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# Geodemographic aware electric vehicle charging location planning for equitable placement using Graph Neural Networks: Case study of Scotland metropolitan areas

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ABSTRACT

The widespread adoption of electric vehicles (EVs) is crucial for decarbonizing transport, but charging infrastructure development lags behind, creating a bottleneck. Current EV charging station (EVCS) distribution favors affluent areas, potentially reinforcing inequalities. We address this using a spatially-aware Graph Neural Network (GNN) model that learns urban dynamics and socio-economic factors for equitable EVCS placement. Our methodology analyzes charging patterns across residential, working/industrial, and commercial zones by integrating EVCS utilization, traffic patterns, urban structure, parking availability, and deprivation indices. Our analysis revealed EVCS infrastructure concentration in commercial zones, with less deployment in working/industrial areas and significant gaps in residential zones. Glasgow showed higher utilization rates, particularly in residential areas, while Edinburgh demonstrated utilization disparities in residential zones, with deprived areas showing lower usage despite need. To solve this issue, GNN-leveraged recommendations were utilized for strategic charger deployment in underserved areas. The findings indicate that in residential areas, 22 kW chargers show substantial benefit to underserved communities, with higher output chargers becoming more effective only beyond  50 initial installations. Working areas show similar patterns, while commercial areas demonstrate lower improvement across all charger types, confirming infrastructure saturation. These findings provide policymakers a framework to prioritize EVCS deployment for reducing disparities and accelerating EV adoption. Overall, our results demonstrate the effectiveness of this approach in identifying potential locations for EVCS deployment, particularly in underserved communities.

## 1. Introduction

Electric vehicles (EVs) have emerged as a cornerstone in the strategy towards decarbonization of the transport sector and the wider transition towards net-zero. A comprehensive range of solutions and policy interventions have been proposed, aimed at promoting the ownership of EVs and reducing economic costs for end-users [1]. Globally, EV ownership reached 26 million by the end of 2022 and is expected to rise to over 240 million by 2030 [2]. Notably, China, as the world's leading EV market, accounted for 14.1 million of these vehicles [2]. Meanwhile, in the UK, more than 950,000 EVs were registered by the end of 2022, with numbers predicted to escalate quickly in response to increasing demand [3]. Recent advancements in EV technology and the gradual shift towards price parity with conventional vehicles are lowering barriers to entry, making EVs increasingly accessible and attractive to consumers. In addition, a suite of tax benefits and financial incentives are facilitating this trend in all leading EV markets, including China, the European Union, the United States, and the United Kingdom (UK). The UK had approximately 37,000 public EV charging devices at the end of 2022, equivalent to approximately 26 EVs to one charging point [2], though according to recent studies [4], the optimal ratio is 12 to 1. Although home charging currently meets a large portion of charging demand, publicly accessible charging is increasingly needed to provide accessibility, comfort, and facilitate long-distance driving akin to refueling a fossil fuel vehicle. This is particularly important in dense urban areas where access to home charging is more limited and public charging infrastructure is a key enabler for EV adoption. To this end, several leading economies have developed national EV charging infrastructure strategies: China has announced plans to accommodate charging infrastructure for more than 20 million EVs by 2025 [5]; the United States announced plans to invest up to $5 billion to promote the penetration of EVs through introduction of 500,000 public chargers by 2030, fiscal incentives and subsidies [5]; Japan pushed forward

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the national target of 150,000 charging points by 2030, including 30,000 fast chargers [2]; the European Parliament announced the alternative fuel infrastructure regulation aimed at delivering charging infrastructure with a particular focus on fast charging stations and charging for heavy-duty vehicles [2]; the UK has allocated £1.3 billion in government funding aimed to support the rollout of the charging infrastructure, with a particular focus on local on-street residential charging and targeted plug-in vehicle grants [5].

However, while major economies have announced ambitious charging infrastructure plans, current deployment patterns risk reinforcing socio-economic inequalities. Previous studies have highlighted numerous barriers that hinder the widespread adoption of EVs [6]. The high initial costs associated with EVs pose a significant challenge. Without adequate financial subsidies, steep upfront expenses can deter potential buyers. As discussed above, this challenge has been the main focus of national efforts worldwide. The time required for a full battery recharge – which far surpasses the refueling time for fossil fuel vehicles – further complicates the attractiveness of EVs [7]. Furthermore, driving range anxiety, *i.e.*, the fear that an EV will not have sufficient battery capacity to complete a desired journey, remains a significant concern. Recharge time and range anxiety have mostly been addressed from the perspective of investments in the development of battery technology, lightweight body and material design, and improved powertrain, leading to better utilization, higher capacity, and improved driving range. However, effective installation of charging infrastructure directly or indirectly addresses the above concerns of potential EV adopters. Early adopters of EV technology tend to be homeowners residing in high-income areas, utilizing home-based charging [8]. On the other hand, to achieve widespread adoption of EVs, a substantial number of newer EV adopters should belong to moderate-income groups residing in multifamily residential communities that are less likely to have access to home charging [9]. Thus, public EV Charging Station (EVCS) infrastructure holds a substantial importance for the adoption of EVs, especially in deprived communities [10]. Previous research suggests that areas with greater deprivation and lower economic position are associated with higher levels of pollutants [11]. In the context of EV adoption, this means that those who could benefit the most from low-carbon technology are the least able to afford it. Therefore, as EV adoption continues to rise, ensuring that EV infrastructure is placed in a fair and just way that benefits all members of society is of utmost importance for achieving an equitable transition towards net-zero, in line with UN Sustainable Development Goals (SDGs) [12], specifically, SGD 9.1 regarding equitable access to infrastructure and SDG 11.2 regarding sustainable and accessible transport systems for all.

### 1.1. Literature review

While numerous studies have explored optimal placement strategies for EVCS, the socio-economic dimensions of these placements have often been overlooked. Existing research has predominantly focused on technical and operational optimization criteria, such as accessibility, speed, and cost of charging, without adequately addressing the disparities in EVCS distribution across different locations and socio-economic groups [10]. This has resulted in EVCS infrastructure that is often dense in high-income neighborhoods while being sparse and/or underutilized in socially disadvantaged communities [13–15]. As a result, despite the advancements in EVCS placement strategies, there is a pressing need to address the inequities in EVCS distribution. Equity in EVCS placement ensures that charging infrastructure is accessible to all community segments.

While prior studies have advanced EVCS placement strategies, some critical gaps remain in addressing spatial interdependencies, land-use-specific deployment, and holistic equity integration. Existing approaches predominantly employ spatial regression [16], clustering [17], or multi-objective optimization [4], treating urban areas as static grids rather than dynamic networks. For instance, [16] utilizes multi-scale geographically weighted regression to analyze the spatial heterogeneity in intra-city public EVCS distribution but neglects the interconnected nature of urban zones, overlooking how charger placement in one area influences demand in adjacent regions. Similarly, [4] applies multi-objective optimization and TOPSIS optimization to propose equitable placement by balancing site development costs, equity access, and demand fulfillment. However, the decisions are made without modeling the spatial propagation of charging needs across a city's graph structure, a limitation our GNN methodology directly addresses. While [18] employs agent-based modeling to simulate charging behavior, it treats urban networks as homogeneous grids rather than interconnected graphs. Similarly, [19] applies linear regression to correlate charger density with deprivation indices but ignores demand spillover effects between adjacent zones. Secondly, while land use categorization is acknowledged in studies like [20], which manually labels zones, prior works mostly fail to provide granular, land-use-specific policy recommendations. For example, [21] evaluates accessibility across broad census tracts and evaluates horizontal and vertical equity using spatial autocorrelation but does not differentiate optimal charger types (*e.g.*, 22 kW vs. fast chargers) for residential versus industrial zones. Similarly, [19,22] identifies correlations between EVCS distribution and income levels but provides no framework for zone-specific (residential/commercial) deployment. This gap is critical, as our analysis reveals charger utilization varies dramatically by land use, a finding enabled by our land-use-aware approach. Third, equity considerations in existing frameworks are often reductionist. Studies like [23] correlate EVCS distribution with income levels but omit multi-dimensional deprivation indices and real-time utilization patterns. [18] models income-based charging access but omits multi-dimensional deprivation metrics (*e.g.*, health, education). [22] uses census-based approach but fails to integrate real-time utilization data, masking disparities in deprived areas. Our integration of individual SIMD components such as Population density, Working population, Income rate, Employment count, Reachability metrics, and Crime rate with parking availability, POI data and EVCS usage reveals nuanced disparities: in Edinburgh's deprived areas, charger utilization is 32% lower than in affluent zones despite comparable EV ownership potential, highlighting the inadequacy of single-factor equity models. Table 1 summarizes recent studies on equitable placement of EVCS.

Above recent research highlights work emerging to cater for inclusive EVCS placement that considers various socio-economical factors. However, these prior studies generally contain the following limitations: (i) EVC placement decisions are often made without understanding the spatial dynamics of the urban network, a crucial aspect of interconnected systems such as urban EVCS infrastructure, (ii) most works fail to address the challenge of targeted infrastructure deployment within specific urban land uses, which is becoming increasingly important as government funding is often targeted within certain urban areas of the city, for example, residential, industrial, or other, and (iii) insufficient consideration of equity, and a lack of integration of multiple factors influencing equity and local contexts;

### 1.2. Contributions

In contrast to prior work that exhibits one or more of the previously mentioned limitations, this study presents a methodology that jointly addresses all of the aforementioned gaps by proposing a novel approach leveraging Graph Neural Networks (GNN) to optimize EVCS placement. By embedding diverse multi-modal data sources, including existing EVCS utilization, infrastructure information, traffic flow patterns, points of interest, deprivation indices, and parking infrastructure, our model provides a holistic and practical solution to EVCS distribution. The focus on underserved areas through the proposed placement utilization metric and the consideration of specific land uses directly addresses equity concerns often overlooked in previous studies. Our approach offers targeted recommendations for different land

**Table 1**
Comparative analysis of equitable EV charging infrastructure studies.

| Citation | Study area | Objectives | Data Sources | Methodology |
|---|---|---|---|---|
| [20] | Chicago (North America) | Assess disparities in EVCS accessibility across regions of Chicago metropolitan area | EVCS location, land use | DBSCAN clustering, manual land use labeling, accessibility analysis |
| [4] | San Francisco (North America) | Equitable placement by balancing three objectives: site development costs, equity access, and EV demand fulfillment | QoL index, EVCS location, power distribution data, installation and construction cost | Multi-objective optimization, TOPSIS |
| [24] | Los Angeles (North America) | Assess social equity access to mobile charging stations (MCSs) in underserved communities, determining optimal smart parking lot (SPL) components | EVCS data (SPL capacity, photovoltaic output), socio-economic indices, EV charging behavior, event-specific data | Analytical hierarchy process, mixed-integer linear programming |
| [23] | California (North America) | Assess disparities in public EV charger access across racial/ethnic groups and income levels, identify policy implications for infrastructure equity | EVCS location data, socio-economic data, reachability data | Generalized Additive Models (GAMs) |
| [16] | Beijing (Asia) | Analyze spatial heterogeneity in intra-city public EVCS distribution, focusing on impacts of built environment and socio-economic factors | EVCS location and power, POI data, land cost, population data, road network data | Quantitative metrics, spatial regression using multi-scale geographically weighted regression (MGWR) |
| [21] | Hong Kong (Asia) | Identify socio-demographic factors influencing charging inequity, evaluate horizontal and vertical equity using spatial autocorrelation and Gini index | Census data, EVCS location and power output, POI data, parking demand data | Gaussian-based accessibility measures, spatial autocorrelation, spatial heterogeneity of demographic correlations using geographically weighted regression (GWR) model |
| [17] | Beijing (Asia) | Investigate the impact of charging station accessibility and agglomeration effects on utilization rates and provide data-driven placement recommendations | EVCS location and utilization data, road and POI data, parking data | Accessibility index metric, regression models to analyze accessibility and agglomeration impacts, Heterogeneity analysis |
| [19] | Ireland (Europe) | Investigate equity impacts of EV subsidies on income and deprivation, assess spatial disparities in EVCS distribution | EVCS location data, census data | Linear regression to correlate charger density with socio-economic variables, spatial analysis |
| [22] | New York (North America) | Identify factors correlated with EVCS distribution, propose equity-focused policy frameworks in infrastructure rollouts | EVCS location data, census data, transportation data | Correlation analysis |
| [18] | UK (Europe) | Assess equity implications of EV incentive regimes and charging infrastructure demands | national travel survey, income data, charging access data | Agent based modeling simulating charging behavior |
| [25] | Trondheim (Europe) | Determine optimal placement of energy hubs by considering investment costs, charging radius, distance from substations, and renewable energy generation | renewable energy availability, land use, traffic density, EVCS data | Pareto front analysis, Multi-objective linear programming |

use types (residential, working/industrial, commercial), acknowledging the varying charging needs across urban contexts. We conduct extensive infrastructure placement evaluations using multi-source data from the selected urban areas of major cities of Scotland. Specifically, the methodology brings the following contributions by modeling of GNNs aimed to achieve equitable, geodemographic aware EVCS planning:

- Modeling of urban EV charging demand via graphs and development of a novel GNN architecture to learn complex urban dynamics and correlation between charging demand influencing factors to facilitate identification of optimal areas for EVCS placement.
- Multi-dimensional equity integration through fusion of individual factors influencing deprivation, parking availability, POIs, EVCS location, traffic flow and utilization data.
- Detailed analysis of EVCS utilization and distinct usage patterns in residential, working/industrial, and commercial zones, as well as between deprived and non-deprived areas in major cities of Scotland.
- Targeted placement decisions informed by urban land use requirements, historical EVCS utilization and EVCS power output, ensuring that placements are aligned with local policy goals.
- Quantified impact and equity of targeted EV infrastructure deployment across various land uses and areas of deprivation.

The rest of the paper is organized as follows. Section 2 discusses the case study and data collection process. The proposed methodology related to graph construction, clustering and site selection is described in Section 3, while Section 4 discusses the key findings of the study. Finally, Section 5 provides concluding remarks as well as directions for future work.

## 2. Data processing and labeling methodology

### 2.1. Case study

The primary objective of the electrification of transport is to mitigate GHG emissions on a global scale. However, EVs are often powered by electricity derived from non-renewable energy sources, specifically power stations run on fossil fuels. This means that while EVs themselves do not directly emit GHG, the overall reduction in GHGs depends largely on how the electricity they use is generated. Therefore, for EVs to effectively benefit the climate and to ensure the sustainability of the entire energy system, the use of renewable energy sources for EV charging is essential. To this end, Scotland represents an interesting case study, as it is the UK leader in renewable energy production, continuously generating more electricity than it needs, with net electricity exports amounting to 15.9 TWh in 2023. In Scotland, the total electricity generation from renewable sources in 2023 was 33.3 TWh, of which 77.5% came from wind energy, 13.8% from hydro, and the rest from biomass and other sources [26]. As a result, in the context of EV ownership, Scotland was identified as a UK region with the highest lifecycle assessment evaluations aimed at quantifying the reduction of carbon footprint per vehicle [27]. Given its leading position in renewable energy generation, Scotland can more effectively leverage public EV charging to achieve higher EV uptake, charging utilization, and a substantial decrease in GHG emissions, setting a standard for other UK regions to follow.

Glasgow and Edinburgh were selected as primary case cities to extend the relevance and application of this study. These cities represent distinct urban morphologies with significant variations in spatial layout, population density, and transportation infrastructure, which are primary factors affecting EV charging demand patterns. The sociodemographic diversity within these cities spans multiple critical dimensions, including substantial variations in income levels (from affluent neighborhoods to areas of high deprivation), car ownership rates, racial makeup of population, housing types (detached homes to high-density apartments), and transportation access. This justifies our case study choice as representative of other cities where equity is a concern, as highlighted in previous studies, summarized in Table 1.

Glasgow and Edinburgh are not only the two largest in Scotland but also present EV adoption and existing infrastructure, vital for a comprehensive analysis: Glasgow contains 391 or 7.8% of Scotland's total number of active charging points, whereas Edinburgh has a total of 298 charging points. Furthermore, the selected cities exhibit high variability in socio-economic conditions, reflected in their deprivation indices. Consideration of such factors is essential to understand potential barriers to EV adoption and to ensure that the benefits of the electrification of transport are equitably distributed.

### 2.2. Data collection and processing

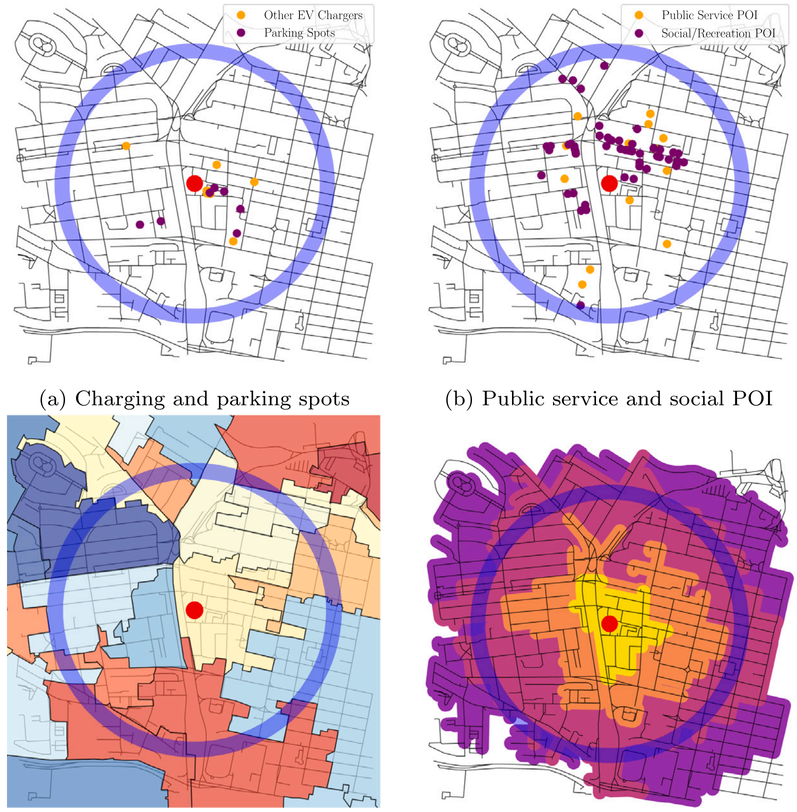
To fully capture metrics that drive charging demand, we base our analysis on the various charging demand influencing factors [28]. To effectively capture these factors within a specific area, we introduce the concept of charging demand nodes. These nodes are defined as 500-m radius circles centered around charging stations or parking spots, a distance that aligns with the observed preference for shorter walking distances to charge vehicles [29]. This approach allows us to encapsulate and analyze the relevant influencing factors within a practical and accessible range. To illustrate this concept, we provide visual representations of these charging demand nodes in Fig. 1, where each subfigure showcases a demand node centered on a charging station. The 500-m radius of these nodes encompasses a variety of pertinent influencing factors that contribute to charging demand. Our study takes into account a diverse range of these factors, which we will explore in detail, to provide a holistic understanding of the dynamics driving electric vehicle charging demand in urban environments.

#### 2.2.1. Existing EVCS infrastructure and charging utilization data

To collect EVCS infrastructure data, National Chargepoint Registry [30] was used. The registry contains detailed records of over 4,000 public EVCSs in Scotland, including station name, location, operational status, tariffs, availability, charging power output, charging plug type, etc. To collect EVCS session data, ChargePlace Scotland registry [31] was utilized. Developed as a national network of EVCS on behalf of the Scottish Government, ChargePlace Scotland registry includes detailed historical records of public EV charging across Scotland. For the purpose of this study, key factors such as the geographic coordinates of each station, charging power output, types of connectors available, and the frequency and duration of charging sessions are used. Fig. 2 illustrates the public EVCS heatmaps for Glasgow and Edinburgh, which indicates locations where charging sessions were performed between October 2022 and January 2024. Only active, public EV chargers were considered.

#### 2.2.2. Parking infrastructure data

The process of identifying potential locations for EVCS relies on OpenStreetMap (OSM) data, a comprehensive and crowd-sourced mapping resource [32]. The data collection encompasses a wide range of parking locations, including on-street parking, as well as parking facilities at event venues, hospitals, universities, and other key locations, all identified through the 'parking' amenity type in OSM. While our study does not explicitly model investment costs, the methodology inherently considers cost efficiency through its strategic focus on existing parking infrastructure. By identifying potential EVCS locations exclusively from existing parking spots, we significantly reduce installation costs by eliminating the need for land acquisition, demolition, or major construction work. In addition, this approach significantly reduces initial capital expenditure by eliminating the need for land acquisition and new construction. Second, existing parking lots are already integrated into the urban fabric, ensuring immediate accessibility and connectivity




(a) Charging and parking spots (b) Public service and social POI

(c) SIMD values per data zone (d) Isochrone distance from node

**Fig. 1.** Charging demand node area description and data used in this study.

— factors crucial for user convenience and adoption rates. By repurposing existing parking spaces, this strategy aligns with sustainable urban planning principles, minimizing the environmental impact typically associated with new construction projects. Lastly, this approach also facilitates quicker deployment of charging infrastructure, accelerating the transition to EVs and supporting broader environmental and public health goals.

### 2.2.3. Demographic and deprivation data

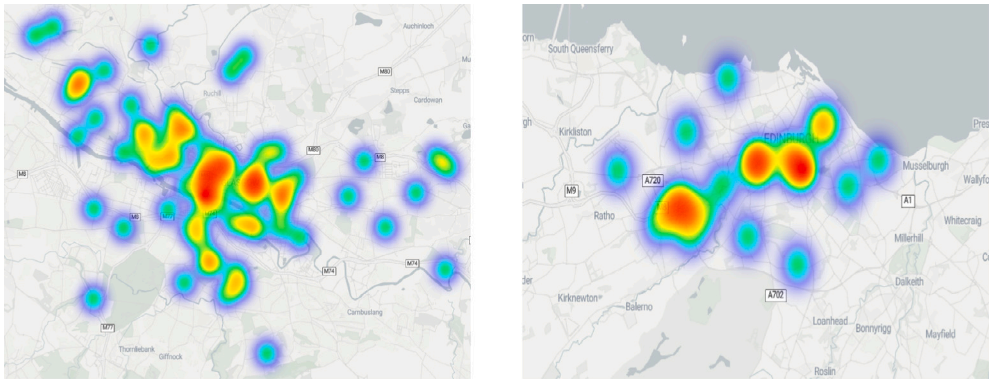
The study incorporates elements related to the Human Development Index, as detailed in the Scottish Index of Multiple Deprivation (SIMD) dataset [33]. Notably, SIMD data is organized into "data zones", which are specific areas designated for small-scale statistics related to deprivation in Scotland (as seen in Fig. 1.c). These statistics include relevant domains such as income, employment, education, housing, health, crime, and geographical access. Integrating SIMD data into the analysis offers valuable insights into the socioeconomic context of potential EVCS sites, ensuring that infrastructure is strategically placed to be effective and beneficial, particularly in areas that might otherwise lack sufficient EV infrastructure. For each existing or potential charging spot, we collect data based on the data zone it is located within, enabling us to precisely align socio-economic and spatial factors in our placement strategy. In this study, we classify areas as "deprived" if they fall within the lower 50th percentile of the SIMD index, while those above this threshold are categorized as "non-deprived". For the purpose of this study, the latest SIMD report was utilized [33]. To address potential biases, instead of relying on the aggregate SIMD rank, a charging demand node incorporates individual socioeconomic indicators that comprise SIMD as node attributes, specifically: Population density, Working population, Income rate, Employment count, Reachability metrics, and Crime rate.

### 2.2.4. Point of interest (POI) data categorization

POIs represent specific locations or landmarks within a city that are relevant to travelers, residents, or urban planners. These are typically places that people might want to visit, navigate to, or use as reference points when moving around a city. Previous research consistently identifies POIs as crucial indicators of EV charging demand [25,34,35]. Our study leverages the comprehensive OpenStreetMap (OSM) [32] dataset to collect and analyze POI data, providing a rich source of information on potential charging demand hotspots. In our approach, we categorize POIs into two primary types: social and recreational. Social POIs encompass locations such as educational institutions (schools and universities), healthcare facilities (hospitals and GP practices), financial centers (banks), and other essential services (pharmacies). These represent areas where people spend significant time during their daily routines. Recreational POIs, on the other hand, include leisure and entertainment venues like restaurants, cafes, theatres, cinemas, and shopping centers, which attract visitors for shorter duration but often in higher volumes. The inclusion of both social and recreational POIs ensures that our charging infrastructure planning accounts for a wide spectrum of public activities, from daily necessities to leisure pursuits. The distribution of POIs aids in strategically placing charging stations in areas where drivers are likely to spend significant time, enhancing charging convenience.

### 2.2.5. Traffic flow data creation

Traffic flow data is sourced from the UK Government's Road Traffic Statistics [36], and includes vehicle movement patterns, traffic volumes, and peak usage times across the national road network. By incorporating this data into our model, we can accurately identify high-traffic areas where the demand for EV charging is likely to be significant. Traffic count data is typically collected at specific points along roads, using methods such as fixed sensors or periodic manual counts. However, EV charging demand is not limited to these




(a) Glasgow (b) Edinburgh

**Fig. 2.** Heatmaps of historical EVCS utilization.

specific data collection points but extends to broader areas where vehicles might park and charge. This mismatch between point-based data collection and area-based charging demand necessitates a method to approximate traffic data to cover potential charging locations. To overcome this, we developed a robust, adaptive approach that captures spatial variability and accounts for data sparsity. Starting with a 1 km radius around each potential charging location, we collect all available traffic flow data points within this area. We then calculate an initial average traffic flow for each potential charging location. Subsequently, the algorithm enters a recursive phase, expanding the dataset in each iteration by incorporating both official traffic data and previously calculated approximations for charging points. This expansion allows for the estimation of traffic flow at locations initially lacking data by considering newly calculated values from nearby areas. The process iterates, progressively refining and propagating traffic flow information across the network of potential charging locations. Convergence is reached when successive iterations yield no significant changes in traffic flow estimates, indicating a stable and comprehensive set of values.

#### 2.2.6. Land use label creation via clustering

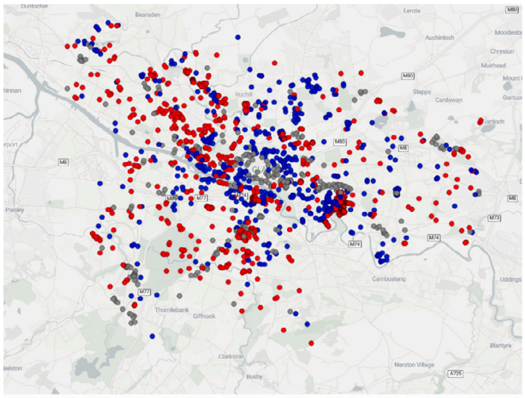
Land use is a critical factor in determining optimal locations for EV charging stations. It influences accessibility, demand patterns, and dwell times, which are essential for meeting charging needs efficiently. Different land uses offer varying levels of existing electrical infrastructure, affecting installation costs and feasibility. Zoning regulations and future development plans tied to land use also impact where stations can be placed. However, detailed land use information for Scotland is not easily accessible. To improve the placement of new EVCS infrastructure, we conducted a comprehensive land use labeling process for both existing and potential locations. This approach is crucial for maximizing accessibility and efficiency, as strategic alignment with existing and planned land use ensures that charging infrastructure effectively supports high-demand areas such as residential neighborhoods, commercial zones, industrial hubs, and transportation hubs, thereby enhancing convenience for EV users. Our methodology employs k-means clustering on a range of geodemographic influencing factors throughout the whole of Scotland. These factors included income deprivation rates, traffic flow, counts of social and recreational POIs, existing charger numbers, reachability metrics, normalized population and employment deprivation figures, and crime rates. Setting $k = 4$, this initial clustering yielded four distinct land use groups that were labeled as: Residential, Rural, Working/Industrial, and Commercial areas, closely aligning with previous findings reported in [34].

This initial clustering, performed on a Scotland-wide scale, provided a general categorization of land use. However, refinement was necessary due to the distinct urban fabric of Glasgow and Edinburgh compared to the broader Scottish context used in the initial clustering. To refine the initial cluster labels, we utilized OSM Landuse data [37]. OSM Landuse dataset describes the primary use of land by humans, where land use features are identified with a landuse tag. The database contains over a thousand tag values for landuse used in the OSM Landuse dataset. In this work, we refined our results by using 'residential' tag to denote Residential land use, 'industrial' tag to denote Industrial/Working land use, and 'retail' tag to denote Commercial land use. In cases where initial clustering labels differed, the land use was refined based on the corresponding OSM Landuse tag. This allowed us to more accurately classify areas within these cities, particularly in distinguishing between residential and working/industrial areas, a challenge in urban settings where these uses often overlap or exist in close proximity. The impact of this refinement is substantial and clearly demonstrated by the shifts in classification for both cities.

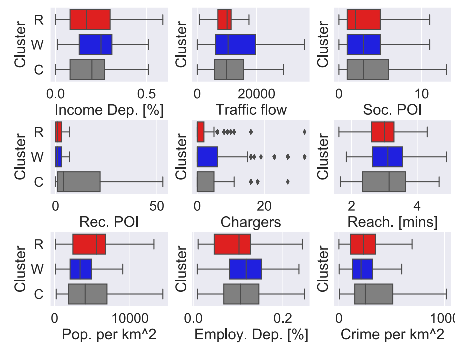
OSM land use data was collected based on the location of each potential EVCS location within OSM tiles, supplemented with gap-filled data if stations fell outside tile boundaries. No rural areas were detected within Glasgow City or City of Edinburgh councils. This refined approach enabled a more nuanced classification, rectifying many areas initially identified as working/industrial that were, in fact, predominantly residential. The result is a more accurate representation of land use patterns, crucial for informed EVCS placement decisions. To illustrate the outcomes of this labeling process, we provide a visual overview of the labeled areas for all charging and available parking infrastructure in Glasgow and Edinburgh, along with per-area statistics, in Fig. 3. Differences in charging frequency, duration, energy consumption, utilization, and charging power output within various land use types are shown in Table 2.

### 2.3. Utilization-based charging demand node labeling

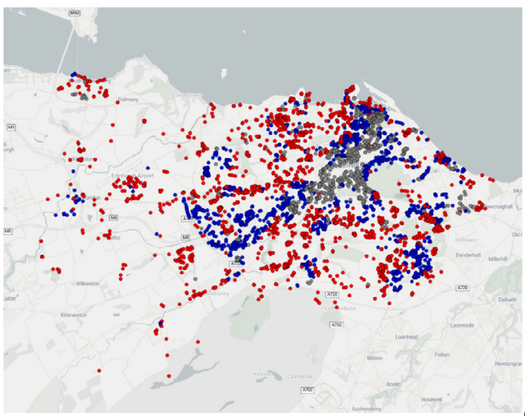
In our effort to improve the placement of EVCSs, we recognize the critical importance of leveraging historical data to inform future infrastructure decisions. To this end, we have developed a methodology that utilizes historical utilization rates of existing charging stations to identify areas with potential for successful EVCS deployment. The cornerstone of our approach is the analysis of EVCS utilization that includes detailed historical charging demand information. By examining this data, we aim to uncover patterns and factors that contribute to the success of charging stations in different locations. This data-driven method allows us to move beyond theoretical assumptions and base our decisions on actual usage patterns, thereby increasing the likelihood of placing new EVCS infrastructure in areas where they are most needed and likely to be well-utilized. To facilitate this analysis, we classify existing charging nodes into three distinct categories based on their historical utilization records: low, medium, and high utilization. This classification serves as a ground-truth labeling system, enabling us to identify the characteristics and contextual factors associated with



(a) Refined Glasgow City Sites per Area




(b) Refined Glasgow City Sites per Area Statistics



(c) Refined City of Edinburgh Sites per Area


(d) Refined City of Edinburgh Sites per Area Statistics

**Fig. 3.** Site statistics per location (R - residential, W - working/industrial, C - commercial) after refinement with land use data.

**Table 2**
Daily average EV charging session statistics for different locations.

| City | Location | Daily sessions | Charge duration per session (mins) | Energy delivered per session (kWh) | Utilization rate (%) | Charger power output (kW) |
|---|---|---|---|---|---|---|
| Glasgow | Residential | 1.35 | 198.11 | 19.70 | 7.36 | 17.31 |
| | Working/Industrial | 1.00 | 132.87 | 23.38 | 4.05 | 35.95 |
| | Commercial | 1.43 | 167.82 | 12.58 | 4.56 | 16.60 |
| Edinburgh | Residential | 1.96 | 172.86 | 16.71 | 5.33 | 25.42 |
| | Working/Industrial | 0.83 | 134.16 | 17.98 | 4.70 | 18.53 |
| | Commercial | 0.96 | 209.44 | 14.78 | 2.68 | 22.00 |

well-performing charging stations. In calculating EVCS utilization, we adopt an energy-based metric rather than a time-based one, as proposed by [7]. This choice is motivated by the need to account for potential overstay periods and to more accurately reflect the actual usage and efficiency of each charging station. The utilization rate for an EVCS over a $T$-hour period is calculated as:

$$U_j^T = \frac{1}{c_j * T} \sum_i \epsilon_i^j, \tag{1}$$

where $U_j^T$ represents the utilization rate of EVCS $j$ over period $T$, $c_j$ denotes the power output of EVCS $j$ in kilowatts (kW), and $\epsilon_i^j$ signifies the energy consumed by EV $i$ from station $j$.

Crucially, we extend this classification system to nearby parking infrastructure. Parking spots within the charging demand node radius of an existing EVCS are labeled with the same utilization potential as the charging station itself. This process allows us to identify the potential of parking areas for EVCS installation, even if they do not currently have charging facilities. To ensure comprehensive coverage and account for the influence of neighboring areas, we employ a recursive labeling algorithm. Initially, we label parking spots within the immediate radius of existing charging stations based on the historical utilization potential of the station. For subsequent iterations, we consider both the labeled parking spots and the original charging stations. This expanded dataset allows us to label previously unlabeled parking areas that fall within the radius of newly labeled spots. We repeat this process, propagating potential labels across the network of parking infrastructure until reaching convergence, a point where no new parking spots are labeled or changed in an iteration. By analyzing the utilization patterns of existing and potential stations, we can identify areas with similar characteristics that currently lack adequate charging infrastructure. These areas are then classified as having potential for new EVCS placement. We split the data into three balanced classes: low, medium, and high utilization.

## 3. Methodology for geodemographic-aware EVCS location planning for equitable placement

Our proposed framework for optimizing EVCS infrastructure placement integrates geodemographic data with a spatially-aware GNN approach, as illustrated in Fig. 4. This approach comprises four key components designed to capture the complex dynamics of urban charging demand and inform strategic infrastructure decisions: (1) First,

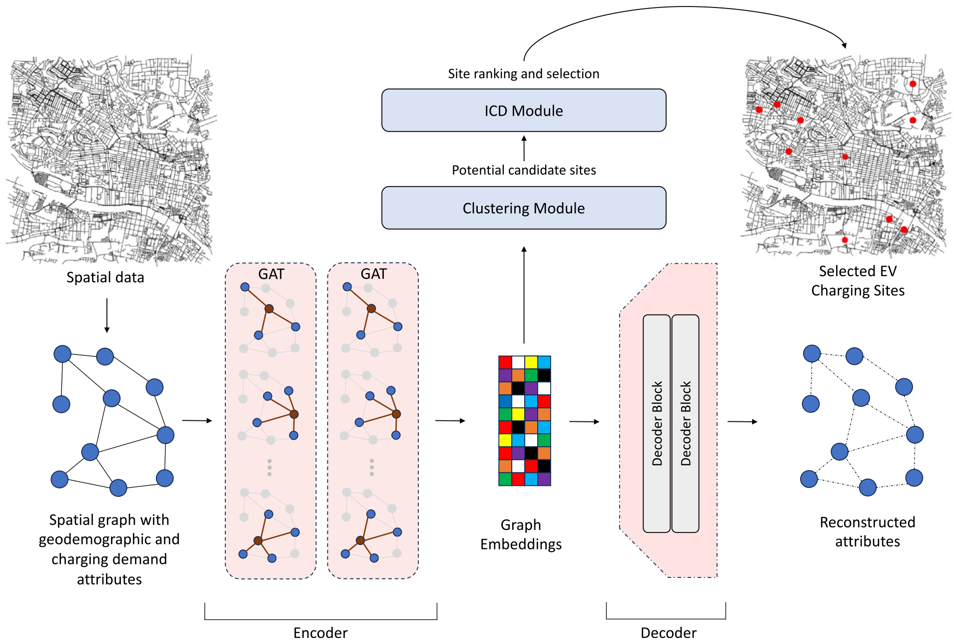



**Fig. 4.** ChargeDEM EV charging site selection approach.

we employ graph representation learning to model and analyze the intricate relationships within the urban charging ecosystem, capturing spatial dependencies and connectivity patterns [Sections 3.1, 3.2]; (2) Building upon these representations, we utilize a clustering module to categorize nodes based on their characteristics and identify low, medium and high potential installation areas based on historical EVCS utilization [Section 3.3]; (3) Finally, we employ a utility-informed site selection process based on area potential, taking into account installation requirements, such as the number of chargers to be installed, their installation utility, and how they affect the overall charging potential of surrounding areas within specific land use [Section 3.3]. This integrated approach allows for a holistic evaluation of potential EVCS sites, considering both micro-level factors and macro-level impacts. In the following subsections, we describe each component in detail.

### 3.1. Geodemographic-aware graph neural network

Let $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ represent a graph where $\mathcal{V}$ and $\mathcal{E}$ denote sets of nodes and edges, respectively. In the context of the EVCS placement problem, we define a charging demand node $v \in \mathcal{V}$ as the area within a radius $r$ of an existing EV charger site. The edges $\mathcal{E}$ represent undirected connections between proximate nodes, with two nodes being connected if their physical distance does not exceed $r$. These edges define the physical and functional connectivity within the network, affecting the flow and demand of EV charging. We define $A \in 0, 1^{|\mathcal{V}|\times|\mathcal{V}|}$ as the adjacency matrix of the graph, where $a_{u,v} = 1$ if an edge exists between nodes $u$ and $v$, and $a_{u,v} = 0$ otherwise, for all pairs of nodes $u, v \in \mathcal{V}$. Additionally, we set $a_{u,u} = 0$ for all $u \in \mathcal{V}$, as self-loops are not considered in this model.

Each node in the graph is characterized by an $F$-dimensional feature vector, $\mathbf{h} \in \mathcal{H}$, where $\mathcal{H} \subset \mathbb{R}^{|\mathcal{V}|\times F}$. This feature vector encapsulates a diverse array of information within the radius $r$ of each node, including socio-demographic composition, land use, density and types of POIs, traffic patterns, and existing parking infrastructure. By incorporating this multifaceted dataset into the graph structure, we can develop a sophisticated understanding of the EV charging demand dynamics at each node.

GNN are particularly well-suited for the EVCS placement problem due to their ability to model complex spatial and relational data structures inherent in transportation networks. This approach enables the creation of EVCS placement systems that accurately capture the intricate topology of urban road networks, with nodes representing potential station locations and edges denoting connecting routes. Furthermore, this framework facilitates the seamless integration of heterogeneous data sources, such as geospatial, demographic, land use, and traffic flow information, as node and edge features, providing a comprehensive basis for informed decision-making in the placement of EVCS.

### 3.2. Urban charging graph representation learning

We approach the challenge of capturing structural information and encoding the relational context of urban charging demand through the lens of graph representation learning, specifically utilizing graph autoencoders. This approach allows us to effectively capture and leverage the complex relationships inherent in the graph structure of urban charging demand. These relationships encompass a wide array of influencing factors, including spatial characteristics, existing demand patterns, urban vitality indicators, demographic composition, traffic flow dynamics, area reachability, and safety considerations. Using graph auto-encoders, we can distill these multifaceted and interconnected elements into a comprehensive representation that faithfully reflects the intricacies of urban EV charging ecosystems.

The application of autoencoders for unsupervised graph representation learning based on GNNs has been proposed in [38]. An autoencoder architecture typically comprises three key components: an encoder, latent representations, and a decoder. The primary role of an encoder function is to map the input data into a compact latent space, while the decoder attempts to reconstruct the original input from these latent representations. This reconstruction process is guided by a specified reconstruction criterion, ensuring that the learned representations capture essential features of the input data. In the context of graph autoencoders, let $f_e$ denote the graph encoder function and $f_d$ represent the graph decoder function. The fundamental objective of graph autoencoders is to learn the following mappings:

$$H' = f_e(A, X), G' = f_d(A, H'), \tag{2}$$

where for an input $X$, $H'$ denotes the latent space, while $G'$ represents the reconstructed features of the graph computed by the decoder.

[39] introduced completely symmetric graph convolutional autoencoders that leverage both the graph structure and node attributes throughout the entire encoding-decoding process. This approach addresses the instability issues commonly associated with graph convolutional layers by incorporating Laplacian sharpening layers, which counteract the smoothing effects typically observed in these models. While this method effectively resolves several common graph representation learning challenges, it does not provide a mechanism for dynamically weighting node importance. In the context of GNNs, node representations are typically learned using a set of node features. The conventional GNN approach involves node-level feature aggregation within a defined neighborhood, iteratively learning node representations by aggregating information from neighboring nodes to create a latent representation $H'$. However, this standard methodology often assumes uniform importance across all neighbors, assigning aggregation weights based solely on degree distance. This uniform weighting approach, while computationally efficient, may not accurately capture the nuanced relationships and varying degrees of influence between nodes in complex networks, such as those representing urban EV charging demand. The inability to dynamically adjust node importance can potentially limit the model's ability to discern and leverage critical patterns in the data, particularly in scenarios where certain nodes or relationships carry disproportionate significance in determining optimal EVCS placement.

To address these limitations, we employ the self-attention mechanism during the encoding phase using Graph Attention Networks (GATs) [40]. Unlike conventional GNNs, GATs dynamically assign weights to neighboring nodes based on their relative importance within the neighborhood, utilizing a masked attention mechanism. The input to a GAT layer is a set of node features $X = X_1, X_2, \dots, X_{|\mathcal{V}|}$, where $X_i \in \mathbb{R}^F$ represents the feature vector of node $i$. The layer then computes an output $H' = H'_1, H'_2, \dots, H'_{|\mathcal{V}|}$, where $H'_i \in \mathbb{R}^{F'}$ and cardinality $F'$ may differ from the input feature dimension $F$. The key innovation of GATs lies in their computation of attention coefficients $\alpha_{ij}$. These coefficients quantify the importance of the feature vector of node $j$ to node $i$. The coefficients are computed only for nodes $j \in \mathcal{N}_i$, where $\mathcal{N}_i$ represents a defined neighborhood of node $i$ in the graph.

$$\alpha_{ij} = \frac{exp(a(\mathbf{W}H_i, \mathbf{W}H_j))}{\sum_{k\in\mathcal{N}_i} exp(a(\mathbf{W}H_i, \mathbf{W}H_k))}, \tag{3}$$

where $\mathbf{W} \in \mathbb{R}^{F' \times F}$ represent a network weight matrix, and $a$ denotes the attention function. This masked self-attention mechanism allows the model to focus on relevant local structures while ignoring irrelevant or distant nodes.

As an urban graph tends to have a large amount of neighbors, to address the "neighbor explosion" problem often encountered in large urban graphs, we implement a data sampling procedure inspired by [41]. This approach involves obtaining a set of subgraphs by sampling the original training graph and then constructing the graph autoencoder based on these subgraphs. This sampling strategy allows for efficient processing of large-scale urban networks while maintaining the integrity of local structures.

### 3.3. Node clustering and site selection algorithm

The generated graph embeddings are utilized as input for a k-means clustering procedure, employed to create a classification of the utilization potential of EVCS locations. The classification scheme is based on utilization data, which was categorized into three balanced classes: low, medium, and high utilization. By classifying areas into these utilization categories, we can prioritize medium and high utilization zones for further analysis in the charging station placement process, thereby optimizing the potential impact and efficiency of new EVCS installations.

To identify the best charging location among a set of potential candidate sites, we focus our analysis on medium and high utilization areas identified through clustering techniques. Our primary objective is to maximize area demand coverage by simulating the impact of adding new charging stations that can fully meet existing local demand. To quantify this impact, we introduce Incremental Coverage Difference (ICD) metric. The ICD metric evaluates the "usefulness" of potential infrastructure placement by measuring the incremental change in an area's total charging output when a new station is added. This metric is designed to favor locations where new chargers can completely fulfill the existing demand in the area, thus maximizing the "impact" of each new installation. The ICD metric is based on the core charging demand factors and requires knowledge of three key elements: 1) total annual EV flow within the demand node, 2) average annual power requirement of an EV, and 3) maximal annual power output of a demand node. To estimate the approximate number of EVs in each city, we multiply the number of registered private vehicles $N^c_{CAR}$ with the assumed 10% EV penetration rate: $N^c_{EV} = 0.1 \times N^c_{CAR}$. Applying this formula to our case study cities yields the following estimates: $N^{Glasgow}_{EV} = 20{,}480$ and $N^{Edinburgh}_{EV} = 17{,}850$.

**Table 3**
Battery capacity and range of the most sold EVs in the UK in the year 2023 [3].

| Vehicle model | Battery capacity (kWh) | Range (km) |
|---|---|---|
| Tesla Model Y | 60–75 | 455–542 |
| MG4 | 51–77 | 349–520 |
| Audi Q4 e-tron | 82 | 455–543 |
| Tesla Model 3 | 60–78 | 513–528 |
| Polestar 2 | 82 | 555-653 |
| Volkswagen ID.3 | 62–82 | 430–558 |
| Kia e-Niro | 68 | 463 |
| BMW i4 | 83.9 | 413-589 |
| Volkswagen ID.4 | 82 | 515–550 |
| Skoda Enyaq iV | 82 | 538–547 |

To quantify the charging frequency of EVs within city limits, we first establish key parameters based on existing data. Drawing from statistics on the most purchased vehicles in the UK shown in Table 3, we set the average EV driving range to $range_{avg}$ = 466.45 km and the average battery capacity to $capacity_{avg}$ = 68.20 kWh. These figures provide a baseline for our calculations. We then incorporate traffic data from the UK Department of Transport Road Traffic Statistics for 2022, which reports total annual traffic for private cars and taxis as $t^{Glasgow} = 2.684$ billion kilometers in Glasgow City and $t^{Edinburgh} = 2.293$ billion kilometers in the City of Edinburgh. Using these figures, we calculate the average annual travel distance per car in each city using the formula:

$$d^c_{CAR} = \frac{1}{N^c_{CAR}} t^c [\frac{km}{year}], \tag{4}$$

This yields $d^{Glasgow}_{CAR} = 13{,}105.47 \frac{km}{year}$ for Glasgow and $d^{Edinburgh}_{CAR} = 12{,}845.94 \frac{km}{year}$ for Edinburgh.

Assuming that EV users typically recharge their vehicles only when the battery capacity falls below 20%, we can calculate the yearly charging frequency of an EV:

$$f^c_{EV} = d^c_{CAR} \div (range_{avg} \times 0.8)[\frac{charges}{year}] \tag{5}$$

This yields $f^{Glasgow}_{EV} = 35.12 \frac{charges}{year}$ for Glasgow and $f^{Edinburgh}_{EV} = 34.42 \frac{charges}{year}$ for Edinburgh.

Similarly, the average charging need of an EV per year is:

$$e^c_{EV} = f^c_{EV} * (capacity_{avg} * 0.8)[\frac{kW}{year}] \tag{6}$$

which results in $e^{Glasgow}_{EV} = 1916.14 \frac{kW}{year}$ for Glasgow and $e^{Edinburgh}_{EV} = 1877.96 \frac{kW}{year}$ for Edinburgh.

To determine the charging power output of each station, we focus on a circular area with a radius of 500 m centered on each charging station. This radius is chosen based on previous studies, such as [29], which indicate that 500 m is generally considered a comfortable walking distance to a charging station. This approach allows us to define charging demand nodes that realistically represent areas where EV users are likely to utilize a given charging station. Within each of these 500-m radius nodes, we calculate the annual traffic flow, taking into account the assumed 10% EV penetration rate. This calculation is crucial for estimating the potential charging demand in each node $i$ and is expressed as:

$$flow^i_{EV} = 0.1 \times flow^i_{CAR}. \tag{7}$$

where $flow^i_{EV}$ represents the annual EV traffic flow within node $i$, and $flow^i_{CAR}$ is the total annual traffic flow in that node.

Building upon our previous calculations, we next determine the total annual energy requirement for each demand node:

$$C^i_{total} = flow^i_{EV} \times e_{EV} [kWh]. \tag{8}$$

To assess the current charging need within each demand node, we calculate its annual output based on the existing infrastructure. This calculation takes into account the average charger power output ($O_{avg}$) measured in kW, and assumes maximal (24-hour) energy utilization. The current annual output of a demand node is expressed as:

$$C^i_{current} = 24 \times 365 \times no\_chargers^i \times O^i_{avg} [kWh]. \tag{9}$$

As a result, the current demand node coverage can be estimated as:

$$C^i = min[\frac{C^i_{current}}{C^i_{total}}, 1][\%]. \tag{10}$$

To evaluate the impact of adding a new charging station to a demand node, we calculate the updated coverage of the node. This calculation considers the additional charging power output provided by the new charger, which has an output of $c_{out}$ measured in kilowatts (kW). The new coverage of the demand node after adding this charger is expressed as:

$$C^i_{new} = min[\frac{C^i_{current} + 24 \times 365 \times c_{out}}{C^i_{total}}, 1][\%]. \tag{11}$$

In this formula, $C^i_{new}$ represents the new total coverage of demand node $i$ after the addition of the new charger.

To quantify the impact of adding a new charging station to a demand node, we introduce the Incremental Coverage Difference (ICD) metric. This metric provides a measure of the improvement in output relative to the node's energy requirements. The ICD is calculated using the following formula:

$$ICD^i = C^i_{new} - C^i [\%]. \tag{12}$$

As a result, this study adopted a problem setup tailored to identify areas or communities that would benefit most from the installation of a single charging point. Our approach focuses on a methodology that assesses the impact and accessibility for underserved regions rather than following traditional optimization frameworks. We model the urban context by framing a graph-based problem where each potential or existing charging point represents a charging demand node that holds information about existing charging and parking infrastructure, traffic flow, socio-demographic factors, POIs, and charging utilization within the demand node area, as defined in GNN graph construction process explained in Section 3.1. Following the node clustering step, as indicated in Fig. 4, the potential sites are ranked based on their ICD values. Each potential site is a binary variable: either it gets a charging point or not, while constraints include the number of sites selected, ensuring geographic spread, and the selected nominal power of a charging point. Algorithm 1 presents a systematic method for identifying locations for new charger installations based on their ICD scores. This approach considers the installation of $k$ number of new chargers with a predefined power output and assesses the incremental benefit of adding a new charging station to an existing demand node. The algorithm focuses on a charging demand node area, which contains $n_{charging}$ existing chargers and $n_{parking}$ parking stations. As a result, the

**Algorithm 1** Site Selection Algorithm for New Charging Stations

**Require:** Charging nodes $\mathcal{V}$, Number of chargers to be installed $k$, New chargers power output $c_{out}$ [kW]

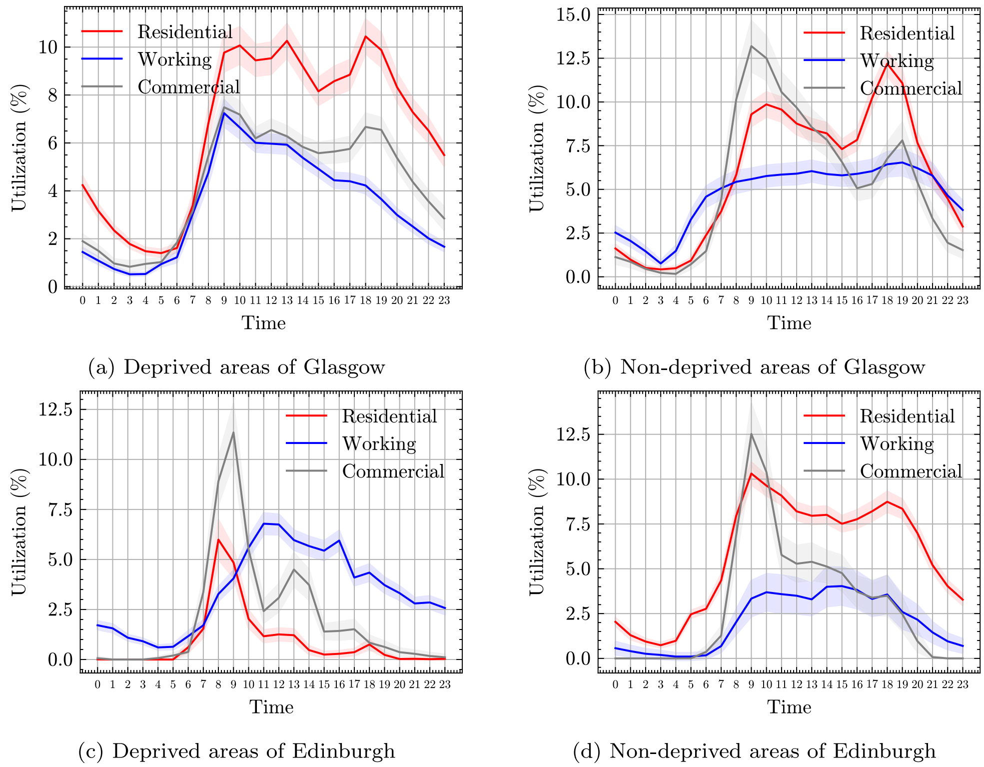
Initialize list of new stations: $newStations \leftarrow []$
**for** $i = 1$ to $k$ **do**
  $maxICD \leftarrow 0$
  $maxICDStation \leftarrow null$
  **for** each node $v \in \mathcal{V}$ **do**
    Calculate $ICD^v$ (Eq. (12))
    **if** $v_{type} == parking$ and $n^v_{parking} \geq 1$ **then**
      **if** $ICD^v > maxICD$ **then**
        $maxICD \leftarrow ICD^v$
        $maxICDStation \leftarrow v$
      **end if**
    **end if**
  **end for**
  Add site $maxICDStation$ to $newStations$
  **for** $v \in \mathcal{V}$ **do**
    Calculate the distance $dist^v$ from node $v$ to $maxICDStation$
    **if** $dist^v \leq r$ **then**
      $n^v_{parking} \leftarrow n^v_{parking} - 1$
      $n^v_{charging} \leftarrow n^v_{charging} + 1$
      Recalculate node coverage given newly added $c_{out}$ (Eq. (11))
    **end if**
  **end for**
**end for**
**return** $newStations$

computed ICD values are sorted in descending order, as seen in Figs. 7 and 8. A higher ICD score indicates a demand node with unmet charging needs due to insufficient infrastructure, where installation of a new charging point would make a significant impact on meeting the area needs, making it a prime candidate for new charger installation. Conversely, sites that already meet or exceed the local charging demand are excluded from consideration, ensuring efficient resource allocation. This data-driven approach allows for targeted expansion of the charging network, prioritizing areas where new installations will have the most substantial impact on improving charging accessibility and meeting the growing demands of EV users. As a result, by systematically evaluating potential sites based on their ICD scores, urban planners and policy-makers can make informed decisions that optimize the distribution of charging infrastructure across the city, ultimately enhancing the overall EV ecosystem.

### 3.4. EVCS access equity evaluation

To address broader transportation justice concerns and ensure that the proposed methodology does not exacerbate existing socio-spatial disparities, Lorenz curves and the associated Gini coefficients were calculated based on data-zone-level EVCS accessibility. Given increasing policy emphasis on just transition in transportation electrification, this metric provides valuable insight in distributional inequality. This is further motivated by previous work in evaluating equity of spatial planning [42,43]. In the context of EVCS infrastructure, the Lorenz curve plots the cumulative percentage of the population on the horizontal axis against the cumulative percentage of accessibility to EVCS infrastructure on the vertical axis. A perfectly equal distribution corresponds to a 45-degree line, often called the line of equality, where each fraction of the population has equal access to EVCS infrastructure. The area between the Lorenz Curve and the line of equality quantitatively captures inequality within the distribution, where a larger area indicates greater inequality. Formally, the Lorenz Curve $L(p)$ can be defined mathematically as:

$$L(p) = \frac{\int_0^p F^{-1}(q)\, dq}{\int_0^1 F^{-1}(q)\, dq}$$




(a) Deprived areas of Glasgow (b) Non-deprived areas of Glasgow

(c) Deprived areas of Edinburgh (d) Non-deprived areas of Edinburgh

**Fig. 5.** Average hourly EVCS utilization statistics per area.

$L(p)$ is the value of the Lorenz curve at percentile $p$, $F^{-1}(x)$ is the inverse cumulative distribution function of EVCS accessibility values, while $p$ represents the proportion of the population. The Lorenz Curve facilitates the computation of numerical measures of inequality, such as the Gini coefficient, which quantifies the deviation of the observed distribution from perfect equality. The Gini coefficient is calculated as twice the area between the line of equality and the Lorenz Curve:

$$\text{Gini} = 1 - 2\int_0^1 L(p)\,dp$$

A Gini coefficient of 0 represents perfect equality (the Lorenz curve follows the line of perfect equality), while a value of 1 indicates maximum inequality.

## 4. Experimental results and discussion

### 4.1. Clustering evaluation metrics

To assess the quality of utilization-based clustering, we use three common performance evaluation metrics: Accuracy, Adjusted Rand Index (ARI) [44], and Normalized Mutual Information (NMI) [45]. Accuracy evaluates classification accuracy within three possible utilization classes, while the Rand Index (RI), defined as:

$$RI = \frac{p+q}{\binom{n}{2}}, \tag{13}$$

calculates a similarity between two cluster results by comparing all points within the same cluster. $p$ is the number of pairs correctly placed in the same cluster, $q$ is the number of pairs correctly placed in different clusters, and $n$ is the total number of elements. Adjusted Rand Index (ARI), defined as:

$$ARI = \frac{\text{RI} - \mathbb{E}[\text{RI}]}{\max(\text{RI}) - \mathbb{E}[\text{RI}]}, \tag{14}$$

extends RI by accounting for different models of random clusterings, with values ranging from approximately 0 for random labeling to 1 for perfect agreement. Normalized Mutual Information (NMI), calculated as:

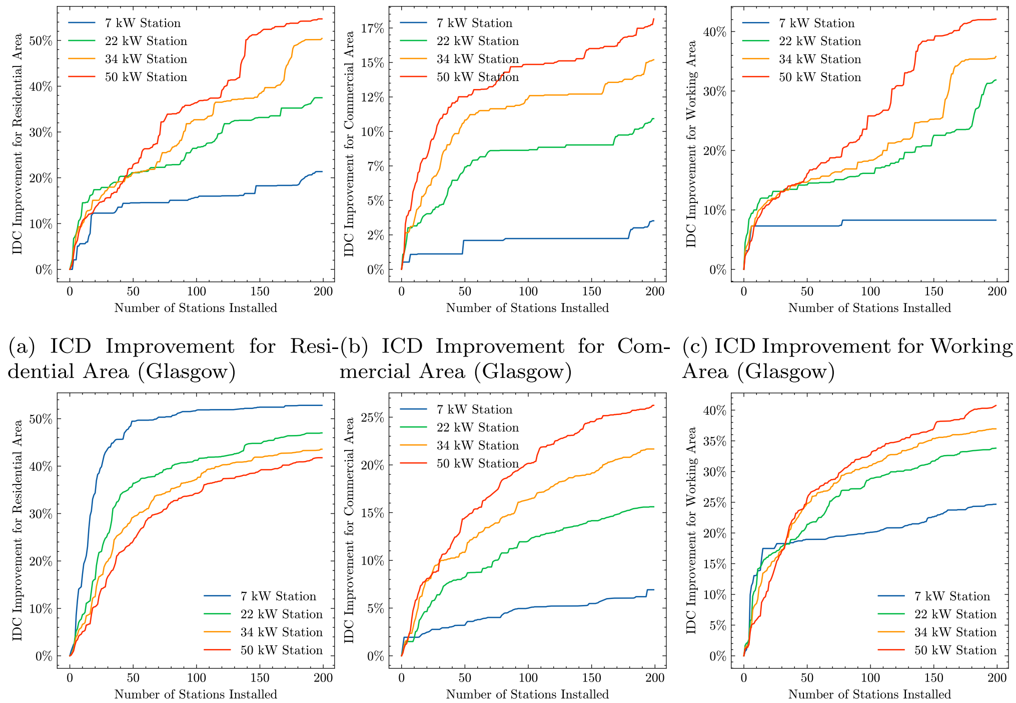
$$NMI = 2 \times \frac{I(U,V)}{H(U)+H(V)}, \tag{15}$$

quantifies the shared information between predicted and true clusterings, where $I(U,V)$ is the mutual information and $H(U)$, $H(V)$ are the entropies of the clusterings. NMI ranges from 0 (no sharing) to 1 (perfect correlation).

These complementary metrics offer a comprehensive assessment of our algorithm's clustering performance, capturing different aspects of the results' quality and reliability.

### 4.2. Results: EVCS land use identification and statistical analysis

A key component of our proposed approach involves the localization of land uses within the council limits of Glasgow City and the City of Edinburgh. The land use clustering procedure, as illustrated in Fig. 3, reveals distinct patterns in local land use characteristics across both cities. In Glasgow and Edinburgh, the analysis identifies commercial areas predominantly within the city centers. These zones correlate strongly with a high concentration of social and especially recreational POIs, reflecting the diverse entertainment options typically found in urban cores. Notably, these commercial areas also coincide with lower car traffic volumes, likely influenced by the implementation of low-emission zones in both city centers. The distribution of EVCS infrastructure shows a significant concentration within commercial zones. This pattern may indicate a potential saturation of charging facilities in these areas, suggesting a need for strategic reassessment of future EVCS placements. Commercial zones also exhibit lower rates of income (measured by the percentage of the population receiving income support) and employment deprivation (measured by the percentage of the population who are employment deprived), but also the highest population density and the highest incidence of reported crime, aligning with typical urban center characteristics. Working areas, as identified by our analysis, are characterized by higher traffic counts




(a) ICD Improvement for Residential Area (Glasgow) (b) ICD Improvement for Commercial Area (Glasgow) (c) ICD Improvement for Working Area (Glasgow)

(d) ICD Improvement for Residential Area (Edinburgh) (e) ICD Improvement for Commercial Area (Edinburgh) (f) ICD Improvement for Working Area (Edinburgh)

**Fig. 6.** ICD performance results.

**Table 4**
Clustering performance for Glasgow (left) and Edinburgh (right)

| Algorithm | Accuracy | ARI | NMI |
|---|---|---|---|
| Kmeans | 0.2566 | 0.0015 | 0.0009 |
| Spectral | 0.3837 | 0.0394 | 0.0213 |
| Agglomerative | 0.2020 | 0.0017 | 0.0002 |
| GraphSage | 0.3589 | 0.0124 | 0.0079 |
| Proposed (Ours) | 0.5770 | 0.0458 | 0.0138 |

| Algorithm | Accuracy | ARI | NMI |
|---|---|---|---|
| Kmeans | 0.2383 | 0.0682 | 0.0520 |
| Spectral | 0.3262 | 0.0279 | 0.0303 |
| Agglomerative | 0.3262 | 0.0656 | 0.0510 |
| GraphSage | 0.3817 | 0.0293 | 0.0264 |
| Proposed (Ours) | 0.6258 | 0.1467 | 0.0838 |

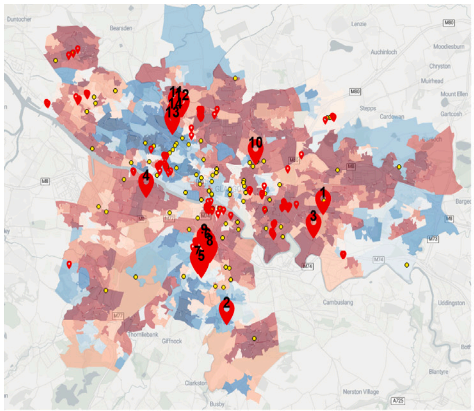
and notably, the highest rates of income and employment deprivation. The distribution of EVCS infrastructure in working areas appears less consistent, with some zones showing a lack of facilities compared to residential areas, while others contain large concentrations of deployed EVCS infrastructure. Residential areas, in contrast, generally report lower levels of traffic in Glasgow, while showing high variability in Edinburgh, possibly due to a large number of residential housing along major roads. Results indicate that EVCS infrastructure is severely lacking in residential areas in both cities.

Observing per-area hourly EVCS utilization shown in Fig. 5, the data reveals distinct patterns in EVCS usage across Glasgow and Edinburgh, highlighting urban disparities and lifestyle differences. Glasgow generally shows higher utilization rates than Edinburgh, particularly in residential charging within deprived areas. In Glasgow, deprived residential areas show similar utilization compared to non-deprived areas. This suggests possible under-utilization of non-deprived charging, explained by the fact that the majority of Glasgow falls within deprived areas, as seen in Fig. 7. The city center falls within non-deprived areas, where the majority of EVCSs are located. Thus, the results could indicate a general under-utilization of city center EVCS charging. In terms of time patterns, the utilization generally peaks around 6 PM, coinciding with the approximate time of commute home from work. Commercial areas indicate utilization peak around 9 AM, possibly due to the large amount of commuters parking their cars within the city center charging locations, where there is the highest overall recorded utilization peak. Working areas of Glasgow showcase similar utilization patterns as commercial areas in deprived areas, peaking in the morning hours and gradually lowering the utilization, which is explained by workers commuting back home. In non-deprived areas, this trend is less apparent and the utilization is relatively consistent throughout the working hours.

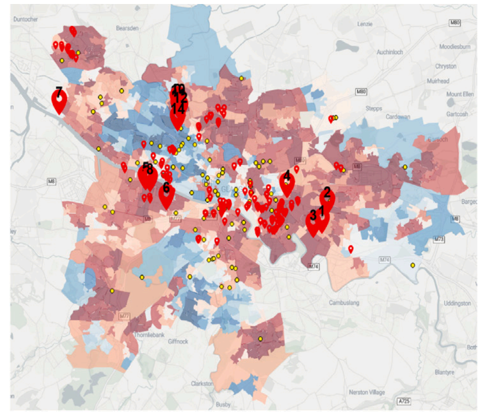
In Edinburgh, the most striking difference in utilization is between deprived and non-deprived residential areas. While non-deprived utilization peaks at around 10% in the morning, deprived areas experience only 5% utilization, which rapidly lowers throughout the day. This indicates limited access to public charging within deprived areas of Edinburgh, which has a direct impact on utilization due to high overstay periods and limited charging opportunities in the second half of the day. Utilization in commercial areas is relatively consistent between deprived and non-deprived communities, peaking in the morning, and sharply declining until the end of the day. Interestingly, utilization in working areas, while lower, experiences a similar pattern between non-deprived working areas of Glasgow and Edinburgh, indicating similar charging behavior within these areas.

### 4.3. Results: Utilization-based clustering

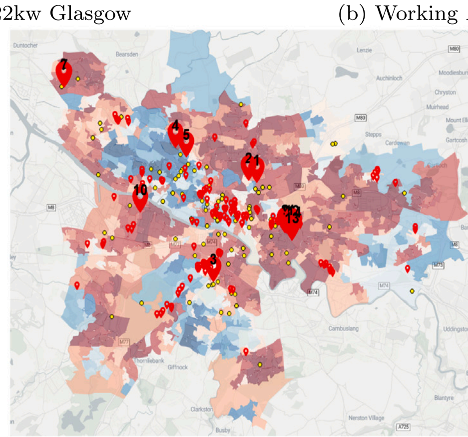
In this subsection, we present the results of our proposed placement methodology, focusing on the performance of our GNN-based clustering approach for selecting potential candidate sites based on their utilization potential, as described in Section 2.3. Table 4 compares the performance of our proposed method against several widely-used



(a) Residential 22kw Glasgow



(b) Working Area 22kW Glasgow



(c) Comercial Area 34kW Glasgow

**Fig. 7.** Proposed EVCS infrastructure placement sites in Glasgow. The top 15 results are displayed with a number on top. Yellow markers are existing charging stations in the selected areas. Red-blue overlay corresponds to area deprivation, where blue is less deprived and red more deprived.

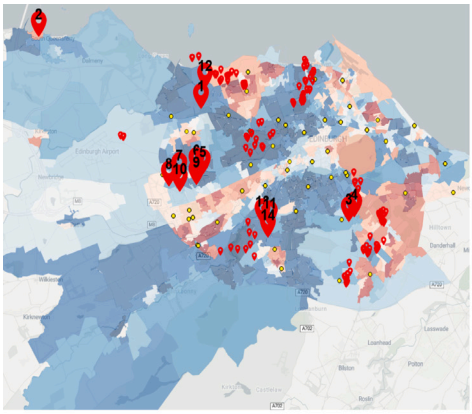
clustering techniques, including K-means, Spectral, and Hierarchical Agglomerative Clustering, as well as other graph-based approaches such as [46]. This comparison provides a comprehensive evaluation of our approach within the broader context of clustering methodologies. K-means and spectral clustering analyze the data based solely on its inherent features, offering a baseline for traditional clustering techniques. In contrast, GraphSAGE employs an unsupervised graph representation technique, aggregating feature information from a node's location and environment.

The performance discrepancies observed in Table 4 between traditional clustering methods and our proposed GNN-based approach highlight the inherent complexity of identifying high charging demand areas for EV infrastructure. Traditional clustering techniques, while effective in many scenarios, struggle to capture the non-linear relationships between the diverse factors influencing charging demand. This limitation is particularly evident in Glasgow, where the accuracy of conventional methods is notably lower, primarily due to the city's intricate urban topology and mixed-use nature of many neighborhoods. Such a diverse and interconnected urban landscape makes it challenging to delineate clear boundaries between high, medium, and low utilization areas using conventional clustering techniques. The blending of different land uses and activities creates a more nuanced charging demand pattern that requires a more sophisticated analytical approach. In contrast, Edinburgh presents a somewhat easier scenario for traditional clustering methods. The city's urban structure exhibits a clearer separation between high, medium, and low utilization areas, likely due to a more distinct spatial organization of land use areas. Our GNN-based approach demonstrates superior accuracy by effectively capturing the spatial relationships between charging demand nodes. By propagating information through the graph structure, the GNN incorporates broader contextual information about the surrounding area, which is crucial for understanding the intricate dynamics of urban charging demand. This ability to account for complex spatial interactions and the multifaceted nature of factors influencing EV charging demand allows our method to outperform traditional techniques, particularly in complex urban environments like Glasgow.

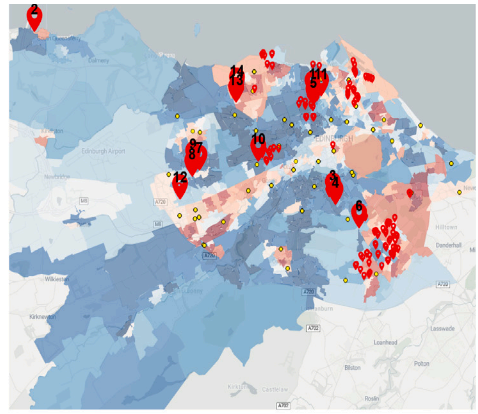
### 4.4. Discussion: EVCS localization

The three proposed placement strategies (working/industrial, residential and commercial) are defined based on the land use processing described in the study (see Section 2.2.6). The "residential area" policy aims to populate public parking available in residential areas with appropriate power output of charging stations based on their ICD values. Similarly, the other two policies focus on commercial and working/industrial areas. As shown in Fig. 6, the proposed model behaves differently depending on the proposed land use and battery capacity. In residential areas, noticeable differences in behavior were observed between Glasgow and Edinburgh. In Glasgow, the installation of higher power output stations (34 kW and 50 kW) significantly improved ICD, with the 50 kW stations achieving around 55%. Conversely, lower power output stations (7 kW) showed more modest increases, highlighting the limited efficacy of low-power stations in residential urban settings, likely due to already sufficient residential charging within the city limits. On the other hand, 22 kW stations showed the best improvement over the initial 50 installations, indicating high potential for 22 kW infrastructure placement in Glasgow's residential areas.

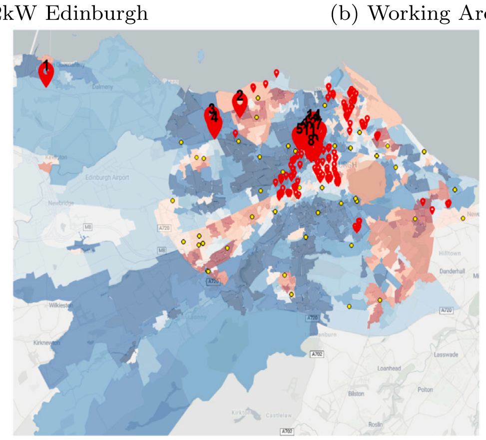
Observing the EVCS placements shown in Fig. 7, the east end of Glasgow has been identified as a high-potential area, particularly the Shettleston constituency (Fig. 7.a - rank 1,3, and Fig. 7.b - rank 1,2,3),



(a) Residential 22kW Edinburgh



(b) Working Area 22kW Edinburgh



(c) Commercial Area 34kW Edinburgh

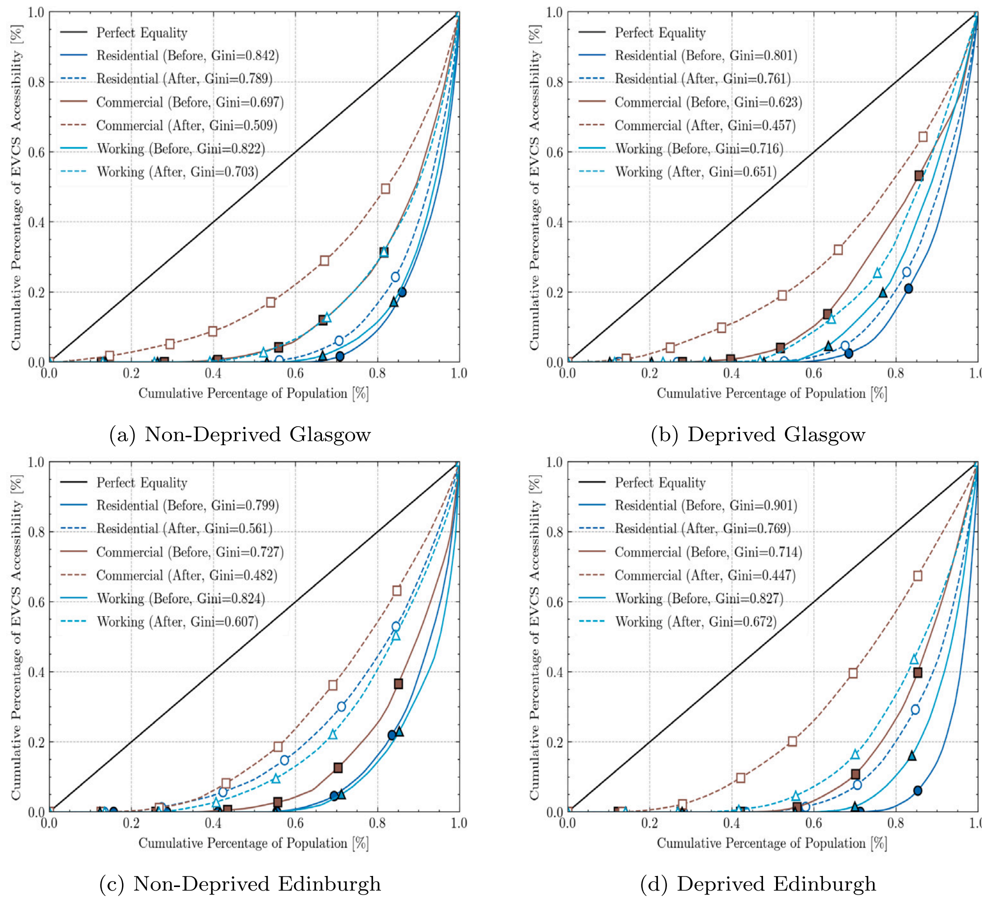
**Fig. 8.** Proposed EVCS infrastructure placement sites in Edinburgh. Top 15 results are displayed with a number on top. Top 15 results displayed with a number on top. Yellow markers are existing charging stations in the selected areas. Red-blue overlay corresponds to area deprivation, where blue is less deprived and red more deprived.

which is a good site for fair infrastructure placement, providing much-needed infrastructure to region scoring higher than average on the deprivation index. Additionally, this area also offers high utilization potential due to its proximity to large supermarkets and parks. The residential EVCS placement with rank 2 is located in an underserved area near major Linn Park, filling the infrastructure gap between the non-deprived area in the northwest and the deprived area in the southeast of the potential EVCS placement location. Other high-potential residential areas include the borders of Maryhill and Canal wards (Fig. 7.a - rank 11–14), as well as Southside Central ward areas around Queens Park, known for its many restaurants and other POIs (Fig. 7.a - rank 5–9). Interestingly, Edinburgh exhibited a more pronounced response to slow residential charging, with 7 kW stations facilitating up to a 50% improvement in ICD, indicating that residential areas of Edinburgh significantly lack needed infrastructure that would fulfill demand by installation of slow overnight charging. To this end, as suggested in [47], utilization of existing lamp posts for on-street EV charging in residential areas might be an effective method for faster expansion of slow overnight charging.

Policy focused around the installation of slow overnight charging is especially effective for deprived areas of Edinburgh, where statistical analysis performed in Section 4.2 showed a general lack of infrastructure which has a further pronounced impact on overall EVCS utilization (as seen in Fig. 5) due to high overstay periods resulting in unavailability of charging options. Observing the results in Fig. 8, the ward of Almond (Fig. 8.a - rank 2) shows high potential for EVCS placement due to its lower-than-average EVCS infrastructure numbers, as well as the Liberton area (Fig. 8.a - rank 3–4), which is close to major roads and large retail areas. The non-deprived Corstorphine area (Fig. 8.a - rank 5–10), featuring numerous shops and major roads, as well as Edinburgh Zoo, also shows great potential for 7–22 kW residential charging.

When it comes to EVCS placement in working and industrial areas of Glasgow, the results suggest a similar strategy to residential areas, where 22 kW installations might provide the best utility-to-cost ratio, with around a 30% overall ICD improvement. Based on Fig. 7, high-potential areas include deprived areas at the eastern end of Shettleston (Fig. 7.b - rank 1–3), close to large factories, and the Haghill area near a university campus and a large retail park (Fig. 7.b - rank 4), largely due to a lack of infrastructure and high charging demand. Other high-potential areas include the Govan area (Fig. 7.b - rank 5,6,8), which hosts a large recycling center, business centers, the UK Visa and Immigration center, warehouses, and a subway depot, and lacks general charging infrastructure. Overall, Edinburgh displays higher potential for ICD improvement within working and industrial areas. While maximum improvement for fast charging is similar, 7 kW EVCS placements display large improvements over the initial 50 installations. The highest potential lies in the South Queensferry area (Fig. 8.b - rank 2), an area of high importance due to the construction of a new bridge carrying the M90 motorway, connecting northern Scotland with Edinburgh. Contrary to residential land use, the difference in utility gained from installing slow 7 kW and other charging stations, while low in Edinburgh, is significant in Glasgow, suggesting a need for rapid infrastructure in the working and industrial areas. This insight is invaluable for stakeholders, indicating that working and industrial areas of Glasgow, often close to major roads, are lacking in EVCS infrastructure.

The proposed policy for infrastructure placement in commercial areas shows the lowest potential across Glasgow and Edinburgh. In Glasgow, the installation of higher power output stations (34 kW




(a) Non-Deprived Glasgow
(b) Deprived Glasgow
(c) Non-Deprived Edinburgh
(d) Deprived Edinburgh

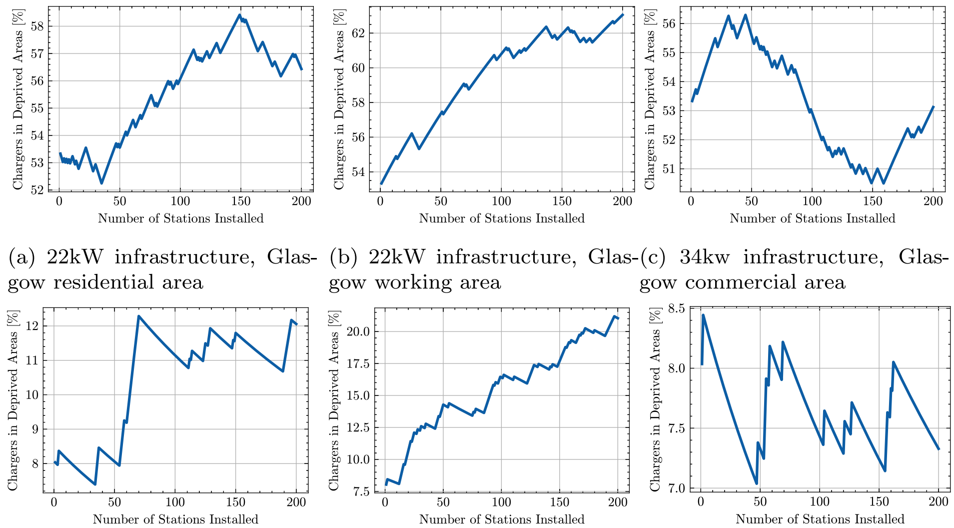
**Fig. 9.** Lorenz curves for EVCS accessibility across different land use and deprivation areas before and after the proposed approach.

and 50 kW) demonstrated a modest improvement in ICD, with the 50 kW stations achieving around 17%. In contrast, Edinburgh achieved an improvement of more than 25% with 50 kW charging stations. Interestingly, the relative improvement between the desired charging capacities is similar between the two cities, suggesting predictable behavior within commercial areas due to similarities in existing infrastructure, residential density, presence of points of interest, and traffic behavior. The preference for higher EVCS output suggests a potential saturation of slow EV charging and the need for faster infrastructure. In Glasgow, areas away from the city center are favored, which is a welcome policy, as the city center is designated as a low-emission zone. High-potential areas include deprived areas in Dennistoun, close to a large retail park, and retail centers in the deprived Drumchapel area. In Edinburgh, high-ranking areas include retail areas in South Queensferry, Silverknowes, and the area close to the historic city center.

### 4.5. Discussion: EVCS placement and equity in access to EVCS

In this subsection, we discuss the relation of the proposed new EVCS localization to deprivation, shown in Figs. 9 and 10. Examining the Lorenz curves shown in Fig. 9 reveals profound inequities in EVCS accessibility across different urban contexts. Prior to implementation of the new placement strategy, residential areas exhibited the most severe inequality, with high Gini coefficients ranging from 0.799 to 0.901, with deprived Edinburgh representing the most extreme case. The steep curvature of these residential lines indicates that approximately 80% of the population has access to less than 20% of available charging infrastructure, creating significant accessibility deserts. Commercial zones, while still inequitable, demonstrated relatively better distribution (Gini coefficients 0.623–0.727), potentially reflecting the concentration of existing infrastructure in business districts and retail centers. Working areas similarly suffered from poor distribution (Gini coefficients 0.716–0.827). Notably, a clear socioeconomic gradient emerged, with deprived areas consistently experiencing higher inequality than their non-deprived counterparts, except for commercial zones in Glasgow where the pattern was reversed. Geographic disparities were also evident, with Edinburgh displaying more extreme inequality than Glasgow, particularly in residential contexts. This landscape reveals systemic biases in EVCS distribution that likely reflect broader patterns of infrastructure investment prioritizing commercial centers and affluent neighborhoods, while neglecting residential and working areas, especially in deprived communities. The extreme bowing of most curves indicates severe concentration of accessibility resources, potentially creating substantial barriers to EV adoption among disadvantaged populations and reinforcing existing transportation inequities.

Following implementation of the proposed placement strategy, the Lorenz curves reveal significant improvements in EVCS accessibility distribution across all urban contexts. Commercial areas exhibited the most dramatic transformation, with Gini coefficients falling to the 0.447–0.509 range, representing the closest approximation to equitable distribution among all land use types. This substantial improvement indicates that strategic placement effectively countered pre-existing commercial concentration biases. Working areas showed moderate improvements (post-intervention Gini coefficients 0.607–0.703), with Non-Deprived Edinburgh experiencing the most substantial gains. Residential zones, while improved, retained the highest level of inequality (Gini coefficients 0.561–0.789), suggesting these areas remain the most challenging for achieving equitable EVCS distribution—likely due to complex residential density patterns and infrastructure limitations. Importantly, these positive outcomes stand in sharp contrast




(a) 22kW infrastructure, Glasgow residential area
(b) 22kW infrastructure, Glasgow working area
(c) 34kw infrastructure, Glasgow commercial area
(d) 7kW infrastructure, Edinburgh residential area
(e) 22kW infrastructure, Edinburgh working area
(f) 34kW infrastructure, Edinburgh commercial area

**Fig. 10.** Increase in the ratio of chargers in deprived zones per land use area after the proposed infrastructure placement strategy.

to what would have occurred with a poor placement strategy. Had the proposed EVCS installation strategy merely reinforced existing infrastructure patterns or prioritized areas with already sufficient coverage, Gini coefficients would have increased rather than decreased, further exacerbating socioeconomic and geographic disparities. Encouragingly, the intervention diminished the socioeconomic gradient, with deprived areas experiencing proportionally larger improvements than non-deprived areas in most contexts. This is particularly relevant for the case of Edinburgh, where the non-deprived residential areas achieved the lowest post-intervention Gini coefficient (0.561) among all residential contexts. While perfect equity remains unachieved, the consistent flattening of all Lorenz curves demonstrates that the proposed strategic placement can substantially redistribute accessibility resources. The post-intervention landscape shows that approximately 60% of the population now has access to 20%–30% of charging infrastructure (compared to under 10% pre-intervention), representing a significant step toward more inclusive EV infrastructure development, though persistent gaps indicate ongoing challenges in achieving truly equitable distribution. Fig. 10 provides critical insight into the mechanism behind these equity improvements, illustrating how the proposed station ranking method progressively affects the proportion of chargers in deprived areas during installation. Glasgow's working areas (Fig. 10b) show the most consistent upward trajectory, increasing from approximately 54% to 62% charger presence in deprived areas, explaining the substantial Gini coefficient improvement in this context. Similarly, Edinburgh's working areas (Fig. 10e) demonstrate the most dramatic proportional increase, more than doubling from 7.5% to around 20%. The fluctuating patterns in commercial areas (Fig. 10c, Fig. 10f) align with their more moderate equity improvements, while residential installations show varied patterns between cities, with Glasgow (Fig. 10a) exhibiting earlier prioritization of deprived areas compared to Edinburgh, with sharp increase after initial 50 installations (Fig. 10d).

### 4.6. Discussion: Scalability and transferability

The proposed methodology can be adapted across different cities, and more readily within the UK, including cities in England and Wales. Direct application is possible due to equivalent socio-economic indicators - the Index of Multiple Deprivation (IMD) for England and the Welsh Index of Multiple Deprivation (WIMD) for Wales are directly comparable to the SIMD data used in our study. These indices share similar underlying domains including income, employment, health, education, and geographical access, enabling consistent node feature construction across UK cities. Outwith the UK, while specific deprivation metrics may differ, a mapping of pertinent deprivation metrics to the application domain can be made. Regardless, the core methodology of constructing charging demand nodes and their relationships, as described in Section 3, is applicable to all application domains. The approach requires three fundamental data categories that are typically available in most urban areas: (1) spatial infrastructure data (obtainable through OpenStreetMap), (2) socio-economic indicators (available through national census or similar demographic surveys), and (3) mobility patterns (accessible through traffic counts or similar transportation data). Cities lacking historical EVCS utilization data could initially calibrate the model using proxy metrics such as vehicle ownership rates, parking utilization, or traffic flow patterns. The graph construction methodology, based on 500-m radius nodes and their spatial relationships, is geography-agnostic and can be applied to any urban environment. The GNN architecture itself is flexible enough to accommodate varying numbers and types of input features, allowing for adaptation to locally available data while maintaining the core principles of geodemographic-aware infrastructure planning.

## 5. Conclusions and future work

This research presents a novel geodemographic aware approach to EVCS placement through GNN modeling. By fusing socio-demographic data, spatial dynamics, and post-installation impacts, our methodology addresses the critical gaps in existing infrastructure planning strategies. The case study of Glasgow and Edinburgh demonstrates the effectiveness of this approach, optimizing EVCS placement for efficiency and equity. Key advantages of using GNNs include consideration of underserved communities, nuanced understanding of urban dynamics, and maximization of new charging station utilization. Experimental results validate the utility of the proposed method, showing significant improvements in strategic placement and use of EV charging stations. The proposed GNN-based approach demonstrates strong scalability potential for larger urban environments. Our model leverages GATs which are inherently more efficient than traditional GNNs due to their selective attention mechanism that focuses on important node relationships, and can also mitigate over-squashing issues related to large-scale graphs [48]. From a computational perspective, the scalability of GNN architectures has been demonstrated in substantially larger applications, including citation networks with millions of nodes, social networks with billions of edges, and molecular graphs analyzing hundreds of thousands of compounds. The urban context, being relatively constrained in comparison, with node numbers in the range of thousands, presents a more computationally manageable environment.

However, we acknowledge certain limitations of our work. The primary limitations center around the temporal analysis constraints, as our model primarily focuses on static spatial patterns and does not fully incorporate temporal aspects such as seasonal fluctuations or long-term EV adoption trends. Building on this, to improve estimations of the potential EV count used for ICD calculation, demographic profiling of potential EV consumers alongside comprehensive surveys could be utilized. Additionally, notable gaps include the absence of electrical grid power output considerations and associated infrastructure upgrade requirements, which could significantly impact implementation feasibility, as well as aspects related to renewable energy availability and the carbon footprint associated with charging infrastructure deployment, both of which could greatly impact sustainability outcomes. Lastly, refining accessibility calculations at specific charging demand nodes could provide more precise insights, enabling more targeted analysis and improved placement strategies at localized levels. Future research should address these gaps by incorporating temporal dynamics, analyzing grid stability impacts, examining carbon footprint implications, investigating relationships with other transportation modes, and performing comparative analyses across different urban environments. Promising research directions include studying EVCS placement effects on power grid stability, enhancing GNN models to include alternative transportation options, and developing reinforcement learning frameworks for dynamic charging recommendations. Additionally, proximity to brownfield sites presents an opportunity for more sustainable placement decisions that could help mitigate potential grid constraints. These enhancements would collectively contribute to more robust, adaptable, and equitable EVCS placement strategies. This research presents a novel geodemographic aware approach to EVCS placement through GNN modeling. By fusing socio-demographic data, spatial dynamics, and post-installation impacts, our methodology addresses the critical gaps in existing infrastructure planning strategies. The case study of Glasgow and Edinburgh demonstrates the effectiveness of this approach, optimizing EVCS placement for efficiency and equity. Key advantages of using GNNs include consideration of underserved communities, nuanced understanding of urban dynamics, and maximization of new charging station utilization. Experimental results validate the utility of the proposed method, showing significant improvements in strategic placement and use of EV charging stations. The proposed GNN-based approach demonstrates strong scalability potential for larger urban environments. Our model leverages GATs which are inherently more efficient than traditional GNNs due to their selective attention mechanism that focuses on important node relationships, and can also mitigate over-squashing issues related to large-scale graphs [48]. From a computational perspective, the scalability of GNN architectures has been demonstrated in substantially larger applications, including citation networks with millions of nodes, social networks with billions of edges, and molecular graphs analyzing hundreds of thousands of compounds. The urban context, being relatively constrained in comparison, with node numbers in the range of thousands, presents a more computationally manageable environment. However, we acknowledge certain limitations of our work. The primary limitations center around the temporal analysis constraints, as the model focuses mainly on static spatial patterns without fully incorporating seasonal variations or long-term EV adoption trends. Additionally, notable gaps include the absence of electrical grid power output considerations and associated infrastructure upgrade requirements, which could significantly impact implementation feasibility, as well as renewable energy availability, and the carbon footprint of the charging infrastructure. Future work should focus on incorporating temporal dynamics, investigating grid stability and carbon footprint, exploring multi-modal transportation relationships, and conducting cross-city comparisons. Some of the possible research directions include: examining EVCS placement impacts on the power grid, refining GNN construction to integrate alternative transportation modes, and framing the methodology as a reinforcement learning problem for real-time charging recommendations. To address the possibility of grid constraints, proximity to brownfield sites could act as an opportunity for more sustainable placement decisions. By addressing these areas, future research can build upon this foundation to create more robust, adaptable, and equitable EVCS placement strategies.

## CRediT authorship contribution statement

**Djordje Batic:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Vladimir Stankovic:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition. **Lina Stankovic:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

## Declaration of competing interest

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

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## Data availability

Data will be made available on request.

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