International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 11, CONFLUENCE - 2026

EVision: A Data-Driven Intelligent System for EV Charging Infrastructure Analysis and Decision-Making Support

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Abstract - Electric vehicles (EVs) are becoming increasingly popular, and the demand for easily accessible and convenient charging stations is growing. However, infrastructure coverage is uneven, and vehicles have different charging needs, making it difficult for drivers to find compatible stations and for developers to find new facilities. This study introduces EVision, a platform for analysing charging infrastructure, recommending appropriate stations, and evaluating possible investment scenarios across five states of South India and Pondicherry.

The platform integrates Open Charge Map station records, VAHAN vehicle registration data for 2022–2026, and vehicle charging specifications. Data cleaning and geospatial analysis help study the distribution of stations. Min-max normalization, weighted scoring, and dense ranking are applied to identify infrastructure gaps and investment priorities. The vehicles are matched with the charging stations based on the connector type by a rule-based recommendation algorithm. The rule-based recommendation algorithm matches a vehicle with a station according to the connector type and charging power. The platform estimates the selected assumptions, potential revenue, operating costs, and payback periods using business assumptions.

As per the Open Charge Map dataset- there are currently 1,306 charging-station listings and 350 driver recommendations. The revised Andhra Pradesh dataset records 82 operational charging locations and 88 charge points. Business-priority analysis designates Tamil Nadu and Karnataka as high-priority investment zones. These results are presented through an interactive dashboard and a two-mode analytics assistant designed for drivers and infrastructure planners. By combining rule-based recommendation, geospatial analysis, and financial assessment within a single platform, EVision supports informed charging and investment decisions.

Keywords: Electric Vehicles, EV Charging Infrastructure, Weighted Scoring Algorithm, dense ranking and Geospatial Analysis.

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1. INTRODUCTION

The development of e-mobility requires the creation of a charging network that is easily accessible, well-distributed, and meets users' needs. This involves decision-making in terms of ~~the~~ placement, capacity, operating cost, and ability to integrate charging stations into the power grid [1]. These decisions are based on various sources of information. Therefore, the problem of availability of high-quality data arises in the area of charging infrastructure studies [2].

Previous studies have highlighted the advantages of a data-based analysis of the processes related to the use of electric vehicles. Thus, Pevec et al. pointed to the lack of access to good data and the absence of any universal method of placing charging stations [2]. Additionally, in Ranjbar et al., focused on infrastructure planning, economic management, and connection to the power grid and noted the need to combine technical, behavioural, and economic factors [1]. It should be noted that the aforementioned paper proves the possibility of developing analytical systems which incorporate all relevant information [1,2]

Geospatial analysis and MCDM represent tools that allow us to identify possible priority sites for the construction of stations. Among others, the study of Ghosh et al. represented an analysis of geoinformation and fuzzy multi-criteria approach to selecting priority locations for building charging stations in Howrah, India. Their study proved the significance of socio-economic factors and population density [3]. In another study, Benayad et al. developed EVPLAN, which is an interactive geographic decision support system that allows the user to modify the criteria and examine the effect on the suitability of the charging station [4]. Mazzei and Michelotti developed a web application that combines open spatial data and several planning methods for comparing locations based on different criteria and assumptions [5].

Recommendations for charging can also be better with the inclusion of users' geographical position and charging preference. According to Seo et al., there is an improvement in the performance of the charging station recommendation model when spatial context and charging preferences are taken into account [6]. The aspect of infrastructure development should also be economically feasible. It was proven by Hecht et al. that the usage of charging and financial implications differ with different types of chargers and operating conditions [7].

These factors result in the creation of the framework named EVision, which is an approach for data analysis regarding the EV charging infrastructure and decision-making support in the states of Andhra Pradesh, Telangana, Karnataka, Kerala, Tamil Nadu, and Puducherry. This framework will utilize information on the list of charging stations obtained from Open Charge Map, vehicle registrations in VAHAN between 2022-2026, as well as the characteristics of

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vehicles and chargers. Data cleaning and geospatial analysis allows the analysis of patterns of infrastructure deployment in the region. Min-Max Normalization, weighted score, and ranking methods provide a basis for comparing priorities in the region.

The aim of this study is to examine the ways of using publicly available government information and analytical techniques in making decisions concerning charging stations in South India.

2. RELATED WORK

EV charging station research examines the need for the station, compatibility of the charger with the EV, and the cost effectiveness of the installation. Ranjbar et al. [1] examined the relationship of planning, control, and economic analysis. Pevec et al. [2] pointed out the need for dependable data and methodologies as areas of ongoing research.

2.1 Data Preprocessing and Infrastructure Analysis

The authors of the EV-Insights framework introduced EV-charging datasets in a standardized form [11]. EVision Dataset makes use of the Open Charge Map station lists, VAHAN registration list stored, and car specifications. The data is cleaned of duplicates, coordinates verified within the state boundaries, and comparable fields normalized. This allows infrastructure analysis across six South Indian states despite the fact that results depend upon the quality of data provided.

2.2 Regional Planning and Priorities

Ghosh et al. [3] carried out the prioritization of the candidate locations using fuzzy multi-criteria evaluation. EVPLAN [4] and the methodology proposed by Mazzei and Michelotti [5] have permitted interactive planning through scoring and optimization**.** Their results depended on the selected criteria, weights and local data. Li et al. [10] utilized vehicle trips in conjunction with geographic data, though insufficient rural trips reduced the quality of their recommendations. EVision utilizes Min-Max Normalization and weighting to score the regions. Coverage and business scores separate regions requiring improved charging provision from the regions having a bigger market.

2.3 Analysis of Demand

Orzechowski et al. [8] predict charging demand from history of sessions. Meanwhile, Mauritius et al. [9] apply spatial imputation with classification, whereas Straka et al. [13] used transactions together with geographic information systems data for station popularity prediction. All of the above techniques require observation or labelling, which is not possible in our case. Therefore, registration trends and number of registrations per charger or charging

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station were considered. Ratio will show the level of stress that could be created by the infrastructure, but does not show the utilization of each charger.

2.4 Recommendation for Vehicles and Chargers

Seo et al. [6] recommend vehicles and chargers by applying graph neural networks with location and type of charging preference and simulating driver behaviour to evaluate recommendations. Preferred charging speed is not enough to guarantee connectivity of charging connector. In EVision, the type of connector family and recorded power are compared to the requirements of the vehicle, and the distance is used to recommend nearby chargers.

2.5 Business Viability and Contribution to the Project

Hecht et al. [7] used profitability analysis with respect to charging events. Farhadi et al. [12] focused on optimizing infrastructure design depending on future scenarios. The above findings depend on the characteristics of the region, as well as some assumptions concerning the cost structure and demand. This tool facilitates the computation of energy sales, operational surplus, and the payback period specific to the charger case. The innovation of this work lies in the integration of regional characteristics, coverage, business features, vehicle matching, and economic analysis within a single dashboard. This type of tool can be employed for the planning process using available information. However, further tests should be conducted to measure its efficiency

3 METHODOLOGY

3.1 Data sources and preparation

EVision is developed to compare charging provision, identify regional priorities, find suitable chargers for a selected vehicle and examine business costs. The study covers Andhra Pradesh, Karnataka, Kerala, Puducherry, Tamil Nadu and Telangana. The fixed records stored within the original dashboard are utilized, ensuring that each figure presented below can be traced back to its corresponding saved results.

Table 1. Datasets and their importance in this study

Input	Content used	Purpose
Open Charge Map [14]	1,306 distinct station listings; 1,286 recorded as operational	Locations, points, connectors, power and status
VAHAN [15]	Saved annual registration series, 2022–2026, for six regions	Registration trends and regional pressure indicators

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Input	Content used	Purpose
Population Table [16]	Project copy of 2011 population figures	Population-based descriptive comparisons
Vehicle requirements [17]	Seven models with connector and power fields	Vehicle–station compatibility screening
Boundary file [18]	South India state polygons in GeoJSON format	Coordinate-based state assignment

The 2026 registration values cover only the period recorded in the saved files. They are not a completed annual total or cumulative EV fleet. The population figures refer to 2011. The vehicle and boundary files are project inputs [14,18] are listed in the References.

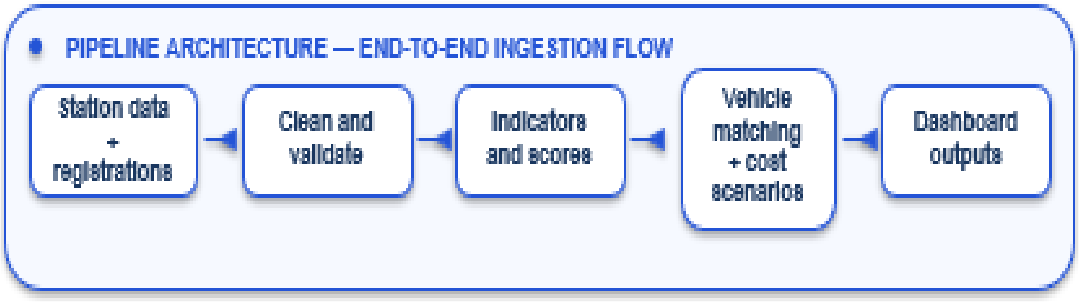
Algorithm 1 Preprocess the datasets

Input: Station IDs, boundaries, registrations, population, and number of vehicles

Output: Processed station data and region data

1. S ← process station IDs for removal of duplicates
2. Associate station with region based on coordinates
3. S ← retain stations that fall into the six regions
4. Normalize values; assign missing point values 0 and missing power values unknown
5. Add connector data and aggregate station operations data by region
6. RETURN region summary with registration and population information

Figure 1: Basic workflow from source records to dashboard outputs.



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A station location may contain several charging points; therefore, that are counted separately. Operational status describes the saved record, not live availability. Missing point counts and incomplete directory coverage can understate the recorded network.

3.2 Regional indicators and priority scores

Registrations are compared with the number of operational locations and points. Let E be a region's saved 2026 registration count, S its operational locations and Q its operational points. The bigger ratio indicates more registrations for the same amount of infrastructure capacity listed; it does not indicate number of charging periods or lines.

Registrations per location = E / S registrations per point = E / Q (1)

Locations with maximum recorded power of at least 40 kW are considered fast. Their share uses all the listed locations. To combine indicators with different units, scale each indicator across the same six regions:

$$N(x) = (x - \text{minimum } x) / (\text{maximum } x - \text{minimum } x) \quad (2)$$

D is the scaled registration count, and L and P are the scaled registrations per location and per point, respectively. F equals one minus the scaled fast-location share; therefore, poorer fast-charging provision receives a larger value. These are the elements used in the computation of both scores:

$$\text{Coverage score} = 100 \times (0.40D + 0.30L + 0.20P + 0.10F) \quad (3a)$$

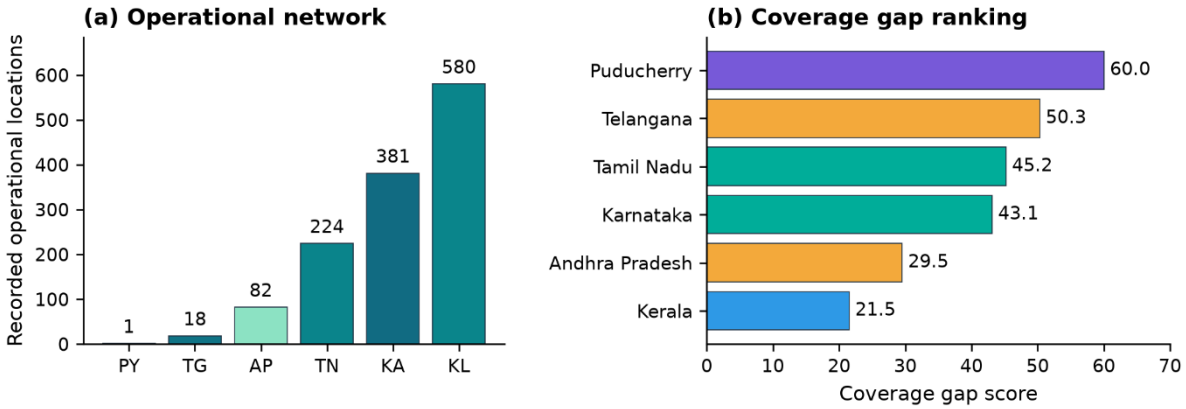
$$\text{Business score} = 100 \times (0.50D + 0.25L + 0.15P + 0.10F) \quad (3b)$$

Algorithm 2 Regional Priorities Calculation
Inputs: Registrations in region, operational location, points, fast location
Outputs: Coverage score, business score, ranking, priority
1. D, L, P, F are the scaled inputs according to Equation (2)
2. G is the coverage score according to Equation (3a)
3. IF registrations ≥ 20,000 THEN B is Equation (3b) ELSE B is not defined
4. Rounding of G and B to one decimal place, ranking is from highest to lowest with dense ranking
5. Position 1-2 are tagged as High Priority, 3-4 tagged as Medium and all others tagged as Low Priority
6. IF B is not defined THEN label is Coverage Watch
7. Output G, B, rankings and labels

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Figure 2: Original dashboard results. AP, KA, KL, PY, TN, and TG denote the six study regions. Left: color follows fast-location share. Right: teal = high, amber = medium, blue



= low business priority, and purple = Coverage Watch.

The saved results have Tamil Nadu and Karnataka first on business opportunity at 53.3 and 52.5, respectively. Puducherry comes first on coverage score at 60.0; yet, it is still Coverage Watch. The weights and eligibility threshold are project decisions rather than the learned parameters from the observed returns. Listing sparsity can lead to distorted pressure ratio calculations.

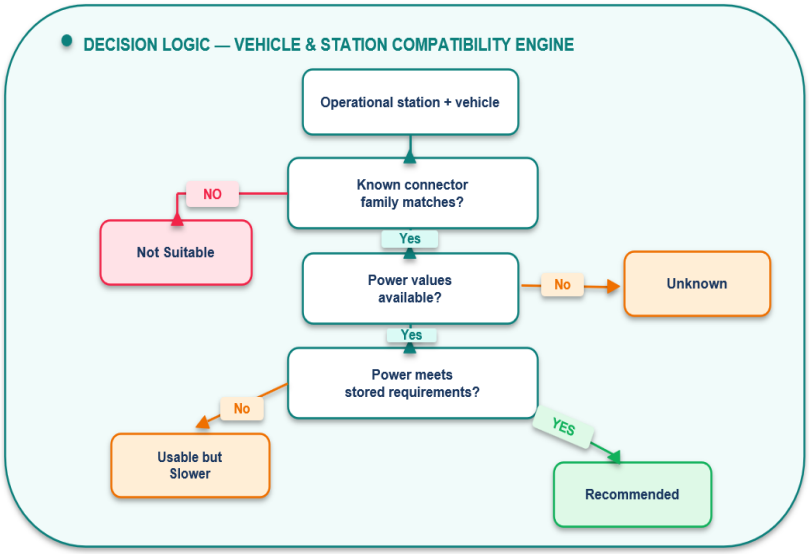
3.3 Vehicle matching and neighbouring stations

Each of the seven vehicles was evaluated in relation to each operational station. The names of the connectors were grouped in CCS, CHAdeMO, Type 2, Type 1, and GB/T families. Unknown connector families could not be matched. The subsequent step involves testing whether the station power exceeds both the vehicle's minimum and preferred power levels.

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Figure 3: below displays the order of tests.



Basic flow for compatibility decision Failure to identify a preferred power value does not affect the recommended outcome when the minimum is satisfied

Algorithm 3 Match vehicles and chargers
Input: Chosen vehicle, operational stations, and search coordinates (if applicable)
Output: List of ranked vehicle-station pairs
1. FOR each operational station,
2. IF families of connectors differ: label ← Not Suitable
3. ELSE IF station or power below minimum is unknown: label ← Unknown
4. ELSE IF power is lower than minimum or preferred power: label ← Usable but Slower
5. ELSE: label ← Recommended
6. END FOR; discard Not Suitable pairs
7. Sort according to class, greater power and more points; select 10 of each kind and region
8. IF coordinates are provided: return 3 pairs, Recommended first and closest next
9. ELSE: RETURN shortlisted pairs

Distance is calculated directly using the Haversine formula, where the Earth's radius is 6,371.0088 km. This approach may be used to calculate distances between coordinates that lie close to one another; however, it does not calculate distance via roads or the time taken to reach that point. The search shall be performed in the selected data only.

Table 2. Reproduced matching results

Output	Count	Meaning
Vehicle–station comparisons	9,002	7 models × 1,286 operational locations

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Output	Count	Meaning
Saved recommendations	350	Vehicle–station associations, not unique stations
Recommended / Usable but Slower	202 / 148	Classes retained after filtering and ranking

This is the outcome of the rule-based screening. The maximum power of one station may be related to another connector. The labels imply that the connectors satisfy certain rule-based conditions and not based on actual testing. No queues, charging rates, or interaction models are used here.

3.4 Business cases and verification of results

The economics of 60 kW, 120 kW, and 180 kW DC charging stations is estimated using the set of assumptions already established in the project. Utilization is the use of maximum potential for work during the available period. The base business cases rely on the same assumptions in each region; hence, regional prioritizations will not influence the financial outcomes.

The model is based on 24 hours of availability per day, 30 days per month, electricity selling price INR 18/kWh, electricity cost of INR 8/kWh, and monthly fixed costs of INR 40,000. The total investment consists of capital costs plus a 10% contingency of the stated capital cost.

Generated Energy = k x 24 x 30 x u (4)

Where:

Charger Power = k as a ratio, Utilization factor = u as a ratio.

Monthly Net Surplus = Monthly Energy x (Selling Cost - Electricity Cost) – Monthly Fixed Costs (5)

Simple Payback Period = Total Investment / (12 x Monthly Net Surplus) (6)

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Algorithm 4 Charger Economics Analysis
Input: Power of charger, its utilization, prices, fixed costs, capital costs Output: Income, margin and payback period 1. Monthly energy <- power × 24 × 30 × utilization 2. Income <- monthly energy × selling price 3. Margin <- income – (monthly energy × electricity price) – fixed costs 4. Investment <- capital cost × 1.10 5. IF margin > 0 THEN payback <- investment / (12 × margin) 6. ELSE payback <- undefined 7. RETURN income, margin and payback

Table 3. Base Case Results

Power	Utilization	Investment INR lakh	Monthly surplus INR	Payback years
60 kW	15%	19.8	24,800	6.7
120 kW	20%	35.2	132,800	2.2
180 kW	25%	52.8	284,000	1.5

For example, a 60-kW charger has a monthly production of 6,480 kWh per unit-month. The revenue is INR 116,640, and the expenditure is INR 51,840. Thus, the net profit is INR 24,800. These figures were computed and not actual profits. Large chargers imply high use; therefore, this table is not a controlled experiment of charger power.

Implementation and Validation

Python, pandas and NumPy are used for data preparation and computation, while Shapely is used for checking geographic borders. Charting is done using Dash and Plotly Validation covered station ID uniqueness, regional totals, both planning scores, all 9,002 compatibility labels, and three financial scenarios. Figure 2 uses values from the original dashboard chart code. These checks confirm computational consistency; however, user experience and real-world outcomes remain untested.

4. RESULTS AND DISCUSSION

EVision analysed 1,306 charging-location records across six South Indian regions, including 1,286 marked as operational.

4.1 Infrastructure and Regional Priorities

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Kerala recorded the most operational locations, followed by Karnataka and Tamil Nadu. Puducherry and Telangana had the highest coverage-gap scores, while Tamil Nadu and Karnataka led the business ranking.

Region	Operational locations	Coverage-gap score	Business score
Andhra Pradesh	82	29.5	31.5
Karnataka	381	43.1	52.5
Kerala	580	21.5	26.3
Tamil Nadu	224	45.2	53.3
Telangana	18	50.3	48.0
Puducherry	1	60.0	—

The scores are relative indices and not percentages.

Puducherry remained under "Coverage Watch" because it fell below the business-ranking threshold. Separate scores distinguish coverage needs from market potential.

4.3 Financial Scenarios

The 60, 120, and 180 kW scenarios estimated monthly operating surpluses of ₹24,800, ₹1,32,800, and ₹2,84,000, with simple payback periods of 6.7, 2.2, and 1.5 years, respectively. Higher-capacity scenarios also assumed higher utilization The same assumptions about a region lead to the same financial results which are only estimates, not actual profits.

5. CONCLUSION AND FUTURE RESEARCH

EVision combines regional planning, compatibility screening, and financial analysis into a single dashboard. However, incomplete station listings, partial 2026 registrations, and missing charging session observations limit the interpretation. The financial estimates exclude taxes, demand charges, financing, charging losses, and local cost differences. The payback calculations were undiscounted. In its explicit criteria for scoring and matching, it offers a clear framework for decision-making in preliminary charging and investment opportunities, based on the publicly available data. The site allows identification of regions and charging options that are worth exploring, but one should bear in mind that the real-life potential of the regions and their economic viability have to be evaluated further. Future development might include integration of information about the live availability of stations, more up-to-date station data, and district-level evaluation.

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