

Formulations for the Green Vehicle Routing Problem

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Level / Defense date: Master's degree / (19/10/2020)

RESUMO

Este trabalho¹ investiga o Problema de Roteamento de Veículos Verdes, ou *Green Vehicle Routing Problem* (G-VRP), um problema NP-difícil que generaliza o Problema de Roteamento de Veículos, ou *Vehicle Routing Problem* (VRP), e o integra com a logística verde. No G-VRP, veículos elétricos com autonomia limitada podem reabastecer em Estações de Combustível Alternativo, ou *Alternative Fuel Stations* (AFSs). Os custos ambientais, geopolíticos e financeiros da dependência mundial de veículos movidos a gasolina estão se tornando cada vez mais óbvios e, como consequência, os governos e as empresas de logística, reconhecendo as emissões de carbono e a demanda por energia, têm a responsabilidade especial de tornar suas operações mais verdes, portanto, muitos deles estão procurando novas abordagens para gerenciar o carbono de maneira eficaz, desde a aquisição e produção até a distribuição e reciclagem do produto. Esse trabalho pode auxiliar empresas e governos, ajudando-os a eletrificar suas frotas de veículos, a fim de baratear custos, reduzir emissões e melhorar sua imagem pública. Neste trabalho, duas versões do G-VRP são investigadas, (i) onde visitas consecutivas a AFSs não são permitidas, e (ii) onde visitas consecutivas a AFSs são permitidas. Esta pesquisa propõe propriedades combinatórias, desigualdades válidas, formulações MILP, condições de pré-processamento e limitantes inferiores que possuem o potencial de fortalecer formulações matemáticas para ambas versões do G-VRP, e portanto melhorar suas soluções exatas.

PALAVRAS CHAVE. programação linear inteira mista, programação matemática, problema de roteamento de veículos, otimização combinatória, logística verde

ABSTRACT

This work² investigates the Green Vehicle Routing Problem (G-VRP), which is an NP-hard problem that generalizes the Vehicle Routing Problem (VRP) and integrates it with the green logistics. In the G-VRP, electric vehicles with limited autonomy can recharge at Alternative Fuel Stations (AFSs). The environmental, geopolitical, and financial costs of the world's dependence on gasoline-powered vehicles are becoming increasingly obvious, and as a consequence, logistics companies and governments, recognizing the carbon emissions and demand on energy, have a special responsibility to make their operations greener, thus, many of them are looking for new approaches to manage carbon effectively from procurement and production to distribution and product afterlife. This work can assist companies and governments, helping them to electrify their vehicle fleets, in order to lower costs, reduce emissions, and improve their public image. In this work, two G-VRP versions are investigated, (i) where consecutive AFSs visits are not allowed, and (ii) where consecutive AFSs visits are allowed. This research proposes combinatorial properties, valid inequalities, MILP formulations, preprocessing conditions and lower bounds which have the potential to strengthen the mathematical formulations for both G-VRP versions, thus improving their exact solution.

KEYWORDS. mixed integer linear programming, mathematical programming, vehicle routing problem, combinatorial optimization, green logistics

¹Financiado pela FAPESP (proc. 2018/25950-5).

²Supported by FAPESP (proc. 2018/25950-5).

1. Introduction

In the Vehicle Routing Problem (VRP) a set of customers must be serviced by a homogeneous fleet of vehicles with limited capacity. The objective is to minimize the total cost of the vehicles routes [Baldacci et al., 2008].

Another research field that has gained traction in the past decades is green logistics, which emerged like a discipline focused on the planning and operation of logistic systems with high energy efficiency and low levels of carbon emission [Leggieri and Haouari, 2017].

Among VRP variants dealing with green logistics, there is the Green Vehicle Routing Problem (G-VRP). The G-VRP has additional challenges associated with operating a fleet of Alternative Fuel Vehicles (AFV) and incorporating stops at Alternative Fuel Stations (AFS) [Erdoğan and Miller-Hooks, 2012]. One of the biggest challenges modeled by G-VRP is the reduced number of alternative fuel stations and the low autonomy of alternative fuel vehicles. A VRP solution example is depicted in Subfigure 1a. While Subfigure 1b presents a G-VRP solution built over the VRP solution given at 1a.

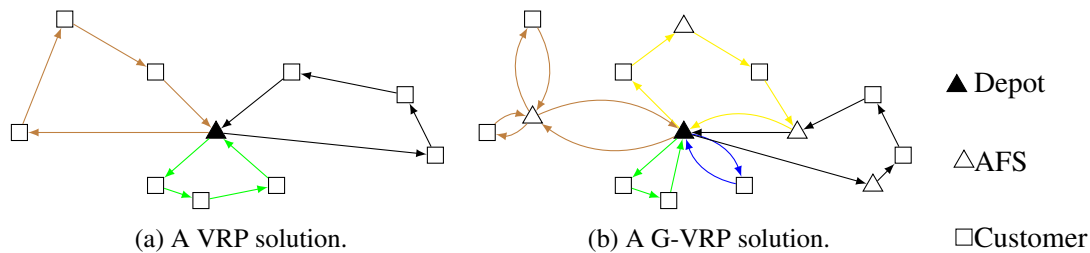


Figura 1: Highlighting the differences between VRP and G-VRP.

1.1. Motivation

In distribution management, it is often necessary to determine a combination of least-cost vehicle's routes through a set of geographically scattered customers, subject to side constraints [Gendreau et al., 1999]. The environmental, geopolitical, and financial costs of the world's dependence on gasoline-powered vehicles are becoming increasingly obvious [Kuby and Lim, 2007]. The transport sector has high levels of CO₂ emissions. For example, the transport sector in 2016 accounted for 28.5% of CO₂ emissions from the United States [U.S. Environmental Protection Agency, 2016], and in 2014 accounted for 20.45% of CO₂ emissions worldwide [Ritchie and Rosser, 2016]. Recognizing the environmental dimensions (such as carbon emissions and demand on energy), logistics companies have a special responsibility to make their operations greener, thus, many logistics companies are looking for new approaches to manage carbon effectively from procurement and production to distribution and product afterlife [Yang and Sun, 2015]. Furthermore, there is a strong tendency in the world towards the development of *clean* motor vehicles that do not pollute the environment, that is, that do not emit harmful substances in their exhaust fumes and which create less noise without causing other types of pollution [Ćirović et al., 2014]. The adoption of AFVs has been regarded as one of the most promising strategies to address the issues of energy dependence, air quality, and, more recently, climate change [Yeh, 2007]. Electric commercial vehicles are gaining tractions in firms that deliver products, goods, or services. For example, Staples Inc., PepsiCo, FedEx Corp, and AT&T Inc. [Lin et al., 2016]. Organizations electrify their vehicle fleets to lower costs, reduce emissions, and improve their public image [Worley et al., 2012].

1.2. Problem definition

In the G-VRP proposed by Erdoğan and Miller-Hooks [2012], a set of customers with known service times must be attended by a set of homogeneous alternative fuel vehicles, which operate from a common depot. These vehicles have a lower autonomy in terms of traveled distance, forcing them to stop and refuel in AFSs. Each customer must be visited once by exactly one vehicle and the time spent by a vehicle in a route cannot exceed a maximum operation time. The objective is to reduce the total traveled cost.

Consider a complete directed graph $G(V, E)$, with $V = C \cup F \cup \{v_0\}$, where C is the set of customers, F is the set of AFSs, and $v_0 \in V$ is the depot. Edges $(i, j) \in E$ have metric costs c_{ij} . A positive vehicle energy consumption rate ρ is considered, and $e_{ij} = c_{ij}\rho$ is the required energy to traverse edge (i, j) . A positive vehicle average speed ξ is considered, and $t_{ij} = \frac{c_{ij}}{\xi}$ is the required time to traverse the edge (i, j) . In the depot, there is a set $M = \{1, \dots, |C|\}$ of homogeneous vehicles with an autonomy of β and maximum operation time T . The goal of G-VRP consists in determining at most $|M|$ routes with minimum cost satisfying the following constraints:

- Each customer $v_i \in C$ has a service time $s_i \geq 0$, and each AFS $v_f \in F$ has a refueling time $s_f \geq 0$.
- Each route begins and ends at the vertex depot v_0 ;
- Each vertex $v_i \in C$ is visited once by exactly one route;
- The autonomy of a vehicle decreases in e_{ij} when it traverses edge $(i, j) \in E$. It is not possible for a vehicle to traverse an edge with a required energy higher than its autonomy. When the vehicle visits an AFS, its autonomy is restored to β ;
- The time spent by a route must not exceed T .

2. Contributions and Results

2.1. Summary of Contributions

The dissertation proposes several contributions to the state of the art of the problem, e.g.:

- Provides a thorough mathematical analysis for two versions of the problem, (i) where no consecutive AFSs visits (Chapter 5 [Andrade, 2020]), (ii) where consecutive AFSs visits (Chapter 6 [Andrade, 2020]). Integer Programming formulations and instances for both versions are provided. Figure 2 uses the same example given in Subfigure 1b with a smaller autonomy β , forcing the previous black arcs route to be split into two routes, one with black arcs, and consecutive AFSs visit, and another with red arcs.

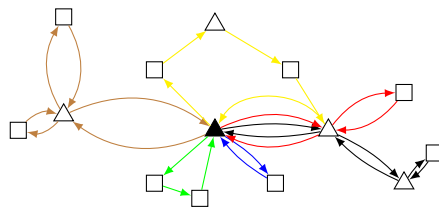


Figura 2: A G-VRP solution with consecutive AFSs visits.

- Adds new combinatorial properties (Chapter 4 [Andrade, 2020]) to the current body of knowledge of the literature. These properties result in valid inequalities and lower bounds, which strengthen the mathematical formulations by reducing their search spaces for both G-VRP versions, thus improving exact solution methodologies. The proposed combinatorial properties are divided into three categories:
 - AFSs properties, concerning bounds on the number of visits to the AFSs;
 - Fuel consumption properties, which bound the fuel consumption for any vehicle route; and
 - Route properties, which uses the previous properties to derive bounds on the total number of routes and their total cost.
- Six mathematical formulations for the two versions of the problem are given in the dissertation (Chapter 5 and 6 [Andrade, 2020]). The contributions for the G-VRP with consecutive AFSs visits sets the new state-of-the-art on exact solution approaches;
- New sets of preprocessing (Sections 6.1 and 6.2 [Andrade, 2020]) were shown to be stronger than those already proposed by the literature [Leggieri and Haouari, 2017];
- Two new representative sets of instances were designed (Sections 7.1 [Andrade, 2020]), one set for each version of the problem. The instances were generated in order to explore the impact of the number of AFSs and the vehicle autonomy in the optimal solution, GAP, and execution time.

The contribution of the dissertation resulted in five published works (one book chapter, four conference papers). In addition, a full paper is under final revision for submission to the Transportation Research Part E. In the following sections, a closer view of each contribution is provided.

2.2. The Electric Capacitated Covering Tour Problem (ECCTP) - Proceedings of the LI SBPO (Brazilian Symposium of Operations Research)

Arakaki, R.K. & Maziero, L.P. & Andrade, M.D. & Usberti, F.L. 2019

URL: proceedings.science/sbpo-2019/papers/the-electric-capacitated-covering-tour-problem

In the Capacitated Covering Tour Problem (CCTP), a customer can be serviced by any vehicle which transits inside a pre-established neighborhood radius of that customer. This paper links aspects of vehicle routing by covering and green logistics, resulting in a new VRP variant called Electric Capacitated Covering Tour Problem (ECCTP), in which a homogeneous fleet of electric vehicles are used to service the demands of customers by covering.

The ECCTP can be defined, along with the notations presented in Subsection 1.2, by considering $V = U \cup W \cup F$, where U , W , and F are disjoint. U represents the traffic vertices, and W represents the customer vertices. Instead of time limit T , each vehicle has a demand capacity Q . For each vertex $w \in W$ is associated with a demand $d_w > 0$. $D(v) : D(v) \cap F = \emptyset$ is the set of vertices that are covered by $v \in (U \cup W) \setminus \{v_0\}$, and $C(w) : w \in C(w)$ is the set of vertices that cover $w \in W$. All vertices of W must be served by coverage or visit. The goal of ECCTP consists of defining a set of up to $|M|$ fuel feasible routes of minimum length where: (i) each vertex $v \in (U \cup W)$ is visited at most by one route; (ii) each vertex $w \in W$ must be serviced by at least one route, i.e., it must be serviced by some vertex $v \in C(w)$ that is visited by a route; (iii) the demand of a vertex $w \in W$ can be serviced by a route $k \in M$ if there is a vertex v visited by the

route k such that a $v \in C(w)$ or w is visited by route k ; (iv) the total demand of a route, the sum of the demands of the vertices $w \in W$ serviced, must not exceed the capacity Q of the vehicle. Based on the example given in the Subfigure 1b, Figure 3 presents an ECCTP example in which some vertices are customers and others are traffic vertices. A traffic vertex does not have demand and may be visited or not. Both traffic and customer vertices can be used to service the demands of neighboring customers by covering.

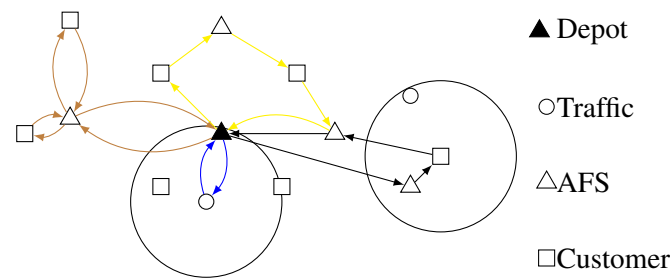


Figura 3: An ECCTP solution.

The paper proposes a mathematical formulation, a heuristic method, and a new set of benchmark instances for the ECCTP (based on a set of public VRP benchmark instances). Computational experiments on the benchmark instances are conducted with the proposed methodologies.

2.3. Routing Electric Vehicles with Remote Servicing - Modeling and Optimization in Green Logistics, Springer

Arakaki, R.K. & Maziero, L.P. & Andrade, M.D. & Hama, V.M.F. & Usberti, F.L. 2019

DOI: 10.1007/978-3-030-45308-4_8

This paper presents a new Mixed-Integer Linear Programming (MILP) model, and a biased random-key genetic algorithm (BRKGA) for the ECCTP. Computational experiments are conducted with the proposed methods to evaluate the effectiveness of the approaches and to extract useful information for transportation decision-making.

A new set of benchmark instances for the problem was created based on public benchmark instances originally proposed for the VRP. In contrast to previous formulations of electric vehicle routing problems, the presented MILP model does not make any assumptions or restrictions concerning the number of times a vehicle visits the recharging station. The BRKGA decoder's main features are: (i) a Split procedure, which optimally splits a single non-capacitated route into capacitated routes; (ii) a dynamic programming procedure that optimally inserts stations visits in each vehicle route. The computational experiments were conducted with the proposed methods to evaluate the effectiveness of the approaches and to extract useful information for transportation decision making. Also, the computation experiments allowed analyzing how the parameters of electric vehicle battery capacity and coverage neighborhood size could impact the optimal solution cost and the difficulty to solve the instances. The proposed methods were found to be sensitive to the neighborhood size concerning the solution GAP. Moreover, the analysis emphasized the importance of vehicle autonomy when addressing the economic feasibility of a transportation plan.

For the smaller instances ($|W| \leq 20$) the solution quality of the MILP formulation was superior. On the other hand, BRKGA has a processing time much faster than the MILP formulation for instances of all sizes: on average, the BRKGA is approximately 70 times faster. Regarding the hardest instances ($|W| \geq 30$) the performance of BRKGA is superior in both solution cost and processing time. Moreover, for these instances, the BRKGA average time was approximately

35 times faster. This shows that the BRKGA is the most suitable method for the hardest ECCTP instances. On the other hand, the MILP formulation can be used to obtain good solutions for small instances and obtaining lower bounds.

The number of vehicles can be quite important regarding the optimization difficulty, where if the value is too low, it may be difficult to find any feasible solution. On the other hand, a large value can turn the instances unnecessarily difficult to be solved by the MILP formulation since the number of variables relies on the number of vehicles. The coverage size, the number of nodes covered by each traffic and customer node, is crucial for the difficulty of the instances and cost of optimal solutions. The vehicle fuel capacity β also showed a substantial impact on solution costs. It was observed a substantial decrease of solution cost when increasing the vehicle batteries capacity. The economic interpretation of these results is that the increase in the battery capacity has diminishing returns concerning transportation costs. This kind of analysis could support the decision-making process for which vehicles model should be used given their autonomies and potential cost reductions. Regarding the difficulty of optimizing the largest instances, for many of them, the MILP method did not obtain any feasible solution. This probably is related to the energy constraints since this happened especially more frequently for small β and less frequently for large ones. This suggests that reformulating the problem using a stronger set of constraints to model the battery capacities may be a promising research topic. On the other hand, BRKGA was shown to be an effective approach to obtain feasible solutions.

2.4. Valid Inequalities for the Green Vehicle Routing Problem - V Computer Theory Meeting at the XL Brazilian Society Computing Congress

Andrade, M.D. & Usberti, F.L. 2020

DOI: 10.5753/etc.2020.11086

This work proposes combinatorial properties, valid inequalities, a MILP formulation, and preprocessing conditions for the G-VRP. The combinatorial properties are composed of a set of mathematical proofs that asserts G-VRP properties, such as upper bounds on the number of times an edge and an AFS will be visited in an optimal solution. Furthermore, the properties give upper and lower bounds on the amount of fuel a route can consume. Based on the combinatorial properties, several valid inequalities reducing the MILP search space are presented. The proofs for these theoretical results as well as computational experiments using the combinatorial properties on the proposed formulation are given in [Andrade, 2020].

2.5. Combinatorial Properties for the Green Vehicle Routing Problem (accepted for publication) - LAGOS 2021: XI Latin and American Algorithms, Graphs and Optimization Symposium

Andrade, M.D. & Usberti, F.L. 2021

This paper introduces new properties, proofs, and lower bounds for the G-VRP. These properties are divided into three categories: AFSs properties, concerning bounds on the number of visits to the AFSs; Fuel consumption properties, which bound the fuel consumption for any vehicle route; and Route properties, which uses the two previous properties to derive bounds on the total number of routes and their total cost. The AFSs and Fuel properties extend the properties proposed in the work [Andrade and Usberti, 2020] by adding new ideas including new Route properties setting stronger lower bounds for the G-VRP. Two G-VRP versions are investigated, (i) where consecutive AFSs visits are not allowed, and (ii) where consecutive AFSs visits are allowed, i.e., a solution may have an edge between two AFSs. The proposed combinatorial properties and lower bounds have the potential to strengthen the mathematical formulations for both G-VRP versions, thus improving exact solution methodologies. Finally, some of the theoretical results are expressed

as valid inequalities in a formulation borrowing the ideas presented in [Andrade and Usberti, 2020], and computational experiments with the new formulation are presented in [Andrade, 2020].

Sections 2.5.1 and 2.5.2 present an excerpt of the combinatorial properties given by [Andrade and Usberti, 2020].

2.5.1. AFSs properties

Lemma 2.1. *If the edges costs are symmetric, then there exists an optimal solution in which in every route each edge will be visited at most once.*

Demonstração. If an edge is adjacent to a customer, then by the problem definition such edge can be used at most once. However, for the case where an edge has two AFSs as terminals, consider the route $R = (v_0, r_1, \dots, r_i, r_{i+1}, r_q, \dots, r_k, r_i, r_{i+1}, r_m, \dots, r_{l-1}, v_0)$, where r_i and $r_{i+1} \in F$. Note that edge (r_i, r_{i+1}) is used twice in R . Since the graph is symmetric and R is a feasible route, then path $(r_i, r_k, \dots, r_q, r_{i+1})$ is valid and it has the same cost of the path $(r_{i+1}, r_q, \dots, r_k, r_i)$. Thus, we can create another route $R' = (v_0, r_1, \dots, r_i, r_k, \dots, r_q, r_{i+1}, r_m, \dots, r_{l-1}, v_0)$, which is a valid route, that visits all the customers of route R , and has cost strictly less than route R . Thus, a contradiction of route R being optimal.

Subfigures 4a and 4b present routes R and R' .

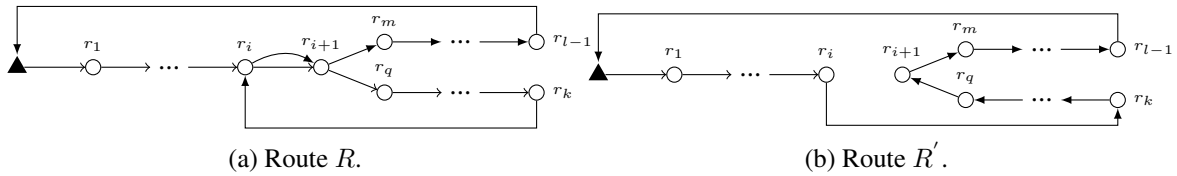


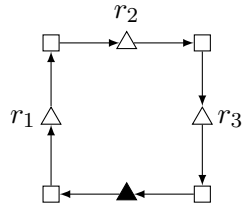
Figura 4: Routes R and R' .

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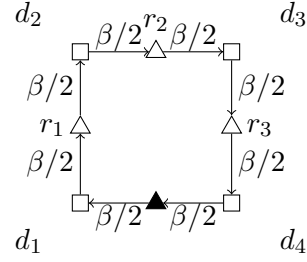
2.5.2. Fuel consumption properties

Some relevant definitions are provided next.

- $R = (v_0, v_1, \dots, v_n, v_{n+1})$ is an arbitrary feasible route, where $v_{n+1} = v_0$, and $\{v_1, \dots, v_n\} \subseteq V \setminus \{v_0\}$;
- $p(R) \geq 0$ is the number of AFSs visits made by the route R ;
- $R_F = (r_1, \dots, r_{p(R)})$ is the sequence of AFSs visited by route R in the order they are visited in R ; Subfigure 5a presents an example of route R and its R_F .
- $\lambda = \min_{v_f \in F} \{e_{0f}\}$ is the energy required to visit the nearest AFS starting from the depot;
- $\psi = \min_{v_f, v_r \in F: v_r \neq v_f} \{e_{fr}\}$ is the minimum energy required to traverse the edge between two AFSs;
- $\alpha = \min\{\psi, \lambda\}$;
- d_i is the amount of fuel spent between r_{i-1} and r_i by R for $1 < i \leq p(R)$, d_1 is the amount of fuel spent between v_0 and r_1 , and $d_{p(R)+1}$ is the amount of fuel spent between $r_{p(R)}$ and v_0 ;



(a) An example of a route with its AFSs visits represented as r_i .



(b) An example of a route with its fuel consumption between its AFSs visits represented as d_i .

Figura 5: An example of a notations R_F and d_i .

- $c(R) = \sum_{i=1}^{p(R)+1} d_i$ is the amount of fuel spent by R (it can be seen as $\sum_{i=0}^n e_{i,i+1}$ as well); Subfigure 5b presents an example of route R and its d_i .

Lemma 2.2. $c(R) \leq (p(R) + 1)\beta$.

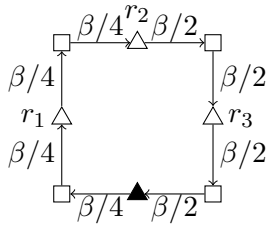
Demonstração. Note that $d_i \leq \beta$ for $1 \leq i \leq p(R) + 1$, otherwise R would be an infeasible route. Therefore, $\sum_{i=1}^{p(R)+1} d_i \leq (p(R) + 1)\beta$, i.e., $c(R) \leq (p(R) + 1)\beta$.

Figure 5b presents an example of a route that consumes exactly $(p(R) + 1)\beta$ of fuel. $\square$

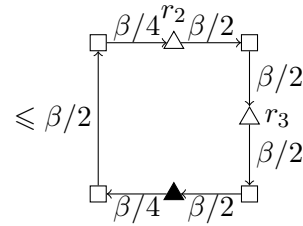
Lemma 2.3. If the instance edges costs are metric and the instance is feasible, then there exists an optimal solution in which in any route R , $d_i + d_{i+1} > \beta$ for $1 \leq i \leq p(R)$.

Demonstração. Let's suppose that $d_i + d_{i+1} \leq \beta$ for $1 \leq i \leq p(R)$, then the AFS $r_i \in R_F$ is being visited redundantly, hence r_i could be removed from R without affecting the route feasibility and eventually allowing to reduce the route cost. Therefore, $d_i + d_{i+1} > \beta$ for $1 \leq i \leq p(R)$. $\square$

Bellow has presented two Subfigures, the Subfigure 6a presents an example of route R and its d_i with a redundant AFS visit made in r_1 , where $d_1 + d_2 \leq \beta$, whereas Subfigure 6b presents the same route but without AFS visit r_1 .



(a) An example of a route R with its d_i and one redundant AFS visit r_1 .



(b) The same route presented in Subfigure 6a but without the redundant AFS visit r_1 .

Figura 6: Lemma 2.3 example.

Theorem 2.4. If a route R belongs to an optimal solution and $p(R) \geq 1$, then $c(R) \geq 2\lambda + (p(R) - 1)\psi$.

Demonstração. Since $c(R) = \sum_{i=1}^{p(R)+1} d_i = d_1 + \sum_{i=2}^{p(R)} d_i + d_{p(R)+1}$, $\lambda \leq d_1, d_{p(R)+1}$, and $\psi \leq d_i$ $2 \leq i \leq p(R)$, then $c(R) \geq 2\lambda + (p(R) - 1)\psi$. $\square$

Theorem 2.5. *If a route R belongs to an optimal solution, and $p(R)$ is odd, then $c(R) > (p(R) + 1)\beta/2$.*

Demonstração. Since $c(R) = \sum_{i=1}^{p(R)+1} d_i$, $p(R)$ is odd (consequently $p(R) + 1$ will be even), and Lemma 2.3 is valid, then $c(R) > (p(R) + 1)\beta/2$. $\square$

Theorem 2.6. *If a route R belongs to an optimal solution, and $p(R) \geq 1$ is even, then $c(R) > p(R)\beta/2 + \alpha$.*

Demonstração. Since $c(R) = \sum_{i=1}^{p(R)+1} d_i$, $p(R)$ is even, then $c(R) > p(R)\beta/2 + d_{p(R)+1}$. By the definition of λ and α we have that $d_i \geq \lambda \geq \alpha$ for $1 \leq i \leq p(R) + 1$, hence $p(R)\beta/2 + d_{p(R)+1} > p(R)\beta/2 + \alpha$, and consequently $c(R) > p(R)\beta/2 + \alpha$ when $p(R)$ is even. $\square$

Theorem 2.7. *If a route R belongs to an optimal solution, and $p(R)$ is odd, then $c(R) > p(R)\beta/2 + \alpha$.*

Demonstração. Let's consider two cases:

- $\alpha \leq \beta/2$: By Theorem 2.5 we have that $c(R) > (p(R) + 1)\beta/2$, and since $\alpha \leq \beta/2$, then $c(R) > p(R)\beta/2 + \alpha$.
- $\alpha > \beta/2$: Note that by the definition of α and by the triangle inequality $d_i \geq \alpha$ for $1 \leq i \leq p(R) + 1$, and since that $\alpha > \beta/2$ then $d_i > \beta/2$ for $1 \leq i \leq p(R) + 1$. Hence $\sum_{i=1}^{p(R)+1} d_i > p(R)\beta/2 + d_{p(R)+1} \geq p(R)\beta/2 + \alpha$, i.e., $c(R) > p(R)\beta/2 + \alpha$ when $p(R)$ is odd and when $\alpha > \beta/2$.

Therefore, $c(R) > p(R)\beta/2 + \alpha$ when $p(R)$ is odd. $\square$

Theorem 2.8. *If a route R belongs to an optimal solution, and $p(R) \geq 1$, then $c(R) > p(R)\beta/2 + \alpha$.*

Demonstração. This proof follows as result of 2.7 and 2.6. $\square$

2.6. Instance Generation Framework for Green Vehicle Routing (approved for publication) - Special Volume of the AIRO Springer Series 2021

Andrade, M.D. & Usberti, F.L. 2021

The previous G-VRP literature accounted for two sets of G-VRP instances. The first was proposed by [Erdoğan and Miller-Hooks, 2012] and comprises 52 instances with 20 to 500 customers and 3 to 28 AFSs. Each instance was randomly generated assuming a grid of 330 by 300 miles. The majority of the instances in this set contain 20 customers and have been randomly generated to simulate different scenarios in terms of customer and AFSs distribution. The depot location was fixed and assumed to be located near the center of the grid in all scenarios. The larger instances [Erdoğan and Miller-Hooks, 2012] were created by using a medical textile supply company depot location in Virginia and a customer pool based on hospital locations in Virginia, and the District of Columbia. The refueling stations correspond to actual biodiesel stations located in the region. The number of customers in these larger instances ranges from 111 to 500. It should be mentioned that these instances may contain some infeasible customers. According to [Erdoğan and Miller-Hooks, 2012], a customer is infeasible if it cannot be visited by a route making at most

one refueling stop. Motivated by the fact that most of these instances are small, and the five larger instances with 111 customers only differ in the number of refueling stations (ranging from 21 to 28), [Andelmin and Bartolini, 2017] proposed a new set of G-VRP instances. This set contains four additional instances by extracting the first 75 and 100 customers from the two 111-customer instances having 21 and 28 stations.

The current G-VRP literature lacks a more general set of instances as well as a systemized framework to generate relevant sets of instances. Andrade and Usberti [2021] introduces such a framework to generate feasible G-VRP instances by solving a Maximum Leaf Spanning Tree (MLST) problem. The MLST consists in finding a spanning tree of a connected graph with the maximum number of leaves. The paper considers the leaves as customers and the internal vertices as AFSs and the depot and uses Augerat's VRP instances [Augerat, 1995] as base instances.

The proposed framework is very fast, resulting in execution times of at most six seconds for every instance. An interesting observation is that in Augerat's VRP instances [Augerat, 1995] with the same number of customers, the trade-offs among parameters β , $|F|$ and T become apparent. In particular, as more AFSs are allocated, the smaller β becomes, forcing the vehicles to make more stops to refuel. These trade-offs analysis could assist in the decision-making process of AFS allocation of a city, for example, given the estimates of the average vehicles autonomies.

Figure 7 contains three subfigures, Subfigure 7a shows an example of an MLST instance, and the two remaining subfigures present examples of valid solutions for that instance, where the nodes in grey are the leaves. Subfigure 7b shows a non-optimal solution, whereas Subfigure 7c shows the optimal solution.

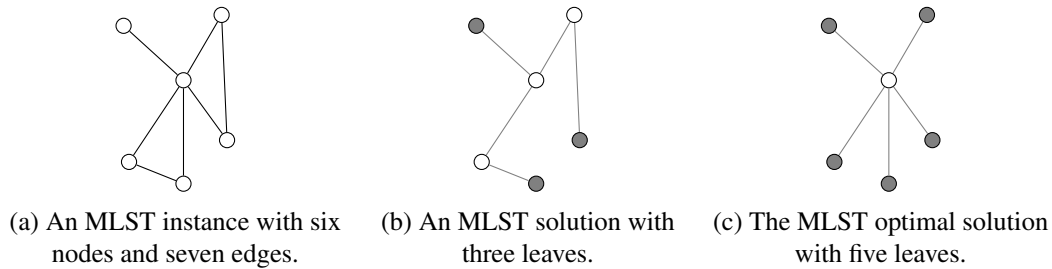


Figura 7: An MLST instance and two examples of solutions.

2.7. Formulations for the Green-Vehicle Routing Problem (to be submitted) - Transportation Research Part E

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This paper proposes a thorough literature review and MILP formulations for the G-VRP. Some of these formulations are based on the formulations proposed by [Çağrı Koç and Karaoglan, 2016; Leggieri and Haouari, 2017], and on the properties proposed in the work *Combinatorial Properties for the Green Vehicle Routing Problem*. Furthermore, an extensive computational study is conducted using the proposed formulations over the instances sets proposed in *Instance Generation Framework for Green Vehicle Routing*.

3. Conclusions

In this thesis we addressed the G-VRP in two distinct versions, the version with consecutive AFSs visits, and the version without consecutive AFSs visits. Proposing combinatorial properties, valid inequalities, lower bounds, preprocessing conditions, MILP formulations, sets of

instances, and benchmarkings for both versions. Among the properties presented by the combinatorial properties, some interesting is the relation between the number of AFSs visits with the route minimum required spent fuel, and the relation between the number of visited customers of a route with the route maximum number of allowed AFSs visits.

Concerning future research, the proposed results can be modified by considering more realistic aspects of the G-VRP including customer demands, time windows, multiple depots, limited number of visits to each AFSs. CO₂ emissions or other greenhouse gas emissions can be also embedded into the objective function. With respect to methodologies, alternative approaches that can be used to solve this problem are: column generation, heuristic/metaheuristic, and approximate algorithms. Finally, another way of seeing this problem is by reducing it to a VRP in multigraphs, and consequently the available results for VRP in multigraphs in the literature may be adapted to this problem.

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