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Optimal Placement of EV Charging Stations Using GIS and Optimization Techniques

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ABSTRACT

Electric vehicles (EVs) are increasingly popular and need reliable, accessible and efficient charging infrastructure. But the current and uneven spatial distribution of EV demand, road accessibility differences, limited service coverage and impacts on the electrical grid make it inefficient to deploy charging stations uniformly. This study suggests an optimization framework that combines "Geographic Information System (GIS)" capabilities to achieve the optimal location and size of "Electric Vehicle Charging Stations (EVCS)". The methodology is based on the HERO Geospatial EV Charging Demand Dataset; it includes 5 x 5 km² grid-based EV-density estimation, road-classification weighting, Candidate POI generation, Maximum covering location optimization, Voronoi-based service-area allocation and charger sizing using knapsack. The results show that there is a notable spatial difference in EV demand, from between 18 and 130 EVs/grid. The power loss was reduced with optimized placement and charger size by approximately 62% at 10 km, 84% at 25 km and 96% at 50 km with average distance rising from 8.7 km to 18.9 km. The authors conclude that incorporating GIS and optimization offers a systematic and scalable solution to EV charging infrastructure planning, meeting demand and providing a sustainable approach.

KEYWORDS: *Electric Vehicle Charging Stations (EVCS), Geographic Information System (GIS), EV Charging Demand, Optimal Location Allocation, Maximum Covering Location Problem, Charger Sizing Optimization.*

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1. INTRODUCTION

High energy and environmental costs of transportation exist due to the energy consumed by transportation, emission of air pollutants and greenhouse gases from conventional internal combustion vehicles [1]. An alternative that has come to the fore are Electric Vehicles (EVs) which utilize electricity instead of fossil fuels and can emit lower amounts of pollutants. Consumers awareness, environmental regulations, technology advances and drop in battery prices and government support are some of the factors that have propelled their use worldwide [3]. This however requires a sufficient and accessible charging network [4]. EV charging station types include slow, moderate, fast and ultra-fast stations appropriate in various applications and locations: residential, or along highway corridors [5-7]. Unfortunately, poorly planned networks result in underutilized stations or an overcrowded network, both leading to range anxiety and decreasing user confidence [8-9]. Spatial, economical, environmental and transportation aspects should therefore be taken into consideration for optimal placement, such as the travel demand, population distribution, road accessibility, electricity infrastructure and land use [10-11].

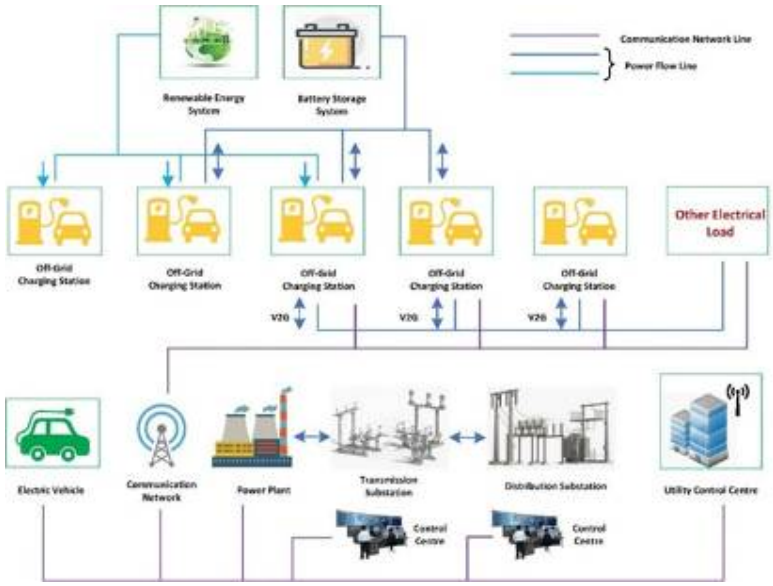


Figure 1: Schematic diagram of charging infrastructure for electric vehicle

Geographic Information Systems (GIS) are an integral part of this process as they allow the use and analysis of spatial information on roads, population density, land use and existing charging infrastructure [12-13]. When used in conjunction with "Multi-Criteria Decision Analysis (MCDA)", GIS helps planners assign weights and rank priority criteria, and combine them to create suitability maps which rank areas according to the suitability of locating charging stations [14]. These suitability zones are further refined to give exact optimal locations through optimization techniques like location-allocation modeling, linear and integer programming, genetic algorithms and particle swarm optimization [15].

There are five key sections of the paper. Section 1 provides an introduction to problems of EV charging infrastructure and research objectives. The previous section (2) critically examines the previous studies conducted on GIS, MCDA and optimization based studies regarding EVCS and pinpoints the research gaps. In Section 3, the proposed methodology chosen is explained, comprising the data set collection, preprocessing, EV-density estimation, service-area allocation, and charger sizing process. Section 4 presents results based on coverage, distance, demand and power-loss. The study is completed in Section 5, which points to the effectiveness of the optimization using GIS.The study is aimed at:

- To analyze the spatial and demand-related factors (population density, traffic patterns, land use, road accessibility and electricity infrastructure) that influence optimal EV charging station placement.
- To develop a GIS-based Multi-Criteria Decision Analysis (MCDA) framework for evaluating and mapping site suitability across different geographic zones.
- To apply optimization techniques (e.g., location-allocation modeling, genetic algorithms) to identify the most efficient and cost-effective candidate locations from GIS-derived suitability zones.
- To assess region-specific challenges and opportunities, particularly in the Indian context, for planning a flexible, scalable charging network across varied urban, semi-urban and rural settings.

2. Literature Review

Bishal and Hussein (2026) [16] proposed an integrated Genetic Algorithm (GA)–Analytic Hierarchy Process (AHP) based system for optimal location of Electric Vehicle Charging Station (EVCS) is proposed. Based on integrating TOPSIS and NSGA-III, Zhang et al. (2025) [17] built a multi-objective EVCS location model for Lanzhou City. Construction cost, user satisfaction and convenience were all taken care for at the same time. Model produced 232 acceptable sites, many of which were in business and metro areas, consistent with EV usage. Razeghi et al. (2024) [18] studied the placement of solar-powered EV charging stations by considering geological, technical, economic and environmental factors, by analyzing the ArcGIS 10.8.2. The findings showed that out of the total number of investigated cities 90% had the potential to be powered in this way.

Fotis et al. (2024) [19] proposed a Binary Random Dynamic Arithmetic Optimization Algorithm (BRDAOA) to solve the placement of EVCS in an IEEE 33-bus distribution network from an electrical-grid point of view. Loss Sensitivity Factor (LSF), system voltage and real-power load and system losses were taken into account to locate suitable charging sites. Choi et al. (2024) [20] conducted a study on EVCS relocation and optimisation with the

aim of determining the location and the optimisation of EVCS, based on urban and transportation parameters, such as parking availability, public-transport connectivity, and land-use planning. It was revealed that only 63% of fast charging stations, where selected stations were relocated to petrol stations, reduced travel distance, travel time and resulted in a significant carbon emission reduction.

Charley et al. (2023) [21] used a GIS based approach to identify community EV charging sites in Dublin. 770 excellent sites were found for initial charging stations and another 3,080 were identified as suitable for future installation based on 2030 needs. Over large geographical areas, Prakobkaew et al. (2023) [22] suggested a Grid Partitioning optimization algorithm along with GIS for the location and size optimisation of EVCSs. The approach involved the use of a maximum coverage location modelling, integer programming, a knapsack problem and Voronoi diagrams. El Hafdaoui et al. (2023) [23] presented an EVCS placement model based on the genetic algorithm method that considers traffic, population, parking areas, gas station, road width, power availability, vehicle autonomy, cost, and ambient temperature. Optimized locations were communicated using interaction GIS maps. Alanazi et al. (2023) [24] investigated demographic disparities in EVCS accessibility in the United States, taking into account social, economic and environmental factors. Their linear-regression analysis was able to hit the mark in 90% of cases, and achieved 94% precision, 89% recall, and a 91% F1-score, and Texas was the region that outperformed other areas analyzed on how well EVCS can be placed. Deeum et al. (2023) [25] studied the placement of EVCS in a distribution grid with photovoltaic (PV) and battery energy-storage system (BESS). The study optimized EVCS locations using GA and forward-backward sweep analysis minimizing the active and reactive power losses.

A significant advancement of EVCS optimization via mathematical, metaheuristic and multi-objective, respectively, optimization algorithms and techniques using GIS has been shown. But the approaches that exist are largely focused on just one aspect of the issue, like accessibility, traffic, the economy, the environment, etc., or on the performance of electrical-grids. Few studies consider EV demand dynamics in combination with time-varying traffic, charging-load distribution, renewable-energy generation, and EV adoption and the capacity of the electricity grid in a single spatial optimization framework.

3. Research Methodology

The proposed methodology in figure 2 intends to find the best geographical point and suitable size for installing charging stations for EVs over a large geographical region based on the GIS data and partitioning of the region by grid.

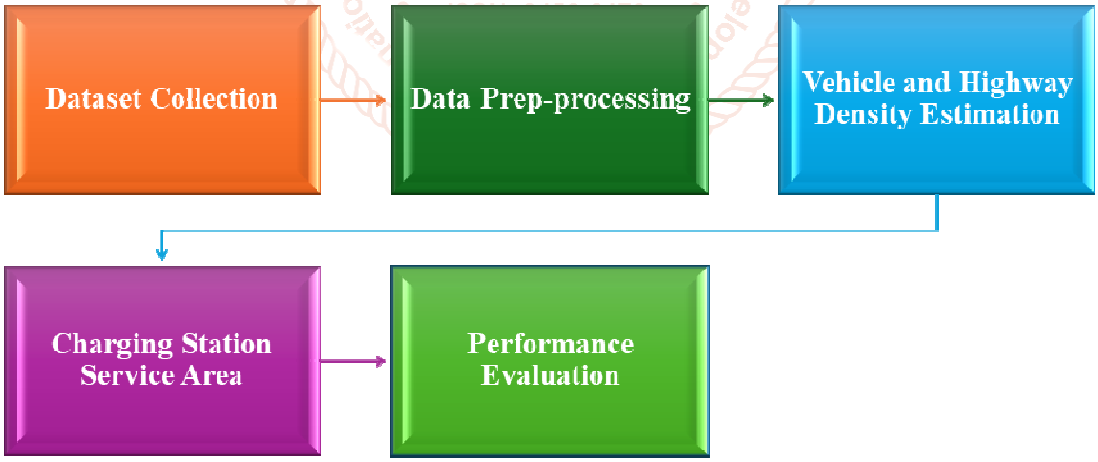


Figure 2: Proposed Methodology

3.1. Dataset Collection

This study leverages the HERO: Geospatial EV Charging Demand Dataset [26] to investigate spatial patterns of EV charging demand and identifies appropriate sites for EV charging stations. The data set includes geographical data on the grid level as well as spatial, transport, infrastructure and demand information. These variables can be used to determine the location areas that have relatively high charging needs and assist in selection of possible charging locations. The dataset has a grid-based structure, which is beneficial for partitioning and spatial analysis using GIS.

3.2. Data Prep-processing

In the absence of optimization, all spatial datasets are first converted to a consistent spatial reference system. The number of duplicated spatial records is diminished and the missing or incorrect coordinates are detected and corrected. Geographically

inaccessible areas, such as dense forestry, mountains, water bodies and limited areas, are not included in the analysis.

➢ **Removal of Duplicate Spatial Records**

The duplicate spatial records are eliminated to prevent duplication of spatial location or charging-related entities. Multiple entries could be misleading for EV-demand estimation, spatial density calculation and optimization. Unique identifiers, latitude and longitude and other attribute values are used to compare each record. The number of different records is:

$$N_{unique} = N_{total} - N_{duplicate} \quad (1)$$

Where: N_{unique} represents the final unique records, N_{total} is the original number of records and $N_{duplicate}$ denotes duplicated records.

➢ **Correction of Missing Coordinates**

GIS-based spatial analysis is preceded by the detection and correction of missing or invalid latitude/longitude values. When a location is missing, incomplete records are looked at based on the information available to them such as geographical references, associated spatial information or the location attributes records have. The fraction where there are missing co-ordinates is:

$$M_R = \frac{N_{missing}}{N_{total}} \times 100 \quad (2)$$

Where: M_R represents the missing-coordinate rate, $N_{missing}$ is the number of records with missing coordinates and N_{total} is the total number of records.

➢ **Conversion of Road Data into GIS-Compatible Layers**

Road-network data is digitized to create GIS compatible vector layers for ease of spatial analysis and accessibility analysis. Road geometries, lengths, intersections, road categories and other attributes are converted into suitable GIS formats. The geographical geometry and the attributes of each road segment are used to represent each road segment. The road layer may be described as:

$$L_{road} = f(G, A) \quad (3)$$

Where: L_{road} represents the GIS road layer, G denotes road geometry and A represents associated road attributes.

➢ **Integration of EV-Registration Data with Geographical Boundaries**

The EV-registration information is linked to administrative or geographical boundaries to estimate the geographical distribution of EV demand. Registered EVs are joined to geographic units by using spatial joins. To highlight those areas more likely to have higher charging needs, EV density is calculated:

$$D_{EV} = \frac{N_{EV}}{A} \quad (4)$$

Where: D_{EV} represents EV density, N_{EV} denotes the number of registered Evs and A represents the geographical area.

➢ **Identification of Existing Charging Stations**

Existing EV charging stations are identified and georeferenced, providing a basis for understanding the spatial distribution of charging infrastructure. Each station is identified by geographic coordinates (latitude and longitude) and, if applicable, by the properties of the stations (charger type, capacity and availability). The number of stations that already exist is represented by:

$$S_{existing} = \sum_{i=1}^{n} S_i \quad (5)$$

Where: $S_{existing}$ denotes the total existing charging stations and S_i represents an individual station.

➢ **Spatial Joining of Vehicle Data with Road and Grid Layers**

Data that relate to vehicles are spatially joined to road networks and grid layers to create relationships between EV demand and transportation infrastructure and geographical locations. The relationship between the vehicles and the spatial elements of the grid or road segment are determined by spatial proximity or by intersections. The spatial join may be represented by:

$$J = V \cap R \cap G \quad (7)$$

Where: J represents the integrated spatial dataset, V denotes vehicle data, R represents road layers and G represents grid-based geographical units.

3.3. Vehicle and Highway Density Estimation

The potential EV charging demand is quantified in different geographical grids and in different transportation corridors using vehicle and highway density estimation. There are different weights given to road segments based on their functional importance (motorways, trunk roads have higher weights than tertiary and unclassified roads). The EV density of each grid is calculated as:

$$D_{EV,i} = \frac{N_{EV,i}}{A_i} \quad (8)$$

Where: $D_{EV,i}$ represents EV density in grid i, $N_{EV,I}$ denotes the estimated number of Evs and A_i represents the grid area.

3.4. Charging Station Service Area

The charging station service area is determined to delineate the geographic area of coverage for each EV charging station selected. This step sets out the connection between the charging-station locations and the EV demand point locations nearby. In order to match each demand location with the best possible charging station, the spatial partitioning method is used. Service areas are created based on Voronoi diagrams and the EV demand is assigned to the related EV station.

➢ Voronoi Diagram

A Voronoi diagram is used to segment the geographic areas into unique service areas for charging stations. The locations in each Voronoi cell are closer to the charging station it contains than to any other charging station. For any Demand Point p, the closest charging station s_i is found based on either Euclidean or GIS distance:

$$s^* = arg\min_{s_i \in S} d(p, s_i) \quad (9)$$

Where: S represents the set of selected charging stations and $d(p, s_i)$ denotes the distance between demand point p and station s_i.

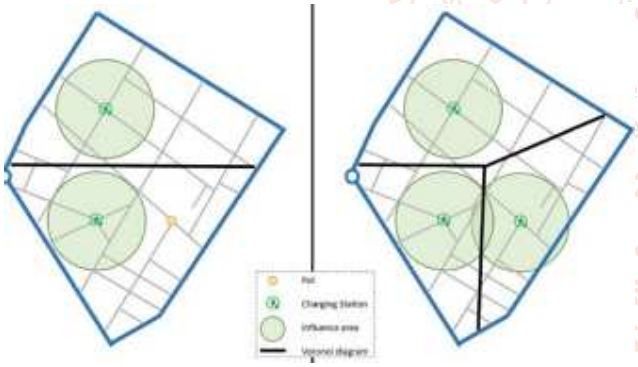


Figure 3: Voronoi-Based Service Areas [27]

➢ EV-to-Charger Ratio

The ratio EV-to-charger is used to estimate the initial charging requirement of each station selected. It is the number of Evs that can get served by one charging unit in the planning period considered. The number of chargers that are assumed to be necessary for station j can be estimated as:

$$N_{c,j} = \left| \frac{D_j}{R_{EV/C}} \right| \quad (10)$$

Where: $N_{c,j}$ represents the required number of chargers at station j, D_j is the estimated EV demand and $R_{EV/C}$ denotes the predefined EV-to-charger ratio.

➢ Knapsack Optimization

Knapsack optimization is used to find out which type and sizes of chargers are best with the capacities of the station. There are different technologies used to charge the product and the technologies may have different prices, offer different powers and may be able to charge the product in different ways. The optimization is performed so as to select the combinations of chargers that allow to charge as much as possible utilising the charging station constraints. The objective can be expressed as:

$$\max Z - \sum_{k=1}^{K} P_k x_k \quad (11)$$

Where: P_k represents the power capacity of charger type k, x_k denotes the number of chargers of type k and K represents the total number of charger types considered.

3.5. Performance Evaluation

➢ Coverage

$$Coverage\ (\%) = \frac{N_{covered}}{N_{total}} \times 100 \quad (12)$$

➢ Average Distance

$$D_{avg} = \frac{1}{N} \sum_{i=1}^{N} d_i \quad (13)$$

➢ EV-to-Charger Ratio

$$R_{EV/C} = \frac{N_{EV}}{N_{charger}} \quad (14)$$

➢ Number of Stations

$$N_{station} = \sum_{j=1}^{J} x_j \quad (15)$$

➢ Potential Power Loss

$$P_{loss} = \sum_{l=1}^{L} I_l^2 R_l \quad (16)$$

➢ Loss-Reduction Percentage

$$LR\ (\%) = \frac{P_{loss,base} - P_{loss,proposed}}{P_{loss,base}} \times 100 \quad (17)$$

4. Result & Analysis

The results and analysis demonstrate the effectiveness of the methodology for placing the EV charging station optimally, using GIS and optimization methods. Analysis takes into account EV density, charging demand, road access, current charging infrastructure and spatial suitability factors.

Figure 4: shows the estimated EV density in 20 representative 5 × 5 km² grid cells. Values between 18 and 130 EVs/grid show a significant spatial variation in charging demand. The estimated density of EVs ranges from 18 EVs in the lowest density grid (1) to 130 EVs in the highest density grid (19). Within this, there are some cells with relatively high demand and these cells would be given a higher priority in candidate POI generation, such as cell number 10, 12, 13, 16, 17, 19, 20.

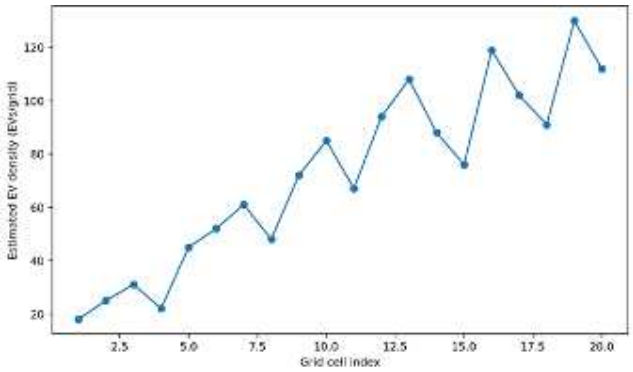


Figure 4: Estimated EV Density Across Grid Cells

Figure 5 is a relative weight given to the road classes used to estimate vehicle and highway densities. It is recognized that motorways have a normalized weight of = 1.00, while the numerical value for trunk roads is 0.85 and the primary roads 0.70. The weight on secondary roads is reduced to 0.50 and the weight on unclassified roads is reduced to 0.15. In this illustrative weighting scheme, the influence of a motorway is around 6.7 times that of an unclassified road, numerically.

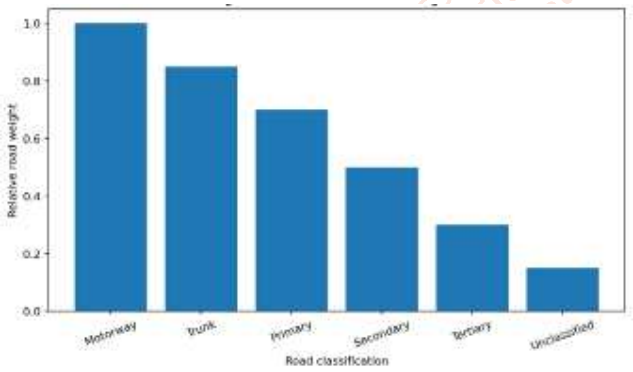


Figure 5: Road Classification Weights

The number of candidate Points of Interest is displayed in figure 6 as a function of the minimum EV-demand. 46 candidate POIs are left at 20 EVs/grid threshold. Having an even higher threshold (e.g., 40, 60, 80 EVs) will narrow down the pool of candidates to 39, 31 and 23. There are 14 candidates left after 100 EVs, 7 candidates are left after 120 EVs. The number of points in the candidate set falls by 39 points on the interval [20, 120] which is equivalent to a reduction of about 85%.

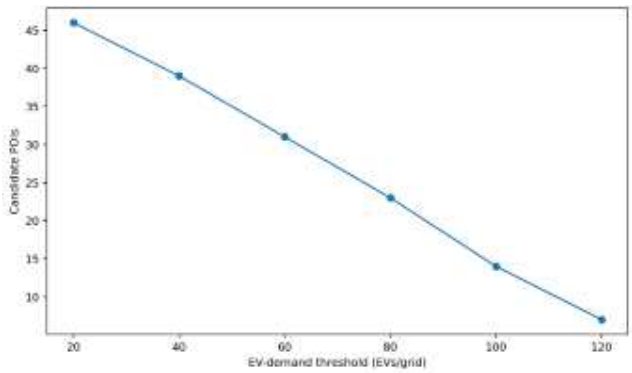


Figure 6: Candidate POIs vs Demand Threshold

The EV demand distribution shown in figure 7 is illustrative and represents the 8 charging stations following the spatial service-area allocation. These serve as the demand levels for these three stations: S4 is 780 EVs, S6 is 690 EVs and S2 is 610 EVs. The lowest assigned demand is at Station S7 (310 EVs). The difference between S4 and S7 is 370 EVs and the demand of S4 is 370/470 times of S7 or 370/470 x 2.52 = 4.52 EVs. This is an "uneven distribution" since Voronoi partitioning assigns demand based on "spatial proximity" and the underlying demand density is not uniform.

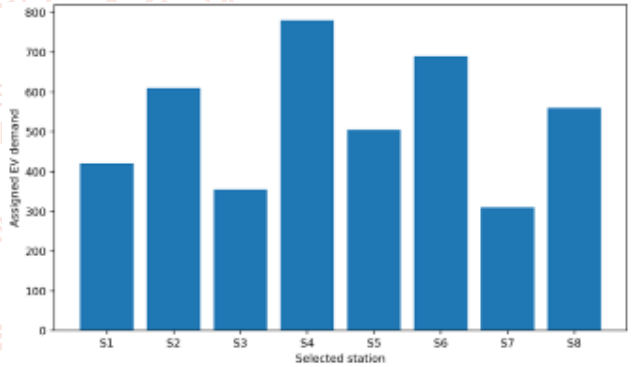


Figure 7: EV Demand Assigned to Selected Stations

The figure 8 relate their estimated EVs demand at each identified station to the number of chargers estimated using an illustrative ratio of EVs per charger at the station of 35. Demand values are between 310 and 780 and would result, after applying the ceiling function, in an approximate number of chargers of 9 to 23. For instance a 420 EV station needs 12 chargers while a station of 780 EVs needs 23 chargers.

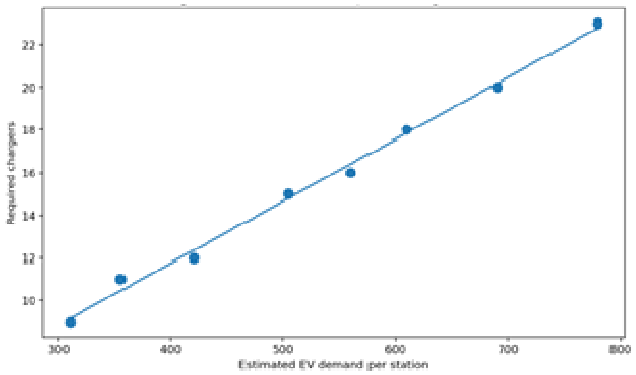


Figure 8: EV Demand vs Required Charger Count

Sensitivity analysis compares service radius of charging stations of 10, 25 and 50 km with the figure 9 showing about 62% charging station coverage is achieved at 42 stations at 10 km service radius. If you increase the radius to 25km, the illustrative number of stations is reduced to 24 and the coverage to 84%. At 50km, 14 stations will cover ~96% and only 14 are needed.

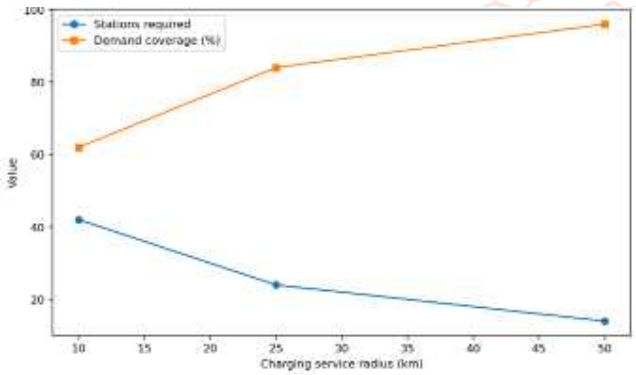


Figure 9: Sensitivity to Charging-Service Radius

5. Conclusion

This study is to create an integrated GIS based optimization methodology for optimal sizing and location of EVCSs. The proposed methodology involved spatial data preprocessing, partitioning in 5 × 5 km², EV-density estimation, road-classification weighting, charging-service range analysis, generation of candidate Point-of-Interests, optimization of the location of the charging services (maximum coverage), charging-service area allocation using Voronoi diagrams and charger sizing by knapsack. The results showed significant spatial variation in EVs' demand, thus suggesting that a uniform deployment of charging stations can result in inefficient use of the charging infrastructure. Optimization search space was reduced using demand based candidate selection, sensitivity analysis revealed that increasing service radius can enhance coverage and decrease number of stations needed, but increase average travel distance. Station-level demand estimation also allowed the allocation of the chargers based on local demand.

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