, \tag{1.3}$$

$$\sum_{i,j \in S} x_{ij} \leq |S| - 1, \ S \subset V, \ 2 \leq |S| \leq |V| - 2, \tag{1.4}$$

$$x_{ij} \in \{0, 1\}, \ \forall i, j \in \{1, \ldots, |V|\}, \ i \neq j. \tag{1.5}$$

Constraints (1.2) and (1.3) are degree constraints: they specify that every vertex is visited exactly once (1.2) and left exactly once (1.3). Constraints (1.4) are subtour elimination constraints to prohibit the formation of subtours. For instance, if there was a subtour on a subset $S \subset V$ of vertices, this subtour would contain $|S|$ arcs and as many vertices. Constraint (1.4) would then be violated for this subset since its left-hand side would be equal to $|S|$ and its right-hand side equal to $|S| - 1$. Finally, constraints (1.5) define binary variables x_{ij}.

The multiple traveling salesman problem (mTSP) is a generalization of TSP, where more than one salesman is allowed. This problem is highly related to VRP and proposes a relaxation of VRP without considering the vehicle capacity or customers' demands (Cheikhrouhou and Khoufi, 2021).

The VRP differs from the TSP and mTSP because the VRP can generate multiple routes to visit all customer locations, and routes are subject to vehicle capacity and customers' demands are known. In this regard, the capacitated vehicle routing problem (CVRP) is the most tackled variant of the VRP (see Figure 1.2).

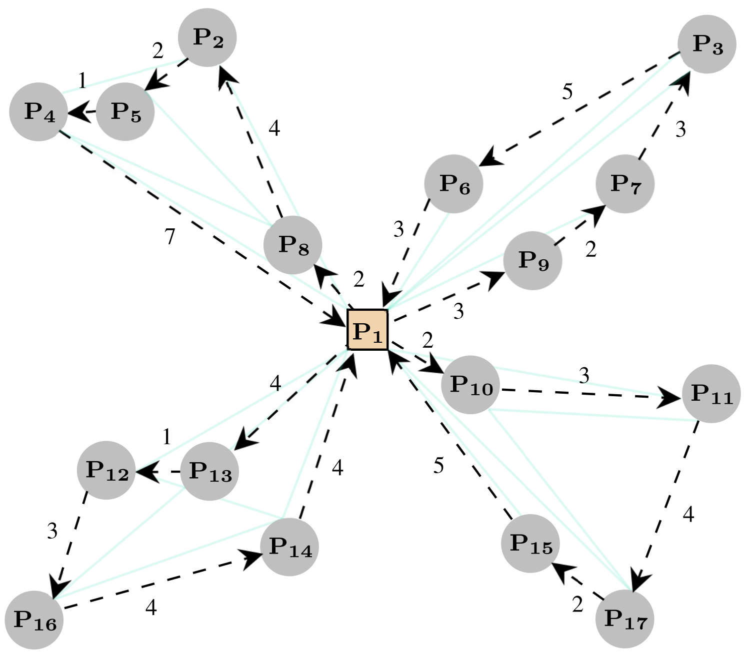

Figure 1.2: Illustration of a VRP scenario considering the minimization of the distances traveled.

The CVRP can be defined as follows. Let a directed or undirected graph G representation, as we previously defined. The vertex 1 represents the depot. A fleet of homogeneous vehicles S with $\forall s \in \{1, 2, \ldots, |S|\}$. All vehicles have the same load capacity $Q > 0$, and each customer $i \in V \backslash \{1\}$ has a demand for goods q_i. A traveling distance, $d_{ij} > 0$, is defined for each arc between each pair of vertices $(i, j), i, j \in V, i \neq j$. The binary variable x_{ij} is modified to x_{ij}^s and takes the value of 1 if a vehicle s drives from i to j, 0 otherwise. To ensure no subtour formation, a variable u_i gets a value for each vertex, except for the depot. If a vehicle drives from vertex i to vertex j, the value of u_i has to be smaller than the value of u_j (i.e., $u_i < u_j$). In the symmetric case, when the cost of moving goods between i and j does not depend on the direction, the graph G is complete and undirected with arc set $A = \{a = \{i, j\} = \{j, i\} : i, j \in V, i \neq j\}$ and arc costs c_{ij} with $\forall i, j \in A$. For the asymmetric case, if at least one pair of vertices $i, j \in V$ has asymmetric costs $c_{ij} \neq c_{ji}$ then the underlying graph is a complete digraph with arc set $A = \{(i,j) \in V \times V : i \neq j\}$ and arc costs c_{ij} with $\forall i, j \in A$. The following model is defined for the problem.

The objective function minimizes the total traveled distance:

$$\text{minimize} \quad \sum_{s=1}^{|S|}\sum_{i=1}^{|V|}\sum_{j=1}^{|V|} c_{ij}x_{ij}^s \tag{1.6}$$

$$\text{subject to:} \quad \sum_{i=1}^{|V|} x_{ij}^s = \sum_{i=1}^{|V|} x_{ji}^s, \quad \forall j \in \{1,\dots,|V|\},\ \forall s \in \{1,\dots,|S|\}, \tag{1.7}$$

$$\sum_{s=1}^{|S|}\sum_{i=1}^{|V|} x_{ij}^s = 1, \quad \forall j \in \{2,\dots,|V|\}, \tag{1.8}$$

$$\sum_{j=2}^{|V|} x_{1j}^s = 1, \quad \forall s \in \{1,\dots,|S|\}, \tag{1.9}$$

$$\sum_{i=1}^{|V|}\sum_{j=2}^{|V|} q_j x_{ij}^s \leq Q, \quad \forall s \in \{1,\dots,|S|\}, \tag{1.10}$$

$$u_j - u_i \geq q_j - Q(1 - x_{ij}^s),\ \forall i, j \in \{2,\dots,|V|\}\ i \neq j,\ \forall s \in \{1,\dots,|S|\}, \tag{1.11}$$

$$q_i \leq u_i \leq Q,\ \forall i \in \{2,\dots,|V|\}, \tag{1.12}$$

$$x_{ij}^s \in \{0,1\},\ \forall i,j \in \{1,\dots,|V|\},\ \forall s \in \{1,\dots,|S|\}, \tag{1.13}$$

$$u_i \geq 0,\ \forall i \in \{2,\dots,|V|\}. \tag{1.14}$$

Constraints (1.7) ensure that the number of times a vehicle enters a vertex is equal to the number of times it leaves that vertex. Constraints (1.8) ensure that every vertex is visited only once. Constraints (1.9) guarantee every vehicle arrives back at the depot. Constraints (1.10) establish the capacity of load for each vehicle. Constraints (1.11) and (1.12) ensure no subtour formation following the Miller-Tucker-Zemlin (MTZ) formulation (see (Miller et al., 1960)). Finally, constraints (1.13) define binary variables x_{ij}^s and constraints (1.14) ensure the no negativity of the variables u_i.

1.1.2 The green vehicle routing problem

A sustainable transportation scheme with less harmful effects on the environment and ecology must replace the existing transportation plan as part of the environmental logistic strategy. Currently, there are several problems concerning green transportation, for example, atmospheric emissions, noise pollution, and road traffic accidents. To cope with these environmental concerns, a variety of solutions have been proposed, e.g., promoting alternative fuels, electric vehicles, green intelligent transportation systems, and many other eco-friendly infrastructures (Eglese and Bektaş, 2014). These sustainable transportation schemes would be more easily attained through improved vehicle usage, and cost-effective vehicle routing solutions (Lin et al., 2014); turning green distribution networks using vehicle routing models is a principal challenge.

In VRP literature, VRP variants take into account sustainable transportation issues. Those problems compose the green vehicle routing problem family. Green VRPs are characterized by the objective of harmonizing the environmental and economic costs (e.g., minimizing fuel consumption and carbon dioxide (CO_2 emissions)) by implementing effective routes to meet environmental concerns and financial indexes. Note that the CO_2 emissions produced by a vehicle are directly proportional to fuel consumption (Olgun et al., 2021) and there are several factors that can affect fuel consumption (see Figure 1.3).

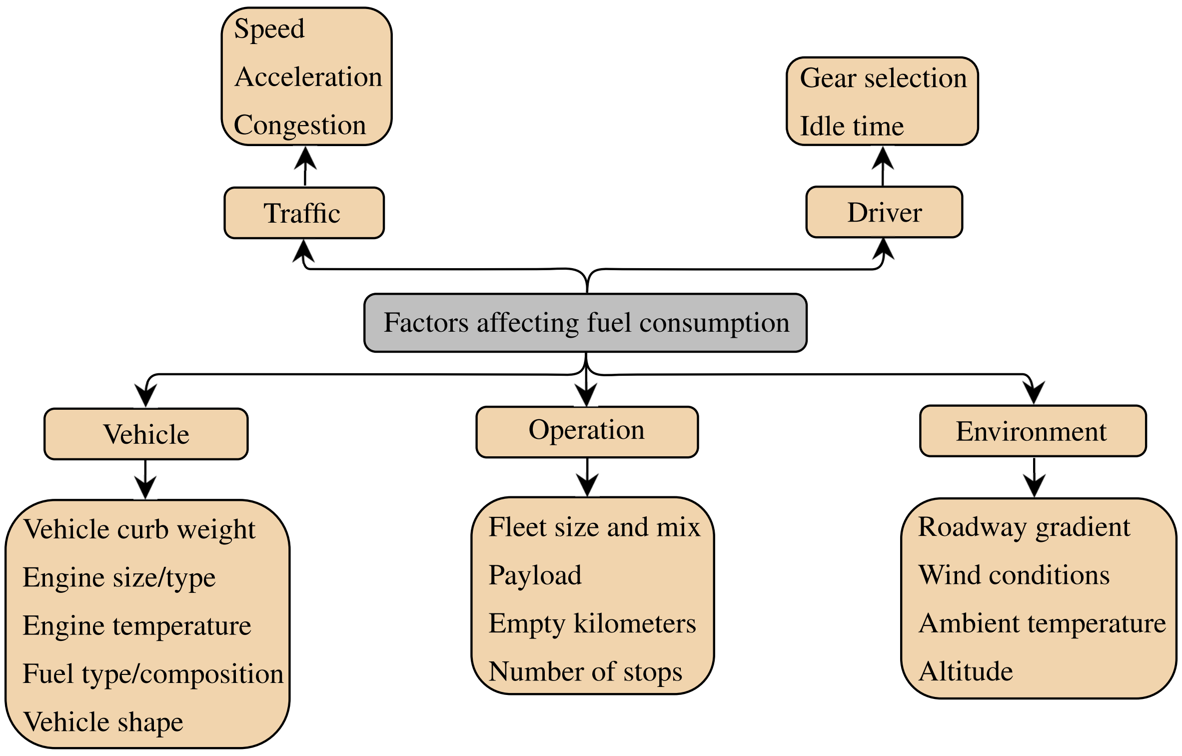

Figure 1.3: Principal determinant factors of fuel consumption behavior. This figure was inspired in the research of Demir et al. (2014b).

Moreover, there are several methodologies to estimate fuel consumption and emissions in traditional VRPs. The most used are based on analytical fuel consumption (or emission) models (Eglese and Bektaş, 2014). These fuel consumption models are devoted to estimating consumption based on the characteristics of vehicles, the environment, and traffic-related parameters (e.g., vehicle speed, load, road gradient, and acceleration). According to the research of Demir et al. (2014b), emissions models are classified into three categories: (i) emission factor models, (ii) macroscopic models (e.g., COPERT in Kouridis et al. (2010), MEET in Hickman et al. (1999)), and (iii) microscopic models (e.g., CMEM in Scora and Barth (2006)). The former category is rather simplistic with major disadvantages such as their inability to represent driving cycles with good accuracy; however, the remaining models are based on speed-related functions to estimate emissions at a road network scale and use precisely detailed parameters, such as acceleration and road gradient, which are obtained from a vehicle characteristics. More details on how emissions have been considered in GVRPs regarding emissions models are discussed in Section 2.3.

Due to the evident, environmental concerns in the freight transportation sector GVRPs have been proposed, and their resolutions have attracted increasing interest from researchers and relevant stakeholders, resulting in a wide range of mathematical models and computational methods for green transportation planning. Below, in Figure 1.4, we identify and describe some relevant GVRP variants and show a timeline of the progress of the problems:

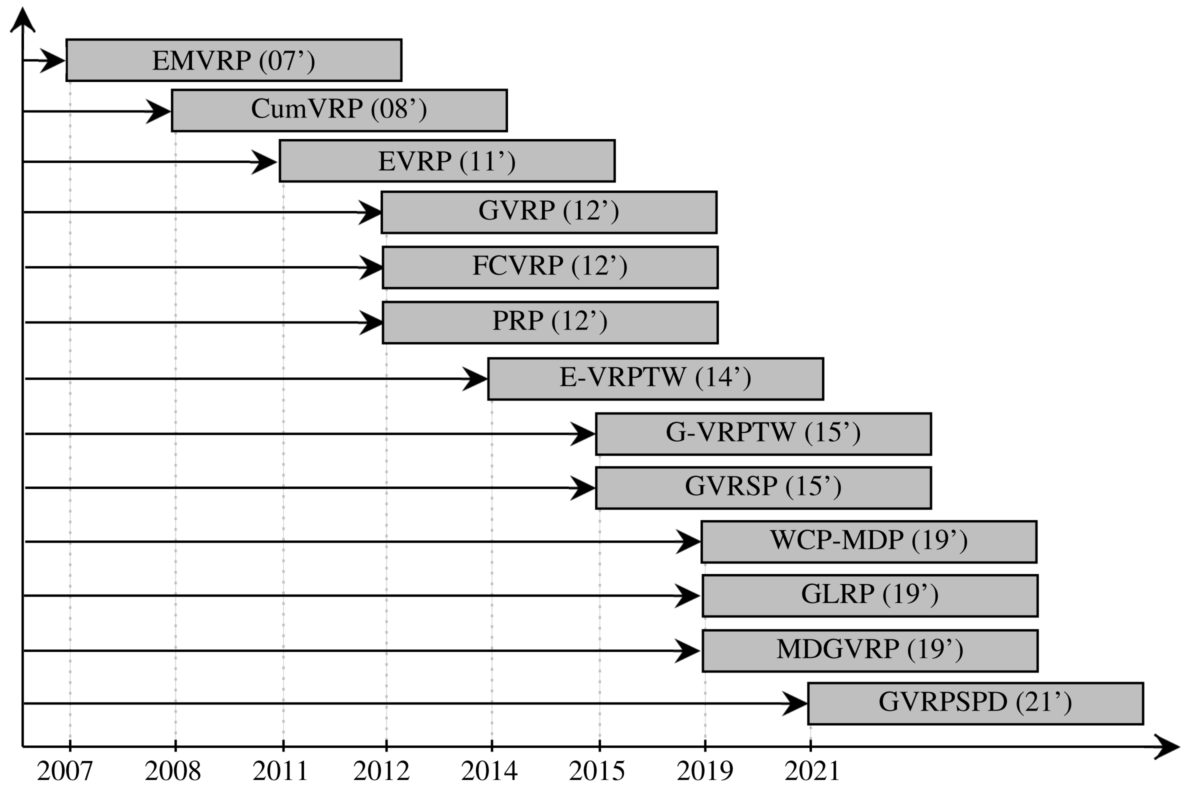

Figure 1.4: Timeline of different GVRP variants over the last decades.

- Energy minimizing VRP (EMVRP) and cumulative VRP (CumVRP). They consider a cost function as a sum of the product between load and distance for each arc (Kara et al., 2007, 2008).

- Electric VRP (EVRP). It considers time and capacity restrictions and assumes a time for recharging the EVs, calculated from the distance traveled and the range using one battery charge (Gonçalves et al., 2011).

- Green VRP (GVRP). It contemplates alternative fuel-powered vehicles (AFV) with restricted range and where there are few alternative fuel stations (AFS) where the vehicles may refuel (Erdoğan and Miller-Hooks, 2012).

- Fuel-consumption VRP (FCVRP). It considers a fuel consumption rate (FCR) as a load-dependent function and was included in the CVRP to minimize fuel consumption. Also, the distance traveled and the load are considered determining factors of fuel consumption (Xiao et al., 2012).

- Pollution-routing problem (PRP). This variant of the VRP-TW determines the vehicle speeds on each route segment to minimize a function comprising fuel, emission, and driver costs (Demir et al., 2012).

- Electric VRP-TW (E-VRPTW). This variant of the EVRP incorporates time windows, recharging stations, and providing the possibility of refueling at any available station using an appropriate refueling scheme (Schneider et al., 2014).

- Green VRP with time windows (G-VRPTW). It considers vehicle routes with time windows minimizing the distance traveled, total fuel consumption, and carbon emissions(Küçükoğlu et al., 2015).
- Green VRP and scheduling problem (GVRSP). It considers time-dependent traffic circumstances and minimizes the CO_2 emissions while satisfying the assignment of vehicles to customers and the travel schedule (Xiao and Konak, 2015).
- Waste collection problem with midway disposal pattern (WCP-MDP). It considers gathering wastes from different areas (e.g., public service and logistics activity), loading and transporting them by vehicles, and dumping them at disposal facilities. This problem can be seen as VRP with dynamic disposal trips and the minimization of total carbon emissions (Wei et al., 2019).
- Green location-routing problem (GLRP). This GVRP variant contemplates locating depots in several locations, the routing process, and finally establishing the speed in each arc of the path so that customers are served within their respective time windows (Dukkanci et al., 2019).
- Multi-depot GVRP (MDGVRP). It considers multiple depots, and during the servicing process, share transportation resources occur within the same depot and among multiple depots to minimize carbon emissions and operational costs (Wang et al., 2019).
- Green VRP with simultaneous pickup and delivery (GVRPSPD). It contemplates the satisfaction of customer pickup and delivery demands simultaneously while the fuel consumption costs are minimized (Olgun et al., 2021).

1.2 Optimization techniques

This section provides the theoretical background concerning the optimization techniques used in this dissertation. Firstly, we provide detailed descriptions of the mathematical programming bases used to define VRPs, as seen in the previous section. Secondly, we describe the approximate techniques and particular hybrid approaches.

1.2.1 Mathematical programming

Exact algorithms provide global optimal solutions for combinatorial problems. To solve routing problems, several exact algorithms have been used (e.g., dynamic programming, constraint programming, branch and bound). One of the most used methodologies for solving VRPs is mathematical programming (MP). MP concerns the optimum assignment of resources among competing activities under a set of constraints considered on the problem at hand. When the mathematical representation has linear functions, we are talking about a linear programming (LP) model (Bradley et al., 1977).

These constrained problems can be classified as constraint satisfaction problems (CSP), which represent a way to represent constrained optimization problems by using mathematical representations. The goal consists of finding values to assign to variables in such a form that the values must satisfy the constraints (Apt and Wallace, 2006). The following definition formalizes CSP:

$CSP = \langle X, D, C \rangle$, where:

- $X = \{x_1, \ldots, x_{|X|}\}$: variable set,
- $D = \{d_1, \ldots, d_{|D|}\}$: domain set,
- C : constraint set.

A solution of a CSP means finding one or all possible solutions or proving the CSP is unfeasible. A CSP is feasible (SAT) if there is at least one feasible solution; otherwise, it is unfeasible (UNSAT) when no feasible solution exists.

Note that in the definition of CSP, an objective function was not included because a CSP that involves an objective function becomes a constraint satisfaction optimization problem (CSOP). CSOP pretends to optimize (minimize or maximize) a quality measure satisfying a set of constraints (C), and the objective function (f) is an additional component to the previous CSP definition: $CSOP = CSP \cup f = \langle X, D, C, f \rangle$. Solving a CSOP means finding the optimal solution(s) or proving that the CSOP is not feasible.

On the other hand, mixed-integer linear programming (MILP) constitutes a modeling paradigm within the interplay of CSOP and mathematical formulation that aims to provide an effective structure and solution to a problem. MILP seeks to solve problems known as linear programs that involve decision variables constrained to be integers while other variables are allowed to be non-integers. Variables in linear programs can only take non-negative real values. The objective function is linear, and the constraints are linear equations/inequalities.

$$\begin{aligned} \text{minimize} \quad & c^T X \\ \text{subject to:} \quad & AX \leq b, \\ & X \geq 0, \\ & x_i \in \mathbb{Z}, \ \forall i \in I. \end{aligned}$$

Let $|X| = n$ be decision variables, m be the number of constraints, c^T is a coefficient vector with $c \in \mathbb{R}^n$, $A \in \mathbb{R}^{m \times n}$ is a matrix of variable coefficients and $b \in \mathbb{R}^m$ is a column vector. The set I identifies all variables that must be integral in a solution, all other variables can take on continuous values. If $I = \varnothing$, then the program is a linear program (LP) (i.e., all variables are continuous). If $n = |I|$, then the program is called an integer linear programming (ILP) model (i.e., all variables must take on discrete values). If $x_i \in \{0, 1\}, \forall i \in I$, the program is called binary integer programming (BIP).

1.2.2 Heuristics

The resolution of the mathematical programming models becomes complex because often the number of variables and constraints increases. There are a vast number of real-life optimization problems in engineering, economics, and business that are intractable or difficult to solve. Many of these problems are classified as NP-Hard, and they cannot be solved in an exact manner (i.e., seeking global optimum) within a reasonable amount of time (Hasle and Kloster, 2007; Laporte, 1992).

Approximate algorithms is a branch of computer science and applied mathematics that has been a principal alternative for solving VRPs and has become one of the most popular resolution techniques in the last decades. According to Talbi (2009), approximate algorithms are classified as specific heuristics and metaheuristics based on seeking local optima. The former category represents ad-hoc solutions for specific problems. On the other hand, metaheuristics are faster and more applicable to any optimization problems and capable of solving hard scenarios by exploring a large solution search space.

1.2.3 Hybrid approaches and decomposition matheuristics

Most research efforts for tackling GVRPs have been concentrated on studying and implementing heuristics and hybrid techniques to provide more efficient behavior and higher flexibility when dealing with real-world and large-scale problems (see Section 2.4). Hybrid techniques arise by combining a meta-/heuristic with components from other meta-/heuristics or techniques from artificial intelligence and operations research (Blum et al., 2011). The merging of these algorithms promotes exploiting their complementary advantages through the combination of their algorithmic strategies. This can be achieved, for example, by integrating the complementary strengths of meta-/heuristics on one side and complete methods such as branching techniques or mathematical programming on the other side. In general, hybrid metaheuristic approaches can be classified as collaborative combinations (Blum and Roli, 2008; Puchinger and Raidl, 2005). Choosing a suitable collaborative combination of algorithmic concepts can be the key to achieving top performance in solving many complex optimization problems.

Regarding collaborative integration approaches, there is the concept or approaches named *matheuristic*, which are based on the integration of meta-/heuristic and exact techniques that are able to efficiently solve combinatorial problems related to VRPs (Boschetti and Maniezzo, 2022; Faramarzi-Oghani et al., 2022). The growing advances of the exact techniques in terms of software and hardware have allowed MILP formulations can be solved up to or close to optimality within a reasonable time (Archetti and Speranza, 2014). Then, the research of these integration methods has oriented to design heuristics frameworks that embedded phases where mathematical programming models are solved. For example, the research of Coelho et al. (2012), Demir et al. (2012), and Kramer et al. (2015), integrated mathematical formulations in the matheuristic approach for GVRP variants.

Matheuristics-based on decomposition approaches (i.e., cluster first-route second, two-phase, partial optimization, rolling horizon) are commonly used when the data size to process is large (Taillard, 2023). The objective consists of identifying smaller and simpler subproblems to solve than the original problem. These subproblems are solved independently. Eventually, a feasible solution to the original problem is obtained from the solutions to the subproblems. For example, routing problems generally consider two basic types of decisions: the grouping of customers assigned to each vehicle and the sequence of customer visits on each route belonging to each vehicle. This characteristic makes it natural to use a decomposition approach. The research of Archetti and Speranza (2014) provided an in-depth guide about decomposition matheuristic approaches applied to VRP.

In this dissertation, we focused on decomposition approaches, specifically cluster first-route second and partial optimization for solving GVRP variants considering emissions. Cluster first-route second divides the two major decisions that characterize routing problems: the assignment of customers to vehicles and the sequence of customer visits on each route. This is a case of two-phase approaches, where different phases are resolved separately. Partial optimization uses one or more mathematical models to handle one part of the problem while keeping all decisions related to the remaining parts constant. In VRPs partial optimization approaches, MILP models are generally used to handle the part that does not include routing decisions, which are the most difficult to handle using a mathematical formulation. The embedded mechanism for both approaches was based on an exact technique, i.e., mathematical programming formulations, which provided optimal or closest optimal values for subproblems.

1.3 Research goals

This thesis defines the following main goal:

- Delve into the study of problems related to GVRPs considering emissions. Design, develop and analyze matheuristic decomposition approaches, to exploit the advantages of approximate and exact algorithms for solving these problems.

To achieve that goal, we define the following specific objectives:

- Study and describe the existing GVRP variants and formalize emerging GVRPs considering emissions.
- Design and develop algorithms that incorporate different matheuristic approaches based on decomposition for solving of GVRPs.
- Propose benchmarks that contain current and relevant transport characteristics for the environment, allowing adequate analysis of the algorithms in GVRPs.
- Evaluate the performance of the proposed approaches to solve the studied GVRPs.

1.4 Research contributions

The successful outcome of this research contributes to the current state of the art in GVRPs within the context of optimization techniques applied to green routing problems. Specific research contributions are described individually in the following chapters. The following lines describe the general research contributions.

This research makes significant scientific contributions to vehicle routing research in the following aspects:

1. Analysis and discussion of the different GVRP existing variants that consider the emissions and how those emissions have been considered in the literature. Also, the identification of which solution methodologies, such as heuristics and hybridization, were used for solving the GVRPs and related variants. Moreover, highlight the leading strategies employed in each solution method.
2. Development of mathematical formulations and matheuristic approaches for emerging GVRPs considering emissions. Investigation of two variants of GVRPs:
   - Definition and modeling of the cumulative VRP with hard and soft time windows, CumVRP-HTW and CumVRP-STW, respectively. The purpose of the hard time windows case is to reduce the total cost based on fuel consumption and CO_2 emissions while meeting customers' time limitations. In the soft case, the goal is to investigate the environmental impact of allowing being late at customers' locations at the expense of a penalization.

     Development of a matheuristic approach based on cluster first-route second that integrates mathematical programming and the constructive metaheuristic greedy randomized adaptive search procedure (GRASP), for solving the CumVRP-HTW and CumVRP-STW.

- Definition and modeling of the multi-depot green vehicle routing problem with pickups and deliveries (MDGVRP) incorporating pickup and delivery orders. Construction of a set of vehicle routes considering multiple depots and one-to-one pickup and delivery operations to minimize carbon emissions through fuel consumption, which depends on weight and travel distance.

  Development of a matheuristic approach based on POPMUSIC, the matheuristic version of this template proposed by Lalla-Ruiz and Voß (2016), where subproblems are solved to optimality by using exact approaches instead of approximate ones, for solving the MDGVRP-PD.

3. Proposition of a set of modified benchmarks for CumVRP-TW by adding priority values to the benchmark proposed in Kramer et al. (2015) related to transportation contexts where customers are classified based on importance (i.e., the weight of demands). This benchmark set incorporates priority values for better addressing transportation contexts where customers are classified based on importance.

   Regarding context on multiple depots and pickups and delivery operations in a green context, creation of a set of modified benchmarks from existing ones (Sartori and Buriol, 2020) by adding multiple depot vertices and paired locations of pickup and delivery customers.

1.5 Dissertation overview

The chapters of this doctoral dissertation are structured as follows. Chapter 2 presents state-of-the-art relevant literature related to GVRP considering emissions. Chapters 3 and 4 investigate and solve emerging variants of GVRPs. Finally, Chapter 5 provides conclusions and draws directions for future work. We provide a summary of each chapter below.

Chapter 2 reviews the literature relevant to this dissertation. The review analyses and discusses current progress on green vehicle routing problems addressing emissions concerning heuristics and hybrid algorithms for solving them. Firstly, we show principal characteristics related to the components of the mathematical model. Secondly, we characterized heuristics' main features, and heuristic hybridizations developed, focusing on strategies and methodologies employed in each solution method. Moreover, the review summarizes relevant benchmark instances proposed in the related literature. The work in this chapter is based on our literature review in the *Journal of Advanced Transportation* (Fernández et al., 2022b).

Chapter 3 proposes two mathematical formulations for CumVRP variants incorporating customers' time windows, as well as a cluster first-route second matheuristic algorithm. Regarding the second formulation, we introduce a trade-off between emissions, costs, and penalties due to customers' time windows. The violation of time windows constraints could reduce emissions. We conducted several experiments related to our formulations and approach and compared them using a modified set of instances from the literature, which incorporates customers' priority values. The work in this chapter extends our previously published research in the Proceedings of the 11*th International Conference on Computational Logistics, ICCL* 2020 (Fernández et al., 2020) and an extended version in the *Annals of Operations Research* (Fernández et al., 2022a).

Chapter 4 investigates and formulates the multi-depot GVRP incorporating pickups and delivery orders. This study put into practice a multiple-depot routing problem considering a one-to-one scheme for pickup and delivery operations while minimizing emissions through fuel consumption, which depends on weight and travel distance. Furthermore, the mathematical formulations have been used as part of a developed partial optimization matheuristic approach where an exact approach handles the subproblems to optimality or closest. Finally, in the experiments, we propose a new modified benchmark that incorporates pickup and delivery paired vertices following the one-to-one scheme and multiple depot locations. The work in this chapter extends our previously published research in the Proceedings of the 12*th International Conference on Computational Logistics, ICCL* 2021 (Fernández et al., 2021) and an extended version (working paper) to be sent to an operational research journal.

Chapter 5 concludes this dissertation with a summary of the principal findings and recommendations for future research.

Chapter 2

Literature review

Most research efforts for tackling GVRPs have been concentrated on studying and implementing heuristics and hybrid methods to provide the best trade-off among robustness, accuracy, computational speed, and flexibility (Sbihi and Eglese, 2010). The GVRPs enclose large and complex optimization problems related to freight transportation and environmental pollution. These problems cannot be solved to optimality for realistic instance sizes within reasonable computational time. In this regard, approximate algorithms, for example, heuristics and metaheuristics, are a solid alternative to solve this type of problems. Their main motivation is to provide fast and robust methods for hard problems (Talbi, 2009). The hybridization of these algorithms promotes exploiting their complementary advantages through the combination of their algorithmic strategies. Choosing a suitable combination of algorithmic concepts can be the key to achieving top performance in solving many hard optimization problems (Blum et al., 2011). As a result, the study of these methods has presented a considerable increase in the number of research works carried out especially in the last five years (see Figure 2.1).

In this section, we present a literature review of heuristic and hybrid methods for solving GVRPs that consider emissions. The main sections of this review are outlined as follows: A description of the methodology used to carry out the state-of-the-art (see Section 2.1). An extensive systematic literature review analyzing and discussing the different GVRP variants addressing emissions and how those emissions have been considered (see Section 2.2 and 2.3). This analysis provides the main characteristics related to compositions of the restrictions, objectives, emission models, and types of emissions, among others. A comprehensive study of heuristics' main features and heuristics hybridizations developed for solving the GVRP and related variants (see Section 2.4). To shed the added value, we highlight the leading strategies and methodologies employed in each solution method, for example, initial solution procedures, the structure of neighborhoods in a heuristic scheme, and operators used in evolutionary approaches, among others. A detailed description of the benchmark instances is proposed in the related

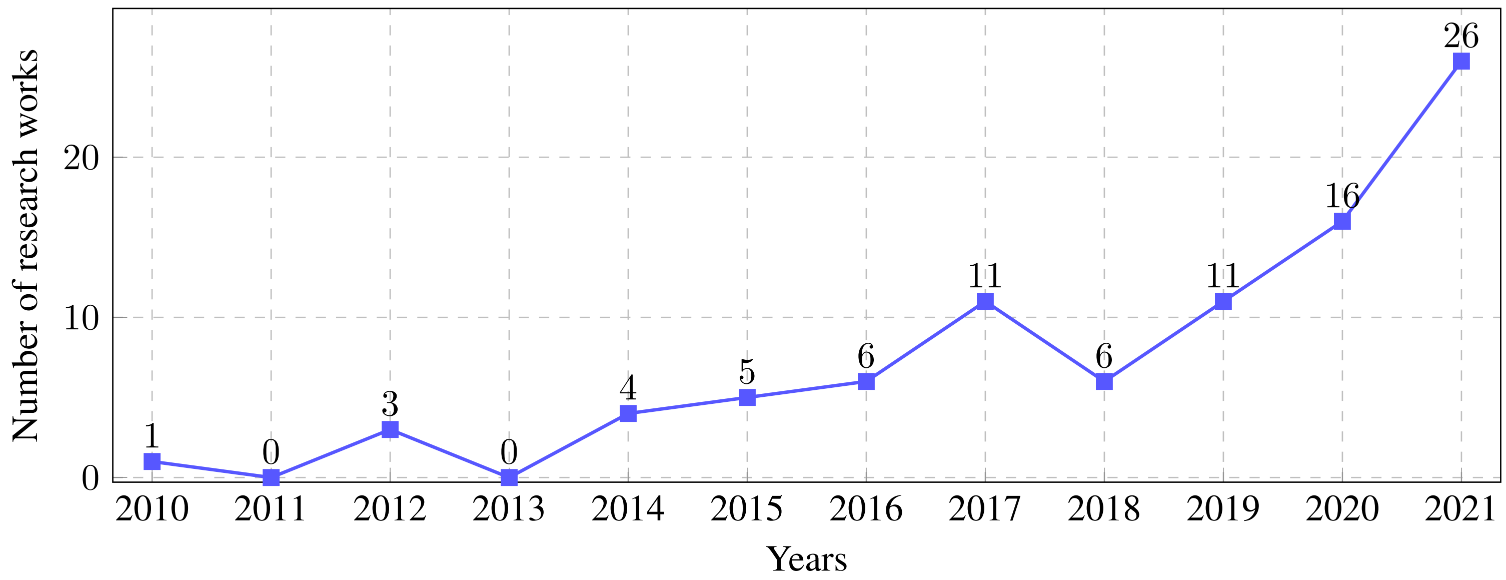

Figure 2.1: Illustration of the number of publications in Scopus and Web of Science per year. The resulting publications are based on research papers that address GVRPs considering emissions using heuristics and hybrid methods.

literature and used to assess the algorithms' performance (see Section 2.5).

2.1 Review methodology

The increased number of the applications around GVRPs is highlighted in various surveys, see for example, the reviews by Asghari and Mirzapour Al-e-hashem (2021); Moghdani et al. (2021) and Erdelić and Carić (2019a), and the book chapter by Macrina et al. (2020). These reviews are focused on the problem domain and generally describe the solution approaches, but none of them analyzes nor details the basic features and components of the algorithms used to solve the GVRPs. On the other hand, to the best of our knowledge, there is no literature review that studies the emissions in GVRPs and an in-depth analysis of the heuristics and hybrid methods used.

This review was performed as a systematic literature review (SLR). According to Cook et al. (1997), SLRs are clear information gathering procedures enabling the reproduction of results. One of the initial steps in SLRs is the definition of research questions. These are the focal points that guide the phases of analysis and investigation. In our research work, the following research questions were defined:

- What are the most used heuristics/hybrid methods to solve GVRPs considering emissions?
- How emissions have been considered in GVRPs?
- How heuristics and hybrid methods have been applied to solve the studied GVRPs?
- What are the basic strategies used as part of heuristics and hybrid methods?
- What benchmarks have been proposed for GVRPs with emissions?

In the time of electronic databases and bursts of technical publications, a determining aspect when collecting and reviewing the literature is the definition of the keywords to be used in the information search process. The keywords selected for collecting works are based on the problem domain, application, and optimization methodology. The following box shows the query string used for databases searches:

> TITLE-ABS-KEY (((‘emission*’ OR ‘CO2’ OR ‘gas’ OR ‘pollution’ OR ‘decarbonization’ OR ‘greenhouse’ OR ‘contamination’) AND (‘green VRP’ OR ‘green vehicle routing’ OR ‘GVRP’ OR ‘G-VRP’ OR ‘VRP’ OR ‘vehicle routing’) AND (‘heuristic*’ OR ‘metaheuristic*’ OR ‘meta-heuristic*’ OR ‘hyper-heuristic*’ OR ‘hyperheuristic*’ OR ‘matheuristic*’ OR ‘math-heuristic*’ OR ‘hybridheuristic*’ OR ‘hybrid-heuristic*’)))

The methodology used for selecting papers is based on the preferred reporting items for systematic reviews and meta-analyses (PRISMA, Page et al. (2021)). It establishes an evidence-based minimum set of items for reporting SLRs using databases and registers. For that purpose, in this research, we use Scopus and Web of Science as research and educational databases. The identification and selection procedure is divided into three stages as shown in Figure 2.2.

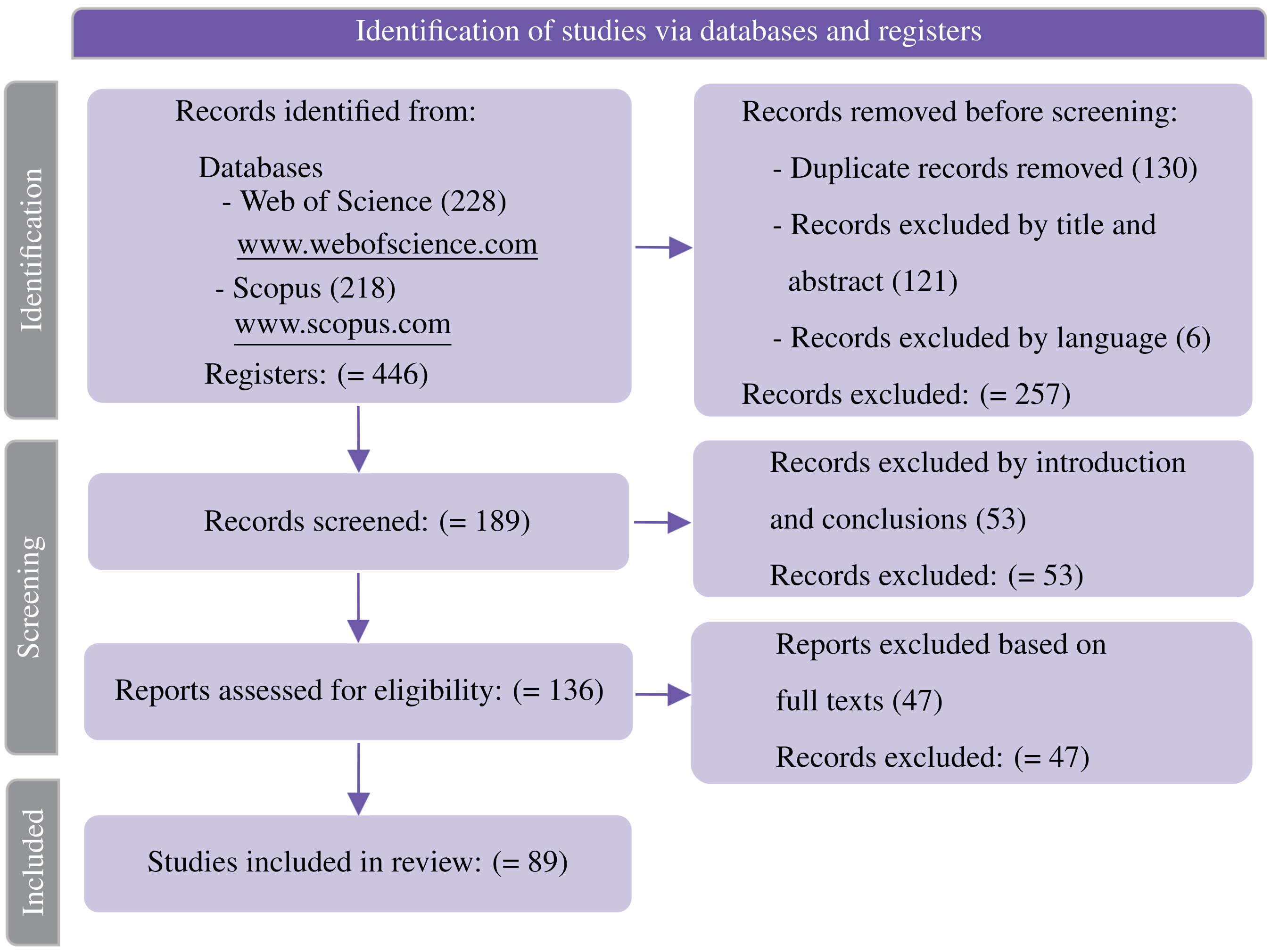

Figure 2.2: Screening and selection stages using the PRISMA flow diagram. This diagram shows the different stages that are part of the methodology proposed to carry out this survey.

In the identification stage, we identified the relevant papers using the previously defined search query. The result of that search was 446 papers from journals, conferences, and book chapters. After the search, we removed 130 duplicated studies from different sources (Elsevier, Springer, Wiley, INFORMS, etc.), 121 records were excluded by analyzing the title and abstract, and the other 6 works due to not being in English. The outcome of stage 1 was 189 papers. In the screening stage, the papers were chosen after reviewing their introduction and conclusions regarding the main contribution. Out of this stage, 136 papers were chosen. For the final stage, 136 papers were studied with regard to their full texts although some of them have been removed. Finally, a selection of 89 papers has been considered for this review. Figure 2.3 shows the amount of research related to emission-related GVRPs carried out per year in the main journals. Only journals with at least two published works are listed.

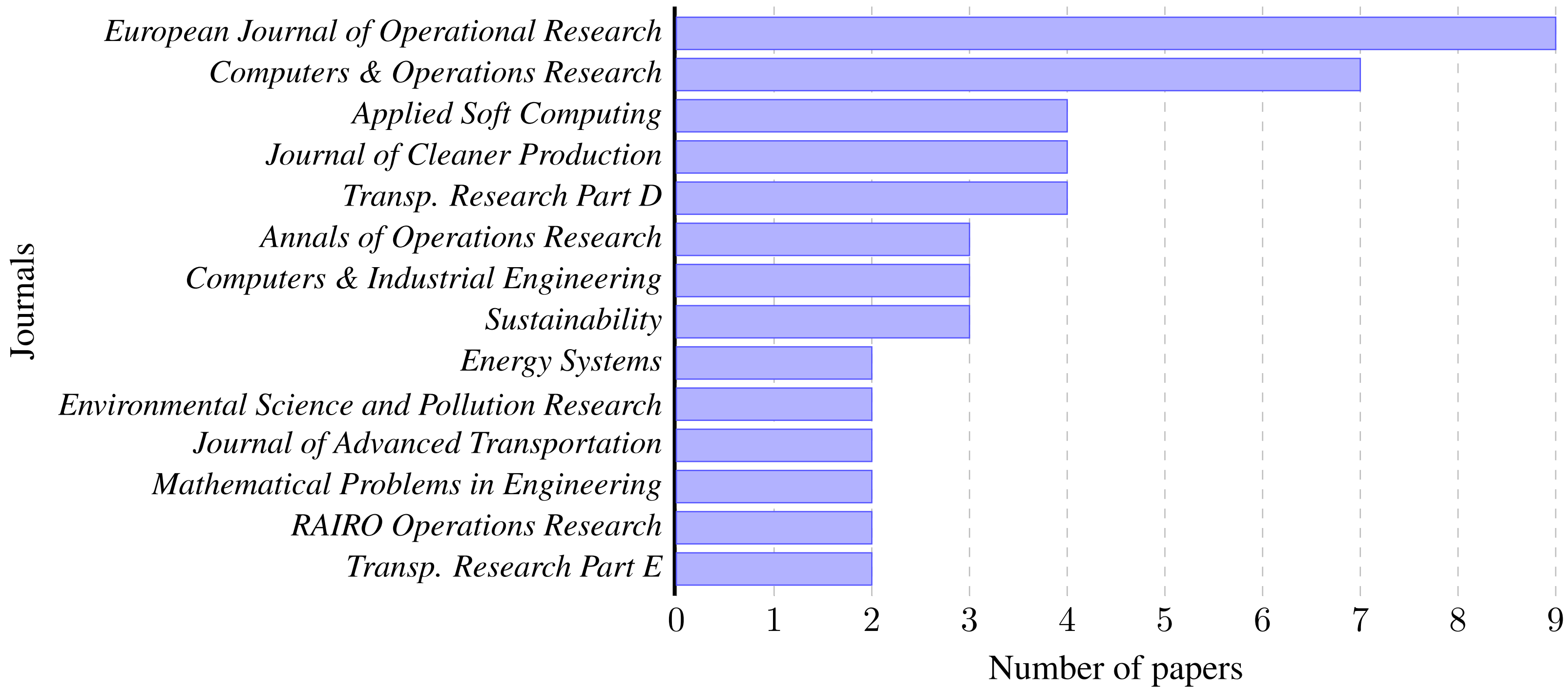

Figure 2.3: Number of papers published in (main) journals. Note that the journals with more than two articles are shown.

2.2 Algorithms for GVRPs considering emissions

This section presents a description of the problem and algorithms used to solve GVRPs considering emissions. To conduct the analysis, we cluster the research works according to the classification of the addressed problem. In each subsection, an initial short description of the corresponding problem is provided. After that, we describe the investigations conducted related to that problem variant. Their overall description will be complemented with the analysis of their emission models and solution approaches in detail in Sections 2.3 and 2.4, respectively.

2.2.1 Green vehicle routing problems (GVRP)

Field that addresses the negative environmental impact due to the use of vehicles in their routing operations. This research direction considers the use of AFVs, that is, electric vehicles, natural gas vehicles, and fuel cell electric vehicles, among others, as well as other management strategies to reduce efficiently the emissions. Compared to ICEVs, AFVs work on sustainable energy such as electricity and hydrogen. In this context, the doctoral thesis of Palmer (2007) was one of the first studies to take into account environmental aspects in VRPs, such as traffic congestion and vehicle speeds to produce a CO_2 emissions grid. Following the same environmental purpose, the work of Erdoğan and Miller-Hooks (2012) formally introduced the GVRP as a problem. Their aim for proposing the GVRP was to address vehicle routing problems to overcome the difficulties arising from the limited number of refueling stations and the short range of AFVs. The formulation of their problem is based on minimizing the distances traveled by vehicles and, thus, indirectly reducing emissions. In the work of de Oliveira da Costa et al. (2018), they addressed the GVRP with the objective of minimizing CO_2 emissions from VRP routes of a set of light-duty diesel delivery vehicles. To solve that problem, they proposed a Clarke and Wright (C&W, Clarke and Wright (1964)) saving heuristic as a construction heuristic for creating initial routes that allow their merge when an improvement of cost savings can be obtained by combining routes with capacity constraints. Moreover, they proposed a genetic algorithm (GA) with the addition of 3-opt neighborhood moves as a mutation operator. Omidvar and Tavakkoli-Moghaddam (2012) presented simulated annealing (SA) and GA algorithms to address vehicle transportation and routing model for AFVs (e.g., electric, biofuels, hybrid vehicles, and others) that minimizes energy and fuel consumption. Wei et al. (2020) proposed a nondominated sorted genetic algorithm II (NSGA-II) algorithm for the green demand-responsive airport shuttle services (DRASS) with time-varying speeds. This problem consists of assigning a set of AFVs located in different depots, where each of them must visit each demand location in a defined time and transport them to the airport. Their NSGA-II-based approach is two-phased, where the first stage is oriented to assign demand locations and depots to various AFVs and the departure time of each AFV. In the second stage, an A^* algorithm is used as part of NSGA-II to create each path of the AFV, which includes leaving the depot, visiting the demand locations, and returning to the airport.

Dewi and Utama (2021) proposed a hybrid whale optimization algorithm (HWOA) to minimize distribution costs that consider fuel consumption, carbon emissions, and vehicle usage costs in GVRP. The HWOA integrates WOA, tabu search (TS), and a local search (LS) improvement method. WOA is an algorithm that mimics the behavior of humpback whales when hunting prey (see Mirjalili and Lewis (2016)). The study by Yavuz and Çapar (2017) presented the mixed-fleet green vehicle routing problem (MGVRP) considering the impact of introducing AFVs on fleet operations composed of gasoline and diesel vehicles (GDVs). They present a variable neighborhood search (VNS) heuristic to solve the problem for a single objective and an adapted version of the VNS to bi-objective optimization. Soysal et al. (2021b) proposed a DP based heuristic (DPH) algorithm to optimize transport emissions in the GVRP. The algorithm DPH computes routes for each vehicle in turn; that is, there is only one active vehicle whose route is computed at a given time. This allows the algorithm to keep track of vehicle utilization and time.

In several logistic contexts, the procurement of perishable materials and goods is determined as a pivotal prerequisite for economic and environmental development. The perishable goods must be delivered to consumers as early as possible given their limited lifespan. The work of Talouki et al. (2021) modeled the dynamic green vehicle routing problem (DGVRP) for controlling and organizing the transportation of perishable products to minimize total cost and carbon emissions, and maximize customers satisfaction. In doing so, they proposed and applied multi-objective solving methods (e.g., Pareto front and ϵ-constraint). Additionally, the authors presented a heuristic solution to the proposed model with an augmented ϵ-constraint exploratory method to relax the binary variables.

Camacho-Vallejo et al. (2021) considered a problem where two companies had to interact in an environmentally hierarchical way within a supply chain. In that context, one of the two companies had the role of purchasing and distributing various goods through a selected subset of customers, while the other company was in charge of manufacturing the goods demanded by selected customers. For the distribution of goods, both companies considered that the routes are designed to satisfy the chosen subset of customers to maximize profit while reducing carbon emissions. This problem was modeled as a two-level programming problem with two upper-level objectives and a single lower-level objective. The upper level is associated with the distributor, while the lower level is associated with the manufacturer. To solve that problem, a nested bi-objective tabu search (NBOTS) algorithm was applied to approximate the Pareto front of the problem.

Joint distribution implies that several logistics companies share transportation resources and customers, and the work is performed under unified planning and scheduling. Liu et al. (2020) introduced the joint distribution-green vehicle routing problem (JD-GVRP) considering carbon emissions in the joint distribution vehicle routing problem in cold chain logistics. For addressing this problem, they proposed the SA approach.

2.2.2 Inventory routing-related problems (IRP)

The inventory routing problem or IRP is a logistics problem that arises from the combination of routing, inventory, and replenishment scheduling decisions Coelho et al. (2014). Concerning GVRPs, the work of Alkaabneh et al. (2020) introduced the perishable inventory routing problem (PIRP) and considered the estimation of fuel costs and emissions. To solve this problem, they proposed a benders decomposition algorithm and a two-phase approach. The first phase is based on the relaxation treatment of the original PIRP model. The second phase uses the set of feasible solutions found at the end of the previous phase in the construction phase of the greedy randomized adaptive search procedure (GRASP) algorithm for providing a high-quality solution.

2.2.3 Location routing-related problems (LRP)

. The location routing problem (LRP) is a well-known combinatorial optimization problem in many applications in which locating facilities and vehicle routing are two connected options. To jointly handle location and routing decisions, the LRP combines these two types of decisions. Dukkanci et al. (2019) presented two heuristic techniques based on the speed optimization algorithm (SOA) and iterated local search (ILS) to tackle the green location routing problem (GLRP), where the operational cost depends on both the traveled distance and the load of the vehicle. Both techniques decomposed the GLRP into subproblems, i.e., the cumulative LRP (CumLRP) and the speed optimization problem (SOP) and solved each hierarchically. The placement of the depots and the routes of the vehicles were established after the CumLRP was solved. A C&W was used to construct the initial solution for the SOA method to find optimal vehicle speeds. Next, the ILS based on removal and insertion operations between tours was applied.

Leng et al. (2018) presented the regional low-carbon LRP with reality constraint conditions (RLCLR-PRCC), where customers and depots are located in zones with different speed limits. This problem aims at optimizing the total cost by including vehicle renting cost, depot opening cost, fuel consumption cost, CO_2 emission cost, and penalty cost. To solve it, the authors proposed a hyperheuristic approach (HH) that includes two levels (i.e., low and high). At the lower level, a set of heuristics is considered to deal with the scheduling part and, at the high level, a selection strategy based on a common mechanism and a self-adaptive acceptance criterion is used to select a promising heuristic and maintain the diversity of the selection. Leng et al. (2020) considered the location routing problem-based low-carbon cold chain (LRPLCCC) considering simultaneous pickup and delivery with heterogeneous fleet and hard time windows. The authors presented a decomposition method within a multi-objective hyperheuristic framework (MOHH/D). That framework comprises two parts: (i) low-level heuristic (LLH) that uses a large neighborhood defined by several operators (e.g., 2-opt and swap) and (ii) high-level heuristic (HLH) composed of three selection strategies to improve the performance of MOHH/D (e.g., choice function, random simple, and fitness rate rank-based multiarmed bandit).

2.2.4 Multi-depot routing-related problems (MDVRP)

The multi-depot vehicle routing problem (MDVRP) extends the classical VRP, where a fleet of vehicles serves customers from several depots and returns to the same depot. Several investigations address the green version of the multi-depot vehicle routing problem (MDVRP), that is, MD-GVRP. This variant is relevant for practical and real-life logistics supply chain scenarios that usually require the utilization of multiple depots to carry out its logistics operations while also taking into account environmental aspects.

The authors of Pérez-Bernabeu et al. (2015) presented a multi-depot VRP variant for horizontal cooperation in road transportation (HC-MDVRP) and argued that this practice is essential for reducing delivery costs and carbon emissions. The authors presented an ILS method for providing high-quality solutions in a collaborative scenario. Jabir et al. (2017) proposed three mathematical formulations for the multi-depot green VRP (MD-GVRP), which aims to minimize the objectives in terms of economic and emission costs while also being integrated with equal priorities. To solve the MD-GVRP, they proposed a hybrid metaheuristic method that combines ant colony optimization (ACO) with a coupled VNS. The solution provided by the ACO algorithm is later refined by the VNS after a complete route is constructed. Kaabachi et al. (2017) presented another ACO approach in this case for the MDGVRP with time windows (MDGVRP-TW).

Wang et al. (2019) presented a hybrid heuristic that integrates the C&W (termed as CWSHA), the sweep algorithm (SwA), and a multi-objective particle swarm optimization algorithm (MOPSO) for the MD-GVRP optimization. First, the CWSHA and SwA generate the initial population, and then the MOPSO is employed for local search. Then, the C&W, as part of CWSHA, builds the entire networkâ€™s distance matrix and generates a vehicle route by linking customers to the depot. The integration of these methods seeks to improve solution search in general and the quality of nondominated solutions produced by the hybrid method.

The work of Fernández et al. (2021) used the matheuristic version of the partial optimization metaheuristic under special intensification conditions (POPMUSIC, Lalla-Ruiz and Voß (2016)) framework for solving the MD-GVRP with pickups and deliveries (MDGVRP-PD). POPMUSIC is able to solve large-scale scenarios by decomposing them into subsets of parts. Subsets of parts are bundled and used to create subproblems, which are then solved by means of a mathematical programming approach.

2.2.5 Multi-trip routing-related problems (MTVRP)

The multi-trip VRP (MTVRP) differs from the classical VRP by allowing vehicles to perform multiple trips. Lyu and He (2021) presented a two-phase hybrid metaheuristic approach (TSHM) for solving the MTVRP which involves prioritizing customers and transporting incompatible goods (MTHVRP-PCIC). MTHVRP-PCIC aims to find a set of routes that result in minimal costs, including fixed costs, travel costs, and carbon emission costs. The internal mechanism of the TSHM is based on an improved version of GRASP to generate initial feasible solutions. In an improvement phase, a hybrid GA is used to improve the initial population, where mutation and crossover operators are applied to the population in each iteration.

2.2.6 Multi-echelon distribution-related problems (NE-VRP)

Multi-echelon VRP distribution problems (NE-VRPs) consider more than a single layer of intermediate depots or satellites, where the delivery to customers is made from these depot locations. Li et al. (2016) proposed a two-phase approach that uses the C&W for generating initial solutions and a best improvement local search phase to solve the time-constrained VRP with two echelons in line-haul delivery systems (2E-TVRP) considering CO_2 emissions. The improvement phase consists of a neighborhood-based inter-route termed as cross-exchange neighborhood. Liu and Liao (2021) addressed the two-echelon collaborative waste collection VRP (2E-CWCVRP) through a three-phase strategy. This strategy uses the k-means clustering method plus a hybrid heuristic combining a C&W and an adaptive large neighborhood search (ALNS, Shaw (1998)). Moreover, this approach uses the roulette wheel (RW, Lipowski and Lipowska (2012)) mechanism that relies on the selection of destruction and repair operators. Similarly, Anderluh et al. (2021) used the RW and large neighborhood search (LNS) approaches to optimize a multi-objective VRP for two-echelon VRP with vehicle synchronization (2E-VRPSyn) considering economic and environmental aspects. The solution of 2E-VRPSyn consists of creating routes, assigning customers to echelons, and inserting the required synchronized meetings between vehicles from various echelons. Moreover, Mühlbauer and Fontaine (2021) tackled the two-echelon capacitated VRP with swap containers (2E-CVRPSC) by introducing a parallelized LNS (PLNS) approach enhanced by a heuristic and using two traditional neighborhoods, 2-opt neighborhood (intra-route) and 2-optâˆ— neighborhood (inter-route). This heuristic creates an initial feasible solution by inserting the active satellites in a tour, taking into account the least expensive position, respectively, in decreasing distance from the depot.

Jie et al. (2019) considered a two-echelon capacitated electric vehicle routing problem with battery swapping stations (2E-EVRP-BSS). They presented an economic analysis to assess the effect on emissions' reduction. For solving it, they applied a hybrid algorithm (called CG-ALNS) based on the integration of the column generation algorithm (CGA) and ALNS. The CGA solves the relaxed problem, and after applying a heuristic, the procedure provides a feasible solution to the optimization problem. First, the CG-ALNS starts by providing a solution to the second echelon, and with that, they solve the first echelon. Then, in the second echelon, the goods are delivered from the satellites to the customers considering them as depots and solving a multi-depot EV distribution routing problem (MDEVRP) by means of an ALNS. CG-ALNS can be classified as a relaxation-based approach because it provides a feasible solution to the problem from the optimal solution of the relaxed problem.

Validi et al. (2021) faced a sustainable three-echelon distribution network by proposing a mathematical formulation that aims at optimizing the routing throughout the transportation network while minimizing carbon emissions and transportation operating costs. The authors presented three metaheuristic approaches to address this problem, that is, the multi-objective genetic algorithm of type II (MOGA-II), the MOPSO, and the NSGA-II.

2.2.7 Period vehicle routing-related problems (PVRP)

The period vehicle routing problem (PVRP) optimizes vehicles' routes where the planning horizon is extended to a number of days or periods. The research of López-Sánchez et al. (2021) dealt with the bi-objective periodic vehicle routing problem with service choice (Bi-PVRP-SC). This problem aims to minimize total emissions and maximize the service quality by optimizing a set of vehicle routes for each day of a planning horizon for a fleet of vehicles that starts and ends at a single depot. Customers have to be visited as a minimum of a predetermined number of trips during the planning horizon. The authors proposed a two-phase algorithm consisting of a multi-start multi-objective local search (MSMLS) algorithm. The first phase of MSMLS consists of generating feasible solutions. The second phase attempts to approximate the Pareto front by improving those solutions through local searches using multiple neighborhoods.

2.2.8 Pollution-routing-related problems (PRP)

The pollution-routing problem (PRP) is an extension of the classical VRP with time windows (VRPTW) which involves environmental costs, such as fuel consumption costs and greenhouse gas (GHG) emissions, as well as operating costs Eglese and Bektaş (2014). Demir et al. (2012) proposed a two-phase approach based on ALNS and SOA for the PRP. The authors used the C&W method to generate initial solutions and the SOA to achieve an optimal driving speed. In a later study, Demir et al. (2014a) introduced the bi-objective PRP to simultaneously reduce fuel consumption and travel time. As a solution method, they developed a bi-objective adaptation of their previous two-phase approach and compared four a posteriori methods, including the weighting method, the weighting method with normalization, the ϵ-constraint method, and a new hybrid method based on the scalarization of the two objective functions. The work of Kramer et al. (2015) presented a one-shot matheuristic approach for the PRP called ILS-SP-SOA that combines an ILS embedding integer linear programming (ILP) algorithm to solve a set with a set-partitioning (SP) formulation and an SOA for the PRP. Also, two particular cases of the PRP were studied: the fuel consumption VRP (FCVRP) and the energy minimizing VRP (EMVRP).

Koç et al. (2014) introduced a fleet size and mix PRP (FSMPRP) as a new PRP variant and proposed a hybrid evolutionary algorithm (HEA++). The HEA++ is a heterogeneous ALNS (HALNS) metaheuristic, where a tournament selection mechanism is used to select survivors to determine which individuals are excluded and which remain in the next generation. Koç et al. (2019) presented an approach using a geographic information system (GIS)-based on a TS heuristic to solve a variant of PRP, which considers the impact of routing on CO_2 emissions on real instances of a real grocery retail chain. Other metaheuristic techniques for PRPs can be found in the exploration of the practical version of PRP (PPRP) Suzuki (2016), time-dependent PRP (TD-PRP) Franceschetti et al. (2017); Guo and Liu (2017), and sustainable traveling purchaser problem with speed optimization (STPPS) Cheaitou et al. (2021), an extension of the single-product traveling purchaser problem model and the PRP.

Kumar et al. (2016) presented a multi-objective model for multi-vehicle PPRP with a time windows (MMPPRP-TW), where the location and inventory decisions are taken into account and solved by a multi-objective self-learning PSO (MOSLPSO) and an NSGA-II. Costa et al. (2018) investigated the bi-objective PRP in the context of green logistics with a focus on reducing CO2 emissions and driver salaries. The authors developed a multi-objective approach based on the two-phase local search heuristic. Using the two-phase method, they provided an approximation to the Pareto front, where the first phase was for solving a set of weighted sum PRPs and the second phase consisted in applying a Pareto LS procedure. The work of Kargari Esfand Abad et al. (2018) presented three multi-objective metaheuristic algorithms which are NSGA-II, a nondominated ranking genetic algorithm (NRGA), and a MOPSO to address a pickup and delivery PRP variant considering integration and consolidation shipments in cross-docking. The NSGA-II implementation generates a certain number of parent solutions on each iteration. They applied a tournament selection method to select suitable parents. Also, to generate a new population, they used genetic operators, i.e., mutation, and crossover on parent solutions. The population was sorted regarding the nondomination scheme of individuals, i.e., a rank-based selection method is used to assign a rank to each individual. Lastly, NRGA differs from NSGA-II in the chromosome selection mechanism.

Fang et al. (2017) introduced and modeled the PRP with reverse logistics and simultaneous pickups and deliveries (PRPSPD) with the aim of reducing carbon emissions under different carbon prices. The authors used a matheuristic algorithm classified as a heuristic branching according to the taxonomy of Archetti and Speranza (2014). This algorithm is based on a branch-and-cut (B&C) algorithm. The B&C separates candidate sets for branching is a form of implementation of the heuristic methods described by Lysgaard et al. (2004). Furthermore, to generate the initial solution, the authors applied C&W and a guided VND (GVND) as the improvement algorithm.

2.2.9 Electric vehicles-related problems (E-VRP)

Several factors influence the increase in the use of EVs, such as government incentives to reduce GHGs or the possibility of using these vehicles with lower acquisition costs due to government subsidies. The driving range limitations of electric vehicles combined with drivers' tendency to overestimate distances is a trending problem in the use of EVs. In this context, there are several investigations studying the use of fleets of heterogeneous vehicles, including EVs, that proposed trade-off analysis considering the environmental costs associated with the use of vehicles.

Eskandarpour et al. (2019) presented a bi-objective model to minimize total costs and CO_2 emissions in a fleet of heterogeneous vehicles with multiple loading capacities and driving ranges (HeVRPMD). The fleet comprises EVs, ICEVs, and plug-in hybrid electric vehicles (PHEVs). In the HeVRPMD, the driving range of electric vehicles is limited because of their battery capacity. To solve this problem, they developed an enhanced variant of the multi-directional LS (EMDLS) to approximate the Pareto front. The EMDLS is an enhanced version of the improved multi-directional LS introduced by Lian et al. (2016). Due to battery driving range limitation, Yang and Sun (2015) investigated how to simultaneously optimize battery swap stations (BSSs) and the routing plan of a fleet of EVs. It deals with range and efficiency analysis for reducing vehicle emissions when EVs are used in the logistics area. To cope with this problem, the authors presented a four-phase heuristic (named SIGALNS) and a two-phase TS-modified C&W (TS-MCWS). In the first phase of SIGALNS, a modified SwA algorithm generated an initial routing plan that leads to the BSSs location subproblem, which is then solved in the second phase using an iterated greedy heuristic. In the third phase, the vehicle routes resulting from the location subproblem are determined by applying an ALNS with several new neighborhood structures. Even further, at the end of SIGALNS, the solution is enhanced by the fourth phase split procedure. Finally, as for TS-MCWS, the TS algorithm searches for the most appropriate location strategy, and the C&W method makes the routing decision based on this location solution. Raeesi and Zografos (2022) introduced the E-VRPTW with recharging stations and synchronized mobile battery swapping (EVRPTW-RS-SMBS). This problem involves increasing the driving range of EVs by coordinating the intra-route recharging at an intermediate RS. With this, it is possible to reduce operational costs, total amount of well-to wheel CO_2 emitted, the range of anxiety, and synchronize the battery exchange services between routes carried out by battery swapping vans (BSV) in a pre-established time. The range of anxiety occurs when an EV driver feels that the battery charge is low and the usual recharging stations are unavailable. The authors proposed a path-based formulation on a multi-graph (MG) representation for this problem, and further developed an efficient dynamic programming (DP) based heuristic algorithm. They replaced the core DP in the DP-based intensified large neighborhood search (DP-ILNS) algorithm and finally the complete algorithm (MG-DPILNS). Arroyo et al. (2020) presented the green vehicle routing problem with multiple technologies and partial recharges (GVRP-MTPR) that takes into account optimizing the cost savings by using partial recharges. The multiple technologies refer to the several forms of battery recharge, which can be done using different technologies (e.g., charging points for EVs, CHAdeMO fast charging method, wireless charging systems, and others). The research focused on the impact of a possible carbon pricing policy that would affect energy costs and subsidies on the purchase price. The results showed that carbon pricing is little effective when having a low daily traveled distance. Its effectiveness increases as mileage increases. To solve the problem, the authors used the 48A heuristic algorithm (see Felipe et al. (2014)) that consists of a greedy constructive phase to generate an initial solution and, after a local search algorithm, to improve the initial solution.

Yu et al. (2021) addressed the green mixed-fleet VRP with realistic energy consumption and partial recharges (GMFVRPREC-PR). The authors presented an ALNS heuristic with a DP algorithm integrated within it to solve it. The DP determines an optimal recharging station sequence to visit for the EVs. Macrina et al. (2019a) proposed a mathematical model and a constructive heuristic based on Solomon's sequential insertion heuristic (SIH, Solomon (1987a)) for the GVRP with a mixed fleet, partial battery charging, and time windows (GMFVRP-PRTW). The mathematical formulation presented an objective function based on the minimization of the sum of several costs (i.e., recharging, routing, and activation of commercial electric vehicles), and included a restriction that limited the pollution emissions. Due to the heterogeneous fleet characteristics, the authors established two customer groups served by EVs and ICEVs. The constructive heuristic used to solve this problem consists of two distinct parts. The first part aims to define the routes used to serve the customers with the ICEVs, while the second part creates the routes for the customers served by the EVs.

The closed-loop inventory routing problem (CIRP, Soysal et al. (2021a)) is a variant of the IRP, where the execution of the vendor managed inventory policy requires a vendor to deal with an integrated problem consisting of its own forward and backward routing decisions and inventory decisions of customers. Regarding this problem and environmental considerations, Soysal et al. (2021a) investigated on the CIRP with realistic energy estimations with the aim to provide economic and environmental benefits. The authors proposed a rolling horizon technique based on a fix and optimize approach (F&O) for solving the CIRP under a mixed fleet of electric and conventional vehicles, where a vendor-managed inventory system is run and there is also a mixed fleet of EVs and ICEVs. As for the heuristic algorithm, F&O divides the planning horizon into subperiods. The method modifies the lower and upper bound values of the 0-1 variables for each of the subperiods. The lower and upper bound values for the fixing subperiods are set to best-known variable values. The lower and upper limits are set to 0 and 1 in the optimizing subperiods to allow the model to choose the values of the binary variables based on the fixed variable values.

2.2.10 Pickups and deliveries-related problems (PDVRP)

The pickup and delivery VRP (PDVRP) involves conducting a set of pickup and delivery orders between pairs of locations. Fatemi-Anaraki et al. (2022) presented a clustered version of the bi-objective green delivery and pickup problem. The authors used k-means for assigning customers to distinct clusters, and after that, a vehicle is randomly allocated to each cluster. Once that assignment is done, the GA algorithm is applied to each cluster to find a near-optimal solution. The solution of this stage is provided to the initial population of the NSGA-II to find the Pareto optimal solutions for the bi-objective model proposed. Olgun et al. (2021) proposed the GVRP with simultaneous pickup and delivery (G-VRPSPD), and a hyperheuristic (HH-ILS) based on the integration of ILS and variable neighborhood descent (VND). The ILS is used as a high-level algorithm in the HHILS algorithm. The solutions are perturbed at the beginning of each iteration by applying a certain number of neighborhood structures. A local search technique is used to improve the perturbed solution: inter-route and intra-route neighborhood structures. Srijaroon et al. (2021) used a self-adaptive learning particle swarm optimization (SAL-PSO) for solving the GVRP with mixed and simultaneous pickup and delivery problems, time windows, and road types (GVRPMSPDTW-RT). The SAL-PSO can achieve the minimum transport costs (including fuel consumption) among the personal best values of all the particles to be an overall best value and proceed to the next iteration of the optimization process until the stop criteria are known. In addition, the authors introduced a PSO parameter adjustment with a combination of adaptive inertia weight and acceleration coefficient mechanisms.

Asghari and Mirzapour Al-e-hashem (2020) developed a bi-objective model for the green delivery-pickup problem for home hemodialysis machines (HHMs). The authors showed for the first time how incorporating the idea of item sharing into the business model of a private home-care service has a significant positive impact on the environment. They differ from the conventional PDVRP by allowing the system to provide HHMs either from the company's central depot or from individual owners. To evaluate the environmental and economic properties of the proposed model, the authors developed a metaheuristic based on self-learning NSGA-II for medium and large-scale scenarios. Moreover, their approach considers adjusting the set of crossing and mutation probabilities in response to changes in the value of the fitness function after operations in the next iteration.

Solano et al. (2021) addressed a VRP variant with simultaneous pickup and delivery and time windows (VRPSPDTW) involving the pickup and delivery of beer bottles to multiple customer locations with early and late deadlines and predetermined pickup and delivery requirements. For solving this problem, they used an integration of a TS and a greedy algorithm. First, based on the nearest neighbor criteria, the greedy algorithm generates an initial solution to seek out the different customers using a time grid as a guide. After that, the TS is used to improve the initial solution by expanding the exploration space until a better solution is found that reduces the total distance traveled.

Majidi et al. (2017) proposed a fuzzy green vehicle routing problem with simultaneous pickup and delivery and time windows (F-GVRPSPDTW) where the optimization model considers uncertainty in both pickup and delivery requirements. To solve this problem, the authors provided a fuzzy algorithm that deals with uncertainty and an ALNS. This approach uses the comprehensive modal emissions model (CMEM, Barth et al. (2005)) to calculate fuel consumption and CO_2 emissions. Lu and Huang (2020) developed a distance-based ALNS (DALNS) to solve the green pickup and delivery problem with time windows (Green-PDPTW) to reduce carbon dioxide emissions associated with product transportation. Inside their ALNS, the SA method decides whether to apply the destruction or repair heuristic. The authors introduced the concept of order pool when creating the original solution; that is, the elements of each pool are determined by the distance and time windows of all customers.

2.2.11 VRP with backhauls-related problems (VRPB)

The VRP with backhauls (VRPB) comprises two sets of customers, such as linehaul and backhaul customers. The linehaul customers require a certain quantity of goods to be delivered, while the backhaul customers require pickup services. Each vehicle must serve both sets of customers so that linehaul customers must be visited in outbound trips before the backhaul customers are visited for the pickup service in its inbound trip to the depot Irnich et al. (2014). VRPB is part of the pickup and delivery problem with time windows (PDPTW), where pickup and delivery activities can be performed on the same route. The research of Zhao et al. (2020b) faces the two-dimensional multi-depot CVRP with backhauls (2L-MDCVRPB). The problem's objective function seeks to minimize the total carbon emissions. To solve it, the authors propose a quantum-behaved PSO (QPSO) and an exploration heuristic LS algorithm (EHLSA).

2.2.12 Scheduling-related problems (VRSP)

The vehicle routing and scheduling problem (VRSP) refers to the case where customers have specific service time requirements (e.g., precedence relationships, arrival times, and others). The green vehicle routing and scheduling problem (GVRSP) extends the VRSP with the aim to minimize emissions in logistics systems through better scheduling deliveries pickups by a fleet of vehicles. Xiao and Konak (2015) introduced the GVRSP, which takes into account general time-dependent traffic circumstances with the primary goal of reducing CO_2 emissions and delays. In addition, the authors proposed a new formulation of the GVRSP where a vehicle is allowed to travel an arc in multiple periods. To solve this problem, the authors proposed an SA algorithm where the continuous variables of the model were determined using a simple heuristic procedure that provides near-optimal schedules for a given set of routes and approximate schedules. Later, the same authors Xiao and Konak (2016) expanded the GVRSP by considering heterogeneous fleet and the effect of vehicle weights on emissions. That research refers to the heterogeneous green vehicle routing and scheduling problem (HGVRSP) and considers the features such as vehicle types, CO_2 emissions, load, and fuel capacities. To address large-scale instances of this problem, the authors applied a combination between a partial-MILP optimization and iterative neighborhood search (INS) called P-MIP-INS. This approach seeks to fix a set of decision variables and use the partial-MILP to optimize a subset of the binary variables from the MILP model during the search process. The work of Gang et al. (2016) presented a GVRSP of free picking up and delivering customers for airline ticketing companies that have to pick-up customers and bring them to the airport, with the goal of reducing carbon emissions and operational costs. The authors proposed a hybrid heuristic-metaheuristic approach that integrates a single heuristic to generate the initial solution for the TS algorithm. The authors of Alizadeh Foroutan et al. (2020) addressed the GVRSP by considering a heterogeneous fleet, reverse logistics in the form of returned goods pickup, the cost of total CO_2 emissions, weighted costs for early arrivals, and tardiness costs. They proposed two metaheuristics, that is, SA and GA, to solve this problem. Several operators were implemented to generate new solutions for the GA offspring (e.g., crossover, mutation, and others) and a swap operator is implemented for the SA.

In the work of Liao (2017), the author proposed a mathematical model and hybrid metaheuristic (GA-tabu) based on GA and TS for solving the online VRP with real-time demands that takes into account real-time requirements and minimizes costs related to economics and CO_2 emissions. It is based on a two-stage method that includes offline route planning and online route updates. In the first phase (offline phase), the initial routes for dispatching a fleet are determined based on known demands. In the second phase (online phase), the initial routes are then re-optimized using a GA to account for new demands and real-time traffic data to solve the mathematical model. In addition, the demand lists are regularly updated using a tabu list.

Sousa Matos et al. (2018) investigated the GVRSP with split delivery (GVRSP-Split) to reduce emissions in logistics systems by improving the scheduling of deliveries from a fleet of vehicles. To deal with the GVRSP-Split, they provided a hybrid multi-start method (MS-ILS-SC) that combines the ILS heuristic with random VND (RVND) location search as the initial phase and an exact set covering (SC) model as the intensification phase. Zhou et al. (2017) presented a decision support system to assist the implementation of a green real-life field scheduling problem. This system uses two instantaneous emissions models, for example, methodology for calculating transport emissions and energy consumption (MEET, Hickman et al. (1999)) and national atmospheric emissions inventory (NAEI, NAEI (2012)) used in the literature, which can predict the emissions in each second. For solving these scheduling problems, they applied the TS algorithm with random neighborhood generators and VND and reduced variable neighborhood search (RVNS). Finally, Jiang et al. (2021) faced a green transportation planning problem with multiple vehicles and one-cargo (MVOC). The authors presented a metaheuristic approach for solving this problem through the Pareto-based multi-objective method TS (MOTS), where local improvements are sought to generate promising neighbor individuals.

2.2.13 Time windows-related problems (VRPTW)

In the VRP with time windows (VRPTW), service to each customer involves pickup and/or delivery of goods within a specified time windows Solomon (1987a). These can be defined as hard or soft windows depending on the application. In the hard time windows case, a vehicle must serve customers exactly within a specific time interval. If the vehicle arrives earlier than the time window, it has to wait. Late arrivals at customer locations are not allowed. In the soft time windows case, violating the time window constraints is allowed at the cost of some penalty. The work of Molina et al. (2014) proposed a mathematical model to solve the heterogeneous fleet VRP with time windows (HVRP-TW) and the C&W algorithm for solving the same problem within time windows restrictions (HVRP). The fleet of vehicles in HVRP is characterized by different capacities, costs, and emission factors. The authors also considered hard time windows. Furthermore, they formulated a multi-objective eco-efficiency model to minimize the total internal cost, CO_2 emissions, and air pollutant emissions. Maden et al. (2010) presented a heuristic algorithm named LANTIME to solve the VRPTW using time-varying data with the aim to reduce the total travel time. In their problem, the time it takes for a vehicle to travel on any road in the network varies as a function of travel time. These variations are caused by congestion, which is typically the greatest during the morning and evening rush hours. The authors provided an estimation of the CO_2 emissions from a distance traveled. LANTIME generates the initial solution using the parallel insertion algorithm Potvin and Rousseau (1993), which builds routes in parallel and uses a generalized regret measure, total unrouted customers, to select the next candidate for insertion. Rezaei et al. (2019) addressed the green VRP with time windows (GVRPTW) considering the heterogeneous fleet of vehicles and the hard time windows constraint. They used GA and a population-based SA (PBSA) algorithm to solve this variant. The PBSA uses the population's capacity to find different parts of the search space, thus hedging against bad decisions in the initial solution and increasing the diversity of solutions.

Masmoudi et al. (2018) presented three variants of the artificial bee colony (ABC) for solving the heterogeneous fleet VRP with synchronized visits (HF-VRPS). To model this problem, the authors presented a mathematical model based on CMEM, proposing a variation related to the calculation of the fuel consumption rate for AFVs by considering bio-diesel instead of diesel. On the other side, the metaheuristic variants of ABC are the hybrid ABC algorithm with demon (ABC-DA), the hybrid ABC algorithm with acceptance of old bachelor acceptance (ABC-OBA), and the hybrid ABC algorithm with record-to-record travel (ABCRRT). Zhao et al. (2020a) proposed an evolutionary algorithm based on an improved multi-objective ACO (ACOMO) for solving a cold chain logistics path optimization problem which consists of the optimization of customer satisfaction while reducing costs and carbon emissions during the distribution process. The authors used the concept of soft time windows by establishing a penalty cost for early or late arrivals times to improve customer satisfaction. To solve this problem, they used the evolutionary approach to improve customer satisfaction in distribution service, with higher demands on the organization and coordination of cold chain companies. Islam and Gajpal (2021) presented an ACO and VNS hybridization algorithm to solve a mixed fleet of logistics problems conventional vehicles and green vehicles with carbon emission cap in the supply network. The implementation of ACO defines trail intensity as the intensity ants travel between the visit of one customer to another. Moreover, the VNS is integrated into the ACO algorithm as an LS to handle the premature convergence of ACO and obtain an improved solution quality of the algorithm. In reference Luo et al. (2021), the authors presented another variant of ACO to solve the home health care (HHC) problem with synchronized visits and carbon emissions. The carbon emissions of each route are calculated using a DP algorithm.

Sanchez et al. (2016) presented a formulation for G-VRPTW with the CO_2 footprint aspect as a constraint and a scatter search (SS) for solving it. The SS algorithm has been analyzed from the perspective of game theory to evaluate the stability of the coalition after pooling resources. In addition, resource pooling is considered to evaluate carbon emissions in terms of economic benefits. Ren et al. (2020) investigated the bi-objective mixed-energy green VRP with time windows (B-MFGVRPTW), where the mixed-energy fleet comprises a set of vehicles using mixed energy. To determine the Pareto front of the model, an improved VNS with a selection mechanism is provided. During the iterative phase, the selection mechanism can ensure that there is a diversity of solutions and that the process is not stuck in a local optimum. Fernández et al. (2020) addressed the cumulative VRP with hard (CumVRP-hTW) and soft time window (CumVRP-sTW) constraints. The main objective of CumVRP is to minimize the cumulative cost, which considers the distance and weight over a traveled arc and can be proportional to the emissions of greenhouse gases. To address this problem, the authors presented a decomposition matheuristic approach based on the cluster first route-second by integrating a mathematical formulation and a GRASP algorithm. In each step of the approach, a feasible solution (a set of routes) is constructed using GRASP. Then, the solution is optimized using an MILP optimizer.

There are other works with applications of heuristics to solve GVRPs, such as ALNS for multi-compartment vehicles for city logistics and G-VRPTW (Eshtehadi et al., 2020; Yu et al., 2020), GA for the effect of governmental time window policy on the routing planning decisions of cold chain distribution companies (Zhang et al., 2020b), fuzzy hierarchical clustering method and GA for the customer-oriented routing problem with consideration of the environment (Meng et al., 2019), and a TS and VNS for VRP in the home health care sector called VRPTW with synchronization, precedence, and fuel consumption constraints (VRPTWSPFC) (Ettazi et al., 2021).

2.2.14 Time-dependent-related problems (TDVRP)

The time-dependent VRP (TD-VRP) considers the travel times between any pair of nodes, that is, customers and depots, depending on the distance between the nodes or the time of the day (e.g., rush hours, weather conditions, and urban congestion). Also, time windows restrictions for serving customers and the maximum allowed duration of each route (i.e., driver workday) can also be specified. In reference Çimen and Soysal (2017), the authors presented the green stochastic time-dependent capacitated vehicle routing problem (GSTDCVRP), which is a variant of TD-CVRP with stochastic vehicle speeds on arcs that incorporates environmental concerns like energy usage and CO_2 emissions while planning delivery decisions. They proposed the approximate DP (ADP) based heuristic algorithm for solving that problem because the classical DP method cannot be calculated for optimal routes of the problem instances studied with stochastic considerations. The DP uses the full-backup concept to compute the exactly expected returns of each action for each state in each stage. The ADP uses a sample-backup which is an advantage when using simulation for obtaining a return of a single action taken to update the value function estimation of a single state. The same authors in Soysal and Çimen (2017) addressed the GSTDCVRP using weighted random sampling to form the restricted list in restricted DP (RDP). Their approach chooses $H + S$ partial tours, which are then enlarged in the following step, which uses weighted random sampling to select S partial tours.

Hooshmand and MirHassani (2019) presented the TDGVRP-AF, which is the union between the original GVRP proposed by Erdoğan and Miller-Hooks (2012) and the TD-VRP. This problem consists of designing routes for AFVs in congested urban areas. At the same time, they considered refueling decisions to reduce CO_2 emissions, taking into account time-dependent travel speeds, limited fuel range, and load restrictions. To solve this problem, they applied a two-phase algorithm based on a GRASP with path-relinking strategy and SA. Zulvia et al. (2020) presented a G-VRPTW and time dependency to address scenarios considering perishable products. The solution to this problem consists of optimizing multiple objectives such as operational cost, deterioration cost, and CO2 emissions. To solve this multi-objective problem, the authors employed a many-objective gradient evolution (MOGE) algorithm, which explores the search space by using several operators capable of handling continuous variables (e.g., vector updating, jumping, and refreshing).

Liu et al. (2014) studied the minimal-carbon-footprint time-dependent heterogeneous fleet VRP with alternative paths (MTHVRPP). This problem simultaneously considers different vehicle types and alternative path choices to increase its applicability in practical situations. The authors developed a GA to address this problem, which starts with a population of chromosomes and evaluates this population. Then, selection, crossover, mutation, capacity check, alternative path selection, and evaluation are repeated until the termination conditions are met. The termination criteria consist of two options: first, to set the maximum number of generations, and second, to set the maximum number of unimproved generations (if the best fitness value has not improved in the last several generations, the evolutionary process is stopped).

Küçükoğlu et al. (2015) dealt with the green VRP with time windows (G-VRPTW). The goal of this work is to construct vehicle routes with time windows that minimize distance traveled, total fuel consumption, and CO_2 emissions. The authors considered applying a penalty cost when a vehicle arrives at a customer after its time window upper bound (soft time windows case) and even if the load at the depot exceeds the load of the vehicle. For solving it, an adapted SA to the storage structure is used to solve this problem.

2.2.15 Waste collection-related problems (WCVRP)

The waste collection vehicle routing problem (WCVRP) considers taking back waste from the collection points and transporting the collected waste to a specific landfill. This is a reverse logistics problem as well as a crucial waste management logistics operation Han and Cueto (2015). The authors of Qiao et al. (2020) addressed municipal solid waste (MSW) for the sustainable management of municipal solid waste collection. Their goal was to balance the workload of each disposal facility to reduce fuel consumption and improve social equity. They presented a two-phase algorithm involving PSO and TS. The results showed that the PSO algorithm usually got stuck into the local optimum when looking for an initial solution, but through TS, that could be improved while also reducing the probability of premature convergence.

Wei et al. (2019) investigated the WCVRP with a realistic midway disposal pattern (MDP) for minimizing total carbon emission cost. To solve this problem, they developed a hybrid ABC approach (called HABC-MDT) based on the ABC algorithm and a midway disposal trip selection heuristic. Also, to achieve a good performance, the HABC integrates an enhanced ABC (EABC) and a VND algorithm. To generate the initial population, they used neighborhood operators selected in random ways (e.g., random swap, random insertion, and others). Then, through the roulette wheel method, the best solutions were updated to produce the new population. Finally, the VND was used as an LS improvement of the current population by intensifying candidate solutions.

Another recent problem related to the WCVRP is the recovery and collection of electronic and electrical equipment waste. Malekkhouyan et al. (2021) introduced the integrated multistage vehicle routing and mixed-model robotic disassembly sequence scheduling problem on an e-waste management system. The problem objective is to minimize total costs of collocation and transportation, total pollution of CO_2 emissions by vehicles, the carbon footprint by robots, and the total cost of disassembling products simultaneously. For solving this problem, they proposed a bio-inspired swarm algorithm called the grasshopper optimization algorithm (GOA) Saremi et al. (2017) that simulates the group behavior of grasshoppers for getting hold of food.

Molina et al. (2019) introduced the eco-efficient WCVRP (Eco-WCVRP) by designing waste collection routes with a single landfill using eco-efficiency as a performance indicator. In this problem, there are a limited number of heterogeneous vehicles departing from a single depot. Eco-WCVRP considers carbon emissions, nitrogen oxides (NO_x), nonmethane volatile organic compounds (NMVOC), and particulate matter (PM) emissions, which are of particular concern in urban areas. To solve this problem, they proposed a variable neighborhood tabu search (VNTS). The approach consists of the VNS algorithm extended by the TS as a local search procedure. To generate the initial solutions, a semiparallel insertion heuristic is used, which creates a subtour for each available vehicle at each iteration. Thus, the algorithm starts with an empty route and collection points are iteratively inserted until none can be inserted in the route due to capacity constraints

2.2.16 Prize-collecting vehicle routing problems (PCVRP)

The prize-collecting vehicle routing problem (PCVRP) is an extension of the prize-collecting traveling salesman problem (PCTSP) proposed by Balas (1989). In the PCVRP, customers do not need to be visited, but a prize can be collected from each customer when they are visited. This problem aims to maximize the sum of prizes collected from visited nodes while minimizing the fixed cost (e.g., vehicle utilization) and variable cost (e.g., fuel consumption). Trachanatzi et al. (2021) presented the first work to formally study a variant of the PCVRP called environmental PCVRP (E-PCVRP), where the cost minimization objective, that is, total distance traveled, is replaced by a load-distance function to minimize CO_2 emissions. To solve this problem, the authors proposed a teaching-learning-based optimization (TLBO) algorithm. TLBO is a population-based heuristic optimization algorithm. As a part of the

TLBO approach, the authors integrated a heuristic encoding/decoding technique to map the solution in a continuous domain, that is, Cartesian space, and converted to the original structure after using the learning mechanisms which take Euclidean distance into account.

2.2.17 Hydrogen vehicles in routing problems (HV)

Hydrogen vehicles (HVs) are novel and different generation of electric vehicles. their operations are based mainly on a chemical reaction between hydrogen and oxygen inside the batteries to generate electrical power. According to Islam et al. (2021), the HVs show better autonomy than EVs (e.g., driving range and short refueling time). Despite this, the driving range and refueling time of HVs are identical to ICEVs, and HVs are an alternative that contribute to reducing carbon emissions and improve environmental sustainability over ICEVs. Also, the same authors introduced the mixed-fleet based green clustered logistics problem (MFGCLP) that considers both hydrogen and conventional vehicles. Moreover, they proposed a hybrid approach based on PSO and a neighborhood search to solve this problem. The neighborhood search includes several well-known local searches (e.g., 2-opt, exchange, and others) at both the cluster and customer level. Each local search operation at a cluster level is started with an additional penalty function concerning three constraints, that is, vehicle capacity, time windows, and carbon emission constraints.

2.3 Analysis of emissions in GVRPs

This section analyzes the GVRP works related to emissions models and restrictions applied either within the mathematical models and/or solution approaches. This way, Table 2.3 reports how the emissions have been considered. Column 1 shows the corresponding reference, column 2 shows the type of emissions addressed in each work. Column 3 reports the place of calculating the emissions for each research. Column 4 indicates the fuel consumption model. Column 5 provides the classification of the objectives or fitness function used. Finally, columns 6, 7, and 8 present defining problem features, such as types of time restrictions, fleet composition, and the consideration of variable speed and load over each traveled arc.

To support the summarized works outlined in Section 2.2, we described those essential characteristics for the GVRPs considering emissions. Many of these works take into account the carbon dioxide (CO_2) emissions in road transportation. The CO_2 emissions are produced when hydrocarbon fuels (i.e., coal, oil, diesel, and gasoline) are burned. Another type of GHG emissions is nitrogen oxide or NO_x, produced when the fuel is combusted in the engine in the presence of air.

Regarding the composition of the restrictions and objectives pursued in the solution approaches, we found the specific parts where the calculation of emissions takes place. In doing so, we classified these parts as (i) internal and (ii) external. The internal part refers to when the emission calculation is considered in the problem definition, for example, part of the objective function and part of restrictions. The external part considers the calculation outside the solution approaches, mostly found in the experimental sections of the investigations, for example, determining the emissions of a given solution after the optimization process.

To calculate the fuel consumption, there are several fuel consumption models. According to the investigation of Demir et al. (2014b), the fuel consumption models can be classified as factor models, macroscopic models, and microscopic models:

- Factor models. These models are based on fuel consumption rate (e.g., litre per kilometers or gallons per miles). Using this type of model, the CO_2 emissions can be estimated using fuel consumption approach, i.e., $e = fuel\_consumption \times heating\_value \times emission\_factor$, where $heating\_value$ represents the heat content of fuels; or traveled distance approach, i.e., $e = traveled\_distance \times emission\_factor$. The emission factor can be expressed as kg CO_2e/liter, (see DEFRA (2012); Veidenheimer (2014)).

- Macroscopic models. This type of model uses average network parameters (e.g., variety of trips, each with a different average speed) to estimate network emission rates, e.g., MEET by Hickman et al. (1999) and a computer program to calculate emissions from road transport (COPERT) by Kouridis et al. (2010).

- Microscopic models. This type of model estimates the instantaneous vehicle fuel consumption and emission rates at a more detailed level. It is used to predict traffic emissions more accurately because it is based on instantaneous vehicle kinematic variables (e.g., speed, acceleration, and others). One of the most used microscopic models for solving GVRPs is the CMEM Barth et al. (2005); Scora and Barth (2006), where, in order to generate accurate estimations, it is necessary to provide specific parameters of the vehicles (e.g., engine friction coefficient, air density, vehicle engine speed, and others).

Concerning other features considered in the works, the types of objective (and fitness) functions can be classified as single-objective or multi-objective. About the composition of the fleet, there are investigations based on homogeneous fleets and heterogeneous fleets. As part of the models, there are many characteristics related to time restrictions that became widely used in the investigations on GVRPs because consideration of travel times, traffic congestion, and delivery times are frequent factors involved in emissions. Others aspects relate to works where speeds are variable and the load of vehicles on each arc influences the fuel consumption.

With regards to emission aspects, we note that only one investigation does not study the emission of $\mathrm{CO_2}$ while NO_x is only studied in 4.49% of the investigations collected. In 82.02% of the cases, the calculation of emissions is explicit either in the mathematical model or in the algorithm, so it is considered internal. Regarding the fuel consumption models, the factor model is the mostly used one for about 49.44% followed by the microscopic model for about 35.96% of the investigations. On the other hand, when analyzing the specific characteristics of the problem, the single-objective functions represent about 69.66%. For its part, the use of time windows is the most used time restriction for about 60.67% followed by the limitations on the duration of the route with 37.08%. Most of the fleets (64.04%) are made up of homogeneous fleets. Finally, the special considerations related to speed and load were found for about 52.81% and 66.29% of the investigations studied in this research.

Table 2.1: Relevant features of the reviewed papers consider emission aspects and model components.

Reference	Emissions types		Emissions calculations		Fuel consumption models			Objectives		Time restrictions			Fleet compositions		Others	
	CO_2	NO_x	Internal	External	Microscopic	Macroscopic	Factor	Single-objective	Multi-objective	Time windows	Time dependency	Limited duration	Homogeneous	Heterogeneous	Speed	Load
Green vehicle routing problems																
Camacho-Vallejo et al. (2021)	✓		✓				✓		✓			✓		✓		
Dewi and Utama (2021)	✓		✓					✓					✓		✓	✓
Soysal et al. (2021b)	✓		✓				✓	✓					✓		✓	
Talouki et al. (2021)	✓		✓						✓	✓	✓		✓		✓	
Liu et al. (2020)	✓		✓				✓	✓		✓			✓			✓
Wei et al. (2020)	✓		✓				✓		✓	✓				✓	✓	
de Oliveira da Costa et al. (2018)	✓		✓			✓	✓	✓					✓			✓
Yavuz and Çapar (2017)	✓		✓				✓	✓				✓		✓		
Omidvar and Tavakkoli-Moghaddam (2012)	✓		✓				✓	✓		✓	✓	✓	✓		✓	
Inventory routing-related problems																
Alkaabneh et al. (2020)	✓		✓				✓	✓					✓		✓	✓
Location routing-related problems																
Leng et al. (2020)	✓		✓		✓				✓	✓				✓	✓	✓
Dukkanci et al. (2019)	✓		✓		✓			✓		✓			✓		✓	✓
Leng et al. (2018)	✓		✓		✓			✓		✓				✓	✓	✓

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Reference	Emissions types		Emissions calculations		Fuel consumption models			Objectives		Time restrictions			Fleet compositions		Others	
	CO_2	NO_x	Internal	External	Microscopic	Macroscopic	Factor	Single-objective	Multi-objective	Time windows	Time dependency	Limited duration	Homogeneous	Heterogeneous	Speed	Load
Multi-depot routing-related problems																
Fernández et al. (2021)	✓			✓			✓	✓		✓		✓	✓			✓
Wang et al. (2019)	✓		✓		✓				✓	✓	✓		✓		✓	✓
Jabir et al. (2017)	✓		✓				✓	✓		✓			✓			✓
Kaabachi et al. (2017)	✓		✓		✓			✓		✓			✓		✓	✓
Pérez-Bernabeu et al. (2015)	✓			✓			✓	✓				✓	✓			
Multi-trip routing-related problems																
Lyu and He (2021)	✓		✓				✓	✓				✓		✓		✓
Multi-echelon distribution-related problems																
Anderluh et al. (2021)	✓		✓				✓		✓			✓	✓			
Liu and Liao (2021)	✓		✓		✓				✓				✓		✓	✓
Mühlbauer and Fontaine (2021)	✓			✓			✓	✓						✓		
Validi et al. (2021)	✓		✓				✓		✓			✓		✓		
Jie et al. (2019)		✓		✓			✓	✓						✓		
Li et al. (2016)	✓		✓				✓	✓		✓		✓	✓			✓
Period vehicle routing-related problems																

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Table 2.1 – *Continued from previous page*

Reference	Emissions types		Emissions calculations		Fuel consumption models			Objectives		Time restrictions			Fleet compositions		Others	
	CO_2	NO_x	Internal	External	Microscopic	Macroscopic	Factor	Single-objective	Multi-objective	Time windows	Time dependency	Limited duration	Homogeneous	Heterogeneous	Speed	Load
López-Sánchez et al. (2021)	✓			✓					✓				✓			
Pollution-routing-related problems																
Cheaitou et al. (2021)	✓		✓		✓				✓				✓		✓	✓
Koç et al. (2019)	✓		✓		✓			✓				✓		✓	✓	✓
Costa et al. (2018)	✓		✓		✓				✓	✓			✓		✓	✓
Kargari Esfand Abad et al. (2018)	✓		✓		✓				✓				✓		✓	
Fang et al. (2017)	✓		✓		✓			✓					✓			✓
Franceschetti et al. (2017)	✓		✓		✓			✓		✓	✓		✓		✓	✓
Guo and Liu (2017)	✓		✓		✓			✓		✓	✓		✓		✓	✓
Kumar et al. (2016)	✓		✓		✓				✓	✓			✓		✓	✓
Suzuki (2016)	✓			✓			✓	✓					✓		✓	✓
Kramer et al. (2015)	✓		✓		✓			✓		✓		✓	✓		✓	✓
Demir et al. (2014a)	✓		✓		✓				✓	✓			✓		✓	✓
Koç et al. (2014)	✓		✓		✓			✓		✓				✓	✓	✓
Demir et al. (2012)	✓		✓		✓			✓		✓			✓		✓	✓
Electric vehicles-related problems																
Raeesi and Zografos (2022)	✓			✓			✓		✓	✓		✓	✓			

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Table 2.1 – *Continued from previous page*

Reference	Emissions types		Emissions calculations		Fuel consumption models			Objectives		Time restrictions			Fleet compositions		Others	
	CO_2	NO_x	Internal	External	Microscopic	Macroscopic	Factor	Single-objective	Multi-objective	Time windows	Time dependency	Limited duration	Homogeneous	Heterogeneous	Speed	Load
Soysal et al. (2021a)	✓			✓	✓			✓						✓		✓
Yu et al. (2021)	✓		✓		✓			✓		✓				✓	✓	✓
Arroyo et al. (2020)	✓		✓				✓	✓				✓		✓		
Eskandarpour et al. (2019)	✓		✓				✓		✓					✓		
Macrina et al. (2019a)	✓		✓				✓	✓		✓		✓		✓		✓
Yang and Sun (2015)	✓	✓		✓			✓	✓					✓			
Pickups and deliveries-related problems																
Fatemi-Anaraki et al. (2022)	✓		✓				✓		✓					✓		✓
Olgun et al. (2021)	✓		✓				✓	✓					✓			✓
Solano et al. (2021)	✓			✓			✓	✓		✓		✓	✓			
Srijaroon et al. (2021)	✓		✓		✓			✓		✓	✓	✓	✓		✓	✓
Asghari and Mirzapour Al-e-hashem (2020)	✓		✓				✓		✓	✓		✓		✓		✓
Lu and Huang (2020)	✓		✓				✓	✓		✓			✓			
Majidi et al. (2017)	✓		✓		✓			✓		✓			✓		✓	✓
VRP with backhauls-related problems																
Zhao et al. (2020b)	✓		✓				✓	✓					✓			
Scheduling-related problems																

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Table 2.1 – *Continued from previous page*

Reference	Emissions types		Emissions calculations		Fuel consumption models			Objectives		Time restrictions			Fleet compositions		Others	
	CO_2	NO_x	Internal	External	Microscopic	Macroscopic	Factor	Single-objective	Multi-objective	Time windows	Time dependency	Limited duration	Homogeneous	Heterogeneous	Speed	Load
Jiang et al. (2021)	✓		✓						✓	✓			✓		✓	✓
Alizadeh Foroutan et al. (2020)	✓		✓			✓	✓	✓			✓	✓		✓	✓	✓
Sousa Matos et al. (2018)	✓		✓				✓	✓		✓	✓	✓		✓	✓	✓
Liao (2017)	✓		✓				✓	✓		✓	✓		✓		✓	✓
Zhou et al. (2017)	✓		✓			✓		✓		✓	✓	✓		✓	✓	
Gang et al. (2016)	✓		✓		✓				✓	✓		✓	✓			✓
Xiao and Konak (2016)	✓		✓		✓	✓		✓		✓	✓			✓		✓
Xiao and Konak (2015)	✓		✓		✓	✓			✓	✓	✓		✓		✓	
Time windows-related problems																
Ettazi et al. (2021)	✓		✓				✓	✓		✓			✓			
Islam and Gajpal (2021)	✓		✓		✓			✓		✓		✓		✓	✓	✓
Luo et al. (2021)	✓		✓			✓		✓		✓		✓	✓			
Eshtehadi et al. (2020)	✓		✓		✓			✓		✓		✓	✓		✓	✓
Fernández et al. (2020)	✓			✓			✓	✓		✓			✓			✓
Ren et al. (2020)	✓	✓	✓			✓			✓	✓				✓		
Yu et al. (2020)	✓		✓				✓	✓		✓		✓	✓			✓
Zhang et al. (2020b)	✓			✓			✓	✓		✓		✓		✓		✓

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Table 2.1 – *Continued from previous page*

Reference	Emissions types		Emissions calculations		Fuel consumption models			Objectives		Time restrictions			Fleet compositions		Others	
	CO_2	NO_x	Internal	External	Microscopic	Macroscopic	Factor	Single-objective	Multi-objective	Time windows	Time dependency	Limited duration	Homogeneous	Heterogeneous	Speed	Load
Zhao et al. (2020a)	✓		✓		✓				✓	✓			✓		✓	✓
Meng et al. (2019)	✓		✓				✓	✓		✓		✓	✓		✓	✓
Rezaei et al. (2019)	✓		✓				✓		✓	✓				✓		✓
Masmoudi et al. (2018)	✓		✓		✓			✓		✓		✓		✓	✓	✓
Sanchez et al. (2016)	✓		✓				✓	✓		✓			✓	✓		
Küçükoğlu et al. (2015)	✓			✓				✓		✓	✓		✓		✓	✓
Molina et al. (2014)	✓	✓	✓				✓		✓	✓		✓		✓		✓
Maden et al. (2010)	✓			✓			✓	✓		✓		✓		✓		
Time-dependent-related problems																
Zulvia et al. (2020)	✓		✓				✓		✓	✓	✓	✓	✓		✓	✓
Hooshmand and MirHassani (2019)	✓			✓		✓		✓			✓	✓	✓		✓	
Çimen and Soysal (2017)	✓			✓		✓		✓			✓		✓		✓	
Soysal and Çimen (2017)	✓		✓			✓		✓			✓		✓		✓	
Liu et al. (2014)	✓		✓		✓			✓			✓			✓	✓	✓
Waste collection-related problems																
Malekkhouyan et al. (2021)	✓		✓						✓	✓		✓	✓			✓
Qiao et al. (2020)	✓		✓				✓	✓					✓			✓

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Table 2.1 – *Continued from previous page*

Reference	Emissions types		Emissions calculations		Fuel consumption models			Objectives		Time restrictions			Fleet compositions		Others	
	CO_2	NO_x	Internal	External	Microscopic	Macroscopic	Factor	Single-objective	Multi-objective	Time windows	Time dependency	Limited duration	Homogeneous	Heterogeneous	Speed	Load
Molina et al. (2019)	✓		✓			✓		✓						✓	✓	✓
Wei et al. (2019)	✓		✓		✓			✓					✓		✓	✓
Prize-collecting vehicle routing problems																
Trachanatzi et al. (2021)	✓		✓				✓	✓					✓			✓
Hydrogen vehicles in routing problems																
Islam et al. (2021)	✓		✓		✓			✓		✓				✓	✓	✓

2.4 Strategies and components used in the solution approaches

This section presents and analyzes the main strategies and components of the solution methods found in the related literature. We cluster the approaches according to six essential aspects, that is, initial solution, neighborhood, local search method, genetic operators, selection method, and methodologies. The solution methods are classified considering the classification of Talbi (2009) for single and hybrid metaheuristics. For single metaheuristics, the classifications are single-solution based metaheuristics (SMH), population-based metaheuristics (PMH), metaheuristics for multi-objective optimization (MH-MO), and hyperheuristics (HH). Regarding hybrid metaheuristics, we consider metaheuristics-heuristics (MH-H), metaheuristics-metaheuristics (MH-MH), metaheuristics with mathematical programming (MATH), and hybrid metaheuristics for multi-objective optimization (HMH-MO).

Table 2.4 reports those aspects as well as their components that will be below described. Column 1 indicates each reference and the proposed method. The referral to the method follows the format <method(classification)> which allows knowing the method used and the most suitable classification in the literature. Subsequently, columns 2, 3, and 4 indicate for each work the used initial solution procedures, how neighborhoods are structured in a heuristic scheme, and the local search criteria of neighbor selection. Column 5 provides the operators used in evolutionary approaches, and column 6 presents the selection heuristic methods found. Finally, column 7 shows the methodologies employed to conduct the search of solutions.

In the initial solution column, we consider how starting solutions are generated as these might have a relevant influence on the quality of the best solution found as well as the speed to reach it. This review considers that the initial solutions are generated using four main methods. The C&W method is based on the merging of routes, while their combination causes a saving or reduction of the pursued objective. Greedy methods (Resende and Ribeiro, 2016), are based on the selection of the element that best represents the immediate quality in each case. Heuristics that take into account the characteristics of the problem and, finally, random generation.

The improvement algorithms and local search commonly start from an initial solution and explore the neighborhood to find the best solution. To generate the neighborhood, these algorithms apply well-defined neighborhood operators. Considering the reviewed papers, we classify the works based on five neighborhoods generated by different operators:

- Cross-exchange. It eliminates a series of consecutive nodes of a route and inserts these nodes into another route and vice versa.
- Exchange. It exchanges two vertices of the solution.

- 2-opt*. It removes arcs from two routes and replaces these with two arcs connecting the routes.
- Or-opt. It replaces three arcs with three new arcs, that is, moving the sequence of three vertices. In some neighborhood-based local search algorithms, it is necessary to specify how the next move to be executed should be selected.
- 2-opt. It replaces two arcs with two new arcs to reconnect the route. The large neighborhood is based on destroying and repairing operators, and the first partially disintegrates the solution and the second rebuilds it.

From the reviewed works, the main methods are the first and best improvement methods. The best improvement selects one from the set of possible moves that produce the best improvement. On the other hand, the first improvement selects the first movement that produces an improvement. In evolutionary algorithms, genetic operators are used for generating the population of solutions for the next generations. The most commonly used types of genetic operators are mutation and crossover. Mutation operators are commonly used to maintain population diversity and are based on a defined chromosome change. Crossover operators, on the other hand, are based on the creation of a pair of individuals that combine the characteristics of their parents (pairs of individuals).

Four selection methods are identified from the collected literature, particularly in the context of population-based algorithms. The roulette wheel assigns each individual a selection probability proportional to its relative fitness. This algorithm is closely related to rank-based and stochastic universal sampling. The former is based on the rank of each individual rather than the quality of the individual in question. In the second one, the selection points are stochastically distributed in the roulette. The tournament selection considers selecting k individuals randomly and then the element with the best quality is chosen.

Considering the taxonomy proposed by Archetti and Speranza (2014) and based on the algorithms studied in this research, we classify the works into eight solution methodologies.

- Two-phase and three-phase. It covers algorithms based on decomposing the problem into two/three phases and solving them separately. In the classification of two-phase approaches, the approaches classified as cluster first-route second are not included
- Rolling horizon. The basis of this methodology is the resolution of a subproblem corresponding to a short period, which serves as the basis for updating the information of the following subproblem.
- Relaxation-based. It provides a feasible solution to a problem from the solution of the relaxed problem.
- Partial optimization. It employs one or more MILP models to solve one part of the problem while

keeping all the decisions related to the remaining parts fixed.

- One-shot. It proposes a feasible solution to a problem provided by a heuristic. After that, this solution is improved by a MILP model, which is applied exactly once.
- Heuristic branching. It employs branching algorithms to increase the convergence of the solution method by branching heuristically. These aim to prune various nodes of the search tree to converge to a solution quickly.
- Cluster first-route second. It divides the problem into two main decisions, that is, the assignment of customers to vehicles and the order of how customers are visited in each route.

When analyzing the main strategies and components of the algorithms, we note that approximately 46.07% of works use randomness to generate initial solutions and 34.83% is based on the use of specific heuristics. In this sense, the least used algorithm to generate the initial population is C&W with a 15.73% utilization, and Greedy is used in 19.10% of the investigations. Regarding the neighborhood generation operators, the most representative in the literature is the exchange and 2-opt operators, used in 35.96% and 25.84% of the works, respectively. The next most commonly used neighborhood is a large neighborhood generated by different types of operators for about 21.35%. The rest of the neighborhood generation operators do not appear in more than 15% of the investigations. Among the population operators, the mutation and crossover operators are used with similar percentages, presenting a difference of only 3.37%. On the other hand, among the local search methods, the best improvement is observed to be the most popular one with 37.08% utilization compared to the 17.98% corresponding to the first improvement approach. Regarding selection methods, the roulette wheel present in 20.22% of the investigations is the mostly used method. Finally, the two-phase approach present in 26.97% of the investigations is the most widely used methodology in the algorithms described in the literature. In this sense, the wide use of this methodology can be found connected with the nature of the related problems. The rest of the selection methods and methodologies are not present in more than 8% of the investigations.

In order to analyze which algorithms are most commonly used to solve green routing problems, Figure 2.5 shows the techniques that were used in at least five investigations specifying the number of times it was used to solve each type of problem. TS is the most commonly used technique, presented in approximately 15.73% of the investigations. In addition, TS is frequently used to solve problems related to VRSPs, and this problem classification represents approximately 21.43% of investigations where TS is used. The next most commonly used algorithm is ALNS with a 13.48% representation and is used in 33.33% of the cases to solve problems related to PRPs. The eother algorithms used in more than 10% of the investigations are GA and SA, with 11.24% and 10.11%, respectively.

Table 2.2: Main strategies used in the heuristic methods for the GVRPs.

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
Green vehicle routing problems																										
NBOTS (MH-MO) Camacho-Vallejo et al. (2021)				✓																						
HWOA (MH-MH) Dewi and Utama (2021)				✓						✓	✓															
DPH (H) Soysal et al. (2021b)			✓																							
SA (SMH) Liu et al. (2020)				✓																						
NSGA-II (MH-MO) Wei et al. (2020)				✓									✓	✓											✓	

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
GA (PMH) de Oliveira da Costa et al. (2018)	✓			✓									✓					✓								
VNS (SMH) Yavuz and Çapar (2017)			✓						✓	✓		✓														
SA (SMH), GA (PMH) Omidvar and Tavakkoli-Moghaddam (2012)			✓										✓	✓				✓								
Inventory routing-related problems																										
GRASP (SMH) Alkaabneh et al. (2020)		✓		✓																					✓	
Location routing-related problems																										

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
MOHH (HH) Leng et al. (2020)				✓	✓							✓	✓	✓		✓										
ILS (SMH) Dukkanci et al. (2019)	✓			✓	✓						✓															
HH (HH) Leng et al. (2018)				✓	✓		✓			✓						✓										
Multi-depot routing-related problems																										
POPMUSIC (MATH) Fernández et al. (2021)		✓																				✓				
CWSHA-MOPSO-SwA (HMH-MO) Wang et al. (2019)	✓									✓	✓		✓	✓											✓	

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
ACO-VNS (MH-MH) Jabir et al. (2017)			✓	✓					✓	✓	✓															
ACO (PMH) Kaabachi et al. (2017)		✓		✓	✓					✓	✓															
ILS (SMH) Pérez-Bernabeu et al. (2015)	✓			✓							✓															
Multi-trip routing-related problems																										
TSHM (MH-MH) Lyu and He (2021)		✓		✓	✓		✓			✓	✓		✓	✓											✓	
Multi-echelon distribution-related problems																										

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution: Clarke and Wright	Initial solution: Greedy	Initial solution: Heuristic initialization	Initial solution: Random	Neighborhoods: 2-opt	Neighborhoods: Or-opt	Neighborhoods: 2-opt*	Neighborhoods: Cross Exchange	Neighborhoods: Large	Neighborhoods: Exchange (Swap)	LS methods: Best improvement	LS methods: First improvement	Genetic operators: Mutation	Genetic operators: Crossover	Selection methods: Rank-based	Selection methods: Roulette wheel	Selection methods: Stochastic	Selection methods: Tournament selection	Methodologies: Cluster first-route second	Methodologies: Heuristic branching	Methodologies: One-shot	Methodologies: Partial optimization	Methodologies: Relaxation-based	Methodologies: Rolling horizon	Methodologies: Two-phase	Methodologies: Three-phase
LNS (SMH) Anderluh et al. (2021)		✓		✓	✓		✓		✓		✓					✓										
ALNS-C&W (MH-H) Liu and Liao (2021)	✓			✓					✓		✓					✓			✓							✓
PLNS (SMH) Mühlbauer and Fontaine (2021)		✓		✓	✓		✓		✓		✓															
MOGA-II, MOPSO, NSGA-II (MH-MO) Validi et al. (2021)			✓	✓									✓	✓	✓										✓	
CG-ALNS (MATH) Jie et al. (2019)			✓						✓							✓							✓			
C&W (H) Li et al. (2016)	✓							✓			✓														✓	

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
Period vehicle routing-related problems																										
MSMLS (SMH) López-Sánchez et al. (2021)				✓						✓	✓														✓	
Pollution-routing-related problems																										
GA (PMH) Cheaitou et al. (2021)				✓									✓													
TS (SMH) Koç et al. (2019)		✓								✓																
Pareto LS (MH-MO) Costa et al. (2018)			✓				✓	✓				✓													✓	

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
NSGA-II, NRGA, MOPSO (MH-MO) Kargari Esfand Abad et al. (2018)													✓	✓	✓			✓								
C&W,GVND-B&C (MATH) Fang et al. (2017)							✓	✓		✓	✓									✓						
ALNS (SMH) Franceschetti et al. (2017)			✓						✓			✓				✓										
HE (H) Guo and Liu (2017)			✓																						✓	
NSGA-II (MH-MO) Kumar et al. (2016)				✓									✓			✓										
SA-TS (MH-MH) Suzuki (2016)				✓	✓							✓													✓	

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
ILS-SP-SOA (MATH) Kramer et al. (2015)			✓		✓	✓	✓					✓									✓					
ALNS (SMH) Demir et al. (2014a)	✓								✓		✓					✓									✓	
HALNS-HEA-SOA (MH-MH) Koç et al. (2014)	✓								✓		✓							✓							✓	
ALNS (SMH) Demir et al. (2012)	✓								✓		✓					✓									✓	
Electric vehicles-related problems																										
MG-DP-ILNS (MH-H) Raeesi and Zografos (2022)									✓																	
F&O (H) Soysal et al. (2021a)			✓																					✓		

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
ALNS (SMH) Yu et al. (2021)			✓				✓		✓		✓															
48A (H) Arroyo et al. (2020)				✓	✓																				✓	
EMDLS (SMH) Eskandarpour et al. (2019)			✓						✓																	
ILS (SMH) Macrina et al. (2019a)			✓							✓	✓															
SIGALNS, TS-MCWS (H, MH-H) Yang and Sun (2015)	✓									✓	✓					✓									✓	
Pickups and deliveries-related problems																										

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
GA, NSGA-II (PMH, MH-MO) Fatemi-Anaraki et al. (2022)			✓										✓	✓				✓								✓
ILS-VND (HH) Olgun et al. (2021)			✓	✓	✓			✓	✓	✓	✓					✓										
Greedy-TS (MH-H) Solano et al. (2021)		✓								✓	✓															
SAL-PSO (PMH) Srijaroon et al. (2021)		✓																								
NSGA-II (MH-MO) Asghari and Mirzapour Al-e-hashem (2020)				✓									✓	✓	✓											
DALNS (SMH) Lu and Huang (2020)		✓							✓		✓															

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
ALNS (SMH) Majidi et al. (2017)			✓								✓					✓										
VRP with backhauls-related problems																										
QPSO-EHLSA (MH-H) Zhao et al. (2020b)				✓	✓					✓																
Scheduling-related problems																										
NSGA-II, MOTS (MH-MO, MH-MO) Jiang et al. (2021)				✓						✓	✓		✓	✓												
SA, GA (SMH, PMH) Alizadeh Foroutan et al. (2020)				✓						✓			✓	✓												

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
MS-ILS-SC (MATH) Sousa Matos et al. (2018)		✓		✓	✓					✓															✓	
GA-TS (MH-MH) Liao (2017)				✓							✓		✓	✓			✓								✓	
TS, VND, RVNS (SMH) Zhou et al. (2017)			✓		✓	✓	✓		✓	✓	✓	✓														
H-TS (MH-H) Gang et al. (2016)		✓								✓	✓															
P-MIP-INS (MATH) Xiao and Konak (2016)	✓								✓													✓				
SA (SMH) Xiao and Konak (2015)				✓																						
Time windows-related problems																										

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
TS, VNS (SMH) Ettazi et al. (2021)		✓								✓	✓															
ACO-VNS (MH-MH) Islam and Gajpal (2021)			✓							✓																
HACO (MH-H) Luo et al. (2021)			✓		✓		✓				✓														✓	
ALNS (SMH) Eshtehadi et al. (2020)	✓				✓				✓							✓										
GRASP-MILP (MATH) Fernández et al. (2020)		✓		✓				✓				✓							✓							
VNS (SMH) Ren et al. (2020)			✓							✓																
ALNS (SMH) Yu et al. (2020)			✓						✓																✓	

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution: Clarke and Wright	Initial solution: Greedy	Initial solution: Heuristic initialization	Initial solution: Random	Neighborhoods: 2-opt	Neighborhoods: Or-opt	Neighborhoods: 2-opt*	Neighborhoods: Cross Exchange	Neighborhoods: Large	Neighborhoods: Exchange (Swap)	LS methods: Best improvement	LS methods: First improvement	Genetic operators: Mutation	Genetic operators: Crossover	Selection methods: Rank-based	Selection methods: Roulette wheel	Selection methods: Stochastic	Selection methods: Tournament selection	Methodologies: Cluster first-route second	Methodologies: Heuristic branching	Methodologies: One-shot	Methodologies: Partial optimization	Methodologies: Relaxation-based	Methodologies: Rolling horizon	Methodologies: Two-phase	Methodologies: Three-phase
GA (PMH) Zhang et al. (2020b)			✓	✓									✓	✓				✓								
ACOMO (MH-MO) Zhao et al. (2020a)			✓													✓										
Fuzzy HC, GA (PMH) Meng et al. (2019)			✓	✓									✓	✓												
GA, PBSA (MH, PMH) Rezaei et al. (2019)				✓	✓					✓			✓	✓		✓										
ABC (PMH) Masmoudi et al. (2018)			✓		✓		✓	✓								✓										✓
SS (PMH) Sanchez et al. (2016)			✓		✓					✓	✓															
SA (SMH) Küçükoğlu et al. (2015)		✓	✓				✓				✓	✓			✓											

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
C&W (H) Molina et al. (2014)	✓																									
TS (SMH) Maden et al. (2010)			✓					✓		✓																
Time-dependent-related problems																										
MOGE (MH-MO) Zulvia et al. (2020)			✓	✓											✓											
GRASP-SA (MH-MH) Hooshmand and MirHassani (2019)		✓		✓	✓					✓															✓	
ADP (H) Çimen and Soysal (2017)		✓	✓														✓									

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
RDP (H) Soysal and Çimen (2017)			✓																							
GA (PMH) Liu et al. (2014)				✓									✓	✓				✓								
Waste collection-related problems																										
GOA (PMH) Malekkhouyan et al. (2021)				✓																						
PSO-TS (MH-MH) Qiao et al. (2020)			✓	✓						✓							✓								✓	
VNTS (MH-MH) Molina et al. (2019)			✓		✓			✓		✓	✓														✓	
HABC-MDT (MH-MH) Wei et al. (2019)				✓	✓					✓						✓										

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Table 2.2 – *Continued from previous page*

Solution approach (type) and reference	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
	Clarke and Wright	Greedy	Heuristic initialization	Random	2-opt	Or-opt	2-opt*	Cross Exchange	Large	Exchange (Swap)	Best improvement	First improvement	Mutation	Crossover	Rank-based	Roulette wheel	Stochastic	Tournament selection	Cluster first-route second	Heuristic branching	One-shot	Partial optimization	Relaxation-based	Rolling horizon	Two-phase	Three-phase
Prize-collecting vehicle routing problems																										
TLBO-CRE (MH-H) Trachanatzi et al. (2021)	✓									✓	✓			✓											✓	
Hydrogen vehicles in routing problems																										
PSO-NS (MH-H) Islam et al. (2021)				✓	✓					✓		✓													✓	

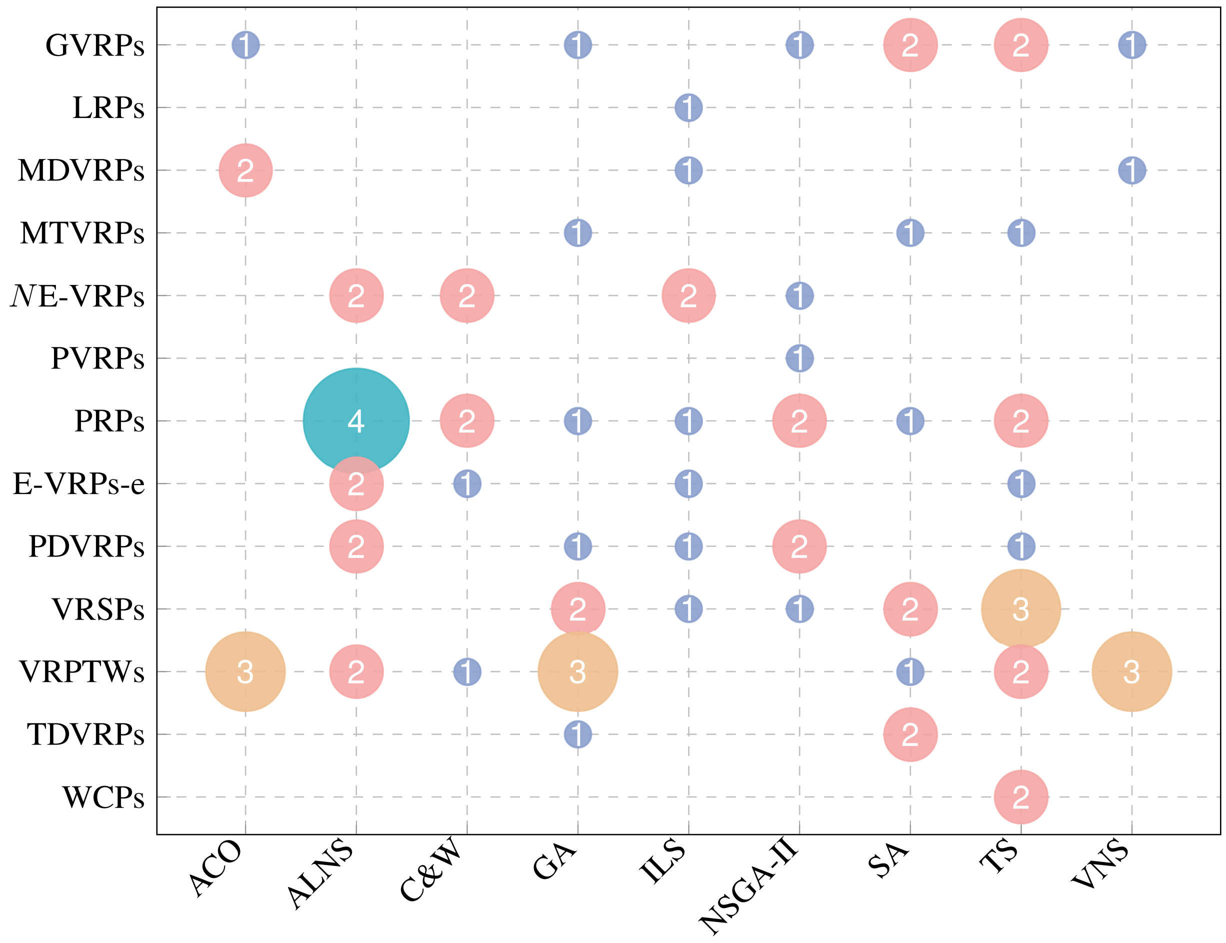

Figure 2.4: Bubble chart shows how many times a method has been used to solve GVRPs. Note that one method can be used to solve different variants.

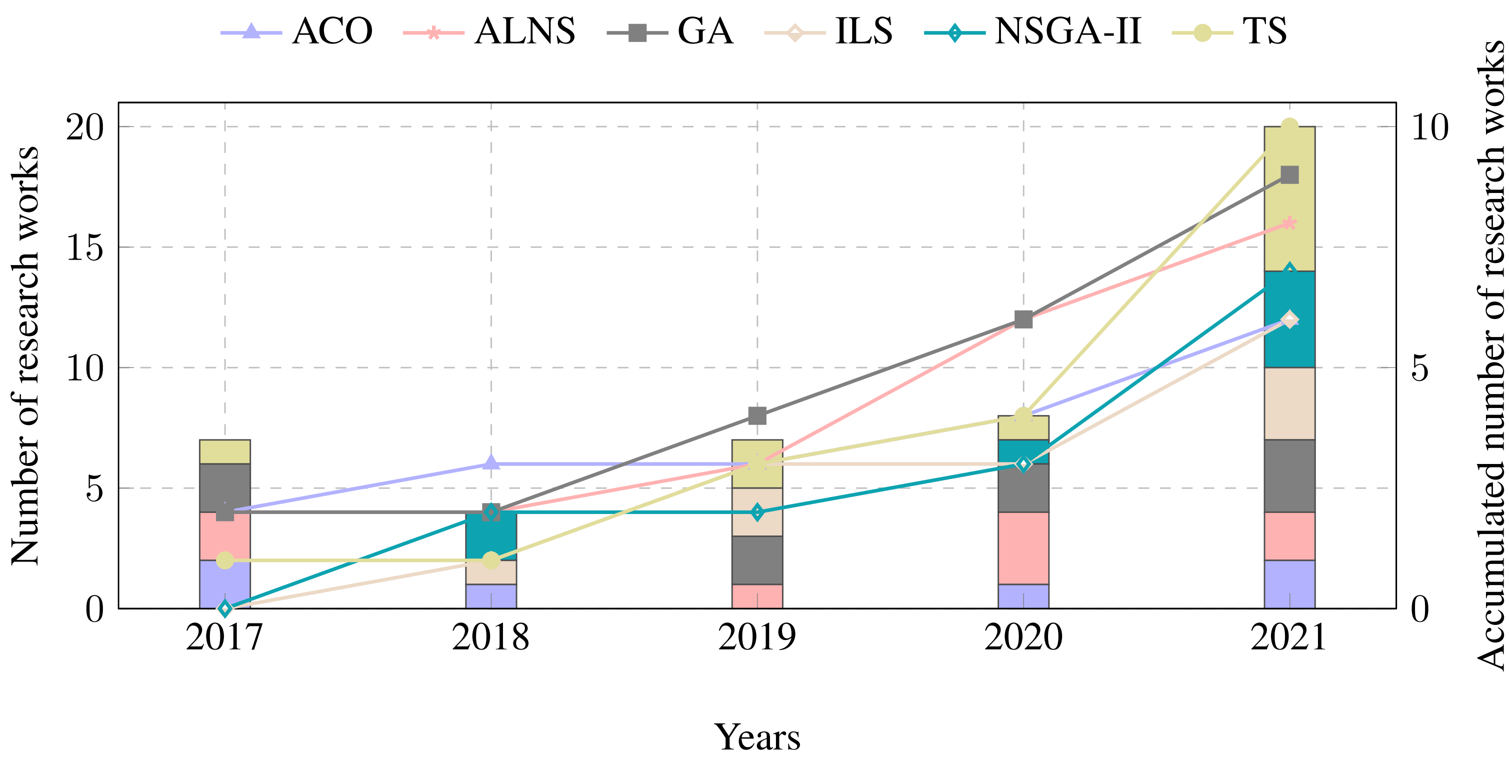

Figure 2.5: Number of solution methods most commonly used in the last five years. The stacked bar chart shows the number of works per year, while the line chart shows the cumulative number of works.

Figure 2.5 shows the main methods for solving the related GVRPs in the last five years. In the figure, we show those methods that have been used in at least five research works (i.e., ACO, ALNS, GA, ILS, NSGA-II, and TS). The y-axis on the right side of the figure represents the cumulative number of works. In contrast, the bars and the y-axis on the left side of the figure represent the number of works in which these algorithms were applied each year.

The figure shows that the use of TS in the last years is representative, experiencing an increase of 60% during the last year. This behavior is not reflected in the ALNS and GA, which have shown stable growth since 2017. This is followed by ACO and NSGA-II. ACO shows a stable growth during the analyzed period, while NSGA-II shows a growth of more than 50% of investigations in 2021, and behaviors are also represented by ILS. On the other hand, if we analyze the use of the above algorithms as a whole, their use in 2021 is at least 21.57% higher than in previous years.

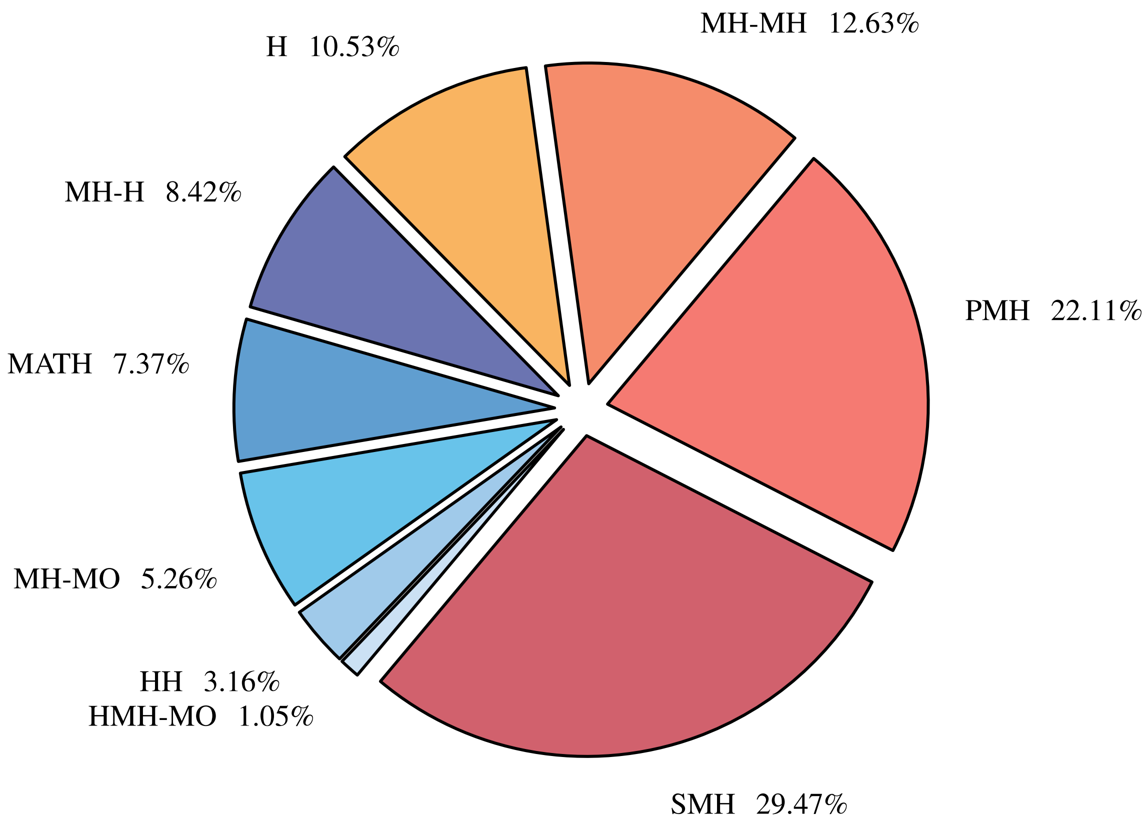

Figure 2.6: Distribution of proposed solution methods for GVRPs. The pie chart displays the percentage of use of each method among the reviewed articles.

Figure 2.6 shows the distribution of methods in percentages. The main four used methods for solving GVRPs are SMH, PMH, MH-MH, and H. As can be observed, the methods classified as H, SMH, and PMH are the most commonly used ones given that these are often employed for generating initial solutions or improving them (see Table 2.4).

The population-based methods PMH are used by 22.11%. In this category, the use of GAs and especially the well-known NSGA-II can be highlighted as most relevant. The hybridization of metaheuristic algorithms MH-MH is used by 12.63% of investigations. In addition, we note that the other methods are less used, accounting for a total percentage of 25.26%.

2.5 Benchmark instances

In the related GVRP literature, several works propose benchmarks based on real-world data as well as artificially created instances. Given that GVRP belongs to the family of VRPs, there are also sets of instances initially generated for VRP and later used in GVRPs. Table 2.5 shows each known benchmark and the works proposing such benchmarks as well as those works using them. The first column corresponds to the investigations where a set of benchmarks were introduced. Subsequently, columns 2 and 3 indicate if the benchmarks used on each investigation are based on real-world data and/or artificially generated. Finally, the last column shows those research works that use the corresponding benchmark set. In addition, the source URL (https://github.com/affernan/vrpdataset) to obtain several of them is provided.

The benchmarks provided by Christofides and Eilon (1969) and Christofides et al. (1979) are some of the oldest but most widely used VRP instances. These are used in numerous GVRPs, such as PRP in Kramer et al. (2015), PPRP in Suzuki (2016), WCP-MDP in Wei et al. (2019), among others. The instances proposed by Christofides et al. (1979) present 14 generated instances for the CVRP from the literature and on some structured problems. In their proposed instances, the number of customers ranges from 50 to 199 and have single depots. Features such as maximum allowable time or unloading time are also included.

Another well-known set of instances is the one proposed by Eilon et al. (1971) for the PDVRP. In that work, the authors proposed two sets of instances for single-depot problems, one composed of 20 and the other of 50 customers. Both sets consider Cartesian coordinates and, just for the 20-customer set, there are four cases representing different demands, namely, the demands vary in dependency of each case, that is, case 1 presents demands equal to 1 unit, case 2 between 1 and 10 units, case 3 between 1 and 100, and case 4 from 1 to 1000. López-Sánchez et al. (2021) used these instances for the Bi-PVRP-SC. The research of Gaskell (1967) presented six cases of study for the CVRP. The first case considers 36 customers in a matrix point of 50×50 miles square area and a simple depot located in a default position, and there is no load restriction. The second case is taken from the research presented by Clarke and Wright (1964). The remaining four cases consider between 21 and 32 customers and include the maximum load and miles for the vehicles, mileage allowance for routes, and locations coordinates and demands for each customer. These four cases are used by Dewi and Utama (2021) for the GVRP.

Table 2.3: Benchmarks used for the GVRPs.

Benchmark source	Based on real-world data	Artificially generated	Research works using this benchmark
Fatemi-Anaraki et al. (2022)		✓	Bi-objective green delivery and pickup problem, Fatemi-Anaraki et al. (2022)
Raeesi and Zografos (2022)		✓	EVRPTW-RS-SMBS, Raeesi and Zografos (2022)
Anderluh et al. (2021)	✓	✓	2E-VRPSyn, Anderluh et al. (2021)
Camacho-Vallejo et al. (2021)		✓	Green logistics bi-objective bi-level problem, Camacho-Vallejo et al. (2021)
Cheaitou et al. (2021)		✓	STPPS, Cheaitou et al. (2021)
Fernández et al. (2021)		✓	MDGVRP-PD, Fernández et al. (2021)
Islam et al. (2021)		✓	MFGCLP, Islam et al. (2021)
Islam and Gajpal (2021)		✓	Mixed fleet logistics distribution problem under CO_2 emission cap, Islam and Gajpal (2021)
Jiang et al. (2021)	✓		MVOC, Jiang et al. (2021)
Luo et al. (2021)		✓	HHC with synchronized visits and carbon emissions, Luo et al. (2021)
Lyu and He (2021)	✓		MTHVRP-PCIC, Lyu and He (2021)
Malekkhouyan et al. (2021)		✓	WCVRP, Malekkhouyan et al. (2021)
Solano et al. (2021)	✓		VRPSPDTW, Solano et al. (2021)
Srijaroon et al. (2021)		✓	G-VRPMSPDTW-RT, Srijaroon et al. (2021)
Talouki et al. (2021)	✓		DGVRP, Talouki et al. (2021)
Trachanatzi et al. (2021)		✓	E-PCVRP, Trachanatzi et al. (2021)

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Table 2.3 – *Continued from previous page*

Benchmark source	Based on real-world data	Artificially generated	Research works using this benchmark
Validi et al. (2021)	✓		Three-echelon distribution network, Validi et al. (2021)
Alizadeh Foroutan et al. (2020)		✓	GVRSP, Alizadeh Foroutan et al. (2020)
Alkaabneh et al. (2020)		✓	PIRP, Alkaabneh et al. (2020)
Asghari and Mirzapour Al-e-hashem (2020)	✓		Green delivery-pickup problem for HHMs, Asghari and Mirzapour Al-e-hashem (2020)
Arroyo et al. (2020)	✓		GVRP-MTPR, Arroyo et al. (2020)
Eshtehadi et al. (2020)	✓	✓	G-VRPTW, Eshtehadi et al. (2020)
Leng et al. (2020)		✓	LRPLCCC, Leng et al. (2020)
Liu et al. (2020)	✓		JD-GVRP, Liu et al. (2020)
Wei et al. (2020)		✓	Green DRASS with time-varying speeds, Wei et al. (2020)
Zhang et al. (2020b)	✓	✓	VRPTW in cold chain distribution, Zhang et al. (2020b)
Zhao et al. (2020b)		✓	2L-MDCVRPB, Zhao et al. (2020b)
Zulvia et al. (2020)	✓		G-VRPTW and time dependency for perishable products, Zulvia et al. (2020)
Chen and Shi (2019)		✓	G-VRPTW, Eshtehadi et al. (2020)
Eskandarpour et al. (2019)		✓	HeVRPMD, Eskandarpour et al. (2019)
Hooshmand and MirHassani (2019)		✓	TDGVRP-AF, Hooshmand and MirHassani (2019)
Koç et al. (2019)	✓		Variant of PRP, Koç et al. (2019)

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Table 2.3 – *Continued from previous page*

Benchmark source	Based on real-world data	Artificially generated	Research works using this benchmark
Meng et al. (2019)	✓		Customer-oriented routing problem with environment consideration, Meng et al. (2019)
Molina et al. (2019)	✓		Eco-WCVRP, Molina et al. (2019)
Rezaei et al. (2019)		✓	G-VRPTW, Rezaei et al. (2019)
Wang et al. (2019)		✓	MD-GVRP, Wang et al. (2019)
de Oliveira da Costa et al. (2018)	✓		GVRP, de Oliveira da Costa et al. (2018)
Kargari Esfand Abad et al. (2018)		✓	Pickup and delivery PRP variant considering integration and consolidation shipments in cross-docking, Kargari Esfand Abad et al. (2018)
Leng et al. (2018)		✓	RLCLRPRCC, Leng et al. (2018)
Masmoudi et al. (2018)		✓	HF-VRPS, Masmoudi et al. (2018)
Sousa Matos et al. (2018)		✓	GVRSP-Split, Sousa Matos et al. (2018)
Fang et al. (2017)		✓	PRPSPD, Fang et al. (2017)
Guo and Liu (2017)		✓	TD-PRP, Guo and Liu (2017)
Jabir et al. (2017)		✓	MD-GVRP, Jabir et al. (2017)
Kaabachi et al. (2017)		✓	GMDVRPTW, Kaabachi et al. (2017)
Liao (2017)	✓		On-line VRP considers real-time demands, Liao (2017)
Yavuz and Çapar (2017)	✓	✓	MGVRP, Yavuz and Çapar (2017)

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Table 2.3 – *Continued from previous page*

Benchmark source	Based on real-world data	Artificially generated	Research works using this benchmark
Zhou et al. (2017)	✓		Green real-life field scheduling problem, Zhou et al. (2017)
Gang et al. (2016)	✓		GVRSP of free picking up and delivering customers for airlines ticketing company, Gang et al. (2016)
Li et al. (2016)	✓	✓	2E-TVRP, Li et al. (2016)
Goeke and Schneider (2015)		✓	GMFVRPREC-PR, Yu et al. (2021)
Kramer et al. (2015)		✓	Bi-objective PRP, Costa et al. (2018) | TD-PRP, Franceschetti et al. (2017) | PRP, FCVRP, EMVRP, Kramer et al. (2015)
Xiao and Konak (2015)		✓	GVRSP, Xiao and Konak (2015)
Demir et al. (2014a)		✓	BiPRP, Demir et al. (2014a)
Liu et al. (2014)		✓	MTHVRPP, Liu et al. (2014)
Molina et al. (2014)	✓		HVRP-TW, Molina et al. (2014)
Schneider et al. (2014)		✓	EVRPTW-RS-SMBS, Raeesi and Zografos (2022) | GMFVRP-PRTW, Macrina et al. (2019a)

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<table>
<tr><th>Benchmark source</th><th>Based on real-world data</th><th>Artificially generated</th><th>Research works using this benchmark</th></tr>
<tr><td>Demir et al. (2012)</td><td>✓</td><td></td><td>CIRP under a mixed fleet of electric and conventional vehicles, Soysal et al. (2021a) | GVRP, Soysal et al. (2021b) | CumVRP-TW, Fernández et al. (2020) | GLRP, Dukkanci et al. (2019) | Bi-objective PRP, Costa et al. (2018) | GSTDCVRP, Çimen and Soysal (2017) | TD-PRP, Franceschetti et al. (2017) | F-GVRPSPDTW, Majidi et al. (2017) | GSTDCVRP, Soysal and Çimen (2017) | MMPPRP-TW, Kumar et al. (2016) | GVRSP, Xiao and Konak (2016) | PRP, FCVRP, EMVRP, Kramer et al. (2015) | BiPRP, Demir et al. (2014a) | FSMPRP, Koç et al. (2014) | PRP, Demir et al. (2012)</td></tr>
<tr><td>Omidvar and Tavakkoli-Moghaddam (2012)</td><td></td><td>✓</td><td>Congestion in VRP with AFVs, Omidvar and Tavakkoli-Moghaddam (2012)</td></tr>
<tr><td>Perboli et al. (2011)</td><td></td><td>✓</td><td>2E-CVRPSC, Mühlbauer and Fontaine (2021) | 2E-EVRP-BSS, Jie et al. (2019)</td></tr>
<tr><td>Maden et al. (2010)</td><td>✓</td><td></td><td>VRPTW using time-varying data, Maden et al. (2010)</td></tr>
<tr><td>Bredström and Rönnqvist (2008)</td><td></td><td>✓</td><td>VRPTW-SPFC, Ettazi et al. (2021) | HF-VRPS, Masmoudi et al. (2018)</td></tr>
<tr><td>Iori et al. (2007)</td><td></td><td>✓</td><td>2L-MDCVRPB, Zhao et al. (2020b)</td></tr>
<tr><td>Li and Lim (2003)</td><td></td><td>✓</td><td>Green-PDPTW, Lu and Huang (2020)</td></tr>
<tr><td>Dethloff (2001)</td><td></td><td>✓</td><td>G-VRPSPD, Olgun et al. (2021)</td></tr>
<tr><td>Gehring and Homberger (2001)</td><td></td><td>✓</td><td>G-VRPTW, Yu et al. (2020) | G-VRPTW, Küçükoğlu et al. (2015)</td></tr>
<tr><td>Salhi and Nagy (1999)</td><td></td><td>✓</td><td>G-VRPSPD, Olgun et al. (2021)</td></tr>
</table>

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Table 2.3 – *Continued from previous page*

Benchmark source	Based on real-world data	Artificially generated	Research works using this benchmark
Golden et al. (1998)		✓	HeVRPMD, Eskandarpour et al. (2019) | PPRP, Suzuki (2016) | PRP, FCVRP, EMVRP, Kramer et al. (2015) | BSS-EV-LRP, Yang and Sun (2015)
Cordeau et al. (1997)		✓	2E-CWCVRP, Liu and Liao (2021) | MSW, Qiao et al. (2020) | HC-MDVRP, Pérez-Bernabeu et al. (2015)
Augerat (1995)		✓	E-PCVRP, Trachanatzi et al. (2021) | HeVRPMD, Eskandarpour et al. (2019) | WCP-MDP, Wei et al. (2019) | BSS-EV-LRP, Yang and Sun (2015)
Chao et al. (1995)		✓	Bi-PVRP-SC, López-Sánchez et al. (2021)
Taillard (1993)	✓	✓	Eco-WCVRP, Molina et al. (2019) | BSS-EV-LRP, Yang and Sun (2015)
Solomon (1987a)		✓	2E-VRPSyn, Anderluh et al. (2021) | Mixed fleet logistics distribution problem under CO_2 emission cap, Islam and Gajpal (2021) | HHC with synchronized visits and carbon emissions, Luo et al. (2021) | MTHVRP-PCIC, Lyu and He (2021) | B-MFGVRPTW, Ren et al. (2020) | G-VRPTW, Yu et al. (2020) | Cold-chain logistics path optimization, Zhao et al. (2020a) | G-VRPTW, Sanchez et al. (2016) | PRP, FCVRP, EMVRP, Kramer et al. (2015) | G-VRPTW, Küçükoğlu et al. (2015) | PRP, Demir et al. (2012) | Congestion in VRP with AFVs, Omidvar and Tavakkoli-Moghaddam (2012)
Christofides et al. (1979)		✓	E-PCVRP, Trachanatzi et al. (2021) | HeVRPMD, Eskandarpour et al. (2019) | GVRP, de Oliveira da Costa et al. (2018) | PPRP, Suzuki (2016) | PRP, FCVRP, EMVRP, Kramer et al. (2015)
Eilon et al. (1971)		✓	Bi-PVRP-SC, López-Sánchez et al. (2021)

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<table>
<tr><th>Benchmark source</th><th>Based on real-world data</th><th>Artificially generated</th><th>Research works using this benchmark</th></tr>
<tr><td>Christofides and Eilon (1969)</td><td></td><td>✓</td><td>GVRP, Dewi and Utama (2021) | 2E-CVRPSC, Mühlbauer and Fontaine (2021) | E-PCVRP, Trachanatzi et al. (2021) | WCP-MDP, Wei et al. (2019) | GVRP, de Oliveira da Costa et al. (2018)</td></tr>
<tr><td>Gaskell (1967)</td><td></td><td>✓</td><td>GVRP, Dewi and Utama (2021)</td></tr>
</table>

Augerat (1995) proposed the *Augerat* instances with three sets of instances. Set A and B consider random locations for customers and the depot. In addition, in Set B, the customers are clustered by region. On the other hand, Set P is made with modified instances existing in the literature Christofides and Eilon (1969); Eilon et al. (1971). Some investigations used this set for experimental purposes such as E-PCVRP in Trachanatzi et al. (2021), HeVRPMD in Eskandarpour et al. (2019).

Taillard (1993) proposed 13 instances in his benchmark for CVRP with a range of customers from 75 to 385. This set is based on the fourteen instances reported in Christofides et al. (1979). In addition, the author introduced a new real instance with 385 customers based on the canton of Vaud in Switzerland. These instances are used in the research conducted by Yang and Sun (2015) to test the approach for BSS-EV-LRP, and by Molina et al. (2019) to solve the Eco-WCVRP. Golden et al. (1998) introduced 20 large-scale VRPs (LSVRPs) set of instances with customers ranging between 200 and 483. These instances present a particular configuration related to the locations of customers; for example, the customers are located in concentric circles around the depot, or concentric squares with the depot in a corner, or in concentric squares around the depot. Some authors used these benchmark instances in their research, that is, Kramer et al. (2015) for FCVRP and EMVRP; Yang and Sun (2015) created a large-size set with 20 instances with up to 480 customers to test the BSS-EV-LRP and considered that all node locations are candidate battery swap stations.

The instances known as *Solomon* instances proposed by Solomon (1987a) for the VRPTW are a popular VRP benchmark that have been also used in GVRPs, for example, G-VRPTW, PRP, LRPLCCC. This benchmark consists of a set of 56 problem instances divided into six different categories with 100 customers per instance so-called C1, C2, R1, R2, RC1, and RC2. Based on the *Solomon* benchmark, Gehring and Homberger (2001) proposed six groups of instances for VRPTW. The first group consists of the same 56 instances of *Solomon*. The remaining 5 groups, named G02, G04, G06, G08, G010, consider 200, 400, 600, 800, and 1000 customers, respectively. The benchmark proposed by Li and Lim (2003) is based on those instances for the PDPTW. In this case, the set of problem instances, named LC1, LC2, LR1, LR2, LRC1, and LRC2, are based only on the set of instances categorized as C1. This adapted set of instances have a range of customers between 25, 50, and 100. The customer locations are randomly paired to compose the pickup and delivery customers, adding two new columns that establish the corresponding partner customer. Furthermore, arithmetic signs are added to the demands, classifying the customers with negative demand as deliveries customers and positive demands as pickups customers. The research of Lu and Huang (2020) used the set of 100 customers of this benchmark for the Green-PDPTW. The work of Küçükoğlu et al. (2015) also used this instance set for the G-VRPTW. Chen and Shi (2019) proposed a set of instances for MCVRPTW based on the Solomon's benchmark with groups of instances with 25, 50, and 100 customers. The investigation of Eshtehadi et al. (2020)

used this benchmark to test their approach for solving G-VRPTW. Schneider et al. (2014) introduced benchmark instances for E-VRPTW through a set of 36 small and 56 large instances based on Solomon ones (see GMFVRP-PRTW in Macrina et al. (2019a)). Each instance comprises 21 charging stations, and 5, 10, and 15 customers for small instances and 100 customers for large instances. To guarantee the feasibility of the instances, the original time windows were modified. The battery capacity is set to the maximum between the charge needed to travel 60% of the average route length of the best-known solution to the corresponding VRPTW instance and twice the amount of battery charge required to travel the longest arc between a customer and a station. Based on Schneider et al. (2014), Raeesi and Zografos (2022) presented a set of instances for E-VRPTW with recharging stations and synchronized mobile battery swapping (EVRPTW-RS-SMBS). In order to increase the complexity of instances, instead of using the time windows presented by Schneider et al. (2014), the authors proposed to modify the time windows presented by Solomon (1987a).

Another proposed instance set related to time windows was presented by Bredström and Rönnqvist (2008) for VRPTWSyn. This set is used in a simulation context of the home-care staff scheduling problem with synchronized visits. The authors proposed five small-size instances (20 customers) and five real-size instances (between 50 and 80 customers). This set is classified into five groups depending on the duration of time windows: no time windows restrictions (A), ranging from fixed (F), small (S), medium (M), and large (L). This set is used in the research conducted by Ettazi et al. (2021) to test the approaches for VRPTW-SPFC, and by Masmoudi et al. (2018) to solve the HF-VRPS.

In order to address simultaneous pickup and delivery demands in the GVRP context, two set of instances are used by Olgun et al. (2021) to solve the G-VRPSPD. The first set of instances is based on those proposed by Salhi and Nagy (1999), which are based on Christofides et al. (1979) instances and proposed a set of 28 instances for the VRPSPD with customers between 50 and 199, using the same coordinate sets and demand matrices. The first 14 instances are known as CMTX, while CMTY is used to denote the remaining ones, which are generated based on CMTX by exchanging the delivery and pickup demands for customers. The second set is based on the instances of Dethloff (2001) with 40 cases involving 50 customers. Two distinct geographic scenarios (SCA and CON) are investigated for this collection. The coordinates of the customers are evenly dispersed throughout the interval between 0 and 100 in the scenario SCA, whereas, in CON, half of the customers are dispersed in the same way as in the SCA scenario, but the coordinates of the other half are in the range between $100/3$ and $200/3$.

Regarding the existing benchmark for PVRP, *Chao-Golden-Wasil* Chao et al. (1995) presented a set of 19 instances (e.g., López-Sánchez et al. (2021) for Bi-PVRP-SC). The locations of the customers and depot in this set take the form of a windmill (1-10) or a Star of David (11-19) with planning periods of 4 and 6 days, respectively. In addition, there are three types of customers for each form depending on the number and frequency of visits required. Referring to the instances generated for MDVRP, the most frequently used one is that which is cited by Cordeau et al. (1997), named as *Cordeau* instances. The authors presented a set of 23 instances based on the sets from Christofides et al. (1979) (instances 1-7), Gillett and Johnson (1976) (instances 8-11), and Chao et al. (1995) (12-23). There are many investigations on green multi-depot VRP that used this set of instances, such as MD-GVRP in Wang et al. (2019), GMDVRPTW in Kaabachi et al. (2017).

On the other hand, Iori et al. (2007) presented a set of instances for the 2LCVRP that has been used by several investigations on GVRP, such as cold chain logistics path optimization in Zhao et al. (2020b) and the 2L-MDCVRPB in Zhao et al. (2020a). These instances are based on the CVRP instances Reinelt (1991); Toth and Vigo (2002), using the same capacity of the vehicles and the coordinates and weights for customers. The 2LCVRP benchmark is divided into five classes of instances. The fist class consists of assigning each customer a single item having both sizes equal to 1 and by setting the width and height equal to the total number of customers. The remaining classes are generated by using an adaptation to a two-dimensional bin packing problem following a heuristic procedure proposed by Martello et al. (2000). Perboli et al. (2011) introduced four sets of instances for the 2ECVRP. These sets contain up to 50 customers and one depot. The first three sets are based on Christofides and Eilon (1969) (denoted as E-n13-k4, E-n22-k4, E-n33-k4, and E-n51-k5). The fourth set is from the work of Crainic et al. (2010) and consists of randomly produced examples that replicate customer and satellite distributions typical of city logistics distribution. See the investigations proposed by Mühlbauer and Fontaine (2021) about 2E-CVRPSC and Jie et al. (2019) for 2E-EVRP-BSS, which used this set of instances in green multi-echelon distributions contexts.

Recently, based on several cities from the United Kingdom with requirements associated with time intervals and service times, Demir et al. (2012) proposed the PRPLIB. This library consists of nine sets of 20 instances with a number of customers between 10 and 200. PRPLIB is one of the most commonly used benchmarks in the literature (e.g., TD-PRP in Franceschetti et al. (2017), FSMPRP in Koç et al. (2014), PRP in Kramer et al. (2015)) and has served as the basis for the creation of new sets of instances. For instance, Kramer et al. (2015) modified the PRPLIB to create two additional sets called tighter time windows (e.g., BiPRP in Costa et al. (2018), TD-PRP in Franceschetti et al. (2017)). On the other hand, Goeke and Schneider (2015) adjusted the PRPLIB for the E-VRPTW with a mixed fleet (see GMFVRPREC-PR in Yu et al. (2021)).

From the proposed benchmarks, 54.81% were based on artificially generated instances used, while the rest considered real-world data. In order to analyze the use of proposed instance sets, Figure 2.7 shows how the proposed benchmarks have been used in terms of the number of works. As can be seen, many studies were focused on the instances proposed by Demir et al. (2012) (24.59%). Also, the set proposed by Solomon (1987a), besides being commonly used in VRPs problems, is also relevant in GVRPs (19.67%). The instances proposed by Christofides and Eilon (1969) and Christofides et al. (1979) are part of the first instances presented in the literature for CVRP and have been moderately used in GVRPs (with 8.20% each). This behavior is also observed for the instances proposed by Augerat (1995) and Golden et al. (1998), which are only used in 6.56% of the investigations studied. The remaining instances have usage percentages below 5%, and the sum of them represents 26.24%. It is worth noting that their low usage can be due to the fact that these instances consider specific characteristics from their corresponding problems (see the previous Table 2.5).

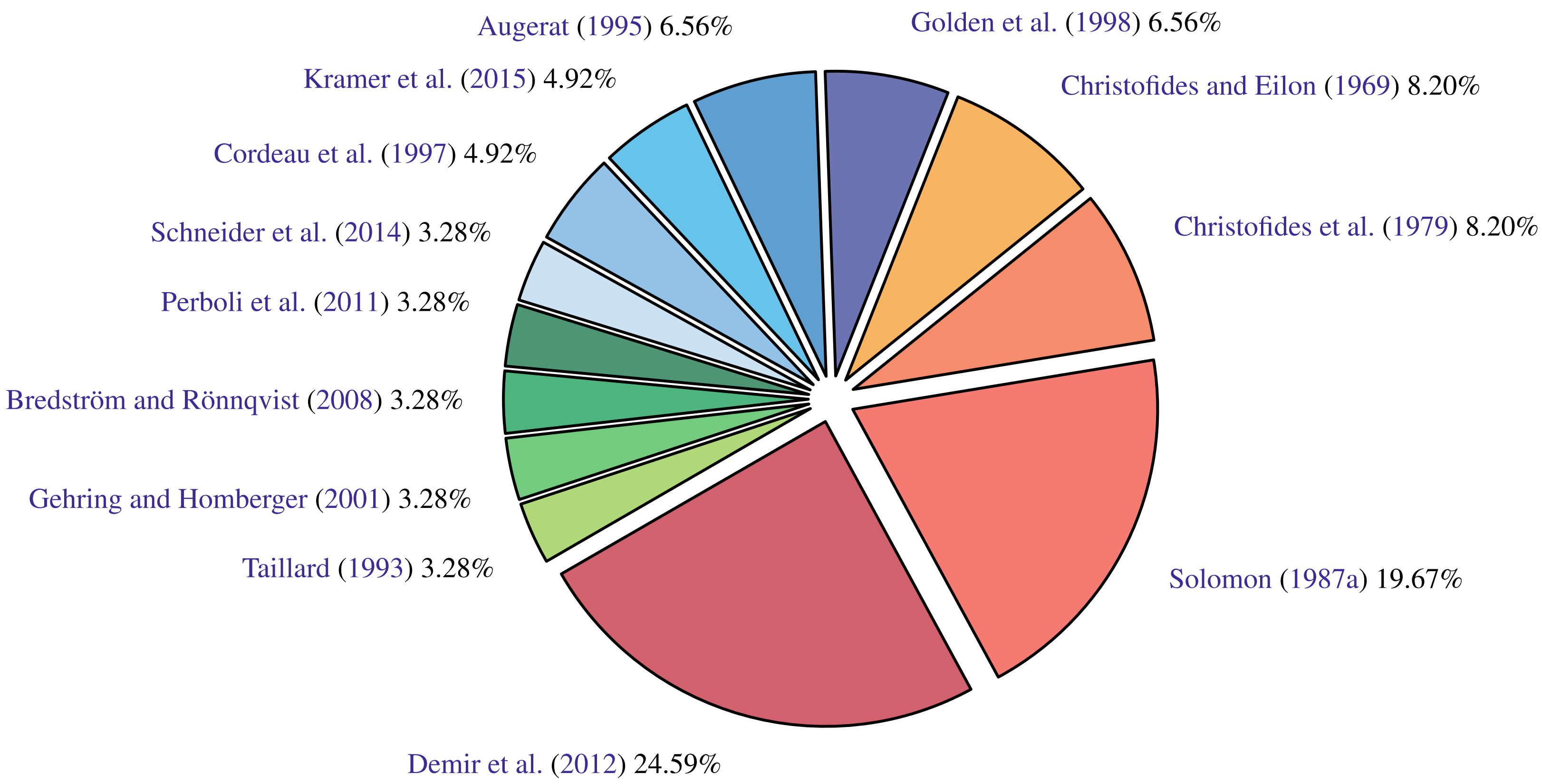


Figure 2.7: Pie chart of the different benchmarks used for GVRPs. The pie chart visualizes the utilization percentage of each benchmark instance for the reviewed papers.

Chapter 3

Soft and Hard Time Windows in Cumulative VRP

3.1 Introduction

Fuel consumption is the main factor for calculating emissions due to road transport. It can be defined by several factors (Demir et al., 2014b), e.g., distance traveled, weight and speed of the vehicle and traffic. Thus, given the current need to reduce environmental pollution, optimization problems are being reviewed to consider it during the freight distribution planning process. In this regard, the cumulative vehicle routing problem (CumVRP) (Kara et al., 2008) emerged as a relevant routing variant for taking into account environmental aspects. Its objective is to minimize a cumulative cost function, enabling the calculation of emissions based on the distance traveled by a vehicle carrying a certain load along with the realization of the route. In the last decades, CumVRP has attracted more attention since it considers fuel consumption as an important component when optimizing resources to reduce CO_2 emissions (Singh and Gaur, 2017), an aspect that places it in the green routing field (Demir et al., 2014b).

Another common variant in freight distribution is the vehicle routing problem with time windows (VRP-TW) (Laporte, 1984; Laporte et al., 1988; Solomon, 1987b), where customers must be visited within predefined time windows. VRP-TW has to be frequently faced by several transport and logistics companies, such as courier, parcel and express mail services where customers must be served within a given time interval. When considering time windows, it can be distinguished between hard and soft time windows. In the hard time windows case, a vehicle must serve customers strictly within the specified time interval, if the vehicle arrives earlier it will have to wait to start the service and late arrival is not allowed. The soft time windows case defines a specific interval in which each customer must be attended, but the violation of the time window constraints is allowed subject to some penalty (Xia and Fu, 2019). Depending on the application, the use of soft time windows can reflect practical situations much better than hard time windows (Fagerholt, 2001). Currently, transport companies are committed to caring for the environment but at the same time want to keep their customers as satisfied as possible in terms of the time slots they have or prefer to receive the service.

Here, we are focused on the integration in an extensively mathematical formulation for hard and soft cases of a different cumulative objectives that considers fuel consumption parameters and vehicles' load along routes as well as customers' time window restrictions. These variants, CumVRP with Hard TW (CumVRP-HTW) and with Soft TW (CumVRP-STW), permit evaluating the trade-off between time windows, emissions, and costs.

Furthermore, to obtain a trade-off between time windows and emissions, the soft time windows version is also proposed. In that version, we seek to reduce fuel consumption through delays in the service start time. Such delays are subject to penalties and customers' priority that will depend on the importance of each customer defined by the company or logistics context. By means of this version, solution approaches can look for a balance between the reduction of fuel consumption and penalties due to time-windows delays.

The details of this study are presented as follows. Section 3.2 provides a summary of the related works. The proposed optimization problem, CumVRP-TW considering hard and soft time windows is introduced in Section 3.3. Section 3.4 describes the analytical fuel consumption model used to optimize the environmental impact. In Section 3.5, a matheuristic approach is developed and presented for solving this problem. Section 3.6 reports the computational experiments and results.

3.2 Related works

Green routing promotes sustainable mobility, safety, and reduce negative effects on the environment (Eglese and Black, 2015; Moghdani et al., 2021). In this regard, CumVRP belongs to the problems within the green routing area as their consider vehicles load gradually getting lighter when the delivery process is performed, causing less CO_2 emissions as the vehicle is moving through a route (Demir et al., 2014b). In the following, we discuss the literature related to our current research. In doing so, we first review works related to CumVRP. Second, we consider related studies that model green aspects (e.g., fuel consumption, environmental pollution) and take into account time windows constraints.

Several approaches in the literature considered the contribution of vehicles' load on fuel consumption, and in consequence on CO_2 emissions. Kara et al. (2007) and Kara et al. (2008) were the first vehicle routing work proposed a cost function as a sum of the product between load and distance for each arc. The authors demonstrated that routes showing energy reductions tend to be longer than solutions based on minimizing distances. Cinar et al. (2016) presented a two-phase constructive heuristic algorithm for solving CumVRP with Limit Duration and minimizing the total fuel consumption. The authors used the classification of vehicle categories proposed by Kopfer et al. (2014) for determining the fuel consumption parameters. The same authors in Cinar et al. (2015) presented a MILP and simulated annealing (SA) for solving the Cumulative Multi-Trip VRP with Limited Duration. The authors considered the minimization of fuel consumption as the objective function taking into account multiple trips and a limited duration in the travel time for each vehicle. Moreover, that objective considered the distance and load of the vehicle and the fuel consumption parameters from (Kopfer et al., 2014). According to the reported results, a 10% of reduction in fuel consumption was achieved without increasing the distance and the number of vehicles for small instances of customers. The SA provided high-quality results for large size instances where the performance of the MILP was limited.

In addition to VRPs considering cumulative costs, there are several studies considering time windows and green aspects. For instance, Tang et al. (2009) proposed the VRP with Fuzzy Time Windows by means of a multi-objective formulation aiming to minimize the distance and maximize the service level. The key aspect of that formulation was the use of fuzzy membership functions to characterize the service level issues related to time window violations. The results showed improvements in terms of distance and time when the relaxation of time window constraints is allowed. Also, they indicated that time windows can sometimes be violated for economic, operational, or even environmental reasons. We seek to verify this in this study by comparing the use of hard and soft time windows. Macrina et al. (2019b) investigated the Green Mixed-Fleet VRP with Partial Recharges and Time Windows. The authors proposed a MILP formulation with the objective function based on the sum of four components: cost of the energy recharged during the route, cost of the energy recharged to the depot, and fuel and travel costs. For solving their problem, the authors use their optimization model for solving small-scale instances, and an iterative local search for large-scale instances. Song et al. (2020) addressed the Heterogeneous VRP-TW in the cold chain logistic where all vehicles have different capacities and energy consumption values. In that problem, the objective was to minimize the total cost and energy consumption. Bektaş and Laporte (2011) presented the pollution routing problem (PRP), which seeks to minimize both operational and environmental costs by taking into account customers' time-windows constraints. The total travel distance, the amount of load carried per distance unit, the vehicle speeds, and the duration of the routes were the main costs. The results showed the positive impact of using speed variable decisions under time windows constraints. Kramer et al. (2015) developed a matheuristic approach integrating a local search-based metaheuristic with MILP formulation for the PRP. The authors proposed two additional instance sets with a tighter time window by modifying those already existing in the PRPLIB. This set of benchmarks is suitable for this study because it has tighter time windows and, in this sense, will allow us to observe the advantages of violating time windows in the benefit of reducing emissions. Xu et al. (2019) proposed a multi-objective nonlinear model for solving the green vehicle routing problem (GVRP) that minimizes carbon emission while maximizing customer satisfaction by considering soft time windows constraints. For solving that problem, the authors presented an improved non-dominated sorting genetic algorithm considered a method to optimize multi-objective problems. Their computational experiments showed that emissions can be significantly reduced with a negligible decrease in customer satisfaction. This study has focused on the objective function presented in Cinar et al. (2016) which is more realistic in terms of fuel consumption and the limited duration constraints consider a single time interval for the depot and we consider the existence of time slots for all customers.

Concerning the calculation of fuel and emissions costs in routing problems, there are several studies measuring and evaluating the environmental and monetary impact on routing operations in diverse ways. For instance, Palmer (2007) was one of the first to take into account environmental aspects in VRPs, such as congestion and vehicle speeds to produce a CO_2 emissions grid. The author investigated the effect of speed in reducing emissions for different traffic congestion scenarios and also takes into account time windows restrictions. Zhang et al. (2020a) addressed the multi-depot version of the GVRP to minimize the total carbon emissions that were calculated by multiplying the total traveled distances by the carbon emission conversion factor (CCF) for hydrogen-fueled vehicles. It is worth highlighting that in this study we consider the distances multiplied by the vehicles' load in terms of fuel consumption and a carbon emission conversion factor for fuel consumption (e.g., petrol, diesel). With regards to vehicles' fuel consumption, there is a set of indicators used in research to consider in fuel consumption models. A unit of litre of fuel consumed has an estimated emissions factor value of 2.32 kgCO_2e/litre for petrol vehicles (Veidenheimer, 2014). Also, there were several works estimated the social costs of CO_2 emissions, as well as the costs of reduction. Piecyk et al. (2015) for instance, reported the cost of CO_2 per ton emitted is equivalent to €25. The paper by Ehmke et al. (2018) used the fuel price of €1.19/litre. Moreover, in the context of costs related to time windows problems, Hossain et al. (2017) reported penalty cost for late arrivals to the customer of \$2190 per year (equivalently \$6 per day).

Regarding penalty costs, the companies can provided themselves with the highest penalty cost for customers with the highest importance, that is, the highest priority. A preference priority can be assigned to the customers such that preferred customers can be visited as first (Tarhini et al., 2022). Consequently, there were many approaches to establish customers' priority (e.g., time-based priority, distance-based priority, demands/weight-based priority). The work of van Benthem et al. (2020) presented an approach to address a Bi-objective Rich VRP considering customers' prioritization. The authors minimized transportation costs and customer' waiting times. They proposed a customers' classification: (i) priority customers with smaller time windows, and (ii) non-priority customers with bigger time windows. Also, to differentiate between both types of customers, the time deviations were penalized by a specific value that can be set higher for priority customers than for non-priority customers. Moghaddam et al. (2012) addressed a CVRP variant with uncertain demands where each customer that has the closest distance to a vehicle's location will have a high priority to be allocated to that vehicle. The authors of Tang et al. (2013) tackled a Split-Delivery Weighted VRP where the weight was used as the importance or priority of customers in the delivery goods process. Other approaches based on customers' prioritization can be seen in Adebayo et al. (2019) and Carreto and Baker (2002). We consider in this study an approach for customer priority based on customer's demands, which can provide the importance that each customer has for a specific company.

Considering the aforementioned discussion, in this study we calculate the costs associated with fuel consumption based on the CumVRP presented in Cinar et al. (2016), the cost presented in Ehmke et al. (2018); Piecyk et al. (2015), and emission factor described in Veidenheimer (2014). Furthermore, we study the effects of soft time windows on fuel consumption and CO_2 emissions to verify if the behavior of soft time windows reported in VRP investigations persists when we assess CumVRP. The penalty costs due to delays are based on Hossain et al. (2017). We assume in this research the fuel consumption parameters α and β proposed in Kopfer et al. (2014), which are obtained according to vehicle gross weight and load capacity.

3.3 Problem definition

The cumulative vehicle routing problem with time windows (CumVRP-TW) can be defined as follows. Let $G = (V, A)$ be a directed graph, where V is the node set that contains all nodes (i.e., customer and depot) and A is the set of arcs. A travelling distance, $d_{ij} > 0$, is defined for each arc between each pair of vertices $(i, j), i, j \in V, i \neq j$. In the CumVRP-TW, the number of vehicles is unlimited and all vehicles have the same capacity Q. The vehicle's speed $\mathcal{V}$ is set to a constant value, 90 km/h. Moreover, each customer $i \in V$ demands a quantity of goods q_i and has time interval $[l_i, u_i]$ that represents the lower and upper limits of the time window during which each customer must start to be served (see Figure 3.1(a)) and s_i is the service time it takes to serve a customer, $s_i > 0$. Also, in this research we consider the soft time windows case where there is a priority p_i for each customer. The δ_1 and δ_2 parameters of transformations are the fuel cost and penalty cost associated to the delivery tardiness, respectively. Figure 3.1(b) shows the $\rho_{max} > 0$ allowance for violation of time windows, indicating that the time windows per customer can be extended into the range $[l_i,\, u_i + \rho_{max}]$.

The CumVRP-TW aims at minimizing the cumulative cost due to fuel consumption when performing the delivery to customers while respecting their corresponding time windows. Furthermore, a solution has to satisfy the following conditions: (a) each customer has to be served exactly by one vehicle, (b) each route starts and ends at the depot, (c) for each tour, the flow on the arcs increases as much as preceding node's supply in the case of collection or diminish as much as preceding node's demand in the case of delivery, (d) the flow on any arc of each tour does not exceed the flow capacity of the arcs, and (e) the total demand of the customers must be satisfied.

In the following, we introduce mathematical formulations for solving two cases of CumVRP-TW studies in this investigation. Namely, the hard time window case (i.e., CumVRP-HTW) and the soft time window case (i.e., CumVRP-STW), both extended from CumVRP (Kara et al., 2008; Singh and Gaur, 2017). The main objective of these formulations is to minimize the costs due to fuel consumption, the emissions deduced from fuel consumption and the total penalty for delays. To calculate fuel and emission costs, we use the parameter of transformation δ_1 defined as follows:

$\delta_1 = C_F + C_E E_F$

where C_F represent a fuel cost, C_E is an emission price, and E_F is the emissions factor.

The decision variables are the following:

- x_{ij} takes the value of 1 if any vehicle goes from i to j, 0 otherwise.
- t_i represents the time at which the service begins for the customer i.

The mathematical models for the CumVRP-TW, depending on the time windows consideration, are defined as follows.

$$(\textit{CumVRP-HTW}) \text{ minimize } \quad f_K = \delta_1 \sum_{i=0}^{|V|} \sum_{j=0}^{|V|} d_{ij}(\alpha x_{ij} + \beta w_{ij}) \tag{3.1}$$

This objective minimizes the total cost based on fuel consumption and CO_2 emissions, assuming the proportionality between the rate of fuel consumption per unit of distance and the weight of the vehicle. The parameters α and β represent the cost of moving an empty vehicle per unit of distance and the cost of moving the unit weight of goods per unit distance, respectively.

$$(\textit{CumVRP-STW}) \text{ minimize } \quad f_S = f_K + \delta_2 \sum_{i=0}^{|V|} p_i \Delta_i^u \tag{3.2}$$

This objective minimizes the value of f_K added to the penalty cost due to service delay, where $\Delta_i^u = \max\{0,\ t_i - u_i\}$ represents the violation of time windows.

subject to:

$$\sum_{i=0}^{|V|} x_{ij} = 1, \qquad \forall j \in \{1 \dots |V|\} \tag{3.3}$$

$$\sum_{i=0}^{|V|} x_{ij} - \sum_{k=0}^{|V|} x_{jk} = 0, \qquad \forall j \in \{0 \ldots |V|\} \tag{3.4}$$

$$w_{0j} \leq Q x_{0j}, \qquad \forall j \in \{1 \ldots |V|\} \tag{3.5}$$

$$w_{i0} = 0, \qquad \forall i \in \{1 \ldots |V|\} \tag{3.6}$$

$$\sum_{j=0}^{|V|} w_{ji} - \sum_{k=0}^{|V|} w_{ik} = q_i, \qquad \forall i \in \{1 \ldots |V|\} \tag{3.7}$$

$$w_{ij} \leq (Q - q_i) x_{ij}, \qquad \forall i,j \in \{0 \ldots |V|\} \tag{3.8}$$

$$t_i \geq l_i, \qquad \forall i \in \{0 \ldots |V|\} \tag{3.9}$$

$$t_i \leq u_i, \qquad \forall i \in \{0 \ldots |V|\} \tag{3.10}$$

$$t_j \geq (t_i + s_i + (\frac{d_{ij}}{\mathcal{V}})) x_{ij}, \qquad \forall i,j \in \{1 \ldots |V|\} \tag{3.11}$$

$$u_0 \geq (t_i + s_i + (\frac{d_{i0}}{\mathcal{V}})) x_{i0}, \qquad \forall i \in \{1 \ldots |V|\} \tag{3.12}$$

$$\sum_{j=1}^{|V|} x_{0j} \geq \left\lceil \frac{\sum_{j=0}^{|V|} q_j}{Q} \right\rceil, \tag{3.13}$$

$$x_{ij} \in \{0,1\}, \qquad \forall i,j \in \{0 \ldots |V|\} \tag{3.14}$$

$$w_{ij} \geq 0, \qquad \forall i,j \in \{0 \ldots |V|\} \tag{3.15}$$

$$t_i \geq 0, \qquad \forall i \in \{0 \ldots |V|\} \tag{3.16}$$

Constraints (3.3) establish that each customer is only accessed through an arc. Constraints (3.4) enforce the in-degree of each customer to be equal to the out-degree. The curb weight of the truck is not considered in the flow allowed in an arc. Constraints (3.5) ensure that the initial flow of a route does not exceed the maximum capacity of the vehicle. Constraints (3.6) guarantee that vehicles do not return loaded to the depot. Constraints (3.7) establish that the demand required by each customer is satisfied. Constraints (3.8) activate the variable x_{ij} if there is a flow greater than 0 by the arc (i, j). Constraints (3.9)-(3.11) guarantee that the start time of customer service i is within the defined time window limits for the vertex i. Constraints (3.12) guarantee that there is no delay in the return time to the depot. Constraint (3.13) sets a lower bound over the number of vehicles required to serve the customers. Constraints (3.14) define binary variables x_{ij}. Constraints (3.15) and (3.16) ensure the no negativity of the variables w_{ij} and t_i, respectively.

For the soft time windows case, constraints (3.3)-(3.9) and (3.11)-(3.16) remain the same in the in the model. However, constraints (3.10) are replaced by (3.17) to allow a threshold ρ_{max} of delay.

$$t_i \leq u_i + \rho_{max}, \qquad \forall i \in \{1 \ldots |V|\} \tag{3.17}$$

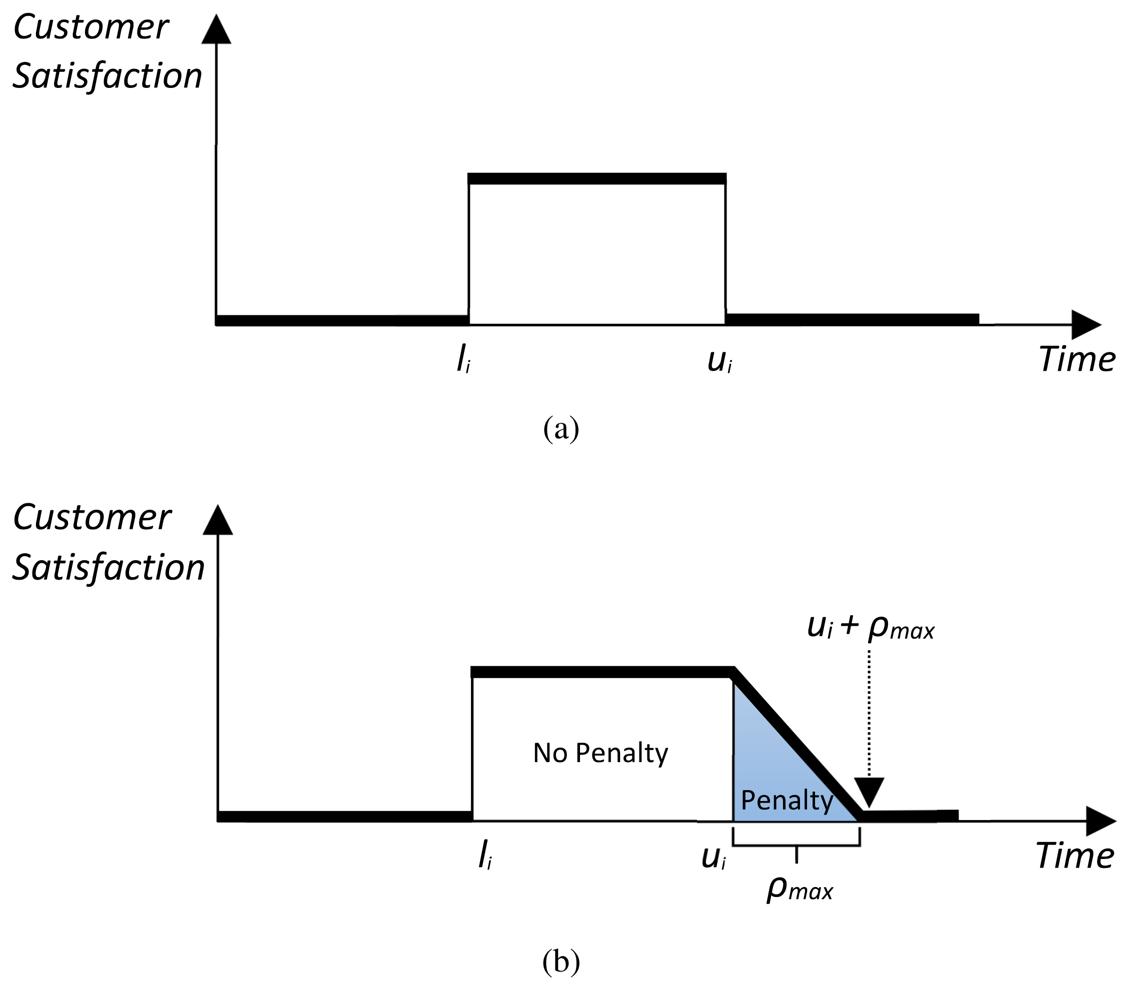


Figure 3.1: Illustration of customer satisfaction region without early or late arrivals (a) and customer satisfaction region and allowing late arrival of vehicles (b).

3.3.1 Problem example

In order to improve understanding of the CumVRP-HTW and CumVRP-STW, we show an example composed of 10 customers $\{c_1, c_2, \ldots, c_{10}\}$, a node depot and unlimited vehicles with load capacity of 3.650 ton (3650 Kg). The coordinates, demands, and time windows of each customer are reported in Table 3.1.

Figure 3.2 shows an example of a solution of the CumVRP-HTW and CumVRP-STW. The time window limits $[l_i, u_i]$ as well as the start time service s_i for each customer are provided. The thick lines represents the level of load of the vehicle that is diminishing as the customers are being serviced. Figure 3.2(a) shows the route performed among thick lines in hard time case. The route followed by the $vehicle_1 = \{c_6, c_5, c_{10}, c_9, c_3, c_7\}$ and by $vehicle_2 = \{c_2, c_4, c_1, c_8\}$. The $vehicle_1$ depart from the depot and initially visits the customer c_6 with the start time service of 6462 sec, satisfying time windows constraints. The total load carried by the vehicle between depot and customer c_6 is 3.425 ton, while the distance travelled is 33.00 km. After servicing that customer, the vehicle load is reduced in 0.679 ton (customer demand) and is updated to 2.746 ton. The route of both vehicles is carried out respecting in each case the corresponding time windows constraint. The total value of cumulative cost equivalent to fuel consumption for this solution is 90.14 litres, composed by the following values: $\big((cost_{0,6} = 7.45)$ + $(cost_{6,5} = 6.68)$ + $(cost_{5,10} = 11.99)$ + $(cost_{10,9} = 6.48)$ + $(cost_{9,3} = 7.29)$ + $(cost_{3,7} = 8.82)$ +

Table 3.1: Example customer parameters.

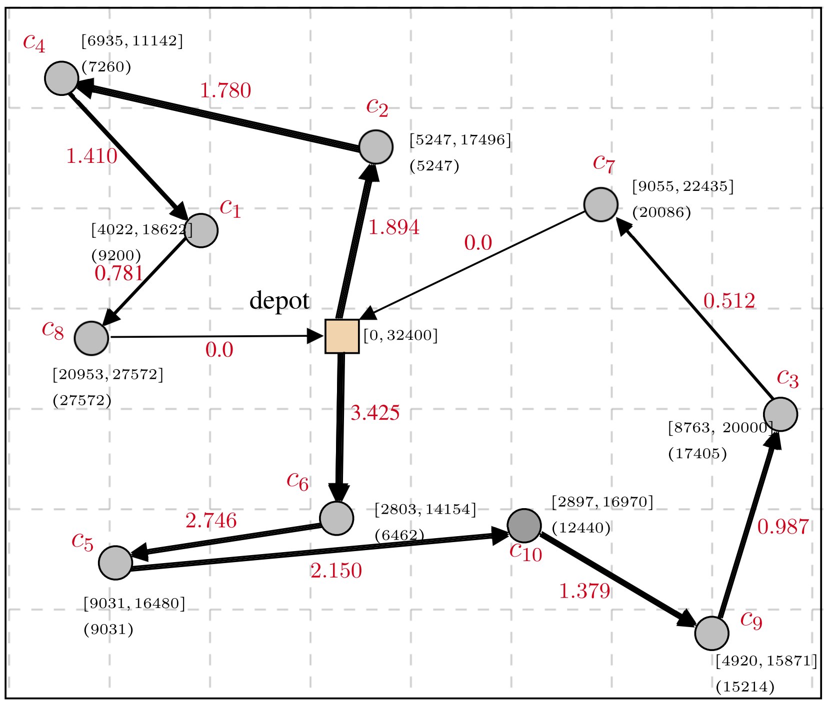
Customer	Coordinate ($\cdot 10^3$)	Demand (t)	Time Windows
0	[45, 58]	0.000	[0, 32400]
1	[25, 7]	0.629	[4022, 18622]
2	[50, 87]	0.114	[5247, 17496]
3	[104, 44]	0.475	[8763, 20000]
4	[70, 990]	0.370	[6935, 11142]
5	[15, 21]	0.596	[9031.16480]
6	[45, 25]	0.679	[2803, 14154]
7	[80, 80]	0.512	[9055, 22435]
8	[12, 58]	0.781	[20953, 27572]
9	[95, 10]	0.392	[4920, 15871]
10	[70, 28]	0.771	[2897, 16970]

$(cost_{7,0}\ =\ 8.26)$) + (($cost_{0,2}$ = 6.31) + ($cost_{2,4}$ = 9.53) + ($cost_{4,1}$ = 6.32) + ($cost_{1,8}$ = 4.41) + ($cost_{8,0}$ = 6.60)$\big)$. Figure 3.2(b) shows the route performed in soft time case. The routes for the different vehicles are: $vehicle_1 = \{c_5, c_6, c_{10}, c_9, c_3, c_7\}$ and by $vehicle_2 = \{c_2, c_4, c_1, c_8\}$. The fuel consumption value of this solutions is 86.92 litres. In this case, the time windows of the customers can be violated incurring in a penalty time, and at the customer c_9 is violated in 702 sec (reflected in red color) and this make different route for $vehicle_1$. The penalty time is calculated of the following values: $(s_{c9} - u_{c9})/60 = (16573 - 15871)/60 = 11.70$ min.

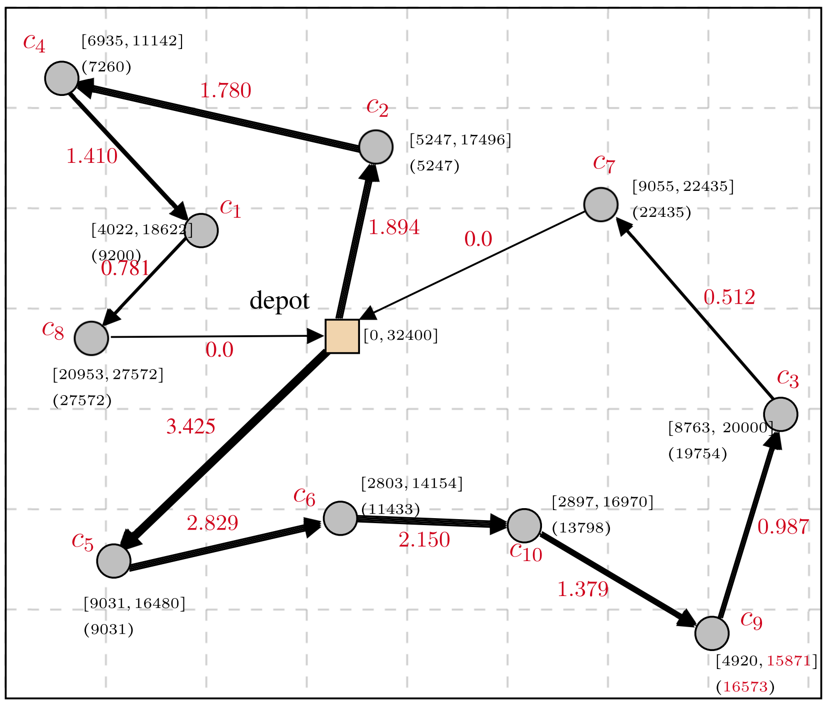
As can be seen in this illustrative example, the use of soft time windows allows a short delay time of 11.70 min in the start time of service to a customer, representing a reduction in fuel consumption of 3.22 litres. The use of late arrival penalties achieves more effective reductions in fuel consumption as problem instances increase in size.

3.4 Optimising environmental impact

According to Eglese and Bektaş (2014), there are two ways to estimate fuel consumption for vehicles: on-road measurements, which are based on the real-time collection of information on emissions in vehicles in operation; and the analytical fuel consumption models, which estimate fuel consumption based on the variable parameters of a vehicle, traffic parameters, such as vehicle speed, load and acceleration.



(a)



(b)

Figure 3.2: Example of a solution for (a) CumVRP-HTW and (b) CumVRP-STW with 10 customers.

In this research, we use the analytical fuel consumption model based on the investigations of Cinar et al. (2016) and Gaur and Singh (2017), where the cumulative cost is used as a notion of fuel consumption. Our estimation takes into account the so-called fuel consumption parameters α and β, that is, the cost of moving an empty vehicle per unit of distance and the cost of moving the unit weight of goods per unit distance, respectively. These parameters were presented as part of classification vehicle categories by Kopfer et al. (2014) and it can see en Table 3.2.

Table 3.2: Classification of vehicle categories proposed by Kopfer et al. (2014).

Vehicle category VC_{VWG} (-)	Gross vehicle weight GVW (ton)	Load capacity Q (ton)	Fuel consumption F_K $(litre/100\,km)$ $\alpha + (\beta/ton)q$
$VC_{3.5}$	3.50	1.50	8.00 + (3.31/ton)q
$VC_{7.5}$	7.50	3.25	15.00 + (1.54/ton)q
VC_{12}	12.00	5.50	20.00 + (0.76/ton)q
VC_{40}	40.00	25.00	26.00 + (0.36/ton)q

The vehicle emissions are directly proportional to fuel consumption. To estimate the CO_2 emissions, we use the fuel-based calculation method. This method multiplies the amount of fuel consumed on a particular route by the corresponding emissions factor $E_F = 2.32$ kgCO_2e/litre for vehicles that use petrol as fuel (see Veidenheimer (2014)). Thus, the formula applied for the calculating emissions is as follows:

$$CO_2\_emissions(kg) = fuel\_consumption(litres) \times emission\_factor(kgCO_2e/litre) \quad (3.18)$$

3.5 Matheuristic approach for the CumVRP-TW

In order to solve CumVRP-TW introduced in the previous section, we propose a matheuristic approach that combines a Greedy Randomized Adaptive Search Procedure (GRASP) metaheuristic algorithm and the exact solving of the optimization model. The GRASP algorithm (Feo and Resende, 1995) is a multi-start or iterative method where each iteration has three main phases: pre-processing, constructive, and post-processing. There are several applications of this technique to a wide range of VRPs, such as multiple-routes (Martínez-Salazar et al., 2015), multi-period pickup and delivery (Al Chami et al., 2018), and waste-collection (Expósito-Márquez et al., 2019).

Our matheuristic is based on the cluster first-route second approach. The basic idea is to group the customers in several sets, through a clustering process to partition the customers, considering the distance among customers and obtaining $V_c = \{cs_i, cs_{i+1}, \ldots, cs_k\}$ clusters with each $cs_i = \{c_j, c_{j+1} customers, \ldots, c_n\}$, $\forall c_j \in V$. Clustering algorithms consider that locations within a short distance (Santini et al., 2021). Subsequently, starting from clustered customers V_c, we proceed with a routing process using a constructive heuristic resulting in a set of subtours. As post-processing, a partial optimization procedure inspired in the research of Queiroga et al. (2021) and Lalla-Ruiz and Voß (2020) is applied to improve the solution obtained. This partial optimization method creates several subproblems up to a specific dimension, and each subproblem is solved through an exact solution approach. This routing and improvement process are repeated for a fixed number of iterations.

Algorithm 1 describes the generic structure of GRASP matheuristic approach. This approach has four inputs: (i) rcl value for the constructive phase; (ii) σ value for the dimension of each subproblem; (iii) an exact solver Φ to solve the created subproblems; and (iv) number of iterations of the matheuristic Max_Iter. Initially, a pre-processing procedure is carried out where the data is read and ordered, the necessary parameters are initialized, and the customers are clustered (line 2). In each iteration, starting from the sets of clustered customers, an initial solution of the problem is constructed (line 5). An improvement procedure is performed on the initial solution provided (line 6), and the best solution found is updated (lines 7-8). Finally, the matheuristic's output consist of the best solution found in all iterations $\mathcal{S}_{best}$.

In Figure 3.3, we have a solutions of our matheuristic approach for all phases.

Algorithm 1: The generic structure of matheuristic approach

Input parameters: $rcl\,, \sigma\,, \Phi\,, Max\_Iter$
$V_c\,, Q_c$:= Pre-processing_phase ();
$\mathcal{S}_{best} := \varnothing$, i := 0;
while $i < Max\_Iter$ **do**
    $\mathcal{S}$:= Construction_phase $(rcl\,, V_c\,, Q_c)$;
    $\mathcal{S}^+$:= Post-processing_phase $(\mathcal{S}\,, \sigma\,, \Phi\,)$;
    if $f(\mathcal{S}^+)$ *improves* $f(\mathcal{S}_{best})$ **then**
        $\mathcal{S}_{best} := \mathcal{S}^+$;
    $i = i{+}1$;
Output $\mathcal{S}_{best}$;

3.5.1 Pre-processing

The pre-processing phase considers two steps: (i) clustering the set of customers V using k-medoid resulting V_c (also named partitioning around medoids (PAM) (Aggarwal and Reddy, 2014)); and (ii) initializing a set of vehicle capacities Q_c with Q.

The first step consists of using the clustering method to generate a set of clustered customers V_c with a possible meaningful impact on the constructive solution quality. k-medoid is a widely used partitional clustering method (see Bührmann and Bruwer (2021); Qi et al. (2012); Wang et al. (2014)), which given the set of representative customers or medoids k, the remaining customers in the cluster cs_i are assigned to the closest (employing the distance metric) representative one. Medoids are changed in an iterative procedure, looking for a better distribution of the clusters. The goal is minimizing the sum of the distances of the respective medoids to all items $\left(\sum_{c_i}^{|k|}\sum_{c_j}^{|cs_i|} d_{c_i,c_j}\right)$. The number of medoids and clusters is determined as $|k| = |V_c| = \left\lceil \frac{\sum_{i=1}^{|V|} q_i}{Q} \right\rceil$.

In the second step, we generate the set of Q_c consisting of k vehicle's capacities with identical load capacities Q. Q_c provides to the routing phase the initial number of vehicles in fulfillment with the constraints (3.13).

3.5.2 Construction

The construction phase uses a greedy heuristic algorithm to route the customers. The algorithm iteratively selects a new random element (candidate) from the Restricted Candidate List (RCL) to be assigned to the vehicle or subtour in progress. This routing considers in the heuristic the capacity restrictions of the vehicle on each arc, as well as the existing time windows for each customer.

Algorithm 2 depicts a construction phase of our matheuristic approach and received the previous parameters rcl , V_c , and Q_c. Initially, at each iteration, a feasible solution to the problem is constructed to make as few subtours as possible. Each subtour starts at the depot, and for each pair of customers in a cluster, the possible start services time are calculated (lines 5-11). Subsequently, $V_c[k]$ is sorted using the greedy heuristic function, i.e., min $(c_i.t_i < c_{i+1}.t_{i+1})$ (line 12). The RCL is constructed by limiting the candidate list size in the first rcl candidates (lines 13 and 14). After that, in (line 15), a candidate is randomly selected from the RCL considering the available capacity of the vehicle and upper bound time windows restrictions (see constraints (3.10) and (3.17) for hard and soft time windows cases, respectively), the candidate is added to the corresponding subtour (lines 16-19). Note that for the soft time windows case, the threshold value ρ_{max} is added to the upper bound time windows of the selected candidate, that is $cand.u_p + \rho_{max}$ in (line 16). If the demand of the customer is greater than the current capacity of the vehicle or the start services times are not satisfied, the current candidate is assigned to the next cluster to try to assign it to another subtour (line 26). Note that if the index k matches the number of clusters, new variables and capacities are generated (lines 22-26). The subtour construction process is performed while there are unvisited customers (line 4). Once the routing process for the subtours construction is finished, complying with the hard or soft time windows, a feasible solution to the problem is generated in $\mathcal{S}$.

3.5.3 Post-processing

The post-processing phase aims to improve the quality of the feasible solution $\mathcal{S}$ provided by the construction phase. In this phase, we implement a procedure to optimize partially subproblems built from the original subtours of $\mathcal{S}$ (see Algorithm 3). At the beginning of the algorithm, we copy the initial solution $\mathcal{S}$ into $\mathcal{S}^+$. $\mathcal{S}^+$ contains a set of subtours (routes) $\{r_i, r_{i+1}, \dots, r_{|\mathcal{S}^+|}\}$. In order to know the subtours that contain poor quality seeds, the original format of $\mathcal{S}^+$ is transformed, replacing each subtour r_i as a pair $(r_i, 0)$ or $(r_i, 1)$, with $i \in |S^+|$. In addition, if a subtour has a size greater than the subproblem's dimension σ, the corresponding tuple will be $(r, 1)$ (line 3). π represents the subproblem to be optimized, while π' represents a copy of π that will be used in case π returns an unsuccessfully optimized (line 5). To build π we randomly select a r_{seed} subtour of $\mathcal{S}^+$ (lines 6 and 7). The first customer of r_{seed} will be considered as seed $seed$ (line 8). The subtour r_{seed} is added to π and π' and removed from $\mathcal{S}^+$ (lines 9-11). As long as the number of customers of π is less than σ then the routes $\tilde{r}$ with the first customer closest to $seed$ and $\tilde{r} \notin R$ (lines 12-19) are included. At line 20, a MILP optimizer Φ tries to improve the

Algorithm 2: Construction phase

Function parameters: $rcl\,, V_c\,, Q_c$
$\mathcal{S} := \varnothing$;
$k := 0$;
while *there are customers in* V_c *to be assigned* **do**
  for $j := 0, 1, \ldots, |V_c[k]|$ **do**
    $c_j := V_c[k][j]$;
    if $\mathcal{S}[k] == \varnothing$ **then**
      $c_j.t_j :=$ max$(c_j.l_j,\, \frac{d_{0,c_j}}{\mathcal{V}})$;
    else
      $c_{prev} := V_c[k][|V_c[k]| - 1]$;
      $c_j.t_j :=$ max$(c_j.l_j,\, c_{prev}.t_j + c_{prev}.s_j + \frac{d_{c_{prev},c_j}}{\mathcal{V}})$;
  Apply greedy heuristic to $V_c[k]$;
  $U_b :=$ min $(rcl, |V_c[k]|)$;
  Build the Restricted Candidate List with $RCL := \{V_c[k][0], \ldots, V_c[k][U_b]\}$;
  Select a candidate $(cand \in RCL)$ from a randomly position (p);
  if $Q_c[k] - cand.q_p \geq 0$ ***and*** $cand.t_p \leq cand.u_p$ **then**
    $\mathcal{S}[k] := \mathcal{S}[k] \cup cand$;
    $V_c[k] := V_c[k] \backslash cand$;
    $Q_c[k] := Q_c[k] - cand.q_p$;
  else
    $V_c[k] := V_c[k] \backslash cand$;
    if $k == |V_c|$ **then**
      $Q_c := Q_c \cup \{Q\}$;
      $\mathcal{S} := \mathcal{S} \cup \{\varnothing\}$;
      $V_c := V_c \cup \{\varnothing\}$;
    $V_c[k+1] := V_c[k+1] \cup cand$;
  if $|V_c[k]| == \varnothing$ **then**
    $k := k + 1$;
Return $\mathcal{S}$;

subproblem's solution π. The objective function $f(\pi)$ used into mathematical formulation is based on equations (3.1) and (3.2) for hard and soft time window cases, respectively. Also, the constraints of hard and soft time windows are considered in these formulations. Subsequently, $\mathcal{S}^+$ is updated (lines 21-23). The algorithm is stopped when the time-limited is exceeded, or there are no more improvements (line 4). Finally, the best solution found so far $\mathcal{S}^+$ is returned.

Algorithm 3: Post-processing phase

1 **Function parameters:** $\mathcal{S}$, σ , Φ

2 $\mathcal{S}^+ := \mathcal{S}$;

3 Transform each item $r \in \mathcal{S}^+$ in a pair of $(r, 1)$ if $|r| > \sigma$, or $(r, 0)$ otherwise;

4 **while** *time limit is not exceeded **and** there are improvements* **do**

5     $\pi := \varnothing, \pi' := \varnothing, R := \varnothing$;

6   Generate a random number (rnd) between 0 and $|\mathcal{S}^+|$, $\forall (r, x) \in \mathcal{S}^+, x = 0$;

7     $r_{seed} := \mathcal{S}^+[rnd]$;

8     $seed := r_{seed}[0][0]$;

9     $\pi := \pi \cup (r_{seed}[0], 1)$;

10     $\pi' := \pi' \cup (r_{seed}[0], 1)$;

11     $\mathcal{S}^+ := \mathcal{S}^+ \backslash r_{seed}$;

12   **while** $|\pi| \leq \sigma$ ***and*** $|R| < |S^+|$ **do**

13         $\tilde{r} := \text{argmin}_{\{r \in \mathcal{S}^+, r \notin R\}}\{\min\,(d_{seed,r[0][0]})\}$;

14   **if** $|\pi| + |\tilde{r}| \leq \sigma$ **then**

15             $\pi := \pi \cup \tilde{r}$;

16             $\pi' := \pi' \cup \tilde{r}$;

17             $\mathcal{S}^+ := \mathcal{S}^+ \backslash \tilde{r}$;

18   **else**

19             $R := R \cup \tilde{r}$;

20   Solve π with the optimizer Φ using $f(\pi)$ as the initial upper bound;

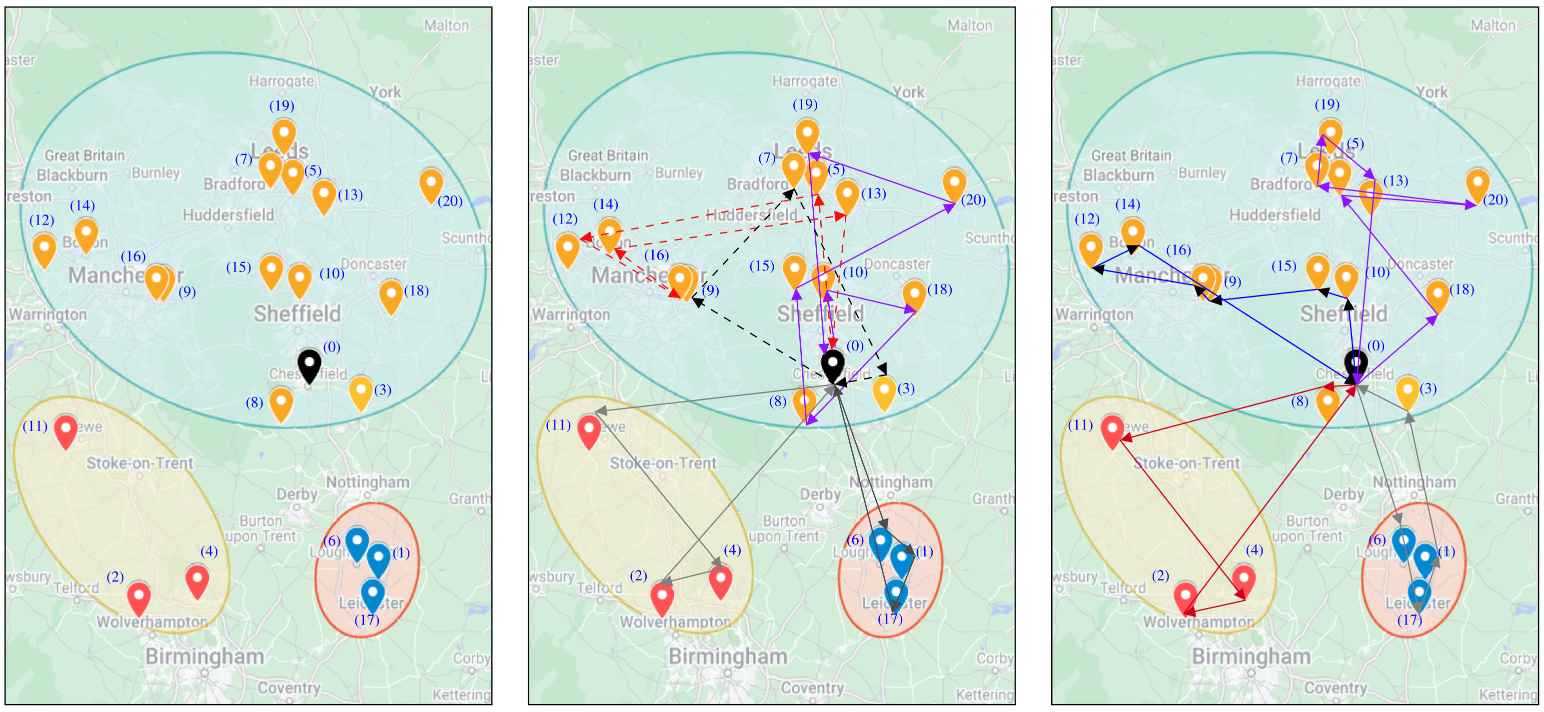
21   **if** $f(\pi) < f(\pi')$ **then**

22         $\mathcal{S}^+ := \mathcal{S}^+ \cup \{(\pi_1, 0), \ldots, (\pi_n, 0)\}$;

23   **else**

24         $\mathcal{S}^+ := \mathcal{S}^+ \cup \pi'$;

25 **Return** $\mathcal{S}^+$;



(a) (b) (c)

Figure 3.3: Example of a solution for CumVRP-HTW provided for the matheuristic approach using the UK20_01-D instance from PRPLIB. This instance contains 20 customer locations and a depot node (0). (a) shows the clustered customer locations with k = 3 set; (b) represents the constructive solution with $|S|$ = 5 subtours; and (c) shows the improved solution with $|S^{+}|$ = 4 subtours.

3.6 Experiments

This section is devoted to present the computational experiments conducted to evaluate the performance of the optimization models as well as of our matheuristic approach for tackling CumVRP-TW (see Section 3.2). The problem instances used in this research are those proposed by (Kramer et al., 2015) for the PRP. Additionally, a new modified set of problem instances generated based on (Kramer et al., 2015) is proposed. With this new set of instances, we incorporate customers' priority on the importance that each customer has for a company. By means of above-mentioned benchmark instances[1], we aim to provide the possibility of comparing approximate and exact approaches for the CumVRP-TW. The mathematical models for hard and soft time windows were implemented in IBM ILOG CPLEX v12.9.0 C++ API with a time limit of 7200 sec per instance (2 hours) and the number of threads set to 2. The matheuristic approach was tested for 100 iterations. The equipment used for the tests was a processor Intel(R) Xeon(R) E312xx (Sandy Bridge) CPU 2.0 GHz with 16 GB RAM memory on CentOS Linux release 7.6.1810.

[1]All CumVRP-TW used instances are online available at: https://github.com/affernan/prplib_set_d

3.6.1 Test instances

The main benchmark suite considered in this section was proposed by Kramer et al. (2015), which is a modified PRPLIB instances set that was initially presented in Demir et al. (2012). This set of instances is suitable for our work as it is based on real distances collected from randomly chosen UK cities for a related problem. The benchmark suite consists of two sets of instances Set-B and Set-C with a customer numbers between 10 and 200. These sets consider a time horizon in the range [32, 400] and the time windows for customers belonging to Set-B is [2000, 5000], that is tighter than Set-C where customer time windows lies in the range [2000, 15000].

However, these instances do not present priority values for customers, such that it is possible for a company to prioritize a customer during deliveries. In view of this, for the soft time windows case, we created an additional set of instances (Set-D), that includes priority values p_i for each customer $i \in V$, by modifying those of Set-B instances. The priority values of the new set are based on the demand of each customer as the higher the demand, the more profitability for the company. In doing so, for all customers, a parameter κ is defined as a range and let $q_{min} = \min\{q_i, \dots, q_{|V|}\}$ and $q_{max} = \max\{q_i, \dots, q_{|V|}\}$. By means of that κ the different customer priorities are obtained:

$$\kappa = (q_{max} - q_{min})/4 \tag{3.19}$$

$$p_i = \begin{cases} 0.1, & [q_{min}, \;\; q_{min} + \kappa + 1], \\ 0.4, & [q_{min} + \kappa + 2, \;\; q_{min} + 2\kappa + 3], \\ 0.7, & [q_{min} + 2\kappa + 4, \;\; q_{min} + 3\kappa + 5], \\ 1.0, & [q_{min} + 3\kappa + 6, \;\; q_{min} + 4\kappa + 7]. \end{cases} \tag{3.20}$$

3.6.2 Cost parameters

Considering the literature studied in Section 3.2, we define the following parameters costs for the computational experiments:

- *CO_2 emissions cost (C_E)*: this reflects the price per ton of CO_2 emitted, which is €25, as stated in Piecyk et al. (2015);

- *Fuel cost (C_F)*: this reflects the fuel price per litre, which was €1.19, as stated in Ehmke et al. (2018);

- *Penalty cost (PC)*: this reflects the penalty cost for late arrivals to the customer of \$2190 per year, as stated in Hossain et al. (2017).

The value of δ_1=€1.248 is calculated as sum of the cost of fuel consumption and the cost of emissions, and the value of δ_2 is set to €0.0034. Taking as reference the related work (Hossain et al., 2017), we set the minimum penalty value as €0.0034 per minute (equivalent a \$6/day or approximately €4.92/day). The values corresponding to the priorities are in the range between 0 and 1, so δ_2=€0.0034 corresponding to the case when the priority is 1, so that with lower priority then lower will be the cost per penalty to pay.

3.6.3 Parameters setting

In order to determine the best parameters configuration for our matheuristic approaches, we used the tuning algorithm ParamILS proposed by Hutter et al. (2009). ParamILS is an iterated local search algorithm that works searching for better-quality parameters setting in the neighborhoods of the current one. Table 3.3 reports the parameter values used, for example, the Restricted Candidate List size rcl, the different values of σ for building a subproblem, and the maximum number of iterations of the matheuristic Max_Iter. Also, we point out that the parameter rcl was established according to the cardinality-based (CB) mechanism to build the RCL (see Festa and Resende (2011)).

We performed two different parameters setting processes, one for the matheuristic approach for CumVRP-HTW and the second for CumVRP-STW. We used a set of five instances with different sizes from 10 to 200 customers. The results of this tuning process indicate that values of rcl = 3, σ = 20, and Max_Iter = 100 are the most suitable parameters for both approaches.

Table 3.3: Parameter setting values for the matheuristic approach.

Parameter	Values
rcl	$\in \{3, 4, 5\}$
σ	$\in \{10, 15, 20\}$
Max_Iter	$\in \{50, 100\}$

Figure 3.4 shows the performance of our matheuristic in terms of fuel consumption by box plot format that explains the empirical distribution of data. All box plot graphs was generated for 10 runs and for the CumVRP-HTW and CumVRP-STW variants on different set of instances. Note that the instances with 10 and 20 are not represented because the matheuristic approach always found the optimal solution.

The stability of our matheuristic approach can be determined by the location of its box plot in fuel consumption terms. The boxes show a small variability in the solutions obtained with almost 8.21% and 13.50% variation for hard and soft time window cases, respectively. In addition to the stability of the

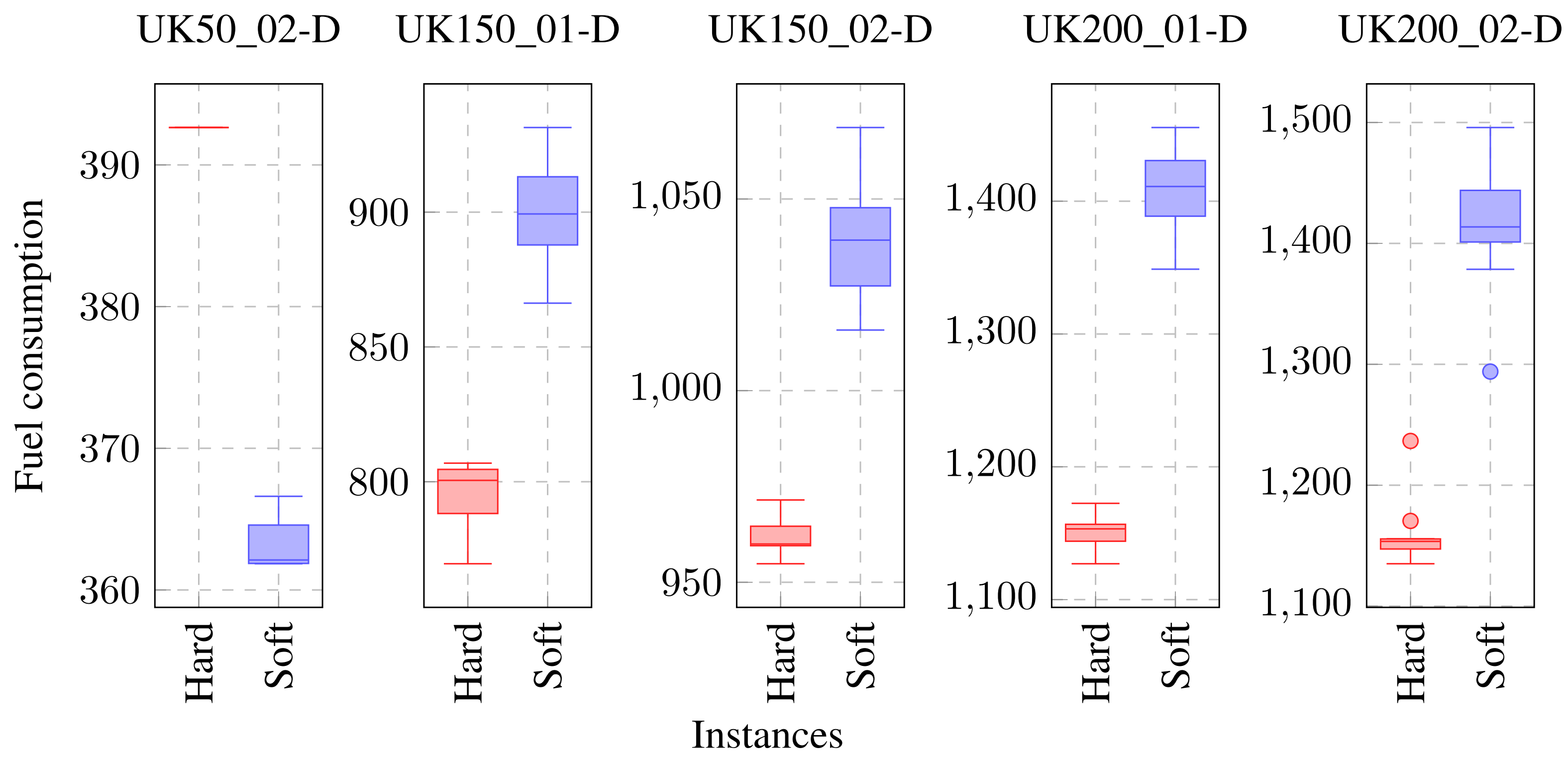


Figure 3.4: Box plots corresponding to the matheuristic approach for CumVRP-HTW and CumVRP-STW using instances with different numbers of customers.

algorithm, this figure shows the quality of solutions between both cases, where the hard case presents good quality solutions in a more stable way. Note, in the case of the instance UK200_02-D, the best value reported for the soft case is an out layer, while the behavior of the hard case is stable, finding good quality solutions.

3.6.4 Results

This subsection reports the performance of the CumVRP-TW formulations, i.e., with hard and soft constraints, CumVRP-HTW and CumVRP-STW, respectively and our GRASP matheuristic approach. This way, to evaluate the contribution of our models, we test a set of selected instances with different customer sizes as shown in Table 3.4. The size of the instance can be identified with the number after UK. This way UK10_01-D represents the first scenario of 10 customers. In this table, we report the calculated total cost (Total cost_1=Fuel cost + Emissions cost; Total cost_2=Fuel cost + Emissions cost + Penalty cost), fuel consumption, fuel cost, carbon emissions, carbon emissions cost, the relative error of the models Gap(%), the execution time in seconds Time(sec) and in soft time windows case we show the late arrival times to the customer and the penalty cost for late arrival. Finally, in the last two columns, Imp_F and Imp_E, we report the difference between fuel consumption and emissions. This values was calculating as Imp_F = Fuel_{Hard} - Fuel_{Soft} and Imp_E = Emissions_{Hard} - Emissions_{Soft}.

Table 3.5 compares the performance between CPLEX and the matheuristic approach . We assess the performance of our matheuristic on instances in terms of total costs, execution time and penalty time, take into account the hard and soft case. The value of Gap_2(%), is the performance of the CPLEX models by means of percentage improvement with respect to GRASP matheuristic, and this has been calculated according to the following expression:

$$Gap_2(\%) = (Obj_{Math} - Obj_{CPLEX})/Obj_{CPLEX} \times 100\% \tag{3.21}$$

where Obj_{Math} and Obj_{CPLEX} stand for the solutions values of CPLEX and the matheuristic, respectively. The matheuristic was run 10 times and the best results are presented.

We first analyze the results for instances with 10 and 20 customers with CPLEX. Table 3.4, shows that our models converge to optimal solutions consistently with a reduction in the total cost, fuel consumption, and emissions costs. CPLEX can find optimal solutions within 1.34 sec. Besides, there is an environmental improvement between the model for CumVRP-HTW and CumVRP-STW, according to the values of fuel consumption and CO_2 emissions. For the instances of 50 customers in the hard time windows case, the mathematical model always finds the optimal solution in at most 1540.93 sec, presenting on average execution time values lower than those of the matheuristic. In the soft time windows case, the optimum was reached for the UK50_05-D instance, maintaining Gap(%) values between 0.00% and 8.89%, indicating good quality in the solutions found. Note that, when comparing the results of both cases (hard and soft), despite optimal values are not found for the soft time windows case, lower values of fuel consumption and CO_2 emissions are always provided.

The exact solutions for instances composed of 150 and 200 customers, show that the Gap(%) averages in most scenarios increase accordingly with the increase in the number of customers to serve. In the time interval of 7200 sec, the values provided for several instances in the case of soft time windows are higher than for the case of hard time windows. This behavior shows that the search space for the soft case is greater than for the hard case, which represents greater resolution complexity.

The matheuristic approach reports the optimal solution for the instances of 10 and 20 customers and for the hard time windows case in the instances of 50 customers (see Table 3.5). In the soft time windows case with 50 customers, low $Gap_2(\%)$ values are obtained, but always negative and with considerably lower execution time values. For the instances of 150 and 200 customers, negative $Gap_2(\%)$ values are always provided, reaching a value of approximately −70% in the UK200_01-D and UK200_04-D instances for the soft time windows case.

Table 3.4: Computational results of the optimization models for the CumVRP-TW.

	CPLEX$_{CumVRP-HTW}$							CPLEX$_{CumVRP-STW}$									Environmental Improvement	
Instance	Total Cost	Fuel	Fuel Cost	Ems.	Ems. Cost	Gap (%)	Time (sec)	Total Cost	Fuel	Fuel Cost	Ems.	Ems. Cost	Penalty Time	Penalty Cost	Gap (%)	Time (sec)	Imp_F	Imp_E
UK10_01-D	136.29	109.20	129.95	253.35	6.33	0.00	0.04	121.93	97.62	116.17	226.48	5.66	3584.60	0.09	0.00	0.13	11.58	26.87
UK10_02-D	173.15	138.74	165.10	321.88	8.05	0.00	0.03	170.84	136.88	162.89	317.56	7.94	1537.20	0.01	0.00	0.06	1.86	4.32
UK10_03-D	141.11	113.07	134.55	262.32	6.56	0.00	0.03	141.11	113.07	134.55	262.32	6.56	0.00	0.00	0.00	0.03	0.00	0.00
UK10_04-D	151.03	121.02	144.01	280.66	7.02	0.00	0.05	144.94	116.04	138.09	269.22	6.73	2682.60	0.11	0.00	0.07	4.98	11.54
UK10_05-D	152.89	122.50	145.78	284.21	7.11	0.00	0.03	139.78	111.99	133.27	259.81	6.50	1260.40	0.02	0.00	0.04	10.61	24.40
Average	150.89	120.91	143.88	280.60	7.01	0.00	0.04	143.72	115.12	136.99	267.08	6.68	1812.96	0.05	0.00	0.07	5.79	13.43
UK20_01-D	252.77	202.54	241.03	469.90	11.75	0.00	0.09	246.55	197.49	235.01	458.18	11.45	4531.00	0.08	0.00	1.34	5.05	11.72
UK20_02-D	276.55	221.59	263.70	514.10	12.85	0.00	0.26	268.36	214.99	255.84	498.77	12.47	1632.40	0.05	0.00	0.25	6.60	15.33
UK20_03-D	151.80	121.63	144.74	282.18	7.05	0.00	0.07	151.74	121.57	144.67	282.04	7.05	905.80	0.02	0.00	0.13	0.06	0.14
UK20_04-D	266.08	213.21	253.72	494.64	12.37	0.00	0.08	257.79	206.52	245.76	479.14	11.98	1220.20	0.04	0.00	0.87	6.69	15.50
UK20_05-D	224.29	179.72	213.86	416.95	10.42	0.00	0.07	218.37	174.96	208.21	405.91	10.15	524.40	0.01	0.00	0.25	4.76	11.04
Average	234.30	187.74	223.41	435.55	10.89	0.00	0.11	228.56	183.11	217.90	424.81	10.62	1762.76	0.04	0.00	0.67	4.63	10.65
UK50_01-D	463.75	371.59	442.20	862.10	21.55	0.00	136.74	429.43	343.99	409.35	798.05	19.95	7433.20	0.14	2.36	7200.00	27.60	64.05
UK50_02-D	490.65	393.15	467.84	912.10	22.80	0.00	376.51	453.07	362.75	431.67	841.58	21.04	10445.68	0.36	6.51	7200.00	30.40	70.62
UK50_03-D	450.81	361.23	429.86	838.05	20.95	0.00	1540.93	433.76	347.30	413.29	805.74	20.14	8498.80	0.32	4.79	7200.00	13.93	32.31
UK50_04-D	540.62	433.19	515.50	1005.00	25.13	0.00	507.01	526.87	421.94	502.11	978.90	24.47	9621.00	0.29	8.89	7200.00	11.25	26.10
UK50_05-D	515.28	412.88	491.33	957.89	23.95	0.00	139.19	484.88	388.39	462.19	901.07	22.53	5544.00	0.17	0.00	3403.82	24.49	56.82

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Table 3.4 – *Continued from previous page*

Instance	$\text{CPLEX}_{CumVRP-HTW}$							$\text{CPLEX}_{CumVRP-STW}$									Environmental Improvement	
	Total Cost	Fuel	Fuel Cost	Ems.	Ems. Cost	Gap (%)	Time (sec)	Total Cost	Fuel	Fuel Cost	Ems.	Ems. Cost	Penalty Time	Penalty Cost	Gap (%)	Time (sec)	Imp_F	Imp_E
Average	492.22	394.41	469.35	915.03	22.88	0.00	540.08	465.60	372.87	443.72	865.07	21.63	8308.54	0.26	4.51	6440.66	21.53	49.96
UK150_01-D	1030.03	825.35	982.16	1914.81	47.87	10.65	7200.00	1130.00	905.34	1077.35	2100.39	52.51	3946.20	0.14	35.03	7200.00	-79.99	-185.58
UK150_02-D	1333.04	1068.14	1271.09	2478.10	61.95	18.02	7200.00	1550.00	1241.33	1477.18	2879.89	72.00	21108.60	0.82	35.62	7200.00	-173.19	-401.79
UK150_03-D	1056.70	846.71	1007.59	1964.37	49.11	11.01	7200.00	1230.00	984.10	1171.08	2283.11	57.08	53442.60	1.85	31.92	7200.00	-137.39	-318.74
UK150_04-D	1350.03	1081.75	1287.29	2509.67	62.74	24.47	7200.00	1403.79	1124.54	1338.20	2608.93	65.22	12443.40	0.37	26.85	7200.00	-42.79	-99.26
UK150_05-D	1320.01	1057.70	1258.66	2453.87	61.35	28.07	7200.00	1215.68	973.95	1159.00	2259.56	56.49	10661.40	0.20	27.58	7200.00	83.75	194.31
Average	1217.96	975.93	1161.36	2264.16	56.60	18.42	7200.00	1305.89	1045.85	1244.56	2426.38	60.66	20320.44	0.68	31.40	7200.00	-69.92	-162.21
UK200_01-D	1515.40	1214.26	1444.97	2817.09	70.43	18.02	7200.00	5700.00	4567.28	5435.07	10596.10	264.90	543.60	0.03	77.01	7200.00	-3353.02	-7779.01
UK200_02-D	1800.26	1442.52	1716.59	3346.64	83.67	31.29	7200.00	1640.60	1313.92	1563.57	3048.30	76.21	26947.20	0.83	28.56	7200.00	128.60	298.34
UK200_03-D	1770.01	1418.28	1687.75	3290.41	82.26	29.20	7200.00	1691.91	1354.94	1612.41	3143.52	78.59	20452.20	0.62	30.89	7200.00	63.34	146.89
UK200_04-D	1660.00	1330.13	1582.85	3085.90	77.15	26.09	7200.00	5000.01	4006.41	4767.63	9294.88	232.37	0.00	0.00	76.73	7200.00	-2676.28	-6208.98
UK200_05-D	1930.02	1546.49	1840.32	3587.86	89.70	35.72	7200.00	1775.11	1421.70	1691.82	3298.34	82.46	22998.60	0.83	28.31	7200.00	124.79	289.52
Average	1735.14	1390.34	1654.50	3225.58	80.64	28.06	7200.00	3161.53	2532.85	3014.10	5876.23	146.91	14188.32	0.48	48.30	7200.00	-1142.51	-2650.65

Table 3.5: Computational results of matheuristic approach on solving CumVRP-TW.

Instance	CPLEX$_{CumVRP-HTW}$			Math$_{CumVRP-HTW}$			CPLEX$_{CumVRP-STW}$						Math$_{CumVRP-STW}$					
	Total Cost	Gap (%)	Time (sec)	Total Cost	Gap$_2$ (%)	Time (sec)	Total Cost	Fuel Cost	Penalty Time	Penalty Cost	Gap (%)	Time (sec)	Total Cost	Fuel Cost	Penalty Time	Penalty Cost	Gap$_2$ (%)	Time (sec)
UK10_01-D	136.29	0.00	0.04	136.29	0.00	11.22	121.93	116.17	3584.60	0.09	0.00	0.13	121.93	116.17	3584.40	0.09	0.00	27.53
UK10_02-D	173.15	0.00	0.03	173.15	0.00	9.99	170.84	162.89	1537.20	0.01	0.00	0.06	170.84	162.89	1537.20	0.01	0.00	25.33
UK10_03-D	141.11	0.00	0.03	141.11	0.00	8.00	141.11	134.55	0.00	0.00	0.00	0.03	141.11	134.55	0.00	0.00	0.00	10.89
UK10_04-D	151.03	0.00	0.05	151.03	0.00	19.85	144.94	138.09	2682.60	0.11	0.00	0.07	144.94	138.09	2682.60	0.11	0.00	22.94
UK10_05-D	152.89	0.00	0.03	152.89	0.00	13.97	139.78	133.27	1260.40	0.02	0.00	0.04	139.78	133.27	1260.60	0.02	0.00	10.76
Average	150.89	0.00	0.04	150.89	0.00	12.61	143.72	136.99	1812.96	0.05	0.00	0.07	143.72	136.99	1812.96	0.05	0.00	19.49
UK20_01-D	252.77	0.00	0.09	252.77	0.00	33.31	246.55	235.01	4531.00	0.08	0.00	1.34	246.55	235.01	4531.20	0.08	0.00	757.60
UK20_02-D	276.55	0.00	0.26	276.55	0.00	92.49	268.36	255.84	1632.40	0.05	0.00	0.25	268.36	255.84	1632.60	0.05	0.00	123.85
UK20_03-D	151.80	0.00	0.07	151.80	0.00	26.30	151.74	144.67	905.80	0.02	0.00	0.13	151.74	144.67	906.00	0.02	0.00	91.68
UK20_04-D	266.08	0.00	0.08	266.08	0.00	48.08	257.79	245.76	1220.20	0.04	0.00	0.87	257.79	245.76	1220.40	0.04	0.00	394.21
UK20_05-D	224.29	0.00	0.07	224.29	0.00	29.02	218.37	208.21	524.40	0.01	0.00	0.25	218.37	208.20	524.40	0.01	0.00	122.50
Average	234.30	0.00	0.11	234.30	0.00	45.84	228.56	217.90	1762.76	0.04	0.00	0.57	228.56	217.90	1762.92	0.04	0.00	297.97
UK50_01-D	463.75	0.00	136.74	463.75	0.00	1057.74	429.43	409.35	7433.20	0.14	2.36	7200.00	427.25	407.16	10881.00	0.25	-0.51	1135.59
UK50_02-D	490.65	0.00	376.51	490.65	0.00	660.51	453.07	431.67	10445.68	0.36	6.51	7200.00	451.92	430.71	9462.00	0.34	-0.25	905.82
UK50_03-D	450.81	0.00	1540.93	450.81	0.00	1514.83	433.76	413.29	8498.80	0.32	4.79	7200.00	431.24	413.26	9190.20	0.33	-0.58	1793.02
UK50_04-D	540.62	0.00	507.01	540.62	0.00	1205.83	526.87	502.11	9621.00	0.29	8.89	7200.00	524.20	499.62	8962.80	0.30	-0.51	1468.21
UK50_05-D	515.28	0.00	139.19	515.28	0.00	336.72	484.88	462.19	5544.00	0.17	0.00	3403.82	484.88	462.18	5544.00	0.17	0.00	808.08
Average	492.22	0.00	540.08	492.22	0.00	955.13	465.60	443.72	8308.54	0.26	4.51	6440.76	463.90	442.59	8808.00	0.28	-0.37	1222.14

Continued on next page

Table 3.5 – *Continued from previous page*

Instance	CPLEX$_{CumVRP-HTW}$			Math$_{CumVRP-HTW}$			CPLEX$_{CumVRP-STW}$						Math$_{CumVRP-STW}$					
	Total Cost	Gap (%)	Time (sec)	Total Cost	Gap$_2$ (%)	Time (sec)	Total Cost	Fuel Cost	Penalty Time	Penalty Cost	Gap (%)	Time (sec)	Total Cost	Fuel Cost	Penalty Time	Penalty Cost	Gap$_2$ (%)	Time (sec)
UK150_01-D	1030.03	10.55	7200.00	960.44	-6.76	2199.48	1130.00	1077.35	3946.20	0.14	35.03	7200.00	1081.68	1030.83	19887.60	0.61	-4.28	2385.58
UK150_02-D	1333.04	18.02	7200.00	1191.63	-10.61	2003.60	1550.00	1477.18	21108.60	0.82	35.62	7200.00	1268.57	1209.21	15721.80	0.43	-18.16	2403.51
UK150_03-D	1056.70	11.01	7200.00	1027.02	-2.81	2185.44	1230.00	1171.08	53442.60	1.85	31.92	7200.00	1190.37	1134.56	23436.60	0.52	-3.22	2294.83
UK150_04-D	1350.03	24.47	7200.00	1192.05	-11.70	2358.85	1403.79	1338.20	12443.40	0.37	26.85	7200.00	1308.69	1247.07	27553.80	0.84	-6.77	2858.37
UK150_05-D	1320.01	28.07	7200.00	1022.01	-22.58	2168.80	1215.68	1159.00	10661.40	0.20	27.58	7200.00	1159.63	1105.24	17438.40	0.53	-4.61	2213.29
Average	1217.96	18.42	7200.00	1078.63	-10.89	2183.23	1305.89	1244.56	20320.44	0.68	31.40	7200.00	1201.79	1145.38	20807.64	0.59	-7.41	2431.12
UK200_01-D	1515.40	18.02	7200.00	1406.49	-7.19	2450.36	5700.00	5435.07	543.60	0.03	77.01	7200.00	1684.43	1605.07	35194.20	1.13	-70.45	2765.02
UK200_02-D	1800.26	31.29	7200.00	1416.52	-21.32	2152.16	1640.60	1563.57	26947.20	0.83	28.56	7200.00	1615.85	1539.82	36287.40	0.97	-1.51	2291.68
UK200_03-D	1770.01	29.20	7200.00	1389.10	-21.52	2305.37	1691.91	1612.41	20452.20	0.72	30.89	7200.00	1639.80	1562.62	32924.40	1.02	-3.08	2589.37
UK200_04-D	1660.00	26.09	7200.00	1326.53	-20.09	2228.41	5000.01	4767.63	0.00	0.00	76.73	7200.00	1536.93	1464.72	31777.80	0.82	-69.26	2568.03
UK200_05-D	1930.02	35.72	7200.00	1528.68	-20.79	2406.59	1775.11	1691.82	22998.60	0.83	28.31	7200.00	1653.80	1576.07	29903.40	0.90	-6.83	2702.98
Average	1735.14	28.06	7200.00	1413.46	-18.18	2308.58	3161.53	3014.10	14188.32	0.48	48.30	7200.00	1626.16	1549.66	33217.44	0.97	-30.23	2583.42

Figure 3.5 shows a comparison performance for both approaches and problem cases of 200 customers, where the solutions provided by matheuristic provided less fuel consumption and running times than CPLEX.

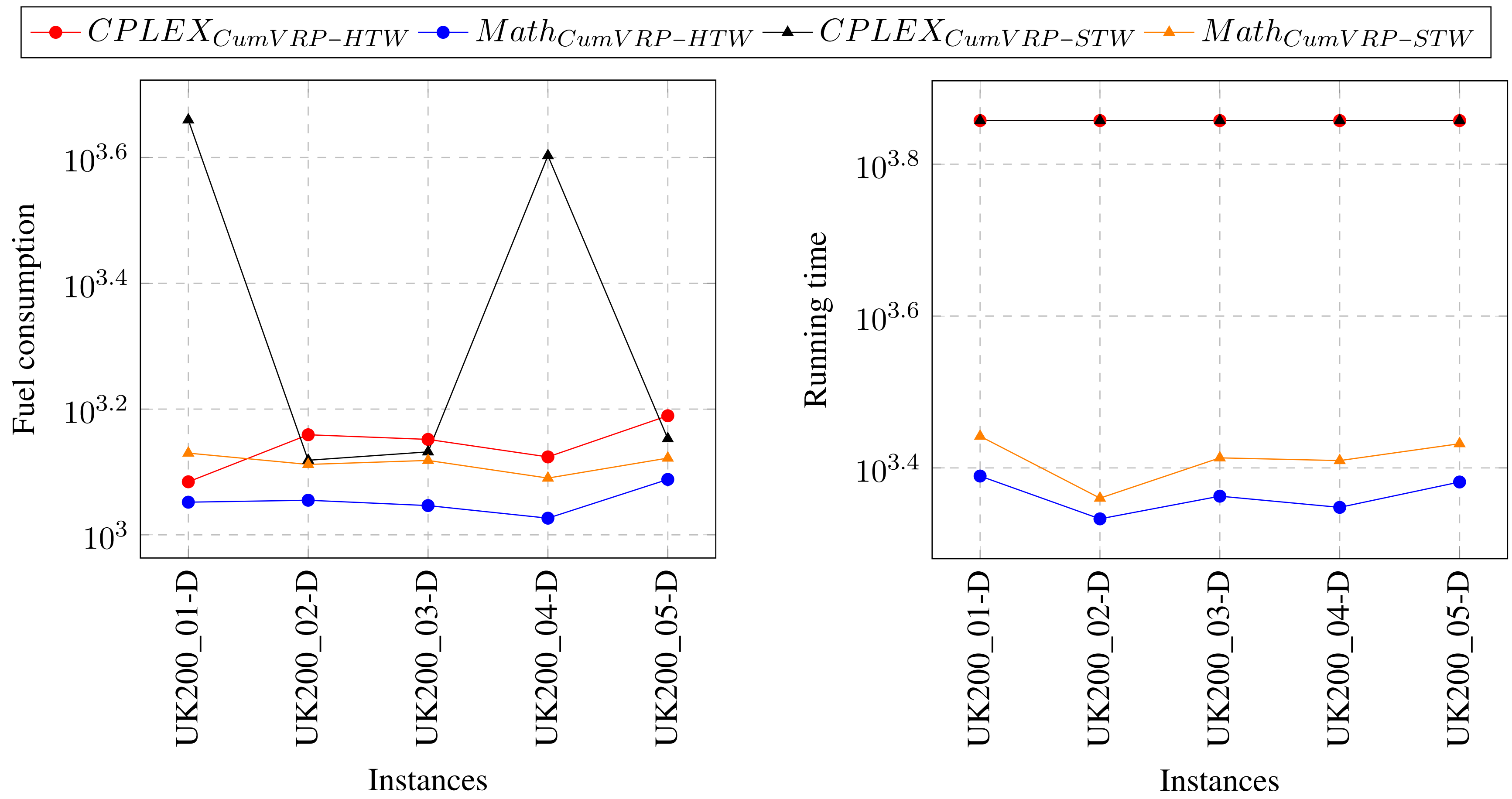


Figure 3.5: Performance of CPLEX and matheuristic approach for CumVRP-HTW and CumVRP-STW on instances of 200 customers.

The computational effort of route enhancement with CPLEX and the matheuristic is illustrated as the percentage of total execution time spent between both approaches in Figure 3.6. The figure reveals that the matheuristic requires more effort for instances of 10 and 20 customers in both cases and for instances of 50 customers in hard time windows. Note that although the matheuristic requires more effort, the total time values are low, especially in the instances of 10 and 20 customers. On the other hand, in the case of soft time windows of instances for 50 customers and both cases of instances for large-scale customers (150 and 200), the matheuristic always takes advantage of total execution time. We can conclude that our matheuristic performs well in terms of run time and solution quality for the set of instances.

3.6.4.1 Environmental impact of soft time windows

The environmental impact of freight transportation can be related to the use of soft time windows, if we allow delays in the time windows the amount of fuel consumption can be reduced and as a consequence, the fuel cost and CO_2 emissions cost are reduced. Figure 3.7 shows a comparative analysis in monetary terms for CumVRP-HTW and CumVRP-STW, considering equal terms (instances with optimal values) and to evaluate the environmental impact of soft time windows. The costs associated with fuel cost and

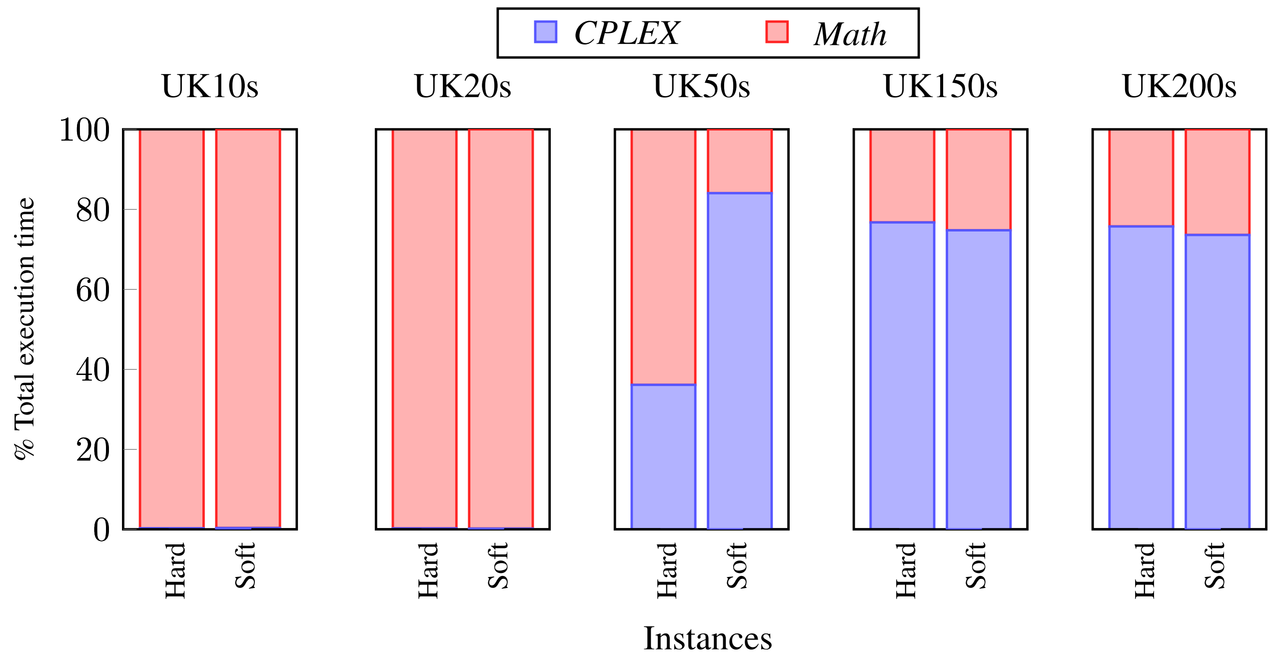


Figure 3.6: Percentage of computational effort required by GRASP matheuristic vs. CPLEX.

CO_2 emissions are represented by orange bars and those referring to penalties by blue ones. Note that since the penalty cost values are so small with respect to the cost values of fuel cost and emissions cost, they are little visible.

Figure 3.7 shows a reduction in fuel consumption and carbon emission costs when delays are allowed, up to approximately 10% in instances of 10 customers, incurring penalty costs of at most €0.29. The monetary losses caused by late arrivals to the locations of customers are buffered with the reduction of carbon emission costs incurred.

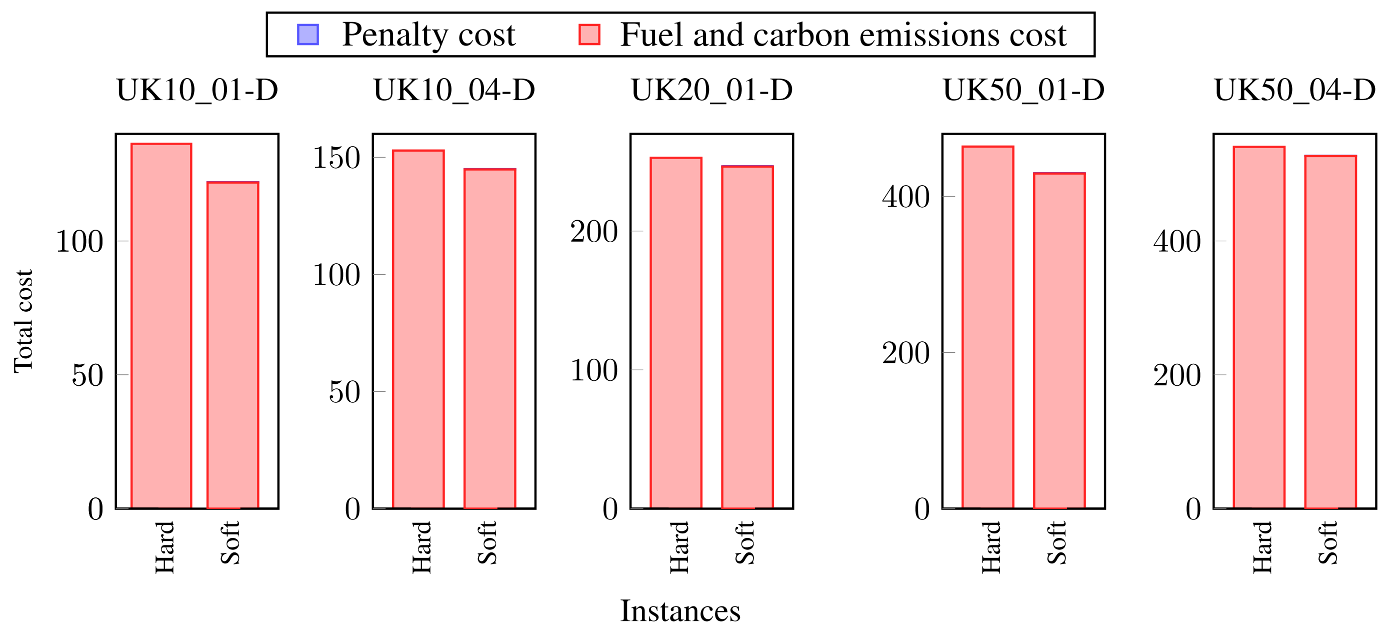


Figure 3.7: Comparison in monetary terms for CPLEX solutions for CumVRP-HTW and CumVRP-STW.

In this regard, in Table 3.4 it can be verified that for the instances with optimal values in both cases, the corresponding total costs are lower in the soft case. Note that in the case of the UK10_01-D instance, the total penalty cost of €0.09 causes a reduced cost per fuel and CO_2 emissions of approximately €14. Moreover, this performance can be observed (without equal terms) in Table 3.5 on matheuristic approaches. The instances of 50 customers present an average reduction in CO_2 emissions and fuel consumption of 49.96 and 21.53, respectively, even when optimal values have not been found. We analyze the costs related to emissions and fuel consumption for these instances and we found an average reduction cost of (49.96×0.025) + (21.35×1.19) = €26.87. Such a benefit can become attractive for transport companies, especially if we consider rising emissions prices.

The consideration of soft time windows will be of great impact on transport companies coping with environmental-related costs and customer-related time windows. Similarly, the environmental impact is strongly influenced by the commitment of companies, being that if the costs for delays are too high the reduction of emissions will be unremarkable.

3.7 Conclusions

In this research, we have investigated the cumulative vehicle routing problem (CumVRP-TW) with hard and soft time windows. To solve these problem variants, we have developed a matheuristic optimization approach that combines a greedy randomized adaptive search procedure (GRASP) integrates with an exact solution method.

The results show that including soft time windows constraints, lead to significant reductions in environmental costs. In this sense, this consideration of the time windows might reflect better situations than hard time windows, especially considering dynamic changes in problem features. However, when considering the violation of a time window, a customer's dissatisfaction occurs, but despite this, there is a correct trade-off between time windows penalties and environmental related costs. Our matheuristic approach shows that the quality of the solutions increase when each subtour is seen as a low complexity subproblem that can be solved by a mathematical programming approach.

Chapter 4

Pickup and Delivery Operations in Multi-Depot GVRP

4.1 Introduction

One way to reduce the carbon footprint of vehicles is using better operational strategies and establishing sustainable supply chains in the logistics industry. Therefore, it is essential to achieve optimal vehicle routing that properly considers sustainability factors. In literature, there exist variants of the VRP that have been considered in the field of green logistics. The cumulative vehicle routing problem (CumVRP) introduced by Kara et al. (2007, 2008) is a widely studied optimization problem that involves a weighted load function (load multiplied by distance). Another variant investigated by Soysal et al. (2018) is the green one-to-one pickup and delivery (Green PDVRP) problem with road segmentation, which satisfies a set of pickup and delivery requests between location pairs and takes into account explicit fuel consumption, variable speed, and road categorization. According to Battarra et al. (2014) the type of demand and route structure in PDVRPs can be done as follows: many-to-many (multiple products are transported between multiple origins and destinations), one-to-many-to-one (multiple products are transported from one depot to many clients and vice versa) and one-to-one (each product is transported from a single origin to a single destination). An interesting aspect of studying PDVRPs is the influence of the load because the load influences the effort and fuel consumption when the journey is made to a delivery location. In addition, the multi-depot vehicle routing problem (MDVRP) presents a notable increase in its study (Montoya-Torres et al., 2015). In the MDVRP, vehicles serve customers from several depots and return to the same depot. The MDVRP is essential for companies with a wide range of business fields and has more than a single depot because the solution of MDVRP could support these companies decrease their transport costs and improve their economic fulfillment. There are a few investigations that consider MDVRPs combined with environmental factors (see Fan et al. (2021); Jabir et al. (2017); Li et al. (2019); Wang et al. (2019)). However, to the best of our knowledge, the multi-depot green vehicle routing problem (MDGVRP) with pickups and deliveries variant has not yet been investigated in the literature.

In this study, a one-to-one variant of the PDVRP in a multi-depot context considering the load on each arc (MDGVRP-PD) is studied to minimize fuel consumption. For this variant, we only work with the restriction related to that a goods must first be pick up and then deliver to its corresponding partner, but it is not necessary to perform this process consecutively (see Figure 4.1). To provide feasible solutions for the MDGVRP-PD, this study proposes a mathematical programming model and a POPMUSIC matheuristic approach (Taillard and Voß, 2002). POPMUSIC is capable of addressing large scenarios by decomposing them into subsets of parts. Subsets of parts are bundled and used to create subproblems, which are then solved.

The remainder of this study is organized as follows. Section 4.2 reviews related works. Section 4.3 describes the problem definition of the MDGVRP-PD. The POPMUSIC approach is presented in Section 4.4. Computational experiments and results are given in Section 4.5, and finally, we present the conclusions and future work in Section 4.6.

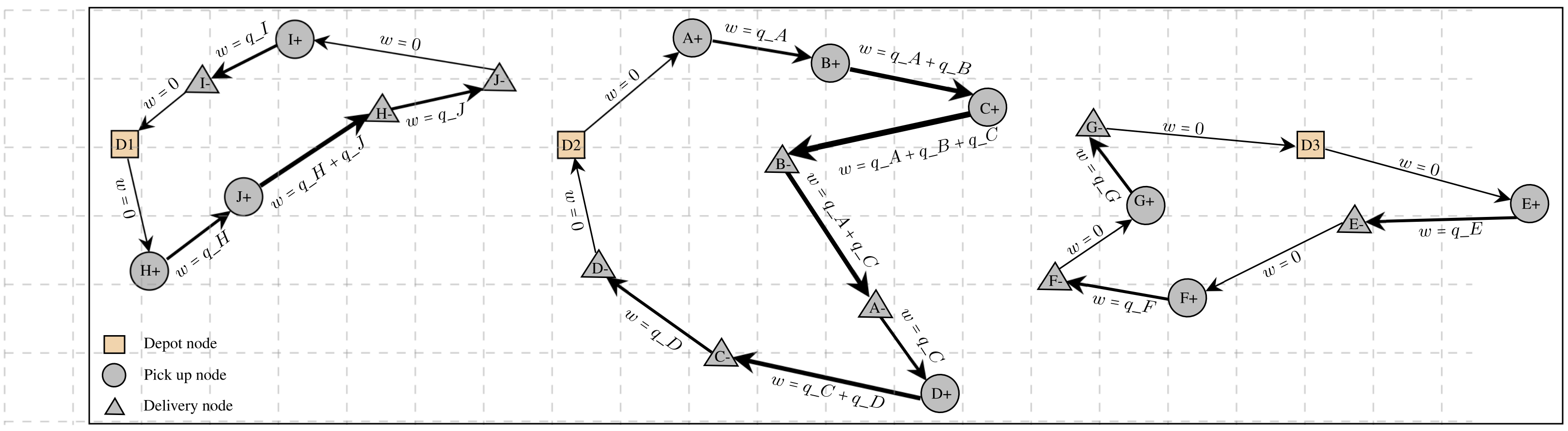


Figure 4.1: Illustrative example of one-to-one forms in PDVRP. Note that node labels with positive or negative signs mean positive or negative demands. Thicker lines mean more cumulative weight on an arc.

4.2 Related works

Freight transportation is a significant component in logistic distribution activities and inevitably the largest consumer of fuel compared to other forms of transportation (Bektaş et al., 2019). Therefore, the importance of achieving optimal routing plans that include sustainability factors is increasing because societies need transportation services that are efficient and comfortable, reporting low in CO_2 emissions and costs. Furthermore, the green routing problems are characterized by achieving a sustainable supply chain network design and have attracted the scientific community's interest, especially in Operations Research and Artificial Intelligence fields (e.g., Bektaş et al. (2019); Erdelić and Carić (2019b); Lin et al. (2014); Moghdani et al. (2021)).

Several authors have researched the optimization models and solution approaches for green vehicle routing problems (GVRPs), considering the effects of vehicle's load on fuel consumption to reduce environmental pollution. The studies Kara et al. (2007) and Kara et al. (2008) presented the energy minimizing vehicle routing problem and cumulative vehicle routing problem (CumVRP), which were the first vehicle routing studies proposing a cost function as a sum of the product between vehicles' load and distance for each arc. The authors of Cinar et al. (2016) presented a two-phase constructive heuristic approach to solve CumVRP with limited duration restrictions and minimizing the fuel consumption. In this study, we used the fuel consumption parameters of vehicle categories propose in Kopfer et al. (2014). In Bektaş and Laporte (2011), the authors presented the pollution routing problem, which seeks to minimize both operational and environmental costs by taking into account customers' time-windows constraints. The total travel distance, the amount of load carried per distance unit, the vehicle speeds, and the duration of the routes were the main costs.

While the GVRPs are suitable for solving single depots problems, supply chain networks primarily consist of multi-depots and multiple delivery points, which require more practical approaches such as multi-depot vehicle routing problems (MDVRP) (Cordeau et al., 1997). Furthermore, there exists a requirement for transportation and logistics businesses to minimize their environmental footprints. In comparison to the MDVRP, the MDGVRP considers more factors in the green logistic (e.g., load, speed, traffic congestion, etc.), which increases the complexity of the problem and the difficulty of solving it. In Li et al. (2019), the authors studied the MDGVRP aiming to maximize the income (multiplication between the total demand for a product and the price) and minimizing costs, time, and emissions using an improved ant colony optimization algorithm. A bi-objective model for MDGVRP is proposed to minimize total carbon emissions, and operational cost by Wang et al. (2019) by implementing transportation resource sharing within the same depot and among multiple depots. Similarly, to solve the MDGVRP efficiently, Jabir et al. (2017) presented a hybrid approach based on ant colony optimization and variable neighborhood search approaches to minimize cost and emission.

Besides the aforementioned works, some authors investigate PDVRPs, in which a set of pickup and delivery requests between customer couples are satisfied (Battarra et al., 2014). In Battarra et al. (2014), the authors classified three different forms of pickup and delivery: one-to-one, one-to-many-to-one, and many-to-many. Each commodity can be a request regarding one-to-one, has a given origin, and a given destination. The PDVRP is classified as a NP-Hard problem due to complexity and the excessive consumption of computational time in its resolution. There are a few PDVRP studies where the emissions are taking into account (see Asghari and Mirzapour Al-e-hashem (2020); Soysal et al. (2018); Wang et al. (2018)). However, as far as we know, the green PDVRP variant has not yet been investigated in a multi-depot green scenario. Considering the constraint of pickup and delivery and the impact of vehicle's load on fuel consumption and emissions in multi-depot distribution networks contribute to optimize the routes and reduce environmental impact. In this study, we present a green variant of the multi-depot one-to-one pickup and delivery, where the objective is to design a set of optimal routes starting and ending at different depots to satisfy pickup and delivery requests under minimal emissions.

Other than in previous works, we develop a partial optimization metaheuristic under special intensification conditions (POPMUSIC) (Taillard and Voß, 2002) in its matheuristic version proposed in Lalla-Ruiz and Voß (2016) for solving the MDGVRP-PD. POPMUSIC is capable of addressing large scenarios by decomposing them into a set of parts. It has been successfully applied to multi-depot vehicle routing problems, i.e., Lalla-Ruiz and Voß (2020).

4.3 Problem definition

The multi-depot green VRP with pickups and deliveries (MDGVRP-PD) can be defined as follows. Let $G = (V, A)$ be a complete directed graph, where $V = \{N \cup M\}$ is the node set that contains all customer and depot nodes, and $A = \{(i, j) : i, j \in V, i \neq j\}$ is the arc set. Node set $N = \{P \cup D\}$ with $P = \{1, \ldots, n\}$ represents the set of pick-up nodes and $D = \{n + 1, \ldots, 2n\}$ the sets of delivery nodes, whereas node set $M = \{1, 2, \ldots, m\}$ represents the set of m uncapacitated depots. Each customer $i \in N$ demands a quantity of goods q_i for pick-up or delivery, respectively, and has time service $s_i > 0$. There exist a homogeneous set of vehicles $S = \{1, 2, \ldots, s\}$, each with capacity Q. the vehicle's speed $\mathcal{V}$ is set to 90 km/h. A travelling distance $d_{ij} > 0$, is defined for each arc between each pair of vertices (i, j), $i, j \in V, i \neq j$.

We estimate the fuel consumption through an approach based on the work of Singh and Gaur (2017). Each vehicle emits a specific quantity of greenhouse gas when traveling over an arc (i, j). Certain factors produce this quantity of emissions (e.g., load, fuel consumption, vehicle components). Because of this, in the MDGVRP-PD, we consider the total vehicles' weight, represented by a carried load w_{ij} on arc (i, j), and it is a measure that helps reducing fuel consumption and environmental pollution.

In the following, we introduce the mathematical formulation for solving MDGVRP-PD that extends CumVRP (Kara et al., 2008) to consider multiple depots. The decision variables are the following:

- x_{ij}^s =1 if vehicle s travels from node $i \in V$ to node $j \in V$, 0 otherwise,

- t_i^s is the time at which vehicle s arrives at node $i \in N$,

- w_{ij}^s is the total load transported from node i to node j by vehicle s for $i, j \in V$.

We propose the following mathematical model with the objective to minimize the total fuel consumption by evaluating the distance d_{ij} and the carried load w_{ij} on arc $i, j \in V$:

$$\text{Minimize} \quad \sum_{i=0}^{|V|}\sum_{j=0}^{|V|}\sum_{s=0}^{|S|} d_{ij}(\alpha x_{ij}^s + \beta w_{ij}^s) \tag{4.1}$$

subject to:

$$\sum_{i=0}^{V}\sum_{s=0}^{S} x_{ij}^s = 1, \quad \forall j \in N, \tag{4.2}$$

$$\sum_{j=0}^{V} x_{ij}^s - \sum_{h=0}^{V} x_{h,n+i}^s = 0, \quad \forall i \in P,\ \forall s \in S, \tag{4.3}$$

$$\sum_{i=0}^{V} x_{ij}^s - \sum_{h=0}^{V} x_{jh}^s = 0, \quad \forall j \in V,\ \forall s \in S, \tag{4.4}$$

$$\sum_{i=0}^{M}\sum_{j=0}^{V} x_{ij}^s = 1, \quad \forall s \in S, \tag{4.5}$$

$$\sum_{i=0}^{M}\sum_{j=0}^{V} x_{ji}^s = 1, \quad \forall s \in S, \tag{4.6}$$

$$\sum_{s=0}^{S}\sum_{j=0}^{N} w_{ij}^s - \sum_{s=0}^{S}\sum_{h=0}^{V} w_{hi}^s = q_i, \quad \forall i \in P, \tag{4.7}$$

$$\sum_{s=0}^{S}\sum_{j=0}^{N} w_{ji}^s - \sum_{s=0}^{S}\sum_{h=0}^{V} w_{ih}^s = -q_i, \quad \forall i \in D, \tag{4.8}$$

$$w_{ij}^s \le Q, \quad \forall i, j \in N,\ \forall s \in S, \tag{4.9}$$

$$w_{ij}^s = 0, \quad \forall i \in M,\ \forall j \in P,\ \forall s \in S, \tag{4.10}$$

$$w_{ij}^s \le M x_{ij}^s, \quad \forall i, j \in N,\ \forall s \in S, \tag{4.11}$$

$$t_i^s \le t_{n+i}^s, \quad \forall i \in P,\ \forall s \in S, \tag{4.12}$$

$$t_j^s \ge (d_{ij}/\mathcal{V}) x_{ij}^s, \quad \forall i \in M, \forall j \in N, \forall s \in S, \tag{4.13}$$

$$t_j^s \ge (t_i^s + s_i + (d_{ij}/\mathcal{V})) x_{ij}^s, \quad \forall i, j \in N, \forall s \in S, \tag{4.14}$$

$$u_j \ge (t_i^s + s_i + (d_{ij}/\mathcal{V})) x_{ij}^s, \quad \forall i \in D, \forall j \in M, \forall s \in S, \tag{4.15}$$

$$x_{ij}^s \in \{0, 1\}, \quad \forall i, j \in V, \forall s \in S, \tag{4.16}$$

$$w_{ij}^s \ge 0, \quad \forall i, j \in V, \forall s \in S, \tag{4.17}$$

$$t_i^s \ge 0, \quad \forall i \in V, \forall s \in S. \tag{4.18}$$

The objective function (4.1) minimizes the fuel consumption based on traveled distance and the carried load on each arc and fuel consumption parameters (see Kopfer et al. (2014)). The parameters α and β represent the cost of moving an empty vehicle per unit of distance and the cost of moving the unit weight of goods per unit distance, respectively. Constraints (4.2) state that each node must be visited. Constraints (4.3) ensure that a vehicle visits a delivery location after it has visited the corresponding pickup location. Constraints (4.4) enforce the in-degree of each node to be equal to the out-degree. Constraints (4.5) and (4.6) establish that each vehicle starts and finishes at a depot $i \in M$. Constraints (4.7) and (4.8) ensure flow conservation at pickup and delivery locations. Constraints (4.9) represent the capacity restriction of each vehicle. Constraints (4.10) ensure that there is no flow from a depot node to a pickup location. Constraints (4.11) activate the variable x_{ij}^{s} if there is a flow greater than 0 by the arc $(i,j) \in \mathcal{A}$. Constraints (4.12) force the start time service in a pickup node by vehicle s has to be less than the start time service in its corresponding delivery partner node. Constraints (4.13)-(4.15) guarantee that the start times of each node comply with the order of service on the route. Constraints (4.16) define binary variables x_{ij}^{s}. Constraints (4.17) and (4.18) ensure the no negativity of the variables w_{ij}^{s} and t_{i}^{s}, respectively.

4.4 Matheuristic approach for the MDGVRP-PD

The POPMUSIC approach is a decomposition-based method, originally proposed by Taillard and Voß (2002) as a metaheuristic and revised as a matheuristic in Lalla-Ruiz and Voß (2016). This approach divides a problem into smaller subproblems. Some or all of these subproblems are solved through metaheuristics or mathematical programming methods to optimality or suboptimality (i.e., matheuristic version).

To be precise, POPMUSIC works on an initial generated solution of the problem $\mathcal{S}$, which then will be decomposed into t parts $\{s_1, \ldots, s_t\}$. Each part corresponds to a subtour of $\mathcal{S}$. Next, some of these parts will be joined to build a subproblem SP using a proximity measure between parts. Subproblems are built by first selecting one of the t parts (called *seed-part*) and taking into account the r nearest parts ($SP = \{s_{seed}, s_1, s_2, \ldots, s_r\}$) according to the lexicographic strategy. The parameter r delimits the size of the subproblems. A mathematical programming method is used to optimize SP, and if there is an improvement over SP, then this improvement contributes to the total solution $\mathcal{S}$.

Algorithm 4 shows our matheuristic approach for solving the MDGVRP-PD. This approach has seven parameters as inputs: (i) r value means the subproblem' size; (ii) N, M, P, Q, d were previously described in Section 4.3; (iii) tl establish the time limited duration of a tour. Initially, a feasible starting solution is constructed by a clustering strategy consisting of a set of parts or subtours (line 2). After the initial solution has been generated, the solution $\mathcal{S}$ is divided into t parts creating the set $H = \{s_1, \ldots, s_t\}$ (line 3). A set U is created to control the set of parts that have not been used as *seed-part* for building a subproblem (lines 4 and 5). Then, a *seed-part* is selected randomly (line 6). A subproblem SP is constructed by considering its r closest parts and is locally optimized by an exact method (lines 7 and 8). If the solution has been improved, then the solution $\mathcal{S}$ is updated (lines 9-11). Once U contains all the parts of the complete solution (line 5), the process ends as all subproblems have been explored without improved results.

Algorithm 4: POPMUSIC pseudocode

1 **Input parameters:** r, N, M, P, Q, tl, d
2 $\mathcal{S}$:= Generate an initial solution (N, M, P, Q, tl, d);
3 Decompose $\mathcal{S}$ into t parts, $H := \{s_1, \ldots, s_t\}$;
4 Set $U := \varnothing$;
5 **while** $U \neq \{s_1, \ldots, s_t\}$ **do**
6   Select a *seed-part*, $s_{seed} \in H$, at random and $s_{seed} \notin U$;
7   Build a subproblem SP composed of the r parts of $\mathcal{S}$ which are the closest to s_{seed};
8   Optimize SP by using a mathematical programming approach;
9   **if** SP *improved* **then**
10   Update solution $\mathcal{S}$ with SP;
11         $U := \varnothing$;
12   **else**
13   Insert s_{seed} in U;
14 **Output** $\mathcal{S}$;

4.4.1 Solution representation

To represent a solution, we use a solution structure based on a two-dimensional vector of parts s_i, where each item represents a set of routes belonging to the same depot (see Figure 4.2). Furthermore, each route must comply with the pickup and delivery constraints. That is, the delivery nodes must be visited after visiting the corresponding pickup nodes.

We consider three types of nodes in our problem. Each route is represented by a depot node (o), pickup node (p), and delivery node (y) (see Figure 4.2). The sequencing of visiting is related to the one-to-one variant of the PDVRP; for example, the visiting order can be done by firstly visiting a pickup node

$$\mathcal{S} = \begin{array}{c} s_1 \\ s_2 \\ \vdots \\ s_t \end{array} \begin{bmatrix} [o_1, p_1, y_{11}], & [o_1, p_2, y_{12}, p_5, y_{15}] & \cdots & [o_1, p_i, y_{|P|+i}, \cdots] \\ [o_2, p_7, p_{11}, y_{17}, y_{21}], & [o_2, p_6, y_{16}] & \cdots & [o_2, p_i, y_{|P|+i}, \cdots] \\ \vdots & \vdots & \ddots & \vdots \\ [o_m, p_{13}, y_{23}], & [o_m, p_{16}, y_{26}] & \cdots & [o_m, p_{|P|}, y_{|D|}, \cdots] \end{bmatrix}$$

Figure 4.2: Solution structure composed of parts.

then going directly to deliver the goods to their corresponding delivery node and then performing another pickup, or first all pickups and then all deliveries; any other form of mixed pickup and deliveries satisfying the sequencing restrictions.

4.4.2 Initial solution strategy

For the operation of POPMUSIC, a key point is the generation of an initial solution. To do this, we have developed and tested a clustering construction strategy that considers the haversine distance $d = 2R \arcsin \sqrt{\sin^2 \frac{\varphi_2 - \varphi_1}{2} + \cos\varphi_1 \cos\varphi_2 \sin^2 \frac{\lambda_2 - \lambda_1}{2}}$ of each node to each depot.

The clustering strategy was defined to build a solution considering one element (node) at a time. Initially, those depot nodes with less distance are determined for each node. We then consider candidate elements as a tuple composed of the pickup node and its corresponding delivery partner. Finally, considering the candidate element, the feasibility test is carried out, verifying that the partial solution is viable. This process is carried out until all the elements of the set of candidates have been considered or until a solution is constructed.

Algorithm 5 shows the pseudocode of the initial solution. Initially, for each node, the closest depot is determined (lines 2-4). Next, the vehicle index and its capacity load were initialized (lines 5 and 6). Following, a pickup node and its corresponding delivery node, as well as its closest depot, are obtained (lines 7-11). With this, a check is performed whether the trip's time duration and the vehicle's capacity constraints are satisfied (lines 12 and 13). If the nodes can be assigned to the vehicle, then a tour is built until it is part of the problem's solution (lines 14 and 15); otherwise, we proceed with another vehicle and construct a new tour (lines 17-20). Finally, the assignment of the nodes to the tour is performed by fulfilling the sequencing constraints of pickup and delivery nodes.

Algorithm 5: Clustering algorithm pseudocode

```
Function parameters: N, M, P, Q, tl, d
for i := 0, 1, ..., |N| do
    for j := 0, 1, ..., |M| do
        minD[i] := argmin(d_ij);    ▷ Haversine formula
current_vehicle = 1;
max_payload := Q;
for i := 0, 1, ..., |M| do
    for j := 0, 1, ..., |N|/2 do
        p_node := N[j];
        d_node := N[|P| + j];
        if minD[j] == i then
            time := calculate travel time;
            if time ≤ tl and p_node.q_j ≤ Q then
                Q := Q − p_node.q_j;
                p_node, d_node added to route S[current_vehicle];
            else
                current_vehicle := current_vehicle + 1;
                Q := max_payload;
                time := 0;
                i := i − 1;
Return S;
```

4.4.3 Subproblem generation strategy

The lexicographic strategy presented in Lalla-Ruiz and Voß (2020) is used to group the parts of a subproblem. This strategy consists of randomly selecting a seed-part s_{seed} and r parts of increasing index concerning the index θ of the seed-part. For example, if the initial solution is divided into 4 parts, and we consider r=2, then we can have the following subproblems: $SP = \{s_1, s_2, s_3\}$, $SP = \{s_2, s_3, s_4\}$, and $SP = \{s_3, s_4, s_1\}$. The previous strategy can be grouped as a disjoint set and can be generalized by $\dot\bigcup_{p=\theta}^{\theta+r}$.

4.5 Experiments

This section is devoted to analyzing the performance of the POPMUSIC approach for solving the MDGVRP-PD variant. All implementations were done in C++ using Visual Studio v15.9.2 IDE and IBM ILOG CPLEX v12.9.0 API on Windows 10 OS. The tests were performed on an Intel(R) Xeon(R) E3-1220L (Sandy Bridge) CPU 2.20 GHz with 16GB RAM memory. The matheuristic approach was tested for 10 executions for each instance. The POPMUSIC approach was run in single-thread mode.

4.5.1 Test instances

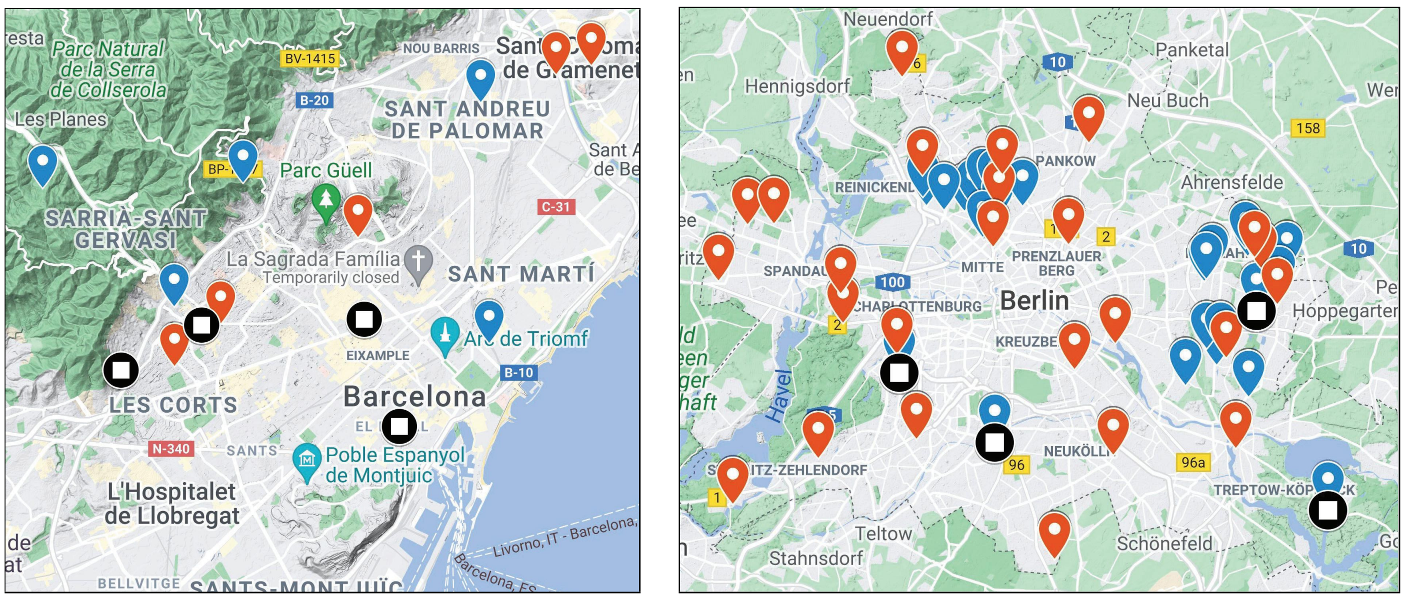
To test our matheuristic approach for the MDGVRP-PD, we modified subsets of the $n100$ and $n200$ groups of instances proposed in Sartori and Buriol (2020), where the authors consider real urban locations, and where a set of routes can be performed in a single labor day (eight hours). An example of these modified instances can be seen in Figure 4.3.

The modified instances[1] have $n + m$ locations. There are n customer locations and m depots. The n locations are paired to form a total of n requests (pickup and delivery couples). The n locations for pickup (P) and other n locations for delivery (D) are paired, where $|P|$=$|D|$=n, in a one-to-one way. The instance set consists of three different groups, ranging from 10 to 200 customers and are classified in three different complexity levels: small-scale with the first 10 or 50 customers from the original n100 group from Sartori and Buriol (2020); medium-scale with the first 70 or 100 customers from $\{n100; n200\}$, and the last group for the large-scale with the first 150 or 200 customers. For all instances considered in this section, the time limit of the tour duration is 240 minutes, and we add four depot locations from the remaining locations that were not used in the generated instances. The customers' demands and the capacity of the vehicles are considered in kilogram. Also, the vehicle parameters are based on light-duty type with a curb-weight of 3500 kg and a maximum payload of 4000 kg, known as the gross vehicle weight rating.

4.5.2 Parameter setting

A parameter tuning process was performed by executing them on all problem set instances. The only tuned parameter for POPMUSIC is r, with $r \in \{1, 2\}$. We have run a Friedman-k Related Samples test (Friedman, 1940) to show the importance of our results. The test indicates no significant differences for both samples, with mean rank r=1 (1.44) and r=2 (1.56), showing both parameters have a

[1] All MDGVRP-PD used instances are online available at: https://github.com/affernan/MDGVRP-PD



(a) n10-1 with 10 locations.

(b) n50-1 with 50 locations.

Figure 4.3: Example of two modified instances. Blue and red circles are pickups and delivery locations, respectively. The black circles are the depots.

small difference. Due to this, an analysis of the results will be carried out, considering the case of r=1 (POPMUSIC^{r1}) and r=2 (POPMUSIC^{r2}).

4.5.3 Results

This section compares the performance of the optimization model and POPMUSIC. In doing so, we assess the performance of these approaches on all problem instances in terms of objective function value and computational time. Table 4.1 shows the results provided by the CPLEX and POPMUSIC with $r \in \{1, 2\}$. POPMUSIC was executed considering both values of r, and we denoted it as POPMUSIC^{r1} and POPMUSIC^{r2}. In this table, column 1 reports the instance studied, and columns 2, 5, and 8 provide the objective function values in terms of fuel consumption. Column 6 and 9 represent the relative gap errors (Gap$_2$(%)) and (Gap$_3$(%)) between the mathematical model and the versions of the POPMUSIC matheuristic. Its are calculated according to $100 \times (Obj_{math} - Obj_{cplex})/Obj_{math}$, where Obj_{math} represents the best value for fuel consumption provided by POPMUSIC approaches. The presence of a negative value in these columns shows that the objective function values have been improved.

The results show that CPLEX cannot obtain optimal values for all instances within the time limit of 2 hours. On the instances with 10 nodes, CPLEX can obtain better or equal objective function values than POPMUSIC approaches. For the rest of the instances, CPLEX cannot get any feasible results before the time limit. For most instances, POPMUSIC provides better quality results within a reasonable execution time. These results also indicate, as discussed in Lalla-Ruiz and Voß (2016), the suitability of the matheuristic POPMUSIC for using and exploiting the exact optimization method in treatable subproblems that permit solving them to optimality within reasonable computational times.

Table 4.1: Computational results of the CPLEX and POPMUSIC approach with r=1 and r=2 on generated instances. The best values are given in bold face.

Instance	CPLEX$_{MDGVRP-PD}$			POPMUSIC^{r1}			POPMUSIC^{r2}		
	Fuel	Gap (%)	Time (sec)	Fuel	Gap$_2$ (%)	Time (sec)	Fuel	Gap$_3$ (%)	Time (sec)
n10-1	**6.44**	5.91	7200.00	**6.44**	0.00	127.60	11.53	44.15	213.84
n10-2	**4.61**	27.71	7200.00	6.54	29.51	276.16	4.89	5.73	204.65
n30-1	68.39	84.76	7200.00	**42.12**	-62.37	212.16	45.70	-49.65	208.80
n30-2	57.79	73.00	7200.00	**41.66**	-38.72	201.08	41.92	-37.86	206.25
n50-1	-	-	7200.00	**151.19**	-	202.41	152.48	-	207.32
n50-2	-	-	7200.00	120.66	-	230.14	**114.45**	-	211.56
n70-1	-	-	7200.00	**99.11**	-	204.68	105.05	-	206.21
n70-2	-	-	7200.00	138.73	-	249.90	**137.83**	-	217.80
n100-1	-	-	7200.00	108.17	-	206.64	**103.42**	-	289.79
n100-2	-	-	7200.00	**112.87**	-	417.72	**112.87**	-	339.57
n150-1	-	-	7200.00	214.44	-	205.02	**214.07**	-	205.53
n150-2	-	-	7200.00	**288.96**	-	232.79	297.19	-	201.81
n200-1	-	-	7200.00	**271.66**	-	201.93	272.03	-	205.36
n200-2	-	-	7200.00	**418.66**	-	202.58	422.33	-	202.46
Average	34.31	47.84	7200.00	144.37	-17.89	226.49	145.41	-9.41	222.93

On the other hand, we assess the performance of POPMUSIC^{r1} and POPMUSIC^{r2} on all problem instances in terms of objective function values of all iterations performed (see Table 4.2).

In this table, the first column reports the instance studied, and columns $Fuel^{r1}_{min}$, $Fuel^{r2}_{min}$ and $Fuel^{r1}_{max}$, $Fuel^{r2}_{max}$ provide the minimum and maximum objective function values found, respectively. Columns $Fuel^{r1}_{start}$ and $Fuel^{r2}_{start}$ show the objective values of the initial solution provided by the greedy algorithm. Columns λ_{r1} (%) and λ_{r2} (%) represent the improvement between the best objective value and the initial solution value for each instance. The values of λ_{r1} (%) and λ_{r2} (%) are calculated using $100{\times}(Fuel^{r}_{min}$-$Fuel^{r}_{start})/Fuel^{r}_{start}$, with $r = r1$ or $r2$. Columns Time (sec)$_{r1}$ and Time (sec)$_{r2}$ represent the computational times. The last column shows the relative difference Gap(%) between POPMUSIC^{r1} and POPMUSIC^{r2}. It is calculated according to $100 \times (Fuel^{r1}_{min} - Fuel^{r2}_{min})/Fuel^{r2}_{min}$, where POPMUSIC^{r1} represents the best values for fuel consumption provided by our matheuristic approach. A negative value in columns λ_{r1} (%), λ_{r2} (%), and Gap % shows improvements.

The results show that POPMUSIC^{r1} generally obtains better objective function values ($Fuel^{r1}_{min}$) than POPMUSIC^{r2} ($Fuel^{r2}_{min}$), having 9 best values obtained from a total of 14 instances with different complexities. The difference between the minimum and maximum values ($Fuel^{r1}_{max}$, $Fuel^{r2}_{max}$) obtained shows that the matheuristic generally maintains a stable behavior. The initial solution values ($Fuel^{r1}_{start}$, $Fuel^{r2}_{start}$) concerning the best values obtained ($Fuel^{r1}_{min}$, $Fuel^{r2}_{min}$) are always improved during the POPMUSIC process (see λ_{r1} (%) and λ_{r2} (%)). Only for instance n10-2, the gap value (Gap$_4$ (%)) of 33.74% is significant. Furthermore, these results also indicate, as discussed in Lalla-Ruiz and Voß (2016), the suitability of the matheuristic POPMUSIC for using and exploiting the exact optimization method for subproblems that allow solving them to optimality within reasonable computational times.

4.5.3.1 Effects of loading on fuel consumption

To analyze the effect of the load on fuel consumption and emissions and bearing in mind the previous results, we made a trade-off between the objective function (see equation (4.1)) and one of the most used objective functions in the literature for VRPs, i.e., the minimization of travel distances.

First, the set of values $Fuel^{r1}_{min}$ and $Fuel^{r2}_{min}$ for all instances with the estimation of the amount of fuel consumption using the objective function (4.1), in which the load carried over an arc w_{ij} was showed in Table 4.2. Second, let $Fuel'^{r1}_{min}$ and $Fuel'^{r2}_{min}$ denote the set of values for all instances with the estimation of the amount of fuel consumption considering a modified objective function considering only the distance d_{ij} traveled by the vehicle as $\sum_{i=0}^{|V|}\sum_{j=0}^{|V|}\sum_{s=0}^{|S|} d_{ij}x^{s}_{ij}$ and keeping the flow constraints.

Table 4.2: Computational results for the POPMUSIC variants with r=1 and r=2 on modified instances. The best values are given in bold face.

Instance	POPMUSIC^{r1}					POPMUSIC^{r2}					
	Fuel$^{r1}_{min}$	Fuel$^{r1}_{max}$	Fuel$^{r1}_{start}$	λ_{r1} (%)	Time$_{r1}$ (sec)	Fuel$^{r2}_{min}$	Fuel$^{r2}_{max}$	Fuel$^{r2}_{start}$	λ_{r2} (%)	Time$_{r2}$ (sec)	Gap$_4$ (%)
n10-1	**6.44**	7.00	11.53	-44.15	127.60	11.53	11.53	11.53	0.00	213.84	-44.15
n10-2	6.54	6.70	7.83	-16.48	276.16	4.89	7.07	7.83	-37.55	204.65	33.74
n30-1	**42.12**	56.37	51.48	-18.18	212.16	45.70	61.51	51.48	-11.23	208.80	-7.83
n30-2	**41.66**	50.26	53.08	-21.51	201.08	41.92	53.08	53.08	-21.02	206.25	-0.62
n50-1	**151.19**	175.05	166.58	-9.24	202.41	152.48	178.05	166.58	-8.46	207.32	-0.85
n50-2	120.66	133.51	133.42	-9.56	230.14	**114.45**	139.15	133.42	-14.22	211.56	5.43
n70-1	**99.11**	137.89	121.55	-18.46	204.68	105.05	132.46	121.55	-13.57	206.21	-5.65
n70-2	138.73	189.44	159.74	-13.15	249.90	**137.83**	161.18	159.74	-13.72	217.80	0.65
n100-1	108.17	111.82	110.71	-2.29	206.64	**103.42**	113.19	110.71	-6.58	289.79	4.59
n100-2	**112.87**	120.27	112.87	0.00	417.72	**112.87**	112.87	112.87	0.00	339.57	0.00
n150-1	214.44	234.04	219.40	-2.26	205.02	**214.07**	238.38	219.40	-2.43	205.53	0.17
n150-2	**288.96**	301.30	299.82	-3.62	232.79	297.19	304.79	299.82	-0.88	201.81	-2.77
n200-1	**271.66**	324.21	287.94	-5.65	201.93	272.03	289.09	287.94	-5.53	205.36	-0.14
n200-2	**418.66**	429.19	432.08	-3.11	202.58	422.33	439.84	432.16	-2.27	202.46	-0.87
Average	144.37	162.65	154.86	-11.98	226.49	145.41	160.16	154.87	-9.82	222.93	-1.31

Table 4.3 shows a comparison of the experiments between fuel consumption and emission values. Columns $Fuel^{r1}_{min}$ and $Fuel^{r2}_{min}$ are the same as used for Table 4.3. The amount of fuel consumption without considering the weight component in the objective function is represented in columns $Fuel'^{r1}_{min}$ and $Fuel'^{r2}_{min}$. Also, we calculate the emissions of CO_2 for all fuel consumption values using the emission factor defined as 2.72 Kg/litre of fuel consumption (DBEIS, 2018), see columns $Ems.^{r1}$, $Ems.'^{r1}$, $Ems.^{r2}$, and $Ems.'^{r2}$. Furthermore, columns $Imp.^{r1}$ and $Imp.^{r2}$ show the environmental percentage of improvement between ($Ems.^{r1}$ and $Ems.'^{r1}$), and ($Ems.^{r2}$ and $Ems.'^{r2}$) in terms of emissions. The average percentage of improvement for POPMUSIC^{r1} and POPMUSIC^{r2} is 30.79% and 25.50%, respectively.

Figure 4.4 shows the values of $Fuel^{r1}_{min}$, $Fuel'^{r1}_{min}$, $Fuel^{r2}_{min}$, and $Fuel'^{r2}_{min}$, for all instances. The blue and red line represents the values for $Fuel^{r1}_{min}$ and $Fuel'^{r1}_{min}$, which show a decrease in the fuel consumption values concerning $Fuel'^{r1}_{min}$. The black and gray line represents the values for $Fuel^{r2}_{min}$ and $Fuel'^{r2}_{min}$, which shows similar behavior as the previous one. This illustration remarks the significance of considering the fuel consumption depending on weight and travel distance as it is proportional to the reduction in emissions.

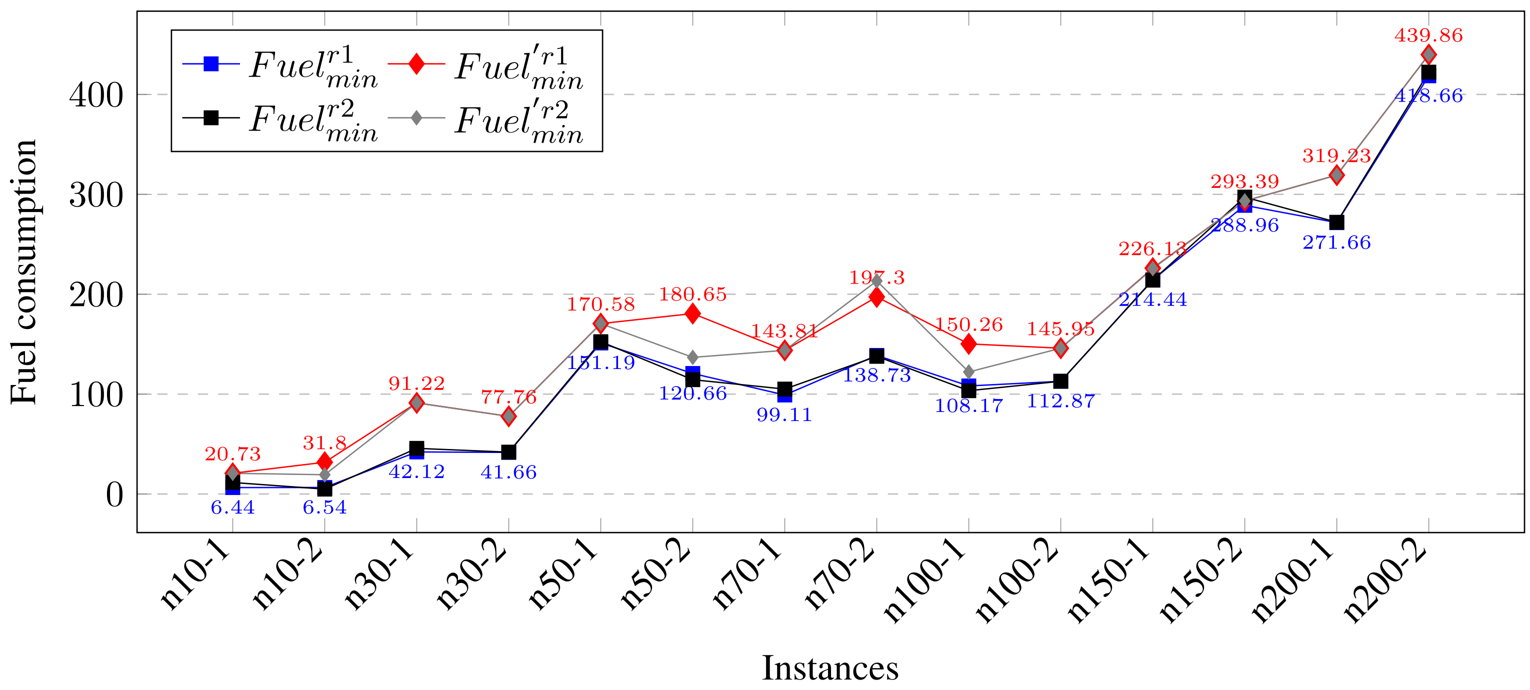


Figure 4.4: Comparison between fuel consumption values for $Fuel^{r1}_{min}$, $Fuel'^{r1}_{min}$, and $Fuel^{r2}_{min}$, $Fuel'^{r2}_{min}$ for all instances.

Table 4.3: Computational results of the POPMUSIC approaches for the MDGVRP-PD considering fuel consumption with and without the weight component in the objective function. The environmental improvement average % values are given in boldface.

Instance	POPMUSIC^{r1}					POPMUSIC^{r2}				
	Fuel$^{r1}_{min}$	Ems.^{r1}	Fuel$'^{r1}_{min}$	Ems.$'^{r1}$	Imp.^{r1}	Fuel$^{r2}_{min}$	Ems.^{r2}	Fuel$'^{r2}_{min}$	Ems.$'^{r2}$	Imp.^{r2}
n10-1	6.44	17.52	20.73	56.39	**-68.93**	11.53	31.36	20.73	56.39	**-44.38**
n10-2	6.54	17.79	31.80	86.50	**-79.43**	4.89	19.31	19.31	52.52	**-63.24**
n30-1	42.12	114.57	91.22	248.12	**-53.83**	45.70	124.30	91.22	248.12	**-49.90**
n30-2	41.66	113.32	77.76	211.51	**-46.42**	41.92	114.02	77.76	211.51	**-46.09**
n50-1	151.19	411.24	170.58	463.98	**-11.37**	152.48	414.75	170.58	463.98	**-10.61**
n50-2	120.66	328.20	180.65	491.37	**-33.21**	114.45	311.30	136.79	372.07	**-16.33**
n70-1	99.11	269.58	143.81	391.16	**-31.08**	105.05	285.74	143.81	391.16	**-26.95**
n70-2	138.73	377.35	197.30	536.66	**-29.69**	137.80	374.82	213.29	580.15	**-35.39**
n100-1	108.17	294.22	150.26	408.71	**-28.01**	103.42	281.30	122.17	332.30	**-15.35**
n100-2	112.87	307.01	145.95	396.98	**-22.67**	112.87	307.01	145.95	396.98	**-22.67**
n150-1	214.44	583.28	226.13	615.07	**-5.17**	214.07	582.27	225.66	613.80	**-5.14**
n150-2	288.96	785.97	293.39	798.02	**-1.51**	297.19	808.36	293.39	798.02	**1.30**
n200-1	271.66	738.92	319.23	868.31	**-14.90**	272.03	739.92	319.23	868.31	**-14.79**
n200-2	418.66	1138.76	439.86	1196.42	**-4.82**	422.33	1148.74	439.86	1196.42	**-3.99**
Average	144.37	392.69	177.76	483.51	**-30.79**	145.41	395.94	172.84	470.12	**-25.25**

4.6 Conclusions

This research presented a matheuristic based on the POPMUSIC approach to the multi-depot green vehicle routing problem with pickups and deliveries (MDGVRP-PD). By proposing a novel mathematical programming formulation with a decomposition approach based on partial optimization inherent to POPMUSIC, we solved size instances from modifying the literature benchmark to optimality or close to optimality that had been out of reach for the optimal solution before.

The results provided in this investigation highlight the application of our matheuristic approach for solving large-sized problems. In this regard, the POPMUSIC approach proposed has great potential for recognizing relaxed constraints in the parameter space of the problem by leveraging the information obtained by solving the subproblems. As a result, our approach can provide an average percentage of improvement in the emission of almost 30.79% when the objective function considers the weight multiplied by distance.

Chapter 5

Conclusions

This dissertation analyses current progress on GVRPs considering emissions as well as proposes solution approaches based on decomposition matheuristics for emerging emissions-related GVRPs. The methods decompose the original problem into smaller subproblems, which are solved using mathematical programming. One of these methods is the cluster first-route second approach, that first carries out the assignment of customers to vehicles and, subsequently, generates the routes per vehicle. Similarly, the partial optimization approach employs the MILP models to solve the subproblem/s out of the original problem considering constant all remaining routing decisions involving the remaining subproblems. The idea behind using mathematical programming methods is to solve each subproblem to optimality and use that information within the heuristic schemes.

Firstly, we presented an extensive literature review about heuristic and hybrid techniques for solving GVRPs considering emissions using the PRISMA methodology. Based on this scope, we surveyed 89 research works, and for each, we identified and analyzed the GVRP variant, emission model, and main strategies and components within their proposed solution methods. Moreover, we studied and mapped the problem instances proposed in the literature. Our findings show that most works explicitly calculate emissions within the mathematical model or algorithm, being the factor model the main fuel consumption model used. Also, we found predominant characteristics in the addressed GVRPs, for instance, single-objective, homogeneous fleets, and constraints associated with customers' time windows. Regarding the leading strategies and components in the proposed solution methods, we found that using randomness to generate the initial solution is the most frequent approach. Moreover, we also observed several widely used aspects, such as the use of exchange and 2-opt as neighborhood generation operators, best improvement as a local search method, roulette wheel as a selection method, and two-phase approach as the methodology. On the other hand, the most used type of approach is the single-solution-based metaheuristic, while the most commonly used techniques are the tabu search and adaptive large neighborhood search. Concerning benchmarks, we reported that although the generation of own instance sets is the predominant approach, a representative percentage of the investigations were based on real data and the well-known PRPLIB instances based on real locations.

Considering our findings from the literature reviewed, we presented the cumulative vehicle routing problem with time windows (CumVRP-TW) by means of two variants, i.e., with hard (CumVRP-HTW) and soft time (CumVRP-STW) windows constraints. For both problem variants, we defined two mathematical models based on MILP. Also, we developed a cluster first-route second matheuristic algorithm for also solving large-size instances. This uses the MILP models separately within a GRASP, i.e., one for each case of time windows, and an improvement technique based on partial optimization algorithm, which considers the subtours as subproblems and optimizes subproblems of at most the dimension established as a parameter. Besides using instances from the related literature, a new set of PRPLIB instances, including customers' priorities, was introduced to establish how much a customer represents for a company in monetary terms. As part of the experiments, we used a parameter tuning and algorithm configuration based on ParamILS to determine the best parameter performance of our approach. Box plots out of the experimental results confirm the relevant performance of our matheuristic in terms of small variability in the provided solutions for hard and soft time window cases. The results show that the optimization models provided good results for small-size instances in terms of optimality achievement and computational times. However, due to the complexity of medium and large-size problem instances, the exact solver cannot provide optimal solutions within the 2-hour limit. For those cases, the proposed matheuristic was capable of providing better solutions with less computational effort.

We further analyzed the trade-off between the environmental cost due to emissions and the impact of penalties for delayed delivery, defining the customers' priorities based on demand. The results indicate that the inclusion of soft time window constraints decreases fuel consumption costs and carbon dioxide emissions. Evaluating this trade-off helps transport companies when looking for a balance between cost-efficient logistics operations and environmental sustainability.

Nowadays, many freight road transport enterprises must make routing plans considering multiple depots. In this context, we present the multi-depot green vehicle routing problem with pickups and deliveries (MDGVRP-PD). To solve this problem, we formulate a MILP and a matheuristic approach consisting of a partial optimization matheuristic. The initial solution for the matheuristic approach was supported by a clustering algorithm as a starting point for the partial optimization metaheuristic under special intensification conditions (POPMUSIC). POPMUSIC takes advantage of the efficiency of exact solutions to solve simple subproblems of the original problem. We proposed a set of instances for the MDGVRP-PD based on real urban locations to test our approach.

The results show that POPMUSIC is used to exploit the exact optimization method for solving subproblems to optimality, show that it offers suitable performance for routing problems with several depots. Furthermore, an analysis of the effect of the carried weight on fuel consumption (proportional to the emissions) showed significant reductions in the emissions compared to the case when only distances are taken into account. As a result, if the weight carried on the routes as part of the fitness measure is considered, our matheuristic approach provides an average percentage improvement in emissions of 30.79%, compared to a fitness measure that only takes into account the distances of the routes.

We discuss general directions for future research regarding the underlying findings presented in the dissertation:

- The work of Santini et al. (2021) studies the use of clustering algorithms for CVPR (e.g., barycentre clustering) in the decomposition procedure. The authors provide better solutions than those algorithms that do not decompose the problem. Thus, future work aims to study the behavior of these clustering algorithms in emerging problems with multiple characteristics that can influence clustering (e.g., multiple recharging stations, pickup and delivery operations, and waste collection).
- The study of multi-depot VRP with time windows consideration and the use of novel emission models, e.g., CMEM or MEET, like the work of Wang et al. (2019), can help improve environmental issues and provide better analysis of the characteristics of vehicle fleets. Future studies can be oriented to evaluate the effect of speed on the cumulative cost for multi-depot VRP that consider soft time windows and use accuracy models based on characteristics of the vehicles (e.g., engine speed, heating value, rolling resistance coefficient). In addition, there is a lack of studies to consider sloping roads in the process of routing planning. Further studies can be oriented to use geographic information systems (e.g., GIS, OpenStreetMap) to retrieve relevant data (e.g., road gradients from cities with hill ranges) and feed the previous emission formulas with that.
- According to Moons et al. (2017), most studies on VRPs only aim for a single objective, mainly focusing on operational cost minimization or service level maximization. However, the use of multiple objectives in GVRPs becomes relevant given the need to also consider transport costs (e.g., distances, driver wages, etc.) or service-oriented objectives (e.g., waiting time) jointly with environmental indicators (e.g., emissions, fuel consumption, etc.). For instance, Wang et al. (2019) employ a shared transportation fleet and minimizes a multi-objective function based on distances, vehicle utilization, and carbon emissions. Validi et al. (2021) consider concurrent minimization of total cost and carbon emission in a three-echelon LRP context. Besides those works, our findings show that few works tackling GVRPs as a multi-objective problem or with multi-objective-based heuristics (see MH-MO, HMH-MO percentages indicators in Section 2.4). Thus, addressing this

multi-objective perspective on GVRPs provides an interesting and relevant line of research.

- As indicated in Blum and Roli (2008); Martí et al. (2013), the influence of initial solutions on approximate algorithms' performance might have a meaningful impact on solutions' quality. Thus, developing tailored solution generation methods and incorporating inherent characteristics related to the problem to generate the initial solution might lead to better solutions. For instance, in GVRPs, the authors of (Cinar et al., 2016) generate initial solutions for the CumVRP by extending the Clarke and Wright to include the load to generate the initial solution. Moreover, in the work of Majidi et al. (2017), they indicate the importance of initial solutions when solving the F-GVRPSPDTW. In doing so, they proposed a parallel insertion-based construction heuristic considering vehicle load-carrying as an insertion criterion. In addition, Fan et al. (2021) show that the quality of initial solutions can be improved by spatiotemporal clustering of customers.

- Investigate the incorporation of AFVs based on hydrogen vehicles can improve the pollutants indicators thanks to their benefit on driving range and refueling times, among other relevant aspects of this technology (Islam et al., 2021). Further studies can be oriented on incorporating this type of vehicle in AFSs, for example, by estimating the emissions produced in the energy generation process and the charging time influence on emissions.

- Most of the investigations only consider carbon emission estimations; however, other types of greenhouse gas emissions (e.g., methane, nitrous oxide, hydrofluorocarbons, among others) might need to be considered. In addition, factor-based models are the most used emissions model. Nevertheless, using macroscopic and microscopic emission models provides accurate emission estimations (Demir et al., 2014b). Hence, using macroscopic and microscopic models stands as a relevant research direction in GVRP applications.

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