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Research Article

Evaluation of Suitability Index Selection of Electric Vehicle Charging Stations Through MCDM Approaches

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Abstract:

The rapid adoption of electric vehicles (EVs) necessitates the strategic development of charging infrastructure to support seamless mobility and sustainability goals. This study presents an integrated multi-criteria decision-making (MCDM) framework for the optimal selection of Electric Vehicle Charging Stations (EVCS) by combining Hellwig's Method and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The hybrid models—Hellwig's-TOPSIS and TOPSIS enhanced with Mahalanobis distance—are applied to evaluate potential locations based on 14 diverse criteria that encompass technical, economic, environmental, and accessibility factors. The criteria include Daily Traffic Volume, EV Density in the Area, Peak Demand Times, Renewable Energy Integration, Revenue Potential, and Installation Cost, among others, with relative weights determined through a systematic approach. The Hellwig's method is employed to handle factor scores and construct synthetic indicators, while the Mahalanobis distance enhances TOPSIS robustness by accounting for correlations among attributes. The results offer a comprehensive ranking of EVCS locations, ensuring effective decision-making support for urban planners and policymakers. This framework aids in optimizing resource allocation and maximizing socio-economic and environmental benefits associated with EV infrastructure deployment.

1. Introduction

The global shift towards sustainable transportation has accelerated the adoption of electric vehicles (EVs), driven by concerns over fossil fuel dependency, environmental degradation, and urban air pollution. As electric mobility gains momentum, the development of a reliable and accessible Electric Vehicle Charging Infrastructure (EVCI) has become a critical enabler. Strategic planning and optimal location selection of Electric Vehicle Charging Stations (EVCS) are essential not only to support EV users but also to ensure economic viability, environmental sustainability, and efficient land use.

The selection of EVCS locations involves multiple, often conflicting, criteria ranging from proximity to high-traffic areas and public transport hubs to cost-related factors like land acquisition, installation, and operational expenses. Additionally, environmental considerations such as integration with renewable energy sources and air quality improvement potential, along with traffic and demographic metrics like daily traffic volume and EV density, further complicate the decision-making process. This multifaceted nature of the problem necessitates a robust, systematic, and integrated evaluation framework.

Multi-Criteria Decision-Making (MCDM) methods offer powerful tools to address such complex problems. This study proposes an integrated framework combining Hellwig's Method and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), along with a variant incorporating Mahalanobis distance, to ensure a more accurate reflection of the interdependencies

among criteria. The Hellwig's method is employed to compute synthetic development measures, capturing the relative advantage of alternatives, while TOPSIS, enhanced with Mahalanobis distance, addresses the correlation structure among evaluation factors for improved precision.
The framework is applied to assess potential EVCS locations based on 14 critical factors, with relative weights determined to reflect their importance in the decision-making process. The proposed hybrid approach provides a comprehensive and adaptable model to support urban planners, transport authorities, and energy providers in identifying the most suitable sites for EVCS deployment, ultimately contributing to a more efficient, user-friendly, and sustainable urban transport ecosystem.

2. Literature Review

The deployment of Electric Vehicle Charging Stations (EVCS) has attracted significant attention in recent years as cities and governments strive to support the growing electric vehicle (EV) ecosystem. A critical challenge lies in the optimal siting of charging stations, which involves multiple, often conflicting, criteria spanning economic, environmental, technical, and spatial domains.

2.1 Location selection using MCDM methods

The problem of selecting optimal locations for Electric Vehicle Charging Stations (EVCS) has been widely addressed through Multi-Criteria Decision-Making (MCDM) techniques due to the complex interplay of economic, spatial, technical, and environmental criteria.
Early studies leveraged methods like the Analytical Hierarchy Process (AHP) for structuring decision problems and evaluating spatial suitability. Zhang et al. [1], utilized a GIS-based AHP approach to determine appropriate charging locations, integrating technical feasibility with spatial characteristics. Similarly, Sadeghi-Bazargani et al. [2], applied AHP and GIS to analyze EVCS site suitability in Tehran, emphasizing infrastructure availability and road networks.
While effective, traditional TOPSIS assumes independence among criteria. To overcome this limitation, Shen et al. [3], applied the standard TOPSIS method to prioritize EVCS locations based on accessibility, cost, and usage factors, whereas Li and Zhao [4], introduced a Mahalanobis distance-enhanced TOPSIS to address inter-criteria correlations and improve the ranking reliability [5].

a) Hybrid and integrated approaches

Recognizing the limitations of single MCDM methods, researchers have proposed hybrid approaches to improve the robustness and adaptability of the decision-making process. Govindan et al. [6], introduced a hybrid AHP-TOPSIS model for evaluating sustainable logistics locations, demonstrating the value of integrating expert judgment with performance-based metrics.
Kumar, Jain, and Kumar [7], extended this concept to EVCS planning by combining Fuzzy AHP and Fuzzy TOPSIS, enabling decision-makers to handle uncertainty in expert evaluations. Similarly, Yazdani et al. [8], used integrated MCDM techniques to assess sustainable transport alternatives, emphasizing the need for a holistic and flexible framework that can accommodate both quantitative and qualitative criteria.
The incorporation of Mahalanobis distance into hybrid models has also gained momentum.
Kumar and Singh [9], applied Mahalanobis-Taguchi systems to enhance the discriminatory power of decision models dealing with correlated and high-dimensional datasets.

b) Hellwig's method and composite scoring

Hellwig's method, though traditionally employed in socio-economic and regional development studies, has gained traction in MCDM applications due to its ability to compute synthetic indicators based on deviation from an ideal solution. Wysocki and Kołodziejczak [10], demonstrated the method's effectiveness in ranking development levels of agricultural regions, while Kozera et al. [11], applied it to assess rural development.
In sustainability assessment, Turskis et al. [12], proposed integrating Hellwig's method with other MCDM techniques to generate more robust and comprehensive evaluations. Its utility lies in simplifying complex evaluation problems by converting multi-dimensional criteria into a single synthetic measure, which can then be used to rank alternatives.
Despite its potential, Hellwig's method remains underexplored in the domain of EVCS planning. Integrating it with techniques like TOPSIS—particularly its Mahalanobis-enhanced version—can offer a balanced perspective by combining sensitivity to ideal solutions with multidimensional scoring capabilities.

c) Environment and policy-oriented considerations

With increasing emphasis on climate goals and sustainable urban development, environmental and policy considerations have become integral to EVCS planning. Metrics such as proximity to green spaces, integration with renewable energy sources, and air quality improvement potential are now key decision criteria.

Chen et al. [13], proposed a multi-objective model that considers environmental impacts, land use compatibility, and energy grid constraints in EVCS site selection. Liu et al. [14], further incorporated urban traffic and air quality metrics into GIS-based planning models to align charging infrastructure with sustainable mobility goals.

Habib et al. [15], stressed the significance of including traffic patterns, usage forecasts, and demand zones when planning EVCS locations. They highlighted the importance of aligning infrastructure development with user behavior and urban traffic dynamics.

These studies collectively underscore the importance of adopting integrated, environmentally conscious planning frameworks that can support the growth of EV infrastructure while contributing to urban sustainability targets.

Incorporation of real-world indicators such as EV density, renewable energy integration, and air quality improvement potential is now recognized as crucial for the holistic evaluation of EVCS sites [16],

Literature review summary is presented in Table 1.

Table 1. *Literature review summary*

S.No.	Author(s)	Method(s)	Focus area	Key contribution
1	Zhang et al. (2017)	AHP + GIS	EVCS site selection	Spatial and technical criteria integration using GIS.
2	Sadeghi-Bazargani et al. (2019)	AHP + GIS	EVCS planning in Tehran	Urban suitability assessment based on spatial data.
3	Shen et al. (2020)	TOPSIS	EVCS ranking	Criteria-based ranking using TOPSIS.
4	Li & Zhao (2021)	TOPSIS + Mahalanobis Dista	Enhanced decision-making	Addressed correlation among criteria for better rankings.
5	Kumar et al. (2020)	Fuzzy AHP-TOPSIS	EVCS evaluation	Handled uncertainty in expert judgment and rankings.
6	Govindan et al. (2018)	AHP-TOPSIS	Sustainable logistics	Demonstrated hybrid model for green infrastructure.
7	Kumar & Singh (2021)	Mahalanobis -Taguchi System	Performance evaluation	Applied to high-dimensional correlated data.
8	Wysocki & Kołodziejczak	Hellwiga's Method	Rural development scoring	Applied synthetic scoring for comparative development.
9	Turskis et al. (2021)	Hellwig+ MCDM	Sustainability evaluation	Integrated synthetic scoring with MCDM tools.
10	Chenetal. (2020)	Multi-objective model	Environmental EVCS planning	Considered grid, air quality, and land use impacts.
11	Liuet al. (2018)	GIS-based Approach	EVCS with traffic data	Integrated pollution, transit, and urban data for sittings.
12	Habib et al. (2015)	Review + Demand Modeling	EV infrastructure challenges	Emphasized demand, traffic flow, and user-centric planning.
13	Yazdani et al. (2022)	Hybrid MCDM	Transport sustainability evaluation	Promoted integrated criteria for sustainable planning.
14	Kozera et al. (2016)	Hellwiga's Method	Rural development scoring	Demonstrated the use of Hellwiga's method for regional development measurement.
15	Wang et al. (2019)	MCDM Approaches	EV charging infrastructure in urban Ai	Applied MCDM methods to evaluate urban EV infrastructure with environmental and service

The reviewed literature highlights a growing trend in using MCDM techniques for EVCS site selection, with methods like AHP, TOPSIS, and their fuzzy or GIS-integrated variants forming the foundation. Hybrid models further enhance decision robustness, and recent studies have begun incorporating environmental and urban traffic data into planning frameworks. Hellwig's method, though well-established in socio-economic analysis, remains underutilized in EV infrastructure evaluation despite its potential for simplifying multi-criteria data.

However, notable gaps remain:

- Limited application of Hellwig's method in EVCS planning.
- Lack of integrated frameworks that combine Hellwig's synthetic scoring with TOPSIS using Mahalanobis distance.
- Insufficient incorporation of comprehensive environmental and socio-economic indicators alongside traditional technical and cost-related factors.
- A need for real-world, weighted multi-factor models that reflect urban planning realities and sustainability priorities.

The present study addresses these gaps by proposing a novel integrated framework combining Hellwig's Method, standard TOPSIS, and Mahalanobis distance-enhanced TOPSIS, evaluated over 14 weighted criteria reflecting spatial, technical, environmental, and financial perspectives.

3. MCDM Methods for Selection of EV Charging Stations

3.1 TOPSIS method

3.1.1 TOPSIS stages

The TOPSIS ranking method is based on comparing alternatives (watersheds) with respect to their theoretical distance from the positive ideal and negative ideal solutions. What follows are the mathematical stages for prioritizing the alternatives attributed by multiple criteria (drought indices) [66].

3.1.2 Decision matrix construction

The decision matrix D is constructed, where each element X_{jj} represents the performance of watershed i concerning drought indices j:

$$D = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_j \\ \vdots \\ A_m \end{array} \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1j} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2j} & \cdots & X_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{i1} & X_{i2} & \cdots & x_{ij} & \cdots & X_{in} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mj} & \cdots & X_{mn} \end{bmatrix} \quad (1)$$

3.1.3 Decision matrix normalization

Each element of the decision matrix is normalized to obtain dimensionless values, following equation. (2).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (2)$$

3.1.4 Creating a weighted normalized decision matrix

The normalized decision matrix is weighted by multiplying each element by the corresponding weight ω_j assigned to each index:

$$\upsilon_{ij} = \omega_j r_{ij} \quad (3)$$

We used Shannon's entropy method to assign weights to different drought metrics and indices (i.e., the frequency and duration of the SPEI, VHI, and PDSI). This method is completely data-driven and calculates the weights of criteria (indices) based on the inherent information and variability in the dataset. It does not rely on subjective judgments, making it suitable for situations where human bias needs to be avoided in decision-making. This mathematical procedure behind this method is provided further below.

3.1.5 Ideal and negative-ideal solution identification

The ideal solution A^+ and negative-ideal solution A^- are determined by selecting the best (equation (4)) and worst (equation (5)) values for each index:

$$A^+ = \{\max(\upsilon_{ij}) \mid j = 1,2,\ldots,n\},$$
$$A^- = \{\min(\upsilon_{ij}) \mid j = 1,2,\ldots,n\} \quad (4)$$

$$A^+ = \{\min(\upsilon_{ij}) \mid j = 1,2,\ldots,n\},$$
$$A^- = \{\max(\upsilon_{ij}) \mid j = 1,2,\ldots,n\} \quad (5)$$

3.1.6 Separation measure calculation

The Euclidean distanced between each alternative and the ideal solutions is calculated as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(\upsilon_{ij} - A_j^+\right)^2}$$
$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(\upsilon_{ij} - A_j^-\right)^2} \quad (6)$$

3.1.7 Calculating the relative closeness to the ideal solution

The relative closeness C_i of each watershed to the ideal solution is computed as follows:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (7)$$

3.2 Integrated TOPSIS with Mahalanobi's distance

A combined application integrating TOPSIS (technique for order of preference by similarity to ideal solution) into the Mahalanobis Distance was used to rank the alternatives based on the material criteria. The coupled TOPSIS and Mahalanobis Distance method exceeds standalone multi-criteria prioritization methods by considering the inherent independence approach combines the distance measures of TOPSIS and the correlation-sensitive Mahalanobis Distance to incorporate the multivariate context of data. The equations can be integrated as follows:

$$MD_i^+ = \sqrt{\left(A_j^+ - r_i\right)^T \Omega^T \Sigma^{-1} \Omega \left(A_j^+ - r_i\right)} \qquad (8)$$

$$MD_i^- = \sqrt{\left(r_i - A_j^-\right)^T \Omega^T \Sigma^{-1} \Omega \left(r_i - A_j^-\right)} \qquad (9)$$

$$\Omega = diag\left(\sqrt{W_1}, \sqrt{W_2}, ..., \sqrt{W_n}\right) \qquad (10)$$

$$C_i^* = \frac{MD_i^-}{MD_i^+ + MD_i^-} \qquad (11)$$

3.3 Hellwig's method

Calculating the Hellwig's measure Hi or Hellwig's measure based on Euclidean *HEi* and Mahalanobis distance *HMi* for the ***i***-th alternative using the formula;

- Classical approach (H measure based on Euclidean distance):

$$H_i = 1 - \frac{dE_i}{d_0}$$

where $d_0 = \bar{d} + 2S,$ for

$$\bar{d} = \frac{1}{m}\sum_{i=1}^{m} dE_i,\ S = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(dE_i - \bar{d})^2}.$$

- Extended approach (HM measure based on Mahalanobis distance):

$$HM_i = 1 - \frac{dM_i}{d_0}$$

where $d_0 = \bar{d} + 2S,$ for

$$\bar{d} = \frac{1}{m}\sum_{i=1}^{m} dM_i,\ S = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(dM_i - \bar{d})^2}.$$

Ranking of alternatives according to descending HE_i or HM_i values.

4. Illustrative Example

To fulfil such increasing demands in the market, charging infrastructure for EVs should be built. They will eventually resolve the anxiety of EV users and secure the convenience for their use. However, due to high price of installation cost of the chargers and huge financial burden to install the charger in every prospective petrol station, it is important to select optimal location. Data on the petrol stations within a specific latitude and longitude (17.68680° North,83.2185° East) is presented below.

4.1 Data on Prospective Locations

Data is generated through Python code and is presented in Table-2

4.2 Factors for selection of EV charging stations

In the study, fourteen factors are considered and the relative weights of the factors are presented in Table-3.

4.3 Decision matrix

A decision matrix is presented to illustrate the proposed case study in Table-4.

5. Results and Discussion

This section presents the outcomes of the integrated MCDM framework developed for the optimal selection of Electric Vehicle Charging Stations (EVCS). The analysis was carried out using three distinct methods: Hellwig's-TOPSIS, TOPSIS with Mahalanobis distance, and the standalone Hellwig's method. These methods were applied to evaluate alternative locations based on 14 comprehensive and weighted criteria, encompassing spatial, technical, financial, and environmental dimensions.

5.1 TOPSIS

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is implemented to evaluate the alternative locations for Electric Vehicle Charging Stations (EVCS). The analysis was conducted using a decision matrix comprising 100 alternatives and 14 decision criteria, reflecting spatial, technical, economic, and environmental factors. The criteria values, rated on an ordinal scale from 1 to 3, were designed to preserve the predefined correlation structure among the factors. Through normalization, weighting, and distance-based evaluation, TOPSIS facilitates the identification of the most suitable alternatives by comparing their proximity to the ideal and anti-ideal solutions. The results offer insights into the relative performance of the alternatives and support informed decision-making for sustainable EVCS planning.

5.1.1 Weighted normalized decision matrix

Weighted normalized matrix is shown in Table-5.

5.1.2 Separation measures from PIS/ NIS and closeness coefficient

Separation measures are determined as discussed in section 3.1 and are presented in the following Table-6.

The TOPSIS analysis yielded Closeness Coefficient (CC) values for 100 EVCS alternatives, ranging approximately from 0.23 to 0.80, indicating varying.

Table 2. *Locations of petrol stations*

Station ID	Latitude	Longitude	Station ID	Latitude	Longitude	Station ID	Latitude	Longitude	Station ID	Latitude	Longitude
EVCS1	17.7007	83.1710	EVCS26	17.6738	83.1895	EVCS51	17.63795	83.24057	EVCS76	17.7363	83.2 3349
EVCS2	17.6643	83.1908	EVCS27	17.6635	83.2622	EVCS52	17.70497	83.2222	EVCS77	17.6806	83.2 2026
EVCS3	17.7104	83.2362	EVCS28	17.7016	83.2294	EVCS53	17.66348	83.2326	EVCS78	17.6489	83.19097
EVCS4	17.7260	83.1772	EVCS29	17.6539	83.2414	EVCS54	17.64796	83.21198	EVCS79	17.6706	83.2 2733
EVCS5	17.6790	83.1715	EVCS30	17.6531	83.2064	EVCS55	17.68217	83.263 88	EVCS80	17.6598	83.19052
EVCS6	17.6587	83.2190	EVCS31	17.7358	83.2325	EVCS56	17.72439	83.19484	EVCS81	17.6439	83.23161
EVCS7	17.6395	83.1884	EVCS32	17.6925	83.2370	EVCS57	17.68686	83.18637	EVCS82	17.6597	83.2 5904
EVCS8	17.7018	83.2230	EVCS33	17.7211	83.2461	EVCS58	17.72806	83.255 55	EVCS83	17.7228	83.17559
EVCS9	17.6588	83.2274	EVCS34	17.6597	83.1717	EVCS59	17.66664	83.232 39	EVCS84	17.6606	83.2354
EVCS10	17.7177	83.1691	EVCS35	17.6683	83.1953	EVCS60	17.6977	83.18378	EVCS85	17.6582	83.18173
EVCS11	17.7174	83.2383	EVCS36	17.6579	83.2628	EVCS61	17.71305	83.22244	EVCS86	17.7304	83.2256
EVCS12	17.6708	83.1840	EVCS37	17.7244	83.2000	EVCS62	17.71466	83.22154	EVCS87	17.6841	83.2 4696
EVCS13	17.7325	83.2022	EVCS38	17.7023	83.2081	EVCS63	17.63686	83.20092	EVCS88	17.7175	83.18754
EVCS14	17.6461	83.1782	EVCS39	17.7283	83.2144	EVCS64	17.63875	83.26141	EVCS89	17.6465	83.21161
EVCS15	17.7215	83.2289	EVCS40	17.6633	83.1932	EVCS65	17.72467	83.25167	EVCS90	17.6792	83.2152
EVCS16	17.7175	83.2415	EVCS41	17.6929	83.1948	EVCS66	17.66755	83.17429	EVCS91	17.7097	83.2 3584
EVCS17	17.6904	83.2658	EVCS42	17.6953	83.2583	EVCS67	17.7246	83.26319	EVCS92	17.7352	83.17834
EVCS18	17.6747	83.2237	EVCS43	17.6767	83.1904	EVCS68	17.64537	83.2171	EVCS93	17.6771	83.2 0243
EVCS19	17.7197	83.2304	EVCS44	17.7366	83.2195	EVCS69	17.64372	83.24456	EVCS94	17.723	83.19337
EVCS20	17.7230	83.2262	EVCS45	17.6459	83.1732	EVCS70	17.71338	83.18134	EVCS95	17.6558	83.21336
EVCS21	17.7073	83.1731	EVCS46	17.6478	83.2312	EVCS71	17.68433	83.22348	EVCS96	17.679	83.19635
EVCS22	17.6596	83.1974	EVCS47	17.7160	83.2107	EVCS72	17.66331	83.25574	EVCS97	17.6618	83.2 6083
EVCS23	17.6448	83.1918	EVCS48	17.6432	83.2067	EVCS73	17.67911	83.18968	EVCS98	17.6811	83.2 5463
EVCS24	17.6469	83.1963	EVCS49	17.7364	83.2214	EVCS74	17.69073	83.24149	EVCS99	17.6918	83.17356
EVCS25	17.7004	83.2050	EVCS50	17.7339	83.2546	EVCS75	17.65692	83.19967	EVCS100	17.7367	83.2521

Table 3. *Factors for selection of EV statins and relative weights*

S. No.	Factor	Rel. wt.
1	Proximity to High-Traffic Areas (F1)	0.0506
2	Parking Space Availability (F2)	0.0522
3	Ease of Access (F3)	0.051
4	Proximity to Public Transport Hubs (F4)	0.0505
5	Land Acquisition or Rental Cost (F5)	0.0838
6	Installation Cost (F6)	0.0834
7	Operational and Maintenance Cost F7)	0.0838
8	Revenue Potential (F8)	0.0644
9	Distance from Green Areas (F9)	0.0643
10	Air Quality Improvement Potential (F10)	0.0683
11	Renewable Energy Integration (F11)	0.0706
12	Daily Traffic Volume (F12)	0.0928
13	EV Density in the Area (F13)	0.093
14	Peak Demand Times (F14)	0.0913

Table 4. *Decision matrix*

Station ID	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14
EVCS 1	2	1	1	1	2	1	1	1	2	3	3	2	2	1
EVCS 2	1	2	2	2	1	1	2	3	1	3	3	1	3	1
EVCS 3	1	2	1	1	1	1	1	3	2	1	1	1	2	2
EVCS 4	1	1	1	1	2	2	2	1	3	1	2	1	1	1
EVCS 5	1	1	2	1	2	3	3	1	1	1	1	1	1	1
EVCS 6	1	2	1	1	2	3	2	1	2	2	1	1	1	1
EVCS 7	2	1	2	3	3	3	2	1	2	2	2	3	2	3
EVCS 8	2	1	2	2	2	1	2	2	2	1	2	2	2	2
EVCS 9	1	1	1	1	3	2	3	1	2	2	3	1	1	1
EVCS 10	3	2	2	2	3	2	3	2	1	3	3	2	3	3
EVCS 11	2	1	1	2	3	2	3	2	1	3	3	2	2	3
EVCS 12	1	1	1	2	1	2	2	2	2	1	2	2	3	1
EVCS 13	2	1	2	2	3	2	3	1	2	1	1	2	2	3
EVCS 14	1	1	1	1	2	2	1	1	3	1	1	1	1	1
EVCS 15	1	1	1	3	3	1	2	1	3	1	2	1	1	2
EVCS 16	2	3	3	1	1	2	1	2	1	1	1	2	2	2

Station ID	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14
EVCS 17	1	2	3	3	2	1	1	2	1	3	2	2	3	3
EVCS 18	3	2	2	3	3	2	2	3	3	1	3	3	3	2
EVCS 19	1	1	1	1	1	2	1	1	2	2	2	1	1	1
EVCS 20	2	3	2	3	2	2	2	2	3	1	2	2	1	2
EVCS 21	2	2	2	2	1	1	2	2	2	2	3	1	2	1
EVCS 22	3	3	3	1	1	2	2	3	3	2	1	2	3	3
EVCS 23	1	2	1	2	2	1	2	1	3	2	1	3	2	2
EVCS 24	2	1	3	3	2	1	1	2	2	2	1	2	2	1
EVCS 25	3	1	2	2	3	3	3	3	1	2	3	2	3	3
EVCS 26	2	3	3	1	1	1	1	2	1	2	3	2	1	1
EVCS 27	3	1	3	3	2	1	1	2	2	3	3	3	2	3
EVCS 28	2	1	3	2	3	3	3	2	3	2	2	2	2	1
EVCS 29	3	1	3	3	3	3	3	3	1	2	2	3	3	3
EVCS 30	1	1	2	2	2	3	2	1	3	2	1	1	1	2
EVCS 31	1	3	2	1	2	3	2	1	3	1	1	1	1	1
EVCS 32	3	1	3	3	2	2	2	3	1	3	3	3	3	3
EVCS 33	2	3	2	1	1	2	2	2	1	2	3	2	2	3
EVCS 34	3	3	3	3	2	1	1	3	3	3	2	3	3	3
EVCS 35	1	1	1	2	3	3	2	1	1	2	2	1	1	2
EVCS 36	2	1	1	2	3	3	3	1	1	1	2	2	2	2
EVCS 37	1	1	1	1	3	3	2	1	1	2	3	2	1	2
EVCS 38	3	3	3	3	1	1	1	3	3	1	1	2	3	1
EVCS 39	1	2	3	2	2	2	1	2	2	2	2	2	1	1
EVCS 40	3	3	1	2	1	2	1	2	2	3	2	3	2	2
EVCS 41	1	2	2	1	1	2	1	3	2	2	3	1	3	1
EVCS 42	2	1	1	2	3	3	3	1	3	1	1	1	1	1
EVCS 43	3	3	3	3	1	1	1	3	1	3	1	3	3	3
EVCS 44	2	2	1	1	3	3	3	1	1	3	1	1	2	1
EVCS 45	2	2	2	1	1	2	1	3	3	1	1	3	3	2
EVCS 46	3	2	2	3	1	1	2	3	1	3	3	3	3	3
EVCS 47	1	3	3	2	1	1	1	2	2	1	3	1	2	2
EVCS 48	3	3	2	2	1	1	1	3	2	3	2	3	2	3
EVCS 49	2	3	1	2	3	3	3	1	2	3	3	3	1	2
EVCS 50	3	3	3	3	1	1	1	3	3	2	1	3	3	3
EVCS 51	1	1	2	1	3	3	3	1	3	1	1	1	1	1
EVCS 52	1	2	1	1	3	2	3	2	1	3	1	1	2	2
EVCS 53	1	3	2	2	1	1	1	3	2	3	3	1	3	1
EVCS 54	1	1	3	3	2	2	1	1	2	3	2	1	1	2
EVCS 55	2	2	2	2	2	2	3	2	2	3	2	3	1	2
EVCS 56	3	3	3	3	1	1	1	3	2	3	3	3	3	3
EVCS 57	1	3	3	3	1	1	1	3	3	3	2	2	3	1
EVCS 58	3	3	3	1	2	1	2	3	3	2	2	3	3	3
EVCS 59	2	2	1	3	1	1	1	1	2	3	1	2	2	2
EVCS 60	3	3	3	2	2	2	3	3	3	2	1	3	3	3
EVCS 61	1	1	2	1	2	2	3	1	2	1	1	1	1	1
EVCS 62	2	3	3	1	1	2	2	2	1	3	1	2	1	1
EVCS 63	2	3	2	3	3	1	2	2	3	1	2	3	2	3
EVCS 64	3	3	2	3	2	1	1	1	1	3	3	3	1	1
EVCS 65	1	1	1	1	2	3	3	1	1	1	2	1	1	1
EVCS 66	3	1	1	3	3	3	3	2	3	2	1	3	3	2
EVCS 67	1	1	1	1	2	2	3	1	2	1	1	1	1	1
EVCS 68	2	2	3	1	1	1	1	3	1	2	2	2	2	1
EVCS 69	1	2	2	1	3	1	3	2	2	2	2	1	1	2
EVCS 70	3	3	2	3	3	3	2	3	3	1	3	3	3	3
EVCS 71	3	2	2	3	2	3	3	3	2	3	3	3	3	3
EVCS 72	1	1	1	1	2	2	1	1	1	3	1	1	1	1
EVCS 73	2	2	1	1	3	3	2	3	2	2	3	2	3	1
EVCS 74	2	3	3	3	3	2	2	2	3	1	2	3	2	3
EVCS 75	3	3	3	2	3	3	3	1	1	3	1	2	2	3
EVCS 76	2	2	1	2	3	2	3	1	3	2	3	1	2	2
EVCS 77	2	2	2	3	2	2	3	3	1	3	3	2	3	3
EVCS 78	2	2	3	3	1	1	1	3	1	2	2	3	2	3
EVCS 79	3	1	1	3	3	3	3	1	3	1	1	2	1	2
EVCS 80	2	1	1	1	2	3	1	2	1	3	2	1	1	2
EVCS 81	2	1	1	3	3	3	3	1	2	1	1	1	1	2

Station ID	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14
EVCS 82	3	2	1	2	3	2	3	2	2	2	2	2	2	1
EVCS 83	3	2	3	2	3	3	2	1	2	3	2	2	1	3
EVCS 84	1	2	2	1	1	3	3	3	2	2	1	1	2	1
EVCS 85	2	3	3	2	2	1	1	2	2	2	1	2	1	2
EVCS 86	2	2	2	2	2	3	3	2	3	2	2	2	2	1
EVCS 87	3	3	2	2	1	1	1	3	3	1	3	3	3	2
EVCS 88	1	3	3	2	2	3	3	2	3	1	1	1	1	3
EVCS 89	2	2	1	1	1	3	2	2	1	1	3	1	2	3
EVCS 90	1	3	3	1	3	3	3	1	3	1	1	2	2	2
EVCS 91	3	3	2	2	2	3	2	1	1	1	2	1	1	2
EVCS 92	3	2	3	3	1	1	1	3	1	3	3	3	3	3
EVCS 93	3	2	1	3	3	3	1	2	3	1	3	3	3	3
EVCS 94	2	3	3	2	1	2	2	3	3	1	2	3	3	1
EVCS 95	1	2	3	1	1	1	2	2	1	3	1	1	2	2
EVCS 96	3	3	2	3	2	1	3	3	3	2	3	2	3	2
EVCS 97	3	2	1	3	3	2	2	2	3	1	3	3	3	3
EVCS 98	2	1	1	1	1	3	2	3	1	3	3	3	3	3
EVCS 99	3	3	3	2	1	1	2	3	2	2	2	3	2	2
EVCS 100	3	3	2	3	1	2	1	2	1	3	3	3	1	2

Table 5. *Positive/negative ideal solutions*

PIS/NIS	Fl	F2	F3	F4	F5	F6	F7	F8	F9	F10	Fil	F12	F13	F14
PIS	0.0070	0.0072	0.0071	0.0070	0.0117	0.0116	0.0117	0.0090	0.0089	0.0095	0.0098	0.0129	0.0130	0.0127
NIS	0.0023	0.0024	0.0024	0.0023	0.0039	0.0039	0.0039	0.0030	0.0030	0.0032	0.0033	0.0043	0.0043	0.0042

Table 6. *Closeness coefficients of EVCS*

EVSC	Si+	Si-	CC	EVSC	Si+	Si-	CC
EVCS 1	0.0191	0.0123	0.3914	EVSC 51	0.0203	0.0149	0.4232
EVCS 2	0.0189	0.0150	0.4432	EVSC 52	0.0169	0.0151	0.4718
EVCS 3	0.0214	0.0093	0.3040	EVSC 53	0.0192	0.0154	0.4447
EVCS 4	0.0211	0.0096	0.3126	EVSC 54	0.0189	0.0124	0.3948
EVCS 5	0.0215	0.0119	0.3558	EVSC 55	0.0132	0.0166	0.5568
EVCS 6	0.0205	0.0107	0.3433	EVSC 56	0.0138	0.0210	0.6030
EVCS 7	0.0116	0.0191	0.6225	EVSC 57	0.0175	0.0168	0.4910
EVCS 8	0.0160	0.0114	0.4176	EVSC 58	0.0115	0.0203	0.6372
EVCS 9	0.0195	0.0141	0.4192	EVSC 59	0.0189	0.0117	0.3828
EVCS 10	0.0097	0.0208	0.6810	EVSC 60	0.0094	0.0216	0.6962
EVCS 11	0.0124	0.0187	0.6012	EVSC 61	0.0213	0.0103	0.3255
EVCS 12	0.0180	0.0126	0.4110	EVSC 62	0.0193	0.0122	0.3881
EVCS 13	0.0148	0.0165	0.5259	EVSC 63	0.0128	0.0188	0.5937
EVCS 14	0.0228	0.0081	0.2620	EVSC 64	0.0190	0.0157	0.4526
EVCS 15	0.0199	0.0127	0.3899	EVSC 65	0.0212	0.0121	0.3638
EVCS 16	0.0186	0.0114	0.3802	EVSC 66	0.0112	0.0211	0.6534
EVCS 17	0.0154	0.0171	0.5253	EVSC 67	0.0217	0.0100	0.3156
EVCS 18	0.0100	0.0207	0.6742	EVSC 68	0.0195	0.0113	0.3669
EVCS 19	0.0226	0.0067	0.2280	EVSC 69	0.0179	0.0138	0.4343
EVCS 20	0.0151	0.0139	0.4797	EVSC 70	0.0078	0.0233	0.7491
EVCS 21	0.0187	0.0113	0.3757	EVSC 71	0.0060	0.0233	0.7961
EVCS 22	0.0136	0.0186	0.5774	EVSC 72	0.0227	0.0084	0.2698
EVCS 23	0.0165	0.0141	0.4607	EVSC 73	0.0134	0.0184	0.5779
EVCS 24	0.0186	0.0114	0.3807	EVSC 74	0.0107	0.0196	0.6471
EVCS 25	0.0099	0.0217	0.6856	EVSC 75	0.0125	0.0201	0.6159
EVCS 26	0.0207	0.0115	0.3568	EVSC 76	0.0145	0.0167	0.5345
EVCS 27	0.0140	0.0187	0.5714	EVSC 77	0.0101	0.0204	0.6692
EVCS 28	0.0132	0.0178	0.5750	EVSC 78	0.0164	0.0167	0.5045
EVCS 29	0.0089	0.0229	0.7199	EVSC 79	0.0166	0.0172	0.5093
EVCS 30	0.0185	0.0128	0.4097	EVSC 80	0.0193	0.0126	0.3953
EVCS 31	0.0205	0.0124	0.3777	EVSC 81	0.0186	0.0154	0.4521
EVCS 3 2	0.0102	0.0213	0.6757	EVSC 82	0.0140	0.0157	0.5277
EVCS 3 3	0.0147	0.0154	0.5112	EVSC 83	0.0132	0.0185	0.5829
EVCS34	0.0121	0.0212	0.6362	EVSC 84	0.0185	0.0143	0.4363
EVCS 35	0.0186	0.0134	0.4186	EVSC 85	0.0181	0.0117	0.3916
EVCS 3 6	0.0153	0.0161	0.5122	EVSC 86	0.0133	0.0162	0.5486

EVSC	Si+	Si-	CC	EVSC	Si+	Si-	CC
EVCS 3 7	0.0173	0.0150	0.4654	EVSC 87	0.0158	0.0184	0.5372
EVCS 3 8	0.0189	0.0160	0.4583	EVSC 88	0.0169	0.0174	0.5083
EVCS 39	0.0181	0.0110	0.3781	EVSC 89	0.0176	0.0151	0.4626
EVCS 40	0.0152	0.0157	0.5085	EVSC 90	0.0148	0.0178	0.5468
EVCS 41	0.0189	0.0141	0.4274	EVSC 91	0.0182	0.0133	0.4214
EVCS 42	0.0199	0.0151	0.4310	EVSC 92	0.0149	0.0203	0.5765
EVCS 43	0.0161	0.0197	0.5496	EVSC 93	0.0118	0.0219	0.6506
EVCS 44	0.0183	0.0159	0.4642	EVSC 94	0.0150	0.0178	0.5432
EVCS 45	0.0166	0.0164	0.4971	EVSC 95	0.0196	0.0114	0.3672
EVCS 46	0.0135	0.0203	0.5999	EVSC 96	0.0113	0.0196	0.6345
EVCS 47	0.0194	0.0122	0.3855	EVSC 97	0.0104	0.0212	0.6713
EVCS 48	0.0152	0.0178	0.5396	EVSC 98	0.0136	0.0205	0.6016
EVCS 49	0.0131	0.0200	0.6048	EVSC 99	0.0144	0.0163	0.5304
EVCS 50	0.0153	0.0198	0.5639	EVSC 100	0.0167	0.0165	0.4971

levels of suitability. Alternatives such as EVCS71 (0.7961), EVCS70 (0.7491), and EVCS29 (0.7199) emerged as top candidates, demonstrating the shortest distance to the ideal solution and the farthest from the anti-ideal. These locations reflect optimal trade-offs among all considered criteria. Conversely, alternatives like EVCS19 (0.2280) and EVCS14 (0.2620) showed the lowest suitability, indicating a need for further evaluation or elimination. Overall, the CC values serve as a robust EVCS Suitability Index, guiding stakeholders in prioritizing locations for sustainable EV infrastructure deployment.

5.2 Mahalanobis distance based TOPSIS

To enhance the robustness of decision-making, the TOPSIS method was extended using Mahalanobis distance, which accounts for correlations among criteria. This section presents the results of the analysis, highlighting the relative closeness of alternatives to the ideal solution based on the adjusted distance metric.

5.2.1 Mahalanobis distance based on positive/ negative ideal solution

A Python Code is developed to find Mahalanobis distances from positive and negative ideal solutions. From these mahalanobis distances, closeness coefficients of alternative EVCs are found and presented in Table-7.

The Mahalanobis distance-based TOPSIS analysis provided a refined ranking of EVCS alternatives by accounting for the interdependencies among criteria. The Closeness Coefficient (CC) values ranged from approximately 0.35 to 0.71, indicating notable variation in suitability across locations. Alternatives such as EVCS62 (0.7067), EVCS32 (0.6785), and EVCS60 (0.6575) exhibited the highest closeness values, suggesting their strong alignment with the ideal solution. In contrast, alternatives like EVCS14 (0.3510) and EVCS70 (0.3518) demonstrated the lowest CC scores, implying limited suitability under the given criteria. The Mahalanobis approach proved beneficial in enhancing result sensitivity by capturing the underlying correlation structure, offering a robust alternative to the traditional Euclidean-based TOPSIS.

5.3 Hellwig’s method

The method discussed in the literature (Ewa Roszkowska, 2024) is extended by calculating Hellwig measure based on positive and negative ideal solutions (Table-8). Finally, closeness coefficient of the alternatives are arrived. Hellwig’s measures of Euclidean (HE+), Mahalanobis (HM+) based on positive ideal Solution are determined as discussed in section 3.3.
Also, Hellwig’s measures of Euclidean (HE-), Mahalanobis (HM-) based on negative ideal solution are determine and presented in the following Table-9.

Closeness coefficients:

Closeness coefficients of Hellwig’s measure based on Euclidean/Mahalanobis based are determined and presented in the Table-10

The Hellwig’s measure, evaluated using both Euclidean (CC_HE) and Mahalanobis (CC_HM) distances, reveals consistent yet nuanced variations in the ranking of EVCS alternatives. Alternatives like EVCS62, EVCS32, and EVCS11 recorded the highest CC values under both methods, indicating strong suitability. Notably, the Mahalanobis-based CCs often demonstrated greater differentiation and range, capturing inter-criteria correlations more effectively. In contrast, alternatives such as EVCS14, EVCS63, and EVCS70 consistently ranked low across both models. This comparison highlights the added sensitivity and robustness of

Table-7: *Closeness coefficient based on Mahalanobis distance*

EVCS	Mahalanobis D+ (PIS)	Mahalanobis D- (NIS)	Mahalanobis Closeness	Rank	EVCS	Mahalanobis D+ (PIS)	Mahalanobis D- (NIS)	Mahalanobis Closeness	Rank
EVCS 1	4.6633	6.1529	0.5689	15	EVCS 51	5.8741	5.3930	0.4786	62
EVCS 2	6.3432	5.1993	0.4505	76	EVCS 52	4.4735	6.7473	0.6013	7
EVCS 3	5.8795	4.7908	0.4490	77	EVCS 53	5.7366	5.4612	0.4877	56
EVCS 4	6.1570	5.1398	0.4550	75	EVCS 54	5.4398	6.5705	0.5471	27
EVCS 5	5.1341	6.2308	0.5482	26	EVCS 55	6.6630	4.4340	0.3996	96
EVCS 6	4.2928	6.6564	0.6079	6	EVCS 56	6.3560	6.1593	0.4921	53
EVCS 7	4.9290	6.3032	0.5612	17	EVCS 57	5.7355	5.4281	0.4862	58
EVCS 8	6.2307	4.8772	0.4391	82	EVCS 58	5.2767	6.5577	0.5541	22
EVCS 9	5.9752	6.5090	0.5214	38	EVCS 59	4.9372	5.9480	0.5464	28
EVCS 10	5.4689	6.3912	0.5389	31	EVCS 60	3.6139	6.9387	0.6575	3
EVCS 11	3.8569	7.1302	0.6490	4	EVCS 61	5.2884	6.5762	0.5543	21
EVCS 12	5.7058	6.2211	0.5216	37	EVCS 62	3.2392	7.8067	0.7067	1
EVCS 13	7.0246	4.0443	0.3654	98	EVCS 63	6.7389	4.0761	0.3769	97
EVCS 14	6.9176	3.7421	0.3510	100	EVCS 64	6.7893	5.1137	0.4296	86
EVCS 15	6.9306	4.9712	0.4177	91	EVCS 65	5.4913	5.8472	0.5157	42
EVCS 16	4.4169	6.0830	0.5793	12	EVCS 66	4.6502	5.8393	0.5567	19
EVCS 17	5.2292	5.6326	0.5186	39	EVCS 67	6.2557	5.4212	0.4643	69
EVCS 18	5.0718	6.5259	0.5627	16	EVCS 68	6.0894	5.8460	0.4898	54
EVCS 19	6.9023	4.6663	0.4034	95	EVCS 69	5.1531	6.0729	0.5410	29
EVCS 20	4.9865	6.2604	0.5566	20	EVCS 70	8.0271	4.3557	0.3518	99
EVCS 21	6.6719	5.0978	0.4331	84	EVCS 71	5.1779	5.7925	0.5280	34
EVCS 22	6.2252	5.4833	0.4683	67	EVCS 72	5.8181	5.0888	0.4666	68
EVCS 23	5.7863	5.9810	0.5083	44	EVCS 73	5.5925	5.7484	0.5069	48
EVCS 24	6.1226	5.1999	0.4593	71	EVCS 74	6.1530	5.1591	0.4561	73
EVCS 25	5.5002	5.6768	0.5079	46	EVCS 75	6.4604	4.7695	0.4247	88
EVCS 26	5.9605	5.5789	0.4835	60	EVCS 76	6.1155	5.7335	0.4839	59
EVCS 27	5.0014	6.8621	0.5784	14	EVCS 77	6.7574	4.9408	0.4224	89
EVCS 28	5.2645	6.4439	0.5504	23	EVCS 78	6.7871	4.6625	0.4072	94
EVCS 29	5.4978	5.9172	0.5184	40	EVCS 79	5.7564	6.2984	0.5225	36
EVCS 30	6.1808	5.3032	0.4618	70	EVCS 80	5.6461	5.3932	0.4885	55
EVCS 31	5.6445	5.5758	0.4969	51	EVCS 81	5.0937	7.0802	0.5816	9
EVCS 32	3.2896	6.9427	0.6785	2	EVCS 82	6.1144	4.6713	0.4331	85
EVCS 33	6.0736	4.9480	0.4489	78	EVCS 83	4.6463	5.6701	0.5496	24
EVCS 34	5.4674	6.3135	0.5359	32	EVCS 84	5.8347	4.5427	0.4378	83
EVCS 35	6.6491	4.6389	0.4110	93	EVCS 85	6.6017	6.1008	0.4803	61
EVCS 36	6.5204	5.2620	0.4466	79	EVCS 86	6.4803	4.7130	0.4211	90
EVCS 37	6.7389	4.7195	0.4119	92	EVCS 87	6.1452	5.1353	0.4552	74
EVCS 38	5.5551	5.7282	0.5077	47	EVCS 88	5.2988	6.0124	0.5315	33
EVCS 39	4.9165	5.4215	0.5244	35	EVCS 89	5.2357	6.1396	0.5397	30
EVCS 40	4.7319	6.5059	0.5789	13	EVCS 90	4.5471	5.7392	0.5579	18
EVCS 41	5.7471	4.3001	0.4280	87	EVCS 91	6.0951	6.0588	0.4985	50
EVC5 42	5.8342	4.9502	0.4590	72	EVCS 92	6.2245	5.6270	0.4748	64
EVCS 43	5.6179	5.0478	0.4733	65	EVCS 93	6.3959	5.7912	0.4752	63
EVCS 44	5.7951	4.5729	0.4411	80	EVCS 94	4.4629	6.2023	0.5815	10
EVCS 45	6.1689	5.4970	0.4712	66	EVCS 95	5.8559	6.2691	0.5170	41
EVCS 46	4.5734	7.7930	0.6302	5	EVCS 96	5.6704	5.5161	0.4931	52
EVCS 47	5.7966	5.4965	0.4867	57	EVCS 97	5.4975	5.6744	0.5079	45
EVCS 48	5.9144	5.9323	0.5008	49	EVCS 98	5.2991	5.5365	0.5110	43
EVCS 49	4.3850	6.5877	0.6004	8	EVCS 99	6.2355	4.8880	0.4394	81
EVCS 50	4.7818	6.6453	0.5815	11	EVCS 100	5.6455	6.8777	0.5492	25'

Table 8. *Hellwig's measures based on positive ideal solution*

EVCS	HEi+	HM+	EVCS	HEi+	HM+
EVCS 1	0.4062	0.3636	EVCS 51	0.2832	0.1983
EVCS 2	0.1877	0.1343	EVCS 52	0.4829	0.3895
EVCS 3	0.1778	0.1976	EVCS 53	0.2321	0.2171
EVCS 4	0.2207	0.1597	EVCS 54	0.4681	0.2576
EVCS 5	0.3269	0.2993	EVCS 55	0.0975	0.0907
EVCS 6	0.3812	0.4141	EVCS 56	0.0947	0.1326
EVCS 7	0.4435	0.3273	EVCS 57	0.1458	0.2172

EVCS	HEi+	HM+	EVCS	HEi+	HM+
EVCS 8	0.1168	0.1497	EVCS 58	0.3178	0.2799
EVCS 9	0.1409	0.1845	EVCS 59	0.4121	0.3262
EVCS 10	0.2717	0.2536	EVCS 60	0.5288	0.5068
EVCS 11	0.4087	0.4736	EVCS 61	0.4299	0.2783
EVCS 12	0.2089	0.2213	EVCS 62	0.5833	0.5579
EVCS 13	0.1563	0.0413	EVCS 63	0.1304	0.0803
EVCS 14	-0.0096	0.0559	EVCS 64	0.0477	0.0734
EVCS 15	0.0947	0.0541	EVCS 65	0.2419	0.2506
EVCS 16	0.4930	0.3972	EVCS 66	0.5088	0.3654
EVCS 17	0.3121	0.2863	EVCS 67	0.0302	0.1462
EVCS 18	0.3352	0.3078	EVCS 68	0.1722	0.1689
EVCS 19	0.0313	0.0580	EVCS 69	0.1793	0.2967
EVCS 20	0.3647	0.3195	EVCS 70	0.0937	-0.0955
EVCS 21	0.0818	0.0894	EVCS 71	0.3086	0.2933
EVCS 22	0.1358	0.1504	EVCS 72	0.3308	0.2060
EVCS 23	0.1990	0.2103	EVCS 73	0.2436	0.2368
EVCS 24	0.1678	0.1644	EVCS 74	0.1461	0.1603
EVCS 25	0.3220	0.2493	EVCS 75	0.0455	0.1183
EVCS 26	0.2773	0.1865	EVCS 76	0.1646	0.1654
EVCS 27	0.4182	0.3174	EVCS 77	0.0633	0.0778
EVCS 28	0.2884	0.2815	EVCS 78	0.1126	0.0737
EVCS 29	0.2301	0.2497	EVCS 79	0.2462	0.2144
EVCS 30	0.1055	0.1565	EVCS 80	0.2883	0.2294
EVCS 31	0.3063	0.2297	EVCS 81	0.3035	0.3048
EVCS 32	0.5765	0.5511	EVCS 82	0.2491	0.1655
EVCS 33	0.2120	0.1711	EVCS 83	0.4385	0.3659
EVCS 34	0.3302	0.2538	EVCS 84	0.1633	0.2037
EVCS 35	0.2006	0.0925	EVCS 85	0.2780	0.0990
EVCS 36	0.1712	0.1101	EVCS 86	0.2479	0.1156
EVCS 37	0.1291	0.0803	EVCS 87	0.1975	0.1613
EVCS 38	0.2342	0.2419	EVCS 88	0.2086	0.2768
EVCS 39	0.4008	0.3290	EVCS 89	0.3076	0.2855
EVCS 40	0.3682	0.3542	EVCS 90	0.4153	0.3794
EVCS 41	0.2764	0.2157	EVCS 91	0.2969	0.1682
EVCS 42	0.2894	0.2038	EVCS 92	0.2532	0.1505
EVCS 43	0.2917	0.2333	EVCS 93	0.2948	0.1271
EVCS 44	0.1829	0.2091	EVCS 94	0.4394	0.3909
EVCS 45	0.1179	0.1581	EVCS 95	0.3049	0.2008
EVCS 46	0.4687	0.3758	EVCS 96	0.2358	0.2261
EVCS 47	0.2473	0.2089	EVCS 97	0.1490	0.2497
EVCS 48	0.2884	0.1928	EVCS 98	0.2266	0.2768
EVCS 49	0.4386	0.4016	EVCS 99	0.1047	0.1490
EVCS 50	0.4251	0.3474	EVCS 100	0.3035	0.2295

Table 9. *Hellwig's measures based on negative ideal solution*

EVCS	Hi-	Hm-	EVCS	Hi-	Hm-
EVCS 1	0.0182	6.1529	EVCS 51	0.0180	5.3930
EVCS 2	0.0143	5.1993	EVCS 52	0.0189	6.7473
EVCS 3	0.0134	4.7908	EVCS 53	0.0166	5.4612
EVCS 4	0.0150	5.1398	EVCS 54	0.0203	6.5705
EVCS 5	0.0170	6.2308	EVCS 55	0.0132	4.4340
EVCS 6	0.0196	6.6564	EVCS 56	0.0156	6.1593
EVCS 7	0.0196	6.3032	EVCS 57	0.0139	5.4281
EVCS 8	0.0133	4.8772	EVCS 58	0.0205	6.5577
EVCS 9	0.0164	6.5090	EVCS 59	0.0183	5.9480
EVCS 10	0.0191	6.3912	EVCS 60	0.0215	6.9387
EVCS 11	0.0207	7.1302	EVCS 61	0.0195	6.5762
EVCS 12	0.0147	6.2211	EVCS 62	0.0215	7.8067
EVCS 13	0.0119	4.0443	EVCS 63	0.0105	4.0761
EVCS 14	0.0096	3.7421	EVCS 64	0.0113	5.1137
EVCS 15	0.0140	4.9712	EVCS 65	0.0168	5.8472
EVCS 16	0.0180	6.0830	EVCS 66	0.0185	5.8393
EVCS 17	0.0161	5.6326	EVCS 67	0.0119	5.4212
EVCS 18	0.0175	6.5259	EVCS 68	0.0152	5.8460
EVCS 19	0.0117	4.6663	EVCS 69	0.0133	6.0729

EVCS	Hi-	Hm-	EVCS	Hi-	Hm-
EVCS 20	0.0183	6.2604	EVCS 70	0.0148	4.3557
EVCS 21	0.0134	5.0978	EVCS 71	0.0173	5.7925
EVCS 22	0.0140	5.4833	EVCS 72	0.0160	5.0888
EVCS 23	0.0152	5.9810	EVCS 73	0.0176	5.7484
EVCS 24	0.0139	5.1999	EVCS 74	0.0150	5.1591
EVCS 25	0.0181	5.6768	EVCS 75	0.0100	4.7695
EVCS 26	0.0178	5.5789	EVCS 76	0.0164	5.7335
EVCS 27	0.0199	6.8621	EVCS 77	0.0117	4.9408
EVCS 28	0.0163	6.4439	EVCS 78	0.0132	4.6625
EVCS 29	0.0171	5.9172	EVCS 79	0.0168	6.2984
EVCS 30	0.0141	5.3032	EVCS 80	0.0155	5.3932
EVCS 31	0.0167	5.5758	EVCS 81	0.0193	7.0802
EVCS 32	0.0196	6.9427	EVCS 82	0.0137	4.6713
EVCS 33	0.0147	4.9480	EVCS 83	0.0184	5.6701
EVCS 34	0.0180	6.3135	EVCS 84	0.0124	4.5427
EVCS 35	0.0139	4.6389	EVCS 85	0.0176	6.1008
EVCS 36	0.0173	5.2620	EVCS 86	0.0168	4.7130
EVCS 37	0.0137	4.7195	EVCS 87	0.0145	5.1353
EVCS 38	0.0161	5.7282	EVCS 88	0.0156	6.0124
EVCS 39	0.0171	5.4215	EVCS 89	0.0177	6.1396
EVCS 40	0.0187	6.5059	EVCS 90	0.0168	5.7392
EVCS 41	0.0121	4.3001	EVCS 91	0.0181	6.0588
EVCS 42	0.0159	4.9502	EVCS 92	0.0160	5.6270
EVCS 43	0.0160	5.0478	EVCS 93	0.0173	5.7912
EVCS 44	0.0136	4.5729	EVCS 94	0.0187	6.2023
EVCS 45	0.0145	5.4970	EVCS 95	0.0190	6.2691
EVCS 46	0.0217	7.7930	EVCS 96	0.0160	5.5161
EVCS 47	0.0165	5.4965	EVCS 97	0.0147	5.6744
EVCS 48	0.0172	5.9323	EVCS 98	0.0164	5.5365
EVCS 49	0.0196	6.5877	EVCS 99	0.0128	4.8880
EVCS 50	0.0195	6.6453	EVCS 100	0.0186	6.8777

Table 10. *Closeness coefficients of Hellwig's measures based on Euclidean/Mahalanobis*

EVCS	CC_HE	CC_HM	EVCS	CC_HE	CC_HM
EVCS 1	0.7201	0.7000	EVCS 51	0.6344	0.4326
EVCS 2	0.3588	0.3190	EVCS 52	0.7960	0.8399
EVCS 3	0.3188	0.3657	EVCS 53	0.5006	0.4640
EVCS 4	0.4213	0.3514	EVCS 54	0.8869	0.7233
EVCS 5	0.6060	0.6734	EVCS 55	0.2002	0.1880
EVCS 6	0.8082	0.8268	EVCS 56	0.2566	0.4611
EVCS 7	0.8320	0.7077	EVCS 57	0.2912	0.4598
EVCS 8	0.2344	0.3115	EVCS 58	0.8619	0.7362
EVCS 9	0.3723	0.6331	EVCS 59	0.7290	0.6394
EVCS 10	0.7060	0.6732	EVCS 60	0.9914	0.9135
EVCS 11	0.9155	0.9561	EVCS 61	0.8210	0.7401
EVCS 12	0.3977	0.6018	EVCS 62	0.9949	1.1460
EVCS 13	0.2591	0.0849	EVCS 63	0.2025	0.1541
EVCS 14	-0.0176	0.1031	EVCS 64	0.0909	0.1975
EVCS 15	0.2120	0.1455	EVCS 65	0.5233	0.5589
EVCS 16	0.7480	0.7060	EVCS 66	0.7833	0.6476
EVCS 17	0.5534	0.5576	EVCS 67	0.0633	0.3634
EVCS 18	0.6408	0.7463	EVCS 68	0.3678	0.4605
EVCS 19	0.0642	0.1388	EVCS 69	0.3199	0.6401
EVCS 20	0.7082	0.6937	EVCS 70	0.2293	-0.3112
EVCS 21	0.1777	0.2293	EVCS 71	0.6123	0.5883
EVCS 22	0.2799	0.3778	EVCS 72	0.5600	0.4056
EVCS 23	0.4040	0.5397	EVCS 73	0.5707	0.5284
EVCS 24	0.3204	0.3646	EVCS 74	0.3231	0.3542
EVCS 25	0.6660	0.5300	EVCS 75	0.0785	0.2550
EVCS 26	0.6132	0.4430	EVCS 76	0.4095	0.4366
EVCS 27	0.8435	0.8443	EVCS 77	0.1213	0.1945
EVCS 28	0.5402	0.7084	EVCS 78	0.2245	0.1699
EVCS 29	0.5284	0.5703	EVCS 79	0.5280	0.6121
EVCS 30	0.2339	0.3648	EVCS 80	0.5075	0.4687
EVCS 31	0.5759	0.4943	EVCS 81	0.7450	0.9142

EVCS	CC_HE	CC_HM	EVCS	CC_HE	CC_HM
EVCS 32	0.8656	0.9207	EVCS 82	0.4072	0.3155
EVCS 33	0.4000	0.3476	EVCS 83	0.7468	0.6223
EVCS 34	0.6653	0.6548	EVCS 84	0.2772	0.3509
EVCS 35	0.3604	0.2029	EVCS 85	0.5993	0.3780
EVCS 36	0.4622	0.2837	EVCS 86	0.5316	0.2465
EVCS 37	0.2627	0.1856	EVCS 87	0.3758	0.3532
EVCS 38	0.4786	0.5305	EVCS 88	0.4301	0.6126
EVCS 39	0.6574	0.5622	EVCS 89	0.6341	0.6442
EVCS 40	0.7353	0.7674	EVCS 90	0.6523	0.6409
EVCS 41	0.3856	0.3447	EVCS 91	0.6461	0.4992
EVCS 42	0.5223	0.3884	EVCS 92	0.4945	0.3976
EVCS 43	0.5326	0.4314	EVCS 93	0.5960	0.3822
EVCS 44	0.3303	0.3595	EVCS 94	0.7690	0.7240
EVCS 45	0.2659	0.3914	EVCS 95	0.7201	0.5894
EVCS 46	1.0171	1.2257	EVCS 96	0.4794	0.4818
EVCS 47	0.5137	0.4593	EVCS 97	0.3196	0.5300
EVCS 48	0.5889	0.5089	EVCS 98	0.4878	0.5352
EVCS 49	0.8288	0.8068	EVCS 99	0.2052	0.3115
EVCS 50	0.8148	0.7974	EVCS 100	0.6862	0.8028

Mahalanobis-enhanced Hellwig analysis in reflecting the multidimensional nature of EVCS site selection.

The relative importance of each criterion, derived through a systematic weighting process, played a pivotal role in influencing the ranking of alternatives. High-weighted factors such as EV Density in the Area, Daily Traffic Volume, and Peak Demand Times contributed significantly to the prioritization, while environmental and cost-related aspects also influenced the final decision matrix.

The discussion further explores how each method interprets and balances trade-offs among criteria, the influence of factor weights, and the implications of selecting one method over another in real-world urban planning contexts. The findings aim to assist decision-makers in identifying locations that not only maximize service coverage and operational efficiency but also align with long-term environmental and urban mobility goals.

Comparison of closeness coefficients obtained by proposed method:

Comparison of closeness coefficients obtained by the proposed method are present in Table-11.

Through comparative evaluation, the study highlights the consistency and divergence in rankings produced by the different methods. The Hellwig's-TOPSIS approach effectively combines synthetic scoring and proximity-based ranking, while Mahalanobis distance-enhanced TOPSIS offers robust performance under correlated criteria conditions. The standalone Hellwig's method serves as a baseline for validating the consistency of the integrated models.

The correlation matrix reveals key insights into the consistency and divergence among the four proposed methods for EVCS site selection. The traditional TOPSIS method shows weak correlation with the other approaches, particularly with Mahalanobis-based Hellwig's method (0.1265) and MD-TOPSIS (0.1754), suggesting that it is relatively less sensitive to the interdependencies among criteria.

On the other hand, MD-TOPSIS exhibits a very strong correlation with Mahalanobis-based Hellwig's method (0.9669) and a high correlation with Euclidean-based Hellwig's method (0.8615), indicating that incorporating Mahalanobis distance consistently aligns results across different MCDM formulations. Similarly, the Euclidean and Mahalanobis versions of Hellwig's method also show strong agreement (0.8486), validating the robustness of the Hellwig framework across different distance metrics.

Overall, methods that account for inter-criteria correlations (i.e., Mahalanobis-based) tend to agree more closely, emphasizing the importance of incorporating such relationships for more accurate and realistic evaluations in multi-criteria decision-making.

6. Concluding Remarks

This study proposed an integrated MCDM framework combining Hellwig's Method and TOPSIS—including its Mahalanobis-enhanced variant—for the systematic evaluation and ranking of Electric Vehicle Charging Station (EVCS) locations. The approach successfully incorporated diverse technical, economic, environmental, and accessibility-related criteria, enabling a holistic assessment of EVCS suitability. The Hellwig's method offered a reliable mechanism for synthesizing factor scores, while the integration of

Mahalanobis distance into TOPSIS significantly improved result sensitivity by capturing inter-criteria correlations. The comparative analysis revealed consistent yet insightful differences across

Table 11. *Comparison of closeness coefficients*

EVCS	TOPSIS	MD_TOPSIS	HEE (Hellwig's method)	HEM (Hellwig's method)	Expected suitability index	EVCS	TOPSIS	MD_TOPSIS	HEE (Hellwig's method)	HEM (Hellwig's method)	Expected suitability index
EVCS1	0.3914	0.5689	0.7201	0.7000	0.58195	EVCS51	0.4232	0.4786	0.6344	0.4326	0.5044
EVCS2	0.4432	0.4505	0.3588	0.3190	0.39017	EVCS52	0.4718	0.6013	0.7960	0.8399	0.6701
EVCS3	0.3040	0.4490	0.3188	0.3657	0.36509	EVCS53	0.4447	0.4877	0.5006	0.4640	0.4737
EVCS4	0.3126	0.4550	0.4213	0.3514	0.38463	EVCS54	0.3948	0.5471	0.8869	0.7233	0.6390
EVCS5	0.3558	0.5482	0.6060	0.6734	0.53547	EVCS55	0.5568	0.3996	0.2002	0.1880	0.3482
EVCS6	0.3433	0.6079	0.8082	0.8268	0.62606	EVCS56	0.6030	0.4921	0.2566	0.4611	0.4454
EVCS7	0.6225	0.5612	0.8320	0.7077	0.68610	EVCS57	0.4910	0.4862	0.2912	0.4598	0.4184
EVCS8	0.4176	0.4391	0.2344	0.3115	0.34599	EVCS58	0.6372	0.5541	0.8619	0.7362	0.7009
EVCS9	0.4192	0.5214	0.3723	0.6331	0.49188	EVCS59	0.3828	0.5464	0.7290	0.6394	0.5682
EVCS10	0.6810	0.5389	0.7060	0.6732	0.64067	EVCS60	0.6962	0.6575	0.9914	0.9135	0.8179
EVCS11	0.6012	0.6490	0.9155	0.9561	0.77987	EVCS61	0.3255	0.5543	0.8210	0.7401	0.5979
EVCS12	0.4110	0.5216	0.3977	0.6018	0.48859	EVCS62	0.3881	0.7067	0.9949	1.1460	0.7950
EVCS13	0.5259	0.3654	0.2591	0.0849	0.30770	EVCS63	0.5937	0.3769	0.2025	0.1541	0.3458
EVCS14	0.2620	0.3510	-0.0176	0.1031	0.17200	EVCS64	0.4526	0.4296	0.0909	0.1975	0.2857
EVCS15	0.3899	0.4177	0.2120	0.1455	0.28804	EVCS65	0.3638	0.5157	0.5233	0.5589	0.4807
EVCS16	0.3802	0.5793	0.7480	0.7060	0.59026	EVCS66	0.6534	0.5567	0.7833	0.6476	0.6635
EVCS17	0.5253	0.5186	0.5534	0.5576	0.53850	EVCS67	0.3156	0.4643	0.0633	0.3634	0.2890
EVCS18	0.6742	0.5627	0.6408	0.7463	0.65549	EVCS68	0.3669	0.4898	0.3678	0.4605	0.4236
EVCS19	0.2280	0.4034	0.0642	0.1388	0.21699	EVCS69	0.4343	0.5410	0.3199	0.6401	0.4826
EVCS20	0.4797	0.5566	0.7082	0.6937	0.60434	EVCS70	0.7491	0.3518	0.2293	-0.3112	0.2428
EVCS21	0.3757	0.4331	0.1777	0.2293	0.30444	EVCS71	0.7961	0.5280	0.6123	0.5883	0.6415
EVCS22	0.5774	0.4683	0.2799	0.3778	0.42679	EVCS72	0.2698	0.4666	0.5600	0.4056	0.4220
EVCS23	0.4607	0.5083	0.4040	0.5397	0.47604	EVCS73	0.5779	0.5069	0.5707	0.5284	0.5448
EVCS24	0.3807	0.4593	0.3204	0.3646	0.38410	EVCS74	0.6471	0.4561	0.3231	0.3542	0.4584
EVCS25	0.6856	0.5079	0.6660	0.5300	0.59717	EVCS75	0.6159	0.4247	0.0785	0.2550	0.3448
EVCS26	0.3568	0.4835	0.6132	0.4430	0.47775	EVCS76	0.5345	0.4839	0.4095	0.4366	0.4681
EVCS27	0.5714	0.5784	0.8435	0.8443	0.70892	EVCS77	0.6692	0.4224	0.1213	0.1945	0.3663
EVCS28	0.5750	0.5504	0.5402	0.7084	0.60375	EVCS78	0.5045	0.4072	0.2245	0.1699	0.3301
EVCS29	0.7199	0.5184	0.5284	0.5703	0.59585	EVCS79	0.5093	0.5225	0.5280	0.6121	0.5489
EVCS30	0.4097	0.4618	0.2339	0.3648	0.36098	EVCS80	0.3953	0.4885	0.5075	0.4687	0.4605
EVCS31	0.3777	0.4969	0.5759	0.4943	0.48306	EVCS81	0.4521	0.5816	0.7450	0.9142	0.6765
EVCS32	0.6757	0.6785	0.8656	0.9207	0.78949	EVCS82	0.5277	0.4331	0.4072	0.3155	0.4211
EVCS33	0.5112	0.4489	0.4000	0.3476	0.42775	EVCS83	0.5829	0.5496	0.7468	0.6223	0.6330
EVCS34	0.6362	0.5359	0.6653	0.6548	0.61557	EVCS84	0.4363	0.4378	0.2772	0.3509	0.3695
EVCS35	0.4186	0.4110	0.3604	0.2029	0.33575	EVCS85	0.3916	0.4803	0.5993	0.3780	0.4711
EVCS36	0.5122	0.4466	0.4622	0.2837	0.41677	EVCS86	0.5486	0.4211	0.5316	0.2465	0.4238
EVCS37	0.4654	0.4119	0.2627	0.1856	0.32942	EVCS87	0.5372	0.4552	0.3758	0.3532	0.4353
EVCS38	0.4583	0.5077	0.4786	0.5305	0.49396	EVCS88	0.5083	0.5315	0.4301	0.6126	0.5209
EVCS39	0.3781	0.5244	0.6574	0.5622	0.52625	EVCS89	0.4626	0.5397	0.6341	0.6442	0.5646
EVCS40	0.5085	0.5789	0.7353	0.7674	0.64433	EVCS90	0.5468	0.5579	0.6523	0.6409	0.5995
EVCS41	0.4274	0.4280	0.3856	0.3447	0.39307	EVCS91	0.4214	0.4985	0.6461	0.4992	0.5221
EVCS42	0.4310	0.4590	0.5223	0.3884	0.45191	EVCS92	0.5765	0.4748	0.4945	0.3976	0.4863
EVCS43	0.5496	0.4733	0.5326	0.4314	0.49466	EVCS93	0.6506	0.4752	0.5960	0.3822	0.5228
EVCS44	0.4642	0.4411	0.3303	0.3595	0.39827	EVCS94	0.5432	0.5815	0.7690	0.7240	0.6550
EVCS45	0.4971	0.4712	0.2659	0.3914	0.39812	EVCS95	0.3672	0.5170	0.7201	0.5894	0.5468
EVCS46	0.5999	0.6302	1.0171	1.2257	0.88305	EVCS96	0.6345	0.4931	0.4794	0.4818	0.5338
EVCS47	0.3855	0.4867	0.5137	0.4593	0.45743	EVCS97	0.6713	0.5079	0.3196	0.5300	0.5033
EVCS48	0.5396	0.5008	0.5889	0.5089	0.53797	EVCS98	0.6016	0.5110	0.4878	0.5352	0.5375
EVCS49	0.6048	0.6004	0.8288	0.8068	0.71167	EVCS99	0.5304	0.4394	0.2052	0.3115	0.3703
EVCS50	0.5639	0.5815	0.8148	0.7974	0.68938	EVCS100	0.4971	0.5492	0.6862	0.8028	0.6392

Table 12. *Correlation among the methods*

Proposed Methods	TOPSIS	MD TOPSIS	Euclidean based (Hellwig's method)	Mahalanobis based (Hellwig's method)
TOPSIS	1.0000	0.1754	0.1902	0.1265
MD TOPSIS	0.1754	1.0000	0.8615	0.9669

Euclidean based (Hellwig's method)	0.1902	0.8615	1.0000	0.8486
Mahalanobis based (Hellwig's method)	0.1265	0.9669	0.8486	1.0000

methods, supporting robust decision-making for EV infrastructure planning.

Looking ahead, the framework can be extended in several directions. Incorporating real-time dynamic data such as energy demand fluctuations, traffic congestion levels, and grid load capacities could further enhance decision accuracy. Additionally, integrating stakeholder preferences through fuzzy logic or incorporating spatial analytics via GIS tools may enrich the model's applicability in real-world urban planning. Future research may also explore the inclusion of carbon offset potential and user behaviour analytics to align EVCS development with broader sustainability and smart city initiatives.

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