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Electric Vehicles Route Planning using Best Route Optimizer

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Summary

Although the electric vehicles (EVs) market is growing, range anxiety for longer routes using EV is due to technical vehicle characteristics and poor charging stations (CSs) location. There are already developed some EV route planners, but very few consider multiple-criteria such as power, distance, and price. We propose a novel algorithm, denoted by BRO - Best Route Optimizer, that allows EV route optimization in terms of cost and time using (i) multiple-criteria decision analysis, (ii) user preferences, i.e., the initial State Of Charge (SOC), the start and end trip points, (iii) CS characteristics (iv) EV characteristics, i.e., brand and model, and (v) free and open source tools. BRO is tested using the Portuguese EV charging network.

This approach is useful to substantially increasing EV adoption and trust based on current EV technologies.

Keywords: optimization, EV (electric vehicle), mobility concepts, EVSE (Electric Vehicle Supply Equipment), state of charge

1 Introduction

EVs market is rising all over the world due to climate questions and hence, several automakers have at least one electric model as a solution to the consumer. Despite of being one of the future mean of transportation they still tease some range anxiety for the users due to small batteries capacities, CSs (or EVSE - Electric Vehicle Supply Equipment) location and charging times, as explained in [1]. In order to help the users in getting personalized route planners, several EV routing approaches have already been proposed about the problem of optimal EV routing. For example, [2] presents a model that aims to minimize the total distribution costs of the EV route while satisfying the technological constraints. More examples can be found in Table 1 together with our proposed model to optimize the EV route planner. Most of these examples use web based applications such that the user can easily choose the options for the EV route planner. Three main differences stand out from Table 1, namely the consideration of energy prices, route saved CO_2 emissions and the multiple-criteria decision analysis.

The goal of this work is to improve the EV route planning application compared to the existing works. The main idea is to create an EV route planner algorithm that optimizes the user inputs in terms of cost and time using (i) a multiple-criteria decision analysis with trade-off calculation, (ii) user preferences, i.e., the EV initial State Of Charge (SOC), the start and end trip points, (iii) CS characteristics (iv) EV characteristics, i.e., brand and model, and (v) free and open source tools and finally integrates it in a mobility platform, such as the MOBI.ME [3] together with the services that are already available.

This work uses a mathematical based model as methodology and has a simple interface to the user to show the metrics of interest. It also considers real data provided by the Portuguese public CSs network named MOBI.E [4]. This network has about 500 CSs and around 1250 charging sockets. Table 2 explains the charging modes available in this network and Table 3 shows the charging power levels available at CSs [5]. The model proposed uses data gathered from MOBI.E network [4], such as the name of the CS and its sockets, CSs coordinates (latitude and longitude), socket amperage, socket power and socket type. Our model also applies EV charging prices from Spanish energy market, "*Tarifa Supervalle*" of *Precio voluntario para el pequeño consumidor* (PVPC) [6] and it contributes with CO_2 information about EV route in order to be in line with world climate conferences and to show user's carbon footprint.

Table 1: Comparison among current EV route planners and BRO

	[7]	[8]	[9]	[10]	[11]	BRO
Connector type selection	x			x	x	x
EV characteristics selection	x	x	x		x	x
Select start and end SOC		x	x			x
Multiple waypoints	x	x		x	x	Improving
Charging station/socket energy price						x
Charging station/socket power	x					x
Charging station/socket radius	x	x		x	x	x
Charging stop point information			x		x	x
Saved CO_2 emissions						x

Table 2: Charging modes description

Mode type	Electricity type	Description
Mode 1	AC[1]	Industrial plugs without In-Cable Control Box (ICCB)
Mode 2	AC	Industrial plugs with ICCB
Mode 3	AC	Mennekes plugs
Mode 4	DC[2]	CHAdeMO plugs

Table 3: Charging stations nomenclature and its power levels

Charging station nomenclature	Power (kW)
Normal	3.7 (AC)
Semi-rapid	7.2 (AC) and 22 (AC)
Fast	43 (AC) and 50 (DC)

BRO implementation is based on R language and it uses free open source tools as:

- *RStudio* (version 0.99.486) [12] to program the model in R (version 3.2.3) and its Shiny framework to show the results;
- *GraphHopper* Routing Application Programming Interface (API) (version 5) [13] to get driving directions, distance and time in encoded polyline format;
- CO_2 signal API (v1) [14] to get CO_2 equivalent emissions ($kgCO_{2eq}$) and total energy production of a specific country;
- e.sios API (v2) [15] to get EV charging minimum and maximum energy prices from [6].

The remainder of the paper is organized as follows. Section 2 provides the structure of the model, while section 3 gives the evaluation of the model proposed. The conclusions are presented in section 4.

[1] Alternating current
[2] Direct current

2 Structure of EV Route Planning Model

BRO is built to help EV drivers planning their routes and to feel safe about where to charge. It uses mathematical concepts as clustering techniques and Dijkstra algorithm for route calculation. Our contributions focus on how we apply these concepts and how we optimize the selection of the best CS considering the user requirements.

2.1 Definitions

2.1.1 Model inputs and EV characteristics

The model stated needs some user inputs enumerated in the following:

- Vehicle brand and model, regarding algorithm database information;
- Initial and final trip points (city or street address);
- Initial trip SOC (0-100%);
- Charging station's power level selection (Normal, Semi-Rapid, Fast or All types).

To estimate EV energy consumption, our model uses the vehicle brand and model and gets:

- EV full battery capacity (kWh);
- EV autonomy (km), in full battery capacity.

EV consumption is considered linear (kWh/km) regarding each EV characteristics but this assumption is not constant during a real route, so we create a heuristic by multiplying all the EV autonomies by a factor of 0.9 to avoid false charging routes due to autonomy questions. To protect EV battery and its lifecycle, the maximum and minimum standard SOC are 80% and 20% respectively. For some cases, these limits are set up to 100% and 5% due to CSs proximity.

2.1.2 Charging stations energy price

As described in section 1, each socket of a CS has associated a tariff for the charging energy to simulate a real scenario. When attributing socket's prices the algorithm knows automatically the minimum and maximum prices of a certain day through an API, in this case e.sios API, and then, generates a random value between these limits for each CS socket. For example, EV charging prices for 11-05-2017 [6] are as follows:

- minimum price: 0.04813 €/kWh;
- maximum price: 0.13744 €/kWh.

2.2 Methodology

2.2.1 Charging stations clustering

BRO model uses clustering algorithms to find and create groups of CSs in order to reduce the size of large input data sets when processing the algorithm steps described in section 2.3. This approach is useful because some CSs are close to each other and each CS usually has more than one socket, thus, the algorithm is much faster when searching for clusters instead of CS sockets.

The clustering algorithm used in this model is the agglomerative hierarchical clustering (bottom-up approach) where the clusters are organized as a hierarchical tree. This hierarchical technique calculates the ideal number of clusters regarding the CSs mesh. In our approach, we "cut" the dendrogram, i.e., a representation of a tree diagram, by a distance, i.e., the maximum distance between clusters, and we get a set of clusters that interests to the algorithm.

A clustering technique needs a proximity matrix with distances among all the data set points to differentiate them in clusters, named as dissimilarity matrix. BRO uses great circle distances (GCDs) proximity criteria

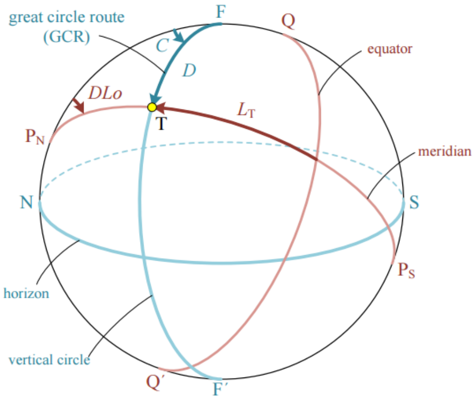

Figure 1: Great circle distance example. "F" is the departure point and "T" is the destination point.

to calculate these distances through an R package. Basically, the GCD is the shortest distance on a spherical earth model, as represented in Figure 1, by great circle route (GCR) [16]. Then, BRO applies GCD in the average linkage method (AL) to compute the distances among clusters. This method defines the distance among two clusters as the average distance among all data points in the first cluster and all data points in the second cluster. Equation (1) shows the formula of AL method applied in the algorithm,

$$d\,(c1, c2) = \frac{1}{n_{c1} \times n_{c2}} \sum_{i=1}^{n_{c1}} \sum_{j=1}^{n_{c2}} d(x_{c1i}, x_{c2j})\,, \tag{1}$$

where n_{c1} is the number of elements of cluster 1, n_{c2} is the number of elements of cluster 2, x_{c1i} is an element of cluster 1, x_{c2j} is an element of cluster 2, $d(x_{c1i}, x_{c2j})$ is the distance between two points of different clusters and finally $d\,(c1, c2)$ is the average distance among the clusters.

2.2.2 Route calculation

BRO uses *GraphHopper* Routing API [13] to calculate optimized routes by car. This API applies Dijkstra algorithm to find the best path between two points. Route time is achieved by the specific speeds of different road types assigned by *GraphHopper* developers. We also get the route in an encoded polyline format that needs decoding to be able to plot the route layer in a map.

2.2.3 Charging stations multiple-criteria decision analysis with trade-off calculation

To be able to differentiate the CSs sockets, a multiple-criteria decision analysis with trade-off calculation between electric power (kW), route distance by car (km), and energy price (€/kWh) is performed using equations (2) to (7). Using these equations, the optimization algorithm finds the best suited CS socket to charge the EV, named as $best\_suited\_CS$, and is based on the minimum trade-off between power, route distance, and energy price as shown in equations, (2), (3) and (4) as follows:

$$best\_suited\_CS = min(s_j)\,, \tag{2}$$

$$s_j = \sum_{i=1}^{n} v_i \times k_i\,, \tag{3}$$

$$\sum_{i=1}^{n} k_i = 1\,, \tag{4}$$

where s_j represents the trade-off of a charging station socket j, v_i is the linear value's function of electric power, route distance, and energy price respectively described in equations (5), (6) and (7), k_i are the weights for electric power, route distance, and energy price respectively, defined by the user and represent his/her preferences on the CSs search algorithm, with $i = \{1, \ldots, n\}$ and $n = 3$.

Equation (5) relates to linear value function of electric power,

$$v_1 = \frac{Power_{max} - Power_j}{Power_{max} - Power_{min}}, \tag{5}$$

where $Power_{max}$ is the maximum socket power (kW) available on the selected clusters, $Power_{min}$ is the minimum socket power (kW) available on the selected clusters and $Power_j$ is the power of each individual socket (kW) of the selected clusters. Equation (6) relates to linear value function of distance,

$$v_2 = \frac{Distance_{min} - Distance_j}{Distance_{min} - Distance_{max}}, \tag{6}$$

where $Distance_{max}$ is the maximum distance (km) between a CS of the selected clusters and the minimum SOC point, $Distance_{min}$ is the minimum distance (km) between a CS of the selected clusters and the minimum SOC point and $Distance_j$ is the distance (km) of each CS socket of the selected clusters relative to the minimum SOC point. Finally, equation (7) relates to linear value function of energy price,

$$v_3 = \frac{Price_{min} - Price_j}{Price_{min} - Price_{max}}, \tag{7}$$

where $Price_{max}$ is the maximum socket price (€/kWh) for the selected clusters, $Price_{min}$ is the minimum socket price (€/kWh) for the selected clusters and $Price_j$ is the price (€/kWh) of each socket for the selected clusters.

Analyzing the linear equations, v_1 favors maximum power, v_2 favors minimum distance and v_3 favors minimum price, i.e., the best suited CS has the minimum trade-off between these three factors, meaning:

- $Power_j = Power_{max}$;
- $Distance_j = Distance_{min}$;
- $Price_j = Price_{min}$.

2.3 Algorithm general workflow

The BRO starts with the introduction of the inputs by the user, as explained in section 2.1. Then, the algorithm calculates the best route using [13], follows the route decoding of encoded polyline format and, finally, executes the general steps presented in flowchart of Figure 2. A brief explanation of each step is detailed below.

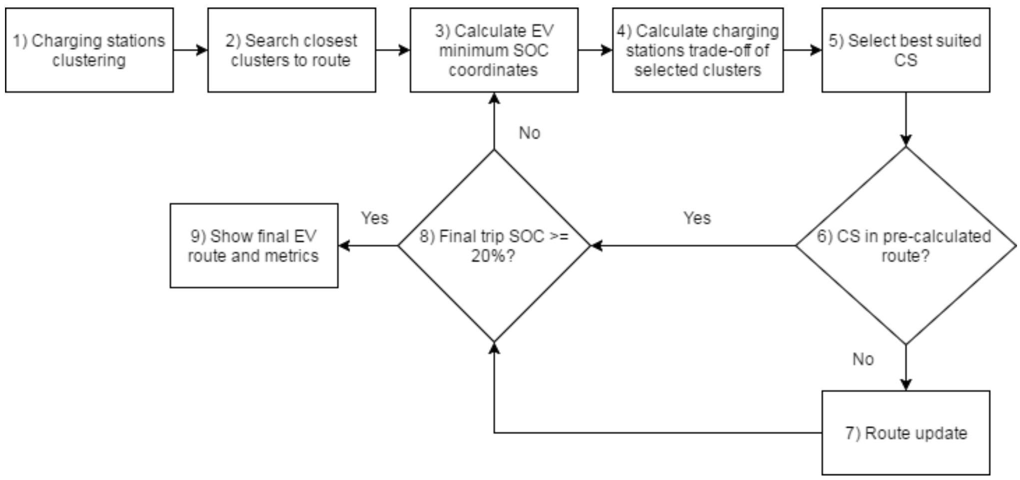

Figure 2: General workflow of BRO

STEP 1): Agglomerative hierarchical clustering of all CSs.

STEP 2): Searching of the closest clusters to the calculated route. As we have the route in an encoded polyline format, we can access the set of coordinates that are part of it. With this information, it is possible to count the frequency that a cluster of CSs is closer to this set of route coordinates and then we understand which CSs are the closest. This method allows to filter charging stations that are far away from the route, i.e., CSs with the distance, in meters, between them and the route higher than $dist$, represented in equation (8),

$$dist = \frac{SOC_{min} \times Range_{nom} \times kmTom}{100\ \%}, \tag{8}$$

where SOC_{min} is the minimum SOC (standard of 20%, but customizable), $Range_{nom}$ is the nominal range considered on algorithm of the selected EV by the user, in km, and $kmTom$ is used to convert distance in kilometers to meters.

STEP 3): Calculation of minimum SOC coordinates during the route. As we know the electric consumption of the vehicle (kWh/km), the model predicts where the 20% SOC coordinates are going to be.

STEP 4): Calculation of trade-off for each CS socket. This step applies the formulas explained in section 2.2.3 to each CS set of closest cluster. Trade-off is a mean of CS sockets characterization.

STEP 5): Selection of the CS socket with the minimum trade-off. On each stop the EV increases its SOC until 80%, which is the standard charging SOC. Just in special cases, when the next CS is far away, the charge can be between 80% and 100%.

STEP 6): Verification if the CS is in the initial pre-calculated route. If the CS is not, it will go to step 7), if yes, it continues to step 8).

STEP 7): Route update, in case of the CS location being out of the pre-calculated route. This step includes the CS coordinates on the route.

STEP 8): Verification if the SOC at the destination point is bigger than 20%. The minimum SOC defined for the EV is 20%, but in special cases these values can decrease up to 5% due to CSs absence. If the condition is not verified then, it goes to step 3), if yes, it continues to step 9).

STEP 9): The algorithm ends with the calculation of some useful trip metrics, charging sockets details and still shows the charging route. The trip metrics and charging socket details are:

- Final SOC (%);
- Energy consumed (kWh);
- Charging time (h);
- Route time (h);
- Charging costs (€);
- Saved CO_2 emissions ($kgCO_{2eq}$);
- Socket power (kW);
- Socket price (€);
- Energy to charge (kWh).

To fully understand the meaning of the output metrics we describe them below:

- Final SOC (%) – the final SOC when the EV reaches the destination initially inserted by the user;
- Energy consumed (kWh) – the sum of the real energy consumed by EV battery;
- Charging time (h) – the sum of charging times on each stop;
- Route time (h) – the sum of the normal route time (given by *GraphHopper* Routing API) with charging time;
- Charging costs (€) – the sum of charging costs on each stop;
- Saved CO_2 emissions ($kgCO_{2eq}$) – the total emissions regarding the energy charged on EV (named EVE in equation (9)) comparatively to a Diesel vehicle (DV) doing the same route with an average CO_2 emissions of 120 g/km (named DVE on equation (9)) [17]. We can achieve this value by,

$$savedCO_2 = DVE - EVE\ , \tag{9}$$

where $savedCO_2$ are the total saved CO_2 emissions by EV, in $kgCO_{2eq}$, DVE are the Diesel vehicle emissions, in $kgCO_{2eq}$, and EVE are the electric vehicle emissions regarding the electric energy charged, in $kgCO_{2eq}$. DVE and EVE are calculated for the same route;

- Socket power (kW) – the maximum power of the socket at the CS;
- Socket price (€) – the price that the user pays for the "Energy to charge" at a given socket;
- Energy to charge (kWh) – the estimated energy to charge the EV at a given socket considering the next stops or its final trip point.

To calculate the emissions of the energy charged on EV, the emission factors about Portuguese energy production types are given in Table 4. The emission factors are defined for different energy types used in the proposed algorithm.

Table 4: CO_2 emission factors of each energy production type in Portugal, where a) Coal, b) Geothermal, c) Fuel Oil, d) Solar Renewable, e) Nuclear, f) Fossil Cogeneration, g) Natural Gas, h) Renewable Cogeneration and Municipal Solid Waste (MSW), i) Wind and j) Hydraulic

Electric energy production type	a)	b)	c)	d)	e)	f)	g)	h)	i)	j)
Emission factor ($kgCO_{2eq}$/kWh)	980	N.A.[3]	1000	0	N.A.	327	354	841	0	0

2.4 Assumptions of BRO model

The EV route planning model considers the following assumptions:

- EV energy consumption is considered linear;
- EV charging power rate is considered linear, i.e., it is done using CS maximum power;
- EV charging times are calculated using the assigned CS socket power but some EVs do not support all the nominal CS power and they will charge slowly;
- Route time and encoded polyline do not consider traffic constraints;
- EV brand and model selection are limited to our database information;
- Superchargers, such as Tesla superchargers, are not considered because they do not belong to Portuguese public network;
- Energy from regenerative braking is not considered;
- Route elevation is not considered.

[3] Not Attributed

3 Evaluation of Optimization Model

This section resumes the performance of our work with two simulations. Firstly, we present some inputs of the algorithm and then we show the BRO results to the end-user. Table 5 shows the characteristics of a Nissan LEAF 2016 version and Renault ZOE 2017 version and Table 6 shows the values of the weights used in the simulations in order to consider the trade-off. These weights exemplify a user that prefers to charge faster, the distance has a moderate importance, while the prices are not relevant. Figure 3 shows the BRO user interface (UI) through Shiny framework. This UI has the user input side (number 1 in Figure 3), the route map with charging points and minimum SOC coordinates (number 2 in Figure 3) and the final metrics and charging sockets details (number 3 in Figure 3). Regarding the route map in Figure 3, the grey circles represent the 20% SOC of EV, while the green circles represent the CS location picked for charging along the calculated route. The EV starts with 80% SOC and at every stop it recharges until 80% again.

Table 5: EVs characteristics

EV Model	Battery Capacity (kWh)	Average Range (km)	Average Range on algorithm (km)[4]	Electric Consumption (kWh/km)	Used in
Nissan LEAF 2016	30	172	154.8	0.19	Simulation 1
Renault ZOE 2017	41	300	270	0.15	Simulation 2

Table 6: Values of trade-off weights

k1 (power)	k2 (distance)	k3 (price)
0.55	0.4	0.05

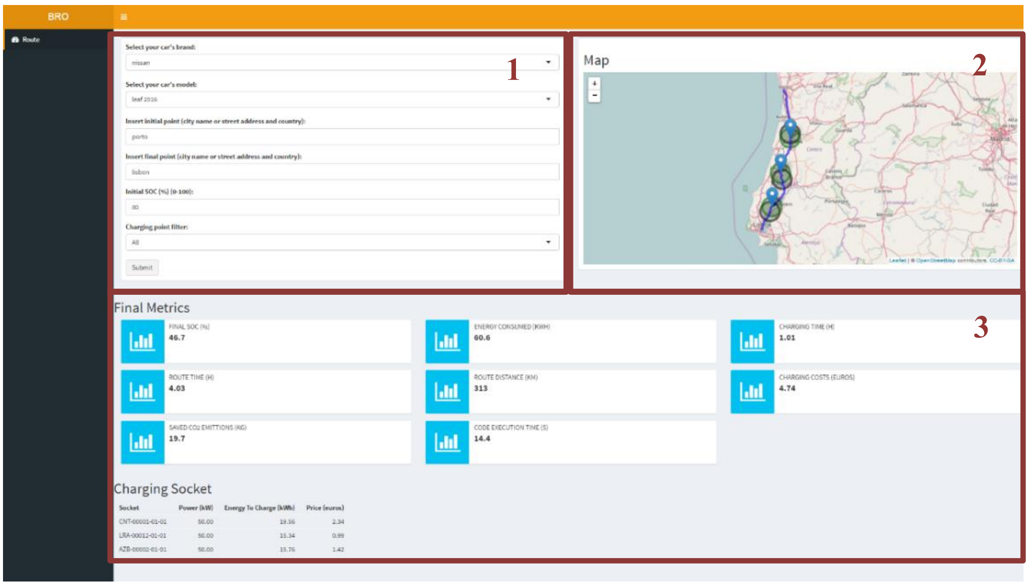

Figure 3: BRO UI with a usage example.

[4] Average range on algorithm corresponds to 90% of EV average range

To perform the model evaluation, BRO runs in a computer with Intel(R) Core(TM) i5 processor - 2540M CPU @ 2.60GHz, 2 Core(s), 4 Logical Processor(s), 8Gb of RAM and a 64-bit operating system. The average execution time of Simulation 1 and Simulation 2 is about 13s.

3.1 Simulation 1

In Simulation 1 we test a trip between Porto and Lisbon, exemplified in Figure 3. Because of the illegibility of the values and names in Shiny interface in Figure 3, we show the benefits of our proposed algorithm in Table 7.

Table 7: Results of Simulation 1

Inputs	Vehicle brand	Nissan		
	Vehicle model	LEAF 2016		
	Start point	Porto		
	End point	Lisbon		
	Start SOC (%)	80		
	Charging Point Selection (%)	All		
Outputs: Final Metrics	Final SOC (%)	46.7		
	Energy consumed (kWh)	60.6		
	Charging time (h)	1.01		
	Route time (h)	4.03		
	Route distance (km)	313		
	Charging costs (€)	4.74		
	Saved CO_2 emissions ($kgCO_{2eq}$)	19.7		
Outputs: Charging Sockets	Socket description	Socket power (kW)	Energy to charge (kWh)	Socket price (€)
	CNT-00001-01-01	50.00	19.56	2.34
	LRA-00012-01-01	50.00	15.34	0.99
	AZB-00002-01-01	50.00	15.76	1.42
	TOTAL	-	50.66	4.75

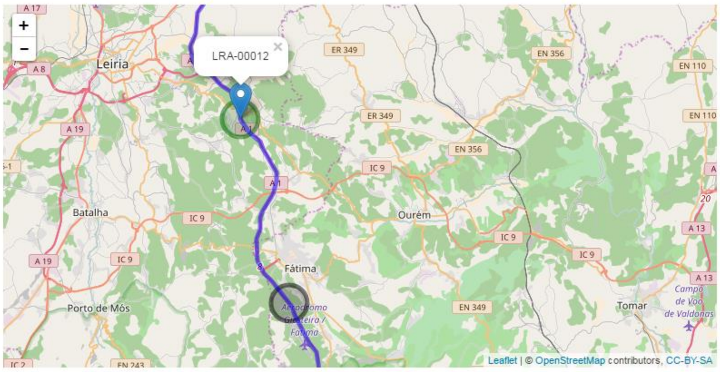

Figure 4: Second CS location and minimum SOC point of Simulation 1

When we analyze the simulation results, we verify that it is possible to do an EV trip between Porto and Lisbon and charge only in DC CSs. If we compare EV route time (including charging time) with a Diesel vehicle in the same route, the second one needs 1 hour less [18], but at the same time the EV avoids the emission of 19.7 $kgCO_{2eq}$. and the total price to charge 50.66 kWh is only 4.75€.

Comparing energy to charge with EV needs and assuming we need to charge 60% of the battery capacity, this corresponds to $0.6 \times 30 = 18$ kWh. Only the first charge is higher than 18 kWh and at the second stop the EV charges before its minimum SOC and thus, it charges less energy. If we compare the metric "Energy consumed" with "Energy to charge" we conclude that they are not equal, because they have different meanings as explained in 2.3. If "Energy to charge" is higher than "Energy consumed" than it means that the EV may started trip with a low SOC or finished with a high SOC.

Figure 4 allows to view that in the second CS (LRA-00012) the EV charged before reaching the minimum SOC point.

3.2 Simulation 2

On Simulation 2, we test again a trip between Porto and Lisbon with one difference relatively to Simulation 1: Simulation 2 uses a different EV, i.e., Renault ZOE 2017 version. Despite of this EV advertises a range of 400 km regarding NEDC (New European Drive Cycle), the real range is 300 km [19]. Table 8 illustrates the BRO inputs and outputs of this case.

Table 8: Results of Simulation 2

Inputs	Vehicle brand	Renault		
	Vehicle model	ZOE 2017		
	Start point	Porto		
	End point	Lisbon		
	Start SOC (%)	80		
	Charging Point Selection (%)	All		
Outputs: Final Metrics	Final SOC (%)	30.8		
	Energy consumed (kWh)	47.5		
	Charging time (h)	1.24		
	Route time (h)	4.24		
	Route distance (km)	313		
	Charging costs (€)	3.04		
	Saved CO_2 emissions ($kgCO_{2eq}$)	25.9		
Outputs: Charging Sockets	Socket description	Socket power (kW)	Energy to charge (kWh)	Socket price (€)
	LRA-00012-03-01	43.00	27.34	3.04

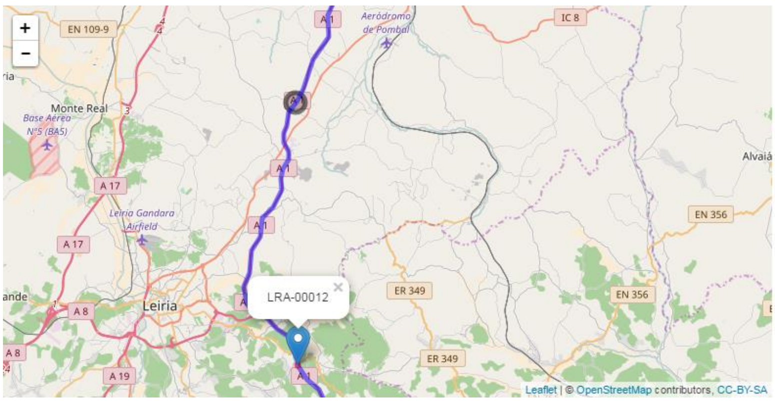

Figure 5: CS location and minimum SOC point of Simulation 2

The EV used on this simulation allows to make fewer stops than in Simulation 1. This EV also has a technical charging restriction and it cannot charge either on DC CSs, as CHaDeMo, or at power ratings equal or higher than 43 kW on AC CSs. The maximum charging power of a Renault ZOE 2017 version is 22 kW. If we analyze Table 8 we see that the only stop to charge is in a CS with rated power of 43 kW, but what happens in Simulation 2 is the EV charges at 22 kW maximum. Due to this technical constraint, charging time is about 0.2 hours higher than in Simulation 1.

Regarding the energy charged, this case is an example of the evolution of batteries' technology and therefore this EV just needs to stop to charge once. Doing the same approach as in Simulation 1, assuming the EV just needs 60% of SOC (remember safe SOC limits between 20% and 80%), it is the same as $0.6 \times 41 = 24.6$ kWh. This amount of energy is similar to the energy charged verified in Table 8.

Figure 5 tells us that the EV charged after its minimum SOC point (grey point) and so its SOC was lower than 20% (13,3% achieved). These cases may happen due to number of CSs and their locations, but they are restricted because the algorithm considers that to stop at a CS the EV needs a minimum of 5% SOC. If BRO achieves a solution where the SOC is lower than 5% at a CS, it does not present this charging solution in order to guarantee user safety.

About the charging price to the user, Simulation 2 achieves a lower price than Simulation 1 due to the EV battery technology, i.e., the total price to charge 27.34 kWh is 3.04€. Renault ZOE 2017 enables to store more energy and so it needs to charge less.

If we compare EV route time (including charging time) with a Diesel vehicle using the same route, in fact the second one needs 1.2 hours less [18], but at the same time the EV avoids the emission of 25.9 kgCO_{2eq}.

Both of the simulations maintain the initial calculated route and they can be confirmed by [18].

4 Conclusion

This paper contributes with a new EV route planner aiming to help the user to easily plan his route. BRO helps to mitigate the charging infrastructure problems because it uses all the information available about this network to find a charging solution without concerns to the user. We show that our algorithm can plan EV routes in a more convenient way.

The effectiveness of the proposed method is verified by the BRO evaluation, and we can claim that our optimization algorithm uses various tools and approaches in order to cover several important metrics. However, the computational time of BRO is higher than the other solutions mentioned in section 1.

About the development of this work, we find that BRO:

- can increase the EV adoption;
- has evolved mathematical tools that allows to find the best suited CS;
- brings out some match problems between EV inlets and EVSE sockets;
- is able to cover more inputs about the CSs characterization, such as, availability in real time;
- is useful to plan and restructure the actual Portuguese charging network because it allows to understand where the minimum SOC points can be reached.

The main applications of this algorithm are going to be implemented on MOBI.ME platform and although the model evaluation is only for electric vehicles it can be applied to plug-in hybrid vehicles too. Our model applies information about Portuguese EV charging network, but it can be also adaptable to other countries where other specifications may exist.

BRO will evolve onto a web interface and a smartphone application for the user. The next steps will focus on considering multiple waypoints in addition to the effect of road-type and elevation constraints on battery autonomy. Execution time will also be one step to develop.

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References

[1] M. Baum, J. Dibbelt, A. Gemsa, and D. Wagner, “Towards route planning algorithms for electric vehicles with realistic constraints,” *Comput. Sci. - Res. Dev.*, vol. 31, no. 1–2, pp. 105–109, May 2016.

[2] H. Yang, S. Yang, Y. Xu, E. Cao, M. Lai, and Z. Dong, “Electric vehicle route optimization considering time-of-use electricity price by learnable partheno-genetic algorithm,” *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 657–666, 2015.

[3] CEiiA, “CEiiA | Mobility.” [Online]. Available: https://www.ceiia.com/mobility-mobi-me. [Accessed: 08-Jun-2017].

[4] “MOBI.E - Mobilidade Eléctrica.” [Online]. Available: http://www.mobie.pt/portal/postoscarregamento. [Accessed: 14-Dec-2016].

[5] MOBI.E, “FAQ’S.” [Online]. Available: https://www.mobie.pt/faqs. [Accessed: 10-May-2017].

[6] “PVPC | ESIOS electricidad · datos · transparencia.” [Online]. Available: https://www.esios.ree.es/es/pvpc. [Accessed: 30-May-2016].

[7] “RouteChargers.com | Home Page.” [Online]. Available: http://routechargers.com/. [Accessed: 13-Dec-2016].

[8] “EV Trip Planner.” [Online]. Available: https://evtripplanner.com/index.php. [Accessed: 13-Dec-2016].

[9] “Home Page - EVRoute.” [Online]. Available: http://evroute.controtex.com/. [Accessed: 13-Dec-2016].

[10] “EVHighwayStatus - The alternate electric car charger status map for all your devices.” [Online]. Available: https://evhighwaystatus.co.uk/. [Accessed: 13-Dec-2016].

[11] “PlugShare - EV Charging Station Map - Find a place to charge your car!” [Online]. Available: http://www.plugshare.com/#. [Accessed: 13-Dec-2016].

[12] RStudio Team, “RStudio: Integrated Development Environment for R.” Boston, MA, 2015.

[13] P. Karich, S. Schröder, and M. Zilske, “Routing API - GraphHopper Directions API Documentation.” [Online]. Available: https://graphhopper.com/api/1/docs/routing/. [Accessed: 16-Dec-2016].

[14] “CO2 Signal | Use electricity when its carbon footprint is lowest.” [Online]. Available: https://www.co2signal.com/. [Accessed: 10-May-2017].

[15] “Information download from API | ESIOS electricity · data · transparency.” [Online]. Available: https://www.esios.ree.es/en/page/api. [Accessed: 11-May-2017].

[16] T.-P. Hsu, C.-L. Chen, and T.-H. Hsieh, “A Graphical Method for Great Circle Routes,” *Polish Marit. Res.*, vol. 24, no. 1, pp. 12–21, Jan. 2017.

[17] European Environment Agency, “Reported CO2 emissions from new cars continue to fall,” Denmark, 2017.

[18] “GraphHopper Maps - Driving Directions.” [Online]. Available: https://graphhopper.com/maps/?point=Porto%2C Portugal&point=Lisbon%2C Portugal&locale=pt-PT&vehicle=car&weighting=fastest&elevation=true&use_miles=false&layer=Omniscale. [Accessed: 19-May-2017].

[19] Renault, “Novo Renault ZOE | Automóveis Elétricos | Renault Portugal.” [Online]. Available: http://www.renault.pt/gama/veiculos-eletricos/zoe/novo-zoe/nova-bateria-ze40.jsp. [Accessed: 08-Jun-2017].

[20] CEiiA, “PED - Personal Energy Device.” [Online]. Available: http://ped.ceiia.com/. [Accessed: 08-Jun-2017].

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