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Identifying Suitable Location for Electric Vehicles Charging by Using Fermatean Fuzzy-based Personalized Decision Model

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ABSTRACT

Electric vehicles (EVs) are gaining significant attention in the transport industry. With global leaders combating climate change and enforcing green practices, EVs are viable options for transportation. One crucial challenge is charging EVs and identifying appropriate locations to establish EV charging stations. The location identification problem is considered a multi-criteria decision problem (MCDP) involving diverse criteria. Previous studies on location selection for EV charging could not effectively model uncertainty, handle subjective randomness, capture experts' hesitation, or consider personalized grading of locations. Motivated by these gaps, this paper puts forward an integrated framework that comprises Fermatean fuzzy preferences, entropy measure, and a modified WASPAS with Copeland approach to model uncertainty with reduced subjective randomness, effectively capture experts' hesitation, and obtain both individualistic and cumulative grades for EV charging locations. The practicality of the framework is demonstrated through a case example of location grading in Tamil Nadu, India. The results infer that 'Singanallur' and 'Peelamedu' are the top two locations for setting charging points, and criteria such as pollution, cost, and eco-impact are relatively important for location identification. The paper presents a novel combination that methodically calculates weights and ranks locations in both personalized and combined contexts. Its applicability to location selection is unique, with the locations considered being novel for the study. The study faces the following limitations: (i) partial information cannot be modelled, (ii) experts' weights are not methodically obtained, and (iii) a GIS-based selection process is not followed.

1. Introduction

The transport sector is contributing heavily to air and noise pollution, and considering the issue, globally, nations are trying to actively adopt sustainable and green practices to mitigate the ill effects [1]. In developing countries like India, there is an urge to balance pollution and logistics efficiently to maintain the country's economic status. Global leaders have seen electric vehicles (EVs) as a viable

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alternative to combat the growing environmental pollution [2]. In the recent past, it can be noted that people have adopted fossil fuels driven vehicles for their transport, and this causes a significant threat to the environment owing to the release of greenhouse gases causing global warming and climate change. As a promising alternative, EVs are launched globally that significantly reduce pollution levels and help in environmental safety [3].

Notably, one core challenge with EV adoption is the setting up of charging stations and identification of apt locations for the same involves various criteria specifically from the triple bottom context, which motivated researchers to consider the problem as a multi-criteria decision problem (MCDP) where different alternative locations for setting up of EV charging points are rated based on multiple criteria by a diverse set of experts to obtain a grade for each location that facilitates ranking of locations.

Reports from iqair.com show that India is ranked fifth in air pollution, and a study in 2019 showed that 21 cities out of 30 highly polluted cities were from India. Such facts infer the need for a rapid and reliable transport alternative, specifically EVs, provided the challenge of location identification for the apt installation of charging points is sorted out. In the next section, authors review some recent and relevant models for location identification/selection for EVs charging, which concludes some research gaps such as (i) uncertainty is not handled flexibly; (ii) hesitation of experts during the rating process can be better modeled; (iii) personalized grading of locations based on individual rating data is lacking, and (iv) intra/inter sensitivity analysis can be performed comprehensively to understand model's stability better.

Driven by these issues, in this article, a new integrated framework is presented, which considers the following:

i. Fermatean fuzzy data (FFD) [4] for rating EVs and criteria. The FFD captures uncertainty from three dimensions: membership, non-membership, and hesitancy. Considering the window factor as three, the experts can effectively express their degree of preference and non-preference in a broader perspective compared to the earlier orthopair forms. For example, a candidate's communication can be graded as (0.85, 0.65) when dealing with FFD. However, the earlier orthopair forms do not allow the rating since the inequality constraint does not hold for window factors two and one.
ii. Similarly, an entropy measure is put forward that can determine criteria weights methodically by reducing biases and inaccuracies along with better modeling of experts' hesitation.
iii. Finally, a modified WASPAS algorithm is presented to determine personalized grades for locations to charge EVs and the Copeland approach for determining the net grades for locations.

Typically, these contributions address the gaps/issues stated above and provide a mathematical framework for MCDP that could be used to organize the decision-making process in such critical applications. The rest of the article follows the organization as Section 2 for the literature review dealing with earlier works in location selection for EV charging, followed by decision methods with FFD. The methodology is provided in detail with a stepwise explanation in Section 3. A case example is demonstrated in Section 4 to understand the practicality of the developed approach. In Section 5, sensitivity and comparison are provided better to infer the pros and cons of the model. Finally, a conclusion with future research scope is provided in Section 6.

2. Literature review

2.1 EV charging locations grading models

The growing interest in electric vehicles (EVs) and the need for efficient charging infrastructure have sparked numerous studies exploring the selection and optimization of charging station locations, employing various methodologies such as genetic algorithms, fuzzy multi-criteria decision-making (MCDM), Bayesian networks (BN), and geographical information systems (GIS) to address the complex and multi-dimensional aspects of sustainable electric vehicle charging station (EVCS) site selection. Ren *et al.* [5] demonstrated the benefits of using grey incidence decision and grey target theory for ease of operation and low data collection and processing requirements. They suggested a genetic algorithm solution for minimizing the overall social cost and building an evaluation index system based on five location-influencing factors to determine the optimal location of an EVCS. Pagany *et al.* [6] proposed the electric charging demand location (ECDL) model, which uses user behavior, GIS, and point of interest (POI) data to determine the best locations for EVCS, taking into account variables like dwell times, visiting frequencies, and walking distance to ensure thorough coverage of charging demand. Hosseini & Sardar [7] introduced a BN model for locating sustainable EVCS, considering both quantitative and qualitative aspects and showing how helpful BN is for making decisions in electrical energy management.

Liu *et al.* [8] proposed a fuzzy MCDM approach to choose the best sites for charging stations for an electric car-sharing company's sustainable growth by combining the fuzzy grey relation analysis, fuzzy grey Delphi method, and optimization models. Guler & Yomralioglu [9] proposed an integrated approach using GIS techniques and MCDM methods, such as the fuzzy analytical hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS), to find suitable locations for electric vehicle charging stations, providing a reliable answer for decision-makers and policymakers in urban planning. Napoli *et al.* [10] aimed to support the implementation of sustainable mobility initiatives and the Directive on the Deployment of Alternative Fuels Infrastructure by proposing a methodology to identify the best locations for electric vehicle infrastructures in a highway network, taking into account supply and demand factors as well as the psychological component of drivers. Ghosh *et al.* [11] presented a hexagonal fuzzy set MCDM methodology for selecting optimal sites for electric vehicle charging stations, incorporating GIS and fuzzy AHP with a practical example in Howrah, India, demonstrating the applicability and effectiveness of the proposed model, supported by comparative and sensitivity analyses. Mishra *et al.* [12] proposed a novel single-valued neutrosophic information-based additive ratio assessment (ARAS) approach for evaluating and prioritizing sustainable EVCS sites, incorporating a similarity-measure-based procedure and expert subjective. Feng *et al.* [13] presented an integrated MCDM method that incorporates 13 sub-criteria from technical, economic, social, environmental, and resource perspectives and employs the linguistic entropy weight (LEW) method and fuzzy axiomatic design (FAD) to select a suitable site for an EVCS. Mall & Anbanandam [14] employed fuzzy AHP and Visekriterijumska optimizacija I kompromisno resenje (VIKOR) approach to evaluate and rank alternative EVCS based on expert views, emphasizing the importance of charging time and favoring battery swapping as the preferred solution. Carra *et al.* [15] proposed a unified approach using AHP and Monte Carlo simulation to identify and select key indicators of sustainable locations for electric vehicle charging stations, resulting in five overlapping indicators that can inform the planning of sustainable charging infrastructure in cities. Mahdy *et al.* [16] presented a methodology for supporting the planning of optimal charging infrastructure locations for EVs in Winchester City and District, UK, using an MCDM approach based on the AHP and GIS, resulting in 44 suitable EV charging point locations that were validated against actual locations, demonstrating the accuracy and generalizability of the proposed methodology for other cities.

Abdel-Basset *et al.* [17] presented an MCDM approach based on neutrosophic theory and type-2 neutrosophic numbers to evaluate and determine the most sustainable location for an EVCS in Zagazig, Egypt, taking into account six critical factors and nineteen sub-factors, with the economic factor identified as the most important, followed by the technical aspect, providing valuable information for policymakers and demonstrating the reliability, strength, and scalability of the EVCS. Rane *et al.* [18] focused on determining optimal locations for new EVCS in Mumbai, taking thirteen parameters into account and employing Multi Influencing Factor (MIF) weights, a GIS for weighted overlay analysis, and the TOPSIS to assign ranks based on suitability index values, providing a precise solution for EVCS placement and assisting policymakers and administrators. Mousavi *et al.* [19] proposed a model utilizing the R-numbers and combined compromise solution method (R-CoCoSo) for the sustainable evaluation of energy sources in charging stations for EVs and incorporates the combinative distance-based assessment (CODAS) method and linear programming model to assess project risk and allocate contractors' workload, with a confirmed case in Tehran, Iran, demonstrating the model's accuracy and applicability in building charging stations. The diverse range of methodologies and approaches discussed in the literature highlights the significance of considering multiple criteria and factors for the selection and optimal siting of EVCS, with each method offering valuable insights and solutions for sustainable EVCS deployment. Addressing research gaps in the selection of EVCS can contribute to developing robust and efficient methodologies for EVCS site selection, ultimately supporting the broader adoption of electric vehicles and the transition to sustainable transportation systems. Hence, the authors propose an integrated decision system for selecting EVCS in Coimbatore.

2.2 FFD-based decision models

The estimation of decision-making under uncertain conditions has successfully resolved those uncertainty conditions over certain conditions in recent years. Atanassov [20] proposed the intuitionistic fuzzy set (IFS), which solves most of the decision-making problems under uncertain environments but does not cover more data points (u, v) such that $u^2 + v^2 \leq 1$. Senapati & Yager [4] introduced FFS as an extension of IFS, focusing on their properties and applications in MCDM problems. FFS has the advantage of accommodating more points than IFS, allowing for a more fine-grained representation of uncertainty and more flexible modeling of complex decision-making scenarios since it can cover more data points (u, v) such that $u^3 + v^3 \leq 1$.

Since the inception of FFS, many researchers have used FFS and its extensions in various applications of MCDM. Akram *et al.* [21] explored the concept of FFS and extended well-known multi-attribute evaluation methods to handle FFS, showcasing their applicability in determining the best COVID-19 testing laboratory using simple additive weighting (SAW), additive ratio assessment (ARAS), and VIKOR and comparing the results with existing FFS-based decision methods. Gul *et al.* [22] developed a novel fuzzy risk assessment method that combined TOPSIS and FFS to rank manufacturing potential hazards, giving occupational risk analysts a useful tool to prioritize risks and improve workplace safety. Keshavarz-Ghorabaee *et al.* [23] proposed a novel methodology for evaluating and selecting green suppliers in the construction industry, taking into account uncertainty, combining weighted aggregated sum product assessment (WASPAS) and the simple multi-attribute rating technique (SMART) with FFS to address the problem of supplier evaluation sustainably and efficiently. Mishra *et al.* [24] introduced the concept of interval-valued hesitant Fermatean fuzzy sets (IVHFFS) and presented their basic operations, distance measures, aggregation operators, and their application in decision analysis, demonstrating the effectiveness of the proposed method for evaluating desalination technologies under various criteria and uncertainties. Akram *et al.* [25] introduced the linguistic Fermatean fuzzy set, a hybrid structure combining Fermatean fuzzy sets and linguistic term sets, for qualitative decision-making problems, providing a comprehensive framework and demonstrating its efficacy through practical applications and comparative analysis. Qahtan *et al.* [26] proposed an Agri4SC benchmarking framework based on Fermatean probabilistic hesitant fuzzy sets (FPHFSs) and multiple criteria decision-making methods to evaluate and rank Agri4SC alternatives considering supply chain visibility, supply chain resource integration, and sustainable performance criteria.

Kirişci [27] introduced new metrics for measuring similarity and distance between Fermatean fuzzy sets, including cosine similarity and a method for constructing similarity measures that satisfy the axiom of similarity measure, and provides a practical example comparing the proposed method with existing ones. Görçün *et al.* [28] addressed the research gap in selecting the most suitable blockchain platform for the logistics industry, presenting a novel and robust MCDM tool using FFS and Dombi aggregation that effectively navigates complex uncertainties and validates its findings through comprehensive sensitivity and comparative analyses. The unique features of FFS, such as the capability to handle uncertainty and model fine-grained uncertainty representation, have made them valuable in decision-making under uncertain conditions. By incorporating FFS into decision models and methodologies, decision-makers can enhance their decision outcomes' robustness, reliability, and accuracy. FFS-based approaches offer a more comprehensive and accurate evaluation of alternatives, providing decision-makers with a deeper understanding of the uncertainty inherent in the decision context. Hence, the authors propose using FFS to solve the MCDP problem of EVCS location identification.

3. Methodology

3.1 Preliminaries

Let's review some content pertaining to the orthopair fuzzy set:

Definition 1 [20]: BI is a fixed set, and $XV \subset BI$ is fixed. Then, $\overline{XV}$ is an IFS in BI given by,

$$\overline{XV} = \{bi, \mu_{\overline{XV}}(bi), \upsilon_{\overline{XV}}(bi) | bi \epsilon BI\} \tag{1}$$

where $\mu_{\overline{XV}}(bi)$, $\upsilon_{\overline{XV}}(bi)$, and $\pi_{\overline{XV}}(bi) = 1 - \left(\mu_{\overline{XV}}(bi) + \upsilon_{\overline{XV}}(bi)\right)$, are the grades of preference, dislike, and hesitancy, $\mu_{\overline{XV}}(bi)$, $\upsilon_{\overline{XV}}(bi)$, and $\pi_{\overline{XV}}(bi)$ are [0,1] and $\mu_{\overline{XV}}(bi) + \upsilon_{\overline{XV}}(bi) \leq 1$.

Definition 2 [4]: BI is like before and $bi \in BI$. Then the FFS MX on BI is given by,

$$MX = \{bi, \mu_{MX}(bi), \upsilon_{MX}(bi) | bi \epsilon BI\} \tag{2}$$

where $\mu_{MX}(bi), \upsilon_{MX}(bi)$ are in [0,1] and denote preference and non-preference grades. Besides, $0 \leq \left(\mu_{MX}(bi)\right)^3 + \left(\upsilon_{MX}(bi)\right)^3 \leq 1$.

Note 1: Here, $MX = \left(\mu_p, \upsilon_p\right) \forall p = 1,2, \dots, n$ is Fermatean fuzzy number/data (FFN/FFD) and its collection is FFS.

Definition 3 [4]: MX_1 and MX_2 are two FFNs. Some operations with FFNs are given by,

$$\eta MX_1 = \left((1 - (1 - \mu_1^3)^\eta)^{1/3}, \upsilon_1^\eta\right), \eta > 0 \tag{3}$$

$$MX_2^\eta = \left(\mu_2^\eta, (1 - (1 - \upsilon_2^3)^\eta)^{1/3}\right) \tag{4}$$

$$MX_1 \oplus MX_2 = \left(\left(1 - (1 - \mu_1^3)(1 - \mu_2^3)\right)^{1/3}, \upsilon_1\upsilon_2\right) \tag{5}$$

$$MX_1 \otimes MX_2 = \left(\mu_1\mu_2, \left(1-(1-\upsilon_1^3)(1-\upsilon_2^3)\right)^{1/3}\right) \tag{6}$$

$$A(MX_1) = \mu_1^3 + \upsilon_1^3 \tag{7}$$

$$S(MX_2) = \mu_2^3 - \upsilon_2^3 \tag{8}$$

Equations shown above are used for arithmetic operations of FFD, and they include scalar multiplication, power operation, addition, multiplication, score, and accuracy measures.

3.2 Weight via entropy measure

This section provides a detailed stepwise procedure for determining the weights of the criteria. Broadly, criteria weights are determined either with some partial information or no information about the criteria. In the former context, there exists some overhead concerning the consideration of partial information, while in the latter, there is no such extra information with respect to the criteria.

The approach presented here is from the latter category, and the main purpose of the approach is to determine criteria weights methodically and capture the hesitation of experts rationally. Earlier methods in this category, such as AHP, require a pairwise comparison matrix that complicates the computational process, and consistency of rating is an ordeal task to achieve. Entropy is an interesting approach that could quantify uncertainty effectively, and Shannon entropy is a popular approach for quantifying the randomness of any event, which is inspired by Boltzman (Aggarwal) [29].

The procedure for calculation is provided below:

Step 1: Form opinion vectors of $1 \times r$ from q experts by considering Likert-scale values that are transformed to FFD based on pre-determined values.

Step 2: Determine the accuracy of FFD from Step 1 by applying Eq. (7). An accuracy matrix is obtained with an order $q \times r$.

Step 3: Calculate entropy values for each criterion to form a vector of $1 \times r$ order that is further normalized to obtain the importance/weights of criteria. Eqs. (9)-(10) are applied for determining the weights of criteria that are in the unit interval with sum equals unity.

$$Y_j = \sum_{l=1}^{q}\left(-\left(\frac{A(MX_{lj})}{\sum_l\left(A(MX_{lj})\right)} ln\left(\frac{A(MX_{lj})}{\sum_l\left(A(MX_{lj})\right)}\right)\right)\right) \tag{9}$$

$$w_j = \frac{Y_j}{\sum_j Y_j} \tag{10}$$

where Y_j is the entropy and w_j is the weight of criterion j.

3.3 Personalized Ranking of Locations

This section provides the rank values and the ordering of locations for charging EVs by considering rating data from experts and weights of criteria (determined via the previous section). The ranking is a crucial step in MCDP, where the alternative locations are graded based on the rating values from experts, and a suitable location is selected for setting up charging stations for EVs.

WASPAS [30] is a popular ranking algorithm that follows the linearly combined formulation of weighted sum and weighted product with a strategy factor to model the attitudinal trait of the expert.

Based on the review made above, authors gain motivation to present the WASPAS algorithm with some amelioration to facilitate consideration of criteria type and personalized ordering of locations based on each expert data. Steps for calculating grades of locations are given below:

Step 1: Form q decision matrices of $o \times r$ order with qualitative rating information that is further converted to FFD by using the pre-determined values. Also, obtain the weight vector from Section 3.2.

Step 2: Homogenize the data by considering Eq. (11). This forms a matrix of order $o \times r$ that is further fed as input to the WASPAS parameters.

$$a_{ij}^{l} = \begin{cases} a_{ij}^{l} \; for\ benefit \\ 1 - a_{ij}^{l} \; for\ the\ cost \end{cases} \tag{11}$$

where a_{ij}^{l} homogenized accuracy measure.

Step 3: Determine weighted sum and product vectors by applying Eqs. (12)-(13) that is primarily of order $1 \times o$. It must be noted that these measures are determined for each expert separately.

$$S_i^l = \sum_{j=1}^{r} w_j . a_{ij}^{l} \tag{12}$$

$$T_i^l = \prod_{j=1}^{r} \left(a_{ij}^{l}\right)^{w_j} \tag{13}$$

where S_i^l is the weighted sum, and T_i^l is the weighted product.

These values are determined for each expert and given as input to the next step for determining the rank values of locations.

Step 4: Determine the net grade by considering Eq. (14), and these values help in ordering the locations that support the suitable selection of locations.

$$G_i^l = \tau . S_i^l + (1 - \tau) . T_i^l \tag{14}$$

where G_i^l is the grading value of location I based on expert l rating data and τ is the strategic value in the unit interval.

Step 5: Apply the Copeland strategy to obtain rank fusion of locations so as to gain a cumulative grade for locations that eventually leads to the final ordering of locations.

i. Form $o \times q$ rank order matrix;
ii. Determine the sum of the order for each location;
iii. Determine the maximum sum value from the location vector and subtract each value from the maximum;
iv. Subtract the quantity from (b) with (c);
v. Arrange the values in ascending order to obtain the net ordering of locations.

As a result, the locations' cumulative ordering is obtained, and this helps in the final grading of locations based on rating data from a group of experts.

Figure 1 depicts the working model of the developed framework. Qualitative data from experts are collected that are transformed to FFD using pre-determined values. Typically, the experts rate the locations for EVCS and also share her/his opinions on the criteria, which are considered the baseline for rating these locations. Based on these data, the weights of experts are calculated by presenting entropy measures. Further, the weights, along with rating data, are given as input to the ranking algorithm, where the locations are graded both in a personalized fashion as well a cumulative fashion. As a result, we can obtain grades in the individualistic form as well as the net form. The modified WASPAS method with the Copeland strategy is combined to develop the ranking algorithm.

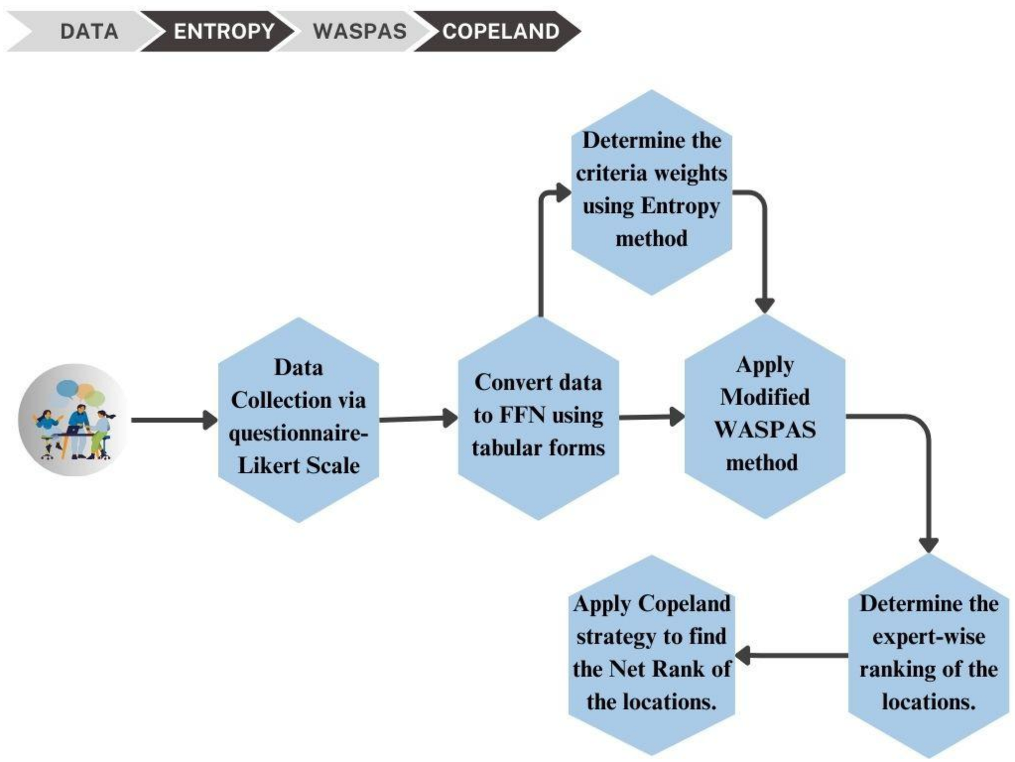


Fig. 1. Research model

4. Case example

The usefulness of the proposed model is testified via a case example of location identification for EV charging within Coimbatore – a city in Tamil Nadu state (India). The city has been recognized as a potential hub for launching the smart city project, an initiative from India through the AMRUT scheme. Out of 500 chosen cities across the country, Coimbatore also gained potential opportunities for being the next smart city. Primarily, the AMRUT scheme focuses on improving the quality and health of individuals within the city by offering clean water, air, food, quality urban transportation, and efficient sanitation and waste disposal systems.

In order to achieve the transport goal of reduced pollution rates within such cities, one attractive option is the adoption of EVs. But as discussed above, the prime issue with EVs is setting up charging points in apt locations so as to avoid transport hindrances. Specifically, such smart cities must actively plan locations for charging EVs to build a robust and scalable city that could effectively meet people's present and future demands.

In this regard, we present a decision model that aims to grade locations for EV charging points setup (EVCS). Coimbatore as a use case is considered in this research work, where the idea is to find suitable locations for setting up EV charging stations. Initially, a panel comprises four experts with electrical, civil, legal, and financial backgrounds with close to six years of work experience in the respective field. Experts primarily are from power engineering, energy economics, survey and planning, and audit zone, and for simplicity, they are represented as I1, I2, I3, and I4. These experts allocate survey and scrutiny tasks to their sub-ordinates to assess different locations within Coimbatore to set the charging points. A total of 13 locations are brought to the focus of the panel, which have potential opportunities for EVCS.

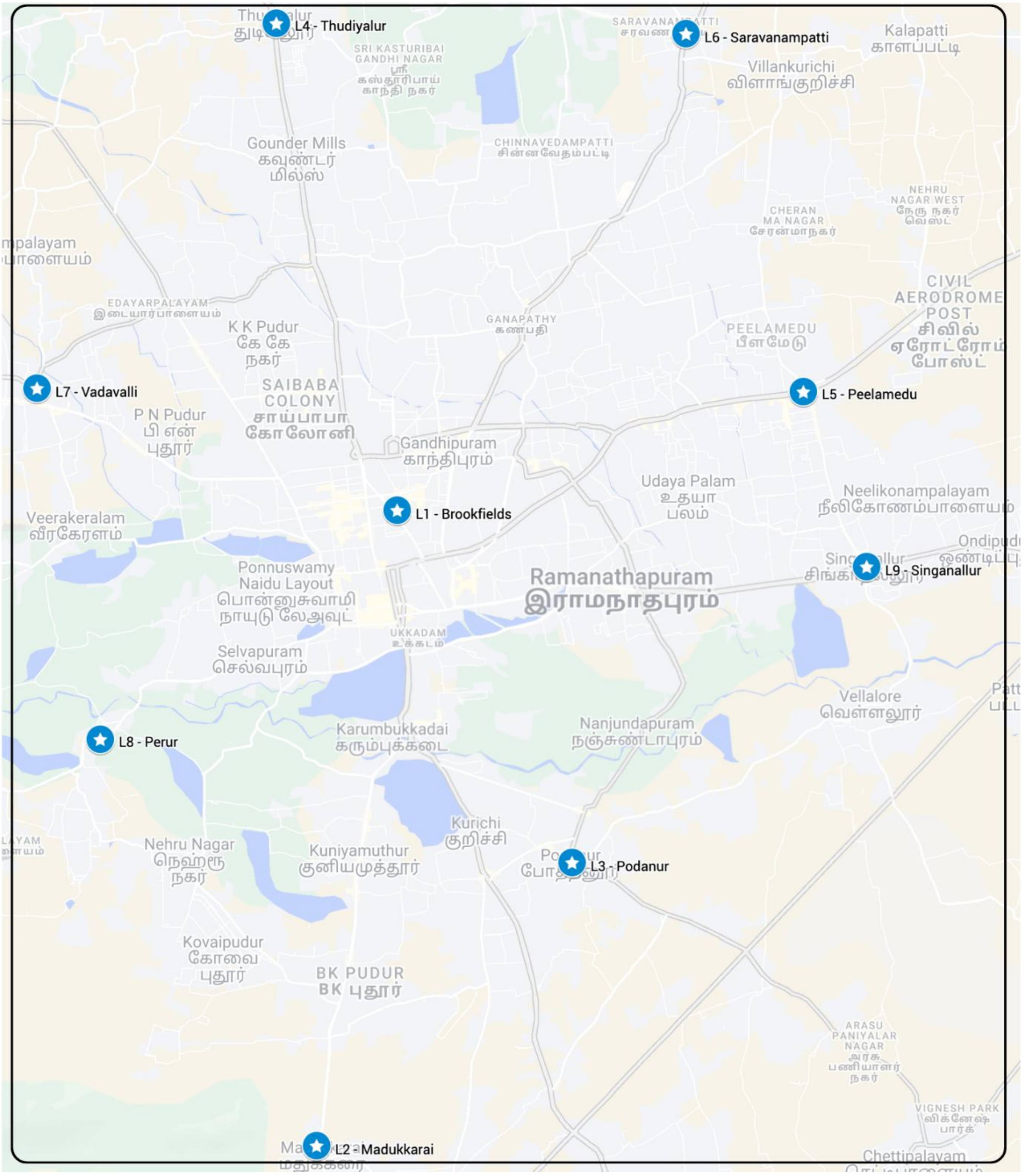


Fig. 2 Map for EV charging locations

These experts then conduct personal visits, phone and email conversations, and discussions with authorities to finalize nine locations for the process. Figure 2 depicts these nine locations within the Coimbatore city map. These nine locations are high scope for installing charging points for EVs. After careful investigation and pre-evaluation, these nine places are shortlisted for the study by the panel. The developed model is considered for grading these nine locations so that the policymakers can further investigate the process and decide on other feasibility aspects to make the installation viable/possible. The names of these nine locations are Brookfield (Krishnasamy road), Madukkari, Podanur, Thudiyalur, Peelamedu, Saravanapatti, Vadavalli, Perur, and Singanallur. The four experts rate these nine locations based on 11 triple-bottom-line criteria that associate with social, environmental, and economic aspects. For choosing these locations and criteria, experts adopted the

Delphi process followed by a voting mechanism. Criteria considered for the study are location from the utility center, traffic density, digitalization, security, green zone, people mindset, waste management, job creation, air/water pollution, construction cost, and eco-impact. The last three are cost-type criteria, and the rest are benefits. Each location is referred as L1, L2, L3,…, and L9 and criteria are denoted as B1, B2, B3, …., and B11.

The steps involved in determining the apt location for EVCS are provided below:

Step 1: Rate locations based on criteria to form matrices of 9×11 order from four experts. A qualitative rating is adopted that is converted to FFD using pre-determined values, Table 1.

Table 1
Rating data from experts on locations

B	L1	L2	L3	L4	L5	L6	L7	L8	L9
B1	(H,M,MH,MH)	(M,MH,L,L)	(ML,L,MH,MH)	(VH,MH,L,H)	(M,MH,ML,ML)	(H,H,VH,VH)	(H,MH,ML,VH)	(M,VH,L,ML)	(H,H,MH,L)
B2	(M,L,MH,H)	(M,ML,H,VL)	(L,L,MH,VL)	(VH,L,H,MH)	(MH,ML,ML,VH)	(L,M,L,L)	(ML,M,L,L)	(H,H,H,M)	(H,VL,MH,MH)
B3	(VL,ML,L,L)	(L,M,VH,ML)	(VH,VL,L,H)	(M,ML,VL,M)	(M,H,M,ML)	(M,H,H,ML)	(M,VH,ML,ML)	(H,L,M,H)	(M,MH,ML,M)
B4	(M,H,M,L)	(M,ML,H,ML)	(M,H,ML,MH)	(MH,ML,M,L)	(ML,H,M,VH)	(VL,H,M,MH)	(VH,H,H,ML)	(H,L,ML,MH)	(L,M,VH,ML)
B5	(MH,MH,M,L)	(L,ML,L,ML)	(VH,VH,L,H)	(H,ML,ML,L)	(VH,ML,H,ML)	(H,M,VH,L)	(VL,H,H,M)	(VL,ML,ML,L)	(VH,MH,H,ML)
B6	(M,VH,H,H)	(VH,VL,M,M)	(L,M,L,H)	(ML,ML,H,M)	(MH,L,H,L)	(MH,MH,L,H)	(H,M,L,ML)	(L,M,L,L)	(ML,L,VH,H)
B7	(H,VL,H,ML)	(H,H,M,M)	(MH,L,VH,H)	(ML,ML,ML,VL)	(VL,ML,VH,L)	(M,H,L,H)	(VL,MH,M,MH)	(L,ML,M,ML)	(H,ML,H,H)
B8	(ML,MH,ML,M)	(VH,ML,ML,L)	(L,ML,VH,H)	(H,H,MH,VH)	(ML,MH,M,MH)	(MH,H,L,VL)	(VL,MH,H,VH)	(H,ML,ML,MH)	(M,MH,ML,ML)
B9	(L,H,MH,H)	(MH,VH,H,H)	(H,L,VH,H)	(VH,ML,ML,VL)	(ML,M,H,M)	(M,MH,MH,VL)	(MH,MH,VH,VH)	(H,L,MH,ML)	(ML,M,H,ML)
B10	(MH,MH,MH,M)	(ML,VH,M,ML)	(ML,MH,H,H)	(H,ML,VL,M)	(MH,M,L,VH)	(VL,M,VH,MH)	(MH,VH,ML,MH)	(M,L,VL,MH)	(ML,MH,ML,H)
B11	(MH,ML,MH,H)	(VL,L,MH,H)	(L,L,L,ML)	(MH,H,L,L)	(H,MH,MH,L)	(L,L,MH,ML)	(VH,M,ML,L)	(H,L,H,VH)	(M,H,L,VH)

Step 2: Criteria are also rated by experts to form an evaluation matrix of 4×11 order (Table 2). This is also rated qualitatively and converted to FFD.

Table 1
Rating data from experts on criteria

B	I1	I2	I3	I4
B1	MP	MP	HP	LP
B2	HP	HP	VHP	MHP
B3	HP	VHP	MP	MP
B4	VHP	MP	MP	LP
B5	HP	MLP	HP	HP
B6	HP	MP	LP	MHP
B7	LP	MLP	MP	HP
B8	LP	MHP	MLP	MP
B9	MHP	MLP	MP	VHP
B10	MHP	HP	MP	MLP
B11	LP	MP	MLP	MLP

Step 3: Calculate the weights of the criteria by using the procedure presented in Section 3.2. By applying Eq. (7), the accuracy is calculated, which forms an accuracy matrix of 4×11 based on the data from Step 2. Eq. (9) is applied to determine the entropy measure that is further normalized to obtain criteria weights from Eq. (10). Figure 3 provides the pictorial view of the entropy values with respect to each expert.

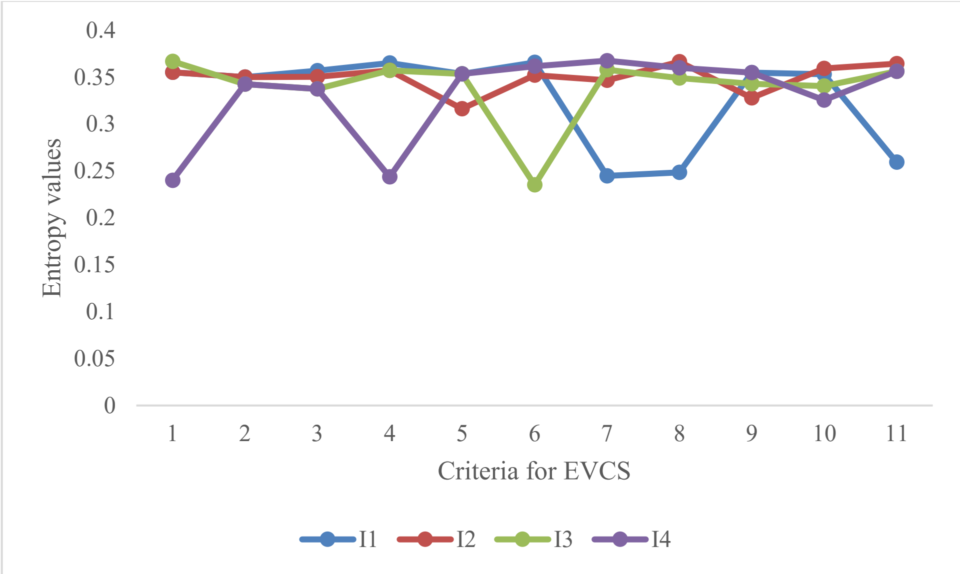


Fig. 1 Entropy values with respect to each expert

Based on the procedure in Section 3.2, the weights are calculated as 0.089, 0.093, 0.093, 0.089, 0.093, 0.089, 0.089, 0.089, 0.093, 0.093, and 0.093, respectively.

Step 4: Consider the vector from Step 3 and data from Step 1 to grade locations for EVCS, Table 3.

Table 2
Ranking algorithm paramter values

L	S_i^l	T_i^l	G_i^l
L1	(0.62,0.52,0.53,0.43)	(0.58,0.46,0.48,0.38)	(0.60,0.49,0.50,0.40)
L2	(0.46,0.58,0.49,0.51)	(0.40,0.54,0.43,0.46)	(0.43,0.56,0.46,0.49)
L3	(0.55,0.54,0.45,0.62)	(0.49,0.48,0.39,0.57)	(0.52,0.51,0.42,0.60)
L4	(0.52,0.46,0.55,0.51)	(0.46,0.43,0.48,0.44)	(0.48,0.44,0.52,0.48)
L5	(0.57,0.50,0.57,0.48)	(0.52,0.46,0.53,0.44)	(0.54,0.48,0.55,0.46)
L6	(0.56,0.61,0.47,0.46)	(0.49,0.56,0.41,0.39)	(0.53,0.59,0.44,0.42)
L7	(0.55,0.56,0.47,0.50)	(0.48,0.52,0.43,0.46)	(0.52,0.54,0.45,0.48)
L8	(0.49,0.59,0.43,0.45)	(0.41,0.55,0.38,0.41)	(0.45,0.57,0.41,0.44)
L9	(0.56,0.51,0.62,0.51)	(0.52,0.46,0.59,0.47)	(0.54,0.49,0.60,0.50)

Table 3 provides the rank parameters associated with each expert, and finally, via Copeland, the net order is determined. The ordering is determined as L9 > L5 > L7 > L1 > L2 > L3 > L6 > L4 > L8. In Table 3, the rank values with respect to each expert are provided in the last column that is considered for Copeland to determine the net ordering of locations. The other two columns, with four values in each cell, denote the weighted sum and weighted product based on each expert's data.

5. Sensitivity and comparison

This section offers the efficacy points associated with the developed approach. In this line, we first consider sensitivity analysis with respect to weights of criteria as well as strategy values. The inter-analysis deals with a variation of criteria weight values obtained via rotation of weights, and as a result, we get 11 new sets of criteria weight vectors that are given as input to the procedure in Section 3.3. Rank values and ordering of locations are obtained for each weight set, and in the intra context, within a weight set, the strategy values are altered in a unit interval step size.

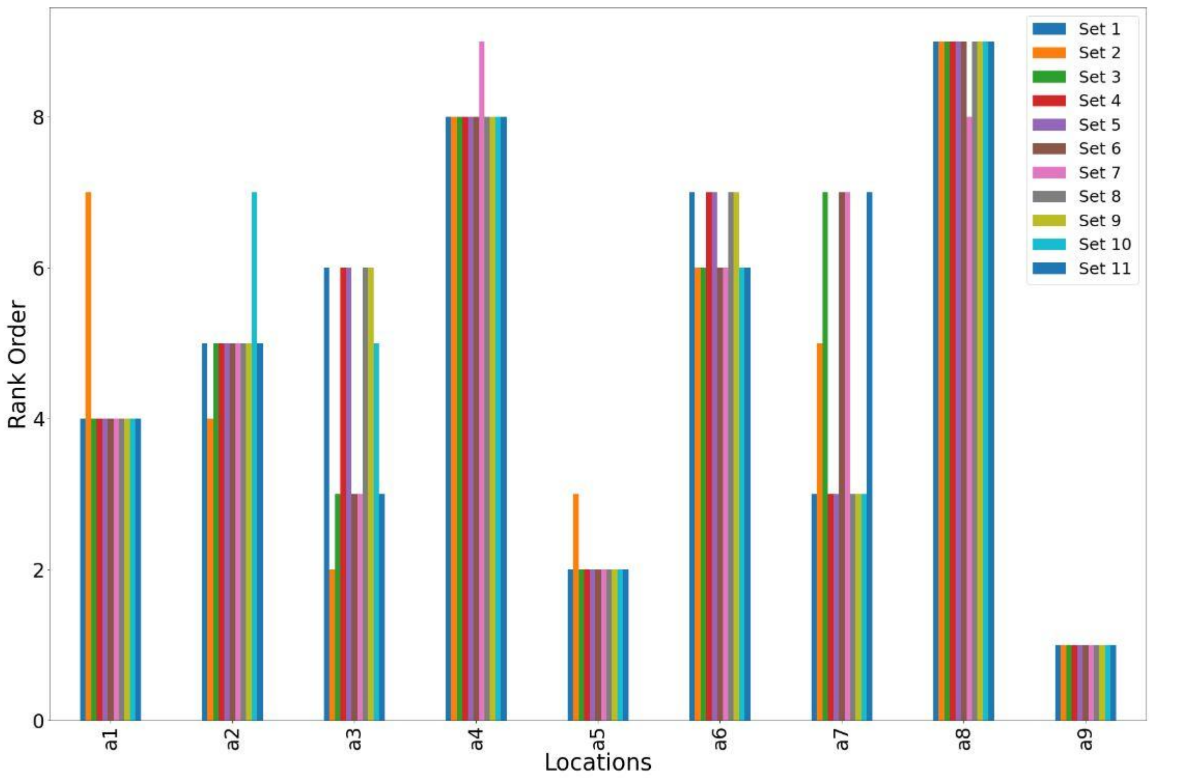
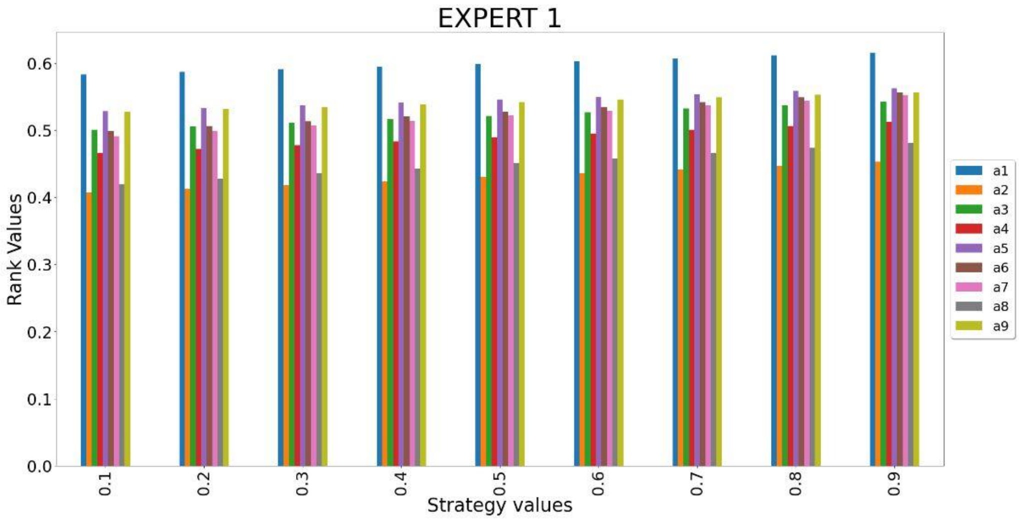


Fig. 4 Rank values of locations for different weight sets

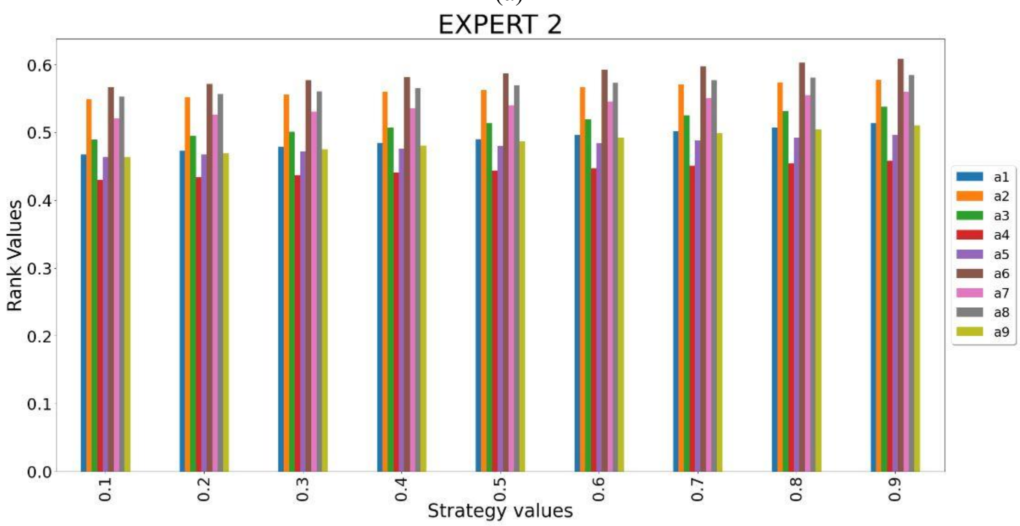
Figure 4 depicts the rank values of locations for different weight sets generated via rotation of weights. Clearly, it can be seen that there is slight fluctuation in the ordering, but for maximum occasions, the ordering is intact, indicating that the model is robust to weight alterations. Specifically, the location L9 position remains unaltered for all 11 sets, and similarly, the L8 location retains its last rank for maximum occasions. The second preferred location L5 also retains its place a maximum number of times, and this evidence show that the model is robust in the inter-sensitivity analysis; hence, alterations to weights of criteria do not affect the ordering drastically.

In Figure 5, we consider the different cases pertaining to four experts. The strategy values are altered from 0.10 to 0.90, and the rank values of each location are determined. It can be seen that though there is a change in the values, the ordering remains unaffected. This indicates that the model is robust in the intra-scenario as well. The change in rank values is due to the change in the weight values. From Figure 4 and Figure 5(a) – 5(c), it is noted that the ordering is intact even after alterations to criteria weights and strategy values, inferring that the developed approach is robust.

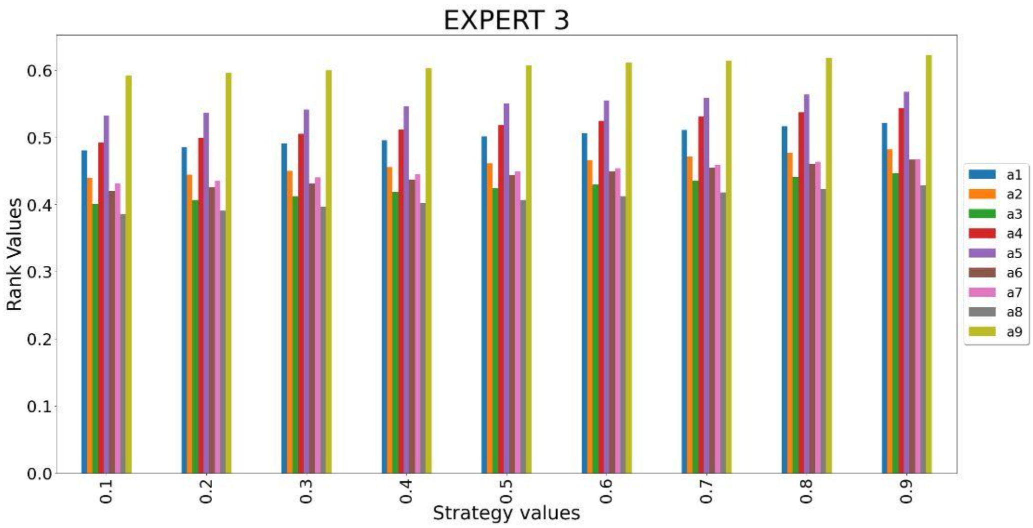
Further, in the context of the application point of view, authors consider EVCS models from the literature, viz., Guler & Yomralioglu [9], Ayildiz [31], Karasen *et al.* [32], and Zhang *et al.* [33] that are compared with the proposed model and Table 4 summarizes the features.



(a)



(b)



(c)

Fig. 5 Rank values for different strategy values ((a) to (c) is experts I1 to I3)

Table 4
Characteristics summary of different EVCS decision models

Features	Proposed	[31]	[32]	[33]	[9]
Input	FFD	PFS	Fuzzy	NWHFS	Fuzzy
Experts' hesitancy	Captured	Not captured	Not captured	Captured	Not captured
Computational overhead	Moderate	Moderate	High	Moderate	High
Uncertainty modeling	Better	Moderate	No	Moderate	No
Criteria type	Considered	Considered	Considered	Not considered	Considered
Personalization	Yes	No	No	No	No
Individualistic ranking	Yes	No	No	No	No
Rank fusion	Yes	No	No	No	No

Note: NWHFS – normal wiggly hesitant fuzzy set

Some innovative aspects of the proposed approach are:

i. FFD is considered for rating that is capable of modeling uncertainty from three dimensions, such as preference, dislike, and hesitation grades, along with a broader window for expression compared to its counterparts, IFS and PFS. Besides, fuzzy sets and NWHFS cannot provide such flexibility in the preference elicitation process.
ii. Weights of criteria are methodically determined to reduce human intervention, bias, and inaccuracy in the decision process. Moreover, the hesitation of experts can be captured during the preference-sharing process.
iii. Furthermore, the computational overhead of the developed approach is moderate when compared with extant models that incorporate pairwise comparison in the decision process, which induces certain overhead from the consistency check and repair mechanism.
iv. Unlike the traditional WASAPS ranking scheme, the proposed algorithm allows consideration of criteria type, which ameliorates the earlier variant of the ranking scheme and makes it more suitable for a wide range of decision applications.
v. Unlike the earlier models, in the proposed approach, individualistic and cumulative ranks are determined, which provides a sense of personalization in the decision-making process. Further, the formulation encourages a rank fusion mechanism where the ranks of locations are determined as a cumulative entity based on the individual rank vectors of locations determined via the data/rating from each expert.

Besides, the uniqueness of the developed approach is investigated using Spearman correlation, which is applied to proposed as well as extant models (Kamali Saraji *et al.* [34] ; Rani *et al.* [35]; [4]; Rani & Mishra [36]) and it is inferred from Figure 6 that the proposed model yields unique rank ordering for locations, which can be intuitively interpreted as the formulation that considers individual expert's data for rank determination and finally fused using Copeland strategy. Such a procedure is lacking in extant approaches. The data is given as input to all the models, and rank orders for locations are determined. For the extant models, the data is aggregated with geometric operators, and then it is fed to the model for rank estimation. It is seen that the Spearman correlation values for the proposed other models are determined as (1.0, 0.40, 0.30, 0.50, 0.30), respectively.

Similarly, in the method context, a simulation study is performed to realize the discrimination ability of the proposed model in comparison with the extant approach. 400 matrices of 9 by 11 order is considered with weights of criteria as described above. These matrices are fed as input to the proposed and extant model and rank values of all 400 matrices are obtained. Variance for the rank vectors is determined and plotted in Figure 6.

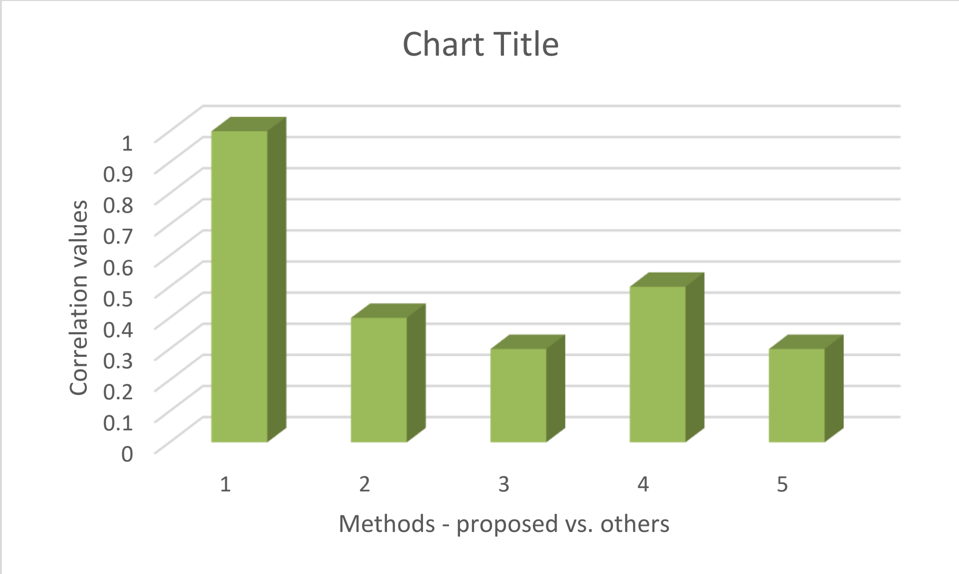


Fig. 6 Test for uniqueness using Spearman correlation (1 is proposed vs. proposed; 2 is proposed vs. [34]; 3 is proposed vs. [35]; 4 is proposed vs. [4]; and five is proposed vs. [36])

6. Results and Discussion

EVs are an attractive alternative to combat pollution from the transport sector, and it can be seen that the major contributor to air pollution is the transport industry, which is constantly pointed out by global leaders. To resolve the issue, EVs are considered a viable option that can reduce pollution levels by avoiding dependence on fossil fuels, But the core challenge to EVs is the installation of charging stations so as to avoid the risk of mobility mismanagement.

Typically, the location identification problem is seen as an MCDM problem as there are diverse criteria associated with the selection process. Coimbatore – a potential candidate for the smart city project in TN, is also a hub for industrial activities, and there is an urge for EV adoption in the city to ensure green and sustainable trends. Furthermore, the city aims to reduce carbon trace by adopting sustainable mobility practices – of which emissions from on-road vehicles (Pamucar *et al.* [37]) play a major role. One way out is to encourage people for public transport and/or EVs (Ferrero *et al.* [38]; Vidhi & Shrivastava, [39]). In this regard, this research adds value to the mission and provides policymakers with a ready-to-use tool for supporting their decision process.

The constituted panel for this study considered nine potential locations within Coimbatore city, and they were rated based on 11 criteria. Criteria such as traffic density, digitalization, green zone, air/water pollution, construction cost, and eco-impact are crucial criteria with high importance from the panel's perception, and they contribute about 55.80%. From the nine locations considered for this study, Singanallur (L9) is the highly preferred location for EVCS, based on the rating data from the panel. Following this, Peelamedu (L5), Vadavalli (L7), and Brookfields (L1) locations are preferred considering the data from experts.

It can be noted that works from Karasen *et al.* [32], Abdel-Basset *et al.* [17], and alike are in line with the present study in terms of the objective and criteria from the triple bottom category. Also, these locations graded by the proposed system are in line with the practical consideration within the city as these places are gaining attention in the recent past for EVCS (Sathiyan *et al.* [40]). As discussed earlier, the developed approach can grade locations both in a personalized fashion and cumulative fashion by considering individual rating information from each expert and fusing rank orders to obtain a holistic ordering of EV chagrining locations.

7. Conclusion

The model developed in this article is a valuable addition to the EV research domain as the primary and crucial phase of EV adoption is the proper placement of charging stations to avoid hindrances in sustainable transport. Mainly the model presents a rational, method-driven, and less human-involved integrated approach for apt location identification for EVCS. In this line, FFD is adopted to better model uncertainty and flexibly express preferences. Further, an entropy measure is presented for criteria weight calculation, followed by a novel ranking algorithm that considers modified WASPAS formulation along with the Copeland approach to determine both individualistic and cumulative rank orderings of locations.

Such an integrated approach facilitates rational grading of locations for EVCS and allows less intervention from humans. Results infer that the developed model yields unique rank ordering for locations and produces broader grades that aid in better discrimination of locations to rationally assign backup alternatives in the case of any issue/problem. The developed model can perform effectively from both the application and method points of view.

Some implications to be noted are: (i) developed model can be used as a ready-to-use tool for location identification for EVCS; (ii) the framework can be used to assess grades for multiple locations so as to gain an ordering of locations and effectively plan backup mechanism to avoid abandoning of the project due to certain natural/man-made issues/problems; (iii) uncertainty is managed effectively by the FFD and experts gain flexibility to express their preferences; (iv) parameters such as weights and rank values are methodically estimated to avoid human intervention and biases during the decision process; (v) experts need some hands-on training via hands-on sessions or seminars to gain knowledge on the working of the model and use the same effectively for making rational decisions; and (vi) finally, experts can take the result from the systems as a supplementary value addition to cross-check their decisions and revert back to reasons for selection owing to its mathematical ability and formulation.

Some limitations of the research are: (i) experts' weights are not calculated; (ii) subjective weights of criteria are not considered; and (iii) data is assumed to be complete and missing records are not considered. In the future, plans are made to resolve these limitations. Moreover, plans are made to extend the developed approach for new applications in the location selection, sustainability, health, engineering, education, and business domains. Specifically, we can extend the model for power plant location selection, hospital location selection, barrier assessment in adopting sustainable entities, technology assessment in education, and so on. Also, we have plans to extend the framework to new fuzzy variants such as hesitant fuzzy sets, linguistic versions, and interval and probabilistic variants of such fuzzy sets, along with the inclusion of data curation and recommendation concepts for large-scale rational decision-making. Finally, plans are being made to develop a mobile app-based framework for instantaneous decision-making with anywhere-anytime features.

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Conflicts of Interest
The authors declare no conflicts of interest.

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