Neurocomputing 529 (2023) 214–221

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Interurban charging station network: An evolutionary approach

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ARTICLE INFO

Article history:
Received 6 May 2022
Revised 22 December 2022
Accepted 30 January 2023
Available online 2 February 2023
Communicated by Zidong Wang

Keywords:
Genetic algorithm
Charging station
Electric vehicle
Interurban mobility

ABSTRACT

In recent years, there has been a strong desire to meet the challenge of electrification of vehicles in order to achieve the decarbonization objective. However, as sales of electric vehicles have increased, there is a significant lack of infrastructure to support the charging of this type of vehicle. The infrastructural deficiencies are even more evident in the interurban environment, where the autonomy in kilometers of the battery is a critical issue. To minimize the substantial economic costs involved in installing sufficient charging points to ensure any interurban journey, it is necessary to establish mechanisms that evaluate appropriate locations to deploy the necessary stations. Accordingly, this paper proposes using an evolutionary approach to calculate the most suitable locations in an interurban environment for electric charging stations. For this purpose, different input information is taken into account in the allocation process. The proposed algorithm has been tested using real data from the USA. The results assess the current infrastructure and show the advantages of the locations proposed by the algorithm.

1. Introduction

Road transport continues to have the largest share of EU and USA freight and passenger transport performance. This results, for example, that around 26% of total USA energy consumption in 2020 was for the transportation of people and goods, and the value is similar in Europe. Moreover, almost the entire transport sector is dependent on oil, a scarce fossil resource in most of the industrialized world, with the aggravating factor of the impact of emissions associated with fuel combustion on people's health and global warming. To date, efforts to move towards more sustainable mobility models have not been sufficient to counteract the effects of the growth in the number of trips and the distances traveled by vehicles to move people and goods.

To reduce the impacts associated with the current mobility model, we need a firm commitment to comprehensive works that reconsider mobility in the interurban network and focus on infrastructure design towards a lower use of fossil resources based on demand management, the promotion of collective and alternative modes of transport, the reduction of polluting emissions, and the use of renewable energies.

In this sense, the use of electric vehicles (EVs) is currently a crucial element in developing policies aimed at a significant reduction in the use of fossil resources and gas emissions. However, the massive introduction of EVs is being delayed, among other factors, by the lack of charging infrastructures. The report elaborated by BlombergNEF[1] indicates that annual sales of electric vehicles were around 5.6 million units in 2021, compared to 2.1 million recorded in 2019 and 3.1 million in 2020. In other words, 7.2% of new cars sold globally in the first half of this year were electric, an increase of 4.6% in two years. Despite all this, global road transport emissions are rising again after the 2020 drop due to the Covid-19 pandemic. This makes it clear that there is still much work to decarbonize the road transport sector.

The lack of EV charging infrastructure is a worldwide problem. Even though EV sales have been growing, according to Statista, in a sustained manner over the last few years,[2] EV penetration continues to be relatively low. Using the USA as an example, in 2025, penetration is expected to be 25%, while it is not expected to exceed 30% in 2030. While there has been a clear increase, yet not sufficient, in electric vehicle sales over the past year, increasing from 543,610 to just over a million, the growth in public charging points in the USA has not quite matched that, rising from 98,422 to 128,554 in the same period, an increase of only about 31% (according to the 2022 EV Charging Station Report elaborated by Zutobi[3]).

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[1] https://about.bnef.com.
[2] https://www.statista.com/statistics/913958/projected-north-american-all-electric-vehicle-penetration-rate/.
[3] https://zutobi.com/us/driver-guides/the-us-electric-vehicle-charging-point-report.

https://doi.org/10.1016/j.neucom.2023.01.068
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This problem of lack of infrastructure is generalized in other countries and can lead to what is known as "range anxiety" [1,2], which implies the presence of stress in drivers in case they do not have enough energy to get to their destination. In recent years, we can find initiatives that have tried to facilitate finding electric charging points by providing better and updated information on the available network of charging points. We can highlight initiatives such as Electromaps,[4] Plugsurfing,[5] Ionity,[6] or Plugshare.[7] While providing useful information to the user, all these services are useless if the infrastructures are insufficient.

Within recent works, different approaches have been used to analyze the distribution of electric charging stations in urban areas. A review of different works along these lines can be found in [3]. Most existing works try to estimate the number and location of charging stations needed in a city to optimize some parameters related to vehicle utility. However, the location problem at the interurban level has received much less attention. Planning for an interurban deployment of charging stations presents specific challenges with respect to urban deployment. On the one hand, traveled distances are longer, increasing the drivers' risk to experience range anxiety. Longer trips also imply larger power expenses, and thus electric batteries with higher capacity are favorable. On the other hand, the power of the charging stations must also be assessed. While most urban-centered works focus on fast chargers, an interurban network may be better supplied by a different type. Finally, according to a charging station's specific (non-urban) location, access to the electric grid with adequate power may not be possible.

According to this, the main contribution of this work is to determine an optimal set of charging point locations that make up a network of EV charging stations in a given interurban area. The proposed network must guarantee EV charging for any journey within this area. To this end, the proposal considers establishing a maximum distance between adjacent charging points so that EVs have sufficient autonomy to make journeys within the considered interurban area. The advantages of such a system are multiple since it allows obtaining the best possible locations for a network of charging stations, improves the confidence of EV drivers, and minimizes the investment in the installation of charging points, ensuring a potentially better service of the proposed stations.

The proposed approach has been tested on the territory of the USA, although it can be extended to any geographical area for which the necessary information is available. For this purpose, different data sources have been used, analyzed, and processed as input for the proposed algorithm. The primary purpose of the experiments was to test the locations proposed by our algorithm against the current deployment of charging stations.

The rest of the paper is structured as follows: Section 2 analyzes the related state of the art; Section 3 describes the proposed algorithm for the interurban EV charging stations location; Section 4 describes in detail the data used, the experimental setup and the results obtained from the experiments carried out; finally, Section 5 shows the conclusions and future work.

2. Related work

In this section, we comment on relevant works for the topic at hand. First, we assess review papers that highlight the topic's research gaps. Then, works that discuss the adoption of EVs and the impact this could have on power demand are mentioned. After that, we analyze works that propose EV charging infrastructure distributions following various methodologies. Finally, our own approach is presented together with the motivation for each of the employed techniques.

L. Adenaw and S. Krapf [4] highlight the lack of a common set of criteria for the emplacement of EV charging infrastructure. Their review of the state of the art clusters the employed influencing factors, analyzing how they affect charging demand. T. Unterluggauer et al. [5] identify many research gaps, among which the need for a shift to large-scale and real-world case studies stands out. Around 59.6% of the reviewed literature tackles urban allocation of charging stations, while only 10.6% focused on highways, which could be understood as nationwide traveling. In addition, they point out the need to coordinate planning activities both in the transportation and the power distribution network in order to deploy an efficient charging infrastructure.

The main motivation for the nationwide deployment of EV charging infrastructure is a transition to purely electric-powered transportation. This, in turn, will have a strong impact on a country's energy demand. A. Mangipinto et al. [6] use an EVs charging transactions dataset from the Netherlands, provided by ElaandNL, to assess the impact that an uncontrolled deployment of EVs would have on the power system on a national level. Their model shows a potential rise of 35–51% of the peak power demand, depending on the country. Their results indicate that the best way to palliate this is the application of smart charging strategies and not the improvements in battery density or changing infrastructure. In this line, L. Knapen et al. [7], employ activity-based models to forecast prospective EV energy needs in Belgium's Flanders area. Their models identify certain areas of the region that may be used for smart-grid design, despite the fact that, as the writers point out, precise data on EV electricity use in real-world scenarios is lacking.

Many works present approaches for the planning, deployment and evaluation of EV charging infrastructure. H. M. Abdullah et al. [8] propose an EV infrastructure planning and analysis tool, which relates the feasibility of charger deployment with the rate of EV adoption. Their case study, however, is set on a university campus. Analyzing works with a nationwide approach, L. Victor-Gallardo et al. [9] describe a series of heuristic algorithms used by Costa Rica's administration to designate the sites of 34 charging stations. Their approach innovates with the inclusion of road altitude, although the model is limited by a strong bias toward the allocation of stations in heavily inhabited areas. A. Colmenar-Santos et al. [10] present configurations for a nationwide fast-charging network in Spain. Their technique considers a maximum distance between stations based on highway speed restrictions, weather patterns, and the mean autonomy of commercial EVs presenting, however, the bare minimum number of stations, as their goal is to deploy the cheapest infrastructure possible. F. Xie and Z. Lin [11], set their deployment in the USA. Their methods are based on mathematical modeling and consider only the main interstate highways for the placement of stations. The authors demonstrate, however, how applying a state-independent perspective for the deployment of stations, following their modeling, yields worse results than the interstate approach. Finally, A. Ramirez-Nafarrate et al. [12] evaluate the existing charging station infrastructure for a concrete intercity trip between two cities of Mexico through a simulation-based approach. Their results show how current infrastructure falls way behind the requirements and suggests locations for new chargers.

Given the described research gaps, our work proposes a large-scale deployment (interstate level) of charging infrastructure in the whole USA (real-world setting). Regarding emplacement criteria, our model considers station coverage, in terms of reachability and uniquely covered area; Points of interest (POI) for charger location; residential population and traffic flow. The locations of current petrol stations in the USA are used as a candidate to deploy

[4] https://www.electromaps.com/.
[5] https://www.plugsurfing.com/.
[6] https://ionity.eu/en.
[7] https://www.plugshare.com.

an electric charging station. This presents a combinatorial problem that is solved through a genetic algorithm (GA), an evolutionary approach that obtains near-optimal solutions in a reasonable computing time. We bypass the reviewed previous work's limitation by setting a target budget for the infrastructure, thus not aiming for minimal costs but for the best service. In addition, we implemented evaluation metrics that penalize solutions that deprive sparsely populated areas of service and ensure an EV traveling between any two points of the country will not run out of power.

The work of J. Jordán et al. [13] presents a multi-agent simulation platform that integrates an early version of a GA for charging infrastructure deployment. Such a version included aspects such as the input of POIs and the Voronoi division of the area to populate. Subsequently, J. Palanca et al. [14] refine the algorithm, presenting a multi-objective version that balances utility and cost. Both of the aforementioned works, however, have an urban-centered scope, being their use cases applied to the city of Valencia (Spain) and Lima (Peru), respectively. It was not until the current research that the interurban perspective was applied. With it came many design modifications to the GA, including new metrics for the evaluation of individuals (*pua* and *ld*, in Section 3), as well as improved data processing (Section 4.1). Finally, the current paper is an extension of the work of J. Jordán et al. [15], setting the experimentation on a new and more complex use case in the USA. In addition, we present an extended set of experiments comparing our results with the current network of electric charging stations in the USA.

3. Proposed method for interurban EV charging stations distribution

An intelligent decision support system that simplifies and enhances human work is beneficial to make a distribution of charging stations, especially in the case of placing an extensive set of stations over a vast territory such as a country or a set of countries. Moreover, since the number of possible locations is large (e.g., existing gas stations), an optimization algorithm such as mixed-integer linear programming (MILP) would have a low performance compared to the meta-heuristic exploration of genetic algorithms (GAs). On the other hand, MILP would not be applicable since our utility function is non-linear, as we will see below.

A GA has been developed to place a set of charging stations in an interurban environment based on the available geographical data. This GA receives as input a large set of points of interest where charging stations could be placed. In addition, the GA will also determine the number of stalls to be placed in each of the stations that are decided to be installed. This way, more stalls will be placed to cover areas where more demand is expected. Thus, for a set of n points where a station may be placed (we call them Points of Interest or PoIs), a GA individual is represented as an array of n integers. The integer value indicates the stalls to be placed in that PoI and can range from 0 to a maximum number specified as an input parameter.

3.1. Utility

In addition to receiving the PoIs, the GA receives geopositioned data on population, traffic density, and social network activity as input. This way, a PoI will be selected as a charging station depending on the amount of these data falling within the area of influence of that PoI.

Thus, we define the utility of the placement of charging stations (with the specific number of stalls at each station) as a function of the amount of population, traffic density, and social network activity in the area of influence of the PoI in which one or more stalls are placed as specified in Eq. 1:

$$utility\ (individual) = \sum_{\forall s_i > 0 \in individual} s_i \cdot (p_i \cdot \omega_P + t_i \cdot \omega_T + a_i \cdot \omega_A) \quad (1)$$

where s_i indicates the number of stalls included in the PoI $i; p_i, t_i$, and a_i are the population, traffic density, and social network activity covered by the i-th PoI; and ω_P, ω_T, and ω_A, are the weights used to calibrate each factor's relevance.

To calculate the *area of influence* of a PoI, the intersection between two geometric elements is used: a circumference centered on the PoI with a defined *influence radius*, and the Voronoi polygon corresponding to the PoI. To do this, the Voronoi diagram is calculated with the PoIs where a stall will be placed. This way, each PoI where a station is placed has a Voronoi polygon that depends on the polygons of the neighboring PoIs with a station. Thus, by intersecting the circumference and the Voronoi polygon, the area of influence of the station is obtained, which will be larger or smaller depending on whether it has other stations nearby. To calculate the utility of a given station, only the information (population, traffic density, and social network activity) that falls within this area of influence is considered.

Fig. 1 shows an example with several charging stations located in the USA, where we can see the area of influence of each one of them in gray. As the area of influence is formed by the intersection between the Voronoi polygon and the circumference centered on the station (with a radius of 100 km in this case), when several stations are nearby, their areas are reduced depending on their proximity. This reduces the utility obtained by placing stations too close to each other since they cannot cover so much area of influence alone. However, the area of influence is almost complete (with the 100 km radius circumference) when there are no nearby stations, as in the station on the right of this example.

3.2. Distance to nearest station and percentage of uncovered area

Although one of the priorities is to cover as much demand as possible in the most active areas (regarding population, traffic density, and social network activity), it is also necessary to prioritize the coverage of all possible interurban areas with the network of charging stations. This can guarantee the possibility of charging vehicles for travelers with intercity journeys. For the GA to consider this, two metrics have been included to be minimized: the longest distance to the nearest station of all stations (*ld*) and the percentage of uncovered area (*pua*).

One of the objectives of having a suitable network of electric vehicle charging stations is that the distance between one station and the next should be as short as possible. This would reduce the so-called "range anxiety" as users would be sure to find a charging station within the limits of their vehicle's range. Therefore, one of the measures to be minimized in the GA is the **longest distance to the nearest station of all stations (*ld*)**. To do this, the distance to the nearest station is calculated for each station to be placed. We keep the largest of all these n distances, as this would mark the worst case in which a user would have to travel that distance to find a charging station. Thus, a GA individual would be categorized as more suitable the smaller this measure is.

This value is calculated using Delaunay triangulation (related to the Voronoi diagram) to obtain the neighbors of each PoI where a stall is placed. In this way, we only calculate the distances to the neighbors. Moreover, since this computation will be done for each individual to be evaluated with the GA, the computation can be reduced by having the distances between all PoIs precomputed. To complement the previous measure, the **percentage of uncovered area (*pua*)** is considered. This measure is defined as the areas not covered by the influence radius of the charging stations to be positioned in the total study area. Thus, a lower percentage of uncovered area in an individual of the GA is considered adequate.

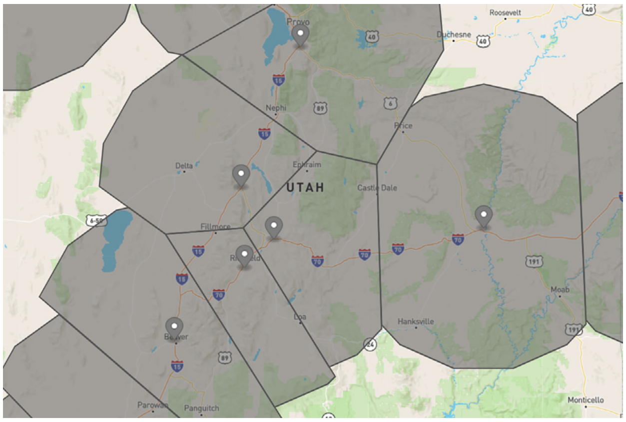


Fig. 1. Example of charging stations with their area of influence composed of its corresponding Voronoi polygon and the circumference centered on the charging station with the defined *influence radius* of 100 km.

The calculation of the *pua* is performed by aggregating the previously defined area of influence (intersection between the Voronoi polygon and the circumference centered on the PoI with the defined radius of influence) of all stations and making the difference with the polygon that defines the total area of the interurban area of the problem.

3.3. Fitness and evolutionary algorithm

The fitness function comprises the aforementioned *utility* and the *ld* and *pua* metrics. Thus, the GA is multi-objective since it will **maximize the utility**, and **minimize the ld and pua** metrics. Hence, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [16] is used. NSGA-II aims to optimize all objectives by obtaining solutions near the Pareto frontier. Thus, an objective is not improved at the cost of penalizing another since the solutions are not Pareto-dominated.

We selected the uniform technique as a crossover operator as it performs well under general conditions. This operator randomly selects each attribute (gene) from one of the two parents to generate a child. On the other hand, the uniform integer technique is used as a mutation operator, which generates an integer to modify a gene if an independent mutation probability is exceeded. The selection operator is that of the NSGA-II since it keeps the best individuals with respect to the objectives based on the Pareto frontier.

To summarize, Fig. 2 shows the steps performed by the genetic algorithm to select the best solution, as shown in this section.

4. Experimentation

In order to evaluate the algorithm proposed in this work, a series of experiments will be carried out on the territory of the USA. The objective of the set of experiments is to test the locations proposed by our algorithm and compare them with the current deployment of charging stations. In addition, the coverage of the territory will be tested.

4.1. Exploratory data analysis

As seen in previous sections, to calculate the most suitable distribution of charging stations in interurban territories with the algorithm proposed in this work, a set of datasets must be prepared and pre-processed to be ingested by the genetic algorithm. These datasets are: points of interest (PoI), population data, traffic density, and social network activity. Table 1 summarizes the main characteristics of each dataset. Next, we analyze these datasets and present relevant data about them.

4.1.1. Points of interest

In this work, the GA presented uses an array of points as a candidate solution or individual where it is evaluated whether or not to place a charging station. When a 0 appears in the array, it indicates that a station will not be placed at that point, and when a positive number appears, it indicates that a station is proposed to be placed at that point (the number indicates the number of stalls at that station).

Each position of the array is linked to a position of a dataset of Points of Interest that are set as input. For this problem, we have selected as Points of Interest a set of gas stations downloaded from OpenStreetMap (OSM) using the Overpass API[8] (data captured in April 2022). This API allows us to download a specific type of amenity from OSM, and we selected the *fuel* amenity since it is an excellent initial distribution for possible charging stations around the US territory and, in addition, each fuel station presumably has an electrical power supply available. Fig. 3 shows the location of the 36,508 fuel stations included as Points of Interest to the GA. The structure of the dataset is a list of coordinates representing each PoI.

4.1.2. Population

The population is one of the three values used to compute the utility function of the GA. In an interurban context, population density is a value that cities have, so the larger the city's population, the greater the attraction of charging stations within its limits, as presumably its car fleet will be larger.

The USA has a number of cities, towns, and villages of 19,502 (as of July 2019). Among them, 16,610 have 10,000 inhabitants or less, and only 10 have more than one million inhabitants (see Fig. 4).

At this point, two circumstances have led to the decision-making process. On the one hand, almost 20,000 cities and towns are a huge number for the utility function to work efficiently since it has to perform spatial joins with each of them. In addition, most of them (84%) have a small population (below 10,000) which has little influence on the utility function. On the other hand, it is not very easy to obtain complete and updated datasets of the USA population due to the particular census process carried out in the country. For this reason, it was decided to take a reduced dataset of the 1,000 most populated cities and towns in the USA[9] This is a sufficiently large and well-distributed dataset to be representative. Fig. 5 shows the selected city shapes' bounding boxes. Bounding boxes have been selected to buffer a city's influence area and simplify the spatial intersection with each Point of Interest since a four coordinates box is much simpler than a complex multipolygon that perfectly fits the shape of a city. This way, as is shown in Fig. 5, the dataset is composed of a list of cities represented by four coordinates (the bounding box), the city name, and its population.

4.1.3. Traffic density

Traffic density is another data used for the utility function of the GA. In this case, for the United States, we have decided to use only the principal arterial information from the Highway Performance Monitoring System (HPMS) of the Federal Highway Administration (US Department of Transportation).[10] The HPMS is a national highway data system that contains information on the country's highways' size, condition, performance, traffic, and operation. Fig. 6 (a) shows an example of the traffic intensity in Alabama. The color code

[8] http://overpass-api.de.
[9] https://www.biggestuscities.com/.
[10] https://www.fhwa.dot.gov/policyinformation/hpms.cfm.

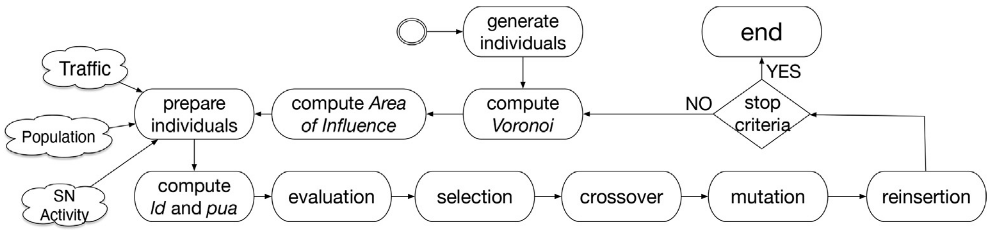


Fig. 2. Genetic algorithm steps.

Table 1
Main characteristics of the employed datasets.

Dataset Name	Size	Date	Origin
Points of Interest	36,508	2022	OpenStreetMap
Population	1,000	2021	US Government
Traffic	8,098	2017	Highway Performance Monitoring System (US)
Social	335,338	2015–2019	Twitter API

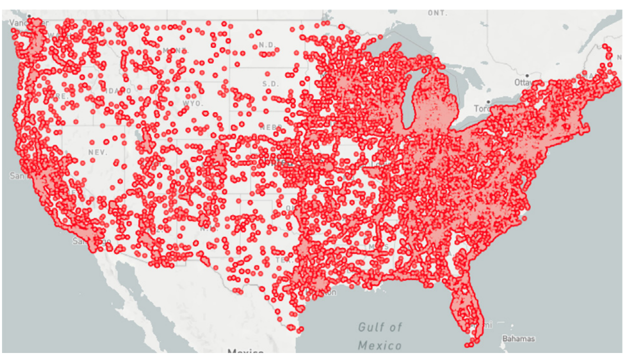


Fig. 3. Fuel stations used as Points of Interest.

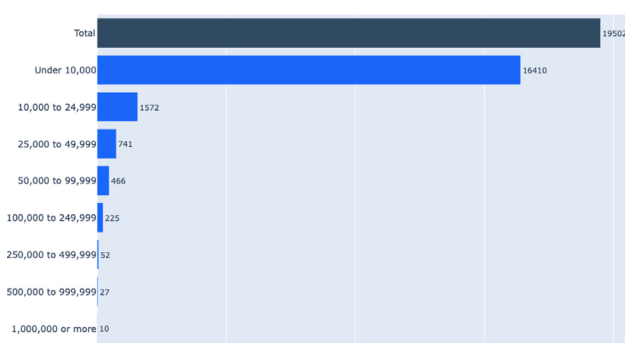


Fig. 4. Number of US cities, towns, and villages by population.

refers to the traffic intensity. The darker the color, the higher the intensity (zoom made for visibility reasons).

In this case, to make the spatial join of the utility function more efficient again, these roads' traffic intensity values have been assigned to the corresponding polygons according to the geohash coding. Geohash is a geocoding system created in 2008 for the public domain that encodes a geographic position into a character array. It is a hierarchical spatial data structure that subdivides space into grid-like cubes, which is one of many applications of what is known as a Z-order curve. The dataset's structure is a list

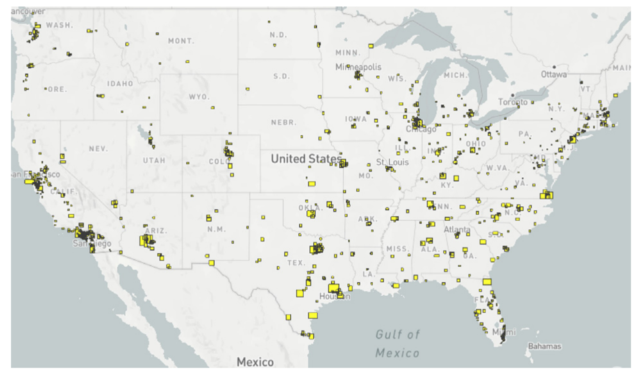


Fig. 5. US cities and towns bounding boxes.

of elements composed of four coordinates (the geohash cell) and the accumulated traffic density in that box during the measured period (2017). These are 8098 cells that represent the US area covered by the traffic dataset with the geohash representation.

4.1.4. Social network activity

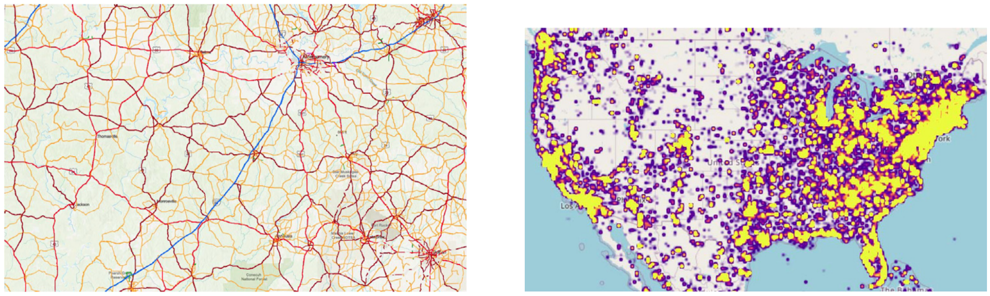
Finally, the third input that the utility function of the GA uses is social network activity. The goal of this data is to know where there is more activity of people. To this end, we collected geolocated tweets in the USA. This clearly represents how the activity is distributed throughout the territory. Although the social networks do not represent 100% of the activity, they are sufficiently representative to compare the territories with each other.

We have collected tweets in the USA for five years, excluding the pandemic years, which are outliers. Fig. 6 (b) shows a heatmap of the distribution of the collected tweets. In this case, we have also imputed each tweet to the corresponding geohash cell to optimize the utility function. The dataset is a list of elements composed of four coordinates (for the geohash cell) and the number of tweets located inside each cell during the measurement period (2015–2019).

4.2. Experimental setup and results

A series of experiments were run to test our evolutionary approach, varying the total number of charging stalls to be distributed. In addition, a maximum number of 16 stalls for a single charging station was set (based on the stall distribution of Tesla[11] charging stations). The algorithm can assign several stalls ranging from 0 to 16 to each PoI, ensuring that the total number of stalls is preserved. Therefore, a problem solution is identified by its number of charging stations (PoIs with more than 0 stalls) and the number of stalls in each station. The rest of the input data is described in subSection 4.1. Regarding the utility of a problem solution, the influence (weight) of population, traffic and social network activity data was equal; i. e: $\omega_P = \omega_T = \omega_A = \frac{1}{3}$ in Eq. 1. Finally, the influence

[11] https://www.tesla.com/findus.



(a) Traffic density example, Alabama (b) Heatmap of tweets at USA between 2015-2019

Fig. 6. Maps of traffic density and tweets activity.

Table 2
Results of experiments conducted for the placement of different numbers of charging stalls in the USA. The number of stalls, number of stations, utility, the longest distance to the nearest station of all stations in km (*ld*), and the percentage of the uncovered area (*pua*) are shown.

	stalls	stations	utility	*ld*	*pua*
proposals	1000	1000	0.01078	273.6	6.62
	1500	1500	0.01714	245.8	4.73
	2000	2000	0.02295	201.1	4.09
	2500	2500	0.02848	183.4	3.93
	3000	3000	0.03292	182.2	3.97
	5000	3022	0.03538	164.6	3.93
	7500	3789	0.04195	164.6	3.91
	10000	4050	0.04679	164.6	3.90
	15000	4207	0.04955	197.1	3.88
	18000	4490	0.05106	182.2	3.88
	20000	4604	0.05673	164.6	3.88
alternative	3000	632	0.01983	368.9	38.17
tesla	18023	1755	0.03688	343.7	15.75
tesla ∪ alt.	19398	2202	0.03102	343.7	15.16

radius (see Section 3.1) of a charging station was set to 100 km (62.14 miles).

The meta–parameters of the GA were set as follows: population (μ) = 150, children per generation (λ) = $\frac{\mu}{2} = 75$, crossover rate = 70%, mutation rate = 20%, generations = 350.

The results of the experimentation are gathered in Table 2. We present different proposals, one per line, according to the number of distributed charging stalls. Moreover, each proposal presents the number of charging stations among which the stalls have been divided. A number of stations equal to the number of stalls indicate a solution in which each station has a single stall. The values that evaluate a solution (utility, *ld* and *pua*) are also presented. Please be aware that our algorithm aims to maximize the former while reducing the last two. The values shown for concrete proposals are the best solution obtained after running five instances of the GA.

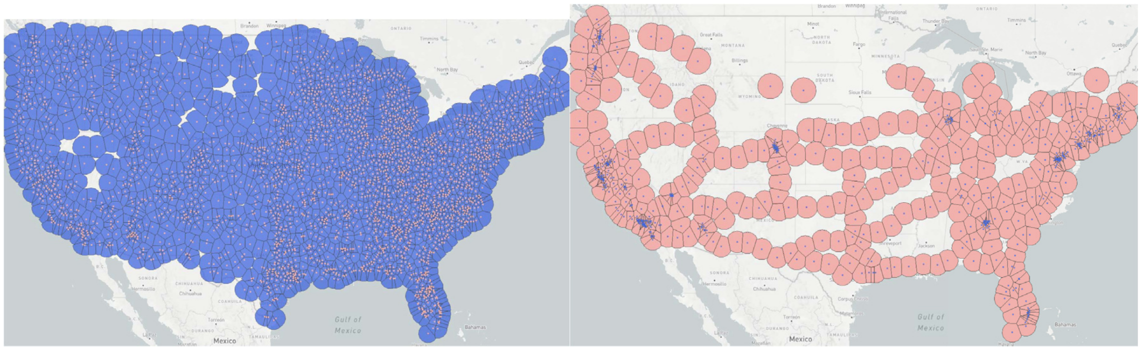
Besides our infrastructure proposals, we show in the last three lines of Table 2 the number of stalls, stations, and the evaluation (according to our metrics) of three infrastructures: the *alternative* infrastructure contemplates all electric charging stations present in the National Renewable Energy Laboratory (NREL)[12] of the US Department of Energy which do not belong to the Tesla company. On the other hand, *tesla* infrastructure represents the electric stations deployed by the Tesla company. Finally, *tesla ∪ alt.* presents a union of both infrastructures. These existing charger networks have served as an inspiration to assess the deployment of a similar number of charging stalls. In addition, we will use them to compare the quality of our proposals.

Going over our proposals, it stands out how with simply 2000 stations, we achieve coverage of 95.91% of the USA area. Compared with the currently implemented stations (tesla ∪ alt.), our algorithm reduces the uncovered area from 15.16% to 4.09%. This is coherent with our algorithm's optimization criteria, which is concerned with reducing areas and distances without charging infrastructure. Such a criterion probably differs from the one chosen to deploy the currently existing infrastructure, which would also explain the high *ld* it presents. Fig. 7 shows a visualization of various charging infrastructures, emphasizing their differences in area coverage.

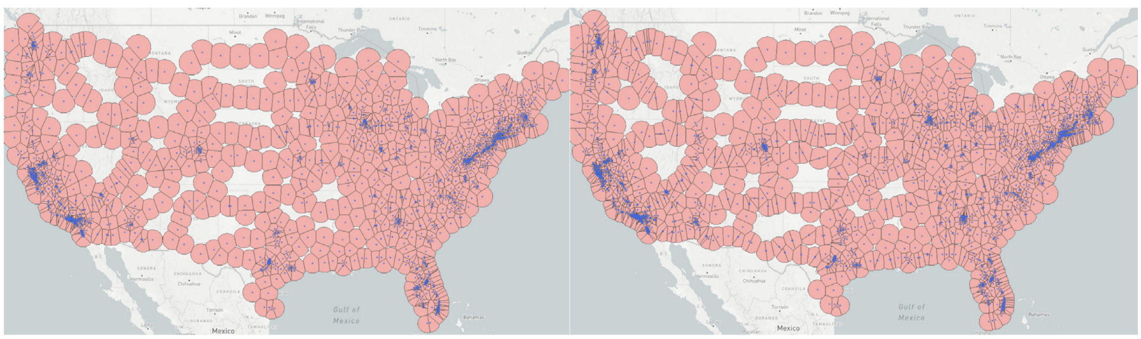
Solutions ranging from 1000 to 3000 stalls assign only one stall per charging station, as this is the way to maximize coverage. However, this may be inconvenient as the stations could not serve more than one vehicle at a time. Because of that, we kept increasing the number of stalls until reaching a magnitude comparable to the existing infrastructure (approx. 20,000 charging points). Once we surpass the 3000 stall barrier, the GA begins assigning more than one stall to some stations. It is interesting to observe the evolution of the number of stations with respect to the number of stalls. Opposite to what one might expect, the number of stations grows with a lower slope than the number of stalls. As it can be seen in a proposal like that of 15,000 stalls, a higher number of stalls does not necessarily imply a more optimized solution. The search process in a multi-objective GA is partially guided by the individuals generated in the initialization. For the discussed proposal, the algorithm has optimized utility and *pua*, which caused relative negligence of the *ld*, which has a higher value with respect to proposals with fewer stalls. Even so, an increment of around 30 km over the minimum *ld* found (197.1 vs. 164.6) is a slight deviation, both algorithmically and in real life.

The *pua* decreases as the number of stalls is incremented and reaches a minimum of 3.88%. The *ld* experiences a decrease as the station network becomes more numerous, but the minimum

[12] https://developer.nrel.gov/docs/transportation/alt-fuel-stations-v1/.



(a) Genetic (3000 stalls, 3000 stations) (b) Alternative (3000 stalls, 632 stations)



(c) Tesla (18023 stalls, 1755 stations) (d) Tesla and Alternative (19398 stalls, 2202 stations)

Fig. 7. Charging stations distributions. Each station (dot) is drawn together with its area of influence (intersection of the influence circumference and the Voronoi diagram).

of 164.6 km is achieved sooner with the proposal of 3022 stations. If a station was placed at each PoI, the *ld* would not go below 164.6 km, however, the *pua* would be 0.55%. Thus, we can assume that while the algorithm has reached the global minimum with the *ld*, it has not been optimal to lower the *pua*. Even with more than 20,000 charging stalls, the area covered by the infrastructure and the longest distance among any two stations would remain similar to those previously assessed. The reason for this is twofold: on the one hand, the number of possible station locations is limited by the PoIs. On the other hand, some locations have no data on population, traffic density, or social network activity; therefore, the placement of a station would not yield any utility.

As illustrated by the results, our algorithm is strongly inclined to mainly ensure the charging network's coverage. Even those areas where the data (population, traffic density, and social network activity) is not present are ensured to have a nearby charging station, thus guaranteeing the completion of a journey that departs anywhere inside the USA territory, finishing in any other location. This is extremely useful not only for regular private vehicle drivers but also for transporting goods and people on a larger scale. We want to clarify that the current charging station infrastructure is not presented as an objectively worse deployment with respect to our proposals. Instead, networks like those of Tesla and the *alternative* seem to have followed other priorities for allocating their stations.

5. Conclusions

In this paper, an evolutionary technique based on genetic algorithms has been presented to propose the best possible location for the distribution of electric vehicle charging stations in interurban environments. When considering the deployment of this type of station along with a vast territory, one of the main objectives will be to maximize the availability of the stations while minimizing the cost. This will mean always having a station within reach of the approximate autonomy of the vehicle and covering the largest possible percentage of the territory; hence, the coverage of the charging stations is the maximum possible without increasing costs. The genetic algorithm proposed in this work is specially adapted to interurban environments, using value information that the utility function of the algorithm will be able to use for decision making. The algorithm mainly uses population density, traffic density, and activity (measured from social networks) to decide where it is more interesting to place a station and how many stalls to consistently provide service (without oversizing the stations).

Extensive experimentation has been carried out on the USA territory to evaluate the algorithm. For this purpose, information has been collected (mainly from open sources) on the inputs required by the utility function. Also, data on Points of Interest candidates to be selected for installing a charging station have been loaded into the algorithm. Finally, the results obtained by the algorithm have been compared with the current deployment of electric charging stations in the United States. These results have shown how the utility of the distribution and the station's territory coverage is improved for a similar number of stalls.

In future work, it is proposed to include more actual costs for the installation and deployment of the stations, taking into account not only a fixed cost per station and additional costs for each stall but also the distance to the nearest electric transformation center and the cable run required from the center to the installation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work is partially supported by grant PID2021-123673OB-C31 funded by MCIN/AEI/10.13039/501100011033 and by "ERDF A way of making Europe". Jaume Jordán is supported by grant IJC2020-045683-I funded by MCIN/AEI/10.13039/501100011033 and by "European Union NextGenerationEU/PRTR". Pasqual Martí is supported by grant ACIF/2021/259 funded by the "Conselleria de Innovación, Universidades, Ciencia y Sociedad Digital de la Generalitat Valenciana".

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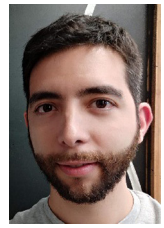

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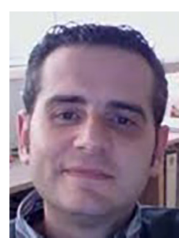

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