***Enhancing Urban EV Charging Networks: A Case Study of Bhubaneswar***

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***Abstract*—** ***As electric vehicles (EVs) continue to gain popularity across India—particularly in emerging urban centers like Bhubaneswar—the demand for an efficient and well-distributed charging network is becoming increasingly critical. This research introduces a structured approach to strategically placing EV charging stations throughout Bhubaneswar, Odisha. The methodology integrates geospatial tools like QGIS for mapping and analysis, while using Gaussian Mixture Models (GMM) to identify high-demand clusters. It further applies advanced optimization techniques, including Particle Swarm Optimization (PSO) and the Shortest Distance Method (SDM), to refine location choices. Key practical factors—such as proximity to power infrastructure, adequate spacing between stations, and regional service coverage—are also incorporated. The result is a scalable, data-driven model tailored to meet Bhubaneswar’s specific transportation and energy needs.***

***Keywords— electric vehicle charging station; optimal location; gaussian mixture model; particle swarm optimization; shortest distance method.***

# Introduction

Bhubaneswar, home to over 1.2 million people, is experiencing a noticeable surge in electric vehicle (EV) adoption as more residents shift toward sustainable mobility. However, the city’s existing infrastructure is struggling to keep pace. At present, there are only 18 public EV charging stations available to serve more than 2,300 EVs, resulting in an average of over 140 vehicles per station. This figure is well above the globally recommended range of 10 to 50 EVs per charging point, highlighting a significant infrastructure gap.

This imbalance is especially evident in busy urban areas like Master Canteen, Khandagiri, and Vani Vihar, where long queues and extended wait times at charging points have become increasingly common. In contrast, cities such as Bangalore and Delhi have made considerable progress, maintaining healthier EV-to-charger ratios—approximately 1:60 in Bangalore and 1:43 in Delhi, thereby offering a smoother user experience.

To address this growing disparity and support Bhubaneswar’s green mobility goals, this study adopts a multi-method approach aimed at identifying 20 optimal new locations for EV charging stations across the city

The approach integrates:

* **Gaussian Mixture Model (GMM)** to cluster areas based on EV demand
* **Particle Swarm Optimization (PSO)** for determining optimal site placement
* **Shortest Distance Method (SDM)** to ensure accessibility and coverage across key urban zones
* **QGIS** for detailed geospatial visualization and analysis

# Methodology

* 1. *Gaussian Mixture Method for Demand Zone Analysis in Bhubaneswar*

Gaussian Mixture Model (GMM) is a robust probabilistic clustering method that models a dataset as a weighted combination of multiple Gaussian (normal) distributions. It is particularly well-suited for identifying latent and overlapping structures within complex spatial data—an essential requirement in electric vehicle (EV) infrastructure planning [1]. In real-world urban environments, factors like population density, vehicular movement, and user trip behaviors often follow non-linear and overlapping patterns that cannot be effectively captured using traditional clustering techniques such as K-means, which rely on rigid, hard boundaries.GMM overcomes this limitation by employing soft clustering, where each data point is assigned a probability of belonging to each cluster, rather than being forced into a single one. This probabilistic nature allows GMM to reflect real-world uncertainty and spatial ambiguity more accurately—critical for modeling demand hotspots where usage patterns may shift throughout the day or vary based on transient events like holidays or traffic disruptions [2].

The clustering process is powered by the Expectation-Maximization (EM) algorithm, an iterative optimization technique that alternates between estimating the expected cluster memberships (E-step) and updating the Gaussian parameters (means, variances, and mixing coefficients) to maximize the likelihood of the data (M-step) [3]. Through this process, GMM automatically determines the optimal number of Gaussian components that best represent the data's underlying structure. Each component corresponds to a potential demand zone, with its own spatial center, spread,

|  |  |  |  |
| --- | --- | --- | --- |
| **S.No** | **Name** | **Location** | **Coordinates** |
| 1 | Tata Power – Dion Automotives | Lewis Road, Samantarapur, Old Town | 20.2245° N, 85.8330° E |
| 2 | Tata Power – MG Bhubaneswar | Pahala, NH-16 | 20.3347° N, 85.8038° E |
| 3 | TML Tirupati Enterprises | Bhagabanpur Industrial Area | 20.2961° N, 85.8194° E |
| 4 | Tata Power – Regalia Mall (DN Square) | Bhagabanpur Industrial Estate | 20.2961° N, 85.8194° E |
| 5 | Tata Power – GUGNANI TYRES | CRP – DAV Road, Nilakantha Nagar, Nayapalli | 20.2961° N, 85.8194° E |
| 6 | Tata Power – DN Wisdom Tree | K-2, Kalinganagar | 20.2961° N, 85.8194° E |
| 7 | Tata Power – BMC Bhawani Mall | Saheed Nagar | 20.2961° N, 85.8194° E |
| 8 | Tata Power – MLCP Saheed Nagar | Plot No.150(P), Saheed Nagar | 20.2961° N, 85.8194° E |
| 9 | Tata Power – GUGNANI AUTOCARS | Mancheswar Industrial Estate, Sector A, Block C | 20.2961° N, 85.8194° E |
| 10 | Tata Power – CSM Technologies | OCAC Building, Acharya Vihar, | 20.2961° N, 85.8194° E |
| 11 | Tata Power – DN Group Corporate | VIP Colony, IRC Village, Nayapalli | 20.2961° N, 85.8194° E |
| 12 | Kazam – Rasulgarh | Rasulgarh | 20.2961° N, 85.8194° E |
| 13 | Tata Power – Audi Bhubaneswar | Utkal Signature, NH16 | 20.2961° N, 85.8194° E |
| 14 | HPCL – Regional Office | 7RRW M8H, Saheed Nagar | 20.2961° N, 85.8194° E |
| 15 | Charger – Geetanjali | Service Road West, Acharya Vihar | 20.2961° N, 85.8194° E |
| 16 | GLIDA DLF Bhubaneswar – Statiq | Idco Info Park | 20.2961° N, 85.8194° E |
| 17 | Statiq – Nexus Esplanade | Unit No. 32, 721,Rasulgarh | 20.2961° N, 85.8194° E |
| 18 | Statiq – Yellowings ITC Cuttack Station | ITC Cuttack | 20.2961° N, 85.8194° E |

1. Current Locations of EV Charging Stations

and weight [4]. Rather than forcing strict cluster boundaries, GMM estimates the probability distribution of demand across the urban landscape. The final solution—often taken as the weighted average or centroid of the Gaussian means—represents high-demand regions that are central, statistically significant, and likely to support infrastructure placement. This approach enables planners to prioritize station locations that best reflect aggregate user behavior while accounting for uncertainty and data noise [5].

Compared to conventional clustering models, GMM excels in environments where the data is non-uniform, noisy, or spatially complex. For example, in EV infrastructure planning, charging demand may cluster near commercial zones during the day and shift toward residential areas at night. GMM’s flexibility in adapting to variations in variance, density, and orientation of clusters allows it to model such transitions more effectively than rigid methods [6]. It is particularly effective when used with spatiotemporal data collected from real-world sensors, surveys, and trip logs.Studies have demonstrated that GMM-based clustering yields significantly higher accuracy and predictive reliability, especially in high-dimensional urban datasets [7] . When integrated with downstream optimization algorithms like Particle Swarm Optimization (PSO), GMM provides a nuanced and informative input space, enhancing the overall performance of the optimization process. PSO, in turn, benefits from this probabilistic representation by directing search efforts toward the most relevant and statistically supported regions, thereby improving both solution quality and computational efficiency [8].

In summary, GMM serves as a foundational tool in modern EV infrastructure planning, enabling adaptive, data-driven decisions in dynamic urban contexts. Its ability to handle ambiguity, represent overlapping clusters, and model demand with high fidelity makes it indispensable in the broader pipeline of intelligent mobility and energy systems design.

A GMM models the data as a mixture of several Gaussian distributions. The probability density of a data point x, which is a D-dimensional feature vector, is expressed through the likelihood function :

Here, represents the number of Gaussian components. Each component is a Gaussian distribution defined by a mean vector , a covariance matrix , and a mixture weight .

The form of each Gaussian component is:

The mixture weights are constrained to sum to 1: . The model parameters are denoted as , with ranging from 1 to .

For a dataset of independent observations , where , the likelihood of the data given the parameters is:

The optimal parameters are found using the Maximum Likelihood Estimate (MLE), which maximizes the likelihood:

The likelihood function must be carefully chosen to highlight features that enhance the distinction between likelihood ratios, thereby improving the GMM's clustering effectiveness.

**Clustering Inputs and Methodology:**

The clustering approach using Gaussian Mixture Model (GMM) was designed around six input variables that represent key spatial and behavioral indicators relevant to EV infrastructure planning:

* **EV Count** – This variable estimates the average daily number of electric vehicles in a particular locality. It directly reflects potential charging demand. High EV Count areas are prioritized for infrastructure deployment due to their consistent usage patterns.
* **Traffic Score** – Represents the density and intensity of vehicular traffic across urban regions. High traffic areas imply frequent road usage, which correlates with increased EV activity and battery usage, making these zones more likely to require charging support.
* **Footfall Score** – Captures pedestrian activity in a given zone. Areas with high footfall typically host commercial or transit facilities where EVs are likely to park or idle, presenting ideal conditions for charger placement.
* **Distance From Grid** – Measures proximity to the existing electrical grid. Areas closer to the grid are more favorable due to lower installation costs and simpler connectivity, making this a critical infrastructural constraint in site selection.
* **Latitude and Longitude** – These geospatial coordinates help map the physical location of each area, enabling spatially aware clustering. This prevents over-concentration of stations and ensures even distribution across the city.
* **GMM Clustering Logic** – GMM applies a soft clustering approach, allowing each area to belong probabilistically to multiple clusters. This captures overlapping demand patterns more effectively than hard clustering. The model iteratively determines the optimal number and parameters of Gaussian components, ultimately identifying zones with the highest likelihood of EV charging demand.

These variables were first normalized to ensure uniformity in scale and were then processed through the GMM algorithm. GMM assigns each data point (or location) to a probabilistic cluster by evaluating similarities across both behavioural patterns (like demand or usage intensity) and geographical context. Unlike rigid clustering algorithms that enforce strict boundaries, GMM allows for overlap, making it ideal for cities where urban functions often blend together [4].

The GMM analysis produced four distinct clusters, each representing a different type of location based on the input features:

**Cluster 0:** Areas with high EV counts, significant traffic, and close proximity to the grid, making them ideal urban locations for charging stations.

**Cluster 1:** Locations with moderate EV presence and footfall, and a moderate distance from the grid, indicating balanced charging demand.

**Cluster 2:** Regions with low EV counts and traffic, and greater distance from the grid, marking them as low-priority rural or peripheral areas.

**Cluster 3:** Areas with high footfall, moderate EV presence, and proximity to the grid, suitable for commercial or transit-focused locations.

The table below summarizes the locations analyzed, their assigned clusters, EV counts, and distances from the grid:

1. CLUSTER SUMMARY TABLE

|  |  |  |  |
| --- | --- | --- | --- |
| ***Cluster*** | **Zone/Location** | **EV Count** | **Distance from Grid (km)** |
| *0* | Saheed Nagar | 105 | 1.2 |
| *0* | Vani Vihar | 85 | 1.5 |
| *0* | Jaydev Vihar | 72 | 2.0 |
| *0* | Satya Nagar | 57 | 1.8 |
| *0* | Tankapani Road | 51 | 2.7 |
| *0* | Sishu Bhawan | 47 | 2.1 |
| *1* | Nayapalli | 78 | 3.4 |
| *1* | Palasuni | 54 | 3.9 |
| *1* | Pokhariput | 50 | 4.3 |
| *1* | Badagada | 44 | 3.0 |
| *2* | Jagamara | 56 | 5.7 |
| *2* | Mancheswar | 46 | 4.9 |
| *2* | Kalinga Stadium | 45 | 5.2 |
| *3* | KIIT | 60 | 6.8 |
| *3* | Chandrasekharpur | 58 | 6.4 |

## Optimization with Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a computational technique inspired by the social behavior of birds and fish, where individual particles explore a problem space by adjusting their positions based on their own and their neighbors' best experiences.

Particle Swarm Optimization (PSO) is a powerful metaheuristic algorithm inspired by the social behavior patterns observed in birds flocking and fish schooling. In this method, individual particles—representing potential solutions—continuously update their positions within the solution space by considering both their own best-known positions and those of neighboring particles . This social-cognitive learning mechanism allows the swarm to converge rapidly toward optimal or near-optimal solutions, even in high-dimensional and multi-objective problem spaces [9] .In the context of electric vehicle (EV) infrastructure planning, PSO proves exceptionally valuable for solving complex problems involving dynamic constraints such as optimal placement of charging stations, real-time load distribution, and adaptive energy management. It balances conflicting objectives—such as minimizing user distance, ensuring cost-effectiveness, and maximizing grid performance—while also ensuring compliance with policy and practical implementation limits [10].

The optimization process is initiated by constructing a spatially rich dataset, incorporating layers like traffic density, road connectivity, power grid reach, and land-use zoning through Geographic Information Systems (GIS) such as QGIS. Each particle in the swarm represents a potential configuration of charging station locations, and the fitness function evaluates these configurations based on a set of performance metrics, including average user distance to stations, demand-weighted proximity, load balancing across grid zones, and route accessibility [11] . This ensures that the proposed configurations are not only mathematically optimal but also practically viable and policy-aligned .To improve the model’s realism, a Gaussian Mixture Model (GMM) is integrated to simulate user mobility patterns and identify probabilistic demand hotspots. Unlike static zoning, GMM-based clustering adapts to dynamic population flows, assigning higher priority (or weight) to locations with higher predicted demand. This results in a more responsive and intelligent PSO search behavior that naturally gravitates toward high-traffic areas, improving the system's real-world efficiency [12].

Furthermore, PSO is adapted to fine-tune charging protocols, including dynamic adjustments of Constant Current Constant Voltage (CCCV) parameters. By optimizing the interplay between current and voltage delivery, PSO ensures minimized charging times while maintaining battery health, thus improving user experience and extending battery life [13] .A significant enhancement to this framework is the integration of the Spatial Durbin Model (SDM). SDM accounts for spatial autocorrelation and spillover effects, meaning the installation of a new charging station in one region can impact not only local demand but also influence the performance and utility of stations in adjacent zones [14] . By embedding SDM-derived spatial feedback into the PSO fitness function, the algorithm becomes sensitive to regional interdependencies, enabling it to avoid over-saturating one zone while neglecting nearby underserved regions. This spatial intelligence enhances the macro-level decision-making capabilities of the system [15].

|  |  |
| --- | --- |
| PSO ALGORITHM PSEUDOCODE**:** | |
| INPUT f, swarm\_size, max\_iter  INIT swarm positions, velocities  best\_global = best position in swarm | FOR i = 1 TO max\_iter:  FOR particle IN swarm:  fitness = f(particle.pos)  IF fitness < particle.best\_fitness:  particle.best\_pos = particle.pos  particle.best\_fitness = fitness  IF fitness < best\_global.fitness:  best\_global = particle.pos  UPDATE particle.velocity  UPDATE particle.pos |

In summary, the collaborative integration of PSO, QGIS, GMM, and SDM enables a comprehensive and scalable optimization framework. It handles both micro-level efficiencies— such as individual station performance, user wait times, and routing convenience—and macro-level objectives, like equitable access, long-term scalability, and grid impact management. This multi-disciplinary approach exemplifies how swarm intelligence, spatial analytics, and machine learning can be combined to create smart, adaptive, and sustainable EV charging ecosystems.

Top 5 PSO Combinations (All 33 Stations)

**Combination 1 (Fitness 0.6598)**

**['Saheed Nagar', 'Charger – Geetanjali', 'Tata Power – BMC Bhawani Mall', 'Tata Power – Dion Automotives', 'HPCL – Regional Office', 'Palasuni', 'Sishu Bhawan', 'Tata Power – DN Group Corporate', 'Vani Vihar', 'Tata Power – MG Bhubaneswar', 'Tata Power – Regalia Mall (DN Square)', 'Kazam – Rasulgarh', 'Tata Power – CSM Technologies', 'Statiq – Yellowings ITC Cuttack Station', 'Tata Power – DN Wisdom Tree', 'Tata Power – GUGNANI TYRES', 'Jagamara', 'Tata Power – Audi Bhubaneswar', 'Jaydev Vihar', 'Tankapani Road', 'Tata Power – MLCP Saheed Nagar', 'Pokhariput', 'KIIT', 'Nayapalli', 'GLIDA DLF Bhubaneswar – Statiq', 'Statiq – Nexus Esplanade Mall', 'Kalinga Stadium', 'Mancheswar', 'Chandrasekharpur', 'Satya Nagar', 'TML Tirupati Enterprises', 'Badagada', 'Tata Power – GUGNANI AUTOCARS']**

**Combination 2 (Fitness 0.6486)**

**['Tata Power – BMC Bhawani Mall', 'Vani Vihar', 'Saheed Nagar', 'Nayapalli', 'Statiq – Yellowings ITC Cuttack Station', 'Tata Power – DN Group Corporate', 'Kazam – Rasulgarh', 'Charger – Geetanjali', 'KIIT', 'Jagamara', 'Tata Power – Regalia Mall (DN Square)', 'Tata Power – MLCP Saheed Nagar', 'Kalinga Stadium', 'GLIDA DLF Bhubaneswar – Statiq', 'Jaydev Vihar', 'Tata Power – MG Bhubaneswar', 'Tata Power – CSM Technologies', 'TML Tirupati Enterprises', 'Tankapani Road', 'Tata Power – GUGNANI TYRES', 'Sishu Bhawan', 'HPCL – Regional Office', 'Tata Power – Audi Bhubaneswar', 'Pokhariput', 'Tata Power – Dion Automotives', 'Palasuni', 'Tata Power – DN Wisdom Tree', 'Statiq – Nexus Esplanade Mall', 'Badagada', 'Mancheswar', 'Satya Nagar', 'Tata Power – GUGNANI AUTOCARS', 'Chandrasekharpur']**

**Combination 3 (Fitness 0.6480)**

**['Saheed Nagar', 'Nayapalli', 'Statiq – Nexus Esplanade Mall', 'Tata Power – BMC Bhawani Mall', 'Tata Power – Audi Bhubaneswar', 'Jagamara', 'Vani Vihar', 'Statiq – Yellowings ITC Cuttack Station', 'Tata Power – Regalia Mall (DN Square)', 'Charger – Geetanjali', 'Tankapani Road', 'Tata Power – Dion Automotives', 'Sishu Bhawan', 'Chandrasekharpur', 'Badagada', 'Kazam – Rasulgarh', 'HPCL – Regional Office', 'Tata Power – CSM Technologies', 'Pokhariput', 'Tata Power – MLCP Saheed Nagar', 'Kalinga Stadium', 'Tata Power – GUGNANI TYRES', 'GLIDA DLF Bhubaneswar – Statiq', 'Tata Power – DN Group Corporate', 'Tata Power – MG Bhubaneswar', 'Mancheswar', 'Jaydev Vihar', 'KIIT', 'Tata Power – DN Wisdom Tree', 'Tata Power – GUGNANI AUTOCARS', 'Palasuni', 'Satya Nagar', 'TML Tirupati Enterprises']**

**Combination 4 (Fitness 0.6479)**

**['Saheed Nagar', 'Tata Power – Regalia Mall (DN Square)', 'Sishu Bhawan', 'Tata Power – BMC Bhawani Mall', 'GLIDA DLF Bhubaneswar – Statiq', 'Vani Vihar', 'Nayapalli', 'HPCL – Regional Office', 'Tata Power – DN Group Corporate', 'Tata Power – MLCP Saheed Nagar', 'Mancheswar', 'Jagamara', 'Kazam – Rasulgarh', 'Tata Power – CSM Technologies', 'Tata Power – Dion Automotives', 'Pokhariput', 'Charger – Geetanjali', 'Tankapani Road', 'Satya Nagar', 'KIIT', 'Tata Power – GUGNANI AUTOCARS', 'Tata Power – Audi Bhubaneswar', 'Palasuni', 'Tata Power – GUGNANI TYRES', 'Jaydev Vihar', 'Tata Power – MG Bhubaneswar', 'Chandrasekharpur', 'Badagada', 'Tata Power – DN Wisdom Tree', 'TML Tirupati Enterprises', 'Statiq – Nexus Esplanade Mall', 'Kalinga Stadium', 'Statiq – Yellowings ITC Cuttack Station']**

**Combination 5 (Fitness 0.6462)**

**['Saheed Nagar', 'Vani Vihar', 'GLIDA DLF Bhubaneswar – Statiq', 'Charger – Geetanjali', 'Tata Power – MG Bhubaneswar', 'Tankapani Road', 'Jaydev Vihar', 'Nayapalli', 'Kalinga Stadium', 'Jagamara', 'Tata Power – Dion Automotives', 'Satya Nagar', 'Tata Power – GUGNANI AUTOCARS', 'Tata Power – Regalia Mall (DN Square)', 'Tata Power – Audi Bhubaneswar', 'Tata Power – BMC Bhawani Mall', 'Tata Power – CSM Technologies', 'Palasuni', 'Badagada', 'Tata Power – MLCP Saheed Nagar', 'TML Tirupati Enterprises', 'Sishu Bhawan', 'Statiq – Nexus Esplanade Mall', 'Tata Power – GUGNANI TYRES', 'KIIT', 'Chandrasekharpur', 'Mancheswar', 'Statiq – Yellowings ITC Cuttack Station', 'Tata Power – DN Wisdom Tree', 'Tata Power – DN Group Corporate', 'Pokhariput', 'HPCL – Regional Office', 'Kazam – Rasulgarh']**

## Accessibility Filtering with Shortest Distance Method (SDM)

Shortest Distance Method (SDM) plays a pivotal role in refining electric vehicle (EV) charging infrastructure planning by addressing the critical aspect of user accessibility. While clustering algorithms like Gaussian Mixture Model (GMM) identify high-demand regions, and optimization techniques such as Particle Swarm Optimization (PSO) determine optimal charging station placements based on multiple constraints, SDM acts as a spatial validation mechanism [16] . It ensures that the selected charging station locations are not only theoretically optimal but also practically reachable and spatially efficient from the perspective of everyday EV users .The core objective of SDM is to evaluate how conveniently users can access proposed stations, minimizing both travel distance and travel time. This is achieved by implementing a mixed-integer optimization framework, which explicitly considers the geometric and topological properties of the urban layout. Instead of relying on straight-line (Euclidean) distance, SDM incorporates real-world transportation data, such as road network geometry, traffic flow, and route constraints, to calculate the shortest path distance between each demand node (which could represent a user, a neighborhood, or a hotspot) and potential charging station sites [17].

This process helps to minimize overall user access costs, which includes not only physical distance but also time, energy expenditure, and route complexity. Additionally, the SDM framework incorporates constraints that prevent the spatial clustering of charging stations in already saturated regions, thereby encouraging a more balanced and equitable distribution of infrastructure across both urban cores and peripheral or underserved areas [18]. Another significant feature of SDM is its ability to support multi-scale demand modeling. Demand is assessed both at a macro level (e.g., traffic zones, commercial districts) and at a micro level (e.g., individual travel patterns and trip logs), enabling a more granular understanding of where and when charging is needed [19]. This dual-resolution approach provides a highly accurate proxy for estimating anticipated charging requirements, facilitating service coverage evaluations that reflect real-world behaviour.

|  |  |
| --- | --- |
| SDM ALGORITHM PSEUDOCODE: | |
| INPUT sets, coords  dist(a, b):  return distance(a, b)  total(sites):  sum = 0 | for i < j in sites:  sum += dist(sites[i], sites[j])  return sum  best\_dist = ∞  best\_set = NULL  for s in sets:  d = total(s)  if d < best\_dist:  best\_dist = d  best\_set = s |

To further improve spatial equity, SDM includes a threshold-based accessibility analysis, which flags underserved or inaccessible zones. If the shortest distance from a given demand point to the nearest station exceeds a pre-defined limit—often derived from policy guidelines or user comfort tolerances—those areas are classified as coverage gaps [20]. These gaps are then fed back into the optimization loop, serving as corrective feedback to PSO. As a result, subsequent iterations of site selection take these deficiencies into account, continuously improving the network’s reach and inclusivity [21]. By integrating SDM into the broader EV infrastructure planning pipeline, the system transitions from being merely optimized on paper to being actionable and user-centric in practice. The synergy of PSO's global optimization capabilities, GMM's demand clustering accuracy, and SDM's accessibility analysis leads to a charging network design that is technically robust, socially equitable, and operationally viable [22] . This ensures that infrastructure serves all urban regions fairly—supporting high-demand, high-density areas as well as more sparsely populated suburban or rural zones—thereby promoting broader EV adoption and enhancing the user experience.

**Output -**

Combination 1 (Fitness 0.6598) distance: 2324.07 km

Combination 2 (Fitness 0.6565) distance: 2324.07 km

Combination 3 (Fitness 0.6532) distance: 2324.07 km

Combination 4 (Fitness 0.6499) distance: 2324.07 km

Combination 5 (Fitness 0.6466) distance: 2324.07 km

## Geospatial Mapping with QGIS

QGIS (Quantum Geographic Information System) was used as the primary platform for generating, analyzing, and visualizing spatial data throughout this study. As a powerful open-source GIS tool, QGIS offers a wide range of geoprocessing functions and customization options, making it ideal for both academic and practical applications in urban planning. In this research, it enabled the digitization and layering of key spatial datasets such as road networks, land use zones, population distribution, electric grid coverage, and Points of Interest (POIs). Its support for diverse formats like shapefiles (.shp), GeoJSON, raster layers, and CSV files—ensured smooth integration of both vector and tabular data.

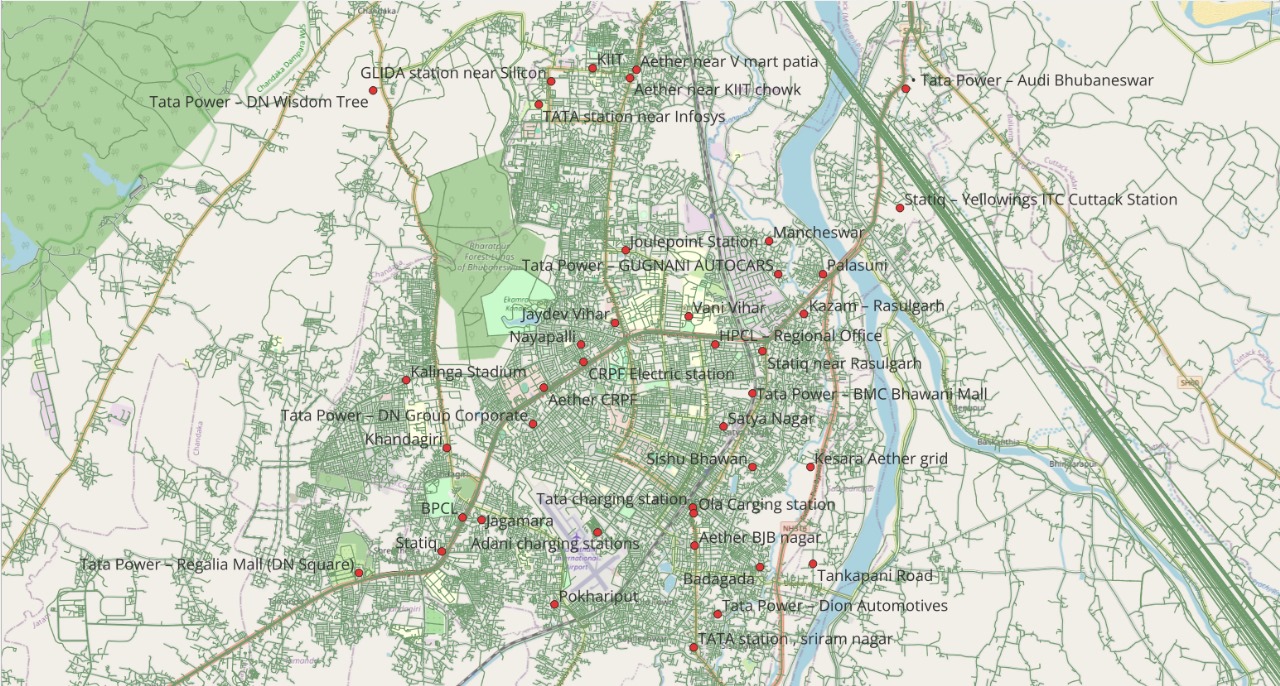
Advanced features like attribute queries, spatial joins, and heat mapping were instrumental in identifying demand clusters and optimal locations for EV charging stations. Plugins such as “MMQGIS” and “Heatmap” enriched the analysis by supporting spatial clustering and density visualization. QGIS also excels in cartographic design, which helped create clear, publication-quality maps highlighting demand zones, infrastructure gaps, and proposed station sites [23].

Custom symbology, labeling, and dynamic layer control improved the clarity and impact of these visuals, making them accessible to both technical and non-technical audiences. Tools for adding layout elements like legends, scale bars, and north arrows contributed to the professional presentation of the final maps.

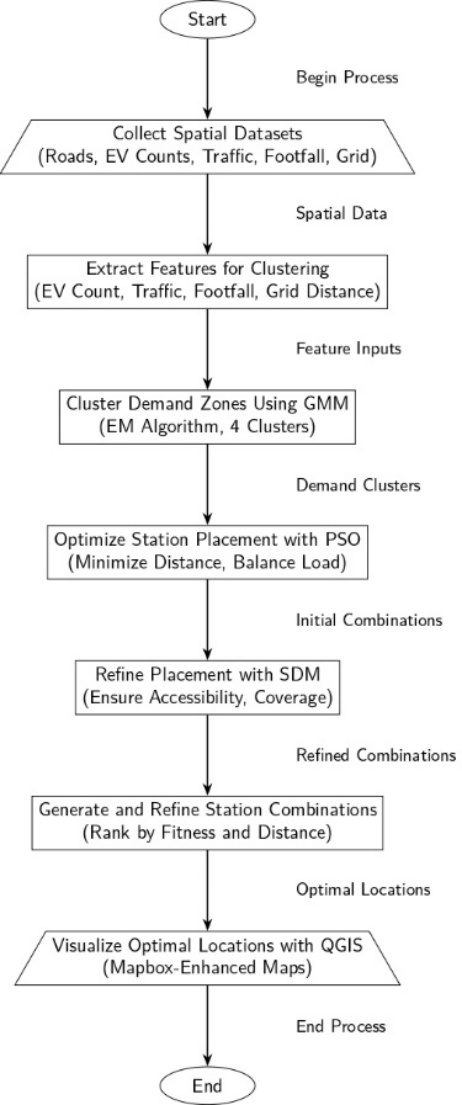
To enhance visual clarity and add real-world context, Mapbox was integrated into QGIS using the XYZ Tile feature.

This brought in high-resolution, modern basemaps that accurately reflected Bhubaneswar’s streets, blocks, and landmarks. By using Mapbox as a backdrop, overlays such as EV station markers and road networks aligned precisely with real-world geography, making the maps more intuitive and informative. This integration supported a visually rich and data-driven approach to planning EV infrastructure in Bhubaneswar.

1. Bhubaneswar EV Charging Station Planning Map



# Conclusion

This study establishes a structured and technically grounded approach to EV charging infrastructure planning in Bhubaneswar. By integrating spatial mapping with QGIS, demand clustering via GMM, and site optimization through PSO and SDM, the framework addresses not only location selection but also practical concerns such as grid accessibility, route coverage, and urban demand intensity.

Our findings highlight that thoughtful siting of EV stations, especially in growth-prone and underrepresented areas, can drastically improve user convenience, reduce queuing delays, and contribute to environmental sustainability. Moreover, the methodology is scalable and adaptable to other urban centers across India.

As Odisha looks to accelerate its electric mobility mission, this model serves as a replicable, data-driven roadmap for smart city planners, urban transport engineers, and policy-makers aiming to future-proof their city’s transportation infrastructure.

# **Best combination by total pairwise distance:**

• Tata Power – BMC Bhawani Mall

• Vani Vihar

• Saheed Nagar

• Nayapalli

• Statiq – Yellowings ITC Cuttack Station

• Tata Power – DN Group Corporate

• Kazam – Rasulgarh

• Charger – Geetanjali

• KIIT

• Jagamara

• Tata Power – Regalia Mall (DN Square)

• Tata Power – MLCP Saheed Nagar

• Kalinga Stadium

• GLIDA DLF Bhubaneswar – Statiq

• Jaydev Vihar

• Tata Power – MG Bhubaneswar

• Tata Power – CSM Technologies

• TML Tirupati Enterprises

• Tankapani Road

• Tata Power – GUGNANI TYRES

• Sishu Bhawan

• HPCL – Regional Office

• Tata Power – Audi Bhubaneswar

• Pokhariput

• Tata Power – Dion Automotives

• Palasuni

• Tata Power – DN Wisdom Tree

• Statiq – Nexus Esplanade Mall

• Badagada

• Mancheswar

• Satya Nagar

• Tata Power – GUGNANI AUTOCARS

• Chandrasekharpur

**Total pairwise distance: 2324.07 km**

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##### References

1. N. Shahraki et al., "Optimal locations of electric public charging stations using real world vehicle travel patterns," *Transportation Research Part D: Transport and Environment*, vol. 41, pp. 165–176, 2015. doi: [10.1016/j.trd.2015.09.011](https://doi.org/10.1016/j.trd.2015.09.011).
2. Z.-K. Huang and K.-W. Chau, "A new image thresholding method based on Gaussian mixture model," *Applied Mathematics and Computation*, vol. 205, no. 2, pp. 899–907, 2008.
3. S.C. Kim and T.J. Kang, “Texture classification and segmentation using wavelet packet frame and Gaussian mixture model,” Pattern Recognition, vol. 40, no. 4, pp. 1207-1221, 2007.
4. I. Frade, A. Ribeiro, G. Gonçalves, and A. Antunes, “Optimal location of charging stations for electric vehicles in a neighborhood in Lisbon, Portugal,” Transportation Research Record: Journal of the Transportation Research Board, vol. 2252, pp. 91-98, 2011.
5. Y. Zhang, Q. Zhang, A. Farnoosh, S. Chen, and Y. Li, "GIS-based multi-objective particle swarm optimization of charging stations for electric vehicles," *Energy*, vol. 169, pp. 844–883, 2019.
6. R. Adam, K. Qian, and R. Brehm, "Electric vehicle user behavior prediction using Gaussian mixture models and soft information," in *2021 10th IEEE PES Innovative Smart Grid Technologies Asia (ISGT Asia)*, 2021, doi: 10.1109/ISGTAsia49270.2021.9715580.
7. A. Y. Ng, M. I. Jordan, and Y. Weiss, "On spectral clustering: Analysis and an algorithm," *Advances in Neural Information Processing Systems*, vol. 14, pp. 849–856, 2002.
8. Z. Miljanic, V. Radulovic, and B. Lutovac, “Efficient Placement of Electric Vehicles Charging Stations using Integer Linear Programming,” IEEE Transactions on Smart Grid, 2020.
9. M. S. Mastoi, S. Zhuang, J. S. Ro, H. M. Munir, M. Haris, M. Hassan, M. Usman, and S. S. H. Bukhari, “An in-depth analysis of electric vehicle charging station infrastructure, policy implications, and future trends,” *Energy Reports*, vol. 8, pp. 11504–11529, 2022.
10. G. Pistoia, *Electric and Hybrid Vehicles: Power Sources, Models, Sustainability, Infrastructure and the Market*. Elsevier, 2010, pp. 517–542.
11. M. E. Kabir, C. Assi, H. Alameddine, J. Antoun, and J. Yan, "Demand aware deployment and expansion method for an electric vehicles fast charging network," *IEEE Transactions on Smart Grid*, vol. 10, no. 1, pp. 172–183, 2019.
12. S. Wang et al., "Stochastic collaborative planning method for electric vehicle charging stations," *IEEE Transactions on Smart Grid*, vol. 7, no. 3, pp. 1327–1334, May 2016.
13. Q. Sun, X. Bai, F. Liu, L. Liu, X. Ji, and J. Hardy, "Multi-objective planning for electric vehicle charging stations considering TOU price," *IEEE Transactions on Smart Grid*, vol. 9, no. 3, pp. 1861–1870, May 2018.
14. P. Jog, S. Shete, R. Kumawat, and D. Palwalia, "Electric vehicle charging station infrastructure: A review," *IEEE Transactions on Industry Applications*, vol. 57, no. 2, pp. 234–241, Mar.-Apr. 2021.
15. Y. Xu et al., "Robust scheduling of EV charging load using stochastic optimization model," *Energy*, vol. 153, pp. 1046–1058, 2018. doi: [10.1016/j.energy.2018.04.106](https://doi.org/10.1016/j.energy.2018.04.106).
16. W. Khan, F. Ahmad, and M. S. Alam, "Fast EV charging station integration with grid ensuring optimal quality power exchange," *Engineering Science and Technology, an International Journal*, vol. 22, pp. 143–152, 2019. doi: [10.1016/j.jestch.2018.08.005](https://doi.org/10.1016/j.jestch.2018.08.005).
17. X. Xi et al., "Simulation–optimization model for location of a public electric vehicle charging infrastructure," *Transportation Research Part D: Transport and Environment*, vol. 22, pp. 60–69, 2013. doi: [10.1016/j.trd.2013.03.005](https://doi.org/10.1016/j.trd.2013.03.005).
18. A. K. Kalakanti and S. Rao, "Charging station planning for electric vehicles," *Systems*, vol. 10, no. 1, p. 6, 2022. doi: [10.3390/systems10010006](https://doi.org/10.3390/systems10010006).
19. A. K. M. Yousuf et al., "Electric vehicle charging station infrastructure: A comprehensive review of technologies, challenges, and mitigation strategies," *Energy Reports*, vol. 7, pp. 2682–2696, 2021. doi: [10.1016/j.egyr.2021.05.045](https://doi.org/10.1016/j.egyr.2021.05.045).
20. P. Sadeghi-Barzani et al., "Optimal fast charging station placing and sizing," *Applied Energy*, vol. 125, pp. 289–299, 2014. doi: [10.1016/j.apenergy.2014.03.077](https://doi.org/10.1016/j.apenergy.2014.03.077).
21. F. Xie et al., "Long-term strategic planning of inter-city fast charging infrastructure for battery electric vehicles," *Transportation Research Part E: Logistics and Transportation Review*, vol. 109, pp. 261–276, 2018. doi: [10.1016/j.tre.2017.11.014](https://doi.org/10.1016/j.tre.2017.11.014).
22. E. Sortomme et al., "Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses," *IEEE Transactions on Smart Grid*, vol. 2, no. 1, pp. 198–205, 2011. doi: [10.1109/TSG.2010.2090913](https://doi.org/10.1109/TSG.2010.2090913).
23. S. S. Ali et al., "An overview of electric vehicle charging data acquisition and grid connection standards for power system studies and EV-grid integration," *Energies*, vol. 13, no. 23, p. 6141, 2020. doi: [10.3390/en13236141](https://doi.org/10.3390/en13236141).
24. L. Wang et al., "Optimal planning of charging stations for electric vehicles based on fuzzy Delphi and hybrid multi-criteria decision making approaches," *Transportation Research Part C: Emerging Technologies*, vol. 97, pp. 102–117, 2018. doi: [10.1016/j.trc.2018.10.019](https://doi.org/10.1016/j.trc.2018.10.019)