Validating state-wide charging station network through agent-based simulation

Pasqual Martí[1 [0000-0001-6406-0641]], Jaime Llopis[1], Vicente Julian[1,2 [0000-0002-2743-6037]], Paulo Novais[3 [0000-0002-3549-0754]], and Jaume Jordán[1 [0000-0003-0400-9136]]

[1] Valencian Research Institute for Artificial Intelligence (VRAIN), Universitat Politècnica de València, Valencia (Spain)
[2] Valencian Graduate School and Research Network of Artificial Intelligence, Universitat Politècnica de València, Valencia (Spain)
[3] ALGORITMI Centre, University of Minho, Braga (Portugal)
pasmargi@vrain.upv.es, jaillohe@ade.upv.es, vjulian@upv.es, pjon@di.uminho.pt, jjordan@dsic.upv.es

Abstract. The electric car market in Europe is growing due to climate change awareness, expectations of fossil fuel depletion, and cost savings. However, the limited number of low-powered public charging stations in the case of Spain impedes longer interurban trips, causing "range anxiety" in users. Currently, there are proposals using genetic algorithms to design an optimal electric charging station network that satisfies the needs of all citizens in any region. The work presented in this paper aims to design and develop a simulation environment to test the allocation results of a genetic algorithm and compare them with the only fast charging station network of Tesla and other possible station distributions.

Keywords: Agent-based Simulation · Electric Vehicles · Genetic Algorithms

1 Introduction

The European Union's 2030 agenda sets among its sustainable development goals access to clean energy as well as resource creation and consumption sustainability. In this line, adopting the electric vehicle (EV) as a generalized individual transport is crucial for reducing air and noise pollution in cities [9]. If we take this problem to the interurban level, a significant percentage of the transport of goods and people is currently carried out with gasoline vehicles. A well-planned charging station network for electric vehicles in interurban areas ensures high-quality service and efficient operations. Previous research studies such as [1] and [12] have emphasized the significance of charging station planning in cities. It is evident from the literature that the planning of charging stations is a complex issue that requires careful consideration. Various approaches have been proposed to address this challenge in recent years, as discussed in reviews presented in [13] and [5]. However, most of these proposals lack sufficient validation, making it difficult to determine their effectiveness in practice. Therefore, it is essential to have a well-designed and validated plan for charging station placement to ensure a smooth transition to electric vehicle usage in interurban areas.

In previous works [2, 4], the installation of an electric grid with a statewide perspective was proposed to enable travel without EV drivers experiencing range anxiety [11, 10]; i.e., the fear of their vehicle running out of charge away from any station. In that work, the studied variables were the number of deployed stations and their location, also considering the total cost of the final infrastructure. It is imperative to emphasize that the currently proposed algorithms remain purely theoretical and require validation through simulation in large-scale interurban vehicle movement scenarios, like in the analysis of the urban case in similar works [3]. This underscores the critical need to verify the efficacy of the proposed models. Intelligent methods for transportation infrastructure deployment would ideally be evaluated through the real-world implementation of their outputs. However, changes in these types of infrastructures tend to greatly impact citizen's life, even redefining previous displacement trends. Because of that, before its implementation, these changes must be validated through software simulations [6]. A general scope proposal such as the present one aims to serve as many users as possible, which implies different EV types. Different EVs vary in autonomy (the average distance that can be traveled when fully charged). Therefore, evaluating a charging network must consider interurban displacements of EVs with various autonomy ranges. In addition, the deployed network would enable en-route recharging of the vehicles' batteries, thus providing a reasonably fast charge, a closer experience to filling up the gasoline tank in a regular vehicle.

Working towards such goals, this paper proposes using multi-agent simulation to evaluate a state-wide network of fast charging stations. An informed genetic algorithm generates such a network. That network, in turn, is compared against other infrastructures built following different patterns. The multi-agent simulator SimFleet is adapted and used to compare and validate the various station distributions. Interurban trips across the territory where the network is deployed are generated. Those trips are to be completed by vehicles (simulated agents) with ranging battery power. Each distribution is evaluated according to specific metrics. The experimental results prove the potential multi-agent simulation has for infrastructure validation as well as the flexibility of the genetic algorithm's approach to station distribution.

The rest of the paper is structured as follows. Section 2 introduces the multi-agent simulator and the genetic algorithm, and afterward characterizes the experimental setup employed to validate the charging infrastructure. Then, Section 3 goes over the experimentation results, adding a discussion that compares them from a global perspective. Finally, Section 4 contains the conclusions drawn from this work and future lines of research.

2 Materials & Methods

This section summarizes the technologies employed to carry out the experimentation. That includes a multi-agent simulator, a genetic algorithm that distributes stations, and finally, the experimental setup used to validate the infrastructure.

2.1 SimFleet

SimFleet [8] is a powerful simulation tool that provides several advantages for testing different mobility strategies. It is based on SPADE [7], a multi-agent system development environment, and specializes in simulating transports and customers interactions for urban mobility solutions. One of the main advantages of SimFleet is its flexibility and ease of use in managing simulated transport fleets. The agent architecture provided by SPADE allows every actor in the simulation to be a proactive and independent agent with its strategy and behavior, which makes scaling the simulation a simple process. In this context, SimFleet greatly facilitates the scheduling of the agents' negotiations in a simulation by abstracting everything related to agent communication. Underneath the abstraction layer is an XMPP[4] server, which makes getting messages sent from one agent to another very simple. It supports asynchronous reception of messages for efficiency so that agents do not have to stop to receive and process them.

In addition, SimFleet uses the OSRM[5] routing software to locate the shortest routes in the road network for vehicle trips. A query to OSRM receives the origin and destination points and returns the shortest route between them. Overall, SimFleet 's flexibility and scalability, coupled with its integration with the OSRM routing software, make it a highly effective simulation tool for testing mobility strategies.

However, the tool has been slightly modified to be used in interurban environments like the one proposed in this paper. On the one hand, a new state ABORTED for transportation agents has been included to indicate a vehicle that aborted its current trip due to a lack of power, i.e., its electric battery ran out. On the other hand, by default, the simulator awaits for every transport agent to be at their destination to finish the simulation. Such a behavior has been modified so that the simulator understands vehicles that aborted their trip have finished their execution too. Finally, the necessary code has been developed to allow transport agents to check their autonomy level and the charging station distribution. With this, agents can choose the closest station to recharge their batteries, implying a lower deviation from their planned trip.

2.2 Genetic algorithm

The distribution that generates a genetic algorithm (GA) is the one presented in the works [4, 2]. This GA uses several datasets to evaluate the potential charging

[4] https://xmpp.org
[5] http://project-osrm.org/

station locations to determine the best locations for electric charging stations in an interurban environment.

The GA creates a population of possible charging station locations and uses a fitness function to assess each location based on the input data. The possible locations are the existing petrol stations to provide a large set of possibilities. The fitness function considers factors such as the population density in the area, the traffic density on nearby roads, and the activity on social networks. The algorithm then uses genetic operators such as mutation and crossover to create new distributions of charging stations and repeats the fitness evaluation. The process continues iteratively until a number of generations are completed to converge on a set of near-optimal charging station locations. The algorithm has been tested using real data from the USA, demonstrating promising results in identifying suitable locations for charging stations.

2.3 Experimental setup

Following, the use case chosen to illustrate the operation of our approach is described. In addition, the distributions against which the system's output is compared and the simulation evaluation metrics are presented.

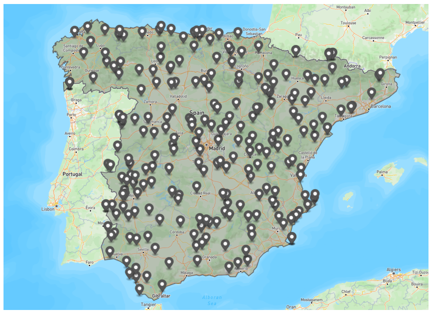
Use case. The peninsular territory of Spain has been chosen to deploy an infrastructure of fast-charging stations with an interurban perspective. The network aims to allow EV drivers to travel between any two points of the territory. The main variables of the experimentation are the total number of stations in the network (50, 100, 250, 500, 750, or 1000) and the maximum autonomy of the EVs, expressed in kilometers (50, 100, 200, or 400km).

Besides the specific charging infrastructure, each simulation contains 500 EVs that perform randomly generated interurban trips within the territory. Each trip has a destination at least 600km away from its origin. With such a trip distance, and considering the tested EV autonomies, drivers are forced to look for a minimum of one station through their journey, and thus the simulation allows us to evaluate a specific distribution of stations.

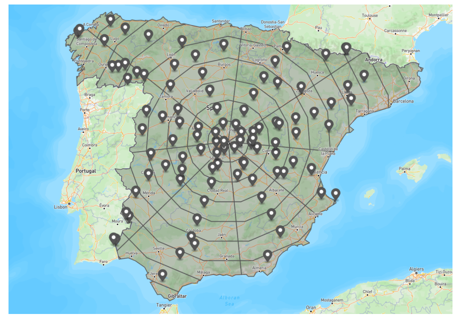
Types of distribution. The genetic algorithm's distribution of charging stations is compared against four different distribution patterns. From those four, three of them are based on the spatial distribution of the stations over the deployment area; meanwhile, the last one is simply a reproduction of Tesla's [6] network of fast electric charging stations; also known as "superchargers". Figure 1 shows a graphical representation of each distribution.

A *Random* distribution of stations (Figure 1a) serves as a baseline for the experimentation. In this distribution, stations are allocated at any valid point within the road network of the deployment area.

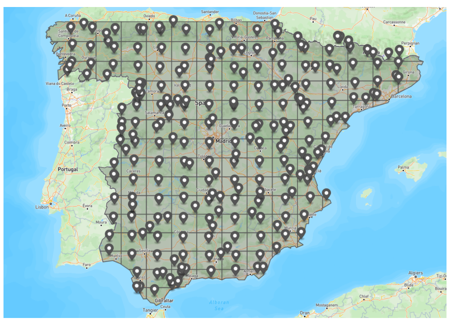
[6] Tesla enterprise website: https://www.tesla.com/ (accessed on 11/04/2023)



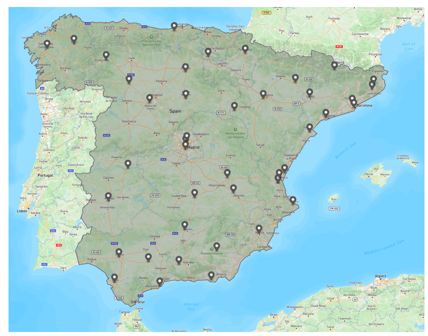
(a) Random distribution



(b) Radial distribution



(c) Uniform distribution



(d) Tesla supercharger distribution

Fig. 1. Visualization of station networks over the peninsular territory of Spain. Images (a) to (c) show the distribution of 250 charging stations following different patterns. Image (d) shows the distribution of Tesla's fast chargers. Each spot represents a charging station with a specific number of charging poles.

Following, a *Radial* distribution (Figure 1b) is implemented, in which the territory is divided into several concentric circles, which in turn, get divided into a configurable number of sectors. Stations are allocated in the centroid of the resulting sectors, thus favoring a high density of stations towards the central point of the deployment area and a more dispersed, spider web-like distribution as the stations move away from the central point.

The last space-based distribution is the *Uniform* one (Figure 1c), in which the deployment area is divided into a series of rows and columns, resulting in several square areas. Then, a station is allocated in the center of each square area until the total number of stations is reached. If there are more stations to allocate than square subareas, some areas are randomly chosen to have more than one station in them.

Finally, the Tesla's network of superchargers (Figure 1d) is a real-life, implemented, state-wide network of charging stations that gives us a real infrastructure against which to compare the GA's output. By the time of writing this paper, the network is composed of 42 charging stations.

Evaluation metrics. The charging station distributions are evaluated by the percentage of aborted trips and the vehicles' mean deviation. The aborted trips comprise the percentage of vehicles that cannot complete the planned trip. Regarding the simulation, this is flagged by the aborted trip state ABORTED of the vehicles, indicating the transport has been unable to complete its planned trip with the current station distribution due to not having proper access to autonomy recharge. For those journeys that can be completed, mean deviation refers to the average total detours, in kilometers, that drivers must perform over their planned path to travel to each of the used charging stations.

The aforementioned metrics are computed as follows. Let a simulation be configured to evaluate the charging station distribution X. Let i be one of the N vehicle agents in X, with a state S_i. Vehicle i has a planned trip with an estimated distance of eD_i km. Upon completing its journey, which may have included a detour to recharge its batteries, vehicle i has traveled a real distance of rD_i km. Equations 1 and 2 describe the computation of aborted trips and mean deviation, respectively.

$$Aborted\ trips(X) = \frac{|A|}{N};\ A = \{i \in N \mid S_i = ABORTED\} \tag{1}$$

$$Mean\ deviation(X) = \frac{\sum_{i \in F}(rD_i - eD_i)}{|F|};\ F = \{i \in N \mid S_i \neq ABORTED\} \tag{2}$$

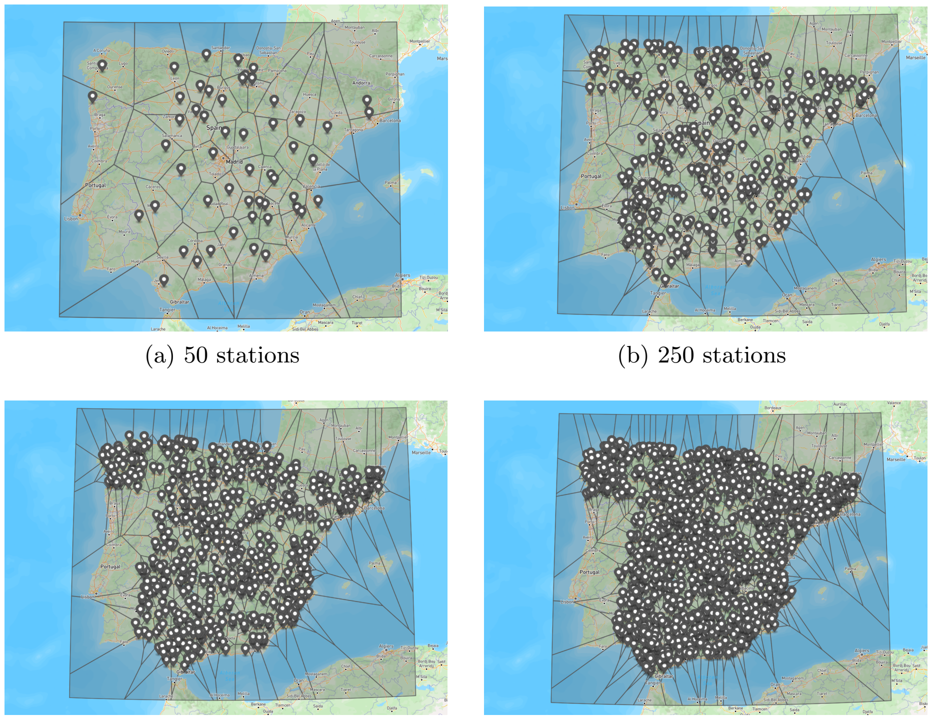
3 Experimental results

This section assesses the simulations that test the GA distribution against distributions with different spatial patterns (random, radial, uniform). In addition, the Tesla network is also tested according to the defined metrics (see Section 2.3). Figure 2 shows a visualization of the distributions that the GA obtains with a different number of stations.

3.1 Aborted trips

Table 1 gathers the results of each simulation classified by vehicle autonomy, number of deployed stations, and type of distribution. The Tesla distribution is only assessed according to vehicle autonomy, as its number of stations is fixed.

The random distribution provides a baseline yet unrealistic network. On average, it performs worse than any other distribution. Allocating 750 stations, all trips are completed for vehicles with +100km of autonomy. However, when 1000 stations are allocated, a few cars cannot complete their journey. This initially



(a) 50 stations

(b) 250 stations

(c) 500 stations

(d) 1000 stations

Fig. 2. Visualization of the genetic algorithm's output for the allocation of the different number of charging stations. Each spot represents a charging station with a specific number of charging poles.

unexpected result is explained because no mathematical criteria are followed to allocate stations. Therefore, increasing the number of stations does not necessarily imply a decrease in aborted trips.

No trips can be completed for the radial distribution and 50km autonomy vehicles with 100 or fewer stations. From 750 stations onward, the percentage of aborted journeys does not change significantly, reducing up to 65%. Then, with an autonomy of 100km, we find significant improvements with 250 stations, as the number of aborted trips decreases to 19.4%. The best value is reached by deploying 750 stations, with only 2.6% of failed displacements. Finally, almost none of the vehicles with +200km autonomy fail to reach their destination.

The uniform distribution performs well in terms of aborted trips. For low-autonomy vehicles, with 500 stations, just 15% of trips are uncompleted. Reaching up to 750 stations decreases the figure to 6.2%, or even 3%, if we locate all possible stations. Then, for the autonomy of 100km, 250 stations are enough for all vehicles to travel freely around the area. Vehicles with +200km autonomy can already travel anywhere with only 50 stations.

Autonomy	Stations	Aborted trips (%)				
		Random	Radial	Uniform	GA	Tesla
50km	50s	100	100	100	100	100
	100s	100	100	100	100	
	250s	100	96.8	100	100	
	500s	77.8	80	14.8	80.6	
	750s	42.6	66.8	6.2	33.2	
	1000s	17.8	64.8	3	19	
100km	50s	99.6	95.4	100	99.8	100
	100s	77	40.8	68.2	93.6	
	250s	5	19.4	0	1.2	
	500s	1.8	12.6	0	0	
	750s	0	2.6	0	3.4	
	1000s	2.2	4.6	0	1.4	
200km	50s	52	0.4	0	12.4	2.2
	100s	0	1	0	0	
	250s	0	0	0	0	
	500s	0	0	0	0	
	750s	0	0	0	0	
	1000s	0	0	0	0	

Table 1. Percentage of aborted trips for each autonomy of 50km, 100km, and 200km (400km is not shown as there are no aborted trips), each amount of stations (ranging from 50 to 1000), and the five presented distributions.

Regarding the Tesla network, we can conclude that it is not possible to use its stations for long trips between municipalities with low (50-100km) autonomy vehicles. However, for the autonomy of 200km, the distribution serves practically the entire Spanish territory since only 2.2% of the transports could not reach their destination. Ultimately, vehicles can complete any journey with the highest autonomy of 400km.

Finally, we assess the results of the GA's distribution, which, in turn, evaluates its capacity to allocate stations. With low autonomy and 250 stations or less, it is not possible to complete any of the trips in the sample. Adding more stations, the distribution efficiency highly increases, leaving about a fifth of the vehicles unable to travel when 1000 are deployed. Results for 100km of autonomy are unfavorable in smaller deployments. However, with 250 stations, the aborted trips drastically decreased to 1%, and all journeys were completed with 500 stations. Note that the number of aborted trips increases again in tests with more than 500 stations. This is explained by the network saturation, i.e., with more than 500 stations, the same efficiency level can be maintained at most. A priori, the efficiency should have been kept at the maximum, but this can happen considering that the station location criteria (the result of the GA) are not additive. The stations do not follow a mathematical model as simple as in the uniform or radial distributions, nor are they additive to what already exists. Therefore, an increase in stations can completely change the location of previously existing stations. The GA's distribution allows vehicles to travel freely for the rest of the tests.

3.2 Trip deviation

Figure 3, shows the average deviation of each simulation, in km, caused by vehicles moving out of their planned path to recharge their batteries. Results are plotted by vehicle autonomy, the number of deployed stations, and distribution type. Simulations with no associated value imply that none of the vehicles in them have been able to complete their journey (100% of aborted trips). Consequently, there is no average trip deviation to be computed.

The random distribution shows high deviation (335-250km) for 50 and 100km of autonomy and up to 500 stations when the value is reduced to 198km. Such a value is improved for the autonomy of 200km and 250 stations, decaying to 125km. The least that can be achieved with this autonomy is 99km. Finally, with the highest autonomy and number of stations, the deviation averages 47km.

The radial distribution initially reports better results than its random counterpart regarding low-autonomy vehicles. However, the reduction in trip deviation evolves similarly to the random distribution one as more simulations are tested. With an autonomy of 200km, the most balanced result is again found by placing 250 stations, leaving the total average deviation at 116km. Then, with 400km of autonomy, 50 stations would add an average of 87km to a trip. Doubling the stations, the deviation drops to 59km. From this point, the figure

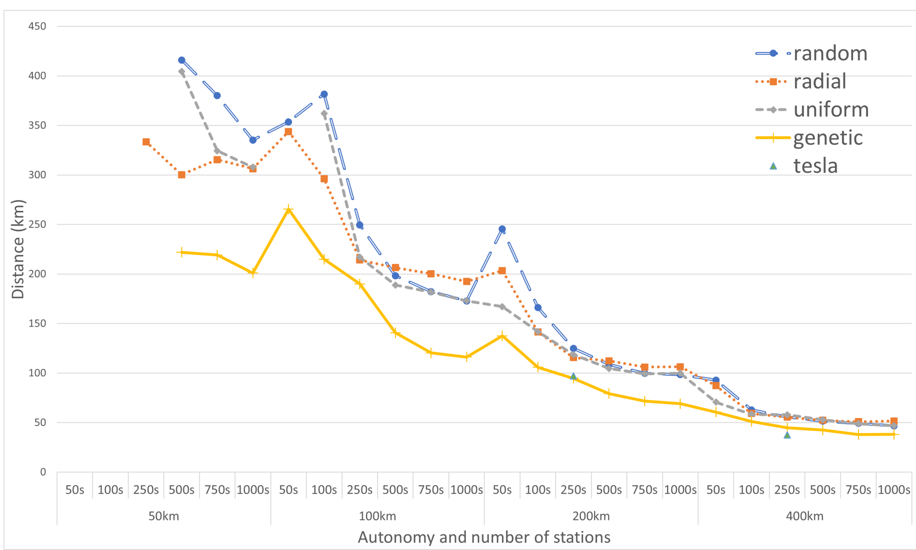


Fig. 3. Distance deviation from the optimal trip for the different distributions, number of stations, and levels of autonomy of the vehicles.

continues to drop asymptotically to 51km, indicating it is not cost-effective to consider placing more than 100 stations.

The uniform distribution, with low-autonomy vehicles, performs slightly better than the random one and slightly worse than the radial. From 200km autonomy upwards, it surpasses the radial, performing generally better and, at worse, similarly. This distribution achieves a deviation of 105km with 500 stations and 200km autonomy vehicles. Then, it improves to 47km with 750-1000 stations and vehicles with the highest autonomy.

The Tesla distribution can only be tested with vehicles with +200km autonomy. It yields excellent results with those with 400km of autonomy, reducing deviations to 38km.

Finally, the GA's distribution outperforms the random, radial, and uniform distributions while matching Tesla's results. For 50km autonomy vehicles, all runs with the most stations on the map have a result that exceeds 200km. Placing more stations has virtually no effect on efficiency. Then, with 100km autonomy, the curve descends linearly as stations are added up to 750, where the average deviation is 120km, less than half the value with which the series started. For cars with 200km autonomy, deviation values show a similar progression according to the number of stations. With 750, the value decreases to 72km. On the other hand, cars with 400km autonomy have to deviate around 61km with 50 stations. With 750 stations, the displacement is reduced to less than 40km.

3.3 Discussion

Following, the results are assessed from a general perspective, comparing the types of station distributions used in the study and highlighting their strengths and weaknesses.

The experimentation with a random distribution proves that it is not strictly necessary to carry out an exhaustive study of the ideal location for the station network since just by placing them at any point on the map, acceptable results can be obtained, although only for the vehicles with a higher (+200km) autonomy. A radial distribution pattern stands out since it quickly shortens the trip deviation with a relatively small number of stations. However, once again, this effect is mainly reflected in vehicles with high autonomy. Nevertheless, we could say the radial is a cheap distribution since it is unnecessary to invest excessive resources to achieve a satisfactory quality for travelers. Finally, the uniform distribution works well for high-autonomy vehicles, presenting lower deviations from the planned trip than the random and radial distributions. In addition, the uniform distribution of 500 stations is the first one in which 50km range vehicles start to complete their journeys. This is a relevant feat, although it must be pointed out that EVs with such low autonomies are not designed for intercity travel. In conclusion, the explored spatial patterns can be acceptable for drivers with high autonomy EVs considering that it is both an expensive and naive deployment of resources.

When it comes to Tesla's network of fast chargers, results indicate that it is well tailored to the enterprise's purposes, allowing its direct customers to travel thanks to their vehicles' high autonomy. Trip deviations are low, as charging terminals are located adjacent to the country's main roads. Meanwhile, lower autonomy EVs that are not of its brand are disregarded. From a global perspective, it does not grant access to all types of EVs, creating an imbalance in the Spanish travelers' fair access to charging infrastructure. To improve this situation, future stations in Tesla could be placed in a greater variety of geographical points within the area, allowing more EVs to recharge batteries instead of accumulating many terminals in the same location.

Finally, the GA shows its best networks when distributing 750 stations, as those experiments present the lowest average deviations and very low instances of aborted trips. While it is true that so many stations involve a high outlay of resources, the algorithm outputs a concrete distribution that could be implemented over time. The trip deviation curves of this method are much more linear than in other distributions (see Figure 3). This implies we can regulate and balance the investment in stations according to the desired effectiveness of the network. In this sense, the GA is a more flexible method for charging infrastructure allocation than its counterparts.

4 Conclusions

This paper focuses on designing and developing a simulation environment to test the allocation results of a genetic algorithm for an optimal electric charging station network in Spain. We propose using multi-agent simulation to evaluate a state-wide network of fast charging stations. Interurban trips with various lengths are generated across the territory where the network is deployed and then simulated with SimFleet to validate each station distribution. Simulations are run in scenarios with a different number of deployed charging stations as well as varying EV autonomy. The results show that the proposed genetic charging station distribution satisfies the needs of interurban travelers, providing more flexibility than Tesla's network and other possible station distributions.

A possible line of future work would be the improvement of the genetic algorithm based on the conclusions drawn from this work. For example, a refinement of the stations' distribution area could increase the algorithm's effectiveness. It has been observed that stations close to main travel routes help to reduce passenger diversion. Favoring the placement of stations on these roads would improve the final allocation of the algorithm.

Another improvement in charging infrastructure evaluation would be to inform the generated intercity trips using a dataset of real intercity displacement in Spain. Additionally, information on the most typically used routes can be employed to improve both station distribution and network evaluation.

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References

1. Brown, S., Pyke, D., Steenhof, P.: Electric vehicles: The role and importance of standards in an emerging market. Energy Policy **38**(7), 3797 – 3806 (2010). https://doi.org/https://doi.org/10.1016/j.enpol.2010.02.059
2. Jordán, J., Martí, P., Palanca, J., Julian, V., Botti, V.: Interurban electric vehicle charging stations through genetic algorithms. In: Hybrid Artificial Intelligent Systems. pp. 101–112. Springer International Publishing, Cham (2021)
3. Jordán, J., Palanca, J., Martí, P., Julian, V.: Electric vehicle charging stations emplacement using genetic algorithms and agent-based simulation. Expert Systems with Applications **197**, 116739 (2022)
4. Jordán, J., Martí, P., Palanca, J., Julian, V., Botti, V.: Interurban charging station network: An evolutionary approach. Neurocomputing **529**, 214–221 (2023). https://doi.org/10.1016/j.neucom.2023.01.068
5. Kchaou-Boujelben, M.: Charging station location problem: A comprehensive review on models and solution approaches. Transportation Research Part C: Emerging Technologies **132**, 103376 (2021)
6. Ouyang, M.: Review on modeling and simulation of interdependent critical infrastructure systems. Reliability engineering & System safety **121**, 43–60 (2014)
7. Palanca, J., Terrasa, A., Julian, V., Carrascosa, C.: SPADE 3: Supporting the New Generation of Multi-Agent Systems. IEEE Access **8**, 182537–182549 (2020)
8. Palanca, J., Terrasa, A., Carrascosa, C., Julián, V.: Simfleet: A new transport fleet simulator based on mas. In: International Conference on Practical Applications of Agents and Multi-Agent Systems. pp. 257–264. Springer (2019)
9. Pautasso, E., Osella, M., Caroleo, B.: Addressing the sustainability issue in smart cities: A comprehensive model for evaluating the impacts of electric vehicle diffusion. Systems **7**(2), 29 (2019)
10. Pevec, D., Babic, J., Carvalho, A., Ghiassi-Farrokhfal, Y., Ketter, W., Podobnik, V.: A survey-based assessment of how existing and potential electric vehicle owners perceive range anxiety. Journal of Cleaner Production **276**, 122779 (2020)
11. Rauh, N., Franke, T., Krems, J.F.: Understanding the impact of electric vehicle driving experience on range anxiety. Human factors **57**(1), 177–187 (2015)
12. Wood, E., Neubauer, J.S., Burton, E.: Measuring the benefits of public chargers and improving infrastructure deployments using advanced simulation tools. Tech. rep., SAE Technical Paper (2015)
13. Zhang, Y., Liu, X., Zhang, T., Gu, Z.: Review of the electric vehicle charging station location problem. In: International Conference on Dependability in Sensor, Cloud, and Big Data Systems and Applications. pp. 435–445. Springer (2019)