Powering Brescia: Optimizing EV Charging Station Allocation

A Maximum Coverage Approach for Sustainable Urban Mobility

Optimization Methods in Business Analytics

Academic Year 2024/25

Brevi Viola, Capelletti Thomas, Pasina Claudio Pietro

May 2025

Index

1 Introduction

The transition to sustainable mobility is transforming the way we think about transportation, with electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) playing a key role in reducing emissions and improving air quality. However, as the adoption of these vehicles increases, so does the need for a corresponding expansion of charging infrastructure. For this transition to be truly effective, we need to ensure that EV charging stations are well-distributed and easily accessible. This is not only a technological challenge, but also a matter of strategic urban and regional planning, with long-term implications for environmental sustainability and economic development.

This project focuses on the allocation of EV charging stations in the Province of Brescia, considering both current mobility needs and how they might evolve over time. In particular, we introduce a scenario analysis extending to the year 2030, chosen based on the recent Motus-E report [14], which provides detailed projections on EV adoption and infrastructure needs for that horizon. Rather than proposing a precise forecast, the 2030 scenario is used as part of a broader *sensitivity analysis*, allowing us to evaluate the robustness and scalability of the current infrastructure planning strategy under conservative growth assumptions. This approach helps identify to what extent the infrastructure proposed today will remain effective in the medium term, thus offering additional value to decision-makers engaged in long-term sustainability planning.

The primary objective of this study is to develop an optimized plan for placing charging stations in a way that maximizes coverage and accessibility, while also accounting for factors like population density, urbanization, and infrastructure development. By incorporating future-oriented considerations and leveraging scenario-based reasoning, we aim to support local authorities in making proactive, data-driven decisions that align with national and European sustainability targets.

Our work began with gathering data from trusted sources, including ISTAT, Piattaforma Unica Nazionale, Motus-E [13], ACI, and regional energy reports. This data provided insights into the current number of EVs and PHEVs, the distribution of existing charging stations, and potential future growth in vehicle numbers and energy demand. Based on these sources, we estimate that the number of EVs in the region could rise from about 10,000 today to approximately 40,000 by 2030 under a conservative scenario. In cases where data was unavailable or incomplete, we relied on estimates derived from demographic, geographic, and infrastructural characteristics.

To improve the precision of our model, we transitioned from a municipality-level analysis to a more detailed spatial approach using a hexagonal grid system (H3). This allowed us to capture finer spatial variations in demand and infrastructure needs by dividing the territory into smaller, more homogeneous and manageable units. We also introduced a weighting system based on the total length of major roads within each hexagon, to ensure that areas with higher infrastructure density are appropriately prioritized for station placement.

For the optimization itself, we applied a Maximum Coverage Problem (MCP) model, which aims to maximize the demand covered by a limited number of charging stations. This approach ensures that the charging network can address both current and future demand efficiently, while respecting practical constraints such as resource availability and budget limitations.

Throughout the process, we faced several challenges, particularly regarding the availability and granularity of local data, and the assumption of evenly distributed demand within municipalities. Nevertheless, the model developed provides a solid foundation for tackling the province's future charging infrastructure needs. As more detailed and updated data becomes available, we aim to refine the model by incorporating additional variables, such as urban versus rural areas, population density dynamics, commuting patterns, and the presence of industrial or commercial zones.

Overall, this project delivers meaningful insights into how EV charging infrastructure can be strategically planned and allocated across the Province of Brescia. It offers a practical and flexible decision-support tool for local institutions, with the potential to adapt to future developments in electric mobility. While the model is subject to improvement, especially in light of evolving data availability, it represents a significant step forward toward ensuring the long-term sustainability and efficiency of the region's charging network.

2 Data Sources and Pre-processing

To support our optimization model, we collected and processed several datasets from ISTAT at the municipal level, focusing on demographic, geographic, and transportation characteristics of the Province of Brescia. In particular, we used data on civil status, altimetry, and motor vehicle registrations, each providing complementary insights relevant to estimating EV demand and infrastructure planning.

The *civil status dataset* [21] includes, for each municipality, the number of residents by marital status (e.g., single, married, divorced, widowed), along with the total population. While not directly related to EV adoption, this data helped us capture the demographic structure and ensure consistency in population estimates when combining data from multiple sources. In addition, demographic characteristics can serve as indirect indicators of household size or income level, which may correlate with vehicle ownership patterns.

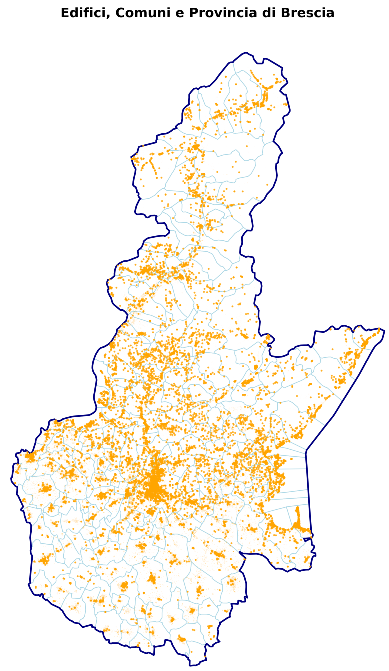
The *altimetry dataset* [18] provides detailed topographic information, including surface area, minimum and maximum altitude, altitude range, mean and median altitude, and standard deviation. This was used as a proxy for terrain complexity, which can influence infrastructure deployment costs and accessibility in rural or mountainous areas. In particular, higher altimetric variability may imply higher installation and maintenance costs for charging infrastructure.

The *vehicle dataset* [20] includes data on the number and type of registered vehicles, disaggregated by fuel type and Euro emission class. From this, we estimated the number of electric vehicles (EVs) [19] per municipality. Although the dataset for EVs is partial, it was used to inform demand modeling and to validate assumptions about vehicle distribution across the province. We also examined the spatial clustering of EVs to identify potential demand hotspots, although the resolution of available data imposes some limitations.

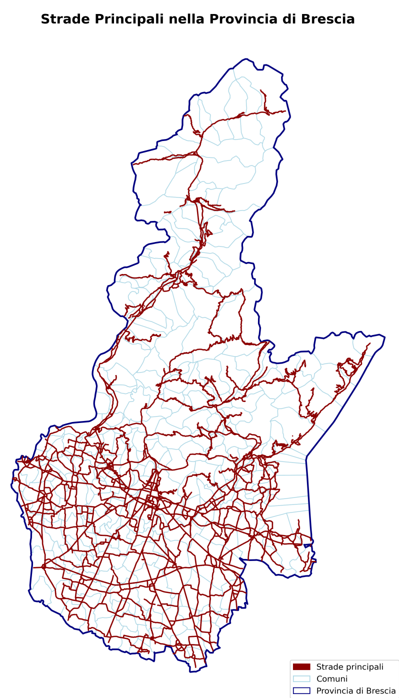
Before merging the datasets, we standardized the column names and ensured that municipality names were consistent across all sources. This was necessary due to small discrepancies in formatting (e.g., spacing or special characters) that would otherwise prevent a successful merge. We then joined the datasets using the *Comune* (municipality name) as the key, and verified the alignment of population totals with official statistics.

From the merged data, we derived additional features such as *population density*, computed by dividing total population by surface area. While the original datasets included multiple variables, for the purpose of our analysis we retained only those most relevant to infrastructure planning: surface area, mean altitude, total population, vehicle fleet size, EV counts, and population density. These features serve as key inputs to the spatial demand model.

In addition to the ISTAT data, we used OpenStreetMap (OSM) data to extract information on the spatial distribution of buildings and main roads. These features were aggregated within a hexagonal grid covering the study area and used to compute an index for each hexagon. This index reflects the built environment and connectivity level, and is later incorporated into the optimization model to better capture the spatial heterogeneity of infrastructure needs. This comprehensive pre-processing phase ensures that the input to the optimization model reflects the real-world complexity of the territory, which is essential for producing actionable and reliable results.



(a) Map of buildings



(b) Map of main roads

Figure 1. Comparative map of buildings and main roads in the province of Brescia.

3 Demand Estimation and 2030 Projections

3.1 Current Demand Estimation

3.1.1 Vehicle Population Analysis

As of December 2023, the electric mobility landscape in the Province of Brescia demonstrates significant growth potential. According to data from the Piattaforma Unica Nazionale[15], there are 6,483 battery electric vehicles (BEVs) registered within the province. Additionally, 43,061 hybrid vehicles are present in the area, though it's important to note that only plug-in hybrid electric vehicles (PHEVs) among these require consideration for charging infrastructure planning due to their dependence on external power sources.
While disaggregated PHEV data is not directly available at the provincial level, we can develop informed estimates based on national trends. Market analysis from Motus-E projects that PHEVs will represent up to 11% of new vehicle registrations by 2026 under conservative scenarios. Applying these projections to the local context, we estimate a total population of approximately 10,000 charging-dependent vehicles (combining BEVs and PHEVs) across the province.
To validate this estimate, we leveraged ISTAT dataset projections that indicate a ratio of 11.5 electric and plug-in hybrid vehicles per 1,000 automobiles. By applying this calculation methodology to the vehicle population of each municipality and aggregating the results, we arrived at a total of 9,661 BEV and PHEV vehicles throughout the province. This figure closely aligns with our initial estimate, providing increased confidence in our assessment of the current electric vehicle landscape.

3.1.2 Charging Infrastructure

To support this growing electric vehicle fleet, the Province of Brescia has developed a substantial charging network comprising:

- 1,623 total charging points, of which 1,581 (97.4%) are publicly accessible and 42 are private with public access
- 631 charging areas distributed throughout the province [16]

It is essential to clearly distinguish between two closely related yet fundamentally different concepts in EV infrastructure. A **charging area** (or station) refers to a designated physical location equipped for electric vehicle charging, which typically includes multiple facilities and serves as a hub for users. Within each charging area, there are one or more **charging points**, which are the actual connectors or sockets where vehicles are plugged in to receive power. Each charging point allows a vehicle to charge independently, meaning that the number of charging points determines how many vehicles can be serviced simultaneously at a given station.
The existing charging infrastructure features a diverse range of power capacities to accommodate different charging needs:

- Slow chargers (0 to 7 kW): 158 points (10.06% of total)
- Quick chargers (7.1 to 22 kW): 680 points (43.29% of total)

- Fast chargers (22.1 to 50 kW): 550 points (35.01% of total)
- Ultra Fast chargers (50.1 to 150 kW): 149 points (9.48% of total)
- High Power Chargers (HPC) (greater than 150 kW): 34 points (2.16% of total)

This distribution reveals that the majority of charging infrastructure falls within the Quick and Fast charging categories, collectively accounting for over 78% of all charging points. While providing adequate charging speeds for many typical use cases, the relatively limited deployment of Ultra Fast and High Power Chargers suggests potential opportunities for infrastructure enhancement to better serve long-distance travelers and commercial electric vehicles requiring rapid charging capabilities.
The current ratio of approximately 10.4 electric vehicles per charging point positions the Province of Brescia favorably compared to European recommendations, which typically suggest 10-15 vehicles per charging point as an optimal balance. However, as electric vehicle adoption accelerates, continued infrastructure expansion will be essential to maintain this favorable ratio and ensure charging accessibility for all users throughout the province.

3.1.3 Demand estimation

Daily electricity consumption for electric vehicle charging represents a critical factor in infrastructure planning due to lack of data. Based on comprehensive analysis of driving patterns, previous research and vehicle efficiency metrics from authoritative sources including Geotab, Enel X, and ENEA, we estimate that the average electric vehicle consumes approximately 18 kWh per 100 kilometers.
Italian drivers typically covers 11,000-12,000 kilometers annually, approximately 33 kilometers daily, this means an average daily consumption of 5.94 kWh per vehicle.
When applied to the estimated 10,000 charging-dependent vehicles in the province, this generates a total daily charging demand of approximately 59,400 kWh. The existing charging infrastructure features a calculated average power capacity of 46.29 kW per charging point, with an estimated daily energy delivery capacity of 555.43 kWh per station during 12 effective operational hours.
This 12-hour operational window represents a realistic utilization period that accounts for two key practical constraints: the significant reduction in charging activity during night hours (10 PM and 6 AM), and the necessary recovery intervals between consecutive charging sessions that prevent continuous 24-hour operation. These intervals are required for system cooling, connection/disconnection procedures, payment processing, and vehicle turnover at each station.
Municipal demand distribution is proportionally calculated based on population share, with each municipality's specific requirements determined by applying its population ratio to the provincial electric vehicle total, then calculating energy demand using the established consumption factors. This municipality-level granularity enables precise infrastructure planning to meet localized charging needs while maintaining optimal coverage throughout the province.

3.2 Projections to 2030

3.2.1 Population growth

Population growth is one of the fundamental drivers of transportation demand and, by extension, the required scale of electric vehicle (EV) infrastructure. According to the latest ISTAT demographic reports and regional planning documents, the current population of the Province of Brescia is approximately 1,257,326 inhabitants. Based on recent trends and scenario-based projections, this number is expected to increase modestly by 2030.
Two alternative demographic scenarios were considered:

- **Conservative scenario**: a projected population of approximately 1,263,613 inhabitants by 2030, corresponding to a +0.5% increase.

- **Optimistic scenario**: a projected population of approximately 1,276,186 inhabitants by 2030, corresponding to a +1.5% increase.

These projections are derived by applying annualized growth rates to current population figures, as outlined in recent ISTAT regional demographic estimates and contextual planning reports [22]. While the projected population increase is relatively limited, its implications are significant when combined with evolving mobility patterns, increasing vehicle ownership, and the ongoing transition toward electrified transport.
Access to population data disaggregated at fine spatial scales (e.g., neighborhood or sub-municipal level) is essential for accurately modeling localized demand for electric vehicle charging infrastructure. However, due to the unavailability of such fine-grained data, we rely on aggregate projections at the provincial level as a reasonable approximation for long-term infrastructure planning.

3.2.2 Future EV Demand Projections – Conservative Scenario

Following the national-level estimates presented in the conservative scenario of the 2024 Motus-E report, Italy is expected to reach approximately **2.6 million battery electric vehicles (BEVs)** and **1.2 million plug-in hybrid electric vehicles (PHEVs)** by the year 2030 [14]. To extrapolate these figures to the Province of Brescia, we apply a population-based scaling approach using Brescia's share of the national population. Given that the province accounts for roughly **2.1%** of Italy's total population (based on a national figure of approximately 59 million inhabitants), we project the local EV fleet as follows:

- **BEVs:** $2.6\,\text{million} \times 0.021 \approx 54,600$

- **PHEVs:** $1.2\,\text{million} \times 0.021 \approx 25,200$

However, this raw scaling does not account for regional disparities in EV adoption, which are influenced by factors such as income levels, urbanization, infrastructure maturity, and vehicle ownership rates. Brescia currently lags behind the national average in terms of EV penetration, with approximately 6,483 BEVs and an unknown but likely limited share of the 43,000 hybrid vehicles registered in 2023.
To align the forecast with local adoption dynamics, we apply an adjustment coefficient

derived from the current local BEV penetration (roughly 0.25% of the population) compared to the national average (around 1%). Assuming that Brescia maintains a slightly lower adoption rate over time, we scale the national projections down accordingly.
This results in a more conservative estimate for 2030:

- **BEVs:** $\approx 30,000$–$32,000$
- **PHEVs:** $\approx 9,000$–$10,000$

The combined EV fleet in Brescia under this scenario is thus expected to reach approximately **40,000–42,000 vehicles** by 2030.
This projection assumes a gradual but steady growth in EV registrations, constrained by potential barriers such as insufficient public incentives, delayed infrastructure rollout, limited model availability, and consumer hesitation. Internal combustion engine vehicles are expected to retain a non-negligible market share throughout the decade, with PHEVs playing a transitional role until cost parity and charging convenience drive full BEV adoption.

3.2.3 Future EV Demand Projections – Optimistic Scenario

The optimistic scenario is based on the upper-bound estimates from Motus-E's accelerated transition model, which predicts that by 2030, there will be **3.6 million battery electric vehicles (BEVs)** and **1.0 million plug-in hybrid electric vehicles (PHEVs)** in circulation nationwide [**motuse2030**]. Assuming that the Province of Brescia follows national adoption trends, we project the following EV demand:

- **BEVs:** $\approx 39,000$–$42,000$
- **PHEVs:** $\approx 9,000$–$10,000$

Thus, the total EV fleet in Brescia would reach approximately **48,000–52,000 vehicles** by 2030 under this scenario. This estimate assumes an acceleration in EV adoption driven by strong regulatory incentives, widespread charging infrastructure availability, and a significant increase in consumer confidence and technology adoption.
The shift to a cleaner, more sustainable transportation system would also necessitate a proportionally larger investment in public and semi-public charging infrastructure to meet the growing demand. The optimistic scenario reflects an environment where both technological improvements and more favorable policies significantly boost the pace of the transition, resulting in a higher rate of EV adoption compared to the conservative scenario.

4 Segmentations by Hexagons

4.1 Municipality-Level Assignment of Hexagons in the Province of Brescia

In this step, we define the assignment of each hexagon to the respective municipality within the province of Brescia. This allows us to perform demand aggregation by municipality and to evaluate the consistency of the spatial data used in the project. We start by creating a list of municipalities included in the dataframe `df_brescia`, which contains the expected administrative boundaries based on official sources. We then generate a base map centered on the province of Brescia and extract its geographic polygon using the `osmnx` package. Using this polygon, we construct an H3 grid of resolution 8, which serves as the reference spatial unit for our project. The resolution value is chosen to ensure a good balance between granularity and computational cost. Subsequently, we extract the polygonal geometries of each municipality listed in `df_brescia`. This step is performed with individual queries for each municipality to maximize accuracy and avoid the inclusion of entities not of interest. Once all municipalities are retrieved, we combine them into a single `GeoDataFrame`. We then perform a spatial join between the generated hexagons and the municipality polygons. Since a hexagon can intersect more than one municipality, we resolve potential overlaps by selecting the first matched municipality. Although this may result in some approximation at the borders, it is negligible for our purposes. To support further analysis and interpretation, we assign a random color to each municipality and plot the hexagons on the map. The centroids of the municipalities are also shown as red circles to allow a visual check of their spatial distribution.
In addition to the visual check, we perform three types of logical validation:

1. **Polygon validity** – We verify whether all municipal polygons are geometrically valid. Invalid geometries may cause errors in spatial operations.

2. **CRS verification** – We confirm that the coordinate reference system (CRS) is consistent across the datasets (EPSG:4326).

3. **Matching municipality names** – We standardize the names of municipalities (lowercase, no extra spaces) across all datasets and identify mismatches between the hexagon assignment and the municipality lists present in:

   - the current scenario (`df_comuni`)
   - the conservative 2030 forecast (`df_2030_conservativo`)
   - the optimistic 2030 forecast (`df_2030_ottimistico`)

The results of these checks highlight potential discrepancies to be resolved in the aggregation and modeling phases. For each comparison, we print the list of municipalities found only in one of the two datasets.

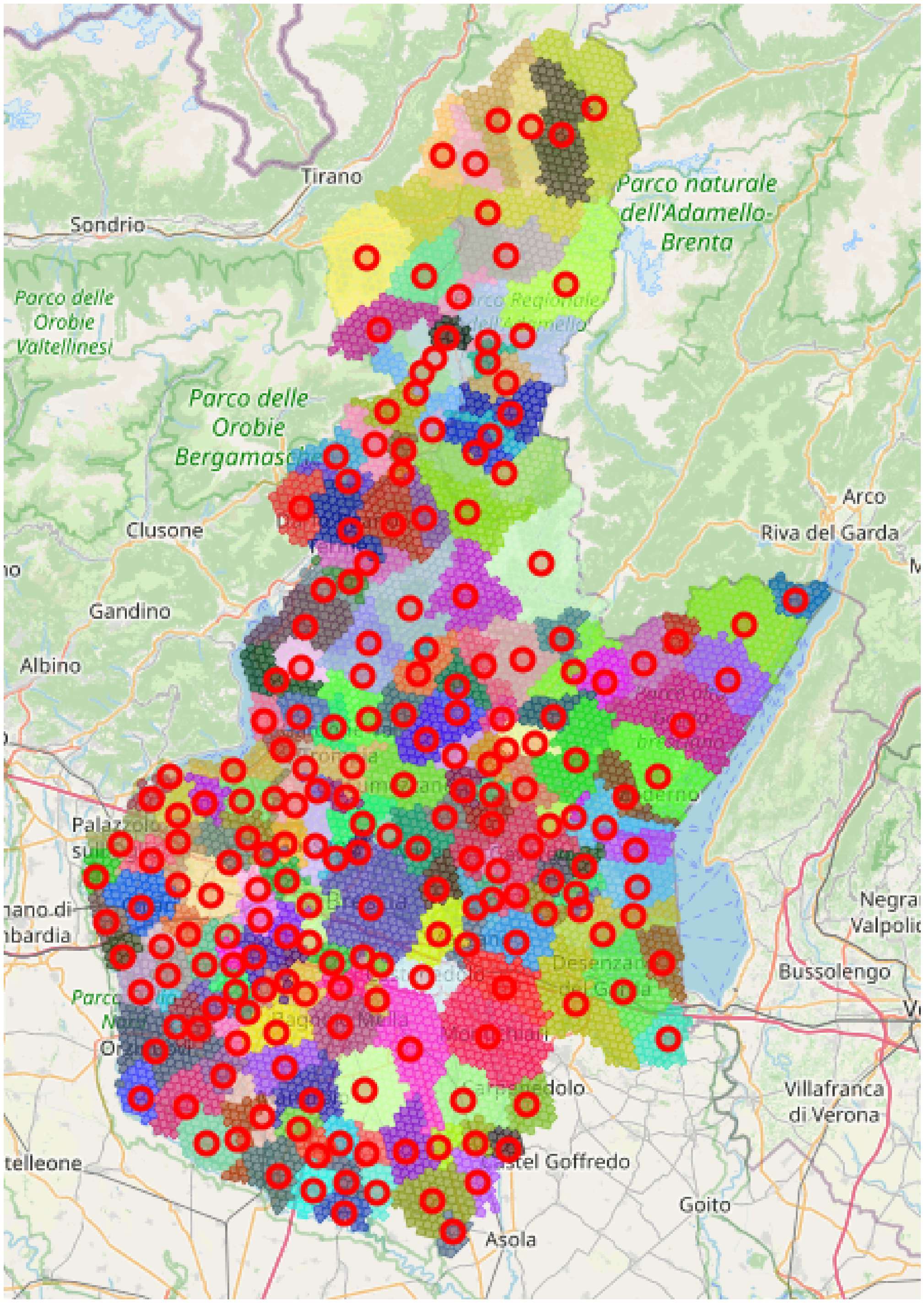


Figure 2. Hexagonal spatial mapping of municipalities in the province of Brescia with centroid markers.

4.2 Assignment of Demand to Hexagonal Polygons

To provide more detailed representation of the charging demand distribution and infrastructure needs across the territory, the estimated municipal data were disaggregated to the level of the hexagons composing the spatial grid. This approach allows for finer spatial resolution for subsequent optimization phases.

Counting Hexagons per Municipality: The number of hexagons for each municipality was calculated. This value (`n_hexagons`) is necessary to proportionally distribute the aggregated municipal values.

Standardization of Municipality Names: To ensure proper merging between datasets, municipality names were standardized (converted to lowercase and spaces removed).

Joining Municipal Data with Hexagonal Grid: The number of hexagons per municipality was added to the municipal dataset (both for the current scenario and the future scenarios) via a merge operation. Municipalities without hexagons were handled by assigning `n_hexagons = 0`.

Calculation of Values per Hexagon: The following indicators were divided by the number of hexagons, obtaining an average estimate per hexagon:

- Number of Electric Vehicles (EVs)
- Daily Energy Demand (kWh)

The division is conditional on the existence of at least one hexagon for the municipality; otherwise, values were set to zero.

Assigning Values to Individual Hexagons: The estimates calculated per hexagon were assigned to each grid polygon via another join, resulting in the datasets:

- `hexagon_df_att` for the current scenario
- `hexagon_df_cons` for the 2030 conservative scenario
- `hexagon_df_opt` for the 2030 optimistic scenario

Automated Checks: Automated checks were performed to identify:

- Municipalities without hexagons
- Hexagons associated with municipalities not present in the demographic datasets
- Municipalities present in the data but not in the grid

Visualization: For each scenario, an interactive map was created where each hexagon is colored based on the **daily energy demand per hexagon**, represented on a **logarithmic scale**. The use of a logarithmic scale was necessary for effective visualization, as a linear scale did not clearly highlight the differences between areas with low and high demand.

The tooltip associated with each hexagon displays the following key information:

- Municipality
- Estimated EVs per hexagon
- Daily Demand (kWh)

5 Index Engineering

5.1 Current Scenario

5.1.1 Introductory Explanation

This section describes the procedure developed to analyze the spatial distribution of potential demand for electric vehicle charging infrastructure in the current scenario. This procedure represents the methodological backbone of the entire study, as it will subsequently be applied to the 2030 projection scenarios, with only minor adjustments. The choice to maintain a consistent analytical structure across all timeframes ensures methodological coherence and facilitates meaningful comparison between scenarios.

The process begins with the creation of a regular hexagonal grid covering the entire provincial territory. This grid allows the analysis to be disaggregated at a sub-municipal level, enabling a more granular and flexible spatial representation of territorial phenomena. For each hexagon, a set of spatial indicators is calculated, representing the variables deemed most relevant for explaining the spatial distribution of charging demand. Specifically, three key components are considered: road network length, average municipal altitude, and building density.

Road length is calculated by intersecting each hexagon with the road network, serving as a proxy for mobility flows and connectivity; altitude is assigned based on the average elevation of the municipality to which the hexagon belongs, representing a morphological factor that may influence energy consumption and travel behavior; finally, building density is estimated using available data on built surfaces, providing an indication of urbanization levels and potential user concentration.

Once these three indicators are obtained for each hexagon, they are normalized to allow comparability and to construct a synthetic index. The final weight assigned to each hexagon is then computed as the simple arithmetic mean of the three normalized components. This composite index reflects the theoretical propensity of each grid cell to attract charging demand and is used to spatially distribute, at a sub-municipal scale, the overall demand estimated for each municipality.

In the following chapters, this same procedure will be applied to the 2030 scenarios. In that context, the only significant methodological change will be the exclusion of the building density component from the weight calculation. This choice is due to the current lack of reliable data to support a meaningful projection of future building development across the territory. The variation introduced is therefore a deliberate assumption, aimed at reducing uncertainty and avoiding distortions in long-term spatial simulations.

5.1.2 Data Loading and Preprocessing

The process begins with loading the data related to the hexagons, which represent specific geographical areas in the province of Brescia. The 'Comune' column is cleaned by removing any leading and trailing spaces and converting the names of the municipalities to lowercase for uniformity. The first few rows of the DataFrame are then displayed to confirm that the data has been loaded correctly. Then additional information about the municipalities, such as altitude, is loaded. In this case, the municipality names are also cleaned to ensure consistency with the names in the first dataset.

5.1.3 Geocoding and Adding Geometry

Once the data is loaded and preprocessed, the next step is geocoding the municipalities using the `osmnx` library. For each municipality, the code attempts to obtain the geographical polygon representing it. If the geocoding is successful, the polygon is added to the DataFrame. Otherwise, an error is recorded, and the polygon for that municipality is set to `None`.
Once the polygons are obtained, the DataFrame is converted into a GeoDataFrame, which is a data structure specifically designed for handling geographical data.

5.1.4 Division into H3 Hexagons

The code proceeds by dividing the geometry of each municipality into H3 hexagons, a global hexagonal grid. For each municipality, the `h3.polyfill_geojson` algorithm is used to obtain the H3 IDs that cover the polygon of the municipality. Each H3 hexagon corresponds to a portion of the territory and is associated with the daily demand (in kWh) for charging in the municipality. This data is recorded in a new DataFrame, which contains the municipality name, the daily demand, and the H3 ID for each hexagon.

5.1.5 Adding Geographical Information

Each H3 ID is then converted into a geographical polygon using the `h3.h3_to_geo_boundary` function. These polygons are added to the DataFrame, which becomes a GeoDataFrame containing geographical information for the H3 hexagons.
Elevation information, previously loaded from the Brescia DataFrame, is merged with the hexagon data based on the municipality name. In addition, a road network is created within the polygon of the province of Brescia using `osmnx`. The road network includes only the major roads (of type ”primary”, ”trunk”, ”secondary”, and ”tertiary”). This network is used to calculate the total length of roads that intersect each H3 hexagon.

5.1.6 Weight Calculation

Before calculating the final weight for each hexagon, we initially experimented with a different normalization approach that scaled all values between 0 and 1 based on their minimum and maximum observed values. While simple, this method proved to be problematic: extreme values (outliers) in the dataset had a disproportionate influence on the normalized results, skewing the final weights and leading to imbalances in the prioritization of areas.
To address this issue, we implemented a more balanced method for computing the weights, which mitigates the influence of outliers and ensures that each factor contributes more equitably. The final calculation considers three main factors: the length of the roads, the elevation, and the density of buildings. Each factor is processed using a custom normalization that blends both average and maximum values, reducing the sensitivity to extremes and yielding more stable, interpretable results.

- **Weight Length**: The weight based on the road length in a hexagon is calculated with the formula:

$$\text{Weight Length} = 0.5 \times \left(\frac{\text{road\_length}}{\text{average\_length}} + \frac{\text{road\_length}}{\text{maximum\_length}} \right)$$

This formulation increases with the road coverage in a hexagon. Importantly, it is designed to exceed 1 in cases where the road length is significantly higher than average, which reflects greater accessibility and supports prioritization.

- **Altitude Weight**: The elevation of a hexagon is used to calculate a weight using the formula:

$$\text{Altitude Weight} = \max \left(0,\ 1 - 0.5 \times \left(\frac{\text{altitude}}{\text{average\_altitude}} + \frac{\text{altitude}}{\text{max\_altitude}} \right) \right)$$

  The weight decreases as altitude increases, clipped at zero to avoid negative values. The factor 0.5 averages the two normalized components and reduces their impact on the final weight. This design ensures that very high altitudes significantly reduce the weight, while low altitudes retain a value close to 1.

- **Building Density Weight**: The number of buildings in a hexagon is normalized against the maximum number of buildings observed throughout the province, using the following formula:

$$\text{Building Weight} = \left(\frac{\text{Number of Buildings in Hexagon}}{\text{Max Number of Buildings Observed}} \right)$$

  This value ranges from 0 to 1, with higher values indicating a higher density of buildings.

5.1.7 Final Weight Calculation

The final weight for each hexagon, which integrates the three factors described above, is calculated as the average of the individual weights:

$$\text{Final Weight} = \frac{\text{Weight Length} + \text{Altitude Weight} + \text{Building Weight}}{3}$$

This value, which ranges from 0.5 to 1, reflecting the combined importance of road length, altitude, and building density for each hexagon. The final weight influences the prioritization of sites for the charging station network.

5.1.8 Weighted Daily Energy Demand

The daily demand for each hexagon is weighted by the final weight. The weighted daily demand is calculated as follows:

$$(\text{Domanda Giornaliera (kWh) - Attuali per esagono}) \times \text{Final Weight}$$

5.1.9 Data Visualization

- **Interactive Map**: The code uses the `folium` library to create an interactive map that visualizes the weighted daily demand of the hexagons. The colors of the hexagons are determined by the values of the weighted demand, which are transformed into a logarithmic scale to improve the visibility of variations in the values.
- **Logarithmic Coloring**: The logarithmic scale is applied to obtain a visible distribution of the demand, with a color gradient ranging from yellow to red, where red indicates higher demand.

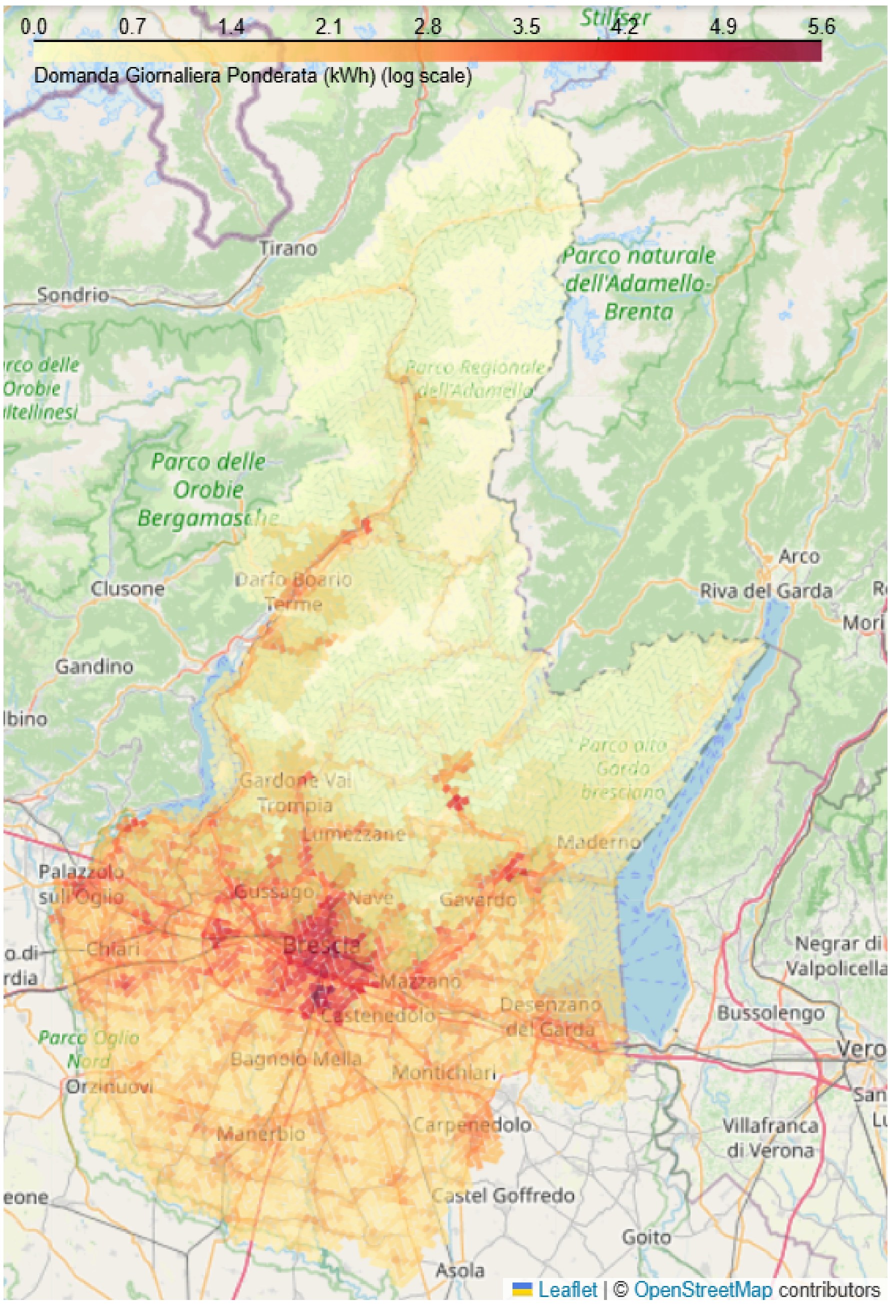


Figure 3. Logarithmic map of the demand distribution for the current scenario.

5.2 Projection to 2030 - Conservative and Optimistic Scenario

5.2.1 Introductory Explanation

This chapter applies the same analytical procedure previously described for the current scenario to the two projection scenarios for 2030, defined as Conservative and Optimistic. In order to ensure methodological consistency and comparability of the results, the entire pipeline is maintained without structural modifications, except for one key adjustment in the computation of the weights assigned to each hexagonal unit.
Unlike the current scenario, where the total weight for each hexagon was calculated as the average of three normalized components (road length, altitude, and building density), the 2030 scenarios exclude the building component. The weight is therefore based solely on the normalized values of road network length and average municipal altitude. This methodological adjustment reflects a deliberate choice rather than a technical constraint. Including building density would require spatially explicit projections of urban development by 2030—estimates that are highly speculative, as they depend on complex and uncertain factors such as planning policies, demographic dynamics, economic conditions, and regulatory frameworks. Introducing such uncertainty could lead to distortions in the spatial prioritization produced by the model, potentially compromising the reliability of the results.
By focusing on road network and altitude, two variables characterized by greater territorial stability and stronger data support, we aim to preserve the robustness of the spatial analysis while acknowledging the simplifications inherent in long-term projections. This choice aligns with the resolution of our available data and the main objective of the study, which is to identify priority areas for the future allocation of electric vehicle charging infrastructure across the province of Brescia.

5.2.2 Data Loading and Preprocessing

The process begins with loading the data related to the hexagons, which represent specific geographical areas in the province of Brescia. The 'Comune' column is cleaned by removing any leading and trailing spaces and converting the names of the municipalities to lowercase for uniformity. The first few rows of the DataFrame are then displayed to confirm that the data has been loaded correctly.
Then additional information about the municipalities, such as altitude, is loaded. In this case, the municipality names are also cleaned to ensure consistency with the names in the first dataset.

5.2.3 Geocoding and Adding Geometry

Once the data is loaded and preprocessed, the next step is geocoding the municipalities using the `osmnx` library. For each municipality, the code attempts to obtain the geographical polygon representing it. If the geocoding is successful, the polygon is added to the DataFrame. Otherwise, an error is recorded, and the polygon for that municipality is set to `None`.
Once the polygons are obtained, the DataFrame is converted into a GeoDataFrame, which is a data structure specifically designed for handling geographical data.

5.2.4 Division into H3 Hexagons

The code proceeds by dividing the geometry of each municipality into H3 hexagons, a global hexagonal grid. For each municipality, the `h3.polyfill_geojson` algorithm is used to obtain the H3 IDs that cover the polygon of the municipality. Each H3 hexagon corresponds to a portion of the territory and is associated with the daily demand (in kWh) for charging in the municipality. This data is recorded in a new DataFrame, which contains the municipality name, the daily demand, and the H3 ID for each hexagon.

5.2.5 Adding Geographical Information

Each H3 ID is then converted into a geographical polygon using the `h3.h3_to_geo_boundary` function. These polygons are added to the DataFrame, which becomes a GeoDataFrame containing geographical information for the H3 hexagons.
Elevation information, previously loaded from the Brescia DataFrame, is merged with the hexagon data based on the municipality name. In addition, a road network is created within the polygon of the province of Brescia using `osmnx`. The road network includes only the major roads (of type "primary", "trunk", "secondary", and "tertiary"). This network is used to calculate the total length of roads that intersect each H3 hexagon.

5.2.6 Weight Calculation

Before calculating the final weight for each hexagon, we initially experimented with a different normalization approach that scaled all values between 0 and 1 based on their minimum and maximum observed values. While simple, this method proved to be problematic: extreme values (outliers) in the dataset had a disproportionate influence on the normalized results, skewing the final weights and leading to imbalances in the prioritization of areas.
To address this issue, we implemented a more balanced method for computing the weights, which mitigates the influence of outliers and ensures that each factor contributes more equitably. The final calculation considers three main factors: the length of the roads, the elevation, and the density of buildings. Each factor is processed using a custom normalization that blends both average and maximum values, reducing the sensitivity to extremes and yielding more stable, interpretable results.

- **Weight Length**: The weight based on the road length in a hexagon is calculated with the formula:

$$\text{Weight Length} = 0.5 \times \left(\frac{\text{road\_length}}{\text{average\_length}} + \frac{\text{road\_length}}{\text{maximum\_length}} \right)$$

  This formulation increases with the road coverage in a hexagon. Importantly, it is designed to exceed 1 in cases where the road length is significantly higher than average, which reflects greater accessibility and supports prioritization.

- **Altitude Weight**: The elevation of a hexagon is used to calculate a weight using the formula:

$$\text{Altitude Weight} = \max \left(0,\ 1 - 0.5 \times \left(\frac{\text{altitude}}{\text{average\_altitude}} + \frac{\text{altitude}}{\text{max\_altitude}} \right) \right)$$

The weight decreases as altitude increases, clipped at zero to avoid negative values. The factor 0.5 averages the two normalized components and reduces their impact on the final weight. This design ensures that very high altitudes significantly reduce the weight, while low altitudes retain a value close to 1.

5.2.7 Final Weight Calculation

The final weight for each hexagon, which integrates the three factors described above, is calculated as the average of the individual weights:

$$\text{Final Weight} = \left(\frac{\text{Weight Length } + \text{Altitude Weight}}{2} \right)$$

This value, which ranges from 0.5 to 1, determines the importance of each hexagon in the context of the charging network, influencing the selection of sites for charging stations.

5.2.8 Weighted Daily Energy Demand

The daily demand for each hexagon is weighted by the final weight. The weighted daily demand is calculated as follows:

$$(\text{Domanda Giornaliera (kWh) - Conservativo or Ottimistico }) \times \text{Final Weight}$$

5.2.9 Data Visualization

- **Interactive Map**: The code uses the `folium` library to create an interactive map that visualizes the weighted daily demand of the hexagons. The colors of the hexagons are determined by the values of the weighted demand, which are transformed into a logarithmic scale to improve the visibility of variations in the values.

- **Logarithmic Coloring**: The logarithmic scale is applied to obtain a visible distribution of the demand, with a color gradient ranging from yellow to red, where red indicates higher demand.

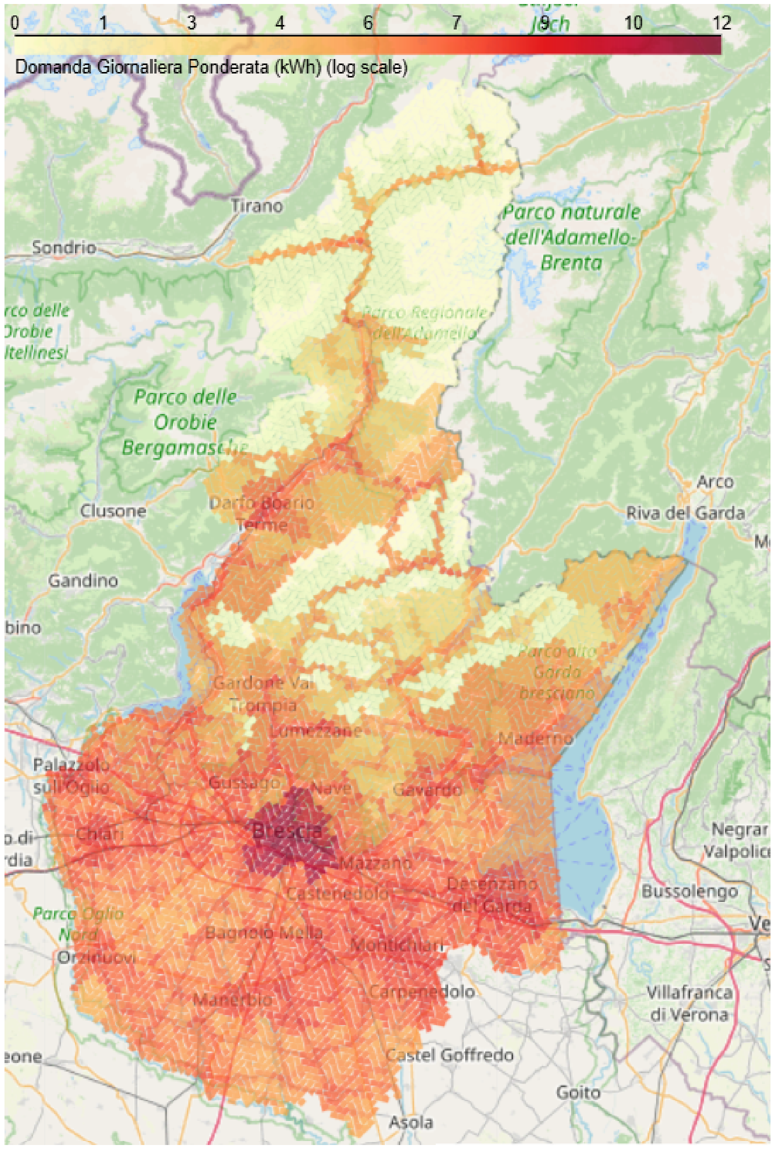


Figure 4. Logarithmic map of the demand distribution for the conservative scenario.

6 Models

6.1 Model Selection and Justification

In the early stages of model development, multiple formulations from the facility location literature were considered to address the problem of allocating EV charging infrastructure across the Province of Brescia. Each model type offered different strengths in terms of optimization objectives, spatial equity, and computational feasibility.
A comparative theoretical and empirical evaluation was conducted to identify the most suitable approach for maximizing the utilization of limited infrastructure resources.
One of the initial candidates was the p-median problem, which minimizes the average distance between demand points and selected facilities. This formulation is widely used in public service and logistics planning [7, 5], and promotes accessibility and user convenience. However, it does not explicitly account for differences in demand magnitude across areas or the delivery capacity of charging stations. As a result, it may underperform in maximizing aggregate demand coverage, especially in spatially heterogeneous contexts like Brescia.
Another considered formulation was the *location set covering problem* (LSCP), originally introduced by [23], which ensures that all demand nodes are within a predefined service radius of at least one facility. Although the LSCP guarantees spatial coverage, it assumes binary coverage and often produces infeasible or overly rigid solutions in scenarios with limited infrastructure budgets [4].
The *capacitated facility location problem* (CFLP) was also explored for its ability to include facility capacity constraints and demand allocation. While it has been used in energy and utility distribution models [9], its objectives often center on minimizing total cost or distance, rather than directly maximizing covered demand. Additionally, the CFLP's computational complexity increases substantially with fine spatial granularity, making it less tractable for large-scale applications.
After evaluating these options, the *Maximum Coverage Problem* (MCP) [4] emerged as the most suitable formulation. The MCP directly targets the maximization of demand coverage under cardinality constraints, making it highly appropriate when the number of deployable facilities is fixed. Its structure is easily extensible, allowing for the incorporation of additional features such as coverage decay, variable facility capacities, and partial coverage scenarios. For this reason, a relaxed MCP variant—featuring integer allocation variables and continuous demand coverage—was ultimately selected as the basis for the final model developed in this study.
As introduced in Section 1, the projections up to 2030 are used primarily as a sensitivity analysis rather than precise forecasts. In this phase, the MCP model is applied to both current and projected future demand scenarios to evaluate its adaptability and robustness over time. This approach enables us to measure how demand coverage and spatial allocation may shift under evolving conditions, providing local decision-makers with actionable insights for proactive planning. By testing the model across different scenarios, we identify potential areas requiring additional infrastructure or policy attention, thus supporting a dynamic, data-driven strategy for sustainable EV charging network development in the Province of Brescia.

6.2 Current models

6.2.1 Model 1: Basic Maximum Coverage Problem

Throughout the development of this study, multiple model formulations were tested and refined to identify the most effective approach for optimizing the allocation of electric vehicle (EV) charging stations. Specifically, seven different model variants were implemented and analyzed, each exploring alternative assumptions and refinements related to demand distribution, coverage mechanics, and capacity constraints. After comparative evaluation, the adopted formulation is based on a relaxed version of the classical Maximum Coverage Problem (MCP), which demonstrated superior balance between computational tractability and practical realism.
The selected model adopts a hexagon-based spatial discretization of the Province of Brescia, wherein the study area is divided into n hexagonal cells using the H3 indexing system. The objective of the model is to allocate a fixed number, p, of charging stations among these hexagons in order to maximize the total daily EV charging demand (expressed in kilowatt-hours, kWh) that is effectively covered. Each charging station is assumed to have a uniform delivery capacity, reflecting both technical constraints and standardization in infrastructure design.
Formally, the model employs two primary decision variables: x_h, representing the number of charging stations installed in hexagon h, and y_h, denoting the amount of daily demand covered in hexagon h. The parameters include D_h, the estimated daily demand in hexagon h, and cap, the maximum daily delivery capacity of a single station, which is set at 555.43 kWh/day based on previously computed estimations. The total number of stations installed across all hexagons is constrained by the budget limit p, ensuring adherence to resource availability.
The optimization problem is structured as follows. The total number of charging stations installed must not exceed the available quantity:

$$\sum_{h=1}^{n} x_h \leq p$$

Additionally, the covered demand in each hexagon cannot surpass the actual local demand:

$$y_h \leq D_h \quad \forall h$$

Furthermore, the covered demand is limited by the cumulative capacity of the stations installed in that hexagon:

$$y_h \leq \text{cap} \cdot x_h \quad \forall h$$

The objective function seeks to maximize the total daily demand covered across the province:

$$\max \sum_{h=1}^{n} y_h$$

This formulation ensures that stations are placed strategically to maximize the volume

of demand served, thereby enhancing the utility and accessibility of the charging infrastructure.
Notably, the model constitutes a relaxed version of the canonical MCP. In its standard form, the MCP typically employs binary decision variables and enforces strict coverage logic, whereby each demand point is either covered or not, depending on proximity to selected facilities. In contrast, the version applied in this study introduces two key relaxations. First, the decision variable x_h is integer-valued rather than binary, allowing for the possibility of multiple stations being installed in a single hexagon to reflect practical scaling. Second, demand coverage y_h is treated as a continuous variable bounded by both demand and capacity constraints, rather than as a binary covered/uncovered status. These relaxations enable the model to capture partial coverage scenarios and to allocate capacity proportionally, thereby offering a more nuanced and flexible representation of real-world charging station deployment where station capacities and local demands vary continuously.
This modeling approach provides a robust analytical framework for guiding the allocation of EV charging infrastructure in Brescia. It integrates spatial demand distribution, infrastructure capacity constraints, and deployment limits in a coherent optimization structure, ensuring that resource allocation decisions are both data-driven and operationally viable.
The optimized allocation model deployed a total of 1,623 charging stations across the hexagonal grid of the Province of Brescia, fully adhering to the infrastructure limit set by the input parameter p. The solution achieves a total daily covered demand of 28,010.36 kWh, which corresponds to approximately 81.2% of the province's total estimated daily demand of 34,500.45 kWh. This coverage rate reflects the balance between the available station capacity and the spatial distribution of demand. While full coverage is not attainable within the current resource constraints, the model ensures that charging infrastructure is concentrated in areas where it can serve the highest aggregate demand, thereby maximizing the utilization efficiency of the deployed stations. These results suggest that, although the present station capacity is substantial, further expansion would be required to achieve complete demand coverage, particularly in lower-density or peripheral areas where current allocations may be insufficient to meet local needs.

6.2.2 Model 2: Aggregated Neighborhood Demand

The Allocating Charging Stations Based on Aggregated Neighborhood Demand is an important extension of the basic maximum coverage formulation. In this variant, the primary objective of maximizing the total daily electricity demand covered is retained, but a new structure of constraints allows each hexagon h to benefit not only from the stations installed within its own area but also from those located in neighboring hexagons, defined by the set $\mathcal{N}(h)$, which represents the neighborhood within a 1-ring radius.
Mathematically, this evolution is reflected in the key constraint of the model: the demand covered y_h in each hexagon is no longer limited to the local station capacity $(\text{cap} \cdot x_h)$ as in the base version, but is instead extended to the sum of available capacities in the hexagon and its neighbors. The constraint

$$y_h \leq \text{cap} \cdot \left(x_h + \sum_{j \in \mathcal{N}(h)} x_j \right)$$

formalizes this logic, introducing a spatial interaction component that allows for a more realistic modeling of electric vehicle users' behavior. These users may be willing to travel to nearby stations located in adjacent areas.
Additionally, the model includes the natural limit that the covered demand y_h cannot exceed the actual demand D_h:

$$y_h \leq D_h \quad \forall h$$

The decision variables remain unchanged from the base formulation: x_h denotes the integer number of stations allocated to hexagon h, while y_h represents the continuous amount of demand covered in h, which is constrained to be non-negative and cannot exceed the actual local demand D_h. The model also includes the global constraint

$$\sum_{h=1}^{n} x_h \leq p$$

which ensures that the total number of stations installed across the entire province does not exceed the maximum permissible p, as dictated by budget or infrastructure planning constraints.
The objective function remains unchanged:

$$\max \sum_{h=1}^{n} y_h$$

However, the new structure of the constraints allows for greater flexibility in the spatial distribution of stations. In particular, the spillover effect made possible by the summation over $\mathcal{N}(h)$ allows for the coverage of demand in peripheral or low-density areas without necessarily requiring the direct installation of infrastructure in those zones. This aspect is crucial in heterogeneous territorial contexts such as the Province of Brescia, which features a mix of densely populated urban areas and less-served rural zones.
The application of this formulation to the case study resulted in global figures consistent with the base model: 1,623 stations allocated, a daily demand covered of 28,010.36 kWh, and a total estimated daily demand of 34,500.45 kWh, equivalent to an overall coverage rate of 81.2%. However, the resulting spatial distribution differs notably, with a more equitable allocation of resources and improved accessibility to charging infrastructure in peripheral areas. This outcome highlights the validity of modeling the interaction between hexagons, as it enables an effective trade-off between demand coverage efficiency and spatial fairness in resource allocation.
Despite the observed benefits, the model confirms that with the current availability of 1,623 stations, full demand coverage across the province is still not achievable.

6.2.3 Model 3: Aggregated Neighborhood Demand Attenuation Factor

The Aggregated Neighborhood Demand model with an attenuation factor introduces an additional refinement to the spatial distribution of charging stations by accounting for the diminishing effect of neighboring stations on local demand coverage. In this formulation, the total daily demand covered in each hexagon is no longer simply the sum of the local station capacity and the aggregated capacity of neighboring hexagons. Instead, a coefficient $\alpha \in [0, 1]$ is introduced to modulate the contribution from adjacent hexagons. This attenuation factor reflects the reduced effectiveness of neighboring stations in fulfilling the demand for a given hexagon as the distance from the station increases or as accessibility decreases.
The objective of the model remains consistent with the previous versions: the goal is to allocate a total of p charging stations among the hexagons in the province of Brescia to maximize the total daily demand covered across all hexagons. However, the introduction of the attenuation factor alters the dynamics of the demand coverage. Specifically, the contribution from neighboring hexagons is reduced by the factor α, which allows for a more nuanced modeling of the interaction between hexagons.
The decision variables in this formulation are as follows: - $x_h \in \mathbb{Z}_{\geq 0}$ represents the number of charging stations installed in hexagon h, - $y_h \in [0, D_h]$ represents the amount of daily demand covered in hexagon h, where D_h is the total daily demand for that hexagon.
The model is subject to the following constraints:

1. **Total Station Limit**:

$$\sum_{h=1}^{n} x_h \leq p$$

This constraint ensures that the total number of charging stations installed across all hexagons does not exceed the maximum allowable number p.

2. **Local Demand Constraint**:

$$y_h \leq D_h \quad \forall h$$

The demand covered in each hexagon cannot exceed the total local demand D_h, ensuring that the model does not overshoot the actual electricity demand in any given area.

3. **Demand Coverage by Local and Neighboring Stations with Attenuation**:

$$y_h \leq \text{cap} \cdot \left(x_h + \alpha \cdot \sum_{j \in \mathcal{N}(h)} x_j \right) \quad \forall h$$

This constraint allows the demand in hexagon h to be covered not only by the stations installed within hexagon h but also by the stations in neighboring hexagons within a 1-ring distance, denoted by the set $\mathcal{N}(h)$. The contribution of the neighboring stations is scaled by the factor α, where $0 \leq \alpha \leq 1$, to account for the fact that the further the stations are from the target hexagon, the less effective they are in meeting the demand.
The objective function of the model is to maximize the total daily demand covered across all hexagons:

$$\max \sum_{h=1}^{n} y_h$$

This maximization ensures efficient demand coverage by considering both local needs and the influence of neighboring infrastructure, modulated by the attenuation factor α. Unlike previous models that fully counted neighboring capacity, this formulation introduces a more realistic spatial interaction, acknowledging that accessibility to stations diminishes with distance. The parameter α provides flexibility: lower values prioritize local coverage, while higher values allow greater spillover from adjacent hexagons, reflecting real-world user behavior.
Applying this model to the case study produces the same aggregate results as previous approaches: 1,623 stations are allocated, covering 28,010.36 kWh of daily demand out of a total of 34,500.45 kWh—an overall coverage rate of 81.2%. Nevertheless, the spatial distribution differs: the attenuation effect shifts station allocation toward high-demand zones, while peripheral areas are primarily served by their own infrastructure rather than distant stations.
This refined allocation strategy improves spatial equity and infrastructure efficiency, but it also underlines the current system's limitations. Even with optimized placement, the existing capacity falls short of covering total demand, highlighting the need for continued investment in charging infrastructure to support growing electric vehicle adoption.

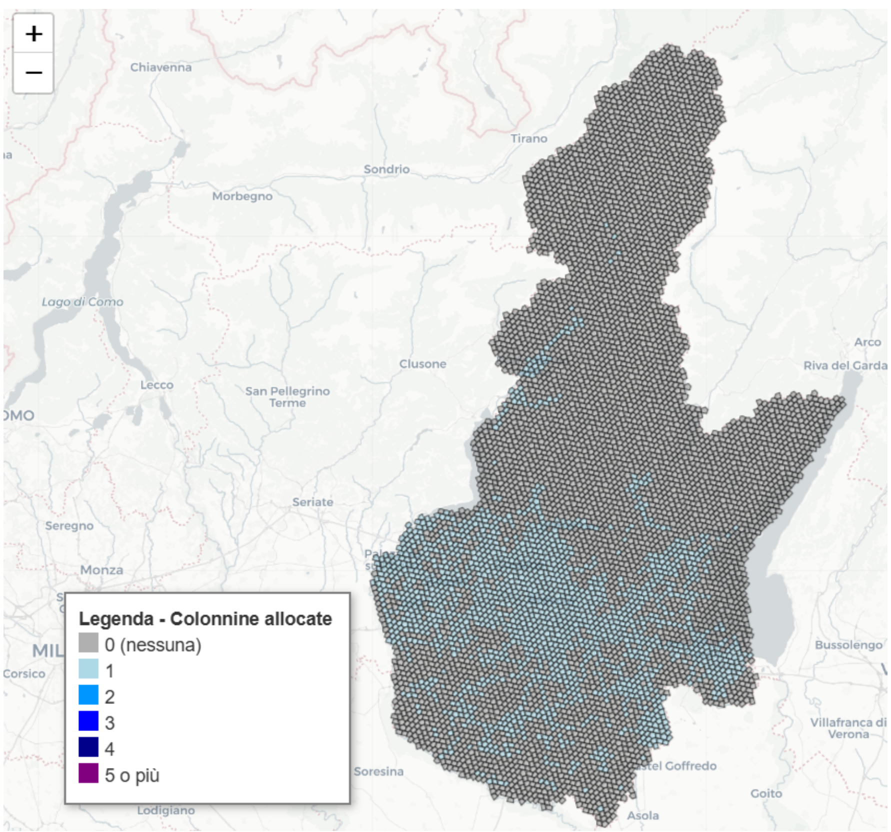


Figure 5. Aggregated neighborhood demand model with attenuation factor visualization.

6.3 2030 conservative models

6.3.1 Model 4: Aggregated Neighborhood Demand

This model estimates the allocation of 4,039 charging stations across the province of Brescia under a conservative 2030 scenario, which anticipates significant increases in electricity demand. Building upon the Aggregated Neighborhood Demand approach, the model accounts for the capacity contributions from neighboring stations to cover local demand. However, it introduces the additional constraint of a maximum of 10 stations per hexagon, reflecting practical infrastructure limitations. Notably, the model excludes the building index, as predicting future building locations and numbers would require a separate, dedicated analysis.

The formulation of this model closely follows that of the Aggregated Neighborhood Demand model, with the main objective being the maximization of total covered daily electricity demand. In this version, the demand coverage for each hexagon is determined by both its own installed stations and the contributions from neighboring hexagons, with the latter being modulated by an attenuation factor. The primary constraints include the total number of stations, the local demand limits, and the maximum capacity per hexagon. The added limitation of a maximum of 10 stations per hexagon ensures that the allocation is feasible within the planning constraints.

The 2030 Conservative Scenario allocates a total of 4,039 charging stations across Brescia, resulting in a total demand coverage of 2,243,381.77 kWh, out of an estimated total demand of 10,009,341.21 kWh. This corresponds to a coverage rate of approximately 22.4%. Although the number of allocated stations is significantly larger than in earlier models, the coverage rate remains relatively low, which highlights the substantial increase in electricity demand projected for 2030.

A comparison with the results from previous models reveals the growing challenge of meeting demand:

- **Base Model (Maximum Coverage)**: Allocated 1,623 stations, covering 28,010.36 kWh out of a total demand of 34,500.45 kWh, yielding a coverage rate of 81.2%.
- **Aggregated Neighborhood Demand Model**: Also allocated 1,623 stations, covering 28,010.36 kWh out of 34,500.45 kWh, with a coverage rate of 81.2%. This model improved spatial equity by considering the spillover from neighboring stations.
- **2030 Conservative Scenario**: Despite allocating 4,039 stations, the coverage rate in this scenario drops to 22.4%, underlining the mismatch between station allocation and the increased demand.

This comparison emphasizes the growing gap between station availability and the increasing demand. Although the number of stations in the 2030 model is much higher, the surge in demand has resulted in a much lower coverage rate, demonstrating the challenge of scaling infrastructure to meet future needs. Moreover, it underscores that merely increasing the number of stations is not sufficient; the strategic placement of these stations is critical to ensuring adequate coverage, especially in areas with concentrated or high demand.

The results of the 2030 Conservative Scenario highlight a pressing need for substantial investment in charging infrastructure. While a larger number of stations are allocated, they do not suffice to meet the demand surge anticipated by 2030. The findings stress the importance of not only expanding the charging network but also strategically deploying stations to maximize coverage efficiency. To meet the future demands of electric vehicle users, continued development of infrastructure is essential, particularly in areas where demand is expected to grow the most. As the province of Brescia anticipates a sharp increase in electricity consumption, this model underscores the necessity of adapting the planning of charging stations to ensure equitable and widespread access to electric vehicle infrastructure.

6.3.2 Model 5: Aggregated Neighborhood Demand Attenuation Factor

This model builds upon the previous formulations and presents an updated allocation strategy for the 2030 conservative scenario, where the demand for electricity is anticipated to increase substantially. The model allocates 4,039 charging stations across the province of Brescia, considering the capacity of both local stations and those from neighboring hexagons, as in earlier models. However, it introduces a key difference in the allocation process, focusing on refining station placement to optimize coverage within the given constraints.
Similar to the previous models, the objective of this model is to maximize the total daily electricity demand covered across all hexagons, while respecting the total station limit and local demand constraints. The contribution of neighboring stations is accounted for to improve coverage in areas where demand may exceed the local station capacity. Additionally, the model enforces a total number of 4,039 stations and considers a maximum of 10 stations per hexagon to ensure feasibility within the provincial planning limits.
The model allocates 4,039 charging stations, covering a total demand of 2,243,381.77 kWh out of an estimated total demand of 10,009,341.21 kWh, resulting in a coverage rate of 22.4%. Although the number of stations is the same as the previous model, the coverage rate remains relatively low. This is indicative of the significant increase in demand expected by 2030, which outpaces the capacity of the allocated charging stations.
A comparison with earlier models reveals the challenges of meeting growing demand:

- **Base Model (Maximum Coverage)**: Allocated 1,623 stations, covering 28,010.36 kWh out of a total demand of 34,500.45 kWh, resulting in a coverage rate of 81.2

- **Aggregated Neighborhood Demand Model**: Also allocated 1,623 stations, covering 28,010.36 kWh out of 34,500.45 kWh, with a coverage rate of 81.2%. This model incorporated the influence of neighboring stations for improved spatial equity.

- **2030 Conservative Scenario**: Allocated 4,039 stations, covering 2,243,381.77 kWh out of 10,009,341.21 kWh, yielding a coverage rate of 22.4

- **Alpha – 2030 Conservative Scenario**: Same allocation and demand coverage as the previous scenario (4,039 stations, 22.4% coverage), but with a refined strategy aimed at further optimizing spatial distribution.

This comparison underscores the challenge of scaling infrastructure to meet increasing electricity demand. Despite a much higher number of charging stations being allocated in the 2030 models, the rapid growth in demand has resulted in a much lower coverage rate.

The results of the Fifth Model (Alpha – 2030 Conservative Scenario) further reinforce the critical need for continued expansion and strategic placement of electric vehicle charging stations. While the allocation of 4,039 stations represents a substantial investment, the rapid rise in electricity demand indicates that future planning must consider not only the quantity of charging stations but also their optimal distribution. To address the anticipated demand and ensure equitable access across Brescia, infrastructure investments must be further scaled up and strategically deployed to keep pace with the growing number of electric vehicles. This model highlights the importance of dynamic and adaptable planning in the development of charging station networks.

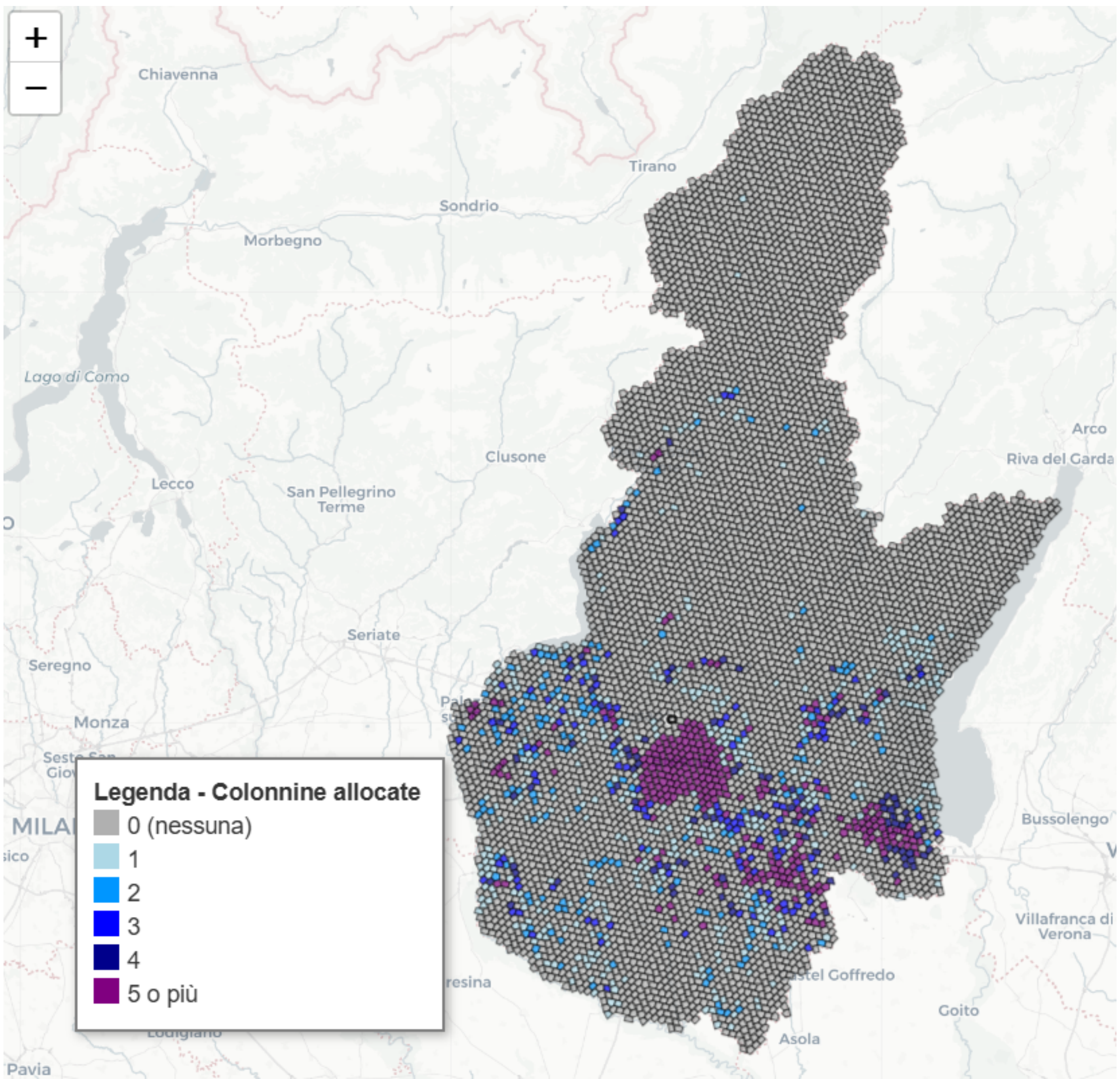


Figure 6. Aggregated neighborhood demand model with attenuation factor visualization for 2030 conservative model.

6.4 2030 optimistic models

6.4.1 Model 6: Aggregated Neighborhood Demand

This model presents the allocation strategy for the province of Brescia under an optimistic 2030 scenario, characterized by an even higher projected electricity demand and a larger planned infrastructure deployment. A total of 7,435 charging stations are allocated across the territory. As with previous future-oriented models, the building index was excluded from this analysis, as predicting future building locations and counts would require a separate and dedicated study.
The structure of this model follows the logic established in previous models, where the objective is to maximize the total covered daily demand while considering the capacity contributions from both local and neighboring charging stations. The key constraints enforce the total allocation limit and the cap on local demand coverage. In this scenario, the total number of charging stations is increased to 7,435 units, reflecting a more ambitious infrastructure plan for 2030.
Under this optimistic scenario, the model allocates 7,435 charging stations, achieving a total covered demand of 4,129,622.05 kWh out of an estimated total demand of 15,014,065.22 kWh. This results in a coverage rate of 27.5%.
While the number of stations is significantly higher compared to both the conservative 2030 scenario and earlier models, the coverage rate, although improved, still indicates a gap between available infrastructure and projected demand.

- **Base Model (Maximum Coverage)**: 1,623 stations allocated, covering 28,010.36 kWh out of 34,500.45 kWh, yielding a coverage rate of 81.2%.
- **Aggregated Neighborhood Demand Model**: 1,623 stations allocated, covering 28,010.36 kWh out of 34,500.45 kWh (81.2% coverage), with improved spatial distribution.
- **2030 Conservative Scenario (with and without Alpha)**: 4,039 stations allocated, covering 2,243,381.77 kWh out of 10,009,341.21 kWh, resulting in a coverage rate of 22.4%.
- **2030 Optimistic Scenario**: 7,435 stations allocated, covering 4,129,622.05 kWh out of 15,014,065.22 kWh, achieving a 27.5% coverage rate.

The results of the 2030 Optimistic Scenario highlight the challenge of keeping infrastructure growth aligned with the accelerating demand for electric vehicle charging. While increasing the number of allocated stations to 7,435 has led to a notable improvement in coverage compared to the conservative scenario, the coverage rate remains below one-third of the projected demand.
This finding underscores the necessity for both scaling up infrastructure and adopting strategic placement methodologies to ensure effective coverage, particularly in high-demand zones. As such, even in optimistic planning contexts, ongoing investment and adaptive planning will be essential to meet future mobility needs in the province of Brescia.

6.4.2 Model 7: Aggregated Neighborhood Demand Attenuation Factor

This model extends the allocation strategy for the province of Brescia under the optimistic 2030 scenario, by incorporating the alpha-based neighborhood contribution mechanism. It follows the same demand projections as the standard optimistic model but allows partial contributions from neighboring hexagons, attenuated by a coefficient α. As before, the building index is excluded due to the complexities involved in forecasting future constructions.

The mathematical structure mirrors the Aggregated Neighborhood Demand with Attenuation model presented earlier. The model aims to maximize the total covered demand while allowing neighboring stations to contribute to demand coverage, weighted by the attenuation factor α. The station allocation is capped at 7,435 units, and standard constraints on local demand and station capacity apply.

In this optimistic scenario with the alpha mechanism, the model allocates 7,435 charging stations, covering a total demand of 4,129,622.05 kWh out of an estimated 15,014,065.2 kWh. This corresponds to a coverage rate of 27.5%, identical to the standard optimistic scenario.

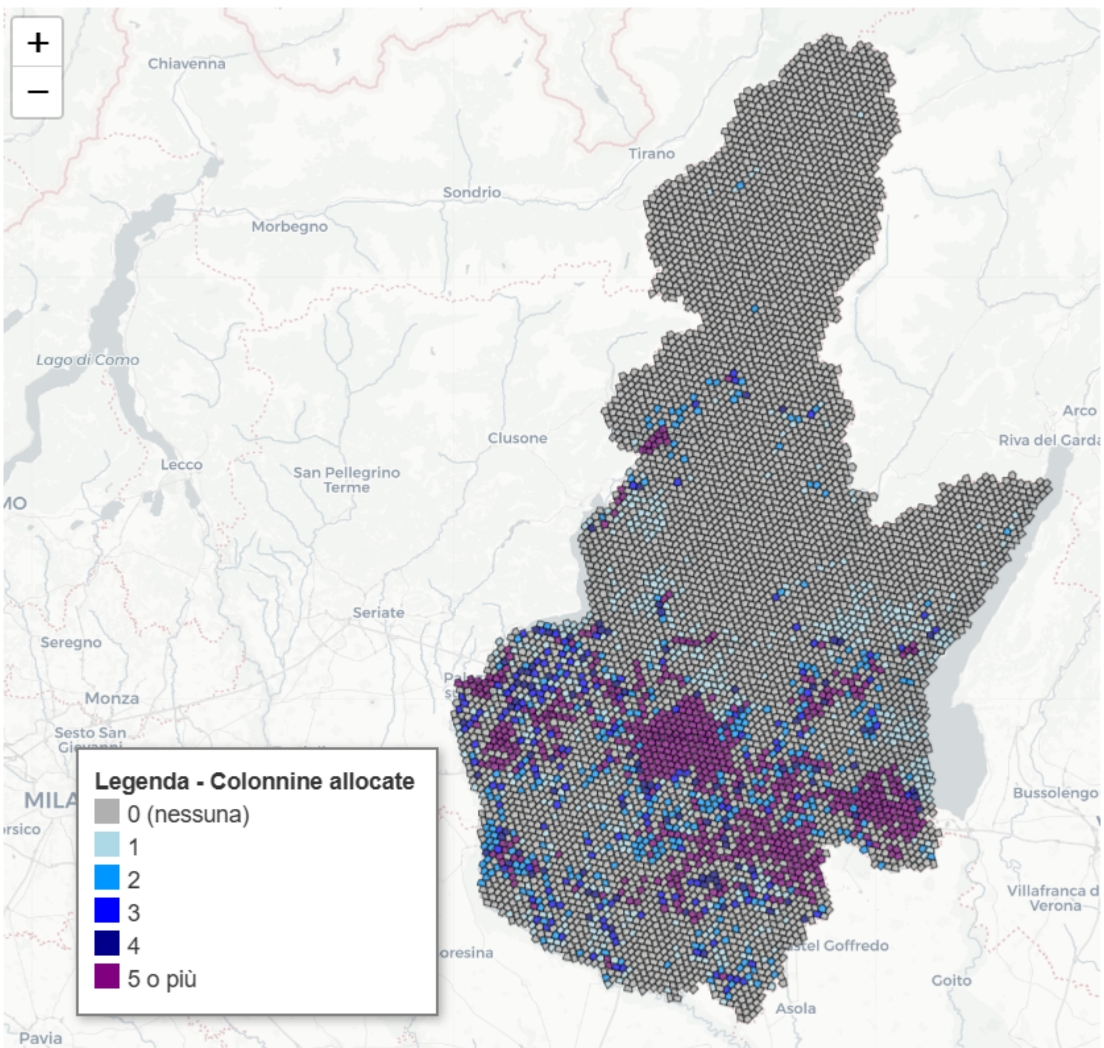


Figure 7. Aggregated neighborhood demand model with attenuation factor visualization for 2030 optimistic model.

6.5 Comparison with Previous Models

- **Base Model (Maximum Coverage)**: 1,623 stations, covering 28,010.36 kWh out of 34,500.45 kWh (81.2% coverage).
- **Aggregated Neighborhood Demand Model**: 1,623 stations, covering 28,010.36 kWh out of 34,500.45 kWh (81.2% coverage).
- **2030 Conservative Scenario (with and without Alpha)**: 4,039 stations, covering 2,243,381.77 kWh out of 10,009,341.21 kWh (22.4% coverage).
- **2030 Optimistic Scenario (with and without Alpha)**: 7,435 stations, covering 4,129,622.05 kWh out of 15,014,065.22 kWh (27.5% coverage).

The results show that, in this case, the application of the alpha-based neighborhood attenuation mechanism does not alter the total coverage outcome compared to the standard optimistic scenario. This suggests that at the scale of 7,435 allocated stations, the network has reached a saturation point where the additional contribution from neighboring hexagons no longer shifts the overall coverage rate.
Nevertheless, the alpha mechanism continues to play a crucial role in improving spatial equity and local accessibility, particularly in regions with dispersed or uneven demand. As infrastructure density increases, further improvements in overall coverage will likely depend more on expanding capacity or integrating demand-side management strategies, rather than on redistributive effects alone.

7 Conclusions

7.1 Summary of Key Findings

The analysis carried out in this study shows that, even when considering optimistic scenarios such as the 2030 demand projections used mainly for sensitivity analysis, the planned charging infrastructure will not be sufficient to meet the expected electric vehicle (EV) charging demand in the Province of Brescia by 2030.
Both the conservative and the more optimistic allocation models, developed within a relaxed version of the Maximum Coverage Problem framework and supported by detailed spatial demand aggregation using the H3 hexagonal grid system, consistently highlight that a significant portion of daily charging demand remains unmet, even in cases where the number of installed stations is substantially increased.
The results are based on solid and up-to-date data from ISTAT, Motus-E, ACI, and regional energy reports, and they align with broader European trends in electric mobility, where the development of infrastructure often fails to keep pace with the growth of electric vehicles [1].
The modeling approach proved effective in identifying territorial gaps and in proposing station locations that maximize coverage. It also emphasized the importance of spatial distribution in managing demand imbalances between urban and peripheral areas. This confirms the relevance of spatially explicit models in supporting planning decisions and in evaluating the adequacy of infrastructure. Nonetheless, the analysis was constrained by limited data availability, both in terms of spatial and socioeconomic detail. For instance, relevant factors such as income levels, land use characteristics, or vehicle ownership patterns could not be included, as they were not accessible at the necessary level of granularity. Incorporating such variables could further refine the model's ability to reflect real-world dynamics and improve the robustness of infrastructure planning.
In conclusion, the findings reveal a clear and persistent shortfall in charging infrastructure that calls for urgent action and well-targeted strategies to enable a sustainable and balanced transition to electric mobility.

7.2 Policy and Planning Implications

The results of this analysis suggest that current infrastructure deployment plans are insufficient to meet future charging demand, even under optimistic projections. This has direct implications for both public policy and infrastructure planning at the provincial and regional level.
One of the key insights emerging from the model is the spatial mismatch between demand concentration and infrastructure coverage. Areas with high projected charging needs do not always coincide with areas receiving the greatest infrastructure investments. This indicates that expanding the number of charging stations, while necessary, may not be effective unless guided by spatial demand analysis [8, 10].
Planning strategies should therefore integrate spatially explicit tools to identify priority areas for station deployment. The use of optimization-based allocation models can support more efficient resource allocation by maximizing coverage where it is most needed, particularly in peripheral or underserved zones. This is especially relevant for aligning EV infrastructure development with broader mobility and sustainability goals,

including access equity.
Furthermore, the results emphasize the need for coordination across different planning domains. Integrating EV charging strategies with urban planning, land use policies, and energy network capacity is essential to ensure the viability and effectiveness of future infrastructure investments. Without this coordination, there is a risk that new stations will face deployment barriers related to local constraints or grid limitations.
The findings also point to a potential role for policy incentives and funding mechanisms that encourage not only the expansion of infrastructure but also its strategic placement. Public funding programs and regional initiatives could benefit from incorporating model-based evaluations into their planning criteria, thereby improving the targeting and long-term impact of investment decisions.

7.3 Future Improvements

While the modeling approach adopted in this study provided valuable insights into the infrastructure gap and offered a solid foundation for spatial allocation analysis, several aspects could be improved in future developments.
A first limitation lies in the assumption of static demand and uniform station capacity. These simplifications, while useful for interpretability and computational tractability, do not fully reflect the evolving nature of electric vehicle usage. Introducing dynamic demand projections that account for temporal variations in charging behavior, seasonal mobility patterns, or long-term adoption trends would make the model more responsive to real-world conditions [24].
Additionally, the model does not currently incorporate the location or capacity of existing charging infrastructure. This omission may lead to allocation patterns that are optimal in theory but less applicable in practice. Integrating up-to-date data on existing stations would help generate more realistic and context-aware deployment scenarios, reducing the risk of redundancy and improving the feasibility of suggested interventions.
Another area of potential improvement is the optimization algorithm itself. The linear programming approach used here is suitable for small to medium-scale problems and offers a high degree of interpretability. However, as the scope of the problem expands, more scalable methods may be required. Heuristic and metaheuristic algorithms, such as greedy methods, genetic algorithms, or simulated annealing, could provide faster solutions while allowing for the inclusion of complex constraints, such as budget heterogeneity, land-use limitations, or power grid availability [12].
Lastly, future work could explore the integration of behavioral factors and user preferences into the allocation process. Considering variables such as routing patterns, preferred charging locations, or station reliability would add a further layer of realism to the model and enhancing its value as a decision-support tool for public and private stakeholders involved in electric mobility planning, and paving the way for more effective and user-centered infrastructure deployment.

References

[1] International Energy Agency. *Global EV Outlook 2023*. Accessed: 2025-05-14. 2023. URL: https://www.iea.org/reports/global-ev-outlook-2023.

[2] Geoff Boeing. *OSMnx: Acquiring, Constructing, Analyzing, and Visualizing Street Networks from OpenStreetMap*. Working Paper. Accessed: 2025-05-18. University of Southern California, 2017. URL: https://github.com/gboeing/osmnx.

[3] Francesco Cenci and Paolo Luciani. *Optimal Planning and Allocation of Electric Vehicle Charging Stations in Urban Areas*. Working Paper. Accessed: 2025-05-18. Università degli Studi Roma Tre, 2024. URL: https://iris.uniroma3.it/retrieve/b92562b0-b60c-4e00-a859-076e6870c6f1/Cenci_Luciani_Annali_2024_p.23_47.pdf.

[4] Richard Church and Charles ReVelle. "The maximal covering location problem". In: *Papers in Regional Science* 32.1 (1974), pp. 101–118.

[5] Mark S. Daskin. *Network and discrete location: models, algorithms, and applications*. John Wiley & Sons, 1995.

[6] Dataset Engineer. *EV Charging Station Data - California Region*. https://www.kaggle.com/datasets/datasetengineer/ev-charging-station-data-california-region. Accessed: 2025-05-18. 2024.

[7] S. L. Hakimi. "Optimum locations of switching centers and the absolute centers and medians of a graph". In: *Operations Research* 12.3 (1964), pp. 450–459.

[8] Yinyu He, Bala Venkatesh, and Liang Guan. "Optimal deployment of public charging stations for plug-in hybrid electric vehicles". In: *IEEE Transactions on Smart Grid* 3.4 (2013), pp. 471–479.

[9] Andreas Klose and Andreas Drexl. "Facility location models for distribution system design". In: *European Journal of Operational Research* 162.1 (2005), pp. 4–29.

[10] Wentao Kong et al. "Charging station location optimization for balancing the performance of battery electric vehicles". In: *Transportation Research Part C: Emerging Technologies* 98 (2019), pp. 1–18.

[11] Akansh Kumar. *Data Science Optimal EV Station Placement*. https://github.com/akansh12/data-science-Optimal-EV-station-placement. Accessed: 2025-05-18. 2024.

[12] Shoubo Luo, Han Yu, and Jie Zhang. "Fast-charging electric vehicle stations: Locating for heterogeneous users under urban constraints". In: *Transportation Research Part B: Methodological* 157 (2022), pp. 1–21.

[13] Motus-E. *Le infrastrutture di ricarica a uso pubblico in Italia 2024*. Accessed: 2024-09-18. 2024. URL: https://www.motus-e.org/wp-content/uploads/2025/03/Motus-E.-Le-infrastrutture-di-ricarica-a-uso-pubblico-in-Italia-2024.pdf.

[14] Motus-E. *Strategy Motus-E Report: Infrastrutture di Ricarica a Uso Pubblico al 2035*. Accessed: 2024-09-18. 2024. URL: https://www.motus-e.org/wp-content/uploads/2024/11/2024.11.06_Strategy_Motus-E_Report-IdR@2035_vFinal.pdf.

[15] Piattaforma Unica Nazionale. *Territory - BEV*. Accessed: 2024-09-18. 2024. URL: https://www.piattaformaunicanazionale.it/territory-bev.

[16] Piattaforma Unica Nazionale. *Territory - Infrastrutture di Ricarica*. Accessed: 2024-09-18. 2024. URL: https://www.piattaformaunicanazionale.it/territory-idr.

[17] Yashu Singhal. *Electric Vehicle Population Dataset*. https://www.kaggle.com/datasets/yashusinghal/electric-vehicle-population-dataset. Accessed: 2025-05-18. 2024.

[18] Istituto Nazionale di Statistica (ISTAT). *Altimetria e superficie dei comuni*. Accessed: 2025-05-01. 2024. URL: https://www.istat.it/classificazione/principali-statistiche-geografiche-sui-comuni/.

[19] Istituto Nazionale di Statistica (ISTAT). *Autovetture elettriche nei comuni capoluogo di provincia*. Accessed: 2025-05-01. 2024. URL: https://aster.istat.it/#/it/ast/categories/7/URBAN_ENV/URBAN_ENV_ENE/IT1,DF_DCCV_URBANENV_ENE4_609_1,1.0.

[20] Istituto Nazionale di Statistica (ISTAT). *Parco veicolare per tipo di veicolo e comune*. Accessed: 2025-05-01. 2024. URL: https://aster.istat.it/#/it/ast/categories/43/203/IT1,41_993,1.0.

[21] Istituto Nazionale di Statistica (ISTAT). *Popolazione residente per stato civile e sesso al 1° gennaio*. Accessed: 2025-05-01. 2024. URL: https://aster.istat.it/#/it/ast/categories/PF/PF_P/POP_1JAN/IT1,DF_22_289_COMUNISEXCIV,1.0.

[22] Istituto Nazionale di Statistica (ISTAT). *Rapporto Annuale 2024*. Accessed: 2025-05-12. 2024. URL: https://www.istat.it/it/files/2024/05/Rapporto-Annuale-2024.pdf.

[23] Costis Toregas et al. "Location of emergency service facilities". In: *Operations Research* 19.6 (1971), pp. 1363–1373.

[24] Yuyue Wang et al. "A realistic EV charging demand model and its application in locating charging facilities". In: *Applied Energy* 188 (2017), pp. 103–113.