Enhancing Urban EV Charging Networks: A Case Study of Bhubaneswar

Debani Prasad Mishra
Department of Electrical & Electronics Engineering
IIIT Bhubaneswar
Odisha, India
debani@iiit-bh.ac.in

Animesh Sharma
Department of Electrical & Electronics Engineering
IIIT Bhubaneswar
Odisha, India
b323007@iiit-bh.ac.in

Subham Kumar Bisoyi
Department of Electrical & Electronics Engineering
IIIT Bhubaneswar
Odisha, India
b323044@iiit-bh.ac.in

Kumar Gaurav
Department of Electrical & Electronics Engineering
IIIT Bhubaneswar
Odisha, India
b323018@iiit-bh.ac.in

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.

I. 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

II. Methodology

A. Gaussian Mixture Method for Demand Zone Analysis in Bhubaneswar

Gaussian Mixture Model (GMM) is a probabilistic clustering technique that identifies latent structures within spatial data by modeling it as a combination of multiple Gaussian distributions. This makes it particularly effective in EV infrastructure planning, where demand points—based on footfall, vehicle density, and trip behavior—exhibit overlapping, non-linear patterns [1]. The EM algorithm is used to fit a GMM to the histogram data, determining the number of Gaussian components and their parameters through an iterative process [3]. This enables the model to estimate the underlying distribution of charging demand without hard clustering boundaries [2]. The optimal solution is then chosen as the average of the means of the Gaussian components in the fitted GMM, which helps in identifying central tendencies within high-demand regions. Unlike traditional clustering methods, GMM accounts for data ambiguity and spatial overlap, making it highly suitable for dynamic urban environments [3]. GMM-based clustering approach is shown to outperform in terms of prediction accuracy and reliability [7], especially when working with real-world, noisy data [4]. The clustered nature of the data is better captured by the GMM model, as it flexibly adapts to the variance and density of each region, providing a more nuanced input for downstream optimization algorithms like PSO.

TABLE 1. CURRENT LOCATIONS OF EV CHARGING STATIONS

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

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 $p(x|\lambda)$:

$$p(x|\lambda) = \sum_{k=1}^{M} \binom{n}{k} \omega_k p_k(x)$$

Here, M represents the number of Gaussian components. Each component $p_k(\mathrm{x})$ is a Gaussian distribution defined by a mean vector μ_k, a $D \times D$ covariance matrix Σ_k, and a mixture weight ω_k.

The form of each Gaussian component is:

$$p_k(\mathrm{x}) = \frac{1}{(2\pi)^{D/2}|\Sigma_k|^{1/2}} \exp\left\{-\frac{1}{2}(\mathrm{x}-\mu_k)^T \Sigma_k^{-1}(\mathrm{x}-\mu_k)\right\}$$

The mixture weights ω_k are constrained to sum to 1: $\sum_{k=1}^{M} \omega k = 1$. The model parameters are denoted as $\lambda = \{\omega_k, \mu_k, \Sigma_k\}$, with k ranging from 1 to M.

For a dataset of N independent observations x_i, where $i = 1, \ldots, N$, the likelihood of the data given the parameters θ is:

$$p(\mathrm{x} \mid \theta) = L(\theta \mid \mathrm{x}) = \prod_{i=1}^{N} \sum_{k=1}^{M} \alpha_k pk(\mathrm{x}_i \mid \theta_k)$$

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

$$\theta^* = \arg\max_{\theta} L(\theta \mid \mathrm{x})$$

The likelihood function $p(\mathrm{x} \mid \lambda)$ 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.

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:

TABLE 2. 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

B. 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. This makes PSO highly suitable for complex optimization problems involving multiple variables and constraints. In electric vehicle (EV) infrastructure, PSO plays a pivotal role in solving challenges such as optimal charging station placement, load distribution, and dynamic energy management. Its fast convergence and adaptability make it ideal for balancing trade-offs between accessibility, cost, and performance [1]. The optimization process begins by mapping spatial data — including traffic flow, road networks, and power grid proximity — using QGIS, enabling each PSO particle to represent a possible station configuration [2]. The fitness function evaluates these configurations based on average user distance, load balancing, and route accessibility, making results both efficient and policy-compliant. To improve demand precision, GMM is used to model user mobility and detect probabilistic demand hotspots, which guide the swarm toward high-priority zones.

This GMM-based probabilistic clustering enables a more realistic input to PSO, assigning dynamic weightage to high-demand areas rather than static zoning [2]. PSO also fine-tunes charging protocols such as Constant Current Constant Voltage (CCCV) by adjusting current and voltage to minimize charge time while preserving battery health. (5) Additionally, the Spatial Durbin Model (SDM) is integrated to account for spatial spillover effects — for example, how a new charging station in one region impacts accessibility or load in neighbouring areas [6]. SDM feedback is looped into the PSO fitness function, making the swarm aware of both local utility and regional interdependencies [7]. Together, the integration of PSO, QGIS, GMM, and SDM creates a holistic and scalable framework that addresses both micro-level efficiency (like charging time and battery health) and macro-level planning (like equitable distribution and long-term scalability). This approach demonstrates the power of swarm intelligence fused with spatial analytics and machine learning to design smart, sustainable EV ecosystems.

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

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']

C. *Accessibility Filtering with Shortest Distance Method (SDM)*

Shortest Distance Method (SDM) enhances EV charging infrastructure planning by validating how accessible proposed stations are to end users. While models like GMM and PSO identify potential zones and optimize site placement, SDM ensures that these choices are spatially efficient and user-friendly [1]. A mixed-integer optimization framework is employed to minimize user access costs and avoid clustering of stations, improving distribution across urban areas. It calculates the shortest distances between demand points and candidate station sites, considering real-world road networks and traffic data [2]. Demand is modeled at both the zone and individual trip level to serve as a proxy for anticipated charging needs, enabling precise evaluation of service coverage.

SDM also flags underserved areas by measuring whether distances to the nearest station exceed defined thresholds. This feedback loop is used to refine the PSO optimization, promoting more equitable coverage. By integrating SDM into the overall framework, the EV network design becomes not only optimized but also practically reachable, ensuring usability and fairness in high-density as well as peripheral zones.

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
```

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

D. *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—

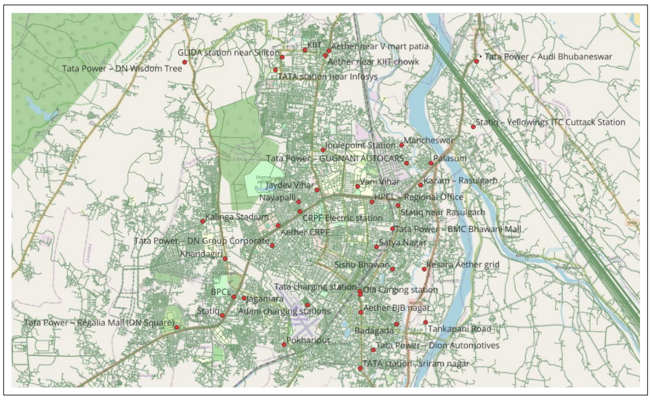
like shapefiles (.shp), GeoJSON, raster layers, and CSV files—ensured smooth integration of both vector and tabular data.

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.

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.

FIGURE 1. BHUBANESWAR EV CHARGING STATION PLANNING MAP

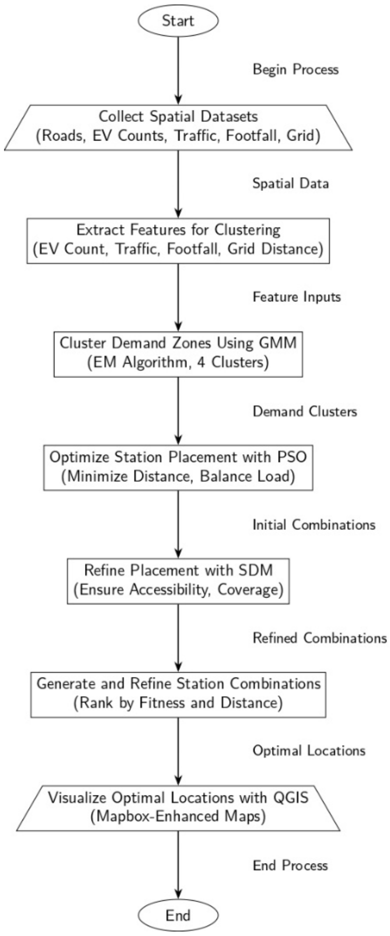


IV. CONCLUSION

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

ACKNOWLEDGMENT

We express our profound gratitude to Dr. Debani Prasad Mishra for his valuable guidance for the successful completion of the research work.

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.

[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.

[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.

[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.

[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.

[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.

[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.

[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.

[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.

[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.

[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