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Selection of electric bus models using 2-tuple linguistic T-spherical fuzzy-based decision-making model

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ABSTRACT

Due to energy's global reliance on fossil fuels and population growth, Greenhouse gas (GHG) emissions and their repercussions have attracted attention. Due to their cheaper cost and cleaner environment, renewable energy modes of transportation like electric vehicles are highly sought after. Electric vehicles are beneficial, but they also emit emissions indirectly in power plants that generate their electricity, which could affect small and medium communities. Thus, it is crucial to assess such modes of transportation's performance while considering key aspects and criteria. However, scholarly works in this field have not fully addressed the deployment of a comprehensive electric vehicle decision-making support system. This study addresses electric bus selection by introducing a novel approach to Multi Criteria Decision Making (MCDM) utilizing a developed integrated fuzzy set. We introduce an integrated approach that combines an Entropy weighting approach with a 2-tuple Linguistic T-Spherical Fuzzy Decision by Opinion Score Method (2TLTS-FDOSM). This approach is designed to tackle the challenges associated with evaluating the feasibility of electric bus models (EBMs) and addressing the theoretical challenge of MCDM in the context of the presented case study. These challenges include dealing with ambiguities and inconsistencies among decision-makers. The former method is utilized to ascertain the significance of assessment criteria, whereas the latter approach is applied to select the most favorable EBM by utilizing the weights obtained. As for the 2TLTS-FDOSM results, out of all the ($n = 6$) EBMs considered, $A3$ (11-E) EBM obtained the highest score value, while the $A3$ (9-E) EBM had the lowest score. The robustness of the results is confirmed through sensitivity analysis.

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1. Introduction

From a global perspective, increased awareness has been directed towards Greenhouse gas (GHG) emissions and their adverse effects. That comes with no surprise given the energy's global reliance on fossil fuels and the increasing population demands, resulting in more green gas emissions like CO2, CH4, NO2, etc. (Kumar et al., 2022a). For this, organizations and governmental authorities worldwide are producing GHG initiatives like the "net-zero" by the European Commission (Sacchi et al., 2022). Furthermore, immediate actions are needed to minimize the effect of GHG emissions into the atmosphere, and many organizations and sectors are required to participate in such initiatives, especially those causing the hardest, that is, transportation and industry, which accounts for 16.2 % and 29.4 % respectively (Ritchie et al., 2020). At the same time, the development of renewable energy transportation options is greatly sought because it promises a cleaner environment at a lower cost, and that can be done through electrification solutions for transportation.

Automotive and transportation industries are considered amongst the most important worldwide, and that can be seen economically and in research and development (Carayannis et al., 2023). With such importance, extensive efforts have been put in place to advance such industries so that passengers and the environment are highly benefited and minimally affected. However, the issue with such efforts is that the former has benefitted from the latter's expenses. GHG has seriously affected the environment, especially given the increasing number of vehicles put into operations daily. For that, alternatives such as new energy vehicles through electrification have been seen as more suitable alternatives owing to their less dependence on oil. Such electrified transportation offered consumers benefits, environmental and socioeconomic benefits (Melander & Wallström, 2023). More specifically, if compared with traditional vehicles, electric vehicles (EV) can offer less emissions, reliability, reduced cost, comfort, better accessibility in urban areas, and extended driving range. However, such types of transportation offer many of the benefits above where significant tailpipe emission is minimized but still produces emissions indirectly in power plants generating the electricity, which could have a notable effect on small and medium communities (Larsen et al., 2010).

It is identified that electrical transportation mediums do not necessarily always discard emissions, and that could affect some communities more than others. It is therefore significantly essential to compare such electricity-based transportation from an objective standpoint to determine their environmental impacts (Liserre et al., 2010), and this ought to be studied in a manner that considers (1) the whole cycle of energy generation, (2) transmission, (3) consumption, and (4) the resulted emissions hand in hand while also considering the urge to provide such equate transportation service in small and medium communities (Chaturvedi & Kim, 2015). A significant reason for considering such communities is that people usually move to such areas to avoid the air pollution and smog of cities. Therefore, it is essential to maintain such advantages for such communities, and in that regard, a friendly vehicle with overall reduced emissions should be considered (Aminian et al., 2023). In addition, in such communities, noise is another significant consideration, and people in such communities, while maintaining less emissions, also value a quiet atmosphere. In that capacity, electric solutions seem more appropriate. However, owing to these solutions' wide range of alternatives, especially while implementing them in small and medium communities, it is pretty challenging to assess them adequately given that some of such transportation vary significantly in terms of costs and performance, making such assessments challenging.

Towards addressing the former issue, a different number of academic works were investigated, but a work proposed by Wang and González (2013) stood out from the rest. The authors argued that implementing electric vehicles with a case study on buses is challenging, especially in small and medium communities, due to tighter budget constraints, higher noise, air quality control standards, and more robust needs for a sense of community. The authors presented an evaluation framework while defining assessment criteria, finalized after deep literature analysis, in addition to other sources like research reports, manufacture consultation, and surveys. It can be clearly seen from the literature that a list of electrical bus performance measurements were considered. Nevertheless, despite these efforts, they only defined assessment criteria. However, at the same time, they did not initiate a proper decision-making support platform that recommends buses while considering the variety of assessment criteria, their levels of importance, and the conflict between their values should more than one electric bus model be considered. These issues present a unique assessment challenge in standard settings for electrical buses that consider all the previous issues, necessitating a more capable decision support platform to address such issues. This platform should be able to present a unique perspective where many criteria in various settings are considered in the decision-making context alongside the other assessment and evaluation challenges, which presents this research challenge as not a typical assessment problem but rather a multiple criteria decision making (MCDM) problem as presented in further details in Section 2.

The proper evaluation and selection process for electrical bus models would facilitate more feasibility for these transportation's utilization in various geographical areas and encourage their implementations amongst small and medium communities. Therefore, this study contributes to the body of knowledge of the given area by developing a novel MCDM-based evaluation/selection approach for electric bus models (EBMs) in small and medium communities, as follows:

(1) To formulate a new evaluation decision matrix for assessing EBMs considering the crisscrossing of all their assessment criteria and alternatives list of EBMs.
(2) To evaluate the significant levels of all EBM assessment criteria from the vehicle and other factors perspectives based on the Entropy MCDM weighting method.
(3) To select the most optimum EBM model based on group MCDM contexts based on a novel MCDM ranking method called 2TLTS-FDOSM ('2-Tuple Linguistic T-Spherical Fuzzy Decision by Opinion Score Method').
(4) To evaluate the robustness of the proposed MCDM approach using several scenario-based sensitivity analyses.

This paper is divided into nine sections. Section 2 discusses the related works on the current state of EBM evaluation and assessment mechanisms and the MCDM integrated approach. Section 3 outlines the case study for the EBMs in this research and the benchmarking decision matrix. Section 4 describes the preliminaries and basic operations, followed by the research methodology applied in this research in Section 5. After that, Section 6 discusses the experimental results for the weighting and evaluation phases for the case study of this research. Section 7 details the validation results of sensitivity analysis, and Section 8 presents this study's implications from different aspects. Finally, Section 9 concludes the study.

2. Related works

This section presents a brief literature review covering topics related to electric vehicle evaluations and assessment case studies from previous academic works, followed by literature on the proposed MCDM approach and its theoretical background.

2.1. Electric transportations evaluation and assessment

Over the years, notable attention has been paid to the world of the electric vehicles industry for various reasons, including their utilization of renewable energy. Other significant reasons can be related to great opportunities in achieving energy security and reducing pollution (Navyasri et al., 2023). At the same time, many electrical electrified transportation solutions are finding their way into the market, necessitating the need for accurately assessing and evaluating their capabilities to ensure better and more informed decision-making is taking place. Within the context of this research, it was necessary to identify some of the most significant contributions related to how different forms of electric transportation aspects were assessed over the years. Kumar et al. (2022b) examined the significance of diffusion models in understanding the diffusion of EVs. They have provided insights into the nature of these models and the difficulties involved in their development and have also conducted a comparative analysis of EV sales across 20 major countries. Furthermore, they have identified the clusters that exhibit the most accurate fit for each country based on various metrics. Wang et al. (2017) evaluated the primary elements and incentives that are taken into account by the Chinese government in order to facilitate the market adoption of EV sales. A component of the study was providing recommendations for designing and developing matching rules, considering factors such as location sensitivities and excluding time sensitivities within a five-year timeframe. The findings of their study indicated that the characteristics under consideration may be further sustained and enhanced to maintain a consistently strong performance in the electric vehicle industry. Ho and Huang (2022) argued the importance of evaluating vehicle power technologies, including combustion engine, hybrid, or pure electric vehicles. Therefore, the authors developed an MCDM evaluation platform using the Analytical Hierarchy Process (AHP), which incorporates technological factors and market criteria to facilitate more suitable decision-making that can aid in allocating resources to various renewable power technologies for passenger vehicles. Their results suggest that Li-Ion technology performed better for purchasing cost, operating cost, and refuel facilities while Fuel Cells outperformed Li-Ion in terms of driving range, battery life, and refuel time. Pevec et al. (2020) examined EV purchasers' preferences compared to internal combustion engine buyers. A comparison of the two target groups focused on the interaction between petrol station infrastructure and EV charging station infrastructure. The study found that EV and non-EV owners agree on the topology of the best petrol station and charging station. Wang et al. (2019) examined the impact of environmental and energy security incentives on EV promotion. The authors found that factors such as charger density, fuel price, and road priority positively correlate with electric vehicle market share, and fiscal incentives no longer explain the significant differences in electric vehicle promotion across countries. Ashfaq et al. (2021) reviewed recent deployment, challenges in EV infrastructure installation, charging power levels, charging techniques, and EV influences on the electric grid. In Chen and Wang (2012), electric differentials (ED) were developed and tested for four-wheel-drive over actuated electric ground vehicles. The authors suggest that the experimental and simulated results confirm the designs of the three EDs because they all achieve almost the same vehicle performances in terms of the EGV sideslip angle, yaw rate, and trajectory. Steen et al. (2012) presented a methodology for managing plug-in electric vehicle (PEV) charging, utilizing charging behavior predictions derived from demographical statistical data. This study examines three distinct charging strategies and evaluates the effects of plug-in electric vehicle (PEV) charging on the distribution system by applying standard load flow calculations. By employing a case study to illustrate the proposed approach, the research findings demonstrate that the impacts of PEVs on the distribution system differ across various regions. Furthermore, the study reveals that these impacts can be mitigated; however, it emphasizes the importance of carefully selecting appropriate control methods to achieve this reduction. Ozdagoglu et al. (2022) compared three well-known Turkish bus brands for long-distance travel based on ten criteria, including technical specifications, customer service, price, and overall reputation. Both bus drivers' and owners' preferences are considered in the study's evaluation of the criteria, which is based on an integrated PIPRECIA and COPRAS-G MCDM approach. According to the findings, one brand stands out as the superior option for long-distance travel. Buran and Erçek (2023) presented a study to select the most suitable bus type for public transportation in the Istanbul metropolitan area; their work provides an MCDM that considers financial, operational, business, and strategic criteria. Since this problem is inherently vague and challenging to solve, the proposed technique employs the Spherical Fuzzy AHP methodology to tackle it. By providing a comprehensive overview of green transport options, this study addresses a critical gap in the literature and offers valuable information to public transport decision-makers and practitioners alike. In the work by He (2022), which used examples of two distinct battery electric bus models produced by four different Chinese manufacturers, the authors developed an objective way of making a final decision. Reliability, cost, and security were the primary criteria used in their analysis. The entropy weight technique was used to consider all relevant factors in order to develop an evaluation system based on the bus's performance during regular operation, and he concluded that high-scoring electric buses were, on average, top performers across all routes. Using entropy and a composite programming approach, Ardil (2023) provided an MCDM solution for selecting the best electric passenger car. The author considered a range of transport options and compared them with an optimal metric that established how distant each was from the ideal. They used essential factors that consumers should think about when shopping for a daily driver electric passenger car (driving range, battery life, engine power, top speed, acceleration). Hamurcu and Eren (2020) presented an AHP-TOPSIS MCDM selection methodology for choosing an electric bus in the central region of Ankara, with a particular focus on densely populated areas, aiming to improve air quality and create more habitable cities. The authors assess six viable electric bus alternatives based on seven criteria to address the growing need for sustainable public transport services in a developing country. The findings indicated that battery capacity and charging time were the primary factors influencing the results. Additionally, it was recommended that hydrogen vehicles and electric autonomous vehicles be considered as potential alternatives in the future. The evaluation and assessment of EVs have been examined in several studies, encompassing various situations, especially the work by Wang and González (2013). The existing research in this field has primarily concentrated on appraising specific designs, regulations, and the methodologies employed by various authors. Despite their commendable accomplishments, none of these individuals have evaluated EVs in a holistic transportation context. Moreover, there has been a noticeable oversight in evaluating EVs within the specific context of low and medium-income communities. Additionally, there is a pressing need for an assessment platform that encompasses a range of EV models, each showcasing diverse performance attributes across various criteria. This particular aspect underscores a pivotal differentiation that distinguishes our work from the existing body of literature. To the best of our knowledge, no prior studies have adopted our approach in the realm of EVs, especially the innovative fuzzy environment MCDM approach that we've employed for the evaluation and assessment of our work. The subsequent section offers a thorough exploration of this novel approach.

2.2. MCDM approach

MCDM is an operational research concept that addresses selection problems for decision-makers for the most suitable option from a set of predetermined available alternatives (Alsalem, Mohammed, et al., 2022; Dağıstanlı, 2023). MCDM primarily functions by running these alternatives against a set of different criteria (David, 2023), where each has its weight on the overall decision process (Vahidinia & Hasani, 2023). MCDM, like any research concept, has its own merits, which warrant it is suitable for addressing complex situations for research and industrial usages, which, in their way, presents a challenging decision-making scenario (Albahri et al., 2022; Rezazadeh et al., 2023; Alsalem, Alamoodi, et al., 2022; Younis Al-Zibaree and Konur, 2023). MCDM has also found its way in various research directions, including health, energy, industry, technology, and many more (Alamoodi et al., 2020). MCDM has significant potential in various areas (Hiba Mohammed et al., 2023). In order to fully understand its potential, it is essential to know about MCDM methods, which vary in their primary aim to either being used for weighting and assigning importance values for the criteria involved in the decisions or selecting the choices for decision makers (DMs), and other MCDM methods can perform both tasks simultaneously (Sharaf et al., 2024). Some of the most trending and well-known MCDM methods include "*Fuzzy-Weighted with Zero-Inconsistency (FWZIC)*" (Mohammed, Zaidan, et al., 2021), "*Full Consistency Method*" (Pamučar et al., 2018), Entropy (Banadkouki, 2023), and others. When it comes to MCDM ranking and selection methods, they include "*Technique for Order of Preference by Similarity to Ideal Solution* (TOPSIS)" (Mohammed, Albahri, et al., 2021), "*Visekriterijumska Optimizacija i Kompromisno Resenje*" (VIKOR) (Malik et al., 2022), "*Multi-Attributive Border Approximation Area Comparison* (MABAC)" (Pamučar & Ćirović, 2015), and others. The MCDM approaches, which can do both, include "*Fuzzy Decision by Opinion Score Method (FDOSM)*" (Salih et al., 2020), "Analytic Hierarchy Process (AHP)" (Khatari et al., 2021), "*Best Worst Method* (BWM)" (Alsalem et al., 2019) and others.

In the context of this research, before determining which MCDM approach is suitable, it is essential to understand that the criteria identified by Wang and González (2013) concerning either "*Vehicle Factors*" or "*External Factors*" were used in this research. All these factors have two to three levels of their related sub-criteria, which all are in pressing need of a proper weighting approach based on the study case at hand; most of the criteria values, which are discussed in detail in Section 3.1 are objectively measured, rendering Entropy weighting a suitable option for utilization in this research. The notion of Entropy was initially brought to the field of information theory by C.E. Shannon, who referred to it as information entropy (Banadkouki, 2023). The entropy weight method can be classified as an objective weight approach. In the context of a particular use, it is possible to determine the relative weight of objective attributes by employing a two-step process. Firstly, the entropy weight of each attribute is calculated using information entropy. Secondly, the weight of each attribute is adjusted based on the degree of variation exhibited by that attribute, utilizing the entropy weight (Yang et al., 2023).

Moreover, the entropy method is beneficial for analyzing discrepancies among sets of information. If distinct alternatives have the same values for some criteria, it is necessary to delete such attributes. This approach has found widespread application in engineering technology and social economics (Zhang et al., 2023). One notable benefit of employing the entropy technique is its capacity to mitigate decision-makers' subjective influence, enhancing objectivity in the decision-making process (Sitorus & Brito-Parada, 2022). Based on all these details above, Entropy was found suitable for utilization. Additionally, another MCDM method is required to consider the output weight and utilize it in the decision-making context for selecting the suitable EV bus mode of transportation. Towards that end, there is a need to consider robust and suitable MCDM ranking techniques based on having different ones available and widely utilized in decision-making challenges; some of their implementation problems should be considered, especially given that some are more significant than others, and in that regard, MCDM methods have been generally classified into conventional and fuzzy-set based methods (Ghoushchi et al., 2021).

In MCDM research, uncertainty is among the most challenging problems, which refers to the lack of complete or accurate information about the criteria, alternatives, preferences, or outcomes involved in the decision-making process. In that regard, traditional MCDM approaches are deemed inadequate to be used in complex decision-making problems (Pradhan et al., 2022), and that gave rise to the notion of fuzzy set (FS) by Zadeh (1965). The FS concept relies on membership degree to indicate the level of element inclusion to a (fuzzy set) which can establish a more informed and improved decision-making outcome. Inspired by this, FS has attracted many scholars to utilize it in their respective research areas, including but not limited to areas like medicine (Liu et al., 2021), engineering (Lin et al., 2022), and many more. Owing to this popularity, MCDM research did not fall behind in the race and utilized various FS environments with MCDM techniques for solving real-world decision-making problems. Nevertheless, as FS is continuously used, a typical FS could not effectively address uncertainty. Towards that end, several FS environments were continuously developed to determine which is suitable for an MCDM problem. This includes "*Bipolar Soft Sets*" (Mahmood, 2020), "*Picture Fuzzy Sets*" (Ganie et al., 2020), "*Spherical Fuzzy Sets* (SFSs)" (Kutlu Gündoğdu & Kahraman, 2019), "*Intuitionistic Fuzzy Sets (IFSs)*" (Alcantud et al., 2020), and "*Interval-valued Intuitionistic Fuzzy Sets* (IVIFSs)" (Liu & Jiang, 2020), "*Pythagorean Fuzzy Sets* (PFSs)" (Yager, 2013), "*Hesitant Fuzzy Sets* (HFSs)" (Torra, 2010), "*Fermatean Fuzzy Sets*" (Akram & Niaz, 2022), and "*Neutrosophic Fuzzy Sets (NFSs)*" (Broumi et al., 2019). All these types of FSs still exhibit their issues when addressing concrete inaccuracies where maximum choice is often characterized by vagueness and fuzziness in decision-making. Besides the previously mentioned FSs, the notion of linguistic variables (LVs) introduced by Zadeh (1975) was also utilized. To overcome the deficiencies in implementing LVs, the 2-tuple linguistic representation model (2TLRM) by Herrera and Martinez (2000a, 2000b) was developed, resulting in the proposal of various methodologies for decision-making and linguistic assessment objects based on 2TLRM. Motivated by this concept, the notion of a 2-tuple linguistic complex-rung orthopair fuzzy set (2TLCq-ROFS) (Naz et al., 2022) was presented where the fusion of q-rung orthopair fuzzy set with 2-tuple linguistic is established resulting in operational guidelines, scoring mechanisms, and accuracy functions, but still suffer in exclusively covering two dimensions of human perception: favorability and disfavor.

While it is true that human opinions often incorporate elements of restraint and dismissal, according to Cuong and Kreinovich (2014), the representation of an IFS or its generalized form as a pair captures the human opinion in terms of MD (membership degree) and NMD (non-membership degree) while disregarding the abstinence degree (AD) and refusal degree (RD). This oversight results in a loss of knowledge. Consequently, the introduction of the picture fuzzy set (PFS) was motivated by the need to incorporate the triplets of membership degrees (MD), abstinence degrees (AD), and non-membership degrees (NMD) in a manner that ensures their cumulative sum does not exceed one. Subsequently, the research conducted by Kutlu Gündoğdu and Kahraman (2019) enhanced the structure of PFSs, resulting in the development of SFSs. This was achieved through the introduction of certain aggregation operators (AOs). In a further study by Mahmood et al. (2019), the concept of T-spherical fuzzy sets (T-SFSs) was proposed as an additional extension that combines the principles of both SFSs and PFSs. The capability of T-SFSs in representing the evaluation values of decision-makers with MCDM techniques has been demonstrated in several cases.

On the other hand, the 2TLRM possesses an enhanced capacity for describing linguistic information and can mitigate the loss of information distortion when addressing linguistic choice problems. Nevertheless, the current theories of T-SFSs and the 2TLRM, each on its own, are not fully efficient in representing uncertain information. Combining the advantages of both models and using the 2-tuple Linguistic T-spherical fuzzy sets (2TLT-SFSs) is a more efficient approach for expressing the evaluation values of the decision makers in the MCDM problems.

It can be seen that the 2TLT-SFS, as a novel integration of fuzzy approaches, has many benefits that can be utilized in this research for the ranking method to be used after the entropy weighting approach. Amongst the most recent ranking approaches comes FDOSM, which has been proven robust in addressing many MCDM case study challenges. FDOSM has been developed by Salih et al. (2020) to address various issues, including the inconsistent ratio resulting from pairwise comparisons. This discrepancy has been found to consume a significant amount of time and give rise to a related problem known as abnormal comparisons. Furthermore, the FDOSM addresses the issue of measuring distances between ideal and alternate solutions. FDOSM has garnered significant interest from scholars in recent studies. However, there has been a lack of effort in expanding the application of FDOSM to the 2TLT-SFS domain. To sum up the above discussions, this study's main innovations can be seen through its integration of the Entropy weighting approach for assessing the evaluation criteria for EVs, along with a new formulation of 2TLTS-FDOSM for selecting the EV models as an effective tool to address better ambiguities and inconsistencies with decision-makers appreciation over the EV models to assess their feasibility in small and medium-sized communities.

3. Electric buses in small and medium-sized communities

This section discusses three main points, starting with the electric buses assessment and evaluation factors, followed by EBM alternatives (*i.e., models*) for assessment, and a benchmarking decision matrix comprising the two against each other. Both criteria and EBM alternatives were adopted from the work by Wang and González (2013) and were used as alternatives and proof of concept in the current study.

3.1. EB evaluation factors

Several evaluation criteria were included to assess the EBM alternatives in small and medium-sized communities related to (1) Vehicle or (2) External factors, as discussed below.

***C_1*: Vehicle Factors:** In the context of this research, this main criterion refers to all EV aspects from *passenger*, *speed*, *range*, and *gradability* points of view, which are to be used in the evaluation and assessment.

***$C_{1\text{-}1}$*: Passenger Capacity (*Persons*):** This criterion refers to the number of passengers involved in an EB ride; the number of passengers determined is based on seated and standee passengers. This benefit criterion indicates that the more passengers involved, the better the EB model is.

***$C_{1\text{-}2}$*: Maximum Speed (*km/hr.*):** This criterion refers to the maximum kilometre EB speed that an EB model can reach per hour; given the variety of models, their performance might differ, and therefore max speed in this research is deemed a benefit criterion.

***$C_{1\text{-}3}$*: Range (km):** This main criterion is meant to measure distance in a kilometre, and it has two sub-criteria: ($C_{1\text{-}3\text{-}1}$) "*Distance in KM*" and ($C_{1\text{-}3\text{-}2}$) "*Hours of continuous operation*". The former ($C_{1\text{-}3\text{-}1}$) refers to the kilometre range a bus can achieve on one full charge, while the latter ($C_{1\text{-}3\text{-}2}$) refers to the hours a bus can continuously operate while maintaining the same speed of 16.41 km/hr. All the ($C_{1\text{-}3}$) $_{\text{sub}}$-criteria are considered benefit criteria.

***$C_{1\text{-}4}$*: Gradeability:** This criterion refers to the highest incline a bus can travel up while maintaining a minimum speed of 1 mph (*equivalent to 1.61 km/h*). This criterion is also a benefit criterion.

***C_2*: External Factors:** In this research context, this main criterion refers to all EV aspects from ($C_{2\text{-}1}$) Financial Impact and ($C_{2\text{-}2}$) Environmental Impact aspects. Each aspect has its sub-criterion with details as follows.

***$C_{2\text{-}1}$*: Financial Impact:** This main criterion exhibits several subs and sub-sub criteria, which all revolve around the financial and cost aspects to be considered in evaluating the EB model. The first sub-criterion is ($C_{2\text{-}1\text{-}1}$) *"Energy Cost" (per year),* which refers to the energy cost required for operating an EB model in a year in USD currency. The next sub-criterion is the "*Capital Initial Cost" ($C_{2\text{-}1\text{-}2}$)* criterion, which refers to the expenses associated with purchasing a bus, excluding supplementary accessories, facility alterations, charging infrastructure, or additional battery units. The following sub-criterion ($C_{2\text{-}1\text{-}3}$), *"Capital Initial Costs Per Passenger (\$= Passenger)",* refers to the exact previous criterion cost but per passenger. Following criteria ($C_{2\text{-}1\text{-}4}$), "*Maintenance Cost \$=year"* refers to costs for regularly servicing or repairing buses. The following sub-criteria ($C_{2\text{-}1\text{-}5}$) *"Battery Charge Cost \$=year"* is divided into two: the first is ($C_{2\text{-}1\text{-}5\text{-}1}$) *"Battery Cost"* for one "*average cost*" for a battery, and the second is ($C_{2\text{-}1\text{-}5\text{-}2}$) "*Charger Cost*" for the cost required for purchasing a new charger. The following sub-criteria ($C_{2\text{-}1\text{-}6}$), *"Emissions Cost \$=year",* refers to the average annual expenditures associated with the damage caused by pollutants. The last three sub-criteria involved within the financial impact include ($C_{2\text{-}1\text{-}7}$) *"Noise Cost \$=year",* ($C_{2\text{-}1\text{-}8}$) *"Average Discount on Property Values (%)"*, and finally ($C_{2\text{-}1\text{-}9}$) *"Equivalent Uniform Annual Cost (EUAC)".* All the sub-criteria, details, and financial impact aspects are deemed cost criteria, indicating that the more they increase, the less desirable they become. This applies to all the criteria except the ($C_{2\text{-}1\text{-}8}$), which is determined as the only benefit criteria in this aspect.

***$C_{2\text{-}2}$*: Environmental Impact:** This main criterion refers to all the aspects that can impact the environment in small and medium-sized communities, and it exhibits several subs to be considered in evaluating the EB model. The first sub-criterion is ($C_{2\text{-}2\text{-}1}$) "*Emissions Quantity*", which includes three sub-aspects associated, starting with ($C_{2\text{-}2\text{-}1\text{-}1}$) "*Total SOX emissions (kg = year)*", ($C_{2\text{-}2\text{-}1\text{-}2}$) "*Total NO_X emissions (kg = year)"*, and ($C_{2\text{-}2\text{-}1\text{-}3}$) "*Total CO2 Emissions (kg = year)*". *The last sub-criteria in the environmental impact aspect ($C_{2\text{-}2\text{-}2}$) is "Noise Quantity Noise above ambient level (dBA)",* which refers to measuring the ambient noise in addition to noise emitted on the left and right sides of buses undergoing full acceleration from standstill.

3.2. Benchmarking decision matrix

In the decision-making process, the decision matrix is one crucial and essential component needed to make a reliable decision. This research refers to this decision matrix as a benchmarking decision matrix. It requires two elements for construction: a list of alternatives (*i.e., EB models*) and evaluation criteria (*i.e., evaluation factors with all their subs in this study*). Both elements have been mentioned and discussed in this section. Therefore, the benchmarking decision matrix for EBMs, aimed at assessing the feasibility of EBMs in small and medium-sized communities, is presented in Table 1.

Table 1 displays the decision matrix employed to evaluate the viability of EBMs in small and medium-sized communities across several evaluation criteria, encompassing both primary and secondary levels. All the values in the table are expressed in objective values, encompassing a range of costs and numerical quantities, as presented in the base work by Wang and González (2013). In brief, Table 1 illustrates the obstacles encountered in human-driven decision-making when striving to achieve dependable outcomes without employing the MCDM methodology. The results indicate that various EBMs demonstrate varying levels of effectiveness when evaluated against specific criteria related to their characteristics.

4. Preliminaries

In this section, the basic concepts and operations of 2TLTS are presented as follows.

Definition 1 (Herrera & Martínez, 2000a, 2000b): A linguistic term set (LTS) of an odd cardinality $(\Gamma+1)$

$$S=\{s_{0,}s_1,s_2\cdots,s_\Gamma\}$$

Is a set of ordered linguistic descriptors, e.g., $S=\{s_0 = not\ \ likely, s_1 = somewhat\ \ likely, s_2 = very\ \ likely\}$, each linguistic term covers a range of numerical values.

Definition 2 (Herrera & Martínez, 2000a, 2000b): Aggregating some labels in (S) by a symbolic method might result in a numerical value $\beta \in [0,\Gamma]$ which is not an integer. The non-integer value β can be divided to a 2-tuple $(s_\ell, \mathscr{L})$, ℓ is an integer value denoting the linguistic label center of information and $\mathscr{L}\in[-0.5,0.5)$ denoting the translation from β to the nearest index ℓ in S.

Definition 3 (Herrera & Martínez, 2000a, 2000b): To find the 2-tuple that expresses the non-integer value β, the following function is used

Table 1
Benchmarking Decision Matrix.

Criteria/Alternative				EBM-1 (A_1)	EBM-2 (A_2)	EBM-3 (A_3)	EBM-4 (A_4)	EBM-5 (A_5)	EBM-6 (A_6)
Vehicle Factors (C_1)	*Passenger Capacity (Persons)* ($C_{1\text{-}1}$)			77	61	61	85	28	26
	Maximum Speed (km = hr.) ($C_{1\text{-}2}$)			48.3	80	80	104.6	64.4	64.4
	Range ($C_{1\text{-}3}$)	*(Distance)* ($C_{1\text{-}3\text{-}1}$)		6	500	500	80	86	65
		(Hours of cont. operation) ($C_{1\text{-}3\text{-}2}$)		0	30	30	5	5	4
	Gradeability ($C_{1\text{-}4}$)			12	11.3	11.3	9.1	8.6	6.7
External Factors (C_2)	Financial Impact ($C_{2\text{-}1}$)	*Energy Costs* ($C_{2\text{-}1\text{-}1}$)		$1,742	$1,345	$860	$1,719	$1,848	$1,824
		Capital Initial Cost ($C_{2\text{-}1\text{-}2}$)		$500,000	$490,190	$490,190	$1,000,000	$305,000	$217,498
		Capital Initial Costs Per Passenger ($C_{2\text{-}1\text{-}3}$)		$6,494	$8,036	$8,036	$11,765	$10,893	$8,365
		Maintenance Cost ($C_{2\text{-}1\text{-}4}$)		$19,036	$19,036	$19,036	$19,036	$19,036	$19,036
		Battery and Charging Cost ($C_{2\text{-}1\text{-}5}$)	*Battery* ($C_{2\text{-}1\text{-}5\text{-}1}$)	$65,000	$437,760	$279,680	$89,984	$12,920	$9,576
			Charger ($C_{2\text{-}1\text{-}5\text{-}2}$)	$120,000	$60,000	$60,000	$60,000	$60,000	$60,000
		Emissions Cost ($C_{2\text{-}1\text{-}6}$)		$10,641	$8,220	$5,252	$10,500	$6,587	$6,501
		Noise Cost ($C_{2\text{-}1\text{-}7}$)		$962	$962	$962	$962	$962	$962
		Discount on Property Values ($C_{2\text{-}1\text{-}8}$)		N/A	N/A	N/A	N/A	3.32 %	6.04 %
		EUAC ($C_{2\text{-}1\text{-}9}$)		$264,696	$298,883	$271,619	$345,187	$470,598	$419,295
	Environmental Impact ($C_{2\text{-}2}$)	*Emissions Quantity* ($C_{2\text{-}2\text{-}1}$)	*Total SOX emissions* ($C_{2\text{-}2\text{-}1\text{-}1}$)	162.4	125.5	80.2	160.3	172.4	170.1
			Total NOX emissions ($C_{2\text{-}2\text{-}1\text{-}2}$)	71.1	55	35.1	70.2	75.5	74.5
			Total CO2 emissions ($C_{2\text{-}2\text{-}1\text{-}3}$)	38271.4	29564.1	18888.2	37764.6	40612.7	40084.8
		Noise Quantity above ambient level ($C_{2\text{-}2\text{-}2}$)		N/A	N/A	N/A	N/A	8.4	15.3

EBM = Electric Bus Model, C = Criterion, A = Alternative.

$$\Delta : [0,\Gamma] \rightarrow S \times [-0.5, 0.5)$$

$$\Delta(\beta) = (s_{\ell}, \mathscr{L}), \text{ with } \begin{cases} s_{\ell}, \ell = round(\beta), \\ \mathscr{L} = \beta - \ell, \mathscr{L} \in [-0.5, 0.5). \end{cases}$$

Conversely, the inverse function Δ^{-1} transforms a 2-tuple to the non-integer value $\beta \in [0,\Gamma]$:

$$\Delta^{-1} : S \times [-0.5, 0.5) \rightarrow [0, \Gamma]$$

$$\Delta^{-1}(s_{\ell}, \mathscr{L}) = \ell + \mathscr{L} = \beta$$

Definition 4 (Akram et al., 2023): On a universal set X, a 2 tuple linguistic T-spherical fuzzy set (2TLT-SFS) is a T-spherical fuzzy set whose grades are expressed by a 2TRM. Hence, it has the form

$$\mathbb{T} = \left\{ \langle x, (S_{\phi}(x), \Phi(x)), (S_{\psi}(x), \Psi(x)), (S_{\gamma}(x), \Upsilon(x)) \rangle | x \in X \right\},$$

where $(S_{\phi}(x), \Phi(x)), (S_{\psi}(x), \Psi(x))$, and $(S_{\gamma}(x), \Upsilon(x))$ are the positive membership degree, the neutral membership degree, and the negative membership degree, respectively. These degrees satisfy

$$-0.5 \le \Phi(x), \Psi(x), \text{ and } \Upsilon(x) < 0.5$$

$0 \le \Delta^{-1}(S_{\phi}(x), \Phi(x)) \le \Gamma, 0 \le \Delta^{-1}(S_{\psi}(x), \Psi(x)) \le \Gamma, 0 \le \Delta^{-1}(S_{\gamma}(x), \Upsilon(x)) \le \Gamma$, and

$$0 \le \left(\Delta^{-1}(S_{\phi}(x), \Phi(x))\right)^q + \left(\Delta^{-1}(S_{\psi}(x), \Psi(x))\right)^q + \left(\Delta^{-1}(S_{\gamma}(x), \Upsilon(x))\right)^q \le \Gamma^q.$$

Definition 5: The score function of a 2TLT-SFS is calculated by.

$$\text{Score}(\mathbb{T}) = 1 + \left(\frac{\Delta^{-1}(S_{\phi}, \Phi)}{\Gamma}\right)^q - \left(\frac{\Delta^{-1}(S_{\psi}, \Psi)}{\Gamma}\right)^q - \left(\frac{\Delta^{-1}(S_{\gamma}, \Upsilon)}{\Gamma}\right)^q.$$

Definition 6: To aggregate 2TLT-SFSs $\{\mathbb{T}_1, \mathbb{T}_2, \cdots, \mathbb{T}_r\}$ by means of a weighting vector $w = (w_1, w_2, \cdots, w_r)$, $w_i \in [0,1]$, and $\sum_{i=1}^{r} w_i = 1$, the 2-tuple linguistic T- spherical weighting averaging operator (2TLT-SFWA) is defined as

$$2TLT-SFWA\{\mathbb{T}_1, \mathbb{T}_2, \cdots, \mathbb{T}_r\} = \left(\Delta\left(\Gamma \sqrt[q]{1 - \prod_{i=1}^{r} \left(1 - \left(\frac{\Delta^{-1}(S_{\phi}, \Phi)}{\Gamma}\right)^q\right)^{w_i}} \right), \Delta\left(\Gamma \prod_{i=1}^{r} \left(\frac{\Delta^{-1}(S_{\psi}, \Psi)}{\Gamma}\right)^{w_i} \right), \Delta\left(\Gamma \prod_{i=1}^{r} \left(\frac{\Delta^{-1}(S_{\gamma}, \Upsilon)}{\Gamma}\right)^{w_i} \right) \right).$$

5. Study methodology

This study's integrated Entropy-2TLTS-FDOSM MCDM model comprises two main methodological phases. Both are working in sequence after one another to fulfill the requirements of this study. The first phase (*Entropy*) will explain the utilized approach's steps to assess the importance of all the factors/criteria considered in this study (*i.e., all the vehicle and external factors*), followed by phase two, where 2TLTS-FDOSM steps are discussed to evaluate and assess the feasibility of the EBMs adopted in this study using the extracted weights of the evaluation factors.

5.1. Entropy weight method

The objective of this section is to provide a detailed explanation of the steps involved in assigning the importance weights for the assessment criteria (Table 1) using the Entropy weighting method. Entropy weighting, as previously discussed, works by considering the assessment of uncertainty in a continuous probability distribution, which becomes more evident when there is a higher degree of dispersion in the values of an index, highlighting the significance of said index (Ullah et al., 2020). Using Entropy includes five consequent steps, which are discussed as follows.

1st Step. *Decision Matrix Formulation*: This Step begins the Entropy process, which includes the matrix that contains m alternatives (*EBMs*) and n criteria, and all the m alternatives are evaluated against the n criteria.

2nd Step. *Decision Matrix Normalization*: This Step involves normalizing the decision matrix values. First, the evaluations are normalized due to the difference in measurement units based on Eqs. (1) and (2). Then, it is normalized once again based on Eq. (3) to be suitable for processing by the Entropy method.

$$X_{ij} = \frac{a_{ij}}{\max_j a_{ij}}, \quad \text{for the benefit criteria,} \tag{1}$$

$$X_{ij} = \frac{\min_j a_{ij}}{a_{ij}}, \quad \text{for the cost criteria.} \tag{2}$$

$$p_{ij} = \frac{X_{ij}}{\sum_{j=1}^{m} X_{ij}}, \quad \text{for normalization} \tag{3}$$

3rd Step. *Entropy Measurement*: In this Step, the entropy value for each criterion is measured using Eq. (4) based on the data expressed for each of the m alternatives (EBMs).

$$E_i = -K\sum_{j=1}^{m} p_{ij}Ln(p_{ij}), whereK = \frac{1}{Ln(m)}. \tag{4}$$

4th Step. *Entropy Uncertainty Degree*: In this Step, after the measurement of each criterion entropy, their uncertainty or degree of deviation (d_i) is measured using Eq. (5)

$$d_i = 1 - E_i \tag{5}$$

5th Step. *Final Weight Determination*: In the last Entropy step, the weight of each criterion (W_i) is determined using Eq. (6).

$$W_i = \frac{d_i}{\sum_{i=1}^{n} d_i} \tag{6}$$

Upon the completion of all these entropy steps and equations, the weight for the final criteria weight is used to convey their level of importance, which will be used in the decision-making process.

5.2. 2-Tuple linguistic T-spherical fuzzy decision by opinion score method (2TLTS-FDOSM)

Upon completing the Entropy weighting phase, the weights are passed to another MCDM method, known for its robustness in addressing and ranking EBMs, to assess their feasibility for usage in small and medium-sized communities. The method used in this research for such purpose is FDOSM, which was first developed by Salih et al. (2020). The initial design of FDOSM showed sufficient capability in addressing a range of MCDM concerns, including handling inconsistent ratios resulting from pairwise comparisons, abnormal comparisons, and other related challenges. Nevertheless, FDOSM encountered several issues stemming from data representations that yielded ambiguous and imprecise information, and towards that end, it has been extended over different fuzzy environments such as "*Interval Type 2 Trapezoidal Fuzzy Sets*" (IT2TFS) (Krishnan et al., 2021), "*Interval-Valued Pythagorean Fuzzy Sets*" (Al-Samarraay et al., 2021), NFSs (Alamoodi et al., 2022) and others. However, FDOSM has garnered significant interest from scholars in recent studies, and formulating such a superior method has not been achieved by taking advantage of 2TLT-SFS, which are presented based on single and group decision-making processes in the present study. The 2TLT-FDOSM stages and their steps are formulated as follows:

First Stage: This section outlines the data entry procedure to construct the MCDM approach's primary element, namely a selection decision matrix (SDM). The SDM is used to rank and select EBMs, as shown in Table 1 above. In this scenario, six EBMs, serving as alternatives, are evaluated against a set of nineteen criteria (*n = 19*). The summarised process is presented in Eq. (7) as follows.

$$SDM = \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} \begin{bmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{m1} & \cdots & c_{mn} \end{bmatrix} \tag{7}$$

This formulation is achieved by intersecting the list of all alternatives (*EBMs*) (*i.e., Electric Bus Models*) and their evaluation and assessment criteria (C_n).

Second Stage: During the second stage, the transformational process is implemented using the (2TLTS-FDOSM) approach, following the generation of the SDM in the previous phase. This is achieved by selecting an optimal solution based on the performance of each evidence-based model against each criterion. The subsequent section provides an exposition and elucidation of the requisite procedures to be undertaken at that point.

Step 1: Selecting the most suitable alternative based on the expertise of decision-making specialists. Given these considerations, a comprehensive response can be described using Eq. (8) as follows:

$$A^* = \left\{ \left[\left(\underset{i}{mxv_{ij}} | j \in J \right), \left(\underset{i}{mnv_{ij}} | j \in J \right), (cv_{ij} \in I.J) | i = 1.2.3.\cdots.m \right] \right\} \tag{8}$$

where

mx is the most optimal for the maximum selection criteria, *mn* is the most optimal for the minimum selection criteria, and cv_{ij} Is the most optimal for the critical selection criteria (neither *mx* nor *mn*), which a decision-maker specialist can choose.

Step 2: A comparison was made between the optimal solution and alternative values per criterion utilized in the selection procedure. The language factors are compared using a set of five scales, namely)*"no difference," "slight difference," "difference," "big difference," and "huge difference."(*. Once the ideal solution has been chosen, the subsequent Step involves comparing the value of the optimal solution with the alternatives, using the precise selection criterion outlined in Eq. (9).

$$LOM = \left\{ \left(\left(\underset{ij}{\widetilde{r}} \otimes r_{ij} | j \in J \right) . | i = 1, 2, 3, \cdots, m \right) \right\} \tag{9}$$

where

Table 2
Linguistic Variables and their Corresponding 2TLT-SFS for Evaluating the Alternatives.

Linguistic Variable	Abbreviated Term	2TLT-SFS
No Difference	ND	$\langle(S_9,0),(S_1,0),(S_1,0)\rangle$
Slight Difference	SD	$\langle(S_7,0),(S_3,0),(S_3,0)\rangle$
Difference	D	$\langle(S_5,0),(S_5,0),(S_5,0)\rangle$
Big Difference	BD	$\langle(S_3,0),(S_3,0),(S_7,0)\rangle$
Huge Difference	HD	$\langle(S_1,0),(S_1,0),(S_9,0)\rangle$

Table 3
Criteria Final Weight by Entropy.

Criteria/Alternative				Final Weight
Vehicle Factors (C_1)	*Passenger Capacity (Persons) (C_{1-1})*			0.036
	Maximum Speed (km = hr.) (C_{1-2})			0.012
	Range (C_{1-3})	*(Distance) (C_{1-3-1})*		0.217
		(Hours of cont. operation) (C_{1-3-2})		0.226
	Gradeability (C_{1-4})			0.0078
External Factors (C_2)	Financial Impact (C_{2-1})	*Energy Costs (C_{2-1-1})*		0.019
		Capital Initial Cost (C_{2-1-2})		0.043
		Capital Initial Costs Per Passenger (C_{2-1-3})		0.0081
		Maintenance Cost (C_{2-1-4})		0
		Battery and Charging Cost (C_{2-1-5})	*Battery ($C_{2-1-5-1}$)*	0.258
			Charger ($C_{2-1-5-2}$)	0.01
		Emissions Cost (C_{2-1-6})		0.014
		Noise Cost (C_{2-1-7})		0
		Discount on Property Values (C_{2-1-8})		0.052
		EUAC (C_{2-1-9})		0.0091
	Environmental Impact (C_{2-2})	*Emissions Quantity (C_{2-2-1})*	*Total SO_X emissions ($C_{2-2-1-1}$)*	*0.019*
			Total NO_X emissions ($C_{2-2-1-2}$)	*0.019*
			Total CO2 emissions ($C_{2-2-1-3}$)	*0.019*
		Noise Quantity above ambient level (C_{2-2-2})		*0.0301*

$\otimes$ refers to the process of the comparison between the optimal solution ($\widetilde{r}_{ij}$) and other alternatives' values per exact selection criterion (r_{ij}), and *LOM* represents the linguistic opinion matrix for the selection approach, as shown in Eq. (10).

$$LOM = \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} \begin{bmatrix} lom_{11} & \cdots & lom_{1n} \\ \vdots & \ddots & \vdots \\ lom_{m1} & \cdots & lom_{mn} \end{bmatrix} \tag{10}$$

Third Stage: In the third stage, three steps were included as follows.

Step 1: Initially, the fuzzification formulation was executed by converting LOM representations provided in the work of (Akram et al., 2023) into a fuzzy LOM using a 2TLT-SFS basis. The processing of the LOM was successfully achieved. In this procedure, the linguistic variables were replaced by 2TLT-SFS, which were determined based on their corresponding membership functions using an LTS $= \{S_0, S_1, \cdots, S_{10}\}$ is outlined in Table 2.

It is essential to understand that two decision-making processes were used in this study: single and group decision-making. Three specialist decision-makers were involved in evaluating the alternatives.

Step 2: After the completion of the fuzzy LOM, the aggregation technique is employed to compute a fuzzy performance score for each alternative in the selection strategy. This is achieved by utilizing the 2-tuple linguistic T-spherical weighting averaging operator (2TLT-SFWA), as shown in Eq. (11).

Step 3: To calculate the crisp performance score for each potential alternative, the defuzzification procedure was determined using Eq. (13).

$$\text{Score}(\mathbb{T}) = \Delta\left(\frac{\Gamma}{2}\left(1 + \left(\frac{\Delta^{-1}(S_\phi, \Phi)}{\Gamma}\right)^q - \left(\frac{\Delta^{-1}(S_\gamma, \Upsilon)}{\Gamma}\right)^q\right)\right). \tag{12}$$

Step 4: The prioritization of all alternatives can be determined following the equation determination discussed earlier in the selection procedure. Each alternative is assigned precise and definitive performance values, which are subsequently ranked in descending order from the most favorable to the least favorable. Priority will be given to the alternative that has achieved the greatest rating score in the selection procedure.

6. Experimental results

In this section, two main results are presented and discussed. The first is the Entropy weighting result for the evaluating criteria used in assessing EBMs in the context of small and medium-sized communities, followed by evaluating results by 2TLTS-FDOSM.

6.1. Weighting determination results using Entropy

This sub-section presents and discusses the weighting Entropy results for the criteria included in the assessment of EBMs. Different sets of processes were executed to generate these results, which have been discussed in detail in Section 4.1. The process begins with the decision matrix formulation, established in Table 1; this was followed by the normalization of its values and then measuring their Entropy to see the degree of variation exhibited by each attribute achievement against its alternative. Next, the uncertainty degree was measured, leading to the final weighting determination, presented in Table 3.

Table 3 shows the weighting results for all the criteria are established. It should be noted that a total of ($n = 19$) final set criteria have been assessed in both C_1 (*Vehicle Factors*) and C_2 (*External Factors*) aspects. Out of all the criteria, the "*Battery Cost*" (*$C_{2-1-5-1}$*) with a value (*0.258035378*) has been designated as the most crucial criterion for assessing EBM models, and that does not come as a surprise given that EBM models are primarily functions on electricity, and consumers have always given it through consideration in their purchase decisions. The following most crucial criterion have been attributed to none other than "*Hours of continuous Operation*" (*C_{1-3-2}*) with value (*0.225969138*), which also, in reality, shows that intention purchase for EBM considers how much a bus can go without stopping to get as many customers and more profit. This significance can be seen in that the following most crucial criterion, "*Range/Km*" (*C_{1-3-1}*), was also linked to the distance range a bus can go full charge with value (*0.217*). All the remaining criteria have been assigned with different importance levels based on EBMs performance recorded.

Notwithstanding, some interesting facts have come to light. To start with, the worst two performing criteria have been attributed to *"Maintenance Cost \$=year" (C_{2-1-4})* and *"Noise Cost \$=year" (C_{2-1-7})*, where each of their importance value has been recorded as (*0*), indicating lowest levels of importance. Such findings are not surprising given that each EBM considered in the assessment process against these criteria has

$$2TLT - SFWA\{\mathbb{T}_1, \mathbb{T}_2, \cdots, \mathbb{T}_r\} = \left(\Delta\left(\Gamma \sqrt[q]{1 - \prod_{i=1}^{r}\left(1 - \left(\frac{\Delta^{-1}(S_\phi, \Phi)}{\Gamma}\right)^q\right)^{w_i}}\right), \Delta\left(\Gamma \prod_{i=1}^{r}\left(\frac{\Delta^{-1}(S_\psi, \Psi)}{\Gamma}\right)^{w_i}\right), \Delta\left(\Gamma \prod_{i=1}^{r}\left(\frac{\Delta^{-1}(S_\gamma, \Upsilon)}{\Gamma}\right)^{w_i}\right)\right). \tag{11}$$

Table 4
Expert Opinion Matrix.

Criteria/Alternatives	9-E (A1)			10-E (A2)			11-E (A3)			12-E (A4)			13-E (A5)			14-E (A6)		
	E1	E2	E3	E1	E2	E3	E1	E2	E3	E1	E2	E3	E1	E2	E3	E1	E2	E3
$C_{1\text{-}1}$	S.D	S.D	D	D	D	D	D	D	D	N.D	N.D	N.D	H.D	B.D	B.D	H.D	B.D	B.D
$C_{1\text{-}2}$	H.D	H.D	B.D	D	S.D	S.D	D	S.D	S.D	N.D	N.D	N.D	B.D	H.D	B.D	B.D	H.D	B.D
$C_{1\text{-}3\text{-}1}$	H.D	H.D	H.D	N.D	N.D	N.D	N.D	N.D	N.D	B.D	H.D	H.D	B.D	H.D	H.D	B.D	H.D	H.D
$C_{1\text{-}3\text{-}2}$	H.D	H.D	H.D	N.D	N.D	N.D	N.D	N.D	N.D	D	H.D	B.D	D	H.D	B.D	D	H.D	B.D
$C_{1\text{-}4}$	N.D	N.D	N.D	S.D	N.D	N.D	S.D	N.D	N.D	D	S.D	D	D	S.D	D	B.D	S.D	B.D
$C_{2\text{-}1\text{-}1}$	H.D	H.D	H.D	B.D	H.D	H.D	N.D	N.D	N.D	H.D	H.D	H.D	H.D	H.D	H.D	H.D	H.D	H.D
$C_{2\text{-}1\text{-}2}$	B.D	H.D	H.D	B.D	H.D	H.D	B.D	H.D	H.D	H.D	H.D	H.D	S.D	D	D	N.D	N.D	N.D
$C_{2\text{-}1\text{-}3}$	N.D	N.D	N.D	B.D	H.D	D	B.D	H.D	D	H.D	H.D	D	H.D	H.D	D	B.D	H.D	D
$C_{2\text{-}1\text{-}4}$	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
$C_{2\text{-}1\text{-}5\text{-}1}$	B.D	D	H.D	H.D	H.D	H.D	H.D	H.D	H.D	B.D	D	H.D	B.D	D	D	N.D	N.D	N.D
$C_{2\text{-}1\text{-}5\text{-}2}$	D	H.D	B.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
$C_{2\text{-}1\text{-}6}$	H.D	H.D	B.D	B.D	H.D	B.D	N.D	N.D	N.D	H.D	H.D	H.D	B.D	D	B.D	B.D	D	B.D
$C_{2\text{-}1\text{-}7}$	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D	N.D
$C_{2\text{-}1\text{-}8}$	D	B.D	B.D	D	B.D	B.D	D	B.D	B.D	D	B.D	B.D	S.D	D	D	N.D	N.D	N.D
$C_{2\text{-}1\text{-}9}$	N.D	N.D	N.D	D	B.D	N.D	D	B.D	N.D	H.D	B.D	B.D	H.D	B.D	H.D	H.D	B.D	H.D
$C_{2\text{-}2\text{-}1\text{-}1}$	H.D	H.D	B.D	B.D	H.D	B.D	N.D	N.D	N.D	H.D	H.D	B.D	H.D	H.D	B.D	H.D	H.D	B.D
$C_{2\text{-}2\text{-}1\text{-}2}$	H.D	B.D	H.D	D	B.D	H.D	N.D	N.D	N.D	H.D	H.D	H.D	H.D	H.D	H.D	H.D	H.D	H.D
$C_{2\text{-}2\text{-}1\text{-}3}$	H.D	H.D	B.D	B.D	H.D	B.D	N.D	N.D	N.D	H.D	H.D	B.D	H.D	H.D	B.D	H.D	H.D	B.D
$C_{2\text{-}2\text{-}1}$	B.D	H.D	B.D	B.D	H.D	B.D	B.D	H.D	B.D	B.D	H.D	B.D	N.D	N.D	N.D	B.D	B.D	S.D

E = *Expert.*
H.D = *Huge Difference*, B.D = *Big Difference*, D = *Difference*, S.D = *Slight Difference*, N.D = *No Difference.*

achieved the same results and that, according to the Entropy concept, shows no variation degree and is thus deemed less significant compared with others. This can change in other circumstances should more EBM models be considered in the future, but for the current case at hand, these were the findings. Finally, the criteria that acquired the least measured weight was attributed to "*Gradeability" ($C_{1\text{-}4}$)*, which was recorded with a value (*0.0078*). It cannot be surprising that in small and medium-sized communities, most bus operations are not within inclining distance like those on the mountains, and should EBMs be utilized in different residential settings, this criterion might have been given more priority. All the remaining criteria have been assigned importance values between the best and worst criteria value, and as the value of a criterion gets higher, the most it reflects its importance in purchase decisions for any of the EBMs models included. All these weighting results now clearly indicate what each criterion's importance represents in the decision-making context, and the following results will show the assessment of all the EBMs considered in this study in light of the weights generated.

6.2. EBMs evaluation using 2-tuple linguistic T-spherical fuzzy decision by opinion score method

This sub-section presents the EBM evaluation results using 2TLTS-FDOSM. The evaluation procedure began once the Entropy-based weighting was finalized. Three experts have provided feedback on the EBMs' effectiveness in this study. These professionals have more than seven years of experience conducting computer science research focused on energy applications and decision support systems, and their findings have been presented at international conferences and published in high-impact academic journals, which made them suitable candidates for the evaluation process in the context of this research. Consequently, this process resulted in three distinct opinion matrices in line with FDOSM's original philosophy, as seen in Table 4.

As shown in Table 4, three opinion matrices were represented using a 5-point Likert scale; each presents a unique expert perspective regarding their overall assessment of the EBMs included in this work. The assessment process was established by allowing each expert to express his/her point of view for each EBM against its peers while considering its criteria for performance achievement. The process was applied for each expert individually across the ($n = 19$) final criteria. After this Step, each linguistic term was transformed into its fuzzy equivalence. After that, these fuzzy equivalence results were computed for each expert to obtain the final evaluation results, which in this MCDM analysis represent group decision-making (GDM) contexts, as seen in Table 5.

Table 5 represents the final evaluation results for the EBMs considered in this study based on group decision-making (*GDM*) context. The importance levels of the three experts expressed earlier resulted in having three sets of ranking scenarios, each representing its designated expert. However, during the evaluation process, it turned out that each expert's preferences computation after using the weights and later using 2TLT-FDOSM for the evaluation resulted in the same rank for each expert despite having slightly different scores. In such a scenario, the presentation of expert final evaluation results is not needed. The GDM context is a much more unified approach given that no evaluation ranking differences were observed, and thus, representing EBMs evaluation from the GDM context is more suitable. The table demonstrates the "*Fuzzy Performance Score*," "*Crisp Performance Score*," and the final rank. The higher the score, the better evaluation an EBM got, making it better

Table 5
GDM Results.

Expert	Alternative	EBMs	Fuzzy score	Crisp Score
GDM	$A1$	9-E	$\langle(S_3, 0.3110)(S_2, -0.4741)(S_7, 0.3814)\rangle$	0.542
	$A2$	10-E	$\langle(S_7, 0.4449)(S_1, 0.2947)(S_3, 0.0057)\rangle$	1.447
	$A3$	11-E	$\langle(S_8, -0.1661)(S_1, 0.2164)(S_3, -0.4957)\rangle$	1.536
	$A4$	12-E	$\langle(S_4, 0.1129)(S_2, -0.1014)(S_7, -0.4476)\rangle$	0.704
	$A5$	13-E	$\langle(S_4, 0.3866)(S_2, 0.4058)(S_6, 0.0960)\rangle$	0.763
	$A6$	14-E	$\langle(S_7, -0.0440)(S_1, 0.4955)(S_4, -0.4137)\rangle$	1.333
$A3 > A2 > A6 > A5 > A4 > A1$				

in ranking than its peers. A total of ($n = 6$) EBMs were considered, and the best ranking one was attributed to 11-E ($A3$) which acquired the highest score (*1.536*), followed by 10-E ($A2$) as the second best with score (*1.448*). The third-best EBM was achieved by 14-E ($A6$) with score (*1.333*). The last three EBMs performed lowest in the evaluation process rank as follows 13-E ($A5$) ranked 4th with score (*0.763*), followed by 12-E ($A4$) with score (*0.704*), and finally the last ranked and worst performing one 9-E ($A1$) with lowest score (*0.542*).

It should be noted that when implementing the entropy method, a major obstacle was faced. The data of two criteria was incomplete, "*the average discount on property values*" criterion and "*the noise quantity above ambient level*" criterion. Herein, to estimate these missing values, we had to rely on the experts' evaluations used in the 2TLTS-FDOSM technique. From the first expert's opinion, the performance of 14-E ($A6$) for "*the average discount on property values*" does not differ from the optimal performance, and that of the 13-E ($A5$) differs slightly. Since "*the average discount on property values*" is a benefit criterion, the maximum value is the best. Hence, from Table 4, "*ND*" corresponds to the value 6.04 %, and "SD" corresponds to the value 3.32 %. Making a reduction with the same decrement pattern, we get the equivalent value of his "*D*" evaluation as 1.83 %. The third expert also evaluated the performance of 14-E ($A6$) as the best, and his "*ND*" also corresponds to the value of 6.04 %.

Meanwhile, his evaluation of 13-E ($A5$) differs significantly from the best, giving a "*D*" evaluation. Therefore, his "*D*" corresponds to the value 3.32 %. Tracking the decrement pattern, we get 1.96 % as the equivalent value for his "*BD*". Then, "*the average discount on property values*" criterion is given an equivalent evaluation of 1.83 % and 1.96 % for the first four alternatives by the first expert and the third expert, respectively. Consequently, we assign the first four alternatives the mean value of these two experts, which is 1.9 % for this criterion. For the criterion "*the noise quantity above ambient level*", from Table 4, the three experts agreed on the 13-E ($A5$) to have the best performance. As this criterion is a cost criterion, the best value is the minimum. From Table 4, "ND" corresponds to the value 8.4 for the three experts. We also have "*BD*" equivalent to 15.3 from the first and second experts' opinions, and "*SD*" corresponds to 15.3 from the third expert's opinion. Following the increment pattern of each expert, "*BD*" for the first expert is 15.3, "*HD*" for the second expert is 17.6, and "*BD*" for the third expert is 29.1. Taking the average of these three values, the first four alternatives are assigned the value 20.67 for this criterion. After completing these ranking results, and in order to ensure the reliability and validity of the findings, it is imperative to conduct robustness checks. Additionally, a thorough assessment procedure should be implemented to assess the outcomes of the ranking and criteria weights, as elaborated on in the subsequent section.

7. Sensitivity analysis

Validation and verification of the EBMs to assess their feasibility for utilization in small and medium-sized communities have been conducted. Such assessment means MCDM research can be applied through sensitivity analysis (Talal et al., 2023). It is a method applied to change the criteria weight to assess their impact on the overall final ranking/evaluation for the EBMs in this study. There are various ways in which sensitivity analysis can be conducted through different application settings and weighting scenarios. When different scenarios are used, it becomes possible to assess the effectiveness of the criteria in contributing to the overall results. This method is particularly useful in understanding how sensitive the outcomes are to changes in the weights assigned to the criteria (Basil et al., 2023). As indicated earlier, there are different ways in which sensitivity analysis can be conducted; in the context of this research, sensitivity analysis has been applied through 4 main scenarios. In each scenario, weighting settings are adjusted to generate a new set of weights. In the first three scenarios, quarter of the original weight of each of the highest three criteria "*Battery Cost*" ($C_{2\text{-}1\text{-}5\text{-}1}$), "*Range Distance/KM*" ($C_{1\text{-}3\text{-}1}$), and "*Hours of cont. operation*" ($C_{1\text{-}3\text{-}2}$) has been replaced (*according to each scenario*) with their original values, and the remaining weighting values have been equally divided over the remaining ($n = 16$) criteria (*without considering the two criteria which achieved 0 value*). As for the fourth scenario, the same concept was applied while considering all three main criteria together, as shown in Table 6.

Table 6 presents the new set of weights for the new evaluation process. These weighting scenarios are based on the explanation mentioned above, and their main aim is to show how much of a difference the change in weights can affect the evaluation/ranking process. These new weights have been again introduced to the 2TLT-FDOSM method to re-evaluate the EBMs, as shown in Table 7.

As seen in Table 7, 4 sensitivity analysis scenarios were applied, and their scores and new ranks were presented and compared with the original weight-based rank. It is seen that only the best ($A3$), and the worst alternatives ($A1$) only maintained their ranking consistently with the original across all four scenarios. This shows that their dominance and weight introduction did not affect their overall rank. On the other hand, new weight sets have shown some effect on overall rank, especially between the 2nd best ($A2$) original which became the 3rd best in scenarios ($S1$, $S2$, and $S4$) respectively. Other differences are seen in Table 7, but for a more precise visual representation, the following Fig. 1

Table 6
Sensitivity Analysis Results.

Criteria	Original Weight	S1	S2	S3	S4
$C_{1\text{-}1}$	0.036130975	0.046299868	0.046723278	0.048226	0.068988
$C_{1\text{-}2}$	0.01181784	0.021986733	0.022410143	0.023913	0.044674
$C_{1\text{-}3\text{-}1}$	0.216936394	0.054234099	0.227528698	0.229031	0.054234
$C_{1\text{-}3\text{-}2}$	0.225969138	0.236138032	0.056492285	0.238064	0.056492
$C_{1\text{-}4}$	0.007828378	0.017997271	0.018420681	0.019923	0.040685
$C_{2\text{-}1\text{-}1}$	0.019044035	0.029212928	0.029636338	0.031139	0.051901
$C_{2\text{-}1\text{-}2}$	0.043281897	0.05345079	0.0538742	0.055377	0.076139
$C_{2\text{-}1\text{-}3}$	0.008129469	0.018298363	0.018721773	0.020224	0.040986
$C_{2\text{-}1\text{-}4}$	0	0	0	0	0
$C_{2\text{-}1\text{-}5\text{-}1}$	0.258035378	0.268204272	0.268627682	0.064509	0.064509
$C_{2\text{-}1\text{-}5\text{-}2}$	0.010086564	0.020255457	0.020678867	0.022182	0.042943
$C_{2\text{-}1\text{-}6}$	0.013774934	0.023943828	0.024367237	0.02587	0.046632
$C_{2\text{-}1\text{-}7}$	0	0	0	0	0
$C_{2\text{-}1\text{-}8}$	0.052314641	0.062483534	0.062906944	0.06441	0.085171
$C_{2\text{-}1\text{-}9}$	0.009108017	0.01927691	0.01970032	0.021203	0.041965
$C_{2\text{-}2\text{-}1\text{-}1}$	0.019044035	0.029212928	0.029636338	0.031139	0.051901
$C_{2\text{-}2\text{-}1\text{-}2}$	0.01919458	0.029363474	0.029786884	0.03129	0.052051
$C_{2\text{-}2\text{-}1\text{-}3}$	0.019119307	0.029288201	0.029711611	0.031214	0.051976
$C_{2\text{-}2\text{-}1}$	0.030184419	0.040353312	0.040776722	0.042279	0.063041

S = Scenario.

Table 7
Sensitivity Analysis-based EBM Evaluation.

Alternative/Scenario	Original		*S*1		*S*2		*S*3		*S*4	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
*A*1	0.542	6	0.684	6	0.689	6	0.643	6	0.872	6
*A*2	1.447	2	1.286	3	1.278	3	1.509	2	1.073	3
*A*3	1.536	1	1.464	1	1.460	1	1.629	1	1.450	1
*A*4	0.704	5	0.810	5	0.781	5	0.791	5	0.931	4
*A*5	0.763	4	0.846	4	0.825	4	0.800	4	0.908	5
*A*6	1.333	3	1.393	2	1.384	2	1.072	3	1.178	2

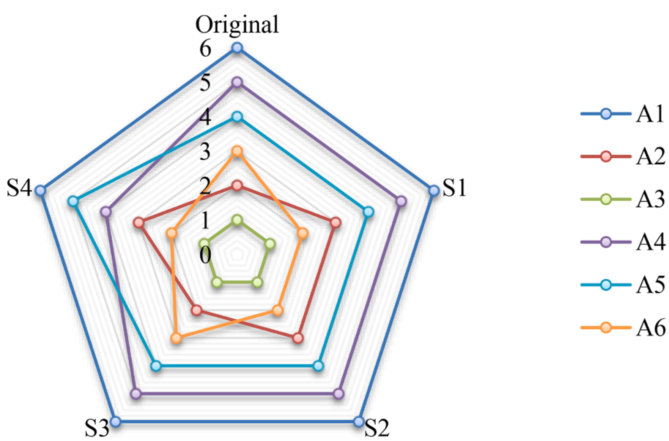

Fig. 1. Sensitivity Analysis-Based New EBMs Evaluation's Visualization.

is presented.

As seen in Fig. 1, the sensitivity analysis visualization is presented; while considering the four scenarios mentioned, it is clear that there are some similarities and differences. Only *A*1, and *A*3 maintained consistent ranking when compared with the original. On the other hand, none of the remaining alternatives maintained a 100 % consistent ranking with the original, and there were some slight differences. Such findings emphasize the importance of thoughtful weight allocation in decision-making processes to ensure well-informed choices in EBMs for small and medium-sized communities.

8. Study implications

Assessing the viability of implementing electric bus models in small and medium-sized communities carries substantial implications across multiple dimensions. Firstly, this approach offers a means to measure and assess the potential environmental advantages, such as mitigating greenhouse gas emissions, air pollution, and noise pollution. These quantifiable benefits are crucial in pushing for sustainable transport policy and getting financial support. Furthermore, through the implementation of cost-benefit analyses, this study has the potential to provide valuable insights into the enduring economic benefits, specifically for smaller communities that face financial limitations. These benefits involve reductions in energy consumption and maintenance expenses.

Furthermore, it guides infrastructure planning, explicitly addressing the distinctive obstacles these towns may have in developing essential charging infrastructure suitable for electric buses and other transportation modes. Furthermore, assessing the public health implications, such as the enhancement of air quality achieved by appropriately choosing evidence-based interventions, can contribute to the cultivation of community backing and attract the notice of municipal authorities. Moreover, this raises concerns regarding the capacity and modernization of the energy grid to ensure that the integration of electric buses is in line with the energy resources and capabilities of the region. This research has the potential to yield technological breakthroughs specifically designed to cater to the requirements of these communities, hence stimulating innovation in the development of electric bus models. Furthermore, it plays a role in developing laws and regulatory frameworks that promote and streamline the implementation of electric buses in smaller communities. Gaining knowledge from successful case studies and implementing best practices offers significant insights for other communities contemplating the deployment of electric buses.

9. Conclusion

From a global perspective, an increased awareness has been directed towards GHG emissions and their adverse effects, which can be observed in light of energy's global reliance on fossil fuels and the increasing population demands. Governmental authorities and organizations worldwide are producing various GHG countermeasure initiatives in many fields, especially transportation. For that, the development of renewable energy transportation options like electric vehicles is greatly sought after since they bring a cleaner environment at a lower cost. Nevertheless, despite electrical vehicles benefits, they still produce emissions indirectly in power plants generating the electricity in which they operate, which could have a notable effect on small and medium communities. Toward that end, it was necessary to evaluate the performance of such modes of transportation while considering the significant factors and criteria that could affect the evaluation process.

However, previous academic works in this domain have not thoroughly addressed the implementation of a comprehensive decision-making support system that provides recommendations for electric vehicles. These recommendations should take into account various assessment criteria, their respective levels of significance, and the potential conflicts between their values, particularly when evaluating multiple electric vehicle models. The objective of this study was to tackle the concerns above by presenting a comprehensive MCDM methodology that was deemed suitable for the specific case study in question. This methodology involved the utilization of two MCDM approaches, namely Entropy and FDOSM, to assess and evaluate the EBM models. These approaches were employed for the purpose of weighting the assessment criteria of the EBMs and evaluating the existing EBMs. The research introduces the FDOSM approach, which is developed within a unique 2TLTS environment. This method aims to tackle the theoretical challenge of improving assessments when there are uncertainties and inconsistencies among decision-makers. The main contributions of this study include the development of a novel decision matrix for evaluating electrical bus models, the implementation of an objective assessment method using Entropy to determine the importance of assessment criteria for the electrical bus models, and the identification of the most suitable electrical bus model for small and medium-sized communities using the 2TLTS-FDOSM approach. The robustness of the proposed approach was confirmed using a sensitivity analysis.

However, a limitation of this study was the failure to consider the relative contribution or importance of each expert's knowledge or viewpoints. This oversight might potentially impact the final determination of criteria weights and the selection of alternatives in the case study under investigation, as well as any prospective future cases. One of our forthcoming endeavors involves addressing this issue through the proposition of a novel mechanism for assigning distinct weights to individual experts, which can subsequently be utilized in the determination of criteria weights. An alternate evaluation process will follow this. In conclusion, the integration of novel fuzzy sets and precise fuzzy operators with the suggested MCDM techniques holds promise as a potential avenue for future scholarly contributions.

CRediT authorship contribution statement

A.H. Alamoodi: Writing – original draft. **O.S. Albahri:** Writing – original draft. **Muhammet Deveci:** Conceptualization, Writing – review & editing, Visualization. **A.S. Albahri:** Conceptualization, Methodology. **Salman Yussof:** Conceptualization. **Hasan Dinçer:** Project administration. **Serhat Yüksel:** Writing – review & editing. **Iman Mohamad Sharaf:** Writing – review & editing.

Declaration of competing interest

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

Data availability

The data that has been used is confidential.

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