Strategies for Electric Location-routing Problems Considering Short and Long Term Horizons

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Abstract: Recent climate data has risen attention to many problems related to the global warming effect caused by the emission of greenhouse gases. The rise in the global average temperature has many consequences and it is very close to the established threshold in which, immediate actions must be taken or the damage to our planet will be irreversible. The transportation sector, responsible for 23% of the global CO_2 emissions, and the public power, aware of the situation, have been trying to innovate and solutions such as electric vehicles are getting much attention and growing in popularity. This work aims to help logistic companies by proposing a metaheuristic algorithm and a novel methodology for the planning of electric vehicle infrastructures composed by battery recharging stations and battery swap stations. Different from previous works, we consider a long-term horizon planning by using the proposed algorithm itself to pre-process data and improve results by considering the synergy of long-term location and short-term routing problems. Computational experiments shows that our algorithm is able to reduce the cost of electric vehicles infrastructures compared to previous work.

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, 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. Zhao et al. (2019), analyze China's GHGs emission and shows that electric vehicle (EV) deployment has a better long-term decarbonization 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 emis-

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sion 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, other actions such the improvement in the cleanliness of energy production must be taken and will be 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 et al., 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 to 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, 2021) 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 Electric Location-Routing Problem (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, 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 and Walther, 2017); combination of BRSs and BSSs (Paz et al., 2018); and stations with different charging speed (Li-Ying and Yuan-Bin, 2015).

In this work we study the Multi-Depot Electric Location-Routing Problem with Time Windows, Battery Swapping and Partial Recharging (Paz et al., 2018; Corrêa and dos 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 subproblems 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 2 we present a brief review on the literature related to electric vehicle infrastructures; in Section 3 we present a formal definition of the problem; in Sections 4 and 5 we present a heuristic algorithm and our methodology to improve solutions with a preprocessing procedure; in Section 6 we present the test instances elaborated for the experiments and the results obtained with them; and finally, in Section 7 we discuss the results and present some insights for future works.

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 et al., 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 and 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 et al., 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.

Schiffer and Walther (2017) define 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 obtained utilizing all of the 5 objective functions proposed. As suggestion for future works they 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 et al., 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 simultaneous BSS and BRS is presented by (Paz et al., 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 and dos 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 limited to two hours. 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 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 et al., 2018; Corrêa and dos 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 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.

4 VARIABLE NEIGHBORHOOD SEARCH

The Variable Neighborhood Search (VNS) (Hansen and 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 1 illustrates the solution representation. Vertex 0 is the depot, vertexes 1 and 2 are BSSs - BSS 2 is sited and 1 is not - and the rest are customers.

0	5	8	7	2	6	0
0	4	3	0			

Figure 1: The solution 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 dos Santos (2020) verifies if the route is feasible. `addStations` is a procedure that generates a recharge plan for a route, i.e., 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, i.e., 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 cannot 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 given instance is infeasible. The initial solution algorithm is detailed in Algorithm 1.

Algorithm 1: 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);
            end
        end
        C ← aux;
        route ← last(routes);
        if isEmpty(route) = false then
            routes.remove(route);
            depotOk ← false;
        else
            addEmptyRoute(routes, D);
        end
    end
end
```

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, reconstructed 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 both structures are achieved similarly. The 2OPT is achieved by 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.

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.

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.

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 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, after a worsening solution is found, a random neighborhood is chosen independently from the previous one. The parameters for the Select BSS subset Algorithm were set to x = 5 and y = 5, i.e., for the long-term location problem, at least 5% 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.

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, and 7 are used in this work, namely: Alto Paranaíba, Central, Centro-Oeste, Mata, Rio Doce, Sul and Triângulo. The remaining 3 regions were not used because they are very sparse and were not fit to our instance generation method. Each instance set 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. The distance matrix was obtained with the Open Source Routing Machine (OSRM) and the cities' population were gathered from the Brazilian Institute of Geography and Statistics (IBGE) information retrieval system SIDRA[1], considering the last census done in the country in the year 2010.

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.

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 20% of the number of cities.

6.2 Results

In order 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 1 report the results. Column 'Initial' displays the average solution cost in the first algorithm step (VNS). Column '%BSS' displays the percentage reduction of BSSs in the second step, i.e., 100 - x. Column 'Improv.' the percentage of cost reduction in the second VNS execution with the BSSs limited. Column 'Time' shows the average execution time in seconds.

Table 1: Average results for each instance set.

inst	Initial	%BSSs	Improv.	Time
alto_paranaiba_20	219147	0	-	3
alto_paranaiba_50	229406	0	-	8
alto_paranaiba_80	236943	0	-	22
central_20	308337	5	1,25	55
central_50	343652	10	1,79	963
central_80	373142	10	1,19	5537
centro_oeste_20	419186	0	-	5
centro_oeste_50	244848	35	3,46	38
centro_oeste_80	252815	25	2,43	134
mata_20	283462	50	9,72	34
mata_50	305084	50	8,68	733
mata_80	325686	50	6,62	3312
rio_doce_20	263211	5	0,93	23
rio_doce_50	286969	50	6,60	274
rio_doce_80	300725	45	5,00	1326
sul_de_minas_20	486770	30	3,57	49
sul_de_minas_50	335420	50	8,87	762
sul_de_minas_80	359989	50	8,20	3953
triangulo_20	226701	10	0,47	3
triangulo_50	248408	10	2,27	12
triangulo_80	257977	10	1,68	33

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 0% did not show cost reduction, 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. We can observe 29% of average reduction percentage in the BSS candidate list and an average of 4,28% in the cost reduction. The 4,28% 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 50% 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.

[1]https://sidra.ibge.gov.br/home/ipca15/brasil

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 on the Variable Neighborhood Search and uses a set of 5 neighborhood structures to explore the solution space with a constructive greed algorithm to provide an 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 evaluate the proposed preprocessing methodology in its capabilities to further reduce electric vehicle infrastructure costs. The results demonstrate a average cost reduction of 4.28% 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.

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REFERENCES

Cecere, G., Corrocher, N., and Guerzoni, M. (2018). Price or performance? A probabilistic choice analysis of the intention to buy electric vehicles in European countries. Energy Policy, 118(March):19–32.

Corrêa, V. H. V. and dos Santos, A. G. (2020). A heuristic algorithm for the Multi-Depot Electric Location-Routing Problem with Time Windows , Battery Swapping and Partial Recharging. In A heuristic algorithm for the Multi-Depot Electric Location-Routing Problem with Time Windows, Battery Swapping and Partial Recharging, page 12, Viçosa.

Cui, S., Zhao, H., and Zhang, C. (2018). Multiple types of plug-in charging facilities' location-routing problem with time windows for mobile charging vehicles. Sustainability (Switzerland), 10(8):2855.

Demir, E., Bektas, T., and Laporte, G. (2012). An adaptive large neighborhood search heuristic for the Pollution-Routing Problem. European Journal of Operational Research, 223(2):346–359.

DHL (2018). Dhl uses electric cars for product distribution in brazil. Accessed: 2021-01-21.

DHL (2021). Streetscooter and the future of electric vehicles. Accessed: 2021-01-26.

Hansen, P. and Mladenović, N. (1997). Variable neighborhood search. Computers & Operations Research, 24(11):1097–1100.

Harveyn, F. (2020). Un secretary general urges all countries to declare climate emergencies. The Guardian. Accessed: 2021-01-21.

Li-Ying, W. and Yuan-Bin, S. (2015). Multiple charging station location-routing problem with time window of electric vehicle. Journal of Engineering Science and Technology Review, 8(5):190–201.

Paz, J. C., Granada-Echeverri, M., and Escobar, J. W. (2018). The multi-depot electric vehicle location routing problem with time windows. International Journal of Industrial Engineering Computations, 9(1):123–136.

Rogelj, J., Shindell, D., Jiang, K., Fifita, S., Forster, P., Ginzburg, V., Handa, C., Kheshgi, H., Kobayashi, S., Mundaca, E. K. L., Séférian, R., and M.V.Vilariño (2018). Mitigation pathways compatible with 1.5°c in the context of sustainable development. in: Global warming of 1.5°c. In Press.

Schiffer, M. and Walther, G. (2017). The electric location routing problem with time windows and partial recharging. European Journal of Operational Research, 260(3):995–1013.

Tianyu, W. (2020). Ev battery-swapping finds new life in china. news.cgtn.com. Accessed: 2021-01-21.

WMO (2019). 2019 concludes a decade of exceptional global heat and high-impact weather. Accessed: 2021-01-23.

Zhang, S., Chen, M., and Zhang, W. (2019). A novel location-routing problem in electric vehicle transportation with stochastic demands. Journal of Cleaner Production, 221:567–581.

Zhao, F., Liu, F., Liu, Z., and Hao, H. (2019). The correlated impacts of fuel consumption improvements and vehicle electrification on vehicle greenhouse gas emissions in China. Journal of Cleaner Production, 207(2019):702–716.