Demand Analysis of EV Charging Stations in Delhi NCR using Python and Power BI

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Abstract - The surge in electric vehicle (EV) adoption in India requires establishment of suitable charging facilities. The National Capital Region of Delhi (NCR) will face a situation where demand for electric vehicle charging stations exceeds available capacity by 2025 because the region currently operates 150000 electric vehicles and 1500 charging stations. This research began in 2023 and studies Delhi NCR charging station requirements through district analysis of vehicle registration data and charging station deployment and demographic indicators until 2025. The study examines charger density and EV-to-charger ratios and future requirements through an SQL-based integration model that uses Power BI visualization. The research shows significant spatial distribution differences because central Delhi has 8 to 10 chargers per 10 square kilometers while outlying districts have fewer than 2 chargers. The current EV-to-charger ratio of around 100:1 is much higher than the 20:1 recommended ratio. The forecasting through regression indicates that there will be a demand for 12,000–15,000 chargers by 2030, with 23 zones marked as the ones lacking service. The research provides an analytical framework that can be repeated to steer infrastructure planning, investment, and policy measures that would support the transition of electric mobility in India.
Keywords- Electric vehicle demand, charging infrastructure, Delhi NCR, demand forecasting, Power BI, SQL, infrastructure planning, sustainable mobility.

I. INTRODUCTION

(a) Motivation & Relevance

Electric mobility serves as a primary solution which enables the transportation industry to reduce its global carbon footprint. In India the transport sector accounts for nearly 20 percent of carbon dioxide emissions while cities like the National Capital Region of Delhi experience extremely poor air quality. The market for electric vehicles (EVs) has experienced explosive growth with vehicle registrations increasing from 380000 in 2020 to over 1 million by 2025 which represents a compound annual growth rate exceeding 35 percent. The National Capital Region of Delhi which contains only 3 percent of the nation complete population base controls 12 percent of all electrical vehicle sales because government policies combined with high consumer spending power and urgent climate change problems create a favorable environment for this transition.

Nevertheless, the swift adoption of electric vehicles in the region exposes a crucial weakness: the lack of charging facilities. There are just 1,500 public charging stations, which is only 15% of the total number in India, so there are still problems regarding sufficiency, accessibility, and distribution. Studies from other countries indicate that bad planning when it comes to electric vehicle charging stations increases the problem of range anxiety and decreases the usage of electric vehicles.

(b) Policy Background

Policy framework case for transitioning to electric mobility in India An Indian electric transport transition is underpinned by a heterogeneous set of policies. At the national level, FAME-II (2019–2024) budgeted ₹10,000 crores to foster EV adoption and charging inf restructure whereas the NEMMP 2020 aimed for EV penetration of 30% by 2030—equivalent to 10–12 million EVs and 1.2–
1.5 million chargers [6]. The 2022 guidelines of the Ministry of Power also imposed the requirement that there should be one charging station every 3 km in cities and every 25 km on highways coupled with standardised norms, faster permitting and interoperability.

The EV Policy 2020 in Delhi is by far the most progressive of its kind in India so far, targeting 25% sales of EVs by 2024 through subsidies, tax exemptions and infrastructure dictate. It focuses on the integrations of charging in new developments, together with a strategic roll-out across hubs and residential zones. These have been supplemented by complementary measures in neighboring NCR states: Uttar Pradesh is targeting 10% EV sales by 2030 with capital subsidies, and Haryana has proposed industrial EV zones and fiscal incentives.

(c) Problem Statement

With 1,500 charging stations and supportive policies in Delhi NCR, infrastructure adequacy gaps remain. The first among them is quantitative scarcity: we note that the current EV-to-charger ratio of 100:1 overwhelmingly lags behind benchmark ratio (20:1) which Bureau of Energy Efficiency (/Tripura Urja Vikas Nigam Limited 2019) and global urban standards (10–15:1). Second, deployment is characterized by spatial inequity - the central districts feature dense networks while outskirt areas like Ghaziabad and Faridabad are poorly served despite high adoption of EVs. Third, planning failures result from overuse of population- or area-based heuristics in place of demand-driven models, leading to inefficient use of resources. Fourth, the data opacity— lack of usage and real-time access measures—prevents evidence-based optimization of infrastructure. Lastly an inter-jurisdictional fragmentation across Delhi, UP & Haryana negates cohesive planning leading to uneven levels of service and compatibility issues. In this paper, we tackle these issues with a systematic demand analysis so that there is data driven basis for infrastructure planning and policy interventions.

Research Objectives

There are four main aims of this study:

Assessment of current state – Assess the existing EV charging infrastructure in delhi NCR including distribution, charger densities and proximity to vehicle registrations/population.

Supply gap analysis presents a spatial and temporal analysis which identifies underserved regions and evaluates their performance against established policy benchmarks and international standards.

Demand forecasting study projects electric vehicle adoption and charging requirements from 2023 through 2035 using historical growth patterns and policy trajectory models and regression analysis.

Policy recommendations provide guidance to help planners and investors choose district deployment areas which should receive priority treatment.

Conceptual_Framework

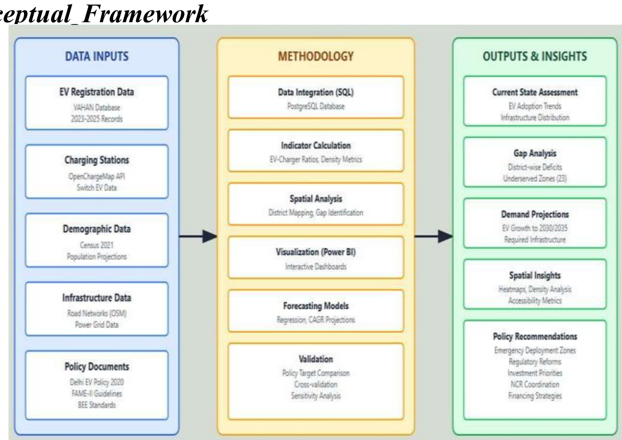


Figure 1: Conceptual Framework

The conceptual framework would visualize the research flow:

INPUTS →

- EV Registration Data (VAHAN)
- Charging Station Database (OpenChargeMap, Switch EV)
- Demographic Data (Census, Population)
- Infrastructure Data (Road Networks, Power Grid)
- Policy Documents (Delhi EV Policy, FAME-II)

METHODOLOGY →

- Data Integration (SQL)
- Indicator Calculation (Density, Ratios, Growth Rates)
- Spatial Analysis (District-level Mapping)
- Visualization (Power BI Dashboards)
- Forecasting (Regression, CAGR)

OUTPUTS →

- Current State Assessment
- Gap Analysis
- Demand Projections (2030, 2035)
- Underserved Zone Identification
- Policy Recommendations

II. SCOPE

(a) *Demographic Scope*

This study considers the mobile and infrastructure scene covered only in the Delhi National Capital Region (NCR). The study area is considered as one compact region of an over all extent of 10,787 km2 (30 million inhabitants).

- Delhi (National Capital Territory): All 11 districts: Central, New Delhi, North, North East, East, South East, South, South West, West and North West and Shahdara.
- Uttar Pradesh Sub-Region: Gautam Buddha Nagar (Noida and Greater Noida) and Ghaziabad.
- Haryana Sub-Region: Districts of Gurugram and Faridabad.

This harmonized definition is framed from the region's contracted economic activity, its network of labor commuting between states and common public transport infrastructure, thus facilitating a holistic approach to one of the world's largest megapolitan agglomerations.

(b) *Data Scope*

Analysis of EV adoption and infrastructure development in the NCR is informed through four principal data dimensions

- The demand-level is primarily proxied through the vehicle registration data (VAHAN database, Ministry of Road Transport & Highways) (2023–2025). The data can be decomposed by vehicle type (2W, 3W, 4W), area and registration.
- Charging Infrastructure Data: Public charging point details—such as location, capacity, type of charger and operational status—were collected from the OpenChargeMap API and Switch EV database, as well as from operator releases. They did not include private and household charging infrastructure for which data were not available.
- Demographic & Urban Indicators: Density of population, motor

vehicles, household income and urban development pattern were integrated from 2021 Census and municipal planning reports to quantitatively distribute the demand over space.

- Policy & Regulatory Data: Policy-related documents, subsidy programmes and infrastructure mandates from the central or state government were also collected to create benchmark standards and targets for adoption.

(c) Academic and Methodological Scope

The research utilizes descriptive and predictive analytics and the methodology of SQL-based data processing and Power BI visualization for descriptive analytic purposes. They also forecast EV adoption by conducting regression analysis along with the application of the Compound Annual Growth Rate (CAGR) method, ruling out modern techniques such as machine learning or agent-based modeling to keep their focus on the method and be candid about it.

III. METHODOLOGY

(a)Data Collection

Data collection leveraged a combination of primary API/database sources and supplementary secondary datasets.

Primary Data Sources:

- VAHAN Database (EV Registration): We were given the opportunity to look at the complete set of EV registration data (Jan 2023 - Jun 2025) for EV registrations across all the districts of Delhi NCR.
- OpenChargeMap API (Charging Stations): The global database of charging stations created by users provided the locations of stations, kinds and capacities of chargers, and the status of charges for the NCR.
- Switch EV Network Data: The operator-verified data given by the partnership included the locations of stations, the timelines for installation, and the anonymized utilization rates for over 400 stations in the NCR.
- Government EV Portals: The Delhi Transport Department, e-Amrit, and the state nodal agencies were the sources from which the ancillary infrastructure data, policy documents, and records of subsidies were obtained for cross-checking.

Secondary Data Sources:

- Demographic Data: We gathered district-level population, household counts, vehicle density, and urbanization metrics from Census 2021, along with population projections for 2025-2030 from the NCR Planning Board.
- Infrastructure Data: The road network GIS data (OpenStreetMap), power grid capacity data from distribution companies, and inventories of parking facilities were included.

(b) Data Preprocessing

Researchers needed to perform extensive data cleansing operations together with data standardization processes in order to achieve reliable analysis results from the raw dataset.

- Cleaning Operations: The process removed duplicate records which resulted in the deletion of 347 duplicate charging station records. The system corrected geocoding errors which affected 89 stations through location accuracy improvements.
- Missing Data Handling: A significant amount of information was missing for certain variables. About 31% of stations lacked operational company information which led to their classification as "Independent/Unknown."
- Transformation: The analysis needed population projections for demand estimation which required all years needed their values computed through linear interpolation to create a continuous dataset.

(C) Key Indicators & Metrics

The research adopts a thorough indicator framework across the dimensions of supply, demand, and integrated metrics:

➢ Supply-Side Indicators

- Charger Density: The public charging stations count per 10 km2 (Benchmark: 5−8 stations/10 km2 for high-density urban areas.)
- Population Coverage: The population throughput as compared to each charging station (Benchmark: 10,000−15,000 persons per station for adequate coverage.)
- Charger Capacity: The total charging capacity (kW) of the district, depicting infrastructural power.

➢ Demand-Side Indicators:

- The EV Penetration Rate measures the percentage of electric vehicles among all registered vehicles.

(d)Forecasting Methodology

The model EVs(t)=a×e b×t was used to apply an exponential regression on 30 months of historical data the resulting models showed strong fit with R2 values of 0.89−0.94 in all districts. The development of alternative scenarios for 2030 projections is executed through three separate scenarios.

The Conservative scenario assumes a compound annual growth rate of 25 percent which results in 1.2 million electric vehicles for the Delhi NCR area because of policy delays and economic headwinds.

The Moderate Base Case scenario assumes a compound annual growth rate of 35 percent which matches recent trends and existing policies and this rate results in 2.1 million electric vehicles.

The Aggressive High Growth model assumes a compound annual growth rate of 45 percent because of advancing policies and fast approaching cost parity which results in 3.5 million electric vehicles.

Required Stations= Projected EVs / 20

The formula calculates electrical vehicle charging requirements based on 70% of charging stations having AC (Level 2) capabilities and 30% of stations offering DC Fast Charge points, which together provide 2.5 charging points.

IV. SYSTEM DESIGN AND IMPLEMENTATION

The methodology consists of the Data Layer (storage/processing), the Analytical Layer (computation/modeling), and the Presentation Layer (visualization/reporting).

(a) *Data Flow Architecture*

The system operates on the separate flows for ingestion, processing, and output:

- Ingestion Flow
  EV Registration Data: A monthly batch import is conducted from the VAHAN API, passing through a CSV staging area, a validation script, and ultimately insertion into the PostgreSQL database.
- Raw data tables are condensed via SQL queries into temporary analytical tables. These temporary tables feed Indicator Calculation Procedures to populate the demand_indicators table. The indicators and base tables are loaded into the Power BI data model, which will refresh every 12 hours as scheduled.
- Output Flow The Power BI data model is the main contributor to creating highly interactive and engaging visualizations in the dashboard.

(b) *Implementation Details*

The database being used is PostgreSQL 14.5 with the PostGIS extension that enhances the performance of spatial operations greatly. For ETL/processing purpose, Python 3.10 (with the help of pandas, geopandas, and scikit-learn) is combined with SQL stored procedures.

Visualization is done using Microsoft Power BI Desktop for development and Power BI Service for cloud hosting and distribution.

Infrastructure consists of the cloud-hosted database (AWS RDS) and local computation for Python scripts.

Data Sources include the integration of REST APIs (VAHAN, OpenChargeMap) and static CSV files (Census, policy data).

- Key Implementation Challenges & Solutions:

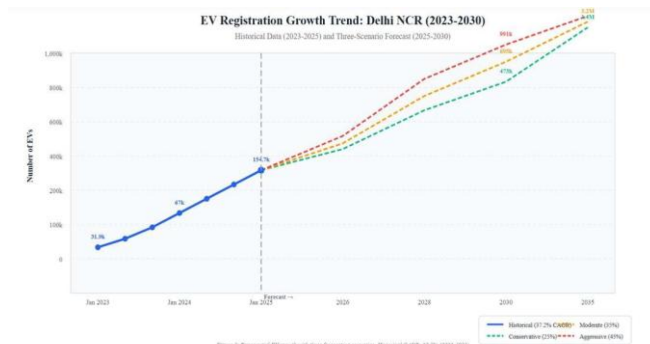
(i) *Challenge 1: Data Quality Issues*

Problem statement: There were 23% duplicate entries in the charging station database, and the names were inconsistent and the status was outdated.

Solution: A multi-stage deduplication algorithm using

Figure 2: EV registration growth from 2023-2030

coordinate clustering (50m threshold) plus manual verification of ambiguous cases was developed. Data quality dashboard was



implemented to track completeness, accuracy, and freshness metrics.

(ii) *Challenge 2: Spatial Analysis Performance*

Problem: Proximity calculations for over 150,000 EVs to more than 1,800 charging stations were very computationally intensive.

Solution: Use of PostGIS spatial indexes and nearest-neighbor algorithms to optimize queries. The time taken for querying was reduced from 45 minutes to 3 minutes.

(iii) *Challenge 3: Dashboard Performance*

Problem: The first Power BI dashboards had slow loading times (20-30 seconds) because the system was aggregating over 1.2M+ registration records in real time.

Solution: Monthly granularity was applied to aggregated data tables, DirectQuery was used only for real-time KPIs, and historical data was imported. The load time was reduced to u

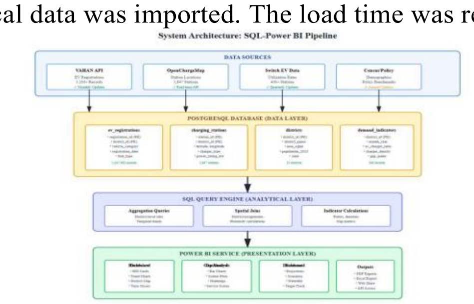


Figure 3: Proposed system architecture

(iv) *Challenge 4: Forecast Integration*

Problem: Power BI's native forecasting capabilities were insufficient for scenario-based projection.

Solution: Forecast scenarios were generated in Python, projections were stored as distinct database tables, and the pre-computed scenarios were visualized in Power BI with scenario selectors.

V. RESULTS

A. EV Adoption Overview

The total registered electric vehicles (EVs) in the Delhi National Capital Region (NCR) as of June 2025 is 154,730, signifying a remarkable growth of 385% from January 2023. The regional Compound Annual Growth Rate (CAGR) of 37.2% is much higher than the national average, thus proving the market is really booming.

B. *Charging Infrastructure Deployment*

As of July 2025, the Delhi NCR has 1,847 public charging stations with a total of 4,231 charging points available for electric vehicles.

- Spatial Concentration: The infrastructure is very concentrated: New Delhi and Central Delhi take up only 17% of the area and yet have 28% of the charging stations. The core districts of Delhi have an average of 76.5 stations per 10 km2, which is 18 times more compared to the peripheral NCR (Ghaziabad/Faridabad) average of 4.2 stations per 10 km2. Shahdara is a major gap in the network.

C. *Demand-Supply Metrics*

The analysis shows that infrastructure exists for distribution but needs repair because the system lacks complete coverage. The regional level shows an electric vehicle to charging station ratio which stands at 84 vehicles for each charging station which exceeds the Bureau of Energy Efficiency BEE standard of 20 vehicles for every charging station by 4.2 times.

D. *Critical Findings*

1. Systemic Deficit: A ratio of 84:1 in the region is very much against the BEE benchmark (20:1) showing a hard infrastructure shortfall of 4.2 times.
2. Paradoxical Distribution: There are only two districts (New Delhi, Central Delhi) which fulfill the adequacy standards although they have the lowest number of EVs.
3. High-Demand Districts Underserved: The districts of South Delhi, Gurugram, and Noida together possess 51% of the EVs but are served with ratios exceeding 100:1.

E. *Spatial Gap Analysis*

Tier 1 Critical Gaps (Highest Priority — 8 zones):

1. Outer Ghaziabad (Vasundhara-Indirapuram): 4,200 EVs, 8 stations (525:1 ratio)
2. Dwarka Sector 18-24: 2,800 EVs, 6 stations (467:1)
3. Rohini Sectors 1-15: 3,100 EVs, 9 stations (344:1)
4. Greater Noida West: 3,600 EVs, 12 stations (300:1)
5. Faridabad Sector 15-20: 1,800 EVs, 4 stations (450:1)
6. Shahdara-Seemapuri: 1,600 EVs, 2 stations (800:1)
7. Najafgarh-Dwarka Border: 1,900 EVs, 5 stations (380:1)
8. Ghaziabad Raj Nagar Extension: 2,100 EVs, 4 stations (525:1)

Tier 2: Significant Gaps (9 zones):
Among the locations with a ratio of 100-200:1 and substantial EV count (1,000-3,000 each), Pitampura, Mayur Vihar, Vasant Kunj, and certain sectors of Noida are noticed.

Tier 3: Emerging Gaps (6 zones):
Halves still having average ratios (60-100:1) but severe EV mounting (50%+ CAGR) foreseeing lack within 12-18 months.

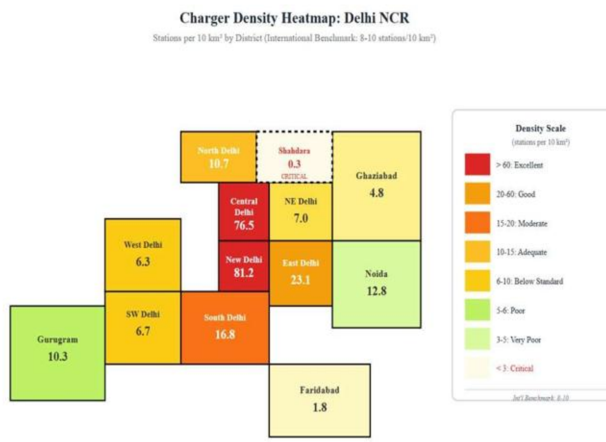


Figure 4: Charger density heatmap

F. *Forecasting Results*

EV Adoption Projections (2025-2035):
The three-scenario forecasts indicate a huge range in the potential adoption of electric vehicles in the National Capital Region by the year 2035 based on the projected Compound Annual Growth Rates (CAGRs):

• 2030 Projections: The number of electric cars is expected to be, depending on the scenario, 473,000 (Conservative) to 991,000 (Aggressive). The base scenario sums up to 695,000 EVs.

• 2035 Projections: The long-term forecast is between 1.4 million and 6.8 million EVs.

(G) Infrastructure Requirement Projections:

• 2030 Infrastructure Need: The need for charging stations range from 23,650 (Conservative) to 49,550 (Aggressive). The Moderate scenario requires 34,750 stations.

• Deployment Challenge: The current deployment rate of approximately 43 stations per month represents only 6% of the monthly addition required (717 stations) for the 2025–2026 Moderate scenario.

VI. SYSTEM INSIGHTS AND DISCUSSION

A. Analysis and Policy Implications

Current Adequacy Assessment

The charging infrastructure in Delhi NCR is a "paradox of progress" in the case where even though 1847 stations (which is 15% of the national infrastructure) have been built, the regional EV-to-charger ratio of 84:1 is still 4.2 times worse than the BEE benchmark, and the gap has widened by 31% since January 2023 regarding the existing infrastructure.

B. Policy Effectiveness Analysis

The Delhi EV Policy 2020 has been a mixture of major successes and failures:

Successes: The policy that was enacted can be credited for the increased adoption of Electric Vehicles from 0.4% to 1.52% primarily through the giving of purchase subsidies (mentioned as a reason by 87% of the buyers) and the speeding up of the regulatory process which reduced the time of station permitting from six months to thirty days.

Shortfalls: The policy was not able to achieve its 25% EV penetration target for 2024, but only 6% of the goal was reached. Furthermore, the number of the 1,847 existing stations is far from the 6,000+ shrunk required for the current EV base and there are no policy measures to prioritize underserved zones at this time.

Root Causes of Underperformance:

- Overambition: The 25% target required an unsustainable 60–70% annual growth rate.
- Implementation Gaps: Infrastructure mandates for new buildings are poorly enforced (estimated 30% compliance).
- Financial Constraints: The initial ₹18 crore infrastructure allocation was grossly insufficient for the required scale (₹500–800 crores estimated for current adequacy).

VII. LIMITATIONS AND FUTURE WORK

A. Data Limitations

The analysis is limited by a number of data incompleteness issues: Charging Station Database Gaps: It is estimated that around 20 to 25 percent of the public chargers that have been installed are not included in the databases that are available. Furthermore, all the private fleet chargers are also absent from the databases.

B. Scope Limitations

The research did not attempt to cover all the possible dimensions but the main ones were simply omitted thus it was easier to manage the research.

C. Future Research Directions

The future study will be based on the integration of missing data and the application of the advanced modeling techniques:

- Real-Time Utilization Integration: By collaborating for anonymized usage data and developing demand models adjusted for utilization, the infrastructure gap estimated can be narrowed down by 20–30% due to better reallocation.
- Enhanced Spatial Modeling: Actual road network distances will be integrated using GIS routing algorithms along with the traffic congestion data.

VIII. RECOMMENDATIONS

Infrastructure deployment will require implementation of infrastructure solutions which need to resolve the "Inverse Distribution Problem" while achieving operational acceleration at a rate that exceeds 17 times the current speed.

Immediate Action (0-12 months): An Emergency Deployment Program will be initiated that will cover the installation of 850 stations in 23 critical gap zones (for instance, Ghaziabad and Greater Noida West) with a permitting mandate of fast tracking 15 days and 60% coverage of CAPEX as subsidy.

Medium-Term (1-3 years): Standards for Differentiated Deployment (e.g., 10:1 ratio for commercially zoned areas and 30:1 for residential areas) would be imposed, along with offering operators access to public land through concessionary 20-year leases.

A. Regulatory Reforms

Building Code Amendments: New large developments will have to ensure that their parking is entirely prepared for electric vehicle charging and they must also set up a minimum of 20% of charging points that would be active at the time of occupancy. Current communities will have to upgrade their parking areas with electrification points as per the following: starting with 5% going to 100% by 2030.

B. Technology & Innovation

Due to the scarcity of resources, a Smart Charging Network is needed to ensure their maximum efficiency.

Grid Intelligence: Smart charging equipment for load management will be deployed and Vehicle-to-Grid (V2G) programs will be piloted to exploit EVs as grid stabilizers.

C. Financing Strategy

The total estimated investment in the Moderate Scenario is between ₹15,800-₹20,000 crores (with ₹12,000-₹15,000 crores specifically for public charging infrastructure) by 2030. Financial Tools: The immediate actions comprise raising the FAME subsidy, the introduction of Viability Gap Funding for the sites that are socially necessary but commercially unviable, and the issuance of Green Bonds (₹2,000 crore issuance) to organize concessional capital.

IX. CONCLUSION

A. Key Findings Synthesis

A thorough demand analysis demonstrates that Delhi NCR even though it is India's leading Electric Vehicle (EV) market with over 154,730 registered EVs, still suffers from a critical situation characterized by an ever-increasing infrastructure gap. The study leads to three inevitable conclusions:

1. Big and Increasing Deficit:

The region experiences an extreme shortage of electric vehicle chargers because the existing chargers fail to meet the demand of 84 electric vehicles per single charger which exceeds the 20:1 standard by 4.2 times. The current situation shows a space-based deficit which leads to distribution problems because central areas have extra resources while the 23 outer NCR areas face severe resource shortages that obtain 2.7% of their required infrastructure yet contain 13.6% of the complete regional electric vehicle population.

2. Development Path That Is Not Enough:

The moderate prediction of 695000 EVs in 2030 requires 34750 charging points which represents an 188-times increase. The electric vehicle to charging station ratio will reach 200 to 1 by 2030 unless charging station installation speeds reach required levels which will create severe charging station shortages that block electric vehicle adoption.

3. *Methodological and Broader Implications*

This study proves the use of an integrated SQL-Power BI analytical framework as a powerful, scalable, and transparent tool for urban infrastructure planning. The strengths of the method revolve around the fact that it is easy to access, can be duplicated, and allows for the merging of different data sources into one; thus, giving insights that are critical in a multi-stakeholder situation where "black box" models are usually rejected.

B. Strategic Imperatives for Action

The shortage will require big governance, regulation and finance-heavy mobilization of actions

- Policy and Regulatory Imperatives:

Urban governance-making and management would demand a wide NCR coordination mechanism—the suggested Delhi NCR EV Infrastructure Council—to get rid of the fragmentation due to different states' jurisdictions and to uniform the users' experience.

- The most important and critical issue in the long run is to reform regulations: to incorporate charging stations into urban planning code.

C. Finances

The forecasted investment need of ₹15,800-₹20,000 crore in the years to come up to 2030 is beyond the capacity of the government's budget alone. A significant contribution of the private sector is needed to be structured through mobilization:

1. Financial Innovation: Issuing of Green Bonds and employing Viability Gap Funding to ensure placements in financially difficult but socially necessary areas.
2. Favorable Tariffs: Power regulation will be required to create a special low-priced electricity tariff for EV charging, to introduce Time-of-Use (ToU) pricing to encourage charging during off-peak hours and to help in controlling grid stability.

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