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Review Article

A Review of Heuristics and Hybrid Methods for Green Vehicle Routing Problems considering Emissions

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Road freight transport is one of the sectors with the highest greenhouse gas emissions and fuel consumption in the logistics industry. In recent years, due to the increase in carbon dioxide emissions, several companies have considered reducing them in their daily logistics operations by means of better routing management. Green vehicle routing problems (GVRPs) constitute a growing problem direction within the interplay of vehicle routing problems and environmental sustainability that aims to provide effective routes while considering environmental concerns. These NP-hard problems are one of the most studied ones in green logistics, and due to their difficulty, there are many different heuristic and hybrid techniques to solve them under the need of having high-quality solutions within reasonable computational time. Given the role and importance of these methods, this review aims at providing a comprehensive overview of them while reviewing their defining strategies and components. In addition, we analyze characteristics and problem components related to how emissions are being considered. Lastly, we map and analyze the benchmarks proposed so far for the different GVRP variants considering emissions.

1. Introduction

The fast development of the logistics industry has encouraged an increase in the sharing of logistics resources as well as in the reduction of energy consumption in freight transport. Although transportation companies are relevant drivers of economic growth, these are one of the leading causes of carbon dioxide emissions [1]. The transportation of goods impairs local air quality, produces noise and vibration, and contributes significantly to global warming [2]. This circumstance has been widely studied in green logistics, which considers the efficient use of resources within the logistics activities and the modification of distribution strategies that minimize the use of energy, reduce waste, and properly manage its treatment [3]. Moreover, for public and private entities, achieving a sustainable transport scheme based on planning eco-friendly and respectful transport with the environment is a growing concern. Given this, the resolution of the GVRPs has attracted increasing interest from researchers, resulting in a wide range of mathematical models, computational methods, and algorithms for transport solutions with the aim of reducing environmental and social impacts within logistic operations.

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. 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 [4]. 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 [5]. 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 1).

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 [6], Moghdani et al. [7], Erdelić and Carić [8], and the book chapter by Macrina et al. [9]. 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.

Based on the previous discussion, in this paper, we present a review of heuristic and hybrid methods for solving GVRPs that consider emissions. The contributions of this work are outlined as follows:

(i) An extensive systematic literature review analyzing and discussing the different GVRP variants addressing emissions and how those emissions have been considered. This analysis provides the main characteristics related to compositions of the restrictions, objectives, emission models, and types of emissions, among others.

(ii) A comprehensive study of heuristics' main features and heuristics hybridizations developed for solving the GVRP and related variants. 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.

(iii) A detailed description of the benchmark instances is proposed in the related literature and used to assess the algorithms' performance.

The remainder of this paper is organized as follows. Section 2 reviews and examines the related works. Section 3, describes the methodology used to carry out this research. Section 4 provides a review of the heuristics and hybrid algorithms for GVRPs. Sections 5 and 6 provide a detailed analysis of the essential characteristics of emissions in GVRPs, as well as the basic strategies used as part of heuristics and hybrid methods in GVRPs studies, respectively. Section 7 exposes the benchmarks used to address this type of problems. Finally, Section 8 presents the conclusions of this work and future research directions. Last, we provide a glossary of abbreviations used in this article.

2. Related Work

This section is devoted to analyzing and contextualizing our review in light of available state-of-the-art works on GVRPs. For each work, we consider their existing focus and contribution as well as their fundamental aspects of interest in the context of green vehicle routing.

Erdelić and Carić [8] surveyed variants and solution approaches for the electric vehicle routing problem (E-VRP). It covered an updated literature review up to 2019 about all VRP variants that take into account a fleet of electric vehicles and their characteristics (e.g., partial recharges, mixed fleets, and hybrid vehicles) and also its main components and structural parts (e.g., charging stations, state of charge, and charging schedule). The review provided descriptions of the E-VRP solving methods divided into several parts, for example, exact and software procedures, heuristics, and constructive and improvements heuristics, among others. Nevertheless, the review of optimization methods did not consider the functionality of intern strategies and mechanisms inside heuristics and hybrid methods. Deleted

Kucukoglu et al. [10] presented a review study of E-VRPs, where they described different E-VRP variants. The goal of their review was to give an up-to-date literature review and offers future research directions. Also, mathematical models, solution approaches, and benchmarks were discussed. According to that review, it provided additional 62 papers not previously analyzed in the E-VRP literature. Nevertheless, due to the scope the review, there is no deep analysis concerning the internal process of each optimization method.

Macrina et al. [9] focused on building an up-to-date classification and discussing solution approaches for GVRP variants. The authors identified two main classifications for GVRPs (e.g., GVRP with conventional vehicles and GVRP with alternative fuel vehicles). The first classification has five subcategories (e.g., time-dependent PRP, multi-objective PRP, heterogeneous fleet PRP, and location PRP) and the second one presents six categories (e.g., GVRP with alternative fuel vehicles and GVRP with EVs, and with locations, GVRP with HEVs, mixed-fleet GVRP, GVRP with EVs, and nonlinear charging function). Moreover, they classified the main characteristics at a problem level (e.g., time windows, time dependency, fleet composition, and others). In addition, they presented a classification for each existing algorithm. They only proposed descriptions of each analyzed work but did not study the main strategies or operations of the heuristic and hybrid solution methods.

The review of Asghari and Mirzapour Al-e-hashem [6] presented a systematic literature review (SLR) with a classification scheme and subcategories based on GVRP variants and focused on internal combustion engine vehicles (ICEVs), alternative fuel vehicles (AFVs), and hybrid electric vehicles (HEVs). The article proposed a conceptual framework to characterize the literature and a comprehensive taxonomy for GVRPs with the aim of classifying solution approaches, objective functions, and types of engines. For each problem variant, the main characteristics of the problem were described (e.g., problem formulation, application areas, and others). The paper investigated a large number of works, proposed a considerable number of classifications, and showed summaries of solution approaches but did not analyze the solution approaches in-

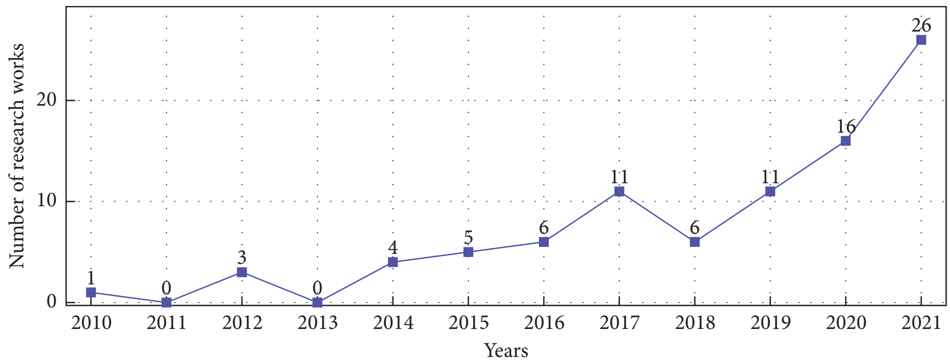

FIGURE 1: Illustration of the number of publications in Scopus and Web of Science per year. The resulting publications are based on research papers that address GVRPs considering emissions using heuristics and hybrid methods.

depth, the different ways of hybridization nor their methodologies.

Moghdani et al. [7] presented an SLR based on several research questions about the main variants of GVRPs, methodological resolution approaches, objective functions, and emerging challenges. The authors reviewed each article and showed summaries and statistics based on each problem's particularities as well as on solution methods. Although a search query is not provided, the number of works is reasonable considering similar state-of-the-art reviews. Furthermore, they provided a general classification of different solution techniques without specifications about the inner strategies of each one (e.g., heuristic and metaheuristics).

Marrekchi et al. [11] presented an SLR on GVRPs as well as on green arc routing problems (GARPs). The papers collected were classified into two sections: one-level optimization problems and multilevel optimization problems. They presented a classification based on characteristics related to the type of problem (e.g., stochastic and deterministic), type of operations (e.g., pickup and/or delivery), the type of objective function (e.g., single-objective or multiobjective), type of vehicles (e,g., homogeneous or heterogeneous), constraints (e.g., time windows or time dependency) and decision variables (e.g., speed and load). For each paper, the authors described the objective to be achieved as well as the proposed solution method.

Ghorbani et al. [12] focused on classifying and discussing environmentally friendly VRPs (EF-VRPs) based on different types (e.g., alternative fuel VRP, electric VRP, and hybrid VRP). For each type, the authors showed typical tabular information related to VRP features and constraints (e.g., fleet size and travel time) and alternative-fuel vehicles with an emphasis on technical constraints (e.g., refueling, load, speed, and others). Moreover, they analyzed the solution methods by discussing exact and heuristic algorithms designed for the EF-VRPs. The study involved the analysis of the methods, but did not consider some specifications related to how those methods or their inner strategies have been applied to solve EF-VRPs.

From the point of view on the last stage in the delivery process of goods, the survey of Patella et al. [13] presented an SLR about green vehicles in the last-mile logistics distribution. In doing so, they used search queries related to emerging research domains such as autonomous-green vehicles, drones, and last-mile and urban logistics. The review followed three main criteria for the classification of the papers: (i) operation research problems, (ii) policy focusing on governance, planning, regulations, others, and (iii) sustainability by considering environmental and economic aspects. In their review, solution methods or benchmarks were analyzed.

As seen from the previous discussion, this review paper contributes and distinguishes itself from other reviews in the following: (i) recent works are now reviewed, this also involves including recent research on electric vehicles and hydrogen vehicles taking into account emissions; (ii) the hybrid solution approaches (e.g., heuristics, metaheuristics, and hybridization approaches for GVRPs) are analyzed in detail concerning their components and strategies for solving GVRPs considering emissions; and (iii) the way emissions are considered in each work is reviewed, and a diverse benchmark is used to evaluate algorithms mapped.

3. Review Methodology

This review was performed as a systematic literature review (SLR). According to Cook et al. [14], 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:

(i) RQ1: What are the most used heuristics and hybrid methods to solve GVRPs considering emissions?
(ii) RQ2: How emissions have been considered in GVRPs?
(iii) RQ3: How heuristics and hybrid methods have been applied to solve the studied GVRPs?
(iv) RQ4: What are the basic strategies used as part of heuristics and hybrid methods?
(v) RQ5: 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 ‘hyper-heuristic∗’ 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. [15]). It establishes an evidence-based minimum set of items for reporting SLRs using databases and registers. For that purpose, in this work, 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.

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 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.

4. Review of the 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 is complemented with the analysis of their emission models and solution approaches in detail in Sections 5 and 6, respectively.

4.1. Green Vehicle Routing Problems. The green vehicle routing field 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 [16] 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 [17] 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. [18], 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 [19]) 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 [20] 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. [21] 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 [22] 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 [23]). The study by Yavuz and Çapar [24] 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 presented a variable neighborhood search (VNS)

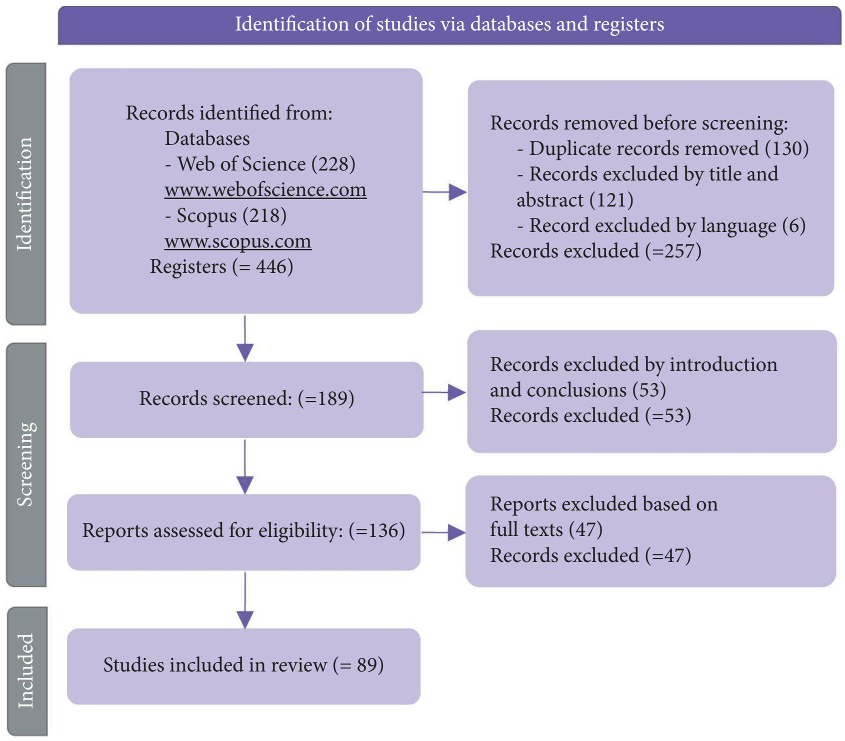

FIGURE 2: Screening and selection stages using the PRISMA flow diagram. This diagram shows the different stages that are part of the methodology proposed to carry out this survey.

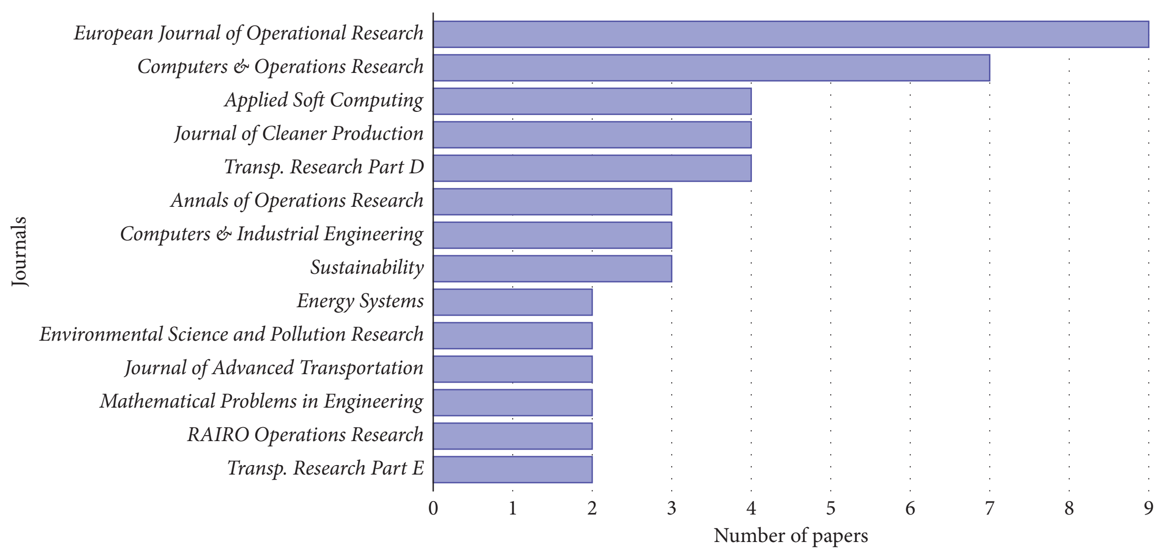

FIGURE 3: Number of papers published in (main) journals (note that the journals with more than two articles are shown).

heuristic to solve the problem for a single objective and an adapted version of the VNS to bi-objective optimization. Soysal et al. [25] 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. [26] 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. [27] 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. [28] 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.

4.2. Inventory Routing-Related Problems. The inventory routing problem (IRP) is a logistics problem that arises from the combination of routing, inventory, and replenishment scheduling decisions [29]. Concerning GVRPs, the work of Alkaabneh et al. [30] 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.

4.3. Location Routing-Related Problems. 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. [31] 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. [32] presented the regional low-carbon LRP with reality constraint conditions (RLCLRPRCC), 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. [33] 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).

4.4. Multi-depot Routing-Related Problems. 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. [34] 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. [35] 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. [36] presented another ACO approach in this case for the MD-GVRP with time windows (MDGVRP-TW).

Wang et al. [37] 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 network'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. [38] used the matheuristic version of the partial optimization metaheuristic under special intensification conditions (POPMUSIC, Lalla-Ruiz, and Voß [39]) 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.

4.5. Multi-trip Routing-Related Problems. The multi-trip VRP (MTVRP) differs from the classical VRP by allowing vehicles to perform multiple trips. Lyu and He [41] 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.

4.6. Multi-echelon Distribution-Related Problems. 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. [42] 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 linehaul 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 [43] 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 [44]). Moreover, this approach uses the roulette wheel (RW, Lipowski and Lipowska [45]) mechanism that relies on the selection of destruction and repair operators. Similarly, Anderluh et al. [46] 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 [47] 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-opt $*$ 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. [48] 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. [49] 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.

4.7. Period Vehicle Routing-Related Problems. 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. [50] 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.

4.8. Pollution-Routing-Related Problems. 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 [1]. Demir et al. [51] 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. [52] 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. [53] 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. [54] 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. [55] 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) [56], time-dependent PRP (TD-PRP) [57, 58], and sustainable traveling purchaser problem with speed optimization (STPPS) [59], an extension of the single-product traveling purchaser problem model and the PRP.

Kumar et al. [60] presented a multi-objective model for multivehicle 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. [61] investigated the bi-objective PRP in the context of green logistics with a focus on reducing CO_2 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. [62] 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. [63] 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 [40]. 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. [64]. Furthermore, to generate the initial solution, the authors applied C&W and a guided VND (GVND) as the improvement algorithm.

4.9. Electric Vehicles-Related Problems. 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. [65] 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 multidirectional LS (EMDLS) to approximate the Pareto front. The EMDLS is an enhanced version of the improved multidirectional LS introduced by Lian et al. [66]. Due to battery driving range limitation, Yang and Sun [67] 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 [68] 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 multigraph (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-DP-ILNS). Arroyo et al. [69] 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. [70]) 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. [71] addressed the green mixed-fleet VRP with realistic energy consumption and partial recharges (GMFVRPREC-PR) [74]. 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. [72] proposed a mathematical model and a constructive heuristic based on Solomon's sequential insertion heuristic (SIH, Solomon [73]) 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, [74]) 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 environmental considerations, Soysal et al. [74] 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 sub-periods. The method modifies the lower and upper bound values of the 0–1 variables for each of the sub-periods. The lower and upper bound values for the fixing sub-periods are set to best-known variable values. The lower and upper limits are set to 0 and 1 in the optimizing sub-periods to allow the model to choose the values of the binary variables based on the fixed variable values.

4.10. Pickups and Deliveries Related Problems. The pickup and delivery VRP (PDVRP) involves conducting a set of pickup and delivery orders between pairs of locations. Fatemi-Anaraki et al. [75] 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. [76] 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 HH-ILS 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. [77] 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 (G-VRPMSPDTW-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 [78] 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. [79] 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. [80] 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. [81]) to calculate fuel consumption and CO_2 emissions. Lu and Huang [82] 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.

4.11. VRP with Backhauls-Related Problems. 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 [83]. 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. [84] faced 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 proposed a quantum-behaved PSO (QPSO) and an exploration heuristic LS algorithm (EHLSA).

4.12. Scheduling-Related Problems. 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 [85] 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 [86] 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. [87] 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. [88] 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 [89], 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 reoptimized 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. [90] 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. [91] 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. [92]) and national atmospheric emissions inventory (NAEI, NAEI [93]) 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. [94] 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.

4.13. Time Windows-Related Problems. In the VRP with time windows (VRPTW), service to each customer involves pickup and/or delivery of goods within a specified time windows [73]. 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. [95] 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. [96] 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 [97], which builds routes in parallel and uses a generalized regret measure, total unrouted customers, to select the next candidate for insertion. Rezaei et al. [98] addressed the green VRP with time windows (G-VRPTW) 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. [99] 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 (ABC-RRT). Zhao et al. [100] 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 [101] 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 [102], 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. [103] 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. [104] 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. [105] 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 multicompartment vehicles for city logistics and G-VRPTW [107, 108], GA for the effect of governmental time window policy on the routing planning decisions of cold chain distribution companies [109], fuzzy hierarchical clustering method and GA for the customer-oriented routing problem with consideration of the environment [110], and a TS and VNS for VRP in the home health care sector called VRPTW with synchronization, precedence, and fuel consumption constraints (VRPTW-SPFC) [111].

4.14. Time-Dependent-Related Problems. 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 [112], 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 [113] 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 [114] presented the TDGVRP-AF, which is the union between the original GVRP proposed by Erdoğan and Miller-Hooks [17] 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. [115] 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 CO_2 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. [116] 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. [117] 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.

4.15. Waste Collection-Related Problems. 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 [118]. The authors of Qiao et al. [119] 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. [120] 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. [121] 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) [122] that simulates the group behavior of grasshoppers for getting hold of food.

Molina et al. [123] 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.

4.16. Prize-Collecting Vehicle Routing Problems. The prize-collecting vehicle routing problem (PCVRP) is an extension of the prize-collecting traveling salesman problem (PCTSP) proposed by Balas [124]. 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. [125] 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.

4.17. Hydrogen Vehicles in Routing Problems. 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. [126], 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.

5. 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 1 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 4, 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

Table 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. [27]	•		•				•		•			•		•		
Dewi and Utama [22]	•		•					•					•		•	•
Soysal et al. [25]	•		•				•	•					•		•	
Talouki et al. [26]	•		•						•	•	•		•		•	
Liu et al. [28]	•		•				•	•		•			•			•
Wei et al. [21]	•		•				•		•	•				•	•	
de Oliveira da Costa et al. [18]	•		•			•	•	•					•			•
Yavuz and Çapar [24]	•		•				•	•				•		•		
Omidvar and Tavakkoli-Moghaddam [20]	•		•				•	•		•	•	•	•		•	
Inventory routing-related problems																
Alkaabneh et al. [30]	•		•				•	•					•		•	•
Location routing-related problems																
Leng et al. [33]	•		•		•				•	•				•	•	•
Dukkanci et al. [31]	•		•		•			•		•			•		•	•
Leng et al. [32]	•		•		•			•		•				•	•	•
Multi-depot routing-related problems																
Fernández et al. [38]	•			•			•	•		•		•	•			•
Wang et al. [37]	•		•		•				•	•	•		•		•	•
Jabir et al. [35]	•		•				•	•		•			•			•
Kaabachi et al. [36]	•		•		•			•		•			•		•	•
Pérez-Bernabeu et al. [34]	•			•			•	•				•	•			
Multi-trip routing-related problems																
Lyu and He [41]	•		•				•	•				•		•		•
Multi-echelon distribution-related problems																
Anderluh et al. [46]	•		•				•		•			•	•			
Liu and Liao [43]	•		•		•				•				•		•	•
Mühlbauer and Fontaine [47]	•			•			•	•						•		
Validi et al. [49]	•		•				•		•			•		•		
Jie et al. [48]		•		•			•	•						•		
Li et al. [42]	•		•				•	•		•		•	•			•
Period vehicle routing-related problems																
López-Sánchez et al. [50]	•			•					•				•			
Pollution-routing-related problems																
Cheaitou et al. [59]	•		•		•				•				•		•	•
Koç et al. [55]	•		•		•			•				•		•	•	•
Costa et al. [61]	•		•		•				•	•			•		•	•
Kargari Esfand Abad et al. [62]	•		•		•				•				•		•	
Fang et al. [63]	•		•		•			•					•			•
Franceschetti et al. [57]	•		•		•			•		•	•		•		•	•
Guo and Liu [58]	•		•		•			•		•	•		•		•	•
Kumar et al. [60]	•		•		•				•	•			•		•	•
Suzuki [56]	•			•			•	•					•		•	•
Kramer et al. [53]	•		•		•			•		•		•	•		•	•
Demir et al. [52]	•		•		•				•	•			•		•	•
Koç et al. [54]	•		•		•			•		•				•	•	•
Demir et al. [51]	•		•		•			•		•			•		•	•
Electric vehicles-related problems																
Raeesi and Zografos [68]	•			•			•		•	•		•	•			
Soysal et al. [74]	•			•	•			•						•		•

Table 1: Continued.

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
Yu et al. [71]	•		•		•			•		•				•	•	•
Arroyo et al. [69]	•		•				•	•				•		•		
Eskandarpour et al. [65]	•		•				•		•					•		
Macrina et al. [72]	•		•				•	•		•		•		•		•
Yang and Sun [67]	•	•		•			•	•					•			
Pickups and deliveries-related problems																
Fatemi-Anaraki et al. [75]	•		•				•		•					•		•
Olgun et al. [76]	•		•				•	•					•			•
Solano et al. [79]	•			•			•	•		•		•	•			
Srijaroon et al. [77]	•		•		•			•		•	•	•	•		•	•
Asghari and Mirzapour Al-e-hashem [78]	•		•				•		•	•		•		•		•
Lu and Huang [82]	•		•				•	•		•			•			
Majidi et al. [80]	•		•		•			•		•			•		•	•
VRP with backhauls-related problems																
Zhao et al. [84]	•		•				•	•					•			
Scheduling-related problems																
Jiang et al. [94]	•		•						•	•			•		•	•
Alizadeh Foroutan et al. [88]	•		•			•	•	•			•	•		•	•	•
Sousa Matos et al. [90]	•		•				•	•		•	•	•		•	•	•
Liao [89]	•		•				•	•		•	•		•		•	•
Zhou et al. [91]	•		•			•		•		•	•	•		•	•	
Gang et al. [87]	•		•		•				•	•		•	•			•
Xiao and Konak [86]	•		•		•	•		•		•	•			•		•
Xiao and Konak [85]	•		•		•	•			•	•	•		•		•	
Time windows-related problems																
Ettazi et al. [111]	•		•				•	•		•			•			
Islam and Gajpal [101]	•		•		•			•		•		•		•	•	•
Luo et al. [102]	•		•			•		•		•		•	•			
Eshtehadi et al. [107]	•		•		•			•		•		•	•		•	•
Fernández et al. [105]	•			•			•	•		•			•			•
Ren et al. [104]	•	•	•			•			•	•				•		
Yu et al. [108]	•		•				•	•		•		•	•			•
Zhang et al. [109]	•			•			•	•		•		•		•		•
Zhao et al. [100]	•		•		•				•	•			•		•	•
Meng et al. [110]	•		•				•	•		•		•	•		•	•
Rezaei et al. [98]	•		•				•		•	•				•		•
Masmoudi et al. [99]	•		•		•			•		•		•		•	•	•
Sanchez et al. [103]	•		•				•	•		•			•	•		
Küçükoğlu et al. [117]	•			•				•		•	•		•		•	•
Molina et al. [95]	•	•	•				•		•	•		•		•		•
Maden et al. [96]	•			•			•	•		•		•		•		
Time-dependent-related problems																
Zulvia et al. [115]	•		•				•		•	•	•	•	•		•	•
Hooshmand and MirHassani [114]	•			•		•		•			•	•	•		•	
Çimen and Soysal [113]	•			•		•		•			•		•		•	
Soysal and Cimen [113]	•		•			•		•			•		•		•	
Liu et al. [116]	•		•		•			•			•			•	•	•
Waste collection-related problems																
Malekkhouyan et al. [121]	•		•						•	•		•	•			•

Table 1: Continued.

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
Qiao et al. [119]	•		•				•	•					•			•
Molina et al. [123]	•		•			•		•						•	•	•
Wei et al. [120]	•		•		•			•					•		•	•
Prize-collecting vehicle routing problems																
Trachanatzi et al. [125]	•		•				•	•					•			•
Hydrogen vehicles in routing problems																
Islam et al. [126]	•		•		•			•		•				•	•	•

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. [127], the fuel consumption models can be classified as factor models, macroscopic models, and microscopic models:

(i) Factor models. These models are based on fuel consumption rate (e.g., liters per kilometers or gallons per miles). Using this type of model, the CO_2 emissions can be estimated using the fuel consumption approach, that is, $e = \text{fuel consumption} \times \text{heating value} \times \text{emission factor}$, where the heating value represents the heat content of fuels, and the traveled distance approach, that is, $e = \text{traveled distance} \times \text{emission factor}$. The emission factor can be expressed in kg CO_2 e/liter, (see DEFRA [128]; Veidenheimer [129]).

(ii) 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, for example, MEET by Hickman et al. [92] and a computer program to calculate emissions from road transport (COPERT) by Kouridis et al. [130].

(iii) 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 commonly used microscopic models for solving GVRPs is the CMEM [81, 131], 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 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 work.

6. 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 [4] 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 hyper-heuristics (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 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 [132] 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:

Table 2: Main strategies used in the heuristic methods for the GVRPs.

	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
Solution approach (type) and reference	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. [27]				•																						
HWOA (MH-MH) Dewi and Utama [22]				•						•	•															
DPH (H) Soysal et al. [25]			•																							
SA (SMH) Liu et al. [28]				•																						
NSGA-II (MH-MO) Wei et al. [21]				•									•	•											•	
GA (PMH) de Oliveira da Costa et al. [18]	•			•									•					•								
VNS (SMH) Yavuz and Çapar [24]			•						•	•		•														
SA (SMH), GA (PMH) Omidvar and Tavakkoli-Moghaddam [20]			•										•	•				•								
Inventory routing-related problems																										
GRASP (SMH) Alkaabneh et al. [30]		•		•																					•	
Location routing-related problems																										
MOHH (HH) Leng et al. [33]				•	•							•	•	•		•										
ILS (SMH) Dukkanci et al. [31]	•			•	•						•															
HH (HH) Leng et al. [32]				•	•		•			•						•										
Multi-depot routing-related problems																										
POPMUSIC (MATH) Fernández et al. [38]		•																				•				
CWSHA-MOPSO-SwA (HMH-MO) Wang et al. [37]	•									•	•		•	•											•	
ACO-VNS (MH-MH) Jabir et al. [35]			•	•					•	•	•															
ACO (PMH) Kaabachi et al. [36]		•		•	•					•	•															

Table 2: Continued.

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 (SMH)																										
Pérez-Bernabeu et al. [34]	•			•							•															
Multi-trip routing-related problems																										
TSHM (MH-MH)																										
Lyu and He [41]		•		•	•	•				•	•		•	•											•	
Multi-echelon distribution-related problems																										
LNS (SMH) Anderluh et al. [46]		•		•	•	•			•		•					•										
ALNS-C&W (MH-H) Liu and Liao [43]	•			•					•		•					•			•							•
PLNS (SMH) Mühlbauer and Fontaine [47]		•		•	•	•		•			•															
MOGA-II, MOPSO, NSGA-II(MH-MO) Validi et al. [49]			•	•									•	•	•										•	
CG-ALNS (MATH) Jie et al. [48]			•						•							•							•			
C&W (H)																										
Li et al. [42]	•						•				•														•	
Period vehicle routing-related problems																										
MSMLS (SMH)																										
López-Sánchez et al. [50]				•						•	•														•	
Pollution-routing-related problems																										
GA (PMH) Cheaitou et al. [59]				•									•													
TS (SMH) Koçetal. [55]		•								•																
Pareto LS (MH-MO) Costa et al. [61]			•			•	•					•													•	
NSGA-II, NRGA, MOPSO (MH-MO) KargariEsf and Abad et al. [62]													•	•	•			•								
C&W, GVND-B&C (MATH) Fang et al. [63]						•	•			•	•									•						
ALNS (SMH) Franceschetti et al. [57]			•						•			•				•										
HE (H)																										
Guoand Liu [58]			•																						•	

Table 2: Continued.

	Initial solution				Neighborhoods						LS methods		Genetic operators		Selection methods				Methodologies							
Solution approach (type) and reference	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 (MH-MO) Kumar et al. [60]				•									•			•										
SA-TS (MH-MH) Suzuki [56]				•	•							•													•	
ILS-SP-SOA (MATH) Kramer et al. [53]			•		•	•	•					•									•					
ALNS (SMH) Demir et al. [52]	•								•		•					•									•	
HALNS-HEA-SOA (MH-MH) Koçetal.[54]	•								•		•							•							•	
ALNS(SMH) Demir et al. [51]	•								•		•					•									•	
Electric vehicles-related problems																										
MG-DP-ILNS (MH-H) Raeesi and Zografos [68]									•																	
F&O (H) Soysal et al. [74]			•																					•		
ALNS (SMH) Yu et al. [71]			•				•		•		•															
48A (H) Arroyo et al. [69]				•	•																				•	
EMDLS (SMH) Esk and arpour et al. [65]			•						•																	
ILS (SMH) Macrina et al. [72]			•							•	•															
SIGALNS, TS-MCWS (H,MH-H) Yang and Sun [67]	•									•	•					•									•	
Pickups and deliveries-related problems																										
GA, NSGA-II (PMH, MH-MO) Fatemi-Anaraki et al. [75]			•										•	•				•								•
ILS-VND (HH) Olgun et al. [76]			•	•	•			•	•	•	•					•										
Greedy-TS (MH-H) Solano et al. [79]		•								•	•															
SAL-PSO (PMH) Srijaroon et al. [77]		•																								
NSGA-II (MH-MO) Asghari and Mirzapour Al-e-hashem [78]				•									•	•	•											
DALNS (SMH) Lu and Huang [82]		•							•		•															
ALNS (SMH) Majidi et al. [80]			•								•					•										

TABLE 2: Continued.

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
VRP with backhauls-related problems																										
QPSO-EHLSA (MH-H) Zhao et al. [84]				•	•					•																
Scheduling-related problems																										
NSGA-II, MOTS (MH-MO, MH-MO) Jiang et al. [94]				•						•	•		•	•												
SA, GA (SMH, PMH) Alizadeh Foroutan et al. [88]				•						•			•	•												
MS-ILS-SC (MATH) SousaMatos et al. [90]		•		•	•					•																•
GA-TS (MH-MH) Liao [89]				•							•		•	•			•									•
TS, VND, RVNS (SMH) Zhou et al. [91]			•		•	•	•	•		•	•	•														
H-TS (MH-H) Gang et al. [87]		•								•	•															
P-MIP-INS (MATH) Xiao and Konak [86]	•								•													•				
SA (SMH) Xiao and Konak [85]				•																						
Time windows-related problems																										
TS, VNS (SMH) Ettazi et al. [111]		•								•	•															
ACO-VNS (MH-MH) Islam and Gajpal [101]			•							•																
HACO (MH-H) Luo et al. [102]			•		•		•				•															•
ALNS (SMH) Eshtehadi et al. [107]	•				•				•							•										
GRASP-MILP (MATH) Fernández et al. [105]		•		•				•				•							•							
VNS (SMH) Ren et al. [104]			•							•																
ALNS (SMH) Yu et al. [108]			•						•																	•
GA (PMH) Zhang et al. [109]			•	•									•	•				•								
ACOMO (MH-MO) Zhao et al. [100]			•													•										
Fuzzy HC, GA (PMH)																										

Table 2: Continued.

Solution approach (type) andreference	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
Meng et al. [110]			•	•									•	•												
GA, PBSA (MH, PMH)																										
Rezaei et al. [98]				•	•					•			•	•		•										
ABC (PMH)																										
Masmoudi et al. [99]			•		•		•	•								•										•
SS (PMH)																										
Sanchez et al. [103]			•		•					•	•															
SA (SMH)																										
Küçükoğlu et al. [117]		•	•				•				•	•			•											
C&W (H)																										
Molina et al. [95]	•																									
TS (SMH)																										
Maden et al.[96]			•					•		•																
Time-dependent-related problems																										
MOGE (MH-MO)																										
Zulvia et al. [115]			•	•											•											
GRASP-SA (MH-MH)																										
Hooshmand and MirHassani [114]		•		•	•					•															•	
ADP (H)																										
Çimen and Soysal [113]		•	•														•									
RDP (H)																										
Soysal and Cimen [113]			•																							
GA (PMH)																										
Liu et al. [116]				•									•	•				•								
Waste collection-related problems																										
GOA (PMH)																										
Malekkhouyan et al. [121]				•																						
PSO-TS (MH-MH)																										
Qiao et al. [119]			•	•						•							•								•	
VNTS (MH-MH)																										
Molina et al.[123]			•		•			•		•	•														•	
HABC-MDT (MH-MH)																										
Wei et al. [120]				•	•					•						•										
Prize-collecting vehicle routing problems																										
TLBO-CRE (MH-H)																										
Trachanatzi et al. [125]	•									•	•			•											•	
Hydrogen vehiclesin routingproblems																										
PSO-NS (MH-H)																										
Islam et al. [126]				•	•					•		•													•	

(i) Cross-exchange. It eliminates a series of consecutive nodes of a route and inserts these nodes into another route and vice versa.

(ii) Exchange or swap. It exchanges two vertices of the solution.

(iii) 2-opt*. It removes arcs from two routes and replaces these with two arcs connecting the routes.

(iv) 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.

(v) 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 [40] and based on the algorithms studied in this work, we classify the works into eight solution methodologies.

(i) 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.

(ii) 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.

(iii) Relaxation-based. It provides a feasible solution to a problem from the solution of the relaxed problem

(iv) 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.

(v) 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.

(vi) 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.

(vii) 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 4 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 other algorithms used in more than 10% of the investigations are GA and SA, with 11.24% and 10.11%, respectively.

Figure 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 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).

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%.

7. 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 3 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 [150] and Christofides et al. [148] are some of the oldest but most widely used VRP instances. These are used in numerous GVRPs, such as PRP in Kramer et al. [53], PPRP in Suzuki [56], and WCP-MDP in Wei et al. [120], among others. The instances proposed by Christofides et al. [148] 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. [149] 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. [50] used these instances for the Bi-PVRP-SC. Gaskell [151] 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 [19]. 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 [22] for the GVRP.

Augerat [145] 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 the region. On the other hand, Set P is made with modified instances existing in the literature [149, 150]. Some investigations used this set for experimental purposes such as E-PCVRP in Trachanatzi et al. [125] and HeVRPMD in Eskandarpour et al. [65].

Taillard [147] 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. [148]. 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 [67] to test the approach for BSS-EV-LRP and by Molina et al. [123] to solve the Eco-WCVRP. Golden et al. [143] 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. [53] for FCVRP and EMVRP; Yang and Sun [67] 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.

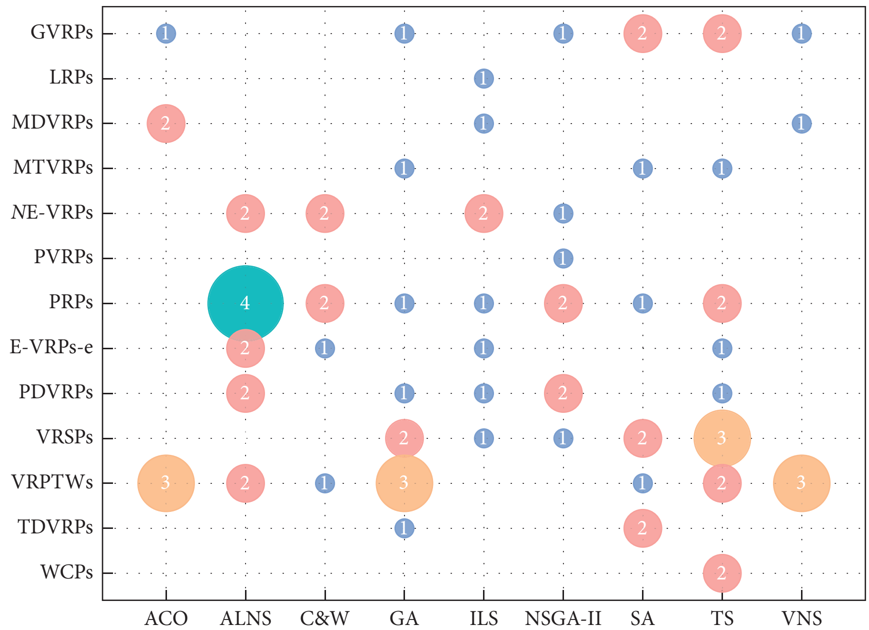

Figure 4: Bubble chart shows how many times a method has been used to solve GVRPs. Note that one method can be used to solve different variants.

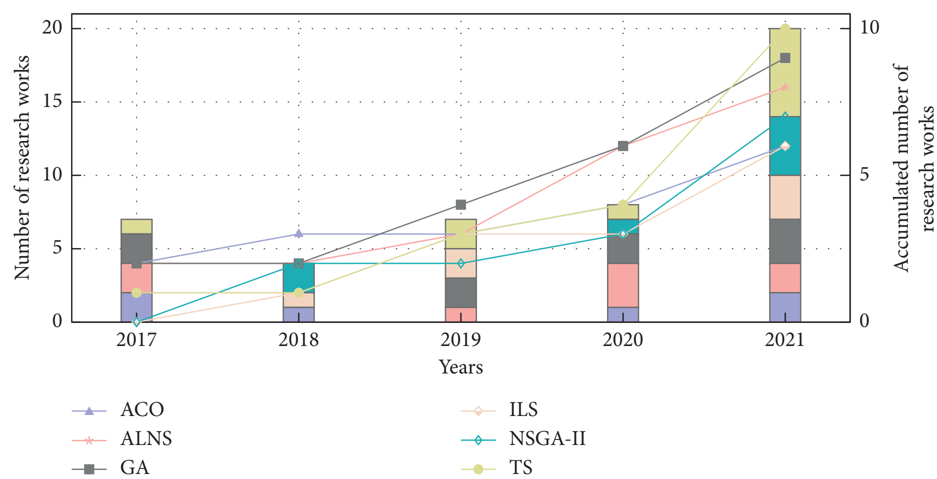

Figure 5: Number of solution methods most commonly used in the last five years. The stacked bar chart shows the number of works per year, while the line chart shows the cumulative number of works.

The instances known as *Solomon* instances proposed by Solomon [73] for the VRPTW are popular VRP benchmark that have been also used in GVRPs, for example, G-VRPTW, PRP, and LRPLCCC. This benchmark consists of a set of 56 problem instances divided into six different categories with 100 customers per instance and so-called C1, C2, R1, R2, RC1, and RC2. Based on the *Solomon* benchmark, Gehring and Homberger [141] 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, and G010, consider 200, 400, 600, 800, and 1000 customers, respectively. The benchmark proposed by Li and Lim [139] 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 delivery customers and positive demands as pickup customers. The research of Lu and Huang [82] used the set of 100 customers of this benchmark for the Green-PDPTW. The work of Küçükoğlu et al. [117] also used this instance set for the G-VRPTW. Chen and Shi [133] proposed a set of instances for MCVRPTW based on the *Solomon*'s benchmark with groups of instances with 25, 50, and 100 customers. The

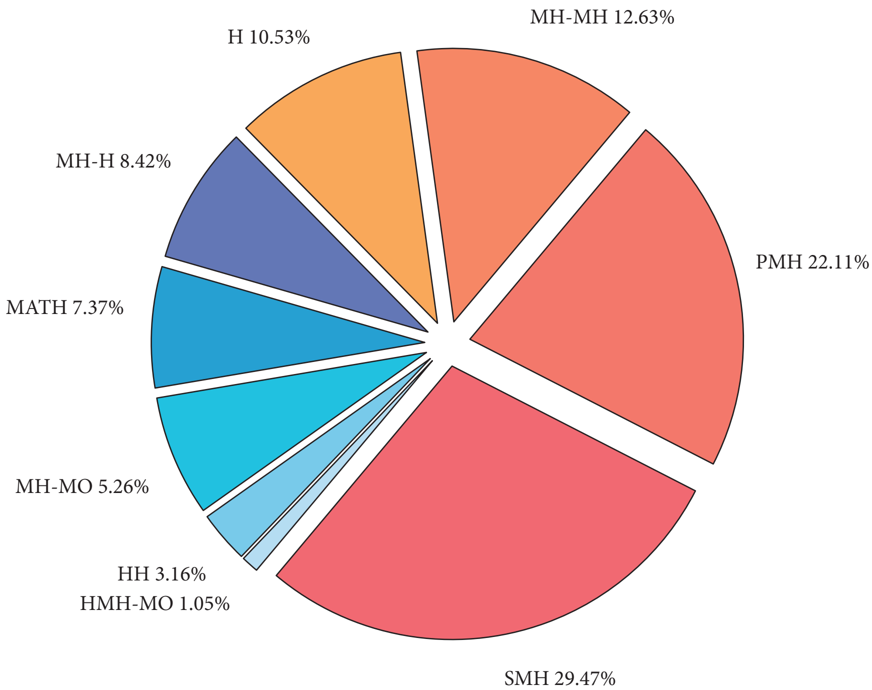

Figure 6: Distribution of proposed solution methods for GVRPs. The pie chart displays the percentage of use of each method among the reviewed articles.

Table 3: Benchmarks used for the GVRPs.

Benchmark source	Based on real-world data	Artificially generated	Research works using this benchmark
Fatemi-Anaraki et al. [75]		•	Bio-bjective green delivery and pickup problem, Fatemi-Anaraki et al. [75]
Raeesi and Zografos [68]		•	EVRPTW-RS-SMBS, Raeesi and Zografos [68]
Anderluh et al. [46]	•	•	2E-VRPSyn, Anderluh et al. [46]
Camacho-Vallejo et al. [27]		•	Green logistics biobjective bilevel problem, Camacho-Vallejo et al. [27]
Cheaitou et al. [59]		•	STPPS, Cheaitou et al. [59]
Fernández et al. [38]		•	MDGVRP-PD, Fernández et al. [38]
Islam et al. [126]		•	MFGCLP, Islam et al. [126]
Islam and Gajpal [101]		•	Mixed-fleet logistics distribution problem under CO_2 emission cap, Islam and Gajpal [101]
Jiang et al. [94]	•		MVOC, Jiang et al. [94]
Luo et al. [102]		•	HHC with synchronized visits and carbon emissions, Luo et al. [102]
Lyu and He [41]	•		MTHVRP-PCIC, Lyu and He [41]
Malekkhouyan et al. [121]		•	WCVRP, Malekkhouyan et al. [121]
Solano et al. [79]	•		VRPSPDTW, Solano et al. [79]
Srijaroon et al. [77]		•	G-VRPMSPDTW-RT, Srijaroon et al. [77]
Talouki et al. [26]	•		DGVRP, Talouki et al. [26]
Trachanatzi et al. [125]		•	E-PCVRP, Trachanatzi et al. [125]
Validi et al. [49]	•		Three-echelon distribution network, Validi et al. [49]
Alizadeh Foroutan et al. [88]		•	GVRSP, Alizadeh Foroutan et al. [88]
Alkaabneh et al. [30]		•	PIRP, Alkaabneh et al. [30]
Asghari and Mirzapour Al-e-hashem [78]	•		Green delivery-pickup problem for HHMs, Asghari and Mirzapour Al-e-hashem [78]
Arroyo et al. [69]	•		GVRP-MTPR, Arroyo et al. [69]
Eshtehadi et al. [107]	•	•	G-VRPTW, Eshtehadi et al. [107]
Leng et al. [33]		•	LRPLCCC, Leng et al. [33]
Liu et al. [28]	•		JD-GVRP, Liu et al. [28]
Wei et al. [21]		•	Green DRASS with time-varying speeds, Wei et al. [21]
Zhang et al. [109]	•	•	VRPTW in cold chain distribution, Zhang et al. [109]
Zhao et al. [84]		•	2L-MDCVRPB, Zhao et al. [84]

Table 3: Continued.

Benchmark source	Based on real-world data	Artificially generated	Research works using this benchmark
Zulvia et al. [115]	•		G-VRPTW and time dependency for perishable products, Zulvia et al. [115]
Eshtehadi et al. [133]		•	G-VRPTW, Eshtehadi et al. [107]
Eskandarpour et al. [65]		•	HeVRPMD, Eskandarpour et al. [65]
Hooshmand and MirHassani [114]		•	TDGVRP-AF, Hooshmand and MirHassani [114]
Koc et al.[55]	•		Variant of PRP, Koç et al. [55]
Meng et al. [110]	•		Customer-oriented routing problem with environment consideration, Meng et al. [110]
Molina et al. [123]	•		Eco-WCVRP, Molina et al. [123]
Rezaei et al. [98]		•	G-VRPTW, Rezaei et al. [98]
Wang et al. [37]		•	MD-GVRP, Wang et al. [37]
de Oliveira da Costa et al. [18]	•		GVRP, de Oliveira da Costa et al. [18]
Kargari Esfand Abad et al. [62]		•	Pickup and delivery PRP variant considering integration and consolidation shipments in cross-docking, Kargari Esfand Abad et al. [62]
Leng et al. [32]		•	RLCLRPRCC, Leng et al. [32]
Masmoudi et al. [99]		•	HF-VRPS, Masmoudi et al. [99]
Sousa Matos et al. [90]		•	GVRSP-split, Sousa Matos et al. [90]
Fang et al. [63]		•	PRPSPD, Fang et al. [63]
Guo and Liu [58]		•	TD-PRP, Guo and Liu [58]
Jabir et al. [35]		•	MD-GVRP, Jabir et al. [35]
Kaabachi et al. [36]		•	GMDVRPTW, Kaabachi et al. [36]
Liao [89]	•		Online VRP considers real-time demands, Liao [89]
Yavuz and Çapar [24]	•	•	MGVRP, Yavuz and Çapar [24]
Zhou et al. [91]	•		Green real-life field scheduling problem, Zhou et al. [91]
Gang et al. [87]	•		GVRSP of free picking up and delivering customers for airlines ticketing company, Gang et al. [87]
Li et al. [42]	•	•	2E-TVRP, Li et al. [42]
Goeke and Schneider, [134]		•	GMFVRPREC-PR, Yu et al. [71]
Kramer et al. [53]		•	Biobjective PRP, Costa et al. [61]; TD-PRP, Franceschetti et al. [57]; PRP, FCVRP, EMVRP, Kramer et al. [53]
Xiao and Konak [85]		•	GVRSP, Xiao and Konak [85]
Demir et al. [52]		•	BiPRP, Demir et al. [52]
Liu et al. [116]		•	MTHVRPP, Liu et al. [116]
Molina et al. [95]	•		HVRP-TW, Molina et al. [95]
Schneider et al. [135]		•	EVRPTW-RS-SMBS, Raeesi and Zografos [68]; GMFVRP-PRTW, Macrina et al. [72]
Demir et al. [51]	•		CIRP under a mixed fleet of electric and conventional vehicles, Soysal et al. [74]; GVRP, Soysal et al. [25]; CumVRP-TW, Fernández et al. [105]; GLRP, Dukkanci et al. [31]; Biobjective PRP, Costa et al. [61]; GSTDCVRP, Çimen and Soysal [113]; TD-PRP, Franceschetti et al. [57]; F-GVRPSPDTW, Majidi et al. [80]; GSTDCVRP, Soysal and Çimen [113]; MMPPRP-TW, Kumar et al. [60]; GVRSP, Xiao and Konak [86]; PRP, FCVRP, EMVRP, Kramer et al. [53]; BiPRP, Demir et al. [52]; FSMPRP, Koç et al. [54]; PRP, Demir et al. [51]
Omidvar and Tavakkoli-Moghaddam [20]		•	Congestion in VRP with AFVs, Omidvar and Tavakkoli-Moghaddam [20]
Perboli et al. [136]		•	2E-CVRPSC, Mühlbauer and Fontaine [47]; 2E-EVRP-BSS, Jie et al. [48]
Maden et al. [96]	•		VRPTW using time-varying data, Maden et al. [96]
Bredstrom et al.[137]		•	VRPTW-SPFC, Ettazi et al. [111]; HF-VRPS, Masmoudi et al. [99]
Iori et al. [138]		•	2L-MDCVRPB, Zhao et al. [84]
Li and Lim [139]		•	Green-PDPTW, Lu and Huang [82]
Dethloff et al. [140]		•	G-VRPSPD, Olgun et al. [76]
Gehring and Homberger [141]		•	G-VRPTW, Yu et al. [108]; G-VRPTW, Küçükoğlu et al. [117]
Salhi and Nagy [142]		•	G-VRPSPD, Olgun et al. [76]

Table 3: Continued.

Benchmark source	Based on real-world data	Artificially generated	Research works using this benchmark
Golden et al. [143]		•	HeVRPMD, Eskandarpour et al. [65]; PPRP, Suzuki [56]; PRP, FCVRP, EMVRP, Kramer et al. [53]; BSS–EV–LRP, Yang and Sun [67]
Cordeau et al. [144]		•	2E-CWCVRP, Liu and Liao [43]; MSW, Qiao et al. [119]; HC-MDVRP, Pérez-Bernabeu et al. [34]
Augerat et al. [145]		•	E-PCVRP, [125]; HeVRPMD, Eskandarpour et al. [65]; WCP-MDP, Wei et al. [120]; BSS–EV–LRP, Yang and Sun [67]
Chao et al. [146]		•	Bi-PVRP-SC, López-Sánchez et al. [50]
Taillard [147]	•	•	Eco-WCVRP, Molina et al. [123]; BSS–EV–LRP, Yang and Sun [67]
Solomon [73]		•	2E-VRPSyn, Anderluh et al. [46]; mixed-fleet logistics distribution problem under CO_2 emission cap, Islam and Gajpal [101]; HHC with synchronized visits and carbon emissions, Luo et al. [102]; MTHVRP-PCIC, Lyu and He [41]; B-MFGVRPTW, Ren et al. [104]; G-VRPTW, Yu et al. [108]; cold chain logistics path optimization, Zhao et al. [100]; G-VRPTW, Sanchez et al. [103]; PRP, FCVRP, EMVRP, Kramer et al. [53]; G-VRPTW, Küçükoğlu et al. [117]; PRP, Demir et al. [51]; congestion in VRP with AFVs, Omidvar and Tavakkoli-Moghaddam [20]
Christofides et al. [148]		•	E-PCVRP, Trachanatzi et al. [125]; HeVRPMD, Eskandarpour et al. [65]; GVRP, de Oliveira da Costa et al. [18]; PPRP, Suzuki [56]; PRP, FCVRP, EMVRP, Kramer et al. [53]
Eilon et al. [149]		•	Bi-PVRP-SC, López-Sánchez et al. [50]
Christofides and Eilon [150]		•	GVRP, Dewi and Utama [22]; 2E-CVRPSC, Mühlbauer and Fontaine [47]; E-PCVRP, Trachanatzi et al. [125]; WCP-MDP, Wei et al. [120]; GVRP, de Oliveira da Costa et al. [18]
Gaskell [151]		•	GVRP, Dewi and Utama [22]

investigation of Eshtehadi et al. [107] used this benchmark to test their approach for solving G-VRPTW. Schneider et al. [135] 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. [72]). 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. [135], Raeesi and Zografos [68] 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. [135], the authors proposed to modify the time windows presented by Solomon [73].

Another proposed instance set related to time windows was presented by Bredström and Rönnqvist [137] 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. [111] to test the approaches for VRPTW-SPFC, and by Masmoudi et al. [99], 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. [76] to solve the G-VRPSPD. The first set of instances is based on those proposed by Salhi and Nagy [142], which are based on Christofides et al. [148] 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 [140] 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 [146] presented a set of 19 instances (e.g., López-Sánchez et al. [50] 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. [144] named as

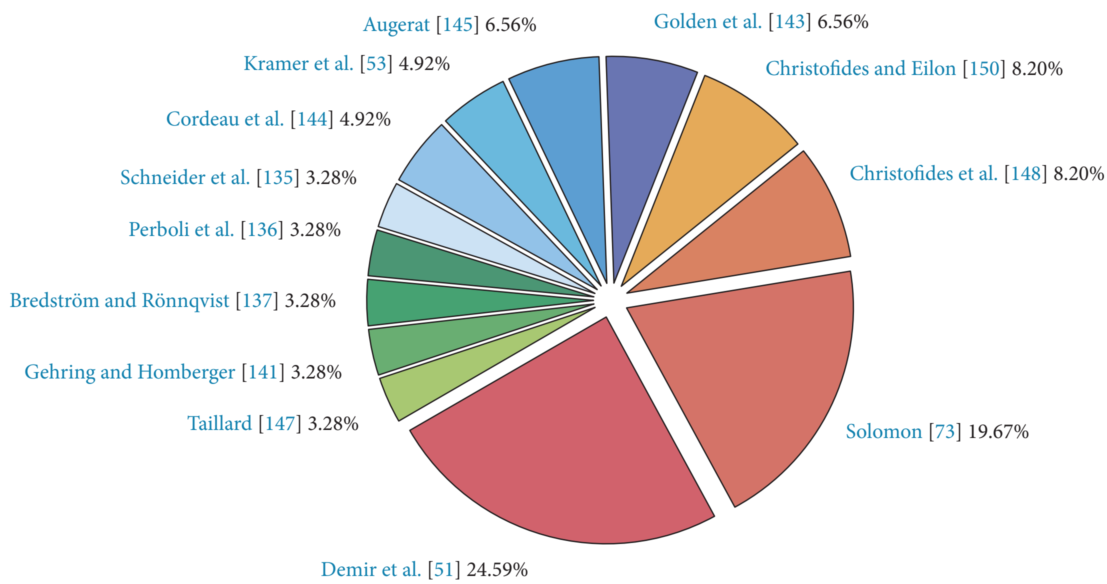

Figure 7: Pie chart of the different benchmarks used for GVRPs. The pie chart visualizes the utilization percentage of each benchmark instances for the reviewed papers.

Cordeau instances. The authors presented a set of 23 instances based on the sets from Christofides et al. [148] (instances 1–7), Gillett and Johnson [152] (instances 8–11), and Chao et al. [146] (12–23). There are many investigations on green multidepot VRP that used this set of instances, such as MD-GVRP in Wang et al. [37] and GMDVRPTW in Kaabachi et al. [36].

On the other hand, Iori et al. [138] presented a set of instances for the 2L-CVRP that has been used by several investigations on GVRP, such as cold chain logistics path optimization in Zhao et al. [100] and the 2L-MDCVRPB in Zhao et al. [84]. These instances are based on the CVRP instances [153, 154], using the same capacity of the vehicles and the coordinates and weights for customers. The 2L-CVRP benchmark is divided into five classes of instances. The first 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. [155]. Perboli et al. [136] introduced four sets of instances for the 2E-CVRP. These sets contain up to 50 customers and one depot. The first three sets are based on Christofides and Eilon [150] (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. [156] 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 [47] about 2E-CVRPSC and Jie et al. [48] for 2E-EVRP-BSS, which used this set of instances in green multiechelon distributions contexts.

Recently, based on several cities from the United Kingdom with requirements associated with time intervals and service times, Demir et al. [51] 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. [57]; FSMPRP in Koç et al. [54]; PRP in Kramer et al. [53]) and has served as the basis for the creation of new sets of instances. For instance, Kramer et al. [53] modified the PRPLIB to create two additional sets called tighter time windows (e.g., BiPRP in Costa et al. [61]; TD-PRP in Franceschetti et al. [57]). On the other hand, Goeke and Schneider [134] adjusted the PRPLIB for the E-VRPTW with a mixed fleet (see GMFVRPREC-PR in Yu et al. [71]).

tFrom the proposed benchmark sets, 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 7 shows how the proposed benchmarks have been used in terms of the number of works. As can be seen, many studies focused on the instances proposed by Demir et al. [51] (24.59%). Also, the set proposed by Solomon [73] besides being commonly used in VRPs problems is also relevant in GVRPs (19.67%). The instances proposed by Christofides and Eilon [150] and Christofides et al. [148] 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 [145] and Golden et al. [143]; which are only used in 6.56% of the investigations studied. The remaining instances present 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 3).

8. Conclusions

This article presented a systematic literature review of the heuristic and hybrid techniques for solving GVRPs considering emissions following the PRISMA methodology. Based on it, we identified 446 papers that after screening concerning their scope, contribution, and topic resulted in 89 papers. For each work, we identified and analyzed the GVRP variant, emission model, and main strategies and components within the proposed solution methods. Lastly, we scoped the problem instances proposed in the literature to assess the proposed algorithms.

From the selected literature, we observed that most of the works explicitly calculate emissions within the mathematical model or algorithm, whereas the factor models are the main fuel consumption model used. Also, we found predominant characteristics in the addressed GVRPs, for instance, single-objective, homogeneous fleets, and restrictions, associated with 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, the roulette wheel as a selection method, and the two-phase approach as the methodology. On the other hand, the most commonly used type of approach is single-solution-based metaheuristics, while the most commonly used techniques are the tabu search and adaptive large neighborhood search. Concerning the 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 on the well-known PRPLIB instances based on real locations.

Considering the reviewed literature, we provide some open challenges and future research directions in the realm of GVRPs:

(i) According to Moons et al. [157], 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 and driver wages) or service-oriented objectives (e.g., waiting time) jointly with environmental indicators (e.g., emissions and fuel consumption). For instance, Wang et al. [37] employed a shared transportation fleet and minimized a multi-objective function based on distances, vehicles utilization, and carbon emissions. Validi et al. [49] considered concurrent minimization of total cost and total carbon emission in a three-echelon LRP context. Besides those works, our findings show few works tackling GVRPs as a multi-objective problem or with multi-objective-based heuristics (see MH-MO, HMH-MO percentages indicators in Figure 6). Thus, addressing this multi-objective perspective into GVRPs provides an interesting and relevant line of research

(ii) As indicated in Blum and Roli [158] and Martí et al. [159], 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 reference [160] generated 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. [80], they indicated the importance of initial solutions when solving the F-GVRPSPDTW. In doing so, they proposed a parallel insertion-based construction heuristic considering the load-carrying by vehicles as a criterion of insertion. In addition, Fan et al. [161] showed that the quality of initial solutions can be improved by spatio-temporal clustering of customers

(iii) Our review shows several works related to the heterogeneous fleet by considering the dimension of vehicles, types of fuels, and loading capacity. In this sense, incorporating AFVs based on hydrogen vehicles can improve the pollutant indicators thank to their driving range and refueling times, among other relevant aspects of this technology [126]. 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

(iv) Another observation extracted from this review is that most of the investigations only consider carbon emission estimations; however, other types of greenhouse gas emissions (e.g., methane, nitrous oxide and hydrofluorocarbons, among others) are needed to be considered. In addition, factor-based models are the most commonly used emissions model; nevertheless, the use of macroscopic and microscopic emission models provide accurate emission estimations [127]. Hence, using macroscopic and microscopic models stands as a relevant research direction in GVRP applications.

Acronyms

2E-CVRP:	Two-echelon capacitated vehicle routing problem
2E-CVRPSC:	Two-echelon capacitated vehicle routing problem with swap containers
2E-CWCVRP:	Two-echelon collaborative waste collection vehicle routing problem
2E-EVRP-BSS:	Two-echelon capacitated electric vehicle routing problem with battery swapping stations
2E-TVRP:	Two-echelon time-constrained vehicle routing problem
2eVRPSyn:	Two-echelon vehicle routing problem with vehicle synchronization
2L-CVRP:	Capacitated vehicle routing problem with two-dimensional loading constraints

2L-MDCVRPB: Two-dimensional multidepot capacitated vehicle routing problem with backhauls
ABC: Artificial bee colony
ABC-DA: Artificial bee colony with demon
ABC-OBA: Artificial bee colony with acceptance of old bachelor acceptance
ABC-RRT: Artificial bee colony with record-to-record travel
ACO: Ant colony optimization
ACOMO: Ant colony algorithm with a multiobjective heuristic
ADP: Approximate dynamic programming
AFV: Alternative fuel vehicles
ALNS: Adaptive large neighborhood search
B-MFGVRPTW: Biobjective mixed-energy green vehicle routing problem with time windows
Bi-PVRP-SC: Biobjective periodic vehicle routing problem with service choice
B&C: Branch-and-cut
BSS: Battery swap station
BSV: Battery swapping vans
C&W: Clarke and Wright savings algorithm
CGA: Column generation algorithm
CIRP: Closed-loop inventory routing problem
CMEM: Comprehensive modal emissions model
CO_2: Carbon dioxide
COPERT: Computer programme to calculate emissions from road transport
CumLRP: Cumulative location routing problem
CumVRP-hTW: Cumulative vehicle routing problem with hard time windows
CumVRP-sTW: Cumulative vehicle routing problem with soft time windows
CVRP: Capacitated vehicle routing problem
DALNS: Distance-based adaptive large neighborhood search
DGVRP: Dynamic green vehicle routing problem
DP: Dynamic programming
DPH: Dynamic programming-based heuristic
DRASS: Demand-responsive airport shuttle services
EABC: Enhanced artificial bee colony
Eco-WCVRP: Eco-efficient waste collection vehicle routing problem
EF-VRP: Environmentally friendly vehicle routing problem
EHLSA: Exploration heuristic local search algorithm
EMDLS: Enhanced variant of multidirectional local search
EMVRP: Energy minimizing vehicle routing problem
E-PCVRP: Environmental prize-collecting vehicle routing problem
EV: Electric vehicle
E-VRP: Electric vehicle routing problem
E-VRPTW: Electric vehicle routing problem with time windows
EVRPTW-RS-SMBS: Electric vehicle routing problem with time windows with recharging station and synchronized mobile battery swapping
F&O: Fix and optimize
FCVRP: Fuel consumption vehicle routing problem
F-GVRPSPDTW: Fuzzy green vehicle routing problem with simultaneous pickup and delivery and time windows
FSMPRP: Fleet mix pollution-routing problem
Fuzzy HC: Fuzzy hierarchical clustering
G-VRPMSPDTW-RT: Green vehicle routing problem with mixed and simultaneous pickup and delivery problem, time windows, and road types
G-VRPSPD: Green vehicle routing problem with simultaneous pickup and delivery
G-VRPTW: Green vehicle routing problem with time windows
GA: Genetic algorithm
GARP: Green arc routing problem
GDV: Gasoline and diesel vehicles
GE: Gradient evolution
GHG: Greenhouse gas emissions
GIS: Geographic information system
GLRP: Green location routing problem
GMFVRP-PRTW: Green mixed-fleet vehicle routing problem with partial battery charging and time windows
GMFVRPREC-PR: Green mixed-fleet vehicle routing problem with realistic energy consumption and partial recharges
GOA: Grasshopper optimization algorithm
GRASP: Greedy randomized adaptive search procedure
Green-PDPTW: Green pickup and delivery problem with time windows
GSTDCVRP: Green stochastic time-dependent capacitated vehicle routing problem
GVND: Guided variable neighborhood descent
GVRP: Green vehicle routing problem
GVRP-MTPR: Green vehicle routing problem with multiple technologies and partial recharges
GVRSP: Green vehicle routing and scheduling problem
GVRSP-split: Green vehicle routing and scheduling problem with split delivery
HABC: Hybrid artificial bee colony
HALNS: Heterogeneous adaptive large neighborhood search
HC-MDVRP: Multidepot vehicle routing problem variant for horizontal cooperation in road transportation
HEA: Hybrid evolutionary algorithm
HEV: Hybrid electric vehicle
HeVRPMD: Heterogeneous vehicle routing problem with multiple loading capacities and driving ranges

HF-VRPS: Heterogeneous fleet vehicle routing problem with synchronized visits
HGVRSP: Heterogeneous green vehicle routing and scheduling problem
HH: Hyperheuristic
HHC: Home health care
HHM: Home hemodialysis machine
HLH: High-level heuristic
HMH-MO: Hybrid metaheuristics for multiobjective optimization
HVRP: Heterogeneous fleet vehicle routing problem
HVRP-TW: Heterogeneous fleet vehicle routing problem with time windows
HV: Hydrogen vehicle
HWOA: Hybrid whale optimization algorithm
ICEV: Internal combustion engine vehicle
ILNS: Intensified large neighborhood search
ILP: Integer linear programming
ILS: Iterated local search
INS: Iterated neighborhood search
IRP: Inventory routing problem
JD-GVRP: Joint distribution-green vehicle routing problem
LLH: Low-level heuristic
LNS: Large neighborhood search
LRP: Location routing problem
LRPLCCC: Location routing problem-based low-carbon cold chain
LS: Local search
MATH: Metaheuristics with mathematical programming
MCVRPTW: Multicompartment vehicle routing problem with time window
MDEVRP: Multidepot electric vehicle distribution routing problem
MD-GVRP: Multidepot green vehicle routing problem
MDGVRP-PD: Multidepot green vehicle routing problem with pickups and deliveries
MDGVRP-TW: Multidepot green vehicle routing problem with time windows
MDVRP: Multidepot vehicle routing problem
MEET: Methodology for calculating transport emissions and energy consumption
MG: Multigraph
MH-H: Metaheuristics-heuristics
MH-MH: Metaheuristics-metaheuristics
MH-MO: Metaheuristics for multiobjective optimization
MDP: Midway disposal pattern
MDT: Midway disposal trip
MGVRP: Mixed-fleet green vehicle routing problem
MILP: Mixed-integer linear programming
MFGCLP: Mixed-fleet based green clustered logistics problem
MMPPRP-TW: Multivehicle production and pollution-routing problem with a time windows
MOGA-II: Multiobjective genetic algorithm II
MOGE: Many-objective gradient evolution
MOHH: Multiobjective hyperheuristic
MOPSO: Multiobjective particle swarm optimization
MOSLPSO: Multiobjective self-learning particle swarm optimization
MOTS: Multiobjective tabu search
MS: Multistart
MSMLS: Multistart multiobjective local search
MSW: Municipal solid waste
MTHVRP-PCIC: Multitrip heterogeneous vehicle routing problem with prioritized customers and incompatible cargoes
MTHVRPP: Minimal-carbon-footprint time-dependent heterogeneous fleet vehicle routing problem with alternative paths
MTVRP: Multitrip vehicle routing problem
MVOC: Multiple vehicles and one-cargo
NAEI: National atmospheric emissions inventory
NBOTS: Nested biobjective tabu search
NE-VRPs: Multiechelon vehicle routing problems distribution problems
NO_x: Nitrogen oxides
NMVOC: Nonmethane volatile organic compounds
NRGA: Nondominated ranking genetic algorithm
NSGA-II: Nondominated sorted genetic algorithm II
PLNS: Parallelized large neighborhood search
PBSA: Population-based simulated annealing
PCTSP: Prize-collecting traveling salesman problem
PCVRP: Prize-collecting vehicle routing problem
PDPTW: Pickup and delivery problem with time windows
PDVRP: Pickup and delivery vehicle routing problem
PHEV: Plug-in hybrid electric vehicle
PIRP: Perishable inventory routing problem
PM: Particulate matter
PMH: Population-based metaheuristics
POPMUSIC: Partial optimization metaheuristic under special intensification conditions
PPRP: Practical pollution-routing problem
PRP: Pollution-routing problem
PRPSPD: Pollution-routing problem with reverse logistics and simultaneous pickups and deliveries
PSO: Particle swarm optimization
PVRP: Period vehicle routing problem
QPSO: Quantum-behaved particle swarm optimization
RDP: Restricted dynamic programming
RLCLRPRCC: Regional low-carbon location routing problem with reality constraint conditions
RS: Recharging station
RVND: Random variable neighborhood descent
RVNS: Reduced variable neighborhood search
RW: Roulette wheel
SA: Simulated annealing

SAL-PSO: Self-adaptive learning particle swarm optimization
SC: Set covering
SIH: Sequential insertion heuristic
SLPSO: Self-learning particle swarm optimization
SLR: Systematic literature review
SMBS: Synchronized mobile battery swapping
SMH: Single-solution based metaheuristics
SOA: Speed optimization algorithm
SOP: Speed optimization problem
SP: Set-partitioning method
SS: Scatter search
STPPS: Sustainable traveling purchaser problem with speed optimization
SwA: Sweep algorithm
TD-CVRP: Time-dependent capacitated vehicle routing problem
TD-PRP: Time-dependent pollution-routing problem
TD-VRP: Time-dependent vehicle routing problem
TLBO: Teaching-learning-based optimization
TS: Tabu search
VND: Variable neighborhood descent
VNS: Variable neighborhood search
VRP: Vehicle routing problem
VRPB: Vehicle routing problem with backhauls
VRPSPDTW: Vehicle routing problem with simultaneous pickup and delivery and time windows
VRPTW: Vehicle routing problem with time windows
VRPTW-SPFC: Vehicle routing problem with time windows, synchronization, precedence and fuel consumption constraints
VRPTWSyn: Vehicle routing problem with time windows and synchronization constraints
VRSP: Vehicle routing and scheduling problem
WCVRP: Waste collection vehicle routing problem
WOA: Whale optimization algorithm.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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