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Recovery center selection for end-of-life automotive lithium-ion batteries using an integrated fuzzy WASPAS approach

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A R T I C L E I N F O

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A B S T R A C T

With the emergence of battery-based electric vehicles, transportation systems gradually leave using fossil fuel-based combustion engines. Due to their reasonable performance, Lithium-ion batteries have become one of the major batteries used for electric vehicles. Although these batteries are being used in most companies, their high production cost, rare raw material, and short life cycle have raised important incentives for their recovery process. However, locating a recovery center for end-of-life Lithium-ion batteries is a multi-aspect decision making problem influenced by many criteria. For this purpose, a novel integrated decision-making model is developed based on Measuring Attractiveness by a Categorical Based Evaluation TecHnique (MACBETH) for calculating the criteria weights and Weight Aggregated Sum Product ASsessment (WASPAS) methods under the fuzzy environment with Dombi norms for evaluating the alternatives to address recovery center location selection problem considering technical as well as environmental, economic, and social aspects. To show the reliability and applicability of the developed method, a real-world case study in Istanbul is investigated. The developed method is used to evaluate six potential locations for the possible establishment of a recovery center. Results showed that Tuzla district is the most suitable location for opening a recovery center for end-of-life Lithium-ion batteries. Tuzla is in a very good position in terms of proximity to suppliers, transportation and location. To illustrate the robustness of the obtained results, extensive sensitivity analysis tests are performed.

1. Introduction

Electric vehicles (EVs) are an appealing solution for the decarburization of the transportation sector (Romero-Ocaño, Cosío-León, Valenzuela-Alcaraz, & Brizuela, 2022; Zhang, Guo, & Zhang, 2020). It is estimated that more than 125 million EVs will be on the road worldwide by 2030 (Hua et al., 2020). Lithium-ion batteries (LiBs) have exponential growth and a key portion of industry investments (Chen et al., 2019; Cui, Gao, Mao, & Wang, 2022). An automobile Lithium-ion battery (ALiB) is a major component of an EV (Pelletier, Jabali, Laporte, & Veneroni, 2017; Ramoni & Zhang, 2013). ALiBs provide the required energy storage for EVs due to the superiority of high energy density, high output voltage, low self-discharge rate, and long cycling life (Tang, Liu et al., 2019; Wang, Xu, Zhang, Jiang, & Feng, 2022). They are composed of a cathode, an anode, an electrolyte, and a separator (Olivetti, Ceder, Gaustad, & Fu, 2017). The useful lifetime of ALiBs is 120,000–240,000 km (Onat, Kucukvar, Tatari, & Zheng, 2016).

Approximately 11 million ALiBs are expected to be sold worldwide by 2020 (Li et al., 2018; Alamerew & Brissaud, 2020). Due to the degradation in capacity and quality, the service life of these complex multiple material products, which belong to class 9 of dangerous goods, is 5–10 years (Li et al., 2018; Chen et al., 2019; Tang, Zhang et al., 2019; Alamerew & Brissaud, 2020; Li, Mu, Du, Cao, & Zhao, 2020). ALiB is replaced when the capacity has reached 70–80 % of its initial capacity (Alamerew & Brissaud, 2020; Hua et al., 2020; Ramoni & Zhang, 2013).

A huge amount of ALiBs will soon reach their end-of-life (EoL) (Wang, Wang, & Yang, 2020). Improper management of EoL ALiBs can compromise the benefits of EV adoption (Ai et al., 2019). A landfill is an unacceptable option for their disposal (King & Boxall, 2019) since it can cause environmental, human health, and safety hazards (Garg, Yun,

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Gao, & Putungan, 2020; Zeng, Li, & Liu, 2015; Zhu, Liu, Li, & Zhu, 2020). On the other hand, viable management options to properly handle EoL ALiBs include remanufacturing, repurposing (e.g., for energy storage), and recovery (Chen et al., 2019; Song et al., 2019; Wu, Lin, Xie, Elliott, & Radcliffe, 2020). Considering the ease of processing and scalability, EoL ALiB recovery is the most broadly applicable solution to process all state-of-health (SOH) and designs (Chen et al., 2019; Kamath, Shukla, Arsenault, Kim, & Anctil, 2020).

EoL ALiB recovery is an emerging industry worldwide. Its market could be worth as much as 2 billion USD by 2022 (Olivetti et al., 2017). At present, the infrastructure for the recovery of EoL ALiBs is still in its infancy (Ai, Zheng, & Chen, 2019). Recovery lowers environmental impacts and provides a source of high-value materials that can be used in producing new batteries (EU, 2000, 2006; Wu, Lin et al., 2020). It is a sequence of collection, selection, treatment, disposal, and distribution activities, aiming at the recovery of valuable materials from EoL ALiBs (Hoyer, Kieckhäfer, & Spengler, 2015; Zhan, Payne, Leftwich, Perrine, & Pan, 2020). Recovery can ensure supply, reduce import dependency, counteract price volatility, and sustainable e-mobility (Hoyer et al., 2015; Yu et al., 2021). EoL ALiBs could be recovered by a battery manufacturer, automotive manufacturer, retailer, or third-party (Alamerew & Brissaud, 2020).

EoL ALiB recovery center location selection problem must be solved to ensure infrastructure readiness when this complex waste flow reaches greater volumes as well as promote the sustainable development of the EV market. Besides, having a local EoL ALiB recovery center is highly advantageous over expensive and risky long-distance transport by road, air, and/or sea. However, the selection of an appropriate location to establish a recovery center for EoL ALiBs is a complicated and multi-aspect decision-making problem that is influenced by multiple evaluation criteria. In this regard, multi-criteria decision-making (MCDM) models can be used as reliable tools to address complex and multi-aspect problems (Yazdani, Torkayesh, & Chatterjee, 2020).

In this paper, we developed an integrated MCDM model by using Measuring Attractiveness by a Categorical Based Evaluation TecHnique (MACBETH) and Weight Aggregated Sum Product ASsessment (WASPAS) to select the most suitable location for an EoL AliB recovery center. The proposed integrated MCDM model is implemented under triangular fuzzy numbers (TFNs) to empower experts with a more flexible decision-making environment. The introduced integrated fuzzy MCDM model is built based on Dombi T-norm and T-conorm to overcome the disadvantages of traditional MACBETH and WASPAS methods due to their max–min operator which only uses one variable to select the optimal decision alternative.

To the best of the authors' knowledge, none of the previous studies in the field of LiB management have addressed the recovery center location selection problem. In real-world recovery center selection problems for EoL ALiBs, not only technical criteria play important role in selecting an appropriate location, but also economic, environmental, and social criteria. They all must be considered to maximize the advantages of the final results. As a result, this study contributes by identifying criteria for locating recovery centers for EoL ALiBs from the relevant literature. Another contribution of this study relies on introducing a novel approach based on the integrated fuzzy MACBETH-D-WASPAS model, where fuzzy MACBETH is used to determine criteria importance, and fuzzy Dombi WASPAS (D-WASPAS) is applied to evaluate location alternatives with respect to the criteria. Besides, this study improves arithmetic operations with Dombi T-norm and T-conorm in a fuzzy environment to enable the fusion of fuzzy numbers regardless of the values with which they are presented. Finally, it should be noted that this is the first study that addresses recovery center location selection problems in a multi-aspect environment to fill the gap in practical decision-making.

The remainder of this paper is organized as follows: Section 2 presents an overview of the related work. Section 3 describes the preliminaries and detailed steps of the proposed methodology. Section 4 presents information related to the real-life case study. Section 5 illustrates the results, sensitivity analysis, and validation. Finally, we conclude in Section 6.

2. Literature review

The literature review is organized into five sub-sections. The first sub-section identifies criteria for locating EoL ALiB recovery centers from the literature. The second sub-section surveys available decision-making approaches for LiB management. The third sub-section reviews the MACBETH method. The fourth sub-section investigates applications of the fuzzy WASPAS method. The last sub-section presents identified research gaps.

2.1. Evaluation criteria

The assessment of appropriate locations for establishing a recovery center for EoL ALiBs is a complicated and multi-aspect decision-making problem that is influenced by multiple evaluation criteria. Since this emerging facility location problem belongs to the engineering research area, its technical aspect needs to be taken into account. Besides, to encourage the green transition of the waste management industry, the three pillars of sustainability (i.e., economic pillar, environmental pillar, and social pillar) have to be considered.

A systematic approach is carried out to identify evaluation criteria for locating recovery centers for EoL ALiBs from the relevant literature. Two electronic databases were comprehensively investigated, i.e., Web of Science and Scopus. Besides, only peer-reviewed journal papers were taken into consideration.

Twenty-four criteria are identified (see Table 1). As can be seen from this table, the comprehensive literature review revealed seven economic, six environmental, five social, and six technical criteria. Each identified criterion is briefly defined in Table 1.

2.2. Decision-Making approaches for Lithium-ion battery management

LiB management attracted a large interest from researchers in recent years. Many state-of-the-art decision-making approaches have been introduced for LiB management (see Table 2).

Richa, Babbitt, Gaustad, and Wang (2014) applied a scenario-driven material flow analysis (MFA) to project the potential volume and timing of EoL ALiBs by addressing acceptance dynamics, lifespan, and constituent materials. Zhang et al. (2014) proposed a genetic algorithm-TOPSIS approach for identifying parameters of multi-physics models for LiBs. Hoyer et al. (2015) introduced a scenario-specific reverse supply-chain optimization model to establish an EoL ALiB network in Germany and generate long-term investment plans. Gu, Liu, and Qing (2017) assessed the effects of a government subsidy on a production quantity and LiB recovery rate under a normally distributed random market demand for EVs.

Gu et al. (2018a,b) presented a three-period ALiB closed-loop supply chain (CLSC) to describe the return, reuse, and remanufacturing processes. Li, Dababneh, and Zhao (2018) formulated a mixed-integer nonlinear program to maximize the profit of a CLSC network for ALiB remanufacturing considering different quality levels and location-allocation decisions. Murrant and Radcliffe (2018) applied the multi-attribute value theory for assessing energy storage projects. Ren (2018) developed an intuitionistic fuzzy MCDM approach for sustainability assessment of LiB, hydro, compressed air, and flywheel energy storage systems. Tang, Zhang, Li, Wang, and Li (2018, Tang, Zhang et al., 2019) introduced a non-cooperative game-theoretical model to analyze the impacts of EoL ALiB recovery under reward-penalty mechanisms. Tosarkani and Amin (2018) formulated a multi-objective battery CLSC model to maximize the total profit and the green performance of EoL ALiB recovery centers. Zhao et al. (2018, 2019) provided hybrid MCDM approaches to prioritize LiB, Lead-acid, Nickel-cadmium, Nickel-

Table 1
Criteria for locating end-of-life automotive Lithium-ion battery recovery centers identified from the literature.

Criteria	Code	Type	Definition	Reference(s)
Economic	MC_1			
Collection cost	C_1	Min	The average special transportation distance from decentralized collection points immediately after returns	Richa et al. (2014), Hoyer et al. (2015), Alamerew and Brissaud (2020), Li, Mu et al. (2020), Wang et al. (2020), Scheller et al. (2021), Yu et al. (2021)
Disposal cost	C_2	Min	The average transportation distance from industrial landfills and related gate fees	Hoyer et al. (2015), Rahman and Afroz (2017), Alfaro-Algaba and Ramirez (2020), Wang et al. (2020), Wu, Zhang, & Yi (2020), Scheller et al. (2021)
Distance to secondary markets	C_3	Min	The average transportation distance to relevant secondary markets	Vieceli, Pedrosa, Margarido, and Nogueira (2016), Li et al. (2018), Tosarkani and Amin (2018), Ai et al. (2019), Chen et al. (2019), Alamerew and Brissaud (2020), Alfaro-Algaba and Ramirez (2020), Rafele et al. (2020), Wang et al. (2020), Yu et al. (2021)
Financial benefit	C_4	Max	The degree of return on investment and indirect financial benefits	Rahman and Afroz (2017), Gu, Ieromonachou, Zhou, and Tseng (2018a), Zhao et al. (2019), Alamerew and Brissaud (2020), Alfaro-Algaba and Ramirez (2020), Liu and Du (2020), Çolak and Kaya (2020), Li, Mu et al. (2020), Li, Mu et al. (2020), Wu, Lin et al. (2020), Scheller et al. (2021), Fazlollahtabar and Kazemitash (2021)
Incentive	C_5	Max	Local financial support for environmentally friendly enterprises	Gu et al. (2017, 2018a), Song and Chu (2019), Tang et al. (2018, 2019), Li, Ku et al. (2020), Çolak and Kaya (2020), Zhu and Li (2020), Zhu et al. (2020)
Investment cost	C_6	Min	A one-time investment in fixed assets; e.g., new facilities, auxiliary equipment, and commissioning	Liu and Du (2020), Çolak and Kaya (2020), Wang et al. (2020), Zhu et al. (2020), Yu et al. (2021)
Operational costs	C_7	Min	Labour, material, energy, inspection, processing, maintenance costs, and fixed asset depreciation	Richa et al. (2014), Hoyer et al. (2015), Gu et al. (2017), Rahman and Afroz (2017), Ren (2018), Tosarkani and Amin (2018), Zhao et al. (2018, 2019), Alamerew and Brissaud (2020), Alfaro-Algaba and Ramirez (2020), Kamath et al. (2020), Li, Mu et al. (2020), Çolak and Kaya (2020), Rafele et al. (2020), Wang et al. (2020), Zhu et al. (2020), Yu et al. (2021)
Environmental	MC_2			
Carbon footprint	C_8	Min	The total greenhouse gas emissions caused by a recovery center	Zeng et al. (2015), Onat et al. (2016), Casals, García, Aguesse, and Iturrondobeitia (2017), Hagman, Ritzén, Stier, and Susilo (2016), Rahman and Afroz (2017), Ren (2018), Tang et al. (2018), Çolak and Kaya (2020), Wang et al. (2020),
Hazardous waste generation	C_9	Min	The average volume of hazardous waste generated	Onat et al. (2016), Ren (2018), Liu and Du (2020), Yu et al. (2021)
Land disruption	C_{10}	Min	The negative impact on the natural ecosystem and an urban population	Hendrickson, Kavvada, Shah, Sathre, and Scown (2015), Çolak and Kaya (2020)
Policy compatibility	C_{11}	Max	Directive 2006/66/EC obliges manufacturers to ensure cost-free take-back of all types of batteries	Hoyer et al. (2015), Rahman and Afroz (2017), Li, Mu et al. (2020), Wu, Zhang et al. (2020), Scheller et al. (2021)
Resource consumption	C_{12}	Min	Resource consumption of raw material, energy, and water during recovery	Alamerew and Brissaud (2020), Çolak and Kaya (2020)
Water pollution	C_{13}	Min	Heavy metals and harmful electrolytes in ALiBs can pollute (ground)water	Liu and Du (2020), Çolak and Kaya (2020), Yu et al. (2021)
Social	MC_3			
Affected population	C_{14}	Min	The ratio of the affected population around an alternative location	Hendrickson et al. (2015), Çolak and Kaya (2020)
Awareness	C_{15}	Max	Public opinions, community engagement, education, and outreach programs	Ren (2018), King and Boxall (2019), Liu and Du (2020), Zhu and Li (2020), Simic, Karagoz, Deveci, and Aydin (2021)
Employment	C_{16}	Max	The full-time equivalent employment created for a local community	Zhao et al. (2019), Liu and Du (2020), Pamucar, Deveci et al. (2020), Çolak and Kaya (2020), Wu, Zhang et al. (2020)
Health & safety impact	C_{17}	Min	Health and safety issues associated with operations of recovery centers	Hendrickson et al. (2015), Zhao, Guo, and Zhao (2018), King and Boxall

(continued on next page)

Table 1 (*continued*)

Criteria	Code	Type	Definition	Reference(s)
				(2019), Albawab et al. (2020), Çolak and Kaya (2020), Hua et al. (2020), Loganathan et al. (2021)
Local development	C_{18}	Max	Public services and community projects	Tang et al. (2018, 2019), Pamucar, Deveci et al. (2020), Milenkov, Sokolović, Milovanović, & Milić, 2020
Technical	MC_4			
Capacity strategy	C_{19}	Max	A robust center includes a wide-ranging recovery capacity to attain economies of scale	Richa et al. (2014), Hoyer et al. (2015), Zhao et al. (2018, 2019), Çolak and Kaya (2020); Liu and Du (2020); Pamucar, Deveci et al. (2020), Zhu et al. (2020)
Flexibility	C_{20}	Max	The flexibility of technology, use of existing mineral processing technology, and preprocessing options	King and Boxall (2019), Pamucar, Deveci et al. (2020)
Land requirement	C_{21}	Min	The area of land that a recovery center occupies	Albawab et al. (2020), Çolak and Kaya (2020), Wu, Zhang et al. (2020), Milosevic, Pamucar, & Chatterjee, 2021
Reliability	C_{22}	Max	Failure-free recovery operations and impact on power grid stability	Song et al. (2019), Alamerew and Brissaud (2020), Çolak and Kaya (2020), Tang, Liu et al. (2019), Wu, Xue et al. (2020), Loganathan et al. (2021)
Technology	C_{23}	Max	The availability of a recovery technology determines the quantity and quality of isolated materials and residues	Ziemann, Müller, Schebek, and Weil (2018), Hoyer et al. (2015), Zhan et al. (2020), Zhu and Li (2020), Scheller et al. (2021)
Waste infrastructure	C_{24}	Max	Availability of a local hazardous waste infrastructure	Zeng et al. (2015), Casals et al. (2017), King and Boxall (2019), Song et al. (2019)

metal Hydride, Sodium-sulfur, and Vanadium Redox Flow battery energy storage systems.

Ai et al. (2019) analyzed EoL ALiB volume at national, state, and county scales in terms of lifespan scenarios, discard probability functions, and sale projections. Bobba, Mathieux, and Blengini (2019) developed a dynamic ALiB stock and flows model to extrapolate information on energy capacity storage and embedded materials within Europe. Deng et al. (2019) built a universal SOH estimation model for LiBs under multi-working conditions based on the support vector machine approach. Li, Wang, Zhang, Zou, and Dorrell (2019) introduced an incremental capacity analysis to establish a LiB degradation model based on SOH performance indicators. Song et al. (2019) created dynamic MFAs of the critical raw materials for the Chinese LiB industry. Tang, Liu et al. (2019a) integrated the concept of mixed membership function, dispersion information on health indicators, and Analytic Hierarchy Process (AHP) to monitor the SOH of LiBs.

Recently, Aikhuele (2020) explored the reliability and safety of a cathode, anode, electrolyte, and separator of a commercial Lithium Manganese Oxide battery by using an intuitionistic fuzzy MCDM approach. Alamerew and Brissaud (2020) a general model for remanufacturing of EoL ALiBs based on the principles of the system dynamics methodology. Albawab, Ghenai, Bettayeb, and Janajreh (2020) coupled two MCDM methods to rank LiBs, lead-acid batteries, supercapacitors, hydrogen, compressed air, pumped hydro, and thermal sustainable energy storage technologies. Alfaro-Algaba and Ramirez (2020) presented a model for the techno-economic and environmental disassembly sequence planning of ALiBs for remanufacturing. Li, Ku, Liu, and Zhou (2020) formulated non-cooperative game models to investigate the optimal prices and production quantities by considering battery recovery under subsidy and dual credit policy. Li, Mu et al. (2020) provided a combined game theory-system dynamics model to analyze the effect of the deposit-refund scheme on ALiB recovery in China. Liu and Du (2020) introduced a dual hesitant Pythagorean fuzzy linguistic term set-based MCDM approach to compare LiBs, high-temperature thermal energy storage, flywheels, and supercapacitors. Çolak and Kaya (2020) formulated a hesitant fuzzy MCDM methodology to prioritize nine energy storage technology alternatives for Turkey. Pamucar, Deveci et al. (2020) presented a fuzzy neutrosophic decision-making approach to select hydrogen storage technology in Romania. Rallo, Benveniste, Gestoso, and Amante (2020) investigated the disassembling process of ALiBs to obtain insights into the costs of each operation. Rafele, Mangano, Cagliano, and Carlin (2020) utilized the scenario-based optimization approach to evaluate different logistics configurations to deliver batteries for EVs. Wang et al. (2020) proposed a mixed-integer linear programming model to minimize costs and carbon dioxide emissions of a real-life ALiB processing network. Wu, Xue et al. (2020) established a recurrent neural network-based approach to enhance the correlation between LiB healthy features and its SOH. Zhang et al. (2020) integrated a Gaussian process regression and hybrid accuracy index importance assessment approaches to estimate LiB remaining useful life. Zhu and Li (2020) explored pricing mechanisms of dual-channel battery CLSC systems under different government subsidies. Zhu et al. (2020) investigated channel choice and capacity allocation decisions of EV manufacturers in the context of battery recovery under non-cooperation and cooperation cases. Loganathan, Mishra, Tan, Kongsvik, and Rai (2021) utilized the simple additive weighting method to assess several LiB types based on the electrode material, including Lithium Cobalt Oxide, Lithium Manganese Oxide, Lithium Nickel Manganese Cobalt Oxide, Lithium Iron Phosphate, and Lithium-Titanate batteries. Scheller, Schmidt, and Spengler (2021) formulated an integrated ALiB master production and recovery supply chain model to consider material prices, demand, technology influence, and processing efficiency. Apart from these models, various models from the literature can be used such as observation process modelling and cognitive systems (Pozna & Precup, 2012), evolving fuzzy models (Precup et al., 2017), COPRAS based hesitant fuzzy sets (Krishankumar et al., 2021), interval type-2 fuzzy best-worst method and combined compromise solution (Tavana, Shaabani, Di Caprio, & Bonyani, 2022), and interval-valued probabilistic hesitant fuzzy set (Krishankumar, Ravichandran, Kar, Gupta, & Mehlawat, 2019).

2.3. MACBETH method

The MACBETH method has become increasingly popular in decision-making. A number of studies using the MACBETH method are summarized in Table 3.

Ertay, Kahraman, and Kaya (2013) assessed five renewable energy alternatives including hydropower, wind, solar, biomass, and geothermal using MACBETH and AHP based on fuzzy sets. Dhouib (2014) proposed an extension of the MACBETH method under uncertainty to evaluate alternatives in reverse logistics for waste tires. Kundakcı and Işık (2016) studied an integrated MACBETH-COPRAS approach to evaluate air compressors for a textile company.

Table 2
Summary of the available decision-making approaches for Lithium-ion battery management.

Author(s) and year	Research focus	GDM (Yes/No)	Parameter type	SA (Yes/No)	Method(s)	Application type
Richa et al. (2014)	Quantity projection	No	Stochastic	Yes	MFA	IE
Zhang et al. (2014)	Parameter identification	No	Deterministic	No	NSGA-II, TOPSIS	IE
Hoyer et al. (2015)	Network design	No	Deterministic	Yes	MILP	Real-life
Gu et al. (2017)	Inventory management	No	Stochastic	Yes	Newsvendor model	IE
Gu et al. (2018a)	Network design	No	Stochastic	Yes	Game theory	IE
Gu, Ieromonachou, Zhou, and Tseng (2018b)	Network design	No	Deterministic	Yes	MINLP	IE
Li et al. (2018)	Network design	No	Deterministic	Yes	MINLP	IE
Murrant and Radcliffe (2018)	Energy storage technology evaluation	Yes	Deterministic	Yes	MAVT	Real-life
Ren (2018)	Energy storage technology evaluation	No	Interval, IF	Yes	AHP, CODAS	IE
Tang et al. (2018, 2019)	Pricing mechanism evaluation	No	Stochastic	Yes	Stackelberg game	IE
Tosarkani and Amin (2018)	Network design	No	Fuzzy	No	FFP, MOFP, ANP	Real-life
Zhao et al. (2018)	Energy storage system evaluation	Yes	Deterministic	No	Delphi, SE, BWM, VIKOR	IE
Ai et al. (2019)	Quantity projection	No	Stochastic	Yes	PFA	Real-life
Bobba et al. (2019)	Quantity projection	No	Deterministic	Yes	MFA	Real-life
Deng et al. (2019)	State-of-health estimation	No	Deterministic	No	LSSVM, GRA	IE
Li et al. (2019)	State-of-health estimation	No	Deterministic	Yes	SE, GRA	IE
Song et al. (2019)	Critical raw material evaluation	No	Stochastic	Yes	MFA	Real-life
Tang et al. (2019a)	State-of-health estimation	No	Fuzzy	Yes	MMF, AHP	IE
Zhao et al. (2019)	Energy storage system evaluation	Yes	Deterministic, fuzzy	Yes	Delphi, BWM, CPT	IE
Aikhuele (2020)	Component evaluation	Yes	Intuitionistic fuzzy	No	OWG operator	IE
Alamerew and Brissaud (2020)	Remanufacturing enablers and barriers	No	Stochastic	No	SDS	Real-life
Albawab et al. (2020)	Energy storage technology evaluation	Yes	Deterministic	Yes	SWARA, ARAS	IE
Alfaro-Algaba and Ramirez (2020)	Disassembly planning	No	Deterministic	Yes	CBA	Real-life
Li, Ku et al. (2020)	Pricing mechanism evaluation	No	Deterministic	Yes	Stackelberg game	IE
Li, Mu et al. (2020)	Pricing mechanism evaluation	No	Stochastic	Yes	Stackelberg game, SDS	Real-life
Liu and Du (2020)	Energy storage technology evaluation	Yes	DHFLT	Yes	ME, GRA	Real-life
Çolak and Kaya (2020)	Energy storage technology evaluation	Yes	Hesitant fuzzy	Yes	Delphi, AHP, VIKOR	Real-life
Pamucar, Deveci et al. (2020)	Energy storage technology evaluation	Yes	Fuzzy neutrosophic	Yes	MAIRCA, DWGAO	Real-life
Rallo et al. (2020)	Disassembly planning	No	Deterministic	No	CBA	Real-life
Rafele et al. (2020)	Network design	Yes	Deterministic	Yes	Brainstorming, TCM	Real-life
Wang et al. (2020)	Network design	No	Deterministic	Yes	MILP	Real-life
Wu, Xue et al. (2020)	State-of-health estimation	No	Deterministic	Yes	LSTM RNN, SE, GRA	IE
Zhang et al. (2020)	Remaining useful life estimation	No	Deterministic	Yes	GPR, SE, AHP	IE
Zhu and Li (2020)	Pricing mechanism evaluation	No	Deterministic	Yes	Stackelberg game	IE
Zhu et al. (2020)	Pricing mechanism evaluation	No	Deterministic	Yes	Stackelberg game	IE
Loganathan et al. (2021)	Type evaluation	No	Deterministic	No	SAW	IE
Scheller et al. (2021)	Network design	No	Deterministic	Yes	MILP	IE
Our study	*Recovery center location selection*	*Yes*	*Fuzzy*	*Yes*	*MACBETH, DWAO, DWGAO, WASPAS*	*Real-life*

Additive Ratio ASsessment: ARAS; Analytic Network Process: ANP; Analytic Hierarchy Process: AHP; Best-Worst Method: BWM; Cost-Benefit Analysis: CBA; Cumulative Prospect Theory: CPT; Dombi Weighted Averaging Operator: DWAO; Dombi Weighted Geometric Averaging Operator: DWGAO; Dual Hesitant Pythagorean Fuzzy Linguistic Term: DHFLT; End-of-Life Automobile Lithium-ion Battery: EoL ALiB; Fully Fuzzy Programming: FFP; Gaussian Process Regression: GPR; Grey Relational Analysis: GRA; Group Decision-Making: GDM; Illustrative Example: IE; Intuitionistic Fuzzy: IF; Least Squares Support Vector Machine: LSSVM; Long Short-Term Memory Recurrent Neural Network: LSTM RNN; Materials Flow Analysis: MFA; Maximum Entropy: ME; Measuring Attractiveness by a Categorical Based Evaluation TecHnique: MACBETH; Mixed Membership Function: MMF; Mixed-Integer Linear Programming: MILP; Mixed-Integer NonLinear Programming: MINLP; Multi Atributive Ideal-Real Comparative Analysis: MAIRCA; Multi-Attribute Value Theory: MAVT; Multi-Objective Fuzzy Programming: MOFP; Nondominated Sorting Genetic Algorithm: NSGA-II; Ordered Weighted Geometric Operator: OWGO; Product Flow Analysis: PFA; Sensitivity Analysis: SA; Shannon entropy: SE; Simple Additive Weighting: SAW; Stepwise Weight Assessment Ratio Analysis: SWARA; System Dynamics Simulation: SDS; Technical-Cost Modeling: TCM; Technique for the Order Preference by Similarity to Ideal Solution: TOPSIS; VIšeKriterijumska Optimizacija i kompromisno Rešenje: VIKOR; Weight Aggregated Sum Product Assessment: WASPAS.

Komchornrit (2017) presented an integrated MACBETH-PROMETHEE model for the evaluation of dry port locations. Pishdar, Ghasemzadeh, and Antuchevičienė (2019) examined the selection of a hub airport in developing countries using a mixed interval type-2 fuzzy-based best-worst MACBETH approach.

2.4. WASPAS method

WASPAS is one of the well-known and frequently used MCDM methods developed by Zavadskas, Antucheviciene, Hajiagha, and Hashemi (2014) to tackle complicated decision-making problems in supply chain management (Ali, Mahmood, Ullah, & Khan, 2021; Pamucar, Torkayesh, & Biswas, 2022), energy management (Schitea et al., 2019), construction management (Turskis et al., 2015), transportation engineering (Tumsekcali, Ayyildiz, & Taskin, 2021), etc. Recent fuzzy set-based WASPAS studies are categorized in Table 4. It can be seen that different fuzzy sets can be used in various application areas.

Table 3
Overview of studies on MACBETH method.

Author(s) and year	Research focus	Parameter type	Combined method(s)	Application		Main criteria	Sub-criteria	Alternatives
				Country	Type			
Ertay et al. (2013)	Energy alternative evaluation	Fuzzy	AHP	Turkey	Real-life	4	15	5
Dhouib (2014)	Reverse logistics assesment	2-tupple fuzzy linguistic	–	Tunisia	Real-life		4	5
Kundakcı and Işık (2016)	Air compressor selection	Deterministic	COPRAS	Turkey	Real-life	–	9	6
Komchornrit (2017)	Dry port location selection	Deterministic	PROMETHEE	Thailand	Real-life	7	12	10
Pishdar et al. (2019)	Hub airport selection	Interval type-2 fuzzy	BWM	Iran	Real-life	–	5	19
Our study	*Recovery center location selection*	*Fuzzy*	*MACBETH, DWAO, DWGAO, WASPAS*	Turkey	*Real-life*	*4*	*24*	*6*

Analytic Hierarchy Process: AHP; Best-Worst Method: BWM; COmplex PRoportional ASsessment: COPRAS; Dombi Weighted Averaging Operator: DWAO; Dombi Weighted Geometric Averaging Operator: DWGAO; Measuring Attractiveness by a Categorical Based Evaluation TecHnique: MACBETH; Preference Ranking Organization METHod for Enrichment Evaluation: PROMETHEE; Weight Aggregated Sum Product Assessment: WASPAS.

Table 4
Overview of studies on fuzzy WASPAS.

Author(s) and year	Research focus	Parameter type	Combined method(s)	Application		Main criteria	Sub-criteria	Alternatives
				Country	Type			
Zavadskas et al. (2014)	Derelict building ranking	IVIF	–	Lithuania	Real-life	–	15	3
Turskis, Zavadskas, Antucheviciene, and Kosareva (2015)	Construction site selection	Fuzzy	AHP	Lithuania	Real-life	–	8	4
Ghorabaee, Zavadskas, Amiri, and Esmaeili (2016)	Green supplier selection	Interval type-2 fuzzy	–	–	IE	–	7	8
Ghorabaee et al. (2016)	3PL Provider Evaluation	Interval type-2 fuzzy	CRITIC	–	IE	–	7	8
Stanujkić and Karabašević (2018)	Website evaluation	Intuitionistic fuzzy	–	–	IE	–	4	3
Alam, Ahmed, Butt, Kim, and Ko (2018)	Cloud service evaluation	Fuzzy	AHP	–	Real-life	5	15	6
Deveci, Canıtez, and Gökaşar (2018)	Car sharing station selection	Interval type-2 fuzzy	TOPSIS	Turkey	Real-life	5	9	4
Kutlu Gundogdu and Kahraman (2019)	Industrial robot selection	Spherical fuzzy	–	–	IE	–	4	5
Mishra et al. (2019)	Green supplier selection	Hesitant fuzzy	–	–	IE	–	10	4
Turskis, Goranin, Nurusheva, and Boranbayev (2019)	Critical information infrastructure	Fuzzy	AHP	Lithuania	Real-life	–	6	3
Agarwal, Kant, and Shankar (2020)	Humanitarian SCM evaluation	Fuzzy	SWARA	–	Real-life	–	29	20
Gireesha, Somu, Krithivasan, and Vs, s. s. (2020)	Cloud service selection	IVIF	–	–	Real-life	–	9	15
Mardani, Saraji, Mishra, and Rani (2020)	Digital technology system ranking	Hesitant fuzzy	SWARA	–	Real-life	–	24	4
Pamucar, Deveci, Canıtez, and Lukovac (2020)	Airport ground access mode selection	Fuzzy	–	Turkey	Real-life	4	14	4
Schitea et al. (2019)	Hydrogen roll-up site selection	Intuitionistic fuzzy	–	Romania	Real-life	5	14	4
Ali et al. (2021)	Supplier selection	Probabilistic linguistic	–	–	IE	–	3	4
Rudnik, Bocewicz, Kucińska-Landwójtowicz, and Czabak-Górska (2020)	Improvement project selection	Ordered fuzzy number	–	Poland	Real-life	9	19	5
Simić, Lazarević, and Dobrodolac (2021)	Last-mile delivery mode selection	Picture fuzzy	–	Serbia	Real-life	4	19	6
Tumsekcali et al. (2021)	Public transportation mode selection	IVIF	Delphi, AHP	Turkey	Real-life	7	19	5
Garg, Krishankumar, and Ravichandran (2022)	Logistics provider selection	PHF	Shannon entropy	–	IE	–	7	8
Our study	*Recovery center location selection*	*Fuzzy*	*MACBETH, DWAO, DWGAO, WASPAS*	Turkey	*Real-life*	*4*	*24*	*6*

Analytic Hierarchy Process: AHP; CRiteria Importance Through Intercriteria Correlation: CRITIC; Dombi Weighted Averaging Operator: DWAO; Dombi Weighted Geometric Averaging Operator: DWGAO; Illustrative Example: IE; Interval-Valued Intuitionistic Fuzzy: IVIF; Measuring Attractiveness by a Categorical Based Evaluation TecHnique: MACBETH; Probabilistic Hesitant Fuzzy: PHF; Stepwise Weight Assessment Ratio Analysis: SWARA; Supply Chain Management: SCM; Technique for the Order Preference by Similarity to Ideal Solution: TOPSIS; Third-Party Logistics: 3PL; Weight Aggregated Sum Product Assessment: WASPAS.

2.5. Research gaps

According to the performed literature review, the recovery center location selection problem is not addressed in the previous studies. As discussed earlier, recovery center location selection is a multi-aspect and complicated problem affected by different criteria under technical, economic, environmental, and social aspects. To the best of our knowledge, this study is the first of its kind in addressing recovery center location selection as one of the critical problems of EVs and EoL ALiBs.

The first contribution of this study is the identification and definition of important influencing criteria for locating EoL ALiB recovery centers under several aspects. Complete identification of appropriate criteria for evaluation of location alternatives is the crucial point. Besides, this study provides a novel integrated MCDM model to empower decision-makers and experts in the field of battery management to efficiently express their preferences and select the most suitable location alternative. The novel MCDM model is constructed using two well-known decision-making methods, MACBETH and WASPAS. The developed method is implemented under TFNs due to uncertain and vague information in real-world applications. Finally, the last contribution of this study is the implementation of the Dombi weighting average according to T-norm and T-conorm to fill the gap of traditional MCDM methods which only use max–min operators. Utilization of Dombi T-norm and T-conorm can increase the reliability and robustness of generated solutions as well as significantly improve flexibility in decision-making.

3. Proposed multi-criteria decision-making framework

The MCDM methodology introduced in this paper (see Fig. 1) presents a model that enables the processing of group information obtained by experts. In addition to processing group information, the proposed methodology allows processing uncertainty in expert preferences using fuzzy linguistic variables. The proposed MCDM model is based on the application of Dombi norms and improves the performance of the traditional WASPAS (Zavadskas, Turskis, Antucheviciene, & Zakarevicius, 2012). Traditional WASPAS method provides objective results in cases where the values of the ratings of alternatives are uniform in initial decision-making matrix. However, when extreme values appear at the position of the most influential criteria in initial decision-making matrix, extreme changes in the values of weighted linear functions occur. This further leads to disproportionate increase in the value of the criterion function of the considered alternative. This phenomenon is most often the consequence of linear character of weighted linear functions in WASPAS method.

Mathematical models for decision-making require objective and rational apparatus enabling realistic view of the interactions between attributes of a decision and the elimination of such anomalies. Therefore, the authors in this paper decided to improve mathematical apparatus of traditional WASPAS model by introducing hybrid fuzzy Dombi weighted averaging (FDWA) and the fuzzy Dombi weighted geometric averaging (FDWGA) functions so as to create compromise strategies. The FDWA and FDWGA functions enable nonlinear information processing in the Dombi WASPAS (D-WASPAS) model with significantly greater flexibility in decision-making. By applying the Dombi functions (Dombi, 2009) in the WAPAS methodology, the information fusion process is much more flexible compared to a traditional method. Flexibility is a consequence of the general parameters that exist in Dombi T-norm and T-conorm (Yazdani, Chatterjee, Pamucar, & Chakraborty, 2020).

Within the multi-criteria framework (see Fig. 1), an extension of the MACBETH methodology using TFNs is presented. A fuzzy linear MACBETH model based on TFNs was developed to determine the weighting coefficients of the criteria. The MACBETH methodology belongs to a group of subjective models for determining weight coefficients of criteria based on pairwise comparisons of criteria (Bana e Costa & Vansnick, 1994). The MACBETH methodology was used for implementation in this study as it has a number of advantages, including: *(i)* Eliminates inconsistencies; *(ii)* The obtained values of weighting coefficients are always optimal; *(iii)* Provides the possibility for theoretical and semantic consistency check; and *(iv)* Maximum of $n(n\text{-}1)/2$ comparisons, but the results can be obtained even after n-1 comparisons. To date, the crisp MACBETH methodology has found wide application for determining the weighting coefficients of criteria and evaluating alternatives in numerous studies (Bana e Costa & Chagas, 2004; Bana e Costa et al., 1994, 2002; Costa, 2001; Kundakcı, 2019; Montignac, Noirot, & Chaudourne, 2009; Rodrigues, 2014). To the best of our knowledge, the application of TFNs in the MACBETH model has not been considered in the literature so far.

In the next part of this section, the preliminaries are briefly provided. After that, based on the preliminary settings, the mathematical formulation of the improved WASPAS method and the fuzzy MACBETH model is presented.

3.1. Preliminaries

Fuzzy set theory (Zadeh, 1965) is one of the most commonly used theories for dealing with uncertainty in MCDM (Ali et al., 2021; Blagojević, Vesković, Kasalica, Gojić, & Allamani, 2020; Bozanic, Milic, Tešic, Salabun, & Pamucar, 2021; Kushwaha, Panchal, & Sachdeva, 2020). To represent uncertainty using fuzzy theory, researchers most commonly use TFNs. The idea of fuzzy sets and TFNs, as well as Dombi T-norm and T-conorm, are given in Appendix A1.

Based on Dombi T-norm and T-conorm (see Appendix A1), we can define Dombi operations on TFNs.

Definition 1. *Let's assume that* $\widetilde{A}_1=(\xi_1^{(l)},\xi_1^{(m)},\xi_1^{(u)})$ *and* $\widetilde{A}_2=(\xi_2^{(l)},\xi_2^{(m)},\xi_2^{(u)})$ *are two TFNs,* $\rho,\ \gamma>0$ *and let it be* $f\left(\widetilde{A}_i\right)$

$$=\left(f\left(A_i^{(l)}\right),f\left(A_i^{(m)}\right),f\left(A_i^{(u)}\right)\right)=$$

$\left(\xi_i^{(l)}/\sum_{i=1}^{n}\xi_i^{(l)},\ \xi_i^{(m)}/\sum_{i=1}^{n}\xi_i^{(m)},\ \xi_i^{(u)}/\sum_{i=1}^{n}\xi_i^{(u)}\right)$ *fuzzy function, then some operational lows of TFNs based on the Dombi T-norm and T-conorm can be defined as follows*:

(1) Addition "⊕".

$$\widetilde{A}_1\oplus\widetilde{A}_2=\left(\begin{array}{c}\sum\limits_{i=1}^{2}\xi_i^{(l)}-\dfrac{\sum_{i=1}^{2}\xi_i^{(l)}}{1+\left\{\left(\dfrac{f\left(A_1^{(l)}\right)}{1-f\left(\widetilde{A}_1^{(l)}\right)}\right)^{\rho}+\left(\dfrac{f\left(A_2^{(l)}\right)}{1-f\left(\widetilde{A}_2^{(l)}\right)}\right)^{\rho}\right\}^{1/\rho}},\\ \sum\limits_{i=1}^{2}\xi_i^{(m)}-\dfrac{\sum_{i=1}^{2}\xi_i^{(m)}}{1+\left\{\left(\dfrac{f\left(A_1^{(m)}\right)}{1-f\left(A_1^{(m)}\right)}\right)^{\rho}+\left(\dfrac{f\left(A_2^{(m)}\right)}{1-f\left(A_2^{(m)}\right)}\right)^{\rho}\right\}^{1/\rho}},\\ \sum\limits_{i=1}^{2}\xi_i^{(u)}-\dfrac{\sum_{i=1}^{2}\xi_i^{(u)}}{1+\left\{\left(\dfrac{f\left(A_1^{(u)}\right)}{1-f\left(A_1^{(u)}\right)}\right)^{\rho}+\left(\dfrac{f\left(A_2^{(u)}\right)}{1-f\left(A_2^{(u)}\right)}\right)^{\rho}\right\}^{1/\rho}}\end{array}\right), \tag{1}$$

(2) Multiplication "$\otimes$".

$$\widetilde{A}_1 \otimes \widetilde{A}_2 = \left(\begin{array}{c} \dfrac{\sum_{i=1}^{2} \xi_i^{(l)}}{1+\left\{ \left(\dfrac{1-f\left(A_1^{(l)}\right)}{f\left(\widetilde{A}_1^{(l)}\right)} \right)^{\rho} + \left(\dfrac{1-f\left(A_2^{(l)}\right)}{f\left(\widetilde{A}_2^{(l)}\right)} \right)^{\rho} \right\}^{1/\rho}}, \\ \dfrac{\sum_{i=1}^{2} \xi_i^{(m)}}{1+\left\{ \left(\dfrac{1-f\left(A_1^{(m)}\right)}{f\left(A_1^{(m)}\right)} \right)^{\rho} + \left(\dfrac{1-f\left(A_2^{(m)}\right)}{f\left(A_2^{(m)}\right)} \right)^{\rho} \right\}^{1/\rho}}, \\ \dfrac{\sum_{i=1}^{2} \xi_i^{(u)}}{1+\left\{ \left(\dfrac{1-f\left(A_1^{(u)}\right)}{f\left(A_1^{(u)}\right)} \right)^{\rho} + \left(\dfrac{1-f\left(A_2^{(u)}\right)}{f\left(A_2^{(u)}\right)} \right)^{\rho} \right\}^{1/\rho}} \end{array} \right), \tag{2}$$

(3) Scalar multiplication.

$$\gamma\widetilde{A}_1 = \left(\xi_i^{(l)} - \frac{\xi_i^{(l)}}{1+\left\{ \gamma \left(\dfrac{f\left(A_1^{(l)}\right)}{1-f\left(A_1^{(l)}\right)} \right)^{\rho} \right\}^{1/\rho}},\ \xi_i^{(m)} - \frac{\xi_i^{(m)}}{1+\left\{ \gamma \left(\dfrac{f\left(A_1^{(m)}\right)}{1-f\left(A_1^{(m)}\right)} \right)^{\rho} \right\}^{1/\rho}},\ \xi_i^{(u)} - \frac{\xi_i^{(u)}}{1+\left\{ \gamma \left(\dfrac{f\left(A_1^{(u)}\right)}{1-f\left(A_1^{(u)}\right)} \right)^{\rho} \right\}^{1/\rho}} \right), \tag{3}$$

(4) Power

$$\widetilde{A}_1^{\gamma} = \left(\frac{\xi_i^{(l)}}{1+\left\{ \gamma \left(\dfrac{1-f\left(A_1^{(l)}\right)}{f\left(A_1^{(l)}\right)} \right)^{\rho} \right\}^{1/\rho}}, \frac{\xi_i^{(m)}}{1+\left\{ \gamma \left(\dfrac{1-f\left(A_1^{(m)}\right)}{f\left(A_1^{(m)}\right)} \right)^{\rho} \right\}^{1/\rho}}, \frac{\xi_i^{(u)}}{1+\left\{ \gamma \left(\dfrac{1-f\left(A_1^{(u)}\right)}{f\left(A_1^{(u)}\right)} \right)^{\rho} \right\}^{1/\rho}} \right). \tag{4}$$

Definition 2. *Let $\widetilde{A}_j = (\xi_j^{(l)}, \xi_j^{(m)}, \xi_j^{(u)})$; $(j = 1, 2, ..., n)$, is a set of TFNs, and $w_j \in [0,\ 1]$ represents its weight coefficient, which fulfills the requirement that it is $\sum_{j=1}^{n} w_j = 1$. Then the FDWA and FDWGA operators can be defined as follows*:

$$FDWA_w\left(\widetilde{A}_1,\ \widetilde{A}_2,\ ..,\ \widetilde{A}_n\right) = \sum_{j=1}^{n} w_j \cdot \widetilde{A}_j = \left(\sum_{j=1}^{n} w_j \cdot \xi_j^{(l)},\ \sum_{j=1}^{n} w_j \cdot \xi_j^{(m)},\ \sum_{j=1}^{n} w_j \cdot \xi_j^{(u)} \right), \tag{5}$$

$$FDWGA_w\left(\widetilde{A}_1,\ \widetilde{A}_2,\ ..,\ \widetilde{A}_n\right) = \prod_{j=1}^{n} \left(\widetilde{A}_j\right)^{w_j} = \left(\prod_{j=1}^{n} \left(\xi_j^{(l)}\right)^{w_j}, \prod_{j=1}^{n} \left(\xi_j^{(m)}\right)^{w_j}, \prod_{j=1}^{n} \left(\xi_j^{(u)}\right)^{w_j} \right). \tag{6}$$

3.2. *Fuzzy MACBETH-D-WASPAS model*

In this section, the fuzzy MACBETH-D-WASPAS model is presented. It has six steps.

Step 1. Formation of the initial decision matrix.

Suppose that in a multi-criteria model it is necessary to evaluate b alternatives. Evaluation of the alternatives from the set $A = \{A_1,\ A_2,\ \dots,\ A_b\}$ is performed concerning criteria from the set $C = \{C_1,\ C_2,\ \dots,\ C_n\}$. Also, suppose that k experts evaluate alternatives using a fuzzy linguistic scale. Then we get a total of k initial decision matrices $ID^e = \left[\widetilde{\zeta}_{ij}^{e}\right]_{b \times n}$ $(e = 1,\ 2,\ ...,\ k)$; i.e., one for each expert from the set $E = \{E_1,\ E_2,\ \dots,\ E_k\}$. The values $\widetilde{\zeta}_{ij}^{e} = \left(\zeta_{ij}^{(l)e},\ \zeta_{ij}^{(m)e},\ \zeta_{ij}^{(u)e}\right)$ represent the elements of the $ID^e = \left[\widetilde{\zeta}_{ij}^{e}\right]_{b \times n}$ matrix that are defined based on the fuzzy linguistic scale. Then by applying the FDWGA operator, we get an aggregated initial decision matrix$ID = \left[\widetilde{\zeta}_{ij}\right]_{b \times n}$:.

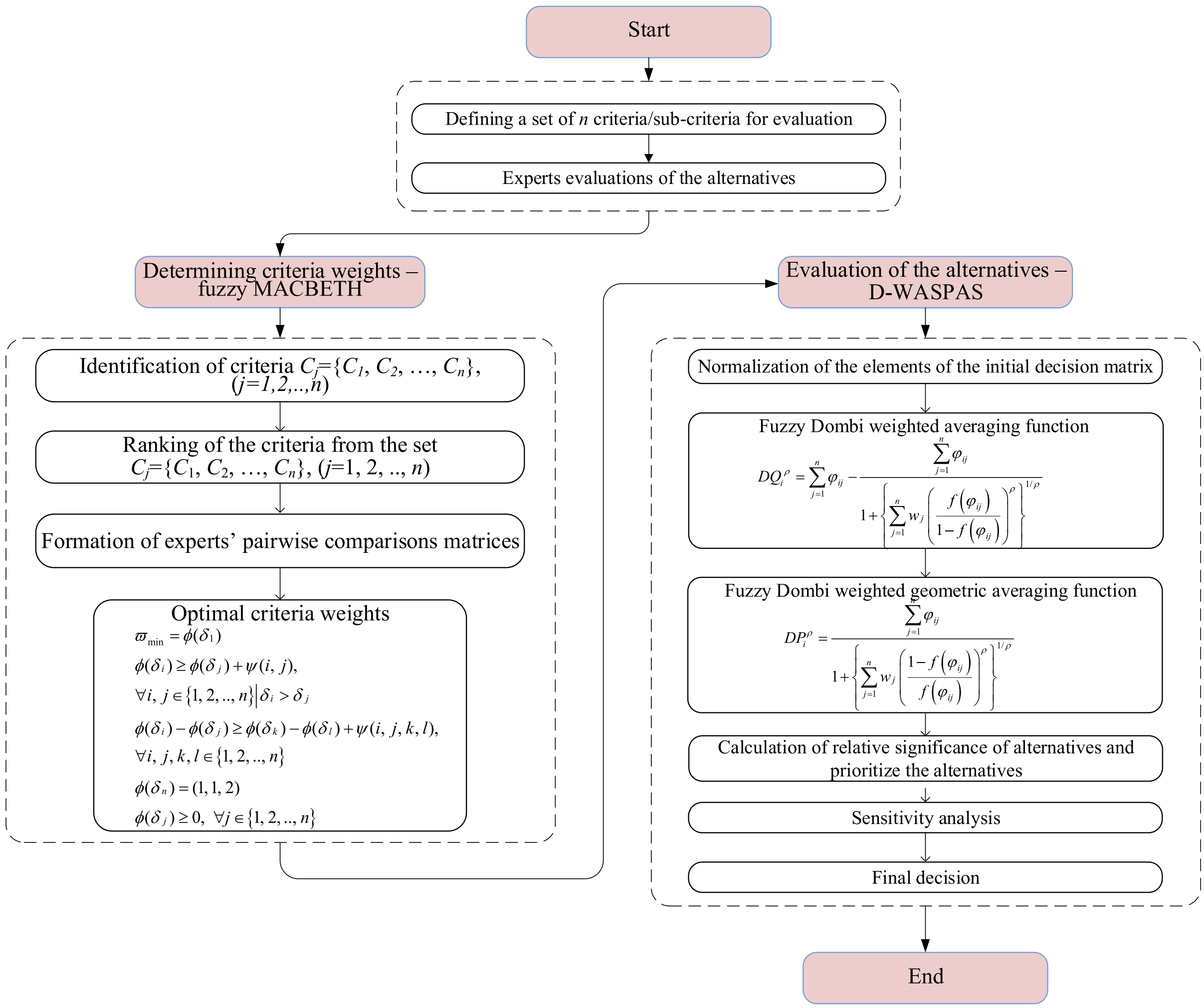

Fig. 1. Fuzzy MACBETH-D-WASPAS multi-criteria model.

$$ID = \begin{bmatrix} \left(\zeta_{11}^{(l)},\ \zeta_{11}^{(m)},\ \zeta_{11}^{(u)}\right) & \left(\zeta_{12}^{(l)},\ \zeta_{12}^{(m)},\ \zeta_{12}^{(u)}\right) & \cdots & \left(\zeta_{1n}^{(l)},\ \zeta_{1n}^{(m)},\ \zeta_{1n}^{(u)}\right) \\ \left(\zeta_{21}^{(l)},\ \zeta_{21}^{(m)},\ \zeta_{21}^{(u)}\right) & \left(\zeta_{22}^{(l)},\ \zeta_{22}^{(m)},\ \zeta_{22}^{(u)}\right) & \cdots & \left(\zeta_{2n}^{(l)},\ \zeta_{2n}^{(m)},\ \zeta_{2n}^{(u)}\right) \\ \vdots & \vdots & \ddots & \vdots \\ \left(\zeta_{b1}^{(l)},\ \zeta_{b1}^{(m)},\ \zeta_{b1}^{(u)}\right) & \left(\zeta_{b2}^{(l)},\ \zeta_{b2}^{(m)},\ \zeta_{b2}^{(u)}\right) & \cdots & \left(\zeta_{bn}^{(l)},\ \zeta_{bn}^{(m)},\ \zeta_{bn}^{(u)}\right) \end{bmatrix}, \tag{7}$$

where $\overline{\zeta}_{ij} = \left(\zeta_{ij}^{(l)}, \zeta_{ij}^{(m)}, \zeta_{ij}^{(m)}\right)$ represent the averaged values obtained using the FDWGA operator.

Step 2. Formation of the normalized matrix$IN = \left[\widetilde{\varphi}_{ij}\right]_{b\times n}$:.

$$IN = \begin{bmatrix} \left(\varphi_{11}^{(l)},\ \varphi_{11}^{(m)},\ \varphi_{11}^{(u)}\right) & \left(\varphi_{12}^{(l)},\ \varphi_{12}^{(m)},\ \varphi_{12}^{(u)}\right) & \cdots & \left(\varphi_{1n}^{(l)},\ \varphi_{1n}^{(m)},\ \varphi_{1n}^{(u)}\right) \\ \left(\varphi_{21}^{(l)},\ \varphi_{21}^{(m)},\ \varphi_{21}^{(u)}\right) & \left(\varphi_{22}^{(l)},\ \varphi_{22}^{(m)},\ \varphi_{22}^{(u)}\right) & \cdots & \left(\varphi_{2n}^{(l)},\ \varphi_{2n}^{(m)},\ \varphi_{2n}^{(u)}\right) \\ \vdots & \vdots & \ddots & \vdots \\ \left(\varphi_{b1}^{(l)},\ \varphi_{b1}^{(m)},\ \varphi_{b1}^{(u)}\right) & \left(\varphi_{b2}^{(l)},\ \varphi_{b2}^{(m)},\ \varphi_{b2}^{(u)}\right) & \cdots & \left(\varphi_{bn}^{(l)},\ \varphi_{bn}^{(m)},\ \varphi_{bn}^{(u)}\right) \end{bmatrix}, \tag{8}$$

where the elements $\widetilde{\varphi}_{ij} = (\varphi_{ij}^{(l)},\ \varphi_{ij}^{(m)},\ \varphi_{ij}^{(u)})$ of the normalized matrix (IN) are determined as follows:

$$\widetilde{\varphi}_{ij} = \left(\varphi_{ij}^{(l)},\ \varphi_{ij}^{(m)},\ \varphi_{ij}^{(u)}\right) = \begin{cases} \varphi_{ij}^{(l)} = \dfrac{\zeta_{ij}^{(l)}}{\zeta_j^{(u)+}};\ \varphi_{ij}^{(m)} = \dfrac{\zeta_{ij}^{(m)}}{\zeta_j^{(m)+}};\ \varphi_{ij}^{(u)} = \dfrac{\zeta_{ij}^{(u)}}{\zeta_j^{(l)+}} & \text{if } j \in B \\ \varphi_{ij}^{(l)} = \dfrac{\zeta_j^{(l)-}}{\zeta_{ij}^{(u)}};\ \varphi_{ij}^{(m)} = \dfrac{\zeta_j^{(m)-}}{\zeta_{ij}^{(m)}};\ \varphi_{ij}^{(u)} = \dfrac{\zeta_j^{(u)-}}{\zeta_{ij}^{(l)}} & \text{if } j \in C \end{cases}, \tag{9}$$

where $\zeta_j^{(u)+} = \max_i(\zeta_{ij}^{(u)})$, $\zeta_j^{(m)+} = \max_i(\zeta_{ij}^{(m)})$,$\zeta_j^{(l)+} = \max_i(\zeta_{ij}^{(l)})$, $\zeta_j^{(u)-} = \min_i(\zeta_{ij}^{(u)})$,$\zeta_j^{(m)-} = \min_i(\zeta_{ij}^{(m)})$, and $\zeta_j^{(l)-} = \min_i(\zeta_{ij}^{(l)})$, B is the set of benefit criteria, and C is the set of cost criteria.

Step 3. Determination of fuzzy weighting coefficients of criteria by using fuzzy MACBETH linear model.

Step 3.1. Formation of comparison matrices.

Suppose that k experts who make comparisons in pairs of criteria participate in a decision-making process. In comparison matrices, criteria are arranged according to importance so that the most influential criterion is in the first position, while the least influential criterion is in the last position. For each expert, we get a comparison matrix $P^e = \left[\widetilde{\psi}_{ij}^e\right]_{n\times n}$ $(e = 1, 2, ..., k)$, where $\widetilde{\psi}_{ij} = \left(\psi_{ij}^{(l)}, \psi_{ij}^{(m)}, \psi_{ij}^{(u)}\right)$ represents a fuzzy value. The fuzzy semantic scale presented in Table 5 is used for pairwise comparisons of the criteria. This scale has been used by experts to evaluate the criteria.

Step 3.2. Determination of optimal fuzzy weighting coefficients of criteria.

The optimal fuzzy weighting coefficients are obtained by solving the fuzzy MACBETH linear model which is formed based on the expert preferences presented in the comparison matrices $P^e = \left[\widetilde{\psi}_{ij}^e\right]_{n\times n}$ $(e = 1, 2, ..., k)$. The elements of the fuzzy linear model are:

1) The objective function:

$$\varpi_{\min} = \phi\left(\widetilde{\delta}_1\right), \tag{10}$$

where $\widetilde{\delta}_1$ represents a fuzzy value of the most influential criterion.

2) Ordinal constraints:

$$\phi\left(\widetilde{\delta}_i\right) \geqslant \phi\left(\widetilde{\delta}_j\right) + \widetilde{\psi}(i, j), \quad \forall i, j \in \{1, 2, .., n\} \,|\, \widetilde{\delta}_i > \widetilde{\delta}_j \tag{11}$$

where $\widetilde{\psi}(i, j)$ represents the preference level difference between $\widetilde{\delta}_i = \left(\delta_i^{(l)}, \delta_i^{(m)}, \delta_i^{(u)}\right)$ and$\widetilde{\delta}_j = \left(\delta_j^{(l)}, \delta_j^{(m)}, \delta_j^{(u)}\right)$..

3) Semantic constraints:

$$\phi\left(\widetilde{\delta}_i\right) - \phi\left(\widetilde{\delta}_j\right) \geqslant \phi\left(\widetilde{\delta}_k\right) - \phi\left(\widetilde{\delta}_l\right) + \widetilde{\psi}(i, j, k, l), \quad \forall i, j, k, l \in \{1, 2, .., n\}, \tag{12}$$

where the value $\widetilde{\psi}(i, j, k, l)$ is defined as the difference between $\widetilde{\psi}(i, j)$ and$\widetilde{\psi}(k, l)$..

4) Non-negativity and other constraints:

$$\varnothing\left(\widetilde{\delta}_n\right) = (1, 1, 2) \tag{13}$$

$$\phi\left(\widetilde{\delta}_j\right) \geqslant 0, \quad \forall j \in \{1, 2, .., n\}, \tag{14}$$

where $\widetilde{\delta}_n$ represents the value of a criterion that has the lowest value of the weighting factor.

Step 3.3. Normalization of fuzzy weighting coefficients of criteria.

The optimal fuzzy weighting coefficients of criteria are normalized as follows:

$$\widetilde{w}_j^e = \frac{\left(\phi\left(\delta_j^{(l)e}\right), \phi\left(\delta_j^{(m)e}\right), \phi\left(\delta_j^{(u)e}\right)\right)}{\max\left(\sum_{j=1}^{n}\phi\left(\delta_j^{(l)e}\right), \sum_{j=1}^{n}\phi\left(\delta_j^{(m)e}\right), \sum_{j=1}^{n}\phi\left(\delta_j^{(u)e}\right)\right)}, \tag{15}$$

where $\phi(\widetilde{\delta}_j^e)$ $(j = 1, 2, ..., n; e = 1, 2, ..., k)$ represents the fuzzy weighting coefficients obtained by solving the linear programming model, while $\widetilde{w}_j^e = \left(w_j^{(l)e}, w_j^{(m)e}, w_j^{(u)e}\right)$ are normalized values of the fuzzy weighting coefficients for the expert e $(e = 1, 2, ..., k)$.

Step 4. Calculation of weighted sum and weighted product of alternatives.

Dombi T-norm and T-conorm are used in the D-WASPAS method to calculate weighted sequences of alternatives. Therefore, the final values of the weighted sequences are defined by using the fuzzy Dombi

Table 5
Fuzzy semantic scale (Pamucar et al., 2022).

Semantic category	Fuzzy scale	Significance
No	(0, 0, 0)	Indifference between criteria
Very weak (VW)	(1, 1, 2)	A criterion is very weakly attractive over another
Weak (W)	(1, 2, 3)	A criterion is weakly attractive over another
Moderate (M)	(2, 3, 4)	A criterion is moderately attractive over another
Strong (S)	(3, 4, 5)	A criterion is strongly attractive over another
Very strong (VS)	(4, 5, 6)	A criterion is very strongly attractive over another
Extreme (E)	(5, 6, 7)	A criterion is extremely attractive over another

weighted averaging function (DQ_i^ρ) and the fuzzy Dombi weighted geometric averaging function (DP_i^ρ). Based on *Definitions 2–3* we can perform: 1) fuzzy Dombi weighted averaging function and 2) fuzzy Dombi weighted geometric averaging function.

Theorem 1. *Let* $(\widetilde{\varphi}_1, \widetilde{\varphi}_2, ..., \widetilde{\varphi}_n)$ *be a set of normalized elements of the initial decision matrix represented by fuzzy numbers* $\widetilde{\varphi}_j = (\varphi_j^{(l)}, \varphi_j^{(m)}, \varphi_j^{(u)})$ $(j = 1, 2, ..., n)$, $\rho \geqslant 0$ *and let* $\widetilde{w}_j = \left(\widetilde{w}_1, \widetilde{w}_2, ..., \widetilde{w}_n\right)^T$ *represent the fuzzy vector of the weight coefficients of the criteria, then the fuzzy Dombi weighted averaging function can be represented as follows:*

$$DQ_i^\rho = \left(DQ_i^{\rho(l)}, DQ_i^{\rho(m)}, DQ_i^{\rho(u)}\right) = \left(\begin{array}{c} \sum_{j=1}^{n}\varphi_{ij}^{(l)} - \dfrac{\sum_{j=1}^{n}\varphi_{ij}^{(l)}}{1 + \left\{\sum_{j=1}^{n} w_j^{(l)}\left(\dfrac{f\left(\varphi_{ij}^{(l)}\right)}{1 - f\left(\varphi_{ij}^{(l)}\right)}\right)^\rho\right\}^{1/\rho}}, \\ \sum_{j=1}^{n}\varphi_{ij}^{(m)} - \dfrac{\sum_{j=1}^{n}\varphi_{ij}^{(m)}}{1 + \left\{\sum_{j=1}^{n} w_j^{(m)}\left(\dfrac{f\left(\varphi_{ij}^{(m)}\right)}{1 - f\left(\varphi_{ij}^{(m)}\right)}\right)^\rho\right\}^{1/\rho}}, \\ \sum_{j=1}^{n}\varphi_{ij}^{(u)} - \dfrac{\sum_{j=1}^{n}\varphi_{ij}^{(u)}}{1 + \left\{\sum_{j=1}^{n} w_j^{(u)}\left(\dfrac{f\left(\varphi_{ij}^{(u)}\right)}{1 - f\left(\varphi_{ij}^{(u)}\right)}\right)^\rho\right\}^{1/\rho}} \end{array}\right), \tag{16}$$

where $\widetilde{w}_j = (w_j^{(l)}, w_j^{(m)}, w_j^{(u)})$ is the fuzzy vector of the weight coefficients of the criteria obtained by solving the fuzzy MACBETH linear model, while $f\left(\widetilde{\varphi}_j\right) = \left(\frac{\varphi_j^{(l)}}{\sum_{j=1}^{n}\varphi_j^{(l)}}, \frac{\varphi_j^{(m)}}{\sum_{j=1}^{n}\varphi_j^{(m)}}, \frac{\varphi_j^{(u)}}{\sum_{j=1}^{n}\varphi_j^{(u)}}\right)$. Then,$DQ_i^\rho$ represents the fuzzy Dombi weighted averaging function. The proof for *Theorem 1* is presented in Appendix A2.

Theorem 2. *Let* $(\widetilde{\varphi}_1, \widetilde{\varphi}_2, ..., \widetilde{\varphi}_n)$ *be a set of normalized elements of the initial decision matrix represented by fuzzy numbers* $\widetilde{\varphi}_j = (\varphi_j^{(l)}, \varphi_j^{(m)}, \varphi_j^{(u)})$ $(j = 1, 2, ..., n)$, $\rho \geqslant 0$ *and let* $\widetilde{w}_j = \left(\widetilde{w}_1, \widetilde{w}_2, ..., \widetilde{w}_n\right)^T$ *represent the fuzzy vector of the weight coefficients of the criteria, then the fuzzy Dombi weighted geometric averaging function can be represented as follows:*

$$DP_i^\rho = \left(DP_i^{\rho(l)},\ DP_i^{\rho(m)},\ DP_i^{\rho(u)}\right) = \left(\begin{array}{c} \dfrac{\sum_{j=1}^{n}\varphi_{ij}^{(l)}}{1+\left\{\sum_{j=1}^{n} w_j^{(l)}\left(\dfrac{1-f\left(\varphi_{ij}^{(l)}\right)}{f\left(\varphi_{ij}^{(l)}\right)}\right)^{\rho}\right\}^{1/\rho}}, \\ \dfrac{\sum_{j=1}^{n}\varphi_{ij}^{(m)}}{1+\left\{\sum_{j=1}^{n} w_j^{(m)}\left(\dfrac{1-f\left(\varphi_{ij}^{(m)}\right)}{f\left(\varphi_{ij}^{(m)}\right)}\right)^{\rho}\right\}^{1/\rho}}, \\ \dfrac{\sum_{j=1}^{n}\varphi_{ij}^{(u)}}{1+\left\{\sum_{j=1}^{n} w_j^{(u)}\left(\dfrac{1-f\left(\varphi_{ij}^{(u)}\right)}{f\left(\varphi_{ij}^{(u)}\right)}\right)^{\rho}\right\}^{1/\rho}} \end{array} \right), \tag{17}$$

where $\widetilde{w}_j = (w_j^{(l)},\ w_j^{(m)},\ w_j^{(u)})$ is the fuzzy vector of the weight coefficients of the criteria obtained by solving the fuzzy MACBETH linear model, while $f\left(\widetilde{\varphi}_j\right) = \left(\frac{\varphi_j^{(l)}}{\sum_{j=1}^{n}\varphi_j^{(l)}}, \frac{\varphi_j^{(m)}}{\sum_{j=1}^{n}\varphi_j^{(m)}}, \frac{\varphi_j^{(u)}}{\sum_{j=1}^{n}\varphi_j^{(u)}}\right)$. Then, DP_i^ρ represents the fuzzy Dombi weighted geometric averaging function. The proof for *Theorem 2* is presented in Appendix A3.

Step 5. Calculation of integrated fuzzy values of alternative utility functions:

$$\widetilde{K}_i = \left(K_i^{(l)},\ K_i^{(m)},\ K_i^{(u)}\right) = \lambda \sum_{j=1}^{n} DQ_i^\rho + (1-\lambda)\sum_{j=1}^{n} DP_i^\rho, \tag{18}$$

where the coefficient λ takes values from the interval [0, 1]. Eq. (18) represents the linear significance of the fuzzy Dombi weighted averaging function (DQ_i^ρ) and the fuzzy Dombi weighted geometric averaging function (DP_i^ρ). The value of the coefficient λ is chosen based on preferences of a decision-maker from the interval $0\leqslant\lambda\leqslant1$. The coefficient λ defines the influence of the DQ_i^ρ and DP_i^ρ functions on the integrated fuzzy value of the utility function of the alternative *i*. The influence of the DP_i^ρ function is higher in the aggregation strategy for the values of $0\leqslant \lambda < 0.5$. On the other hand, the influence of the DQ_i^ρ function is higher in the aggregation strategy when $0.5 < \lambda\leqslant1$. It is recommended to adopt the value $\lambda = 0.5$ when determining the initial solution. Also, it is recommended to perform an analysis of the impact of the change of the coefficient λ ($0\leqslant\lambda\leqslant1$) on the final decision within the analysis of the robustness of the solution in an MCDM problem.

Step 6. Choosing the optimal alternative.

Alternatives are ranked based on K_i, where the best alternative is the one with the highest fuzzy K_i values. When ranking alternatives, it is recommended to transform the integrated fuzzy values of the alternative utility functions into crisp values as follows:

$$def(K_i) = \frac{K_i^{(l)} + 4\cdot K_i^{(m)} + K_i^{(u)}}{6}. \tag{19}$$

4. Case study

As discussed earlier, EVs are becoming promising alternatives for fossil-based vehicles that use high energy and generate too many emissions. Developed and developing countries like Turkey are planning to transform their transportation system to a cleaner energy-based system using EVs. On the other hand, Turkey's energy sector is deeply dependent on imports from other countries which leads to high fuel costs for the transportation system. Therefore, there is a great incentive to improve EV-based transportation in near future. For this purpose, we investigate a real-life case study for Istanbul, the largest city in Turkey as well as the largest European city (in terms of population), to locate a recovery center for EoL ALiBs.

According to the information given by its official website, EXITCOM[1] is the first and only battery recycling facility of Turkey which is established in 2015. This facility is operating to recycle various kinds of batteries collected countrywide. With a recovery rate of 96%, they handle approximately 10,000 ton waste battery per year. However, Turkey is experiencing a noticeable increase in EVs sale each year such that it doubled during January to March 2022 by 243%[2]. Thus, an increase in adoption of EVs in Turkey would soon lead to high number of batteries to be used in such vehicles. In this regard, Turkey needs a specialized facility center for recovery of EoL ALiBs. Generally, there exist three methods for Lithium-ion battery recovery which are Hydrometallurgical process, Pyrometallurgical process, and direct physical process (Zhou, Yang, Du, Gong, & Luo, 2020). Although Pyrometallurgical process and direct physical process have short recovery flow and route, they usually need high operational and technical maintenance and have high energy consumption rate and lower recovery rate. On the other hand, Hydrometallurgical process has higher recovery rate and lower energy consumption rate. The only challenge with Hydrometallurgical process is its long process and wastewater generation. Taking into account its high advantages compared to other methods, this study considers the Hydrometallurgical process as the main recovery method to be used in the new recovery center.

The geographical locations of six candidate locations for the establishment of a recovery center are shown in Fig. 2. Alternative locations are selected according to several factors such as logistics availability, environmental legislation, locations of municipal waste recycling centers, distance from crowded residential areas, and many other factors. Below, brief descriptions of candidate locations are given.

- *Büyükçekmece* (A_1), located in the western part of the European side of Istanbul, is a large industrial area outside the core residential area of Istanbul. It has a population of over 250,000 and a total area of 139.17 km^2. This district is one of the newly built areas with modern architecture and modern industrial sites.
- *Arnavutköy* (A_2) is the second candidate location which is located on the upper side of Büyükçekmece in the western part of the European side of Istanbul. It borders the Black Sea with a total of 22 km coastline. The district is known for its rich water resources and its transportation significance, as Istanbul Airport is located there. Currently, most small and big manufacturing factories are the main economies of the district which are mostly used for the textile industry.
- *Sarıyer* (A_3) is the third and last candidate location in the northernmost European side of Istanbul with a direct coastline with the Black Sea and Bosphorus. Most of Sarıyer is mostly covered with green natural areas, several villages as well as industrialized and trade centers.
- *Tuzla* (A_4), the fourth candidate location, is located in the easternmost part of Istanbul, with a direct border of the Marmara Sea and Kocaeli province. The district is very small with a population of fewer than 200,000 residents and a very low population density. Small and big manufacturing factories have been inseparable parts of the district over the decades.
- *Beykoz* (A_5) is a district located in the northern part of the Anatolian side of Istanbul with a direct coastline of the Bosphorus and the Black

[1] https://www.exitcom.com.tr.

[2] https://www.dailysabah.com/business/automotive/turkeys-electric-car-sales-leap-2439-in-january-march.

Sea. It is very well-known due to its high ratio of green area and very low population. However, one of the main problems of Beykoz is related to its poor transportation modes.

- *Ümraniye* (A_6) is another candidate location on the Anatolian side of Istanbul with a population of over 600,000 residents and a population density of 4000 residents per km^2. Although there exist a very limited number of industrial areas in the district, the government is executing large projects to increase its economic capacity.

The criteria for determining the recovery center location for EoL AliBs include four main criteria together with 24 sub-criteria. The structure of the decision-making hierarchy is shown in Fig. 3.

5. Results and discussion

The evaluation of the alternatives was performed using an integrated fuzzy MACBETH-D-WASPAS model which was realized through the next six steps.

Step 1. In the multi-criteria model, four experts participated in the research and six alternatives were evaluated. For the evaluation of alternatives, twenty-four criteria are used, which are grouped within four clusters. In this study, a survey was prepared to evaluate the criteria and alternatives. Each criterion is ranked based on the alternatives by the experts. The survey was sent to four experts. The four experts (three male and one female with an average experience of 6 six years) are selected based on their expertise in fields of waste management and battery recovery management for electric vehicles. As locating a recovery center for EVs in a big city like Istanbul is of high significance, this study aimed to only involve experts that their current main profession is directly related to EVs waste management. This is an important step to ensure that the input for the decision-making models would lead to realistic and reliable solutions. In this regard, all four experts are provided with complete information on the problem scope and definition, profile of alternative locations, recovery method for the new facility, and required criteria for evaluation of location alternatives. The fuzzy linguistic scale given in Table 6 is used to present expert preferences in initial decision matrices.

The experts evaluated the alternatives under defined criteria with the aim of forming initial decision matrices. After the evaluation of the alternatives, the initial decision matrices are obtained (see Table 7).

In order to evaluate the considered alternatives, it is necessary to aggregate the values from the expert initial decision matrices (see Table 7) into the final aggregate initial decision matrix. The aggregated initial decision matrix (see Table 8) is obtained by the fusion of the expert preferences from Table 7 with the FDWGA operator defined in Eq. (17).

For example, at position A_1-C_1, we obtained the following values in the expert correspondent matrices (Table 7): $\widetilde{\zeta}_{11}^1 = (2,\ 3,\ 4)$, $\widetilde{\zeta}_{11}^2 = (3,\ 4,\ 5)$, $\widetilde{\zeta}_{11}^3 = (2,\ 3,\ 4)$, and $\widetilde{\zeta}_{11}^4 = (1,\ 1,\ 1)$. As stated in the previous part of the paper, four experts participated in the research and were assigned the same values of weight coefficients $w_E = (0.25,\ 0.25,\ 0.25,\ 0.25)^T$. Based on the presented expert evaluation of the alternatives, Eq. (17) and $\rho = 1$, the aggregation of values at position A_1-C_1 is performed as follows:

$$FDWGA^{\rho=1}\left(\widetilde{\zeta}_{11}\right) =$$

$$\begin{pmatrix} \zeta_{11}^{(l)} = \dfrac{\sum_{e=1}^{4}\zeta_{11}^{(l)e}}{1+\left\{\sum_{e=1}^{4} w_j\left(\dfrac{1-f\left(\zeta_{11}^{(l)e}\right)}{f\left(\zeta_{11}^{(l)e}\right)}\right)^{\rho}\right\}^{1/\rho}} = \dfrac{8}{1+\left(0.25\times\left(\dfrac{1-0.25}{0.25}\right)+\cdots+0.25\times\left(\dfrac{1-0.125}{0.125}\right)\right)} = 1.71, \\ \zeta_{11}^{(m)} = \dfrac{\sum_{e=1}^{4}\zeta_{11}^{(m)e}}{1+\left\{\sum_{e=1}^{4} w_j\left(\dfrac{1-f\left(\zeta_{11}^{(m)e}\right)}{f\left(\zeta_{11}^{(m)e}\right)}\right)^{\rho}\right\}^{1/\rho}} = \dfrac{10}{1+\left(0.25\times\left(\dfrac{1-0.27}{0.27}\right)+\cdots+0.25\times\left(\dfrac{1-0.09}{0.09}\right)\right)} = 2.09, \\ \zeta_{11}^{(u)} = \dfrac{\sum_{e=1}^{4}\zeta_{11}^{(u)e}}{1+\left\{\sum_{e=1}^{4} w_j\left(\dfrac{1-f\left(\zeta_{11}^{(u)e}\right)}{f\left(\zeta_{11}^{(u)e}\right)}\right)^{\rho}\right\}^{1/\rho}} = \dfrac{14}{1+\left(0.25\times\left(\dfrac{1-0.29}{0.29}\right)+\cdots+0.25\times\left(\dfrac{1-0.07}{0.07}\right)\right)} = 2.35 \end{pmatrix} =$$

$$(1.71,\ 2.09,\ 2.35)$$

where the values of $f\left(\zeta_{11}^{(l)e}\right)$, $f\left(\zeta_{11}^{(m)e}\right)$, and $f\left(\zeta_{11}^{(u)e}\right)$ represent additive fuzzy functions. The additive fuzzy functions at position A_1-C_1 for the correspondent initial decision matrix of the first expert are calculated as follows: $f\left(\zeta_{11}^{(l)1}\right) = \zeta_{11}$

$$^{(l)1}\Big/\sum_{e=1}^{4}\zeta_{11}^{(l)e} = 2/8 = 0.25,$$

$f\left(\zeta_{11}^{(m)1}\right) = \zeta_{11}^{(m)1}/\sum_{e=1}^{4}\zeta_{11}^{(m)e} = 3/11 = 0.27$, $f\left(\zeta_{11}^{(u)1}\right) = \zeta_{11}^{(u)1}/\sum_{e=1}^{4}\zeta_{11}^{(u)e} = 4/14 = 0.29$.

The aggregation of the remaining values from Table 8 is performed similarly.

Step 2. In order to form weighted strategies of alternatives, it is necessary to normalize the elements of the initial decision matrix. Normalization implies the transformation of all elements into an interval [0,1]. Using Eq. (9), the elements of the aggregated initial decision matrix are normalized (see Table 9).

Step 3. The fuzzy weight coefficients of the criteria are defined using the fuzzy MACBETH linear model. The model is formed through the next three sub-steps.

Step 3.1. The first step of the MACBETH methodology involves ranking the criteria from the most influential to the least influential. Four experts participated in the research and each proposed priorities of the main criteria (clusters) and the sub-criteria within each cluster (see Table 10).

Besides, the experts made comparisons in pairs of the main criteria and sub-criteria based on the presented priorities of the main criteria and sub-criteria, respectively. The comparison in pairs was performed within the first level of criteria and each cluster of sub-criteria separately. The fuzzy semantic scale shown in Table 5 was used for comparison in pairs. Table 11 presents the comparison matrices for the first level criteria.

The mutual comparisons of the criteria presented in Table 11 were performed in order to form a linear fuzzy MACBETH model which was used in the next step to define the final fuzzy values of the cluster / criterion weight coefficients.

Step 3.2. Based on the expert preferences presented in the comparison matrices, fuzzy linear models for determining weight coefficients are formed. Since we have first-level criteria within which sub-criteria are grouped, five fuzzy linear models are formed for each expert. For example, the linear models for the level of main criteria are:

$$
\begin{gathered}
\text{Expert } 1\\
\text{- - - - - - - - - - -}\\
\varpi_{\min}=\phi\left(\tilde{\delta}_1\right)\\
\phi\left(\tilde{\delta}_1\right)\\
\geqslant\phi\left(\tilde{\delta}_4\right)+(1,\ 2,\ 3);\ \phi\left(\tilde{\delta}_1\right)\geqslant\phi\left(\tilde{\delta}_2\right)+(2,\ 3,\ 4);\phi\left(\tilde{\delta}_1\right)\geqslant\phi\left(\tilde{\delta}_3\right)\\
+(4,\ 5,\ 6);\ \phi\left(\tilde{\delta}_4\right)\geqslant\phi\left(\tilde{\delta}_2\right)+(1,\ 2,\ 3);\phi\left(\tilde{\delta}_4\right)\geqslant\phi\left(\tilde{\delta}_3\right)\\
+(3,\ 4,\ 5);\ \phi\left(\tilde{\delta}_2\right)\geqslant\phi\left(\tilde{\delta}_3\right)+(1,\ 2,\ 3);\ \ldots\phi\left(\tilde{\delta}_4\right)-\phi\left(\tilde{\delta}_3\right)\geqslant\phi\left(\tilde{\delta}_2\right)\\
-\phi\left(\tilde{\delta}_3\right)+(1,\ 3,\ 4);\phi\left(\tilde{\delta}_3\right)\\
=(1,\ 1,\ 2);\ \phi\left(\tilde{\delta}_j\right)\geqslant 0,\ \forall j
\end{gathered}
$$

$$
\begin{gathered}
\text{Expert } 2\\
\text{- - - - - - - - - - -}\\
\varpi_{\min}=\phi\left(\tilde{\delta}_1\right)\\
\phi\left(\tilde{\delta}_1\right)\geqslant\phi\left(\tilde{\delta}_4\right)+(3,\ 4,\ 5);\ \phi\left(\tilde{\delta}_1\right)\geqslant\phi\left(\tilde{\delta}_2\right)+(4,\ 5,\ 6);\\
\in\{1,\ \ldots,\ 4\}.\quad\phi\left(\tilde{\delta}_1\right)\geqslant\phi\left(\tilde{\delta}_3\right)+(4,\ 5,\ 6);\ \phi\left(\tilde{\delta}_4\right)\geqslant\phi\left(\tilde{\delta}_2\right)+(1,\ 2,\ 3);\\
\phi\left(\tilde{\delta}_4\right)\geqslant\phi\left(\tilde{\delta}_3\right)+(3,\ 4,\ 5);\ \phi\left(\tilde{\delta}_2\right)\geqslant\phi\left(\tilde{\delta}_3\right)+(1,\ 1,\ 2);\\
\ldots\\
\phi\left(\tilde{\delta}_4\right)-\phi\left(\tilde{\delta}_3\right)\geqslant\phi\left(\tilde{\delta}_2\right)-\phi\left(\tilde{\delta}_3\right)+(1,\ 3,\ 4);\\
\phi\left(\tilde{\delta}_3\right)=(1,\ 1,\ 2);\ \phi\left(\tilde{\delta}_j\right)\geqslant 0,\ \forall j\in\{1,\ \ldots,\ 4\}.
\end{gathered}
$$

$$
\begin{gathered}
\text{Expert } 3\\
\text{- - - - - - - - - - -}\\
\varpi_{\min}=\phi\left(\tilde{\delta}_1\right)\\
\phi\left(\tilde{\delta}_1\right)\geqslant\phi\left(\tilde{\delta}_4\right)+(2,\ 3,\ 4);\ \phi\left(\tilde{\delta}_1\right)\geqslant\phi\left(\tilde{\delta}_2\right)+(3,\ 4,\ 5);\\
\phi\left(\tilde{\delta}_1\right)\geqslant\phi\left(\tilde{\delta}_3\right)+(3,\ 4,\ 5);\ \phi\left(\tilde{\delta}_4\right)\geqslant\phi\left(\tilde{\delta}_2\right)+(2,\ 3,\ 4);\\
\phi\left(\tilde{\delta}_4\right)\geqslant\phi\left(\tilde{\delta}_3\right)+(3,\ 4,\ 5);\ \phi\left(\tilde{\delta}_2\right)\geqslant\phi\left(\tilde{\delta}_3\right)+(1,\ 2,\ 3);\\
\ldots\\
\phi\left(\tilde{\delta}_4\right)-\phi\left(\tilde{\delta}_3\right)\geqslant\phi\left(\tilde{\delta}_2\right)-\phi\left(\tilde{\delta}_3\right)+(0,\ 2,\ 3);\\
\phi\left(\tilde{\delta}_3\right)=(1,\ 1,\ 2);\ \phi\left(\tilde{\delta}_j\right)\geqslant 0,\ \forall j\in\{1,\ \ldots,\ 4\}.
\end{gathered}
$$

$$
\begin{gathered}
\text{Expert } 4\\
\text{- - - - - - - - - - -}\\
\varpi_{\min}=\phi\left(\tilde{\delta}_1\right)\\
\phi\left(\tilde{\delta}_1\right)\geqslant\phi\left(\tilde{\delta}_4\right)+(3,\ 4,\ 5);\ \phi\left(\tilde{\delta}_1\right)\geqslant\phi\left(\tilde{\delta}_2\right)+(4,\ 5,\ 6);\\
\phi\left(\tilde{\delta}_1\right)\geqslant\phi\left(\tilde{\delta}_3\right)+(4,\ 5,\ 6);\ \phi\left(\tilde{\delta}_4\right)\geqslant\phi\left(\tilde{\delta}_2\right)+(2,\ 3,\ 4);\\
\phi\left(\tilde{\delta}_4\right)\geqslant\phi\left(\tilde{\delta}_3\right)+(2,\ 3,\ 4);\ \phi\left(\tilde{\delta}_2\right)\geqslant\phi\left(\tilde{\delta}_3\right)+(1,\ 1,\ 2);\\
\ldots\\
\phi\left(\tilde{\delta}_4\right)-\phi\left(\tilde{\delta}_3\right)\geqslant\phi\left(\tilde{\delta}_2\right)-\phi\left(\tilde{\delta}_3\right)+(1,\ 3,\ 4);\\
\phi\left(\tilde{\delta}_3\right)=(1,\ 1,\ 2);\ \phi\left(\tilde{\delta}_j\right)\geqslant 0,\ \forall j\in\{1,\ \ldots,\ 4\}.
\end{gathered}
$$

Similarly, fuzzy linear sub-criteria models are formed. Lingo 17.0 software was used to solve the fuzzy MACBETH linear models and generate optimal fuzzy weighting coefficients.

Step 3.3. In the previous step, the fuzzy weighting coefficients of the criteria were calculated for each expert separately. Therefore, it is necessary to aggregate the obtained fuzzy weighting coefficients and define the optimal fuzzy weighting coefficients. The optimal fuzzy weighting coefficients of the criteria are firstly normalized by using Eq. (15). Then, normalized values obtained for each expert are averaged using the FDWGA operator, introduced in Eq. (17). Global fuzzy weights of the sub-criteria are obtained by fusion of corresponding fuzzy weights (Table 12).

Table 12 presents the global and local values of the weight coefficients of the criteria. The global weights of the criteria are obtained by multiplying the weight coefficients of the clusters with the weight coefficients of the sub criteria.

Step 4. Aggregated sequences of the alternatives are calculated by using the fuzzy Dombi weighted averaging function and the fuzzy Dombi weighted geometric averaging function defined in Eq. (16) and Eq. (17), respectively. The elements of the normalized matrix (Table 9) and the aggregated fuzzy weighting coefficients (Table 12) are used to calculate the DQ_i^ρ and DP_i^ρ functions. The obtained functions are:

$$DQ_i^{\rho=1} = \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \end{array} \begin{bmatrix} (0.160,\ 0.685,\ 2.630) \\ (0.101,\ 0.427,\ 1.569) \\ (0.095,\ 0.415,\ 1.557) \\ (0.167,\ 0.712,\ 2.903) \\ (0.096,\ 0.423,\ 1.687) \\ (0.097,\ 0.407,\ 1.526) \end{bmatrix},\ DP_i^{\rho=1} = \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \end{array} \begin{bmatrix} (0.380,\ 0.710,\ 1.250) \\ (0.254,\ 0.490,\ 0.866) \\ (0.235,\ 0.453,\ 0.780) \\ (0.468,\ 0.835,\ 1.399) \\ (0.226,\ 0.424,\ 0.718) \\ (0.200,\ 0.383,\ 0.663) \end{bmatrix}.$$

It is adopted that the value of the parameter ρ is 1 to calculate the DQ_i^ρ and DP_i^ρ functions. For example, the DQ_i^ρ function of the first alternative is computed as follows:

$$DQ_1^{\rho=1} = \left(\begin{array}{l} DQ_1^{(l)} = \sum_{j=1}^{24} \varphi_{1j}^{(l)} - \dfrac{\sum_{j=1}^{24} \varphi_{1j}^{(l)}}{1 + \left\{ \sum_{j=1}^{n} w_j^{(l)} \left(\dfrac{f\left(\varphi_{1j}^{(l)}\right)}{1 - f\left(\varphi_{1j}^{(l)}\right)} \right)^{\rho} \right\}^{1/\rho}} = 12.8 - \dfrac{12.8}{1 + \left(0.014 \times \left(\dfrac{0.04}{1-0.04}\right) + \cdots + 0.005 \times \left(\dfrac{0.06}{1-0.06}\right)\right)} = 0.160, \\ DQ_1^{(m)} = \sum_{j=1}^{24} \varphi_{1j}^{(m)} - \dfrac{\sum_{j=1}^{24} \varphi_{1j}^{(m)}}{1 + \left\{ \sum_{j=1}^{n} w_j^{(m)} \left(\dfrac{f\left(\varphi_{1j}^{(m)}\right)}{1 - f\left(\varphi_{1j}^{(m)}\right)} \right)^{\rho} \right\}^{1/\rho}} = 18.29 - \dfrac{18.29}{1 + \left(0.040 \times \left(\dfrac{0.05}{1-0.05}\right) + \cdots + 0.012 \times \left(\dfrac{0.05}{1-0.05}\right)\right)} = 0.685, \\ DQ_1^{(u)} = \sum_{j=1}^{24} \varphi_{1j}^{(u)} - \dfrac{\sum_{j=1}^{24} \varphi_{1j}^{(u)}}{1 + \left\{ \sum_{j=1}^{n} w_j^{(u)} \left(\dfrac{f\left(\varphi_{1j}^{(u)}\right)}{1 - f\left(\varphi_{1j}^{(u)}\right)} \right)^{\rho} \right\}^{1/\rho}} = 28.31 - \dfrac{28.31}{1 + \left(0.098 \times \left(\dfrac{0.05}{1-0.05}\right) + \cdots + 0.027 \times \left(\dfrac{0.05}{1-0.05}\right)\right)} = 2.630 \end{array} \right)$$

$$= (0.160,\ 0.685,\ 2.630)$$

The value of the DP_i^ρ function for alternative A_1 is obtained as follows:

$$DP_1^{\rho=1} = \left(\begin{array}{l} DP_1^{(l)} = \dfrac{\sum_{j=1}^{24} \varphi_{1j}^{(l)}}{1 + \left\{ \sum_{j=1}^{n} w_j^{(l)} \left(\dfrac{1 - f\left(\varphi_{1j}^{(l)}\right)}{f\left(\varphi_{1j}^{(l)}\right)} \right)^{\rho} \right\}^{1/\rho}} = \dfrac{12.8}{1 + \left(0.014 \times \left(\dfrac{1-0.04}{0.04}\right) + \cdots + 0.005 \times \left(\dfrac{1-0.06}{0.06}\right)\right)} = 0.380, \\ DP_1^{(m)} = \dfrac{\sum_{j=1}^{24} \varphi_{1j}^{(m)}}{1 + \left\{ \sum_{j=1}^{n} w_j^{(m)} \left(\dfrac{1 - f\left(\varphi_{1j}^{(m)}\right)}{f\left(\varphi_{1j}^{(m)}\right)} \right)^{\rho} \right\}^{1/\rho}} = \dfrac{18.29}{1 + \left(0.040 \times \left(\dfrac{1-0.05}{0.05}\right) + \cdots + 0.012 \times \left(\dfrac{1-0.05}{0.05}\right)\right)} = 0.710, \\ DP_1^{(u)} = \dfrac{\sum_{j=1}^{24} \varphi_{1j}^{(u)}}{1 + \left\{ \sum_{j=1}^{n} w_j^{(u)} \left(\dfrac{1 - f\left(\varphi_{1j}^{(u)}\right)}{f\left(\varphi_{1j}^{(u)}\right)} \right)^{\rho} \right\}^{1/\rho}} = \dfrac{28.31}{1 + \left(0.098 \times \left(\dfrac{1-0.05}{0.05}\right) + \cdots + 0.027 \times \left(\dfrac{1-0.05}{0.05}\right)\right)} = 1.250 \end{array} \right)$$

$$= (0.380,\ 0.710,\ 1.250)$$

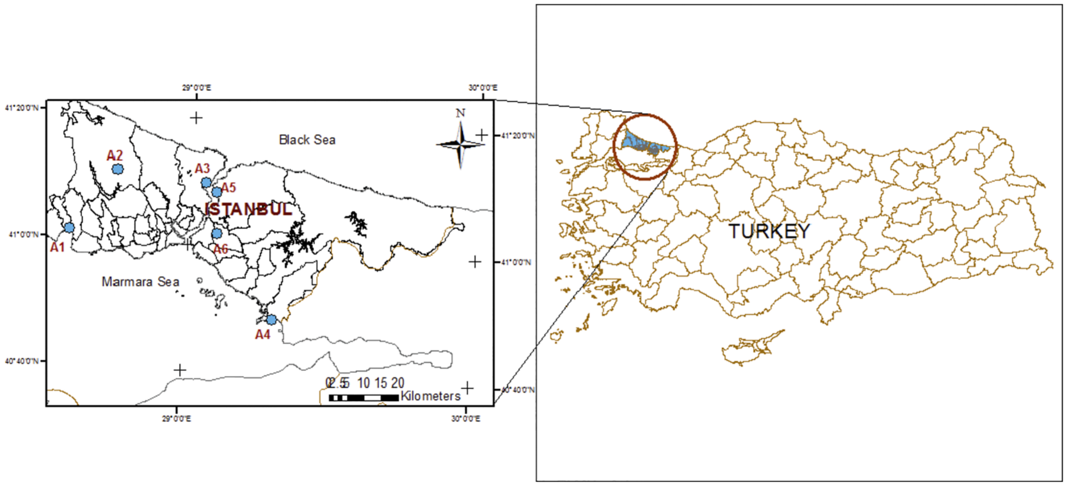

Fig. 2. The locations of recovery center alternatives.

Steps 5 and 6. After calculating the individual weighted alternative strategies, it is necessary to define the integrated fuzzy values of the alternatives. The final integrated values of the alternatives are used to define the final rank, and it is desirable that the alternative has the highest possible K_i. Integrated fuzzy values of alternative utility functions are calculated by using Eq. (18). It is adopted that the value of the coefficient λ is 0.5 to compute the relative significance of the alternatives. The values of the utility functions and the final ranking of the alternatives are given in Table 13.

Based on the results from Table 13, the initial ranking of the alternatives is $A_4 > A_1 > A_2 > A_3 > A_5 > A_6$. According to the results, Sariyer is selected as the most appropriate location for a recovery center for an EoL ALiB recovery center. In addition, Büyükçekmece is selected as the second suitable location for the facility. On the other hand, Ümraniye is the identified as the least preferred alternatives for establishment of an EoL ALiB recovery center.

5.1. Validation of the results

Validation of results of multi-criteria models represents the final phase before the implementation of a final decision. Therefore, it is necessary to examine the quality of the proposed solution and select the dominant alternative from the considered set. Today, there is no single methodology in the literature for conducting sensitivity analysis and validation of results in multi-criteria problems. Some authors (Saaty, 1980, 1994; Barron and Schmidt, 1988; Mukhametzyanov and Pamucar, 2018) suggest conducting a sensitivity analysis of the multi-criteria model through the variation of input parameters in the initial decision matrix. Other authors (Bozanic, Tešić, & Milić, 2020; Yazdani, Torkayesh, Santibanez-Gonzalez, & Otaghsara, 2020) suggest verification of results through comparison with other multi-criteria models. Also, some authors (Pamucar & Jankovic, 2020; Yager, 2001; Zhao, Wang, Liang, Leng, & Xu, 2019) believe that it is necessary to define the influence of subjectively defined input parameters in the multi-criteria model on decision-making results.

Since in our model, there are two parameters (parameter λ and ρ) which are defined based on subjective preferences of the decision-maker, in the following part the analysis of the sensitivity of the proposed multi-criteria framework to the variation of the stated parameters is performed. In the first phase of sensitivity analysis, a simulation of the influence of the parameter λ on the definition of integrated values of alternative utility functions (K_i) is presented. In the second phase, a simulation of the influence of the parameter ρ on the calculation of weighted sequences of alternatives DQ_i^{ρ} and DP_i^{ρ} is presented.

a) The impact of changing parameter λ on the ranking results

The WASPAS method requires defining a value of the parameter λ from the interval [0, 1] to calculate integrated values of alternative utility functions. The parameter λ in Eq. (26) has a significant influence on the integrated values of utility functions and the final decision. Therefore, in the next part, a total of 100 scenarios are formed in which the change of the parameter λ is simulated and the influence on the utility functions of the alternatives is analyzed. In the first scenario, the value of λ is set to 0. In each subsequent scenario, the value of λ is increased by 0.01. The influence of the parameter λ is shown in Fig. 4.

The results depicted in Fig. 4 show that the increase in the value of the parameter λ in the interval $0 \le \lambda \le 1$ affects the growth of the utility functions of the alternatives. Since by its nature the function DQ_i^{ρ} is an increasing function, while DP_i^{ρ} is a decreasing function, values of the parameter λ that are in the interval $0.5 < \lambda \le 1$ favor the DQ_i^{ρ} function, while values of the parameter λ that are in the interval $0 \le \lambda < 0.5$ favor the DP_i^{ρ} function. Therefore, it is expected that the change in the value of the parameter λ through the presented 100 scenarios leads to an increase in the value of the utility functions of the alternatives.

By analyzing the results, we notice that through 100 scenarios there is no change in the ranks of the two first-ranked alternatives (A_4 and A_1) and the last ranked alternative A_6. This confirmed the dominance of alternatives A_4 and A_1 in relation to the remaining alternatives from the considered set of locations. Minor changes in ranks occur with the remaining alternatives (A_2, A_3, and A_5). The alternative A_2 retains the initial rank for the values of the parameter λ in the interval $0 \le \lambda \le 0.81$. For the values of the parameter λ in the interval $0.82 \le \lambda \le 1$, alternative A_2 becomes the fourth-ranked, while the third-ranked is the alternative A_5. The fourth-ranked alternative A_3 holds its position for the values of parameter λ in the interval $0 \le \lambda \le 0.52$, while for the values of parameter λ in the interval $0.53 \le \lambda \le 1$ it replaces its position with the alternative A_5.

This analysis confirmed the dominance of alternatives A_4 and A_1 over the remaining alternatives. Despite the minor changes in the ranks of individual alternatives during 100 scenarios, we can conclude that there are no significant changes in the ranks and that the initial rank ($A_4 > A_1 > A_2 > A_3 > A_5 > A_6$) is confirmed. This conclusion is confirmed by Spearman's correlation coefficient (average value of 0.95), which showed that there is a significant statistical correlation between the initial rank and the ranks obtained through 100 scenarios.

b) The impact of changing parameter ρ on the ranking results

The change in the parameter ρ has a direct impact on the

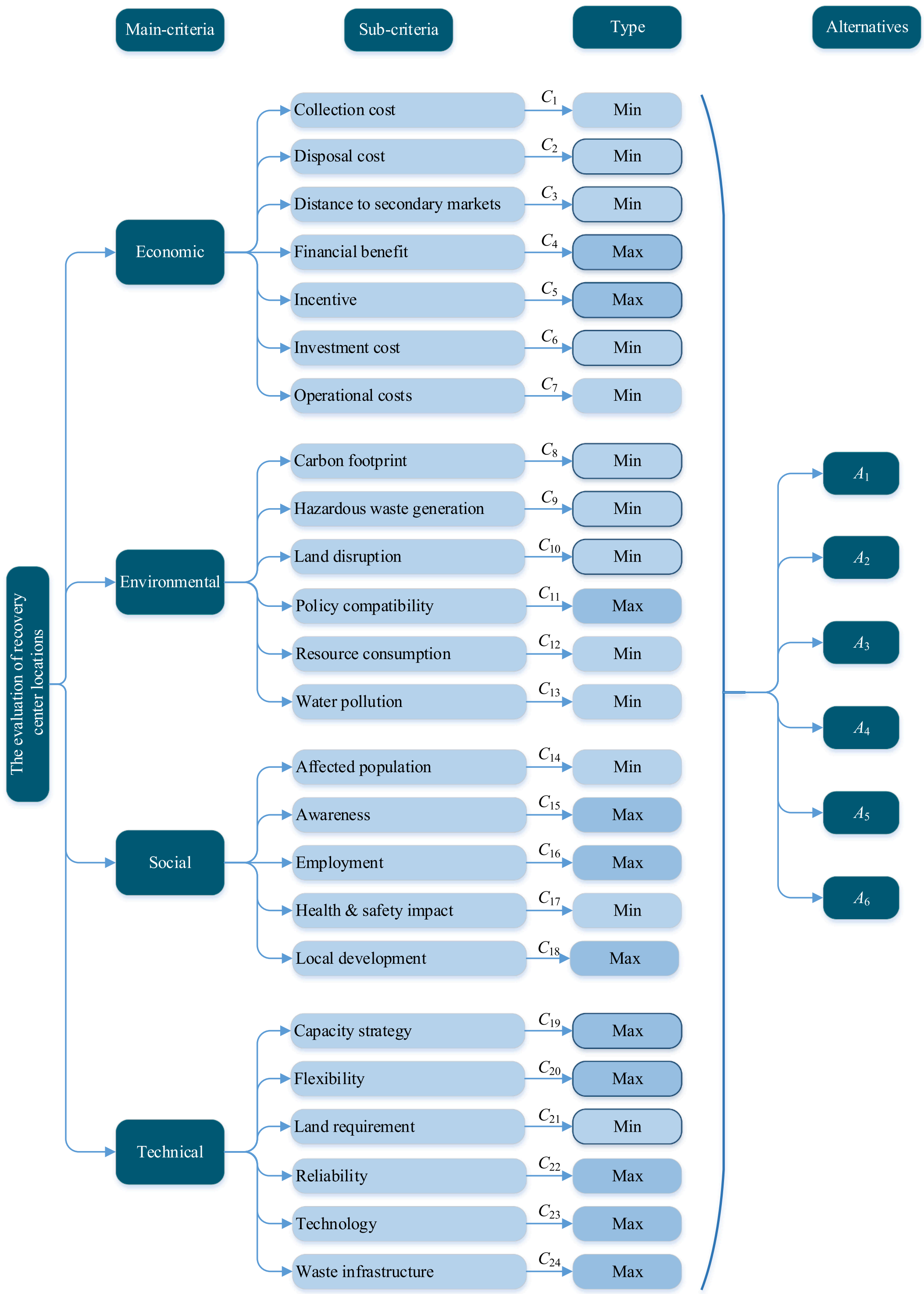

Fig. 3. Three-level decision-making hierarchy structure for the recovery center location selection.

Table 6
Fuzzy linguistic scale for evaluating alternatives.

Linguistic term	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 (EH)	(7, 8, 9)
Absolutely high (AH)	(8, 9, 9)

increasing or decreasing of the integrated values of the functions. Since DQ_i^{ρ} is an increasing function, the change of the parameter ρ affects its further growth, while with the DP_i^{ρ} function, the change of the parameter ρ affects the decrease of the integrated values of the functions. In some alternatives, this increase/decrease may be proportional to the increase or decrease of the integrated values. In such situations, changing the parameter ρ will not affect the change in the rankings. However, in some alternatives, a change in the parameter ρ may lead to a larger increase/decrease in the integrated values of the

Table 7
Experts' evaluations of the alternatives.

Crit.	Alternative					
	A_1	A_2	A_3	A_4	A_5	A_6
C_1	L, ML, L, AL	H, MH, E, ML	MH, H, MH, MH	VL, L, VL, VL	H, EH, MH, AH	EH, AH, EH, EH
C_2	L, AL, E, MH	ML, L, VL, L	E, E, E, E	AL, AL, VL, L	EH, H, AH, EH	AH, MH, EH, EH
C_3	L, EH, AH, H	H, MH, H, E	EH, E, E, E	E, VL, E, MH	EH, L, MH, MH	VL, AL, MH, EH
C_4	MH, EH, E, E	E, H, EH, EH	ML, E, E, MH	EH, AH, EH, EH	VL, ML, L, VL	AL, VL, L, AL
C_5	EH, AH, EH, EH	MH, MH, EH, AH	VL, AL, L, VL	AH, EH, AH, H	AL, AL, L, VL	L, ML, E, MH
C_6	ML, AL, L, VL	MH, MH, H, MH	E, EH, MH, H	VL, VL, E, MH	EH, AH, MH, E	H, H, EH, EH
C_7	L, AL, VL, L	E, E, E, MH	H, H, E, MH	L, AL, EH, AH	AH, EH, VL, L	EH, MH, VL, L
C_8	AL, VL, L, L	ML, E, E, ML	MH, H, MH, MH	VL, L, VL, L	MH, H, MH, H	H, EH, AH, EH
C_9	E, ML, E, E	MH, E, E, ML	E, ML, E, ML	ML, L, VL, VL	H, MH, EH, AH	AH, AH, EH, EH
C_{10}	L, VL, L, VL	E, MH, EH, MH	MH, H, H, EH	AL, AL, VL, VL	H, AH, H, MH	H, EH, MH, EH
C_{11}	AH, EH, AH, EH	H, MH, AH, AH	L, ML, L, L	AH, AH, EH, H	VL, L, L, ML	EH, H, MH, H
C_{12}	ML, L, VL, VL	E, ML, L, ML	MH, E, E, E	L, AL, VL, L	EH, AH, EH, EH	H, EH, MH, H
C_{13}	ML, E, ML, ML	L, ML, L, ML	AL, VL, L, L	MH, H, MH, E	VL, L, VL, L	H, AH, AH, EH
C_{14}	ML, L, VL, VL	E, MH, H, H	MH, H, H, MH	L, VL, L, L	EH, AH, AH, EH	ML, E, MH, H
C_{15}	ML, L, E, ML	ML, E, E, E	H, EH, AH, EH	VL, AL, L, L	AH, EH, MH, H	MH, H, MH, MH
C_{16}	ML, L, E, ML	MH, E, E, E	E, ML, L, ML	AH, EH, AH, AH	H, MH, MH, H	EH, H, EH, AH
C_{17}	ML, ML, VL, L	ML, E, E, ML	L, ML, ML, E	H, EH, EH, EH	VL, L, L, ML	MH, H, MH, EH
C_{18}	AH, EH, AH, EH	H, MH, MH, MH	MH, E, E, E	E, ML, VL, L	MH, H, H, EH	ML, L, VL, L
C_{19}	EH, AH, EH, H	MH, E, L, ML	E, ML, ML, ML	AH, EH, EH, H	ML, L, L, ML	VL, AL, VL, L
C_{20}	AH, EH, AH, H	E, ML, L, ML	MH, E, E, E	EH, H, MH, H	H, MH, MH, MH	L, VL, L, VL
C_{21}	E, MH, EH, AH	MH, H, H, H	H, EH, MH, E	L, VL, L, E	H, EH, EH, H	EH, AH, EH, EH
C_{22}	H, MH, H, EH	MH, E, L, ML	E, ML, ML, E	AH, AH, AH, EH	ML, L, VL, L	L, AL, AL, VL
C_{23}	ML, L, VL, AL	E, ML, ML, AL	MH, H, H, MH	EH, AH, AH, MH	H, EH, AH, AH	H, EH, AH, EH
C_{24}	H, EH, EH, H	MH, E, MH, H	ML, L, VL, L	AH, EH, EH, MH	VL, AL, VL, L	AH, EH, MH, H

Absolutely low: AL; Very low: VL; Low: L; Medium low: ML; Equal: E; Medium high: MH; High: H; Very high: EH; Absolutely high: AH.

functions, so it is necessary to determine whether in such situations the initial rank of the alternatives is violated.

Three experiments are performed in which the change of the parameter ρ in the interval $1 \le \rho \le 130$ is simulated. The upper limit of the interval is limited to 130 since it is found that for larger values there are no changes in the values of the integrated functions. In the first experiment (Fig. 5a), the influence of the change of the parameter ρ on DQ_i^ρ is analyzed, while the value $\rho = 1$ is adopted for DP_i^ρ. Similarly, another experiment is conducted (Fig. 5b), where the influence of the change of the parameter ρ on DP_i^ρ is analyzed, while the value $\rho = 1$ is adopted for DQ_i^ρ. In the third experiment (Fig. 5c), a simulation of the influence of the parameter ρ on the DP_i^ρ and DQ_i^ρ functions is performed simultaneously.

It can be seen from Fig. 5 that the change of the parameters ρ in the interval [1, 130] significantly affects the change of the integrated functions of the alternatives. Through all three experiments, it is confirmed that alternatives A_4 and A_1 represent predominantly the best solutions from the considered set. In the first experiment (Fig. 5a), the change in the parameter ρ represents an optimistic scenario in which the value of the integrated alternative functions increases with the change in the value of the parameter ρ. The initial rank of all alternatives is

Table 8
Aggregated initial decision matrix.

Crit.	Alternative					
	A_1	A_2	A_3	A_4	A_5	A_6
C_1	(1.71, 2.09, 2.35)	(4.21, 5.27, 6.3)	(5.22, 6.22, 7.23)	(1.14, 2.18, 3.2)	(6.3, 7.33, 8.16)	(7.23, 8.23, 9)
C_2	(2.05, 2.35, 2.56)	(1.71, 2.82, 3.87)	(4, 5, 6)	(1.14, 1.41, 1.55)	(6.93, 7.94, 8.73)	(6.55, 7.58, 8.4)
C_3	(4.28, 5.62, 6.7)	(5.11, 6.13, 7.15)	(4.48, 5.52, 6.55)	(2.35, 3.75, 4.94)	(3.84, 5.05, 6.18)	(1.71, 2.23, 2.52)
C_4	(4.75, 5.78, 6.81)	(5.69, 6.75, 7.78)	(3.87, 4.9, 5.92)	(7.23, 8.23, 9)	(1.41, 2.53, 3.58)	(1.14, 1.41, 1.55)
C_5	(7.23, 8.23, 9)	(5.99, 7.02, 7.88)	(1.14, 1.71, 2.09)	(7.15, 8.16, 8.73)	(1.14, 1.41, 1.55)	(3.12, 4.21, 5.27)
C_6	(1.41, 1.92, 2.24)	(5.22, 6.22, 7.23)	(5.27, 6.3, 7.33)	(1.63, 2.93, 4.1)	(5.57, 6.64, 7.52)	(6.46, 7.47, 8.47)
C_7	(1.33, 1.85, 2.18)	(4.21, 5.22, 6.22)	(5.11, 6.13, 7.15)	(2.26, 2.55, 2.72)	(2.26, 3.74, 4.97)	(2.17, 3.56, 4.78)
C_8	(1.33, 1.85, 2.18)	(3.43, 4.44, 5.45)	(5.22, 6.22, 7.23)	(1.33, 2.4, 3.43)	(5.45, 6.46, 7.47)	(6.93, 7.94, 8.73)
C_9	(3.69, 4.71, 5.71)	(3.87, 4.9, 5.92)	(3.43, 4.44, 5.45)	(1.41, 2.53, 3.58)	(6.3, 7.33, 8.16)	(7.47, 8.47, 9)
C_{10}	(1.33, 2.4, 3.43)	(5.05, 6.08, 7.1)	(5.92, 6.93, 7.94)	(1, 1.33, 1.5)	(6.08, 7.1, 7.94)	(6.13, 7.15, 8.16)
C_{11}	(7.47, 8.47, 9)	(6.49, 7.52, 8.16)	(2.18, 3.2, 4.21)	(7.15, 8.16, 8.73)	(1.71, 2.82, 3.87)	(5.92, 6.93, 7.94)
C_{12}	(1.41, 2.53, 3.58)	(2.82, 3.87, 4.9)	(4.21, 5.22, 6.22)	(1.33, 1.85, 2.18)	(7.23, 8.23, 9)	(5.92, 6.93, 7.94)
C_{13}	(3.2, 4.21, 5.22)	(2.4, 3.43, 4.44)	(1.33, 1.85, 2.18)	(4.9, 5.92, 6.93)	(1.33, 2.4, 3.43)	(7.15, 8.16, 8.73)
C_{14}	(1.41, 2.53, 3.58)	(5.11, 6.13, 7.15)	(5.45, 6.46, 7.47)	(1.6, 2.67, 3.69)	(7.47, 8.47, 9)	(4.21, 5.27, 6.3)
C_{15}	(2.82, 3.87, 4.9)	(3.69, 4.71, 5.71)	(6.93, 7.94, 8.73)	(1.33, 1.85, 2.18)	(6.3, 7.33, 8.16)	(5.22, 6.22, 7.23)
C_{16}	(2.82, 3.87, 4.9)	(4.21, 5.22, 6.22)	(2.82, 3.87, 4.9)	(7.72, 8.73, 9)	(5.45, 6.46, 7.47)	(6.93, 7.94, 8.73)
C_{17}	(1.85, 3, 4.07)	(3.43, 4.44, 5.45)	(2.82, 3.87, 4.9)	(6.72, 7.72, 8.73)	(1.71, 2.82, 3.87)	(5.64, 6.65, 7.67)
C_{18}	(7.47, 8.47, 9)	(5.22, 6.22, 7.23)	(4.21, 5.22, 6.22)	(1.92, 3.12, 4.21)	(5.92, 6.93, 7.94)	(1.71, 2.82, 3.87)
C_{19}	(6.93, 7.94, 8.73)	(3.12, 4.21, 5.27)	(3.2, 4.21, 5.22)	(6.93, 7.94, 8.73)	(2.4, 3.43, 4.44)	(1.14, 1.71, 2.09)
C_{20}	(7.15, 8.16, 8.73)	(2.82, 3.87, 4.9)	(4.21, 5.22, 6.22)	(5.92, 6.93, 7.94)	(5.22, 6.22, 7.23)	(1.33, 2.4, 3.43)
C_{21}	(5.57, 6.64, 7.52)	(5.71, 6.72, 7.72)	(5.27, 6.3, 7.33)	(1.78, 2.93, 4)	(6.46, 7.47, 8.47)	(7.23, 8.23, 9)
C_{22}	(5.92, 6.93, 7.94)	(3.12, 4.21, 5.27)	(3.43, 4.44, 5.45)	(7.72, 8.73, 9)	(1.71, 2.82, 3.87)	(1.14, 1.41, 1.55)
C_{23}	(1.41, 1.92, 2.24)	(2.09, 2.35, 2.55)	(5.45, 6.46, 7.47)	(6.75, 7.78, 8.4)	(7.15, 8.16, 8.73)	(6.93, 7.94, 8.73)
C_{24}	(6.46, 7.47, 8.47)	(4.9, 5.92, 6.93)	(1.71, 2.82, 3.87)	(6.55, 7.58, 8.4)	(1.14, 1.71, 2.09)	(6.3, 7.33, 8.16)

Table 9
The normalized matrix.

Crit.	Alternative					
	A_1	A_2	A_3	A_4	A_5	A_6
C_1	(0.49, 1, 1.37)	(0.18, 0.4, 0.56)	(0.16, 0.34, 0.45)	(0.36, 0.96, 2.06)	(0.14, 0.28, 0.37)	(0.13, 0.25, 0.33)
C_2	(0.45, 0.6, 0.75)	(0.3, 0.5, 0.9)	(0.19, 0.28, 0.39)	(0.74, 1, 1.35)	(0.13, 0.18, 0.22)	(0.14, 0.19, 0.24)
C_3	(0.25, 0.4, 0.59)	(0.24, 0.36, 0.49)	(0.26, 0.4, 0.56)	(0.35, 0.6, 1.07)	(0.28, 0.44, 0.66)	(0.68, 1, 1.48)
C_4	(0.53, 0.7, 0.94)	(0.63, 0.82, 1.08)	(0.43, 0.6, 0.82)	(0.8, 1, 1.25)	(0.16, 0.31, 0.5)	(0.13, 0.17, 0.21)
C_5	(0.8, 1, 1.25)	(0.67, 0.85, 1.09)	(0.13, 0.21, 0.29)	(0.79, 0.99, 1.21)	(0.13, 0.17, 0.21)	(0.35, 0.51, 0.73)
C_6	(0.63, 1, 1.59)	(0.2, 0.31, 0.43)	(0.19, 0.3, 0.43)	(0.34, 0.66, 1.37)	(0.19, 0.29, 0.4)	(0.17, 0.26, 0.35)
C_7	(0.61, 1, 1.64)	(0.21, 0.35, 0.52)	(0.19, 0.3, 0.43)	(0.49, 0.72, 0.96)	(0.27, 0.49, 0.96)	(0.28, 0.52, 1.01)
C_8	(0.61, 1, 1.64)	(0.24, 0.42, 0.64)	(0.18, 0.3, 0.42)	(0.39, 0.77, 1.64)	(0.18, 0.29, 0.4)	(0.15, 0.23, 0.31)
C_9	(0.25, 0.54, 0.97)	(0.24, 0.52, 0.93)	(0.26, 0.57, 1.04)	(0.39, 1, 2.54)	(0.17, 0.34, 0.57)	(0.16, 0.3, 0.48)
C_{10}	(0.29, 0.56, 1.13)	(0.14, 0.22, 0.3)	(0.13, 0.19, 0.25)	(0.67, 1, 1.5)	(0.13, 0.19, 0.25)	(0.12, 0.19, 0.24)
C_{11}	(0.83, 1, 1.21)	(0.72, 0.89, 1.09)	(0.24, 0.38, 0.56)	(0.79, 0.96, 1.17)	(0.19, 0.33, 0.52)	(0.66, 0.82, 1.06)
C_{12}	(0.37, 0.73, 1.55)	(0.27, 0.48, 0.77)	(0.21, 0.35, 0.52)	(0.61, 1, 1.64)	(0.15, 0.22, 0.3)	(0.17, 0.27, 0.37)
C_{13}	(0.26, 0.44, 0.68)	(0.3, 0.54, 0.91)	(0.61, 1, 1.64)	(0.19, 0.31, 0.45)	(0.39, 0.77, 1.64)	(0.15, 0.23, 0.31)
C_{14}	(0.39, 1, 2.54)	(0.2, 0.41, 0.7)	(0.19, 0.39, 0.66)	(0.38, 0.95, 2.24)	(0.16, 0.3, 0.48)	(0.22, 0.48, 0.85)
C_{15}	(0.32, 0.49, 0.71)	(0.42, 0.59, 0.82)	(0.79, 1, 1.26)	(0.15, 0.23, 0.31)	(0.72, 0.92, 1.18)	(0.6, 0.78, 1.04)
C_{16}	(0.31, 0.44, 0.63)	(0.47, 0.6, 0.81)	(0.31, 0.44, 0.63)	(0.86, 1, 1.17)	(0.61, 0.74, 0.97)	(0.77, 0.91, 1.13)
C_{17}	(0.42, 0.94, 2.1)	(0.31, 0.64, 1.13)	(0.35, 0.73, 1.37)	(0.2, 0.37, 0.58)	(0.44, 1, 2.26)	(0.22, 0.42, 0.69)
C_{18}	(0.83, 1, 1.21)	(0.58, 0.73, 0.97)	(0.47, 0.62, 0.83)	(0.21, 0.37, 0.56)	(0.66, 0.82, 1.06)	(0.19, 0.33, 0.52)
C_{19}	(0.79, 1, 1.26)	(0.36, 0.53, 0.76)	(0.37, 0.53, 0.75)	(0.79, 1, 1.26)	(0.28, 0.43, 0.64)	(0.13, 0.22, 0.3)
C_{20}	(0.82, 1, 1.22)	(0.32, 0.47, 0.69)	(0.48, 0.64, 0.87)	(0.68, 0.85, 1.11)	(0.6, 0.76, 1.01)	(0.15, 0.29, 0.48)
C_{21}	(0.24, 0.44, 0.72)	(0.23, 0.44, 0.7)	(0.24, 0.46, 0.76)	(0.44, 1, 2.25)	(0.21, 0.39, 0.62)	(0.2, 0.36, 0.55)
C_{22}	(0.66, 0.79, 1.03)	(0.35, 0.48, 0.68)	(0.38, 0.51, 0.71)	(0.86, 1, 1.17)	(0.19, 0.32, 0.5)	(0.13, 0.16, 0.2)
C_{23}	(0.16, 0.24, 0.31)	(0.24, 0.29, 0.36)	(0.63, 0.79, 1.04)	(0.77, 0.95, 1.18)	(0.82, 1, 1.22)	(0.79, 0.97, 1.22)
C_{24}	(0.76, 0.99, 1.29)	(0.58, 0.78, 1.06)	(0.2, 0.37, 0.59)	(0.77, 1, 1.28)	(0.13, 0.23, 0.32)	(0.74, 0.97, 1.25)

Table 10
Priorities of the main criteria and sub-criteria.

Level	Expert			
	E_1	E_2	E_3	E_4
Main criteria	$MC_1 > MC_4 > MC_2 > MC_3$	$MC_1 > MC_4 > MC_2 > MC_3$	$MC_1 > MC_4 > MC_2 > MC_3$	$MC_1 > MC_4 > MC_2 > MC_3$
Economic sub-criteria	$C_6 > C_3 > C_7 > C_1 > C_5 > C_2 > C_4$	$C_4 > C_6 > C_7 > C_5 > C_3 > C_1 > C_2$	$C_6 > C_7 > C_3 > C_4 > C_5 > C_1 > C_2$	$C_4 > C_6 > C_7 > C_5 > C_1 > C_3 > C_2$
Environmental sub-criteria	$C_{13} > C_{12} > C_{11} > C_9 > C_8 > C_{10}$	$C_{13} > C_{11} > C_8 > C_9 > C_{10} > C_{12}$	$C_{13} > C_{11} > C_{12} > C_8 > C_9 > C_{10}$	$C_{11} > C_{13} > C_{12} > C_8 > C_{10} > C_9$
Social sub-criteria	$C_{18} > C_{17} > C_{14} > C_{16} > C_{15}$	$C_{17} > C_{16} > C_{18} > C_{14} > C_{15}$	$C_{18} > C_{16} > C_{17} > C_{14} > C_{15}$	$C_{17} > C_{18} > C_{16} > C_{14} > C_{15}$
Technical sub-criteria	$C_{20} > C_{23} > C_{24} > C_{21} > C_{19} > C_{22}$	$C_{21} > C_{19} > C_{23} > C_{20} > C_{22} > C_{24}$	$C_{23} > C_{19} > C_{21} > C_{20} > C_{22} > C_{24}$	$C_{23} > C_{19} > C_{21} > C_{20} > C_{22} > C_{24}$

confirmed, except for the third-ranked and fourth-ranked alternatives (A_2 and A_3). They change their positions for the values of the parameter $4 \le \rho \le 130$.

In the second experiment (Fig. 5b), the change of the parameter ρ represents a pessimistic scenario in which the values of the integrated functions of the alternatives decrease with the change of the value of the parameter ρ. However, this does not produce significant changes in the ranks of the alternatives, as the ranks of the first four ranked alternatives have been confirmed. Ranking changes occur only in the last two ranked alternatives (A_5 and A_6). These two alternatives change their positions for the values of the parameter $5 \le \rho \le 130$.

In the third experiment (Fig. 5c), there are only minor changes in the ranks of alternatives A_2, A_3, A_5, and A_6, while the dominance of alternatives A_4 and A_1 is confirmed. The changes in the ranks of the alternatives in the third experiment are shown in Fig. 6.

The relative importance of the alternative A_4 (first-ranked) and the alternative A_1 (second-ranked) after the initial decrease, tends to increase for the values of the parameter $5 \le \rho \le 130$. Fig. 5c shows that the relative importance of alternative A_1 grows faster than the relative importance function of alternative A_4. However, these changes are not sufficient to change the ranks of alternatives A_4 and A_1, so the advantage of alternative A_4 over alternative A_1 is confirmed in all 130 scenarios. The relative importance of alternative A_2 (third-ranked), alternative A_5 (fifth-ranked), and alternative A_6 (sixth-ranked) grow proportionally through all scenarios. Since the score function of alternative A_5 grows faster than the score functions of alternatives A_2 and A_6, for scenarios $3 \le \rho \le 130$, alternative A_5 holds the third rank, while alternatives A_6 and A_2 are in the fourth and sixth position, respectively. From the presented analysis, we can conclude that alternatives A_4 and A_1 stand out as the best solutions from the investigated set of locations, while alternatives A_5 and A_6 represent the worst solutions.

c) Comparison of fuzzy MACBETH-D-WASPAS models and other MCDM models

In this section, the results of the fuzzy MACBETH-D-WASPAS model were compared with other extensions of the WASPAS method in the MCDM field: fuzzy WASPAS model (Mishra, Rani, Pardasani, & Mardani, 2019), rough WASPAS model (Stevic, Pamucar, Subotic, Antuchevičiene, & Zavadskas, 2018), intuitionistic fuzzy WASPAS (Stanujkić and Karabašević, 2018) and spherical fuzzy WASPAS method (Kutlu Gundogdu & Kahraman, 2019). Using the above extensions of the WASPAS method, the results shown in Table 14 were obtained.

Table 14 presented that the dominance of alternatives A_4 and A_1 was confirmed by applying all the considered extensions of the WASPAS methodology. Also, according to all MCDM techniques, the worst alternative is the A_6. The spherical fuzzy WASPAS method and rough WASPAS confirmed the initial rank, while the fuzzy WASPAS method changed the rank of alternatives A_3 and A_2. Similar changes in alternatives A_3 and A_5 have occurred with the intuitionistic fuzzy WASPAS method. Such rank changes are expected since there is little difference

Table 11
The comparison matrices for the main criteria.

Expert 1					Expert 2				
Crit.	MC_1	MC_4	MC_2	MC_3	Crit.	MC_1	MC_4	MC_2	MC_3
MC_1		W	M	VS	MC_1		S	VS	VS
MC_4			W	S	MC_4			W	S
MC_2				W	MC_2				VW
MC_3					MC_3				
Expert 3					**Expert 4**				
Crit.	MC_1	MC_4	MC_2	MC_3	Crit.	MC_1	MC_4	MC_2	MC_3
MC_1		M	S	S	MC_1		S	VS	VS
MC_4			M	M	MC_4			M	S
MC_2				W	MC_2				VW
MC_3					MC_3				

Very weak: VW; Weak: W; Moderate: M; Strong: S; Very strong: VS.

Table 12
Aggregated fuzzy weighting coefficients.

Criteria /sub-criteria	Local	Global	Criteria /sub-criteria	Local	Global
MC_1	(0.270, 0.491, 0.848)	–	MC_3	(0.044, 0.056, 0.075)	–
C_1	(0.052, 0.082, 0.116)	(0.014, 0.040, 0.098)	C_{14}	(0.029, 0.04, 0.057)	(0.001, 0.002, 0.004)
C_2	(0.024, 0.034, 0.042)	(0.006, 0.017, 0.035)	C_{15}	(0.032, 0.061, 0.107)	(0.001, 0.003, 0.008)
C_3	(0.069, 0.103, 0.153)	(0.019, 0.051, 0.130)	C_{16}	(0.102, 0.208, 0.403)	(0.005, 0.012, 0.030)
C_4	(0.053,0.079, 0.109)	(0.014, 0.039, 0.092)	C_{17}	(0.157, 0.281, 0.539)	(0.007, 0.016, 0.041)
C_5	(0.071, 0.123, 0.202)	(0.019, 0.060, 0.171)	C_{18}	(0.177, 0.358, 0.648)	(0.008, 0.020, 0.049)
C_6	(0.137, 0.240, 0.415)	(0.037, 0.118, 0.352)	MC_4	(0.178, 0.308, 0.513)	–
C_7	(0.116, 0.201, 0.345)	(0.031, 0.099, 0.293)	C_{19}	(0.103, 0.174, 0.306)	(0.018, 0.054, 0.157)
MC_2	(0.089, 0.136, 0.223)	–	C_{20}	(0.083, 0.166, 0.256)	(0.015, 0.051, 0.131)
C_8	(0.047, 0.096, 0.225)	(0.004, 0.013, 0.050)	C_{21}	(0.116, 0.201, 0.365)	(0.021, 0.062, 0.188)
C_9	(0.041, 0.064, 0.098)	(0.004, 0.009, 0.022)	C_{22}	(0.039, 0.055, 0.084)	(0.007, 0.017, 0.043)
C_{10}	(0.025, 0.043, 0.068)	(0.002, 0.006, 0.015)	C_{23}	(0.148, 0.255,0.417)	(0.026, 0.079, 0.214)
C_{11}	(0.110, 0.249, 0.456)	(0.010, 0.034, 0.102)	C_{24}	(0.029, 0.037, 0.052)	(0.005, 0.012, 0.027)
C_{12}	(0.054, 0.084, 0.114)	(0.005, 0.011, 0.026)			
C_{13}	(0.156, 0.320, 0.558)	(0.014, 0.044, 0.125)			

Table 13
The relative importance and the final ranking of alternatives.

Alternative	*Fuzzy* K_i	*Crips* K_i	Rank
A_1	(0.705, 0.697, 1.505)	0.833	2
A_2	(0.483, 0.459, 0.911)	0.538	3
A_3	(0.438, 0.434, 0.896)	0.511	4
A_4	(0.783, 0.773, 1.686)	0.927	1
A_5	(0.407, 0.424, 0.957)	0.510	5
A_6	(0.380, 0.395, 0.863)	0.470	6

between the criterion functions of alternatives A_2, A_3 and A_5, so changes in the mathematical formulation of uncertainty can lead to rank changes, which is the case in this example. To understand the methodological advantages of the fuzzy MACBETH-D-WASPAS model in Table 15, a comparison of the presented MCDM techniques is presented.

The comparisons between the proposed method and the four existing methods can be pointed out as follows:

(1) The aggregation functions of the four existing WASPAS methods are linear and do not have adaptive parameters, while the fuzzy

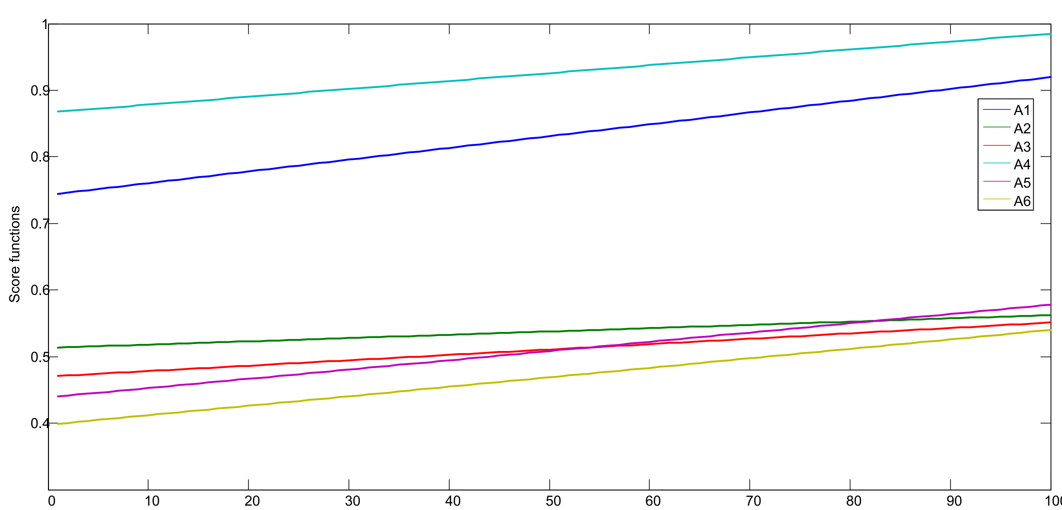

Fig. 4. The analysis of the influence of the parameter λ.

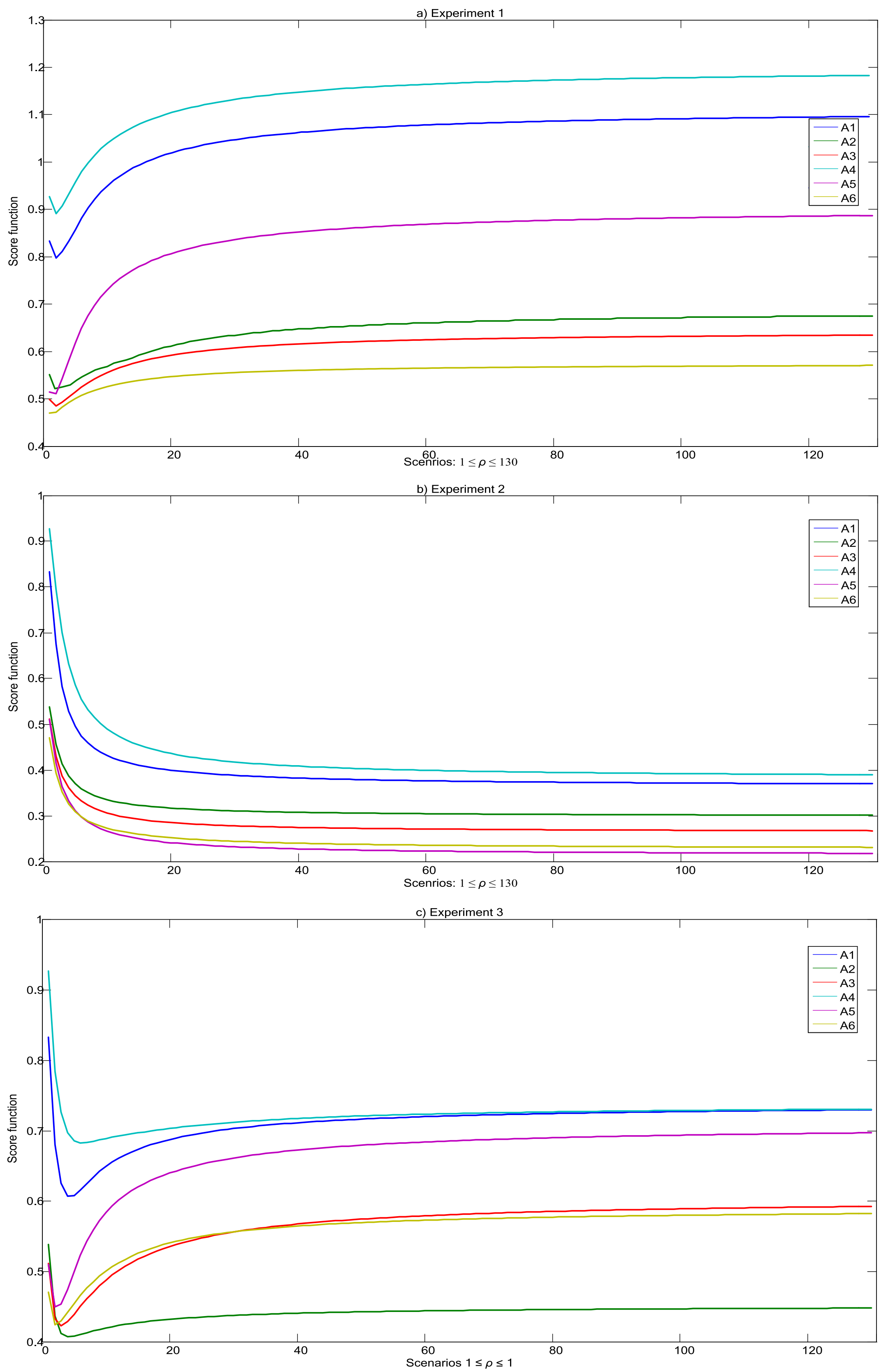

Fig. 5. Influence of the parameter ρ on change of the integrated alternative functions.

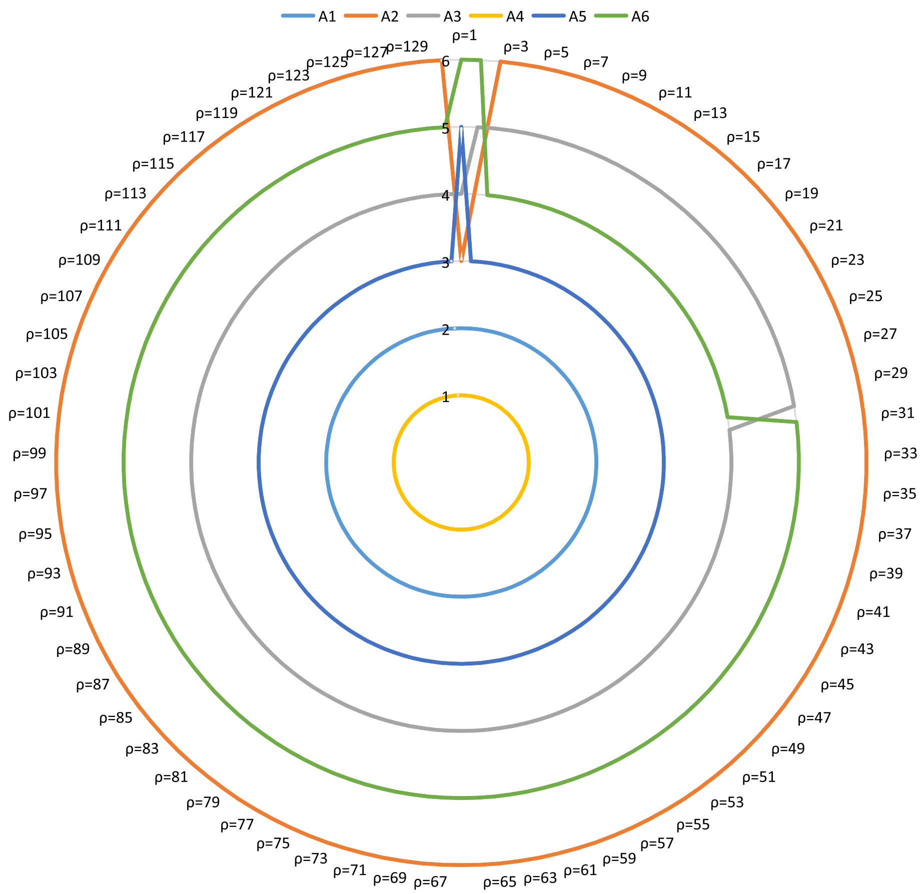

Fig. 6. Ranking of the alternatives through scenarios in experiment 3.

Table 14
Ranks of the alternatives based on different MCDM techniques.

MCDM metodologies	Rank
Fuzzy MACBETH-D-WASPAS (Proposed)	$A_4 > A_1 > A_2 > A_3 > A_5 > A_6$
Fuzzy WASPAS model (Mishra et al., 2019)	$A_4 > A_1 > A_3 > A_2 > A_5 > A_6$
Rough WASPAS model (Stevic et al., 2018)	$A_4 > A_1 > A_2 > A_3 > A_5 > A_6$
Intuitionistic fuzzy WASPAS (Stanujkić & Karabašević, 2018)	$A_4 > A_1 > A_2 > A_5 > A_3 > A_6$
Spherical fuzzy WASPAS method (Kutlu Gundogdu & Kahraman, 2019)	$A_4 > A_1 > A_2 > A_3 > A_5 > A_6$

Table 15
The comparisons of different methods.

MCDM methodology	Flexible decision making due to decision makers' risk attitude	Flexibility in real world applications	Clearly defined rank alternative	Algorithm complexity
Fuzzy MACBETH-D-WASPAS (Proposed)	Yes	Yes	Yes	Partially
Fuzzy WASPAS model (Mishra et al., 2019)	No	No	Yes	No
Rough WASPAS model (Stevic et al., 2018)	No	No	Yes	No
Intuitionistic fuzzy WASPAS (Stanujkić & Karabašević, 2018)	No	Partially	Yes	Partially
Spherical fuzzy WASPAS method (Kutlu Gundogdu & Kahraman, 2019)	Yes	Partially	Yes	Partially

MACBETH-D-WASPAS methods use nonlinear Dombi functions. Fuzzy Dombi functions enable nonlinear information processing, which contributes to significantly greater flexibility in decision-making. Also, the application of Dombi functions enables the simulation of different scenarios, which affects the adaptability of the multi-criteria model intending to make objective and rational decisions.

(2) The information fusion process presented in the fuzzy MACBETH-D-WASPAS methodology is much more flexible compared to the existing extensions of the WASPAS method from the literature.

(3) To facilitate the calculation of the initial results using the D-WASPAS method, the value $\rho = 1$ was adopted. Furthermore, since the flexible parameter should meet condition $\rho > 0$, the D-WASPAS method allows the validation of results through the simulation of different attitudes of decision makers depending on the level of risk in the information. Therefore, we can conclude that the D-WASPAS method is more suitable for solving realistic decision problems.

6. Conclusions

The emergence of EVs has been a noticeable point for transportation systems to transform from fossil fuel-based vehicles to cleaner vehicles which require lower energy costs and also produce lower negative environmental, economic, and social impacts. The utilization of ALiBs is of great importance for EVs, but more and more valuable resources are being depleted without appropriate recovery. Therefore, countries should consider establishing recovery centers for ALiBs as soon as possible. However, locating a recovery center is a complex and multi-aspect decision-making problem. For this purpose, we developed a novel decision-making approach based on the MACBETH-D-WASPAS model under the fuzzy environment. The proposed integrated fuzzy decision-making approach empowers experts in the field of LiB management to enhance their decision-making capabilities and select the most suitable location for an EoL ALiB recovery center. Besides, the real-life case study of Istanbul is provided to show the feasibility and applicability of the developed methodology for solving the recovery center location selection problem. Results showed that Sariyer and Büyükçekmece are top first and second locations that a recovery center for an EoL ALiB recovery center. On the other hand, results pointed out that Ümraniye is the least preferred location for establishment of an EoL ALiB recovery center.

One of the limitations of the proposed methodology is the computational complexity. This limitation can be eliminated by creating user-oriented software that would possess the modules presented in this judge. Also, one of the limitations of the proposed methodology is the inability to address neutrality in information adequately. Therefore, it is necessary to direct future research towards improving the performance of the proposed method through the application of intuitionistic fuzzy sets and picture fuzzy sets. This would enable more accurate processing of expert assessments.

One primary direction is to use the developed methodology for solving other complex decision-making problems in the field of supply chain management, energy management, transportation engineering, etc. Another important direction is to use the introduced integrated fuzzy MACBETH-D-WASPAS model to tackle other complex problems related to ALiBs like the evaluation of repurposing alternatives, location selection of a remanufacturing facility, etc. Also, further research should focus on enhancing the adaptability of the fuzzy D-WASPAS methodology by implementing Einstein, Aczel–Alsina, and Hamacher norms. Also, an exciting direction for further research is the implementation of neutrosophic and gray sets in the MACBETH-DWASPAS methodology.

CRediT authorship contribution statement

Dragan Pamucar: Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Ali Ebadi Torkayesh:** Conceptualization, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Muhammet Deveci:** Conceptualization, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Vladimir Simic:** Conceptualization, Validation, Formal analysis, Investigation, Writing –original draft, Writing – review & editing, Visualization.

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.

Appendix A1

A fuzzy number $\widetilde{A}$ on R to be a TFN if its membership function $\mu_{\widetilde{A}}(x) : \mathrm{R} \to [0, 1]$ is equal to the following (Pamucar & Ecer, 2020):

$$\mu_{\widetilde{A}}(x) = \begin{cases} \dfrac{x-l}{m-l}, & l \leqslant x \leqslant m \\ \dfrac{u-x}{u-m}, & m \leqslant x \leqslant u \\ 0, & otherwise \end{cases}, \tag{1a}$$

where l and u are the lower and upper bounds of the fuzzy number $\widetilde{A}$, and m is the modal value for$\widetilde{A}$..

The operational laws of TFNs $\widetilde{A}_1 = (\xi_1^{(l)}, \xi_1^{(m)}, \xi_1^{(u)})$ and $\widetilde{A}_2 = (\xi_2^{(l)}, \xi_2^{(m)}, \xi_2^{(u)})$ are showed as the following equations (Ecer & Pamucar, 2020; Gorcun, Senthil, & Küçükönder, 2021):

$$\widetilde{A}_1 \oplus \widetilde{A}_2 = \left(\xi_1^{(l)}, \xi_1^{(m)}, \xi_1^{(u)}\right) \oplus \left(\xi_2^{(l)}, \xi_2^{(m)}, \xi_2^{(u)}\right) = \left(\xi_1^{(l)} + \xi_2^{(l)}, \xi_1^{(m)} + \xi_2^{(m)}, \xi_1^{(u)} + \xi_2^{(u)}\right), \tag{2a}$$

$$\widetilde{A}_1 \otimes \widetilde{A}_2 = \left(\xi_1^{(l)}, \xi_1^{(m)}, \xi_1^{(u)}\right) \otimes \left(\xi_2^{(l)}, \xi_2^{(m)}, \xi_2^{(u)}\right) = \left(\xi_1^{(l)} \times \xi_2^{(l)}, \xi_1^{(m)} \times \xi_2^{(m)}, \xi_1^{(u)} \times \xi_2^{(u)}\right), \tag{3a}$$

$$\widetilde{A}_1 - \widetilde{A}_2 = \left(\xi_1^{(l)}, \xi_1^{(m)}, \xi_1^{(u)}\right) - \left(\xi_2^{(l)}, \xi_2^{(m)}, \xi_2^{(u)}\right) = \left(\xi_1^{(l)} - \xi_2^{(u)}, \xi_1^{(m)} - \xi_2^{(m)}, \xi_1^{(u)} - \xi_2^{(l)}\right), \tag{4a}$$

$$\frac{\widetilde{A}_1}{\widetilde{A}_2} = \frac{\left(\xi_1^{(l)},\ \xi_1^{(m)},\ \xi_1^{(u)}\right)}{\left(\xi_2^{(l)},\ \xi_2^{(m)},\ \xi_2^{(u)}\right)} = \left(\frac{\xi_1^{(l)}}{\xi_2^{(u)}},\ \frac{\xi_1^{(m)}}{\xi_2^{(m)}},\ \frac{\xi_1^{(u)}}{\xi_2^{(m)}}\right), \tag{5a}$$

$$\widetilde{A}_1^{-1} = \left(\xi_1^{(l)},\ \xi_1^{(m)},\ \xi_1^{(u)}\right)^{-1} = \left(\frac{1}{\xi_1^{(l)}},\ \frac{1}{\xi_1^{(m)}},\ \frac{1}{\xi_1^{(u)}}\right). \tag{6a}$$

Definition 1a. (Dombi, 1982). *Let ξ_1 and ξ_2 be any two real numbers. Then, the Dombi T-norm and T-conorm between p and q are defined as follows*:

$$O_D(\xi_1,\ \xi_2) = \frac{1}{1 + \left\{\left(\frac{1-\xi_1}{\xi_1}\right)^{\rho} + \left(\frac{1-\xi_2}{\xi_2}\right)^{\rho}\right\}^{1/\rho}}, \tag{7a}$$

$$O_D^c(\xi_1,\ \xi_2) = 1 - \frac{1}{1 + \left\{\left(\frac{\xi_1}{1-\xi_1}\right)^{\rho} + \left(\frac{\xi_2}{1-\xi_2}\right)^{\rho}\right\}^{1/\rho}}, \tag{8a}$$

where $\rho > 0$ and$(\xi_1,\ \xi_2) \in [0,\ \ 1]$..

Appendix A2

Proof. *for Theorem* 1.

Eq. (5) is decomposed into segments in order to gradually derive Eq. (16).
From Eq. (3) and Eq. (5) we get that:

$$\widetilde{w}_j \cdot \widetilde{\varphi}_j = \left(w_j^{(l)} \cdot \varphi_j^{(l)},\ w_j^{(m)} \cdot \varphi_j^{(m)},\ w_j^{(u)} \cdot \varphi_j^{(u)}\right)$$

$$= \left(\varphi_j^{(l)} - \frac{\varphi_j^{(l)}}{1 + \left\{w_j^{(l)}\left(\frac{f\left(\varphi_j^{(l)}\right)}{1-f\left(\varphi_j^{(l)}\right)}\right)^{\rho}\right\}^{1/\rho}},\ \frac{\varphi_j^{(m)}}{1 + \left\{w_j^{(m)}\left(\frac{f\left(\varphi_j^{(m)}\right)}{1-f\left(\varphi_j^{(m)}\right)}\right)^{\rho}\right\}^{1/\rho}},\ \frac{\varphi_j^{(u)}}{1 + \left\{w_j^{(u)}\left(\frac{f\left(\varphi_j^{(u)}\right)}{1-f\left(\varphi_j^{(u)}\right)}\right)^{\rho}\right\}^{1/\rho}}\right).$$

Then, by applying Eq. (1) we obtain the fuzzy Dombi weighted averaging function [Eq. (16)]:

$$DQ^{\rho}\left(\widetilde{\varphi}_1,\ \widetilde{\varphi}_2,\ \ldots,\ \widetilde{\varphi}_n\right) = \sum_{j=1}^{n} \widetilde{w}_j \cdot \widetilde{\varphi}_j = \left(\begin{array}{c} \sum_{j=1}^{n} \varphi_j^{(l)} - \frac{\sum_{j=1}^{n} \varphi_j^{(l)}}{1 + \left\{\sum_{j=1}^{n} w_j^{(l)}\left(\frac{f\left(\varphi_j^{(l)}\right)}{1-f\left(\varphi_j^{(l)}\right)}\right)^{\rho}\right\}^{1/\rho}}, \\ \sum_{j=1}^{n} \varphi_j^{(m)} - \frac{\sum_{j=1}^{n} \varphi_j^{(m)}}{1 + \left\{\sum_{j=1}^{n} w_j^{(m)}\left(\frac{f\left(\varphi_j^{(m)}\right)}{1-f\left(\varphi_j^{(m)}\right)}\right)^{\rho}\right\}^{1/\rho}}, \\ \sum_{j=1}^{n} \varphi_j^{(u)} - \frac{\sum_{j=1}^{n} \varphi_j^{(u)}}{1 + \left\{\sum_{j=1}^{n} w_j^{(u)}\left(\frac{f\left(\varphi_j^{(u)}\right)}{1-f\left(\varphi_j^{(u)}\right)}\right)^{\rho}\right\}^{1/\rho}} \end{array}\right),$$

where $\widetilde{w}_j = (w_j^{(l)},\ w_j^{(m)},\ w_j^{(u)})$ is the fuzzy vector of the weighting coefficients of the criteria, while$f\left(\widetilde{\varphi}_j\right) = \left(\frac{\varphi_j^{(l)}}{\sum_{j=1}^{n}\varphi_j^{(l)}},\ \frac{\varphi_j^{(m)}}{\sum_{j=1}^{n}\varphi_j^{(m)}},\ \frac{\varphi_j^{(u)}}{\sum_{j=1}^{n}\varphi_j^{(u)}}\right)$..

Appendix A3

Proof. *for Theorem* 2.

Eq. (6) is decomposed into segments in order to gradually derive Eq. (17).
From Eq. (4) and Eq. (6) we get that:

$$\left(\widetilde{\varphi}_j\right)^{\widetilde{w}_j} = \left(\left(\varphi_j^{(l)}\right)^{w_j^{(l)}}, \left(\varphi_j^{(m)}\right)^{w_j^{(m)}}, \left(\varphi_j^{(u)}\right)^{w_j^{(u)}}\right)$$

$$= \left(\frac{\varphi_j^{(l)}}{1 + \left\{ w_j^{(l)} \left(\frac{1 - f\left(\varphi_j^{(l)}\right)}{f\left(\varphi_j^{(l)}\right)} \right)^{\rho} \right\}^{1/\rho}}, \frac{\varphi_j^{(m)}}{1 + \left\{ w_j^{(m)} \left(\frac{1 - f\left(\varphi_j^{(m)}\right)}{f\left(\varphi_j^{(m)}\right)} \right)^{\rho} \right\}^{1/\rho}}, \frac{\varphi_j^{(u)}}{1 + \left\{ w_j^{(u)} \left(\frac{1 - f\left(\varphi_j^{(u)}\right)}{f\left(\varphi_j^{(u)}\right)} \right)^{\rho} \right\}^{1/\rho}} \right).$$

Then, by applying Eq. (2) we obtain the fuzzy Dombi weighted geometric averaging function [Eq. (17)]:

$$DP^{\rho}\left(\widetilde{\varphi}_1, \widetilde{\varphi}_2, ..., \widetilde{\varphi}_n\right) = \prod_{j=1}^{n} \left(\widetilde{\varphi}_j\right)^{\widetilde{w}_j}$$

$$= \left(\frac{\sum_{j=1}^{n} \varphi_j^{(l)}}{1 + \left\{ \sum_{j=1}^{n} w_j^{(l)} \left(\frac{1 - f\left(\varphi_j^{(l)}\right)}{f\left(\varphi_j^{(l)}\right)} \right)^{\rho} \right\}^{1/\rho}}, \frac{\sum_{j=1}^{n} \varphi_j^{(m)}}{1 + \left\{ \sum_{j=1}^{n} w_j^{(m)} \left(\frac{1 - f\left(\varphi_j^{(m)}\right)}{f\left(\varphi_j^{(m)}\right)} \right)^{\rho} \right\}^{1/\rho}}, \frac{\sum_{j=1}^{n} \varphi_j^{(u)}}{1 + \left\{ \sum_{j=1}^{n} w_j^{(u)} \left(\frac{1 - f\left(\varphi_j^{(u)}\right)}{f\left(\varphi_j^{(u)}\right)} \right)^{\rho} \right\}^{1/\rho}} \right).$$

where $\widetilde{w}_j = (w_j^{(l)}, w_j^{(m)}, w_j^{(u)})$ is the fuzzy vector of the weighting coefficients of the criteria, while$f\left(\widetilde{\varphi}_j\right) = \left(\frac{\varphi_j^{(l)}}{\sum_{j=1}^{n} \varphi_j^{(l)}}, \frac{\varphi_j^{(m)}}{\sum_{j=1}^{n} \varphi_j^{(m)}}, \frac{\varphi_j^{(u)}}{\sum_{j=1}^{n} \varphi_j^{(u)}} \right)$..

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