Electric Vehicle Charging Stations Emplacement using Genetic Algorithms and Agent-Based Simulation

Jaume Jordán[a] (jjordan@dsic.upv.es), Javier Palanca[a] (jpalanca@dsic.upv.es), Pasqual Martí[a] (pasmargi@vrain.upv.es), Vicente Julian[a] (vjulian@upv.es)

[a] Valencian Research Institute for Artificial Intelligence (VRAIN). Universitat Politècnica de València, Camino de Vera s/n, 46022, València, Spain

Corresponding Author:
Jaume Jordán
Valencian Research Institute for Artificial Intelligence (VRAIN). Universitat Politècnica de València, Camino de Vera s/n, 46022, València, Spain
Tel: +34 963877350
Email: jjordan@dsic.upv.es

Electric Vehicle Charging Stations Emplacement using Genetic Algorithms and Agent-Based Simulation

Jaume Jordán*, Javier Palanca, Pasqual Martí, Vicente Julian

Valencian Research Institute for Artificial Intelligence (VRAIN).
Universitat Politècnica de València, Camino de Vera s/n, 46022, València, Spain

Abstract

The increasingly evident incorporation of the electric vehicle in urban environments is an already undeniable change. Electric vehicles are appearing on the market with more autonomy and lower prices, which is facilitating the progressive change of the vehicle fleet. However, the electric vehicle brings with it the need to provide enough charging stations distributed throughout the city, so that the autonomy of the vehicle is not a problem. This work presents how a genetic algorithm that analyzes the open data sources of a city is used to propose the most suitable locations for these stations. This proposal is the input for a series of experiments that simulate the impact that has the placement of these stations along the city, in order to measure the benefits of the solution proposed by the genetic algorithm. To do this, an agent-based simulation infrastructure was built around a fleet simulator.

Keywords: genetic algorithm, electric vehicle, charging station, mobility, agent-based simulation

1. Introduction

The **motivation** of this work comes from the unquestionable incorporation of the electric vehicle (EV), which represents a substantial change in the mo-

*Corresponding author

Email addresses: jjordan@dsic.upv.es (Jaume Jordán), jpalanca@dsic.upv.es (Javier Palanca), pasmargi@vrain.upv.es (Pasqual Martí), vjulian@upv.es (Vicente Julian)

bility of current cities. This incorporation is an opportunity to improve the efficiency in the mobility and to reduce emissions into the atmosphere. EV is currently emerging as a market segment that will cover part of the mobility of the future. Its success depends on social acceptance, and this depends on good government policies and country regulations. Policies to promote electric mobility via regulation, economical aids, or the development of good infrastructure that facilitate charging, can change the growth perspective of the EV and the citizens' view with respect to its use. Total EV sales will grow from 2.5 million in 2020 to 11.2 million in 2025, then reaching 31.1 million by 2030 according to the study made by Deloitte[1]. The design of supranational, national and municipal policies will be essential for consumers to use EVs. Incentives and the installation of public charging infrastructure will help to achieve the expected impact and efficiency.

Without a doubt, one of the challenges in today's cities is to have a network of charging points that offer an adequate service to their citizens without entailing an extremely high expense. Most cities have chosen to install a reduced number of charging points without previously carrying out an appropriate planning of which are the most suitable locations for their installation. In the medium to long term, this may result in charging points in unsuitable locations or with a very little use. An adequate planning not in the short term, but taking into account an orderly location of the charge points as they are installed, will suppose a better service to the citizens and a more efficient use of the infrastructures. A good planning of charging stations has a relevant impact on the service quality and operation efficiency as is stated in (Brown et al., 2010) and (Wood et al., 2015), and can reduce some anxiety in citizens who want to buy an electric car (Dong et al., 2014).

If we study the literature related to this problem, we find a **state of the art** where, in recent years, different approaches have appeared trying to offer

[1] `https://www2.deloitte.com/content/dam/Deloitte/rs/Documents/about-deloitte/DI_Electric-Vehicles.pdf`

solutions to the problem of the adequate installation of charging points in a city. As an example, in (Zhang et al., 2019) a study of recent approaches is presented. As it will be seen in the analysis made in the following section, most of the proposals lack of an adequate validation given the difficulty of demonstrating that the proposed solutions are the most appropriate. On the other hand, the provided solutions are a fixed picture of a set of locations without taking into account a timeline in the installation of the proposed charging points.

According to all of this, this paper presents an approach based on a multi-objective genetic algorithm that, based on real information about a city, determines the most appropriate set of charging point locations. To do this, the algorithm takes into account, on the one hand, maximizing the service provided to citizens and, on the other hand, trying to minimize the cost of these locations. In addition, the algorithm allows prioritizing some locations against others so that an installation sequence can be established over a given period of time.

The deployment of a charging station network, as with any modification performed over the urban traffic system, involves a high investment of resources and may have a great impact on the system's users. Testing urban traffic changes on the real world is therefore inadvisable, as the removal of the changes can be even more costly than its implementation. Because of that, we find it necessary to use simulators, software that reproduces real-world scenarios in virtual settings, to test and validate any solution before its implementation. As researchers, we must differentiate between the optimization of a mathematical function that describes our problem and the real impact that our solutions will have on the citizenship. Simulators enable us to ensure the mathematical modeling describes solutions that can be adapted to real cities and measure the consequences of implementing them.

In accordance with the stated above, the paper introduces a complete simulation infrastructure that allows the evaluation of the proposed solutions against other approaches. This infrastructure is an agent-based simulation software that makes use of real data on mobility in the city. These data allows a detailed analysis of the efficiency and use of the installed charging points. This simulation infrastructure has been used to make a comparative analysis with data from the city of Valencia (Spain).

Summarizing, the main **contribution** of this work is the validation through agent-based simulation of a genetic algorithm developed by the authors for the selection of the most suitable locations for the installation of electric charging stations. For this purpose, a simulation has been used with real data on traffic, population and activity of the city under study. These contributions include: (1) development of a urban vehicle movement simulator with real-world data, (2) comparison with other charging station location algorithms based on the average time that vehicles must wait at charging stations when they are full, and (3) study of the amount of time that stations remain idle in order to determine whether or not the location of that station was necessary.

Therefore, these contributions allow to experimentally test whether the genetic algorithm developed by the authors provides better solutions than other approaches to generate better locations for EV charging stations. We will consider that a solution is better if it minimizes the time that vehicles must be waiting at a station and there is the least possible number of underutilized stations that increase the installation cost unnecessarily.

The **structure of the paper** is as follows. Next section presents an analysis of the state of the art in this area. Section 3 explains the main characteristics of the genetic algorithm which decides the emplacement of the EV charging stations. Section 4 introduces the resources used for simulation and experimentation of this work. Section 5 presents the experiments performed to evaluate the suitability of the genetic algorithm compared to other approaches. Finally, last section draws the main conclusions and future work.

2. Background

The efficient charging of EV has become one of the key issues in order to consolidate the implementation of EV. Currently, a large part of the research work is focused on trying to optimize the EV charge in a decentralized way. On the other hand, other approaches optimize the use of the power grid trying to reduce the possible impact of EV on the grid (Ma and Mohammed, 2014).

Today we can find different guidelines, such as those of (EV Infrastructure Corridor Development Toolkit; Association, 2019) whose purpose is to help governments and administrations for the proper implementation of EV charging stations and determine where it is best to place them. Along the same lines, the guide (Planning for Electric Vehicle Charging Infrastructure: A Toolkit) proposes processes for planning and implementing EV according to the previous experience of governments.

Currently, a key issue in this area is determining the most appropriate locations for a set of stations in a specific area (a city, a region, a country, etc.). An appropriate location appears to be fundamental to facilitate the ability to satisfy demand and thus promote its use. This problem has been addressed in different ways, as discussed below in the following works.

In (Zhang et al., 2019) a review of dozens of related papers after 2000 is presented. The study analyses the proposed EV charging station location models and algorithms. According to this study, the proposed algorithms usually include Genetic Algorithms, Simulated Annealing, Tabu Search, Particle or Swarm Optimization. Location selection algorithm is currently an interesting research area. Current research on location selection algorithms is out of this work, for more details please consult (Farahani et al., 2010) or (Uyanik et al., 2018). More recently, hybrid approaches have been employed as a combination of different algorithms. As an example, in (He et al., 2012) authors propose a hybrid genetic algorithm that combines a standard genetic algorithm with an alternate location allocation algorithm (Cooper, 1964). Lastly, the popularity of neural network and the good results obtained for multivariate optimization has generated several works in that line. Due to the existence of numerous related works, we will focus on the most recent works that present some kind of validation of the results.

According to this, in (Kaya et al., 2020) a hybrid approach is proposed in a two stages process. First a Fuzzy AHP (Fuzzy Analytic Hierarchy Process) is employed for the weighting of the previously selected criteria. Then, spatial analyses of the criteria are carried out with GIS and the performance evaluation of charging station locations is done with TOPSIS (Technique for Order Preference by Similarity to Ideal Solution).

The work presented in (Kong et al., 2019) consists of a two-layer location planning composed of a construction cost-based preliminary planning and an operational cost-based accurate selection. Authors employ dynamic real-time data instead of statistical data like many of the previous approaches. Moreover, the work includes a simulation platform for EV charging station location planning in different cities or areas. Although there is not much information about the availability of the tool.

A fuzzy multi-criteria decision-making methodology is employed in (Liu et al., 2020) to select potential charging station locations. The process is divided into three phases. The phase 1 establishes a comprehensive evaluation criteria, phase 2 employs a fuzzy best-worst method for the determination of subjective criteria weights, and finally, phase 3 makes use of a fuzzy gray relation analysis-based model for the ranking of alternatives. The work makes a comparative and sensitivity analyses with other similar approaches using a numerical example.

In the work presented in (Mao et al., 2019), a location planning model of fast charging stations is proposed considering its impact on the critical power grid assets. The core of the proposal is a planning model which is a generalization of Knapsack Problem (Kellerer et al., 2004). Specifically, the heuristic cross-entropy optimization method was employed for the planning process. The same authors in (Mao et al., 2020) validate the proposal on a synthetic power-transportation coupled network.

Another interesting approach is presented in (Gong et al., 2019) with a non-deterministic polynomial model. The approach is tested using agent-based model developed in Anylogic[2] in order to analyze the charging frequencies and sharing charging level for the charging stations. In this case, a validation of the

[2]`https://www.anylogic.com/`

proposal is made although the tests carried out are on a very low scale with only a dozen of charging stations.

Most of the reviewed works tend to use a genetic algorithm as the main part of the decision-making process of selecting the most appropriate locations. Genetic algorithms have been used in a general way not only for the problem proposed here, but also for other types of problems associated with localisation in particular or with engineering in general. A very interesting work is presented in Roy et al. (2019) where a Novel Memetic Genetic Algorithm (NMGA) is presented to solve the well-known traveling salesman problem. The proposed GA is the combination of a multi-parent crossover technique with a Boltzmann probability selection and can be adapted for a multitude of problems related to urban mobility. In this line, the work proposed in Biswas and Pal (2019) proposes a GA to solve the congestion management problem in electric power transmission lines.

Finally, genetic algorithms are being used recently to try to optimise the location of different infrastructures such as hospitals Kaveh et al. (2020), bus stations Taghavi et al. (2021) or parks Ge et al. (2020). As is evident, one of the difficulties of these works is to validate that the generated solutions are indeed appropriate given that the real implementation of the proposed infrastructures is very expensive and, also, is impossible to compare with other options in real terms.

After the analysis of different works, we can detect the existence of different proposals in which there are certain differences in terms of input criteria, and fundamentally there is a lack on the validation where the effectiveness of the proposals should be made in environments as close to reality as possible, as commented in (Zhang et al., 2019). In particular, authors comment that current algorithms stay at a theoretical level and the need of verifying the proposed models through simulation in a large-scale vehicle movement scenarios. Moreover, most of the analyzed approaches focus on proposing a set of charging stations on a static situation, without taking into account the evolution of cities over the next few years. In this way, a multi-year planning can be interesting to indicate a possible deployment of the potential charging stations over a period of time.

According to these detected problems, other approach is the presented in (Palanca et al., 2020a) where a multi-objective genetic algorithm is proposed to optimize the charging station locations by maximizing the utility using traffic information and minimizing the cost using power grid information. The current paper is an evolution of that algorithm where the problem of multi-year planning is addressed. Moreover, the development of an associated simulation infrastructure is proposed, which allows to test the efficiency of the proposed solutions compared to other options.

3. Genetic algorithm for the emplacement of EV charging stations

In order to find the best possible solution for the location of EV charging stations, a genetic algorithm has been designed to find a solution that maximizes the utility and minimizes the cost among the wide search space available. A genetic algorithm is a type of evolutionary algorithm that is based on the creation of multiple consecutive generations where the information of the best past solutions is recombined in order to improve the population of solutions in each generation.

Combinatorial problems such as the one described in this paper can be approached with many techniques. Nevertheless, their high computational cost must be taken into account to favor approaches that obtain solutions in a reasonable time. In addition, we are performing multi-objective optimization, maximizing the utility of our infrastructure but also reducing the costs of its implementation. Because of that, the list of suitable techniques is narrower.

At a first glance, a reasonable approach would be well-known Mixed Integer Linear Programming (MILP), which has been successfully applied to resource allocation problems such as ours and returns optimal solutions. Nevertheless, ~~we can not apply MILP to our problem because our~~ the utility function that characterizes our problem, and therefore ~~, one of the functions that~~ must be optimized, is nonlinear, as we prove below. Besides that~~In addition~~, for multi-objective optimization we would need to select a specific nonlinear multi-objective solver, a complex approach which would most likely take a long time to return any solution. With this in mind, we opted to use metaheuristic techniques instead of MILP, as they provided us with near-optimal solutions in a reasonable computation time. Many of these techniques could be applied to our problem, provided we formulated it adequately, and have the potential of obtaining a good solution. The crucial feature that made us decide on genetic algorithms was its reliable implementation for multi-objective optimization, the Non-dominated Sorting Genetic Algorithm II. The efficiency of this algorithm has been proved by multiple works and, to the best of our knowledge, was the most promising approach given our problem formulation.

The genetic algorithm for the emplacement of EV charging stations proposed by the authors in (Palanca et al., 2020a) and (Jordán et al., 2018) is designed to find the best emplacements for EV charging stations from a set of initial Points of Interest. These Points of Interest are all the possible locations in a city to install a charging station, defined by an expert in city planning or randomly generated. A possible solution is an array of integers where each position is related to a Point of Interest and its value is the number of charging poles for that station. If the value is 0 it means that there would not be a charging station at that location. Otherwise, for a value of $cp > 0$, it is assumed that the solution would propose the installation of a station with cp charging poles.

In addition, the genetic algorithm allows defining constraints such as the maximum number of poles per station and the maximum number of poles in the city. In this way it is possible to control the maximum expenditure to be invested in the target city. Also, the algorithm takes into account the previously installed stations in the city, which are considered as fixed. When any of these constraints is infringed, the individual's fitness is penalized in proportion to how far it is from being feasible.

The key to the success of a genetic algorithm is a good design of its fitness function. This is done using information extracted from open sources in the city where it is being run. This information allows to approximate the quality of the solution or *utility*, taking into account data such as the population covered by the proposed solution, the amount of traffic passing through the selected points and even the activity registered in social networks with geo-localization among others. Additionally, the monetary *cost* of a solution is also considered. Each charging station and each charging pole have a fixed cost, which means that a solution that takes advantage of the stations by putting several poles on them will have a more reasonable cost than putting more single-pole stations. The cost of each station also considers the distance to the nearest power plant (called transformer substations) from which it would obtain power.

Nevertheless, the utility of placing a station is influenced by whether or not there are other stations in the surrounding area. This is because for a distribution of stations in the city (the selected PoIs that will be stations), the centroidal Voronoi tessellation is calculated. Hence, each station acts as the centroid of its Voronoi polygon that limits with the nearest stations. Then, the geometric intersection between the Voronoi polygon and the circumference formed by the influence radius (a parameter of the problem) of each station is done. The resulting area is defined as the *influence area* of the station. So only the geographical data that falls inside that area is considered as covered by the station (population, traffic, and social networks activity).

Figure 1 represents a neighborhood in Valencia in which there are three PoIs. The left part of the figure shows that if only two of these PoIs are selected as charging stations, their areas of influence do not coincide. However, in the right part of Figure 1 we can see that if the three PoIs are selected as stations, their areas of influence are reduced by making the intersection between the Voronoi polygon (for simplicity, we do not represent all the lines of the polygons) and the circumference with the radius of influence of each station.

The utility of each station depends on the surrounding stations, since if they are close to each other, their area of influence is reduced when the Voronoi polygon intersects the circumference of the radius of influence around the station. This causes the utility function to be **nonlinear**, so linear programming

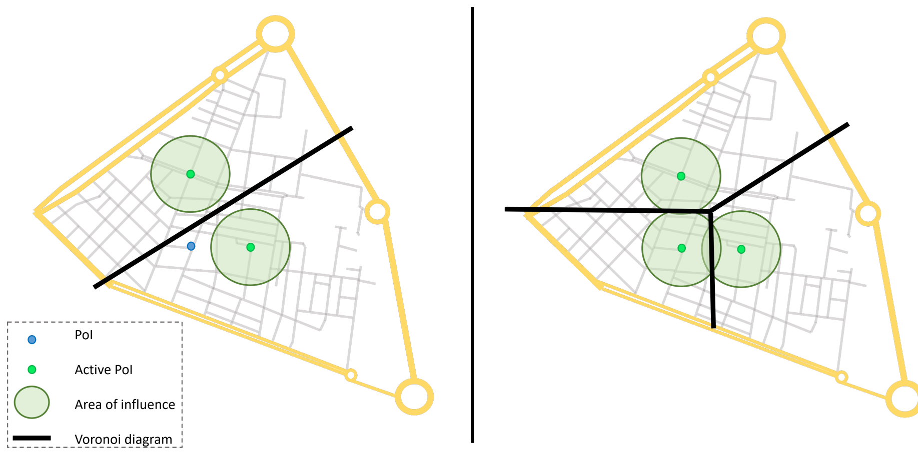


Figure 1: Example of a neighborhood in Valencia with three PoIs where two or three of them are selected to be charging stations. In each case, the resulting *influence area* of each station formed by the intersection between its circumference of influence and the Voronoi polygon can be seen.

techniques cannot be used to solve this problem.

The utility of an individual Φ is defined as the sum of the attributes that cover the area of the corresponding PoI (i.e., population, traffic, and social activity). This is done for every PoI cp_i in which at least one charging pole is placed. The equation is as follows:

$$utility = \sum_{\forall cp_i > 0 \in \Phi} (\omega_P \cdot P_i + \omega_T \cdot T_i + \omega_A \cdot A_i) \qquad (1)$$

where P_i is the covered population of the station in the *influence area*[3] of the PoI ; T_i represents the covered traffic of the streets in the *influence area* of the PoI; A_i is the number of social activity items~~tweets~~ that are geo-located in the *influence area* of the PoI; and each ω is the corresponding weight of the different attributes that are considered for the utility. The social activity items represent coordinates that show the activity of social networks users at some moment. An example of these items is geo-located tweets from the Twitter social network.

[3]The geometric intersection between the Voronoi polygon and the circumference formed by the influence radius.

The cost (Θ) of an individual Φ is defined as:

$$\Theta = \sum_{\forall cp_i > 0 \in \Phi} (\Theta_{cp} \cdot cp_i + \Theta_{E_i}) + \Theta_S \cdot |\Phi| \quad (2)$$

where Θ_{cp} is the fixed cost of a charging pole; cp_i is the number of charging poles at each PoI of the individual; Θ_{E_i} is the energy cost of cp_i; Θ_S is the fixed cost of a station; and $|\Phi|$ is the number of activated stations in Φ where at least one charging pole is located (and hence a station is placed). In other words, $|\Phi|$ is the number of $cp_i \in \mathbb{N}_1$ (where $\mathbb{N}_1 = \{x \in \mathbb{N} | x > 0\}$).

Since there are two objectives to optimize in the fitness function, we use a multi-objective approach such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002) to **maximize the utility** while **minimizing the cost** of installing stations. The rank 1 solutions[4] returned by the NSGA-II algorithm are not dominated, which means that one objective value cannot be improved without decreasing another objective value. Figure 2 shows a result of the multi-objective algorithm along the explored generations.

The NSGA-II algorithm uses its own selection operator that chooses the best individuals with respect to the Pareto frontier. The crossover operator that we use in our implementation is the uniform technique, in which each attribute (gene) is randomly selected from one of the parents to create a child. Finally, the selected mutation operator is the uniform integer technique, which generates a new integer value within a provided range with an independent probability of each attribute (gene) being mutated.

The genetic algorithm is implemented using the $\mu + \lambda$ approach of the *deap*[5] library of *Python*, where μ is the number of individuals to select for the next generation, and λ is the number of children to produce at each generation. We consider a μ value equal to the population size (number of individuals) of the problem, and a λ value of half the population size.

[4] There may be solutions of lower ranks (2, 3, etc.). Any lower rank solution would be dominated by higher rank solutions, and thus, rank 1 solutions are not dominated.

[5] `https://github.com/DEAP/deap`

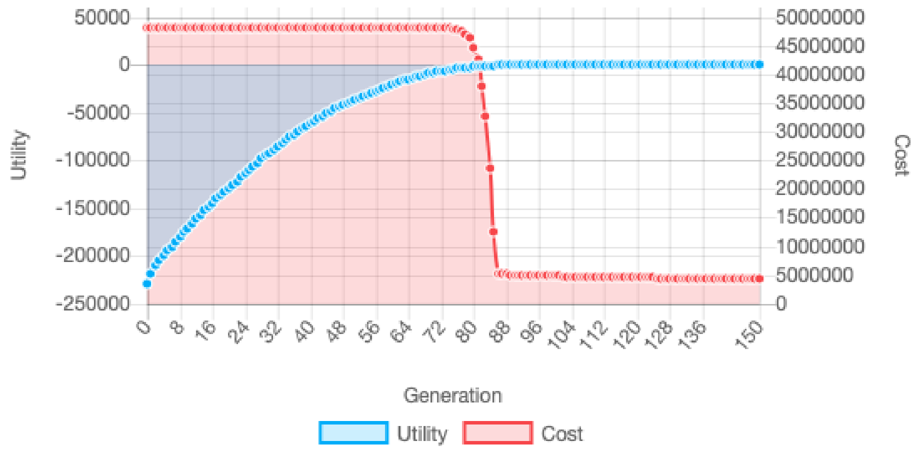


Figure 2: Utility and cost throughout 150 generations. The blue line shows how the utility grows until it reaches a positive value (with no penalties). Also the red line shows the cost, which is drastically reduced near the 88th generation.

3.1. Long-term urban planning

The possibility of including previously installed stations has also been used to be able to plan stations in a city not only in one-shot but over time. It is common in the urban planning decisions of a city to carry out the projects in different phases over time and not with a single initial investment. To this end, the genetic algorithm we present is capable of planning a deployment of stations over time, specifying the speed of deployment and the number of new stations each year. This allows to go towards a long-term planning that optimizes the use of the stations in the city and minimizes the investment.

The way the algorithm develops this behavior is thanks to its ability to receive a series of fixed stations as input. It starts computing the solution for the first year, with the constraints that are established for that year in terms of number of stations, number of poles per station, etc. Then the output of this year is used as input for the next year of the series, by interpreting the input as fixed stations that can not be removed. The stations will be permanently included in the deployment plan, but they can be upgraded with more poles over the stages computed by the algorithm for each year. This way, the algorithm can make a deployment plan for several years in a city, where each year more stations and poles are installed until it reaches the final stage where the goal of installed stations is reached.

Figure 3 shows an example of how the urban plan for installing stations changes over the years. In the figure three snapshots of three years (2022, 2026 and 2030) are shown and the number of poles per station (green pins) and the number of stations (green and yellow circles) grow over the years in those points of interest where the genetic algorithm determines that is more important.

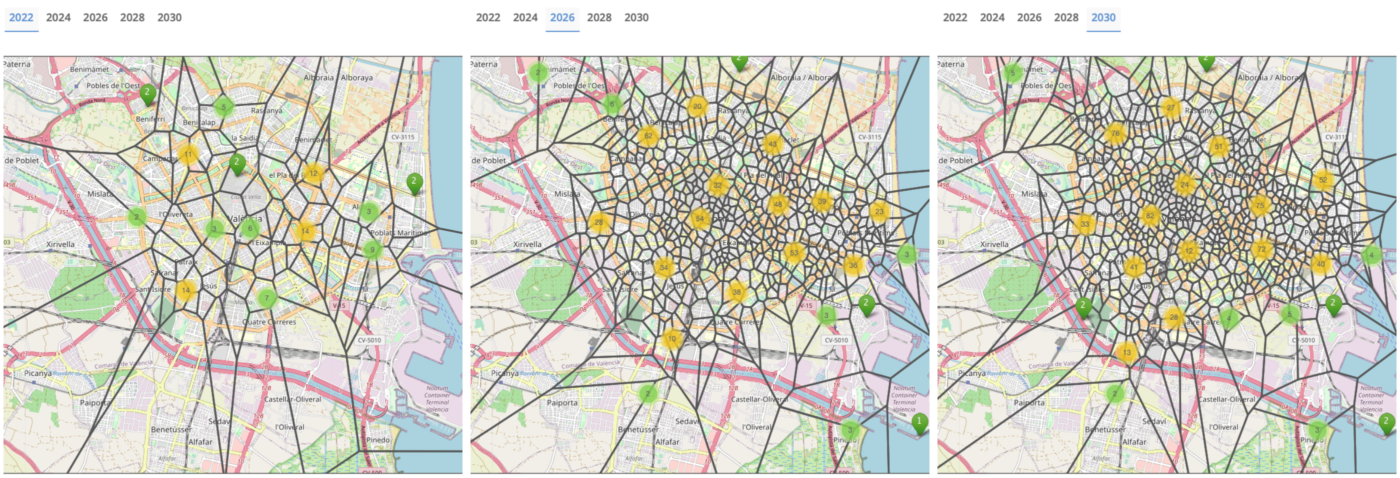


Figure 3: An example of the proposed solution over the years. These figures show how the number of stations grow and the area assigned to each station (represented as Voronoi polygons) decrease over the years.

The rest of this paper deals with the experimentation that has been carried out to validate the advantage of the proposed solutions and the modifications that have been made to a tool also developed by the authors, SimFleet, to run the experiments.

4. Materials & Methods

In this section, we present how we have prepared the experimentation that shows how the results of the genetic algorithm improve non-informed results.

For this purpose, the experimentation has been designed through simulation. A simulation software of open urban fleets, called SimFleet, has been used. This simulation package has been developed by the authors and allows to check how the use of the charging stations and the traffic flow evolves with different configurations of location of charging stations. Additionally, it has been necessary to develop a series of complements for the SimFleet simulator in order to adapt it to the experiments needed in this work. In this section, we present the SimFleet simulator, the necessary components that have been developed for the experimentation, and the experiments setup.

4.1. SimFleet

SimFleet (Palanca et al., 2019) is a multi-agent based simulator of urban fleets based on the SPADE platform (Escrivà et al., 2006; Palanca et al., 2020b). In this work, we make use of SimFleet to test different configurations of charging stations in a city. For that, we execute simulations over the same city area but varying the amount of distribution of charging stations as well as the number of EVs that drive around the scenario.

Since SimFleet is a multi-agent simulator, each of the elements that take part in the simulation are represented by an intelligent agent. This allows to define an intelligent behavior for each vehicle, station or any other element that takes part in the simulation.

SimFleet is an open fleet simulator which has three main roles: the vehicle, the passenger and the fleet manager. The user of this simulator may introduce different behaviors for each of the roles (or ultimately for each of the individual agents) to get different measures of the simulation (i.e. number of travels, distance traveled, mean time that the passengers were waiting for a transport, etc.). SimFleet is a simulator originally focused on the management of open fleets, like taxi fleets or last mile delivery fleets, so an important part of its architecture are the fleet managers. Fleet managers are designed to serve as brokers between customers and fleet drivers, in order to select the best transport for a trip (the closest vehicle, the cheapest driver, etc.). To do this, the

SimFleet user may configure the strategies that each role is going to run. You can configure the strategy for a customer to accept or refuse a trip proposal, the strategy for a vehicle to make an offer for a trip and even the strategy of a fleet manager to decide which vehicles to redirect a trip request. By now the reader will have observed that SimFleet is focused on the negotiation of vehicle fleets, but not for the simulation of independent vehicles that do not belong to any fleet and that do not have to pick up passengers to take them from one point to another. To this end, some changes have been made to the simulator in order to make it appropriate for the experiments we wanted to run. As a side effect, the result has been a more generic and versatile simulator that allows to make much more interesting experiments with vehicles in urban scenarios. In the next sections 4.1.1 and 4.1.2 we present some of the changes that have been added to SimFleet. These changes, as well as the simulator itself, can be downloaded and used with an open source license from the SimFleet's repository[6].

4.1.1. Free-floating vehicles

In the previous versions of SimFleet (1.x) vehicles were supposed to be professional drivers that belong to a fleet and whose work is to pick up passengers from a start point and to take them to a destination point. The most common example is a fleet of taxis, but this is also valid for last mile delivery transports where a driver may use her vehicle (no matter if it is a bike, a car, etc.) to pick up a package and deliver it to the customer.

However, for the experiments of this work we wanted to simulate drivers that move along a city for their common trips (going to work, going home, etc.). This kind of trips do not involve to pick up a passenger after a negotiation process, but the vehicle knows in advance where it has to go. To this end, SimFleet has been modified to include free-floating vehicles which are completely free to move along the whole map without any previous negotiation nor passenger pick up process. This allowed us to simulate traffic flows and how some changes in

[6]`https://github.com/javipalanca/simfleet`

the city (like the position of charging stations) influence the city's traffic.

4.1.2. Station role

In order to allow vehicles to go to a fuel station or EV charging station we needed to create a new role in the simulator, the Station role. This role is played by agents who represent a charging station. A charging station has a fixed position in the map (defined by its latitude and longitude) and, in the case of an EV charging station, it has some properties that define its capabilities. Some of these properties are the number of charging poles, which define how many cars can be charging their batteries simultaneously, and the power of the stations, which defines how much time a vehicle needs to be using the station to get its batteries filled.

With these elements, we included the station role in the simulation and then vehicles can request a place in the station to charge their batteries. When the charging poles are used by other vehicles the requesting vehicle may wait in a queue until a pole is free.

Additionally, some measures are collected to analyze how good the distribution of stations is in the city. Some of these measures are the mean waiting time in the queues or the mean time that the stations are idle.

4.2. Load and Charging Stations Generators

The Load Generators, introduced in (Martí et al., 2020), enable SimFleet users to create complex simulation experiments that present different distributions of agents and elements. To do so, they create or fill a SimFleet configuration file, which describes the simulations in SimFleet, according to some user-defined parameters. Following, we briefly explain how the generators work and what are they used for in this work.

In general, the generators work with a GeoJSON file which represents the area of the city where the simulation will take place. The city area is then divided according to the desired type of distribution. Afterwards, the area is populated with the agents and other elements of the simulation experiment.

Such elements will always be placed on valid positions; i.e: positions that correspond to a street or road. This positions are represented by latitude-longitude points, obtained by OSRM[7], a routing engine that finds shortest paths in road networks. In this case, we use it to obtain the nearest valid point to a certain pair of coordinates. Two generators where developed: a *Charging stations generator*, which distributes exclusively charging stations over the city area; and a *Load generator of movements in a city*, which populates the city area with a certain number of agents and assigns a route to them, thus creating movement or simulation load.

4.2.1. Charging stations generator

The charging stations generator creates a *random, uniform, radial* or *probabilistic* distribution of n charging stations with p available charging poles. As explained above, this distribution is performed over the area of the city where the simulation will take place. According to the type of distribution, the generator splits the area into a series of polygons in which stations will be allocated. The first three distributions are based on a geometric division of the simulation area, while the probabilistic one populates the map based on real city data, and is therefore arguably informed.

The random distribution generates n valid points with random x and y coordinates that are within the city area. Such points serve as the emplacement for the stations of the simulation experiment.

The uniform distribution trims the city area against a grid of a similar size, effectively dividing the city area into squared-like polygons. The number of cells in the grid is determined by the number of stations n. If n is a perfect square, the grid will have $\sqrt{n}$ rows and columns and, consequently, exactly n cells. Otherwise the grid will have one more column than rows if the map is wider than higher or vice-versa if the map is higher than wider. Once the city area is divided, stations are located in the centroid of every polygon, iteratively.

[7] `http://project-osrm.org/`

If the number of stations is higher than the number of polygons, the process may locate two or more stations in the same polygon choosing, however, random valid points inside it instead of the already occupied central point.

As for the radial distribution, it is performed by trimming the city area against c concentric circles that define the city in ring-like polygons. Those rings are, in time, divided into eight parts by intersecting them with a squared area divided in eight triangles that go from every vertex and middle point of a side to the center of the area. The stations are again allocated in the centroid of the resulting polygons although this time the allocation starts in the inner circle and moves towards the outer. Similarly as in the uniform distribution, if there are more stations to place than polygons, the process will begin again but placing stations in random valid points of each polygon.

In the aforementioned distributions, the assignation of charging poles to charging stations is, by default, uniform, having each station either p/n or $p/n - 1$ poles. There is an alternative method that assigns a random amount of charging poles to a random station. The latter method ensures both that every station has at least one pole and that no station has more than a certain percentage of the total stations.

The probabilistic distribution receives, in addition to the charging poles to distribute, a minimum distance between stations (*min_dist*) and a maximum number of poles that can be allocated in a single station (*max_poles*). The allocation begins by dividing the city uniformly into a configurable number of cells, much like the uniform distribution does. Then, it uses cadastral, traffic, and social network activity data to assign a probability to each cell. These probabilities define the chances a polygon has to be selected to install a station in it. The allocation of charging poles is done by iteratively selecting one polygon and adding a pole to the closest valid point to its centroid. The selection of polygons is performed semi-randomly according to their probabilities. A polygon can be selected more than once, which would increase the amount of charging poles in its station. Finally, the distribution ensures that every station is at least *min_dist* apart from another station and that no station has more *max_poles* charging poles. This distribution stands out from the geometry-based alternatives due to the use of real-world data to base the location of the stations on.

4.2.2. Load generator of movements in a city

This generator creates simulation load in terms of agent movement in the city where the simulation is performed. The agent movement is characterized by n agents of type t that follow a route of at least *min_dist* meters. The agents can spawn upon the start of the simulation or be delayed by d seconds. In addition, the n agents may be divided in batches of *agents_per_batch* agents, having every batch an incremental delay. The movement (routes) performed by the agents may be random or based on real data. For the random movement, routes are generated choosing random origin and destination points for each agent, always considering they must be at least *min_dist* meters apart. Once an agent spawns, it will do so on its route's origin point and its execution will finish once it reaches its destination.

In order to base the movement of agents on real data, thus creating realistic routes, the informed movement generator was developed. This generator uses information about the population, traffic and social network activity in different areas of the city to select origin and destination points of the routes accordingly, similarly to the probabilistic charging station generator. Initially, a *granularity* is defined, which indicates in how many areas will the main city area be divided. A higher granularity will result in smaller areas and therefore more possible points to build routes. Once the city is divided, the amount of information (population, traffic, social network activity) that occurs in each area is used to define a probability distribution over all areas of the city, assigning to each one a selection probability. According to that probability, the routes will be created selecting two different areas at least *min_dist* meters away from each other, and then a point within each area is selected as an origin or destination, as appropriate in each case. By adjusting the weight of each type of data over the selection probability, we can base routes for electric vehicle agents which are more influenced by traffic and population in contrast to routes for taxi customers, more based on population and social network activity, for instance. For further clarification on how the probability distribution is created and employed, please refer to (Martí et al., 2020).

In this work, the charging stations generator was used to compare different distributions of charging stations over the city of Valencia, Spain. Uniform, radial, random, and probabilistic distributions of electric stations were created and compared against the one obtained by the genetic algorithm described in Section 3. On the other hand, the informed movement generator was used to populate the city area with transport agents representing electric vehicles (EVs) and assign them realistic routes. During the development of their movements, EVs will require to charge their batteries and will do so going to the nearest station. Finally, by comparing SimFleet's metrics for simulation evaluation among various executions, we can analyze the effect of different distributions of charging stations over the time EVs waited in a station to charge, being therefore able to tell apart more efficient distributions.

4.3. Experiments setup

With all the previous elements we have prepared a set of experiments that allows us to check how the solutions proposed by the genetic algorithm work compared to other. Figure 4 shows how the different elements of the simulation were interconnected.

The experimentation through simulations has been focused on the city of Valencia, Spain. The working area considered for Valencia is depicted in Figure 5. We have all the necessary data (cadastral, traffic, and social network activity) to generate vehicle movements that reproduce reality, as well as to compute solutions from our genetic algorithm for the placement of electric vehicle charging stations.

Our final objective is to compare the suitability of the distribution of electric vehicle charging points in the city of Valencia generated by the proposed genetic algorithm against other distribution alternatives, such as: uniform, radial, and

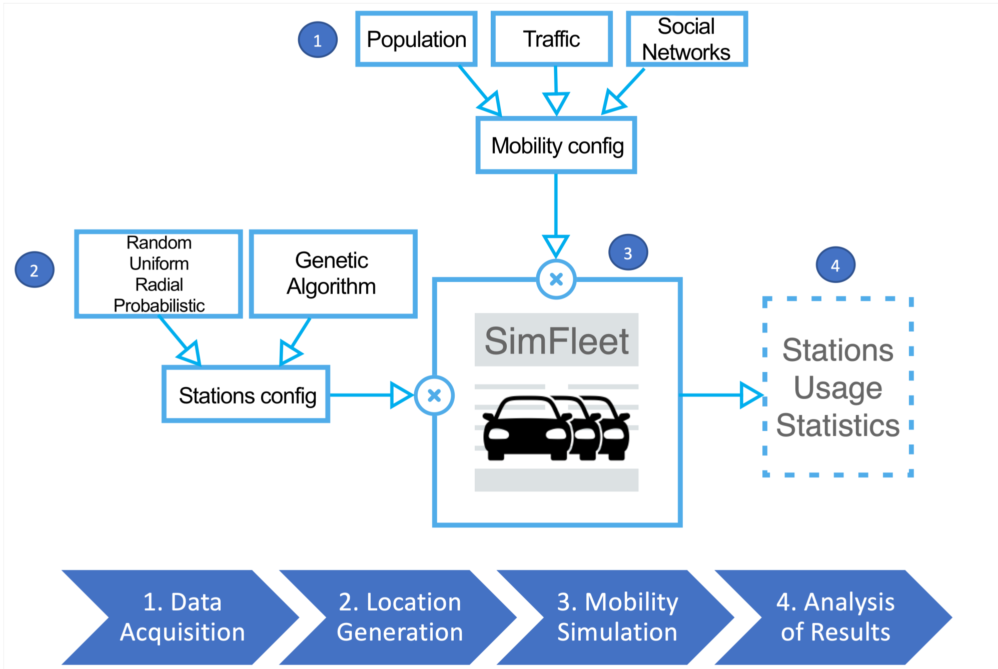


Figure 4: Schematic overview of the whole experimental process

random. Figure 6a shows an example of 50 charging poles obtained by the
545 genetic algorithm within the working area of Valencia (a number in a point represents the amount of charging poles in that station, while the absence of a number implies that there is only one charging pole).

The uniform, radial, random, and probabilistic distributions are generated using the algorithms proposed in (Martí et al., 2020) and described above for the
550 automatic generation of charging station locations. In the following paragraphs, we briefly explain how each of these distributions are created for the city of Valencia. For further details we refer the reader to (Martí et al., 2020).

The uniform distribution divides uniformly[8] the working area of the city into

[8]The uniform distribution does not refer to a probability distribution but to how charging

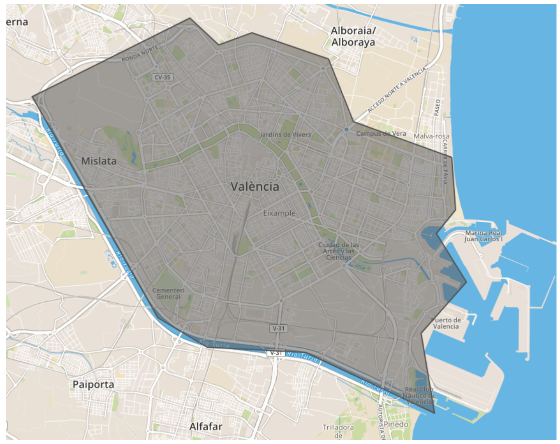


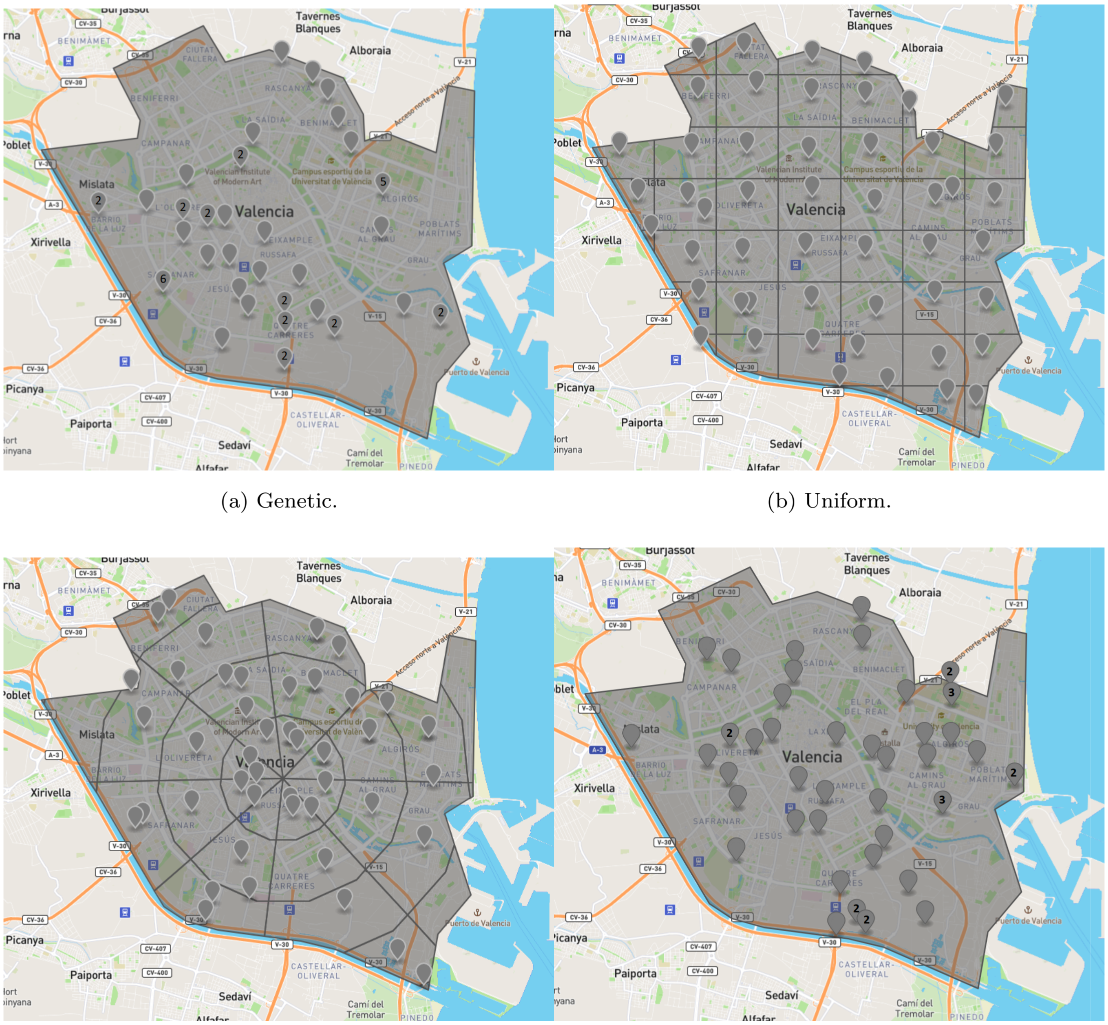
Figure 5: Working area of Valencia city.

equal size cells to place the charging stations in the closest valid points (it has to be a street of the city) of the centroid of each cell. If there are not enough cells because of the shape of the map, the rest of charging points are distributed randomly in different cells of the grid in a random position inside that cell. Figure 6b shows a uniform distribution of 50 stations with the corresponding polygons.

The radial distribution divides the city into a series of determined concentric circles and triangles that cut them to determine the polygons where the charging stations will be located. Then, each station is allocated in the closest valid point of the centroid of each polygon. To perform this allocation the algorithm considers both the amount of stations per circle as well as the polygons a circle has in order to allocate the stations as uniformly as possible. Figure 6c shows a radial distribution of 50 stations with the corresponding polygons in Valencia.

The random distribution of charging points is created by generating random x and y coordinates inside the working area of the city for each charging point that has to be located. Then, the closest valid point in the map (it has to be a street of the city) is obtained and it is stored as a station location if it is

points are divided in the city.



(a) Genetic. (b) Uniform.

(c) Radial. (d) Probabilistic.

Figure 6: 50 charging poles in different distributions with polygons.

still contained in the city map; otherwise, new coordinates are generated until finding a valid location.

Finally, the probabilistic distribution divides the working area similarly to the uniform distribution and assigns a selection probability to each polygon. The probability is computed according to the amounts of population, traffic and social network activity that occur inside each polygon. When a polygon is selected, a charging station will be deployed inside it. If a polygon is selected more than once, the number of charging poles of the station will be increased in one each time. The selection of polygons is performed semi-randomly according to their probabilities, taking into account a minimum distance among station and a maximum number of charging poles in a single station. Figure 6d presents a probabilistic distribution of 50 charging poles within the working area of Valencia.

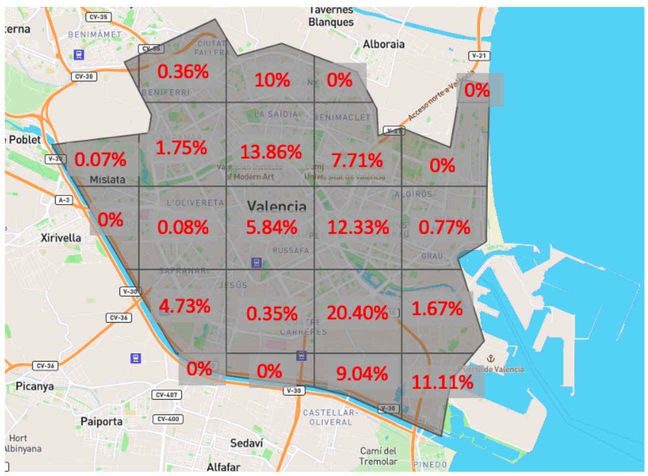


Figure 7: Vehicles informed movement probabilities in a 22-cell grid.

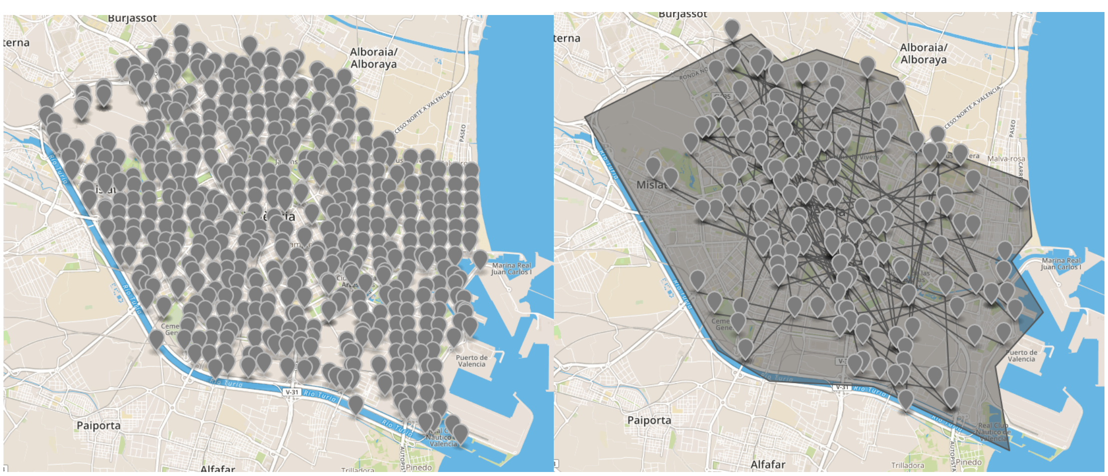
In order to test the suitability of a distribution of charging points, we will measure values such as waiting time of vehicles at stations that represents congestion, among others. Thus, two types of vehicle movement or mobility patterns are generated in the city.

On the one hand, the vehicles random movement is generated by putting random points of origin and destination in the city for each of the vehicles in the experiment with a minimum distance *min_dist* established between the origin and destination.

On the other hand, the vehicles informed movement is generated using cadastral, traffic, and social network activity data, in a similar way to the probabilistic station distribution, to determine the probability of vehicles in each area of the city. These probabilities are used to generate the points of origin and destination of vehicles, always having a minimum distance min_dist between these points. Figure 7 depicts a 22-cell grid with the corresponding probabilities of locating the origin/destination point of a vehicle (we note that for the experiments of Section 5, the grid has 930 cells).

It should be noted that the informed movement is much more adjusted to reality than the random one since the former is generated considering the real data that determine the greater or lesser presence of vehicles in the city. In this sense, tests are proposed with a number of electric vehicles between 2500 and 4500 that want to charge their batteries at the same time in the city.

As an example for both random and informed vehicles movement, Figure 8a presents a $30x30$ grid of points to be possible origin and destination points of vehicles in the city. We should note that in the case of the informed movement each point corresponding to the centroid of a cell has an associated probability while in the random movement the probability would be the same to each point. In addition, Figure 8b represents 100 routes of vehicles in the city that are generated using the previous points.



(a) 30 rows and columns. (b) 100 routes.

Figure 8: Load granularity in a 30x30 map and 100 routes example.

The electric vehicles in the simulations in the city of Valencia move to the nearest charging station, without considering other parameters such as the occupation of the station or the length of the queue. This is a realistic way to represent what is currently happening in the gas stations or charging points, so the distribution of the charging points in a city should be done adapting it to the actual demand. Therefore, it is out of the scope of this work to use other techniques such as those proposed in (Jordán et al., 2018) and (Jordán and Onaindía, 2015; Jordán et al., 2020) to optimize and coordinate the rational use of charging points that involve communication and having knowledge of what other agents could do at any time.

Finally, in order to test all this, three different experiments have been defined depending on the number of charging points that are placed in the city, 50, 100, and 200. It should be noted that in the case of our genetic algorithm these charging points are placed in an incremental manner, i.e., the 100 charging point experiment consists of the 50 charging points of the previous experiment plus another 50 additional points, and the same with the 200 experiment that is based on the 100 charging point experiment above. In this way, we can recreate an incremental installation over several years of charging points in a city to better meet demand.

Table 1 presents the parameters used to run the genetic algorithm in the city of Valencia. The first four parameters, represent the initial population of the genetic algorithm, the number of generations to obtain a final solution, and the probabilities of crossover and mutation. Then, the initial number of Points of Interest in the city is 1333, but these points are reduced through a clustering algorithm to 234 points, so there is at least 300 meters between each possible station. The charging poles to locate are 50, 100, and 200 in each experiment, while the maximum number of charging poles per station is 10. The weights for the population (ω_P), traffic (ω_T), and social network activity (ω_A) are determined as 0.2, 0.4, and 0.4, respectively. In addition, the cost for each charging station is 50000€ (including one pole), and each additional charging pole costs 10000€. Each meter from the charging station to the transformer

Parameter	Value
population	1000
generations	100
crossover prob.	0.5
mutation prob.	0.05
number of PoIs	1333 $\rightarrow$ 234 (after clustering)
distance PoIs	300
total poles to locate	50, 100, 200
max poles per station	10
ω_P	0.2
ω_T	0.4
ω_A	0.4
cost station	50000
cost pole	10000
cost distance energy	150
energy radius	100
influence radius	300

Table 1: Genetic algorithm parameters for Valencia.

substation costs 150€. Finally, the maximum energy radius to connect the charging station is 100 meters, and the influence radius of the station is 300 meters, that is, it only considers the data of that area for the utility value.

5. Results

This section presents the experimental results that have been made to test the suitability of the distribution proposed by our genetic algorithm of the EV charging stations against other distributions by simulating mobility in SimFleet. Three experiments have been mainly carried out in which 50, 100 and 200 charging points have been placed, respectively, in the city of Valencia. Therefore, the main measure with which we evaluate the suitability of each distribution in these experiments is the mean waiting time of the vehicles in the queue at the charging stations. In addition, we also analyze the percentage of stations that remain idle in the experiments. Finally, an overall discussion is held on the results obtained in these experiments.

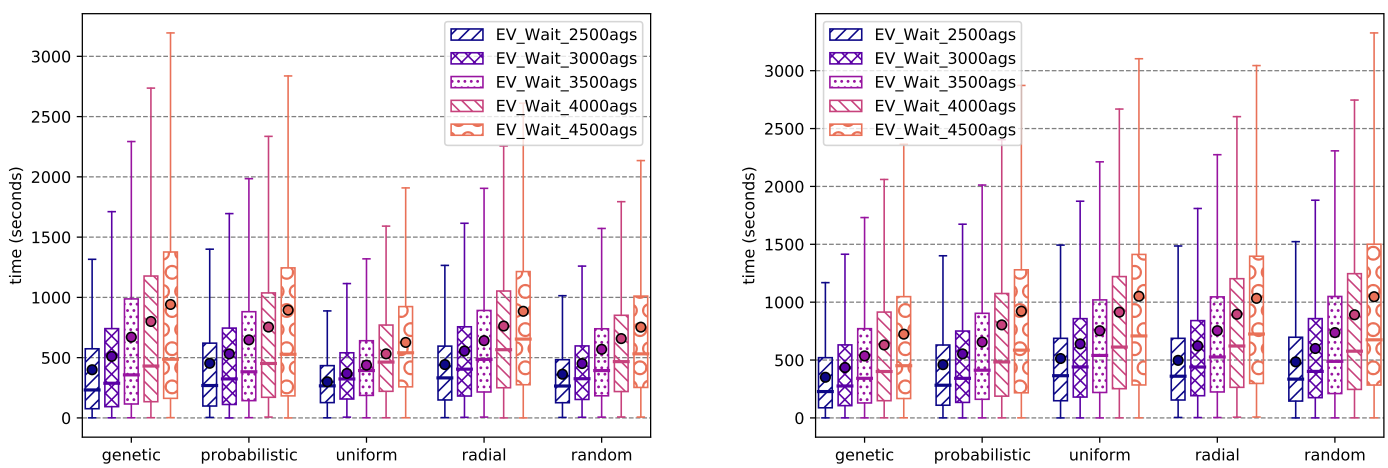
5.1. Experiment 1: 50 charging points

The first experiment we propose consists of 50 charging points that can be distributed throughout the city of Valencia, specifically in the designated working area (Figure 5). This experiment aims to show a first implementation of charging points as the demand they could adequately meet is not very high, but could be sufficient for the number of current electric vehicles in the city.

The measure by which we will assess the suitability of the five charging point distributions (i.e. genetic, probabilistic, uniform, radial, and random) is the waiting time of the vehicles in the queue of the charging stations. It should be noted that when a charging station has no free points, vehicles that have moved there must wait in order of arrival until there is a free slot to charge. Thus, when a high demand area of the city has few charging points, the waiting time for vehicles will increase. This overall measure is therefore intended to determine whether the distribution of charging points in the city is in line with vehicle demand.

In the figures below concerning the experiments, we show the waiting time in a box plot. In this sense, a box plot shows the mean, median (Q2 or 50th percentile), minimum (Q0 or 0th percentile) and maximum (Q4 or 100th percentile) values (the whiskers) excluding outliers, and the quartiles 1 (Q1 or 25th percentile) and 3 (Q3 or 75th percentile) that define the box and the interquartile range. With this representation it is easy to see both the mean values of a data series as well as its variability.

Figure 9a shows the box plot of the electric vehicles waiting time for 2500 to 4500 vehicle agents in the city of Valencia with random movement for the five different charging point distributions. Generally, the uniform distribution gets the best results in this case, followed by the random distribution. The distributions genetic, probabilistic, and radial obtain similar results between them depending on the number of agents, but are the worst overall with respect to the other distributions. Since these are random vehicle movements, i.e. the points of origin and destination of the vehicles are random points in the city (separated by a minimum distance, in this case 1500 meters), the distributions that have a shorter waiting time for the vehicles are those that distribute the charging stations uniformly or randomly. Thus, their waiting times are shorter because we are dealing with between 2500 and 4500 agents, so the randomness of movements with so many agents is distributed evenly throughout the city, but without attending to any criteria or real data.



(a) Random movement

(b) Informed movement

Figure 9: Box plot of waiting time of vehicles to charge with 50 charging points in the city, in different distributions and number of agents. In each box, the circle represents the mean and the horizontal line represents the median.

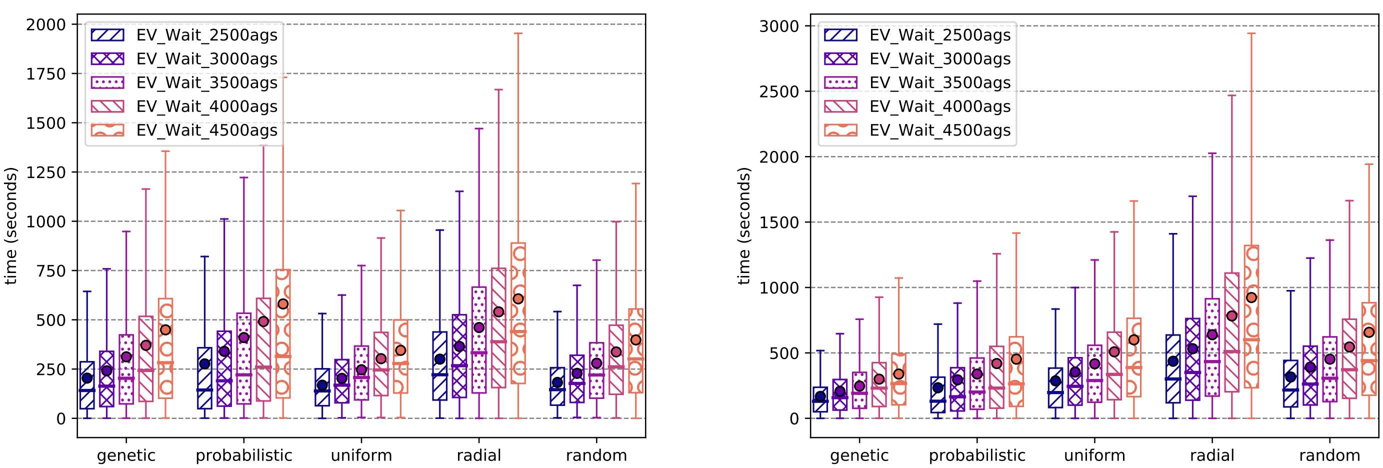
Therefore, in order to check how the distributions of charging points behave in more realistic conditions, we are going to analyze the waiting time of the vehicles but with informed movements that have been created considering the real mobility data of the city of Valencia, as already indicated above. In Figure 9b, we can see the waiting time of vehicles with informed movement for a number of agents between 2500 and 4500 for each of the distributions mentioned above. In this case, the distribution of the genetic algorithm obtains significantly better results than the other distributions, followed by the probabilistic distribution. This is because the genetic algorithm and the probabilistic distribution do consider the real data of the city, so the distributions of charging points are made with respect to the actual traffic and movement in the city. For the genetic distribution, it should be noted that even in the instances with more agents, the waiting time does not grow as quickly as it does in the other distributions.

In conclusion, the distribution of charging stations of the genetic algorithm is less appropriate than some of the other distributions if the movements of vehicles are completely random, however, the distribution of the genetic algorithm far surpasses all other distributions (including the probabilistic one) when dealing with vehicle movements generated with real data.

In the following experiment the number of charging points is increased to 100 in the city, with the particularity that the 50 in this experiment are retained for the distribution of the genetic and random algorithm. For probabilistic, uniform and radial distributions, it is necessary to re-distribute the charging points according to the new dimensions of the polygons that divide the city map.

5.2. Experiment 2: 100 charging points

Figure 10a presents the results of the waiting time for vehicles with random movements for different numbers of vehicles and different distributions with 100 charging points in the city. In general, the radial distribution obtains the worst results, while the uniform distribution obtains the best results followed by the random one. However, it is noteworthy that the difference between the results of the genetic distribution with respect to the uniform or random distribution is not very significant. The reason behind this may be that by placing 100 charging points in the city, and even if the movement is random, the distribution of the genetic already covers relatively homogeneously the whole city. That is why the results do not differ so much with the distributions that work best, as it was the case in the previous experiment with 50 charging points (Figure 9b) because the city could not be covered uniformly to accommodate distributed random movements.



(a) Random movement

(b) Informed movement

Figure 10: Box plot of waiting time of vehicles to charge with 100 charging points in the city, in different distributions and number of agents. In each box, the circle represents the mean and the horizontal line represents the median.

For the case of the 100-point distribution of informed vehicle movement represented in Figure 10b, the waiting time of the vehicles at the stations is significantly lower for the resulting distribution of the genetic algorithm compared to the other distributions. In fact, in this case this difference is much greater than in the case with 50 charging points in the previous experiment (see Figure 9b). The probabilistic distribution behaves similar to that of the genetic algorithm with respect to the rest of the distributions, however, the genetic algorithm distribution provides lower mean waiting times (between 33.6-42.5% difference) than the probabilistic one.~~The probabilistic distribution also performs~~

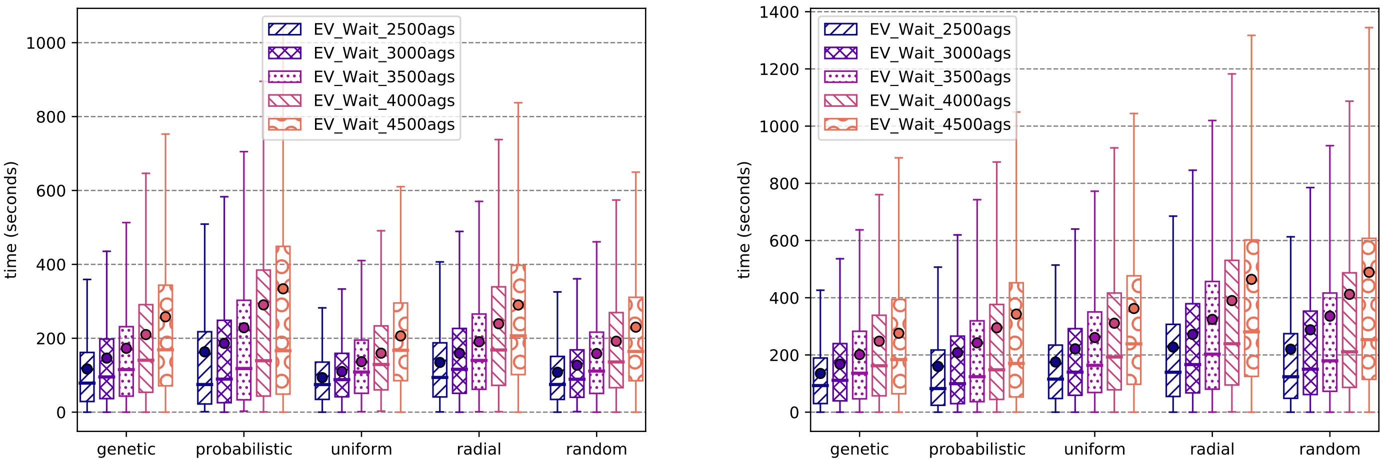
~~well behind the distribution of the genetic algorithm. However, the difference it is slightly significant.~~ Thus, it is confirmed that the distribution obtained with the genetic algorithm is much more appropriate to reality than the other distributions, as could already be suspected in the previous experiment.

Again, in order to further check the feasibility of each of the distributions, we move to the next experiment in which we double the number of charging points to 200. We remind that, in the case of the distribution of the genetic algorithm, the 200 charging points experiment is built starting from the previous experiment of 100 points, which in turn already started from the 50 charging points experiment.

5.3. Experiment 3: 200 charging points

The results of the waiting time of the vehicles for this experiment with 200 charging points and random movement represented in Figure 11a are quite similar to the equivalents of the previous experiment with 100 charging points (see Figure 10a). However, in this case the probabilistic distribution has the worst results followed by the radial distribution. On the other hand, the uniform distribution has the best results, followed by the random distribution, and then the genetic distribution. In this case, it becomes clear again that with random vehicle movements the uniform or even the random distribution get good results because they cover the whole city almost uniformly. This is so for the randomly generated movement because we are considering substantial amounts of agents (2500 in the smallest case) that creates a uniform distribution of the agents' positions in the city.

Figure 11b presents the results of the vehicle waiting time for the 200 charging points experiment and vehicle movement based on real data. In this case, the best results are still for the distribution of the genetic algorithm followed by the probabilistic distribution, as in the previous experiments with the informed vehicle movements (Figures 9b and 10b). It can be seen in Figure 11b that after the genetic and probabilistic distributions, the next best results are with the uniform distribution, followed by the radial and finally the random distribu-



(a) Random movement

(b) Informed movement

Figure 11: Box plot of waiting time of vehicles to charge with 100 charging points in the city, in different distributions and number of agents. In each box, the circle represents the mean and the horizontal line represents the median.

tion. Thus, these results seem most natural and intuitive when we imagine how different distributions can work in a city, that is, when there are enough stations to place, a probabilistic or a uniform distribution still works relatively well; a radial distribution works a little worse if the city does not have totally centralized traffic (for example, Valencia has a central area with a very limited access to traffic in the old town); and a random distribution, although it can behave similar to a uniform one if there are enough charging points to be distributed, it is still deficient with 200 points considering vehicle movements based on real data.

In conclusion, the uniform distribution would be appropriate if the movements of vehicles in the city followed a totally random or uniformly distributed pattern throughout the map. However, it is unlikely that the traffic of any city in the world has this behavior, and specifically, this has not been observed in Valencia, the city object of our study. Therefore, if we consider the actual movement of vehicles (based on real data) in the city, the best distribution of charging points of electric vehicles among those compared in this study has been obtained by the genetic algorithm proposed by our work (Palanca et al., 2020a). Thus, we can say that it is demonstrated by simulation with real data the viability of our approach after analyzing different experiments.

5.4. Analysis of idle stations in the experiments

In the previous subsections, we have analyzed the results of the waiting time of the vehicles at the charging stations for the different distributions. In order to complement this analysis and to better understand what happens in the different distributions, we will now show the percentage of charging stations that remain idle in the previous experiments. The objective in this case is twofold: on the one hand, if there is a high percentage of stations which are not used, this may mean that the waiting time at the other stations will be greater, as they must serve more vehicles. On the other hand, from the point of view of the administrators or municipalities which place the charging stations in the city, this implies a disbursement of money which results in a poor use of resources, as well as a worse service to users.

Table 2 presents the percentage of idle stations for the previous experiments of 50, 100, and 200 charging points with the different distributions and number of agents for the case of random vehicle movement. Overall, it can be seen that the radial distribution has the highest percentage of idle stations in all three experiments, with between 14% and 28%. This may be due to the nature of this distribution, which puts many points in the central area of the city and some of these points take up most of the vehicles in the area and leave others idle. In this sense, it is also worth remembering that the city of Valencia has a central area with a very limited traffic flow and that is almost not accessible by car. In addition, the radial distribution can also put some points in areas too far from the activity very close to the city limits (see example of Figure 6c), where it is likely that no traffic is generated.

Regarding the uniform and random distributions in Table 2, the percentage

	50 charging points				
	distribution				
agents	genetic	probabilistic	uniform	radial	random
2500	**0%**	**0%**	2%	14%	**0%**
3000	**0%**	**0%**	2%	14%	**0%**
3500	**0%**	**0%**	2%	14%	**0%**
4000	**0%**	**0%**	2%	14%	**0%**
4500	**0%**	**0%**	2%	14%	**0%**

	100 charging points				
	distribution				
agents	genetic	probabilistic	uniform	radial	random
2500	**0%**	**0%**	**0%**	28%	3%
3000	**0%**	**0%**	**0%**	27%	3%
3500	**0%**	**0%**	**0%**	28%	3%
4000	**0%**	**0%**	**0%**	27%	3%
4500	**0%**	**0%**	**0%**	28%	3%

	200 charging points				
	distribution				
agents	genetic	probabilistic	uniform	radial	random
2500	**0%**	**0%**	5%	23.5%	3.5%
3000	**0%**	**0%**	4.5%	23%	4%
3500	**0%**	**0%**	4.5%	23.5%	3%
4000	**0%**	**0%**	4%	23%	3%
4500	**0%**	**0%**	4.5%	23%	3%

Table 2: Percentage of idle charging points with random vehicle movement. The best values of each experiment are represented in bold.

of idle stations remains quite low, in some cases being **0%**, and at most 5% and 4%, respectively, in the experiment with 200 charging points. In these cases, as mentioned above, the use of stations is high because the random movement of vehicles is relatively evenly distributed throughout the city when dealing with large numbers of vehicles, so the probability of a station not being used because no vehicle appears nearby is quite low.

Finally, the most remarkable result is that both the distribution of the genetic algorithm and the probabilistic one have no idle stations in any of the experiments of Table 2. Therefore, we can say that the stations are used 100% in these two distributions, which indicates that the location of the stations in these distributions is totally adequate in this sense, even with the random movement that was not the most beneficial for these approaches.

	50 charging points				
	distribution				
agents	genetic	probabilistic	uniform	radial	random
2500	**0%**	**0%**	4%	16%	2%
3000	**0%**	**0%**	4%	16%	2%
3500	**0%**	**0%**	2%	14%	2%
4000	**0%**	**0%**	2%	14%	2%
4500	**0%**	**0%**	2%	14%	**0%**
	100 charging points				
	distribution				
agents	genetic	probabilistic	uniform	radial	random
2500	**0%**	1%	14%	33%	15%
3000	**0%**	1%	15%	33%	17%
3500	**0%**	0.5%	9%	33%	11%
4000	**0%**	**0%**	11%	34%	13%
4500	**0%**	**0%**	**0%**	10%	33%
	200 charging points				
	distribution				
agents	genetic	probabilistic	uniform	radial	random
2500	**1%**	2.5%	25.5%	38.5%	30%
3000	**1.5%**	2.5%	24%	37%	29%
3500	**0.5%**	1.5%	22%	34.5%	25%
4000	**0.5%**	1.5%	22%	36%	25.5%
4500	**0%**	1.5%	20%	33.5%	23.5%

Table 3: Percentage of idle charging points with informed vehicle movement. The best values of each experiment are represented in bold.

The results of the percentage of idle stations for the above experiments and their different distributions with informed movements (based on real data) are found in Table 3. In this case, the same pattern as in the previous results in Table 2 is repeated for the radial distribution. This distribution still has the highest percentage of idle charging stations and in addition, these percentages are a little higher, since they have increased from being in the range of 14-28% to 14-38.5% depending on the case. The reason for this increase may be that, as it is a question of movement based on real vehicle data, the radial distribution is not favored because traffic in Valencia is not totally centered on the midpoint where it coincides with the old town with traffic restrictions.

With regard to the uniform distribution, the percentage of idle stations with informed movement increases notably with respect to that of random movement, specifically in the experiment of 100 charging points it goes from 0% to values between 9-15%, and in the experiment of 200 charging points it goes from values of 4-5% to 20-25.5%. Similarly, the random distribution also increases its percentage of idle stations with respect to the random movement experiments. As with the uniform, this is especially the case in the 100 and 200 charging point experiments, since the 50 charging point experiment, being so few to cover all vehicle activity, is rather unlikely to leave any stations idle. Thus, the random distribution is increased from 3% to a range of 11-17% of idle stations in the 100 charging point experiment, while with 200 charging points the change is from 3-4% to 23.5-30%. Thus, the incidence of the informed movement on the percentage of idle stations is remarkable in both the uniform and the random distribution, since in this case the vehicle movements are not randomly distributed and balanced by the city, but follow the probability that is based on the real activity data.

Regarding the probabilistic distribution, it also has a slightly increase in the percentage of idle stations with respect to the random vehicle movement only in the 100 and 200 charging point experiments. However, the idle stations percentage is just 1% at most with 100 charging points, and 1.5-2.5% with 200 charging points.

Finally, the percentage of idle stations for the distribution of the genetic algorithm is kept at 0% for the informed vehicle movement except in the 200 charging point experiment where it is between 0-1.5%. Thus, in this case the difference with respect to the other distributions is notable (except for the probabilistic distribution, for which the difference is not so significant), which endorses the results obtained in the previous experiments on the waiting time of vehicles. This implies that we can state that the distribution of charging points carried out by the genetic algorithm is the best with respect to the other distributions given its best results in the performed experiments.

5.5. Discussion on the results

In this series of experiments we have analyzed different metrics to assess which may be the best option to decide the location of a set of charging points in Valencia (Spain). To do so, we have compared the distribution performed by the genetic algorithm we propose with respect to a probabilistic distribution (based on the information of the city, i.e., population, traffic, and social networks activity), a uniform distribution, another radial distribution, and a random distribution. In addition, these experiments have been carried out by simulating (using the SimFleet tool) different numbers of vehicles in the range of 2500 to 4500 that want to charge their batteries at the same time in the city, and that follow a random movement pattern or another informed pattern (based on real data of population, traffic, and social network activity in the city under study). The aim was to overload the system to see how each distribution behaves to absorb all the demand. The main conclusions we can draw from all these experiments are the following.

When the vehicles in the simulation follow a random movement (their point of origin and destination is generated randomly anywhere in the city) the distributions of charging points that obtain the best results are the uniform and the random ones. This makes sense since we are dealing with a large number of vehicles which, by placing their origin position at random in the city, end up being distributed more or less evenly. For this reason, uniform distribution, and in part also random distribution (especially in experiments with a greater number of charging points), manage to better cover the demand for vehicle charging. However, it is important to highlight that the random movement of vehicles does not correspond exactly to the reality of a city, since both the morphology of the streets as well as other factors such as the number of inhabitants, traffic restrictions, or the areas of greatest interest determine how vehicles move in the city.

Consequently, the experiments that are most important due to their similarity to the real world are those carried out with the informed movement of vehicles, i.e. those in which the points of origin and destination have been determined based on real data, so that each area into which the city has been divided has a probability of being either a point of origin or destination depending on the activity that is generated in it. With regard to these experiments with the informed movement of vehicles, the best results have been obtained with the distribution of the genetic algorithm that has significantly outperformed the other distributions, including the probabilistic distribution, that also considers the information of the city to locate the charging stations.

Therefore, we can claim that the best distribution for the studied city is made by the genetic algorithm that places stations more intelligently in the city to respond to the actual demand considering the mobility that is recreated with real data.

6. Conclusions

The importance of an infrastructure that promotes the implementation of electric vehicles in an urban context has led to the proposal of a genetic algorithm for the placement of electric vehicle charging stations. This evolutionary algorithm uses multi-objective techniques and considers real data from the city under study. In addition, a long-term solution is also implemented in which new charging points and stations are added in subsequent years according to the needs planned by the municipalities.

Furthermore, to validate the solutions of the genetic algorithm, a complete simulation system (based on the SimFleet simulator) has been implemented in which a considerable number of electric vehicles travel around the city and must charge their batteries. In this sense, a simulation system is necessary since the implementation in reality of any distribution of charging stations is very expensive, making simulation crucial to validate the proposed solutions. This simulation system has been used to compare the station distribution of the genetic algorithm with other distributions that could be made in a city, i.e. uniform, radial, or random.

The main results of the experiments carried out through simulation show that the best distribution of those analyzed is that made by the proposed genetic algorithm. This occurs in the simulations in which the mobility of electric vehicles in the city is based on real data.

This paper has presented as contributions: (1) the development of a simulator for urban vehicles which allows the simulation of vehicle movements by using data extracted from open data sources like traffic, population and social networks geo-located activity, (2) a set of experiments to validate the solution proposed by the genetic algorithm developed by the authors; these experiments validate that the waiting time at charging stations is minimized and (3) a mechanism that allows to detect undesirable situations before the deployment of the solution, like the number of idle stations, this is, stations that are located at unnecessary places or that are underutilized while increasing the installation cost.

As future work, both the genetic algorithm and the simulator could be modified to extend the problem of placing electric vehicle charging stations in an interurban context. In this sense, the installation of charging stations could be planned in areas that include entire regions with various cities involved, or even at the level of an entire country or set of countries. This would provide an interurban or state infrastructure of charging stations that would promote the use of electric vehicles since users would have a sufficiently complete network within reach of the autonomy of their vehicle batteries. More cases of study will be developed, including different cities and public transport systems to make simulations as real as possible. Finally, the genetic algorithm could be improved by using local search techniques such as simulated annealing.

Acknowledgments

This work is partially supported by grant RTI2018-095390-B-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".

References

Association, C.E., 2019. Zap Map Toolkit. https://www.zap-map.com/live/. Accessed on 19-10-2020.

Biswas, P., Pal, B.B., 2019. A fuzzy goal programming method to solve congestion management problem using genetic algorithm. Decision Making: Applications in Management and Engineering 2, 36–53.

Brown, S., Pyke, D., Steenhof, P., 2010. Electric vehicles: The role and importance of standards in an emerging market. Energy Policy 38, 3797 – 3806. doi:https://doi.org/10.1016/j.enpol.2010.02.059.

Cooper, L., 1964. Heuristic methods for location-allocation problems. SIAM review 6, 37–53.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: Nsga-ii. IEEE Transactions on Evolutionary Computation 6, 182–197. doi:10.1109/4235.996017.

Dong, J., Liu, C., Lin, Z., 2014. Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. Transportation Research Part C: Emerging Technologies 38, 44–55.

Escrivà, M., Palanca, J., Aranda, G., 2006. A jabber-based multi-agent system platform, in: Proceedings of the fifth international joint conference on Autonomous agents and multiagent systems, pp. 1282–1284.

EV Infrastructure Corridor Development Toolkit, 2019. EV Infrastructure Corridor Development Toolkit. http://altfueltoolkit.org/ev-infrastructure-corridor-development-toolkit/. Accessed on 19-10-2020.

Farahani, R.Z., SteadieSeifi, M., Asgari, N., 2010. Multiple criteria facility location problems: A survey. Applied mathematical modelling 34, 1689–1709.

Ge, Y., Xin, B., Zhou, L., Li, X., 2020. Selecting park locations using a genetic algorithm and comprehensive satisfaction. International Journal of Machine Learning and Cybernetics 11, 1331–1338.

Gong, D., Tang, M., Buchmeister, B., Zhang, H., 2019. Solving location problem for electric vehicle charging stations—a sharing charging model. IEEE Access 7, 138391–138402.

He, J., Zhou, B., Feng, C., Jiao, H., Liu, J., 2012. Electric vehicle charging station planning based on multiple-population hybrid genetic algorithm, in: 2012 International Conference on Control Engineering and Communication Technology, IEEE. pp. 403–406.

Jordán, J., Onaindía, E., 2015. Game-theoretic Approach for Non-Cooperative Planning, in: Proceedings of the 29th AAAI Conference on Artificial Intelligence (AAAI), pp. 1357–1363.

Jordán, J., Torreño, A., De Weerdt, M., Onaindia, E., 2018. A better-response strategy for self-interested planning agents. Applied Intelligence 48, 1020–1040.

Jordán, J., Torreño, A., De Weerdt, M., Onaindia, E., 2020. A non-cooperative game-theoretic approach for conflict resolution in multi-agent planning. Group Decision and Negotiation URL: https://doi.org/10.1007/s10726-020-09703-0, doi:10.1007/s10726-020-09703-0.

Jordán, J., Palanca, J., Del Val, E., Julian, V., Botti, V., 2018. A multi-agent system for the dynamic emplacement of electric vehicle charging stations. Applied Sciences 8. URL: https://www.mdpi.com/2076-3417/8/2/313, doi:10.3390/app8020313.

Kaveh, M., Kaveh, M., Mesgari, M.S., Paland, R.S., 2020. Multiple criteria decision-making for hospital location-allocation based on improved genetic algorithm. Applied Geomatics 12, 291–306.

Kaya, Ö., Alemdar, K.D., Çodur, M.Y., 2020. A novel two stage approach for electric taxis charging station site selection. Sustainable Cities and Society , 102396.

Kellerer, H., Pferschy, U., Pisinger, D., 2004. Multidimensional knapsack problems, in: Knapsack problems. Springer, pp. 235–283.

Kong, W., Luo, Y., Feng, G., Li, K., Peng, H., 2019. Optimal location planning method of fast charging station for electric vehicles considering operators, drivers, vehicles, traffic flow and power grid. Energy 186, 115826.

Liu, A., Zhao, Y., Meng, X., Zhang, Y., 2020. A three-phase fuzzy multi-criteria decision model for charging station location of the sharing electric vehicle. International Journal of Production Economics 225, 107572.

Ma, T., Mohammed, O.A., 2014. Optimal charging of plug-in electric vehicles for a car-park infrastructure. IEEE Transactions on Industry Applications 50, 2323–2330.

Mao, D., Tan, J., Wang, J., 2020. Location planning of pev fast charging station: An integrated approach under traffic and power grid requirements. IEEE Transactions on Intelligent Transportation Systems .

Mao, D., Wang, J., Tan, J., Liu, G., Xu, Y., Li, J., 2019. Location planning of fast charging station considering its impact on the power grid assets, in: 2019 IEEE Transportation Electrification Conference and Expo (ITEC), IEEE. pp. 1–5.

Martí, P., Jordán, J., Palanca, J., Julian, V., 2020. Load generators for automatic simulation of urban fleets, in: Highlights in Practical Applications of Agents, Multi-Agent Systems, and Trust-worthiness. The PAAMS Collection, Springer International Publishing, Cham. pp. 394–405.

Palanca, J., Jordán, J., Bajo, J., Botti, V., 2020a. An energy-aware algorithm for electric vehicle infrastructures in smart cities. Future Generation Computer Systems .

Palanca, J., Terrasa, A., Carrascosa, C., Julián, V., 2019. SimFleet: A New Transport Fleet Simulator Based on MAS, in: Highlights of Practical Applications of Survivable Agents and Multi-Agent Systems. The PAAMS Collection, Springer International Publishing, Cham. pp. 257–264.

Palanca, J., Terrasa, A., Julian, V., Carrascosa, C., 2020b. SPADE 3: Supporting the New Generation of Multi-Agent Systems. IEEE Access 8, 182537–182549. doi:10.1109/ACCESS.2020.3027357.

Planning for Electric Vehicle Charging Infrastructure: A Toolkit, 2019. Planning for Electric Vehicle Charging Infrastructure: A Toolkit. http://pluginbc.ca/resource/planning-electric-vehicle-charging-infrastructure-toolkit/. Accessed on 19-10-2020.

Roy, A., Manna, A., Maity, S., 2019. A novel memetic genetic algorithm for solving traveling salesman problem based on multi-parent crossover technique. Decision Making: Applications in Management and Engineering 2, 100–111.

Taghavi, A., Ghanbari, R., Ghorbani-Moghadam, K., Davoodi, A., Emrouznejad, A., 2021. A genetic algorithm for solving bus terminal location problem using data envelopment analysis with multi-objective programming. Annals of Operations Research , 1–18.

Uyanik, C., TUZKAYA, G., OĞUZTİMUR, S., 2018. A literature survey on logistics centers'location selection problem. Sigma: Journal of Engineering & Natural Sciences/Mühendislik ve Fen Bilimleri Dergisi 36.

Wood, E., Neubauer, J.S., Burton, E., 2015. Measuring the benefits of public chargers and improving infrastructure deployments using advanced simulation tools. Technical Report. SAE Technical Paper.

Zhang, Y., Liu, X., Zhang, T., Gu, Z., 2019. Review of the electric vehicle charging station location problem, in: International Conference on Dependability in Sensor, Cloud, and Big Data Systems and Applications, Springer. pp. 435–445.