UNIVERSIDADE FEDERAL DE VIÇOSA

VICTOR HUGO VIDIGAL CORRÊA

ALGORITHMS FOR ELECTRIC VEHICLES INFRASTRUCTURE DESIGN WITH LONG-TERM PLANNING

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Dissertation submitted to the Computer Science Graduate Program of the Universidade Federal de Viçosa in partial fulfillment of the requirements for the degree of *Magister Scientiae*.

Advisor: André Gustavo dos Santos

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ABSTRACT

CORRÊA, Victor Hugo Vidigal, M.Sc., Universidade Federal de Viçosa, March, 2021. **Algorithms for infrastructure design for electric vehicles with long-term planning**. Advisor: André Gustavo dos Santos.

The modernization of our lifestyle, originating from the Industrial Revolution in the XVIII century, has led to successive changes in the consumption patterns of the society, raising them to levels never seen before by facilitating the population's access to various goods in increasingly distant markets from the production centers. With the surge of vehicles powered by fossil fuels, it was possible to dispose of products more quickly to markets all over the world, but with the consequence of the emission, over the years, of tons of CO^2 into the atmosphere, accumulating and causing the phenomenon called global warming which, if not tackled, could cause several negative impacts on the planet's ecosystem. As one of several measures proposed to combat global warming, the use of electric vehicles has gained a lot of attention in recent years. Its use is particularly interesting for the transport sector, which is responsible for approximately 25% of global pollutant gas emissions. However, due to the particularities of the sector, the adoption of this means of transportation is still economically unattractive, especially due to the absence of an infrastructure network to efficiently operate its use. To optimize the construction of this infrastructure, this study aimed to present an algorithm aimed at reducing costs, considering a long-term planning of deliveries from a logistics company. Two algorithms are presented, one solves the short-term problem considering factors such as battery replacement, partial recharging, time windows and capacitated vehicles while the second, composed of 3 steps and based on the first, solves the problem considering long-term planning. The algorithms are tested with instances created based on real data from the United Kingdom and the State of Minas Gerais and, by the results obtained in the computational experiments, they were able to reduce the average costs in the long-term operational planning of deliveries by electric vehicles by 5.25% if compared to the algorithm for the problem that does not consider long-term planning.

Keywords: Electric Vehicles. Logistics Infrastructure. Metaheuristics.

RESUMO

CORRÊA, Victor Hugo Vidigal, M.Sc., Universidade Federal de Viçosa, março de 2021. **Algoritmos para o projeto de infraestrutura para veículos elétricos com planejamento de longo prazo**. Orientador: André Gustavo dos Santos.

A modernização do nosso estilo de vida, oriunda da Revolução Industrial no século XVIII, imprimiu sucessivas mudanças nos padrões de consumo da sociedade, elevando-os a patamares nunca antes vistos ao facilitar o acesso da população a diversos bens de consumo em mercados cada vez mais distantes dos centros de produção. Com o surgimento dos veículos movidos a combustíveis fósseis foi possível o escoamento de produtos com maior rapidez para mercados do mundo inteiro, porém com a consequência da emissão, ao longo dos anos, de toneladas de CO_2 na atmosfera. Com as emissões acumuladas o fenômeno denominado de aquecimento global hoje nos assola e, caso não combatido, poderá causar diversos impactos negativos no ecossistema do planeta. Como uma das várias medidas propostas para o combate ao aquecimento global, o uso de veículos elétricos tem ganhado bastante atenção nos últimos anos. Seu uso é particularmente interessante para o setor de transporte que é responsável por aproximadamente 25% das emissões globais de gases poluentes. Entretanto, devido às particularidades do setor, a adoção desse meio de transporte ainda é economicamente pouca atrativa, especialmente devido à ausência de uma infraestrutura para operacionalizar de forma eficiente o seu uso. Para otimizar a construção dessa infraestrutura, este estudo teve como objetivo apresentar um algoritmo voltado para a redução de custos, considerando um planejamento de longo prazo de entregas de uma empresa de logística. São apresentados dois algoritmos, um resolve o problema de curto prazo e considera fatores como a troca de baterias, recarga parcial, janelas de tempo e veículos capacitados, enquanto o segundo, composto por 3 etapas e baseado no primeiro, resolve o problema considerando o planejamento de longo prazo. Os algoritmos são testados com instâncias criadas com base em dados reais do Reino Unido e do Estado de Minas Gerais e, pelos resultados obtidos nos experimentos computacionais, se mostraram capazes de reduzir custos no planejamento operacional de longo prazo de entregas por meio de veículos elétricos. Observou-se uma redução de custo médio de 5.25% se comparado ao algoritmo para o problema que não considera planejamento de longo prazo.

Palavras-chave: Problema de Roteamento de Veiculos Elétricos e Localização de Facilidades. Infraestrutura de Logística. Metaheurística.

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1 INTRODUCTION

Started in England in the 18th century and soon spread to the rest of the world in several waves, the Industrial Revolution made it possible for humanity to live in an extraordinary and continuous technological advance that has enabled an incremental improvement in the society's quality of life. With the improvement of the means of manufacture, the production of goods on a large scale meant that a huge supply of products needed to be transported to the various consumer markets around the world. A very important innovation at the time, which made this flow feasible, was the use of coal and oil as energy sources for steam and internal combustion engines, which allowed vehicles to travel greater distances in a shorter time and transport a greater volume of cargo.

At the time, there was no dimension of the impacts caused by the emission of polluting gases by the burning of the fuels that moved the machines. With this increase in the burning of fossil fuels, year after year, tons of carbon dioxide were emitted into the atmosphere, and it is estimated that between the years 1751 to 1950 the emission of CO_2 resulting from the burning of these fuels had an increase 500 times (KÖNE; BÜKE, 2010). Still growing, the CO_2 emissions accumulated over the years have caused enormous concern in the scientific and political environment due to their impact on the phenomenon of global warming that results from the greater absorption of solar radiation into the atmosphere promoted by several polluting gases.

According to the World Meteorological Organization (WMO), in 2020 the average global temperature was 1.2^o degrees Celsius above that was recorded in the pre-industrial period (WMO, 2021) and, together with the years 2016 and 2019, the 3 largest average temperature records were obtained since the beginning of this measurement. The dimension of the severity of this problem becomes more evident when taking into account that in the year 2020 the natural phenomenon called *La Niña* occurred, which consists of a decrease in the surface temperature of the waters of the Pacific Ocean and has an effect of temporary cooling in certain regions of the planet, showing that anthropological actions have had as great dimensions in climate changes as natural events.

In the face of these facts, the United Nations Secretary-General, António Guterres, during the Climate Ambition Summit 2020 (HARVEYN, 2020), emphasized to all world leaders about the importance of a collective effort to reverse the situation and suggested the declaration of the state of climatic emergency. The increase in the average global temperature of 1.5^o degree Celsius is considered a threshold, as the damage to the planet started to take on greater proportions and the lives of millions of people began to be directly affected by the impacts caused . A study by the Panel on Climate Change (ROGELJ et al., 2018) discusses the impacts of this rise to this level. According to the study, the scenario designed would already be enough to affect the lives of more than 6 million people who live in coastal areas due to rising sea levels. Plantations can also be severely affected with populations of pollinating insects losing their habitat due to changes in flora and, consequently, reducing the productivity of the agricultural sector.

It is also important to pay attention to irreversible impacts such as the loss of biodiversity, as pointed out by Warren et al. (2013). According to the authors, an early mitigation of global warming can considerably reduce this loss, which would be extremely beneficial, considering that we depend on biological balance to maintain the planet's sustainability. It is pointed out that, at the current rate of increase in emissions of polluting gases until the year 2080, about 34% of animals and 57% of plants may be living outside their climatic range, which may cause the extinction of the affected species. With strict restrictions on emissions of polluting gases until the year 2030, it is possible to considerably reduce the risks of biodiversity loss.

The transport sector has a great influence on this scenario of worsening global warming. In Europe, according to the Annual European Union greenhouse gas inventory (EEA, 2020), the sector was responsible for 26% of CO_2 emissions in 2018, representing an increase of 6% compared to 2014. In India, the sector is the third largest emitter of pollutants and the growth rate of emissions has been exponential, and between 2000 and 2012 the growth rate was on average 6.9% annually (SINGH; MISHRA; BANERJEE, 2019). Analysis of emissions from the transportation sector in China shows that the use of electric vehicles has a long-term decarbonization effect on the atmosphere, while regulatory actions in the fuel market show better results in the short term (ZHAO et al., 2019). By adopting these two practices, emissions can reach its peak by 2026, 4 years before the Chinese government agreed at the 2015 United Nations Conference on Climate Change. Worldwide, the sector is responsible for about 23% of the CO_2 issues and companies in the industry have been looking for solutions to contain the impacts of their operations on the global climate.

Since the beginning of the years 2000s, and intensified in the past decade, the adoption of electric vehicles has been gaining a lot of attention in the various economic sectors. In the personal transport sector, companies like Tesla have promoted the use of this type of vehicle as the future of transportation and, year after year, have been registering an increase in their sales. In the cargo transport sector, the situation has been treated with great attention and several companies have replaced part of their fleets of combustion engine vehicles with electric vehicles. For example, FEDEX started deploying electric vehicles in 2009 and now seeks to develop a more robust infrastructure to expand its fleets (FEDEX, 2020); and DHL started in 2014 to incorporate this type of vehicle in its fleets with some vehicles being used even in Brazilian territory operating in the State of Rio de Janeiro (DHL, 2021; DHL, 2018). However, it is evident that, despite efforts, the use of these vehicles is still restricted, seen the carbon emission rates recorded in recent years. Therefore, it is necessary to search for ways that can facilitate the expansion of fleets of electric vehicles in the sector.

One of the great disadvantages of electric vehicles compared to those with an internal combustion engine is their long battery recharge time. While to supply a vehicle with fuel, all you have to do is go to one of the millions of gas stations around the world and, in a matter of minutes, have a full tank, to recharge the battery of an electric vehicle it is necessary to use a special charging station not yet largely available and wait for hours until you have a fully charged battery. This is undoubtedly one of the factors that make it more difficult for logistics companies to adopt electric vehicles in greater quantities. This factor is decisive for logistics companies, whose operations are very time sensitive, as they depend in many cases on restricted time windows to meet delivery deadlines that, if violated, can generate customer dissatisfaction and even contractual fines.

As an alternative to conventional battery charging stations, battery swapping stations began to be made available in China. These stations consist of a machine specialized in removing the battery from the vehicle through its floor and replacing it with a fully charged one. Figure 1 illustrates the difference between the two types of station: on the left side the conventional charging station and on the right the battery swapping station with its apparatus for removing and inserting a new battery. According to NIO, the company responsible for the battery swapping stations, the first station of this type was installed in the year 2018. The company reports that by July 2020, 700.000 battery swaps had been carried out (TIANYU, 2020).

(a) Battery recharging station.

(b) Battery swapping station.

Figure 1 – Example of the two types of station that can be used to refuel an electric vehicle.[1]

Despite the emergence of new technologies related to electric vehicles, it is necessary to enable their use in a more practical way and, for this, infrastructure networks can be used to optimize the operational processes of companies taking into account the use of these technologies. In this context, several studies have proposed modeling of infrastructure networks to optimize the delivery process with electric vehicles in the scope of combinatorial optimization. The most common types of infrastructure modeling for electric vehicles are found in networks composed of battery charging stations (CUI; ZHAO; ZHANG, 2018; WORLEY; KLABJAN; SWEDA, 2012), battery swapping stations (HOF; SCHNEIDER; GOEKE, 2017) and networks that combine these two types of systems for handling vehicles batteries (CORRÊA; SANTOS, 2020; PAZ; GRANADA-ECHEVERRI; ESCOBAR, 2018). In common among the proposed models is the use of the Location-Routing Problem (LRP) model adapted to contemplate several characteristics of infrastructures for electric vehicles. However, this type of modeling has a flaw when applied to this problem, as it does not include infrastructure planning considering a long-term horizon of

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[1] Source: <https://news.cgtn.com/news/2020-08-16/EV-battery-swapping-finds-new-life-in-China-SWZQhFZoEE/index.html>

delivery operations. LRP consists of a combination of two optimization problems, vehicle routing (VRP) and facility location (FLP), both NP-Hard (ARCHETTI et al., 2011; KARIV; HAKIMI, 1979), and thus unifies a short-term problem with a long term one. The problem with using this approach in this context is that, in the case of logistics companies, the data changes from day to day; that is, each day they must serve a different set of customers. Routing by location, considering the two sub-problems only in the short term, would work well if customers were the same every day and this is not the case for logistics companies. To solve this problem, several LRP models consider amortized data; that is, the costs of the long-term part of the problem are amortized, by dividing its total costs by the expected time of using of the long-term components. In this work, we propose another technique to handle the combination of the short and long-term problem solving multiple short-term problems and using its solutions to optimize the electric vehicle infrastructure considering some long-term characteristics.

1.1 Problem Definition

The problem of planning electric vehicle infrastructure networks for logistics companies addressed in this work is based on the modeling of integer linear programming called Multi-Depot Electric Vehicle Location Routing Problem with Time Windows, initially proposed by (PAZ; GRANADA-ECHEVERRI; ESCOBAR, 2018). It is defined as follows: a set of customers must have their demand met by a fleet of electric vehicles respecting their time windows. Vehicles must start their route from a depot, carry out their goods delivering in the route and return to the same initial depot, with the possibility of multiple depots. The vehicles have limited autonomy based on the battery capacity and, to solve this problem, two measures can be taken: (i) take advantage of the service time to recharge at the charging station located at the customer or (ii) go to a battery swapping station and have your battery replaced with a fully charged one. When making the first option, the vehicle can take advantage of the service time to charge the battery, but it should not take more than that. The objective of the model is to determine the routes on which vehicles must travel along with the battery recharge plan that may involve the two options presented, define where the depots will be opened and the location where the battery swapping stations will be installed, as these will be the responsibility of the company itself to operate.

In this work, the problem is expanded to be considered the long-term planning of the use of the infrastructure. In this extension of the problem, the modeling assumptions are the same with the addition of the multi-day factor, in which the logistics companies serve different sets of customers in each day and must reuse the existing infrastructure in their operations over time. In this case, the previous single day definition follows the same with the addition of the long-term component and what changes is the daily set of customers. The goal is to optimize the cost of installing the infrastructure and stimulate the adoption of electric vehicles in the transport sector.

1.2 Objectives

In this section, the general and specific objectives developed throughout this work are presented.

1.2.1 Overall Objective

The objective of this work is to develop a methodology for the optimization of electric vehicle infrastructure networks that considers the long-term planning of the delivery operations of companies in the logistics sector, including the location of depots and battery exchange stations.

1.2.2 Specific Objectives

The following specific objectives are considered:

- Develop an integer linear programming model for the problem considering amortized costs.
- Create test instances that represent the problem of cost optimization of electric vehicle infrastructure to be used in computational experiments.
- Develop an algorithm to solve this problem considering amortized costs.
- Propose a methodology that is able to optimize the problem when considering long-term planning.

1.3 Dissertation Organization

The dissertation is prepared in the format of a collection of papers and Chapters 2, 3 and 4 consist of the 3 papers that were developed during the course of the project. Chapter 2 refers to the first paper that was published in the LII Brazilian Symposium on Operational Research (CORRÊA; SANTOS, 2020). It presents the integer linear programming model (PAZ; GRANADA-ECHEVERRI; ESCOBAR, 2018) from which this research project was derived with minor modifications to suit our needs. Also a set of instances is presented represented by cities in the United Kingdom and a hybrid metaheuristic to solve the problem in large-scale instances. Long-term planning is not taken into account. Chapter 3 refers to the full version paper submitted to International Conference on Enterprise Information Systems (CORRÊA; SANTOS; NOGUEIRA, 2021) as the one published in the proceedings was a short paper. It presents a new metaheuristic to solve the problem considering short-term optimization and a 3-stage algorithm that, using the proposed metaheuristic, optimizes the problem taking into account the long-term planning of the infrastructure. Chapter 4 refers to a paper yet to be submitted and it is an extension of second paper in which optimization techniques are used to improve the previously mentioned 3-step algorithm.

The references of the published papers are listed below:

- CORRÊA, V. H. V.; SANTOS, A. G. d. A heuristic algorithm for the multi-depot electric location-routing problem with time windows, battery swap stations and partial recharging. In: ANAIS DO LII SIMPóSIO BRASILEIRO DE PESQUISA OPERACIONAL. João Pessoa, 2020. Available in: <<https://proceedings.science/sbpo-2020/papers/a-heuristic-algorithm-for-the-multi-depot-electric-location-routing-problem-with-time-windows--battery-swap-stations-and>>. Access in: 21 feb. 2021.
- CORRÊA, V. H. V.; SANTOS, A. G. d.; NOGUEIRA, T. H. Strategies for electric location-routing problems considering short and long term horizons. In: INTERNATIONAL CONFERENCE ON ENTERPRISE INFORMATION SYSTEMS. Online, 2021. (Accepted for publication).

2 A HEURISTIC ALGORITHM FOR THE MULTI-DEPOT ELECTRIC LOCATION-ROUTING PROBLEM WITH TIME WINDOWS, BATTERY SWAPPING AND PARTIAL RECHARGING

2.1 Introduction

With the concerns on the limitations and disadvantages of the non-renewable sources of energy, such as petroleum, researches for alternative technologies independent on them has been growing and having an increase in popularity since the beginning of the years 2000 (HØYER, 2008). One example of those alternative technologies is the electric vehicles that, although was invented in the beginning of the 19th century, only in recent years became more popular and an increasing presence of them in our lives can be seen across the world.

There are many reasons for the yet small market share of electric vehicles, despite the benefits they can bring to society over internal combustion ones according to Carley et al. (2013). In one hand, there are the internal combustion vehicles that in order to be refueled, millions of gas stations are available in every part of the world. In the other hand, electric vehicles require a special power outlet to be charged and those are not common to be found, mainly in the countryside or even on medium sized cities. Other disadvantage of electric vehicles is the battery recharging time, which affects directly the vehicle autonomy. While the fastest recharge type is done using the quick charge outlet, that can provide up to 80% of battery capacity in 40 minutes, and internal combustion vehicle can be refueled in less then 5 minutes. As stated by Cecere, Corrocher and Guerzoni (2018), after the price, the vehicle's range is the most important factor in the decision individuals make to purchase an electric vehicle. Good charging infrastructures can affect directly the vehicles' range by providing alternatives ways to recharge batteries, hence a more efficient distribution of the infrastructure's components throughout the space is vital to the technology's prosperity.

The environmental aspect is also very important. The combustion of fossil fuels produces greenhouse gases (GHG) and they have a major role in the global warming. This happens due to the greenhouse effect, in which the GHGs help the atmosphere to absorb most of the radiation coming from the sun and causing a significantly increase in the global average temperature. The consequences of global warming are severe as stated by the Natural Resources Defense Council (DENCHAK, 2019) and can cause a huge environmental and economical loss for the entire world.

Many studies have shown the effects of internal combustion vehicles in the global emission of greenhouse gases in different countries. According to Zhao et al. (2019), EV deployment has a better long-term de-carbonization effect, while fuel economy regulations shows a better result in the short term. During the 2015 United Nations Climate Change Conference, China government agreed to achieve its emission peak of CO_2 before the year 2030. By adopting a deployment plan of electric vehicles together with fuel economy regulations, by the year 2026, China can reach its peak of gases emissions, reaching their goal. In Europe, the transportation sector is responsible for 26% of the total amount of CO_2 emissions, according to the Annual European Union greenhouse gas inventory (EEA, 2020), a 6% increase relatively to 2014. India's transportation sector is the third most GHG emitter in the country according to Singh, Mishra and Banerjee (2019), and due to the country's huge economical growth, CO_2 emissions by the transportation sector have an exponential growth rate.

For the best of our knowledge there are two, non-excluding, approaches to overcome the difficulties with the electric vehicle network infrastructure problems. The first one is to install a set of recharging stations in several points in the network. This allow vehicles to recharge batteries without spending lots of time and energy moving to a recharging station. In this regard a more effective option would be to install those stations in the places that the vehicles have to head to do some operation and use the operations' time to recharge partially the battery. The second approach is to install battery swap stations instead or with recharging stations. Swap stations can take up to 10 minutes to replace an electric vehicle battery for a fully charged one. They have this very good advantage, however they are much more expensive to be built and must be sited carefully.

Finding a good balance between swap and recharging stations location and the vehicles routes is a difficult task. This problem was modeled as a mixed integer linear programming model called Electric Location-Routing Problem (ELRP) in which many variants were studied involving many characteristics such as: time windows, different types of facility to sit, vehicle capacity, etc. The ELRP consists on a combinatory optimization problem in which a fleet of electrical vehicles must have their routes defined in a way that they will serve a set of customers alongside their travel. Also, one has to be determine the locations where a set of facilities will be installed where the vehicles can recharge or replace their batteries so they can finish their routes. This is a combination of two others well known optimization problems, the facility location and vehicle routing problems. Due to their classification as a NP-Hard problem, the ELRP is also in this category and there is no known algorithm able to solve it in a polynomial time.

Our goal is to propose an algorithm for the Multi-Depot Electric Vehicle Location-Routing Problem with Time Windows, Battery Swapping and Partial Recharging and also apply our algorithm to large-sized real world data. This paper is organized as follows: in Section 2.2 we present a brief review on the literature related to electric vehicle infrastructures; in Section 2.3 we present the problem definition and a mathematical model for it; in Section 2.4 we present the developed algorithm; in Section 2.5 we present the test instances elaborated for the experiments with the model and algorithms and we also show the results obtained with the experiments; in Section 2.6 we discuss the results and present some insights for future works.

2.2 Literature review

An electric vehicle infrastructure can be composed by a range of elements going from battery recharging stations (BRS) to special road lanes that allow cars to have their batteries charged wirelessly while driving. However, most of the studies consider either the use of battery swap stations (BSS), BRS or a combination of both. A slightly different approach was made by Cui, Zhao and Zhang (2018). They considered a special type of BRS that is placed in the truck body, so they can move the station to another place according to the daily traffic flow. This vehicle is called mobile charging vehicle (MCV) and it is requested by customers via a mobile app and must be drove to the scheduled place. The MCV can also support multiple types of charges. The authors present a mathematical formulation for the problem based on the single-depot ELRP. The objective is to minimize the total travelled distance and determine the vehicles' route, the MCV's allocation and the type of charger in each station; while meeting the time-windows, battery charge and vehicle capacity constraints.

Li-Ying and Yuan-Bin (2015) elaborate a mixed integer linear programming model and an algorithm for the Multiple Charging Station Location-Routing Problem with Time Window of Electric Vehicle (EV-MCS-LRPTW). Besides the usual constraints and features of the ELRP like time windows, vehicle battery and vehicle loading capacities constraints, they also consider four types of charging stations: slow charging station (SCS), fast charging station (FCS), super-fast charging station (SFCS), and the BSS. The model's objective function is to minimize the total cost including the cost of siting stations, the cost of electricity to recharge batteries and the drivers wage. The designed algorithm is an Adaptive Variable Neighborhood Search mixed with the Tabu Search algorithm. The results show that the proposed algorithm can find near optimal solutions in the smaller sets of instances and provide convincing results in moderate run time on the largest sets. As future works, they pointed out to extend the problem to multiple depots, to consider a mixed fleet of electric and internal combustion vehicles and also to consider public charging stations.

Schiffer and Walther (2017) define a version of the ELRP in which time windows and partial recharging are considered. Time windows constraints are very common in practical applications and partial recharging allow the electric vehicle to use service time to recharge battery, increasing its autonomy. The authors present a novel mixed integer programming model called Electrical Location-Routing Problem with Time Windows and Partial Recharging (ELRP-TWPR). As suggestion for future works the authors highlight the implementation of heuristic solution method in order to solve large instances for real world problem, the application of the proposed model in practical case studies and extend the model for heterogeneous or mixed fleet.

A mixed integer programming model for the ELRP with simultaneously BSS and BRS is presented by Paz, Granada-Echeverri and Escobar (2018). The authors present, in fact, three models of which two are for the BSS and BRS individually and a third one for BSS and BRS mixed. The model's objective function is to minimize the total traveled distance. In their methodology they use a set of dummy nodes representing duplicated stations, so they can be visited multiple times, being one extra visit per dummy node set. As future works they suggested the design of solutions strategies for large-scale instances and application on real case data.

2.3 Problem definition

The problem is a variant of the ELRP called the Multi-Depot Electric Vehicle Location-Routing Problem with Time Windows, Battery Swapping and Partial Recharging and is defined as follow. A set of customers, each one with time window and demand parameters, must have their demand supplied by an electric vehicle. A set of vehicles must depart from a depot, perform a route delivering goods and return to the same initial depot. The vehicle has a limited autonomy based on its battery capacity and to address this problem two measures can be taken: (i) use the service time to perform a recharge in the customer's BRS or (ii) go to a BSS and have its battery swapped for a fully charged one. When at the customer, the vehicle can use the service time to give its battery a charge but shouldn't stay longer than that. Also, the places where the depots will be sited and the amount of it must be decided. To address the problem of combining a short-term and long-term problem we used a common approach for location-routing problems, that consists in amortizing the installation costs in a daily base, based on the expected use duration of the facility. For example, if the depot siting cost is one million dollars and it is expected to be used for ten years, the amortized cost will be $273.97, this represents the daily cost of the depot.

The goal is to determine where to open the depots and sit battery swap stations, the routes the vehicles should travel delivering goods and determine a recharge plan by defining when and where the vehicle has to recharge or swap the battery; while minimizing the total cost composed by the BSS and BRS installation cost, the vehicle cost, the drivers wage, depot siting cost and energy cost.

2.3.1 Mathematical model

We used the linear programming model presented by Paz, Granada-Echeverri and Escobar (2018) as a base to our research, since they have already created a formulation that incorporate all characteristics we needed. However, we did some modifications, because the original model's objective function was to minimize the total travelled distance and we want to minimize the operational cost. To do so, we had to add a couple more decision variables and implement a few more constraints. The model is presented below with all the modifications done. Also, the original model allowed vehicles to recharge in BRS more time then the service time and allowed the vehicles to revisit BRS vertexes. We believe that in practical terms, this is not a viable option because the customers who provide BRS may have others goods to receive, hence the BRS might be occupied. So we did this modification, not allowing vehicles to revisit BRS and to recharge only during service time. The model is presented below:

Sets:

UD_0, UD_1	Vertices of depots for the dispatch and arrival of vehicles.
C	Customer vertices.
R	Special vertices where BSS can be sited.
SK_i	Dummy vertices associated with a vertex i.
Union sets	$UD = UD_0 \cup UD_1, V = C \cup R \cup SK_i, S = V \cup UD$ $V_0 = V \cup UD_0, V_1 = V \cup UD_1, V_{01} = V \cup UD_0, C_0 = C \cup UD_0$

Parameters:

id_i	Depot identification number, which is the same for both its dispatch and arrival vertices, $i \in UD$.
di_{ij}	Minimum distance between $i \in V_0$ and $j \in V_1$.
td_{ij}	Travel time between $i \in V_0$ and $j \in V_1$, $td_{ij} = di_{ij}/v$, v is the vehicle speed.
s_i	Service time required at vertex $i \in C$.
e_i, l_i	Earliest and latest time, respectively, of the time window of vertex $i \in V_{01}$.
p_i	Demand of vertex $i \in V_0$.
D	Freight capacity of the vehicle.
Q	Battery capacity.
ct	Battery swapping time.
c	Consumption rate of energy per distance unit.
O	Maximum number of recharging points to locate.
M	Very large positive number.
r	Energy charging rate per unit of time.
dc, sc	Cost to site a single depot and a single BSS, respectively.
v	Vehicle speed.
vc	Vehicle cost.
dw	Driver's wage by distance unit driven.
rec, sec	Energy cost in BRS and BSS, respectively.

Decision variables:

x_{ij}	Binary, equal to 1 if a vehicle moves from $i \in V_0$ to $j \in V_1 \| i \neq j$, 0 otherwise.
y_i	Binary, equal to 1 if at vertex $i \in R$ a BSS is located, 0 otherwise.
z_i	Binary, equal to 1 if at vertex $i \in UD_0$ a depot is located, 0 otherwise.
t_i	Moment of time in which a vehicle arrives at the vertex $i \in V_{01}$.
d_i	Amount of freight left when the vehicle arrives at vertex $i \in V_{01}$.
q_i	Amount of energy left in the battery when the vehicle arrives at vertex $i \in V_{01}$.

u_i	Identification number of the depot from which vehicle serving $i \in V_1$ departs.
w_i	Amount of energy to be charged at vertex $i \in C$
v_i	Amount of energy to be charged at vertex $i \in R \cup SK_{h \in R}$

$$\min \sum_{i \in UD_0} z_i \cdot dc + \sum_{i \in R} y_i \cdot sc + \sum_{i \in UD_0} \sum_{j \in V_1 | i \neq j} x_{ij} \cdot vc + \sum_{i \in V_0} \sum_{j \in V_1 | i \neq j} x_{ij} \cdot di_{ij} \cdot dw + \sum_{i \in C \cup SK_c} rec \cdot w_i + \sum_{i \in R} sec \cdot v_i \tag{2.1}$$

s. t.

$$\sum_{j \in V_{+1} | i \neq j} x_{ij} = 1 \qquad \forall i \in C \tag{2.2}$$

$$\sum_{j \in V_{+1} | i \neq j} x_{ij} \leq 1 \qquad \forall i \in \{R \cup S\} \tag{2.3}$$

$$\sum_{i \in V_{+1} | i \neq j} x_{ji} = \sum_{i \in V_0 | i \neq j} x_{ij} \qquad \forall j \in V \tag{2.4}$$

$$\sum_{i \in \{C \cup R\}} y_i \leq O \qquad \forall i \in R \tag{2.5}$$

$$\sum_{j \in V_0 | i \neq j} x_{ji} \leq M \cdot y_i \qquad \forall i \in R \tag{2.6}$$

$$\sum_{j \in V_0 | h \neq j} x_{jh} \leq M \cdot y_i \qquad \forall i \in R, h \in SK_i \tag{2.7}$$

$$t_j \geq t_i + (td_{ij} + s_i) \cdot x_{ij} - M \cdot (1 - x_{ij}) \qquad \forall i \in C_0, j \in V_1 | i \neq j \tag{2.8}$$

$$t_j \geq t_i + td_{ij} \cdot x_{ij} + ct \cdot x_{ij} - M \cdot (1 - x_{ij}) \forall i \in \{R \cup SK_{h \in R}\}, j \in V_1 | i \neq j \tag{2.9}$$

$$t_j \geq t_i + td_{ij} \cdot x_{ij} + w_i / r - M \cdot (1 - x_{ij}) \quad \forall i \in \{C \cup SK_{h \in C}\}, j \in V_1 | i \neq j \tag{2.10}$$

$$e_i \leq t_i \leq l_i \qquad \forall i \in V_{01} \tag{2.11}$$

$$q_j \leq Q - c \cdot di_{ij} \cdot x_{ij} + M \cdot (1 - x_{ij}) \qquad \forall i \in \{R \cup SK_{h \in R}\}, j \in V_1 | i \neq j \tag{2.12}$$

$$q_j \leq q_i - c \cdot di_{ij} \cdot x_{ij} + M \cdot (1 - x_{ij}) \qquad \forall i \in UD_0, j \in V_1 | i \neq j \tag{2.13}$$

$$q_j \leq q_i + w_i - c \cdot di_{ij} \cdot x_{ij} + M \cdot (1 - x_{ij}) \forall i \in \{C \cup SK_{h \in C}\}, j \in V_1 | i \neq j \tag{2.14}$$

$$q_i + w_i \leq Q \qquad \forall i \in \{C \cup SK_{h \in C}\} \tag{2.15}$$

$$q_i \leq Q \qquad \forall i \in UD_0 \tag{2.16}$$

$$d_j \leq d_i - p_i \cdot x_{ij} + D \cdot (1 - x_{ij}) \qquad \forall i \in V_0, j \in V_1 | i \neq j \tag{2.17}$$

$$d_i \leq D \qquad \forall i \in UD_0 \tag{2.18}$$

$$u_j \geq x_{ij} \cdot id_i - M \cdot (1 - x_{ij}) \qquad \forall i \in UD_0, j \in V \tag{2.19}$$

$$u_j \leq x_{ij} \cdot id_i + M \cdot (1 - x_{ij}) \qquad \forall i \in UD_0, j \in V \tag{2.20}$$

$$u_j \geq u_i - M \cdot (1 - x_{ij}) \qquad \forall i \in V, j \in V_1 | i \neq j \tag{2.21}$$

$$u_j \leq u_i + M \cdot (1 - x_{ij}) \qquad \forall i \in V, j \in V_1 | i \neq j \tag{2.22}$$

$$u_j = id_j \qquad \forall j \in UD_1 \tag{2.23}$$

$$w_i \leq r \cdot s_i \cdot y_i \qquad \forall i \in C \tag{2.24}$$

$$w_h \leq r \cdot s_i \cdot y_i \qquad \forall i \in C, h \in SK_i \tag{2.25}$$

$$x_{ij} = 0 \qquad \forall i \in V \setminus \{S\}, j \in SK_i | i \neq j \tag{2.26}$$

$$x_{ji} = 0 \qquad \forall j \in V \setminus \{S\}, i \in SK_j | i \neq j \tag{2.27}$$

$$\sum_{j \in V1} x_{ij} \leq |V_1| \cdot z_i \qquad \forall i \in UD_0 \tag{2.28}$$

$$v_i = Q \cdot \sum_{j \in V_1} x_{ij} - q_i \cdot \sum_{j \in V_1} x_{ij} \qquad \forall i \in R \cup SK_R \tag{2.29}$$

$$x_{ij} \in \{0;1\} \qquad \forall i \in V_0, j \in V_1 | i \neq j \tag{2.30}$$

$$y_i \in \{0;1\} \qquad \forall i \in R \tag{2.31}$$

$$z_i \in \{0;1\} \qquad \forall i \in UD_0 \tag{2.32}$$

$$t_i, d_i, q_i \in \mathbb{R}^+ \qquad \forall i \in V_{01} \tag{2.33}$$

$$u_i \in \mathbb{R}^+ \qquad \forall i \in V_1 \tag{2.34}$$

$$w_i \in \mathbb{R}^+ \qquad \forall i \in C \tag{2.35}$$

$$v_i \in \mathbb{R}^+ \qquad \forall i \in R \cup SK_{h \in R} \tag{2.36}$$

The Objective Function 2.1 represents the total cost of the electric vehicle infrastructure and is divided in 6 parcels: depot installation cost, BSS installation cost, vehicle cost, drivers wage, energy cost in the BRS and BSS. The Constraints 2.2, 2.3 and 2.4 impose the continuity of the routes. Constraints 2.5 imposes a limit on the number of BSS to be allocated. Constraints 2.6 and 2.7 ensure that a route will only use sited BSS. Constraints 2.8, 2.9, 2.10 and 2.11 guarantee the time windows being respected. Constraints 2.12, 2.13, 2.14, 2.15 and 2.16 control the vehicles' battery level. Constraints 2.17 and 2.18 control the vehicle load. Constraints 2.19, 2.20, 2.21, 2.22 and 2.23 impose that each route start and finish in the same depot. Constraints 2.24 and 2.25 guarantee that the vehicle will be partially charged during the service time. Constraints 2.26 and 2.27 block the vehicle to move from a node to a dummy node associated to it. Constraints 2.28 compute the amount of depots used. Constraints 2.29 control over the amount of battery that will be recharged in the BSS after the vehicle swap batteries, this constraint set is quadratic but can be easily linearized. Constraints 2.30, 2.31, 2.32, 2.33, 2.34, 2.35 and 2.36 ensure the decision variables' integrity.

2.4 Algorithms

In order to address our problem to medium and large sized instances we developed a heuristic based on the Simulated Annealing (SA) algorithm with a local search guided by a Greedy Randomized Adaptive Search (GRASP) and Variable Neighborhood Search (VNS) algorithms. We now describe the solution representation, the neighborhood structures and the algorithm itself.

2.4.1 Solution representation

Two solution representations are used in our proposed algorithm. First, the solution is represented by a permutation of customers and then, in local search level, the solution is represented in a more complete way, by having all customers designated to routes, depots opened, BSS sited and recharging plan computed. We refer by this representation as the complete solution representation, and to the first one as permutation representation. Figure 2 illustrates the customers permutation {11, 10, 5, 8, 6, 7, 9} mapped into the complete solution where two routes are defined. The vertex 0 and 12 correspond to the depot, where 0 is the departure vertex and 12 is the arrival vertex; and vertexes 1, 2 and 3 are the BSSs. Each component in this representation have a set of parameters composed by: vehicle battery level, vehicle load, arrival time and quantity of energy recharged.

0	11	2	10	5	1	8	6	12
0	7	3	9	12				

Figure 2 – The permutation {11, 10, 5, 8, 6, 7, 9} transformed into the complete solution.

The customers permutation is mapped into the complete solution by a greed algorithm, divided in three steps. First, we build what we call pseudo routes, they are routes only with customers where no BSS nor recharging plan are set. To do so, we create the first empty route and the customers are sequentially inserted until the vehicle capacity or time windows constraints are violated. We considered time windows constraints at this point just to further minimize the number of time windows violated to be addressed in further steps. If there is any customers not placed, we repeat this procedure with a new empty route and the procedure goes until all customers have a designated route. During the pseudo route generation, in order to be able to compute the parameters; such as arrival time, we choose a temporary depot as being the closest one from the first node that will be inserted. The next two procedures are responsible to optimize the depots sited (*addDepots*) and to generate the recharging plan by siting BSSs and defining where the vehicle must recharge or swap battery (*addStations*).

The *addDepots* procedure is responsible for, with all routes pre-generated, to determine a better depot combination by considering the first and last customer of each route. The procedure works in a greed manner where sum of deviation for each depot is computed from the route's first and last customers and chose the depots with the minimum deviations sum. At this point, at maximum, one depot is chosen for the entire solution, this depot will supply all the customer, but since we don't have the recharging plan, we don't know yet if the chosen depot will be feasible for each route, this problem is addressed further.

The *addStations* procedure, ilustrated by the Algorithm 1, is responsible for the recharging plan. To do so, the procedure computes sequentially all route's parameters (arrival time, battery level, vehicle load, etc), until it finds an unfeasibility point that can be caused by time window or battery level. At this stage the vehicle uses every BRS available to recharge the battery in a greed manner, once reaching a BSS we get the the amount of battery remaining and subtract from previous BRS recharging. Unfeasibilities due to time windows constraints are treated by removing the customer from the current route and pushing it to the end of the next route; if the current route is the last, a new route is created to fit the customer. If the unfeasibility is caused by the battery level we have to determine where to install a BSS so the vehicle can keep travelling. To chose where to install the BSS, the procedure trace back the route looking for the first viable BSS, this search is done by looking to every arc and fitting the minimal detour BSS until reaching a previous sited BSS or the depot. This procedure can be implemented in a greed manner where is chosen the first viable interval with the minimum deviation BSS, or in a semi-greed manner, creating a candidate list of intervals and randomly picking one to receive the BSS.

Once the permutation mapping algorithm is finished, we have a solution with all parameters and recharging plan computed. This is the complete representation that is further used in a local search algorithm.

Algorithme 1 : addStations procedure

```
Input  : A set of routes $RT$
Output : The complete representation (a set of routes $RT$ with the recharge plan)
for route r in RT do
    for vertex v in r do
        Compute v parameters;
        if v is unfeasible to time windows then
            Remove v from r;
            Insert v in $r+1$;
        if v is unfeasible to battery level then
            Choose a route interval to receive a BSS;
            Insert BSS with minimal detour in the interval;
            Set the inserted BSS as the current vertex;
```

2.4.2 Neighborhood structures

As we used two solution representations, we developed two sets of neighborhood structures. One for the permutation representation, used in the SA algorithm and another for the routes representation, used by the local search. Next we describe the structures used.

2.4.3 Permutation neighborhood structures

Two structures are used in the permutation domain, they are the Partial Inversion and the Customer Swap. The Partial Inversion takes part of the permutation and invert its sequence, its implementation is exactly to the classic 2opt neighborhood. The Customer Swap just swap the position of two customers in the permutation.

2.4.4 Complete solution neighborhood structures

In the complete solution domain, 5 structures are used: 2opt, Route Split, Route Junction, Shift Customer and BSS Replacement. Those neighborhood structures, excluding the BSS Replacement, are a subset of structures used by Hof, Schneider and Goeke (2017) to solve a similar problem to electric vehicle infrastructures, we just added the BSS Replacement to fulfil the multi-depot characteristic in our current problem. The 2opt is a neighborhood structure widely used in many routing problem and consists in swap two arcs in the route, making a route segment inverted. The Route Split structure splits a route in two smaller ones, while the Route Junction structure takes two routes and combine in one, if feasible. Shift Customer simply shift, forward or backward, a customer by a given number of positions inside the route. The BSS Replacement structure selects a BSS being used in the solution and replaces it for another BSS that is also already being used.

2.4.5 Local search

The local search is conducted by a GRASP algorithm and is based on the complete representation. In order to generate the greed randomised solutions, we use a slightly different version of the permutation mapping algorithm, where we modify the *addStations* procedure to add the battery swap stations based on a restricted list of candidates. The restricted list of candidates is generated during the step where the algorithm trace back the route to find a proper place the install a BSS. Instead of choosing the first viable place to sit a BSS, the list is generated by adding all intervals where the leaving vertex has a battery level up to a threshold of 30 % of total battery level left, and then a random member of the list is chosen and inserted in the route. By doing so, we allow the vehicle to travel to a BSS a little before it would by the greed criteria and the solutions become more diverse.

The GRASP's local search is conducted by a Basic Variable Neighborhood Search Algorithm. This step is crucial, due to the limitations on the permutation mapping algorithm, as it is not able to generate every solution in the solution space. The VNS also deal with the complete solution representation and is composed by a shake stage and a local search procedure. In the shake stage, the solution suffers a modification in order to escape of the local optima and it has various levels of intensity that are defined by the use of different neighborhood structures. All structures defined in the Section 2.4.4 are used in this step, in a random order. The local search is conducted by a Hill-Descent algorithm with fist improvement.

2.4.6 Metaheuristic

The proposed algorithm is based on the Simulated Annealing metaheuristic. The core element of this algorithm, is the allowance of movement to worsen solutions and, by doing so, the algorithm is capable to escape of local optima solutions and have more chances of approximation of the global optima. In order to control the algorithm convergence, the SA set a temperature variable that as the algorithm runs, decreases and worsening solutions will be accepted according to a probability: the lower is the temperature, the lower is this probability.

The initial solution is generated by the permutation mapping algorithm that is applied to a customers permutation sorted by the due date in ascending order. Next, the algorithm continues iteratively as follow: a neighborhood solution is generated with the Partial Inversion neighborhood structure, a local search is done and the new solution is evaluated and accepted or not according to the current temperature. In the local search step, two algorithm are used, depending on the current temperature level. The option for this strategy is due to the higher GRASP algorithm complexity, that makes this local search be way costly, and also helps to avoid a premature algorithm convergence. At high levels, when the solution are still subject to many worsening movements, a simple Hill-Descent search is used with the Customers Swap structure. At low levels, when the algorithm is approaching the end, the GRASP algorithm is used as local search.

2.5 Experiments

In this section, result are shown for the mathematical model and the proposed algorithm. Also, in order to demonstrate the effectiveness of our local search approach, we show the results for the SA executing only the Hill-Descent algorithm. The test instances and how they were generated is also shown. The experiments were executed in a machine equipped with a processor Intel(R) Core(TM) i7-7700HQ and 8GB RAM. The model was implemented using the solver Gurobi 9.0 and the maximum runtime was set to 7200 seconds, in which the solver finish it execution if the gap 0% was not reached until the maximum runtime. The algorithm was implemented in C++ using the Microsoft Visual Studio compiler and compiled in release mode. Even though the model have one quadratic set of constraints, Gurobi was able so solve it without the linearization. The algorithm was executed only once for each instance.

2.5.1 Instances

The instance set introduced by Demir, Bektas and Laporte (2012) for the Pollution-Routing Problem is used as a base to ours. This instance set is composed by a set of cities from the United Kingdom, each on with a given demand, due date, service time and ready time. In order for them to met all the requirements to be used with our problem, we did some adaptations, such as definition of the vertexes that can be used to install the battery swap stations, definition of new depot vertexes and definition of parameters related to electric vehicles, BRS and BSS. The instances also contain a distance matrix with real world distances the vehicle load capacity and speed parameters. Since the original instance set contains more then 170 instances, we decide to use just a few of them and we selected 3 instances of each size.

To define the set of vertexes candidates to have a BSS, we developed a maximum coverage location problem mathematical model and the electric vehicles, BSS and BRS parameters values are the same used by Li-Ying and Yuan-Bin (2015). Our goal with the model was to obtain a more spread out distribution of vertexes to avoid some areas to became isolated, due to a long distance between them and the nearest BSS.

2.5.2 Results

The Table 1 display the results obtained by the solver and the algorithms. Column ‘cost’ display the objective function results in defined by the total cost of the electric vehicle infrastructure, the column ‘time’ display the total runtime in seconds and the column ‘gap’ display the final gap found by the solver. The SA column refer to the SA algorithm without the

GRASP local search. Cells with '-' means that the model was not able to finding a solution for the instance.

Table 1 – Results for the model and algorithms execution.

	Model			SA		SA + GRASP	
Instances	cost	gap (%)	time (S)	cost	time (S)	cost	time (S)
UK10_01	6373.1	0.00	1053	6383.0	0	6373.1	33
UK10_11	6742.0	0.00	2	6790.9	0	6746.1	3
UK10_20	6339.0	93.75	7200	6339.0	0	6339.0	8
UK15_01	6563.2	0.81	7200	6747.5	0	6613.9	171
UK15_11	6528.2	93.98	7200	6664.6	0	6530.6	171
UK15_20	6365.5	99.25	7200	6375.3	1	6365.5	109
UK20_01	6581.2	97.04	7200	6847.6	0	6711.8	302
UK20_11	6594.9	96.80	7200	6802.0	0	6639.5	188
UK20_20	6565.6	98.38	7200	6703.7	1	6629.3	347
UK25_01	6566.8	98.76	7200	6792.1	1	6577.2	1062
UK25_11	6462.7	98.71	7200	6518.4	0	6478.1	488
UK25_20	-	-	7200	6498.0	1	6471.5	912
UK50_01	13408.4	98.84	7200	7662.1	8	6987.9	6503
UK50_11	-	-	7200	7687.7	8	7147.5	7201
UK50_20	-	-	7200	7757.8	13	7265.5	5437
UK75_01	-	-	7200	9242.2	33	8191.8	7201
UK75_11	-	-	7200	7610.9	34	7197.0	7201
UK75_20	-	-	7200	8709.7	38	7998.1	7201
UK100_01	-	-	7200	10051.6	95	8790.5	7201
UK100_11	-	-	7200	9913.5	131	8512.7	7201
UK100_20	-	-	7200	10684.1	104	8882.0	7201
UK150_01	-	-	7200	10509.3	431	9204.2	7201
UK150_11	-	-	7200	12379.6	380	10332.5	7201
UK150_20	-	-	7200	12566.8	382	10415.9	7201
UK200_01	-	-	7200	12512.3	533	10239.4	7201
UK200_11	-	-	7200	12749.0	454	10075.1	7201
UK200_20	-	-	7200	12956.9	467	11376.9	7201

As we analyze the results in Table 1, we can notice that the solver was able to find only one optimal solution within the time limit set and for most of the instances with 25 customers or more, no solution was found. The SA was able to find one optimal solution, in the instance UK10_01 and match the objective function in the instances UK10_20 and UK15_20. For all instances the solver was not able to find a solution, the SA was able to do so. Comparing results of the SA with the GRASP local search and the SA with the Hill-Descent local search, the benefits of using the second solution representation in the local search is notable by an improvement in the objective function value. Also, it is notable the increase in the final runtime by using another metaheuristic in the local search step. However, we believe the runtime of two hours is reasonable due to the electric vehicle infrastructures long term characteristics.

2.6 Conclusions

In this paper, we presented a novel algorithm for the Multi-Depot Electric Location-Routing Problem with Time Windows, Battery Swapping and Partial Recharging, that was first introduced by Paz, Granada-Echeverri and Escobar (2018). The solution is represented by a permutation of customers that represents the order that each one must be added in the solution. Also, we defined a second solution representation that is composed by the complete solution, that is the permutation after the processing, in which allow us to perform a more precise local search and improve our results. The proposed algorithm was based on the Simulated Annealing metaheuristic and two local search algorithms were used. At higher temperatures a simple Hill-Descent local search is conducted to optimize the runtime and to avoid premature convergence and, at lower temperature, a GRASP algorithm conduct the local search. Also, in the GRASP algorithm, A VNS is used to perform its local search using the complete solution representation to address the permutation's limitation that is not able to represent the entire solution space.

In the result section, we showed the results obtained by the execution of the model, implemented with the solver Gurobi, and the SA algorithm in two variants. The proposed SA algorithm with GRASP local search has been proven to be better then the SA with the simple hill-descent local search in terms of solution cost found and better then the solver because the solver was not able to find solutions in the large-sized instances. As future works, we highlight the strengthen of the formulation, in order to improve the gap and the use of different algorithms to perform the SA local search, in order to improve computational time. Also is we highlight the exploration of other ways to deal with the short-term versus long-term characteristic of location-routing problem, rather then amortizing costs.

3 STRATEGIES FOR ELECTRIC LOCATION-ROUTING PROBLEMS CONSIDERING SHORT AND LONG TERM HORIZON

3.1 Introduction

The concerns on the global warming effect in our planet has risen the attention of many people around the globe and has being an important subject to many heads of state, even generating some conflicts in diplomatic relationships. According to The Guardian (HARVEYN, 2020), during the Climate Ambition Summit 2020, the United Nations secretary general, António Guterres, urged for governments around the world to declare climate emergency due to recent analysis on climate data collected over the last years. As stated by the World Meteorological Organization (WMO) (WMO, 2019), the global average temperature in 2019 was 1.1 degree Celsius above the pre-industrial period - the second highest since the record began - and, such worries rises from the last Intergovernmental Panel on Climate Change (IPCC) report (ROGELJ et al., 2018) that discuss the consequences of an increase of 1.5 degree Celsius in the global average temperature above the pre-industrial era, in both environmental and economic aspects. Among many problems here we cite a few: the decrease of pollination of crops and plants due to insects' lost of habitat, the change in weather events patterns, making them more dangerous to humans and other species, and the endangerment of over 6 million people that live in coastal areas that are vulnerable to the sea-level rise at the given temperature increase.

The IPCC report also discusses how can humanity mitigate the path to the 1.5 degree Celsius increase in the context of sustainable development. One of its highlights is the transportation sector's contribution in the emission of Greenhouse Gases (GHGs) that, in 2014, was responsible for 23% of global energy-related CO_2 emissions.

In Europe, the transportation sector was responsible for 26% of the total amount of its CO_2 emissions in the continent, according to the Annual European Union greenhouse gas inventory (EEA, 2020), a 6% increase relatively to 2014, being the road transportation responsible for the biggest share in the GHGs emissions. India's transportation sector is the third most GHGs emitter in the country (SINGH; MISHRA; BANERJEE, 2019), and due to the country's huge economical growth, its CO_2 emissions has an exponential growth rate. From 2000 to 2012, the growth rate was 6.9% and internal combustion engine (ICE) vehicles running on gasoline and diesel had the major role in this increase, mostly due to the increase in the use of this type of vehicle. (ZHAO et al., 2019), analyze China's GHGs emission and shows that electric vehicle (EV) deployment has a better long-term de-carbonization effect, while fuel economy regulations shows a better result in the short term. It is concluded that by adopting a deployment plan of electric vehicles together with fuel economy regulations, by the year 2026, China could reach its peak of gases emissions, 4 years earlier then what was agreed during the 2015 United Nations Climate Change Conference, where China government agreed to achieve its emission peak of CO_2 before the year 2030. The use of electric vehicle is not the sole solution for this huge climate problem that the world is facing, however it is one of the many measures required to reverse the pathway to the 1.5 degrees Celsius increase.

Changing the engine profile in vehicle fleets is not an easy task. Due to the use of internal batteries to store energy, EVs have some critical differences compared to ICE vehicles that makes this transition much more difficult. EVs require a longer time to recharge the batteries reducing drastically its range, while, in contrast, ICE vehicles require no more than a few minutes to go from empty to full gas tank, extending its range quickly. Due to the limitations in battery technology currently used in EVs, its autonomy has limitations that directly impact its range. While the fastest recharge method, the super charger power outlet, can provide up to 80% of battery capacity in 40 minutes, if one is available, the most common power outlet can take many hours to provide a full battery charge. This makes the vehicle's range the second most important factor that individuals consider when purchasing an electric vehicle, after the price range (CECERE; CORROCHER; GUERZONI, 2018).

Logistics companies are a lot more sensible to this problem since their activities are very time-sensitive and waiting for the vehicle's battery to recharge may cause issues in their delivery performance. Waiting too much for the battery to recharge, can potentially make companies need more vehicles to be able to fulfill all the customers demand, or in some cases make even impossible for the company reach a determined customer in a day. A different approach to the EVs battery recharging problem, that is not exclusive to, but very helpful in the matter of logistic companies, is the battery swapping. This method allows the driver to head the vehicle to a special facility, named battery swap station (BSS), where the battery can be quickly replaced by a fully charged one. This method is getting much attention in China where some companies already use it. A company called NIO has 141 BSSs installed across the country and claims to have made more then 700000 battery swaps (TIANYU, 2020).

Despite the difficulties, companies are trying to incorporate cleaner transportation in their fleets. Given the climate urgency, they are either trying to fit government laws and make use of incentive polices or trying to innovate in order to catch the public attention. Companies such as DHL have already announced back in 2014 that they would start to incorporate EVs in their fleets (DHL, 2019) and in 2018 they even started to operate with electric vehicles in the state of Rio de Janeiro, Brazil (DHL, 2018). To make the adoption of EVs easier for the general public and companies, the presence of a reliable and well built infrastructure network that can provide the services necessary for the vehicle's operation is a decisive step and optimization techniques can be used to design them in a more effective way and with lower costs.

The ELRP is a combinatorial optimization problem in which a fleet of electric vehicles must have their routes defined to serve a set of customers alongside their travel and the location to install a set of facilities must be chosen, where the vehicles can be recharged or have its battery replaced so they can finish their delivery routes. This is a combination of two others well known optimization problem, the facility location and vehicle routing problems. Due to their classification as a NP-Hard problem (ARCHETTI et al., 2011; KARIV; HAKIMI, 1979), the ELRP is also in this category and there is no known algorithm able to solve it in a polynomial time. Many variants have been proposed, for example: the possibility of partial charging at BRS (SCHIFFER; WALTHER, 2017); combination of BRSs and BSSs (PAZ; GRANADA-ECHEVERRI; ESCOBAR, 2018); and stations with different charging speed (LI-YING; YUAN-BIN, 2015).

In this work we study the Multi-Depot Electric Location-Routing Problem with Time Windows, Battery Swapping and Partial Recharging (PAZ; GRANADA-ECHEVERRI; ESCOBAR, 2018; CORRÊA; SANTOS, 2020), for the design of EVs infrastructures that incorporate the well established BRSs and the innovating BSSs in an unified network for logistic companies. We extended the previous works by developing a new heuristic algorithm, due to the ELRP's NP-Hard classification, to solve the problem for large-sized instances and address the two sub-problems simultaneously, one with short-term and the other with long-term characteristics to further optimize electric vehicle infrastructures. It is a step to solve an issue often found in the location-routing problem literature, as in most of the previous works the location component is solved in short-term horizon in order to optimize the routing component, but in real-life applications the solution of the location component is to be used in a long-term horizon, for several short-term routing problems.

The remainder of this work is organized as follows: in Section 3.2 we present a brief review on the literature related to electric vehicle infrastructures; in Section 3.3 we present a formal definition of the problem; in Sections 3.4 and 3.5 we present a heuristic algorithm and our methodology to improve solutions with a preprocessing procedure; in Section 3.6 we present the test instances elaborated for the experiments and the results obtained with the experiments; and finally, in Section 3.7 we discuss the results and present some insights for future works.

3.2 Literature review

An electric vehicle infrastructure can be composed by a range of elements going from battery recharging stations (BRS) to special road lanes that allow cars to have their batteries charged wirelessly while driving. However, most of the studies consider either the use of battery swap stations (BSS), BRS or a combination of both. A slightly different approach was made by Cui, Zhao and Zhang (2018). They considered a special type of BRS that is placed in the truck body, so they can move the station to another place according to the daily traffic flow. This vehicle is called mobile charging vehicle (MCV) and it is requested by customers via a mobile app and must be drove to the scheduled place. The MCV can also support multiple types of charges. The authors present a mathematical formulation of the problem based on the single-depot ELRP. The objective is to minimize the total travelled distance and determine the vehicles' route, the MCV's allocation, and the type of charger in each station; while meeting the time-windows, battery charge and vehicle capacity constraints.

(LI-YING; YUAN-BIN, 2015) elaborate a mixed integer programming model and an algorithm for the Multiple Charging Station Location-Routing Problem with Time Window of Electric Vehicle (EV-MCS-LRPTW). Besides the usual constraints and features of the ELRP like time windows, vehicle battery and vehicle loading capacity constraints, they also consider four types of charging stations: slow charging station (SCS), fast charging station (FCS), super-fast charging station (SFCS), and the BSS. The model's objective function is to minimize the total cost including the cost of siting stations, the cost of electricity to recharge batteries and the drivers wage. The designed algorithm is an Adaptive Variable Neighborhood Search mixed with the Tabu Search algorithm. It was implemented on Java with a single core code and the model implemented on the CPLEX solver. Experiments were conducted with instances for the Pollution-Routing Problem (PRP) (DEMIR; BEKTAS; LAPORTE, 2012), adapted for the EV-MCS-LRPTW, a total of nine sets of instances with different sizes. The results show that the proposed algorithm can find near optimal solutions in the smaller sets of instances and provide convincing results in moderate run time on the largest sets. As future work, they pointed out to extend the problem to multiple depots, to consider a mixed fleet of electric and internal combustion vehicles and also to consider public charging stations.

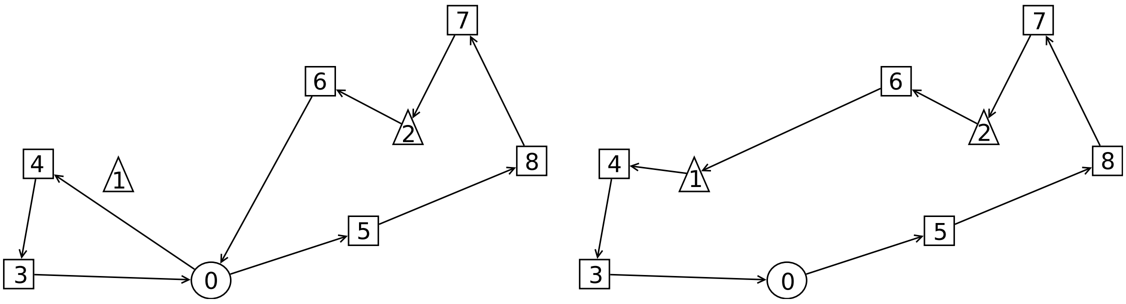
In (SCHIFFER; WALTHER, 2017), is defined a more complete version of the ELRP in which time windows and partial recharging are considered. Time windows constraints are very common in practical applications and partial recharging allow the electric vehicle to use service time to recharge battery, increasing its autonomy. The authors present a novel mixed integer programming model called Electrical Location-Routing Problem with Time Windows and Partial Recharging (ELRP-TWPR). They also provide 5 different objective functions to meet various requirements, e.g. minimizing distance traveled, number of vehicles used, number of charging stations sited, number of vehicles plus number of recharging stations (convex combination) and total costs. They conducted experiments with new instances created based on instances from the literature and compared the solutions gotten utilizing all of the 5 objective functions proposed. As suggestion for future works the it is highlighted the implementation of heuristic solution method in order to solve large instances for real world problems, the application of the proposed model in practical case studies and extend the model for heterogeneous or mixed fleet.

A variant of the ELRP called battery swap station location-routing problem with stochastic demands (BSS-EV-LRPSD) is introduced by (ZHANG; CHEN; ZHANG, 2019). The main contribution is the addition of stochastic demands which turn the proposed model more applicable in real life situations. For this problem they propose an algorithm called Hybrid Variable Neighborhood Search (HVNS) which incorporates the Binary Particle Swarm Optimization (BPSO) and a Variable Neighborhood Search (VNS) algorithms. The basic concept behind it is that both BPSO and VNS are used iteratively to solve the BSS location problem and routing planning. They present as well, a Pareto optimality for the BSS location stage. The HVNS is compared with five others algorithm from the literature and its performance is evaluated using adapted test instances from other authors. In general, the HVNS was able to find better solutions then the other algorithms and showed good stability and convergence. As future works that can be done to improve their model, time windows constrains and BSS capacity can be considered to give more applicability to the model. Their work does not consider the possibility of recharging station and the energy consumption and traveling times are constants.

A mixed integer programming model for the ELRP with simultaneously BSS and BRS is presented by (PAZ; GRANADA-ECHEVERRI; ESCOBAR, 2018). The authors presents three models of which two are for the BSS and BRS individually and a third one for BSS and BRS mixed. The model's objective function is to minimize the total traveled distance. The models were solved with CPLEX 12.5 and the experiments limited to a maximum run-time of 8 hours. It is worth to mention the amount of big M constraints in the model, a total of 12 out of 21 constraints have big M, which makes the model less efficient. Some preprocessing was done to improve the computational time. In their methodology they use a set of dummy nodes representing duplicated stations, so they can be visited multiple times, being one extra visit per dummy node set. They suggested as future works, the design of solution strategies for large-scale instances and application on real case data. A step in this direction was made by (CORRÊA; SANTOS, 2020), who proposed a hybrid heuristic for the same problem: permutations of the customers are generated by a Simulated Annealing (SA) heuristic; a Greedy Randomized Adaptive Search Procedure (GRASP) maps each permutation into an array of routes inserting BSS stations by a greedy choice, later improved by a local search conducted by a VNS. The results were compared to the MILP model solved via Gurobi. While the solver was not able to find solution in most instances, the SA found solution in every case and was able to find some global optimal solutions.

3.3 Problem definition

The problem studied here can be divided in two. First, a daily delivery optimization is considered as a variant of the ELRP called the Multi-Depot Electric Location-Routing Problem with Time Windows, Battery Swapping and Partial Recharging (PAZ; GRANADA-ECHEVERRI; ESCOBAR, 2018; CORRÊA; SANTOS, 2020) and is defined as follow. A set of customers, each one with time window and demand parameters, must have their demand supplied by an electric vehicle within its time window. A set of vehicles must depart from the depots, perform a route delivering goods and return to the same initial depot. The vehicle has a limited autonomy based on its battery capacity and to address this problem two measures can be taken: (i) use the service time to perform a recharge in the customer's BRS or (ii) go to a BSS and have its battery swapped for a fully charged one. When at the customer, the vehicle can use the service time to give its battery a charge but should not stay longer than that . Additionally, the locations of the stations to be sited and the amount of depots must be decided. The goal is to site depots, site battery swap stations, define the route of the vehicles for goods delivering and determine a recharge plan by defining when and where the vehicles have to recharge or swap the battery; while minimizing the total cost composed by the BSSs installation cost, the vehicle cost, the



(a) Solution with two routes and one BSS. (b) Solution with one routes and two BSS.

Figure 3 – Two examples of solution in the same instance with different configurations.

drivers wage, depot siting cost and energy cost in BSSs and BRSs.

The second problem is the short and long-term conflict between the facility location and the vehicle routing problems. Considering that a logistic company will serve certain region for a long period of time, the infrastructure optimized by the ELRP considering a single day might not be optimal or not even be usable for other days of delivery. Considering the given scenario the second problem is the long-term optimization of electric vehicle infrastructures according to the one described as the first problem, but routes are still to be decided for each day.

Figure 3 shows two possible configurations of a electric vehicle infrastructure; the depot is represented by the circle, the customers by squares and the BSS candidates by triangles. In Figure 3a only one BSS is sited and two routes are used. In Figure 3b, two BSS are sited and one route is used. Different configurations might be better depending on the customers parameters such as time windows. While the solution with only one BSS may be cheaper if one considers only this set of customer (as BSS installation cost is higher compared to transportation related costs), installing the two BSSs may be more advantageous in a long-term horizon, if many other customers are to be served near the BSS in the left in future days.

3.4 Variable Neighborhood Search

The Variable Neighborhood Search (VNS) (HANSEN; MLADENOVIĆ, 1997) is a metaheuristic widely used to solve optimization problems and was used in this work. It work as follows: starting from an initial solution, the VNS cycles between a solution shake step and a local search procedure until it reaches a stop criteria. It is essential to define a solution representation, a polynomial algorithm capable of generating an initial solution and a set of neighborhood structures to be used to perform movements in the solution.

The solution is represented as an array of routes, in which every route starts in a depot represented by the first element and finishes in the same depot represented by an arrival node in the last position. Figure 4 illustrates the solution representation.

0	5	8	7	2	6	0
0	4	3	0			

Figure 4 – The solution from Figure 3a represented as an array of routes

The VNS requires to be provided with an initial solution so, a greed algorithm is purposed. The greed algorithm, starts siting a depot in the most populous depot-able city and creating an initial route with this depot and no customer nor BSS. This initial route is then, added to the yet empty set of routes. The algorithm then, search in the last route added in the set for the closest customer from the last visited place on the route . When found, the customer is added in the route and the procedure `addStations` proposed by Corrêa and Santos (2020) verify if the route is feasible . `addStations` is a procedure that generate a recharge plan for a route, that is, determine where the vehicle must recharge its battery and where to swap the battery, so it can complete the route. If a recharge plan is possible, the customer is added into the route, and is removed from the customer set. When no customer is found, that is, the vehicle has not enough battery to keep driving, the route is closed and a new empty route with the current depot is created and the algorithm repeats. When the last created route remains empty after checking every customer, the remaining customers can be reached from any route starting from the current depot, so the last created route is deleted and the process is repeated by opening a depot in the next depot-able city in population size. In the case of the last created route remained empty after checking every customers and the current depot is sited in the last depot-able city, the problem instance is given as infeasible. The initial solution algorithm is detailed in Algorithm 2.

In total, 5 neighborhood structures are used, namely: Union Route, Shift Customer, BSS Replacement, Change Depot and 2OPT. None of them are able to directly modify the solution's recharge plan. They modify characteristics such as BSSs available, depots sited or customers order of visit. However they all use the `addStations` procedure to reconstruct the recharge plan of the modified routes, so they indirectly modify this characteristic. Union Route consists of a neighborhood structure where 2 routes are chosen and a new set of routes is constructed using the customers from those routes. The idea is to solve a subproblem consisting of only customers contained in the two selected routes and use the same logic of the greed initial solution algorithm to reconstruct the routes. Using this structure, 2 routes may generate a larger one or a set of 2 or more different routes . The BSS Replacement neighborhood structure aims to reduce the solution cost by reducing the number of BSSs on it. To do so, it removes any occurrence of a chosen BSS from the solution and the affected routes are reconstructed with the `addStations` procedure. Change Depot works in a similar way as the BSS Replacement, a depot is chosen and all its occurrences are replaced by another depot. The affected routes are then, recostructed with the `addStations` procedure. The 2OPT structure swaps two arcs in a route and the Shift Customer shifts forward or backward a given customer by a certain number of positions in the route. In our solution representation the both structures are achieved similarly. The 2OPT is achieved by

Algorithme 2 : Initial solution algorithm.

```
Input : D = depots, S = stations, C = customers
Output : routes
sort(D); // by population size
routes ← set(); // create the route set
for d in D do
    while depotOk = true do
        depotOk ← false;
        addEmptyRoute(routes, D);
        route ← last(routes);
        while size(C) > 0 do
            c ← searchCustomer(route);
            r_ ← route; // backup route
            addCustomer(c, route);
            addStations(route);
            if isFeasible(r) = true then
                C.remove(c);
                depotOk ← true;
            else
                /* skip customer                                   */
                route ← r_; // restore route
                aux.add(c); C.remove(c);
        C ← aux;
        route ← last(routes);
        if isEmpty(route) = false then
            routes.remove(route);
            depotOk ← false;
        else
            addEmptyRoute(routes, D);
```

removing the route's recharge plan, inverting part of the customer order and reconstructing the recharge plan with the `addStations` algorithm. Analogous, the Shift Customer is achieved by removing the route's recharge plan, shifting backward or forward in an amount of positions a given customer and reconstructing the recharge plan.

The local search is conducted by a best-improvement hill-descent metaheuristic and the stopping criterion adopted is the maximum amount of time running and number of iterations without improvement.

3.5 Pre-processing method for the long-term location

Most of the works dealing with location-routing problem considers an amortization of the costs of installing facilities, as they are to be used for a long period of time, not only for the particular set of customers considered in the routing component of the problem. In addition to the usual amortization approach used to address this short-term and long-term duality in

Location-Routing Problems, we present a novel methodology to further optimize problems based on this model. Considering that logistics companies will install a set of depots and BSSs that will be fixed during a very long period of time, and the customers itself and its demand may vary quickly over the days, our approach consists in the execution of an algorithm to solve the ELRP multiple times considering different days of delivery, extract information about the most frequently used facilities and re-execute the algorithm with a subset of facilities created with the previous solution results. The BSS location is then decided once for the whole planning horizon, while the routing is decide day-by-day using the pre-selected BSSs. For this method, we consider a set of instances consisting in many delivery days and with the same parameters such as vehicle range, number of depot candidates, number of BSSs candidates, etc. The difference among the instances is the customer set, representing the different days of delivery.

We execute the VNS to solve each day individually and then, compute the frequency in which the BSSs were used. Next, a subset of BSSs must be determined to be passed to the VNS again. This is done by sorting the BSSs by frequency of use and doing the following steps. An initial percentage x of BSSs is determined and the top x most frequent BSSs are chosen. To determine whether those BSSs will be enough to at least generate initial solution in each day so the VNS can run, the initial solution algorithm is executed for every day. If a feasible solution is generated for all days, the process stop. If any execution is unable to provide feasible initial solution in any day, the value x is increased by certain amount y and the process is repeated. The worst case scenario happens when $x = 100$, meaning that the method could not remove any BSS, and the ones chosen previously by the VNS are the minimum required to generate feasible initial solutions. The steps of the method are summarized in Algorithm 3.

Algorithme 3 : Select BSS subset algorithm.

```
Input : x, y, B = BSS frequency, I = instance set
Output : x
ok ← true;
while $x \leq 100$ and ok = false do
    selectBSS(B, x); // select the top x more frequent BSSs
    ok ← true;
    for i in I do
        sol ← initialSolutionAlgorithm(i);
        if feasible(sol) = false then
            ok ← false;
            break;
    $x += y$;
```

To evaluate this method, the cost considering all instances must be computed. Instead of simply summing up every solution cost, a special calculation must be done, otherwise, by summing up the solution objective function values, duplicated costs are going to be accounted. To do so, the cost is divided in two parts, the fixed and the variable. The fixed cost is composed by the costs that will be shared across the days, such as acquiring vehicles and siting BSSs and depots. The variable cost is composed by the daily costs incorporating the energy cost in the BSSs and BRSs, the fixed cost of operating a BSS to swap the battery and the drivers wage. For every solution from the VNS daily execution, the four variable costs are summed up and the fixed cost must be processed and then also summed up. The vehicle acquiring cost is determined by the solution with the highest number of routes, the depot cost is determined by the set of depots used in every solution, as well as BSS siting cost that is determined by the set of BSSs used in the daily solutions.

3.6 Computational Experiments

In this section, the results of the computational experiment are shown and also, the test instances and the method used to generate them. The experiments were executed in a machine equipped with a processor Intel(R) Core(TM) i7-7700HQ and 16GB RAM. The model for the Multi-Depot Electric Location-Routing Problem with Time Windows, Battery Swapping and Partial Recharging was solved using the solver Gurobi 9.0 and the maximum run-time was set to 3600 seconds. The algorithm was implemented in C++ using the Microsoft Visual Studio compiler. The VNS was set to stop at 25 iterations without improvement or 3600 seconds of runtime, whichever happens first, and its neighborhood exploration order was set to random, i.e., in each iteration, a random neighborhood is chosen independently from the previous one. The parameters for the Select BSS subset Algorithm were set to x = 70 and y = 5, i.e., for the long-term location problem, at least 70% of the BSSs used in the first VNS round are selected, and 5% more is added until a feasible solution is found by the greedy algorithm for all instances of the set.

3.6.1 Test Instances

Instances set from previous work are limited and are not fit to test our new methodology, we require instances that represents a long-horizon period, with multiple days of delivery to get a more real world representation. Thus, we created a new instance set based on the state of Minas Gerais, Brazil, to contemplate every characteristic needed to represent our problem. The new set has multiple-day instances, i.e., instances representing multiple days of goods' demand in the same geographical space, with each day containing a different set of customers but the same general parameters. The State of Minas Gerais is divided in ten administrative regions, namely: Alto Paranaíba, Central, Centro-Oeste, Jequitinhonha/Mucuri, Mata, Noroeste, Norte, Rio Doce, Sul and Triângulo. Each instance contains customers from one administrative region.

Three real world information were required: the cities geographical coordinate, the distances between each pair of cities, and the cities' population. We get the coordinates by the Open Street Map (OSM), using the Nominatim Python API. Figure 5 shows Minas Gerais' cities plotted in the Cartesian plane with the collected real world coordinates. Observe that there is a great difference in the density comparing the North and West areas with the remaining ones. For the distance matrix, we used the Open Source Routing Machine (OSRM), a C++ API that allow us to pre-process OSM data and to create a local server in order to make queries to obtain the distances required. The cities' population were gathered from the Brazilian Institute of Geography and Statistics (IBGE)[1] information retrieval system SIDRA[2], considering the last census done in the country in the year 2010.

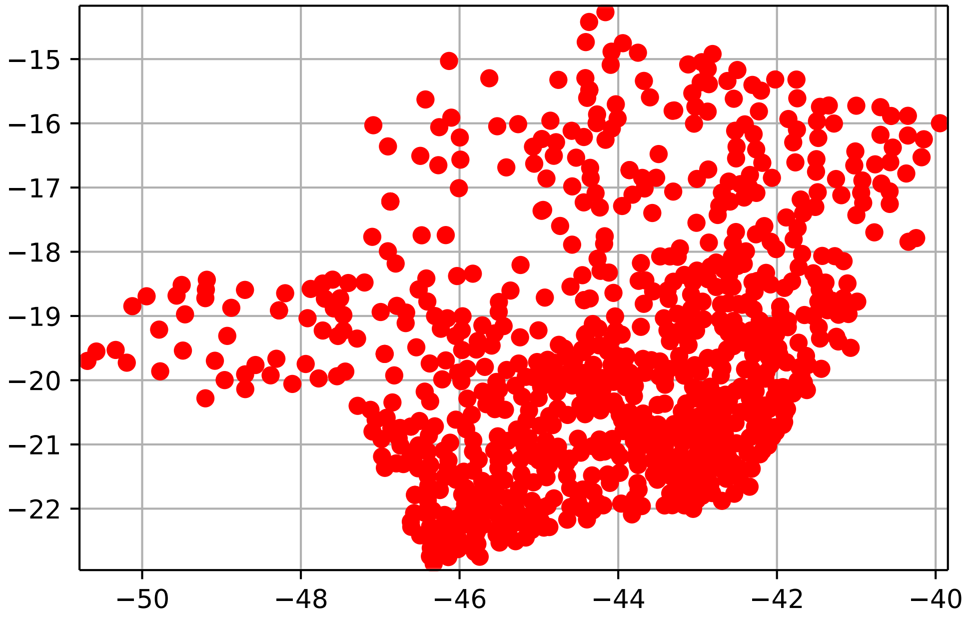


Figure 5 – Cities on Minas Gerais plotted in the cartesian plane.

For each instance set, we had to determine one set of cities to be candidates to receive a depot and another set of cities to be a candidate to receive BSSs. The depot-able set is determined by its city population size. We sort the cities by this criteria and choose the ones with highest population to be part of the set. However, we did not choose near cities and a minimum distance between the cities in this set is established as the half the maximum vehicle range.

The BSS-able set is chosen by solving a facility location model. The intention is to obtain a good distribution of BSSs candidates, hence minimizing the probability of generating infeasible instances, due to cities being very far from the depot with no BSS for a vehicle to reach it. The proposed model is based on the p-Center facility location problem, in which a set of facilities must be assigned to a set of customers in order to minimize the maximum distance of a facility to a customer. In our case, we want to define p cities as candidates to sit BSSs in order to minimize the maximum distance of a city to the nearest BSS candidate. The model is described below:

Parameters:

---

[1] <https://www.ibge.gov.br/>

[2] <https://sidra.ibge.gov.br/home/ipca15/brasil>

N	Set of cities.
di_{ij}	Distance between $i, j \in N$.
p	Number of facilities to be opened

Decision variables:

x_{ij}	1 if city i is supplied by a facility opened in city j. 0 otherwise.
y_i	1 a facility is opened in city i. 0 otherwise.
D	Coverage distance

Model:

$$
\begin{array}{rrcl}
 & \min & D & \\
\text{s. t.} & \sum\limits_{i \in N} x_{ij} & = & 1 \quad \forall j \in N \\
 & x_{ij} & \leq & y_j \forall i, j \in N \\
 & \sum\limits_{j \in N} y_j & = & p \\
 & d_{ij} \cdot x_{ij} & \leq & D \forall i, j \in N \\
 & D \in \mathbb{R} & & \\
 & x_{ij} \in \{0;1\} & & \forall i, j \in V \\
 & y_i \in \{0;1\} & & \forall i, j \in V
\end{array}
\begin{array}{r}
(3.1) \\ (3.2) \\ (3.3) \\ (3.4) \\ (3.5) \\ (3.6) \\ (3.7) \\ (3.8)
\end{array}
$$

The Objective Function 3.1 minimizes the maximum coverage distance. Constraints 3.2 impose that each customer must be reachable by one BSS. Constraints 3.3 define that to each customer a BSS candidate must be assigned and constraint 3.4 forces the model to choose p candidates for BSS. Constraints 3.5 determine the maximum distance D from a customer to the assigned BSS. Constraints 3.6, 3.7 and 3.8 ensure the decisions' variable integrity.

We generated 3 instances set for each region with a total of 30 days of customer's demand. They differ by the percentage of cities chosen to compose each day. For example, the instance set `Central` region has a total of 157 cities. The set `central_20` contains 30 daily customers (20% of the regions size) while the set `central_80`, 121. The parameter p was set as $0.2 \cdot |N|$, i.e., the amount of BSSs chosen is 20% of the number of cities. The regions Norte, Noroeste and Jequitinhonha/Mucuri are not used in this study because the density of cities per Km^2 are too low, and the autonomy of the current batteries would impose a BSS to be sited virtually in every city of some parts of the regions, and on several roads connecting them, Figure 5, they are the northernmost regions. The other regions, however, are composed by 79% of the cities in the state and are all used.

3.6.2 Results

First, we compare the mathematical model for the Multi-Depot Electric Location-Routing Problem with Time Windows, Battery Swapping and Partial Recharging proposed by Paz, Granada-Echeverri and Escobar (2018), Corrêa and Santos (2020) with the VNS. To do so, we run the model with data from the first day of each instance set and then the VNS 10 times to get the average objective function value. Results are reported in Table 2. For the model, we report the solution value in the column ‘cost’, the linear gap returned by Gurobi and the running time. For the VNS we report the average cost of the solucion in the 10 runs, the average time, and the percentage deviation from the solution of the model. As stated by Corrêa and Santos (2020), the model is very inefficient, it was able to find only 2 optimal solutions and in 13 instances was not even capable of finding an initial solution, in this case the ‘cost’ and ‘gap’ are marked with ‘-’. In the other 6 instances, the solver took for the entire time limit to finish with the final gap averaging 76.7%. Considering the instances the model was able to find solution and comparing with the VNS, the solutions are in average only 0.5% worse then the model’s solution. However, in only 0.5 seconds in average, while the model’s average runtime was 2701 seconds. Therefore, for now on, for the multiply-day instances we use only the VNS method.

Table 2 – Results of the model and VNS for the first day of each instance.

	Model			VNS		
Instance	cost	gap	time	avg cost	avg time	%deviation
alto_paranaiba_20_01	6852,20	0,0	3	7252,41	0	0.06
alto_paranaiba_50_01	7175,72	1,3	3600	7305,42	0	0.02
alto_paranaiba_80_01	-	-	3600	7888,84	0	
central_20_01	-	-	3600	8784,63	1	
central_50_01	-	-	3600	10222,7	26	
central_80_01	-	-	3600	11010,8	147	
centro_oeste_20_01	6940,29	88,2	3600	7374,87	0	0.06
centro_oeste_50_01	7226,00	94,1	3600	7932,24	1	0.09
centro_oeste_80_01	7467,81	96,3	3600	8087,62	3	0.08
mata_20_01	7617,17	92,7	3600	8189,74	0	0,07
mata_50_01	-	-	3600	8867,76	16	
mata_80_01	-	-	3600	10181,6	62	
rio_doce_20_01	7624,16	87,6	3600	7997,62	0	0.05
rio_doce_50_01	-	-	3600	9229,43	6	
rio_doce_80_01	-	-	3600	10104,8	31	
sul_de_minas_20_01	-	-	3600	8454,35	1	
sul_de_minas_50_01	-	-	3600	9964,46	14	
sul_de_minas_80_01	-	-	3600	10832,3	78	
triangulo_20_01	7344,00	0,0	5	7477,45	0	0.02
triangulo_50_01	-	-	3600	8045,95	0	
triangulo_80_01	-	-	3600	8536,29	0	

To evaluate our preprocessing methodology, we run 10 times the VNS algorithm followed by the VNS with the pre-processing method for each instance set and compare the VNS execution average cost with the VNS limiting the BSSs. Table 3 report the results. Column ‘D’, ‘S’ and ‘C’ display the number of depot candidates, BSS candidates and customers, respectively. Columns ‘VNS(S)’ and ‘VNS(%S)’ the average solution cost for each VNS execution. Columns ‘improv.’,

’%BSS’, and ’avg time’ shows the economy made by reducing the list of BSS candidates, the BSS canditates list reduction in percentage and the average execution time.

Table 3 – Average results for each instance set.

Instance set	D	S	C	VNS(S)	VNS(%S)	improv.	%BSS	avg time
alto_paranaiba_20	1	6	6	218990	218997	-7	100	3
alto_paranaiba_50	1	6	15	229099	229083	16	100	8
alto_paranaiba_80	1	6	24	236955	236849	106	100	23
central_20	4	30	30	308096	305066	3030	95	58
central_50	4	30	76	343193	337877	5316	90	1077
central_80	4	30	121	375186	368320	6866	90	6156
centro_oeste_20	2	11	10	419223	419224	-1	100	5
centro_oeste_50	2	11	27	244698	237262	7436	75	37
centro_oeste_80	2	11	43	252808	244631	8177	75	136
mata_20	3	27	27	283717	266172	17545	70	39
mata_50	3	27	68	305608	288650	16958	70	757
mata_80	3	27	109	326024	312012	14012	75	3711
rio_doce_20	2	20	19	263080	260251	2829	95	25
rio_doce_50	2	20	49	286650	276450	10200	70	329
rio_doce_80	2	20	78	299919	287271	12648	70	1447
sul_de_minas_20	3	30	29	486738	469771	16967	70	54
sul_de_minas_50	3	30	74	335094	316880	18214	70	1011
sul_de_minas_80	3	30	119	359864	341317	18547	70	4476
triangulo_20	1	7	6	226651	225637	1014	90	3
triangulo_50	1	7	17	248464	242950	5514	90	12
triangulo_80	1	7	27	258461	253684	4777	90	34

The results demonstrate that our algorithm was capable to further optimize the cost after the BSS candidate list reduction. The instance set in which the reduction percentage was a 100% did not show significant cost change, because no BSS could be removed for the second VNS execution, thus both executions were the same. In most of the instances the pre-processing method could reduce the number of BSSs installed, thus reducing the overall cost in the long-term horizon, although the transportation and energy cost on each day may increase because of the reduced number of BSS. For the other instances set, we can observe 83,57% of average reduction percentage in the BSS candidate list and an average of 3.18% in the cost reduction. The 3.18% of average economy can sound a low economy and not worth, however, considering the long run and that BSSs are the second most expensive component in the considered electric vehicle infrastructure, this economy will potentially grow. Take for example the instance set `sul_de_minas_50`. Considering the cost of half a million dollars per BSS (TIANYU, 2020) and the reduction of 30% in the BSS allocation, over time, the sited BSSs will be used more often and, the economy will scale as we consider a bigger period of time.

3.7 Conclusions

In this paper, we present an algorithm for the NP-Hard problem called Multi-Depot Electric Location-Routing Problem with Time Windows, Battery Swapping and Partial Recharging and a novel methodology to address the long and short-term conflict derived from Location-

Routing Problems. The algorithm is based in the Variable Neighborhood Search and uses a set of 5 neighborhood structures to explore the solution space. Additionally, a constructive greed algorithm is shown to provide the VNS with the initial solution. In addition, we presented a novel method to address the long and short-term problem mentioned. This method consists in the use of the presented VNS to optimize individually each day in the instance set and then, select a subset from the used BSS set to reexecute the VNS limiting the BSSs it can use.

We compared the VNS with the mathematical model solved via Gurobi. The model was able to find only two optimal global solutions in the instances we used to test, in 6 instances the average gap was 76.7% and, in 13 instances, the model was unable to find any solution within the set time limit. The VNS was not able to find optimal solutions, however it found solution for every instance tested and, in contrast to the solver that took 1 hour to mostly find high gap solutions or not find solutions at all, the highest VNS execution time was 147 seconds. Having a low runtime is particularly advantageous in our case because our methodology requires multiple VNS executions. We also evaluate the proposed preprocessing methodology in its capabilities to further reduce electric vehicle infrastructure costs. The results demonstrate a average cost reduction of 3.18% considering instances set of 30 days of delivery, however the cost reduction will scale as more delivery days are considered due to the reuse of BSSs over time.

As future works, we suggest the exploration of other ways to decide the subset of BSSs that will be used in the second VNS execution and the creation of instances representing the three regions not used in this work and instances combining different regions to execute the proposed methodology on even bigger instances.

4 A METAHEURISTIC ALGORITHM FOR THE LONG-HORIZON PLANNING OF FACILITIES IN THE ELECTRIC VEHICLE LOCATION-ROUTING PROBLEM CONTEXT

4.1 Introduction

Since the beginning of the global average temperature record, a trend has been observed in its increase with the years 2016, 2019 and 2020 having obtained the 3 highest recorded averages (WMO, 2021). As a result of anthropological actions such as the excessive emission of polluting gases into the atmosphere due to our modern lifestyle, we are currently averaging 1.2^o degree Celsius above that recorded average in the pre-industrial period and, according to World Meteorological Organization, the consequences will be severe and very difficult to reverse if the growth trend is maintained. In a report presented by the Panel on Climate Change (ROGELJ et al., 2018), the damages and consequences considering a scenario where the average increases 1.5^o degree Celsius relatively from the pre-industrial period is discussed. According to the report, impacts such as decreased pollination of crops and reduction of coral reefs generate a great ecological and, consequently, economic imbalance. It is pointed out that several sectors of the economy are responsible for the emission of these pollutants, being only the transport sector responsible for 23% of the global emissions of CO_2. With the upcoming scenario, companies in the sector and governments seek measures to reverse this situation. Over the last years, electric vehicles (EVs) has increased in popularity and its adoption has been seen as one important step to reach independence of foreign oil and also to address the climate situation.

Transport sector companies, responsible for 49% of the worldwide oil consumption and to 26% of GHGs emissions (GHOSH, 2020), have already started to incorporate electric vehicles in their fleets, despite the problems inherent to them such as shorter autonomy and long battery recharge time. Companies such as DHL, have been incorporating electric vehicles in their fleets since 2014 (DHL, 2019), including some vehicles operating in Brazilian territory in the state of Rio de Janeiro (DHL, 2018). Other companies also has started to implement the use of EVs such as UPS, that has committed to purchase 10 000 in the near future (UPS, 2020), and FedEx has started to use electric vehicles in their services since 2009 and now is building its own EV infrastructure (FEDEX, 2020).

Despite efforts, the number of electric vehicles is still low and new technologies can make a difference in this scenario, like the recent battery swapping stations (BSS) that have been gaining a lot of popularity in China (TIANYU, 2020). In addition, to encourage and accelerate the adoption of electric vehicles in the sector, there is still a great need for the development and improvement of infrastructure networks in order to make their use on a large scale more practical. In contrast to combustion engine vehicles, which already have a wide network of fuel stations spread across the planet, electric vehicles still lack a broader infrastructure, especially in developing countries. Many works have been developed for this in the scope of combinatorial optimization, for example, several models of infrastructure networks for electric vehicles has been proposed.

Among the most common types of infrastructure modeling for electric vehicles, there are networks composed of battery charging stations (CUI; ZHAO; ZHANG, 2018; WORLEY; KLABJAN; SWEDA, 2012), battery swapping stations (HOF; SCHNEIDER; GOEKE, 2017) and networks that combine these two types of battery apparatus handling system (CORRÊA; SANTOS, 2020; PAZ; GRANADA-ECHEVERRI; ESCOBAR, 2018). In common among the proposed modeling is the use of the Location-Routing Problem (LRP) model adapted to contemplate several characteristics of infrastructures for electric vehicles. However, this type of modeling has a flaw when applied to this problem, it does not contemplate infrastructure planning considering a long-term horizon of delivery operations. LRP consists of a combination of two optimization problems, the vehicle routing (VRP) and facility location (FLP), and thus unifies a short-term problem with a long-term one. The problem of using this approach in this context is that, in the case of logistics companies, data change from day to day; that is, each day it must serve a different set of customers. Location-Routing considering both problems only in the short term, would work well if customers were the same every day and that is not the case of logistic companies. To address this issue LRP models consider amortized data, i.e., the costs of the long-term part of the problem is amortized considering its daily costs. For example, a battery swap station costing $500 000,0 and with an estimated lifespan of 20 years would have a daily cost considered of $2083,3 in the daily plan horizon. (CORRÊA; SANTOS; NOGUEIRA, 2021) propose a new methodology to address this situation with a 3-stages heuristic algorithm capable of considering a longer horizon plan with different days of delivery, however one of the heuristic steps is a greed algorithm that may limit the overall algorithm reliability in finding good solutions.

In this work we presents a metaheuristic algorithm to further improve the previous algorithm proposed by Corrêa, Santos and Nogueira (2021). We presents a Simulated Annealing metaheuristic to be used in junction with the former algorithm and further improve its capability to optimize EVs infrastructures considering the long-term horizon plan. The remainder of this work is organized as follows: in Section 4.2 we present a brief review on the literature related to electric vehicle infrastructures; in Section 4.3 we describe the Simulated Annealing algorithm; in Section 4.4 the results obtained with the computational experiments; and finally, in Section 4.5 we discuss the results and present some insights for future works.

4.2 Literature Review

Several models of integer linear programming for the problem of optimization of infrastructure networks for electric vehicles have already been proposed in the literature. We can classify them according to the type of apparatus used to charge the battery, namely: networks with battery recharging stations, networks with battery swapping stations or networks that combine these two types of apparatus. One of the first studies in this sense was conducted by Worley, Klabjan and Sweda (2012), in which a modeling of the problem is proposed considering the routing of vehicles along with the allocation of battery charging stations. In a more simplified version of the problem, without considering restrictions such as time windows, the authors demonstrate the benefits of field recharge, i.e., the recharge is done at some point along the vehicles path, which allows the use of fewer vehicles so the total customer demand can be supplied. Li-Ying and Yuan-Bin (2015) propose a modeling that considers multiple types of charging stations, with different charging speeds, and time windows restrictions. Also is presented an algorithm that combines the metaheuristics *Adaptive Variable Neighborhood Search* (VNS) and *Tabu Search* (TB). In experiments comparing the proposed model with a version that considers only one type of charging station, it was demonstrated that the proposed model provides better solutions with lower costs due to its flexibility.

In the context of battery swapping stations, Liu, Gao and Liu (2019) presents an integer linear programming model, as well as a *lowerbound* to determine the minimum number of vehicles to be used and, thus, strengthen the proposed model. The model incorporates time windows and revisit of stations that were previously already visited. To allow revisiting in the BSSs, a set of dummy nodes was created, doubling the stations nodes. It is demonstrated that the model scales very fast in execution time as the size of the problem to be solved increases. Another study in this context is presented by Souza, Souza and Penna (2020) where an algorithm based on the *Iterated Local Search* (ILS) metaheuristic with local search using a *Randomized Variable Neighborhood Search* (RVNS) is presented. In comparison with its results with those of the literature, the algorithm managed to be better in execution time and still present an improvement of up to 3.8% in the total cost of installing the network.

In the scope of infrastructures with both types of station, several studies are found in the literature. One of the most complete encompassing a considerable number of features is presented by Paz, Granada-Echeverri and Escobar (2018) and, later, enhanced by Corrêa and Santos (2020). The first proposes an integer linear programming model that includes features such as time windows, multiple depots, partial recharge and battery swapping. The second presents a hybrid algorithm composed of the *Simulated Annealing* (SA), *Greedy Randomized Adaptive Search Procedure* (GRASP) and *Variable Neighborhood Search* metaheuristics. The model presented is extremely inefficient even for some small instances and, therefore, the heuristic algorithm was necessary. The results obtained by the algorithm shows a long execution time, justified by combining 3 metaheuristics and acceptable by the long-term characteristic of the problem. The algorithm was able to achieve some global optima solutions compared to the model's results and, unlike the model, it provided a solution for all test instances.

Location-Routing Problems considering periodic factors has been taken some attention in other applications rather then in electric vehicles infrastructures problems. Prodhon and Prins (2008) presents a memetic algorithm for the Periodic Location-Routing Problem (PLRP) where only depots are considered without any type of intermediate intra-route facilities. The algorithm considers a planing horizon where each customer must receive its goods a given number of times during the planning horizon and are able to receive it only during predetermined service days. The chromosome is represented by an array divided in two parts. The first represents the depots (index) and the route assigned to it (array value), while The second part represents the routes assigned to the each depot. The value assigned for each depot in the first part indicates from which index in the second part the depot route begins. To deal with the multi-day component, since it is a genetic algorithm, the individuals are represented by a set of chromosomes and the cost is computed as the total cost of all chromosomes. In computational experiments the algorithm proved to be able to find good solutions and outperformed previous algorithms in the literature.

In (RABBANI; HEIDARI; YAZDANPARAST, 2019) a simheuristic is proposed to deal with the problem of stochastic industrial hazardous waste management with multi-period planning horizon. The problem covers the LRP where a set of waste management facilities must be sited and a set of vehicles must collect waste and, also, the inventory management must be taken care due to storage limitation or incompatibility with the different types of waste that are collected. The authors opted to model the problem as a multi-objective mathematical model, thus, they developed a Non-dominated Sorting Genetic Algorithm II (NSGA-II) metaheuristic to compose their methodology with the Monte Carlo Algorithm. The overall procedure goes as follows: an initial population is generated and the Monte Carlo algorithm is used to determine a set of scenarios, which are possible realizations of the stochastic parameters; then, the NSGA-II is executed for a certain amount of generations and the most preferred solution is chosen in the pool of solutions. Compared to results from the literature, the proposed algorithm demonstrated to be very time-consuming, however, was able to find high quality solutions compared to other algorithms in the literature. Also, it is demonstrated that considering the stochastic versions of the problem, the costs where improved by 5.78% if compared to the non-stochastic version.

For the best of our knowledge, the first study addressing the problem of electric vehicles infrastructure networks for the long-term planing horizon was presented by Corrêa, Santos and Nogueira (2021). To address the long and short term conflict of the problem is presented a new algorithm and a new approach for the problem of optimizing infrastructure networks for electric vehicles with charging stations and battery swapping. The first step solves the location-routing problem for each day independently of each other, i.e., choose a set of BSS to install on each day in order the optimize the costs for the day; the second step uses the solutions of the first step as a reference to define a subset of BSSs to install for the whole period, i.e., solve the location component of the problem; The third step solves the location-routing problem for each day again, but considering only the subset of BSSs chosen in the second step, i.e., solves the routing component using only the selected BSSs. A VNS is proposed to solve the first and the third step, while the second is solved by a greedy heuristic. The experiments demonstrated that the new methodology was able to reduce the total cost of infrastructure by 3%, considering a delivery period of 30 days. Such economy scales as a longer planning horizon is considered. It is pointed out that by using a greed algorithm in the second step, the algorithm may be ignoring other BSSs compositions that the greed approach is not able to contemplate. For example, for some instances the greedy algorithm chooses almost all BSSs, and in some cases all of them. Hence, new approaches to solve this step might improve the overall algorithm ability to optimize even more the EVs infrastructures.

4.3 Methodology

As the second step in the algorithm proposed by Corrêa, Santos and Nogueira (2021) is a greed method, it may select a set of BSSs that might not refine the third stage enough to further optimize the long-term horizon plan of the infrastructure network. Therefore, here we present a Simulated Annealing metaheuristic that is used to extend the greed algorithm and is intended to explore different combinations of BSSs to refine the 3-stage algorithm. Also, we present three different evaluation functions so we can contemplate different characteristics of the problem and analyze the algorithm behavior in different situations and determine if any stands out as the best to be used in this context.

The Simulated Annealing is a metaheuristic that requires a solution representation to be defined, a method to generate the initial solution, a neighborhood structure to perform movements in the solution which allow shakes and local search procedures to be done and a method to evaluate the quality of the solutions explored. The overall SA procedure starts with an initial solution provided by a polynomial greed algorithm and consists in iterations where a neighborhood solution is generated, a local search is done to refine the neighbor solution and, according to a probability, the solution is accepted or not even if it is a worsening one. An initial temperature value is set and decreases over the iterations. This temperature value is used in the previous mentioned acceptance step in which the higher the temperature, the higher is the probability of a worsening solution to be accepted. This is the mechanism that allows this metaheuristic to escape of local optima solutions and explore different regions of the solution space. Algorithm 4 illustrates the Simulated Annealing with its local search procedure. The input parameters are s, the initial solution; $InitT$ and $FinalT$, respectively, the initial and final temperatures; α, the cooling rate and $MaxIter$, the maximum amount of iterations before cooling the temperature. Its output is the best solution found s^*. Next we present all the components required for the SA metaheuristic in our problem context.

The solution is represented as a boolean array in which the indexes values indicates if the correspondent BSS in the BSS list is part of the chosen set. The BSS list is the product of the first stage and contains every BSS that were used in the set of solutions obtained in its execution. Considering an example that the daily solutions from the first stage run used the BSSs sited in the cities Viçosa, Ubá, Juiz de Fora, Teixeiras and Rio Casca, respectively sorted by use frequency, the Figure 6 illustrates an example of the boolean array $\{1, 0, 0, 0, 1\}$ generating the chosen BSS

Algorithme 4 : Simulated Annealing.

```
Input : $s$, $InitT$, $FinalT$, $\alpha$, $MaxIter$
Output : $s^*$
$s^* \leftarrow s$;
$Iter \leftarrow 0$ ;
$T \leftarrow InitT$;
while $T > FinalT$ do
    while $Iter < MaxIter$ do
        Generate a Random Neighbor $s' \in N(s)$;
        $s' \leftarrow$ Local Search $s'$ ;
        if $f(s') < f(s)$ then
            $s \leftarrow s'$; // accept the solution
            if $f(s) < f(s^*)$ then
                $s^* \leftarrow s$; // track best solution found
        else
            $p \leftarrow$ random(0, 1); // get random value between 0 and 1
            if $p < e^{\frac{f(s')-f(s)}{T}}$ then
                $s \leftarrow s'$; // accept worsening solution
        $Iter \leftarrow Iter + 1$;
    $T \leftarrow T - \alpha$; // cooling schedule
```

set composed by Viçosa and Rio Casca.

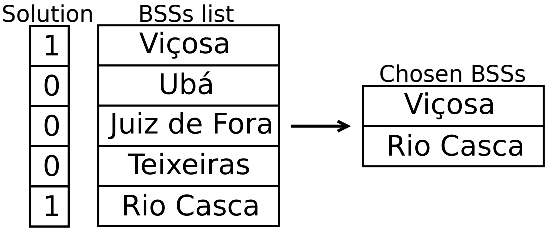


Figure 6 – A solution being used to generate the list of chosen BSSs.

Neighborhood solutions used to perform the SA's shake and local search are simply generated by swapping the values in the solution boolean array. The previous array $\{1, 0, 0, 0, 1\}$ has 5 neighbor solutions obtained by inverting each one of its value. For instance, one possible neighbor is $\{1, 1, 0, 0, 1\}$, hence, the chosen BSSs in this case are Viçosa, Ubá and Rio Casca. The local search is done by a Hill-Descent with best improvement algorithm with the specified neighborhood structure.

The initial solution is obtained with the constructive greedy algorithm presented by Corrêa, Santos and Nogueira (2021) in the previous version of the 3-stage algorithm and is illustrated in Algorithm 5. Its inputs are the values *perc* and *inc* representing the initial percentage of most frequently used BSSs that the algorithm will start to consider and the incremental step, respectively. Also the list of BSSs frequency and the instance set that represents each delivery day must be given. It starts from the value x and goes up to a 100 by steps of *inc* and, for each iteration, the procedure check if for every instance $i \in I$ the top *prec* most frequently used BSSs from the set *B* is enough for the VNS's greed initial solution algorithm to generate feasible solutions. If *perc* reaches 100 the algorithm will use every BSS that was already used, meaning that the third stage of the 3-stage algorithm will be the same as the first, thus shouldn't be executed again. The procedure *selectBSS* is used to get the top *perc* most frequently used BSSs from the BSS list *B*.

Algorithme 5 : Select BSS subset greedy algorithm.

```
Input : perc, inc, B = BSS frequency, I = instance set
Output : perc
ok ← true;
while perc ≤ 100 and ok = false do
    selectBSS(B, perc); // select the top perc more frequent BSSs
    ok ← true;
    for i in I do
        sol ← initialSolutionAlgorithm(i);
        if feasible(sol) = false then
            ok ← false;
            break;
    perc+ = inc;
```

The evaluation function has the purpose of evaluate the quality of a solution according to certain criteria and here we experiment three. The first criteria, named 'MINBSS', is the number of BSSs in the solution, given that they are the second most expensive cost among the three long-term investments for the EV infrastructures (depot and BSSs siting and vehicle acquisition) and depots are not as flexible to change as BSSs and vehicles cost, after amortization, is too low. We consider this criteria representing the minimization of the long-term investment costs. The second criteria, named 'MINSTC', is the total short-term cost, namely: energy costs in BSSs and BRSs, BSSs fixed use costs and drivers wage. The last criteria, named 'MINTC', is the solution total cost including the short and long term investments. The evaluation algorithm can be seen in Algorithm 6. It receives as parameter the set *BSS* that contains the BSSs that will be considered in the solutions and the instance set *I* with all instances representing the days of delivery in the planning horizon. The output is the total cost of the solution considering only the BSSs in the set *BSS*. The evaluation algorithm will run a modified initial solution greedy algorithm generating initial solutions considering only the BSSs from the *BSS* set and the solutions are evaluated according to one of the three criterion presented.

To further understand the evaluation function, take as example a solution the total infrastructure cost is \$339 886.0. Supposing that the long-term cost is \$250 027.25 and the short-term's is \$89 858.75; and the total amount of BSSs sited is 28, the solution values are 28, \$89 858.75 and \$339 886.0 according to each criteria respectively.

Algorithme 6 : Evaluate solution.

```
Input : $BSS$ = set of BSSs used in the solutions from the first stage, $I$ = instance set
Output : $v$ = solution value
$SOL \leftarrow$ []; // empty array to store the feasible solutions
$ok \leftarrow$ true;
for $i$ in $I$ do
    $s \leftarrow$ initialSolutionAlgorithm($i$, $BSS$); // create s considering only BSS set
    SOL.append(s); // store solution
v $\leftarrow f(SOL)$; // get the total cost of the solution set
```

4.4 Computational Experiments

In this section, the results of the computational experiment are shown. They were executed in a machine equipped with a processor Intel(R) Core(TM) i7-7700HQ and 16GB RAM and we tested the Simulated Annealing with the instances first introduced by Corrêa, Santos and Nogueira (2021) that represents regions from the State of Minas Gerais in Brazil. The parameters used in the experiments are $InitT = 1000$, $FinalT = 100$, $\alpha = 100$ and $MaxIter = 10$. Table 4 displays the results obtained in the experiments. Column 'Initial' displays the total EV infrastructure cost obtained in the first stage of the 3-stage heuristic. Columns 'Greed', 'SA MINBSS', 'SA MINTC' and 'SA MINSTC' indicates the percentage of cost reduction in Columns 'improv' and the total percentage of BSSs that were used relatively from the ones used in the first stage 1. Cells in the '% BSSs' column with a '-' indicates that no improvement was found, as no BSS used in first stage was removed, i.e., 100% were used.

The results demonstrate that the proposed SA algorithm was capable to improve the previous 3-stage algorithm. With the evaluation criteria 'MINBSS', considering the minimization of the total number of BSSs, the average cost was reduced in 4.71% instead of 3.18%, a 32.45% increase in performance. However with the other two evaluation criteria no improvement was made and the solution got worse in those cases, with a average cost increase of 2.14% with the 'MINTC' and 13.64% with the 'MINSTC' criteria.

For this first set of experiments, the solution of the Greedy algorithm uses at least 70% of the BSSs, because in Stage 2 the parameter *perc* of the algorithm that selects BSS was set to the value 70, following (CORRÊA; SANTOS; NOGUEIRA, 2021). Notice, however, that the SA was able to reduce the size of this subset, as the final subset has less than 70% in several instances. In order to have a more fair comparison, we made a second experiment run with the parameter *perc* starting from 5. Table 5 displays the results of the second experiment run and shows that with this new parameter the greedy algorithm was slightly improved, the cost reduction was 4.28% instead of 3.18%. However, even with this new parameter setting our SA metaheuristic for the second stage outperforms the greedy method, as the cost reduction was 5.25% in this case.

Table 4 – Comparison of the SA with the 3 proposed evaluation functions.

	Initial	Greed		SA MINBSS		SA MINTC		SA MINSTC	
inst	Stage 1	% BSSs	improv	% BSSs	improv	% BSSs	improv	% BSSs	improv
alto_paranaiba_20	218990	100	-	100	-	100	-	100	-
alto_paranaiba_50	229099	100	-	100	-	100	-	100	-
alto_paranaiba_80	236955	100	-	100	-	100	-	100	-
central_20	308096	95	0.98	60	5.39	100	-	80	4.81
central_50	343193	90	1.55	63	3.02	93	0.96	93	1.19
central_80	375186	90	1.83	63	1.77	93	1.86	89	1.31
centro_oeste_20	419223	100	-	45	3.56	72	1.87	72	1.88
centro_oeste_50	244698	75	3.04	63	3.27	81	2.15	63	3.31
centro_oeste_80	252808	75	3.23	63	2.41	72	3.33	81	2.84
mata_20	283717	70	6.18	29	11.86	66	6.48	76	5.16
mata_50	305608	70	5.55	29	8.95	74	4.78	81	2.56
mata_80	326024	75	4.30	33	8.46	81	3.59	81	2.68
rio_doce_20	263080	95	1.08	50	4.67	85	2.47	89	1.99
rio_doce_50	286650	70	3.56	55	4.10	75	3.95	75	3.99
rio_doce_80	299919	70	4.22	55	3.27	94	0.47	94	1.04
sul_de_minas_20	486738	70	3.49	31	8.05	66	4.48	70	3.50
sul_de_minas_50	335094	70	5.44	37	6.93	60	6.79	55	4.66
sul_de_minas_80	359864	70	5.15	36	3.58	66	5.66	50	4.00
triangulo_20	226651	90	0.45	85	1.52	100	0.02	85	1.47
triangulo_50	248464	90	2.22	85	2.12	85	2.25	85	2.19
triangulo_80	258461	90	1.85	85	1.90	85	1.85	85	1.84

Table 5 – Comparison of the SA algorithm with the MINBSS evaluation criteria against the greed algorithm version.

	Initial	Greed		SA MINBSS	
inst	Stage 1	% BSSs	improv	% BSSs	improv
alto_paranaiba_20	219147	100	-	100	-
alto_paranaiba_50	229406	100	-	100	-
alto_paranaiba_80	236943	100	-	100	-
central_20	308337	95	1.25	60	7.38
central_50	343652	90	1.79	63	2.58
central_80	373142	90	1.19	63	0.55
centro_oeste_20	419186	100	-	45	3.56
centro_oeste_50	244848	65	3.46	63	3.51
centro_oeste_80	252815	75	2.43	63	2.43
mata_20	283462	50	9.72	29	11.93
mata_50	305084	50	8.68	29	7.67
mata_80	325686	50	6.62	33	6.22
rio_doce_20	263211	95	0.93	50	6.85
rio_doce_50	286969	50	6.60	55	6.23
rio_doce_80	300725	55	5.00	55	5.28
sul_de_minas_20	486770	70	3.57	31	9.05
sul_de_minas_50	335420	50	8.87	37	6.87
sul_de_minas_80	359989	50	8.20	36	8.90
triangulo_20	226701	90	0.47	85	1.52
triangulo_50	248408	90	2.27	85	2.22
triangulo_80	257977	90	1.68	85	1.69

4.5 Conclusions

In this paper, we present an algorithm for the improvement of the 3-stage heuristic algorithm proposed by Corrêa, Santos and Nogueira (2021). The 3-stage algorithm is a heuristic composed of 3 steps to solve the NP-Hard problem called Multi-Depot Electric Location-Routing Problem with Time Windows, Battery Swapping and Partial Recharging to address the long and short-term conflict derived from Location-Routing Problems. It relies on a greedy method in its second stage, where the results from the first is processed to extract data in order to refine the third, where the final solutions for the problem are generated. Here we present a Simulated Annealing metaheuristic to replace this second stage greed algorithm and improve the quality of the algorithm proposed by Corrêa, Santos and Nogueira (2021). We also present 3 different evaluation functions that are set to contemplate different characteristics of the problem in question.

The results demonstrate that our new Simulated Annealing algorithm is good to replace the previous greed one when using an evaluation function that minimizes the number off BSS chosen. The improvements on the 3-stage algorithm with the Simulated Annealing being used in the second stage is an average of 5.25% of cost reduction of the EV infrastructure while the previous algorithm presented by (CORRÊA; SANTOS; NOGUEIRA, 2021) improved the cost reduction by 4.28%.

5 CONCLUSIONS

In this work, two metaheuristics were presented for the problem of planning infrastructure networks for electric vehicles based on the Multi-Depot Electric Location-Routing Problem with Time Windows, Battery Swapping and Partial Recharging and an algorithm was proposed for solving the problem when considering the long-term planning of the use of these networks. Two sets of test instances were also created based on real data for computational experimentation of the algorithms. In total, 3 papers were written in an incremental process to improve the proposed 3-stage algorithm.

The experiments of the first paper demonstrated that the proposed hybrid metaheuristic was able to solve the problem and stood out in relation to the integer linear programming model implemented in the solver Gurobi. While the solver was not able to find solutions in most instances, the metaheuristic found a solution in all and even a global optima solution, but, on the other hand, the execution time of the algorithm was considerably high compared to a simplified and not hybrid version of the same.

In the second paper, the objective was to address the problem of long-term planning. For this, a 3-stage algorithm was proposed that would use the first proposed metaheuristic. However, this new algorithm depends on multiple executions of a method that solves the short-term problem, therefore, due to the high execution time of the hybrid metaheuristics, a new one that is more efficient in time and without significant loss of quality of the solutions was proposed to compose the algorithm. The experimental results showed that the 3-stage algorithm was able to reduce operational costs by 3.18% when considering a 30-day planning horizon. The reduction has the potential to be increased as the planning time increases.

The third paper presents an improvement in the 3-stage algorithm of the second paper using a metaheuristic Simulated Annealing in the algorithm's second stage. The computational experiments showed a better performance of 18.5% in relation to the version of the algorithm of the second paper, totaling an average cost reduction of 5.25% in the operations of the EV infrastructure, which can also be scaled with the consideration of a longer planning horizon.

The problem of infrastructure optimization for electric vehicles has enormous potential to make the adoption of this means of transport more attractive to logistics companies. As demonstrated in this study, the use of optimization techniques can reduce operating costs for companies that are willing to adopt electric vehicles, making their use on a large scale more feasible.

Future work can be directed towards exploring new ways of extracting information from the second stage of the proposed algorithm. In this work, the only information used in the second stage was which stations had been allocated and the frequency in which they had been used. Perhaps using machine learning techniques or even different metaheuristics in the second stage, it may be possible to further optimize the solution. Also, a more strengthened mathematical model of the problem or a lower bound technique can be developed in order to more accurately assess the quality of the proposed heuristic algorithm. In order to extend the problem in an even more realistic variant more features such as battery inventory in the swapping stations, capacitated swapping stations with simultaneous service limits or stochastic components with uncertainty can be incorporated in the model so the problem can be more representative of the logistic companies requirements for this type of service.

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