Optimal Placement of Electric Vehicle Charging Stations to Maximize Coverage and Utilization in Dublin

MSc Research Project
Data Analytics

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Shubham Ramrao Jadhav

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Abstract

Globally, electric vehicles (EVs) are spearheading the sustainable transportation movement. To encourage more people to buy electric vehicles, charging stations must be easily accessible and strategically placed (*Zero Emission Vehicles Ireland: Policy documents*; 2023). In order to maximise coverage and usage, this comprehensive analysis optimises the placement of electric vehicle charging stations (EVCS) in Dublin, Ireland. With the use of urban and demographic data, the binary particle swarm optimisation (BPSO) and Greedy algorithms are employed to locate possible EVCS hotspots. This study makes use of spatial analysis, and demographic research. Although the Greedy strategy may perform better in scenarios with constrained resources or phased development, the findings show that the BPSO technique achieves 85.14% station coverage optimization. The knowledge gained from this research is valuable for sustainable development and city planning. Specifically in light of the expansion of EV infrastructure, the research's conclusions are crucial for informing initiatives related to sustainable development and urban planning.

Keywords: Electric vehicle (EV), electric vehicle charging station (EVCS), binary particle swarm optimisation (BPSO).

1 Introduction

Electric vehicles have become a revolutionary technology in the transportation industry, providing a optimistic solution to decrease greenhouse gas emissions, battle air pollution, and improve energy efficiency. Amid mounting worries over environmental sustainability and the exhaustion of fossil fuel resources, governments and communities across the globe are progressively adopting electric transportation. Dublin, being a progressive city, is not an exemption to this pattern. Dublin, the primary urban centre of Ireland, has shown a consistent rise in the acceptance and usage of electric vehicles (*Zero Emission Vehicles Ireland: Policy documents*; 2023). The rise in popularity of electric vehicles can be ascribed to several factors, such as government incentives, developments in EV technology, and an increasing awareness of the environmental consequences of conventional gasoline-powered vehicles (Caulfield et al.; 2022). With the increasing number of Dubliners transitioning to electric vehicles, the demand for a strong charging infrastructure becomes essential. The efficacy and availability of the charging infrastructure are crucial determinants that impact the triumph of electric vehicle adoption. The absence of a dependable network of charging stations can lead to EV owners experiencing range anxiety, restricted mobility, and annoyance (**?**). Therefore, it is crucial to optimise the positioning of electric car charging stations in order to guarantee a smooth experience for EV users and to further promote the acceptance of electric vehicles. Strategic planning of charging station location is vital in Dublin to optimise the advantages of electric vehicles. This entails not only augmenting the quantity of charging stations but also guaranteeing their optimal placement to effectively cover the entire metropolis.

Furthermore, optimising use entails ensuring that the charging infrastructure is utilised in an efficient manner, hence reducing idle time and congestion at charging stations. The placement of electric car charging stations in the most effective way is a challenging problem that necessitates a multidisciplinary approach. It entails taking into account variables such as spatial distribution, population concentration, transportation flow, and urban development. In addition, it is important to incorporate the charging infrastructure into the current electrical grid in order to effectively control the level of demand and guarantee its dependability. The objective of this study is to investigate and provide a complete approach for the most efficient positioning of electric vehicle charging stations in Dublin. This strategy seeks to optimise the extent, usage, and availability while considering the distinct urban and demographic attributes of the city. Through a systematic approach, this study can make a meaningful contribution to the sustainable expansion of electric mobility in Dublin while simultaneously decreasing its carbon emissions.

1.1 Research Questions

This research project aims to investigate the following important research problem in order to confront the challenges of optimising the EV charging infrastructure in Dublin:

- What are the optimal locations for the placement of EVCS in Dublin to maximize coverage and utilization, given the current distribution of EVCS and potential hotspots for electric vehicle usage?

1.2 Research Contributions

The following is the contribution to the research:

- **Insightful Analysis and Strategic Recommendations:** Providing a complete analysis of Dublin's requirements for electric vehicle charging station infrastructure, which will result in strategic suggestions for network extension that are driven by data and take into consideration future trends in the utilisation of electric vehicles.

- **Policy and Planning Framework:** It is important to provide a methodological framework and policy insights that can assist urban planners, policymakers, and stakeholders in making informed decisions regarding the development of EVCS networks and sustainable urban transportation.

1.3 Project Outline

The organisation of this piece is as follows: The literature review, located in Section 2, examines previous research in order to identify areas where knowledge is lacking. Section 3 of the document covers the methodology for optimal placement of EVCS, which encompasses several methodologies such as data collection and sources, identification of potential hotspot location, demographic analysis. This section also includes a discussion of the BPSO and greedy algorithms for EVCS optimization that will be employed.

The necessary implementation which includes coverage matrix and optimization method are specified in Section 4. Also, it includes overall coverage area of the resulting EVCS location. Section 5 consist of design specification. The coverage and utilisation results of the greedy algorithm and BPSO are shown in Section 6, in that order. Additionally, it offers algorithmic performance on line graphs. Component 7, which is the final component of the project, presents a comprehensive summary of the findings and contributions.

2 Related Work

GIS-based community EV charging point finding methods have various limitations, according to the research provided by Charly et al. (2023). First, geographical data including population density, amenities, parking areas, and EV charging infrastructure is essential to these methods. When data is scarce or imprecise, outcomes may be unreliable. Second, GIS-based systems frequently function at a regional or national scale, making it difficult to locate local charging points. These methods also presume that end-user traits and behaviors are adequately captured in the data, which may overlook changes in user behavior over time or between individuals. The methodologies seek to capture the dynamic nature of EV consumption trends, but they may fail to keep up with quick market changes like new charging technology or customer preferences. Finally, EV charging point distribution may not consider equity and accessibility, resulting in the installation of charging points in areas with poor infrastructure or vulnerable populations. In conclusion, GIS-based methods may be useful for identifying community EV charging spots, but they have limitations that must be addressed and further researched.

Barhagh et al. (2023) propose an optimization method to discover the best position and size of electric vehicle charging stations. Although the framework gives valuable insights, its limitations must be considered. The framework needs accurate geographical data. Insufficient or incorrect data may compromise results in some regions. Specific static deployment strategies may also be unable to quickly adapt to shifting demand and network limits, limiting their ability to respond. In contrast, this study used real-time optimization to adjust charging station placement based on demand and network constraints. Electric Vehicle Charging Station location is more versatile and adaptive with this technology. The research also emphasizes the need for multi-criteria decision-making to address sustainability, efficiency, and performance goals in electric car communities. Barhagh et al. (2023) proposed methodology is useful, but more study is needed to incorporate real-time optimization approaches and determine the best EVCS placement and scaling strategies.

Through the utilisation of sophisticated discrete choice models, Campaña and Inga (2023) developed a novel strategy for optimising the placement of charging stations for electric vehicles (EVs). This technique takes into account a variety of elements that have an impact on the charging decisions of electric vehicle drivers and takes into account the fact that different user classes have different preferences and charging requirements. The rolling horizon, greedy, and greedy randomised adaptive search procedure (GRASP) heuristics are utilised in order to solve the obstacles that are associated with computation. A real-world case study was used to illustrate that the strategy was effective in achieving the desired results. The development of efficient heuristics, the demonstration of the usefulness of the strategy, and the introduction of a novel technique to optimising the placement of electric vehicle charging stations are among the most important contributions. The findings can be used to improve the planning and deployment of electric vehicle charging stations, which will maximise their utilisation and benefit drivers of electric vehicles.

A method that is based on deep learning was suggested by Kumar Shah and Singh (2023) for the purpose of estimating the amount of power and energy that EV batteries possess. Through the utilisation of a recurrent neural network (RNN) architecture, more especially a Long Short-Term Memory (LSTM) network, the suggested model is able to effectively represent the intricate temporal dynamics of electric vehicle battery behaviour. The next-generation neural network (LSTM) is trained using a complete dataset of EV battery data, which includes information on voltage, current, temperature, and state of charge (SOC).

An technique that is based on deep learning was developed by Hafeez et al. (2023) in order to maximise the utilisation of EV charging stations through the utilisation of demand side management (DSM). For the purpose of predicting the demand for electric vehicle charging and optimising charging schedules, the methodology makes use of a deep learning model. The model is trained using previous data on electric vehicle charging, which includes arrival times, durations, and charge capacities of the batteries. Therefore, the efficiency of the suggested approach is demonstrated by the fact that it greatly reduces peak demand and optimises the utilisation of electric vehicle charging stations. The technology has the potential to be incorporated in real-world electric vehicle charging station management systems, which would contribute to a power grid that is more fuel-efficient and environmentally friendly. Some of the most important contributions are the creation of an approach that is based on deep learning, the proof of its effectiveness, and the possibility of its use in real settings.

On behalf of ISLAM et al. (2016), author propose an optimisation model for the placement and size of electric vehicle charging stations in Bangi. Using three different algorithms, they determine that the binary gravitational search method is the most efficient. This system suggests ten stations in locations with high traffic and a large concentration of electric vehicle owners, each of which should have ten chargers. These recommendations provide useful insights for the planning of electric vehicle infrastructure in Malaysia.

Csonka and Csiszár (2017) and Ahmad et al. (2022) have conducted research to ensure that electric vehicle charging infrastructure is of the ideal size and location. Specifically, they highlight the economic considerations that are involved in station building and emphasise the significance of taking traffic statistics into account when picking locations that are appropriate.Ahmad et al. (2022) Through the application of their methodology to a case study of the M3 highway in Hungary, they discovered that rest areas are the most suitable places for electric vehicle charging stations. The researchers came to the conclusion that their approach can be utilised to choose the most suitable places for electric vehicle charging stations in other regions as well. However, realistic and thorough depictions of EV charging behavior and the distribution network are frequently absent from current EVCS site models. In order to fill in these gaps, this study suggests a thorough and practical model for the location of EVCS in Dublin, Ireland.

In their study, Pilotti et al. (2023) and Ravi et al. (2023) presented a bi-level optimisation model that was proposed for the purpose of designing an EV fleet charging station that possesses the potential to connect to the grid. Their strategy took into account a number of factors, including the disturbances to the grid that have occurred on the road, the charging needs of the electric vehicle fleet, the capacity of the vehicle-to-grid system, and the pricing of power.

? presents an innovative optimisation framework for the purpose of planning the deployment of fleets of autonomous electric vehicles (AEVs) and the positioning of charging stations throughout the world. The framework takes into account the intricate relationships that exist between the operations of electric vehicle fleets, the infrastructure of charging stations, and the demand for electricity. Its goal is to reduce the overall cost of the system, which includes the cost of purchasing electric vehicles (EVs), the cost of purchasing charging stations, the cost of power consumption, and the cost of lost demand.

EV charging stations (EVCSs) must be strategically placed to solve power dissipation, voltage fluctuations, and distribution line overload due to the rapid adoption of electric vehicles (EVs). Electric vehicle charging stations (EVCS) were optimised in a radial distribution network (RDN) with distributed generation (DG) integration in this study Das et al. (2023). The Symbiotic Organisms Search (SOS) approach, inspired by ecosystem symbioses, was used to locate Electric Vehicle Charging Stations (EVCSs). SOS performance was assessed on the IEEE 33-bus RDN. It reduced active power loss and voltage deviation index better than Grey Wolf Optimizer (GWO) and Whale Optimisation technique (WOA). Distributed generating (DG) units with electric vehicle charging stations (EVCSs) were also strategically added to boost distribution network efficiency. The results underline the need of appropriately allocating EVCS to improve distribution network performance and ensure seamless and efficient operation during EV adoption.

The rise of electric cars (EVs) has necessitated effective EV charging station placement and operation Faridpak et al. (2019). A two-step linear programming (LP) method is used to optimise EVCS placement and operation in this work. The method considers EV charging pattern uncertainty to reduce supply cost, distribution network impact, and charging procedures. The proposed technique was tested on a medium-voltage CIGRE distribution network. The two-step linear programming (LP) strategy reduced supply costs and distribution network impacts while balancing optimisation aims. The statistics imply that the two-step LP technique could optimise EVCS installation and operation, improving distribution network efficiency and reliability as EV demand rises.

Golla et al. (2022) proposed expanding use of electric vehicles (EVs) requires strategically placing EV charging stations (EVCSs) to reduce power losses, stabilise voltage, and increase distribution network efficiency. The Arithmetic Optimisation Algorithm (AOA), a meta-heuristic, was used to optimise EVCS placement in the study. Loss Sensitivity Factor (LSF) was used to determine the most important nodes for EVCS deployment. The AOA approach reduced active power loss and improved voltage profile compared to other optimisation methods. The results show that the AOA-based optimisation framework can optimise EVCS deployment and distribution network performance. This enables efficient and reliable distribution networks as EV use rises.

? suggested that the strategic positioning of fast charging stations for electric vehicles (EVs) is a crucial matter that must be resolved as the usage of EVs grows. This work presents a novel multi-objective optimisation algorithm that utilises the Ant Colony Optimisation (ACO) technique to optimise the positioning of FCSS. The programme takes into account both electrical distribution and traffic situation limitations. The algorithm under consideration was assessed using the IEEE 69-bus distribution network, taking into account 20 possible locations for Fault Current Limiting System (FCS). The results indicated that the ACO algorithm successfully optimised the placement of FCS, resulting in the reduction of total cost, power loss, and traffic congestion. The data indicate that the suggested ACO algorithm is a valuable tool for optimising FCS placement and promoting the growth of efficient and sustainable EV charging infrastructure.

3 Methodology for Optimal Placement of EVCS

The methodology for improving the positioning of EVCS in Dublin is designed to systematically examine and leverage data to identify the most advantageous locations for future installations. This would enable the optimal positioning of charging stations. Figure 1 illustrates a procedure that involves a series of systematic phases aimed at integrating data collection, hotspot identification, optimisation strategies and coverage analysis. The following segments provide a comprehensive breakdown of the above phases, offering specific information.

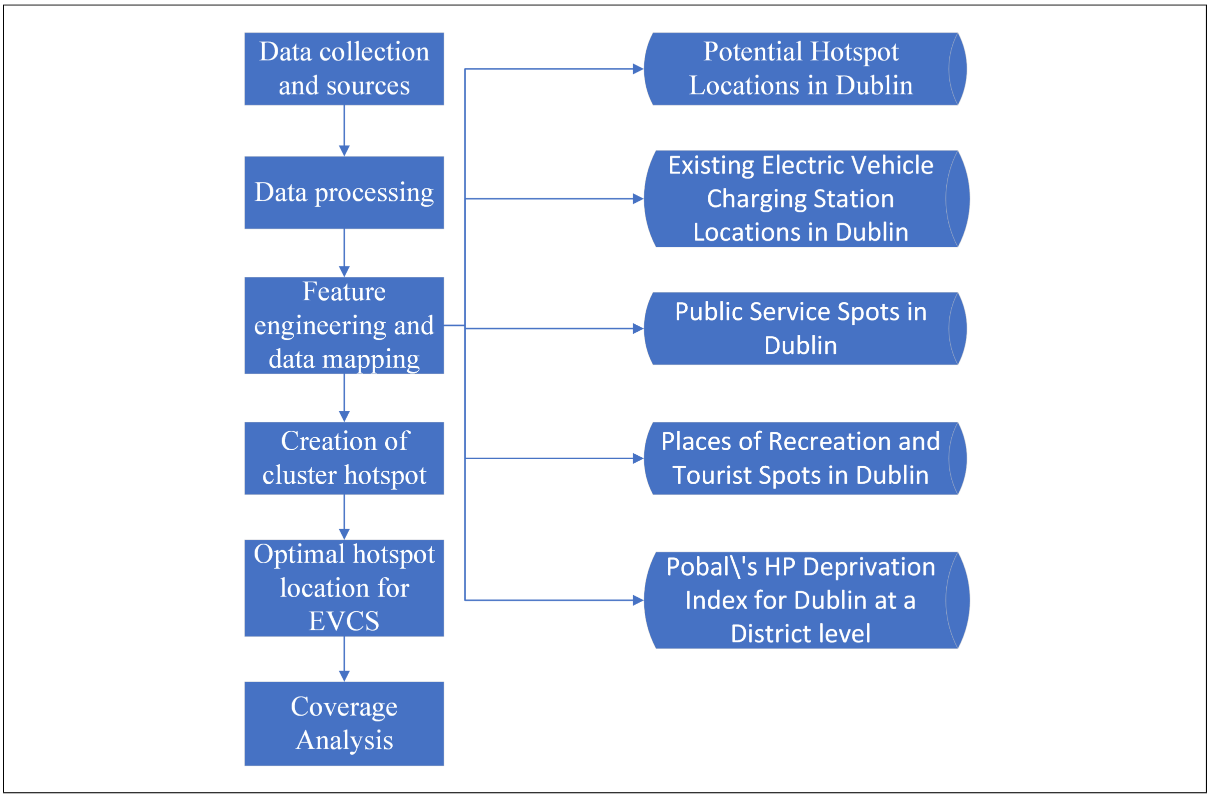

Figure 1: Flow chart for optimal placement of EVCS.

3.1 Data Collection

The foundation of this methodology lies in making decisions that are informed by the facts presented. The project launched a comprehensive data collection procedure to identify the optimal locations for installing additional EVCS. During this stage, this study collected diverse datasets containing data on the precise positions of existing charging stations, demographic factors, traffic intensity, proximity to amenities, and other important attributes that impact the demand for charging stations and usage patterns.

3.1.1 Data Sources:

- OpenStreetMap API: OpenStreetMap (OSM) [1] is an open-source mapping project that offers comprehensive geographical data. Typically, this data include details regarding roadways, structures, and facilities. The acquisition of the geographical data, refer Figure 3, forms the basis of inquiry was achieved by utilising the OpenStreetMap API. This data source offers hotspot tags, valuable insights about the road network and the spatial arrangement of services in Dublin. These hotspot tags include fuel, parking, events venue, college, hospital, university, food court, exhibition centre, town-hall, stadium, and conferencecentre.

- OpenChargeMap API: OpenChargeMap (OCM) [2] is an open-source initiative that maintains a global database of electric vehicle charging station locations. Utilising the OpenChargeMap API, study successfully gathered data regarding the EVCS now situated within a specific distance from Dublin, refer Figure 2. This information encompasses the various charging port options, the power capacities of the charging device, and the geographical coordinates.

- Dublinked: The Dublinked [3] project is an open data initiative located in Dublin, providing users with extensive access to diverse datasets from the public sector. We acquired the datasets pertinent to our research from Dublinked (Smart Dublin; 2023). The files contained data on public service locations, recreational facilities, tourist attractions, Pobal's HP Deprivation Index, and the total population.

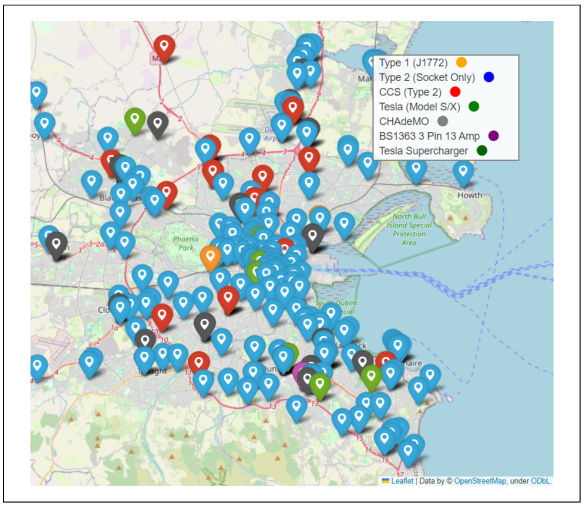

Figure 2: Number of EV charging category in Dublin by connector type.

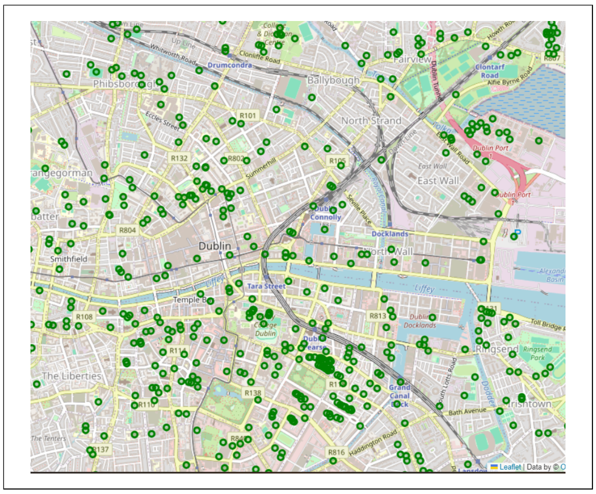

Figure 3: Amenities hotspot tags data in Dublin is shown by green circles on the map.

3.2 Identification of Potential Hotspot Locations

An essential element of the approach is the identification of potential hotspot locations within Dublin. One can achieve this by employing OpenStreetMap (OSM) data to chart

[1] https://github.com/openchargemap/ocm-system
[2] https://openchargemap.org/site/develop/api/
[3] https://www.dublincity.ie/business/economic-development-and-enterprise/smart-cities/dublinked

hotspots situated within a twenty-kilometer radius of Dublin's city centre. The choice of this specific radius was based on its strategic importance, since it includes areas with significant levels of traffic, commercial activity, and public engagement, respectively, refer figure 3. Due to the significant usage that these hotspots are anticipated to see, they are strong contenders for EVCS.

3.3 Existing Locations for EVCS and Public Service Spots in Dublin

Feature engineering, which depends on current EVCS, is necessary for analysing a new, perfect Dublin charging station. Figure 4 shows the different types of electric vehicle charging stations that are currently available in Dublin. With 206 type 2 plugs in Dublin alone, there are a total of six types of electric vehicle chargers available. Not far behind, there are two other well-established charging standards: "CHAdeMO" with 49 stations and "CCS (Type 2)" with 76, refer figure 4. The "Tesla model S/X", "BS1363 3 Pin 13 Amp", and "Type 1 (J1772)" charger types have the fewest chargers 11, 4, and 2 respectively. The charging power distribution in kilowatts is displayed in Figure 5. According to this distribution, 22.0 kW charging stations are extensively distributed and probably serve a sizable percentage of the city's electric vehicle population. This is logical because public charging stations frequently employ 22 KW charging stations to facilitate quick AC charging (*Zero Emission Vehicles Ireland: Policy documents*; 2023).

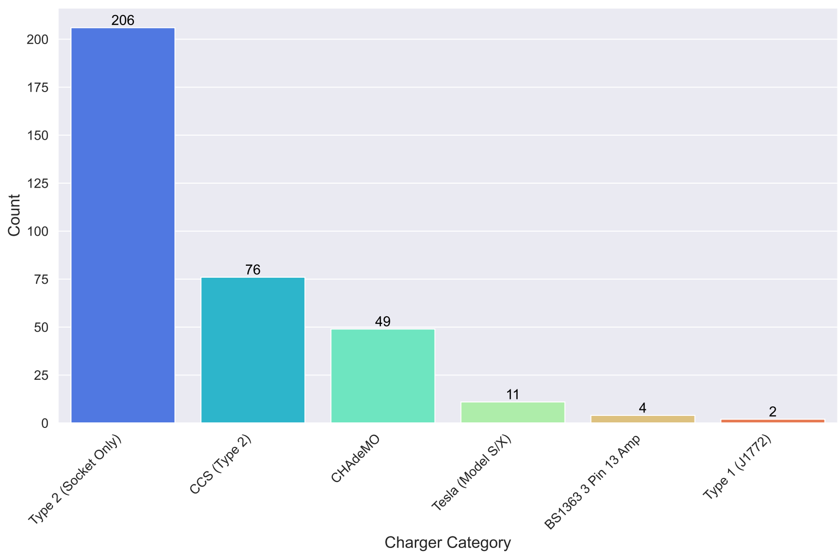

Figure 4: Category and count of EV chargers.

The selection of public service tags relevant to the installation of electric car charging stations is done to enhance the accuracy of the hotspot analysis. This category of amenities encompasses facilities such as gas stations, parking lots, educational institutions, medical facilities, public areas, and other important urban sites. Because these tags identify areas where there is a higher chance of major electric vehicle usage and, hence, a greater demand for EVCS, they are known as hotspot indications. The research

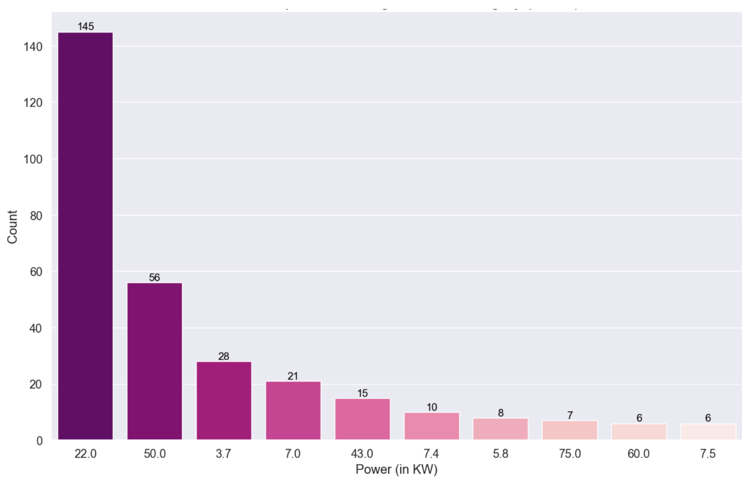

Figure 5: Ranking the top 10 EV chargers based on their power output in kilowatts.

endeavours to identify the most appropriate places for EVCS that correspond with areas of high relevance and demand by giving priority to these hotspot tags in the analysis. By employing this hotspot tags analysis, it is feasible to pinpoint crucial locations that could greatly benefit from the integration of electric vehicle charging infrastructure.

3.4 Mapping of Pobal Deprivation Index with Public Service hotspots using Demographic Analysis:

The multidimensional Pobal HP deprivation score measures deprivation in smaller locations in Ireland. It examines ten markers of adversity in a given location, such as the number of people living in individual dwellings, labour status, and educational accomplishment, using census data. The index is useful for planning and policy since it helps understand and solve local deprivation. The CSO Electoral Divisions [4] data (Ordnance Survey Ireland; 2023) is used to gain insights into the demographic distribution around Dublin. The project combined HP deprivation index and CSO Electoral Divisions data to all collected data from public services.

3.5 Spatial Analysis for Optimal Placement:

In order to determine the best location for electric vehicle charging stations (EVCS), the study used a spatial analytic method called DBSCAN (Density-Based Spatial Clustering of Applications with Noise). The DBSCAN algorithm was used to cluster hotspots that were close together based on their density to pick the best sites for charging stations. This resulted in a more condensed representation of the data. The work could speed up the process of choosing the best sites for charging stations by grouping nearby hotspots together. This would allow us to cover a wider range of geographies without having to duplicate any research.

In addition, this grouping helped us find groups that might have comparable attributes, such socioeconomic status or accessibility to facilities, which helped us make better

[4] https://www.cso.ie/en/census/census2016reports/census2016boundaryfiles/

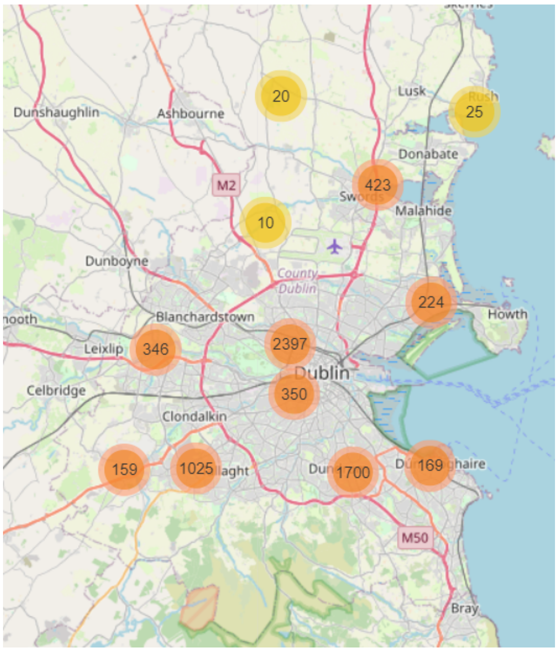

Figure 6: DBSCAN Clustering of EV Charging Stations.

decisions in the phases of our investigation that followed, refer figure 6.

3.6 BPSO and Greedy Algorithm: Strategic Algorithms for EVCS Optimization

Within the framework of EVCS optimisation, this part explores the application of two well-known optimisation techniques, namely BPSO and Greedy techniques.

Binary Particle Swarm Optimization (BPSO): The process of locating the most efficient collection of EVCS locations is accomplished by the application of a technique known as Binary Particle Swarm Optimisation (BPSO). The objective function of the BPSO algorithm takes into account both coverage and closeness in such a way that it maximises coverage while simultaneously minimises proximity. This is accomplished by allowing the algorithm to take into account both of these factors. In order to maximise the efficiency of the placement of charging stations for electric vehicles, the notebook makes use of BPSO. This technique, which is well-known for its efficacy in resolving complex optimisation difficulties, is employed in order to locate the most suitable locations for charging stations. This is accomplished by taking into account a wide range of constraints and objectives (Bin et al.; 2012).

The binary representation of potential solutions distinguishes BPSO. Each swarm particle represents a binary string of EVCS coordinates in this method. The system iteratively modifies particle placements based on individual experiences and swarm knowledge. This method effectively tests various combinations to get the best coverage and accessibility. According to the study, BPSO is crucial to finding the best EVCS locations in Dublin. It excels at browsing large solution areas and finding suitable solutions rapidly. Like Particle Swarm Optimisation (PSO), BPSO gets stuck in local optima and is affected by parameter changes. For binary EVCS placement decision-making, the BPSO algorithm in the paper provides a robust and adaptable solution. The above makes it necessary for the suggested analysis. The BPSO method helps Dublin find the best charging station locations, considering the constraints and goals of increasing electric vehicle infrastructure.

Greedy Algorithm: This algorithm provides a methodical and effective way to arrange Dublin's EVCS in the best possible way. The algorithm achieves this by iteratively choosing the most advantageous location based on the objective value, which is determined by the disparity between coverage and proximity to existing operational stations. During each iteration of the process, the algorithm consistently chooses the site that maximises the goal value. At each step, this algorithm generates a choice that is the best possible inside a specific region, aiming to ultimately find the best possible answer for the placement of charging stations on a worldwide scale (Jungnickel; 2013). Specifically, it is employed to connect new stations to existing ones, so optimising both the extent of coverage and the utilisation of resources. Each selected location contributes to increasing the network's coverage and accessibility.

According to this study, the Greedy Algorithm is an important tool for the systematic and efficient enhancement of the EVCS network. As a result, it is possible to strategically and gradually expand the EVCS network in Dublin by focusing on areas that provide immediate benefits. An integral part of this research on EVCS deployment, this strategy guarantees that the expansion is feasible from a strategic standpoint while also meeting the needs of users right away and working within the restrictions of available resources.

3.7 Analysis and Comparison

The main objective is to optimise the extent of EV charging station coverage. This entails strategically locating stations in areas that can cater to the maximum amount of potential users. In order to evaluate the performance of both the BPSO and the Greedy Algorithm, their capacity to determine ideal sites through the utilisation of coverage maximisation metrics is taken into consideration.

Comparative Analysis of Hotspots: The identified hotspots are evaluated based on their traffic density, demographic attractiveness, and economic feasibility. This facilitates comprehension of the possible use and long-term viability of the charging stations.
Algorithm Performance Evaluation: Both algorithms include a central objective function that is specifically developed to assess the appropriateness of proposed Electric Vehicle Charging Station (EVCS) locations. This function presumably takes into account variables such as geographical coverage, closeness to already established stations, and ease of access.

4 Design Specification

In an electric vehicle charging station system, the figure 7 illustrates the distinct stages that occur in sequential order during the process of data retrieval. The Data Acquisition Layer is the first step in the process. This layer is responsible for gathering information from a wide variety of sources, including public service spots, tourist spots, and HP deprivation index of Dublin. After that, the Data Processing Layer performs preprocessing on the data that has been gathered. This preparation includes activities such as cleaning, formatting, and removing outliers from the data. "Hotspots" are areas that are distinguished by a significant accumulation of electric vehicle charging activity, and the Hotspot Identification Layer is responsible for identifying these areas.

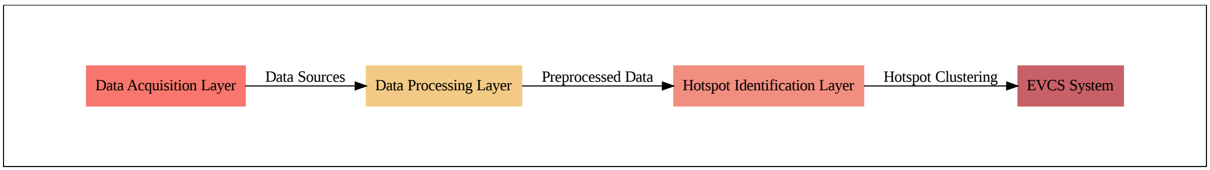

Figure 7: Layer by Layer Architecture of an EVCS System

It is essential that this be done in order to maximise the efficiency of the system and ensure that charging stations are widely available. The Hotspot Clustering Layer is responsible for classifying hotspots according to their geographical location and other pertinent characteristics. This makes it easier to identify areas that could be improved by the inclusion of more charging stations for electric vehicles.

In the end, the EVCS System makes use of the data that has been inspected in order to make well-informed decisions regarding the distribution of resources and the enhancement of the system. The research provides a detailed explanation of each phase, including the data sources, preprocessing procedures, and the significance of hotspot identification and clustering in the process of improving the electric vehicle control system (EVCS). In order for the EVCS system to function properly, the data retrieval process is absolutely necessary. This process enables the system to make decisions that are well-informed by collecting, processing, and analysing significant amounts of data.

5 Implementation

This section explores the practical use of different algorithms and approaches designed to optimise the positioning of EVCS in the city of Dublin. The goal is to strategically place these charging stations in order to ensure optimal coverage and accessibility, hence assuring the efficient use of electric car infrastructure.

5.1 Greedy algorithm using coverage method

The calculate_enhanced_coverage method is used to assess the coverage potential of potential EVCS locations. This evaluation is performed by measuring the distance and examining the effectiveness of a certain location in meeting the needs of its surrounding area. This function utilises the geopy.distance library to calculate the total distance between a candidate EVCS location and all other possible locations within a certain radius. This research based on distance offers valuable insights into the location's accessibility and coverage capabilities. The greedy algorithm utilises the calculate_enhanced_coverage technique to make smart choices. Commencing from an initial position, it methodically determines places that provide the highest potential for coverage. This iterative process persists until a predetermined number of EVCS locations is achieved. The greedy approach is crucial for strategically positioning charging stations to get extensive coverage throughout the city.

5.2 BPSO fitness and optimization method

The bpso_fitness technique is crucial in the BPSO algorithm. The main objective is to evaluate the suitability or efficiency of candidate solutions produced by BPSO, which play a crucial role in selecting the appropriate placement of EVCS. This approach assesses the overall extent of coverage offered by a particular group of EVCS locations, as determined by a potential solution produced within the BPSO algorithm. The solution's applicability is quantified by evaluating its coverage performance, which directs the optimisation process towards configurations that provide the most efficient coverage across the entire city.

The optimisation procedure is fundamental for optimising the location of EVCS. The main objective is to determine the optimal arrangement of EVCS throughout Dublin utilising a swarm-based methodology. The method commences by initialising particles, with each particle indicating a potential solution for the placement of EVCS. The fitness of these particles is evaluated using the bpso_fitness method, and they are subsequently changed repeatedly. The BPSO algorithm aims to achieve convergence towards an optimal solution that maximises coverage while satisfying restrictions and objectives. This eventually determines the best placement of EVCS stations.

5.3 EVCS location coverage maximization method

The process of calculating the covered area involves summing the areas of circles placed at each specified EVCS location. The area of each circle is calculated using the formula $\pi \cdot radius^2$, where the radius corresponds to the radius of coverage. The coverage percentage is determined by dividing the total area included by the proposed EVCS locations by the target area of Dublin, and subsequently multiplying the quotient by 100. This computation yields a measure of the percentage of the city that would be efficiently served by the EVCS stations.

A crucial aspect of the solution is utilising this function to evaluate and compare the level of coverage offered by different location selection methods, notably the Greedy and BPSO algorithms. It is essential to determine which algorithm provides the most efficient arrangement of EVCS to achieve maximum coverage across the entire city in this comparison. Furthermore, the programme incorporates geodesic distance calculations to enhance the accuracy of coverage projections. This involves calculating the distance between each EVCS location and nearby points of interest, such as areas with a large population. Additionally, it considers the population living within the coverage radius of each station. The outcome of the total coverage calculation function involves determining the area covered in square kilometres and the corresponding percentage of coverage for each algorithm. This allows for a comparative analysis of how different algorithms optimise the placement of EVCS across Dublin. Moreover, the function employs geodesic distance calculations to improve the precision of coverage estimations by taking into account the people living within the coverage radius for each EVCS location.

6 Evaluation

County Dublin encompasses 922 square kilometres in total (Wikipedia; 2023). The Greedy Algorithm covers approximately 68.11% of the target region, or 628.0 square kilometres. Taking into account the coverage radii of the chosen places, this indicates

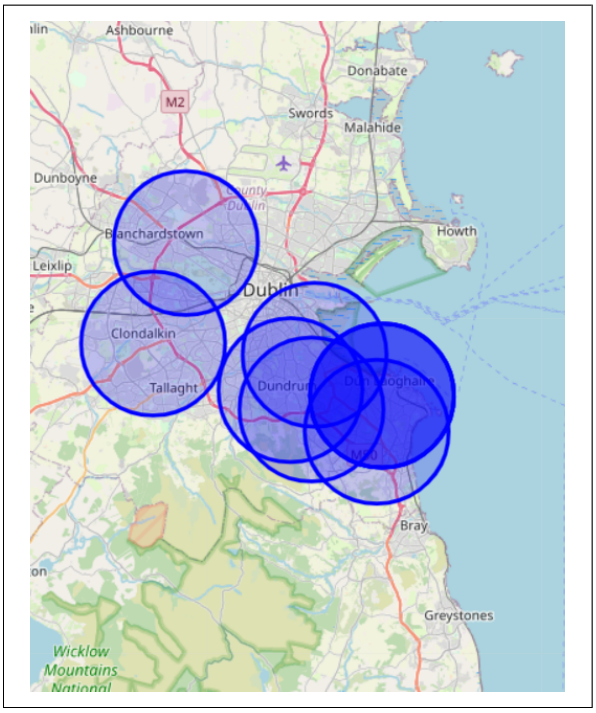

Figure 8: Visualisation of the BPSO Algorithm's Outcome. The blue circles overlay show the extent of the 5-kilometer EVCS coverage in Dublin.

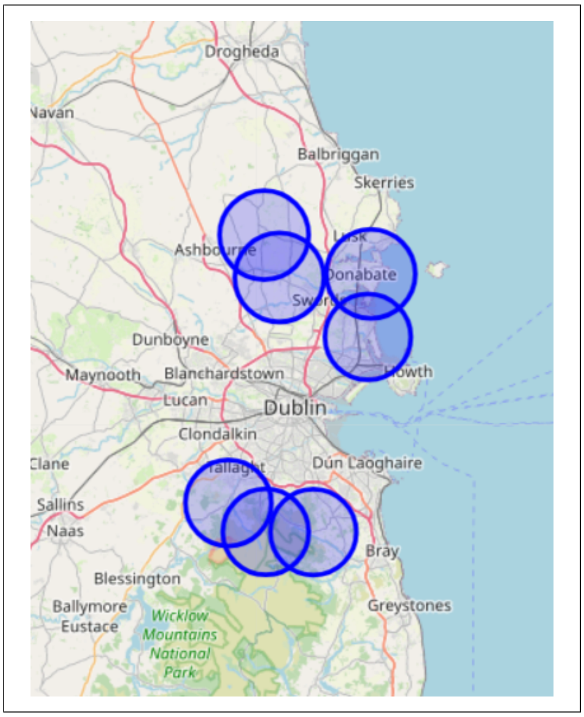

Figure 9: Visualisation of the Greedy Algorithm's Outcome. The scope of the 5-kilometer coverage of EVCS in Dublin is illustrated by the blue circles overlay.

that they encompass a significant chunk of the designated area of interest (for instance, Dublin city). However, the BPSO Algorithm covers 785.0 square kilometres, or roughly 85.14% of the target area, which is a little greater coverage rate, refer Fig 10.

The efficacy of each algorithm in supplying coverage within the region is indicated by these percentages. In this specific instance, the BPSO Algorithm seems to perform marginally better, covering a wider area within the target zone, even if both methods are attaining respectable coverage percentages. The geospatial analysis findings, as displayed in the figure 8 and 9, shows the suggested best positions for placing EVCS. The blue circles overlay illustrates the extent of coverage for each possible EVCS, demonstrating the distribution of stations across various locations of Dublin.

- The BPSO result, refer figure 8, displays a cluster of suggested EVCS in the central region of Dublin, showing notable intersections in the coverage areas. This indicates a significant concentration of potential EV users in the core areas, which justifies the need for numerous stations located close to each other to meet the expected demand.
- On the other hand, the map labelled as Greedy Algorithm in figure 9 shows a more scattered distribution of EVCS, with a wider coverage extending to the suburban regions of Dublin. This proposal outlines a strategic approach to establish EV infrastructure in residential areas, with the aim of potentially boosting the adoption of EVs in those specific places.

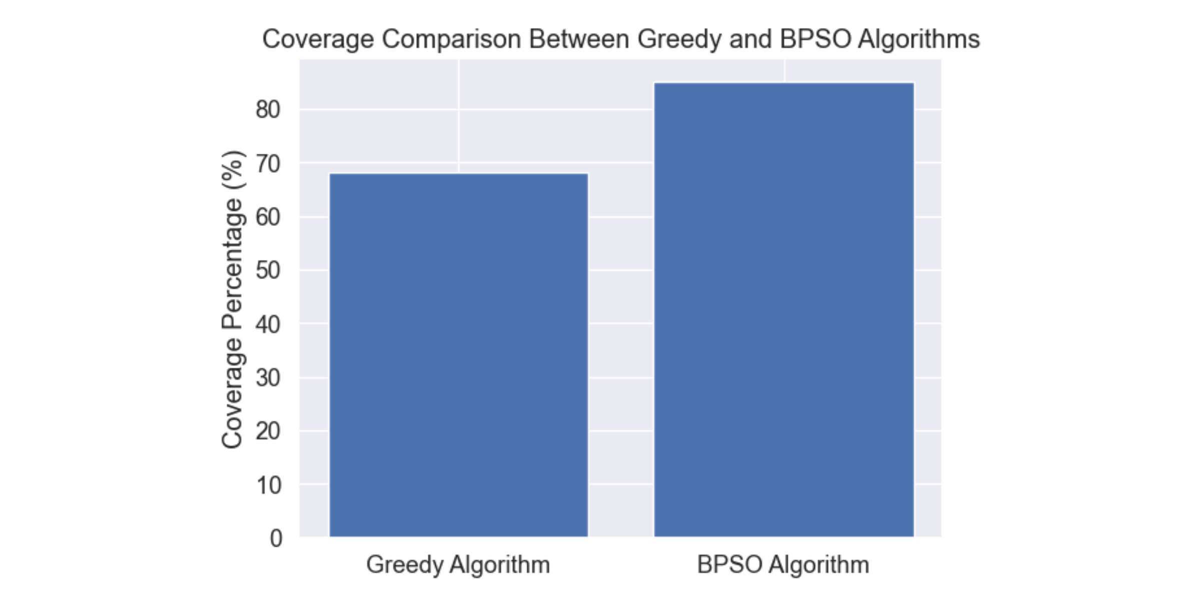

Figure 10: A bar graph is used to compare the algorithms, with the y label representing the coverage percentage over the entire county of Dublin and the x label representing the greedy and BPSO Algorithm.

6.1 Algorithm Performance

The comparison between the number of EVCS locations determined by each approach and the entire area covered within a 5-kilometer radius is shown in the line graph (see figure 11).

- Algorithm Performance of BPSO: The BPSO method demonstrates a sharp linear growth in cumulative coverage as more EVCS locations are added, indicating that each station chosen by the BPSO algorithm plays a substantial role in expanding the service area. The continuous increasing trajectory suggests that the BPSO algorithm effectively discovers spots that together improve the overall coverage.

- Greedy Algorithm Performance:The Greedy Algorithm, conversely, exhibits a more progressive and leveling-off trajectory. The early station placements have a positive impact on coverage, but the further stations provide diminishing returns in terms of improvement. This trend may indicate the algorithm's tendency to prioritise the locally optimal spots first, which offer substantial individual coverage but may not synergize as successfully as the BPSO's choices.

6.2 Implications for EV Infrastructure Planning

The findings from the experiment indicate that the BPSO algorithm is highly suitable for efficiently maximising coverage in the planning of EVCS networks. On the other hand, the Greedy Algorithm may be favoured in situations where there are constraints on initial investments and a gradual approach to infrastructure expansion is necessary. To summarise, the visual and quantitative results, refer figure 11, clearly show that the used

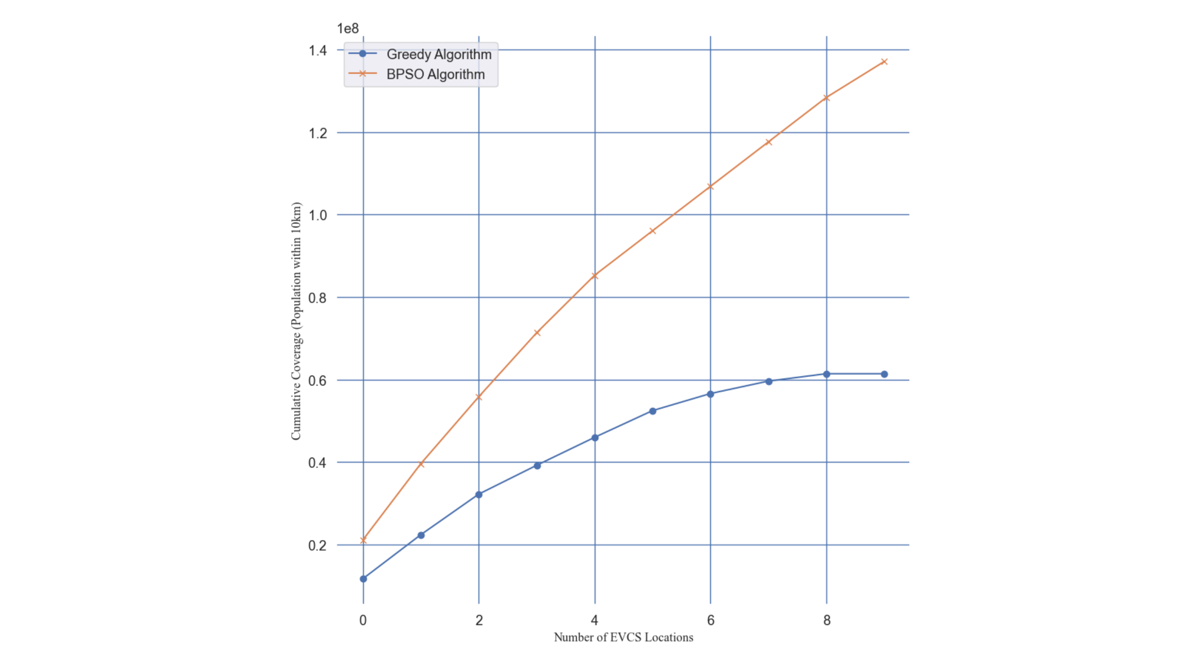

Figure 11: Cumulative Coverage of EVCS Locations.

algorithms are effective and offer practical insights for everyone involved in expanding Dublin's EV infrastructure. The results not only identify the best areas for immediate development, but also provide a foundation for strategic planning as the adoption of electric vehicles expands.

Only specific problems can be solved by the above used algorithms. They may not identify the best answer because they focus on locally optimal judgments at each stage rather than the whole problem or future facts. Even little input data changes might lead greedy algorithms to perform poorly. BPSO may not reach the global optimum due to topologies and parameters.Greedy algorithms may perform poorly if input data is even significantly modified. BPSO may not reach the global optimum due to topologies and parameters.

7 Conclusion and Future Work

7.1 Conclusion

The research described in this thesis offers a thorough methodology for optimising the positioning of EVCS in Dublin. This project effectively employed the BPSO and the Greedy Algorithm to identify sites that provide the highest possible coverage and accessibility to a wider population in urban and suburban areas.

The geospatial study demonstrated the optimal locations for deploying EVCS, with the BPSO algorithm exhibiting strong performance in terms of maximising coverage. The Greedy Algorithm, although showcasing a more cautious expansion in coverage, provided valuable perspectives on prioritising sites when faced with limited resources. The direct comparison of the two algorithms highlighted the appropriateness of BPSO for swift network expansion and the Greedy Algorithm for phased development plans. The research findings augment the existing knowledge in urban planning for EV infrastructure and offer practical insights for policymakers and stakeholders. The suggested sites can act as a model for the implementation of EVCS, aiding the shift towards environmentally-friendly mobility in Dublin.

7.2 Future Work

This thesis provides a number of directions for future investigation, each of which creates new opportunities in the field of environmentally friendly transport infrastructure.

The use of dynamic optimisation algorithms is one important field for further research and development. Real-time adaptive algorithms are becoming more and more necessary as the urban environment and EV usage habits change. These algorithms' integration of real-time data analysis has the potential to greatly improve the precision and effectiveness of EVCS placement techniques. The infrastructure would be kept adaptable to the city's and its residents' changing needs thanks to this dynamic approach.

Thorough research on the behaviour of EV users is another important factor. Future studies can determine possible new locations for EVCS that are based on actual demands rather than theoretical models by analysing the real-world usage patterns of EV drivers. This user-centric strategy may result in charging networks that are more efficient and convenient to use.

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