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Florbela P. Fernandes · Maria F. Pacheco ·
João P. Coelho · José Lima (Eds.)

Communications in Computer and Information Science 1981

Optimization, Learning Algorithms and Applications

Third International Conference, OL2A 2023
Ponta Delgada, Portugal, September 27–29, 2023
Revised Selected Papers, Part I

Part 1

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OL2A INTERNATIONAL CONFERENCE

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Preface

The volumes CCIS 1981 and 1982 contains the refereed proceedings of the III International Conference on Optimization, Learning Algorithms and Applications (OL2A 2023), a hybrid event held on September 27–29.

OL2A provided a space for the research community in optimization and learning to get together and share the latest developments, trends and techniques as well as develop new paths and collaborations. OL2A had the participation of more than four hundred participants in an online and face-to-face environment throughout three days, discussing topics associated with areas such as optimization and learning and state-of-the-art applications related to multi-objective optimization, optimization for machine learning, robotics, health informatics, data analysis, optimization and learning under uncertainty and 4th industrial revolution.

Six special sessions were organized under the topics Learning Algorithms in Engineering Education, Optimization in the SDG context, Optimization in Control Systems Design, Computer Vision Based on Learning Algorithms, Machine Learning and AI in Robotics and Machine Learning and Data Analysis in Internet of Things. The event had 66 accepted papers. All papers were carefully reviewed and selected from 172 submissions. All the reviews were carefully carried out by a scientific committee of 115 PhD researchers from 23 countries.

The OL2A 2023 volume editors,

September 2023

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Contents – Part I

Time-Dependency of Guided Local Search to Solve the Capacitated Vehicle Routing Problem with Time Windows

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Abstract. Research have been driven by the increased demand for delivery and pick-up services to develop new formulations and algorithms for solving Vehicle Routing Problems (VRP). The main objective is to create algorithms that can identify paths considering execution time in real-world scenarios. This study focused on using the Guided Local Search (GLS) metaheuristic available in OR-Tools to solve the Capacitated Vehicle Routing Problem with Time Windows using the Solomons instances. The execution time was used as a stop criterion, with short runs ranging from 1 to 10 s and a long run of 360 s for comparison. The results showed that the GLS metaheuristic from OR-Tools is applicable for achieving high performance in finding the shortest path and optimizing routes within constrained execution times. It outperformed the best-known solutions from the literature in longer execution times and even provided a close-to-optimal solution within 10 s. These findings suggest the potential application of this tool for dynamic VRP scenarios that require faster algorithms.

Keywords: VVRP · Metaheuristic · Scheduling Problems

1 Introduction

One of the century's biggest challenges is global warming, which is now a matter of reaching public authorities and mobilizing nongovernmental organizations

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worldwide. The emission of greenhouse gases is one of the main responsible of the environmental issue. In this regard, the logistics sector must find the smartest solutions to move goods around sustainably. The transportation sector accounts for about 21% of greenhouse gas emissions, emphasizing the urgent need to optimize transportation tasks. Aligned with the environmental need to decrease gas emissions from this activity, there is an increasing demand for more efficient transportation services. According to most updated surveys, e-commerce is growing significantly, requiring delivery services to ship goods purchased online [1]. Increasing demand for this service will also affect the number of trucks travelling on the road, overcoming more emissions. The example mentioned here is only one from a variety of services depending on transportation, and services of this kind will probably increase over the years due to economic development [2]. For almost 70 years, researchers have been studying route optimization to solve a wide range of problems, creating the class of Vehicle Routing Problems (VRP).

Several formulations were created and studied through the years, each attempting to reach similarities with real-life problems [3,4]. The capacity and time constraints are the most explored in the literature, with several algorithms developed to optimize routes so vehicles can provide services [5]. The Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) is the most known formulation that approaches time and capacity as constraints [6]. At first, the objective of the problems was solely focused on reducing distances to save resources. However, in the current scenario, the objective is to consider the environmental impacts of vehicle emissions during the trips [7]. This consideration, at first, is not hard to implement, considering that both cost and emission will be reduced by shortening travelled distances. On the other hand, in problems where time windows are flexible and can be changed, one can choose the proper time window to provide a determined service based on the traffic [8]. For instance, if the vehicle needs to visit the city centre, the responsibility for decision-making regarding the time window to perform this visit can avoid travelling in hours of traffic, avoiding higher carbon emissions [9]. More sophisticated formulations include a deeper analysis of roads and traffic, considering travelling speed and real-time information on traffic to plan the routes more sustainably [10]. Despite the strong literature on this topic, several authors consider static formulations. Considering the increased competitiveness in the sector and the stochastic nature of demands for transports, the development of dynamic formulations represents the unavoidable end [11]. For this purpose, developing faster algorithms to find the shortest path is required, which is often neglected in most works devoted to route optimization [12].

Therefore, in this work, the Guided Local Search metaheuristic available in OR-Tools was tested to solve the Capacitated Vehicle Routing Problem with Time Windows to find optimal distances ensuring feasible execution time. To perform this evaluation, data available in Solomons instances of the CVRPTW were used. The stop criterion was based on execution time since this is the most important parameter considering dynamic operations. The performance of GLS to solve the instances was measured in execution times ranging from 1 to 10 s to evaluate the best execution time to find the best route. The rest of the paper is organized as follows: Sect. 2 brings relevant literature for this topic, Sect. 3 shows the methodology considered to perform this study, Sect. 4 brings the numerical results obtained, and Sect. 5 brings the conclusions and future work.

2 Related Literature

The most updated literature regarding the development of algorithms to solve the Capacitated Vehicle Routing Problem was gathered upon search in the Web of Science and Scopus database using the keyword "Vehicle Routing Problem". Figure 1 shows the evolution of the most relevant author's keywords found in both databases from 2014 to 2022.

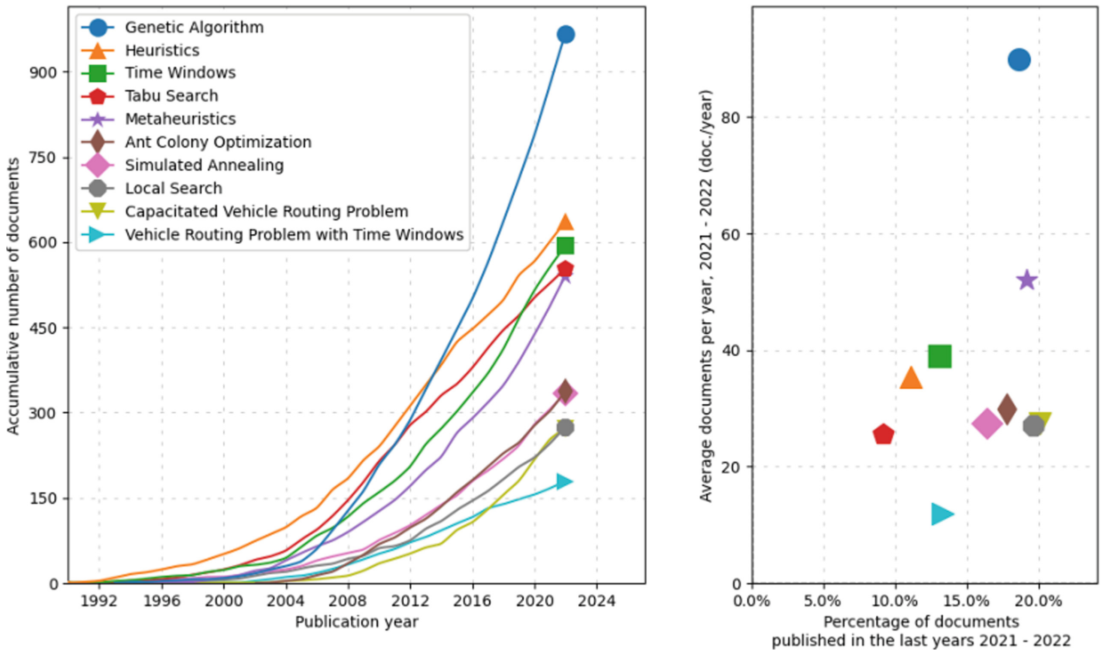

Fig. 1. Authors keywords evolution from 1992 to 2022

The analysis of the most relevant keywords among the published studies reveals a sharp increase devoted to algorithms development since 2004, with Genetic Algorithms dominating the scenario. Regarding the formulation, time windows appear amongst the most relevant keywords in the field, demonstrating the relevance of this constraint in VRP. In the next sections, the most updated literature regarding the algorithms used to solve the CVRPTW and the scenarios in which the formulation was applied will be discussed in more detail.

2.1 Capacitated Vehicle Routing Problem with Time Windows Formulations

Vehicle Routing Problems (VRP) consist of a class of problems devoted to finding the optimal route for a fleet of trucks to serve a determined set of customers. The VRP is the most important problem in delivering or picking up goods and services. Several formulations arose in the last decades from the need to develop problems mimicking real transportation problems. The formulations often attempt to cover actual complications from the real system, which depends on the quality of the service required, customer characteristics, and goods being transported [13]. The most typical complications approached are the vehicles performing multiple routes, the capacities, and the customers accepting the delivery in a specified time window. The simplest formulation is the Capacitated Vehicle Routing Problem (CVRP). A set of trucks at the central depot needs optimal paths to service customers with known demands [14]. Another formulation commonly considered in the literature is the Vehicle Routing Problem with Time Windows which considers the time window for a determined customer in route planning. In some cases, the authors dealing with VRPTW also consider the capacity constraints in their formulation without identifying in the problem name the word "capacitated", which can be conflicting. In other words, some VRPTW formulations are, in fact, Capacitated Vehicle Routing Problem with Time Windows (CVRPTW).

The CVRPTW is considered a distribution management problem that can be used to model many real-life transportation problems. The pioneer formulation specified that the problem was related to designing a set of minimum-cost vehicle routes for a fleet of trucks that serves customers with known demands. Each customer must be served only once without exceeding the vehicles' capacities under allowable delivery times [15]. In 1987, Solomon [16] introduced in the literature a set of VRPTW problems to be used as benchmarks by other authors developing optimization algorithms for CVRPTW, which contributed significantly to the progress in this field. The 6 instances were generated randomly (R1 and R2), clustered (C1 and C2), and semi-clustered (RC1 and RC2). The semi-clustered nomenclature was used to illustrate a dataset that contains a mix of randomly and clustered generated data. Up to date, the authors are devoted to increasing the complexity of the VRPTW by considering other constraints to increase the similarity of the problem with real scenarios. The most reported applications include (but are not limited to) industrial or municipal refuse collection [17], just-in-time delivery [18], school bus routing [19], and postal deliveries [20].

For instance, Masmoudi et al. [17] have proposed an extension of the traditional CVRPTW by studying the utilization of plug-in hybrid electric vehicles powered by two different power sources (electricity and compressed natural gas). Their model approached the realistic fuel consumption of the truck during the route, considering multiple load-outs to be used in other routes. For school bus routing, Hasan et al. [19] have considered the design of another variant of CVRPTW. In their problem, School Bus Routing Problem (SBRP), the authors have considered optimizing transportation costs by minimizing the fleet of vehicles and time spent to complete the task. In their approach, the authors have considered a decision variable related to the student's presence at the bus stop, so the bus will only perform a stop if the student reaches the spot at the correct time. Regarding just-in-time delivery, Nishi et al. [18] have proposed the design of a problem formulation to solve the conflict-free route planning for automated vehicles used in just-in-time delivery to minimize delays or earliness in the total completion time. In their problem, the vehicle can idle at the nodes waiting for the dispatching confirmation of the next delivery task to arrive in the stipulated time window. The time-space in their problem is dynamic, meaning the pickup and delivery tasks are dynamically scheduled. Sitek et al. [20] have proposed a CVRPTW with alternative pick-up, delivery, and time windows for postal delivery services. The problem was formulated by combining VRP variants such as the CVRP, VRPTW, and Vehicle Routing Problem with Pickup and Delivery (VRPPD). The difference in their approach is the introduction of alternative delivery points and parcel lockers incorporated into the distribution network.

2.2 Optimization Algorithms

Many decision problems in business, economics and logistics are too difficult to be solved by exact methods within a reasonable amount of time. Nonetheless, in cases where simply obtaining a feasible solution is not satisfactory, one should investigate procedures and strategies to obtain the best possible solution using exact methods. However, in most cases, the high number of customers considered in CVRPTW, added to the complexity of real-life data, does not allow for solving the problem with exact methods. In this scenario, heuristic and metaheuristic algorithms emerge as tools to find feasible solutions within a reasonable execution time. Both metaheuristic and heuristic algorithms can return feasible solutions but are not necessarily optimal [21].

The exact methods reported in the literature to solve the CVRPTW can be divided into column generation, dynamic programming, and Lagrange relaxation-based methods. These methods perform poorly in solving the VRP class of problems due to the execution time, which can take days to find a moderately decent solution. Authors dealing with exact methods often explore alternatives to decrease the execution time by adapting the space-time of the algorithm or exploring acceleration techniques to reinforce the algorithm's performance. For instance, Yang et al. [22] presented an augmented Lagrangian algorithm to solve the VRP with mixed backhauls and time windows (VRPMBTW). Their experiments based on a 9-node simple network and real-world Chicago sketch network demonstrated that their algorithm performs better than linear Lagrangian relaxation models, with lower conversion times. Regarding the column generation method, Fahram et al. [23] showed a column generation approach to solve the location-routing problem with time windows (LRPTW). Their branch-and-price algorithm performance was reinforced with acceleration techniques and a heuristic approach. Their results demonstrated that column generation acceleration and stabilization combined with a two-stage heuristic based on the problem characteristics can improve significantly the results for bigger instances. Regarding dynamic programming, Kok et al. [24] proposed an algorithm to solve the CVRPTW considering the legislation rules for drivers working hours. The authors proposed a methodology to include the break scheduling for drivers without increasing the algorithm's time complexity. Their computational solutions overcame the benchmark instances with 18% fewer vehicles and 5% fewer travel distances.

The utilization of non-exact algorithms is far more active than exact algorithms in the literature. In this regard, several heuristic algorithms have been reported to solve the CVRPTW and variants in the last few years. The formal definition states that heuristic is a technique that seeks good solutions (near optimal) with a reasonable computational cost without being able to guarantee optimal or how close to optimal the solution is. Heuristic algorithms are often developed to solve specific problems and cannot be used to solve other problems [25]. The heuristic algorithms used to solve the CVRPTW can be classified as route-building and route-improving algorithms depending on the mechanism considered to achieve the solution. Route-building heuristics operate by assembling the route from scratch, whereas route-improving heuristics produce an improved solution using an existing solution. The first class of algorithms was more explored in the past by modifications in savings heuristics and insertion heuristics. Nowadays, route-improving heuristics are mainly used due to the more expressed optimization achieved via this strategy. For instance, Tas et al. [26] presented one heuristic for solving the VRP with Flexible Time Windows (VRPFlexTW). Their algorithm operates in three instances, starting with the generation of a feasible solution, going to the solution improvement using the Tabu Search algorithm, and finishing with the scheduling of the proposed solution.

The last class of algorithms is metaheuristics, considered power techniques that can be applied to various problems. This is the algorithms class currently used to solve different formulations of CVRPTW. Algorithms in this class are known for their capacity to guide and modify the operations of subordinated heuristics by combining the concepts of exploring and exploiting the search space. A random solution is generated to initiate the algorithms and then subjected to modifications through exploit and explore operations until the stop condition is met. Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Simulated Annealing (SA), and Tabu Search (TS) are examples of algorithms reported in the literature. Kaabachi et al. [27] developed an improved ACO algorithm to solve the multi-depot CVRPTW considering the vehicle's speed to minimize fuel consumption. Their IACO overcame the regular ACO by improving the method to generate the first solution. Marinakis et al. [28] has presented a new variant of the PSO algorithm to solve the CVRPTW by exploring different adaptative strategies to evaluate performance improvement. The algorithm has one strategy for initialization (Greedy Randomized Adaptative Search Procedure), movement of the particles from one solution to another (Adaptative Combinatorial Neighborhood Topology), and another adaptative procedure to calculate the parameter of the PSO. The tests performed with benchmarks from the literature revealed that their algorithm is one of the best-performing algorithms to solve the CVRPTW.

2.3 Stochastic and Dynamic Scenarios

The literature is enriched with diverse formulations that are far more complex than the first formulation of the CVRPTW presented decades ago. In addition, the algorithms reported in the literature address previously reported weaknesses and drawbacks pointed out by other authors. The advance in formulations and solutions proposed in the literature is clearly increasing the attention of companies dealing with the transportation sector to the potential optimization of services provision.

Despite the quality and number of works published, formulations and algorithms are developed considering the problem in a static scenario. In this approach, the information required to run the optimization algorithm is known before the execution, and routes obtained in the optimization procedure are scheduled. Considering the dynamic nature of real transportation operations, the formulations and algorithms need to be explored in a more dynamic scenario in which not all information is known before the execution (i.e. routes may change during the execution).

Authors dealing with dynamic formulations of VRP have reported that the algorithm's performance is unaffected by the paradigm shift between static and dynamic scenarios. In other words, the best algorithms in static scenarios will perform similarly in dynamic runs. This can be explained by the fact that altering the formulation from static to dynamic does not affect the algorithm's search mechanism but changes how the algorithm is triggered to find the optimal path. In a typical dynamic test, the algorithm would be responsible for planning the route during truck stops, requiring faster algorithms since truck stops might take less than one minute.

The threats are related to premature utilization of the algorithms in real-life scenarios. Before advancing towards applying the algorithm for a particular case, there is the need to increase the complexity of the simulated scenario considered to run the experiments, trying to cover as much as possible the adversities. Another aspect that should be considered is the accessibility of the proposed solution for the final users. In other words, the algorithm proposed should be able to run dynamically considering the most generic input to finding the solution (i.e. distance matrix and time-windows matrix, for example).

3 Methodology

This work aims to explore the influence of the algorithm's execution time in the performance of GLS, the finest metaheuristic available in OR-Tools, to solve the Solomons instances of CVRPTW. Most studies in the literature deal with algorithm development and tuning to achieve optimized paths, considering static scenarios. However, the future and dynamic formulations of route optimization problems will demand faster algorithms. In this scenario, the influence of the execution time on the algorithm's performance will be important to determine the most feasible execution time to optimize routes. The instances used here to perform the study, from Solomons [16], are widely studied in the literature and comprised of 6 instances divided into randomly generated sets (R1 and R2), clustered sets (C1 and C2), and finally, semi-clustered sets (RC1 and RC2). Sets R1, C1 and RC1 have a limited scheduling horizon and can only accommodate a small number of customers per route (approximately 5 to 10). On the other hand, sets R2, C2 and RC2 have a longer scheduling horizon and can accommodate more customers with the same vehicle (over 30). The number of vehicles ascribed to perform the paths is not fixed in all datasets.

To evaluate the influence of the execution time on the algorithm's performance, we explored execution times from 1 to 10 s. Another long run of 6 min was also performed to evaluate the long-term solution achieved with the algorithm and compare the result with the distances obtained in short runs. The algorithm was also designed to search for the optimized path based on the distance travelled and the minimum number of trucks to execute the paths. The set of solutions obtained for all datasets studied was further gathered and processed to identify patterns and compare the algorithm's performance according to the execution time. Figure 2 brings the overview of the work performed.

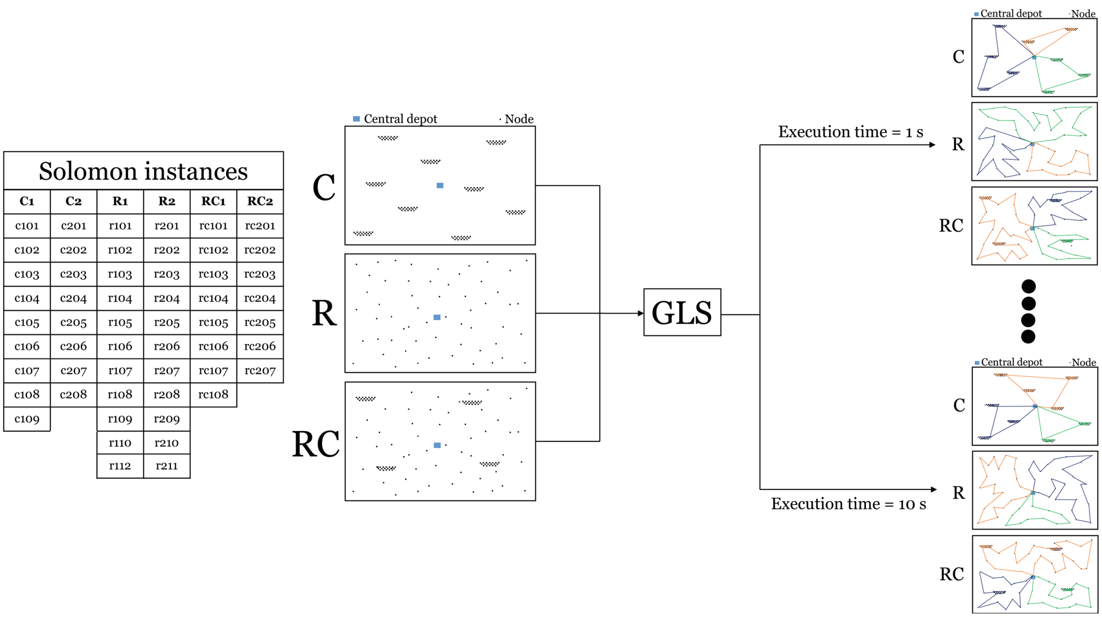

Fig. 2. Representation of the study performed.

3.1 Mathematical Formulation of the CVRPTW

The CVRPTW is one of the most important formulations of VRP problems, being recognized as a basic distribution management problem that can be used to model many real-world problems in the logistics field. In brief, the problem can be summarized as designing a set of minimum-cost routes for a fleet of trucks to perform the delivery or pick-up services to a set of customers with known demands and time windows to receive the visit. The customers must be assigned once, and only once, to a determined vehicle without exceeding the vehicle's capacity and respecting the customer's time windows.

The mathematical formulation of CVRPTW states that the problem is represented by a directed graph $G = (V, C)$, in which the fleet of homogeneous vehicles is denoted by $V = \{1, 2, \ldots, k\}$ and the set of customers is denoted by C. The graph has $|C| + 1$ vertices, where the central depot is represented by the vertex 0 (trucks depart and arrive at this site), and the customers are denoted $1, 2, 3, ..., n$. The CVRPTW is comprised of multiple objectives, such as minimizing total travel time, the number of vehicles used to perform the task, and total travel distance. The set of edges N represents the connection between the central depot and the customers and is denoted by A. All edges begin and terminate in vertex 0 at the central depot. Each edge (i, j) is associated with a cost c_{ij} and a time t_{ij} that can include the service time at customer i, where $i \neq j$. The vehicles have limited capacity Q, the customers have demanded d_i, and they need to be visited within the timestamp defined by the time window $[a_i, b_i]$. The vehicle must arrive at the customer before b_i and after a_i. However, in the latter case, the vehicle needs to wait until a_i to execute the service. The central depot also has a time window $[a_0, b_0]$, and the vehicles must not leave the central depot before a_0 nor arrive after b_0.

The parameters $Q, a_i, b_i, d_i, c_{i,j}$ are non-negative integers, whereas the parameter t_{ij} is assumed to be positive integers. It is assumed that both c_{ij} and t_{ij} satisfy the triangular inequality. The formulation contains two sets of decision variables x_{ijk} and y_{ijk}. For each arc (i, j), where $i \neq 0, j \neq 0, i \neq j$, each vehicle k we define as $x_{ijk} = 1$, if and only if the arc (i, j) is traversed by vehicle k in the optimal solution. The variable will assume null value $(x_{ijk} = 0)$ otherwise. The other decision variable, y_{ijk}, is defined for each vehicle k and each vertex i, and represents the time vehicle k starts the service for customer i. If the vehicle k does not start the service to the customer i, the decision variable y_{ijk} does not mean anything. Considering that $a_0 = 0$ for all trucks we assume that $y_{ijk} = 0$, for all k. The goal of the problem is to design a set of routes, one for each vehicle so that each customer is visited only once. All routes should begin and end at the central depot (vertex 0), and time windows and capacity constraints are respected. In this regard, the mathematical formulation, based on the literature of the CVRPTW [29], is the one that follows:

$$\text{Minimize} \sum_{k \in V} \sum_{i \in N} \sum_{j \in N} c_{ij} x_{ijk} \tag{1}$$

Subject to:

$$\sum_{i \in C} d_i \sum_{j \in N} x_{ijk} \leq Q, \forall k \in V \tag{2}$$

$$\sum_{k \in V} \sum_{j \in N} x_{ijk} = 1, \forall i \in C \tag{3}$$

$$\sum_{j \in N} x_{0jk} = 1, \forall k \in V \tag{4}$$

$$\sum_{i \in N} x_{i0k} = 1, \forall k \in V \tag{5}$$

$$\sum_{i \in N} x_{ihk} - \sum_{j \in N} x_{hjk} = 0, \forall h \in C, \forall k \in V \tag{6}$$

$$a_i \leq y_{ik} \leq b_j, \forall i \in N, \forall k \in V \tag{7}$$

$$y_{ik} + t_{ij} - K(1 - x_{ijk}) \leq y_{jk}, \forall i, j \in N, \forall k \in V \tag{8}$$

$$x_{ijk} \in \{0, 1\}, \forall i, j \in N, \forall k \in V \tag{9}$$

The constraint 2 states that vehicles cannot carry more load than their capacity, and constraint 3 guarantees that each customer is visited exactly once. The next three constraints 4, 5, and 6 are related to the continuity of the route, ensuring that each vehicle leaves the central depot, and leaves again after performing the service to a determined customer, and arrives back at the central depot. Constraint 7 ensures that time windows are respected, and constraint 8 states that a vehicle traversing from i to j cannot arrive at j before $y_{ijk} + t_{ij}$. Finally, constraints 9 are the integrality constraints for the decision variable x_{ijk}.

4 Numerical Results

The numerical results obtained for solving the Solomon instances of the CVRPTW using the GLS metaheuristic available in OR-Tools will be discussed in this section. The main goal is to assess the impact on the algorithm's performance upon increasing the execution time to feasible levels. It is important to highlight that the tests performed in this study are important for the development of faster algorithms required for real-life dynamic applications of VRP. In this scenario, the execution time should be as lower as possible, still keeping the performance of the algorithm acceptable. The short runs (execution times from 1 to 10 s) were compared to the results obtained in a long run of 6 min to evaluate how good the fast solutions are compared to time-expensive solutions.

4.1 Optimal Distances

The Solomon instances considered for this work are the most famous dataset for testing algorithms to solve the CVRPTW. In total, there are 6 big datasets comprised of 9 (C1), 8 (C2), 12 (RC1), 8 (RC1), and 8 (RC2) sub-datasets to be studied. For all sets, the GLS performance to solve the CVRPTW was evaluated by increasing the execution time. To facilitate the representation of the results, the average distance found for each dataset will be reported, such as performed by other authors. Figure 3 brings an overview of the best solution found in this work compared to other solutions reported in the literature using metaheuristic algorithms. The comparison was performed with the works from Rochat and Taillard ([30], RT), Taillard *et al.* ([31], TB), Chiang and Russel ([32], CR), Potvin and Bengio ([33], PB), and Thangia *et al.* ([34], TH).

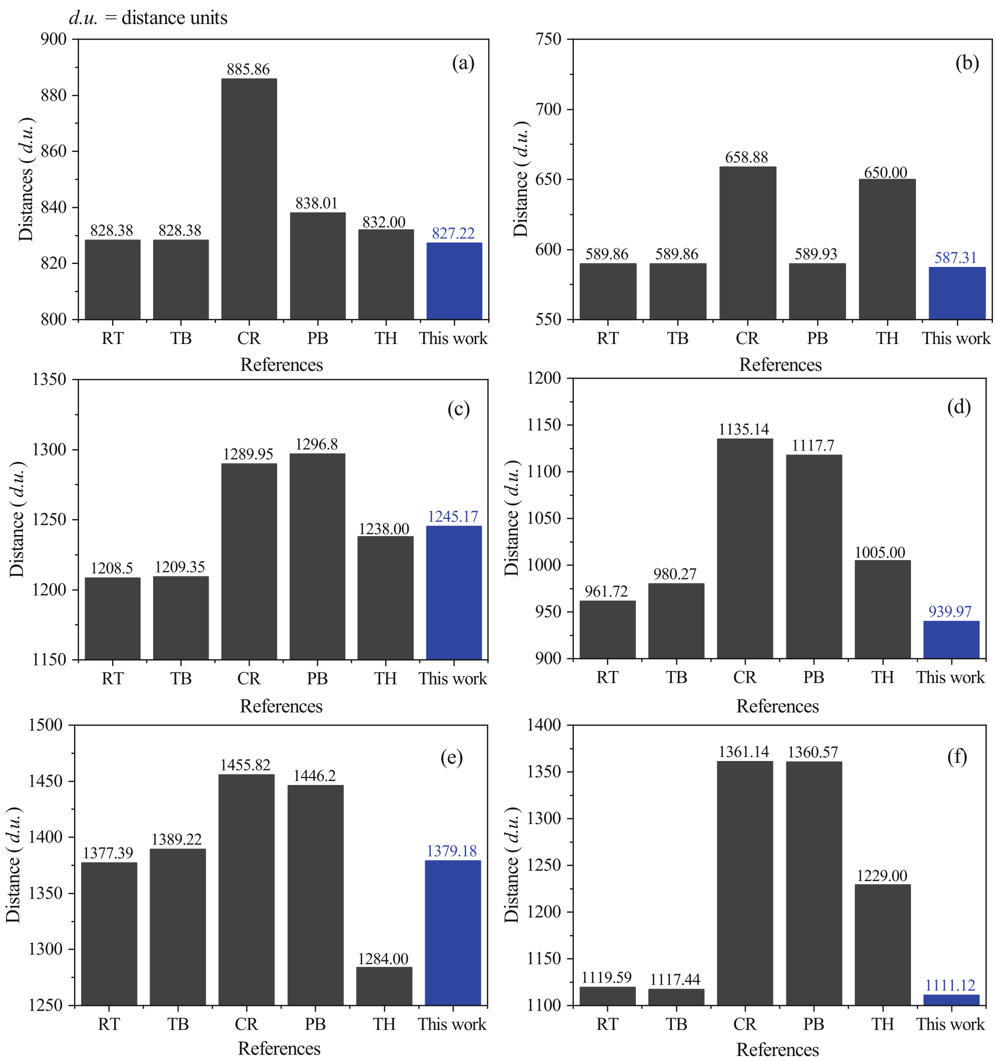

Fig. 3. Results obtained and compared to the literature for instances (a) C1, (b) C2, (c) R1, (d) R2, (e) RC1, and (f) RC2. The interval in X-axis is not proportional to the actual interval.

The results showed that for instances C1, C2, R2, and RC2 the GLS meta-heuristic available in OR-Tools was able to overcome the best reported in the literature. Even for instances R1 and RC1, the algorithm used in the present study was able to overcome the results obtained by 2 other authors [32,33]. Considering the sum of the best solutions achieved by each algorithm reveals that GLS has the second best performance compared to literature, losing only to the algorithm used by authors in RT [30] (6085.44 *d.u.* from RT *vs* 6089.97 *d.u.* using GLS). The minimum number of trucks found in this work was the same as reported in the literature, 10 for C1, 3 for C2, 12 for R1, 3 for R2, 12 for RC1, and 3 for RC2. Despite the routes being assembled considering the same number of vehicles, the difference in distance observed here is related to the route assembly process that is able to find the shortest paths compared to the literature.

4.2 Execution Time as a Key Parameter for the Best Solution

For most sets evaluated in this study, the solution found in the long run was better than the results obtained in the short run. This result is related to the operation mechanism of the algorithm, which is able to easily escape local minima by increasing the execution time. On the other hand, it is important to evaluate the feasibility of increasing the execution time to improve the solution, considering the future application demanding faster algorithms. Figure 4 summarizes route optimization results achieved by increasing the execution time from 1 to 10 s and the long run.

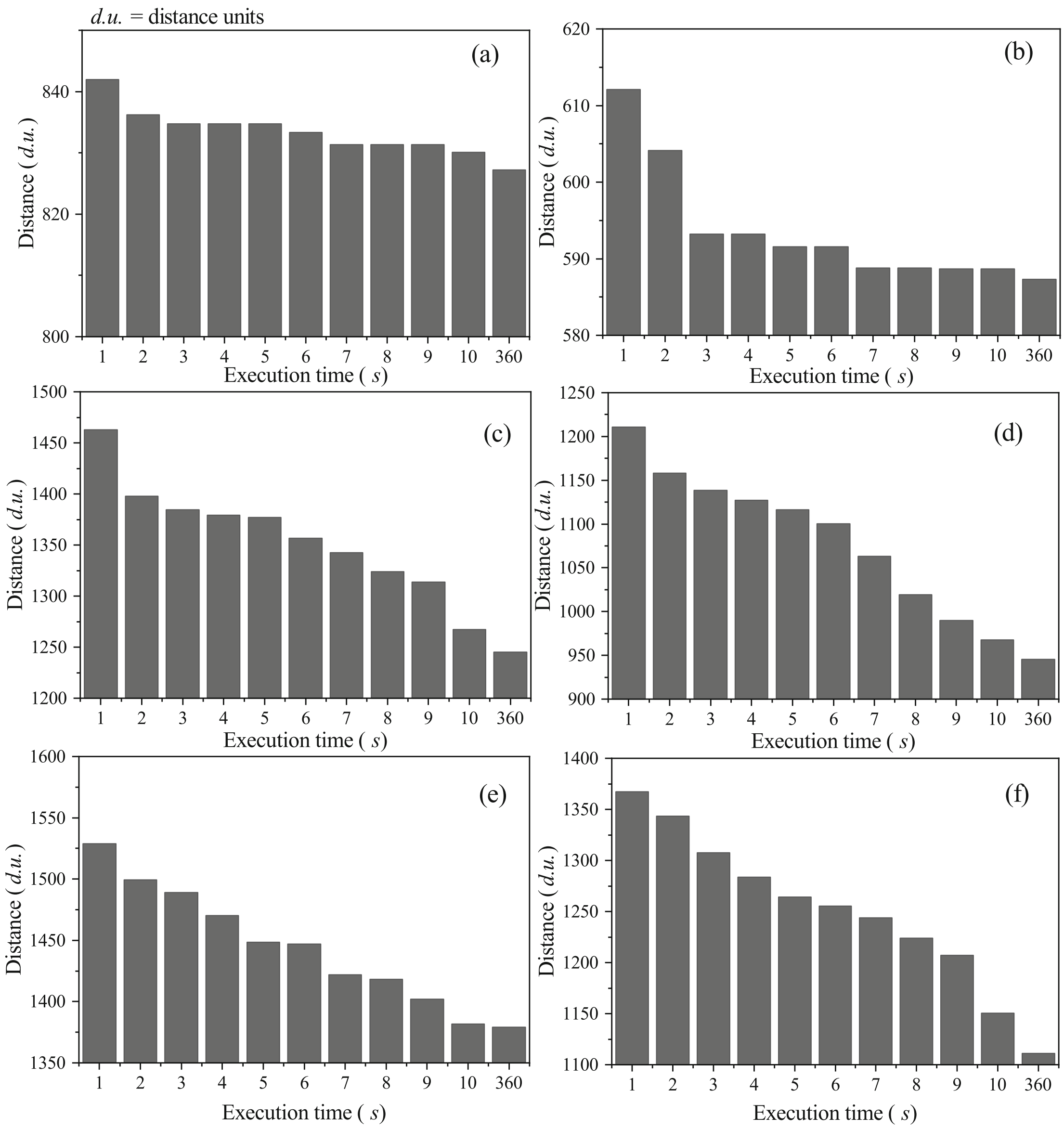

Fig. 4. Shortest distance obtained using GLS changing execution time for instances (a) C1, (b) C2, (c) R1, (d) R2, (e) RC1, (f) RC2. The interval in X-axis is not proportional to the actual interval.

The results demonstrate how powerful execution time increase can be to improve the route optimization results, allowing to achieve higher resource savings in delivery or pick-up services. It is important to highlight that distance shortening obtained with increased execution time is not linear. In other words, the resource savings achieved upon a determined execution time increase might not be efficient or feasible. For instance, despite the better results obtained in the long run, utilizing this approach for real scenarios would not be possible due to the delayed time to execute the algorithm. The numerical results also show that the algorithm has higher difficulty to improve distance shortening for sets C1, R1, and RC1 compared to the other sets, which is related to the smaller time windows in the first class of sets. Nonetheless, the optimization obtained by increasing the execution time from 1 to 10 s is more noticeable compared to increasing the execution time from 10 to 360 s.

The results obtained for the experiment also reveal a versatile behavior of the GLS algorithm, that is able to return satisfying solutions in terms of distance shortening in long runs, but also significant optimization with faster execution time. In other words, if one is more interested in distance savings, no matter the execution time the algorithm could be used with larger execution times. In contrast, aiming for dynamic scenarios and the need for faster algorithms, the GLS could also be used with an execution time of 10 s to return the most efficient solutions, accounting for both distance shortening and fast execution time. It is complicated to compare the algorithm in terms of execution time with the literature due to the lack of information regarding this particular aspect in published studies dealing with the CVRPTW solution. Most authors devoted to the development of algorithms for this purpose are more worried about the capacity of their algorithm to beat others reported in the literature and do not discuss and evaluate aspects to increase the potential feasibility of their solution for real scenarios.

5 Conclusions and Future Work

The GLS metaheuristic available in OR-Tools was able to return better solutions compared to the literature for almost all Solomons instances in the long run. Furthermore, the tests performed for short runs, with execution times lower than 10 s, revealed that increasing the execution time from 1 to 10 s returns significant savings in distance travelled. In this scenario, the utilization of this tool in a dynamic scenario would not be hindered by the execution time, since the algorithm is able to return satisfying solutions within 10 s of execution time. Moreover, the algorithm has also proven its performance in finding the shortest path with increased execution time used in the long run.

For future studies, the evaluation of other metaheuristic algorithms available in OR-Tools, such as SA and TS, will be performed. For instance, other studies already reported that GLS is the finest metaheuristic in OR-Tools, but in that case, CVRP was approached. In addition, the dependency in distance shortening upon increasing the algorithm's execution time will be compared to the time windows and capacities from each Solomons instance to observe the correlations that could be important in real scenarios. Once the relevant parameters are accounted for, the algorithm will be tested using a realistic dataset from a scenario that could be approached by CVRPTW: the waste collection task.

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