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A rough Dombi Bonferroni based approach for public charging station type selection

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ABSTRACT

As the transition to electric mobility accelerates, charging infrastructure is rapidly expanding. Publicly accessible chargers, also known as electric vehicle supply equipment (EVSE), are critical not only for further promoting the transition but also for mitigating charger access anxiety among electric vehicle (EV) users. It is essential to install the proper EVSE configuration that meets the EV user's various considerations. This study presents a multi-criteria decision-making (MCDM) framework for determining the best performing public EVSE type from multiple EV user perspectives. The proposed approach combines a new MCDM model with an optimal public charging station model. While the optimal model outputs are used to evaluate the quantitative criteria, the MCDM model assesses EV users' evaluations of the qualitative criteria using nonlinear Bonferroni functions extended by rough Dombi norms. The proposed MCDM has standardization parameters with a flexible rough boundary interval, allowing for flexible and rational decision-making. The model is tested using real public EVSE charging data and EV users' evaluations from the field. All public EVSE alternatives are studied. Among the five EVSE options, DCFC EVSE is found to be the best performing, whereas three-phase AC L2 is the least performing option. In terms of EV user preferences, the required charging time is found to have the highest degree of importance, while V2G capability is the least important. The comparative analysis with state-of-the-art MCDM methods validates the proposed model results. Finally, sensitivity analysis verified the ranking order.

1. Introduction

Transitioning to electric mobility as an alternative mobility option helps to achieve the desired climate change targets. With the proliferation of electric vehicles (EVs), the number of EV chargers, also known as electric vehicle supply equipment (EVSE) is rapidly increasing [1]. EVSE can be deployed in various public or private locations. Public EV charging stations refer to EVSE charging units that are available to all EV drivers and located in publicly accessible areas, such as city streets, car parks, shopping locations, and along highway corridors. Currently, AC Level-2 EVSEs constitute most of the public charging infrastructure, while public DC fast charging (DCFC) infrastructure is also expanding. Both types of EVSE are expected to grow at a faster rate by 2030 [2]. The projected rapid growth in EV sales, as well as the availability of EVSE infrastructure capacity, can unlock the true potential of public charging. Furthermore, the need to use EVs more frequently and, in some cases, for intra-city travel throughout the day boosted the market trend for public EVSEs. Providing an adequate number of EVSE, especially in publicly accessible areas, helps to promote more rapid adoption of EVs since this is essential to reducing EV users' charger access anxiety [3]. Public EV charging characteristics differ significantly from the workplace or home charging. The distribution of charging behavior throughout the day, as well as EV dwell times make the public charging design unique. In addition, interoperability in terms of communication and data-driven services, which are designed to meet

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Nomenclature

AF	Annuity factor
C_{dc}	Demand charge
C_{EVSE}	EVSE unit hardware cost
C_{ins}	EVSE installation and maintenance cost
C_{op}	Daily charging energy cost
C_{unit}	Daily levelized unit cost of charging
C_{LIC}	Daily levelized EVSE infrastructure cost
$E_{served,i}$	the charging energy served of ith EV
$E_{required,i}$	Required charge energy of ith EV
HC	Hosting capacity of EVSE
F	Electricity pricing vector
N	The number of EVs served at a public charging station
S_j	The number of EVSE units
$t_{plug-in,i}$	The plug-in time of ith EV
$t_{plug-off,i}$	The plug off time of ith EV
$P_{ch,i}$	The optimized charging rate of ith EV
P_i^{rated}	The on-board charger power rate of ith EV
P_J^{rated}	EVSE charging power rate
P_{lim}	Demand power limit
η_i	The efficiency of the on-board charger of ith EV
η_J	The efficiency of the EVSE unit
T	The number of time slots of 1 min resolution
m	Number of alternatives
n	Number of criteria
e	Number of experts
$\underline{\ell}_{ij}^{q}$	Lower limit of rough number
$\overline{\ell}_{ij}^{q}$	Upper limit of rough number
$\mathbb{C}$	Vector of comparative values
Ψ_i	Rough score function
$\bar{\bar{\mathbb{R}}}^{(1)\chi_1,\chi_2,\ell}$	RDB function
$\bar{\bar{\mathbb{R}}}^{(2)\chi_1,\chi_2,\ell}$	RDB function
ζ_i	Weight of criterion

the needs of public charging operations and payment settlement tasks, is another set of challenges for public charging. Hence, planning EVSE-related tasks is becoming an essential part of the work of city planners, utilities, and private companies interested in investing in this segment. Making the optimal design possible in terms of location, size, and type of charging station has been one of the most important planning tasks to complete.

Optimal placement and sizing of public charging stations have attracted significant research attention in recent years. Many technical and economic parameters are included in the design approach [4,5]. In [6], the major parameters in the problem are identified as EV energy consumption to reach the closest charging station and charging station infrastructure costs, followed by the electric grid loss. In [7], the impact of EV user behaviors on the economic evaluation of public charging stations is investigated. Arrival and dwell times are found to have a strong impact on different utilization patterns of the charging demand served. However, many factors linked directly to the charging station economics, such as charging speed or the number of charging stations, are not considered in the evaluation. In [8], charging behavior and service range have been identified as critical parameters in optimizing the locations and sizes of public charging stations to maximize profitability. In [9], by considering several EV user behaviors, an optimal model is developed to determine the optimal layout and types of public charging stations for a community. The optimal layout suggests a mix of EVSE types, with more Level-2 chargers and fewer DCFC. In [10], the impact of EV user travel and charging behaviors on the planning and operation of charging stations is investigated. L. Adenaw and S. Krapf in [11] investigate the impact of a variety of influencing factors used in the literature to locate public charging stations on charging demand. Saravanan et al. in [12] develop models to evaluate EV drivers' preferences for charging services as charging behavior varies among users. In [13], battery capacity, charging time, and the initial state of charge (SOC) are identified as the main factors influencing EV users' charging and location choices. Hardman et al. in [14] present a literature review on the preferences of EV users' perspectives on charging stations, while technical aspects are not included. As the planning of public charging stations involves multi-criteria decision making involving many conflicting criteria, Liu et al. in [15] propose an integrated multi-criteria decision making (MCDM) model with a heuristic multi-objective optimization model for determining the most suitable charging station site. While many technical and economic aspects are considered for optimally placing the charging stations, optimal EVSE configurations in terms of EV users' preferences are still unexplored. Some work has attempted to identify technical and economic EV user considerations at workplaces. The optimal workplace charging scheduling algorithm from EV users' qualitative and quantitative multicriteria perspective is identified in [16]. All cost aspects in a workplace EVSE, from the charging station owner, EV users, and grid perspectives, are quantified in [17]. Based on the identified quantitative parameters, an integrated multi-objective optimization and MCDM model is developed to determine the most feasible EVSE configuration at workplaces in [18]. However, the charging behavior of workplace EVSE differs from that of public EVSE in terms of mobility patterns and uncertainties. Moreover, this study specified the optimal EVSE types from the charging station operator perspective. As a result, the optimal public EVSE configurations meeting EV user preferences need to be explored in order to establish publicly accessible and efficient charging stations.

Since this work involves many technical, economic, and social factors, we define EVSE type selection as an MCDM problem. By incorporating both quantitative and qualitative evaluation, an MCDM framework can yield the best-performing EVSE option that meets EV users' considerations at public charging stations. Various EVSE considerations can be defined from the multi-criteria perspectives of EV users for both quantitative and qualitative evaluation. The MCDM approach can handle both quantitative and qualitative parameters using optimal values by incorporating EV users' opinions into the decision-making process. Rough sets have been successfully applied to address uncertainty in the information [19–21]. The MCDM methods with Dombi Bonferroni have been used to better handle uncertainty in various decision-making applications. Pamucar in [22] proposed a normalized weighted geometric Dombi Bonferroni mean operator under interval grey numbers to solve decision making applications. Wei et al. in [23] developed some novel Dombi Bonferroni mean operators to aggregate 2-tuple linguistic neutrosophic information. Liu et al. [24] presented some novel intuitionistic fuzzy Dombi Bonferroni mean operators, such as the intuitionistic fuzzy based Dombi geometric Bonferroni mean and the weighted Dombi geometric Bonferroni mean, to deal with the aggregation of intuitionistic fuzzy numbers. The proposed operators are tested on a multi-attribute group decision-making problem. Peng and Smarandache [25] investigated the novel operations on single-valued neutrosophic number based on Dombi Bonferroni mean and Dombi geometric Bonferroni mean operators. Saha et al. [26] integrated the generalized Dombi operators and Bonferroni mean (BM) operator to handle multi-criteria group decision-making problems. Wang and Peng [27] improved new aggregation operators, including q-rung orthopair fuzzy Bonferroni mean Dombi averaging and geometric Bonferroni mean Dombi averaging operators for decision making. An overview of the studies on Rough Dombi Bonferroni (RDB) mean operators based MCDM models is summarized in Table 1.

The contribution of this study is based on the evaluation of the following research questions:

Table 1
Overview of the studies on Rough Dombi Bonferroni mean operators based MCDM models.

Author(s)	Method	Sets	Application
Azam et al. [28]	Multiple-criteria decision making	Complex intuitionistic fuzzy sets	Information security management evaluation
Erdogan et al. [16]	Multi-criteria decision-making	Power Heronian functions	Workplace charging scheduling algorithms
Fan et al. [29]	Multi-criteria decision-making	Single-valued triangular neutrosophic sets	Green supplier selection
Jana and Pal [30]	Multiple-criteria decision making	Single-valued neutrosophic number	Road construction companies selection
Liu et al. [15]	Multi-attribute group decision-making	Intuitionistic fuzzy numbers	Numeric example
Mondal and Roy [31]	DEMATEL and MABAC method	Interval type-2 Pythagorean fuzzy	Supply chain management problem
Pamucar [22]	Grey number based decision making	Interval grey numbers	–
Peng and Smarandache [25]	Multiple criteria decision making	Single-valued neutrosophic number	Mobile cloud computing industry evaluation
Saha et al. [26]	Multicriteria group decision-making	Dual probabilistic linguistic	Biomass feedstock selection
Sarkar and Biswas [32]	Multiple criteria decision making	Dual hesitant q-rung orthopair fuzzy	Numeric example
Tanrıverdi et al. [33]	Best–worst method	Triangular fuzzy numbers	Airport selection for air cargo carriers
Wei et al. [23]	Multiple attribute decision making	2-tuple linguistic neutrosophic information	Green supply chain management
Yahya et al. [34]	TODIM method	Fuzzy Credibility information	Analysis of medical diagnosis
Yang et al. [27]	Multiple criteria decision making	Q-rung orthopair fuzzy numbers	New campuse selection
Yaran Ögel et al. [35]	Best–worst method	Triangular fuzzy numbers	Prioritizing of the drivers of retail food waste

1. What are the EV users' perspectives at public charging stations?
2. What is the order of importance of EV users' perspectives at public charging stations?
3. What is the optimal EVSE configuration at public charging points to meet EV user considerations?
4. Do EV users' behaviors differ from the public EVSE configuration?

To investigate the above-mentioned research questions, this study first identifies and ranks the order of importance of EV users' qualitative and quantitative considerations from technical, economic, and social aspects based on the interview with EV users at public charging stations. Second, a new methodology is developed to determine the best performing public EVSE configuration that meets the needs of the EV user. The proposed methodology is based on joint co-simulation models: an EVSE cost optimization model integrated with a public charging behavior model and an improved MCDM model. The proposed MCDM model utilizes nonlinear Bonferroni functions, which are extended using Dombi norms. It has stabilization parameters that enable flexible decision-making and objective result analysis. Moreover, it has an original algorithm for the standardization of the elements of the criteria-alternatives matrix that enables the preservation of the disposition of natural and normalized attribute values. The standardization algorithm also eliminates the displacement of the area of normalized values for the cost and benefit attribution criteria. Lastly, the proposed model has an original aggregation mechanism for the fusion of RDB functions that makes the aggregation process more flexible. Overall, the main salient advantages of the proposed MCDM model can be summarized as follows:

- It transforms inaccuracies in EV user estimates using rough numbers. Unlike the conventional algorithm for generating rough numbers, the proposed algorithm has a flexible rough boundary interval that contributes to objective and rational reasoning in a dynamic environment.
- It uses the reverse sorting mechanism to standardize information, enabling the preservation of the disposition of multidimensional data and the absence of displacement in the areas of normalized values.
- An original aggregation mechanism for the fusion of RDB functions is presented.
- It enables flexible decision-making and consideration of mutual connections between attributes. This feature enables the simulation of various levels of risk via scenarios, as well as adequate verification of the robustness of the results.

The remainder of the paper is structured as follows: Section 2 presents the proposed methodology, including public EVSE alternatives, and EV users' preferences as decision-making criteria. In Section 3, an optimal public EVSE cost model is developed. Section 4 develops the rough Dombi Bonferroni based MCDM model. Section 5 presents experimental results with sensitivity and comparative analyses. Section 6 provides the concluding remarks.

2. Methodology

The proposed methodology combines an optimization public charging station model with a new MCDM model as shown in Fig. 1. In order to determine the best-performing EVSE type, this study first specifies quantitative and qualitative criteria that consider various EV user perspectives at the public charging station. While the proposed optimization model can yield optimal values for the quantitative criteria that are directly fed into the decision-making process, the qualitative criteria are then evaluated by EV users using a 9-point linguistic scale. Finally, the RDB MCDM is applied to determine the weights for the qualitative criteria and to evaluate the public charging station alternatives based on the weighted qualitative and deterministic quantitative criteria.

2.1. Description of public charging station alternatives

As public charging station alternatives, this study considers five EVSE configurations that are currently available in publicly accessible areas. The first and second alternatives, A_1 and A_2 are AC Level-2 or Mode-3 EVSEs. While A_1 is a single-phase EVSE (L2-1P) offering a medium-speed charging up to 7.36 kW (230 V-32A), A_2 is a three-phase EVSE (L2-3P) that allows fast charging at a rate of 22 kW (400 V-32A) [18]. The third alternative, A_3 is the dual-port option of the three-phase EVSE which allows two EVs to charge simultaneously by sharing the supply across the ports. The last two alternatives are DCFC EVSEs that provide rapid charging. A_4 is single-port DCFC at the charging rate of 50 kW while A_5 is the dual-port option of the DCFC. In order to deliver charging electricity to an EV, the Level-2 EVSEs requires standardized AC connectors called Type 1, Type 2, and Type 3 [36] while DCFC utilizes either Combo-2 [37], CHAdeMO [38], or GB/T connectors [39].

2.2. Description of decision-making criteria

Based on EV users' considerations at public charging stations, this study specifies 13 evaluation criteria that entail technical, economic, and social aspects of public charging stations, and are attributed as either benefits or costs. As reported in Table 2, it comprises five quantitative techno-economic criteria whose values are calculated through the developed optimal public charging station model given in Section 3. In addition to the quantitative parameters, 8 qualitative criteria are included to address technical and social considerations of public charging that affect the EV user's convenience. The degree of importance of the qualitative criteria is evaluated individually by the EV users who use

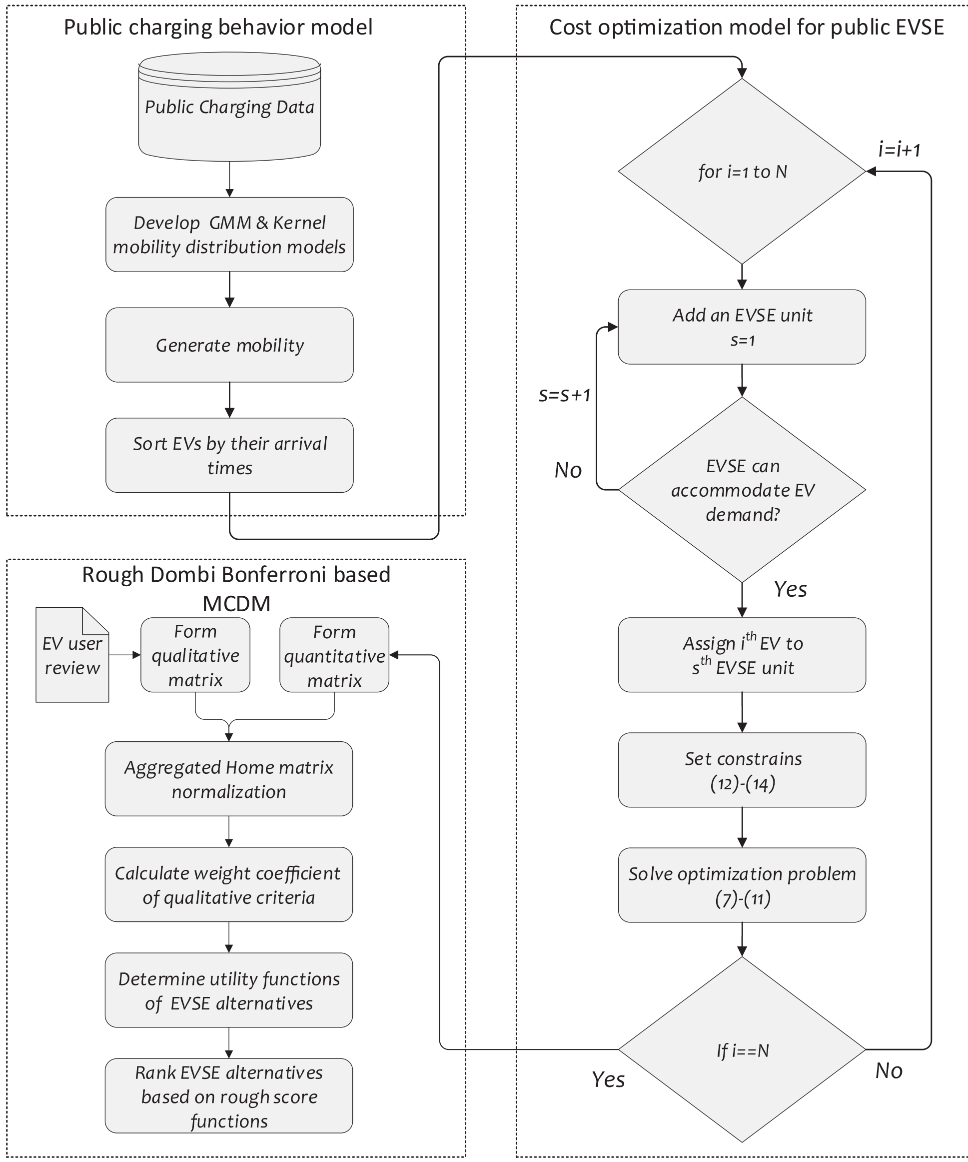

Fig. 1. Flow Chart of the proposed Dombi Bonferroni based MCDM.

Table 2
The evaluation criteria.

Evaluation criteria		Unit	Type	Attribute
C1	Electrical peak power	kW	Quantitative	Cost
C2	Unit cost of charging	Cents/kWh	Quantitative	Cost
C3	Required charging time	min	Quantitative	Cost
C4	Number of EVSE units	unit	Quantitative	Benefit
C5	EVSE Hosting capacity	%	Quantitative	Benefit
C6	EVSE reliability	–	Qualitative	Benefit
C7	Technological and market maturity	–	Qualitative	Benefit
C8	Connector & ICT interoperability	–	Qualitative	Benefit
C9	V2G capability	–	Qualitative	Benefit
C10	Visibility and Aesthetic	–	Qualitative	Benefit
C11	EVSE installation requirement	–	Qualitative	Cost
C12	Impact on EVs battery life	–	Qualitative	Cost
C13	EVSE space requirement	–	Qualitative	Cost

public charging stations. The EV driving experience of the users who participated in the study ranged from 1 year to 5 years.

Electrical peak power is the key technical parameter since EV charging loads can make it fluctuate that increases power systems operational cost and transmission level operation [40]. Therefore, it is included in the optimal charging station model which is set not to exceed a peak power limit. Herein, C_1 refers to the peak of total charging power within a public charging station which includes the required number of EVSEs to serve EV charging needs. As it is usually measured in 15-min, the peak power is the averaged power of 15 min intervals. In terms of the peak power, the optimal behavior of the public charging station alternatives is reported in Table 3. It is obtained that DCFC EVSEs (A_4 and A_5) achieve lower peak power as compared to AC EVSE types in which A_2 causes the highest peak power. This is mainly due to the more effective use of low-cost energy charge time intervals in the utility's provided tariff. The second criterion, C_2 is the unit cost of charging which is the rate of the total cost to total charging energy served within a public charging station. As detailed in

Table 3
Optimal values of quantitative criteria from the model run (Results are averaged among 100 random mobility trials).

Criterion #	A1	A2	A3	A4	A5
C1	154.207	158.204	155.659	151.034	151.322
C2	25.965	28.005	26.495	29.460	29.285
C3	99.463	78.668	87.647	13.112	25.720
C4	8.790	14.120	7.735	2.600	2.350
C5	0.437	0.190	0.347	0.480	0.516

Section 3, the unit cost incorporates the daily levelized EVSE cost and the utility's cost for being able to meet the peak power into the charging cost. The optimal unit cost behavior of the public charging station alternatives is shown in Fig. 2. L2-1P EVSE (A_1) achieves the lowest unit cost followed by dual-port L2-3P EVSE while DCFC EVSEs A_4 and A_5 are the least cost-effective. The primary cost factor is found to be EVSE cost which includes hardware, installation, and maintenance cost. While DCFC EVSEs achieve a lower charging cost and peak power, their EVSE cost is considerably higher as compared to AC EVSE alternatives. The required charging time, C_3 is one of the main concerns for EV users. In this respect, DCFC EVSEs outperforms due to their higher charging capacities. As the optimal values are given in Table 3, the average required charging time per EV with A_4 and A_5 is reduced by 6 and 4-fold, respectively as compared to AC EVSE alternatives. The number of EVSE units is considered as another benefit criterion, C_4 since higher number of units increases availability. In order to charge 100 EVs, the optimal number of EVSE units for the public charging station alternatives considered is calculated as in Table 3. It should be noted that the number of EVSE units is the average value of 100 runs, which results in decimal numbers. The heuristic charging algorithm to solve the optimal model imposes that EV is plugged off whenever its charging process is completed and the subsequent EV is plugged in. As this may decrease convenience for some EV users due to the need to be unplugged quickly, the AC EVSE alternatives outperform from this regard. The last quantitative criterion, C_5 is hosting capacity which is a measure of efficient use of EVSE. It is calculated by

$$\mathrm{HC} = \frac{\sum_{i}^{N} E_{served}(i)}{S_j \cdot \int_{min(tplug-in(1:N))}^{max(tplug-off(1:N))} (P_j^{rated} \cdot \eta_j)\, dt}, \tag{1}$$

where $E_{served,i}$, $t_{plug-in,i}$ and $t_{plug-off,i}$ are the charging energy served, the plug-in and plug off of ith EV, respectively. S_j is the number of EVSE units, P_i^{rated} is the on-board charger power rating of ith EV. η_J are the efficiency of the EVSE unit. The optimal C_5 values are found to be as in Table 3. DCFC EVSEs A_4 and A_5 displays superior hosting capacity performance as compared to AC alternatives. In this regard, A_2 has the lowest hosting capacity of 0.19 due to the inefficient use of their charging capacity of 22 kW by the onboard charging rates of the EVs considered. This is because EV onboard charger rates limit the actual charging capacity of AC EVSEs, whereas the DCFCs have direct access to EV's battery and can charge at their actual charging power rate.

The qualitative criteria are specified to address various EVSE features and requirements which affect the usability and accessibility from the EV user perspective. EVSE reliability at public charging stations is seen critical to EV adoption. C_6 refers to the frequency of failure occurrences and maintenance. EVSEs can be down due to either software or hardware issues. In [41], public AC L2 and DCFC EVSE downtimes were observed 18% and 13% per year, respectively. Technological and market maturity, C_7 is another consideration for EVSE adoption in such early stages of EVSE development. Charging with public EVSEs requires EVs to compatible with their available connectors. While AC L2 EVSEs utilizes standardized SAE J1772 connectors which is supported by most EV manufacturers, a single standard connector for DCFCs compatible

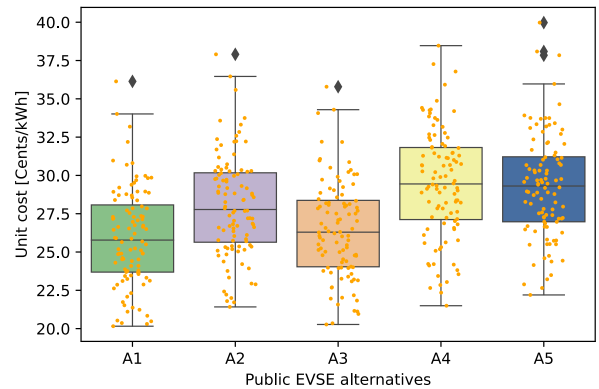

Fig. 2. Distributions of optimal unit cost values for 100 random mobility trials with respect to public EVSE alternatives.

with all EVs is not available. C_8 is therefore an important criterion for public EVSE type selection. As the vehicle-to-grid (V2G) technology enables EVs to use the stored energy in their batteries for other services such as peak shaving, frequency regulation, etc. [40], V2G capability of EVSEs, C_9 is considered as one of the decision-making criteria. In this respect, the V2G through AC EVSEs depends on the onboard charger capability of EVs while DCFC EVSE alternatives make it possible. EVSE installation requirement, C_{11}, refers to whether EVSE requires extensive installation work in terms of cost, time, electrical network upgrade etc. Furthermore, public sites can mostly be limited to installing a higher number of EVSEs. Therefore, EVSE space requirement, C_{13} is considered as another cost criterion in the decision-making. In these regard, DCFC EVSEs require more electrical upgrades and are subject to more site factors including visibility and aesthetics that increase the installation cost and time significantly as compared to AC EVSE alternatives [18]. The durability and health of EV batteries are of primary interest to EV users. The criterion, C_{12} is selected to consider how the charging rate affects the durability and safety of EV's battery. It is demonstrated in [42] that higher charging rates with DCFCs significantly affects the durability and thermal safety of lithium batteries.

3. An optimization model for public charging station

3.1. Public charging behavior

The optimization model requires EVs' charging behaviors at public charging stations. The behavior is characterized by three elements, i.e., charge start and end times, and charging energy need. In order to model realistic public charging behavior, this study utilizes real EV charging data from public charging stations [43]. The data set includes 7891 charging events at several public charging stations in Netherlands in 2019. It provides the charge start, end, total charging energy delivered, and maximum power supplied. The data set does not include the types of EVs served. Based on EV market availability in Netherlands for 2019, five most sold EV models are assumed for the public charging station events and assigned to the recorded charging events by considering total charging energy and the vehicles' battery capacities. The usable battery capacity and charging rate of the EV models considered are as follows: *(i)* 95 kWh, 16.5 kW, *(ii)* 84.7 kWh, 7.4 kW, *(iii)* 28 kWh, 3.3 kW, *(iv)* 28 kWh, 6.6 kW, *(v)* 41 kWh, 22 kW.

3.1.1. Charge start time

EV users' charging behaviors at public charging stations are usually random and their distributions cannot be fitted to normal distribution. Various probability density functions (pdf) such as Kernel Density Estimation (KDE), Gaussian Mixture Models (GMM), and Weibull distributions have been used to model EV charging behaviors [44–46].

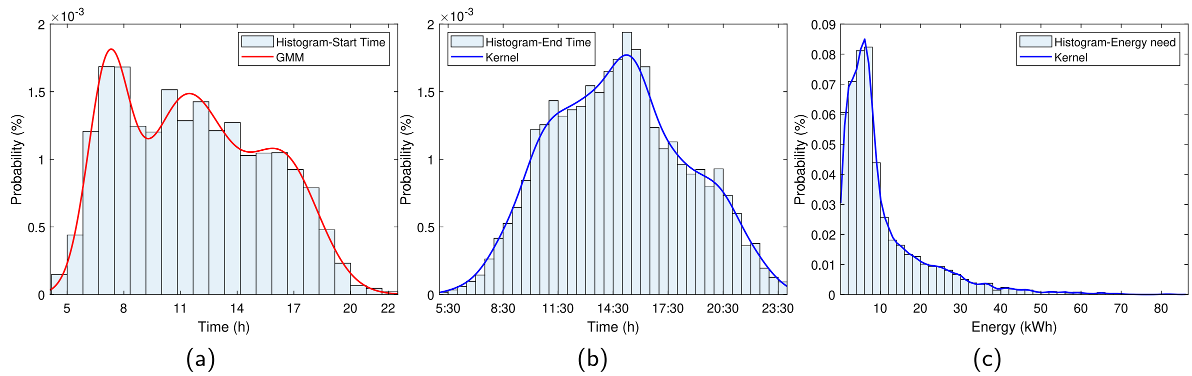

Fig. 3. Distribution of EVs' charging behaviors at public charging stations: (a) charge start time, (b) charge end time, (c) charging energy need.

The pdf alternatives may demonstrate different performances in each behavior and the best fit can be checked with goodness-of-fit. The plug-in or charge start of the events are modeled using Matlab Statistics and Machine Learning Toolbox™ [47] with GMM as the best fit. GMM is a parametric estimator that includes the combinations of several weighted normal distributions (2). GMM requires to define the number of normal distribution components (3). Each are weighted, ω, for best fit and sum of the weights is unity (4), [48]. The number of components is decided as three by the min value of Bayesian Information Criterion (BIC) for a wide range of number of components.

$$f(x) = \sum_{i=1}^{z} \omega_i f_{ND(\mu,\sigma^2)}(x), \tag{2}$$

$$f_{ND(\mu,\sigma^2)}(x) = \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-\frac{(x-\mu_i)^2}{2\sigma_i^2}}. \tag{3}$$

$$\sum_{i=1}^{M} \omega_i = 1, \tag{4}$$

3.1.2. Charge end time and charging energy need

For the charge end time and energy need modeling of the data set, Kernel Density Estimator (KDE) demonstrated better performance in terms of goodness-of-fit. KDE is a non-parametric estimator that provides a kernel function and bandwidth of a random variable and formulated for any real values of x as in (5) where n is the sample size, $K(\cdot)$ is the kernel smoothing function, and h is the bandwidth [48]. Gaussian (normal) kernel given in (6) is commonly used for Kernel estimation [49]. The kernel bandwidth, h, needs to be optimized for the smoothness of the estimation. Matlab Statistics and Machine Learning Toolbox™ [47] is used for kernel density estimation. The distributions of the three behaviors with their fits are demonstrated in Fig. 3.

$$f(x) = \frac{1}{kh} \sum_{i=1}^{k} K\left(\frac{x - x_i}{h}\right), \tag{5}$$

$$K(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}. \tag{6}$$

3.2. The cost optimization model for public charging station

For public EVSE, the cost optimization model is adapted from [50]. The objective is set to minimize the daily levelized unit cost of charging, C_{unit}, as a linear programming in (7). It is defined as the rate of the total cost to total charging energy served, E_{served}(8). Herein, total cost is considered as the sum of daily charging energy cost, C_{op}, demand charge, C_{dc}, and daily levelized EVSE infrastructure cost, C_{LIC}, which includes EVSE unit hardware (C_{EVSE}), installation, and maintenance (C_{ins}) costs. The cost elements are defined in (9) through (11). The demand charge is considered to reflect the contribution of EV charging loads to power demand. It is calculated as the product of peak of average charging load in 15 minute resolution and a demand charge rate, C_{drate} as in (10). The electricity pricing vector, $F = \{f(1)\dots f(T)\}$, and demand charge rate C_{drate}, considered are offered by a utility company as a general demand time-of-use (ToU) tariff with three different rates [51]. In calculating daily levelized EVSE infrastructure cost that considers time value of money, a discount rate of 5% is used for the annuity factor, AF as in (11) [52]. EVSE unit hardware (C_{EVSE}), installation, and maintenance (C_{ins}) costs are taken from [53].

$$\min_{\substack{P_{ch,1}\cdots P_{ch,n} \\ S_j}} C_{unit}, \tag{7}$$

with,

$$C_{unit} = \frac{C_{op} + C_{dc} + C_{LIC}}{\sum_{i=1}^{N} E_{served,i}}, \tag{8}$$

$$C_{op} = \sum_{s_j=1}^{s_j} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(F(t) \times (P_{ch,i,s_j}(t) \cdot \frac{\Delta t}{60}) \right), \tag{9}$$

$$C_{dc} = C_{drate} \cdot (max(\sum_{k=1}^{96} \sum_{t=1}^{15} mean(\sum_{1}^{s_j,n} P_{ch,i,s_j}((k-1) \cdot 15 + t)))), \tag{10}$$

$$C_{LIC} = s_j \cdot AF \cdot \left(C_{EVSE} + C_{ins}\right). \tag{11}$$

The objective function is subject to constraints given in (12) through (14). The required charge energy of an EV, $E_{required,i}$, is satisfied in (12) with the optimized charging rates $P_{ch,i} = \{Pch,i(1)\dots Pch,i(T)\}$. (13) imposes a maximum charging rate of either onboard charger rate P_i^{rated} of ith EV with an efficiency of η_i or EVSE charging rate, P_J^{rated} with an efficiency of η_J. The total charging power is limited to 500 kW, which is the demand limit, P_{lim} in (14) based on the tariff requirements.

$$\sum_{t=1}^{T} P_{ch,i}(t) \cdot \eta_i \cdot \frac{\Delta t}{60} = E_{required,i}, \tag{12}$$

$$\begin{cases} 0 \le P_{ch,i}(t) \le \min\left(\eta_i P_i^{rated}, \eta_J P_J^{rated}\right), \forall J \in \{1,2,3\} \\ 0 \le P_{ch,i}(t) \le \eta_J \cdot P_J^{rated}, \forall J \in \{4,5\}, \end{cases} \tag{13}$$

$$\sum_{t=1}^{T} \sum_{s_j=1}^{s_j} \sum_{i=1}^{N} P_{ch,i,s_j}(t) \le P_{lim}. \tag{14}$$

Based on EVs' plug-in times, a heuristic uninterrupted charging algorithm is employed for scheduling an EV set of $N = \{1,2,\dots n\}$ for the public EVSE set of $S = \{1,2,\dots s\}$. Fig. 1 presents the algorithm as part of the proposed model flow.

4. Rough Dombi Bonferroni multi-criteria decision-making framework

This section presents the preliminary settings of the proposed RDB methodology. Suppose that in a multi-criteria model, there is a set of m alternatives (A_i) and n criteria (C_j) for evaluation. Assume that e EV users $\wp = \{\wp_1, \wp_2, \ldots, \wp_e\}$ participate in the research. Then we can define an algorithm for applying the RDB methodology as follows:

Step 1. Transformation of qualitative home matrix information into rough values. Suppose that in the home matrix $\aleph = [\ell_{ij}]_{mxn}$, there is a set of U qualitative criteria whose values are defined using EV user estimates. Assume that Y is an arbitrary criterion from the set U, and R is a set of e classes ($\ell_{ij}^1; \ell_{ij}^2; \ldots; \ell_{ij}^e$), which includes all qualitative criteria from the U. If the classes are ordered as $\ell_{ij}^1 < \ell_{ij}^2 < \cdots < \ell_{ij}^e$, then $\forall Y \in U$, $\ell_{ij}^q \in R$, $(1 \le q \le e)$, the lower approximation $\underline{Apr}(\ell_{ij}^q)$ and upper approximation $\overline{Apr}(\ell_{ij}^q)$ groups of qualitative criteria ℓ_{ij}^q can be expressed as follows:

$$\underline{Apr}(\ell_{ij}^q) = \cup_{1\le q\le e}\left\{Y \in U / R(Y) \le \ell_{ij}^q\right\},$$
$$\overline{Apr}(\ell_{ij}^q) = \cup_{1\le q\le e}\left\{Y \in U / R(Y) \ge \ell_{ij}^q\right\}, \tag{15}$$

where ℓ_{ij}^q can be represented as a rough number $\bar{\bar{\ell}}_{ij}^q$, which is determined based on the corresponding lower and upper limit ($\underline{\ell}_{ij}^q$ and $\overline{\ell}_{ij}^q$) by (19) and (20). As a result, we can define a rough number $\bar{\bar{\ell}}_{ij}^q = [\underline{\ell}_{ij}^q, \overline{\ell}_{ij}^q](1 \le q \le e)$. By fusing rough values of $\bar{\bar{\ell}}_{ij}^q$, herein, we obtain an aggregated home matrix $\bar{\bar{\aleph}} = [\bar{\bar{\ell}}_{ij}]_{mxn}$.

Step 2. Home matrix standardization. Since different units of measurement represent the elements of the home matrix, it is necessary to unify the matrix's $\bar{\bar{\aleph}} = [\bar{\bar{\ell}}_{ij}]_{mxn}$ information. The elements $[\bar{\bar{\ell}}_{ij}]$ are standardized to present all the same interval range. By applying (16), we obtain a standardized matrix $\aleph^{\aleph} = [\bar{\bar{\eta}}_{ij}]_{mxn}$.

$$\bar{\bar{\eta}} = \begin{cases} \bar{\bar{\eta}} = \left[\dfrac{\underline{\ell}_{ij}}{\sum_{i=1}^m \underline{\ell}_{ij}}, \dfrac{\overline{\ell}_{ij}}{\sum_{i=1}^m \overline{\ell}_{ij}}\right] \quad \text{if } j \in Benefit \\ \bar{\bar{\eta}} = \begin{bmatrix} -\dfrac{\underline{\ell}_{ij}}{\sum_{i=1}^m \underline{\ell}_{ij}} + \max\left(\dfrac{\underline{\ell}_{ij}}{\sum_{i=1}^m \underline{\ell}_{ij}}\right) + \min\left(\dfrac{\underline{\ell}_{ij}}{\sum_{i=1}^m \underline{\ell}_{ij}}\right) \\ -\dfrac{\overline{\ell}_{ij}}{\sum_{i=1}^m \overline{\ell}_{ij}} + \max\left(\dfrac{\overline{\ell}_{ij}}{\sum_{i=1}^m \overline{\ell}_{ij}}\right) + \min\left(\dfrac{\overline{\ell}_{ij}}{\sum_{i=1}^m \overline{\ell}_{ij}}\right) \end{bmatrix} \\ \text{if } j \in Cost \end{cases} \tag{16}$$

where $\bar{\bar{\ell}}_{ij}$ represents elements of the home matrix $\aleph$.

Step 3. Calculation of criterion weight coefficients. Using a predefined scale, EV users $\wp = \{\wp_1, \wp_2, \ldots, \wp_e\}$ evaluate the criteria.

Step 3.1. Based on EV user evaluations $\partial_j^k (1 \le k \le e; j = 1, 2, \ldots, n)$, the comparative significance of the criteria was defined. We obtain aggregate values of $\partial_j (j = 1, 2, \ldots, n)$ by averaging the users' estimates, on the basis of which the vector of comparative values of the criteria is defined (17).

$$\mathbb{C} = (\mathbb{C}_1, \mathbb{C}_2, \ldots, \mathbb{C}_n), \tag{17}$$

where $\mathbb{C}_j = \max_{1\le j\le n} = (\partial_j)/\partial_j$. The rank of the criterion is defined by the value of $\mathbb{C}_j$, provided that a higher value $\mathbb{C}_j$ implies a greater significance of the criterion.

Step 3.2. The final values of the weighting coefficients of the criteria are calculated using the model (18). The final values of the weighting coefficients should satisfy the condition of mathematical transitivity of information, which is defined by the constraints of the model (18).

min ψ *s.t.*

$$\begin{cases} \left|\dfrac{\zeta_{j(b)}}{\zeta_{j(b+1)}} - \mathbb{C}_{b+1}\right| \le \psi, \quad \forall_j \\ \left|\dfrac{\zeta_{j(b)}}{\zeta_{j(b+2)}} - \mathbb{C}_{b+1} \otimes C_{b+2}\right| \le \psi, \quad \forall_j, \\ \sum_{j=1}^n \zeta_j = 1, \zeta_j \ge 0, \quad \forall_j \end{cases} \tag{18}$$

where b represents the rank of the criterion.

Step 4. Determining utility functions of alternatives. From the appendix expressions (A.1) to (A.6), we can derive expressions for calculating the sequential scores of alternatives. Based on the Bonferroni weighted function and Definitions A.1 and A.2, and *A3*, we can derive the RDB rough weighted averaging function, $(\bar{\bar{\mathbb{R}}}^{(1)\chi_1,\chi_2,\ell})$ and the RDB rough weighted geometric function $(\bar{\bar{\mathbb{R}}}^{(2)\chi_1,\chi_2,\ell})$ by (22) and (23). Herein, ζ_j represents the weighting coefficients of the criteria defined in the previous step, while $f(\underline{\eta}_i) = \underline{\eta}_i / \sum_{\chi=1}^n \underline{\eta}_i^{(\chi)}$ and $f(\overline{\eta}_i) = \overline{\eta}_i / \sum_{\chi=1}^n \overline{\eta}_i^{(\chi)}$ (See Box I).

Step 5. Determining rough score functions (Ψ_i), (21).

$$\Psi_i = \frac{\bar{\bar{\mathbb{R}}}^{(1)\chi_1,\chi_2,\ell} + \bar{\bar{\mathbb{R}}}^{(2)\chi_1,\chi_2,\ell}}{1 + \left\{\varpi\left(\frac{1-\bar{\bar{\mathbb{R}}}^{(1)\chi_1,\chi_2,\ell}}{\bar{\bar{\mathbb{R}}}^{(1)\chi_1,\chi_2,\ell}}\right)^\delta + (1-\varpi)\left(\frac{1-\bar{\bar{\mathbb{R}}}^{(2)\chi_1,\chi_2,\ell}}{\bar{\bar{\mathbb{R}}}^{(2)\chi_1,\chi_2,\ell}}\right)^\delta\right\}} \tag{21}$$

where $\delta, \varpi \ge 0$.

The coefficient ϖ has values from the interval $\varpi \in [0, 1]$. A value of $\varpi = 0.5$ is applied when calculating the initial values, which allows the RDB function $(\bar{\bar{\mathbb{R}}}^{(1)\chi_1,\chi_2,\ell}$ and $\bar{\bar{\mathbb{R}}}^{(2)\chi_1,\chi_2,\ell})$ to have an equal effect on the initial results. Alternatives are ranked based on the value of Ψ_i (See Box II).

5. Experimental results

A case study involving the evaluation of five public EVSE alternatives was used to demonstrate the application of the proposed multi-criteria methodology. The criteria were divided into two categories: quantitative and qualitative. The values of qualitative criteria are defined based on the assessments of EV users, whereas the optimal values for quantitative criteria are calculated by running the optimization model. The EV users used a nine-point scale for evaluation: Extremely Low (EL) — 1, Medium Low (ML) — 2, Low (L) — 3, Medium (M) — 4, Medium High (MH) — 5, High (H) — 6, Very High (VH) — 7, Extremely High (EH) — 8, and Perfect (P) — 9.

Step 1. Formation of an aggregated home matrix. The study involved seven EV users who evaluated alternatives for the set of qualitative criteria (C_6–C_{13}) as given in Table 4.

Using (15)–(20), the group of qualitative criteria in Table 4 was transformed into rough numbers. Thus, we obtain the final aggregated home matrix $\bar{\bar{\aleph}} = [\bar{\bar{\ell}}_{ij}]_{5\times 13}$ as in Table 5.

Step 2. Following the formation of the aggregated home matrix, the matrix elements $\bar{\bar{\aleph}}$ were standardized using (16). As a result, Table 6 displays a standardized home matrix in which all elements belong to the interval $\bar{\bar{\ell}}_{ij} \in [0, 1]$.

Step 3. The criteria evaluation was performed using a two-point scale presented in *Step 1*. EV user comparisons of the criteria are given in Table 7.

Step 3.1. Based on EV users' comparisons in Table 6, a vector of comparative significance criteria was defined. The criteria in vector (17) are ranked from most significant to least significant.

Step 3.2. Based on the vector $\mathfrak{I}$, a model (18) is formed based on which the optimal weighting coefficients of the criteria are defined.

min ψ *s.t.*

$$\begin{cases} \left|\frac{\zeta_3}{\zeta_6} - 1.038\right| \le \psi, \left|\frac{\zeta_6}{\zeta_{12}} - 1.058\right| \le \psi, \left|\frac{\zeta_{12}}{\zeta_2} - 1.122\right| \le \psi, \left|\frac{\zeta_2}{\zeta_4} - 1.122\right| \le \psi; \\ \left|\frac{\zeta_4}{\zeta_5} - 1.122\right| \le \psi, \left|\frac{\zeta_5}{\zeta_8} - 1.122\right| \le \psi, \left|\frac{\zeta_8}{\zeta_7} - 1.196\right| \le \psi, \left|\frac{\zeta_7}{\zeta_1} - 1.150\right| \le \psi; \\ ; \ldots ; \\ \left|\frac{\zeta_8}{\zeta_1} - 1.495\right| \le \psi, \left|\frac{\zeta_7}{\zeta_{11}} - 1.677\right| \le \psi, \left|\frac{\zeta_1}{\zeta_{13}} - 1.845\right| \le \psi, \left|\frac{\zeta_{11}}{\zeta_{10}} - 1.990\right| \le \psi; \\ \left|\frac{\zeta_{13}}{\zeta_9} - 2.274\right| \le \psi; \\ \sum_{j=1}^{13} \zeta_j = 1, \zeta_j \ge 0, \quad \forall_j \end{cases}$$

$$\underline{\ell}^{q}_{ij} = \frac{\sum_{t=1}^{e} \ell^{q}_{ijt}}{1+\left\{\frac{1}{\beta_1+\beta_2}\sum_{\substack{x,y=1\\ x\neq y}}^{e} \frac{e(e-1)}{\frac{1}{\left(\beta_1\left(\left(1-f\left(\ell^{(x)}_{ij}\right)\right)/\left(f\left(\ell^{(x)}_{ij}\right)\right)\right)^{\alpha}+\beta_2\left(\left(1-f\left(\ell^{(y)}_{ij}\right)\right)/\left(f\left(\ell^{(y)}_{ij}\right)\right)\right)^{\alpha}\right)}}\right\}^{1/\alpha}} \,\middle|\, \ell^{(x)}_{ij}, \ell^{(y)}_{ij} \in \underline{Apr}\left(\ell^{q}_{ij}\right) \tag{19}$$

$$\overline{\ell}^{q}_{ij} = \frac{\sum_{t=1}^{e} \ell^{q}_{ijt}}{1+\left\{\frac{1}{\beta_1+\beta_2}\sum_{\substack{x,y=1\\ x\neq y}}^{e} \frac{e(e-1)}{\frac{1}{\left(\beta_1\left(\left(1-f\left(\ell^{(x)}_{ij}\right)\right)/\left(f\left(\ell^{(x)}_{ij}\right)\right)\right)^{\alpha}+\beta_2\left(\left(1-f\left(\ell^{(y)}_{ij}\right)\right)/\left(f\left(\ell^{(y)}_{ij}\right)\right)\right)^{\alpha}\right)}}\right\}^{1/\alpha}} \,\middle|\, \ell^{(x)}_{ij}, \ell^{(y)}_{ij} \in \overline{Apr}\left(\ell^{q}_{ij}\right) \tag{20}$$

Box I.

$$\bar{\bar{\mathbb{R}}}^{(1)\chi_1,\chi_2,\ell} = \left[\begin{array}{l} \left(\frac{\sum_{j=1}^{n} \underline{\eta}_{ij}}{1+\left\{1+\frac{1}{\zeta_i\zeta_j(\chi_1+\chi_2)}\sum_{\substack{i,j=1\\ i\neq j}}^{n}\frac{1-\zeta_i}{\frac{1}{\chi_1\left(\left(1-f\left(\underline{\eta}_i\right)\right)/\left(f\left(\underline{\eta}_i\right)\right)\right)^{\ell}+\chi_2\left(\left(1-f\left(\underline{\eta}_j\right)\right)/\left(f\left(\underline{\eta}_j\right)\right)\right)^{\ell}}}\right\}}\right)^{1/\ell}, \\ \left(\frac{\sum_{j=1}^{n} \overline{\eta}_{ij}}{1+\left\{1+\frac{1}{\zeta_i\zeta_j(\chi_1+\chi_2)}\sum_{\substack{i,j=1\\ i\neq j}}^{n}\frac{1-\zeta_i}{\frac{1}{\chi_1\left(\left(1-f\left(\overline{\eta}_i\right)\right)/\left(f\left(\overline{\eta}_i\right)\right)\right)^{\ell}+\chi_2\left(\left(1-f\left(\overline{\eta}_j\right)\right)/\left(f\left(\overline{\eta}_j\right)\right)\right)^{\ell}}}\right\}}\right)^{1/\ell}, \end{array}\right] \tag{22}$$

$$\bar{\bar{\mathbb{R}}}^{(2)\chi_1,\chi_2,\ell} = \left[\begin{array}{l} \left(\sum_{j=1}^{n} \underline{\eta}_{ij} - \frac{\sum_{j=1}^{n} \underline{\eta}_{ij}}{1+\left\{1+\frac{1}{\zeta_i\zeta_j(\chi_1+\chi_2)}\sum_{\substack{i,j=1\\ i\neq j}}^{n}\frac{1-\zeta_i}{\frac{1}{\chi_1\left(f\left(\underline{\eta}_i\right)/\left(1-f\left(\underline{\eta}_i\right)\right)\right)^{\ell}+\chi_2\left(f\left(\underline{\eta}_j\right)/\left(1-f\left(\underline{\eta}_j\right)\right)\right)^{\ell}}}\right\}}\right)^{1/\ell}, \\ \left(\sum_{j=1}^{n} \overline{\eta}_{ij} - \frac{\sum_{j=1}^{n} \overline{\eta}_{ij}}{1+\left\{1+\frac{1}{\zeta_i\zeta_j(\chi_1+\chi_2)}\sum_{\substack{i,j=1\\ i\neq j}}^{n}\frac{1-\zeta_i}{\frac{1}{\chi_1\left(f\left(\overline{\eta}_i\right)/\left(1-f\left(\overline{\eta}_i\right)\right)\right)^{\ell}+\chi_2\left(f\left(\overline{\eta}_j\right)/\left(1-f\left(\overline{\eta}_j\right)\right)\right)^{\ell}}}\right\}}\right)^{1/\ell}, \end{array}\right] \tag{23}$$

Box II.

Table 4
EV users' assessment of alternatives under a group of qualitative criteria.

Criteria	A1	A2	A3	A4	A5
C6	L; MH; H; EH; P; MH; EH	M; H; MH; EH; P; H; EH	ML; VH; MH; EH; P; EH; EH	EH; P; MH; P; VH; P; H	EH; P; MH; P; VH; P; H
C7	L; MH; MH; EH; P; MH; L	M; VH; H; H; P; H; H	ML; VH; MH; H; P; EH; VH	EH; P; MH; H; VH; P; H	EH; P; M; VH; VH; P; H
C8	L; H; H; EH; MH; MH; VH	M; VH; H; H; MH; H; EH	ML; EH; H; H; MH; EH; VH	EH; P; H; VH; M; P; MH	EH; P; H; VH; M; P; MH
C9	L; MH; H; MH; EL; MH; L	M; VH; M; MH; EL; H; H	ML; VH; M; M; EL; EH; H	EH; P; MH; H; P; P; P	EH; P; MH; H; P; P; EH
C10	L; H; H; VH; P; MH; EH	M; VH; MH; H; P; H; MH	ML; H; MH; H; P; EH; M	EH; P; MH; EH; MH; P; MH	EH; P; MH; EH; M; P; MH
C11	L; M; M; EH; EL; MH; P	M; VH; L; VH; ML; H; EH	ML; VH; M; EH; ML; EH; EH	EH; H; M; P; EH; P; P	EH; H; M; P; VH; P; EH
C12	L; VH; H; MH; EL; MH; L	M; VH; H; EH; ML; H; H	ML; EH; H; P; ML; EH; H	EH; H; H; P; P; P; P	EH; H; H; P; VH; P; EH
C13	L; VH; L; M; EL; MH; L	M; VH; M; H; ML; H; VH	ML; H; L; P; ML; EH; VH	EH; H; L; EH; P; P; EH	EH; H; M; P; VH; P; VH

Table 5
Home matrix.

Crit.	A1	A2	A3	A4	A5
C6	[3.59, 5.78]	[4.07, 5.9]	[3.41, 6.11]	[4.94, 6.59]	[4.94, 6.59]
C7	[3.04, 4.99]	[4.19, 5.43]	[3.17, 5.83]	[4.69, 6.26]	[4.44, 6.31]
C8	[3.48, 5.13]	[3.96, 5.22]	[3.15, 5.49]	[4.13, 6.22]	[4.13, 6.22]
C9	[1.95, 3.73]	[2.22, 4.43]	[1.78, 4.56]	[5.19, 6.74]	[5.09, 6.63]
C10	[3.60, 5.76]	[3.84, 5.37]	[2.84, 5.44]	[4.47, 6.09]	[4.15, 6.15]
C11	[1.92, 4.84]	[2.58, 5.06]	[2.51, 5.26]	[4.71, 6.61]	[4.50, 6.42]
C12	[1.93, 4.12]	[3.00, 5.11]	[2.67, 5.51]	[5.53, 6.72]	[5.22, 6.44]
C13	[1.78, 3.55]	[2.81, 4.72]	[2.24, 5.18]	[4.25, 6.43]	[4.44, 6.31]

Lingo 19.0 software was used to solve the nonlinear model, and a vector of weighting coefficients was obtained as follows: $\zeta_j = (0.0532, 01124, 0.1386, 0.1002, 0.0892, 0.1334, 0.0664, 0.0795, 0.0127, 0.0199, 0.0396, 0.1262, 0.0288)^T$.

Step 4. Using (22) and (23), the utility functions of the alternatives are defined as follows:

$$\begin{cases} \bar{\bar{\mathbb{R}}}^{(1)\chi_1=\chi_2=\ell=1} = [0.117, 0.159]; \bar{\bar{\mathbb{R}}}^{(2)\chi_1=\chi_2=\ell=1} = [0.119, 0.164]; \\ \bar{\bar{\mathbb{R}}}^{(1)\chi_1=\chi_2=\ell=1} = [0.119, 0.153]; \bar{\bar{\mathbb{R}}}^{(2)\chi_1=\chi_2=\ell=1} = [0.120, 0.154]; \\ \bar{\bar{\mathbb{R}}}^{(1)\chi_1=\chi_2=\ell=1} = [0.132, 0.177]; \bar{\bar{\mathbb{R}}}^{(2)\chi_1=\chi_2=\ell=1} = [0.134, 0.180]; \\ \bar{\bar{\mathbb{R}}}^{(1)\chi_1=\chi_2=\ell=1} = [0.204, 0.240]; \bar{\bar{\mathbb{R}}}^{(2)\chi_1=\chi_2=\ell=1} = [0.206, 0.242]; \\ \bar{\bar{\mathbb{R}}}^{(1)\chi_1=\chi_2=\ell=1} = [0.199, 0.237]; \bar{\bar{\mathbb{R}}}^{(2)\chi_1=\chi_2=\ell=1} = [0.201, 0.238]; \end{cases}$$

The value of the coefficient $\varpi = 0.5$ was used when calculating rough score functions for the alternatives. This enables the rough functions $\bar{\bar{\mathbb{R}}}^{(1)\chi_1,\chi_2,\ell}$ and $\bar{\bar{\mathbb{R}}}^{(2)\chi_1,\chi_2,\ell}$ to have the same influence on the definition of rough score function alternatives. Since the alternative should have the highest possible value ψ_i, the following rank was obtained: $A_4 > A_5 > A_3 > A_1 > A_2$.

In terms of EV users' ranking of criteria, the results in Table 7 show that the required charging time is found to have the highest

Table 6
Standardized home matrix.

Crit.	A1	A2	A3	A4	A5
C1	[0.201, 0.201]	[0.196, 0.196]	[0.199, 0.199]	[0.205, 0.205]	[0.205, 0.205]
C2	[0.187, 0.187]	[0.201, 0.201]	[0.190, 0.190]	[0.212, 0.212]	[0.210, 0.210]
C3	[0.043, 0.043]	[0.111, 0.111]	[0.082, 0.082]	[0.327, 0.327]	[0.285, 0.285]
C4	[0.216, 0.216]	[0.066, 0.066]	[0.245, 0.245]	[0.390, 0.390]	[0.397, 0.397]
C5	[0.222, 0.222]	[0.096, 0.096]	[0.176, 0.176]	[0.244, 0.244]	[0.262, 0.262]
C6	[0.116, 0.187]	[0.132, 0.19]	[0.110, 0.197]	[0.160, 0.213]	[0.160, 0.213]
C7	[0.105, 0.173]	[0.146, 0.188]	[0.110, 0.202]	[0.163, 0.217]	[0.154, 0.219]
C8	[0.134, 0.220]	[0.117, 0.217]	[0.146, 0.207]	[0.111, 0.181]	[0.111, 0.181]
C9	[0.075, 0.143]	[0.085, 0.170]	[0.068, 0.175]	[0.199, 0.258]	[0.195, 0.254]
C10	[0.129, 0.200]	[0.121, 0.214]	[0.155, 0.211]	[0.099, 0.188]	[0.110, 0.186]
C11	[0.068, 0.172]	[0.092, 0.180]	[0.089, 0.187]	[0.167, 0.234]	[0.160, 0.228]
C12	[0.069, 0.148]	[0.107, 0.183]	[0.096, 0.197]	[0.198, 0.241]	[0.187, 0.231]
C13	[0.169, 0.245]	[0.130, 0.201]	[0.152, 0.183]	[0.075, 0.136]	[0.068, 0.140]

Table 7
EV users' comparisons of criteria.

Crit.	E1	E2	E3	E4	E5	E6	E7	Mean
C1	7	3	5	7	7	6	9	6.29
C2	8	5	4	8	9	6	9	7
C3	7	9	5	8	9	9	8	7.86
C4	7	9	5	6	7	7	8	7
C5	8	7	6	7	8	6	7	7
C6	6	9	6	6	9	9	8	7.57
C7	5	7	5	6	8	9	6	6.57
C8	5	9	6	7	5	9	8	7
C9	7	5	5	5	1	7	5	5
C10	7	4	6	8	1	5	7	5.43
C11	8	4	4	7	5	8	5	5.86
C12	8	7	7	8	5	9	8	7.43
C13	8	5	4	6	4	7	6	5.71

importance degree, followed by EVSE reliability and the impact on the EV's battery life. EVSE hosting capacity, and connector & ICT interoperability are other main factors affecting the ranking, with V2G capability being the least important. The primary reason that DCFC EVSEs are superior alternatives is that they require significantly less charging time. Furthermore, they have been found to be more reliable as compared to AC EVSE counterparts. They also have a higher hosting capacity. While the unit cost and the number of EVSE units have been found to be more important, they have a minor impact on the ranking. The main reason that A_2 is the least favorable option is that it has significantly less hosting capacity due to inefficient charging capacity use. Moreover, the unit cost of A_3 is the highest among AC EVSE alternatives.

5.1. Checking the stability of the results

A sensitivity analysis was used to assess the robustness of the obtained ranking. The impact of five parameters on the final ranking was considered in the sensitivity analysis. The weighted rough function, $\bar{\bar{\mathbb{R}}}^{(1)\chi_1,\chi_2,\ell}$ and $\bar{\bar{\mathbb{R}}}^{(2)\chi_1,\chi_2,\ell}$ is calculated using three parameters. The initial solution was computed using the parameters $\chi_1 = \chi_2 = \ell = 1$. The following section simulates the change of the mentioned parameters in the interval $1 \le \chi_1, \chi_2 \le 100$. The change of rough score functions of the alternatives was monitored concurrently with the change of the stated parameters. The parameters $1 \le \chi_1, \chi_2 \le 100$ were changed in the first experiment, while the parameter ℓ was set to one. Fig. 4 shows the change of the rough score function of the alternatives. The behavior of the rough score function of the alternative A_1, as an example, is shown in Fig. 5.

In the second experiment, the parameters $1 \le \ell \le 100$ were changed while the parameters χ_1 and χ_2 were set to one. Fig. 6 shows the behavior of the rough score functions of the alternatives. Similarly, the behavior of the rough score function of A_2 in the second experiment is provided in Fig. 7. In both experiments, 100 scenarios were created. The first experiment in Fig. 4 confirmed the initial ranking for the parameters $1 \le \chi_1, \chi_2 \le 8$. Changes in the ranks of alternatives A_1 and A_2 are caused by parameter values in the range χ_1, $\chi_2 \le 100$. Despite significant changes in the parameters χ_1 and χ_2, the rank of

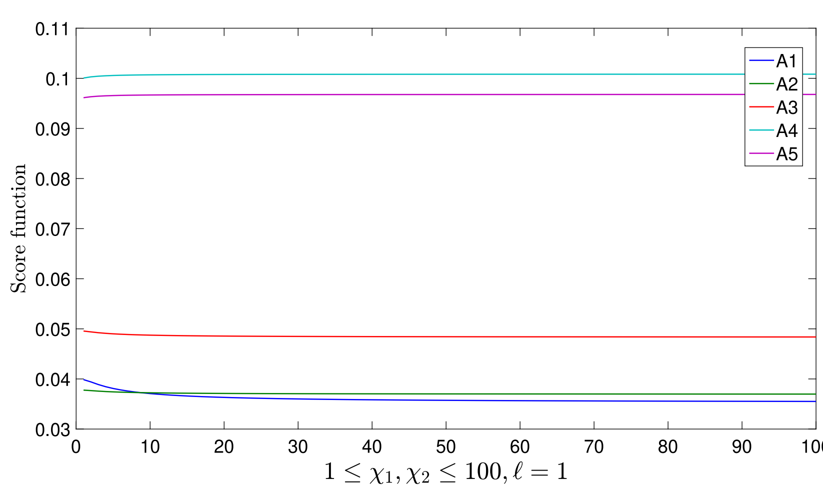

Fig. 4. Behavior of the rough score functions of alternatives for varying χ_1, χ_2.

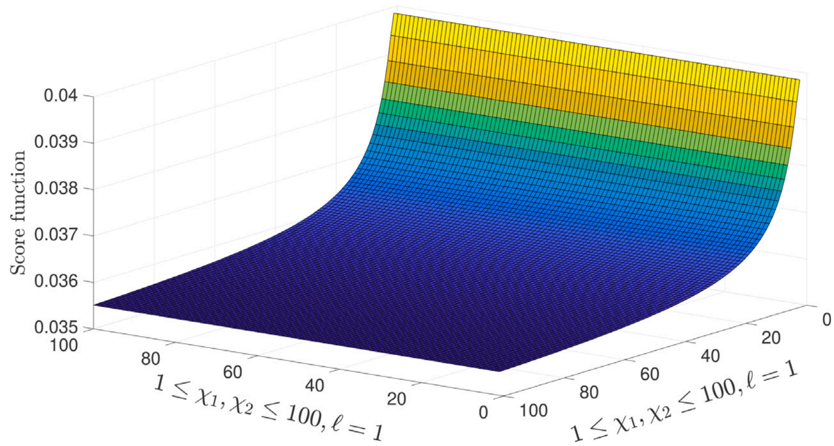

Fig. 5. Behavior of the rough score function of the alternative A_1.

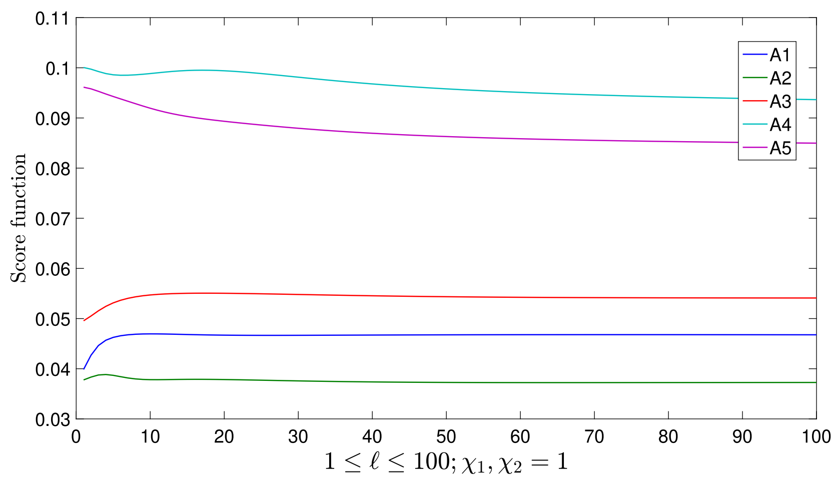

Fig. 6. Behavior of the rough score functions of alternatives for varying ℓ.

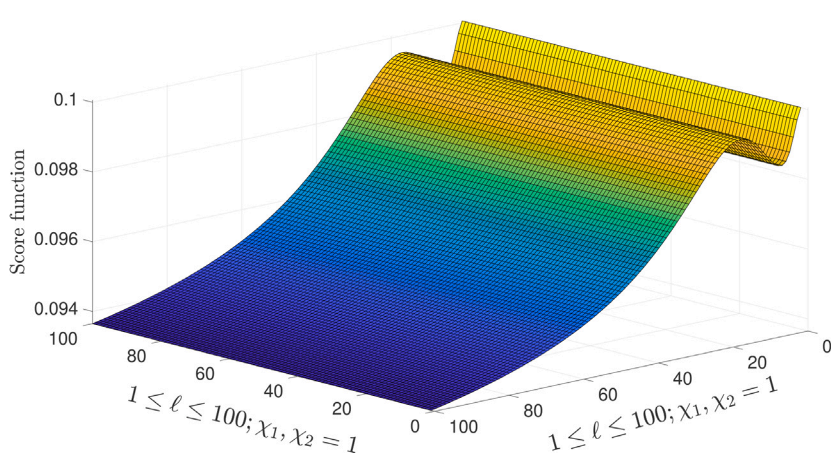

Fig. 7. Behavior of the rough score function of A_2 in the second experiment.

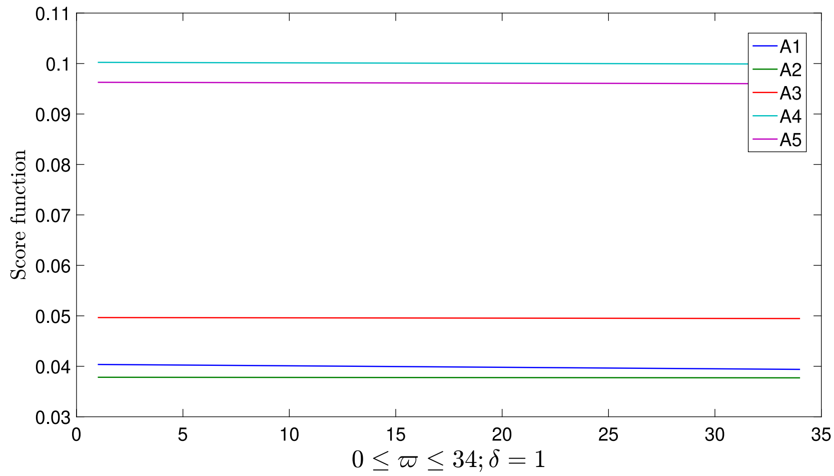

Fig. 8. Behavior of the rough score functions of alternatives for varying ϖ.

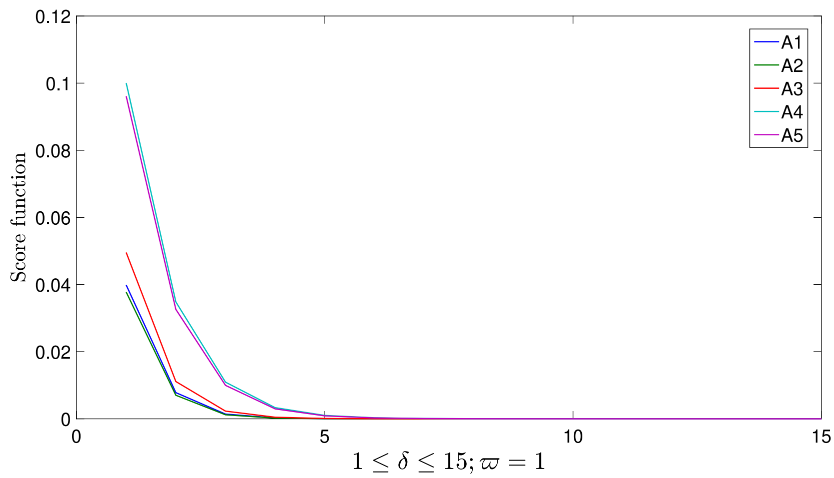

Fig. 9. The analysis of the influence of the parameter $1 \leq \delta \leq 15$.

the dominant alternatives, A_4 and A_5 remained constant. As shown in Fig. 6, there were no changes in the rankings of alternatives in the second experiment. The initial ranking, $(A_4 > A_5 > A_3 > A_1 > A_2)$ is validated by this experiment, indicating that alternative A_4 is the dominant solution.

The impact of the parameters ϖ and δ on the rough score functions of the alternatives was investigated in addition to the parameters χ_1, χ_2, and ℓ. To do so, the following two experiments were carried out as follows: In the first experiment, the value ϖ was first set to zero and increased by 0.03 in each subsequent scenario. As such, thirty-four scenarios were created. Fig. 8 shows the evolution of rough score functions of the alternatives in response to varying ϖ values. The results show that the increase in the ϖ parameter through thirty-four scenarios does not significantly affect the change in rough score functions. Because of the values of the RDB rough weighted averaging functions $\bar{\bar{\mathbb{R}}}^{(1)\chi_1,\chi_2,\ell}$ and $\bar{\bar{\mathbb{R}}}^{(2)\chi_1,\chi_2,\ell}$, the parameter ϖ is unlikely to affect the model's final results significantly.

In the second experiment, the parameter δ was changed in the interval $1 \leq \delta \leq 15$. As shown in Fig. 9, the results display that increasing the parameter δ has an effect on the decreasing rough score functions of the alternatives. Simultaneously, the gap between the alternatives is closing. To clearly see the difference between the alternatives, the value of the parameter δ from the interval $1 \leq \delta \leq 5$ can be suggested. The δ values chosen thus allow for the selection of dominant alternatives, which in turn leads to the making of a rational and objective decision. Despite a significant narrowing of the gap between the alternatives' score functions, the initial ranking was confirmed in all scenarios. The results as in Fig. 9 show that alternative A_4 has a clear advantage and is the best solution.

5.2. Comparative analysis

This section presents a comparison of the RDB methodology with multi-criteria techniques that have been developed for processing uncertainty in information. For comparison, four studies using different approaches for evaluating charging station locations were chosen: (i) Fermatean fuzzy Einstein aggregation operators-based MULTIMOORA [54] (ii) Type-2 fuzzy WASPAS and TOPSIS methodology [55]; (iii) Pythagorean fuzzy SWARA and CODAS methodology [56] and (iv) Fuzzy Entropy and VIKOR based methodology [57]. The selected methodologies have been tested under the same conditions and on the same data set as the RDB model. Minor changes were made to the data in the initial matrix to adapt the data to the methods used for the comparison. However, the modifications were formal and could not affect the deviation of the final results to any extent. Fig. 10 displays the comparison results of the MCDM approaches employed.

From Fig. 10, we can see that applying the discussed MCDM methods leads to similar ranking results. A complete correlation of results was obtained with the Fermatean fuzzy Einstein MULTIMOORA and fuzzy Entropy and VIKOR methods. Somewhat more significant deviations appeared with type-2 fuzzy WASPAS and TOPSIS methodologies. These deviations are the result of different approaches for dealing with

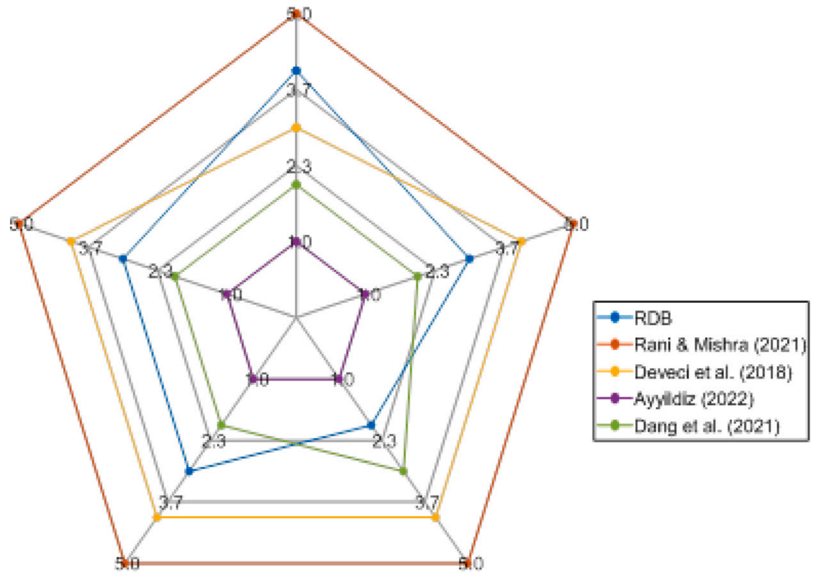

Fig. 10. Comparison of various MCDM methods in the alternative ranking.

uncertainty and imprecision in the information on which a decision is based. However, the dominance of the first-ranked alternative (A_4) and the second-ranked alternative (A_5) was confirmed for all methodologies considered, while alternative (A_2) represents the worst alternative in the considered set.

One of the basic advantages of the RDB methodology compared to other methods is the application of flexible non-linear Dombi Bonferroni functions for group information processing, while other applied methodologies use simple linear functions that, in certain situations, can lead to a violation of the stability of the obtained solution. Furthermore, since rough Dombi Bonferroni functions enable flexible decision-making due to decision makers' risk attitudes, the RDB methodology is more general and flexible than other methods.

The MCDM methods employed in the comparison analysis utilize fuzzy numbers with predefined fuzzy boundary sets to handle uncertainty. That is why, in the mentioned approaches, it is necessary to apply aggregation operators for the fusion of group information, which leads to the generalization of the information in the initial decision matrix. On the other hand, the adaptability of the RDB approach is reflected in the retention of the initial uncertainties in the decision matrix that arose as a consequence of expert subjectivity. Also, the adaptability of the RDB methodology is reflected in the possibility of adjusting the stabilization parameters of the non-linear Dombi Bonferroni functions. The decision maker simulates a different risk attitude by varying the stabilization parameters. We can conclude that the proposed multi-criteria approach is an adequate tool for solving real problems in a dynamic environment.

6. Conclusion

A new MCDM methodology has been presented for selecting the best performing EVSE option from EV users' multi-criteria perspectives at public charging stations. The proposed methodology applies nonlinear Bonferroni functions to weight qualitative criteria and incorporates an optimal public charging station model for evaluating quantitative criteria. The Bonferroni functions are extended using Dombi norms. The evaluations of EV users in the field were used to study all possible public charging station alternatives. In terms of EV user considerations, the required charging time is found to have the highest importance degree, followed by EVSE reliability, the impact on the EV's battery life, EVSE hosting capacity, and connector & ICT interoperability. V2G capability was found to be the least important. The best EVSE configuration was determined to be DCFC at 50 kW, while the least performing option was the AC L2 EVSE at 22 kW. The order of preference for the other options was found to be as follows: $DCFC\ MP > AC\ L2MP > AC\ L2{-}1P$. The validation of the model ranking results has been done by comparing them against those of four MCDM methods in the literature. Moreover, the robustness of the ranking order of public charging alternatives has been validated through various sensitivity analyses.

The RDB model has been shown to be a powerful tool for rational and objective decision-making. The RDB model, however, has some limitations. One of the limitations is the inability to eliminate the impact of extreme and unreasonable arguments in the home matrix. Therefore, additional research into implementing Power averaging (PA) functions in the proposed methodology is required. The application of PA functions could allow for the presentation of the interrelationships between the criteria, increasing the flexibility of the RDB model. Furthermore, further work will focus on improving the adaptability of the RDB model by incorporating Einstein and Hamacher norms.

CRediT authorship contribution statement

Muhammet Deveci: Conceptualization, Formal analysis, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Nuh Erdogan:** Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Software, Validation, Writing – original draft, Writing – review & editing. **Dragan Pamucar:** Formal analysis, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Sadik Kucuksari:** Conceptualization, Formal analysis, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Umit Cali:** Conceptualization, Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data is publicly accessible and we share the link in the references.

Appendix

A.1. Operational laws with Dombi norms

Definition A.1. Let $\mathbb{Q}_1$ and $\mathbb{Q}_2$ be two real numbers, then, the Dombi T-norm and T-conorm are defined as follows [58]:

$$\Delta = \frac{1}{1 + \left\{ \left((1-\mathbb{Q}_1)/\mathbb{Q}_1\right)^{\ell} + \left((1-\mathbb{Q}_2)/\mathbb{Q}_2\right)^{\ell} \right\}^{1/\ell}} \tag{A.1}$$

$$\Delta_c = \frac{1}{1 + \left\{ \left((1-\mathbb{Q}_1)/\mathbb{Q}_1\right)^{\ell} + \left((1-\mathbb{Q}_2)/\mathbb{Q}_2\right)^{\ell} \right\}^{1/\ell}} \tag{A.2}$$

where $\ell > 0$ and $\mathbb{Q}_1, \mathbb{Q}_2 \in [0,1]$.

According to the Dombi T-norm and T-conorm, we define the Dombi operations as given in Definition A.1.

Definition A.2. Suppose $\mathbb{Q}_1$ and $\mathbb{Q}_2$ are two real numbers, $\ell, \hbar > 0$ and $f(\mathbb{Q}_i) = \mathbb{Q}_1 / \sum_{i=1}^{n} \mathbb{Q}_i$, then we can define operational lows of real numbers based on the Dombi norms:

$$\mathbb{Q}_1 + \mathbb{Q}_2 = \left(\mathbb{Q}_1 + \mathbb{Q}_2\right) - \frac{\mathbb{Q}_1 + \mathbb{Q}_2}{1 + \left\{ \left(f(\mathbb{Q}_1) / \left(1 - f(\mathbb{Q}_1)\right) \right)^{\ell} + \left(f(\mathbb{Q}_2) / \left(1 - f(\mathbb{Q}_2)\right) \right)^{\ell} \right\}^{1/\ell}} \tag{A.3}$$

$$\mathbb{Q}_1 \times \mathbb{Q}_2 = \frac{\mathbb{Q}_1 + \mathbb{Q}_2}{1 + \left\{ \left(\left(1/(\mathbb{Q}_1)\right) / \left(f(\mathbb{Q}_1)\right) \right)^{\ell} + \left(\left(1 - f(\mathbb{Q}_2)\right) / f(\mathbb{Q}_2) \right)^{\ell} \right\}^{1/\ell}} \tag{A.4}$$

$$\hbar \times \mathbb{Q}_1 = \mathbb{Q}_1 - \frac{\mathbb{Q}_1}{1 + \left\{ \hbar \left(f(\mathbb{Q}_1) / \left(1 - f(\mathbb{Q}_1)\right) \right)^{\ell} \right\}^{1/\ell}} \tag{A.5}$$

$$\ell_1^{\hbar} = \frac{\mathbb{Q}_1}{1 + \left\{ \hbar \left(\left(1 - f(\mathbb{Q}_1)\right) / f(\mathbb{Q}_1) \right)^{\ell} \right\}^{1/\ell}} \tag{A.6}$$

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