SEEJPH Volume XXVI, 2025, ISSN: 2197-5248; Posted:04-01-25

PRIORITIZING THE CRITERIA OF SELECTION FOR DEPLOYMENT OF ELECTRIC VEHICLE CHARGING STATIONS

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KEYWORDS

Principal component analysis, Multi criteria decision making, Greener transportation solution, EV Charging station

ABSTRACT

The rapid adoption of electric vehicles (EVs) has increased the demand for strategically placed charging stations to ensure seamless mobility and enhance user satisfaction. This study aims to prioritize the critical criteria for the selection of EV charging station deployment sites using three robust Multi-Criteria Decision-Making (MCDM) techniques. PCA method is implemented to reduces dimensionality and identify the most influential criteria, and highlights patterns in the dataset. CRITIC (Criteria Importance Through Intercriteria Correlation) and Entropy methods are developed to prioritize the criteria based on the loadings of the principal components.

The research identifies key criteria, such as location accessibility, energy availability, proximity to demand centers, land cost, environmental impact, and infrastructure feasibility, which influence the optimal placement of EV charging stations. The CRITIC method evaluates the criteria's importance by considering both the contrast intensity and inter-criteria conflict, thereby providing objective weights. The Entropy method quantifies the inherent uncertainty and diversity in the data to derive criterion weights. PCA reduces dimensionality, identifies the most influential criteria, and highlights patterns in the dataset.

The comparative analysis of results derived from these methods ensures robustness in decision-making, offering insights into the alignment and discrepancies among the weighting techniques. The findings provide stakeholders, including urban planners, policymakers, and investors, with a structured framework for making data-driven decisions. This study contributes to the efficient deployment of EV charging infrastructure, supporting sustainable urban mobility and advancing the transition toward greener transportation solutions.

1. INTRODUCTION

The global shift towards electric vehicles (EVs) has accelerated due to concerns over fossil fuel dependency, greenhouse gas emissions, and urban air pollution. As EV adoption grows, the development of a robust charging infrastructure is critical to address range anxiety and ensure convenience for EV users. Charging stations play a pivotal role in bridging the gap between EV penetration and user satisfaction by enabling efficient, accessible, and reliable energy supply.

The deployment of charging stations is a multi-faceted challenge involving technical, economic, environmental, and social considerations. Selecting optimal locations for charging stations requires balancing factors such as accessibility, energy availability, environmental sustainability, infrastructure feasibility, and economic viability. These factors necessitate systematic analysis using quantitative decision-making approaches to support effective planning and implementation.

The deployment of electric vehicle (EV) charging stations is influenced by several key locational criteria that are often interdependent, adding complexity to the decision-making process. Accessibility is a critical factor, emphasizing proximity to highways, urban centers, and parking lots to ensure convenience for users. Energy availability is equally vital, requiring a robust local power grid with sufficient capacity to support charging demands. Demand proximity plays a significant role, necessitating alignment with areas experiencing high EV adoption or dense traffic flows. Economic considerations such as land cost, including the feasibility of acquiring or leasing suitable sites, are also essential. Additionally, environmental impact must be minimized to ensure sustainable integration into the natural surroundings. Finally, infrastructure feasibility, including the presence of supportive elements like well-connected roads and utilities, is indispensable for seamless operation. Balancing these criteria requires a systematic and comprehensive approach to optimize site selection for EV charging stations.

Multi-Criteria Decision-Making (MCDM) methods offer structured approaches for evaluating and prioritizing alternatives when faced with multiple, often conflicting criteria. This study employs three robust MCDM methods: CRITIC, Entropy, and Principal Component Analysis (PCA). The CRITIC method assesses the importance of criteria by considering data variability and the conflict among criteria, assigning weights based on their ability to differentiate alternatives. The Entropy method measures the degree of randomness or uncertainty in the data, assigning higher weights to criteria with greater variability and information content, thus offering an objective perspective. PCA, on the other hand, reduces dimensionality by identifying the most influential components in the dataset, uncovering patterns and relationships among criteria to support informed decision-making. Integrating these methods provides a comprehensive framework for robust evaluation. CRITIC addresses inter-criteria relationships and potential conflicts, Entropy objectively analyses data variability, and PCA identifies key patterns while reducing redundancy. This multi-method approach enhances decision accuracy, ensuring a balanced evaluation and providing valuable insights for policymakers and urban planners in selecting optimal locations for EV charging stations.

In summary, the deployment of EV charging stations is a multi-faceted challenge influenced by diverse and interdependent locational criteria. Addressing these complexities requires the application of structured decision-making tools like MCDM methods, which offer systematic approaches for evaluating and prioritizing alternatives. By integrating CRITIC, Entropy methods with PCA, this study establishes a robust framework to assess and weigh the importance of various criteria, ensuring data-driven and balanced decision-making. This approach not only supports effective planning for EV infrastructure but also aligns with sustainable urban development goals. To further strengthen the foundation of this study, a review of existing literature is conducted to explore previous applications of MCDM methods in similar contexts and to highlight the gaps addressed by this research.

2. LITERATURE REVIEW

Several studies have explored the application of MCDM methods in EV charging station deployment

Guo et al. (2013) investigated the use of hybrid MCDM methods, combining AHP and VIKOR, to evaluate EV charging station sites. The study focused on balancing environmental, technical, and economic factors to ensure sustainable development.

Fan et al. (2014) studied the application of fuzzy AHP in determining the optimal locations for charging stations, incorporating stakeholder opinions and uncertainties in data. Their approach highlighted the importance of accommodating uncertainty in decision-making processes.

Zhou et al. (2015) utilized the PROMETHEE method to rank potential EV charging station locations, focusing on energy availability and proximity to high-demand areas. The research provided a comparative perspective on MCDM techniques for infrastructure evaluation.

Ahmadi et al. (2016) proposed a hybrid framework integrating fuzzy MCDM and GIS for EV charging station location planning, emphasizing environmental sustainability and economic feasibility. Their study underscored the role of hybrid methods in capturing both qualitative and quantitative aspects of decision-making.

Singh et al. (2017) proposed a framework for charging station site selection using AHP and PCA, identifying critical factors through dimensionality reduction and hierarchical analysis. These studies underline the utility of MCDM methods in addressing the multi-dimensional challenges of EV infrastructure planning, offering valuable insights for data-driven and sustainable decision-making.

Huang et al. (2017) examined the application of PCA in identifying the most influential factors for EV infrastructure planning, such as user accessibility and environmental impact. Their findings reinforced the value of dimensionality reduction techniques in simplifying complex datasets.

Liu et al. (2018) investigated the use of the Entropy-TOPSIS method for the deployment of fast-charging stations, focusing on high-demand urban areas. The study highlighted the role of the Entropy method in objectively determining criteria importance based on variability in user preferences.

Rashid et al. (2018) discussed hybrid MCDM approaches integrating CRITIC and Entropy to evaluate sustainable infrastructure projects, providing insights into the complementary nature of these methods in addressing complex decision-making problems.

Wang and Lin (2019) combined PCA with fuzzy logic to prioritize criteria, focusing on environmental and social dimensions. Their study emphasized the need for sustainable and user-friendly solutions in EV infrastructure development.

Chen et al. (2019) applied a hybrid AHP-TOPSIS approach to prioritize EV charging station locations by evaluating criteria such as traffic flow, land use, and electricity supply. Their research demonstrated the effectiveness of combining subjective and objective weighting methods to achieve balanced results

Kumar et al. (2020) demonstrated the effectiveness of the Entropy method in quantifying the uncertainty of locational criteria in urban environments, showcasing its ability to objectively prioritize areas based on variability in data.

Li et al. (2020) explored the integration of GIS-based spatial analysis with MCDM methods such as CRITIC and Entropy to optimize EV charging station locations. The study emphasized the importance of incorporating geographic and demographic data for informed decision-making.

Hao et al. (2020) utilized a fuzzy AHP-VIKOR approach, incorporating expert opinions to determine the most critical factors affecting charging station deployment in smart cities.

Zhang et al. (2021) investigated the optimal placement of charging stations using CRITIC and TOPSIS, emphasizing the critical roles of accessibility and grid capacity. Their findings highlighted the importance of balancing technical and locational criteria for efficient infrastructure planning.

Wang et al. (2021) developed a hybrid AHP-TOPSIS model for urban EV charging station placement, integrating land use, power grid capacity, and user behavior. Their study demonstrated the significance of user accessibility and demand proximity in ensuring higher utilization rates.

Xie et al. (2021) proposed an integrated GIS and MCDM model to identify suitable charging station sites, highlighting environmental and economic feasibility as key drivers.

These studies collectively demonstrate the versatility and effectiveness of various MCDM methods in addressing the complexities of EV charging station planning. They highlight the importance of integrating multiple criteria and utilization of various approaches to support sustainable and efficient infrastructure development.

3. CRITERIA OF SELECTION OF EV CHARGING STATION LOCATIONS

The placement of EV charging stations is a critical factor influencing the usability, convenience, and overall adoption of EVs. An optimal location not only ensures accessibility for users but also enhances the operational efficiency and sustainability of the charging network. The following criteria are developed from the literature and are presented below.

Proximity to High-Traffic Areas: Highways, commercial zones, and residential areas are critical for ensuring consistent usage. Proximity to high-traffic areas maximizes visibility and convenience, increasing the likelihood of frequent use. Charging stations located strategically in these areas can serve multiple user segments, including commuters and shoppers.

Parking Space Availability: Adequate parking space is essential to accommodate multiple vehicles simultaneously, preventing bottlenecks and enhancing user satisfaction. Stations with limited parking may deter users, particularly during peak times.

Ease of Access: Well-planned entry and exit points, along with clear signage, ensure smooth traffic flow and ease of use. Poorly accessible locations can discourage users, even if other criteria are met.

Proximity to Public Transport Hubs: Locations near bus stops, metro stations, or train stations cater to multi-modal transport users and encourage integrated transportation solutions. This also supports areas with limited residential parking.

Accessibility-related criteria directly impact user experience and utilization rates. These factors are fundamental for selecting locations that align with convenience and operational efficiency.

Daily Traffic Volume: High daily traffic increases the exposure and potential usage of charging stations. Locations with significant traffic flows are more likely to achieve higher utilization rates, which improves the economic feasibility of the station.

EV Density in the Area: Areas with higher EV adoption are naturally more suitable for deploying charging stations. Proximity to a substantial number of EV owners ensures that the station meets demand effectively.

Peak Demand Times: Understanding peak usage times allows for better resource allocation, such as charging capacity and staff availability. Locations with predictable demand patterns are easier to manage and optimize.

Demand and traffic-related criteria ensure that stations are positioned to serve the highest number of users efficiently. They also help in forecasting future demand and ensuring long-term relevance.

Zhang et al. (2023) examined the impact of land cost and revenue potential on EV station profitability, advocating for public-private partnerships (PPP) in infrastructure funding**.**

Land Acquisition or Rental Cost: The cost of acquiring or renting land is a significant determinant of financial viability. Urban areas may have high land costs, necessitating a balance between accessibility and affordability.

Installation Cost: The total setup cost, including equipment, grid connection, and construction, impacts the initial investment. Cost-effective solutions without compromising quality are preferred.

Operational and Maintenance Costs: Monthly or annual expenses for operations, repairs, and maintenance affect profitability. Locations with high maintenance demands may reduce overall financial feasibility.

Revenue Potential: Estimated revenue based on pricing strategies and usage projections is critical for determining the financial sustainability of a station. High-demand areas with optimal pricing models offer better revenue potential.

Economic feasibility criteria help determine the financial sustainability of charging stations. Balancing initial and operational costs with revenue projections is crucial for long-term success.

Distance from Green Areas: Avoiding green areas minimizes ecological disruption, aligns with urban planning regulations, and reduces opposition from environmental advocates.

Air Quality Improvement Potential: Charging stations in areas with poor air quality promote the adoption of EVs, contributing to reduced emissions and improved urban air quality.

Renewable Energy Integration: Stations powered by renewable energy sources, such as solar or wind, enhance sustainability and reduce the carbon footprint of the charging infrastructure.

Singh et al. (2023) emphasized the role of renewable energy integration in EV charging station sustainability, recommending solar-powered charging hubs in high-density urban areas.

Environmental criteria ensure that charging stations contribute positively to sustainability goals and align with urban planning and regulatory frameworks. These factors are increasingly important in gaining public and governmental support.

The selection process for EV charging station locations is inherently complex due to the multifaceted nature of these criteria and their potential trade-offs. A structured, multi-criteria evaluation framework is therefore indispensable for decision-making, ensuring balanced consideration of all relevant factors. This comprehensive approach not only supports the development of an efficient charging network but also contributes to the broader goal of fostering sustainable urban mobility.

4. PRINCIPAL COMPONENT ANALYSIS (PCA)

The deployment of Electric Vehicle (EV) charging stations is a crucial step in promoting the adoption of sustainable transportation. Selecting the right locations for these stations involves analysing multiple factors that influence their functionality, usability, and long-term success. These factors are interconnected and span various domains, making it challenging to prioritize and evaluate them comprehensively.

Principal Component Analysis (PCA) offers an effective approach to address this complexity. By reducing the dimensionality of the data, PCA identifies the key underlying components that capture the most significant variation in the dataset. This statistical technique helps consolidate related variables into meaningful groups, enabling a more streamlined and data-driven decision-making process.

Sun et al. (2019) used PCA to reduce the dimensionality of site selection criteria and identify the dominant factors affecting EV user preferences.

Chen et al. (2022) analysed survey data using PCA and identified four key categories: location accessibility, economic feasibility, environmental impact, and traffic demand. Their study aligns with the methodology applied in this research.

The application of PCA for identifying factors in EV charging station deployment involves collecting data on a wide range of variables, analysing their relationships, and grouping them into principal components. These components provide valuable insights into the essential dimensions that influence deployment decisions, ensuring an efficient and strategic allocation of resources.

By leveraging PCA, decision-makers can focus on the most influential factors, simplify the planning process, and ensure that EV charging stations are deployed in optimal locations. This approach not only supports the growth of EV infrastructure but also contributes to broader goals of sustainability and urban development.

5. PRIORITIZATION METHODS

The use of CRITIC and Entropy methods in the prioritization process ensures a balanced integration of objective ratings and subjective importance, addressing the multifaceted nature of EV charging station criteria. These methods provide a robust framework to evaluate variability, uncover key patterns, and assign meaningful weights, enabling informed and data-driven decision-making. This approach not only optimizes the selection process but also aligns with sustainable and efficient urban mobility goals. The proposed methods are implemented by deriving the principal component loadings of the criteria

5.1 Principal Component Analysis (PCA):

PCA is a dimensionality reduction technique that identifies patterns by transforming the data into a new set of uncorrelated variables (principal components). Each component captures as much variance in the data as possible. The methodology is discussed in the following steps:

Step 1: Data Collection: Primary data is collected through questionnaire survey.

Step 2: Perform PCA on the survey data. Minitab 16 is implemented on the data collected through questionnaire to determine eigen values, cumulative variance (cv_j) and principal Component loadings (PC_j).

Step 3: Determine absolute values of the loadings.

Akinci et al. (2022) integrated GIS, PCA, and AHP to determine the best locations for fast-charging stations, prioritizing areas with high urban traffic congestion.

5.2 Criteria Importance through Intercriteria Correlation (CRITIC)

The method considers both the variability of each criterion and its correlation with other criteria. It evaluates the contrast and conflicts between criteria.

Gutiérrez et al. (2021) combined GIS with CRITIC and Entropy methods to evaluate charging station sites, emphasizing the role of spatial data analysis.

Xiao et al. (2022) demonstrated that CRITIC effectively captures interdependencies among criteria by considering their conflict intensity and variability.

The proposed methodology is discussed in the following steps

Step 1: Obtain decision Matrix (x_{ij}): Absolute Loadings of principal component analysis is considered as decision matrix

Step 2: Normalize the decision matrix: The following formula is used to normalize the decision matrix.

$$n_{ij} = \frac{x_{ij}}{x_{max}}$$

Step 3: Determine correlation matrix: Correlation among the principal components are derived through Minitab 16.

Step 4: Determine Conflict degree (c_j): Following formula is used to determine conflict degree of each criterion

$$c_j = \sum_{j=1}^{n} (r_{ij})$$

$$r_{ij} = \text{correlation coefficient}$$

Step 5: Determine Information Content (I_j): information content is determined from the following relation

$$I_j = c_j * \sigma_j$$

where σ_j is standard deviation of criteria

Step 6: Determine weights of the principal components (w_j): The following formula is used to determine the weights

$$w_j = \frac{I_j}{\sum_{j=1,n} I_j}$$

Step 7: Determine weights of the factors (W_i): The following formula is used to determine the weights

$$W_i = \sum_{j=1}^{n} (n_{ij}) * w_j$$

5.3 Entropy

The Entropy method measures the amount of information or randomness each criterion contributes, helping identify important factors by their information content.

Zhou et al. (2020) applied the Entropy method to determine the importance of factors in sustainable transportation planning, showing its capability in handling uncertainty in expert judgment.

The prosed methodology is discussed in the following steps

Step 1: Obtain decision Matrix (x_{ij}): Absolute Loadings of principal component analysis is considered as decision matrix

Step 2: Normalize the decision matrix: Normalize the decision matrix as discussed in step 2 of section 4.2

Step 3: Calculate of the index's entropy.

According to the definition of entropy, entropy of

$$H_j = -\frac{\sum_{i=1}^{n} f_{ij} \ln f_{ij}}{\ln m}, (i = 1, \dots, m; j = 1, \dots, n)$$

Wherein:

$$f_{ij} = -\frac{r'_{ij}}{\sum_{i=1}^{m} r_{ij}}, (i = 1, \dots, m; j = 1, \dots, n)$$

Step 4: Calculate of the index's entropy weight of the principal components from the following relation

$$E_j = \frac{H_j}{\sum_{j=1,n} H_j}$$

Step 5: Determine weights of the factors (W_i): The following formula is used to determine the weights

$$W_i = \sum_{j=1}^{n} (n_{ij}) * E_j$$

6. QUESTIONNAIRE SURVEY

The questionnaire survey is designed to identify the critical factors influencing the deployment of Electric Vehicle (EV) charging stations. The primary objective is to gather insights from stakeholders and quantify their perspectives on various factors to prioritize them using statistical methods like Principal Component Analysis (PCA). The survey consists of three sections: respondent demographics, core questions, and open-ended feedback.

6.1 Demographic Data

The demographic section collects optional details about the participants, including their role in EV infrastructure (Government & Regulators, Power & Energy Providers, private Investors & Operators, EV manufacturers, Business & Commercial Spaces, Public Transport authorities, EV owners and fleet operators, Environmental organization) . This information provides context to the responses and helps in understanding variations in perspectives across different stakeholder groups. The core section of the survey focuses on collecting ratings for factors influencing EV charging station deployment. Participants are asked to evaluate the importance of factors on a Likert scale (1 to 5, where 1 is "Not Important" and 5 is "Very Important"). The factors are categorized into four key dimensions: accessibility and infrastructure, economic viability, environmental sustainability, and traffic and demand potential. Accessibility and infrastructure factors include proximity to high-traffic areas, parking space availability, ease of access, proximity to public transport hubs, and maintenance feasibility. Economic viability factors encompass land acquisition or rental costs, installation costs, operational and maintenance costs, and revenue potential. Environmental sustainability considers proximity to green areas, potential for improving air quality, and integration with renewable energy sources. Traffic and demand potential focuses on daily traffic volume, EV density in the area, and peak demand times.

The final section invites open-ended feedback, allowing participants to share additional insights, highlight challenges, and suggest improvements for EV infrastructure planning. Questions such as "Are there additional factors you think are important for EV charging station deployment?" and "What challenges do you foresee in deploying EV charging stations in your region?" provide qualitative data to complement the quantitative ratings. The survey targets stakeholders involved in EV infrastructure development and is administered. The results from this survey will help identify the most influential factors, group related variables into principal components using PCA, and provide actionable insights to policymakers, planners, and investors for strategic decision-making in EV charging station deployment. The questionnaire is presented in Appendix-A. Demographic data is presented in table 1.

Table 1: Demographic Data

Category	Sub-Category	Number of Respondents	Percentage (%)
Stakeholder Category	Private Investors & Operators	37	12.33
	EV Fleet Operators	35	11.67
	EV Manufacturers	36	12.00
	Business & Commercial Spaces	46	15.33
	Government & Regulators	40	13.33
	Public Transport Authorities	40	13.33
	Power & Energy Providers	35	11.67

Category	**Sub-Category**	**Number of Respondents**	**Percentage (%)**
	Environmental Organization	31	10.33
Region	Urban	261	87.00
	Rural	39	13.00
Experience with EV	1-3 years	168	56.00
	>3 years	132	34.00
EV Ownership Status	Yes	202	67.33
	No	98	32.67

The demographic data reveals a balanced representation of key stakeholders, with strong participation from both public and private sectors. The predominance of urban respondents aligns with current EV adoption trends, but the inclusion of rural voices highlights the need for broader infrastructure development. The mix of experienced and new participants suggests a growing industry with increasing interest. Additionally, the blend of EV owners and non-owners ensures that both user and policymaker perspectives are considered in the decision-making process.

6.2 Data on the Criteria

Data is collected through questionnaire on the criteria as presented in Appendix-A . Basic Statistics of the data is presented below.

Factor	**Count**	**Mean**	**StDev**	**Minimum**	**Maximum**	**Cronbach's Alpha**
Proximity to High-Traffic Areas	300	2.8433	0.583	1	4	0.6143
Parking Space Availability	300	2.8067	0.5863	1	4	0.6078
Ease of Access	300	2.8333	0.5774	1	4	0.6094
Proximity to Public Transport Hubs	300	2.8367	0.5637	1	4	0.6173
Daily Traffic Volume	300	2.8367	0.5008	2	4	0.6546
EV Density in the Area	300	2.8433	0.5225	2	4	0.6532
Peak Demand Times	300	2.8433	0.4963	2	4	0.6445
Land Acquisition or Rental Cost	300	2.8333	0.5226	1	4	0.6258
Installation Cost	300	2.8267	0.5204	1	4	0.6254
Operational and Maintenance Costs	300	2.8333	0.5715	1	4	0.6152
Revenue Potential	300	2.8133	0.5473	1	4	0.6202
Distance from Green Areas	300	2.8067	0.5806	1	5	0.6521
Air Quality Improvement Potential	300	2.8033	0.5881	1	5	0.6628
Renewable Energy Integration	300	2.8233	0.5887	1	5	0.6515

7. RESULTS AND DISCUSSION

7.1 Principal Component Analysis

The data so collected is used and PCA is implemented through Minitab 16.

Eigen values >1 and Explanation ratios are shown in table 2.

Table 2: Eigen Values

Eigenvalue	3.4504	3.2113	2.6351	2.1035
Proportion	0.246	0.229	0.188	0.15
Cumulative	0.246	0.476	0.664	0.814

The PCA results indicate that the first four principal components explain **81.4%** of the total variance, making them sufficient for dimensionality reduction while retaining most of the dataset's information. Since all four eigenvalues are above 1, they significantly contribute to data variation. Principal Components of the criteria are presented in table 3:

Table 3: Principal components

Factors	**PC1**	**PC2**	**PC3**	**PC4**
Proximity to High-Traffic Areas	0.333	-0.375	-0.004	0.089
Parking Space Availability	0.366	-0.334	-0.013	0.088
Ease of Access	0.352	-0.343	0.004	0.094
Proximity to Public Transport Hubs	0.344	-0.338	-0.026	0.068
Daily Traffic Volume	-0.003	0.114	-0.426	0.37
EV Density in the Area	-0.007	0.096	-0.412	0.391
Peak Demand Times	0.013	0.114	-0.386	0.417
Land Acquisition or Rental Cost	0.321	0.34	0.168	0.061
Installation Cost	0.314	0.309	0.183	0.062
Operational and Maintenance Cost	0.331	0.341	0.156	0.116
Revenue Potential	0.293	0.342	0.198	0.121
Distance from Green Areas	-0.18	-0.111	0.369	0.393
Air Quality Improvement Potential	-0.222	-0.104	0.354	0.381
Renewable Energy Integration	-0.185	-0.114	0.335	0.416

PC1: Accessibility and Infrastructure Factors: These factors collectively emphasize ease of use, practicality, and infrastructure quality, which are critical for ensuring that an EV charging station is widely accessible and operationally efficient. By addressing user needs such as convenience, location, and physical infrastructure, these factors directly influence how effectively the charging station serves its purpose. The high loadings for these variables in PC1 indicate their significant contribution to the Accessibility and Infrastructure dimension.

1. Proximity to High-Traffic Areas (0.333)
2. Parking Space Availability (0.366)
3. Ease of Access (0.352)
4. Proximity to Public Transport Hubs (0.344)

PC1 has high positive loadings for variables related to the physical and logistical aspects of the charging station's location. These factors collectively emphasize the importance of convenience, accessibility, and maintenance feasibility, which are critical for EV users.

PC2: Economic Viability Factors: PC2 represents the Economic Viability of EV charging station deployment, ensuring that the project is cost-efficient, financially sustainable, and attractive for stakeholders. These factors emphasize the importance of balancing costs with potential revenue to ensure long-term success.

1. Land Acquisition or Rental Cost (0.34)
2. Installation Cost (0.309)
3. Operational and Maintenance Costs (0.331)
4. Revenue Potential (0.342)

PC2 reflects the financial considerations for deploying EV charging stations. These factors highlight the importance of cost efficiency and revenue generation potential, which are vital for ensuring the project's sustainability from a business perspective.

PC3: Environmental Sustainability Factors: PC3 represents the Environmental Sustainability dimension of EV charging station deployment. It highlights the importance of reducing pollution, integrating renewable energy, and aligning EV infrastructure with ecological priorities. This grouping ensures that environmental goals are not just met but prioritized in planning and deployment decisions.

1. Distance from Green Areas (0.369)
2. Air Quality Improvement Potential (0.354)
3. Renewable Energy Integration (0.335)

PC3 groups factors that focus on the environmental impact and sustainability of the EV charging station. These factors are essential for aligning with green energy initiatives and improving local environmental conditions.

PC4: Traffic and Demand Potential Factors: PC4 represents the Traffic and Demand Potential dimension, focusing on the volume of vehicles, concentration of EVs, and temporal patterns of demand. These factors ensure that the charging station is located strategically to maximize usage and efficiency, directly addressing user demand and traffic-related considerations.

1. Daily Traffic Volume (0.37)
2. EV Density in the Area (0.391)
3. Peak Demand Times (0.417)

PC4 emphasizes the demand potential for the charging station based on traffic volume, the density of EV users, and peak usage times. These factors ensure that the station will have sufficient utilization and cater to high-demand locations.

7.2 Prioritization through PCA Based CRITIC (P-CRITIC)

In the study, prioritization through PCA based CRITIC method as discussed in section 4.2 is implemented with the case study to determine relative weights of the criteria.

7.2.1 Absolute loadings of principal components

Absolute Loadings of principal component analysis is considered as decision matrix as discussed in step 1 of section 4.2. The decision matrix is presented in table 4

Table 4: Absolute Loadings

Factor	**PC1**	**PC2**	**PC3**	**PC4**
Proximity to High-Traffic Areas	0.3330	0.3750	0.0040	0.0890
Parking Space Availability	0.3660	0.3340	0.0130	0.0880
Ease of Access	0.3520	0.3430	0.0040	0.0940
Proximity to Public Transport Hubs	0.3440	0.3380	0.0260	0.0680
Daily Traffic Volume	0.0030	0.1140	0.4260	0.3700
EV Density in the Area	0.0070	0.0960	0.4120	0.3910
Peak Demand Times	0.0130	0.1140	0.3860	0.4170
Land Acquisition or Rental Cost	0.3210	0.3400	0.1680	0.0610
Installation Cost	0.3140	0.3090	0.1830	0.0620
Operational and Maintenance Costs	0.3310	0.3410	0.1560	0.1160
Revenue Potential	0.2930	0.3420	0.1980	0.1210
Distance from Green Areas	0.1800	0.1110	0.3690	0.3930
Air Quality Improvement Potential	0.2220	0.1040	0.3540	0.3810
Renewable Energy Integration	0.1850	0.1140	0.3350	0.4160

7.2.2 Normalized the decision matrix

Normalized decision matrix is determined as discussed in step 2 of section 4.2 and is presented in table 5.

Factor	**PC1**	**PC2**	**PC3**	**PC4**
Proximity to High-Traffic Areas	0.102	0.111	0.001	0.029
Parking Space Availability	0.112	0.099	0.004	0.029
Ease of Access	0.108	0.102	0.001	0.031
Proximity to Public Transport Hubs	0.105	0.100	0.009	0.022
Daily Traffic Volume	0.001	0.034	0.140	0.121
EV Density in the Area	0.002	0.028	0.136	0.127
Peak Demand Times	0.004	0.034	0.127	0.136
Land Acquisition or Rental Cost	0.098	0.101	0.055	0.020
Installation Cost	0.096	0.092	0.060	0.020
Operational and Maintenance Cost	0.101	0.101	0.051	0.038
Revenue Potential	0.090	0.101	0.065	0.039
Distance from Green Areas	0.055	0.033	0.122	0.128
Air Quality Improvement Potential	0.068	0.031	0.117	0.124
Renewable Energy Integration	0.057	0.034	0.110	0.136

7.2.3 Correlation matrix

Correlation among the principal components are derived through Minitab 16 and are presented in table 6.

Table 6: Correlations among Principal components

PCs	PC1	PC2	PC3	PC4
PC1	1.0000	0.8679	-0.8862	-0.8632
PC2	0.8679	1.0000	-0.9218	-0.9801
PC3	-0.8862	-0.9218	1.0000	0.8980
PC4	-0.8632	-0.9801	0.8980	1.0000

7.2.4 Conflict degree (c_j):

Conflict degrees of Principal components are derived as discussed in step 4 of section 4.2 and are presented in table 7.

Table 7: Conflict degrees of PCs

PCs	PC1	PC2	PC3	PC4
PC1	0.0000	0.1321	1.8862	1.8632
PC2	0.1321	0.0000	1.9218	1.9801
PC3	1.8862	1.9218	0.0000	0.1020
PC4	1.8632	1.9801	0.1020	0.0000

7.2.5 Weights of the principal components (w_j)

Weights of the principal components are derived as discussed in step 6 of section 4.2 by calculating as discussed in step 5. Information content and relative weights of the principal components are presented in table 8.

Table 8: Information content and relative weights of PCs

PCs	PC1	PC2	PC3	PC4
Information Content	0.1844	0.1263	0.2390	0.1646
Relative Weights	0.2582	0.1768	0.3346	0.2304

7.2.6 Relative weights of the factors (W_i)

Relative weights of the factors are determined as discussed in step 7 of section 4.2. Relative weights of the factors are presented in table 9.

Table 9: Relative weights of the factors

PCs	Factor	Rel.Wt
Accessibility and Infrastructure (PC1)	Proximity to High-Traffic Areas	0.0531
	Parking Space Availability	0.0545
	Ease of Access	0.0533
	Proximity to Public Transport Hubs	0.0529
Economic Viability (PC2)	Land Acquisition or Rental Cost	0.0810
	Installation Cost	0.0804
	Operational and Maintenance Cost	0.0809

	Revenue Potential	0.0663
Environmental Sustainability (PC3)	Distance from Green Areas	0.0659
	Air Quality Improvement Potential	0.0700
	Renewable Energy Integration	0.0720
Traffic and Demand Potential (PC4)	Daily Traffic Volume	0.0903
	EV Density in the Area	0.0907
	Peak Demand Times	0.0888

7.3 Prioritization through PCA Based ENTROPY (P-ENTROPY)

The Entropy method measures the amount of information or randomness each criterion contributes, helping identify important factors by their information content. The methodology is discussed in the following steps

7.3.1 Decision matrix

Decision matrix is already determined and shown in table 4 as absolute loading matrix

7.3.2 Normalize the decision matrix

Normalize the decision matrix is also determined and shown in table 5.

7.3.3 Index of entropy

Index of entropy of principal components are determined as discussed in step 3 of section 4.3 and presented in table 10.

Table 10. Entropy principal Component

Factors	**PC1**	**PC2**	**PC3**	**PC4**
Proximity to High-Traffic Areas	-0.2329	-0.2441	-0.0087	-0.1027
Parking Space Availability	-0.2454	-0.2289	-0.0234	-0.1019
Ease of Access	-0.2402	-0.2324	-0.0087	-0.1068
Proximity to Public Transport Hubs	-0.2371	-0.2305	-0.0408	-0.0845
Daily Traffic Volume	-0.0064	-0.1144	-0.2757	-0.2551
EV Density in the Area	-0.0132	-0.1013	-0.2711	-0.2626
Peak Demand Times	-0.0220	-0.1144	-0.2623	-0.2713
Land Acquisition or Rental Cost	-0.2281	-0.2312	-0.1602	-0.0779
Installation Cost	-0.2252	-0.2189	-0.1694	-0.0789
Operational and Maintenance Cost	-0.2321	-0.2316	-0.1526	-0.1239
Revenue Potential	-0.2164	-0.2320	-0.1781	-0.1275
Distance from Green Areas	-0.1598	-0.1123	-0.2562	-0.2633
Air Quality Improvement Potential	-0.1828	-0.1072	-0.2507	-0.2591
Renewable Energy Integration	-0.1627	-0.1144	-0.2433	-0.2710
Hj (index of Entropy)	0.9110	0.9525	0.8720	0.9043

Sss

6.3.4 Entropy weight of the principal components

Normalized values of entropy values are determined as discussed in step 4 of section 4.3 and are presented in table 11.

PCs	PC1	PC2	PC3	PC4
Entropy Weights	0.2470	0.1319	0.3554	0.2657

7.3.5 Relative weights of the factors through P-ENTROPY

Relative weights of the factors are determined through P-ENTROPY method as discussed in step 5 of section 4.3 and are presented in table 12.

PCs	Factor	Rel. Wt.
Accessibility and Infrastructure (PC1)	Proximity to High-Traffic Areas	0.0480
	Parking Space Availability	0.0499
	Ease of Access	0.0487
	Proximity to Public Transport Hubs	0.0482
Economic Viability (PC2)	Land Acquisition or Rental Cost	0.0866
	Installation Cost	0.0864
	Operational and Maintenance Cost	0.0868
	Revenue Potential	0.0625
Environmental Sustainability (PC3)	Distance from Green Areas	0.0626
	Air Quality Improvement Potential	0.0667
	Renewable Energy Integration	0.0692
Traffic and Demand Potential (PC4)	Daily Traffic Volume	0.0952
	EV Density in the Area	0.0953
	Peak Demand Times	0.0937

7.3.6 Correlation of methods

The Pearson correlation coefficient between P-ENTROPY and P-CRITIC is 0.994, indicating a very strong positive correlation of weights determined from the methods. This suggests that the factors' relative weights under P-ENTROPY and P-CRITIC are almost identical in terms of their ranking and magnitude.

The P-value of 0.000 is obtained indicates that the correlation is statistically significant at any conventional level (e.g., 0.05 or 0.01). This confirms that the observed relationship between the methods is not due to random chance.

7.3.6 Weight aggregation

The Three-Point Estimate (TPE) is a method typically used in project management or decision-making to calculate an aggregated value by considering three scenarios: optimistic, most likely, and pessimistic. For weight aggregation, it is adopted and relative weights of the principal components and the factors under the respective principal component are presented in table 13

Table 13: Aggregated relative weights of PCs and factors

PCs	Relative wt. of the PCs	Factor	Aggregate wt.
Accessibility and Infrastructure (PC1)	0.2043	Proximity to High-Traffic Areas	0.0506
		Parking Space Availability	0.0522
		Ease of Access	0.0510
		Proximity to Public Transport Hubs	0.0505
Economic Viability (PC2)	0.3155	Land Acquisition or Rental Cost	0.0838
		Installation Cost	0.0834
		Operational and Maintenance Cost	0.0838
		Revenue Potential	0.0644
Environmental Sustainability (PC3)	0.2032	Distance from Green Areas	0.0643
		Air Quality Improvement Potential	0.0683
		Renewable Energy Integration	0.0706
Traffic and Demand Potential (PC4)	0.2770	Daily Traffic Volume	0.0928
		EV Density in the Area	0.0930
		Peak Demand Times	0.0913

The analysis presented in the table emphasizes the relative importance of four principal components (PCs) that influence decision-making: Accessibility and Infrastructure (PC1), Economic Viability (PC2), Environmental Sustainability (PC3), and Traffic and Demand Potential (PC4). Among these, the most significant component, Economic Viability (PC2), has a relative weight of 0.3155. This highlights its substantial role in influencing outcomes, particularly in cost-related factors. Land Acquisition or Rental Costs (0.0838) Operational and Maintenance Costs (0.0838) installation cost (0.0834) emerge as the most critical considerations, followed by Revenue Potential (0.0644). The dominance of these factors reflects the importance of economic feasibility in planning and decision-making processes.

Traffic and Demand Potential (PC4), emerged as second important component with a relative weight of 0.2770, plays a major role in the analysis. The contributing factors, including EV Density in the Area (0.0930), Daily Traffic Volume (0.0928) and Peak Demand Times (0.0913) exhibit relatively important individual weights. This indicates a moderate influence on the overall decision-making framework.

Accessibility and infrastructure (PC1) holds the relative weight of 0.2043, signifying its critical role. Key factors under this component include Parking Space Availability (0.0522), which is the most influential, followed closely by Ease of Access (0.0510), Proximity to High-Traffic Areas (0.0506) and Proximity to Public Transport Hubs (0.0505). The collective contribution of these factors underscores the importance of well-connected and accessible locations.

Environmental Sustainability (PC3), with a relative weight of 0.2032, highlights growing awareness of sustainable practices. Within this component, Renewable Energy Integration (0.0706), Air Quality Improvement Potential (0.0683) followed by Distance from Green Areas (0.0643). Although this component has a lower weight compared to PC1, PC2 and PC4, its inclusion underscores the increasing emphasis on environmental concerns in contemporary decision-making.

Economic viability holds the highest relative importance. This component encompasses critical financial factors such as land acquisition or rental costs, installation costs, operational and maintenance expenses, and revenue potential. These factors directly influence the project's profitability and sustainability, making this the most critical consideration in decision-making.

Traffic and demand potential emphasize the site’s ability to attract and sustain user engagement. Factors like daily traffic volume, EV density in the area, and peak demand times are key indicators of the site's demand dynamics. These considerations ensure that the project will generate sufficient utilization and justify the investment.

Accessibility and infrastructure play a crucial role in the logistical and operational success of the project. Factors such as proximity to high-traffic areas, parking space availability, ease of access, and proximity to public transport hubs ensure user convenience and efficient operations. While ranked third, this component remains essential for the project's practical viability.

Environmental sustainability emphasizes the importance of aligning the project with green practices and regulatory standards. Factors such as distance from green areas, air quality improvement potential, and renewable energy integration contribute to minimizing environmental impact. Although it has the lowest weight, this component is vital for long-term sustainability and societal acceptance.

The prioritization of these components reflects a balanced approach that considers financial feasibility, demand dynamics, operational convenience, and environmental responsibility. This hierarchy ensures that the project is not only viable and profitable but also sustainable and user centric.

8. CONCLUDING REMARKS

The deployment of Electric Vehicle (EV) charging stations is a complex, multi-dimensional decision-making problem that requires the consideration of multiple technical, economic, environmental, and social factors. This study utilized Principal Component Analysis (PCA) to identify the most influential criteria and applied Multi-Criteria Decision-Making (MCDM) methods, namely CRITIC and Entropy, to prioritize these criteria. The analysis revealed that the most critical factors for optimal site selection are:

- Economic Viability (PC2) – The most influential component, highlighting land acquisition costs, installation costs, operational expenses, and revenue potential as primary concerns.
- Traffic and Demand Potential (PC4) – Ensuring high utilization through EV density, daily traffic volume, and peak demand times.
- Accessibility and Infrastructure (PC1) – Key factors such as proximity to high-traffic areas, parking space availability, ease of access, and public transport connectivity.
- Environmental Sustainability (PC3) – The integration of renewable energy, air quality improvement, and ecological considerations to align with sustainability goals.

The weight aggregation of PCA-CRITIC and PCA-Entropy methods confirmed the robustness of the findings, ensuring a data-driven and objective evaluation of site selection criteria.

While this study provides a robust analytical framework, some limitations exist. The subjectivity in survey responses remains a challenge, as expert opinions, despite being statistically weighted, may introduce bias in ranking the importance of criteria. Additionally, regional constraints could affect the findings, as variations between urban and rural settings, along with differences in regional energy infrastructure, may impact the applicability of the results. Furthermore, exploring real-time dynamic charging station deployment models using IoT and AI-driven optimization techniques could significantly improve decision-making by adapting to real-time traffic, energy demand, and user preferences, ensuring more efficient and future-proof EV charging infrastructure.

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