This is an accepted version of the article: Koz{\' a}k, V., Woller, D., V{\' a}vra, V., and Kulich, M. (2020). **Initial Solution Constructors for Capacitated Green Vehicle Routing Problem**. *Modelling and Simulation for Autonomous Systems*, which has been published in a final form at https://doi.org/10.1007/978-3-030-70740-8_16.

Initial Solution Constructors for Capacitated Green Vehicle Routing Problem

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Abstract. This paper presents an analysis of the initial feasible solution constructions for the Capacitated Green Vehicle Routing Problem (CGVRP). CGVRP is a more challenging variant of the conventional Vehicle Routing Problem (VRP), where Alternative Fuel Vehicles (AFVs) are limited by their fuel capacity and the scarce availability of Alternative Fueling Stations (AFSs). The problem also imposes a constraint on the maximum carrying capacity of the vehicle. Presented methods can be used as a starting point for more advanced metaheuristics. Some of the methods can be seen as a generalization of the traveling salesmen problem, where one can draw on the numerous techniques described and known in this domain, other methods belong to the class of divide and conquer techniques, where the subproblems are some variants of the VRP. We use a two-phase approach with several different methods for both the initial VRP route construction and the following CGVRP tour validation and repair procedure. The methods are compared on various instances and their advantages are discussed in relation to common variants of the VRP, together with a possibility of their improvements or extensions.

Keywords: capacitated green vehicle routing problem, combinatorial optimization, traveling salesmen problem

1 Introduction

Route optimization techniques are a powerful tool for reducing costs and pollution caused by transport and mobility operations. The Vehicle Routing Problem (VRP) is an NP-hard combinatorial optimization programming problem designed to minimize the total traveled distance of a fleet of vehicles/agents while visiting a set of customers. It generalizes the well-known Travelling Salesman Problem (TSP) and helps to reduce fuel usage and increase the efficiency of delivery routes. Because the problem is NP-hard, the size of a problem that can be solved optimally by an exhaustive search is limited and various heuristics have to be used to reach a solution that is close to optimal.

Real word applications impose additional constraints on the problem, which resulted over the years in numerous variations of the VRP. Since VRP is often used for distribution companies, one of the most popular variants is the Capacitated Vehicle Routing Problem (CVRP), in which each customer has a specified demand and the maximum carrying capacity of the vehicle is considered. The classical CVRP considers a singe depot, where vehicles can reload their cargo. Other popular variants include a multi-depot variant [2] or a VRP with Pickups and Deliveries (VRPPD), where customers have both positive and negative demands [13].

Another variant reacts to the recent effort to reduce environmental impact by utilizing Alternatively Fueled Vehicles (AFVs), which are, however, limited by their fuel capacity and the scarce availability of Alternative Fueling Stations (AFSs). The Green Vehicle Routing Problem (GVRP) introduced in [8] considers the need for refueling and incorporates intermediate stops at AFSs to extend the possible length of a route traveled by a single vehicle. The same problem also applies to Electric Vehicles (EVs), which are limited by their battery capacity. Recently, the GVRP is especially relevant, since a large number of transportation companies are converting their gasoline-powered vehicle fleets to AFV fleets to reduce environmental impact or to meet new environmental regulations.

The Capacitated Green Vehicle Routing Problem (CGVRP) combines the CVRP and GVRP problems by considering both the maximum carrying capacity and the need for AFS visits. A specific variant of this problem, using EVs is referred to as the Electric Vehicle Routing Problem (EVRP), which often imposes additional constraints specific for EVs [7]. The CGVRP is especially suited for delivery companies operating fleets of AFVs.

This paper provides an evaluation of initial CGVRP route constructors using a two-phase heuristic, in which we combine initial VRP route constructions and subsequent CGVRP repair procedures. Several different methods were developed for each phase and tested on a benchmark data set provided in [14]. Both the intermediate VRP routes and the resulting CCGVRP routes are compared in regards to their performance, complexity and applicability to different VRP variants. The developed methods were then discussed as a base for advanced optimization methods.

2 Related Work

The VRP problem in its numerous variants has already been a subject of research for several decades. The CVRP is one of its more common variants, which offers a large number of methods for its solution developed over the years, as well as numerous test instances for the problem. For example, the CVRP library [21], created by Ivan Xavier and the authors of [18], provides a collection of the most popular test instances in a common framework.

Bard et al. [2] formulated the VRP with Satellite Facilities (VRPSF), an extension of CVRP in which vehicles constrained by their maximum carrying capacity have the option to stop at satellite facilities to reload their cargo, this problem is alternatively referred to as the multi-depot VRP [3], [11], [17]. Techniques developed for the multi-depot VRP were of great relevance for the more recent GVRP, which was first introduced in [8]. While numerous works addressed the classical VRP with capacity and distance constraints, GVRP added the capability to extend a vehicle's distance limitation by visiting an AFS en route.

We draw on methods presented in [22], [19] and [20], developed specifically for the CGVRP, which combines the cargo capacity constraints with the possibility of extending the vehicle's driving range by an AFS visit. In this paper, we work with the basic CGVRP definition, with the intent to provide a general baseline for initial construction methods in this field. Developed methods are evaluated on testing instances provided in [14].

A specific case of this problem is the EVRP, which considers electric vehicles(EVs) instead of general AFSs. While the exact definitions differ, EVRP can be considered an extension to the classical CGVRP problem, and many developed methods apply to both problems. A survey on different EVRP variants was presented in [7]. Those variants extend the original CGVRP by considering the use of hybrid vehicles, heterogenous vehicle fleets, dynamic traffic conditions, different charging technologies, non-linearity of the charging function, et cetera. Out of the EVRP oriented works, [15] should be mentioned. Although this work uses an additional criterion (non-linear fuel consumption based on the current load) the problem is also evaluated on the extended version of the dataset [14].

3 Problem Definition

The CGVRP is a challenging NP-hard combinatorial optimization problem extending the original VRP with the addition of several other constraints. It can be seen as a mixed-integer programming problem for which the mathematical model with its parameters has already been formulated in [22].

The problem can be expressed using a fully connected weighted graph $G = (V, E)$, where V is a set of nodes and E is a set of weighted edges connecting these nodes. The node set V contains a depot D, a set of customers I and a set of AFSs F. A non-negative distance value d_{ij}, representing the distance between nodes i and j, is associated with each edge. Each customer $i \in I$ is assigned a positive demand. We assume a homogeneous fleet of vehicles, where each vehicle is constrained by its maximal carrying capacity C, maximal fuel capacity Q and a set fuel consumption rate h. It is assumed that the fuel consumption rate is constant and each traveled edge consumes the amount hd_{ij} of the remaining fuel.

The objective of CGVRP is to find a set of routes, where each vehicle starts and ends at the depot, and that minimizes the total distance traveled. Every customer can be visited only once and the corresponding demand needs to be satisfied after this visit. For every route, the total demand of visited customers can not exceed the maximal carrying capacity of the vehicle.

After a vehicle leaves a refueling station, the fuel consumption cannot exceed the maximal fuel capacity of the vehicle until it reaches another refueling station or ends in the depot. It is assumed, that the depot is capable of both refueling the vehicles and reloading their cargo. When a vehicle visits either an AFS or the depot, it is refueled to the full tank capacity. It is also assumed that AFSs can be visited multiple times.

4 Selected Methods

As the problem is NP-hard, it is impossible to solve larger instances to optimality in a reasonable time. Therefore, it is suitable to deploy a heuristic approach with polynomial time complexity. The CGVRP is a constrained variant of the VRP, for which many effective construction methods were proposed over the years. Some of the methods presented in this paper are modified variants of constructions proposed for different variants of the VRP, while others are newly designed specifically for CGVRP or EVRP.

Most of the CGVRP constructions presented in this paper are split into two phases. The first phase creates a feasible solution to a TSP problem, either totally or selectively disregarding the AFS nodes and the load and energy constraints. The output of the first phase is typically an invalid CGVRP tour, therefore, the second phase can be seen as a repair procedure. The two-phase approach is convenient for problem modularization which in turn led to robust and comparative results, as it allowed to freely test different combinations of individual methods.

Individual TSP and VRP generating methods were later augmented using the Density-Based Clustering (DBC) metaheuristic. DBC exploits the spatial properties of VRP and considers the distribution of nodes over space. This proved to further improve the construction methods by providing global spatial awareness about local point density which is in common unavailable to basic construction methods.

The description of individual methods follows, together with example solutions on a selected instance from [14], presented in Figure 2. The example presents valid TSP and CVRP solutions, and two different CGVRP solutions.

4.1 Initial TSP Constructions

Nearest Neighbour Algorithm (NN) The NN algorithm was one of the first algorithms used to approximately solve the TSP and is commonly used for the initial TSP construction phase for vehicle routing problems [10]. A set of all the customers I is used as an input for the algorithm. The algorithm starts at a random node and moves on to the nearest unvisited node, this way the remaining nodes are greedily added to the tour. The output of the algorithm is a sequence of nodes $T = \{n_1, n_2, ..., n_n\}$, which starts at a random customer and visits every customer exactly once. The AFSs and the depot are not considered in this phase. A TSP tour created using the NN algorithm can be seen in Figure 2b.

Minimum Spanning Tree Algorithm (MST) The MST-based approximation algorithm [12] starts with a construction of the MST over the set of all customers I. Then a root node is chosen arbitrarily and all nodes are then visited by depth-first search, generating a sequence of visited nodes. Only the first visit of each node is taken from this sequence, and the root node is added at its end, thus generating a feasible TSP solution.

The MSP can be used to assign weights to selected edges, providing a useful tool for algorithms based on ant colony optimization [12]. Another advantage of MST-based methods is, that they can be used to provide both the upper and the lower bound for the problem. When the cost function satisfies the triangular inequality, an approximate algorithm can be designed to generate a tour, whose cost is never more than twice the cost of an optimal tour, while the cost of the best possible TSP tour is never less than the cost of the MST.

Modified Clarke-Wright Savings Algorithm (CWS) This method was originally developed as a heuristic for solving the VRP with a central repository and an unfixed number of vehicles[6]. The heuristic works over the set V' composed of all the customers I and the depot D ($V' = \{I \cup D\}$). An individual route from the depot and back is created for each customer, disregarding the energy constraints and AFSs. The algorithm then starts with a node that is furthest from the depot, and individual routes are then merged while utilizing the saving distance $S_{i,j}$ defined in Equation 1 as a difference between the original and resulting routes. Only the outmost customer nodes of the route are considered during the merge process. In the equation, $d_{i,j}$ represents a distance of an edge from node i to node j.

$$S_{i,j} = d_{i,j} - d_{depot,j} - d_{depot,i} \tag{1}$$

The original CWS algorithm intended for VRP was modified for CVRP by stopping the route merging procedure when there are no more customers that could be connected to the current route without exceeding the maximum cargo capacity, a new route is then created from the remaining customers. The consideration of the depot position in Equation 1 proved to reduce the overall cost of node-to-depot edges created by this approach. Since this is the main advantage of this approach, the capacitated version of the CWS algorithm (C-CWS) will be used in this paper. The output of this algorithm is a valid CVRP tour, however, the satisfaction of the energy constraints is not guaranteed, therefore AFSs generally have to be inserted afterward by one of the CGVRP tour repair procedures. A valid CVRP route, without the consideration of energy constraints, created by the C-CWS algorithm is shown in Figure 2c.

One Route Each (ORE) We have implemented a simple CGVRP route construction method as a simple baseline, intended primarily for comparison. It is also the only stand-alone CGVRP tour construction method presented in this paper. The method takes a list of all customers as an input, and a separate route from the depot and back is planned for each customer. If the customer cannot be reached by traveling directly from the depot and back, an AFS closest to the customer is added to the route before and after visiting the customer. It is assumed here that all AFSs are directly reachable from the depot and the demand of individual customers is lower than the maximum carrying capacity of the vehicle, which holds for all testing instances used in this paper. This method can also be used to verify if a specific CGVRP instance is solvable. An example of a valid CGVRP tour constructed by this method is shown in Figure 2a.

Density-based Clustering Algorithm (DBC) This metaheuristic exploits the spatial properties of the VRP and considers the distribution of nodes over space. This allows us to divide the original set of nodes V into several sub-sets, that can be solved separately for each subproblem, and thus downsize the original planning problem. The implemented DBC algorithm builds on concepts from the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) proposed in [9]. The use of this method in combination with initial TSP constructions was inspired by [8].

The DBC algorithm separates nodes based on a given neighborhood radius ϵ and a density threshold δ. We define the ϵ-neighborhood $N_\epsilon(n_i)$ as a set of nodes within a radius of ϵ from n_i and introduce the condition $|N_\epsilon(n_i)| \geq \delta$ for potential cluster core candidates, wherein all nodes in the ϵ-neighborhood of a core candidate node n_i are considered as directly density-reachable from n_i. Initial clusters are formed by identifying sets of density-reachable nodes based on the core candidates. Nodes outside of these initial clusters are typically considered as outliers and can be treated as separate entities or assigned to the nearest cluster. An illustration of node clustering can be seen in Figure 1, where core candidate nodes are depicted in red, the border nodes in yellow and noise nodes in gray. The δ parameter for the illustration was set to 4 and the ϵ parameter can be seen from the ϵ-neighborhood around the C node. We can see that while the border nodes are directly reachable from the core candidates, the same doesn't hold in reverse.

The algorithm generates a number of cluster sets corresponding to each pair of (ϵ, δ) parameter combinations. Fractions of the maximal distance that can be traveled by a vehicle on a full tank will be used as potential values for the ϵ parameter, since a suitable value for this parameter is largely dependent on individual problem instances. Potential values of the δ parameter are set as integers in an interval $[\delta_{min}, \delta_{max}]$.

The generated cluster sets V_i are subsequently augmented with a depot and AFSs as $V_i' = \{V_i \cup D \cup F\}$ and used as an input for the developed methods for initial TSP tour construction. The Nearest Neighbour and C-CWS initial construction methods have been modified to support cluster sets generated from the DBC algorithm as inputs.

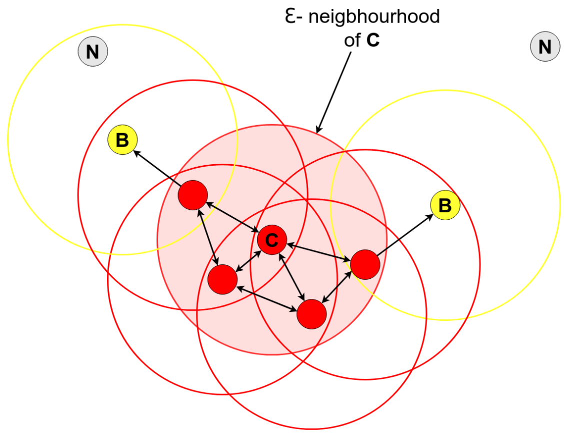

Fig. 1. Illustration of a cluster created by the DBC algorithm

4.2 CGVRP Tour Repair Procedures

Separate Sequential Fixing (SSF) SSF is a novel EVRP tour repair procedure proposed in [20], the procedure is also applicable to the CGVRP. This procedure is split into two subphases. It starts with an initial feasible TSP solution generated by one of the initial TSP construction methods described in Section 4.1, on this tour the load constraint is sequentially checked, and whenever the next customer cannot be satisfied, a depot is inserted, thus, the constraints on the load are fixed.

The energy constraints based on fuel consumption are fixed next. The current tour is again sequentially checked, and if the next customer is reachable from the current node and the vehicle will not get stuck in it (meaning that it can still reach the closest AFS), the customer is added to the final valid tour. Otherwise, SSF adds the AFS closest to the current customer, the AFS closest to the next customer, and any intermediate AFSs in between, if necessary. This AFS sequence is obtained as the shortest path on a graph of all AFSs. After that, the next customer can be safely added.

Relaxed Two-phase Heuristic for CGVRP Another repair procedure is the two-phase heuristic for CGVRP proposed by Zhang, Gajpal and Appadoo in [22] (further referred to as ZGA). The first phase is the TSP route construction solved using the NN algorithm. This phase is already covered by several construction methods in Section 4.1, therefore, our focus will be on the second phase, the CGVRP repair procedure.

The ZGA repair procedure starts from the depot, iterates through the TSP route, and inserts the depot or AFS nodes when needed. The depot is inserted when the demand of the next customer can't be satisfied. An AFS node is inserted if the depot can't be reached via the next customer. If not, the nearest AFS is inserted into the route at the current position. If even the nearest AFS

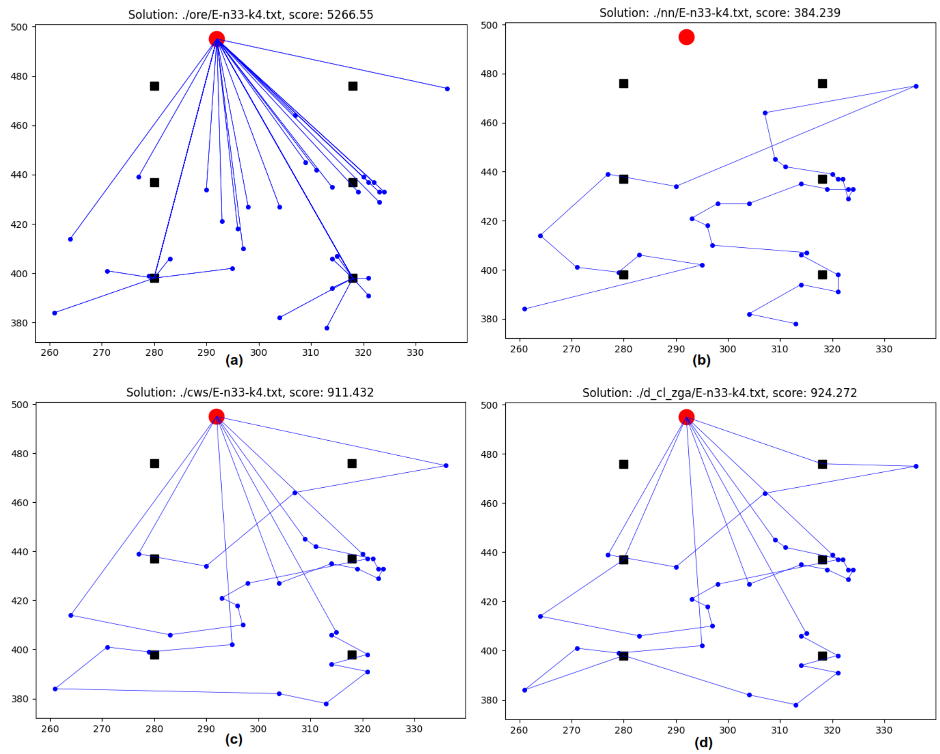

Fig. 2. Example constructions on the E-n33-k4 instance. The depot is represented by the red dot, AFSs are represented by black squares and customers are depicted as the blue dots. Individual constructions were generated by a)the ORE method, b) the NN algorithm, c) the C-CWS algorithm, and d) the C-CWS algorithm originating from cluster sets generated by the DBC metaheuristic, followed by the Relaxed ZGA repair procedure.

cannot be reached, the algorithm backtracks as it changes the current node to the previous one.

While the method as described in [22] works well in general, there are situations when it can get stuck in an endless cycle. It happens when the demand is satisfied, the depot can't be reached via the next customer and the closest AFS can be reached. After adding the closest AFS this sequence repeats for the same customer. This can happen if there exists a node in the instance such that a route from the closest AFS to the depot via this node is too long (demands more energy than the maximum fuel level allows).

We modified the original algorithm by checking whether the closest AFS from the next customer can be reached via the next customer, instead of the original condition which checked only the reachability of the depot. In reaction to this change, an additional option for an AFS visit was added in situations where an AFV is returning to the depot. The modified ZGA algorithm for the

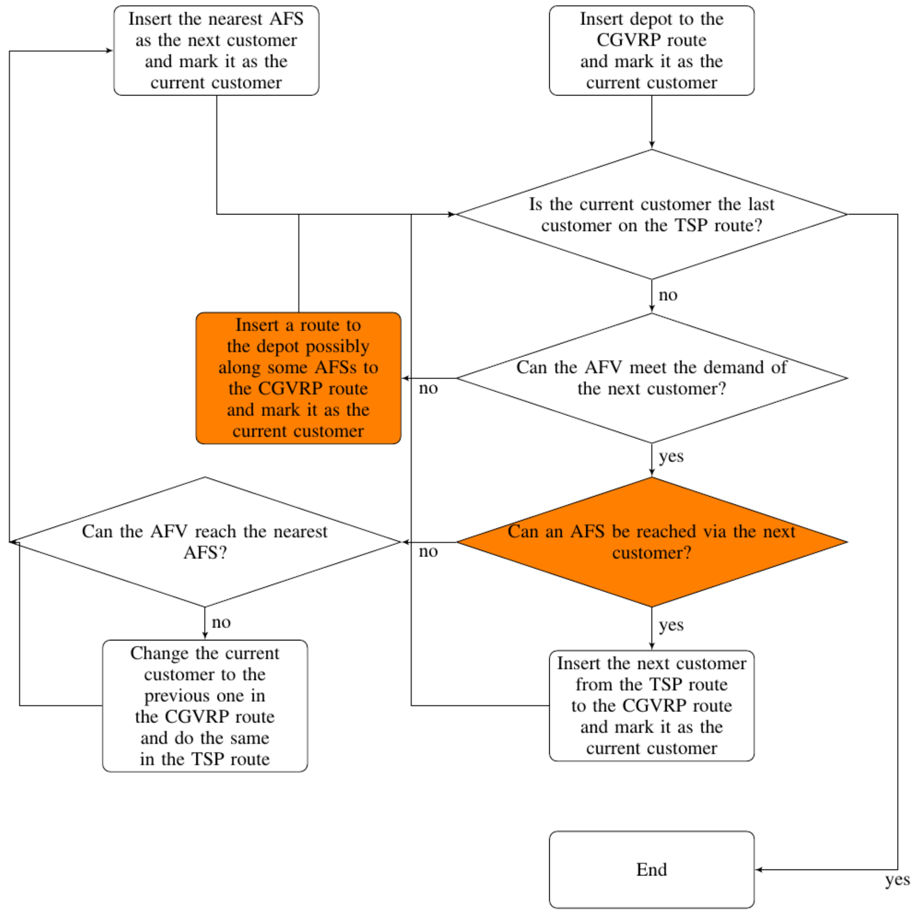

Fig. 3. Modification of the two-phase heuristic proposed in [22]. Changes were made to the orange nodes.

second phase is visualized in Figure 3. Since the first TSP construction phase was omitted, we will further be referring to the modified algorithm as *Relaxed ZGA*. A valid CGVRP route, generated using the C-CWS algorithm originating from cluster sets generated by the DBC method used in combination with the Relaxed ZGA, can be seen in Figure 2d.

WL Decoding Method The last repair procedure for an initial feasible solution construction was proposed by Wang and Lu (further referred to as WL)[19]. This procedure works on a similar principle as the ZGA method, iterating through the TSP route and inserting AFSs and the depot when needed. However, once again a situation may arise when the method gets stuck in an infinite cycle.

This situation arises on occasions when there is a path $P = \{depot, n_1, n_2, ..\}$ on which the first customer n_1 can not be reached directly from the depot, therefore an AFS has to be inserted directly after the depot, and the total demand of the following customers becomes greater than the carrying capacity of the vehicle before visiting another AFS.

In such a situation, the algorithm goes from the depot directly to an AFS before continuing on the TSP route. Customers are served until the sum of the total demand of visited customers and the demand of the next customer exceeds the maximum carrying capacity, in which case the algorithm tries to go to the depot. However, the depot can't be reached directly from the current node, therefore the algorithm backtracks through the previous nodes back to the AFS node. The algorithm then proceeds to the depot, leaving all the customer nodes unvisited. This situation then results in an endless cycle.

We can speculate that the authors considered all customers as directly reachable from the depot, which would eliminate the possibility of the aforementioned situation. Creating the return route to the depot via an AFS when needed could fix this particular issue, however, it would affect the basic principles of the WL algorithm. Therefore, we use this method in its original variant and evaluate its result only on instances where it successfully generated a valid solution.

5 Results and Discussion

The VRP route generating methods described in Section 4 were applied to various test instances and the results are presented in this section. The main evaluation criteria used in this paper is the total distance traveled on the generated route, further referred to as the tour fitness value. Section 5.2 provides an overall evaluation of developed methods, together with their time complexity, the complexity of individual components w.r.t. the number of customers and AFSs, and the number of node-to-node distance evaluations.

5.1 Experiment Setup and Parameters

This paper was inspired by [14], which provides a benchmark set of 17 instances for the EVRP, however, the problem definition for the provided instances is identical to CGVRP. The instances are split into two sets, small (E) and large (X), where the number of customers ranges from 21 to 100 in the E-instances and from 142 to 1000 in the X-instances. All of the instances contain exactly one depot, while the number of AFSs varies. A more detailed description of the instances can be found in [16], wherein the optimal upper-bound values for the E-instances are provided. It should be noted that the E-instances were generated by extending the well-known instances from [5] and the X-instances are an extension of the more recent [18], both used for the conventional CVRP problem.

The NN and MST based algorithms used for initial TSP constructions were implemented in their non-deterministic variants. Both algorithms select a starting node at random, which can result in different TSP routes each time. Therefore, 20 independent runs with random seeds were performed for each instance and the final score was then evaluated based on both the minimal achieved fitness value and the average fitness value.

Values for the ϵ and δ parameters used for the DBC algorithm are shown in Table 1. The ϵ parameter is problem specific and set using fractions of the maximal distance that can be traveled by the vehicle on a full tank, which we define here as *reach*. Values for the δ parameter were set based on our evaluation of the initial results on the test instances. There's a total of 8 ϵ and 4 δ parameter values, which can result in up to 32 different cluster sets. We perform the full initial construction procedure with all unique cluster sets and evaluate the results based on the construction with the best final tour fitness value.

Parameter	Values
ϵ	$[\frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \frac{1}{6}, \frac{1}{8}, \frac{1}{10}, \frac{1}{15}, \frac{1}{20}] \times reach$
δ	2, 3, 4, 5

Table 1. Parameter values for the DBC method.

The experiments were performed on a computer with an Intel Xeon(R) E3-1240 v5 (8M Cache, 3.50 GHz) processor and 32 GB RAM.

5.2 Initial Construction Comparison

The presented methods were able to generate valid solutions for all test instances, with the exception of the WL tour repairing method, which failed at specific instances for reasons closely described in Section 4.2. We rank the construction methods based on their average and minimal scores and provide a more in-depth evaluation based on the VRP variant, computing complexity, and the overall results.

Table 2 presents the best achieved tour fitness values for each specific VRP variant over all instances together with the CGVRP benchmark values provided for the E-instances. The difference in VRP variants can be seen in Table 2, wherein, due to the influence of additional constraints imposed on the problem, the CVRP and CGVRP fitness values are much higher than for the classical TSP route. As some of the developed methods are fully deterministic, the minimal score value is omitted when it's identical to the average value, or completely omitted, when it's irrelevant to the problem.

The initial method evaluation is presented in Table 3, which presents the number of times each method generated a tour with the best score achieved for the instance. The results are further differentiated based on the VRP variant applicable to the generated route. It is not uncommon that more methods generated a route with the same fitness value, especially on smaller instances. The

Instance	Best TSP minimal	Best TSP average	Best CVRP	Best CGVRP minimal	Best CGVRP average	Provided CGVRP benchmark values
E-n22-k4	235.832	256.875	446.539	441.641	452.443	384.955
E-n23-k3	409.893	453.598	630.508	629.25	656.747	571.947
E-n30-k3	311.731	366.52	574.632	-	576.976	509.47
E-n33-k4	384.239	408.869	911.432	-	924.272	840.146
E-n51-k5	467.596	495.138	624.531	-	659.213	532.225
E-n76-k7	574.858	612.257	816.158	845.395	879.895	697.438
E-n101-k8	713.977	758.734	982.484	-	1040.34	836.847
X-n143-k7	9959.79	10656.4	19275.7	-	21339.4	-
X-n214-k11	7152.51	7659.63	13575.3	13896.3	14142.1	-
X-n351-k40	10910.5	11253.7	29298.7	-	30266.1	-
X-n459-k26	12783.7	13118.4	30638.1	30593.5	31624.2	-
X-n573-k30	11093.6	11714.9	56064.0	-	57863.0	-
X-n685-k75	21507.8	22147.1	78800.2	-	81786.1	-
X-n749-k9	18412.7	18744.8	85979.5	-	89326.5	-
X-n819-k171	19656.4	19994.5	167862.0	-	170603.0	-
X-n916-k207	24843.1	25382.8	345951.0	-	350725.0	-
X-n1001-k43	27817.0	28443.4	83036.2	-	85730.7	-

Table 2. Best achieved scores for individual VRP variants.

Construction method	Best TSP minimal	Best TSP average	Best CVRP	Repair procedure	Best CGVRP minimal	Best CGVRP average
Random-seed NN	**12**	9	-	SSF	1	0
				Relaxed ZGA	3	0
				WL	1	0
NN from DBC	9	**11**	-	SSF	0	0
				Relaxed ZGA	2	0
				WL	0	0
C-CWS	0	0	7	SSF	0	0
				Relaxed ZGA	5	6
				WL	1	1
C-CWS from DBC	0	0	**17**	SSF	1	2
				Relaxed ZGA	**10**	**14**
				WL	2	4

Table 3. The number of best minimal and average scores achieved by individual construction methods (out of 17 testing instances).

MST-based methods and the ORE method did not achieve the best score on any of these instances.

Construction method	TSP constructions avg. score	Repair procedure	CGVRP routes avg. score
ORE	-	-	6.8440
Random-seed NN	1.0580	SSF	1.1644
		Relaxed ZGA	1.1157
		WL	1.1629
Random-seed MST	1.1620	SSF	1.2065
		Relaxed ZGA	1.1610
		WL	1.1958
C-CWS	3.5396	SSF	1.0850
		Relaxed ZGA	1.0385
		WL	1.1707
NN from DBC	**1.0520**	SSF	1.1235
		Relaxed ZGA	1.0839
		WL	1.1135
C-CWS from DBC	3.4880	SSF	1.0349
		Relaxed ZGA	**1.0**
		WL	1.0465

Table 4. Initial TSP and CGVRP constructions comparison - relative average score over all instances. Methods using the WL repair procedure did not generate valid solutions for all the instances, and should, therefore, be taken with reservations.

Fitness values from the best TSP and CGVRP methods were used as a reference and qualitative results provided in Table 4 are given as a ratio of the computed fitness in relation to these values. Minimal TSP scores generated by the Random-seed NN are used as a baseline for TSP routes, while CGVRP routes are evaluated in relation to scores generated using the C-CWS algorithm with DBC generated cluster sets, in combination with the Relaxed ZGA repair procedure. The table presents a relative comparison of all VRP and CGVRP route scores for individual construction methods. The scores are averaged over all testing instances using Equation 2, in which F_i^j represents the average fitness of method j achieved on instance i and F_i^{ref} is the reference value for this instance.

$$F^j_{rel\_avg} = \frac{1}{n}\sum_{i=1}^{n}\frac{F_i^j}{F_i^{ref}} \tag{2}$$

Methods using the WL repair procedure are an exception, since these methods generated only an average of 6 valid solutions out of the 17 testing instances, and should, therefore, be taken with reservations. Further comparison can be seen in Figures 4, 5 and 6, where relative minimal and average scores are presented in relation to the problem size on individual instances.

Table 4 shows that solutions generated by the ORE method are far from optimal. While this method is clearly inferior in the initial construction phase, it is the only stand-alone method and has the lowest complexity from the presented methods, it can also be used to ascertain if the problem has a valid solution. The ORE method generates a separate route for each customer, while it may be impractical as a final VRP solution, it may prove beneficial to use the generated route as an input for certain optimization methods, since methods based on local search operators, or evolution algorithms often benefit from more freedom in initial conditions.

We can separate the remaining construction methods by two main aspects. First are the methods used to generate the TSP tour (NN, C-CWS, and MST), second are the tour repair procedures that create a valid CGVRP tour from the original TSP (SSF, Relaxed ZGA and WL). The influence of the DBC metaheuristic will be discussed separately.

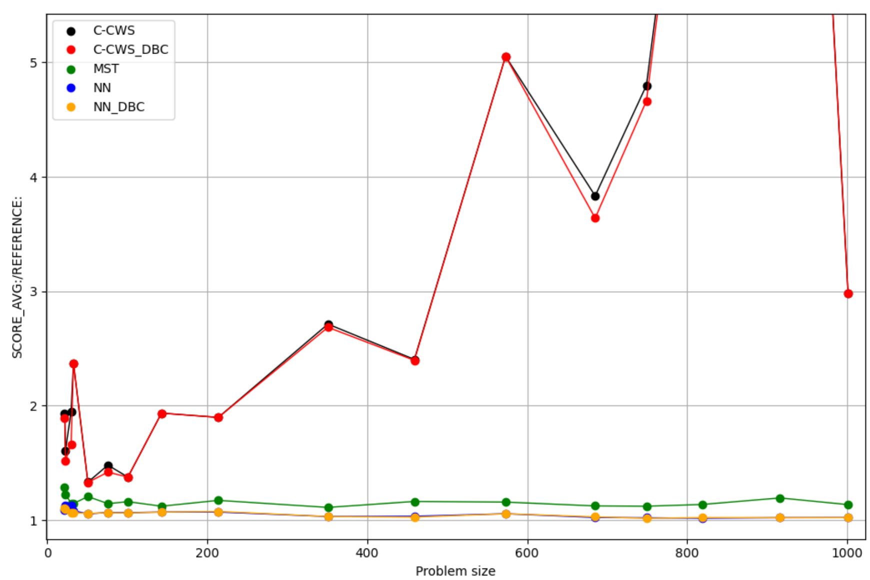

Fig. 4. Comparison of TSP generating methods on all instances.

Methods using the TSP tour generated by C-CWS generally tend to produce better results for the CGVRP, while their performance is largely inferior for the classical TSP. The reason for this is that C-CWS is the only method that directly incorporates the carrying capacity during the TSP tour creation, generating a valid CVRP route. The difference between the TSP and CVRP methods can be seen in Figure 4, were the lengths of C-CWS generated routes are several times higher than for the TSP generated ones, this only increases with the number of customers. The main advantage of the C-CWS method is that it considers the depot position during the initial VRP route creation phase, generating a route more optimal for frequents visits to this specific node.

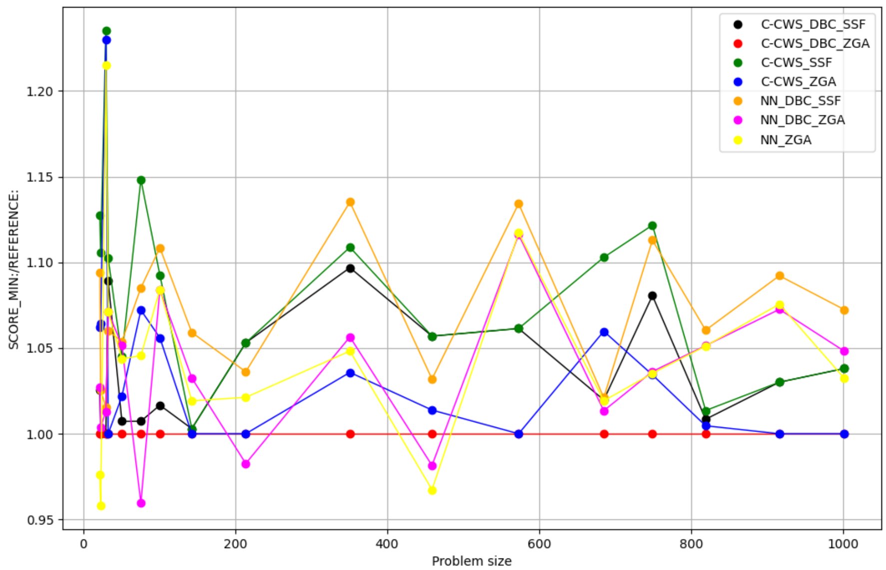

Fig. 5. Minimal score comparison of the top 7 methods on all instances.

The NN algorithm has been a common choice for the TSP for decades due to its simplicity and low computational requirements. As shown in Figure 5, the algorithm performed better than C-CWS on several CGVRP routes. However, Figure 6 shows that its overall performance is slightly worse than that of the C-CWS based methods. Lastly, while MST can be used to provide estimations on the cost of an optimum tour, its performance is lacking in comparison to other methods used in this paper. Nevertheless, it provides a stable performance as can be seen in Figure 4. It is our belief that both C-CWS and NN based TSP methods are generally more suitable for the VRP.

From the repair procedures, the Relaxed ZGA method proved to generate the best results. One of its advantages over the SSF is its approach regarding the carrying capacity. While SSF divides the tour according to the carrying capacity in its first step, Relaxed ZGA updates the current capacity dynamically during the whole tour repairing process. This means that Relaxed ZGA sometimes picks the depot as the nearest AFS for refueling and, at the same time, loads the vehicle, this case is not accounted for in the SSF method. There is also a slight difference in the AFS selection during the process. The WL method presented in [19] failed to generate a valid CGVRP tour on most of the instances. Despite

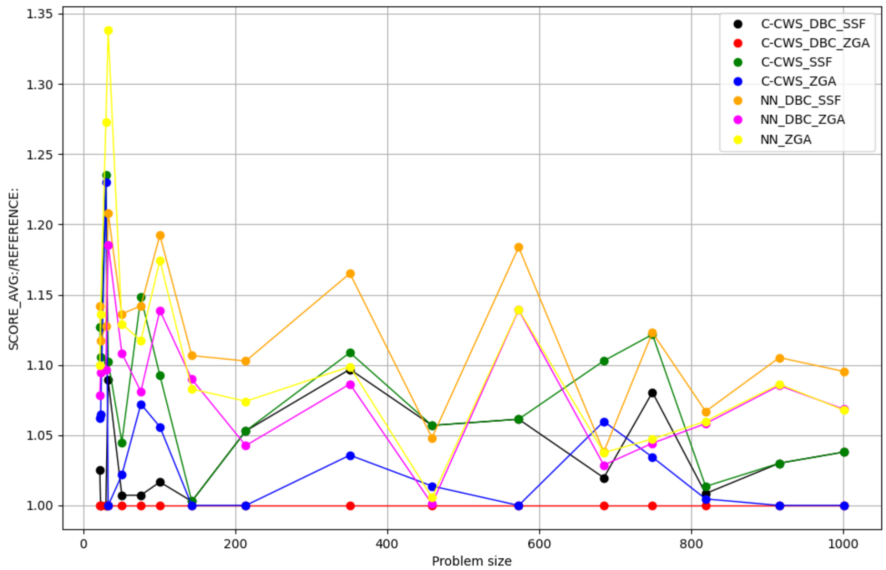

Fig. 6. Average score comparison of the top 7 methods on all instances.

that, the method shows great promises, since it reached the best resulting scores in several instances (see Table 3).

Lastly, we can see that initial constructions originating from clusters generated by the DBC method have a significant chance for improvement over the original methods. Although the improvement is clear, this comes at the cost of higher computational complexity. It would be interesting to compare this to other clustering methods. For example, the sweep algorithm, which generates feasible clusters by rotating a ray centered at the depot, proved to have good results for the CVRP [1], [4]. However, we work with the problem defined by a distance matrix, which is unsuitable for this approach. Therefore, we have chosen the DBC algorithm, which is more general and applicable to a wider range of problems.

The complexity of individual initial construction methods can be seen in Table 5. The complexity for benchmark instances provided in [14] is evaluated as the number of requests for a distance between nodes a and b. Defining the problem as $V = \{D \cup I \cup F\}$ where D is the depot, I denotes the set of customers and F denotes the set of AFSs, we can define $n = \|V\|$, $i = \|I\|$ and $f = \|F\|$ as the size of the problem, number of customers and number of AFSs respectively. In our complexity estimates, we work with the assumption that i is significantly higher than f.

Table 5 also contains the maximal computational time T_{max} for each type of the initial TSP construction methods. The time value presented in the table is the highest computational time out of 20 independent runs over all the test

Type	Complexity	$T_{max}[ms]$
ORE	$i \times f$	1.524
NN-based	i^2	15.83
MST-based	i^2	40.94
C-CWS-based	i^2	19.86
DBC-based	$k \times complexity$	129.9

Table 5. Initial construction complexity and maximal computational times.

instances, needed to achieve a valid CGVRP solution. The time necessary for a valid CGVRP construction for the X-instances was generally in single or double digits (ms), while for the smaller E-instances most methods constructed a valid tour in under one millisecond.

The complexity for constructions initiating from the DBC depends on the spatial distribution of nodes in the problem and the underlying construction method, generally $k \in (10, 17)$. We do not include the comparison for repair procedures, since the complexity of both SSF and Relaxed ZGA is $i \times f$, which is negligible in comparison to the initial TSP construction methods.

6 Conclusions

This paper presents a comparison of initial constructors intended for the CGVRP. A variety of methods for generating a valid initial route construction over a set of customers was developed with the intent to minimize the total traveled distance while respecting the maximum load capacity of the vehicle and incorporating AFSs en route when necessary.

A two-phase heuristic for the CGVRP was presented. This heuristic consists of the initial TSP route construction and the subsequent CGVRP repair procedure. Various methods ware implemented for each phase and their combinations were tested on selected benchmark instances. The results were evaluated based on their performance and complexity, and discussed in regard to different applications and VRP variants.

The developed methods provide a good, fast and reliable solution, making them suitable for a stand-alone TSP or CGVRP route constructions. The repair procedures provide a reliable tool for fast reconstruction of a VRP route. The developed methods can also serve as an initial solution for advanced optimization methods and heuristics. Presented results and discussion should provide insight into these techniques and should serve as a good starting point for the design and development of advanced planning methods.

The two-phase heuristic is applicable to any alternatively fueled or electric vehicle and while the developed methods are focused on CGVRP, the model could be extended to other variants of the VRP. The outcomes motivate future research of initial construction methods in combination with more advanced metaheuristics.

Acknowledgements

This work has been supported by the European Union's Horizon 2020 research and innovation program under grant agreement No 688117. The research leading to these results has received funding from the Czech Science Foundation (GACR) under grant agreement no. 19-26143X. The work has been also supported by the Grant Agency of the Czech Technical University in Prague, grant No. SGS18/206/OHK3/3T/37.

References

1. Akhand, M.A.H., Jannat, Z., Murase, K.: Capacitated vehicle routing problem solving using adaptive sweep and velocity tentative pso. International Journal of Advanced Computer Science and Applications **8** (01 2017). https://doi.org/10.14569/IJACSA.2017.081237
2. Bard, J., Huang, L., Dror, M., Jaillet, P.: A branch and cut algorithm for the vrp with satellite facilities. IIE Transactions **30**, 821–834 (09 1998). https://doi.org/10.1023/A:1007500200749
3. Chan, Y., Baker, S.: The multiple depot, multiple traveling salesmen facility-location problem: Vehicle range, service frequency, and heuristic implementations. Mathematical and Computer Modelling **41**, 1035–1053 (04 2005). https://doi.org/10.1016/j.mcm.2003.08.011
4. Chen, M., Chang, P., Chiu, C., Annadurai, S.P.: A hybrid two-stage sweep algorithm for capacitated vehicle routing problem. In: 2015 International Conference on Control, Automation and Robotics. pp. 195–199 (2015). https://doi.org/10.1109/ICCAR.2015.7166030
5. Christofides, N., Eilon, S.: An algorithm for the vehicle-dispatching problem. Journal of the Operational Research Society **20**(3), 309–318 (1969). https://doi.org/10.1057/jors.1969.75
6. Clarke, G., Wright, J.W.: Scheduling of vehicles from a central depot to a number of delivery points. Operations Research **12**(4), 568–581 (1964). https://doi.org/10.1287/opre.12.4.568
7. Erdelic, T., Carić, T., Lalla-Ruiz, E.: A Survey on the Electric Vehicle Routing Problem: Variants and Solution Approaches (2019). https://doi.org/10.1155/2019/5075671
8. Erdogan, S., Miller-Hooks, E.: A green vehicle routing problem. Transportation Research Part E: Logistics and Transportation Review **48**(1), 100 – 114 (2012). https://doi.org/10.1016/j.tre.2011.08.001, `http://www.sciencedirect.com/science/article/pii/S1366554511001062`
9. Ester, M., Kriegel, H.P., Sander, J., Xu, X.: A density-based algorithm for discovering clusters in large spatial databases with noise. In: Proceedings of the Second International Conference on Knowledge Discovery and Data Mining. p. 226–231. KDD'96, AAAI Press (1996). https://doi.org/10.5120/739-1038
10. Gutin, G., Yeo, A., Zverovich, A.: Traveling salesman should not be greedy: Domination analysis of greedy-type heuristics for the tsp. Discrete Applied Mathematics **117**, 81–86 (03 2002). https://doi.org/10.1016/S0166-218X(01)00195-0
11. Kek, A., Cheu, R., Meng, Q.: Distance-constrained capacitated vehicle routing problems with flexible assignment of start and end depots. Mathematical and Computer Modelling **47**, 140–152 (01 2008). https://doi.org/10.1016/j.mcm.2007.02.007

12. Kheirkhahzadeh, M., Barforoush, A.: A hybrid algorithm for the vehicle routing problem. pp. 1791 – 1798 (06 2009). https://doi.org/10.1109/CEC.2009.4983158
13. Martinovic, G., Aleksi, I., Baumgartner, A.: Single-commodity vehicle routing problem with pickup and delivery service. Mathematical Problems in Engineering **2008** (01 2009). https://doi.org/10.1155/2008/697981
14. Mavrovouniotis, M.: CEC-12 Competition on Electric Vehicle Routing Problem. `https://mavrovouniotis.github.io/EVRPcompetition2020/` (2020)
15. Mavrovouniotis, M., Menelaou, C., Timotheou, S., Ellinas, G.: A Benchmark Test Suite for the Electric Capacitated Vehicle Routing Problem. In: 2020 IEEE Congress on Evolutionary Computation (CEC). pp. 1–8 (2020). https://doi.org/0.1109/CEC48606.2020.9185753
16. Mavrovouniotis, M., Menelaou, C., Timotheou, S., Panayiotou, C., Ellinas, G., Polycarpou, M.: Benchmark Set for the IEEE WCCI-2020 Competition on Evolutionary Computation for the Electric Vehicle Routing Problem. Tech. rep., KIOS Research and Innovation Center of Excellence, Department of Electrical and Computer Engineering, University of Cyprus, Nicosia, Cyprus (2020), `https://mavrovouniotis.github.io/EVRPcompetition2020/TR-EVRP-Competition.pdf`
17. Tarantilis, C., Zachariadis, E., Kiranoudis, C.: A hybrid guided local search for the vehicle-routing problem with intermediate replenishment facilities. INFORMS Journal on Computing **20**, 154–168 (02 2008). https://doi.org/10.1287/ijoc.1070.0230
18. Uchoa, E., Pecin, D., Pessoa, A., Poggi, M., Vidal, T., Subramanian, A.: New benchmark instances for the capacitated vehicle routing problem. European Journal of Operational Research **257** (08 2016). https://doi.org/10.1016/j.ejor.2016.08.012
19. Wang, L., Lu, J.: A memetic algorithm with competition for the capacitated green vehicle routing problem. IEEE/CAA Journal of Automatica Sinica **6**(2), 516–526 (2019). https://doi.org/10.1109/JAS.2019.1911405
20. Woller, D., Kozák, V., Kulich, M.: The grasp metaheuristic for the electric vehicle routing problem (2020)
21. Xavier, I.: Cvrplib - capacitated vehicle routing problem librar. `http://vrp.atd-lab.inf.puc-rio.br/` (2020), last accessed 23 Nov 2020
22. Zhang, S., Gajpal, Y., Appadoo, S.S.: A meta-heuristic for capacitated green vehicle routing problem. Annals of Operations Research **269**(1-2), 753–771 (oct 2018). https://doi.org/10.1007/s10479-017-2567-3