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Sustainable E-scooter parking operation in urban areas using fuzzy Dombi based RAFSI model

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ABSTRACT

Over the last five years, e-scooters have gradually become commonplace in most urban areas. However, shortcomings in infrastructure provision, especially with parking, make it awkward to use these vehicles. This study presents a novel hybrid fuzzy multi-criteria decision-making model for determining optimal e-scooter parking locations by combining the Logarithmic Methodology of Additive Weights (LMAW) and the RAFSI (Ranking of Alternatives through Functional mapping of criterion sub-intervals into a Single Interval) methods. In the first stage, the fuzzy Aczel-Alsina function based LMAW approach is used to address the uncertainty of experts' opinions in the decision process and to calculate the weights of the twelve criteria. Afterward, fuzzy Dombi based RAFSI is applied to obtain the ranking of e-scooter parking locations. A case study is presented to propose a solution for the operation of e-scooter parking by taking into consideration three different alternatives based on four different aspects and twelve criteria. According to the findings, the third option, which is a hybrid operation with geo-fencing hubs in primary catchment areas of public transportation, is the most practical choice for a sustainable operation of e-scooter parking. This option also has the potential to be the most environmentally friendly.

1. Introduction

In response to increased congestion on roads and crowding on public transport in rapidly growing urban areas, the micro-mobility market has emerged in recent years and is only expected to grow. E-scooters are one type of micro-vehicle that can be found in various urban areas across the world. Demand for electric scooters has risen in tandem with the growth of urban areas and the accompanying increase in traffic and transportation challenges. Some of the possible explanations for this are related to changing patterns of travel to and from school, employment, or residences. The statistics back up the notion that this trend will continue. From 2018 to 2019, the number of trips taken on shared bikes, e-bikes, and scooters in the United States climbed by 60%, reaching 136 million (NACTO, 2019). In addition, by 2030, the estimated value of the global market for e-scooters will be $40.6 billion (Glenn et al., 2020).

Some of the benefits of e-scooters may help to explain their long-term sustainability. While the specifics of how e-scooters can help address these challenges vary per location, they undoubtedly do so overall. E-scooters' primary benefits are time savings, reduced vehicle access time, easier access to employment, environmental protection, urban infrastructure and safety (Smith & Schwieterman, 2018). The challenge is to ensure that policymakers engage with stakeholders, including sharing economy providers of e-scooters, in pro-social ways (Mi & Coffman, 2019).

Meanwhile, the decline in urban quality of life is mostly attributable to the increase in congestion, air pollution, and noise (Gössling, 2020). Municipalities and policymakers are urged to employ the use of electric scooters to address these issues. Nonetheless, e-scooters have many challenges, including first- and last-mile difficulties (Ernst & Young Limited, 2020), high voltage stress (Skorvaga, 2021), the dangerous behaviors of riders (Deveci et al., 2022), and inadequate parking. Company safety measures are not effective in preventing e-scooter collisions with cars and pedestrians, and neither are rules aimed at addressing the problems. Most of these issues and injuries can be

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avoided if governments enact more stringent laws, such as those that enhance road and parking lot conditions (Deveci et al., 2022).

However, amongst all these problems, the parking situation requires the most immediate attention. The chief challenges include users parking on private property, damaging property, e-scooters not being parked upright, and or parked in a fashion that prevents access to fire hydrants, bus stops, street furniture, or bike-sharing stations (James et al., 2019). In addition to transfer time delays, improper parking can discourage customers from using private micro-vehicles as an access mode to public transportation terminals (Oesgher et al., 2020). While a result, as precautions vary from location to location, incorrect parking, sidewalk obstruction, and clutter issues can be addressed by employing the clustering approach to calculate parking zones and identifying appropriate parking sites in high-demand regions (Zakhem & Smith-Colin, 2021).

The provision of workable solutions to the parking problem in the interest of making parking operations more environmentally friendly is the motivating force behind this research. Based on four aspects and twelve criteria, the study will make recommendations for three possible alternatives: free-floating operation, locking and charging specified docking station operation, and hybrid operation with geo-fencing hubs in main public transit catchment regions. The third alternative is parking in the primary catchment region for public transportation. This category includes any location that can be reached by public transit in fewer than five minutes.

This study proposes a new multi-criteria framework for determining the e-scooter parking locations in urban areas. The proposed methodology is based on the application of Dombi norms, Aczel-Alsina norms, and fuzzy sets for processing undefined and unclear information representing decision attributes. The multi-criteria framework consists of two modules based on an original mathematical algorithm that enables efficient reasoning and analysis of information in a dynamic environment. The first module was used to define the weighting coefficients of the criteria and involved the implementation of fuzzy Aczel-Alsina norms in the Logarithmic Methodology of the Additive Weights (LMAW) model. The second was used for prioritizing e-scooter parking locations in urban areas and is based on the application of nonlinear fuzzy Dombi functions (Dombi, 1982) to define criterion functions in the RAFSI (Ranking of Alternatives through Functional mapping of criterion sub-intervals into a Single Interval) (Žižovic et al., 2020) model. The multi-criteria framework was developed to process and group uncertain and unspecified information efficiently during the evaluation of e-scooter parking locations. A comprehensive analysis and testing of the proposed methodology showed that the multi-criteria framework offers the possibility of effectively solving location problems and has advantages that are summarized in as follows:

(i) Fuzzy Dombi aggregation functions implemented in the RAFSI model have stabilization parameters that enable flexible decision-making and objective analysis of the obtained results. The adaptability of the traditional RAFSI methodology has been improved by introducing additional stabilization parameters.
(ii) The proposed methodology for determining the weighting coefficients of decision attributes has nonlinear fuzzy Aczel-Alsina functions that enable the processing of complex and uncertain information;
(iii) The methodology of the improved fuzzy LMAW methodology enables a rational and logical representation of the relationships between the criteria, which contributes to the elimination of inconsistencies in information;
(iv) The algorithm of the fuzzy Aczel-Alsin LMAW model enables objective reasoning while respecting the mutual relations between decision attributes.
(v) Fuzzy Aczel-Alsina LMAW and Dombi RAFSI enable flexible decision-making and simulation of different risk levels to effectively check the results' robustness.

The rest of the paper is organized as follows: Section 2 provides a literature review. Section 3 includes the definition of the problem, alternatives, and criteria. Section 4 provides the proposed methodology. The case study, ranking of alternatives using the proposed methodology, sensitivity analysis, and validation, and comparison of the proposed framework with other techniques are presented in Section 5. Sections 6, 7, and 8 give the results and discuss managerial and policy implications and conclusions, respectively.

2. Literature review

Most e-scooter research focuses on proposing solutions to challenges arising from inadequate parking facilities, i.e. inadequate infrastructure. Furthermore, e-scooters pose risks to the health and safety of riders and pedestrians, necessitating the adoption of new rules and regulations (Comer et al., 2020). Even research that focuses on the disadvantages of widespread use of e-scooters provides some solutions to the concerns identified. One solution, which has been taken up (in part because it parallels developments with shared bicycles), is free-floating operation, also known as dockless operation, which describes a system in which e-scooter pick-up and drop-off are irregular. Kim et al. (2022) describe and elaborate on free-floating operations in terms of their benefits and drawbacks. According to them, the free-floating service has the advantage of providing pick-up and drop-off anywhere, but it also has the downside of being unavailable at the desired time and location due to its dispersion across the service area (Kim et al., 2022). The spatiotemporal patterns for free-floating e-scooters are greatly influenced by the service's geographic coverage, which can be specified in two ways: geofencing, where pick-ups and drop-offs are permitted, no-parking zones, or red zones, where e-scooter trips cannot end (Latinopoulos et al., 2021). These studies explore and exhibit variants of the free-floating operation system. Negative externalities are also explored, and it has been shown that over a year, free-floating e-scooters created an additional thirteen thousand tons of CO_2eq under the assumption of one million users, owing primarily to significant shifts from lower-emitting modes such as metro, BRT and active modes (Bortoli & Christoforou, 2020).

In addition to free-floating operation, studies of parking concerns have explored the more traditional method of locking and charging at specified docking stations. This operating method, unlike a free-floating system, comprises docking stations and additional randomly distributed sites to lock and charge without monitoring. Irregular parking problems and the high lifecycle embedded carbon emissions of e-scooters due to free-floating operating systems are causing a shift from dockless to charging station systems, a trend that is contrary to trends in bike sharing (Altintasi & Yalcinkaya, 2022). It has been noticed that charging and locking at specific docking stations prevent cars from blocking a sidewalk, and can inhibit parallel parking; however, this necessitates the installation of extra bike racks to accommodate both owned and shared bikes and scooters (Ferguson & Sanguinetti, 2021). Nonetheless, the public and commercial sectors should work together to assure the distribution of charging and locking stations by developing some system-wide solutions. Studies of recharging docks provide further answers to the additional charging issues. Navarro et al. (2020), for example, investigated the capability of recharging batteries using the energy generated by a solar module when sunlight is available to charge photovoltaic cells. It has been discovered that these devices provide a recharging infrastructure solution for tiny solar-powered e-scooters during everyday urban trips, allowing trip lengths to be extended by employing a sustainable energy source that citizens embrace (Navarro et al., 2020).

Alternative solutions to the two aforementioned strategies are available for parking as well. Studies exploring ‘primary catchment areas’ concentrate on how this approach delivers a better parking system while also investigating the challenges it brings. There are hubs in this process, similar to locking and charging, docking stations. However, primary catchment regions can benefit from e-scooters being docked regularly under monitoring. The goal is to eliminate irregularities and visual pollution. Furthermore, removing these difficulties solves the last-mile problem. It has been noticed that shared micro-mobility systems can improve public transportation by providing options for first- and last-mile connections, expanding the catchment area around stations, and bridging gaps in the transit network (Ferguson & Sanguinetti, 2021). According to Lin et al. (2019), giving incentives for longer bike-and-ride journeys may help extend primary catchment areas. In addition, there is a pressing need for a deeper exploration of the opportunities and constraints presented by the integration of micro-mobility transport and public transportation (Oesgher et al., 2020).

As a result, there is a gap in the literature regarding the availability of safe, convenient, and secure parking infrastructure for micro-mobility service in the catchment regions of public transportation stations. This proposed alternative provides commuters’ the potential and some incentives to use micro-mobility as an access and egress method. Hence, this study differs from previous studies in that it presents three parking alternatives concurrently while identifying the optimal road network for e-scooters.

3. Problem definition

As identified above, one of the most pressing issues in micro-mobility vehicles and e-scooters is parking. The high percentage of irregular parking in public places causes visual pollution and makes these automobiles inaccessible. This study aims to prioritize the three alternatives under twelve criteria for e-scooter parking. The alternatives and criteria listed below are defined.

3.1. Definition of alternatives

A_1: Free-floating operation: A parking system that allows users to pick up an e-scooter and leave it wherever they like is known as a free-floating operation or dockless shared e-scooters. Although it is claimed that free-floating ensures e-scooter accessibility, parking remains inconsistent due to the lack of a station or supervision of the scooter’s operation. Downtown and university districts, open spaces, recreational places, and public transportation enabling free-floating operations are all settings where dockless solutions have been used (Bai & Jiao, 2020). In reality, this approach is seen as a good last-mile option, a method of reducing traffic congestion, and an environmentally preferable means of transportation (Hollingsworth et al., 2019). Failure to handle this function, on the other hand, can result in clutter and clustering of e-scooters, infrastructural flaws, and safety issues (Zakhem & Smith-Collin, 2021). In this way, certain e-scooter rental companies in the United States frequently geofence their systems to specific sections of the city to better manage the fleet, optimize maintenance, and assure an adequate supply (Smith & Schwieterman, 2018).

A_2: Locking and charging specified docking station operation (at random locations without supervision): Although docking stations are provided, there is no supervision for e-scooter riders. Integrated locking and charging stations enable communities to install a hybrid or semi-dockless system to organize the chaos of the recent surge in micro-mobility alternatives, in addition to easing compliance with designated pick-up and drop-off sites (CalAmp, 2019). Docking infrastructure may be required to promote micro-mobility as a viable alternative to private vehicles to minimize rush-hour urban traffic. Thus, docking stations could be a valuable addition to the currently dockless e-scooter networks, breaking the prevalent ‘either-or’ vehicle provision pattern (Reck et al., 2021). This operation’s notable feature of locking and charging e-scooters in a station makes it easier to access vehicles. The absence of supervision, on the other hand, is a drawback.

A_3: Hybrid operation with geo-fencing hubs in primary catchment areas of public transportation (near bus, BRT, metro stations): Primary catchment areas are a type of parking solution that includes both stations and supervision because they are located near bus and metro stations. The fundamental potential of micro-mobility, whether e-scooters or bicycles, in the urban context, is based on enhancing access to public transportation, which in turn would lead to changes in mobility patterns and behaviors targeted at reducing vehicle dependency (Oeschger et al., 2020) and enhancing the resilience of the transport network (Cheng et al., 2021). Primary catchment areas near public transit address this issue. Nonetheless, this contribution includes some performance requirements. For example, the sizes of bicycle catchment areas are positively associated with good metro service, frequent morning trips, diverse users, and long distances to the city center and terminal stations, but adversely associated with metro station density (Lin et al., 2019). The same holds for e-scooters. As long as regular parking is permitted through supervision in this operation, visual pollution will be eliminated, and the operation should be simple to handle.

3.2. Definition of criteria

Within the scope of this investigation, twelve criteria are identified and classified according to the following four aspects:

(1) *User Aspect*

C_1: Accessibility (benefit): The meaning of e-scooter accessibility is the ability of riders to locate an e-scooter quickly. This potential is influenced by five factors: geographical, temporal, economic, physiological, and social (Latinopoulos et al., 2021). The first alternative appears to be more accessible because automobiles are parked in various locations. However, because of the random parking and lack of supervision in the first alternative, users may have difficulty accessing e-scooters. The reason for this is that a vehicle parked in one dock may not be parked at the same dock the next day. The second alternative features more precise docking zones. However, the lack of supervision makes access to these vehicles more difficult because it is unknown whether one will be available when needed. E-scooters in the third alternative appear to be more accessible due to their integration with public transportation.

C_2. Providing last-mile solution (benefit): This criterion is generally met by the third alternative, the primary catchment area. According to a case study illustrating the size of primary catchment areas for a last-mile problem, shared e-scooters are mostly used to connect to or from transit as either first or last-mile connections (Ziedan et al., 2021). In this way, combining micro-mobility with public transportation for last-mile connections can successfully reduce car usage and, as a result, peak-hour road congestion (Latinopoulos et al., 2021). Furthermore, the first alternative solves the difficulty of the last mile. However, the system’s irregularity affects its efficiency.

C_3. Vehicle availability (benefit): Free-floating operations offer users the chance to obtain e-scooters in random areas. However, the lack of supervision and the random-access points make it difficult to gain access to vehicles at any time, thereby restricting usage to leisure and recreation. Availability of vehicles is more likely with the second alternative, but the absence of supervision negatively affects this procedure. Consequently, the primary catchment area is a viable alternative for

vehicle availability at public transportation stops or stations due to its hybridity (Oeschger et al., 2020).

(1) *Public authority aspect*

C_4. Chaotic encroachment on public space (cost): One of the fundamental issues with e-scooter usage is excessive parking in public areas. In reality, the business models focus on growing the supply of e-scooters in heavily populated regions, resulting in the invasion of public spaces for parking, the obstruction of roadways, and visual pollution (Ganesh, 2020). The first proposed alternative has the potential to incur high costs to all stakeholders, whereas supervision eliminates such costs in the primary catchment areas.

C_5. Integrating public transportation modes (benefit): The last-mile solution is connected to this requirement. In other words, a last-mile solution may provide integration among public transit modes. The free-floating system cannot integrate with public transportation modes; but docking stations may perform better against this criterion. However, e-scooters may complement public transportation by allowing for first- and last-mile connections to transit stops (Yan et al., 2021), which may be possible in primary catchment areas.

C_6. The absence of regulation and supervision (cost): The two most important variables in optimizing micro-mobility transportation are regulation and supervision. Newly developed collaborations between cities and operators appear to be a successful solution by providing greater decision-making control and capitalization on the rich information that is acquired thereby helping to generate new policy solutions as well as better legal ones (Latinopoulos et al., 2021). Free-floating and docking station operations do not include monitoring, and the lack of these aspects does not affect these alternatives. However, the lack of supervision and regulation imposes a significant cost on primary catchment areas, as the main core of these places necessitates these factors.

(1) *Service operator aspect*

C_7. Required labor for operation (cost): Employees who park e-scooters, change their batteries and distribute them incur certain costs (Losapio et al., 2021). This requirement is important in free-floating operations since riders must find a suitable area to park them and the batteries must be charged, or the e-scooters may have to be retrieved, re-charged and relocated. The same can be said for docking stations; however, regular parking lowers such expenditures. However, because the sites are consistent, primary catchment areas include a controlled operating system, which causes labor to be distributed in more convenient places. In other words, the third alternative optimizes and lowers labor costs.

*C_8. Optimized fleet management (*e.g.*, vehicle charging, maintenance, meeting the demand) (benefit):* Fleet optimization is the process of determining the best outcome for a fleet of vehicles from the perspective of a fleet operator using a set of operational alternatives such as rebalance optimization, predictive maintenance optimization, battery swap optimization, and route optimization (Almstörm et al., 2021). Fleet management may not be necessary for the first and second choices because parking is at random in these alternatives. However, fleet management optimization is possible for the third alternative because charging, location maintenance, and payment control are more determined and attainable.

C_9. Operation cost (cost): This criterion may have the same negative effect on all three alternatives, as it involves a variety of operations, including parking and battery replacement. Due to differing sharing and charging arrangements, however, operational expenses may be higher or lower depending on the operating model chosen. For instance, it has been shown that e-scooters have a limited battery capacity and require regular charging, which leads to extremely high operational costs and hinders the feasibility of the service. Solar energy is therefore offered as a solution (Zhu et al., 2022). Given that the parking spaces are selected inside the primary catchment areas, this cost does not appear excessive. Additionally, solar energy panels may be installed in these areas to resolve charging issues and improve operations. In this way, an operational cost-based case study reveals how cost influences the utilization of e-scooters. It identifies the cheap operational cost of e-scooters to users as one of the factors that may encourage their adoption (Rejali et al., 2021).

(1) *Urban sustainability and liveability aspects*

C_{10}. *The energy efficiency of transportation (benefit):* While the scooters are being distributed across the system, a vehicle transports them to specific spots within the system. In other words, e-scooters must be brought to a charging station, a task typically performed by diesel trucks, which have a significant impact on the environment due to their high emission levels (Ali & Peci, 2022). When the manufacture, charging, redistribution, and shorter lifespan of e-scooters are considered together, it can be shown that their embedded carbon emissions are substantial (Ganesh, 2020). If e-scooters are confined to specific places, as opposed to being randomly dispersed, emissions, energy consumption, and fuel consumption can be improved and made more efficient by curbing emissions during their operational lives.

C_{11}: *Air quality (benefit)*: Considering the above criterion, the distribution of e-scooters via trucks generates a substantial quantity of emissions. The overall life-cycle impact of electric scooters has been determined to be 126 gs of CO2 equivalent emissions per person per kilometer, nearly comparable to a diesel bus in 2019 (Ernst & Young Limited Company, 2020). As a result, the random deployment of e-scooters and the use of trucks to charge them contribute to air pollution. This means that deploying them in less random locations and with a little more supervision can improve air quality.

C_{12}: *Safety issues related to the interaction of different transportation modes (cost):* When considering interactions between modes of transportation, decision-makers must address safety concerns. E-scooters abandoned in random locations on the highway may cause a vehicle to hit a pedestrian or result in collisions between vehicles. Moreover, e-scooters left carelessly on sidewalks may lead to undesirable hazards to pedestrians in urban spaces and cause other pedestrians to have accidents, crashes, and falls (Altintasi & Yalcinkaya, 2022). As a remedy, however, micro-mobility lanes can be added to high-demand corridors to prevent pedestrian/scooter conflicts, so addressing safety concerns for both micro-mobility users and pedestrians (Zakhem & Smith-Collin, 2021). Considering the first and second possibilities, this is a cost. Therefore, integration between modes is more secure in primary catchment areas. Concerns regarding the interaction of e-scooters with other vehicles, for instance, were identified as a significant aspect of the British government's 2021 regulatory review (Latinopoulos et al., 2021).

4. Proposed methodology

In this section, some basic notations related to Dombi norms and the steps of the proposed model are presented.

4.1. Dombi T-norm and T-conorm

The fuzzy set theory, introduced by Zadeh in 1965 (Zadeh, 1965), is accepted as one of the most powerful tools to deal with uncertainty and with vague concepts in a more tractable and practical way (Sharma et al., 2022). It has been successfully integrated into multi-criteria decision-making approaches. The most widely used fuzzy concept in decision-making models is the triangular membership function of fuzzy numbers (Pamucar & Ecer, 2020; Djukic et al., 2022; Niksirat & Nasseri, 2022). In this study, triangular fuzzy numbers are used to handle the uncertainty in the information. The operations of the Dombi T-norm and

T-conorm were developed by Dombi (1982), which has the advantage of good flexibility with the operational parameter. Some fundamental theories of the Dombi T-norm and T-conorm are defined by:

Definition 1 (Dombi, 1982, 2009). Let $\wp_1$ and $\wp_2$ be any two real numbers. Then, the Dombi *T-norm* and T-conorm between $\wp_1$ and $\wp_2$ are described by:

$$\partial_D(\wp_1,\wp_2)=\frac{1}{1+\left\{\left(\frac{1-\wp_1}{\wp_1}\right)^{\varpi}+\left(\frac{1-\wp_2}{\wp_2}\right)^{\varpi}\right\}^{1/\varpi}}, \tag{1}$$

$$\partial_D^c(\wp_1,\wp_2)=1-\frac{1}{1+\left\{\left(\frac{\wp_1}{1-\wp_1}\right)^{\varpi}+\left(\frac{\wp_2}{1-\wp_2}\right)^{\varpi}\right\}^{1/\varpi}}. \tag{2}$$

where $\varpi>0$ and $(\wp_1,\wp_2)\in[0,1]$.

Dombi operations on triangular fuzzy numbers (TFNs) based on Dombi T-norm and T-conorm can be described as follows:

Definition 2. (Pamucar et al., 2020, 2022) Let $\wp_1=(\wp_1^{(l)},\wp_1^{(m)},\wp_1^{(u)})$ and $\wp_2=(\wp_2^{(l)},\wp_2^{(m)},\wp_2^{(u)})$ be two TFNs, $\varpi>0$ and let it be $f(\wp_i)=(f(\wp_i^{(l)}),f(\wp_i^{(m)}),f(\wp_i^{(u)}))=(\wp_i^{(l)}/\sum_{i=1}^{n}\wp_i^{(l)},\wp_i^{(m)}/\sum_{i=1}^{n}\wp_i^{(m)},\wp_i^{(u)}/\sum_{i=1}^{n}\wp_i^{(u)})$ a fuzzy function, then some operational laws of TFNs based on the Dombi T-norm and T-conorm can be described by:

Addition of two fuzzy numbers $\wp_1$ and $\wp_2$ can be defined as follows:

$$\wp_1+\wp_2=\left(\begin{array}{c}\sum_{i=1}^{2}\wp_i^{(l)}-\dfrac{\sum_{i=1}^{2}\wp_i^{(l)}}{1+\left\{\left(\dfrac{f(\wp_1^{(l)})}{1-f(\wp_1^{(l)})}\right)^{\varpi}+\left(\dfrac{f(\wp_2^{(l)})}{1-f(\wp_2^{(l)})}\right)^{\varpi}\right\}^{1/\varpi}},\\ \sum_{i=1}^{2}\wp_i^{(m)}-\dfrac{\sum_{i=1}^{2}\wp_i^{(m)}}{1+\left\{\left(\dfrac{f(\wp_1^{(m)})}{1-f(\wp_1^{(m)})}\right)^{\varpi}+\left(\dfrac{f(\wp_2^{(m)})}{1-f(\wp_2^{(m)})}\right)^{\varpi}\right\}^{1/\varpi}},\\ \sum_{i=1}^{2}\wp_i^{(u)}-\dfrac{\sum_{i=1}^{2}\wp_i^{(u)}}{1+\left\{\left(\dfrac{f(\wp_1^{(u)})}{1-f(\wp_1^{(u)})}\right)^{\varpi}+\left(\dfrac{f(\wp_2^{(u)})}{1-f(\wp_2^{(u)})}\right)^{\varpi}\right\}^{1/\varpi}}\end{array}\right), \tag{3}$$

Multiplication of $\wp_1$ and $\wp_2$ can be defined as follows:

$$\wp_1\times\wp_2=\left(\begin{array}{c}\dfrac{\sum_{i=1}^{2}\wp_i^{(l)}}{1+\left\{\left(\dfrac{1-f(\wp_1^{(l)})}{f(\wp_1^{(l)})}\right)^{\varpi}+\left(\dfrac{1-f(\wp_2^{(l)})}{f(\wp_2^{(l)})}\right)^{\varpi}\right\}^{1/\wp}},\\ \dfrac{\sum_{i=1}^{2}\wp_i^{(m)}}{1+\left\{\left(\dfrac{1-f(\wp_1^{(m)})}{f(\wp_1^{(m)})}\right)^{\varpi}+\left(\dfrac{1-f(\wp_2^{(m)})}{f(\wp_2^{(m)})}\right)^{\varpi}\right\}^{1/\varpi}},\\ \dfrac{\sum_{i=1}^{2}\wp_i^{(u)}}{1+\left\{\left(\dfrac{1-f(\wp_1^{(u)})}{f(\wp_1^{(u)})}\right)^{\varpi}+\left(\dfrac{1-f(\wp_2^{(u)})}{f(\wp_2^{(u)})}\right)^{\varpi}\right\}^{1/\varpi}}\end{array}\right), \tag{4}$$

Scalar multiplication, where$\eta>0$

$$\eta\wp_1=\left(\wp_i^{(l)}-\frac{\wp_i^{(l)}}{1+\left\{\eta\left(\frac{f(\wp_1^{(l)})}{1-f(\wp_1^{(l)})}\right)^{\varpi}\right\}^{1/\varpi}},\wp_i^{(m)}-\frac{\wp_i^{(m)}}{1+\left\{\eta\left(\frac{f(\wp_1^{(m)})}{1-f(\wp_1^{(m)})}\right)^{\varpi}\right\}^{1/\varpi}},\wp_i^{(u)}-\frac{\wp_i^{(u)}}{1+\left\{\eta\left(\frac{f(\wp_1^{(u)})}{1-f(\wp_1^{(u)})}\right)^{\varpi}\right\}^{1/\varpi}}\right), \tag{5}$$

Power, where$\eta>0$

$$\wp_1^{\eta}=\left(\frac{\wp_i^{(l)}}{1+\left\{\eta\left(\frac{1-f(\wp_1^{(l)})}{f(\wp_1^{(l)})}\right)^{\varpi}\right\}^{1/\varpi}},\frac{\wp_i^{(m)}}{1+\left\{\eta\left(\frac{1-f(\wp_1^{(m)})}{f(\wp_1^{(m)})}\right)^{\varpi}\right\}^{1/\varpi}},\frac{\wp_i^{(u)}}{1+\left\{\eta\left(\frac{1-f(\wp_1^{(u)})}{f(\wp_1^{(u)})}\right)^{\varpi}\right\}^{1/\varpi}}\right). \tag{6}$$

where $f(\wp_j)=(f(\wp_j^{(l)}),f(\wp_j^{(m)}),f(\wp_j^{(u)}))$ and $f(\wp_j)$ represents the normalized value of fuzzy numbers $\wp_1=(\wp_1^{(l)},\wp_1^{(m)},\wp_1^{(u)})$ and $\wp_2=(\wp_2^{(l)},\wp_2^{(m)},\wp_2^{(u)})$.

Definition 3. (Pamucar et al., 2022) Let $\wp_j=(\wp_j^{(l)},\wp_j^{(m)},\wp_j^{(u)})$; $(j=1,2,\ldots,n)$, a set of TFNs, and $\zeta_j\in[0,1]$ denotes the weight of coefficients of $\wp_j$, which fulfills the requirement that it is $\sum_{j=1}^{n}\zeta_j=1$. Then fuzzy weighted averaging (FWA) operator and fuzzy weighted geometric averaging (FWGA) operator can be defined as follows:

$$FWA(\wp_1,\wp_2,..,\wp_n)=\sum_{j=1}^{n}\zeta_j\cdot\wp_j=\left(\sum_{j=1}^{n}\zeta_j\cdot\wp_j^{(l)},\sum_{j=1}^{n}\zeta_j\cdot\wp_j^{(m)},\sum_{j=1}^{n}\zeta_j\cdot\wp_j^{(u)}\right), \tag{7}$$

$$FWGA(\wp_1,\wp_2,..,\wp_n)=\prod_{j=1}^{n}(\wp_j)^{\zeta_j}=\left(\prod_{j=1}^{n}\left(\wp_j^{(l)}\right)^{\zeta_j},\prod_{j=1}^{n}\left(\wp_j^{(m)}\right)^{\zeta_j},\prod_{j=1}^{n}\left(\wp_j^{(u)}\right)^{\zeta_j}\right). \tag{8}$$

where $\wp_j=(\wp_j^{(l)},\wp_j^{(m)},\wp_j^{(u)})$ represents fuzzy numbers that are aggregated, while ζ_j representing the weighting coefficients of fuzzy numbers.

4.2. Determining criteria weights – fuzzy Aczel-Alsina function based LMAW

In the following part, the fuzzy Aczel-Alsina LMAW methodology is presented, which is based on the concept of the traditional Logarithmic Methodology of Additive Weights (LMAW) (Pamucar et al., 2021) and the Alczel-Alsina T-norm and T-conorms (Aczel & Alsina, 1982). Alczel-Alsina norms were implemented to eliminate the shortcomings of the min-max operators that are most often applied to fuzzy sets (Zadeh, 1965). Since the Alczel-Alsina operators satisfy all the axiomatic properties, the key characteristic of the min-max operator, that the result is determined by only one variable, is eliminated. Moreover, the min-max operators are not analytic and their second derivative is not continuous, which is eliminated by applying the Alczel-Alsina operator.

The fuzzy logarithmic function is used in the fuzzy Aczel-Alsina LMAW methodology to determine the relationship between decision attributes. At the same time, the application of the Alczel-Alsina norm enables the representation of mutual relationships between attributes. Furthermore, the Alczel-Alsina norms contribute to a more objective representation of the decision-maker's preferences and improve the elasticity of the traditional LMAW methodology. Fuzzy Aczel-Alsa's LMAW methodology is implemented through four steps, which are presented in the next part:

Step 1. Defining the priority vector. Let us assume that h experts participate in the research and that $1 \le p \le h$, then for each expert, we can define a priority vector ($\mathbb{R}$) as follows:

$$\mathbb{R}^p = \left(\widetilde{\psi}^p_{C_1}, \widetilde{\psi}^p_{C_2}, .., \widetilde{\psi}^p_{C_n}\right), \tag{9}$$

where $\widetilde{\psi}^p_{C_1} = (\psi^{p(l)}_{C_1}, \psi^{p(m)}_{C_1}, \psi^{p(u)}_{C_1})$ represents the preference of expert p concerning criterion C_1 and is defined based on a previously adopted fuzzy scale.

Step 2. Determination of the absolute anti-ideal point (ε). The reference value against which the significance of the criterion is defined is represented by the absolute anti-ideal point (AAIP). The value of AAIP is determined arbitrarily by satisfying the conditions from Eq. (10).

$$\varepsilon < \min_{\substack{1\le j\le n,\\ 1\le p\le h}}\left(\widetilde{\psi}^p_{C_j}\right), \tag{10}$$

where $\widetilde{\psi}^p_{C_j}$ represents the element of the priority vector.

Step 3. Defining a ratio vector. The ratio vector determines the relationship between the criteria within the priority vector. The elements of the ratio vector $\mathbb{Z}^p = (\widetilde{\omega}^p_{C_1}, \widetilde{\omega}^p_{C_2}, .., \widetilde{\omega}^p_{C_n})$ are defined using Eq. (11):

$$\widetilde{\omega}^p_{C_j} = \frac{\widetilde{\psi}^p_{C_j}}{\varepsilon}, \tag{11}$$

where $\widetilde{\psi}^p_{C_j} \in \mathbb{R}^p$, $\widetilde{\psi}^p_{C_1} = (\psi^{p(l)}_{C_1}, \psi^{p(m)}_{C_1}, \psi^{p(u)}_{C_1})$ and $1 \le p \le h$.

Step 4. The final values of the fuzzy vector of weighting coefficients are defined by applying Eqs. (12-14). For each expert, using Eqs. (12) and (13), vectors of weighting coefficients are defined:

$$\widetilde{w}^p_j = \frac{\ln\left(\widetilde{\omega}^p_{C_j}\right)}{\ln\left(\widetilde{\partial}^p_j\right)} = \left(\frac{\ln\left(\omega^{p(l)}_{C_j}\right)}{\ln\left(\partial^{p(l)}_j\right)}, \frac{\ln\left(\omega^{p(m)}_{C_j}\right)}{\ln\left(\partial^{p(m)}_j\right)}, \frac{\ln\left(\omega^{p(u)}_{C_j}\right)}{\ln\left(\partial^{p(u)}_j\right)}\right), \tag{12}$$

where the element $\widetilde{\partial}^p_j = (\partial^{p(l)}_j, \partial^{p(m)}_j, \partial^{p(u)}_j)$ we get by applying Eq. (13):

$$\widetilde{\partial}^p_j = \left(\partial^{p(l)}_j, \partial^{p(m)}_j, \partial^{p(u)}_j\right) = \begin{pmatrix} \sum\limits_{j=1}^{n} \omega^{p(l)}_j \left(e^{-\left(\sum_{j=1}^{n}\frac{1}{n}\left(-\ln\left(f\left(\omega^{p(l)}_j\right)\right)\right)^{\alpha}\right)^{1/\alpha}}\right), \\ \sum\limits_{j=1}^{n} \omega^{p(m)}_j \left(e^{-\left(\sum_{j=1}^{n}\frac{1}{n}\left(-\ln\left(f\left(\omega^{p(m)}_j\right)\right)\right)^{\alpha}\right)^{1/\alpha}}\right), \\ \sum\limits_{j=1}^{n} \omega^{p(u)}_j \left(e^{-\left(\sum_{j=1}^{n}\frac{1}{n}\left(-\ln\left(f\left(\omega^{p(u)}_j\right)\right)\right)^{\alpha}\right)^{1/\alpha}}\right) \end{pmatrix}, \tag{13}$$

where $\alpha > 0$, and $f(\widetilde{\omega}^p_j) = \widetilde{\omega}^p_j / \sum_{j=1}^{n}\widetilde{\omega}^p_j$.

The aggregated fuzzy vector of weighting coefficients is defined by applying the expression (14):

Table 1
Fuzzy linguistic terms and their fuzzy numbers for evaluating criteria and alternatives.

Linguistic terms	Membership function
Absolutely low (AL)	(1, 1, 1)
Very low (VL)	(1, 2, 3)
Low (L)	(2, 3, 4)
Medium low (ML)	(3, 4, 5)
Equal (E)	(4, 5, 6)
Medium high (MH)	(5, 6, 7)
High (H)	(6, 7, 8)
Very high (VH)	(7, 8, 9)
Absolutely high (AH)	(8, 9, 9)

$$\widetilde{w}_j = \left(w^{(l)}_j, w^{(m)}_j, w^{(u)}_j\right) = \begin{pmatrix} \sum\limits_{k=1}^{h} w^{(l)}_{j(k)} \left(1 - e^{-\left(\sum_{k=1}^{h}\frac{1}{h}\left(-\ln\left(1-f\left(w^{(l)}_{j(k)}\right)\right)\right)^{\varphi}\right)^{1/\varphi}}\right), \\ \sum\limits_{k=1}^{h} w^{(m)}_{j(k)} \left(1 - e^{-\left(\sum_{k=1}^{h}\frac{1}{h}\left(-\ln\left(1-f\left(w^{(l)}_{j(k)}\right)\right)\right)^{\varphi}\right)^{1/\varphi}}\right), \\ \sum\limits_{k=1}^{h} w^{(u)}_{j(k)} \left(1 - e^{-\left(\sum_{k=1}^{h}\frac{1}{h}\left(-\ln\left(1-f\left(w^{(l)}_{j(k)}\right)\right)\right)^{\varphi}\right)^{1/\varphi}}\right) \end{pmatrix}, \tag{14}$$

where $\varphi > 0$, $f(\widetilde{w}_{j(k)}) = \widetilde{w}_{j(k)} / \sum_{k=1}^{h}\widetilde{w}_{j(k)}$, and h represents a number of experts.

4.3. Dombi based RAFSI model

This section presents a Dombi based RAFSI model for determining the e-scooter parking locations. We present a solution comprising three consecutive stages: framework, determining the weights of criteria, followed by a ranking stage using the proposed model.

(1) *Framework definition*

Determine the alternative, decision criteria, and the set of experts to structure the proposed model. The set $\mathbb{R}_i = (\mathbb{R}_1, \mathbb{R}_2, \ldots, \mathbb{R}_d)$ having $i = 1, 2, \ldots, d$ alternatives is evaluated by $n$the decision criteria of the set $\mathbb{C}_j = (\mathbb{C}_1, \mathbb{C}_2, \ldots, \mathbb{C}_n)$ having $j = 1, 2, \ldots, n$ criteria with the help of the set of experts $\mathbb{Z}_l = (\mathbb{Z}_1, \mathbb{Z}_2, \ldots, \mathbb{Z}_e)(l = 1, 2, \ldots, h)$. the linguistic terms and their corresponding values are defined.

(1) *Determination of weight coefficients using the fuzzy Aczel-Alsina LMAW methodology*
(2) *Application of Dombi based RAFSI method for ranking the alternatives*

Step 1. Create the initial decision matrices in terms of experts' opinions with the help of the linguistic terms presented in Table 1.

Step 2. Aggregate the initial decision matrix using the fuzzy Dombi weighted geometric averaging (FDWGA) operator as given in Eq. (15).

Theorem 1: Let $(\wp_1, \wp_2, ..., \wp_n)$ be the set of elements of the initial decision matrix represented by the fuzzy numbers $\wp_j = (\wp^{(l)}_j, \wp^{(m)}_j, \wp^{(u)}_j)$, $(j = 1, 2, ..., n)$, let $\varpi \ge 0$, then the fuzzy Θ_i function is defined by:

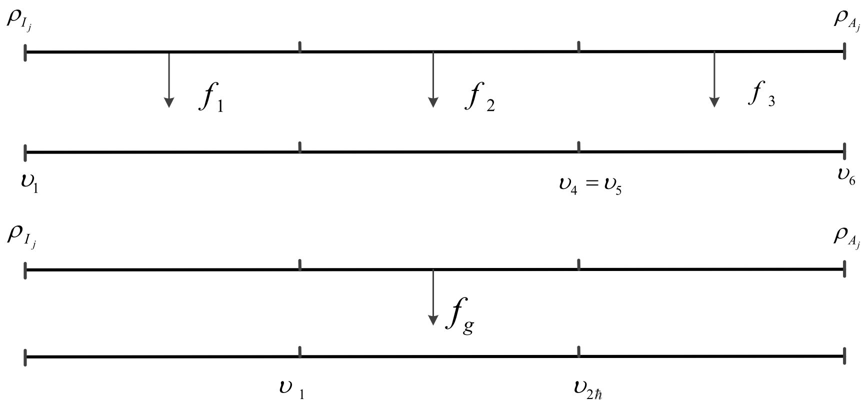

Fig. 1. Mapping of sub-intervals into the criteria interval.

$$\Theta_i^{\varpi} = \left(\Theta_i^{\varpi(l)}, \Theta_i^{\varpi(m)}, \Theta_i^{\varpi(u)}\right)$$

$$= \left(\frac{\sum_{j=1}^{n}\left(\wp_{ij}^{(l)}\right)}{1+\left\{\sum_{j=1}^{n}\xi_j\left(\frac{1-f\left(\wp_{ij}^{(l)}\right)}{f\left(\wp_{ij}^{(l)}\right)}\right)^{\varpi}\right\}^{1/\varpi}}, \frac{\sum_{j=1}^{n}\left(\wp_{ij}^{(m)}\right)}{1+\left\{\sum_{j=1}^{n}\xi_j\left(\frac{1-f\left(\wp_{ij}^{(m)}\right)}{f\left(\wp_{ij}^{(m)}\right)}\right)^{\varpi}\right\}^{1/\varpi}}, \frac{\sum_{j=1}^{n}\left(\wp_{ij}^{(u)}\right)}{1+\left\{\sum_{j=1}^{n}\xi_j\left(\frac{1-f\left(\wp_{ij}^{(u)}\right)}{f\left(\wp_{ij}^{(u)}\right)}\right)^{\varpi}\right\}^{1/\varpi}} \right), \tag{15}$$

where $f(\wp_j) = \left(\wp_j^{(l)} / \sum_{j=1}^{n}\wp_j^{(l)}, \wp_j^{(m)} / \sum_{j=1}^{n}\wp_j^{(m)}, \wp_j^{(u)} / \sum_{j=1}^{n}\wp_j^{(u)}\right)$. Then Θ_i^{ϖ} denotes the fuzzy Dombi weighted averaging function.

Step 3. Calculate the score values of each alternative regarding each criterion using the initial matrix with the help of Eq. (16).

$$\Psi_{ij} = \left(\frac{\Theta_{ij}^{(l)} + 4\Theta_{ij}^{(m)} + \Theta_{ij}^{(u)}}{6}\right), \tag{16}$$

Step 4. Find the ideal and anti-ideal values using Ψ_{ij} with the help of Eq. (17). The experts define two values ρ_{I_j} and ρ_{A_j}, where ρ_{I_j} is the ideal value of $\mathbb{C}_j$, and ρ_{A_j} is the anti-ideal value of $\mathbb{C}_j$. It is obvious that $\rho_{I_j} < \rho_{A_j}$ for min criteria, and $\rho_{I_j} > \rho_{A_j}$ for max criteria.

$$\mathbb{C}_j \in \begin{cases} \left(\rho_{A_j}, \rho_{I_j}\right), \text{ for benefit criteria,} \\ \left(\rho_{I_j}, \rho_{A_j}\right), \text{ for cost criteria.} \end{cases} \tag{17}$$

Step 5. Structure the standardized decision with the help of Eqs. (18) -(20). To equalize all the criteria of the initial decision matrix or to transfer the criteria to the criteria range $[\upsilon_1, \upsilon_{2\hbar}]$, we create a number sequence from the range $\hbar$ with $\hbar - 1$ points added between the highest and lowest values of the criteria range. The mapping of sub-intervals is shown in Fig. 1.

$$(\upsilon_1 < \upsilon_2 \le \upsilon_3 < \upsilon_4 \le \upsilon_5 < \upsilon_6 \ldots \le \upsilon_{2\hbar-1} \le \upsilon_{2\hbar}), \tag{18}$$

A function $f_g(x)$ is defined. It maps sub-intervals into the criteria interval $[\upsilon_1, \upsilon_{2\hbar}]$ with the help of Eq. (19).

$$f_g(x) = \frac{\upsilon_{2\hbar} - \upsilon_1}{\rho_{I_j} - \rho_{A_j}}\rho_{ij} + \frac{\rho_{I_j}\cdot\upsilon_1 - \rho_{A_j}\cdot\upsilon_{2\hbar}}{\rho_{I_j} - \rho_{A_j}}, \tag{19}$$

where $\upsilon_{2\hbar}$ and υ_1 represent the relations indicating how better the ideal value is when compared to the anti-ideal value. ρ_{ij} represents the value of the i th alternative for the j-th criterion from the initial matrix.

$$\mho = [\varphi_{ij}]_{dxn} = \begin{array}{c} \\ \mathbb{C}_1 \\ \mathbb{C}_2 \\ \vdots \\ \mathbb{C}_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \cdots\cdots & A_d \end{array} \\ \begin{pmatrix} \varphi_{11} & \varphi_{12} & \cdots\cdots & \varphi_{1n} \\ \varphi_{21} & \varphi_{22} & \cdots\cdots & \varphi_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \varphi_{1d} & \varphi_{2d} & \cdots\cdots & \varphi_{dn} \end{pmatrix} \end{array}, \tag{20}$$

Step 6. The normalized decision matrix is obtained by Eqs. (21-24).

$$\chi_{ij} = \begin{cases} \dfrac{\varphi_{ij}}{2\sigma} if j \in \max, \\ \dfrac{\theta}{2\varphi_{ij}} if j \in \min. \end{cases} \tag{21}$$

where σ and θ denotes the arithmetic and harmonic means, respectively. The σ and θ values are calculated by Eqs. (22)-(23) for min and max sequence of the elements $\upsilon_{2\hbar}$ and υ_1.

$$\sigma = \frac{\upsilon_1 + \upsilon_{2\hbar}}{2}, \tag{22}$$

$$\theta = \frac{2}{\frac{1}{\upsilon_1} + \frac{1}{\upsilon_{2\hbar}}}, \tag{23}$$

Later, the normalized decision matrix is obtained using Eq. (24).

$$\Delta = [\delta_{ij}]_{dxn} = \begin{array}{c} \\ \mathbb{C}_1 \\ \mathbb{C}_2 \\ \vdots \\ \mathbb{C}_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \cdots\cdots & A_d \end{array} \\ \begin{pmatrix} \delta_{11} & \delta_{12} & \cdots\cdots & \delta_{1n} \\ \delta_{21} & \delta_{22} & \cdots\cdots & \delta_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{1d} & \delta_{2d} & \cdots\cdots & \delta_{dn} \end{pmatrix} \end{array}, \tag{24}$$

where $\delta_{ij} \in [0, 1]$is the elements of Δ.

Step 7. Calculate the criteria function of alternatives α_i with the help of Eq. (25).

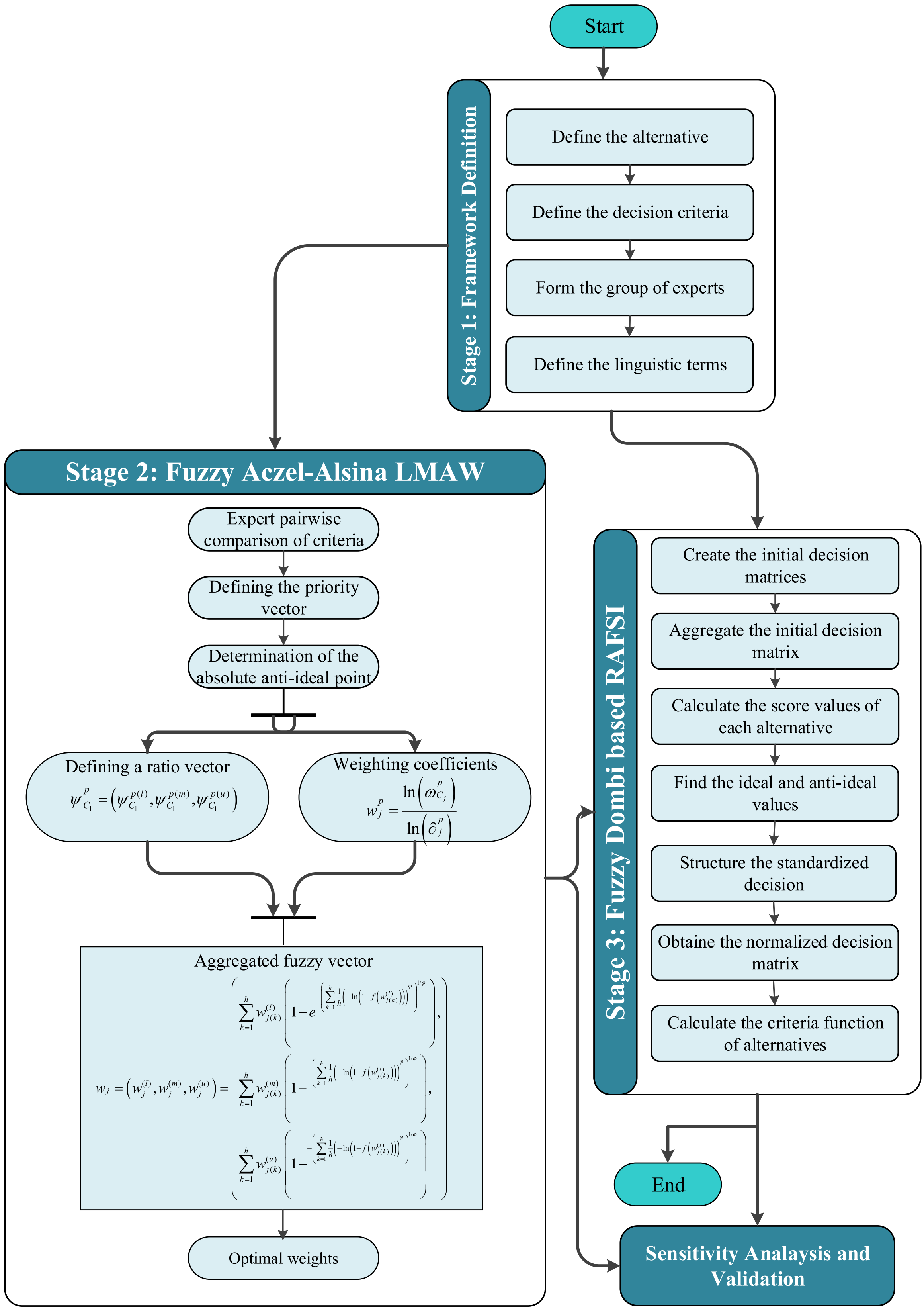

Fig. 2. The flowchart of the proposed model.

Table 2
The criteria list of e-scooter parking.

Main-criteria	Sub-criteria	Types
User Aspect (MC_1)		
C_1	Accessibility	Benefit
C_2	Providing last-mile solution	Benefit
C_3	Vehicle availability	Benefit
Public Authority Aspect (MC_2)		
C_4	Chaotic encroachment on public space	Cost
C_5	Integrating public transportation modes	Benefit
C_6	The absence of regulation and supervision	Cost
Service Operator Aspect (MC_3)		
C_7	Required labor for operation	Cost
C_8	Optimized fleet management	Benefit
C_9	Operation cost	Cost
Urban Sustainability and Liveability Aspect (MC_4)		
C_{10}	The energy efficiency of transportation	Benefit
C_{11}	Air quality	Benefit
C_{12}	Safety issues related to the interaction of different transportation modes	Cost

Table 3
Criteria priority vectors.

Criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
User Aspect (MC_1)						
C_1	(7, 8, 9)	(8, 9, 9)	(8, 9, 9)	(8, 9, 9)	(8, 9, 9)	(7, 8, 9)
C_2	(3, 4, 5)	(7, 8, 9)	(7, 8, 9)	(7, 8, 9)	(6, 7, 8)	(6, 7, 8)
C_3	(8, 9, 9)	(5, 6, 7)	(7, 8, 9)	(8, 9, 9)	(7, 8, 9)	(7, 8, 9)
Public Authority Aspect (MC_2)						
C_4	(4, 5, 6)	(3, 4, 5)	(7, 8, 9)	(5, 6, 7)	(5, 6, 7)	(5, 6, 7)
C_5	(7, 8, 9)	(7, 8, 9)	(8, 9, 9)	(7, 8, 9)	(8, 9, 9)	(7, 8, 9)
C_6	(2, 3, 4)	(6, 7, 8)	(6, 7, 8)	(5, 6, 7)	(7, 8, 9)	(5, 6, 7)
Service Operator Aspect (MC_3)						
C_7	(2, 3, 4)	(2, 3, 4)	(5, 6, 7)	(6, 7, 8)	(3, 4, 5)	(3, 4, 5)
C_8	(8, 9, 9)	(7, 8, 9)	(6, 7, 8)	(6, 7, 8)	(4, 5, 6)	(5, 6, 7)
C_9	(7, 8, 9)	(8, 9, 9)	(7, 8, 9)	(4, 5, 6)	(8, 9, 9)	(7, 8, 9)
Urban Sustainability and Livability Aspect (MC_4)						
C_{10}	(8, 9, 9)	(8, 9, 9)	(8, 9, 9)	(7, 8, 9)	(4, 5, 6)	(7, 8, 9)
C_{11}	(7, 8, 9)	(6, 7, 8)	(7, 8, 9)	(7, 8, 9)	(3, 4, 5)	(6, 7, 8)
C_{12}	(4, 5, 6)	(7, 8, 9)	(6, 7, 8)	(6, 7, 8)	(5, 6, 7)	(4, 5, 6)

$$\alpha_i = \omega_1\delta_{i1} + \omega_2\delta_{i2} + \cdots + \omega_j\delta_{ij} = \sum_{j=1}^{n} \omega_j\delta_{ij}. \tag{25}$$

Later, alternatives are ranked in decreasing order according to the values of α_i.

5. Case study

Especially in large cities and metropolises or metroplexes with high population densities, e-scooters may allow the masses to save time and access their destinations with ease. However, the current use of e-scooters in public settings must be expanded with improved infrastructure and a more methodical approach. Notwithstanding their benefits otherwise, these vehicles may not be suitable for urban mobility due to parking issues, excessive emissions during distribution and redistribution, and poor integration with public transport. Thus, the decision-makers in a large metropolis are supposed to choose among three alternatives that provide effective solutions to parking difficulties, based on twelve criteria and four aspects. The proposed e-scooter parking alternatives, aspects, and criteria were provided to six experts from the sector and academia in the urban transportation field. The flowchart of the proposed model is shown in Fig. 2.

A set of experts $\mathbb{Z}_l (l = 1, 2, \ldots, 6)$is responsible for evaluating $d = 3$ alternatives $\mathbb{R}_i (i = 1, \ldots, 3)$ regarding $n = 12$ criteria $\mathbb{C}_j (j = 1, 2, \ldots, 12)$.

Table 4
Criteria ratio vectors.

Criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
User Aspect (MC_1)						
C_1	(11.67, 16, 22.5)	(13.33, 18, 22.5)	(13.33, 18, 22.5)	(13.33, 18, 22.5)	(13.33, 18, 22.5)	(11.67, 16, 22.5)
C_2	(5, 8, 12.5)	(11.67, 16, 22.5)	(11.67, 16, 22.5)	(11.67, 16, 22.5)	(10, 14, 20)	(10, 14, 20)
C_3	(13.33, 18, 22.5)	(8.33, 12, 17.5)	(11.67, 16, 22.5)	(13.33, 18, 22.5)	(11.67, 16, 22.5)	(11.67, 16, 22.5)
Public Authority Aspect (MC_2)						
C_4	(6.67, 10, 15)	(5, 8, 12.5)	(11.67, 16, 22.5)	(8.33, 12, 17.5)	(8.33, 12, 17.5)	(8.33, 12, 17.5)
C_5	(11.67, 16, 22.5)	(11.67, 16, 22.5)	(13.33, 18, 22.5)	(11.67, 16, 22.5)	(13.33, 18, 22.5)	(11.67, 16, 22.5)
C_6	(3.33, 6, 10)	(10, 14, 20)	(10, 14, 20)	(8.33, 12, 17.5)	(11.67, 16, 22.5)	(8.33, 12, 17.5)
Service Operator Aspect (MC_3)						
C_7	(3.33, 6, 10)	(3.33, 6, 10)	(8.33, 12, 17.5)	(10, 14, 20)	(5, 8, 12.5)	(5, 8, 12.5)
C_8	(13.33, 18, 22.5)	(11.67, 16, 22.5)	(10, 14, 20)	(10, 14, 20)	(6.67, 10, 15)	(8.33, 12, 17.5)
C_9	(11.67, 16, 22.5)	(13.33, 18, 22.5)	(11.67, 16, 22.5)	(6.67, 10, 15)	(13.33, 18, 22.5)	(11.67, 16, 22.5)
Urban Sustainability and Livability Aspect (MC_4)						
C_{10}	(13.33, 18, 22.5)	(13.33, 18, 22.5)	(13.33, 18, 22.5)	(11.67, 16, 22.5)	(6.67, 10, 15)	(11.67, 16, 22.5)
C_{11}	(11.67, 16, 22.5)	(10, 14, 20)	(11.67, 16, 22.5)	(11.67, 16, 22.5)	(5, 8, 12.5)	(10, 14, 20)
C_{12}	(6.67, 10, 15)	(11.67, 16, 22.5)	(10, 14, 20)	(10, 14, 20)	(8.33, 12, 17.5)	(6.67, 10, 15)

The linguistic terms scale and their corresponding values are presented in Table 1 to collect the experts' opinions.

5.1. Determination of weight coefficients using the fuzzy Aczel-Alsina LMAW methodology

Six experts participated in the research and presented their preferences on the significance of the criteria through a questionnaire. As a result, twelve criteria were defined and grouped into four clusters given in Table 2.

In the following part, the definition of the weighting coefficients of the criteria is presented using the fuzzy Aczel-Alsina LMAW methodology.

Step 1: The experts presented their preferences within the fuzzy priority vector using the fuzzy scale presented in Table 1.

The information gathered about the importance of the criteria is represented by the priority vector of the criteria as given in Table 3.

Steps 2 and 3: Applying condition (10) and defining the relationship vector, the value of AAIP $\varepsilon = (0.4, 0.5, 0.6)$ was adopted. Finally, AAIP was used to determine the ratio vector using Eq. (3). The criteria ratio vectors are given in Table 4.

The ratio vector for criterion C_1 is defined using Eq. (11) as follows:

Table 5
Fuzzy vectors of weight coefficients within expert groups.

Criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Rules and Regulations Aspect (MC_1)						
C_1	(0.083,0.092,0.105)	(0.085,0.092,0.099)	(0.081,0.088,0.092)	(0.083,0.09,0.096)	(0.086,0.094,0.102)	(0.081,0.09,0.088)
C_2	(0.057,0.069,0.083)	(0.08,0.088,0.099)	(0.077,0.084,0.092)	(0.079,0.086,0.096)	(0.077,0.086,0.098)	(0.076,0.085,0.085)
C_3	(0.088,0.096,0.105)	(0.07,0.079,0.09)	(0.077,0.084,0.092)	(0.083,0.09,0.096)	(0.082,0.091,0.102)	(0.081,0.09,0.088)
Technology Aspect (MC_2)						
C_4	(0.066,0.077,0.09)	(0.055,0.066,0.079)	(0.077,0.084,0.092)	(0.069,0.078,0.087)	(0.072,0.081,0.093)	(0.07,0.08,0.081)
C_5	(0.083,0.092,0.105)	(0.08,0.088,0.099)	(0.081,0.088,0.092)	(0.079,0.086,0.096)	(0.086,0.094,0.102)	(0.081,0.09,0.088)
C_6	(0.044,0.06,0.075)	(0.076,0.084,0.095)	(0.073,0.08,0.089)	(0.069,0.078,0.087)	(0.082,0.091,0.102)	(0.07,0.08,0.081)
Social and Economic Aspect (MC_3)						
C_7	(0.044,0.06,0.075)	(0.042,0.057,0.071)	(0.068,0.075,0.084)	(0.074,0.082,0.092)	(0.056,0.068,0.081)	(0.055,0.067,0.07)
C_8	(0.088,0.096,0.105)	(0.08,0.088,0.099)	(0.073,0.08,0.089)	(0.074,0.082,0.092)	(0.065,0.075,0.087)	(0.07,0.08,0.081)
C_9	(0.083,0.092,0.105)	(0.085,0.092,0.099)	(0.077,0.084,0.092)	(0.062,0.072,0.082)	(0.086,0.094,0.102)	(0.081,0.09,0.088)
Urban Sustainability and Livability Aspect (MC_4)						
C_{10}	(0.088,0.096,0.105)	(0.085,0.092,0.099)	(0.081,0.088,0.092)	(0.079,0.086,0.096)	(0.065,0.075,0.087)	(0.081,0.09,0.088)
C_{11}	(0.083,0.092,0.105)	(0.076,0.084,0.095)	(0.077,0.084,0.092)	(0.079,0.086,0.096)	(0.056,0.068,0.081)	(0.076,0.085,0.085)
C_{12}	(0.066,0.077,0.09)	(0.08,0.088,0.099)	(0.073,0.08,0.089)	(0.074,0.082,0.092)	(0.072,0.081,0.093)	(0.064,0.074,0.076)

Table 6
Final fuzzy vector of weight coefficients.

Criteria	Fuzzy value
C_1	(0.072, 0.091, 0.115)
C_2	(0.064, 0.083, 0.110)
C_3	(0.069, 0.088, 0.114)
C_4	(0.058, 0.078, 0.104)
C_5	(0.071, 0.090, 0.115)
C_6	(0.059, 0.079, 0.105)
C_7	(0.047, 0.068, 0.095)
C_8	(0.064, 0.084, 0.110)
C_9	(0.068, 0.087, 0.113)
C_{10}	(0.069, 0.088, 0.113)
C_{11}	(0.064, 0.083, 0.110)
C_{12}	(0.061, 0.081, 0.107)

$$\widetilde{\omega}_{C_1}^{1} = \widetilde{\omega}_{C_1}^{6} = \frac{(7,8,9)}{(0.4,0.5,0.6)} = (11.67,16,22.5);$$

$$\widetilde{\omega}_{C_1}^{2} = \widetilde{\omega}_{C_1}^{3} = \widetilde{\omega}_{C_1}^{4} = \widetilde{\omega}_{C_1}^{5} = \frac{(8,9,9)}{(0.4,0.5,0.6)} = (13.33,18,22.5).$$

The remaining elements from Table 4 are calculated similarly.

Step 4: Using Eqs. (12) and (13), the vectors of weighting coefficients are defined within expert groups, Table 5.

By applying Eq. (13), the weighting coefficients from Table 5 were merged, and the final vector of weighting coefficients was defined, which is presented in Table 6.

The graphic representation of the fuzzy vector of weight coefficients is shown in Fig. 3. From Fig. 3, it can be seen that the criteria Accessibility (C_1) and Integrating public transportation modes (C_5) have the biggest influence in the multi-criteria model. It is also observed that the criteria Required labor for operation (C_7) and the Chaotic encroachment on public space (C_4) have minor influences.

Aggregated elements of the fuzzy vector from Table 6 are defined by applying Eq. (14), where it is adopted that all experts have the same

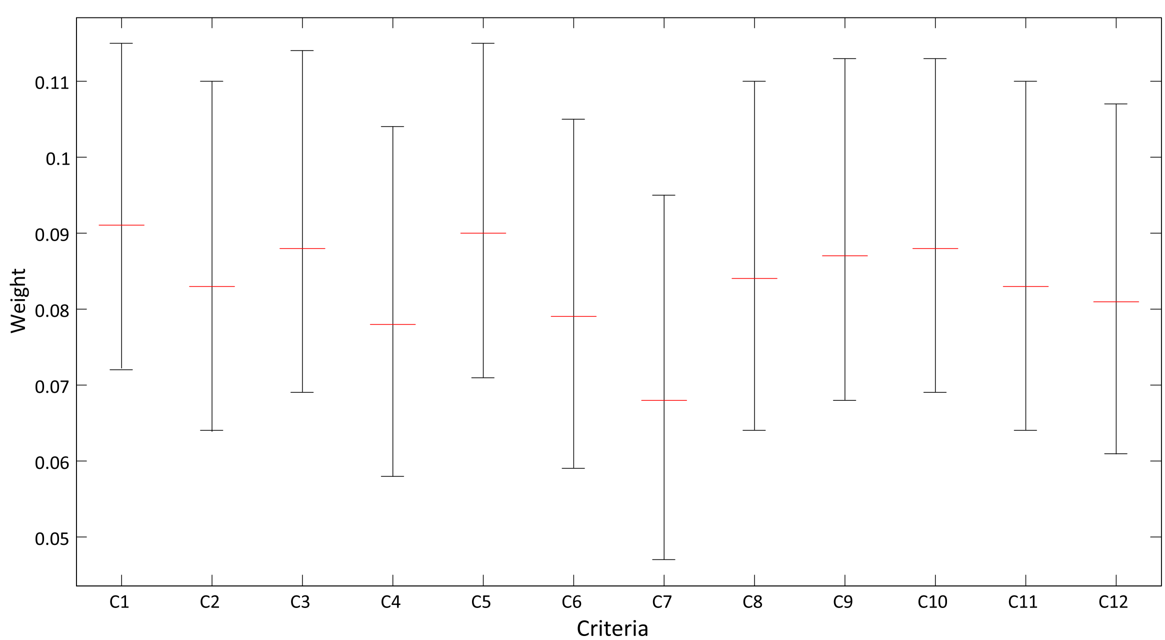

Fig. 3. Fuzzy weight coefficients of criteria.

Table 7
The linguistic assessments of the alternatives with respect to each criterion.

Expert 1	A_1	A_2	A_3	Expert 2	A_1	A_2	A_3	Expert 3	A_1	A_2	A_3
C_1	AH	H	E	C_1	AH	MH	H	C_1	VH	H	MH
C_2	H	VH	L	C_2	VH	ML	AH	C_2	AH	H	MH
C_3	VH	MH	E	C_3	H	VH	VH	C_3	VH	H	MH
C_4	VL	L	AH	C_4	AH	AL	AL	C_4	VL	L	ML
C_5	MH	H	VH	C_5	MH	ML	AH	C_5	VH	H	AH
C_6	VL	L	ML	C_6	H	ML	ML	C_6	AH	VH	H
C_7	VH	L	AL	C_7	H	L	L	C_7	VL	L	E
C_8	ML	MH	VH	C_8	VL	VH	AH	C_8	VH	H	MH
C_9	H	E	L	C_9	VH	ML	ML	C_9	AL	L	E
C_{10}	AH	VH	H	C_{10}	VH	VH	AH	C_{10}	AH	VH	MH
C_{11}	VH	MH	E	C_{11}	VH	VH	AH	C_{11}	VH	MH	MH
C_{12}	ML	VL	AL	C_{12}	MH	MH	VH	C_{12}	VL	ML	E
Expert 4	A_1	A_2	A_3	Expert 5	A_1	A_2	A_3	Expert 6	A_1	A_2	A_3
C_1	AH	MH	MH	C_1	AH	H	MH	C_1	AH	MH	MH
C_2	VH	H	H	C_2	VH	MH	AH	C_2	VH	H	H
C_3	AH	MH	MH	C_3	AH	E	VH	C_3	H	MH	H
C_4	VL	L	ML	C_4	ML	ML	VH	C_4	L	L	VH
C_5	VH	H	VH	C_5	VH	MH	AH	C_5	H	MH	VH
C_6	VH	H	ML	C_6	ML	L	VH	C_6	MH	L	MH
C_7	VL	ML	L	C_7	H	ML	L	C_7	MH	ML	ML
C_8	MH	H	AH	C_8	MH	MH	AH	C_8	L	H	MH
C_9	AL	L	ML	C_9	ML	ML	AL	C_9	VH	ML	E
C_{10}	MH	VH	AH	C_{10}	E	ML	VH	C_{10}	H	H	VH
C_{11}	MH	MH	MH	C_{11}	L	MH	H	C_{11}	VH	H	AH
C_{12}	ML	L	VH	C_{12}	H	L	E	C_{12}	H	MH	VH

Table 8
The initial decision matrix for the alternatives.

Alternatives	C_1	C_2	C_3	C_4
A_1	(7.81,8.82,9)	(7,7.96,8.82)	(5.53,7.92,8.64)	(2.36,2.73,3.84)
A_2	(5.45,6.46,7.47)	(5.85,6.18,7.24)	(7.01,6.2,7.22)	(2.18,2.32,2.73)
A_3	(4.93,5.94,6.95)	(4.05,5.95,6.94)	(3.87,6.48,7.5)	(2.73,3.22,3.46)
Alternatives	C_5	C_6	C_7	C_8
A_1	(2.15,7.05,8.06)	(7.67,4.63,5.86)	(3.18,3.8,5.13)	(2.73,3.89,5.08)
A_2	(2.78,5.93,6.97)	(5.84,3.95,5.06)	(3.69,3.43,4.44)	(3.03,6.77,7.77)
A_3	(3.86,8.47,9)	(6.17,5.07,6.13)	(6.69,2.45,2.83)	(5.2,7.58,8.22)
Alternatives	C_9	C_{10}	C_{11}	C_{12}
A_1	(6.68,2.27,2.36)	(4.35,7,7.81)	(5.68,6,7.17)	(4.02,4.13,5.33)
A_2	(5.19,3.71,4.74)	(5.35,6.72,7.8)	(6.01,6.42,7.43)	(2.68,3.43,4.55)
A_3	(5.02,2.69,3.03)	(7,7.68,8.42)	(7.01,6.68,7.5)	(7.34,3.38,3.6)

Table 9
The score values of alternatives in terms of each criterion.

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6
A_1	8.680	7.942	7.638	2.857	6.401	5.343
A_2	6.461	6.304	6.504	2.367	5.577	4.452
A_3	5.943	5.800	6.214	3.182	7.790	5.427
Type	Max	Max	Max	Min	Max	Min
Alternatives	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
A_1	3.920	3.898	3.019	6.697	6.141	4.312
A_2	3.642	6.311	4.128	6.671	6.521	3.490
A_3	3.220	7.288	3.132	7.688	6.870	4.076
Type	Min	Max	Min	Max	Max	Min

Table 11
The standardized normalized matrix.

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6
A_1	5.484	5.874	5.819	4.096	2.802	5.344
A_2	1.905	2.312	2.483	1.371	1.155	1.631
A_3	1.069	1.218	1.630	5.899	5.579	5.695
Type	Max	Max	Max	Min	Max	Min
Alternatives	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
A_1	5.602	1.136	1.078	1.757	1.705	5.215
A_2	4.211	4.487	5.700	1.657	3.604	1.794
A_3	2.099	5.845	1.551	5.567	5.352	4.234
Type	Min	Max	Min	Max	Max	Min

Table 10
The ideal and anti-ideal values of decision criteria.

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
Ideal	9	8	7.7	2.3	8	4.3	3	7.4	3	7.8	7	3.3
Anti-ideal	5.9	5.7	6	3.2	5.5	5.5	4	3.8	4.2	6.5	6	4.5

Table 12
The normalized matrix.

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.783	0.839	0.831	0.209	0.400	0.160
A_2	0.272	0.330	0.355	0.625	0.165	0.525
A_3	0.153	0.174	0.233	0.145	0.797	0.151
Alternatives	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
A_1	0.153	0.162	0.795	0.251	0.244	0.164
A_2	0.204	0.641	0.150	0.237	0.515	0.478
A_3	0.408	0.835	0.553	0.795	0.765	0.202

Table 13
The overall values of alternatives.

Alternatives	Qi	Rank
A_1	0.455	2
A_2	0.410	3
A_3	0.475	1

significance, i.e. $w_p = 1/6 = 0.167,\ 1 \le p \le h$. Furthermore, since the condition is that $\varphi > 0$, the value of the stabilization parameter of the Aczel-Alsina function $\varphi = 1$ is adopted. In the following part, the aggregation of the weighting coefficient of criterion C_1 is presented:

$$\widetilde{w}_{C1} = \left(w_{C1}^{(l)}, w_{C1}^{(m)}, w_{C1}^{(u)}\right) = \begin{cases} w_{C1}^{(l)} = 0.431\cdot\left(1 - e^{-\left(0.167\cdot(-\ln(1-0.166))^1 + 0.167\cdot(-\ln(1-0.170))^1 + 0.167\cdot(-\ln(1-0.164))^1 + \ldots + 0.167\cdot(-\ln(1-0.161))^1\right)^{1/1}}\right) = 0.072; \\ w_{C1}^{(m)} = 0.546\cdot\left(1 - e^{-\left(0.167\cdot(-\ln(1-0.169))^1 + 0.167\cdot(-\ln(1-0.169))^1 + 0.167\cdot(-\ln(1-0.161))^1 + \ldots + 0.167\cdot(-\ln(1-0.164))^1\right)^{1/1}}\right) = 0.091; \\ w_{C1}^{(u)} = 0.690\cdot\left(1 - e^{-\left(0.167\cdot(-\ln(1-0.185))^1 + 0.167\cdot(-\ln(1-0.173))^1 + 0.167\cdot(-\ln(1-0.162))^1 + \ldots + 0.167\cdot(-\ln(1-0.169))^1\right)^{1/1}}\right) = 0.115; \end{cases} = (0.072, 0.091, 0.115).$$

The remaining elements from Table 6 are defined similarly.

5.2. Ranking of alternatives using the fuzzy Dombi based RAFSI methodology

The alternatives in terms of each criterion are assessed by six experts using the scale given in Table 1, and the linguistic assessments of alternatives are presented in Table 7.

Later, the linguistic terms are transformed into fuzzy numbers using the scale in Table 1.

Steps 1–2. Based on Table 7 and Eq. (15), the expert opinions are aggregated to construct the initial decision matrix. The aggregated decision matrix is presented in Table 8.

Step 3. The score values of each alternative regarding twelve criteria are calculated using Eq. (10), and the values are in Table 8. The score values are provided in Table 9.

Step 4. The ideal and anti-ideal values of each criterion are defined using the values in Table 9 and with the help of Eq. (17). These values are presented in Table 10.

Step 5. The standardized normalized matrix is calculated by Eqs. (18-20) with the help of Tables 9 and 10. This matrix is reported in Table 11.

Step 6. The normalized matrix for the alternatives is obtained by Eqs. (21-24) using the standardized normalized values given in Table 11. The normalized values are provided in Table 12.

Step 7. The overall values are calculated by Eq. (25) with the help of Table 12. The final values of alternatives are reported in Table 13. By comparing the α_i values of the three alternatives as given in Table 13, it can be seen that $\mathbb{Z}_3 > \mathbb{Z}_1 > \mathbb{Z}_2$. Hence, the alternative $\mathbb{Z}_3$ is recommended as an e-scooter parking location in urban areas.

5.3. Sensitivity analysis and validation

In the next section, the sensitivity of the model to the change of three subjectively defined parameters is analyzed: 1) Absolute anti-ideal point (ε); 2) Stabilization parameter of the Aczel-Alsina function (φ); and 3) The relation of the ideal and anti-ideal value in the RAFSI model. Finally, a detailed analysis of the model's sensitivity in the case of changing the mentioned parameters is presented in the following sections.

a) Simulation of change of absolute anti-ideal point (ε)

In this study, the value of the absolute anti-ideal point ε=(0.4,0.5,0.6) was arbitrarily adopted. The specified value is adopted based on condition (10). Since $\min\limits_{\substack{1\le j\le 12,\\ 1\le p\le 6}} \left(\widetilde{\psi}_{C_j}^{p}\right) = 2$ and condition (10) defines that $0<\varepsilon<2$, twenty scenarios were formed in which the AAIP change was simulated. In the first scenario, the value ε=0.001 was adopted, while in each subsequent scenario, the AAIP value was increased by 0.1. In each scenario for a new AAIP value, a new vector of criteria weighting coefficients was obtained, which is shown in Fig. 4.

Since the new vectors of weighting coefficients directly impact the final values of the criteria functions of the alternatives and their ranking, in the following part, in Fig. 5, the changes in the criteria functions through the scenarios are analyzed.

The results from Figs. 5a-d confirm that the proposed multi-criteria framework are sensitive to the change in the weighting coefficients of the criteria. Moreover, the results show that the AAIP affects the change of criterion functions, which can lead to the variation of the ranks of the alternatives. However, the analysis showed that alternative A_3 represents the best solution regardless of the AAIP values and has the potential to be selected as the dominant solution from the considered set.

a) *Simulation of the change in the stabilization parameter of the Aczel-Alsina function (φ)*

When defining the initial solution, the value of the stabilization parameter of the Aczel-Alsina function φ=1 was adopted. Since the condition is φ>0, the impact of other values of φ on the change of the initial solution was analyzed in the next section. In the experiment presented in this section, the change of φ was simulated in the interval $1\le\varphi\le 100$. In the first scenario, the value φ=1 was adopted, while in each subsequent scenario, φ was increased by one. Fig. 6 shows the change in criterion functions of alternatives during 100 scenarios.

Fig. 6a-b show individual changes in the criteria functions of the alternatives through 100 scenarios, while Fig. 6d shows a comparative representation of changes in functions during 100 scenarios. The obtained results (see Fig. 6a-c) show that the proposed multi-criteria methodology is sensitive to the change in the stabilization parameter

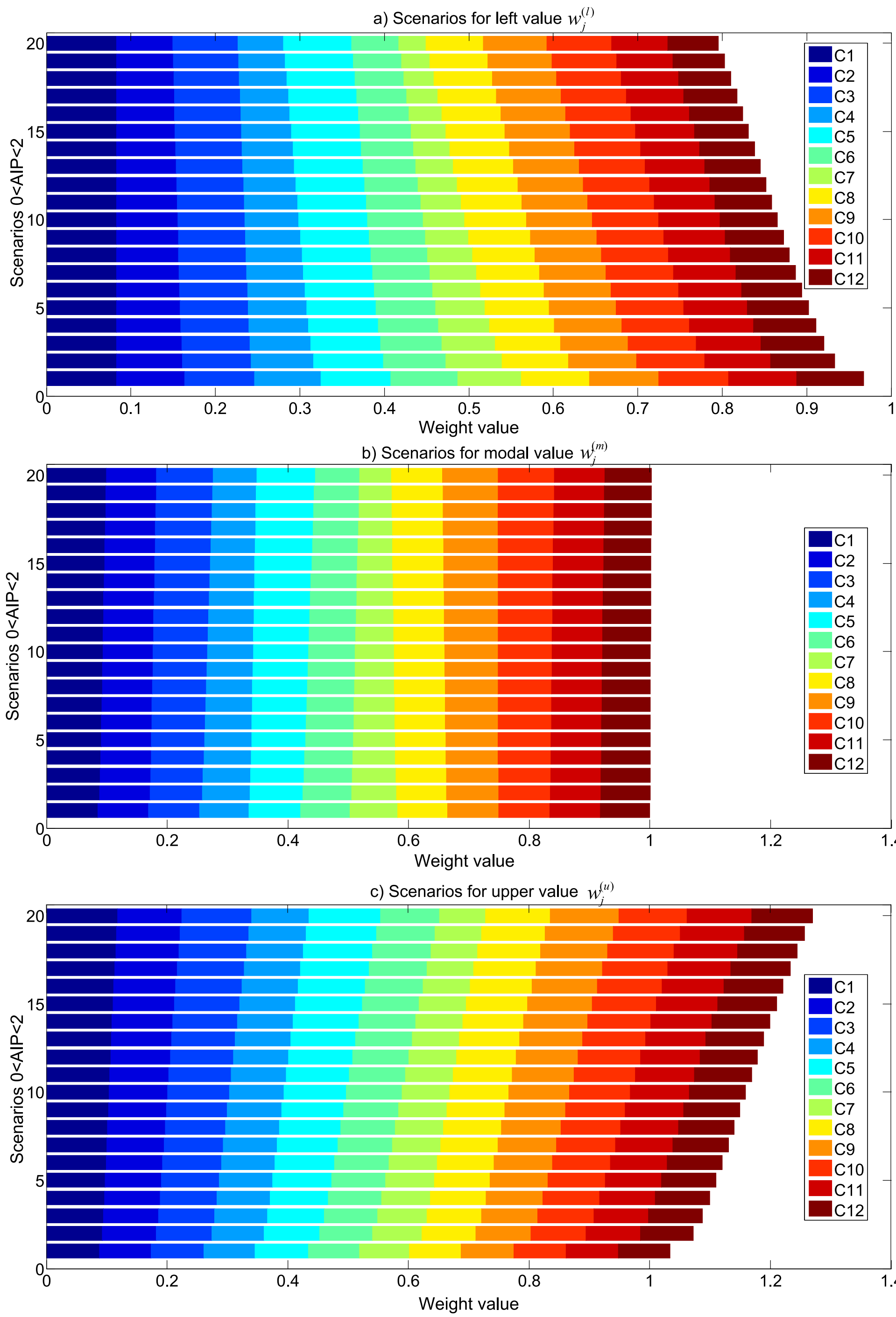

Fig. 4. The influence of AAIP on the change of weight coefficients of criteria.

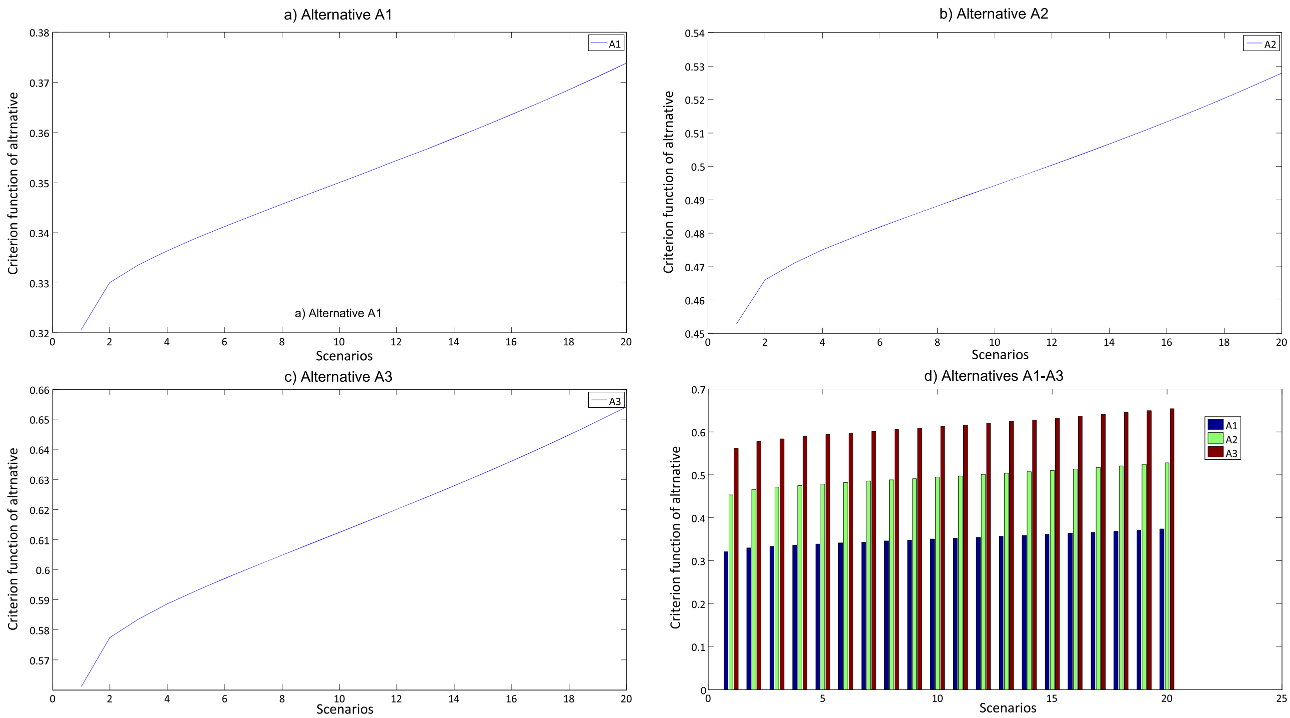

Fig. 5. The influence of AIP on the change of criterion functions of alternatives.

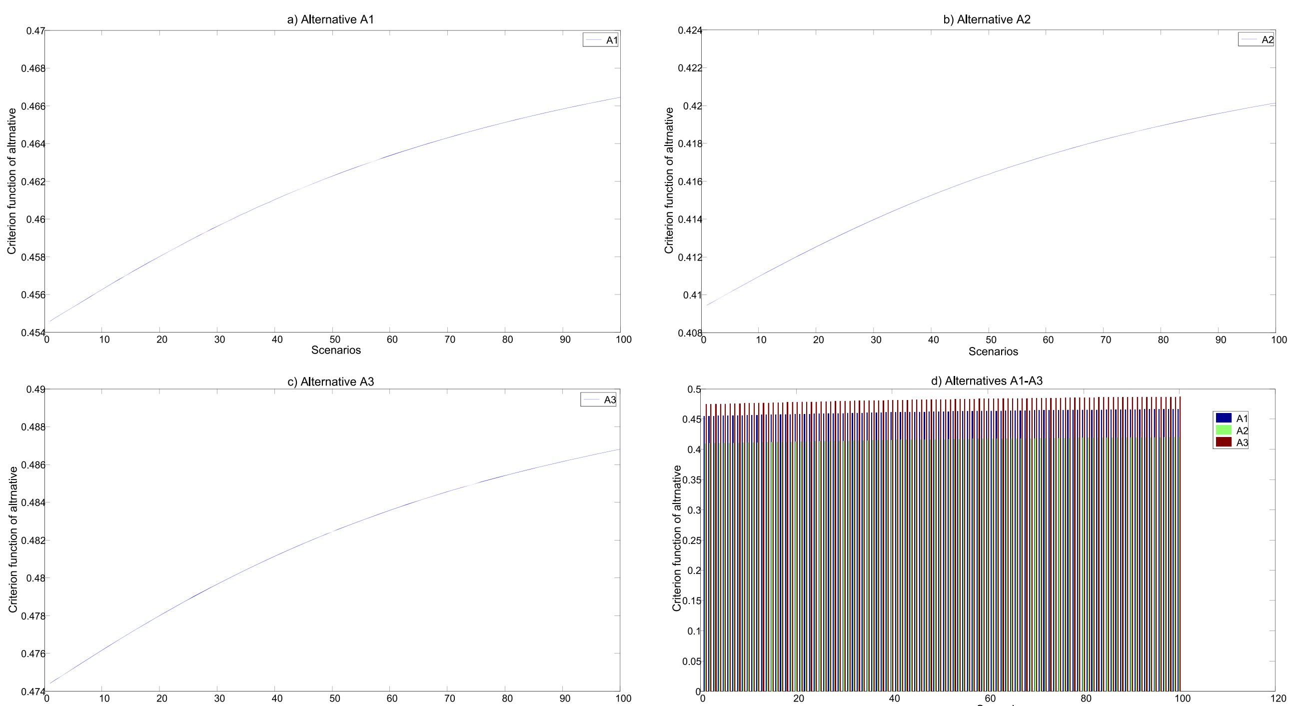

Fig. 6. The influence of the parameter φ.

of the Aczel-Alsina function. Moreover, the results from Fig. 5d show that the initial ranking was confirmed during the experiment, i.e., there was no violation of the initial solution. As seen in Fig. 6d, the criteria functions of the alternatives grow proportionally during the simulation of the change of the parameter φ so that the dominant alternative (A_3) keeps its position despite the changes in the initial values.

a) *Simulation of the change in the relation of the ideal and anti-ideal value in the RAFSI model*

To define the initial solution, it was adopted that the ideal alternative is six times better than the anti-ideal alternative; that is, the ratio a_I:a_{AI} =1:6 was adopted. This relationship in the RAFSI model was adopted based on the recommendations of Zizovic et al. (2020). In the next part, the change of the ratio between the ideal alternative from a_I:a_{AI} =1:6 to

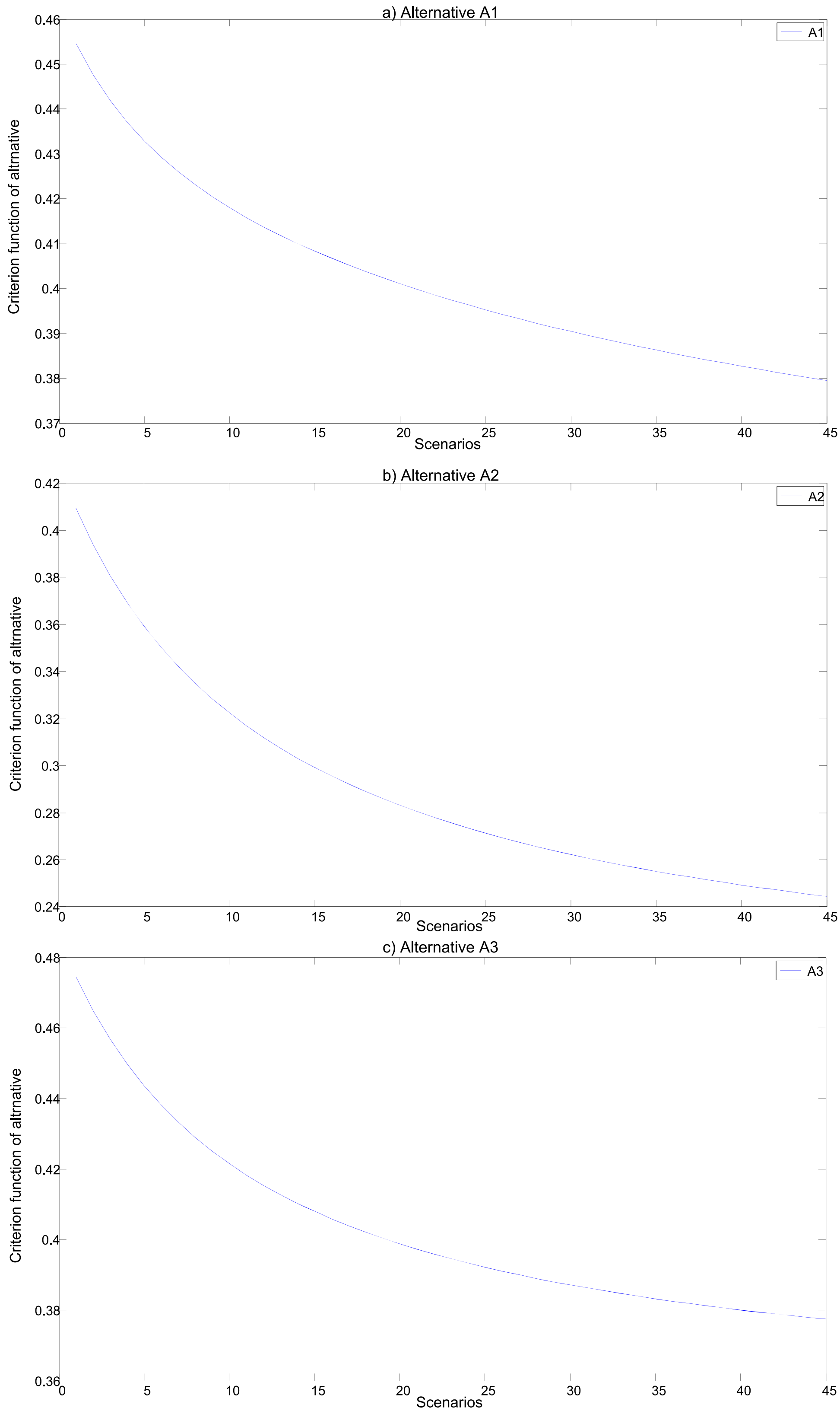

Fig. 7. Simulation of the change in the relation of the ideal and anti-ideal value in the RAFSI model.

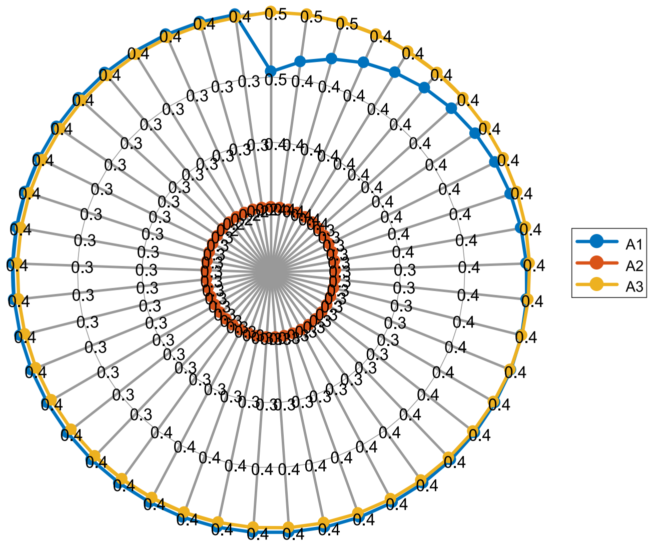

Fig. 8. Comparative presentation of the change in criterion functions of the alternatives.

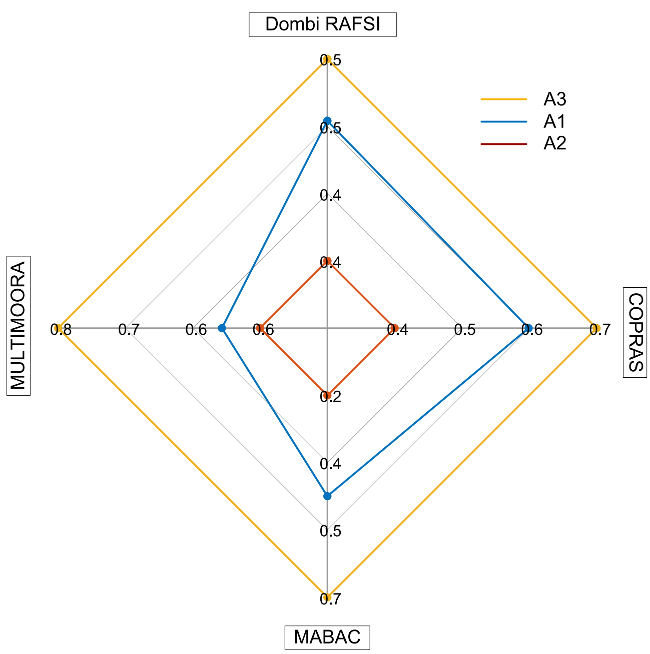

Fig. 9. Results of different MCDM techniques.

a_I:a_{AI} =1:50 is simulated. During the 45 scenarios, the change in the relationship between a_I and a_{AI} was monitored, Fig. 7.

Fig. 7a-c show changes in criterion functions of individual alternatives, while Fig. 8 shows a comparative view of the abovementioned changes.

It is expected that the increase in the ratio causes the decrease of the criterion functions, which is confirmed in Fig. 7a-c. However, these changes occur in a small criterion interval, so they do not cause large changes in the criterion functions of the alternatives. Therefore, based on the above, we can conclude that the initial ranking is confirmed and that alternative A_3 represents the best solution within the considered set.

5.4. *Comparison of the proposed MCDM framework with other techniques*

In the following part, a comparison of the results of the proposed methodology with the results of other MCDM models is presented. The model was chosen based on the method of normalization of the data used in the mathematical model. Since data normalization techniques can lead to different results (Aytekin, 2021), models using different normalization techniques were selected for comparison. Fuzzy extensions of the following models were selected: the COmplex PROportional Assessment (COPRAS) model that uses the additive normalization technique, Multi-Attributive Border Approximation area Comparison (MABAC) model that uses the linear max-min normalization technique, and the Multi-Objective Optimization based on Ratio Analysis plus full multiplicative form (MULTIMOORA) model using the max normalization technique. The results shown in Fig. 9 were obtained by applying the mentioned models.

The results from Fig. 9 show that alternative A_3 represents the best solution within the considered set of alternatives. To see the advantages and limitations of the used MCDM techniques, their comparison was made in Table 14.

While the COPRAS, MABAC, and MULTIMOORA methods use linear aggregation functions, the Dombi RAFSI model uses nonlinear fuzzy Dombi functions for aggregating uncertain information. Dombi RAFSI nonlinear functions have stabilization parameters that enable flexible decision-making and efficient validation of results. In addition, the variation of the stabilization parameters makes it possible to consider different scenarios that may appear due to uncertain dynamic environmental conditions.

In some multi-criteria problems, there are requirements to consider scenarios in which different levels of risk are simulated, so in such situations, the Dombi RAFSI technique is more adequate for application compared to the COPRAS, MABAC, and MULTIMOORA methods. This characteristic makes the Dombi RAFSI model more general and suitable for solving other real-world problems.

Extending the mathematical apparatus of multi-criteria techniques by applying uncertainty theories increases the mathematical complexity of the MCDM model. This also applies to the Dombi RAFSI method, which is based on an iterative assessment of the connections between the evaluation criteria. On the other hand, with the COPRAS, MABAC, and MULTIMOORA methods, the mathematical apparatus is made less complex by applying fuzzy theory. However, increasing the mathematical complexity of the Dombi RAFSI method in a fuzzy environment does not globally undermine its effectiveness. In addition, the complexity of the model can be effectively eliminated by developing software that would enable fast processing of information and decision-making in real-time. This would fully utilize the evident potential of the

Table 14
The comparisons of different methods.

MCDM methodology	Allows the input parameters to support each other	Flexible decision-making due to decision-makers' risk attitude	Flexibility in real-world applications	The possibility of applying the theories of uncertainty
Fuzzy COPRAS (Chaurasiya & Jain et al., 2022)	No	No	No	Yes
Fuzzy MABAC (Stojanovic & Puska, 2021)	No	No	No	Yes
Fuzzy MULTIMOORA (Mishra et al., 2022)	No	No	No	Yes
Fuzzy Dombi RAFSI (Proposed)	Yes	Yes	Yes	Yes

multi-criteria framework presented.

6. Results and discussion

The three alternatives offered have different solutions to e-scooter parking issues. The recommended solutions do not have the same cost-benefit impact when considered alongside the integration of e-scooters and other modes. However, their range of impact varies across the four aspects and twelve criteria. The results demonstrate that the alternatives are ranked in the following order, from least effective to most effective: free-floating operation, locking and charging specific docking station operation, and hybrid operation with geo-fencing hubs in public transportation primary catchment areas ($A_3 > A_1 > A_2$).

In comparison to A_1 and A_3, A_2 is the least effective. Even though fixed docking stations promote orderly, safe, and long-term micro-mobility growth by establishing a more structured and secure parking system, the system suffers from a lack of infrastructure and public awareness of the system, including vandalism (Laborda, 2022). In other words, the system is unstable owing to bike theft and negligent bike management because users cannot be held accountable due to the anonymous coin payment method (Shah, 2020). These issues are primarily the result of a lack of supervision within that operation.

Although A_1 has a favorable impact on climate change and the environment (Bortoli, Christoforou, 2020), these environmental benefits may not always be considered if recycling programs are not planned and recharging is not done using clean energy, and they may harm public health (Foissaud et al., 2022). Furthermore, while the free-floating operation has the advantage of allowing consumers to drop off the e-scooters in the preferred location, there are drawbacks since it might result in traffic accidents and an impaired pedestrian environment due to reckless servicing operations (Kim et al., 2022). Dockless e-scooters also have issues with requiring extra labor and producing air pollution through distribution. As a result, this operation may be less effective in addressing urban transportation issues.

Because it is based on a specific parking site under supervision, A_3 incorporates the most useful approach for offering more sustainable parking operations. It overcomes a last-mile problem, which is one of the fundamental problems in terms of time, by removing irregularity and visual pollution. The primary catchment area as a solution increases vehicle availability and optimizes fleet management. A_3 contributes to decreasing climate change and enabling safer transportation without negatively affecting the environment by considering all these variables.

7. Managerial and policy implications

It is anticipated that the market for electric scooters will reach $42 billion by the year 2030. (Glenn et al., 2020). For the integration of micro-mobility with urban transportation to be made in a way that is both safe and beneficial to the environment, such an expansion will necessitate carefully optimized operations. There is a possibility that the existing infrastructure of the operations may not produce satisfactory outcomes over the course of the integration process. Nevertheless, if primary catchment areas are prioritized for development and improvement, this approach may produce more satisfactory results. To ensure urban mobility that is both safer and more environmentally friendly, officials need to consider the potential benefits of A_3 and work to expand those benefits.

8. Conclusion

It is essential to meet the concerns of users, operators, and public authorities when planning parking spots for e-scooters. However, this must be done without putting the efficient usage of the scooters in jeopardy. According to the findings of this research, the most effective strategy for the arrangement of sustainable parking spots is a hybrid operation that makes use of geo-fencing hubs in main catchment regions of public transit. This conclusion was reached after considering four different characteristics and 12 different criteria to accurately determine where to park the e-scooters. One limitation of the case study is that the alternatives might not be appropriate for use in cities where the public transportation system is poor. As a result, the dynamics of the urban transportation capacities of a city need to be taken into consideration while formulating options in any future research that is conducted on this topic. Furthermore, the number of experts can be raised by considering different groups of users or other stakeholders.

Therefore, encouraging the use of e-scooters in the primary catchment areas of large cities will improve this integrity, bringing regularity, lowering the amount of visual pollution, and conserving energy for a more secure and environmentally friendly traffic environment. In addition, the incorporation of e-scooters alongside these other modes will contribute to the reduction of excessive energy usage and the enhancement of overall performance.

In this study, subjective expert assessments were used to represent criterion values. The fuzzy set theory that expresses uncertainties in human opinions can be successfully used with the MCDM methods to get more sensitive, concrete, and realistic results. This is confirmed in numerous studies published in the literature (Bakır et al., 2021; Zhou et al., 2022; Ashraf et al., 2022; Riaz et al., 2022). The fuzzy theory was used in this study since it became apparent during expert interviews that triangular fuzzy numbers could effectively process uncertainties present in expert assessments. Based on the observed uncertainties and subjectivity, a fuzzy scale was formed, and the number of linguistic variables, membership functions, and threshold values of linguistic variables were defined, which were used for surveying experts. The survey showed that the number of fuzzy linguistic variables and triangular membership functions enables a rational presentation of expert preferences. The choice of type of membership function was influenced by subjective expert assessments and inaccuracies that exist when defining criteria values. Certainly, when applying the fuzzy Aczel-Alsina LMAW methodology in other studies, other membership functions (e.g., trapezoidal membership functions) can be chosen, all to present subjective assessments as objectively as possible.

Applying the Dombi operator in a fuzzy environment enables a more flexible information fusion process compared to the traditional min-max operator. Furthermore, in the case of the min-max operator, the main disadvantage is that the result is determined only by one variable, and the other has no influence. The flexibility of the Dombi operator is a consequence of the general parameters possessed by Dombi T-norms (TN) and T-conorms (TCN). However, one of the limitations of Dombi TN and TCN is the inability to process information that has values outside the interval [0,1]. That is why until now, both Dombi TN and TCN have been used only for the transformation of uncertain numbers that satisfy that condition. To eliminate this limitation, in this paper, the improvement of arithmetic operations with Dombi TN and TCN in a fuzzy environment was performed. The improvement of arithmetic operations with Dombi TN and TCN enables the fusion of fuzzy numbers regardless of the numerical values that define the interval limits of fuzzy numbers.

It is necessary to emphasize that the application of uncertainty theories depends on the degree and form of uncertainty in the information. That is why it is essential to direct future research towards the improvement of the fuzzy Aczel-Alsina LMAW methodology by applying rough theory, neutrosophic theory, and other generalizations of fuzzy theory. This would cover a wide range of uncertainties in information and contribute to the objectification of decision-making.

One of the model's limitations for evaluating e-scooter parking locations is the impossibility of seeing the interrelationships between the attributes in the initial decision matrix. This limitation can be effectively eliminated by implementing hybrid Dombi-Bonferroni and Dombi-Heronian functions in the RAFSI model. Furthermore, by applying the aforementioned earlier hybrid nonlinear functions, additional stabilization parameters are introduced into the multi-criterion framework, which increases the model's flexibility. An exciting direction for further research is the implementation of other uncertainty theories such as rough sets and D numbers to process uncertainty in group decision-making models more efficiently.

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 that has been used is confidential.

Appendix

Table A1. List of symbols and its semantics.

Symbols	Meaning
∂_D	Dombi T-norm
∂^c_D	Dombi T-conorm
$\mathbb{R}$	Priority vector
p	Index of a decision maker
H	Number of experts
E	Absolute anti-ideal point
$\mathbb{Z}$	Ratio vector
d	Number of criteria
Θ_i	Fuzzy Dombi weighted average function of alternative i
j	Index of criteria
$\tilde{w}_j$	fuzzy weight of criterion j
n	Number of alternatives
ρ_{I_j}	the ideal value of criterion j
ρ_{A_j}	the anti-ideal value of criterion j
$f_g(x)$	Mapping function
Δ	The normalized decision matrix
χ_{ij}	The element of the normalized decision matrix
α_i	The criteria function associated with alternative i

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