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METAHEURISTIC APPROACHES FOR THE GREEN VEHICLE ROUTING PROBLEM

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Abstract:. The green vehicle routing problem (GVRP) is a relatively new topic, which aims to minimize greenhouse gasses (GHG) emissions produced by a fleet of vehicles. Both internal combustion vehicles (ICV) and alternative fuel vehicles (AFV) are considered, dividing GVRP into two separate subclasses: ICV-based GVRP and AFV-based GVRP. In the ICV-based subclass, the environmental aspect comes from the objective function which aims to minimize GHG emissions or fuel usage of ICVs. On the other hand, the environmental aspect of AFV-based GVRP is implicit and comes from using AFVs in transport. Since GVRP is NP-hard, finding the exact solution in a reasonable amount of time is often impossible for larger instances, which is why metaheuristic approaches are predominantly used. The purpose of this study is to detect gaps in the literature and present suggestions for future research in the field. For that purpose, we review recent papers in which GVRP was tackled by some metaheuristic methods and describe algorithm specifics, VRP attributes, and objectives used in them.

Keywords: Pollution routing problem, minimization of greenhouse gasses emission, alternative fuel vehicles, recharging stations, sustainability.

MSC: 90B06, 90-02.

1. INTRODUCTION

Due to the rising environmental concerns in recent years, many countries are committed to reducing their greenhouse gasses (GHG) emissions, which have been recognized as the leading cause of global warming. Among all of the GHG pollutants, CO_2 is by far the most common one, accounting for 81% of all GHG in the EU [1]. Most of the CO_2 emissions come from burning fossil fuels, which is also where the most energy comes from [2].

Around 26% of all emissions come from the transportation sector [1]. Because of this, it is important to minimize these emissions as much as possible, either by taking emissions into account while constructing transport routes of the *internal combustion vehicles* (**ICV**) or by switching to *alternative fuel vehicles* (**AFV**), such as electric and hybrid vehicles. Vehicle routing problems that aim to minimize the negative effect of GHG emissions are generally called Green Vehicle Routing Problems (GVRP). Because of the steady rise in the number of electric vehicles worldwide, these problems started attracting much attention in recent years. However, electric vehicles have certain limitations that conventional vehicles do not have, mainly limited range, so the vehicles might need to visit recharge stations several times along the transport route.. Recharging is time-consuming and traveling to a recharge station may prolong a route, thus making it less economically viable.

The goal of this paper is to identify the trends in the field of environmentally friendly transportation and to provide an extensive survey of the recent papers that deal with GVRP using a metaheuristic approach. This paper is structured as follows. In **Section 2**, a detailed description of GVRP is given, considering both AFV-based GVRP and ICV-based GVRP. Additionally, a list of the most common VRP attributes is presented. In **Section 3** we present some of the existing surveys in the field of GVRP. In **Section 4**, a description of each paper considered for this survey is given in detail. Papers are classified according to the metaheuristic approach used in them. The purpose of this part is to give the reader some insight into specific attributes considered in each paper, what are the objectives, which methods are used, and to present some of the implementation details. **Section 5** provides a summary of the methods used in the reviewed papers. The summary was presented for both ICV-based and AFV-based GVRP separately, followed by the overall summary of all of the papers. **Section 6** discusses future trends and recognizes the space for potential improvements, while **Section 7** contains the concluding remarks.

2. GREEN VEHICLE ROUTING PROBLEM

2.1. Vehicle Routing Problem

Vehicle Routing Problem (**VRP**) is a general name for the whole family of combinatorial optimization problems, which can be defined as follows:

Definition 1. *Given a set of transportation requests and a fleet of vehicles, we need to find a set of routes that will allow us to fulfill all (or some) requests in such a way that given constraints are fulfilled while optimizing some objective function.*

In other words, we need to decide which vehicle is going to serve which set of customers and in which order. Objective function from Definition 1 can be based on any given measurement. For example, it can be the minimal distance traveled, the minimal time needed, the minimal number of unserved customers, or any other required criterion. The problem was first introduced in 1959 by Dantzig and Ramser [3], and in 1964 Clarke and Wright proposed the first effective heuristic for solving this problem[4]. Vehicle routing problem belongs to the class of NP-hard problems [5].

An example of *VRP* can be seen in Figure 1. In this figure, 3 vehicles start from the same depot and serve a disjunctive sets of customers.

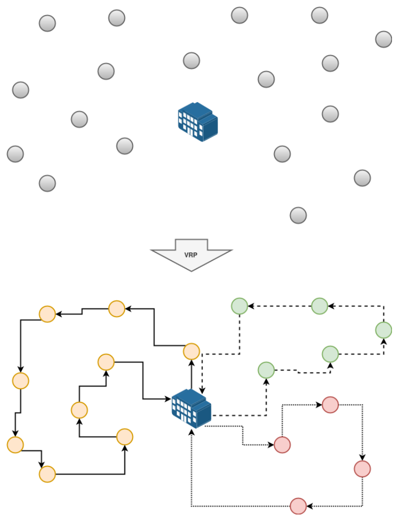


Figure 1: An example of VRP

There are many different variations of the vehicle routing problem, each with different objectives or constraints. These special features of the VRP are called *attributes*. Here we give a brief overview of some of the most common attributes.

- *Capacity constraint* (**C**) - A load of each vehicle cannot exceed the fixed capacity of the vehicle that is given as an input parameter. This attribute is quite common, even when it's not explicitly stated.
- *Asymmetry* (**A**) - If the distance from point A to point B is not necessarily the same as from point B to point A, the problem is considered asymmetric. This attribute is especially important in urban areas because of the large number of one-way streets in cities.
- *Time windows* (**TW**) - A time window is an interval in which a customer has to be served. Time windows can be either hard or soft. Breaking hard

time window constraints results in infeasible solutions, while breaking soft time window constraints is allowed with a certain penalty to the objective function. This attribute became more important with the rise of e-commerce since it allows customers to set a fixed time interval in which they can receive the shipment.

- *Multiple depots* (**MD**) - Several depots are available at different locations. Each depot usually has a predefined number of vehicles and each vehicle that starts from some depot usually has to end its route in the same depot.
- *Multiple trips* (**MT**) - Each vehicle is allowed to undertake several trips, returning to its depot in between to reload, unload or refuel.
- *Multiple compartments* (**MC**) - Vehicles have several compartments, each with its own capacity. Each type of cargo can be loaded only into its designated compartment. This attribute has found its use in waste management, where different types of material have to be stored separately for the purpose of recycling. Another application is in shipping food since different types of food require different storage conditions while being transported.
- *Heterogeneous fleet* (**H/HF**) - Also known as *Mixed Fleet.* Available vehicles can have different characteristics, usually in terms of capacities, speed and costs.
- *Open routes* (**O**) - Vehicles do not return to the depot after serving the last customer.
- *Pickup and Delivery* (**PD**) - Vehicles need to pick up goods at one customer location and deliver it to the other customer location.
- *Backhauls* (**B**) - Two types of customers are considered in this version: the customers that receive goods from the depot (*linehaul*) and customers that send goods to the depot (*backhaul*). The backhaul customers can't be served before all of the linehaul customers are served, except in the *Mixed Backhauls* (**MB**) version of the problem, where this constraint is not imposed.
- *Split Deliveries* (**SD**) - Customers' demands can be split between multiple vehicles. Each customer can be visited multiple times, so the amount of goods delivered by each vehicle has to be determined.
- *Precedence constraints* (**PC**) - Order in which customers are visited is limited in the sense that for some customers, there is a list of other customers that must be served before proceeding to serve that customer.
- *Dynamic requests* (**D**) - New delivery requests can occur during the delivery process and have to be incorporated into a route. This is in contrast to the *static* version of the problem, in which all of the requests are known before vehicles start their routes.
- *Multiple objectives* (**MO**) - several objectives are optimized at the same time. It is also called *Pareto-optimization*, and a set of best solutions with regard to at least one of the objectives is called *Pareto-front.*
- *Partial recharge* (**PR**) - this attribute is important only in the context of routing a fleet of electric vehicles. Considering the fact that recharging an electric vehicle to its full capacity is time-consuming, a partial recharge is enabled. This allows the vehicle to serve the customers in accordance with the given time windows, which wouldn't be possible if the vehicle had to

spend a considerable amount of time at the AFS. Of course, this adds another level of complexity to the problem, since the recharge level has to be determined for every stop at AFS.

The optimization methods can be divided into two main classes: exact and approximate algorithms. *Exact algorithms* provide optimal solutions, given enough time and computer resources. *Approximate algorithms* cannot guarantee the optimality of the provided solution, instead, they are used to provide good estimates for the desired solution within a limited time or memory. These algorithms can be deterministic or stochastic. Another classification involves constructive and improvement algorithms. The class of approximate algorithms encompasses heuristic, metaheuristic, and approximation algorithms. *Heuristic algorithms* are problem-specific, i.e. different problems require different heuristics. Constructive heuristics start from an empty solution and iteratively extend the current solution until it becomes complete. In contrast, improvement heuristics start from a complete solution and iteratively try to improve it. *Metaheuristics* belong to the class of general methods, usually iterative, stochastic, either constructive or improvement algorithms. The term *general* here means that metaheuristics can be applied to a wide range of optimization problems. They are defined as recipes on how to develop the algorithms tailored for each considered problem. A subcategory of metaheuristic algorithms is *matheuristic algorithms*, which are a combination of some metaheuristic methods and mathematical programming. In these algorithms, a metaheuristic method is used to generate MILP subproblems from the original problem, by fixing the values of some variables. These subproblems are then passed to an exact solver to determine the value of the remaining variables. In some cases, matheuristics can be seen as exact methods, given enough time. *Approximation algorithms* are the class of heuristic algorithms that can quickly find an approximate solution (estimate) with the provable guarantee on the solution quality, i.e. they provide some *worst-case* approximation factor for the generated solution. They are problem-specific, as they belong to the class of heuristic algorithms.

The difference between the terms *Approximation algorithms* and *Approximate algorithms* should be pointed out once again. Approximation algorithms are the class of heuristic algorithms with a guarantee on the solution quality, while approximate algorithms are the opposite of the exact algorithms. Approximation algorithms are out of the scope of this paper, so we refer any interested reader to [6, 7] for more details about this class of algorithms.

In Figure 2 we present the aforementioned classification of methods for the problem of VRP. It should be mentioned that this classification should be considered more as a guidance than a definite rule because some algorithms can be placed in different classes based on the situation. For example, MIP-based methods are exact when given enough time and memory, but with limited time or memory, they can be considered heuristic methods.

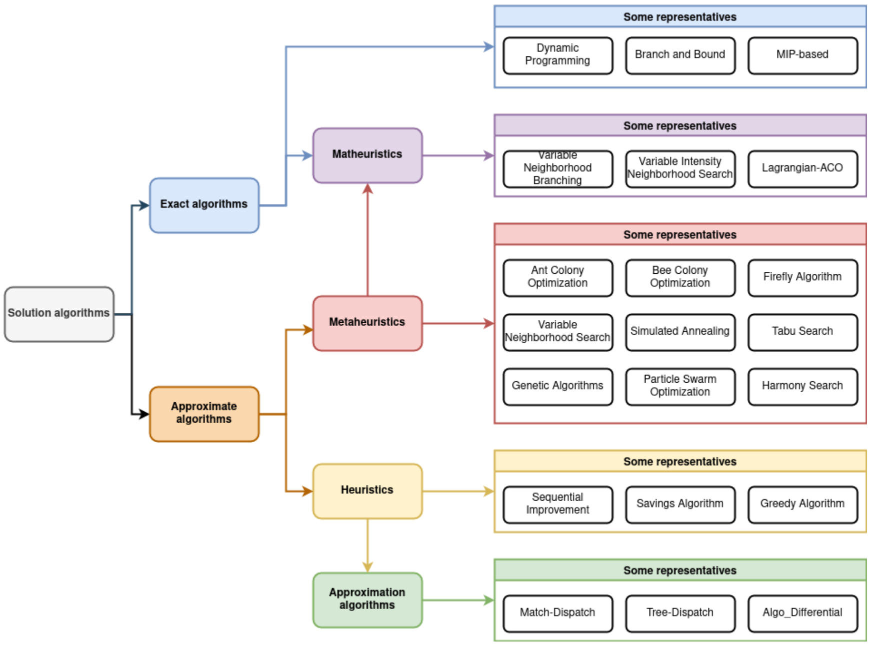


Figure 2: Different solution approaches to VRP

2.2. Green Vehicle Routing Problem

Green Vehicle Routing Problem (**GVRP**) is an extension of the classic VRP, which considers the environmental impact of routing a fleet of vehicles. It is often classified into three subclasses [8]: *Pollution Routing Problem* (**PRP**), Green Vehicle Routing Problem in the narrower sense, and VRP in reverse logistics. This classification is shown in Figure 3.

The *Pollution Routing Problem* was introduced by Bektaş and Laporte [9] in 2011. It is an extension of classical VRP, considering the fleet of ICVs, and including an objective function that takes into account not only the distance traveled but also GHG emissions. The emissions are dependent on several factors, such as the speed of the vehicle, load, or road gradient. PRP is most often multi-objective, balancing between emissions and economic cost.

Green Vehicle Routing Problem in the narrower sense aims to minimize the fuel consumption of the fleet of vehicles. This fleet can consist of ICVs, AFVs, or both. If the fleet consists only of ICVs, the problem highly resembles the PRP, since the higher fuel consumption usually leads to higher GHG emissions. The problem can also consider vehicles that use alternative energy sources, such as electric and hybrid vehicles, with their respective constraints. During the trip, vehicles might need to visit an AFS, so we must assure that each vehicle has enough fuel to reach an AFS at any point. This type of problem was formulated quite recently in this form by Erdoğan and Miller-Hooks [10].

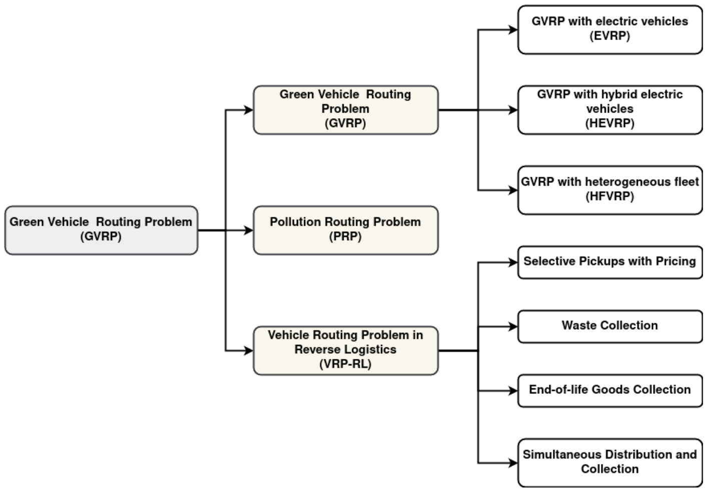


Figure 3: Classification of GVRP

VRP in reverse logistics (**VRPRL**) is sometimes also classified as a GVRP. Most studies on VRPRL aim to optimize waste collection or recycling used materials, therefore addressing some of the environmental issues. Despite its importance, we do not consider VRPRL studies in this paper, mainly because of the fundamental difference in the objective which, compared to PRP and AFV-VRP, does not directly affect vehicle emissions.

In this paper, we use a different classification scheme, in order to remove the ambiguity of the term Green-VRP. We classify problems into two groups: ICV-based (where the fleet consists exclusively of ICVs) and AFV-based (where at least a part of the fleet consists of AFVs). We find this classification to be justified by the fact that the structure and hardness of the problem are much more impacted by the type of the vehicles than the objective function.

ICV-based problems include PRP and fuel-minimizing GVRP that uses only ICVs. The difference between this ICV-based GVRP and classic VRP of most commonly in the objective function.

The AFV-based problems can be formulated on a graph $G = (V, E)$, where V is a set of nodes representing customers, depot, and alternate fuel stations, while E is a set of edges (or arcs, in the case of asymmetric GVRP) that connect nodes from V. Each edge $e \in E$ has a non-negative cost assigned to it. The objective is to find a set of routes that minimizes the total distance traveled so that all of the customers are served. These routes can include one or more visits to an AFS if necessary. On top of that, GVRP can have any number of the aforementioned VRP attributes, adding to the complexity of the problem. An example of GVRP that uses AFVs and partial recharges can be seen in Figure 4, where the triangle represents the depot, circles represent customers, and rhombuses represent AFSs.

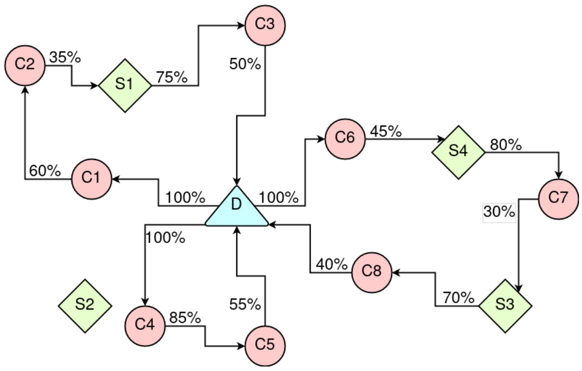


Figure 4: An example of GVRP with electric vehicles and partial recharges

Many different objectives can be used for GVRP. Here, we will present some of the most common objective functions for GVRP.

- *Operation cost* (**OC**) *minimization* - Operation costs are all of the costs related to vehicle usage, such as driver wages, fixed costs like acquisition or maintenance of a vehicle, cost of dispatching a vehicle, etc. It can often be related to the traveled time or distance.
- *Fuel consumption* (**FC**) *minimization* - This is one of the most common goals of GVRP. This objective is not limited to fossil fuels, it also includes all types of energy used by different propulsion engines, such as electricity, hydrogen, etc.
- *Pollutant emission* (**PE**) *reduction* - Reducing emissions of pollutants is another common goal, especially in ICV-based GVRP. Although the most commonly considered pollutant is CO_2, this objective can also be applied to other types of pollutants.
- *Time windows penalty cost* (**TWPC**) *minimization* - TWPC is the price that has to be paid if the customer is not served within the selected soft time window. This objective is sometimes also called *Quality of Service* (**QoS**) or *Service Level* and it is used to measure customer satisfaction.
- *Travel time* (**TT**) *minimization* - The total travel time of all vehicles should be minimized.
- *Revenue maximization* (**RM**) - The revenue is calculated as the sum of prices for all of the demanded goods or services.
- *Total distance* (**TD**) *minimization* - The total distance traveled by all vehicles should be minimized.
- *Number of vehicles* (**NV**) *minimization* - The goal is to employ as few vehicles as possible to serve all of the customers.
- *Quality loss cost* (**QLC**) *minimization* - This criterion is related to transportation of perishable goods, i.e. goods which quality deteriorate over time. The goal is to minimize penalties associated with quality deterioration.
- *ICV usage* (**ICVU**) *minimization* - If the fleet consists of both ICVs and AFVs, the goal is to serve as many customers as possible using AFVs, and to minimize the use of ICVs (engage them only if it is necessary).

- *Maximum overtime* (**MXO**) *minimization* - If a time limit is imposed on each route, the maximum overtime is calculated as a difference between the route duration and time limit, for each route. Minimizing maximum overtime can have a positive impact on the overall cost of transportation, mostly because of the worker wages.
- *Route imbalance* (**RI**) *minimization* - The goal is to distribute the load more or less evenly among the vehicles.
- *Waiting time* (**WT**) *minimization* - Waiting time is the time a vehicle has to wait before serving a customer. It is determined by the time windows.
- *Recharging cost* (**RC**) *minimization* - Related only to electric and hybrid vehicles. The recharging price depends on the recharging technology and the amount of energy.
- *Recharging time* (**RT**) *minimization* - Related only to electric and hybrid vehicles. The goal is to minimize the total time spent by the vehicles at the AFSs.
- *Queuing time* (**QT**) *minimization* - Related only to electric and hybrid vehicles. Queuing time is the time a vehicle has to wait in a queue before it starts recharging at AFS. It could be seen as a special case of the RT goal, however, it may be reduced by redirecting vehicles to alternative AFSs.

We should keep in mind that these objectives are often correlated with each other, for example, lower fuel consumption often leads to lower operational costs. Also, the actual objective function used in many of these papers is a combination of different aforementioned objectives. For example, in many papers, the main objective was to minimize the total cost, which is most often a combination of different costs represented as different objectives, like OC, TWPC, FC, CETC, etc.

3. PREVIOUS SURVEYS ON GVRP

One of the first surveys regarding GVRP was presented by Lin et al. [8]. It reviewed not only GVRP but the classical VRP as well. Papers are classified according to the version of VRP that was examined in them, with the emphasis on the most common VRP attributes. In total, about 280 papers were examined by the authors, but only 28 of them considered the green version of VRP. Out of those 28, 11 considered VRP with the objective of minimizing fuel consumption or CO_2 emissions, while 17 of those concerned themselves by reverse logistics VRP. VRP with AFVs was not included in the study. Both heuristic and exact methods were considered. The authors also observed some possible directions of future development for GVRP, but at the moment of writing this paper, some of those suggestions are already outdated.

Park and Chae [11] presented different approaches to ICV-based GVRP, including exact algorithms, heuristics, and metaheuristics. In total, 40 publications were surveyed, out of which 21 applied some metaheuristic to the problem. The authors also presented different fuel consumption models in their survey. Eglese and Bektaş [12] give us an overall overview of GVRP. It presents different aspects of GVRP, provides us with various emission models and fuel consumption, and introduce a reader to time-dependent GVRP, speed optimization and the multi-criteria analysis. AFV-based GVRP is mentioned, but not reviewed in detail.

In a study by Zhang et al. [13], the authors examined the application of swarm intelligence algorithms to green logistics. A total of 115 papers were considered, from the period between 1995 to 2014. The authors explored many different problems in green logistics, where VRP related papers are in minority and often viewed from the perspective of reverse logistics. Papers considering PRP or AFV-VRP were not reviewed.

Marrekchi et al. [14] wrote a survey primarily interested in the ICV-based version of GVRP. The authors differentiated between exact, heuristic, and metaheuristic solution methodologies, giving a few examples for each of the most commonly used algorithms in these groups. Erdelić and Carić [15] give a detailed review of AFV-based GVRP, more precisely Electric GVRP. The authors presented basic characteristics and applications of EVRP, together with different energy consumption models. Different variations of EVRP were examined, providing examples from the literature. Exact, heuristic, metaheuristic, and hybrid approaches were investigated. For each paper, the authors presented the version of the problem, solution approach, and set of instances that were used for evaluation, together with a short description. Finally, potential space for future research was discussed.

Konstantakopoulos et al. [16] wrote a literature review for VRP in general, with emphasis on different versions of VRP. GVRP was covered in one of the subsections, as a version of VRP. In total, only five papers were reviewed.

Moghdani et al. [17] reviewed 309 papers related to GVRP. The reviewed papers were analyzed according to the problem classification, GVRP variant, uncertainty, solution methodology, objective function, and sustainability. Not all of the reviewed papers were explicitly mentioned, and those that were mentioned were usually not described in much detail. Finally, the authors identified several potential research directions for the future.

Ferreira et al. [18] reviewed 76 papers concerning the multi-objective version of GVRP, from 2012 to 2018. It primarily concentrated on the bibliometric analysis of ICV-based papers, including PRP, GVRP, and reverse logistics, while AFV-based papers were not considered.

Asghari et al. [19] provided an extensive literature review for GVRP. It covers the period between 2000 and 2020, reviewing a total of 313 papers. Papers are classified according to the vehicle engine type and further divided based on VRP attributes and the method used. An insight into potential future research directions and current gaps in the literature is provided.

In order to fill some of the gaps of the previous surveys on GVRP, in this paper we describe in more detail some of the more recent papers in the field. We include both ICV-based and AFV-based papers, and present the most common attributes and objectives in these two groups. Only papers in which some metaheuristic method is used for GVRP are considered. VRP in reverse logistics is out of the scope of this paper.

4. METAHEURISTICS FOR GVRP

As we said earlier, metaheuristics are general-purpose methods that can often find a satisfactory solution to hard optimization problems, while sacrificing the proof of optimality. One of the first classification schemes for metaheuristics was proposed by Birattari et al. [20] and it remained the basis for many other classification schemes that came later. A more complete review of classification schemes for metaheuristics is provided by Stegherr et al. [21]. In Figure 5 we present a classification of some metaheuristics, adopting a classification scheme similar to the one given in [19]. Four characteristics are considered:

- *Nature-inspired* or *Non-nature inspired* - classification based on whether the inspiration for metaheuristic is drawn from nature or not.
- *Population* or *single solution* - classification based on the number of solutions considered at the same time.
- *Deterministic* or *stochastic* - classification based on whether a method has a probabilistic component or not.
- *Memory* or *no memory* - classification based on whether a method uses some memory structure or not.

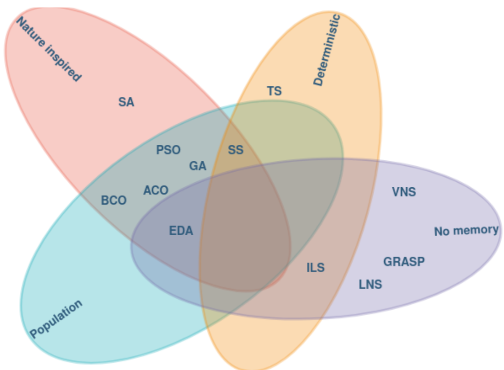


Figure 5: Classification of some metaheuristics: Simulated Annealing (SA), Bee Colony Optimization (BCO), Particle Swarm Optimization(PSO), Ant Colony Optimization (ACO), Genetic Algorithm (GA), Estimation of Distribution Algorithm (EDA), Scatter Search (SS), Tabu Search (TS), Iterated Local Search (ILS), Large Neighborhood Search (LNS), Variable Neighborhood Search (VNS), Greedy Randomized Adaptive Search Procedure (GRASP)

4.1. Simulated Annealing

Simulated annealing (**SA**) is an optimization method proposed by Kirkpatrick et al. [22] in 1983, based on the previous work of Metropolis et al. [23]. The idea behind SA is to simulate small movements of atoms and the change in energy. The algorithm starts with an initial solution, which can be obtained in a number of ways, usually by utilizing some fast heuristic approach. In each iteration, the current solution is transformed in an attempt to improve it. There are several parameters to be considered when designing a SA algorithm, such as the initial value of temperature (T), cooling schedule, number of iterations to be performed at each temperature, and stopping criterion to terminate the algorithm [24]. SA can be used for both single-objective and multi-objective optimization, and it can work with both discrete and continuous variables. Some of the first works on applying the SA to VRP were done by Osman [25] and Chiang and Russell [26], contributing SA to gain in popularity in the following years. An overview of this algorithm can be found in [27].

In paper by Felipe et al. [28], GVRP with multiple recharging technologies and partial recharges is considered. In this problem, the battery of a vehicle can be recharged using different technologies, each of them with its own recharge time and cost. Usually, the decrease in recharge time implies an increase in cost. Also, the battery doesn't have to be fully recharged, reducing the necessary time to serve the customers. For solving this problem, SA was implemented, as well as several other heuristic methods, based on local search. After testing algorithms on different sets of instances, the authors concluded that SA outperforms methods based on deterministic local search on larger instances, with more than 200 customers.

SA is also used for green vehicle routing problem with time windows in Küçükoğlu et al. [29]. The objectives are to minimize fuel consumption and CO_2 emissions. The problem is presented in a form of a mixed-integer linear problem but was not tested using an exact solver, since authors concluded that it would be inefficient for any larger size problem. For the construction of an initial solution for SA, the algorithm uses Solomon's time-oriented nearest neighbor algorithm [30]. Every time a new route is generated, the value of its objective function is stored in a special memory structure, thus avoiding multiple evaluations of the same route. Because of this, the proposed algorithm is referred to as a *memory structure adapted simulated annealing* (**MSA-SA**). Applied to test instances, MSA-SA was able to obtain near-optimal solutions for medium and large size instances, in a relatively short time.

In a paper by Xiao and Konak [31], authors proposed using SA for reducing CO_2 emissions of a fleet of homogeneous vehicles. In their version, soft time windows are considered, where missing the deadline is penalized, but arriving early is encouraged as it can improve customer satisfaction with the service. The speed by which a vehicle travels between customers is time-dependent, which means that the speed of a vehicle traveling from customer i to customer j will differ based on the exact time in which the trip is undertaken. The main objective is to minimize CO_2 emissions, which can be approximated using existing models from the literature. Apart from the main objective, several secondary objectives are considered hierarchically: customer satisfaction level, the total route time, and the total route distance. The authors presented a MILP formulation, as well as the SA metaheuristics for this problem.

Another example of SA being applied to VRP can be found in the paper by Vincent et al. [32]. Here, the authors investigated the *hybrid vehicle routing problem* (**HVRP**), which is an extension of the *green VRP*, since hybrid vehicles can switch at any time between electrical energy and fossil fuel as their main propulsion mode. There are two types of stations: electric station and fuel station. A vehicle can visit a station any number of times. The *nearest neighborhood* heuristic is used to obtain an initial solution. In each iteration, the algorithm explores one of the five predefined neighborhoods, selected at random with the probability $\frac{1}{5}$. To avoid local optimums, the algorithm uses the *restart strategy.*

Karagul et al. [33] studied GVRP with the goal of minimizing the total CO_2 emissions and total distance traveled. Three mathematical models were considered, based on the model from [34, 35]. The models mainly differ in the formulation of the objective function: one was taken from [36], and the other two were proposed in [33]. The problems formulated with these three models were then addressed by using a basic version of SA. The algorithm was tested using CVRP instances from [37, 38]. The experimental evaluations suggest that the approach which uses a convex composition of objectives is able to outperform other approaches in general.

Normasari et al. [39] also considered using AFVs for the CVRP. The objective is to minimize the total distance traveled by all of the vehicles. MILP formulation is proposed, tested with the CPLEX commercial solver. Because of the fact that exact solvers can be impractical for larger instances, the SA approach is also proposed. The problem is represented by a depot node, customer nodes, AFS nodes, and a set of dummy nodes. Dummy nodes also represent AFSs and are included to overcome the constraint which prohibits visiting the same node twice, since the vehicles must be able to visit AFS multiple times. The Nearest Neighbor algorithm is used to generate the initial solution. Four different neighborhood structures are used in this algorithm: *swap*, *insert*, $insert\_AFS$, and $delete\_AFS$. The parameters for SA were tuned using a subset of benchmark instances from [10]. The authors also performed a sensitivity analysis in order to show how varying different parameters affect the value of the objective function and the number of necessary vehicles.

4.2. Tabu search

Tabu search (**TS**) is a metaheuristic first proposed by Glover in 1986 [40]. It is in essence a local search algorithm that penalizes certain moves, in order to prevent cycling and enable escaping from local optimums. Moves have a tabu status only temporarily and can be accessed after a certain amount of time (i.e. after a certain number of iterations). At each step of TS, the algorithm looks for the best possible move to take. Bad moves are never accepted, except in the case when all the other moves are forbidden. A detailed description of the method and some of its applications can be found in a survey paper by Piniganti [41].

In the paper by Kwon et al. [42] the heterogeneous fleet CVRP is considered, with the objective to minimize the total cost, including the carbon trading cost. The *carbon trading* cost represents the cost that companies have to pay to emit a certain amount of CO_2, and it is proportional to the difference between an actual CO_2 emission and a preset upper limit. If the limit is exceeded, the company has to buy additional emission rights, raising the overall cost of transport. A mathematical model for this problem is presented, as well as a TS approach. The initial solution is created by choosing an unassigned customer with the highest demand and assigning it to the vehicle with the highest capacity. If the partial solution is infeasible, the customer is moved to the vehicle with the second-highest capacity, and so on. The initial solution is further improved with the *3-opt heuristic* [43]. The size of the tabu list is calculated according to a dynamic tabu term rule [44]. Three different neighborhood structures were tested: *insert*, *swap*, and *hybrid*. Experimental results have shown that the TS algorithm with the hybrid neighborhood structure (which selects insert or swap operator at random for every iteration) gave the best results.

Another example of GVRP with capacity constraints that aims to minimize CO_2 emissions using TS can be found in Úbeda et al. [45]. The amount of CO_2 emitted by a vehicle is calculated using the quantity of fuel used by that vehicle, taking into consideration the mass of the vehicle and its load. The basic version of TS was applied to a set of 7 real-world instances and was able to reduce CO_2 emissions in some cases, compared to the results of TS being applied to the same set of instances with the objective of minimizing the total distance. Sadly, there is little information on some of the implementation issues, the most important of which is the set of operators used to generate neighborhoods, which is not explicitly stated.

Niu et al. [46] considered a green open CVRP with time windows. The objective is to simultaneously minimize CO_2 emission costs and costs associated with driver wages. For the approximation of the CO_2 emission costs, a *comprehensive modal emission model* (CMEM) is used [47]. The problem also takes into consideration the speed of vehicles, which can vary during the trip. The problem is formulated as a mathematical model, and a TS approach is used to generate high-quality solutions. To obtain an initial solution for the TS algorithm, a *modified nearest neighborhood heuristic* is used. In each iteration, four different neighborhood operators are used to generate a set of neighbors for the current solution, after which a *speed improvement strategy* is used to find the best speed and departure-time for each route [48]. Several real-world situations were analyzed, including traffic jams, different vehicle types, different objectives, and the effect of empty kilometers.

4.3. Variable neighborhood search

The *Variable neighborhood search* (**VNS**) metaheuristic is proposed by Mladenović and Hansen [49] in 1997. The main idea is to systematically change the neighborhoods, as well as to explore distances in the single neighborhood. VNS consists of three main steps: *shaking*, *local search*, and *neighborhood change*. In the shaking step, the algorithm chooses a random solution from a given neighborhood, in order to diversify the search within solution space. The resulting solution is further improved in a local search step, and evaluated in the neighborhood change step, which decides whether to move to the next neighborhood or to return to the smallest neighborhood. There are many variations of this algorithm, some of them described in [50].

A problem considered by Bruglieri et al. [51] is a version of VRP with TW that uses electric vehicles (**EVs**) with partial battery recharge. The objective is to simultaneously minimize the number of EVs, total travel time, total recharging time, and the total waiting time. For this problem, the authors proposed a mathematical model, that was then solved by using *Variable Neighborhood Branching* (**VNB**), which is a *General Variable Neighborhood Search* (**GVNS**) inspired matheuristic developed for solving *0-1 MIP* problems proposed by Hansen et al. [52]. This approach proved to be successful in finding a good solution for electric VRP with TW in an acceptable amount of time.

Heterogeneous-Fleet Green Vehicle Routing Problem (**HFGVRP**) is presented in the paper by Yavuz and Çapar [53]. It is an uncapacitated version of VRP, with a heterogeneous fleet (that can include both AFVs and ICVs), multiple trips, and limited trip duration. This problem is also specific in the sense that vehicles do not simply deliver goods, but offer specific services, which means that a vehicle can spend a certain amount of time servicing a customer. Each vehicle can be fully recharged at any point at AFS, or it can be partially recharged at the site while serving a customer. Four different objectives were proposed: minimizing the total distance traveled, minimizing the total CO_2 emissions, minimizing fuel cost, and minimizing total distance traveled by ICVs. VNS algorithm is proposed for solving this problem, using a set of five different neighborhoods, taken from [54, 55]. The customers are assigned to different groups, which are then optimized according to some of the aforementioned objectives. VNS is also adapted to support Pareto optimization for MFGVRP. Experimental results have shown that having more on-site partial recharges significantly increases the overall performance. On the other hand, increasing the number of AFSs had a smaller impact on overall performance. Considering this, whenever possible, the proposed model with on-site recharges is more likely to be adopted by large companies.

GVRP with a fleet of AFVs is explored by Affi et al. [56], with the objective to minimize the total energy cost. A VNS algorithm is proposed for this problem, using a set of 9 different neighborhood structures. These neighborhoods are split into three types: *customer neighborhoods*, *AFS neighborhoods*, and *node neighborhoods* (which considers both customer and AFS nodes). The shaking step generates a random solution using only the set of node neighborhood structures. In each iteration of the shaking step, a neighborhood structure is chosen at random. In the improvement step of the algorithm, the authors used *Variable Neighborhood Descent* (**VND**) as a local search procedure. Only the customer neighborhoods and AFS neighborhoods are considered during VND. Unlike the classical VNS, where the shaking step precedes the local search step, in the version proposed Affi et al. the local search step is done first. Because of this, the shaking step accepts a solution only if it improves the incumbent solution. This approach is tested using the instances from [10] against solutions proposed in [10, 57, 58, 59]. The proposed algorithm either outperformed other algorithms in terms of the best-found solution or found a solution comparable to some of the other methods.

A mixed-energy green vehicle routing problem with time windows is investigated by Ren et al. [60]. In this version of the problem, a set of electric vehicles is added to a fleet of homogenous ICVs. The objective is to simultaneously minimize total delay time, as well as five different types of pollutant emissions. A delay time refers to the fact that the later the vehicle arrives at the customer, the more likely is that he/she is going to be dissatisfied, even if the arrival time is inside the time window. Instead of recharging EVs in AFSs, each EV has to return to the depot in order to recharge. The authors proposed a mathematical model, as well as VNS for this problem. In the shaking step, two neighborhood operators are used: *1-1 exchange* and *1-0 shift*. The local search procedure is based on the VND procedure, where 9 neighborhoods are defined using 9 different operators: the operator that changes the vehicle type, 4 *intra-route* operators that exchange or move customers inside one route, and 4 *inter-route* operators that exchange or move customers between two routes. The proposed algorithm was able to find satisfactory solutions with regard to both objectives.

4.4. (Adaptive) large neighborhood search

Adaptive large neighborhood search (**ALNS**) is a metaheuristic method introduced by Ropke and Pisinger [61] for solving pickup and delivery problem with time windows. It is based on a *large neighborhood search* (**LNS**), proposed by Shaw [62]. In every iteration of the basic LNS, the algorithm destroys a part of the solution and then repairs the destroyed part. Neighborhood structure is implicitly defined as a set of solutions that can be reached from a current solution by applying the *destroy* procedure, followed by the *repair* procedure. ALNS generalizes this method, by allowing several types of destroy and repair procedures to be used in the same algorithm. Each of the destroy and repair procedures can be called a limited number of times during the search, based on the assigned weight. Weights are updated in every iteration in order to better adapt the algorithm to the instance at hand. More information on LNS and ALSN can be found in the paper by Pisinger and Ropke [63].

Goeke and Schneider [64] considered a CVRP with time windows and heterogeneous fleet, where at least a part of the fleet consists of EVs. A mathematical model is proposed, with three different objectives being considered: minimizing the total travel distance, minimizing the cost of vehicle propulsion and labor, and minimizing the cost of battery replacement. ALNS was developed for this purpose. Construction of infeasible solutions is allowed, but it's penalized in the objective function. The used destroy and repair procedures are described in detail in the paper. Destroying is done by deleting customers from the dynamically selected interval since the experiments suggested that the choice of this interval and its size can greatly influence the quality of the solution. A local search method is introduced to intensify search in promising areas. The SA-based criterion for acceptance is used to escape local optimums, which allows worse solutions to be accepted with a certain probability. This modified version of ALNS was successful in finding satisfactory solutions to a set of 56 benchmark instances from [58] in a moderate amount of time.

Keskin and Çatay [65] tackled the electric vehicle routing problem, with known time windows and partial recharge. They proposed a mathematical model, as well as the ALNS algorithm, with the objective to minimize the total distance traveled. The acceptance criterion is SA-based. Two groups of destroy and repair procedures are used: customer-based and AFS-based. This approach was tested on the set of instances from [58], managing to improve four of the best-known solutions, thus showing that partial recharge can have a positive impact on the overall quality of the solution.

Hiermann et al. [66] considered a heterogeneous fleet VRP with time windows and electric vehicles. The company does not own the vehicles, but rather lease them at a certain price. Each type of vehicle has its own load capacity, energy capacity, and acquisition cost. The objective is to minimize the total cost of travel, as well as the total acquisition cost of vehicles. When visiting an AFS, a vehicle is fully recharged. An ALNS is proposed for the considered problem, with a local search and a labeling procedure to improve the solution. Several different operators are defined for both destroy and repair procedures. In each iteration, the method chooses one of these operators according to the roulette wheel strategy, taking into account weights of operators. These weights are updated over time to better suit the particular instance. Experiments done on a set of benchmark instances show that ALNS is capable of finding good solutions in a reasonable amount of time.

In a study by Macrina et al. [67], a VRP with time windows, heterogeneous fleet and partial recharges is considered. The fleet consists of both conventional vehicles and electric vehicles. The objective is to minimize the total cost, including both fuel and electricity costs. The problem is formulated as a MILP. The authors proposed a matheuristic method for finding a solution to this problem, combining a hybrid version of LNS proposed by Shaw [62] and CPLEX. In this method, an initial feasible solution is generated by CPLEX, after which random removal and insertion operators are applied to the current solution. This method was able to find optimal solutions quicker than CPLEX alone when tested on smaller instances.

In the paper by Yu et al. [68], a GVRP with time windows is considered, with the objective to minimize carbon emission. The authors were especially oriented towards large-scale instances with more than 500 customers, which are hard to solve to optimality. For this purpose, they used the ALNS method, with two newly proposed operators: a destroy operator named *Forward Load Removal Heuristic*, and a repair operator named *Fast Insertion Method*. Forward Load Removal Heuristic makes use of the observation that carbon emissions are proportional to the distance between two customers and the load of the vehicle. Because of this observation, we can expect that it is better to serve customers with higher demand earlier in the tour, thus lowering the load of the vehicle (and consequently CO_2 emissions). Because of this, the proposed operator removes high-demand customers served later in the tour (or earlier, in the case of pickup instead of delivery). Fast Insertion Method aims at reducing the complexity of asserting whether the solution is feasible after insertion of a customer, by taking the advantage of the fact that in some situations, not all of the customers after the inserted one need to be checked to determine feasibility. Computational experiments were performed on two sets of benchmark instances with up to 1000 customers. The proposed method (with new destroy and repair operators) outperformed classical ALNS by 8.49% on average.

4.5. Ant Colony Optimization

Ant colony optimization (**ACO**) is a nature-inspired metaheuristic proposed by Marco Dorigo in the early 1990s [69, 70, 71]. The basic idea of the algorithm is to imitate the cooperative behavior of the real ants in a colony. In nature, while foraging for food, ants deposit chemical substances called pheromones on the trail that evaporate over time. If the trail from the colony to the food source is short, ants can traverse it quickly, depositing more pheromones. Other ants are more likely to choose the path with a stronger pheromone scent, and thus, additionally reinforce the pheromone trail. These characteristics are exploited in the ACO metaheuristic. The algorithm has two main phases: the *construction phase* and the *pheromone update phase*. In most cases, there is a third phase called the *improvement phase*, which performs a local search in the neighborhood of (usually) the best solution generated during the construction phase. Pheromone update phase consists of two steps: evaporation and reinforcement. ACO has been successfully applied to many different combinatorial optimization problems. In the book [72] a reader can find much more extensive information on the algorithm, its variations, and applications.

In paper by Mavrovouniotis et al. [73] the authors explore the ACO algorithm applied to *electric VRP* (**EVRP**). The optimization objective is to minimize the total operation time of a fleet of vehicles. In every iteration of the algorithm, each ant represents a complete EVRP solution. During each step of the construction phase, each ant has to make sure that enough energy is left for the vehicle to visit a charging station. Pheromone update policy is the same as in *MAX-MIN Ant System* ($\mathcal{MMAS}$) [74]. This paper is further improved by Mavrovouniotis et al. [75], where a parallelization method based on several independent colonies is proposed, where the colonies communicate among themselves using a *non-parametric migration policy*. This method was tested on a set of three instances. The results have shown that parallelization of this algorithm improves the quality of the solution compared to the sequential version. On the other hand, non-parametric migration policy had no significant impact on the quality of the solution, probably because sharing the best-found solution leads to the convergence of parallel colonies to the same part of the search space.

Capacitated VRP with AFVs was considered in a paper by Zhang et al. [76]. The authors proposed two approaches to solving this problem: the *two-phase heuristic* and Ant Colony System. The two-phase heuristic consists of solving the TSP version of the problem by using *Nearest Neighbour Criteria*, after which visits to the AFSs and the depot are inserted into the solution, essentially turning it into a solution for the initial CVRP problem. The proposed ACS method has a similar approach when generating new solutions, i.e. the TSP solutions are generated based on *pheromone intensity* and s*aving value*, and then visits to the depot and AFSs are inserted. Algorithms were tested on a set of randomly generated instances. As expected, ACS was able to find better solutions than the two-phase heuristic.

A multi-depot version of the GVRP with capacities (**MDGCVRP**) is studied in a paper by Li et al. [77]. The proposed model has four objectives: 1) revenue maximization, 2) cost minimization, 3) minimization of the travel time, and 4) minimizing CO_2 emissions. Apart from a mathematical model, the authors proposed ACO for solving this problem. As a pheromone update strategy, *Ant-Weight Strategy* (**AWS**) [78] is used.

MDGCVRP is also explored by Zhang et al. [79]. The objective used in [79] is the minimization of the total distance traveled by a fleet of AFVs. At first, each customer is assigned to its nearest depot, after which an Ant Colony System (**ACS**), a variation of ACO, is applied to solve several single-depot GCVRP. The proposed approach was tested on a set of 48 instances, with satisfactory results. This idea is further expanded by Zhang et al. [80].

In paper by Bhattacharjee et al. [81], a multi-depot heterogeneous fleet green vehicle routing problem is considered. The problem at hand has four objectives: 1) revenue maximization, 2) cost minimization, 3) travel time minimization, and 4) CO_2 emission reduction, same as [77]. The algorithm has a lot of similarities with [82], as it also uses clustering as its first step. In that step, the k-nearest neighbors algorithm is used to assign every depot to its nearest customers. In the next step, ACO is used to generate high-quality solutions for the problem, using the results from the previous step. It is not entirely clear how the results obtained by clustering are used in the algorithm, but the author of this paper assumes that ACO is used to solve a single-depot VRP for each of the clusters in parallel, based on similar work [82].

Distribution sharing with electric vehicles is considered in Li et al. [83]. Distribution sharing is a strategy in which several companies may combine their distribution needs and assets in order to cut the cost and lower their emission impact. This version of the problem considers multiple depots, with time and capacity constraints. The objective is to minimize total cost, which includes electricity and environmental costs among others. For the purpose of dealing with this problem, ACO is proposed. The algorithm was tested using both separate distribution and distribution sharing models, different electricity prices, and different carbon taxes. The results suggest that using the distribution sharing model and higher carbon taxes leads to lower CO_2 emissions, while the lower electricity prices increase the total CO_2 emission. On the other hand, increasing carbon taxes lead to a notable increase in overall cost, therefore, the positive and negative effects of this measure should be balanced carefully.

GVRP with AFVs and multiple depots was studied by Zhang et al. [80]. Two algorithms were proposed: *Partition-Based Algorithm* (PBA) and *Two-stage Ant Colony System* (TSACS). PBA uses the idea of splitting customers into two groups: *borderline* customers (that are located approximately between two depots) and *non-borderline* customers. Non-borderline customers are automatically assigned to their nearest depot and GVRP routes are generated for each depot. Lastly, borderline customers are later inserted into existing routes following the cheapest insertion criteria and the local search is performed to further optimize the solution and to remove potentially redundant nodes. TSACS uses two types of ants: *depot-ants* (that assign a customer to a depot) and *route-ants* (that generate routes). After depot-ants assign customers to a depot and route-ants generate routes, a *variable neighborhood scheme* is applied to further improve the quality of a solution. Variable neighborhood scheme closely resembles variable neighborhood search algorithm, with the difference that the neighborhood size in perturbation (shaking) step is not dynamically determined. Finally, another local search is performed, consisting of redundancy removal and relocation operators. Numerical evaluation has shown that TSACS outperforms PBA in terms of solution quality, and CPLEX in terms of average speed.

4.6. Genetic algorithms

Genetic algorithms (**GA**) are a family of metaheuristic algorithms inspired by evolution. The basic algorithm consists of a set of candidate solutions (*population*) for a given problem, and every candidate has a set of properties (*genotype*). A fitness function evaluates the quality of a solution generated by GA. In each iteration of the algorithm, at least three operators are applied: *crossover*, *mutation*, and *selection*, but additional operators can also be applied, for example, *genotype-phenotype mapping*, sometimes also called *decoding*. Most of these genetic operators modify current solutions, except for decoding, which only evaluates the solutions' quality. Crossover operator combines genomes of two or more solutions. Mutation operator probabilistically changes some parts of the genotype of a solution. Genotype-phenotype mapping translates a genotype into a real solution that can be evaluated. A set of solutions is stochastically chosen by the selection operator to be propagated into the next generation, often favoring better quality solutions. A detailed explanation of the algorithm can be found in [84, 85].

In paper by Ayadi et al. [86] authors studied the vehicle routing problem with multiple trips, intending to minimize the total CO_2 emissions, as well as to minimize the maximum overtime of vehicles, which is the maximal difference between the time limit and the actual duration of every route. A modified version of GA is proposed. In each iteration of the algorithm, genetic operators are used for obtaining new solutions, which are then improved using the local search. If the new solutions are of better quality than the worst solutions in the population, they replace those solutions. Experimental results show that this algorithm is able to find high quality solutions in terms of emissions while sacrificing the quality in terms of distance.

A capacitated vehicle routing problem is considered by Adiba et al. [87], with the objective of emissions minimization. In this approach, an emission matrix is created, using the methodology from [88]. The solutions are represented as arrays of integers, each corresponding to a customer, while zero is used as a delimiter between different routes. The initial population is generated making sure that each individual represents a feasible solution. The selection of individuals for crossover is done using a roulette wheel strategy, biased towards best solutions, and a partially-mapped crossover operator (PMX) is then used to produce new individuals. Swap mutation is used. Finally, the elitism strategy is adopted. The algorithm was tested on a small set of instances, providing promising results.

A GVRP with stochastic traffic speeds and the heterogeneous fleet is considered by Hsueh [89]. A path between two customers is further divided into segments, based on gradient, traffic, or other road conditions, all of which can affect the speed of the vehicle. Since we can't account for traffic on each segment, the speed is considered to be a random variable. The objective is to simultaneously minimize the total cost, including emissions cost and fuel consumption cost. A mathematical model is proposed, together with a genetic algorithm. The solutions are represented using two chromosomes, the first of which represents the ordering of customers, and the second represents an index of the last visited customer in the first chromosome for each vehicle. The elements of these chromosomes are considered genes. The tournament method is used for the selection, and the crossover operator chooses two points at random in parent chromosomes and exchanges the parts between these points. This method can lead to children visiting the same customer twice, which is corrected using a mapping set obtained from the exchanged parts of the parents. Two mutation operators are used: exchange, which exchanges two randomly selected genes in a chromosome, and insert, which removes a randomly selected gene from one place and inserts it in the other place.

Tunga et al. [90] studied a CVRP, with two distinctive objectives: minimization of consumed energy and minimization of the route imbalance, in order to distribute the load more or less evenly among the vehicles. A genetic algorithm was proposed, using the *Pareto ranking scheme* for bi-objective optimization. The algorithm uses two *tournament selections*, which select two pairs of chromosomes at random, running a tournament for each pair, and a winners of both tournaments are chosen for crossover. The crossover operator used by Tunga et al. is *greedy crossover* [91], while the mutation is based on the *2-opt* operator. The experiments done with this algorithm suggest that it can obtain a good set of Pareto-optimal solutions.

Cooray and Rupasinghe [92] investigated a version of CVRP focused on minimizing energy consumption. A basic GA is proposed for this purpose. The contribution of the authors is in the usage of machine learning for tuning of parameters, such as mutation rate, number of generations, and the size of population. This approach uses the *k-means* algorithm to cluster the instances according to the total demand and the number of customers. Different parameters correspond to different clusters. Using the *Freedman test*, the authors were able to prove that the means of minimized energy are different for different mutation rates, testing the algorithm on a set of 100 instances taken from *CVRPLib*.

da Costa et al. [93] used a genetic algorithm to minimize CO_2 emissions per route in a basic version of CVRP. The initial population is generated in the following way: the first three individuals are created by using one of the well-known construction heuristics (Nearest Neighbour Algorithm, Clarke-Wright Savings Algorithm, and Random Insertion), while the rest of the population is generated at random. Individuals with the same value of fitness function are not allowed in the population, even if they encode different solutions. Two mutation operators are used: *2-Opt* and *3-Opt*. In each step, one of these operators is selected at random, with a predefined probability. A binary tournament is used to select parents for crossover. A new child replaces the existing individual only if it has a better fitness function. The procedure stops when it reaches a predefined number of successful offsprings or a predefined number of unsuccessful offsprings without improving the current best solution. Each time the procedure stops it is restarted using the partial replacement procedure [94], for the total of R times.

In a study by Hiermann et al. [95], VRP with time windows and the heterogeneous fleet is considered. The fleet consists of three classes of vehicles: conventional, hybrid, and electric vehicles. Additionally, each class can have multiple types of vehicles, differing in capacity, consumption, or battery capacity. The objective is to minimize the total cost, consisting of fixed costs like vehicle acquisition and maintenance, and variable costs like fuel consumption. Routes are represented as sequences of customers, without recharging stations. Route evaluation is done in two levels. During the first level, recharging stations are inserted into routes for EVs and hybrid electric vehicles (HEVs), using dynamic programming. In the second level, further optimization is performed, in order to optimize partial recharge time and engine mode for HEVs. For this purpose, the authors proposed two greedy policies. A genetic algorithm based on [96, 97] is used to obtain the routes. Even though this algorithm is presented as a hybrid by the original authors because it introduces a few non-standard operators based on local search, we do not classify it as a hybrid metaheuristic because it is not a combination of two different metaheuristics. Extensive testing and sensitivity analysis is provided in the paper. The authors also proposed a new set of benchmark instances.

4.7. Particle Swarm Optimization

Particle Swarm Optimization (**PSO**) is a population-based metaheuristic, originally proposed by Kennedy and Eberhart [98]. A particle can be seen as a solution candidate of a given problem, which can memorize its best found position and velocity, as well as the best found position of the whole swarm. In its original version, several particles are placed into the search space, and each of them evaluates the objective function in its current position. In each generation, information from all of the particles is combined to determine new velocities for each dimension of the search space, which is in turn used to calculate new positions for every particle. A detailed description of the algorithm, variations, and applications can be found in [99, 100].

Kumar et al. [101] intended to optimize both *production routing* and *pollution routing problems*. The combined problem considers a situation where a factory needs to optimize its production and deliver products to the customers, assuming that each customer has a storage unit with limited capacity. A bi-objective model is proposed, in which the first goal is to minimize the total operational cost, including production, storage costs, distribution, etc., while the second goal is to minimize total emissions based on fuel consumption. Time window constraints are imposed on this version of the problem. The authors defined a mathematical model for this problem, and a metaheuristic approach based on the *Self Learning PSO* (**SL-PSO**), proposed by Li et al. (2011) [102]. The authors also applied *non-dominated sorting genetic algorithm-II* (**NSGA-II**) [103] to this problem, in order to evaluate the efficiency of SL-PSO. Comparing Pareto-fronts of these two algorithms applied to a set of instances, it can be concluded that SL-PSO outperformed NSGA-II in every case.

In a study by Norouzi et al. [104], a time-dependent version of GVRP is considered. In this version, travel time between two customers depends on the distance between them and the time of day, and the goal is to minimize the total travel time. Additionally, minimizing fuel consumption (and by that, carbon emissions) is considered as a second objective. For this purpose, a modified multi-objective PSO is used.

Poonthalir and Nadarajan [105] studied a version of GVRP where the speed of a vehicle is taken to be a variable, and it's simulated using the *triangular distribution*. Two separate objectives are considered: minimizing the *route cost* and minimizing the *fuel consumption*. A PSO based approach is proposed for solving this problem. The initial population is created using the *nearest neighbor heuristic*. The algorithm uses several additional time-varying parameters while updating the velocity of particles, such as *inertia*, *cognitive acceleration coefficient*, and *social acceleration coefficient*. All three of these parameters change over time and have a goal of improving the global search and convergence. The algorithm also uses a *greedy mutation operator* [106] to avoid getting stuck in local optima. The experiments were performed on a set of benchmark instances from [10]. The results have confirmed that the proposed algorithm improved expected fuel consumption compared to the previously best-known solution presented by Montoya et al. [57].

In a paper by Wang et al. [107], a multi-depot VRP with transportation resource sharing, time-dependent speeds, and time windows is considered. Two objectives are considered simultaneously: minimizing the total CO_2 emissions and minimizing the operating cost. The operating cost consists of transportation costs and vehicle maintenance costs, with added customer satisfaction costs for arriving late to the customer. The authors proposed multi-objective PSO (MLPSO) combined with *Clarke and Wright Savings* algorithm and *Sweep Algorithm*. This approach was tested against pure MLPSO and NSGA-II on a modified set of PRP benchmark instances, providing better results in terms of emissions and distance.

4.8. Other metaheuristics

In a paper by Micale et al. [108], an asymmetrical version of GVRP with time windows, variable delivery times, and vehicle dimensions is considered. Variable delivery times attribute models the fact that delivery time depends on several factors, such as type of the vehicle, road quality, traffic, or weather. Vehicle dimensions are also considered because some vehicles might not be able to serve a specific customer due to size limitations. For finding a set of feasible solutions, the Firefly algorithm (FA) is used, proposed by Yang (2009) [109, 110]. The authors adapted this algorithm by introducing the elitism procedure, which aims to prevent losing a firefly queen and promising solutions. At this point, the goal is to select a subset of vehicles from the initial fleet, considering only the total distance traveled as the objective. In the next step, the TOPSIS method [111] is used to introduce economic and environmental factors, by selecting the best possible solution from the set of feasible solutions created by FA. Several evaluation criteria are taken into account: total distances, utilization coefficient, carbon footprint, and fuel consumption. After the numerical analysis, the author concluded that the quality of provided solution is highly correlated with the initial fleet configuration.

In a study by Macrina et al. [112], a GVRP with a heterogeneous fleet, time windows, and partial recharge is considered. Both EVs and ICVs can be a part of the fleet. The objective is to minimize the total cost, consisting of recharging, routing, and activation of electric vehicles. In addition, pollution emissions are taken into account and are kept under a certain threshold. Customers are clustered into two groups, one served by EVs, and the other served by ICVs. The authors proposed using the Iterated Local Search (**ILS**) for finding a set of routes for both clusters of customers. Experimental evaluation is performed using a modified set of benchmark instances proposed by Solomon [30].

In a paper by Andelmin and Bartolini [113], electric vehicles were considered. The objective was to find a set of routes that minimize the total distance traveled. For this purpose, the authors proposed *Multi-start Local Search* (**MSLS**) method, based on a *multigraph reformulation* proposed by Andelmin and Bartolini [114]. The problem is represented on a multigraph by declaring all customers and the depot as nodes, while arcs represent refuel paths. A refuel path between nodes $i$and j is a path that starts from node i, visits a sequence of consecutive AFSs, and ends in node j. The purpose of this formulation is to avoid explicitly modeling AFSs as a different type of node, as is often the case in the literature. The proposed MSLS algorithm consists of two phases: the first one uses fast constructive operators, while the second improves solutions from phase one by using a wider set of operators. The algorithm was tested on two sets of instances [10, 114].

Peng et al. [115] considered GVRP with electric vehicles, with the objective of minimizing the total distance traveled. A constraint on maximum traveling time is imposed. A memetic algorithm is proposed, incorporating *adaptive local search* as a local search procedure. For generating the initial population, the authors used the *k-Pseudo Greedy method* [28]. In the adaptive local search, reinforcement learning is utilized while choosing moves from one of the 8 proposed neighborhoods. A *backbone-based crossover operator* is used, together with the *longest-common-subsequence-based population updating strategy* [116]. The proposed algorithm was tested against several other algorithms from the literature, including [58] and [113].

Giallanza and Puma [117] considered a GVRP for a three-echelon supply chain with uncertain customer demands. Two distinct objectives are considered simultaneously: minimizing the total cost of transport and minimizing CO_2 emissions. The authors proposed using NSGA-II algorithm for this problem.

Zulvia et al. [118] studied multi-objective GVRP with an emphasis on delivering perishable goods. Four distinctive objectives were considered: operational cost, deterioration cost, carbon emission, and service level. Deterioration cost represents an estimate of a loss due to quality deterioration over time, while the service level is measured based on delivery time, i.e. whether the vehicle delivered goods to a customer within their time window. The *Gradient Evolution* (**GE**) algorithm was used for this problem, which represents a solution as a vector and explores the search space using three operators: vector updating, jumping, and refreshing. The algorithm was tested using a real-world example of a fruit delivery company.

Utama et al. [119] proposed the hybrid *Butterfly Optimization Algorithm* (**BOA**) for finding a solution to GVRP. The goal is to minimize the total cost, including emission costs, fuel consumption, and vehicle use cost. BOA is a metaheuristic method proposed by Arora and Singh [120]. The main idea behind this algorithm is the use of *fragrance* as a communication tool between butterflies (agents). Fragrance corresponds to the quality of a solution and it can attract other butterflies. For the purpose of GVRP, authors combined BOA with TS algorithm from a study by Poonthalir and Nadarajan [105], so that TS updates 10% of the initial butterfly population. Finally, a local search method is used in each iteration to further improve the quality of solutions. This approach was tested against several other metaheuristics, providing better results in terms of solution quality, but often worst results in terms of computation time.

The *Hybrid Whale Optimization Algorithm* (**HWOA**) was applied to GVRP in a study by Dewi and Utama [121], with the goal of minimizing the total cost, including fuel and emission costs. It combines the whale optimization algorithm, as proposed by Mirjalili and Lewis [122], with TS and local search. WOA is based on three behaviours displayed by whales: encircling prey, bubble-net attacking method (exploitation phase), and search for prey (exploration phase). This approach was tested against several other metaheuristics, including TS, SA, ACO, PSO, GA, and WOA.

Utama et al. [123] considered GVRP with time windows, with the objective of minimizing the total cost, consisting of fuel costs and late fees. For this purpose, the *Artificial Bee Colony* (**ABC**) algorithm was used. ABC was proposed by Karaboga and Basturk [124, 125] and is based on the behavior of bees. Three groups of bees are identified: employed bees, onlookers, and scouts. Employed bees go to the previously visited food source, onlookers wait on the dancing area until they choose a food source and become employed, and scouts randomly search for a new food source. ABC was able to find better quality solutions when compared to the nearest neighborhood algorithm.

In a study by Ferreira and Steiner [126], an asymmetric bi-objective version of GVRP is examined. Two objectives that are considered are minimization of total CO_2 emissions and minimization of route disbalance. Several metaheuristics are proposed for this problem: NSGA-II algorithm developed by Holland [127], multi-objective PSO, a hybrid algorithm that combines Clarke and Wright's Savings algorithm (CW) [4] and NSGA-II (CWNSGA-II), and a hybrid algorithm that combines CW, TS, and NSGA-II (CWTSNSGA-II). All four algorithms were evaluated using a newspapers distribution as a case study, with the conclusion that CWNSGA-II and CWTSNSGA-II provide better results than NSGA-II and MO-PSO.

GVRP with stochastic demand was examined by Niu et al. [128]. In this version of the problem, the demand of each customer is unknown before a vehicle visits that customer. If a vehicle does not have enough goods to serve a customer, it has to return to the depot to replenish. Two separate objectives are minimized simultaneously: total cost (including fuel emissions cost) and customer dissatisfaction, which is calculated based on time windows violation. The authors proposed a membrane-inspired multi-objective algorithm (MIMOA) for this problem. The algorithm has three subsystems: two operation subsystems and one control subsystem. Operation systems use a multi-objective evolutionary algorithm with clustering to search for a solution and send it back to the control system, while the control subsystem guides the evolutionary directions of the two operation subsystems. This algorithm was tested against NSGA-II and *skin membrane guided multi-objective membrane algorithm* (SMG-MOMA) [129] on a set of 10 instances with success.

4.9. Hybrid metaheuristics

Hybrid metaheuristics combine two or more metaheuristics into one method, in hope of overcoming the disadvantages of each of those individual metaheuristics. The term *hybrid metaheuristic* can be used to describe a metaheuristic that incorporates some exact method like *Integer Linear Programming*, and this type of hybrid metaheuristics are usually called *matheuristics*. Many papers use hybrid metaheuristics for some version of GVRP, so only a few of the most interesting are mentioned. It's also worth noting that some of the proposed methods use the ideas from other metaheuristics, without being considered a hybrid. For example, papers [64, 65, 58, 130] use the acceptance criterion based on SA, which allows for lower quality solutions to be accepted, but these methods do not incorporate any other important part of SA.

Elbouzekri et al. [36] wrote a paper which explores a version of GVRP that is not based on using alternative fuel vehicles, but rather on estimating and minimizing CO_2 emissions. The algorithm approximates the emission for every pair of nodes and uses that information in its objective function. Apart from this modified objective function, the problem is simply a basic CVRP. The authors proposed an integer linear programming model, as well as a *Hybrid Ant Colony System* (**HACS**). HACS consists of three phases: route construction phase, pheromone update phase, and hybridization phase. The first two phases are done in a classical ACS style, while the hybridization phase uses the *Large Neighborhood Search* (**LNS**) [62] metaheuristic to further improve the solution. Because of the lack of benchmark instances for this type of problem, the algorithm was tested on a set of 10 randomly generated instances with the number of customers ranging from 10 to 300. The tests were then repeated using the traditional objective function which aims to minimize the total distance traveled. Comparing these results, the authors pointed out that total distance rises when using the emission-based objective function, and concluded that those two objectives are not equivalent, as it is often assumed.

A hybrid algorithm that combines TS and VNS is proposed by Schneider et al. [58] for the CVRPTW with electric vehicles (ECVRPTW). The proposed algorithm is in essence a form of VNS, with TS as a local search procedure. The acceptance criterion is based on SA. Infeasible solutions are allowed during the search, but penalized in the objective function. Neighborhoods used in the shaking step are based on the cyclic-exchange operator [131]. For testing purposes, the authors introduced two sets of instances for the ECVRPTW (56 large instances and 36 small instances), based on instances from [30]. The parameters were tuned using a subset of 10 large instances. The algorithm was also tested on sets of benchmark instances for three different problems: multidepot VRP with interdepot routes (MDVRPI), GVRP, and VRPTW. In each case, the algorithm was able to provide good results in a short amount of time.

A multi-objective version of CVRP with multiple depots is analyzed by Jabir et al. [132]. This problem aims to minimize CO_2 emissions, together with the total distribution cost. The approach used by the authors utilizes the ACO algorithm to obtain a set of Pareto-optimal solutions, after which VNS is applied to that set. This approach was tested on a set of randomly generated instances, and it was shown that minimal cost doesn't necessarily mean fewer emissions. The algorithm was not compared to other existing methods, making it hard to estimate the effectiveness of the proposed algorithm.

A green CVRP with heterogeneous fleet and time windows is considered in paper by Ene et al. [133]. The objective is to minimize fuel consumption, as well as to determine the best possible fleet composition. A hybrid metaheuristic is proposed for this problem, combining SA and TS. This approach was tested using several different versions of the problem, such as CVRP, VRPTW, GCVRP, and GVRPTW. In all of these cases, the algorithm was able to successfully find good solutions in terms of fuel consumption, distance, and CPU time.

Another example of SA and TS being used together can be found in a paper by Suzuki [134]. The author describes CVRP with the objective to minimize the total fuel consumption. Since fuel consumption is directly related to route distance and vehicle payload, this problem is presented in a form of a bi-objective model. The distance between the customers is adjusted to encompass different factors that can influence fuel consumption, such as the speed of the vehicle, gradient of the road, and congestion. Note that a decrease in the distance traveled doesn't necessarily imply a decrease in emissions and fuel consumption [36], but the assumption made in [134] is that the best solution is probably going to be a part of the optimal Pareto-front when considering payload and distance as minimization objectives. The method proposed by the author consists of two steps. In the first step, Pareto-front is approximated using the SA algorithm, and in the next step, a modified version of TS is applied to every solution in the Pareto-front, which explores only the neighborhoods that are close to the frontier. Using this method, the author was able to find solutions with lower fuel consumption, compared to the classical, single-objective version of the problem.

In the work by Jabir et al. [135], a multi-depot version of VRP is considered. The authors examined three models, which focus on different uses of this problem. In the first model, the focus is on minimizing the economic cost, which is a standard version of MDVRP. The second model tries to minimize the total amount of emissions, while the third model tries to find the balance between the first two models and simultaneously minimize emissions and economic cost. Two different metaheuristic algorithms are proposed for this problem: ACO and a hybrid between ACO and VNS. In the hybridized version, after each ant constructs its solution, a VNS is applied to improve that solution. After VNS finishes, the global pheromone matrix is updated. The hybrid version provided better results when compared to pure ACO applied to larger instances.

Xiao and Konak [136] considered a similar problem to the one presented by Xiao and Konak [31], i.e. time-dependent vehicle routing and scheduling problem with the objective of minimizing CO_2 emissions. The authors considered a fleet of heterogeneous vehicles and soft time windows, where late visits to customers are penalized by adding a tardiness penalty to the objective function. MILP model is proposed, which can be solved to optimality by commercial solvers only for small size instances. For larger instances, the authors proposed using a hybrid consisting of a genetic algorithm and dynamic programming (DP). The problem is separated into two parts: finding the best routes for vehicles and scheduling when each vehicle is going to travel between particular customers. For the scheduling part, the authors offer a dynamic programming formulation capable of finding the optimal schedule for the given set of routes. The original problem is solved by using a genetic algorithm to create solutions considering only the routing part of the problem, and DP is used as a subroutine that determines the best schedule for each solution. The approach was tested on 30 small-sized instances, as well as 14 CVRP benchmark instances with success.

In a paper by Zhang et al. [137], EVRP is considered. The algorithm first needs to determine the electric energy consumption from battery, taking into consideration vehicle weight, speed, distance, motor efficiency, etc. Next, the indirect CO_2 emissions are estimated. These emissions are the result of electrical energy production in the coal-based power plants, and it is proportional to the energy used by EV from battery. Using this information, the authors formulated the problem in a form of MILP and then applied the ACO algorithm to it. ACO is hybridized with the *iterated local search* (**ILS**) [138], to further improve the quality of a solution. Pheromone matrix is updated according to the elitist rule, in which only a set of ants that found some of the best solutions so far can update the trail. The paper also presents an *adaptive large neighborhood search* (**ALNS**) for solving EVRP in question. The algorithms were tested on a set of generated instances, and the obtained results show that ACO was able to produce near-optimal solutions, with an average gap of 3.20%, outperforming both ILP and ALNS.

The two-stage algorithm is proposed by Li et al. [82] for solving multi-depot green vehicle routing problem with time windows (GVRPTW). The algorithm tries to simultaneously minimize several objectives, including fuel consumption and carbon emission, as well as other types of cost. In the first stage of the algorithm, the *Improved Balanced K-means Algorithm* (IBKA) is used to cluster customers into groups, in order to split the problem into several smaller subproblems. In the second step, all of these subproblems are addressed using a hybrid ACO, which incorporates VNS as a local search strategy.

In article by Li et al. [139], a version of GVRP with time windows that focuses on cold chain logistics is developed. The refrigerated vehicles use more fuel than regular vehicles because they have to maintain a low temperature, thus emitting more greenhouse gasses. The objective is to minimize the total cost, including GHG emission cost (either only CO_2 or all of the GHG), time windows penalty, product freshness, quality loss, vehicle operating cost (such as maintenance and personnel), and energy cost. A modified version of PSO (MPSO) is proposed for this problem, which introduces TS as an intensification method. For testing purposes, a standard PSO algorithm was also implemented, but it was outperformed by MPSO. The study also showed that considering all GHG instead of just CO_2 produces solutions with better overall cost.

In paper by Wang and Lu [130], a green CVRP with a fleet of AFVs is considered. For this purpose, a *memetic algorithm* (**MA**) with a competition mechanism is proposed, combined with VNS. MA is a population-based metaheuristic combined with some local search procedure. Each solution is called an *individual*, and the term *agent* is used for a processing unit that can hold multiple solutions, as well as problem-specific methods for improving solutions. If agents can adapt their methods, we call that version of the algorithm *adaptive MA*. The main part of the algorithm is the *generational step* process and it consists of three main parts: selection, reproduction, and update. Whenever the population converges too much, it is restarted to prevent unnecessary waste of time by exploring just a fraction of search space. The population can be restarted in different ways, for example, a few best individuals are preserved, while other individuals are randomly generated. A detailed description of this algorithm can be found in [140]. The proposed method from [130] represents a solution as a traveling salesman problem (TSP), i.e. a permutation array of customers and AFSs. This array can then be decoded into a GVRP instance. The method starts with the *k-nearest neighbors* algorithm for initializing solutions in the population, starting from a randomly selected point for each individual. For the purpose of intensification, MA is hybridized with a VNS algorithm, that uses SA based acceptance criterion. A competition search used by the authors chooses a certain number of the solutions from the population, based on their quality. These solutions are further improved, first by starting the intensification procedure once again, and then by executing a set of adjustments for customers and AFSs. The idea behind this competitive search is to allocate more processing power to the more promising solutions. After the adjustments are done, a crossover operator is used.

Zhen et al. [141] considered VRP with HEVs. Since HEVs have two modes of running, i.e. HEVs can use both gasoline and electrical energy, it is important to determine which mode is going to be used by a vehicle on each segment of the route in order to minimize the total cost of energy consumption. A PSO algorithm is proposed for this problem, with VNS as a local search method. The paper also introduces a labeling procedure that determines a vehicle mode for each route segment and evaluates the quality of the solution. The approach was tested on three sets of instances: small, medium, and large-scale. For the small-scale instances, the algorithm was able to find the optimal solution in every case, but it also had success with finding a good solution for some of the large-scale instances.

Peng et al. [142] considered a multi-depot version of GVRP, intending to minimize the total cost, which includes CO_2 emission cost. The program is formulated as MILP and tested with CPLEX. A hybrid evolutionary algorithm is proposed, that combines an evolutionary algorithm with VNS as a way of intensifying search in promising areas. In a study by Olgun et al. [143], the authors considered a version of GVRP with simultaneous pickup and delivery. The objective was to minimize fuel consumption of a fleet consisting of conventional vehicles. A hyper-heuristic based on ILS and VND is proposed for obtaining high-quality solutions.

5. SUMMARY AND DISCUSSION OF THE PRESENTED SOLUTION APPROACHES

In this paper, a total of 62 studies were considered, covering the period from 2013 to 2021. The problems described in these papers are classified into two categories: *ICV-based* and *AFV-based vehicle routing problem*. We should mention that the term ICV-based GVRP includes all of the problems that do not use any AFVs, where at least one of the objectives is focused on minimizing GHG emissions or minimizing fuel consumption. The ratio of these two types of problems is presented in Figure 6.

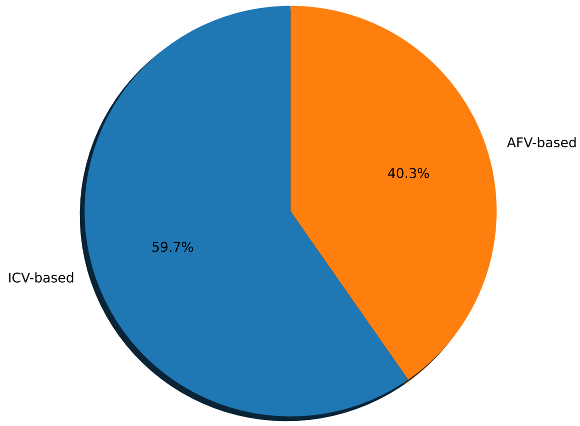


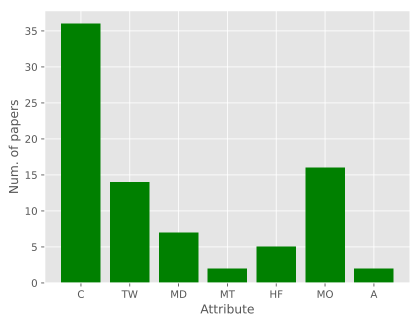
Figure 6: Ratio of ICV-based and AFV-based publications

In Table 1, we summarize the attributes of each ICV-based problem, together with the methods used for that problem. In Figure 7, we can see the distribution of papers over the years, as well as the total number of ICV-based papers for each VRP attribute. From this figure, we can see that almost all of the papers considered a capacitated version of VRP. Optimizing several objectives simultaneously was a very common approach, most often combining the goal of reducing GHG emissions with the goal of reducing the economic cost. Attributes TW, MD, and HF also received some attention, while MT and A were the least investigated attributes among the considered papers.

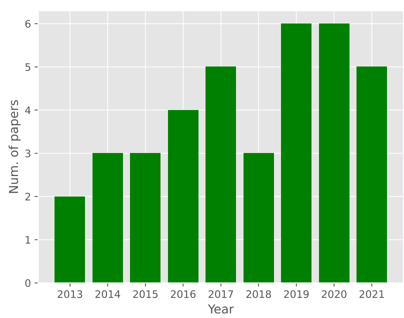
In Figure 8, the ratio of metaheuristics used in these papers is given. It should be noted that hybrid metaheuristics, which are comprised of two individual metaheuristics, count towards both of those metaheuristics. Only metaheuristic approaches are presented in the figure, i.e. mathematical models are not discussed.

Table 1: The summary of ICV-based papers

Paper	C	TW	MD	MT	HF	MO	A	Methods
Adiba et al. [87]	✓							GA
Ayadi et al. [86]	✓			✓				GA
Bhattacharjee et al. [81]	✓		✓		✓	✓		ACO
Cooray and Rupasinghe [92]	✓							GA
da Costa et al. [93]	✓							GA
Dewi and Utama [121]	✓							HWOA
Elbouzekri et al. [36]	✓							ACS-LNS
Ene et al. [133]	✓	✓			✓			SA-TS
Ferreira and Steiner [126]	✓					✓	✓	NSGA-II, PSO, CWNSGA-II, CWTSNSGA-II
Giallanza and Puma [117]	✓		✓			✓		NSGA-II
Hsueh [89]	✓				✓			GA
Jabir et al. [132]	✓		✓			✓		ACO-VNS
Jabir et al. [135]	✓		✓			✓		ACO-VNS, LINGO
Karagul et al. [33]	✓							SA
Küçükoğlu et al. [29]	✓	✓						SA
Kumar et al. [101]	✓	✓				✓		PSO, NSGA-II
Kwon et al. [42]	✓				✓			TS
Li et al. [77]	✓		✓			✓		ACO
Li et al. [82]	✓	✓	✓					ACO-VNS
Li et al. [139]	✓	✓				✓		PSO-TS
Micale et al. [108]	✓	✓				✓	✓	FA
Niu et al. [46]	✓	✓						TS
Niu et al. [128]	✓	✓				✓		MIMOA
Norouzi et al. [104]	✓					✓		PSO
Olgun et al. [143]	✓							ILS-VNS
Peng et al. [142]	✓		✓					EA-VNS, CPLEX
Poonthalir and Nadarajan [105]	✓					✓		PSO
Suzuki [134]	✓					✓		SA-TS
Tunga et al. [90]	✓					✓		GA
Úbeda et al. [45]	✓							TS
Utama et al. [119]	✓							BOA
Utama et al. [123]	✓	✓						ABC
Wang et al. [107]	✓	✓	✓					PSO
Xiao and Konak [31]		✓				✓		SA, CPLEX
Xiao and Konak [136]	✓	✓			✓			DP-GA, CPLEX
Yu et al. [68]	✓	✓						ALNS, CPLEX
Zulvia et al. [118]	✓	✓				✓		GE



(a) The number of papers for each attribute



(b) Number of papers per year

Figure 7: ICV-based papers

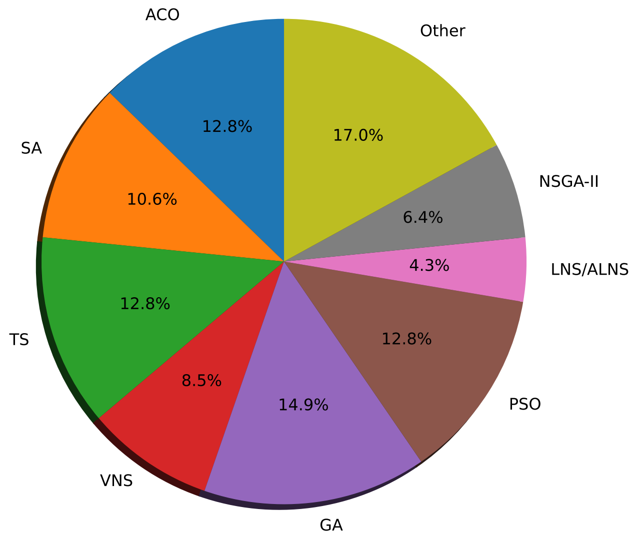
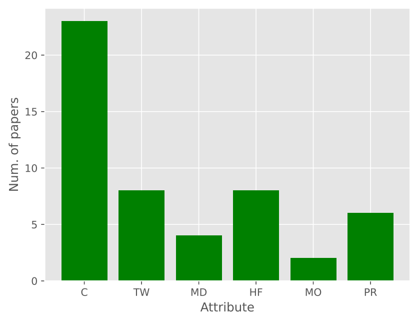
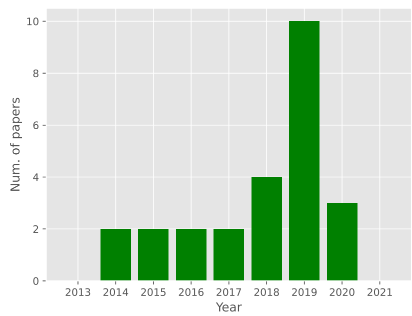


Figure 8: The ratio of metaheuristics used in ICV-based papers

A similar summary for AFV-based VRP is given in Table 2. The distribution of papers per year and the number of papers considering each attribute is shown in Figure 9. Similar to ICV-based papers, capacitated version of VRP was predominantly investigated, but contrary to ICV-based problems, MO attribute was much less common. This is to be expected since the objective of GHG minimization is implicitly taken care of by utilizing AFVs. In Figure 10, the ratio of metaheuristic approaches is shown. We can see that compared to ICV-based versions, VNS and ALNS are much more represented, while GA and TS are much less popular.



(a) The number of papers for each attribute



(b) Number of papers per year

Figure 9: AFV-based papers

Table 2: The summary of AFV-based papers

Paper	C	TW	MD	HF	MO	PR	Methods
Affi et al. [56]	✓						GVNS
Andelmin and Bartolini [113]	✓						MSLS
Bruglieri et al. [51]	✓					✓	VNB, CPLEX
Felipe et al. [28]	✓			✓		✓	SA, CPLEX
Goeke and Schneider [64]	✓	✓		✓			ALNS
Hiermann et al. [66]	✓	✓		✓			ALNS, CPLEX
Hiermann et al. [95]	✓	✓		✓		✓	GA
Keskin and Çatay [65]	✓	✓				✓	ALNS, CPLEX
Li et al. [83]	✓		✓				ACO
Macrina et al. [67]	✓	✓		✓		✓	LNS, CPLEX
Macrina et al. [112]	✓	✓		✓		✓	ILS, CPLEX
Mavrovouniotis et al. [73]	✓						ACO
Mavrovouniotis et al. [75]	✓						ACO
Normasari et al. [39]	✓						SA, CPLEX
Peng et al. [115]							MA
Ren et al. [60]	✓	✓		✓	✓		VNS
Schneider et al. [58]	✓	✓					VNS-TS, CPLEX
Vincent et al. [32]	✓						SA
Wang and Lu [130]	✓						MA-VNS
Yavuz and Çapar [53]			✓	✓	✓		VNS, CPLEX
Zhang et al. [137]	✓						ACO-ILS, ALNS, CPLEX
Zhang et al. [76]	✓						ACS, CPLEX
Zhang et al. [79]	✓		✓				ACS
Zhang et al. [80]	✓		✓				ACS, PBA, CPLEX
Zhen et al. [141]	✓						PSO, CPLEX

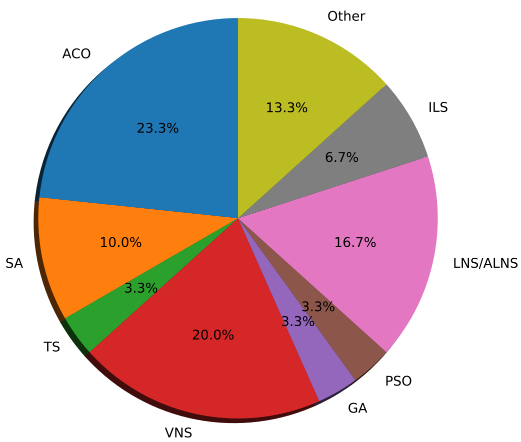
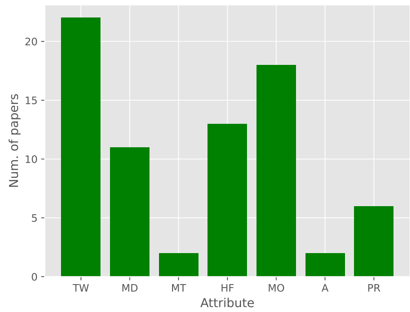
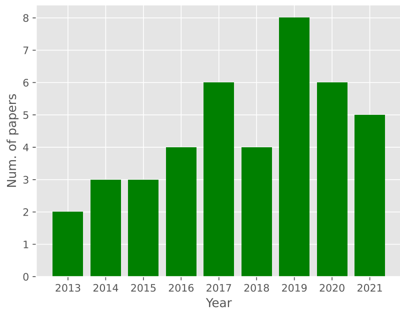


Figure 10: The ratio of metaheuristics used in AFV-based papers

The overall summary can be seen in Figure 11. In order to better visually present the number of papers per VRP attribute, we excluded attribute C from Figure 11a, because all but one paper considered capacitated VRP. We can see that TW, MD, and HF attributes are among the most studied ones, implying that these attributes have real-world importance for many delivery companies. From Figure 12 we can see that the most popular metaheuristics for GVRP are ACO and VNS, followed by SA, TS, GA, and LNS/ALNS. Only ACO and VNS are popular for both ICV-based and AFV-based problems.



(a) The number of papers for each attribute



(b) Number of papers per year

Figure 11: Overall GVRP papers

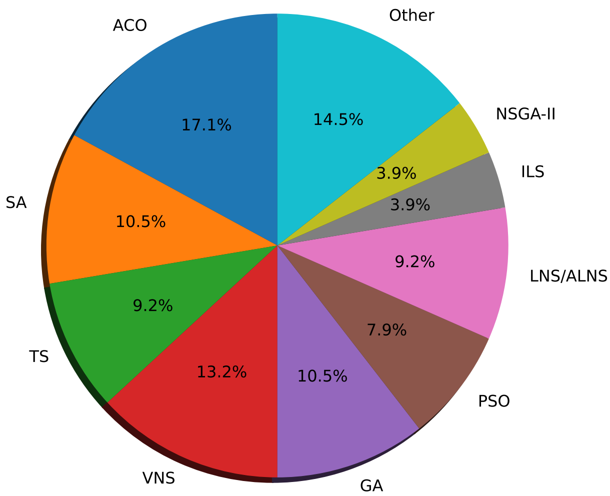


Figure 12: The overall ratio of metaheuristics used

In Table 3, we presented a list of objectives for each of the reviewed publications. These objectives were optimized either combined into one objective or separately with multi-objective optimization methods. In Figure 13, we present the number of papers for each of the objectives. We can see from this figure that the most common objectives used in GVRP were PE, FC, and OC.

Table 3: List of objectives considered in each paper

ICV-based		AFV-based	
Publication	**Objectives**	**Publication**	**Objectives**
Adiba et al. [87]	PE	Affi et al. [56]	FC
Ayadi et al. [86]	PE, MO	Andelmin and Bartolini [113]	TD
Bhattacharjee et al. [81]	RM, TT, PE, OC	Bruglieri et al. [51]	NT, TT, RT, WT
Cooray and Rupasinghe [92]	FC	Felipe et al. [28]	RC
da Costa et al. [93]	PE	Goeke and Schneider [64]	TD, OC, FC
Dewi and Utama [121]	FC, PE, OC	Hiermann et al. [66]	OC
Elbouzekri et al. [36]	PE	Hiermann et al. [95]	FC, OC
Ene et al. [133]	FC	Keskin and Çatay [65]	TD
Ferreira and Steiner [126]	PE, RI	Li et al. [83]	OC, TWPC, FC, PE, QT
Giallanza and Puma [117]	OC, PE	Macrina et al. [67]	FC
Hsueh [89]	FC, PE, OC	Macrina et al. [112]	OC, EC, RC
Jabir et al. [132]	PE, OC, FC	Mavrovouniotis et al. [73]	TT
Jabir et al. [135]	PE, TD, NT	Mavrovouniotis et al. [75]	TT
Küçükoğlu et al. [29]	FC, PE	Normasari et al. [39]	TD
Karagul et al. [33]	PE, TD	Peng et al. [115]	TD
Kumar et al. [101]	OC, FC, TWPC	Ren et al. [60]	PE, TWPC
Kwon et al. [42]	OC, PE	Schneider et al. [58]	NT, TD
Li et al. [139]	PE, TWPC, OC, QLC, FC	Vincent et al. [32]	OC
Li et al. [77]	PE, TT, OC, RM	Wang and Lu [130]	TD
Li et al. [82]	FC, PE, OC	Yavuz and Çapar [53]	TD, PE, FC, ICVU
Micale et al. [108]	TD, PE, FC	Zhang et al. [137]	PE
Niu et al. [46]	PE, OC	Zhang et al. [76]	TD
Niu et al. [128]	TWPC, OC	Zhang et al. [79]	PE
Norouzi et al. [104]	TT, FC	Zhang et al. [80]	PE
Olgun et al. [143]	FC	Zhen et al. [141]	FC
Peng et al. [142]	FC, PE, OC		
Poonthalir and Nadarajan [105]	FC, OC		
Suzuki [134]	FC		
Tunga et al. [90]	FC, RI		
Úbeda et al. [45]	PE		
Utama et al. [119]	EC, FC, OC		
Utama et al. [123]	FC, TWPC		
Wang et al. [107]	PE, TWPC, OC		
Xiao and Konak [31]	PE, TWPC, TT, TD		
Xiao and Konak [136]	PE, TWPC		
Yu et al. [68]	PE		
Zulvia et al. [118]	OC, QLC, PE, TWPC		

In Table 4, we present the number of citations for the six most cited publications in both groups. The data was gathered from *Google Scholar* in October 2021. As we can see from this table, AFV-based papers had generally more citations than ICV-based papers. This shows that even though ICV-based papers are more numerous, there is a greater interest in AFV-based papers. This interest is not surprising, considering that AFV-based problems appeared much more recently and are essentially a unique subclass of VRP problems, with different challenges, which gives researchers more space to achieve significant results. Besides that, electric and hybrid vehicles are becoming more relevant by the year, adding to the appeal of the AFV-based VRP. On the other hand, even though AFV-based VRP is a more interesting research topic, most logistics companies still predominantly use ICVs, making the ICV-based problems more useful at the moment.

Table 4: Number of citations for the most cited reviewed papers

ICV-based		**AFV-based**	
Publication	**Citations**	**Publication**	**Citations**
Li et al. [77]	151	Schneider et al. [58]	865
Kwon et al. [42]	142	Hiermann et al. [66]	441
Kumar et al. [101]	133	Goeke and Schneider [64]	387
Xiao and Konak [136]	118	Felipe et al. [28]	363
Poonthalir and Nadarajan [105]	111	Keskin and Çatay [65]	301
Niu et al. [46]	97	Bruglieri et al. [51]	145
Average (All publications)	45.84	Average (All publications)	137.88

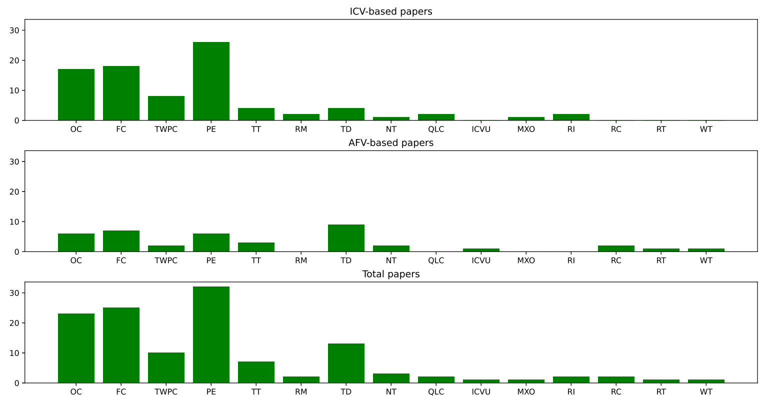


Figure 13: The number of papers considering each objective

In Table 5, we present the distribution of the reviewed papers by journals. Survey papers from Section 3 are also included.

6. FUTURE TRENDS AND PERSPECTIVE

Considering the papers described in section 4, we can draw several conclusions.

- Even though exact methods are available for these problems, they fail to provide a satisfactory solutions in an acceptable amount of time. Because of this, it's safe to say that heuristic and metaheuristic methods are going to receive significant attention in the following period.
- Many relevant attributes that arise from the specific industry demands are not considered in these papers. Attributes like dynamic requests, backhauls, split deliveries, and precedence constraints still remain to be addressed in the context of GVRP. Additionally, the benchmark instances used in these papers assume that the distances between customers are symmetrical. This

limits the usefulness of these instances since delivery companies in urban areas often have to deal with asymmetrical distances, because of the street network properties.

Table 5: Distribution of papers per journal

Journal	**Number of papers**
Journal of Cleaner Production	8 [77, 17, 46, 60, 118, 136, 107, 117]
European Journal of Operational Research	4 [64, 95, 66, 67]
International Journal of Production Economics	3 [19, 134, 137]
Electronic notes in discrete mathematics	2 [51, 93]
Transportation Research Part D: Transport and Environment	2 [135, 42]
Computers & Industrial Engineering	2 [101, 143]
Sustainability	2 [142, 80]
Transportation Science	2 [58, 53]
Expert Systems with Applications	2 [8, 105]
Applied Soft Computing	2 [32, 31]
Journal of Advanced Transportation	2 [119, 15]
Annals of Operations Research	2 [76, 116]
Computers & Operations Research	2 [113, 112]
Journal of Industrial Engineering	1 [92]
Systems Science & Control Engineering	1 [121]
Journal of Theoretical and Applied Information Technology	1 [36]
International Journal of Vehicle Design	1 [133]
Journal of Geographic Information System	1 [126]
Procedia-Social and Behavioral Sciences	1 [132]
Environmental Science and Pollution Research	1 [29]
Industrial Management & Data Systems	1 [139]
Sustainable Futures	1 [108]
Swarm and Evolutionary Computation	1 [128]
Optimization Letters	1 [104]
Journal of the Association of Engineers	1 [90]
Lecture Notes in Management Science	1 [45]
Complexity	1 [68]
International Journal of Industrial Engineering Computations	1 [56]
Transportation Research Part E: Logistics and Transportation Review	1 [28]
Transportation Research Part C: Emerging Technologies	1 [65]
Resources, Conservation and Recycling	1 [83]
Mathematical Problems in Engineering	1 [39]
IEEE/CAA Journal of Automatica Sinica	1 [130]
International Journal of Production Research	1 [141]
Engineering Applications of Artificial Intelligence	1 [13]
Operational Research	1 [16]
Cogent Engineering	1 [18]
International Journal of Advanced Logistics	1 [11]
Proceedings	**Number of papers**
International Conference on Logistics Operations Management	2 [87, 86]
IEEE Symposium Series on Computational Intelligence	2 [73, 75]
CICTP	1 [89]
International Conference on Intelligent Computing	1 [82]
Journal of Physics: Conference Series	1 [123]
Solving Transport Problems: Towards Green Logistics	1 [14]
5th NA International Conference on Industrial Engineering and Operations Management	1 [81]
Book chapters	**Number of papers**
Lean and green supply chain management	1 [33]
Decision Science in Action	1 [79]
Vehicle Routing: Problems, Methods, and Applications, Second Edition	1 [12]

- A great majority of studies concerning GVRP use one of the aforementioned metaheuristics, ignoring many other available metaheuristics, such as Bee Colony Optimization (**BCO**) [144], Grey Wolf Optimization (**GWO**) Mirjalili et al. [145], Bacterial Foraging Optimization (**BFO**) [146], Intelligent water drops [147, 148], and many others. Some of these metaheuristics already proved to be successful when optimizing a standard version of VRP [149, 150, 151, 152, 153], making it probable that they would provide good results for GVRP as well.
- Since replacing a fleet of ICVs with a fleet of AFVs can be very expensive, we can assume that distribution companies are going to undergo this process gradually, by incorporating more and more AFVs into their ICV fleet. Because of this, a heterogeneous fleet attribute is probably going to gain importance in the following years. Another way of overcoming a limited number of AFVs is to focus more on the sharing economy. More precisely, distribution companies could share their fleets, ultimately reducing global emissions.
- Many different factors contribute to GHG emissions. In the ICV-based version of the problem, many of the different factors and types of pollutants are accounted when creating the emission matrix [139, 60]. On the other hand, the AFV version of the problem often does not take into account the indirect emissions, produced while generating electrical energy from non-clean sources. Since most of the world's electrical energy still comes from burning fossil fuels [2], these emissions should be considered in the model as well.
- The increasing number of alternative fuel vehicles creates the need for more alternative fuel stations. These stations have to be positioned in strategic locations, in order to best serve vehicles. Some countries like Belgium and Germany already have a significant number of AFSs, while others still need more AFSs. Positioning AFSs is an optimization problem itself. Additionally, some delivery companies choose to have their own network of AFSs, so the positioning of those stations is of vital interest to the company.
- With the rising environmental concerns and the limited amount of fossil fuels, it is safe to say that the number of electric vehicles is only going to rise in the following years. Many countries started imposing taxes for GHG emissions, as an incentive for delivery companies to switch towards alternative fuels. Considering this, it is highly probable that the AFV-GVRP is going to become even more important in the future, following the wider adoption of AFVs by delivery companies.
- There are still very few benchmark instances for the AFV-VRP. Two sets of instances were presented so far [10, 58], but neither of these sets incorporates all of the VRP attributes. For the purpose of testing, it would be beneficial to generate a set of instances that can be used for many different variations of AFV-VRP.

7. CONCLUSION

Reducing the emissions of GHG is an important issue that receives more and more attention in recent years, and this trend is going to continue with the depletion of fossil fuels. Switching towards alternative fuels is becoming a necessity, so many delivery companies are including AFVs into their vehicle fleet. Since AFVs come with their own problems, mostly in form of limited range due to the battery capacity, it is important to take these limitations into account when planning a delivery route. At the same time, some companies are trying to minimize emissions while still using ICVs, by carefully planing routes and considering many different factors that contribute to the amount of emission. Because of this, GVRP becomes more relevant than ever.

Two versions of GVRP were identified in this paper, which differ in their basic objective. ICV-based version tries to minimize emissions of fuel consumption for the fleet of ICVs, while AFV-VRP minimizes the distance traveled by the fleet of AFVs. Both types of problems have seen a rise in their popularity over the recent years.

In this paper, 62 research studies that use some metaheuristic approach to different variants of GVRP were surveyed. Papers are categorized according to the method used in them. Based on that, future trends were examined, and the space for potential improvements has been recognized. Even though most of these studies are describing idealized versions of the problem, it is our belief that further studies in this field will yield results that could actually have big practical impact on the transport industry.

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