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Optimising Electric Vehicle Charging Infrastructure in Dublin using GEECharge

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***Abstract*—Range anxiety poses a hurdle to the adoption of Electric Vehicles (EVs), as drivers worry about running out of charge without timely access to a Charging Point (CP). We present novel methods for optimising the distribution of CPs, namely, EV portacharge and GEECharge. These solutions distribute CPs in Dublin, in this paper, by considering the population density and Points Of Interest (POIs) or road traffic. The object of this paper is to (1) develop and evaluate methods to distribute CPs in Dublin city; (2) optimise CP allocation; (3) visualise paths in the graph network to show the most used roads and POIs; and (4) evaluate the efficacy of the solutions. The criterion for success used in this paper is that, an EV is within a $500\,\mathrm{m}$ range of the CP, when it runs out of charge. Our findings show that, in Dublin City, 121 CPs are an optimal number for a $1\,\mathrm{km}^2$ area. Discrete event simulation establishes the superiority of the GEECharge method, which exhibits a 2.2% higher efficiency compared to the EV Portacharge method. Population density, POIs, and road usage patterns are crucial factors that demand careful consideration when formulating a comprehensive framework for CP distribution.**

***Index Terms*—Charging Infrastructure, Dublin, Simulation, Charging Stations, Charging Point, Electric Vehicles**

I. Introduction

Electric Vehicles (EVs) have gained popularity as an eco-friendly alternative to conventional vehicles in recent years [1]. When they use low-carbon electricity, for example from renewable micro-grid generation [2], they can help to reduce carbon emissions, accounting for 70% of global emissions [3], and achieve economic decarbonisation targets [4], [5], [6]. Data center networks have been attributed with a comparable level of energy consumption. The authors of [7] reported that 10 % of global energy consumption was due to ICT and network usage. The authors of [8] assert that EVs offer better performance, higher efficiency, and emit no tailpipe emissions. As a result, many countries are focusing on promoting the EV industry to encourage energy saving and reduce carbon emissions [9], [10].

Although EV owners can charge their vehicles at home, they also require access to Charging Points (CPs) outside their homes, as limited battery life typically only allows for a few hundred kilometres of driving [11]. However, the availability of convenient CPs is crucial for drivers to feel comfortable investing in EVs, and the lack thereof contributes to range anxiety - the stress caused by concerns over insufficient charging infrastructure [12]. The challenge of where to locate CPs is addressed in part by urban development strategies, but these solutions are constrained by range anxiety [13], [14], [15].

In recent years, Ireland has started to install CPs; however, range anxiety remains an issue for drivers who worry about the battery life and accessibility of CPs. They prefer to have CPs located along the shortest route between destinations [16], [17]. This paper builds on previous research, addresses gaps in the literature and contributes the following:

- We develop the GEECharge method to distribute CPs in Dublin city considering real-life data such as population density, Points Of Interest (POIs) or road traffic.
- We describe a way to evaluate the solution's efficacy using Discrete Event Simulation (DES).
- We optimise CP allocation to reduce range anxiety.
- We determine the number of CPs required in Dublin City.

This study addresses two important research questions related to range anxiety: (1) What factors influence the selection of CP locations? (2) Which method is best for identifying suitable CP locations? The minimum distance from a CP that an EV driver must consider driving to recharge their vehicle can vary depending on several factors, including the vehicle's remaining range, the driver's comfort level, and the availability of charging infrastructure. The rationale for maintaining 10% to 20% battery charge includes range anxiety, battery degradation [18], [19] and unexpected delays which can add extra distance to the planned route. This paper evaluates the GEECharge method. We demonstrate that it is effective in ensuring that EVs can access CPs when needed. The methods are applied in a case study of Dublin City and evaluated in scenarios where EVs run out of battery within $500\,\mathrm{m}$ of a CP. The decision to use a $500\,\mathrm{m}$ threshold is rooted in the size of our testing cell, which measures $1\,\mathrm{km}^2$. This criterion ensures that the CPs are conveniently located within reasonable proximity for efficient charging without requiring excessive detours. We determine that around 121 CPs are required within a $1\,\mathrm{km}^2$ area in Dublin City.

This paper is organised as follows. In Section II, we summarise CPs distribution literature. In Section III, we describe GEECharge and EV Portacharge methods. In section IV, we discuss the evaluation of the GEECharge. Section V shows the numerical evaluation. Section VI presents recommendations for future work.

II. Charging Points Distribution Literature

Different methods have been used to distribute CPs on a map. Finding a suitable location of a CP requires a multi criteria approach, as EV CP location is a multiple criteria evaluation problem, which is influenced by various conflicting criteria [20], [21]. A popular approach involved discretising a map into cells before using some other process to allocate the CPs. Martí et al. [22] investigated four different optimisation criteria, each accompanied by an algorithm. The first used a random allocation procedure and was used as a benchmark method. The second approach assigned EVs uniformly by dividing the map into square cells. The third approach divided the map into triangles from the centre to concentric circles. The last was a genetic distribution using population information, traffic information, Twitter activity, and the cost of charging stations and points to assign a score to each cell. The cells were Voronoi polygons created around POIs. The higher the score was, the more likely it was to be given a CP. A limitation of this approach is that is that the approximations for the distributions used, may be unrealistic.

Mahdy et al. [23] used a multi-criteria approach to optimise the location of CPs. A map was divided into square cells, and each cell was given a score according to constraints and suitability factors. If a constraint was valid, the constraint score of the cell was assigned to be 0, and otherwise, it was assigned 1. The final score was the weighted sum of all the suitability factor scores multiplied by the constraint score. The constraints included road characteristics and suitability factors, for example, the presence of a petrol station or the population distribution. Again, the weights were manually chosen. This differed from the approach in Martí et al, which used different factors to assign a score to each cell.

Mehmet et al. [20] proposed a GIS-based fuzzy Multi-Criteria Decision Analysis (MCDA) approach for siting EV charging stations. The approach involved defining attributes that helped to choose the optimum places in detail, and then using a fuzzy Analytical Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods to evaluate potential sites based on these attributes. This research presented a case study for Ankara, Turkey, where the proposed approach was applied to identify optimal locations for EV CPs.

Jordán et al. [15] used a genetic algorithm that optimised the location of CPs. The approach used was a Multi-Agent System (MAS) that analyzed a large set of configurations for the placemenent of EV CPs. The algorithm checked the possible locations of the charging stations and tried to distribute the required stations throughout the city. Guo et al. studied the CPs location problem in [24] considering users' range anxiety and distance deviations. They used an adaptive large-neighbourhood search, a k-shortest path algorithm and an iterative greedy heuristic. They applied their method to a real-world road network.

GEECharge differs from previous research by using population density, POIs, and a most used road factor to distribute CPs effectively. This improves the CP success rate and reduces range anxiety for drivers, promoting EV usage.

III. GEECharge and EV Portacharge

This section discusses the implementation of the GEECharge and EV Portacharge methods for CP distribution in the graph G with set of vertices V and edges E, where *G=(V,E)*. Vertices V are defined as $V = \{v_1, v_2, v_3, \ldots, v_n, \ldots, v_N\}$ where v_n is the n^{th} vertex in the graph network and $n = 1, 2, 3, \ldots, N$. The edges are defined as $E = \{e_1, e_2, e_3, \ldots, e_m, \ldots, e_M\}$ where $e_m = \{v_i, v_j\}$. A set of edges is represented by $E = \{\{v_i, v_j\}, \{v_k, v_n\}, \ldots, \{v_m, v_p\}\}$. The location of the i^{th} vertex is represented by $l(v_i)$, where $l(v_i) = (x_i, y_i)$ as x_i and y_i are latitudes and longitudes respectively. The location of the j^{th} vertex is represented by $l(v_j)$, where $l(v_j) = (x_j, y_j)$.

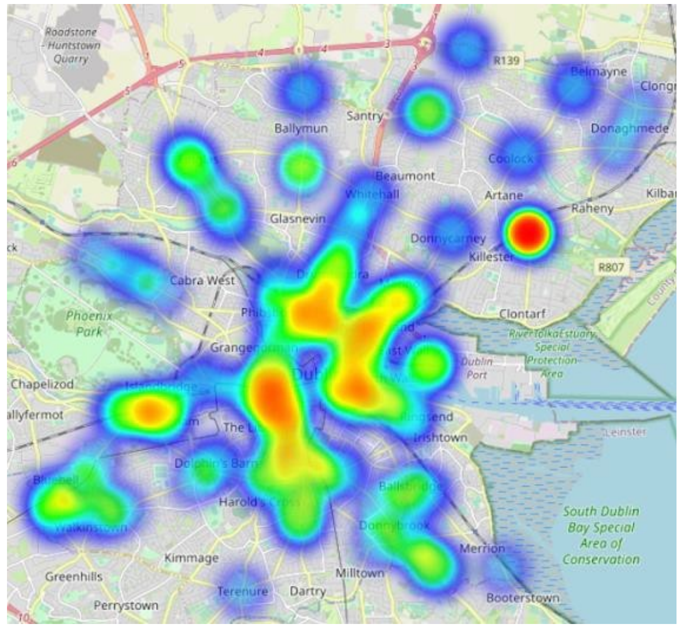

Fig. 1. Heatmap generated by the algorithm. The heatmap displays the congested intersections of Dublin city. The gradient goes from blue (corresponding to zero congestion) to red (corresponding to complete congestion) showing the intensity in the intersections.

The total number of vertices and edges is $N = |V|$ and $M = |E|$ respectively. We obtain data from an open-source government site [25] and use it to generate daily information on the number of cars detected and locations of intersections in a network. The nodes in the network represent frequently used intersections, and each edge e_m has a capacity $c(e_m)$ and weight w, that indicate the maximum traffic flow and length in meters, respectively.

A. Gathering Traffic Data

We collect data on the number of cars passing through each intersection in Dublin every hour and use it to create a heatmap showing the traffic congestion in Fig. 1. We divide the area into $1\text{km} \times 1\text{km}$ square cells [22] to make mapping more efficient. Using Google Earth, we identify the most heavily used roads by connecting nearby points with blue lines as shown in Fig. 2.

B. GEECharge and EV Portacharge Methods

We evaluate two solutions for distributing CPs based on population density and POIs in Dublin city. The first solution

Fig. 2. The Figure shows grid on a Dublin City map and most used roads in June 2021. The grid has been divided into identical square cells of $1\text{km} \times 1\text{km}$ square cells. The graph shows close points connected to each other displaying the most used roads for June 2021 using the blue lines. Row and column indices and cell coordinates are given in black font.

proposed in this paper, namely EV Portacharge, assigns scores based on population density and POIs using the method described in [23]. The second solution proposed in this paper, namely the GEECharge, adds the most used roads in each cell as an element and assigns scores based on the number of POIs within the cell. We use a 2021 map of population density where the lowest population density corresponds to 1 and the highest corresponds to 6. We select various POIs such as university campuses, supermarkets, hospitals, cinemas and tourist places.

- Let $d(r, c)$ be the population density at cell (r, c), where r represents the row number and c represents the column number as illustrated in Fig. 2.
- Let $p(r, c)$ be the number of POIs located in cell (r, c).
- Let $s_1(r, c)$ be the score assigned to cell (r, c) by the EV Portacharge method.
- Let $s_2(r, c)$ be the score assigned to cell (r, c) by the GEECharge method.

Population density cells are denoted as $d(r, c) = d_1, d_2, d_3, \ldots, d_{60}$ where, $d_1 = \{x_1, y_1\}, d_2 = \{x_2, y_2\}, \ldots, d_{60} = \{x_{60}, y_{60}\}$ are the scores about population density. Our grid is a 6×10 matrix thus d_{60} represents the population density score of the cell located at the 6^{th} row and 10^{th} column of the grid. POIs are defined as $p(r, c) = p_1, p_2, p_3, \ldots, p_{60}$ where $p_1(d_1), p_2(d_2), \ldots, p_{60}(d_{60})$ are scores about POIs for each cell. Weights w_d and w_p scale these values, where a larger weight increases the contribution of the associated value. The $s_1(r, c)$ cell score assigned by the EV Portacharge method is calculated as shown below,

$$s_1(r, c) = \frac{d(r, c)w_d + p(r, c)w_p}{\sum_{r=1}^{6}\sum_{c=1}^{10} d(r, c)w_d + p(r, c)w_p} 100. \quad (1)$$

POIs scores are $0 \leq p \leq 20$ and population density score in $1 \leq d \leq 6$. The weight $w_d = 4$ means that we scale the population density by 4 so that its contribution is four times that of the POI term, which has a weight of $w_p = 1$. The final value represents a percentage of all the CPs.

C. GEECharge Method

We consider the most used roads using an analogous calculation. Let $u(t)$ be the road usage score for road t where $u(t)$= t_1, t_2,$\ldots t_{60}$ and w_t the associated weight. The most used roads in the network are defined by the maximum traffic flow between v_i and v_j vertices which is expressed as $f(v_i, v_j)$ where $\forall\{v_i, v_j)\} \in E$. The most used roads are defined as R where, R = sort$(f(v_i, v_j)|\{v_i, v_j\} \in E)$ and R[1] represents the first element of the sorted list of maximum traffic flow between all vertices in the graph network. The score assigned by the GEECharge method is $s_2(r, c)$.

$$s_2(r, c) = \frac{d(r, c)w_d + p(r, c)w_p + t(r, c)w_t}{\sum_{r=1}^{6}\sum_{c=1}^{10} d(r, c)w_d + p(r, c)w_p + t(r, c)w_t} 100. \quad (2)$$

The road scores lie in the range of $0 \leq u \leq 4$ and the weight is $w_t = 10$. The GEECharge method considers road usage as being twice as important as the sum of w_p and w_d. We develop an algorithm to generate CP coordinates based on a defined grid and input data in CSV file. The starting latitude and longitude are denoted by x_1 and y_1. The considered cell coordinates are (x_1, y_1), which is the North West, and (x_6, y_{10}) as illustrated in Fig. 2.

IV. Evaluating the GEECharge

We develop a discrete event simulation method to generate trips on the Dublin City Road network to test GEECharge and EV Portacharge solutions. Let $G_z = (C, E)$ be a subgraph of G that includes the vertices and edges that correspond to the CPs and their connections. An EV located at vertex v_i in G can access the nearest z_j in G_z by finding the shortest path between v_i and z_j in G_z using the Dijkstra algorithm. The set of all CPs in G_z denoted as C, is represented as $C = \{z_1, z_2, z_3, \ldots, z_q, \ldots, z_Q\}$ where q represents the q^{th} CP and Q is the total number of CPs. Finding z_j in the set of CPs C that is closest to the vertex v_i, where dist(i,j) is the distance metric between v_i and CP z_j is expressed as,

$$z^\star \leftarrow \text{argmin}\{\text{dist}(i, j)|z_j \in C\}. \quad (3)$$

When an EV runs out of battery, the Euclidean distance between the EV's current location and the nearest CP is calculated. The Euclidean distance is the shortest distance between EV's current location $l(v_i)$ and CP location $l(z_j)$. The Euclidean distance in metres between a CP and the arrival node is calculated using the haversine formula. The magnitude of the vector formed by the difference between v_i and v_j is,

$$||l(v_i) - l(z_j)|| = ||x_i - x_j| - |y_i - y_j||$$

where $l(v_i) = [x_i, y_i]$ and $l(z_j) = [x_j, y_j]$.

The distance dist(i,j) is calculated as $\varphi = x_j - x_6$, $\lambda = y_j - y_{10}$ and

$$\text{dist}(i,j) = 2R \arcsin \sqrt{\sin^2 \frac{\varphi}{2} + \cos\varphi_1 \cos\varphi_2 \sin^2 \frac{\lambda}{2}}. \quad (4)$$

The radius of the earth is $R \approx 6371\,\text{km}$. The difference between x_6 and x_j is represented by φ. The distance between y_{10} and y_j is represented by λ. The above equation shows dist(i, j) as the Euclidean distance.

V. Numerical Evaluation

We summarize our findings and then use this summary to give structure to the description of our experiments. We establish that: (1) For Dublin City, 121 CPs are sufficient within a $1\,\text{km}^2$ area assuming all EVs have a range of $400\,\text{km}$; (2) The GEECharge method is 2.2% more efficient than the EV Portacharge method; (3) The success rate of the GEECharge method follows a characteristic curve, which motivates the idea that there is a linear relationship between success rate and the number of CPs; and (4) On average, the nearest CP is located at a distance of $415\,\text{m}$.

In our first finding using the GEECharge solution, 119 EV routes were simulated, and 90 EVs were successful in being within $500\,\text{m}$ of a CP at the end of the simulation. Dijkstra's algorithm was used to determine car routes through the network. To assess convenience and success rates, we analysed the total number of CPs located within a $500\,\text{m}$ range. Our findings reveal that out of the total CPs assessed, the 121 CP solution achieved a success rate of approximately 74.0%. This meant that EVs could conveniently access these 121 CPs for charging, as they were situated within $500\,\text{m}$ of the final destination of the EV. The GEECharge solution was 2.2 % more efficient than the EV Portacharge solution when 100 CPs were used for simulation. After conducting tests on 121 CPs and measuring the success rate, we observed variances of approximately 11.11 and 0.8323 respectively, indicating the level of data variability.

We then considered the appropriate number of CPs in Dublin using GEECharge algorithm by examining the sensitivity of the success rate to changes in the number of CPs used. The rate of change between 93 and 96 CPs was 3.1 as illustrated in Fig. 3. However, when more than 121 CPs were used the success rate curve flattened. This indicates that the cells were saturated with CPs. Increasing the number of CPs beyond 121 introduced redundancy, making some CPs idle or have very low usage. This may lead to an inefficient allocation of resources, if a planned amount of redundancy is not an explicit goal. We then determined the percentage of CPs that were within 500m of the EV's current location and computed this measure of success using,

$$\frac{1}{|C|} \sum_{z \in C} I(||l(v_i) - (z_j)|| < 500)$$

where $I(||l(v_i) - (z_j)|| < 500)$ is an indicator function that is equal to 1 if the distance between the EV's current location

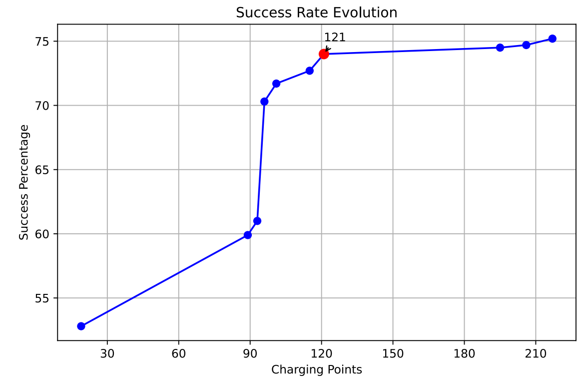

Fig. 3. Success rate evolution: The graph shows success rate percentage against the number of CPs in Dublin city. The rate of change for success rate is 3.1 between 93^{rd} and 96^{th} CP. However, after the 121^{st} CP the curve flattens indicating that the selected cell is saturated with CPs.

TABLE I
GEECharge and EV Portacharge Simulation results.

Runs	Run 1	Run 2	Run 3	Run 4
Parameters	100 CP	50 CP	100 CP	50 CP
Success Rate	71.7	45	69.5	42
Mean distance to the nearest CP (m)	415	455	456	669

v_i and CP z_j is less than 500m, and equal to 0 otherwise. Before stopping, an EV can drive $1\,\text{km}$ at low speed to reach a CP. The simulation assumed around 100 cars passed through an intersection hourly, and most EVs had a range of approximately $400\,\text{km}$. While some EVs, like Tesla's Model S Long Range, offer a higher range of about $637\,\text{km}$, $400\,\text{km}$ is typical for most EVs [26]. Results can be seen in Table I.

- Run 1: GEECharge, 100 CPs, 100 cars, range of $400\,\text{km}$.
- Run 2: GEECharge, 50 CPs, 100 cars, range of $400\,\text{km}$.
- Run 3: EV Portacharge, 100 CPs, 100 cars, range of $400\,\text{km}$.
- Run 4: EV Portacharge, 50 CPs, 100 cars, range of $400\,\text{km}$.

The average distance to the nearest CP was $415\,\text{m}$. Fig. 4 shows how the mean distance to a CP changed with the number of CPs. The parameters used included the number of CPs and the mean distance to a CP. This indicates that, the mean distance decreased with an increase in the number of CPs in the $1\,\text{km}^2$ cell. However, to have an even CP utilization we determined that 121 was the suitable number of CPs.

In conclusion, to ensure a balance of resources is achieved, we need to install a suitable number of CPs in Dublin city. Based on our simulation results, we propose that an ideal number of CPs is around 121 for $1\,\text{km}^2$ in Dublin City. Zhou et al. [27] established that the location of 670 CPs was required in the larger area of Ireland which is $84\,000\,\text{km}^2$. Based on our findings, we believe that this number of CPs could be

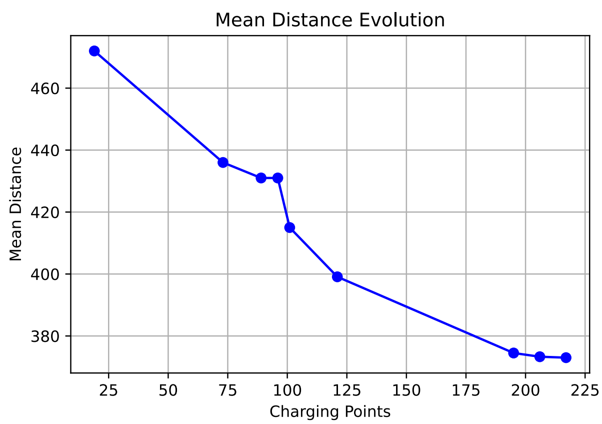

Fig. 4. Evolution of the mean distance to a CP: At 472 m the number of CPs available is 19 and at 121 CPs the mean distance is 399.1 m. The mean distance decreases with an increase in the number of CPs in the 1 km^2 cell area in Dublin.

increased.

Previous research used varying parameters to determine the optimal CP distribution for drivers considering infrastructure, power grid, and environmental benefits. The genetic algorithm used in previous studies was insufficient to account for all constraints. This research develops the GEECharge method, which considers the most used roads, POIs, and population density as key parameters, resulting in an effective solution for CP distribution in Dublin that reduces range anxiety.

A limitation of the research is that GEECharge results can only determine the number of locations to put a CP. We have not considered the problem of determining how the number of plugs for each CP could be adapted to improve the allocation.

VI. Conclusion and Future Work

GEECharge will be helpful in determining the distribution of CPs. However, this research does not consider power distribution in Dublin. We recommend incorporating proximity to the grid infrastructure and number of plugs in the future analysis. This research targets city drivers since they may not have access to private charging at home. The findings provide guidance for policymakers in CP distribution and the framework for gathering data and running the DES is reproducible in other cities.

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References

[1] H. Hao, X. Cheng, Z. Liu, and F. Zhao, "Electric vehicles for greenhouse gas reduction in china: A cost-effectiveness analysis," *Transportation Research Part D: Transport and Environment*, vol. 56, pp. 68–84, 2017.

[2] Y. Kutlu, R. de Fréin, M. Basu, and A. Malik, "Round trip time measurement over microgrid power networks," *IEEE Irish Signals and Systems Conference*, pp. 1–6, June 2023.

[3] E. S. Board, "Empowering low-carbon living | esb annual report," 2021.

[4] KPMG, "Irelands 2030 carbon emissions targets | an economic impact assessment for the agriculture sector," October 2021.

[5] G. of Ireland, "Climate action plan 2021 securing our future," February 2021.

[6] W. Bank, "Electric vehicles: An economic and environmental win for developing countries," 2022, accessed: 2023-05-19. [Online]. Available: https://www.worldbank.org/en/news/feature/2022/11/17/electric-vehicles-an-economic-and-environmental-win-for-developing-countries

[7] M. Nsaif, G. Kovásznai, A. Rácz, A. Malik, and R. de Fréin, "An adaptive routing framework for efficient power consumption in software-defined datacenter networks," *Electronics*, vol. 10, no. 23, 2021. [Online]. Available: https://www.mdpi.com/2079-9292/10/23/3027

[8] J. A. Sanguesa, V. Torres-Sanz, P. Garrido, F. J. Martinez, and J. M. Marquez-Barja, "A review on electric vehicles: Technologies and challenges," *Smart Cities*, vol. 4, no. 1, pp. 372–404, 2021.

[9] M. Khan and N. C. Kar, "Hybrid electric vehicles for sustainable transportation: A canadian perspective," *World electric vehicle journal*, vol. 3, no. 3, pp. 551–562, 2009.

[10] S. Babrowski, H. Heinrichs, P. Jochem, and W. Fichtner, "Load shift potential of electric vehicles in europe," *journal of power sources*, vol. 255, pp. 283–293, 2014.

[11] H. Engel, R. Hensley, S. Knupfer, and S. Sahdev, "Charging ahead: Electric-vehicle infrastructure demand," *McKinsey Center for Future Mobility*, vol. 8, 2018.

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

[13] Y. Ahn and H. Yeo, "An analytical planning model to estimate the optimal density of charging stations for electric vehicles," *PLoS ONE*, vol. 10, 11 2015.

[14] C. Karolemeas, S. Tsigdinos, P. G. Tzouras, A. Nikitas, and E. Bakogiannis, "Determining electric vehicle charging station location suitability: A qualitative study of greek stakeholders employing thematic analysis and analytical hierarchy process," *Sustainability (Switzerland)*, vol. 13, pp. 1–21, 2 2021.

[15] J. Jordán, J. Palanca, E. del Val, V. Julian, and V. Botti, "Using genetic algorithms to optimize the location of electric vehicle charging stations," vol. 771. Springer Verlag, 2019, pp. 11–20.

[16] H. Hickerson, H. Goldsmith, G. Brazil, and V. T. Eckerle, "Electric vehicle charging station permitting guidebook california governors office of business and economic development .lead authors: | second edition," 2023.

[17] I. Government, "Electric vehicle charging infrastructure strategy 2022-2025," 1 2023. [Online]. Available: www.gov.ie/transport

[18] "Bu-1003a: Battery aging in an electric vehicle (ev) - battery university," accessed: 2023-05-19. [Online]. Available: https://batteryuniversity.com/article/bu-1003a-battery-aging-in-an-electric-vehicle-ev

[19] T. Steffen, A. Fly, and W. Mitchell, "Optimal electric vehicle charging considering the effects of a financial incentive on battery ageing," *Energies*, vol. 13, 9 2020.

[20] M. Erba, M. Kabak, E. Özceylan, and C. Çetinkaya, "Optimal siting of electric vehicle charging stations: A gis-based fuzzy multi-criteria decision analysis," *Energy*, vol. 163, pp. 1017–1031, 11 2018.

[21] "Optimal siting of electric vehicle charging stations based on voronoi diagram and fahp method," *Energy and Power Engineering*, vol. 05, pp. 1404–1409, 2013.

[22] P. Martí, J. Jordán, J. Palanca, and V. Julian, "Charging stations and mobility data generators for agent-based simulations," *Neurocomputing*, vol. 484, pp. 196–210, 2022.

[23] M. Mahdy, A. S. Bahaj, P. Turner, N. Wise, A. S. Alghamdi, and H. Hamwi, "Multi criteria decision analysis to optimise siting of electric vehicle charging pointscase study winchester district, uk," *Energies*, vol. 15, no. 7, p. 2497, 2022.

[24] F. Guo, J. Yang, and J. Lu, "The battery charging station location problem: Impact of users range anxiety and distance convenience," *Transportation Research Part E: Logistics and Transportation Review*, vol. 114, pp. 1–18, 2018.

[25] I. Government, "Traffic flow data," 2021, accessed: 2022-10-28. [Online]. Available: https://data.gov.ie

[26] EVdatabase, "Compare electric vehicles," 2022, accessed: 2023-01-30. [Online]. Available: https://ev-database.org

[27] G. Zhou, Z. Zhu, and S. Luo, “Location optimization of electric vehicle charging stations: Based on cost model and genetic algorithm,” *Energy*, vol. 247, 5 2022.